Automatic Monitoring of Physical Activity Related *Affective* States for Chronic Pain Rehabilitation

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I, **Temitayo A. Olugbade**, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Date ________________________

ABSTRACT

Chronic pain is a prevalent disorder that affects engagement in valued activities. This is a consequence of cognitive and affective barriers, particularly low self-efficacy and emotional distress (i.e. fear/anxiety and depressed mood), to physical functioning. Although clinicians intervene to reduce these barriers, their support is limited to clinical settings and its effects do not easily transfer to everyday functioning which is key to self-management for the person with pain. Analysis carried out in parallel with this thesis points to untapped opportunities for technology to support pain self-management or improved function in everyday activity settings. With this long-term goal for technology in mind, this thesis investigates the possibility of building systems that can automatically detect relevant psychological states from movement behaviour, making three main contributions.

First, extension of the annotation of an existing dataset of participants with and without chronic pain performing physical exercises is used to develop a new model of chronic disabling pain where anxiety acts as mediator between pain and self-efficacy, emotional distress, and movement behaviour. Unlike previous models, which are largely theoretical and draw from broad measures of these variables, the proposed model uses event-specific data that better characterise the influence of pain and related states on engagement in physical activities. The model further shows that the relationship between these states and guarding during movement (the behaviour specified in the pain behaviour literature) is complex and behaviour descriptions of a lower level of granularity are needed for automatic classification of the states. The model also suggests that some of the states may be expressed via other movement behaviour types.

Second, addressing this using the aforementioned dataset with the additional labels, and through an in-depth analysis of movement, this thesis provides an extended taxonomy of bodily cues for the automatic classification of pain, self-efficacy and emotional distress. In particular, the thesis provides understanding of novel cues of these states and deeper understanding of known cues of pain and emotional distress. Using machine learning algorithms, average F1 scores (mean across movement types) of 0.90, 0.87, and 0.86 were obtained for automatic detection of three levels of pain and self-efficacy and of two levels of emotional distress respectively, based on the bodily cues described and thus supporting the discriminative value of the proposed taxonomy.

Third, based on this, the thesis acquired a new dataset of both functional and exercise movements of people with chronic pain based on low-cost wearable sensors designed for this thesis and informed by the previous studies. The modelling results of average F1 score of 0.78 for two-level detection of both pain and self-efficacy point to the possibility of automatic monitoring of these states in everyday functioning.

With these contributions, the thesis provides understanding and tools necessary to advance the area of pain-related affective computing and groundbreaking insight that is critical to the understanding of chronic pain. Finally, the contributions lay the groundwork for physical rehabilitation technology to facilitate everyday functioning of people with chronic pain.

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TABLE OF CONTENT

List of Abbreviations

BIC	Bayesian Information Criterion
BLE	Bluetooth Low Energy
CP	Chronic pain
DIP	Dual in-line package
HADS	Hospital Anxiety and Depression Scale
ICC	Intraclass correlation
IMU	Inertia measurement unit
MHG	Marple-Horvat-Gilbey
MRSE	Movement related self-efficacy
RF	Random Forest
RQ	Research question
sEMG	Surface electromyography
SVM	Support Vector Machine
UCL	University College London

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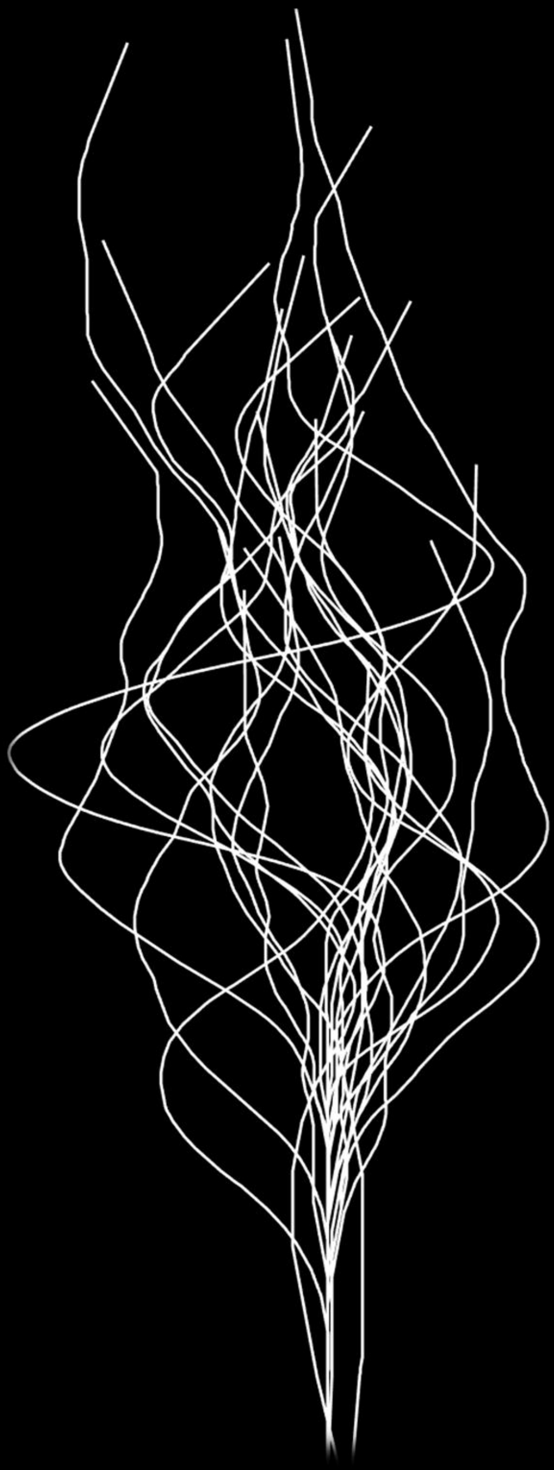

we move as we feel

Honourable Mention, UCL Research Images as Art. 2016-17
(based on graphical plots of the Ubi-EmoPain dataset acquired in the investigation of this thesis)

To **Almighty God**, in whom are hid all the treasures of wisdom and knowledge.

Colossians 2:3
The Holy Bible
(King James Version)

1 INTRODUCTION

"Actions of all kinds, if regularly accompanying any state of mind, are at once recognized as expressive. These may consist of movements of any part of the body, … the shrugging of a man's shoulders, … laboured breathing…, and the use of the vocal ... It has often struck me as a curious fact that so many shades of expression are instantly recognized without any conscious process of analysis on our part."

Charles Darwin (1898, 349–59)

THIS thesis addresses the problem of automatic monitoring of cognitive and affective states that influence physical functioning in chronic pain (CP).

> Chronic pain is a condition where pain persists in the absence of tissue damage and is associated with dysfunctional changes in the nervous system
>
> (Tracey and Bushnell 2009).

This is an important application area as CP is a disabling long-term condition that affects engagement in valued physical activities (The Pain Consortium 2016). The condition also places immense burden on the capacities of healthcare systems in many countries including United Kingdom (The Pain Consortium 2016). Technology is increasingly being seen as a practical tool to facilitate and support long-term management of this condition (Jamison 2016). Indeed, technology could be used to provide intervention remotely, facilitate more economical use of both healthcare resources (on the part of the healthcare service provider) and self-management resources (on the part of the healthcare service recipient) (Zhu and Cahan 2016). Such technology enables provisions of intervention in situ rather than in controlled clinical settings that are not reflective of the challenge in everyday life (Singh, Bianchi-Berthouze, and Williams 2017). Technology also offers the opportunity to continuously capture relevant variables (e.g. movement behaviour) that can inform personalisation for more effective intervention and self-management (Zhu and Cahan 2016; Felipe et al. 2015).

However, while technology that promotes physical rehabilitation has been gaining widespread adoption in recent years, current designs overlook factors that are critical in CP. In this condition, cognitive and affective factors (particularly self-efficacy, fear/anxiety, and depressed mood) significantly contribute to physical functioning outcomes (Vlaeyen, Morley, and Crombez 2016; Asghari and Nicholas 2001). Yet, the state of the art in physical rehabilitation technology is based on design frameworks that focus on engagement in biomechanical terms and in terms of motivation (e.g. interest) to the exclusion of critical cognitive and affective states. Biomechanical measures are not as relevant in CP as they are in acute conditions (such as a sprain) because of the absence of related physical damage from which to recover. Further, while motivation may be a significant consideration when designing to promote physical exercising, it plays a lesser role than pain and related states in engagement in valued activities.

Recent studies such as Singh et al. (2014) that incorporate initial findings on the perspective of people with CP in addition to that of physiotherapists show that physiotherapists aim to help people with CP develop skills to understand and address cognitive (e.g. self-efficacy) and affective (e.g. fear of pain, depressed mood) barriers they face beyond lack of motivation. The study of Singh et al. (2014) also provides evidence that people with CP and their physiotherapists adapt strategies to reduce exposure to negative affective states and promote the use of helpful cognitive strategies to enable physical functioning. The attention that the physiotherapists pay to how the movement of a person with CP is executed is mainly aimed at detecting psychological barriers to engagement with it to be able to provide appropriate support. These findings highlight the need for technology for CP physical rehabilitation to address cognitive and affective barriers in an active and constructive way that is directed towards facilitating functioning. The approach taken by such technology should go beyond logging of emotional states in the form of self-report diaries which is usually used to support post-activity reflection or clinical consultation (Hollis, Konrad, and Whittaker 2015; Li, Dey, and Forlizzi 2012; Longqi Yang et al. 2016) as this does not enable real-time addressing of negative states. Work reported in Olugbade et al. (in review) and inspired by this thesis (but not reported here) with initial work with patients and physiotherapists in Singh et al. (2014) provides a deeper understanding of the forms of real-time support people with CP need to overcome the psychological barriers they encounter while performing everyday physical activities. These analyses revealed opportunities for technology to address these barriers directly as they occur, in addition to opportunities for informed post-activity reflection.

Leveraging of these opportunities, however, requires the capability to automatically detect these states during physical activity so as to enable real-time tailoring of interventions when the need arises and to make available relevant information that enables helpful reflection in the longer term (Olugbade et al., in review). This thesis addresses this requirement.

The thesis contributes to the areas of affective computing and technology for rehabilitation and various areas of pain research. An overview of the thesis is given in the rest of the chapter with an introduction of the research questions and contributions of the thesis in Section 1.1, a list of publications that have resulted from the thesis in Section 1.2, and an outline of the structure of the rest of the thesis in Section 1.3.

1.1 Thesis Contribution

There were three main research questions investigated in this thesis to address the problem of automatic monitoring of pain and related self-efficacy and emotional distress (fear/anxiety and depressed mood) in everyday physical activity settings. Fig. 1.1 gives an overview of these questions and they are discussed in this section.

The first question that needs to be addressed in designing any affect-aware system is of the affective modalities that should be used for assessing the cognitive or affective states of interest, bearing in mind the modalities that further inform intervention in response to detected cognitive or affective needs. The literature on CP suggests that observable pain behaviours (such as bodily, facial, and (para)verbal expressions) are modalities for assessing such experiences in the context of pain (Keefe and Block 1982). Bodily expressions have particularly been identified as the critical one of these behaviour forms as they appear to have a protective role (amongst others), suggesting that they are typically responses intended to minimise threat or harm (Sullivan et al. 2006). Conversely, facial and verbal expressions have a mainly communicative role (e.g. to elicit support) (Sullivan et al. 2006). The action tendency encapsulated in bodily expressions makes them of further significance in providing understanding of how a person with CP engages in physical activity, such as his/her capabilities and the strategies (which may be maladaptive, in exacerbating pain, and need to be disrupted) used to cope with pain experience. Such understanding feeds into clinical intervention. Yet, despite the importance of bodily expressed pain behaviours, formal understanding on them is still limited.

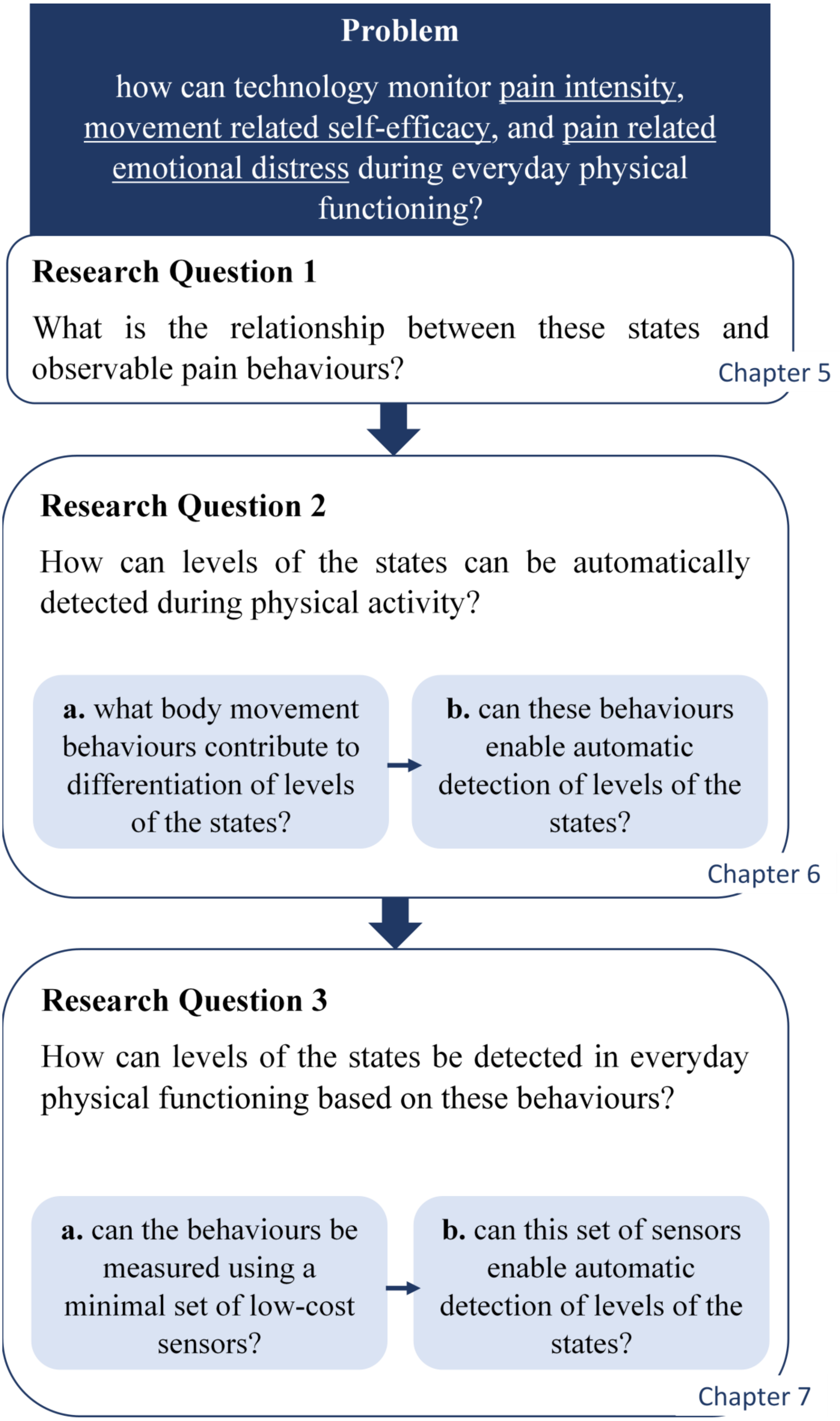

Fig. 1.1. The research questions investigated in this thesis and the chapters where the investigations are reported

A method (Keefe and Block 1982) that specifies three examples of these behaviours (in addition to one facially expressed behaviour and one vocally expressed behaviour) remains the main approach used in assessing pain behaviours. Unfortunately, this form of assessment has usually only been compared with self-report of pain intensity to the exclusion of other psychological factors that are more relevant to behaviour (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004). On the other hand, theories of pain that guide understanding of the influence of pain and related cognitive and affective states on engagement in physical activities have mainly been based on broad physical functioning outcomes (e.g. disability) rather than low level behaviour measures (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004). Further, the proposed assessment method of Keefe and Block has focused on the role of bodily expressed pain behaviours as fear responses whereas other states (e.g. self-efficacy, depressed mood) may contribute to the emergence of other (roles of) pain behaviours (Sullivan 2008). It is, thus, important and timely to address the question, *what is the relationship between observable pain behaviours and pain and related self-efficacy and emotional distress?*, if the extent to which these pain behaviours (as specified in the pain behaviour literature (Keefe and Block 1982)) can be considered a measure of these states is to be understood.

The second question that then needs to be addressed in building the proposed affect-aware system is the question of how bodily expressed pain behaviours enable assessment of pain and related cognitive and affective states. Although bodily expressions have been investigated in the area of affective computing and shown to be an informative and powerful affective modality (e.g. in Fourati and Pelachaud (2015), Kleinsmith, Bianchi-Berthouze, and Steed (2011)), the understanding of how the body expresses pain, movement related self-efficacy, anxiety about pain, or depressed mood in the context of CP is very limited. To build such understanding, there needs to be investigation beyond exploration of gross bodily expressed pain behaviours (e.g. physical activity levels), and specific bodily behaviour signatures need to be analysed. The need for this approach emerges from the results of investigation of the first question that show that the relationship between these states and bodily behaviour specified in pain behaviour literature is complex and fine-grained descriptions of such motor patterns are necessary for automatic classification of the states. This approach addresses the call in pain literature for research into specific strategies used by people with CP in engaging in physical activity (Huijnen et al. 2011) and into deeper understanding of dimensions of bodily expressed pain behaviours with respect to pain and related cognitive and affective states (Sullivan 2008).

Further, the bodily cues need to be considered in terms of both overt expressions and the less explored (in affective computing) muscle activity. The significance of muscle activity in analysing bodily expressed behaviour is supported by findings in both affect studies (Huis In ’t Veld, Van Boxtel, and de Gelder 2014a; Huis In ’t Veld, Van Boxtel, and de Gelder 2014b) and pain literature (Watson et al. 1997; Watson, Booker, and Main 1997). Investigation of the second question was, thus, aimed at contributing a taxonomy of low level bodily behaviours of each of the states investigated and formulae to extract them from movement data, and so enable the design of affect-aware systems that can monitor each of the behaviours during everyday functioning or even in clinical assessment. Such tools can further enable grounding of theoretical models of pain on objectively measured behaviour and better understanding of cognitive and affective dimensions of behaviour. To this end, the thesis addressed the question: *how can the levels of pain and related self-efficacy and emotional distress be automatically detected from bodily expressed pain behaviours during physical activity?*

A third question is on how to integrate affect-aware capability into the setting where physical rehabilitation really takes place. Therapy sessions and situated self-managed exercises are not the main setting where physical rehabilitation occurs for people with CP (Singh et al. 2014; Felipe et al. 2015; Singh, Bianchi-Berthouze, and Williams 2017). Rather, it is everyday functional activity as people with CP have limited physical and psychological resources which they dedicate to functioning in preference to exercising (Singh et al. 2014; Felipe et al. 2015). Further, functional activities are the target of rehabilitation as they directly translate to valued goals (Singh et al. 2014; Papi, Belsi, and McGregor 2015; Singh, Bianchi-Berthouze, and Williams 2017). It is, thus, necessary to understand how affect detection from bodily expressed pain behaviours can be done in everyday settings. One of the problems that must be addressed is the possibility of capturing these behaviours in these settings. Unlike situated exercises, functional activities occur in ubiquitous settings where sensors need to be portable, and so it is necessary to consider low-cost wearable options and understand the extent to which they allow capture of affective bodily expressions. A second problem is whether the same behaviours that enable affect detection in movements in exercise settings (e.g. forward trunk flexion exercise) are valid for the same movements in functional settings (e.g. reaching forward to pick up an object). These problems were addressed in this thesis with investigation of the question: *how can levels of pain and related self-efficacy and emotional distress be detected from bodily expressed pain behaviours in functional movements?* This is a first step towards understanding the possibility of monitoring these states in the ubiquitous settings of everyday functioning.

In addressing these three questions, three secondary contributions emerged. First, an existing pain dataset, EmoPain dataset, was extended with more reliable physiotherapist annotations of guarding and new annotations of movement related self-efficacy to enable the dataset to be leveraged in addressing the first and second questions. Secondly, to investigate the third question, a new dataset of both exercise and functional movements captured with low-cost sensors was acquired as the EmoPain dataset was of exercise movements only and these were captured using systems which are not portable. Finally, at the time the work in the thesis work started, commercially available low-cost devices for body movement sensing were largely not portable (e.g. Microsoft Kinect), even wearable systems (e.g. Animazoo IGS-190), which were additionally expensive. Thus, a custom-built portable wearable system that measures both bodily expressions and muscle activity was developed. While the system itself is not a contribution, its development and use led to understanding of issues related to the design of such systems for data capture in everyday settings. At the time of finishing this thesis, low-cost portable wearable alternatives have begun to emerge (e.g. Notch (Notch Interfaces Inc. 2016)). However, there is not yet a commercial option for integrated sensing of both overt body movement and muscle activity, and so these findings remain relevant especially as the current commercial devices suffer from similar technical issues.

1.2 Publications

Four major peer-reviewed publications have resulted from the investigations of two of the three research questions (the second and third) of this thesis. Citations for these publications are given below:

1. How Do Affect States Matter In Chronic Pain Technology Intervention? And Can Technology Detect Them?

   Olugbade T. A., Singh A., Bianchi-Berthouze N., Marquardt N., Aung M., Williams A.

   ACM Transactions on Computer-Human Interaction (in review)

2. Human Observer and Automatic Assessment of Movement Related Self-Efficacy in Chronic Pain: from Exercise to Functional Activity.

   Olugbade T. A., Bianchi-Berthouze N., Marquardt N., Williams A.

   IEEE Transactions on Affective Computing (2018)

3. Pain Level Recognition using Kinematics and Muscle Activity for Physical Rehabilitation in Chronic Pain.

   Olugbade T. A., Bianchi-Berthouze N., Marquardt N., Williams A.

   Affective Computing and Intelligent Interaction (2015)

4 Bi-Modal Detection of Painful Reaching for Chronic Pain Rehabilitation Systems.
Olugbade T. A., Aung M., Marquardt N., Williams A., Bianchi-Berthouze N.
International Conference on Multimodal Interaction (2014)

A publication resulting from the investigation of the first question is in preparation for a pain journal:

Disentangling Relationships between Pain Behaviour and Pain Related Cognitive and Affective States.
Olugbade T. A., Bianchi-Berthouze N., Marquardt N., Williams A. (venue decision to be finalised)

1.3 Thesis Structure

The rest of the thesis is composed of four parts that together comprise eight chapters:

Part I - Background & Literature Review consists of two background chapters: Chapters 2 and 3. The first of these chapters, Chapter 2, provides a background on CP and current understanding of the influence of associated cognitive and affective states on engagement in physical activities. In addition, the chapter provides a discussion of the opportunities that exist for technology to address the barriers that these states pose to physical functioning and a review of the gaps that exist with the state of the art in physical rehabilitation technology. Chapter 3 discusses existing knowledge in the area of pain related affective computing. The significance of bodily expressed behaviours as an affective modality and the approaches that exists for capturing them are also discussed in the chapter.

Part II - Research Questions & Methodology has only one chapter (Chapter 4) where the research questions that the thesis addresses and the approach used in investigating them are presented.

Part III - Research Studies consists of Chapters 5-8.

In Chapter 5-7 respectively, the three main studies carried out in addressing the three research questions of the thesis (see Fig. 1.1) are reported and discussed.

In Chapter 5, the investigation of the first research question is presented. In the first section of this chapter, the annotation study with physiotherapists, carried out to extend the existing dataset with annotations for guarding behaviour and self-efficacy is reported. The analysis done to investigate the relationships between guarding behaviour and pain and related self-efficacy and emotional distress is described in the second section. The findings of the analysis are reported and discussed in the third section. Findings of analysis of cues the physiotherapists used in estimating movement related self-efficacy is also reported (in the fourth section). These findings are further discussed in the fifth section, highlighting the contributions made and the implication for relevant areas. The conclusion of the main findings of the chapter is provided in the sixth section.

In Chapter 6, the investigation of the second research question is presented. The chapter is divided into six main sections; the first section introduces the notations used in the chapter. Each of the following three sections cover the investigations for each of pain, self-efficacy, emotional distress. In these three sections, the investigations (and their findings) of the body movement features that contribute to discrimination between level of these states are reported and discussed. The findings of these investigations are together discussed in the fifth section while the main findings are highlighted in the concluding section (the sixth section).

In Chapter 7, the investigation of the third research question is presented. In the first section, the development of the custom-built sensing device is reported while the acquisition of the new dataset based on this device is described in the second section. The methods used for analysis of the data is described in the third section and the findings of the analysis are reported and discussed in the fourth section. The findings of these investigations are discussed at a high level in the fifth section and the conclusion of these findings is summarised in the final section of the chapter.

An overarching discussion of the findings of these studies especially their contributions and the opportunities that they open for future research is done in Chapter 8.

Part I

Background
&
Literature Review

2 Background: Chronic Pain and Its Impact on Physical Functioning in Everyday Life

In this chapter, three main bodies of literature are reviewed. First, literature on CP is reviewed to provide a necessary understanding of the condition, its implication in terms of physical functioning, and the significance of associated cognitive and affective states to the challenges in physical functioning with the condition. This review is important as it provides a background to the topic of the thesis and insight into the needs that motivate the questions addressed in it. Secondly, relevant human-computer interaction literature in the area of CP physical rehabilitation is additionally reviewed to highlight the opportunities for technology to address the challenges of physical functioning for people with CP through attention to these states. Thirdly, the state of the art in physical rehabilitation technology is then reviewed to show that these opportunities have not yet been fully leveraged in the area. The research questions that arise from the review of these bodies of literature are discussed towards the end of the chapter.

The chapter is organised into 6 sections. An overview of CP and the challenges of CP physical rehabilitation are discussed in Section 2.1. In Section 2.2, the current understanding of the relationships between physical functioning outcomes and pain and related cognitive and affective states that make physical functioning challenging is reviewed. In Section 2.3, the opportunities that exist for technology to address these states, and so facilitate physical rehabilitation, are presented. The state of the art in physical rehabilitation technology is reviewed in Section 2.4. The main points of these sections for the topic of the thesis and the questions that emerge from them are discussed in Section 2.5 and a conclusion is provided in Section 2.6.

2.1 Chronic Pain

In this section, a definition of CP is given with a discussion of its implication for physical functioning.

2.1.1 Definition

CP is a prevalent long-term condition (The Pain Consortium 2016) where pain persists in the absence of tissue damage and is associated with dysfunctional changes in the nervous system (Tracey and Bushnell 2009).

Modern understanding of CP draws on the gate control theory of pain (Melzack and Wall 1965) which describes how pain signals are moderated and modulated by cognitive and affective processes in the spinal cord and in subsequent transmission between the spinal cord and the brain. For example, descending pathways (originating from the brain and extending to the spinal cord) selectively inhibit or facilitate pain signals with influence from cognitive and affective processes (Bushnell, Čeko, and Low 2013). In CP, regions and mechanisms involved in such regulations are altered (Bushnell, Čeko, and Low 2013). For instance, there is evidence that in the descending pathways in CP, there is both disturbed inhibition and heightened facilitation which provide a basis for the persistence of a sensitized state in this condition (Tracey and Bushnell 2009). The density of gray matter, which is a critical component of the brain, has also been found to be reduced in CP in regions of the central nervous system that belong to these pathways (Tracey and Bushnell 2009). It has additionally been found that processing of pain signals in the brain is shifted in CP towards regions of the brain involved in the regulation of affect (Tracey and Bushnell 2009). This may contribute to emotional distress experienced by people with CP in the presence of pain related stimuli; such distress may affect cognitive regulation of pain (Tracey and Bushnell 2009). In fact, reduced deactivation of the default mode network regions of the brain (which is a region of the brain known to be typically deactivated in healthy persons while engaged in tasks) during task performance has been found in CP supporting the theory of disruption of normal cognitive processes in the condition (Tracey and Bushnell 2009).

2.1.2 Implication for Physical Functioning

People with CP find harmless movement painful with a major consequence being limited engagement in everyday activities, such as work, family and social interactions, household chores, and leisure activities (Breivik et al. 2006).

It is established that cognitive and affective factors, particularly low movement related self-efficacy (MRSE) and pain related fear/anxiety and depressed mood, significantly contribute to this outcome (Vlaeyen, Morley, and Crombez 2016; Asghari and Nicholas 2001). This understanding has led to a shift, in physical rehabilitation methods, from a focus on the biomechanics of movement execution to a multidisciplinary approach to promoting physical functioning in people with CP. In this contemporary approach, cognitive and affective barriers to movement are addressed to facilitate engagement in physical functioning (Singh et al. 2014). In fact, qualitative evidences in Singh et al. (2014) and Olugbade et al. (in review) illustrate that physiotherapists tailor interventions during structured exercising in pain management programs. For example, in providing instructions for the exercises, they use descriptions that encourage patients to execute the movements in ways that are psychologically comfortable (not necessarily meaning physical comfort or the absence of pain, but non-exacerbation of anxiety about pain or physical integrity) for them rather than implying constraints in how the exercises should be executed (Singh et al. 2014). Such tailoring is based on the physiotherapist's assessment of the cognitive and affective needs of the patient and is aimed at facilitating reduction of negative emotions and appraisals. The interventions are designed to support a person with CP in gradually building capability psychologically and physically so that s/he is able to employ helpful cognitive and behavioural strategies in dealing with everyday physical activities despite pain (Singh et al. 2014; Olugbade et al., in review).

The problem, however, is that the tailored interventions received by people with CP are limited to the structured exercising in these programs and are not available during everyday physical functioning. This is a problem because the self-management skills and capabilities developed during such programs may not readily transfer to everyday physical activities (Turk 2015), whereas these activities are more directly related to valued goals (such as employment) than exercises. The disconnect between exercise and physical activity for people with CP is due to the dynamic nature of cognitive and affective barriers in that the barrier faced in the performance of an activity may depend on the type of activity, its length, its complexity, and the settings in which it is performed (Olugbade et al., in review). This points to the need for affect-tailored intervention to be integrated into everyday settings. Indeed, findings in Singh, Bianchi-Berthouze, and Williams (2017) provide evidence that technology that can personalise intervention in these settings can facilitate improved confidence, the employment of learnt skills, and improved engagement in physical activities.

Section 2.1 Highlights

- **In CP, pain does not mean injury.**
- **CP hinders physical functioning via movement related self-efficacy, fear/anxiety, and depressed mood.**
- **Affect-tailored support from physiotherapists during exercising in clinical settings does not transfer easily to everyday settings.**
- **Technology can be leveraged to provide tailored support in everyday functioning as well as in exercising outside of clinical settings.**

2.2 Cognitive and Affective Barriers to Physical Functioning in Chronic Pain

Pain is an important signal of (impending or threatened) bodily harm and is so powerful that it demands attention and interrupts engagement in activities even when the pain is chronic (Eccleston and Crombez 1999; Vlaeyen, Morley, and Crombez 2016). The significance of pain is in the responses that it provokes to escape or protect against (perceived) threat (Sullivan 2008). In CP, where pain persists without an injury and during harmless everyday activities (e.g. initiating a sit-down, picking up a book from a shelf), such responses (e.g. movement avoidance or suboptimal engagement in movement) are unhelpful. This makes it important to promote engagement in physical activity despite pain, but with an understanding of its influence on physical functioning. Even so, as mentioned in the previous section, findings in pain studies suggest that movement related self-efficacy and fear/anxiety are more pertinent factors of physical functioning outcomes in CP. Depressed mood has also been shown to influence these outcomes. In this section, a more elaborate discussion of these three states and their influence on functioning is done based on widely-accepted theories applied in pain research.

2.2.1 Movement Related Self-Efficacy (MRSE)

Self-efficacy is the level of confidence that a person has that s/he can successfully execute the behaviours required to perform a given activity (Bandura 1977).

2.2.1.1 The Self-Efficacy Theory

The self-efficacy theory (Bandura 1977) puts this state at the core of engagement behaviour. According to the theory, self-efficacy can influence the decision of whether or not to engage in an activity. While people will engage in the activity if they perceive themselves to be capable of dealing with possible barriers (such as pain), they will fear and likely avoid the activity if they perceive it to be beyond their capabilities (Bandura 1977). Self-efficacy also determines the amount of effort that they will put into performance of the activity and the level of persistence in performing the activity when confronted with relevant barriers.

The theory highlights performance outcome as one of the factors that influence appraisal of self-efficacy. It suggests that persistent poor outcomes in an activity are likely to undermine self-efficacy for that activity and related ones whereas successful outcomes will likely lead to an improvement in self-efficacy. This points to a danger with avoidance behaviours which do not allow opportunity to disconfirm incorrect appraisals of capability through this means (Vlaeyen, Morley, and Crombez 2016). The theory further suggests that affective responses (such as anxiety) to threat also influence self-appraisals of capabilities.

2.2.1.2 Evidence from Pain Studies supporting The Self-Efficacy Theory

Findings in pain literature support the validity of the self-efficacy theory in CP. For example, Asghari and Nicholas (2001) found self-efficacy to be negatively correlated with avoidance behaviour in adults with non-cancer CP (excluding rheumatoid arthritis and headache). In their study, self-efficacy was assessed using a questionnaire which measures the magnitude and generality of a person's self-efficacy with self-rating of confidence in the ability to perform each of ten categories of everyday activities (such as household chores) despite pain. Avoidance was assessed using a questionnaire that checks whether or not a person typically avoids a range of activities due to pain. Avoidance behaviour is a pertinent measure of physical functioning outcome in CP because it conflicts with the pursuit of valued goals (Vlaeyen, Morley, and Crombez 2016). Based on multiple regression analysis, Asghari and Nicholas (2001) found that low levels of self-efficacy predicted avoidance after controlling for pain intensity and duration, age, gender, neuroticism, disability, depression, and catastrophising (a cognitive state associated with fear (Leeuw et al. 2007)). The other cognitive constructs they investigated were not independently predictive of avoidance. These constructs were: pain permanence (the belief that pain will be persistent), constancy (i.e. belief of pain being currently constant and pervasive in its influence in everyday life), pain responsibility (i.e. belief of responsibility for the management of own pain), and belief about control over pain.

Denison, Asenlof, and Lindberg (2004) also found self-efficacy to be negatively correlated with disability (i.e. problems executing everyday activities (Leeuw et al. 2007)) in adults with CP (excluding rheumatoid arthritis, osteoarthritis, and fibromyalgia). In their study, they measured self-efficacy similar to Asghari and Nicholas (2001) although they used a self-efficacy scale which was originally designed for healthy respondents but was adapted for use with people with CP. They assessed disability using a self-report scale which measures the general level of interference of CP with everyday activities.

2.2.2 Pain Related Fear and Anxiety

Fear and anxiety are both emotional responses to threat; however, where fear is in response to an immediate threat, anxiety is a reaction to a possible future one (Leeuw et al. 2007). In pain literature, fear and anxiety are often used interchangeably (possibly because pain is constantly present) to connote fear that is due to the perception of pain as a prime threat (Leeuw et al. 2007). This interpretation of the two terms is assumed throughout the thesis.

2.2.2.1 The Fear-Avoidance Theory

The fear-avoidance theory of pain (Vlaeyen and Linton 2000) specifies the role of fear in the maintenance of disability in CP. The theory suggests that wrong appraisal of pain as a signal of threat (e.g. in catastrophising) leads to fear which in turn results in avoidance behaviour and reduced engagement in everyday physical activities. Recent discussion of the theory in Vlaeyen, Morley, and Crombez (2016) further postulates that these fear responses (avoidance and reduced engagement) may generalise to other activities that are not initially feared. According to the fear-avoidance theory, the responses lead to a cycle in the long-term as they then result in disability and disuse (i.e. stiffness and loss of muscle fitness) which in turn cause pain threshold to be lowered, leading back to fear. The theory further suggests that pain related fear will also interfere with cognitive processes and cause increased attention to pain, hypervigilance, and over-prediction of pain.

2.2.2.2 Evidence from Pain Studies supporting The Fear-Avoidance Theory

There are several studies that provide evidence of the influence of fear on physical functioning. One is the previously mentioned work of Denison, Asenlof, and Lindberg (2004). They found fear to be positively correlated with disability, and hierarchical multiple regression analysis showed that fear is predictive of disability even after controlling for self-efficacy and pain intensity. In the study, fear was assessed using the Tampa Scale for Kinesiophobia (Miller, Kori, and Todd 1991), which measures general level of fear of pain, movement, and (re)injury. Their participants and disability measures are as mentioned previously (in Section 2.2.1.2).

Findings in Crombez et al. (1999) additionally show that similarly assessed fear also predicts objectively-assessed behavioural performance in specific physical tasks. Here, the participants were people with chronic back pain and the assessed tasks were trunk flexion-extension movements which are typically challenging for this cohort (Watson et al. 1997). A dynamometer was used to assess performance in these tasks.

2.2.3 Pain Related Depressed Mood

An important advance in the understanding of depression in CP is the finding that it is different from clinical depression in that it is characterised by a negative outlook on health and lacks the self-denigration components of the latter (Rusu, Pincus, and Morley 2012; Pincus and Morley 2001). Rusu, Pincus, and Morley (2012) showed this in a sentence completion task: people with CP and depressed mood made more health related completions than people with CP without depressed mood, and than people without CP with or without clinical depression. Interestingly, their health related completions were also more negatively valenced than those of other groups. This supports the theory of Pincus and Morley (2001) that depressed mood in CP is a manifestation of information processing bias towards negative health related information. In the study of Rusu, Pincus and Morley, the participants with CP were people with chronic musculoskeletal pain with pain intensity of 3 or more (on a 0-to-10 pain scale) at the time of the study and on average in the three months before the study. These participants were decided to be of depressed mood status if they had been previously diagnosed with depression, had current symptoms (based on a general practitioner’s assessment), or had been referred to a counselling service for depression.

2.2.3.1 The Diathesis-Stress Theory and Evidence of The Influence of Pain Related Depressed Mood on Physical Functioning

One of the widely accepted modern explanations for the prevalence of depressed mood is the diathesis-stress theory of Banks and Kern (1996). Banks and Kern suggest that similar risk factors (such as the tendency to have a negative outlook on the future) make a person susceptible to the two conditions and that the challenge of living with CP may act as a stressor that activates depression in people with CP. The authors suggest that living with CP may, for example, bring about thoughts about the lack of a permanent cure for their pain in people with

CP and such thoughts may provoke a sense of hopelessness and perceived loss of control (which are symptoms of depression). Unfortunately, such negative appraisals lead people with CP to have an amplified perception of their pain experiences and this in turn causes their outlook to be more negative, leading to a vicious cycle (Banks and Kerns 1996).

Findings in Asghari and Nicholas (2001) show significant correlation of depressed mood with avoidance behaviour although it did not significantly predict this behaviour on multiple regression analysis after controlling for age, gender, and pain intensity and duration. Rusu, Pincus, and Morley (2012) further showed that people with CP with depressed mood report greater disability and interference of pain than people with CP without depressed mood.

Section 2.2 Highlights

- **The influences of MRSE and fear/anxiety on physical functioning outcomes are independent of each other and of pain intensity.**
- **The self-efficacy and fear-avoidance theories of pain are grounded on evidence from analyses of gross measures of the relevant variables.**
- **Pain related depressed mood is different from clinical depression and is tied to pain.**

2.3 Qualitative Understanding of The Cognitive and Affective Barriers to Physical Functioning and Opportunities for Technology to Address Them

The studies reviewed in the previous section show that pain, low MRSE, fear/anxiety, and depressed mood influence engagement in physical activity. However, these studies only aimed to test for effects of the states on physical functioning and, as such, they do not clarify how assessment of the states can inform intervention. To address this gap and gain insight into the barriers that these cognitive and affective states pose to engagement in everyday physical activity and the opportunities for technology to address them for the purpose of facilitating engagement, qualitative analysis was carried out in Olugbade et al. (in review)[1]. Although this

[1] Olugbade et al. (in review) consists of three studies: two quantitative studies, part of the investigations reported in Chapters 6 and 7, and; one qualitative study, which only served to provide a strong motivation for the

analysis was motivated by this thesis, it was not carried out within the thesis investigation (and was done in collaboration with other researchers) but rather served to provide critical understanding of how these states differ in the challenge that they pose and the roles that technology needs to play to enable people with CP overcome these barriers in everyday physical functioning. This is an important background to this thesis as it provides underpinnings for the problem addressed in the thesis and the approach taken to address this problem.

The analysis was based on interviews with 16 people with CP and 3 pain specialist physiotherapists collected and previously analysed in Singh et al. (2014) (but not with a focus on the influence of pain and related cognitive and affective states in CP). In this section, findings of the analysis are discussed. The findings are discussed in three sections for pain, fear/anxiety, and depressed mood respectively. MRSE was not considered in the analysis in Olugbade et al. (in review); however, understanding of the opportunities for technology to address this state emerged in the analysis in Singh et al. (2014) and this will be discussed in a fourth section.

2.3.1 Pain Intensity

Findings in Olugbade et al. (in review) suggest that both high and low levels of pain require intervention although intervention needs differ for the two levels.

In periods of high level pain, a person with CP is likely to avoid physical activity even though this response is maladaptive in the longer term, and so it is important to encourage the person to remain physically active even in these periods (Olugbade et al., in review). When periods of high level pain are prolonged and self-efficacy may be undermined, it is important to further reassure the person that losses in physical capability can be regained (Olugbade et al., in review).

In periods of low level pain, a person with CP may overdo physical activity to achieve postponed goals (Olugbade et al., in review). This is also not a helpful strategy as the substantial, sudden increase in levels of physical activity often worsens pain, and although this does not imply harm from activity, it undermines progress in physical rehabilitation because it leads to association of increased pain with physical activity (Olugbade et al., in review). Thus,

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technological approach and innovation of these two studies (and the investigations reported in this thesis), and so is not reported in this thesis.

it is important to encourage a person with CP to increase physical activity gradually with breaks or changes of physical activity even when pain levels are low (Olugbade et al., in review).

2.3.2 Pain Related Fear/Anxiety

It was also found that regardless of pain levels, pain related fear/anxiety discourages engagement in feared activities even when they are within the individual's physical capability (Olugbade et al., in review). Yet, it is important for people with CP to be (psychologically) capable of engaging in the variety of movements that everyday functioning requires and so it is important to address these feared activities. The analysis in Olugbade et al. (in review) showed that fear/anxiety can vary between contexts, e.g. for different levels of movement complexities or different environmental settings. For example, the authors reported the case of a person with CP who could not flex the trunk while standing, because of fear of pain or injury from the movement, even though he was easily able to perform the same movement while seated. The analysis further revealed the need to enable a person with CP who has high levels of fear/anxiety to become aware of inaccurate appraisals and of unhelpful responses, such as muscle tension, that worsen pain and make the feared activity more difficult. The analysis additionally pointed to the importance of encouraging the use of helpful strategies (such as focus on breathing, breaking down complex movements into simpler components) to defuse fear/anxiety.

2.3.3 Pain Related Depressed Mood

Olugbade et al. (in review) also found that depressed mood makes it more difficult for a person with CP to respond to their levels of pain in a helpful manner and that this state rather than the level of pain itself may discourage physical activity. As with fear/anxiety, drawing attention to unhelpful appraisals about pain may help a depressed person with CP to engage in physical activity. It may also be helpful to make the person aware of positive health related information, such as progress in his or her physical and/or psychological capability, especially as it relates to valued goals (Olugbade et al., in review).

2.3.4 Movement Related Self-Efficacy

Findings in Singh et al. (2014) suggest that increase in physical capability from muscle strengthening exercises does not necessarily translate to improved engagement in everyday physical activities if levels of self-efficacy for those activities remain low.

To deal with this problem, rather than a biomechanical approach that considers the correctness of movement, it is more important to focus on promoting MRSE (Singh et al. 2014).

Gradual increases in physical activity targets can promote levels of MRSE (Singh et al. 2014). Verbal encouragement can also enhance this state (Bandura 1977); however, encouragement must be given with an understanding of the level of MRSE of the person with CP so as to promote independence in higher levels of MRSE (Singh et al. 2014). At these levels, there is the danger of undermining capability if encouragement is not appropriately tailored (Keefe et al. 2004). In fact, physiotherapists gradually withdraw encouragement as MRSE of a patient increases. As MRSE levels increase, there can and should then be effort directed towards encouraging the person to build up in physical functioning and attempt more challenging activities. For example, a person who had only been able to spend 15 minutes in the garden playing with her daughter during the weekends could be encouraged to spend 5 minutes more on the next weekend if her self-efficacy for that activity has been observed to improve.

Section 2.3 Highlights

- **Pain, MRSE, fear/anxiety, and depressed mood play different roles in impeding physical functioning and so must be addressed separately.**
- **Opportunities exist for technology to address pain, MRSE, fear/anxiety, and depressed mood in everyday settings given capability to read them.**
- **The aim of physical rehabilitation intervention is not to simply promote increases in physical activity levels but rather to facilitate psychological capability to engage in the variety of movements that valued activities involve.**

2.4 Technology State of the Art in Addressing Cognitive and Affective Barriers in Physical Rehabilitation

Findings discussed in the previous section underscore the need to address pain, MRSE, fear/anxiety, and depressed mood in order to promote physical functioning in people with CP. In this section, the state of the art in physical rehabilitation technology is reviewed with respect to how they (fail to) address these states and the requirements of CP physical rehabilitation.

2.4.1 State of the Art: Addressing Psychological Barriers

The majority of physical rehabilitation technology designs are still based on the biomechanical approach to physical rehabilitation that is more appropriate for acute conditions (such as ankle sprain) which differ in need from long-term conditions (such as CP or stroke). For example, exergame-based systems developed for stroke rehabilitation in Burke, McNeill, et al. (2009) were designed to provide performance feedback to the user as either reward for expected performance or as penalty for submaximal or incorrect performance. This approach is not helpful in CP where it may trigger anxieties about causing injury due to incorrect execution (Singh et al. 2014). Further, as discovered by Doyle et al. (2010) in their development of technology to support geriatric balance and strength rehabilitation, the feedback that users find informative goes beyond a score of physical performance during exercising. In Doyle et al. (2010), the participants requested aggregated feedback of progress in physical capability. The authors addressed this need with the provision of regular reports from physiotherapists. This approach still relies on clinician support and cannot easily be scaled to everyday settings where rehabilitation is self-managed. In addition, it does not alleviate the demand on the healthcare system.

Despite understanding from CP literature (Turk and Okifuji 2002) and emerging literature on other long-term conditions (Reed et al. 2010; McNaney et al. 2015; Morris 2016; Ayobi et al. 2017) of the importance of bringing psychological intervention to the forefront of physical rehabilitation, only motivation to adhere to prescribed exercises (Alankus et al. 2010; Burke, Mcneill, et al. 2009) is typically addressed in current technology designs. An example is the stroke rehabilitation system based on exergames developed in Alankus et al. (2010). In the design of the system, a focus was placed on reducing boredom and maintaining interest and this was addressed through automatic tailoring of the difficulty of the game to the physical performance of the user. This approach does not address the problem in CP physical rehabilitation where physical capability does not necessarily translate to psychological readiness (such as in improved MRSE) to build on current gains (Singh et al. 2014). A similar approach was also used in the exergame-based system developed for people with CP in Schönauer et al. (2011) where the games followed a storyline and the progression of the story was made interactive by adapting it based on the physical performance of the user. As with Alankus et al. (2010), no consideration was made for levels of pain, MRSE, fear/anxiety, or depressed mood which significantly influence physical functioning in CP (Asghari and Nicholas 2001; Vlaeyen, Morley, and Crombez 2016).

Pain experience was addressed in Gromala et al. (2015) where virtual reality technology was used to facilitate mindfulness and meditation in people with CP. However, the authors focused on pain intensity: the virtual environment was designed to automatically adapt to the arousal levels of the user with the aim of reducing pain intensity. As discussed in Sections 2.2 and 2.3, it may be more important to reduce pain related fear/anxiety and depressed mood and promote MRSE to improve engagement in physical as these states have been found to influence physical functioning independently of pain intensity (Denison, Asenlof, and Lindberg 2004; Olugbade et al., in review; Asghari and Nicholas 2001).

2.4.2 State of the Art: Bringing Technology into Everyday Settings

An additional concern with current physical rehabilitation technology designs is that they only address physical exercise, whereas, as discussed in Section 2.1, capabilities gained in physical exercise do not automatically transfer to functional activities which are more important for achieving valued goals. The need for physical rehabilitation technology to support engagement in both exercises and functional activities is made even more pertinent based on the fact that integrating physical exercises in functional activities has increasingly been found to be valuable in promoting adherence to prescribed exercises (Singh et al. 2014; Bagalkot, Sokoler, and Baadkar 2016). This is because one of the barriers to exercise adherence is poor availability outside everyday routine (Bagalkot, Sokoler, and Baadkar 2016). Bagalkot, Sokoler, and Baadkar (2016) exploited this integration in their technology design for low back rehabilitation. Their system tracked posture during bike riding, a functional activity (typical within the geographical area of the study) that requires use of the lower back, and used the postural information to provide real-time intervention to facilitate the use of more helpful postures. In their study, intervention was in form of obstruction of the speedometer of the bike so that it was only visible to the user when s/he was in a correct posture. As with the systems discussed in Section 2.4.1, this system does not cater to the needs in physical rehabilitation in CP (or other long-term conditions) where it is important to address psychological capability together with and even before physical performance (Singh et al. 2014).

A more relevant system is the one evaluated in Duggan et al. (2015); this system was designed to support everyday functioning of people with CP. The system enabled the user to set daily physical activity goals and reminders were used to alert the user when planned activities were due. The system additionally automatically tracked levels of activity and alerted the user when activity levels were lower or higher than goals set. Their approach relies on a person with CP to be aware of their physical activity needs and capabilities. This can be a challenge for people with CP as the continuous self-monitoring that this requires poses a cognitive burden to people with CP whereas technology could be leveraged to relieve such burden (Felipe et al. 2015; Papi, Belsi, and McGregor 2015).

A similar design is the movement sonification system investigated by Singh and colleagues for both exercises (Singh et al. 2016) and functional activities in the home (Singh, Bianchi-Berthouze, and Williams 2017). In their design, sonification is calibrated by the user to accommodate his/her psychological capability. An advantage of the system is that it provides support at more fine-grained levels of physical activities than the system of Duggan et al. (2015) as movement-generated sound feedback is given at carefully selected points during movement execution in the performance of physical activities. For example, in forward reaching movement, musical notes are produced with each move of the trunk (based on sensor tracking of its orientation). This was found to enable the transfer of skills and capability gained in exercising to physical functioning as the feedback provided during the former was informative and so fed into the latter. For example, some of their participants reported that the system allowed them to discover that they had larger ranges of motion during functional activity than they had believed. The approach used also enabled the exploration of prescribed pain management strategies in everyday life, e.g. one of the participants reported using the system to reorganise her living space to accommodate current cognitive capabilities. However, similar to the design of Duggan et al. (2015), the system relied on people with CP (re-)checking their capabilities, to keep calibration up to date. Findings in Singh, Bianchi-Berthouze, and Williams (2017) and Felipe et al. (2015) show that people with CP have a preference for systems with co-supervisory capability, and so sharing in the responsibility of keeping track of physical capabilities, and coaching capability to facilitate application of pain management strategies (e.g. focusing on breathing when pain related anxiety is high). Such a system would need to be able to automatically track both movement behaviour (physical capability) and pain and related affect (anxiety).

Section 2.4 Highlights

Unmet needs of CP physical rehabilitation in technology state of the art:

- **need to automatically assess and address pain, MRSE, fear/anxiety, depressed mood alongside physical performance**
- **need to assess and address them in both functional and exercise movements**

2.5 Discussion

The aim of this chapter was to review relevant literature to provide understanding of the challenges of CP physical rehabilitation, the opportunities for technology to address these challenges, and the gap that exists in current designs of physical rehabilitation technology. It was shown that a major challenge in CP is reduced engagement in everyday activities and that this challenge is significantly related to pain, MRSE, fear/anxiety, and depressed mood. It was further shown that each of these states poses a different barrier and so needs to be addressed differently. Opportunities were also highlighted for technology to address them. Yet, a look at existing technology designs showed that the state of the art still does not leverage these opportunities. The questions that arise from these findings are discussed in this section; these questions form the basis of the research questions addressed in this thesis.

2.5.1 Is Assessment of Physical Performance Enough to Inform Intervention?

A finding of the review in the chapter was that physical rehabilitation technology designs have often focused on the assessment of physical performance to the exclusion of the cognitive and affective states that underlie it. This raises the question of whether such assessment is enough to inform intervention that address these states.

This question is significant as such observable behaviours are often used to assess (subjective) pain experience in clinical practice and in pain research even though there has been limited investigation of the extent to which expressions of pain (generally referred to as pain behaviours in pain studies) operationalise pain experience. One of the oldest but still relevant studies in the area is the work of Keefe and Block (1982) who provided specification of five observable pain behaviours covering bodily, facial, and (para)verbal expressions. Keefe and Block (1982) showed that these behaviours (guarding, bracing, rubbing, sighing, and grimacing) are collectively and individually (except for grimacing) significantly correlated with self-reported pain intensity. A more recent study by Tang et al. (2007) contrasts this set of behaviours with self-reported pain behaviours showing that the pain behaviours (Keefe and Block's) were indeed significantly correlated with self-reported pain intensity but not to anxiety or depressed mood. Their newer finding had a limitation, however, in that measure of the two variables (behaviour and affect) were mismatched in their study. The authors measured anxiety and depressed mood in terms of usual experience of these affective states, whereas behaviour was assessed for a specific physical activity event (a bag carrying task). This incongruence in assessment may have contributed to their finding of non-significance of correlation between these two variables. Other studies like those discussed in Section 2.2 have focused on analyses of broad self-report of physical functioning (e.g. disability) and behaviour (e.g. tendency to avoid movement in everyday functioning) rather than specific events.

Further investigation of the relationship between pain behaviours and pain experience can help understanding of whether it is possible to understand pain experience based on observable pain behaviour and so whether pain experience can be assessed by observing these behaviours so as to determine appropriate intervention. An inverse problem is the need to understand the extent to which pain experience and behaviours may be disconnected to aid the decision of when underlying pain experience needs to be addressed in addition to disrupting the behaviour. The reason pain behaviours may need to be disrupted is because, as discussed in Section 2.2, they are often maladaptive in that they worsen pain in the long run (Vlaeyen and Linton 2000).

Further, Sullivan, a renowned pain researcher, wrote an opinion piece (2008) advocating for more work to be done on understanding protective pain behaviours (i.e. pain related movement behaviours) such as guarding (i.e. stiffness in movement) in terms of their cognitive and affective components. He proposed that interventions that were designed to address these components may be more effective in addressing such behaviours. He suggests that previous studies that focus on pain intensity (such as Keefe and Block (1982) and Tang et al. (2007)) do not suffice as they do not account for the role of related cognitive and affective states.

It is, thus, pertinent to investigate the question, *what are the relations between pain behaviours and pain intensity, MRSE, and emotional distress (fear/anxiety and depressed mood)?*

2.5.2 How Can Technology Assess Levels of Pain, MRSE, Fear/Anxiety, and Depressed Mood? Can This Be Done in Everyday Functional Activity Settings?

It is evident from the discussion in Section 2.3 that for technology to address the barriers that pain, MRSE, fear/anxiety, and depressed mood pose to physical functioning, it needs to be able to continuously read which states are relevant at any moment so as to appropriately tailor intervention.

Automatic detection of the states is a practical solution to this need (Gunes and Pantic 2010; Calvo and D'Mello 2010; Kleinsmith and Bianchi-Berthouze 2013; Karg et al. 2013). An advantage of automatic detection is that there is no need to interrupt the activity being performed to assess the states. Rather, it enables technology to continuously monitor and (only) intervene when need is sensed. This also allows such technology to be used without repeated self-reporting of the states, which may promote attention to pain (Vlaeyen, Morley, and Crombez 2016; Duggan et al. 2015) and negative emotions and experiences (Li, Dey, and Forlizzi 2011; Hollis, Konrad, and Whittaker 2015).

Automatic detection can also lighten the cognitive burden of repetitive self-monitoring (Felipe et al. 2015; Olugbade et al., in review). Unlike self-logging, which may only support reflection, automatic detection can support both real-time intervention (found necessary for pain, MRSE, fear/anxiety and depressed mood) and long-term reflection (found necessary for fear/anxiety and depressed mood) (Olugbade et al., in review).

An additional benefit of automatic detection is that it allows real-time tracking of these states together with contextual information that allows proper interpretation and appropriate personalisation. Indeed, as discussed in the previous section, observation methods (Keefe and Block 1982) are used in pain research to quantify pain behaviours during movement so as to understand them in relation to pain experiences. There is also the potential of using the understanding of the relationship between these behaviours and the pain experiences in the tailoring of intervention (Sullivan 2008). However, such observation is expensive for clinical practice as it relies on the use of trained coders that need to be regularly re-trained and calibrated (Keefe and Block 1982; Sullivan 2008). Nevertheless, self-report of such behaviours (Cook et al. 2013; Tang et al. 2007) is not a reliable source given its reliance on the ability of a person to be aware of their behavioural responses to pain experiences. On one hand, a person with CP may not be aware of his/her cognitive or affective state until long after its onset when it is difficult to associate the state with its origins (Felipe et al. 2015). On the other hand, a person with CP may not necessarily be aware of behavioural responses due to attention to perceived threat or pain or because the response has become habitual and unconscious. Significant others (e.g. family) have been used to provide a further report of pain behaviour (Cook et al. 2013) but this requires continuous observation by these others. Automatic detection of levels of pain, MRSE, fear/anxiety, and depressed mood together with automatic detection of movement behaviour addresses this problem.

As mentioned in the previous section, many physical rehabilitation technology systems already incorporate observation of movement behaviour into their designs. These considerations motivate the consideration of movement behaviour as modality for automatic detection of the relevant states and prompts the question of how the states can be automatically detected from movement behaviour. An additional question is of the possibility of automatic detection of these states in everyday functional activity settings as it was found in the review done in the chapter that technology needs to be able to address the states in these settings in addition to situated exercise settings.

To address these questions, the state of the art in pain related affective computing is reviewed in the next chapter to understand what has been done, what gaps still exist, and what needs to be done for technology to be able to address pain, MRSE, fear/anxiety, and depressed mood.

2.6 Conclusion

The literature review shows that pain and related fear/anxiety, depressed mood, and low MRSE are barriers that need to be addressed to promote everyday physical functioning in people with CP. Although these barriers have often not been considered in technological intervention for this population, there are opportunities for technology to address them by leveraging automatic detection capability for personalisation of intervention to levels of the states. However, detection of general negative affect is not sufficient as the aforementioned states raise different needs and barriers. Pain behaviour studies suggest movement behaviour as a modality for assessing these states, and for further understanding of how people with CP cope with the challenges they pose; however, there is limited understanding of the information that guarding behaviour, the most understood of pain behaviours, provides about these states. This gap in knowledge is addressed in this thesis with investigation of the relationship between movement behaviour and each of these states. The use of movement behaviour for discriminating between levels of these states is further reviewed in Chapter 3.

3 LITERATURE REVIEW: AUTOMATIC DETECTION OF PAIN AND RELATED AFFECTIVE STATES

IN this chapter, three main topics are reviewed. First, building on the argument initiated in the discussion in Chapter 2 for the use of movement behaviour as modality for automatic detection of levels of pain and related states, additional justification for the use of this modality is discussed. This discussion is important as it completes the rationale on why movement behaviour was focused on as a critical modality for the investigations of automatic pain and related detection in this thesis. Secondly, body movement sensing approaches are reviewed to provide an understanding of the choices available and their limitations with respect to CP physical rehabilitation. Thirdly, previous studies on automatic detection of levels of pain, MRSE, depressed mood, and fear/anxiety are discussed, describing the state of the art in these areas and highlighting the gaps that remain in terms of the requirements for CP physical rehabilitation highlighted in Chapter 2. The research questions that arose in the discussion in Chapter 2 are then re-discussed in the light of the understanding gained from the review of these topics.

The chapter is organised into five main sections. In Section 3.1, the significance of movement behaviour as a modality for automatic detection of pain and related states is discussed. In Section 3.2, a review of the advantages and limitations of various types of body movement sensors is given. In Section 3.3, the state of the art in automatic detection of levels of pain, MRSE, and emotional distress (fear/anxiety and depressed mood) from movement behaviour is discussed. In Section 3.4, an overall discussion of the questions that emerge from these sections is done. A conclusion of the review is provided in Section 3.5.

3.1 A Case for Movement Behaviour as Modality for Pain and Related Detection

In this section, an argument is made for the use of movement behaviour as a modality for automatic detection of pain and related states based on findings in pain studies and affective computing literature.

TABLE 3.1 THE STATE OF THE ART IN THE UNDERSTANDING OF MOVEMENT BEHAVIOUR IN PAIN

	Author	Behaviour	Broader Category	What the Behaviours are Known to be Relevant to
1	(Fordyce et al. 1984)	Physical activity levels	Avoidance behaviour	-
2	(Keefe and Block 1982)	Guarding, grimacing	Motor behaviour	Pain intensity
3	(Sullivan et al. 2006)	Guarding, bracing, rubbing, holding, touching	Bodily expressions	Coping with challenge in physical activity
		Grimacing, wincing	Facial expressions	Communication of pain experience
		Grunts, sighs, moans, and the use of pain words	(Para)verbal expressions	Communication of pain experience

Table 3.1 shows the progression of understanding of the relevance of movement behaviour to the assessment of CP. As highlighted in the table, Fordyce (1984) is a pioneer of the assessment of movement behaviour in the context of pain, although the method (measures of physical activity levels) he proposed for this assessment has not been found relevant to the understanding of pain experience (Fordyce et al. 1984; Huijnen et al. 2011). Building on the groundwork of Fordyce, Keefe and Block (1982) proposed a more fine-grained observation method where motor (bodily and facial) patterns during individual activities are assessed by trained observers. This method has been shown to capture the pain intensity dimension of pain experience although further work in Sullivan et al. (2006) showed that the bodily expressions may be more relevant cues of pain intensity than the facial expressions. The significance of bodily expressions in the context of pain is due to their being primarily adaptive and intended to protect against perceived harm whereas facial expressions are more associated with the communication of pain and so may depend on the presence of an empathic third party (Sullivan et al. 2006). Sullivan (2008) has proposed that pain related bodily expressions may further encapsulate much more than just pain intensity and that related cognitive and affective states may contribute to it; however, as discussed in Chapter 2, there has been limited investigation of this.

Beyond the significance of movement behaviour in the context of pain, this modality has led to favourable results (Kapur et al. 2005; Bianchi-Berthouze and Kleinsmith 2003; Karg, Kühnlenz, and Buss 2010; Dickey et al. 2002; Janssen et al. 2008; Samadani, Ghodsi, and Kulić 2013; Gruebler and Suzuki 2014; Aung et al. 2016; Ahern et al. 1988) in the field of affective computing in general even if it has largely been overlooked in this field. In the specific context of physical rehabilitation, movement behaviour further has advantage over the more favoured modalities (face and voice (Calvo and D'Mello 2010; Hudlicka 2003; Kleinsmith and Bianchi-Berthouze 2013; Gunes et al. 2015)) of the affective computing field in that it is more feasible to track in everyday settings than the face and the voice. In such settings that involve functional activity in addition to situated exercises, environmental conditions may not be controllable and issues such as background noise, sparse vocalisations, poor lighting conditions, and occlusions are necessary concerns for the capture methods for the face and voice in these settings (Hudlicka 2003; Zeng et al. 2009; Calvo and D'Mello 2010). Advances in wearable sensing technology make it possible to continually track movement behaviour in such settings. In addition, unlike physiological signals such as heart rate and skin conductance, affective cues in movement behaviour are not confounded in physical activity settings. This may be due to the degrees of freedom of body movement data compared to physiological signals which are inherently one-dimensional.

3.2 How Should Movement Behaviour Be Captured?

In the previous section, an argument was made for the use of movement behaviour as a modality for automatic detection of pain and related states. It is important to further understand to what extent available sensing techniques enable this functionality to meet the requirements for CP physical rehabilitation. As discussed in the previous section, one of these requirements is for intervention to be available during both exercises and everyday functional activities so as to enable transfer of helpful strategies and capabilities from exercise settings to functional movement settings. Unlike exercises which may be situated and done in controlled settings, everyday functional activities (such as playing with one's daughter in the garden, walking to the train station) are usually less constrained and ubiquitous. In this section, the suitability of camera based systems and wearable sensors for automatic affect detection in these settings are discussed.

3.2.1 Camera Based Sensors

Video has been the most popular method for capturing body movement for affect detection (Camurri et al. 2003; El Kaliouby and Robinson 2004; Gunes and Piccardi 2009; Shan, Gong, and McOwan 2007; Karpouzis et al. 2007; Castellano, Villalba, and Camurri 2007; Sanghvi et al. 2011; Park et al. 2004; Merskey and Bogduk 1994; Joshi, Dhall, et al. 2013; Kessous, Castellano, and Caridakis 2010; M. a. Nicolaou, Gunes, and Pantic 2011; Thrasher et al. 2011; Eyben et al. 2011; S. Chen et al. 2013; Glowinski et al. 2011; Werner et al. 2016; Rivas et al. 2015). The advantage of this method is that it requires virtually no training for the user to set up and video cameras are relatively low cost and readily available, with many personal electronics such as laptops and smartphones equipped with video cameras of decent resolutions. However, video cameras are not practical in everyday physical activity settings as they must be set up such that the subject remains in the field of view of the camera(s) without occlusions and in good lighting conditions. Yet, in everyday physical activity settings, the location of the subject is dynamic, with movements around a room, between rooms, buildings, and across larger geographical expanses, including changing lighting conditions, making video cameras a challenging mode of capture in these settings.

Marker based optical motion capture is another widespread capture method for body movement for affect detection (Pollick et al. 2002; Bianchi-Berthouze and Kleinsmith 2003; Gross et al. 2006; Bernhardt and Robinson 2007; Gong et al. 2010; Karg, Kühnlenz, and Buss 2010; Dickey et al. 2002; Kapur et al. 2005; De Silva et al. 2006; Janssen et al. 2008; Lai et al. 2009; Piana et al. 2014; Samadani, Ghodsi, and Kulić 2013; Grip et al. 2003). This technique uses opto-reflective markers which are placed on target segments of a subject's body and high fidelity infrared cameras that allow reconstruction of the three-dimensional positions of these segments. Marker based optical motion capture does not suffer under poor lighting conditions and it provides rich information about body movement. However, like video cameras, it requires that the target is in the field of view of the camera(s) without occlusions. Furthermore, it requires the use of multiple expensive cameras. These make it also not practical for everyday physical activity settings.

Depth sensing motion capture systems like Microsoft Kinect are a low-cost alternative for three-dimensional motion capture for affect detection (Kapoor and Picard 2005; Piana et al. 2014; Zacharatos, Gatzoulis, and Chrysanthou 2013; Grafsgaard et al. 2014). However, they also depend on cameras and so are prone to the same failings common to the video and marker based optical motion capture.

3.2.2 Wearable Sensors

A more practical approach to the capture of body movement during everyday physical activity is the use of wearable sensors. These sensors have the advantage that they do not use cameras and so are infallible to the problems associated with the camera based methods.

One type of wearable body movement sensors is inertia measurement units (IMUs) which allow the capture of three-dimensional motion with application for affect detection (Kleinsmith, Bianchi-Berthouze, and Steed 2011; Savva and Bianchi-Berthouze 2012; Aung et al. 2016). Another emerging type of wearable body movement sensors are surface electromyography (sEMG) sensors which allow tracking of muscle activity and bodily responses which cannot be detected by IMUs or cameras (Huis In 't Veld, Van Boxtel, and de Gelder 2014a). In fact, IMUs and sEMG sensors are starting to become integrated in the same device (DorsaVi 2016); this offers the opportunity of synchronised capture of data from the two types of sensors. This is important as (non-)concomitance of bodily muscle activity patterns with observable bodily expressions can be a cue of pain experience (Watson et al. 1997; Watson, Booker, and Main 1997). This points to value in fusing both modes of movement behaviour for automatic detection of pain and related states.

There is an increasing number of commercial low-cost wearable sensing systems that allow the tracking of body movement in ubiquitous settings. The use of low-cost wearable sensors for automatic detection is important for CP physical rehabilitation as it provides the opportunity for ubiquitous tracking of affective movement cues, and so tailored intervention integrated into everyday settings. More expensive sensors which may be used in clinical consultation would not be scalable to real-life settings. Belsi, Papi, and McGregor (2016) have shown that people with CP are generally open to the use of such sensors with the belief that it will equip them in self-management of their condition, particularly improving awareness of behaviour. Singh et al. (2014) have shown that such awareness support can relief the burden of continuous monitoring and alleviate over-attention to negative sensations during movement. However, there has been little investigation of the feasibility of the use of data captured by such sensors for the automatic detection of cognitive or affective states within the context of affect-aware CP support. Many of the commercial sensor systems that exist have IMUs only, e.g. Notch (Notch Interfaces Inc. 2016), Moov Now (Moov Inc. 2016), and Physilog (GaitUp 2016). A few systems, such as ViPerform (DorsaVi 2016), that allow synchronised motion capture and muscle activity tracking during physical activities are expensive (> AU$7500 for ViPerform as at 2014) and designed for use in elite sports.

There have been several research investigations into the development of low-cost body movement sensing devices. For example, Cheng et al. (2013) investigated the use of wearable capacitive sensors for tracking movement of the head and neck. They built a neck band containing four of these sensors with data collated from the sensors by an iPhone application via Bluetooth Low Energy (BLE). They tested the use of data captured using their prototype for automatic discrimination between five everyday events: eating, sleeping, no motion, physical activity, and normal. A similar study by Bedri et al. (2015) designed an ear worn sensing unit composed of three infrared proximity sensors which they used to discriminate mouth open from mouth closed in twenty-three subjects performing thirty minutes of routine activities (eating, walking, stair climbing, talking, and resting). Neither study provides understanding of the feasibility of capturing movement of anatomical segments such as the trunk, arms, or legs during these functional activities using those types of sensors.

The system built by Farella et al. (2006) addresses this: their system used three accelerometers placed on the trunk, upper leg, and lower leg respectively with Bluetooth for data transmission. The system was designed to enable rule based discrimination between sitting, standing, and four lying down postures although this was not further investigated. Ylisaukko-oja, Vildjiounatie, Mantyjarvi (2004) similarly built a system that uses five accelerometers for movement capture; their system also used Bluetooth for data transmission. They tested the system in data capture studies indoors during a variety of athletic activities and outdoors during skiing and cross-country racing. In these tests, the sensor nodes were placed on the wrists, ankles, and hip, but only the reliability of the wireless connectivity was evaluated. Munguia Tapia et al. (2007) also used a custom-built system of five accelerometers (wireless transmitting to a PC), on the wrist, upper arm, ankle, thigh, and hip and with a heart rate monitor, to discriminate between walking, cycling, and rowing. Munguia Tapia and colleagues (Intille et al. 2004) also evaluated the use of a network of four accelerometers, on the wrist, ankle, thigh, and arm, for differentiating twenty everyday activities (including walking). In the work of Biswas and Quwaider (2008), fourteen accelerometers were used, with Mica2Dot radio nodes for wireless connectivity; the system they built was used with the sensors placed on the head, arms, wrists, waist, legs, and ankles. They used the data captured for the automatic differentiation of stand, sit, walk, and run. Despite the promise of this system and those discussed earlier, they do not integrate muscle activity sensors with the IMUs. As previously mentioned, muscle activity information is an important part of movement behaviour analysis

(Huis In 't Veld, Van Boxtel, and de Gelder 2014a) especially in the context of CP (Watson et al. 1997).

There have been studies on sEMG sensors for movement sensing, such as Harun et al. (2015) where a muscle activity sensing prototype that uses a single sEMG sensor and transmits the data to a mobile application via Wi-Fi was built, although the system was not tested in user studies. Costanza et al. (2005, 2007) also built a single sEMG sensing device that uses Bluetooth transmission; they evaluated it on the bicep for hands-free interaction with a digital system. In a single-unit armband configuration, Saponas et al. (2010) used six sEMG sensors for a similar purpose, with a focus on discriminating between pinching and pressing gestures of three different fingers. The sensing device transmitted data wirelessly to a PC using ZigBee. Similarly, in Donnarumma, Caramiaux, and Tanaka (2013), a mechanomyogram was used with a single sEMG sensor on the forearm to build a gesture-based music generation system, focusing on three types of arm gestures: fist clenching, forearm rotation, finger flexion/extension. These studies do not integrate IMU sensors with sEMG sensors.

3.3 Review of the State of the Art in Automatic Detection of Pain and Related States

The significance of affect detection in CP physical rehabilitation is the capability it provides for intervention to be tailored to relevant affective states. In Chapter 2, it was shown that pain, MRSE, fear/anxiety, and depressed mood are pertinent states that need to be addressed directly. It was further shown that there are opportunities for technology that can discriminate between low and high level pain, detect fear/anxiety and depressed mood, and read MRSE levels in people with CP to leverage so as to address these states. Beyond the states to be monitored, the modality of detection is also an important consideration as discussed in Chapter 2 and Section 3.1. There is a strong case for movement behaviour as a modality for detection because of its relevance to pain experience and the information that it provides about coping strategies which also feeds into tailoring of intervention. In this section, the state of the art in automatic pain and related detection is reviewed with respect to these requirements for CP physical rehabilitation technology: do existing systems cater to these requirements? what do their findings teach? what gaps exist?

The section is organised into three main headings for pain, MRSE, and emotional distress (fear/anxiety and depressed mood) respectively.

3.3.1 Pain

This has become the most studied of the three states with the boost in investigations (mostly based on the shoulder pain dataset of (Lucey, Cohn, Prkachin, et al. 2011)) on it in the last two years. Table 3.2 provides a summary of all of these studies (published on or before December 2016).

TABLE 3.2 AUTOMATIC PAIN LEVEL/STATUS DETECTION STUDIES
(*AUC = area under receiver operation characteristic (ROC) curve, i.e. curve of true positive rate against false positive rate)

	Author	**Pain Level/Status**	**Modality/Sensor Type**	**Method/Best Performance**	**Setting**
1	(Dickey et al. 2002)	11 levels of low back CP	spine movement/marker-based optical motion capture	Neural Network/average error=0.06 pain points (no cross-validation)	trunk exercises
2	(Gioftsos and Grieve 1996)	low back CP versus previous low back pain versus healthy	force and centre of gravity/force plates; knee, hip, and trunk movement/goniometer	Neural Network/accuracy=0.86	trunk exercises
3	(Ahern et al. 1988)	low back CP versus healthy	back muscle activity/sEMG; trunk movement/goniometer	Discriminant Analysis/accuracy=0.86	trunk exercises
4	(Grip et al. 2003)	neck CP versus healthy	neck movements/marker based optical motion capture	Neural Network/accuracy=0.89	neck exercises
5	(Lai et al. 2009)	knee CP versus healthy	gait features/marker-based optical motion capture; ground force reaction/force platform and light gates	Support Vector Machine/accuracy=0.89 (leave-one-out cross-validation)	walking
6	(Bishop et al. 1997)	2 levels of low back pain	trunk movement/goniometer	Radial Basis Function Neural Network/accuracy=0.86 (no cross-validation)	trunk exercises
7	(Rivas et al. 2015)	2 levels of stroke related pain	hand pressure/game controller	Support Vector Machine/F1>0.72 (10-fold cross-validation)	hand exercises
8	(Walter et al. 2015)	2 levels of experimentally induced pain	shoulder and facial muscle activity/sEMG; head pose/video; skin conductance; electrocardiography	Random Forest/accuracy=0.80	seated
9	(Kachele et al. 2016)	up to 5 levels of experimentally induced pain	shoulder muscle activity/sEMG; skin conductance; electroencephalography	Random Forest/mean squared error=0.89 (5 levels); accuracy=0.86 (2 levels)	seated

TABLE 3.2 AUTOMATIC PAIN LEVEL/STATUS DETECTION STUDIES (CONTINUED)
(*AUC = area under receiver operation characteristic (ROC) curve, i.e. curve of true positive rate against false positive rate)

	Author	Pain Level/Status	Modality/Sensor Type	Method/Best Performance	Setting
10	(Amirian, Kachele, and Schwenker 2016)	2 levels of pain	facial muscle activity/sEMG; blood volume pulse/electrocardiography; skin conductance	Radial Basis Function Neural Network/accuracy=0.84	-
11	(Werner et al. 2016)	5 levels of experimentally induced pain	face/video; head/video	Random Forest/accuracy=0.31	seated
12	(Hammal and Kunz 2012)	acted pain, happiness, surprise, disgust, anger, fear, sadness, and neutral; 2 levels of experimentally induced pain	face/video; context (clinical or not)	Transferable Belief Model/F1>0.8 (acted); F1>0.7 (induced) (no cross-validation)	-
13	(Neshov and Manolova 2015)	16 levels of shoulder pain; 2 levels of shoulder pain	face/video	Linear Regression/mean squared error=1.28 (16 levels); Support Vector Machine/accuracy>0.96 (2 levels, 10-fold cross-validation)	arm exercises
14	(Kaltwang, Rudovic, and Pantic 2012)	16 levels of shoulder pain (observer rated)	face/video	Relevance Vector Regression/mean squared error=1.37	arm exercises
15	(Zhou et al. 2016)	16 levels of shoulder pain (observer rated)	face/video	Recurrent Convolution Neural Network/mean squared error=1.54	arm exercises
16	(Rudovic, Pavlovic, and Pantic 2013)	7 levels of shoulder pain (observer rated)	face/video	Conditional Ordinal Random Field/F1=0.40	arm exercises
17	(Lucey et al. 2012)	6 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/*AUC=0.84	arm exercises
18	(Zebarjadi and Alikhani 2016)	5 levels of shoulder pain (observer rated)	face/video	Support Vector Regression/mean squared error=1.54	arm exercises
19	(Hammal and Cohn 2012)	4 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/average F1=0.56	arm exercises
20	(Rathee and Ganotra 2016)	up to 4 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/average F1=0.94 (2 levels); average F1=0.75 (4 levels)	arm exercises
21	(Roy et al. 2016)	up to 4 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/accuracy=0.82 (4 levels); accuracy=0.87 (2 levels)	arm exercises

TABLE 3.2 AUTOMATIC PAIN LEVEL/STATUS DETECTION STUDIES (CONTINUED)
(*AUC = area under receiver operation characteristic (ROC) curve, i.e. curve of true positive rate against false positive rate)

	Author	Pain Level/Status	Modality/Sensor Type	Method/Best Performance	Setting
22	(Shier and Yanushkevich 2016)	3 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/average precision=0.61	arm exercises
23	(Werner et al. 2016)	up to 3 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/accuracy=0.92 (2 levels); accuracy=0.76 (3 levels)	arm exercises
24	(Irani, Nasrollahi, and Moeslund 2015)	3 levels of shoulder pain (observer rated)	face/video	proprietary method/accuracy=0.70	arm exercises
25	(Hasan et al. 2016)	3 levels of cancer pain	face/video	Support Vector Machine/-	clinical assessment
26	(Lucey, Cohn, Matthews, et al. 2011)	2 levels of shoulder pain (observer rated)	face/video	Support Vector machine/*AUC=0.81	arm exercises
27	(Ashraf et al. 2007)	2 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/accuracy=0.81	arm exercises
28	(Lo Presti and La Cascia 2015)	2 levels of shoulder pain (observer rated)	face/video	Nearest Neighbour/accuracy=0.86	arm exercises
29	(R. Yang et al. 2016)	2 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/accuracy=0.83 (sequence); 0.73 (frame)	arm exercises
30	(Monwar and Rezaei 2006)	2 levels of pain	face/video	Neural Network/accuracy=0.92	-
31	(Khan et al. 2013)	2 levels of shoulder pain (observer rated)	face/video	Nearest Neighbour/accuracy=0.97 (1-fold cross-validation)	arm exercises
32	(Junkai Chen, Chi, and Fu 2016)	2 levels of shoulder pain (observer rated)	face/video	Support Vector Machine/F1=0.54	arm exercises
33	(Alashkar et al. 2016)	2 levels of pain (observer rated)	face/video	Structured Output Support Vector Machine/*AUC=0.8 (2-fold cross-validation)	-
34	(Jixu Chen, Liu, and Tu 2012)	-	face/video	Ensemble/*AUC=0.89 (subject dependent)	-
35	(Werner, Al-Hamadi, and Niese 2012)	no pain vs acted pain	face/video	Support Vector Machine/true positive rate=0.93 (10-fold cross-validation)	-

TABLE 3.2 AUTOMATIC PAIN LEVEL/STATUS DETECTION STUDIES (CONTINUED)
(*AUC = area under receiver operation characteristic (ROC) curve, i.e. curve of true positive rate against false positive rate)

	Author	Pain Level/Status	Modality/Sensor Type	Method/Best Performance	Setting
36	(Littlewort, Bartlett, and Lee 2009)	experimentally induced pain versus acted pain	face/video	Support Vector Machine/accuracy=0.88	forearm in water up to elbow
37	(Niese et al. 2009)	pain, neutral, happy, surprise, disgust, and anger	face/video	Support Vector Machine/-	lying down on a bed
38	(Brahnam et al. 2006)	2 levels of neonatal pain (pre-labelled)	face/photograph	Support Vector Machine/accuracy=0.96 (10-fold cross-validation)	giving blood samples
39	(Lu, Li, and Li 2008)	2 levels of neonatal pain (pre-labelled)	face/photograph	Support Vector Machine/accuracy=0.86	giving blood samples
40	(Gholami, Haddad, and Tannenbaum 2009)	2 levels of neonatal pain (pre-labelled)	face/photograph	Relevance Vector Machine/accuracy=0.91 (leave-one-out cross-validation)	giving blood samples
41	(Michael et al. 2016)	13 levels of shoulder pain	face/photograph	- /mean absolute error=1.67	-
42	(Chu, Zhao, and Yao 2014)	7 levels of pain	blood volume pulse; electrocardiography; skin conductance	Linear Discriminant Analysis/accuracy=0.997 (leave-one-out cross-validation)	seated

As can be seen in the table, a lot of the work has been focused on automatic detection based on facial expressions. While many of the studies have achieved impressive performances (such as mean squared error of 1.28 for 16 pain levels in Neshov and Manolova (2015)), they have been based on observer ratings of pain (based on the Facial Action Coding System (Cohn, Ambadar, and Ekman 2007)). The earlier discussed findings of Sullivan et al. (2006) dispute the use of such ratings in lieu of pain intensity self-report, which is the clinical gold standard (Jensen and Karoly 1992). Further, as discussed in the previous sections, the capture method for the face does not make it a practical modality for automatic detection in CP physical rehabilitation (which comprises both situated exercises and functional activities in ubiquitous settings).

There are about a fourth fewer studies where movement behaviour has been used as a modality. A few of these studies have been on the detection of experimentally induced pain in healthy participants. For example, Walter et al. (2015) used features of head pose, activities of the trapezius (posterior to the shoulder), the zygomatic (around the cheek), and the corrugator supercilii (around the eye) muscles, video based facial expressions, and skin conductance to automatically detect thresholds for heat induced pain. The muscle activity features were based on signal processing methods and included peak height, entropy, stationarity, Fourier coefficients, and statistical moments. Detection accuracy of 0.80 was obtained using these features. In feature subset selection, the authors found that the facial expression features particularly the amount of wrinkling around the nose and the range of the distance from the brow to the mouth were the most relevant for detection of the pain levels. Kachele et al. (2016) similarly used features of the activity of the trapezius muscle with electrocardiography and skin conductance features to automatically detect up to 5 levels of heat induced pain. Their muscle activity features were similar to those used in Walter et al. (2015). They found that fusion of the three modalities led to better detection of 2 levels of pain although the muscle activity features alone led to better than chance level detection accuracy, higher than the accuracy of the electrocardiography modality but lower than for skin conductance. For the two-level detection, they obtained accuracy of 0.86, while mean squared error of 0.89 was obtained for the five-level detection. Unfortunately, the findings in these studies are limited for the understanding of pain level detection in CP physical rehabilitation as the experience of pain in CP is different from experimental pain (Legrain et al. 2009) because it is usually perceived as a long lasting and enduring threat (Leeuw et al. 2007). This may explain the finding in Walter et al. (2015) of the superiority of facial expressions over the bodily expressions for experimentally induced pain contrary to the findings in Sullivan et al. (2006) for CP; limitation of the bodily expressions considered to the upper body may also have contributed to the finding in Walter et al. (2015).

More relevant, therefore, are the studies on people with CP. The earliest of these is the work of Ahern et al. (1988) where features of the activities of the lumbar paraspinal (lower back) muscles and the range of trunk movement during trunk exercises (trunk rotation and flexion, sitting, and standing) were used to automatically differentiate participants with low back CP from healthy participants. The authors obtained accuracy of 0.86. Similarly, Grip et al. (2003) used features such as the range and velocity of the neck in neck rotation and flexion exercises to automatically discriminate between participants with neck CP and healthy participants. They obtained accuracy of 0.89. Another study by Lai et al. (2009) considered participants with knee CP while they walked. The authors used the amplitude and time of ground force reaction peaks and foot movements to obtain accuracy of 0.89. Although these studies do not further classify participants with CP according to their levels of pain, their findings provide understanding of the movement behaviour cues of pain that may be relevant in the context of CP. Their findings particularly suggest that how the painful anatomical segment is handled in movement can betray that a person has CP.

In the study of Dickey et al. (2002), 11 levels of pain in people with low back CP during trunk exercises (stair climbing, flexion and rotation, sit-to-stand-to-sit) were automatically detected with an impressive performance of average error of 0.06 points on the scale (although this result may be biased as it is based on a single fold of validation). A major limitation of the study, however, is that the features used were fine-grained intervertebral movements (vertebral motion and deformation) which were captured using sensors mounted on pedicle screws that had been inserted into the spine (bilaterally on the S1 in the pelvis and the L4 and L5 in the lower back) under general anaesthesia as part of clinical assessment. This capture method is invasive and requires clinical expertise and so the capture of such intricate motions of the spine is not feasible outside of clinical settings. The author found that intervertebral twists (between the S1 in the pelvic region and the L4 or L5 in the lower back) and intravertebral twists (within each of the S1, L4, and L5) may have linear relationships with pain intensity whereas intervertebral and intravertebral flexion and bends may each have a more parabolic relationship with pain intensity. Unfortunately, the delicacy of the acquisition of these features makes it hard to interpret their findings based on more practical capture methods such as using the IMU.

3.3.2 Self-Efficacy Levels

Despite the importance of self-efficacy in many areas of human life (Bandura 1977), there has barely been any interest in automatic detection of levels of the state. The only authors that were found to use the data-driven approach typical in the affective computing community are Grafsgaard et al. (2015), McQuiggan, Mott, and Lester (2008), and Arroyo et al. (2009). In McQuiggan, Mott, and Lester (2008), the authors investigated the automatic detection of up to 5 levels of self-reported learning self-efficacy in an online tutorial setting. They used features of the interaction behaviour of the student in the tutorial system (e.g. how long they interacted with a question), learning outcomes such as the proportion of set goals that the student accomplished, and physiological cues (blood volume pulse and skin conductance). They achieved accuracies (based on 10-fold cross validation) of 0.87, 0.83, 0.79, and 0.75 for two, three, four, and five level self-efficacy detection respectively. Similarly, Arroyo et al. (2009) used interaction behaviour, skin conductance, facial cues, mouse pressure, and sitting posture.

They obtained R^2 of 0.82 for five self-efficacy levels. Grafsgaard et al. (2015) based their own study on facial expressions and obtained R^2 of 0.67. Although these studies provide evidence of the feasibility of automatic detection of self-efficacy, the features they used do not transfer to the context of CP physical rehabilitation where movement behaviour is critical.

The other study found is that of Matsuo et al. (2015). They proposed computation of MSRE levels of an elderly person based on mathematical calculations using quantifications of Bandura's four main self-efficacy factors (1977): physical performance score of the person, physical performance score of an observed peer (a robot), a measure of provided intervention, and the emotional state of the person. However, there is no empirical evidence to support their model and there was no attempt to verify that the model does indeed relate to subjective ratings or observer estimations of MSRE.

3.3.3 Emotional Distress: Depressed Mood and Fear/Anxiety

Tables 3.3 and 3.4 provide summaries of the studies on automatic detection of depressed mood and fear/anxiety respectively.

3.3.3.1 Depressed Mood

Even though a significant proportion of the studies in this area have been based on body movement modality, they have all been limited to sedentary settings. For example, in the study of Cohn et al. (2009), facial and vocal expressions during clinical assessment interviews were used to automatically discriminate between two levels of clinical depression. They obtained accuracy (based on leave-one-out cross-validation) of 0.88 using facial features and 0.79 using acoustic features. Nasir et al. (2016) similarly investigated automatic detection of 2 levels of depressed mood based on facial and vocal features captured during clinical interviews delivered through a virtual agent based on a Wizard-of-Oz setup. They obtained average F1 score of 0.76 based on 10-fold cross-validation. Pampouchidou et al. (2015) considered 4 levels of depressed mood in a similar setting using facial features alone with accuracy of 0.55. In Valstar et al. (2013), 64 levels of depressed mood were classified using facial and vocal features captured during speaking tasks. Based on 5-fold cross validation, they obtained root mean squared error of 14.12 based on acoustic features and root mean squared error of 13.61 using facial features.

Alghowinem et al. (2016) further showed the feasibility of automatic detection of depressed mood based on acoustic features captured in similar settings across a variety of data sets. They used data pooled from three different datasets. The composite dataset consisted of German and

TABLE 3.3 STUDIES ON AUTOMATIC DETECTION OF DEPRESSION (LEVELS) OR DEPRESSED MOOD

	Author	Affective State	Modalities/Sensor Type	Method/Best Performance	Setting
1	(Le Yang et al. 2016)	25 levels of depressed mood	eye and head movement and face/video; speech acoustics; previous emotion labels	Support Vector Regression/root mean squared error=9.1	Wizard-of-Oz clinical interview
2	(Alghowinem et al. 2013)	clinical depression versus healthy	head movement/video	Support Vector Machine/average recall=0.73	clinical interview
3	(Joshi, Dhall, et al. 2013)	2 levels of depression in the clinically depressed	full body movement/video	Support Vector Machine/F1=0.97 (leave-one-out cross-validation)	clinical interview
4	(Joshi, Göecke, Parker, et al. 2013)	clinical depression versus healthy	head, upper body; face/video	Support Vector Machine/F1=0.8	clinical interview
5	(Joshi, Göecke, Alghowinem, et al. 2013)	clinical depression versus healthy	head and shoulder movement and face/video; voice	Support Vector Machine/accuracy=0.92	clinical interview
6	(Pampouchidou et al. 2016)	2 levels of depressed mood	eye and head movement and face/video; speech transcript and acoustics; previous emotion labels	Decision Tree/F1=0.83	Wizard-of-Oz clinical interview
7	(Valstar et al. 2013)	64 levels of depressed mood	face/video; voice	Support Vector Regression/root mean squared error=13.6 (face); root mean squared error=14.1 (voice) (5-fold cross-validation)	speaking tasks
8	(Pampouchidou et al. 2015)	4 levels of depressed mood	face/video	Nearest Neighbour/accuracy=0.55	-
9	(Cohn et al. 2009)	2 levels of depression in the clinically depressed	face/video; voice	Support Vector Machine/accuracy=0.88 (face); Logistic Regression/accuracy=0.79 (voice) (leave-one-out cross-validation)	interview
10	(Alghowinem et al. 2016)	2 levels of depression	speech acoustics	Support Vector Machine/recall=0.75	clinical interview, non-clinical interview, and speaking tasks
11	(Nasir et al. 2016)	2 levels of depressed mood	speech acoustics	Support Vector Machine with Stochastic Gradient Descent learning/F1=0.75	Wizard-of-Oz clinical interview

English (United States) speech data from healthy participants, participants with low and high levels of depressed mood, and clinically depressed participants with low and high levels of depression captured during interviews (clinical and non-clinical, in English) and speaking tasks (in German). They obtained recall of 0.75 for two levels of depressed mood overall (high levels of depressed mood and clinical depression were considered as one class and the others as the second class). However, when one dataset was used to train a model to classify the other two, classification was only marginally better than chance level classification in the best case (recall = 0.52). The worst case (recall = 0.40) was when the dataset with German speech was used to train the model for the other two with English speech. This suggests that affect detection models may be sensitive to within-language acoustic features. The finding that a model built trained on the English datasets and tested on the German dataset was the worst case (recall = 0.50) when two datasets were used to train a model to classify the third (best case recall = 0.58) supports this. This finding suggests that automatic detection across contexts is not a trivial problem and may require deep investigations of cross-context affective features.

The findings of all of these studies provide limited understanding for automatic detection of depressed mood in CP physical rehabilitation settings where, as discussed previously, body movement is the relevant modality. Joshi and colleagues (Joshi, Dhall, et al. 2013; Joshi, Göecke, Alghowinem, et al. 2013; Joshi, Göecke, Parker, et al. 2013) have investigated automatic detection of levels of depressed mood based on body movement modality. For example, in Joshi, Dhall, et al. (2013), they used video-based full-body movement features to discriminate between two levels of clinical depression and obtained F1 score of 0.97 based on leave-one-out cross-validation. They found that the best performance was obtained by combining holistic features (based on spatio-temporal interest points) and features of the relative movement of anatomical segments. In Joshi, Goecke, Parker et al. (2013), they used video-based upper body movement, head movement, and facial features to automatically discriminate between healthy participants and participants with clinical depression. They found that using head movement features alone led to the same performance as the use of facial features alone (accuracy = 0.71) while the use of upper body movement features alone led to better performance (accuracy = 0.77). In Joshi, Goecke, Alghowinem, et al. (2013), they used video-based upper body movement and facial features and acoustic features to discriminate between these two groups. They found that the audio features alone generally led to better performance than the video-based features but the best performance (accuracy = 0.92) was obtained with fusion of the two modalities. In similar work by Alghowinem et al. (2013) where video-based head movements alone were used, recall of 0.75 was obtained. Further, Pampouchidou et al. (2016) and Yang et al. (2016) used a combination of video-based eye and head movement and facial features, speech acoustics (and transcript in Pampouchidou et al.), and features of previous emotion label annotations. Whereas Yang et al. considered automatic detection of 25 levels and obtained root mean squared error of 9.1, Pampouchidou et al. considered 2 levels with accuracy of 0.83.

A limitation of all of these studies is that they are based on data capture during interviews where movement is constrained (in contrast to physical activity settings which is central to CP physical rehabilitation). In addition, they did not investigate pain related depressed mood whose expressions may be different from non-pain depressed mood (Rusu, Pincus, and Morley 2012). Nevertheless, the studies provide understanding of how depressed mood may be detected from movement behaviour although their findings are with respect to video-based features that do not easily transfer to other movement sensors such as IMUs.

3.3.3.2 Fear/Anxiety

The majority of the work done on automatic detection of fear or anxiety have been based on acted data. For example, in Camurri et al. (2003), kinematic features such as velocity, features relating to the use of space (e.g. body contraction/expansion and amount of movement), and other movement quality features (impulsivity and smoothness) were used to discriminate between dance choreographies for fear, anger, grief, and joy. They found that although their model performed better than chance level classification overall (accuracy=0.36 based on 5-fold cross-validation), detection of fear was poorer than chance level. Although they did not elaborate on the possible reasons for this finding, it may have been because the motion features they used were based on video data. Unlike data from other types of movement sensors, video data may be more suited to computer vision features.

In contrast to Camurri et al., very good differentiation of fear (F1 score of 0.88) from sadness, happiness, and anger was possible in De Silva and Bianchi-Berthouze (2004) with better agreement with actor intentions than even observer assessments (F1 score of 0.72). Sadness was the easiest of the four states to differentiate with F1 score of 1. Although full body postures were considered, orientation of arms and the head were found to be the most informative for this discrimination; shoulder and foot poses were not informative. In Fourati and Pelachaud (2015), anxiety, sadness, panic fear, pride, joy, shame, anger, and neutral in acted everyday type activities (lifting/throwing, walking, stand-to-sit, moving books on table,

TABLE 3.4 STUDIES ON AUTOMATIC DETECTION OF FEAR AND ANXIETY

	Author	Affective State	Modalities/Sensor Type	Method/Best Performance	Setting
1	(Rani, Sarkar, and Liu 2005)	anxiety versus (engagement, anger, frustration, boredom)	shoulder and facial muscle activity/sEMG; electrocardiography; impedance cardiography; photoplethysmography; skin conductance; heart sound; temperature	Decision Tree/accuracy=0.89	playing computer game seated
2	(Gross et al. 2006)	imagery induced anxiety, sadness, anger, content, joy, pride, neutral	full body movement/marker-based optical motion capture	Discriminant Analysis/accuracy=0.77	-
3	(Shan, Gong, and McOwan 2007)	acted anxiety, anger, boredom, disgust, joy, puzzle, surprise	body and face/video	Support Vector Machine/accuracy=0.79 (5-fold cross-validation)	-
4	(S. Chen et al. 2013)	acted anxiety, fear, sadness, disgust, happiness, surprise, anger, boredom, puzzlement, uncertainty	hand and head movement, face, and skin colour/video	Support Vector Machine/accuracy>0.75 (3-fold cross-validation)	seated
5	(Gunes et al. 2015)	acted anxiety, fear, sadness, disgust, happiness, surprise, anger, boredom, puzzlement, uncertainty	body movement and face/video	Support Vector Machine/F1=0.83 (3-fold cross-validation)	seated
6	(Fourati and Pelachaud 2015)	acted anxiety, sadness, panic fear, pride, joy, shame, anger, neutral	full body movement/IMU	Random Forest/accuracy=0.87 (out-of-bag validation)	everyday activities
7	(Piana et al. 2014)	acted fear, sadness, happiness, disgust, anger, surprise	body movement/depth sensing optical motion capture	Support Vector Machine/accuracy=0.61	-
8	(Meng, Kleinsmith, and Bianchi-Berthouze 2011)	acted fear, sadness, anger, happiness	body movement	Support Vector Regression/root mean squared error of 0.14	-
9	(Kapur et al. 2005)	acted fear, sadness, joy, anger	body movement/marker-based optical motion capture	Neural Network/accuracy=0.85	-
10	(De Silva and Bianchi-berthouze 2004)	acted fear, sadness, happiness, anger	body posture/marker-based optical motion capture	Discriminant Analysis/accuracy=0.90	-
11	(Camurri et al. 2003)	acted fear, anger, grief, joy	body movement/video	Decision Tree/accuracy=0.36 (5-fold cross-validation)	dance

knocking on a door) were differentiated with accuracy of 0.87 (based on out-of-bag validation). They found that acceleration of the elbow joints (except for in the activity that depended on the elbow, i.e. lifting and throwing an object) and body posture features were the most relevant for detecting panic fear. For anxiety, body posture features, amount of upper body movement (for lifting/throwing alone), and elbow joint acceleration (for books moving and door knocking only) were the most relevant features. In contrast, speed of movement and body posture features were the most relevant for sadness. Further, a study by Gunes et al. (2015) investigated automatic detection of the absence, onset, apex, and offset of anxiety, fear, sadness, disgust, happiness, surprise, anger, boredom, puzzlement, and uncertainty using video-based facial and bodily expression features. They found that the apexes of these emotions were the easiest to detect (accuracy = 0.86, 3-fold cross-validation) while their onset was the most difficult to detect (accuracy = 0.83).

Unfortunately, the findings from these studies are limited as acted expressions do not fully reflect spontaneous expressions in real life because acted expressions are usually exaggerated and so are more salient. Although Rani, Sarkar and Liu (2005) investigated the differentiation of spontaneous anxiety from engagement, anger, frustration, and boredom (based on bodily muscle activity, facial, and physiological cues), this was done in sedentary settings and, as with the other studies, their study of these emotions was not in the context of pain. As discussed in Chapter 2, movement is the object of the fear/anxiety in the context of pain and so, as Tang et al. (2007) show, fear/anxiety in that context is expressed in the execution of the movement. It is, thus, difficult to understand how the findings of bodily expressions of fear and anxiety from these studies may transfer to the context of pain.

Aung et al. (2016) investigated the automatic detection of expressions that have been linked to pain and related fear in physical activity settings (Keefe and Block 1982; Watson, Booker, and Main 1997). In their study, these expressions (guarding, bracing, rubbing, abrupt motion, and limping) of people with low back CP were assessed by expert observers and as such do not necessarily reflect (subjective) pain experiences (Vlaeyen and Linton 2000). Although Aung et al. (2016) do not address the detection of the pain related affect, their finding of average mean square error less than 0.04 based on body movement captured using IMUs and sEMG sensors points to the possibility of automatic detection of pain related states during physical activity using this method. As the data acquired and used in their study was readily available and relevant, it was used for the investigations in this thesis.

3.4 Discussion

The aim of this chapter was to review relevant topics so as to: 1) provide further grounds for using movement behaviour for affect detection for CP physical rehabilitation, 2) review typical sensing approaches available for this modality, and 3) understand existing knowledge on automatic detection of levels of pain, MRSE, and emotional distress. It was shown that there is strong argument for the use of movement behaviour as the main modality for pain and related affect detection; wearable sensing approach (using wearable IMU and sEMG sensors) was further highlighted as a practical means of capturing this modality in ubiquitous settings typical of everyday functioning. A review of the state of the art showed that gaps still exist between current design of affect detection systems and the need for CP physical rehabilitation. The questions raised in Chapter 2 are re-discussed in this section in light of these findings.

3.4.1 What is the Relationship between Movement Behaviour and Pain, MRSE, Depressed Mood, and Fear/Anxiety?

Review of pain behaviour literature in this chapter and in the discussion in Chapter 2 shows that fine-grained movement behaviour is a critical modality for assessing levels of pain in people with CP (Keefe and Block 1982; Sullivan et al. 2006) and that the best developed method of assessing this behaviour in the context of pain is Keefe and Block’s (1982) method based on observer rating of guarding in individual activities.

However, a gap in knowledge exists of the understanding of pain behaviour with respect to the cognitive and affective states related to pain. Studies that have led to the understanding of the influence of these states on physical functioning have mostly been limited to questionnaire-based self-reports (Denison, Asenlof, and Lindberg 2004; Asghari and Nicholas 2001) which like physical activity levels (observed or diary-based) are too broad a measure of movement behaviour (Fordyce et al. 1984; Huijnen et al. 2011). This makes proposal of observed motor patterns such as guarding as a behavioural signature of anxiety, depressed mood, or low MRSE an open question still. As discussed in Section 2.5, understanding if guarding, which is the pain related movement behaviour that is most understood, is a behavioural signature of any of these states can inform the decision of what cues to capture and use for automatic detection of the associated state.

This thus makes important the question: *what are the relations between observable pain behaviour and pain, MRSE, depressed mood, and fear/anxiety*?

3.4.2 How can Levels of Pain, MRSE, Depressed Mood, and Fear/Anxiety be Automatically Detected?

Review of literature clearly shows that levels of pain, self-efficacy, depressed mood, and fear/anxiety can be automatically detected better than chance level estimation (Dickey et al. 2002; McQuiggan, Mott, and Lester 2008; Alghowinem et al. 2016; Fourati and Pelachaud 2015) and, in some cases, even better than human observers (De Silva and Bianchi-berthouze 2004). This suggests that automatic detection is a feasible approach for technology to assess these states so as to tailor intervention to them to enable CP physical rehabilitation.

Strong support has been found for the use of movement behaviour cues to implement this. Not only does this channel complement knowledge about pain experience in informing the design of appropriate intervention (Sullivan 2008), it has also been shown to be a more significant medium of expression of pain experience than other observable modalities like the face and voice (Sullivan et al. 2006; Keefe and Block 1982; Aung et al. 2016). Further, there are evidences that detection performance using the modality is comparable with (and sometimes even better than) these other modalities (Dickey et al. 2002; Joshi, Göecke, Parker, et al. 2013). However, previous work provides limited understanding of the movement behaviour cues of pain, MRSE, fear/anxiety, and depressed mood.

Concerning the assessment of pain level, it has been shown that how the painful anatomical segment is moved may be a cue of whether or not a person has CP (Ahern et al. 1988; Grip et al. 2003; Lai et al. 2009) and findings in Dickey et al. (2002) suggest that this may also be relevant for further assessment of the levels of pain of people with CP. However, the work of Dickey et al. does not provide understanding of how cues beyond those that can be tracked with the use of invasive methods available in hospital settings differentiate between these levels. Such understanding is important to inform the implementation of automatic pain level detection systems in physical rehabilitation technology. Further, it addresses the need highlighted in Sullivan (2008) to understand pain related movement behaviours in terms of their cognitive and affective components so as to inform research on intervention designs for CP physical rehabilitation.

In the case of MRSE level detection, there is little known in literature beyond the study of Keogh, Griffin, and Spector (1981) who investigated video-based observation of this state in gymnastic settings using expert observers (physical education experts and gymnasts). They found very high levels of agreement between the observers suggesting that observation method may be a reliable form of assessing MRSE levels. This points to value in further investigation of automatic detection of levels of the state. On analysing cues that the observers reported using in their assessment, the authors found that the observers paid attention to: 1) movements performed to start the gymnastic routine being performed, such as moving to the appropriate start position or fidgeting, 2) how the routine was performed, 3) timing and sequencing of phases of the routine, and 4) engagement behaviours of the participants, such as looking excessively at the experimenter. Although these cues are a starting point in understanding how levels of these states can be detected, further investigation needs to be done in the context of CP physical rehabilitation where pain may be a confounding factor in how self-efficacy levels are expressed. Further, in this context, movements are less constrained (and may have more individual differences) in how they should be done, in contrast to the choreographed routines typical of gymnastics.

For fear and anxiety detection, it has been shown that posture, kinematics, and amount of movement can be useful cues (Camurri et al. 2003; Fourati and Pelachaud 2015). However, there needs to be further investigation of the relevance of these cues for real fear or anxiety which may be more challenging to detect than acted expressions because they are subtler and less stereotypical (and so with more within-subject variations) (Kleinsmith, Bianchi-Berthouze, and Steed 2011). In fact, fear and anxiety needs to be considered in the context of pain and movement which are central to these states in CP physical rehabilitation. The same need exists for detection of depressed mood where the focus has been on the assessment of clinical depression in sedentary settings. The findings in this area have been further limited for understanding how detection systems for these states can be implemented for CP physical rehabilitation technology due to the use of video-based features that draw on computer vision analysis that are not readily interpretable in terms of movement behaviour descriptions. There are existing psychology and affect studies (e.g. (Waxer 1977; Waxer 1974; Scherer et al. 2013; Lemke et al. 2000; Michalak et al. 2009)) that provide complementary understanding of these cues. However, these studies were also not done in the context of pain. Thus, it remains unclear how these cues differentiate between levels of the states within pain experience and if they are (or how they can be) relevant in physical activity settings.

A question that, thus, needs to be addressed is: *how can levels of pain and related self-efficacy, depressed mood, and fear/anxiety be automatically detected from movement behaviour?* particularly, *what movement behaviour cues contribute to the detection of each of these states? And can these cues enable automatic detection of the states?*

3.4.3 How can Levels of Pain, MRSE, Depressed Mood, and Fear/Anxiety be Automatically Detected in Functional Activities?

An important consideration for the automatic detection of levels of pain, MRSE, fear/anxiety, and depressed mood in CP physical rehabilitation is the possibility of this functionality for both functional movements in ubiquitous settings and exercises, which may be situated and more constrained. As earlier discussed, the importance of this lies in the challenge (for people with CP) of applying skills and capabilities gained in controlled exercise settings to functional activities where the barriers may be different even for the same movement types (Singh, Bianchi-Berthouze, and Williams 2017). As the study of Singh, Bianchi-Berthouze, and Williams (2017) show, technology that is available to a person with CP in both contexts can guide transfer of strategies and better grounding of awareness of capabilities that promote functioning in valued activities, which is the goal of CP physical rehabilitation.

A primary problem then is the need to understand the feasibility of this functionality based on sensing approaches that are practical for such settings. Not only does the sensing system need to be wearable, it also needs to be portable and so as minimal (in the amount of unit sensors required) as possible. It is also important for the system to be low-cost as expensive systems are not practical for use beyond clinical settings where they serve little use in self-managed physical rehabilitation. Although there have been studies (Farella et al. 2006; Ylisaukko-oja, Vildjiounatie, and Mantyjarvi 2004; Biswas and Quwaider 2008; Munguia Tapia et al. 2007; Harun et al. 2015; Costanza et al. 2007; Saponas et al. 2010; Donnarumma, Caramiaux, and Tanaka 2013) that investigated the efficacy of low-cost wearable systems for body movement sensing, no investigation was found of systems with IMU and sEMG integrated. Yet, pain studies (Ahern et al. 1988) point to the significance of fusing data from these two sensors in the assessment of pain experience. Further, the existing studies do not investigate the feasibility of automatic detection of levels of pain, MRSE, fear/anxiety, and depressed mood based on such systems.

An additional problem based on findings in the study of Alghowinem et al. (2016) reviewed in the chapter is that affective cues may not easily transfer between physical activity contexts: exercises versus functional settings. This problem is important to address given the convenience of acquiring training data in controlled exercise settings in contrast to everyday functional movements and so the possibility of a system largely trained on exercise movements to be used in functional movements.

It is, thus, necessary to further ask, *can movement behaviour cues that enable automatic detection of levels of pain and related self-efficacy, fear/anxiety, and depressed mood be detected using low-cost sensors?* and *can these cues enable automatic detection of these states in both exercise and functional movements?*

3.5 Conclusion

The literature review points to movement behaviour (particularly fine-grained descriptions of movement, rather than general activity levels) as an important modality for the automatic assessment of pain and related states in physical activity settings. However, existing studies in pain level detection have mostly focused on facial expressions; where movement features have been considered, the method used in capturing them are impractical for everyday settings. MRSE level and emotional distress detection studies have been limited to sedentary settings (for MRSE) and depressed mood) and acted expressions (for fear/anxiety). Beyond its investigation of the relationship between movement behaviours and these states, this thesis further closes the existing gap by studying low-level movement features that inform discrimination between levels of the states in physical activity settings. The investigation will be based on features tracked using IMU and sEMG sensors, which are practical for everyday settings. The thesis will also investigate the feasibility of automatic detection in functional movements, captured by a low-cost device with integrated IMU and sEMG sensors.

Part II

Research Questions
&
Methodology

4 RESEARCH QUESTIONS AND METHODOLOGY

THIS thesis investigates movement behaviour as a modality for assessment of cognitive and affective needs that emerge during physical activity. The long-term aim is to develop technology that enables such monitoring to occur in everyday life and so enable personalisation of therapy. This aim emerged from the review in Chapters 2 and 3. In Chapter 2, it was shown that pain and related cognitive and affective states, particularly low MRSE, fear/anxiety, and depressed mood, interfere with engagement in physical activities (Asghari and Nicholas 2001; Vlaeyen, Morley, and Crombez 2016). Further, untapped opportunities for these states to be addressed when detected in everyday physical activities (Olugbade et al., in review) so as to facilitate engagement in these activities were highlighted. It also emerged that assessment of movement behaviour is critical to inform such intervention as it provides insight into the coping strategies used by a person with CP to engage in individual movements. In Chapter 3, movement behaviours were shown to be additionally relevant for automatic detection of pain and related cognitive and affective states although still under-investigated in this area. This thesis, thus, focuses on providing understanding of pain, MRSE, and emotional distress (fear/anxiety and depressed mood) dimensions of movement behaviours during everyday physical functioning. With this, this thesis aims to contribute to the fields of pain and affective computing by unlocking new channels for supporting physical rehabilitation. Figure 4.1 provide an overview of the specific research questions addressed in the thesis. These are introduced in more details in the next section followed by a description of the approach, methods, and dataset used to address them.

4.1 Research Questions (RQs)

The research questions of this thesis on the understanding of movement behaviour as a modality for automatic monitoring of pain and related self-efficacy and emotional distress are presented in this section. An overview of the questions and the relations between them is given in Fig. 4.1.

The first research question addressed is:

RQ1 (Chapter 5) - *What are the relations between observable pain behaviour and pain, emotional distress, and self-efficacy?*

RQ 1 - Chapter 5

What is the relationship between observable pain behaviours and pain, self-efficacy, and emotional distress?

- EmoPain dataset extension with physiotherapist annotation
- Quantitative exploration of RQ based on extended dataset
- Analysis of MRSE cues reported by physiotherapists in annotation

RQ 2 - Chapter 6

How can levels of pain, self-efficacy, and emotional distress be automatically detected during physical activity based on movement behaviour cues?

- Movement features investigation based on literature, video analysis with physiotherapists, visual inspection of movement data.
- Modelling based on the movement features (from EmoPain dataset) and using machine learning algorithms
- Analysis of feature relevance based on feature set optimisation and statistical methods

RQ 3 - Chapter 7

How can levels of the states be detected in everyday physical functioning based on these behaviours?

- Prototyping of minimal set of low-cost wearable sensors
- Acquisition of Ubi-EmoPain dataset using prototype
- Modelling based on the movement features (from Ubi-EmoPain dataset) and using machine learning algorithms

Fig. 4.1. The research questions investigated in this thesis and the chapters where the investigations are reported.

This question addresses the need (pointed to in Chapter 2) to understand the extent to which pain and related self-efficacy and emotional distress can be operationalised in terms of pain behaviours which have been specified in pain literature (Keefe and Block 1982) for observational assessment of pain experience. The significance of pain, self-efficacy, and emotional distress (fear/anxiety and depressed mood) is their importance as factors in engagement in physical activities in people with CP (Asghari and Nicholas 2001; Vlaeyen, Morley, and Crombez 2016). The pain behaviour focused on in the investigation of the question is guarding. This is because this behaviour is the most prevalent and relevant (Keefe and Block 1982; Tang et al. 2007; Aung et al. 2016) of Keefe and Block's pain behaviours (1982) and the only one of the pain behaviours shown to be associated with longer term disability (Prkachin, Schultz, and Hughes 2007).

The investigation addresses the shortcoming of the two threads of relevant work in the CP literature. In one thread, understanding of the relationships between physical functioning and pain and related cognitive and affective states has been based on self-reports of behaviour (Asghari and Nicholas 2001; Vlaeyen and Linton 2000) such as levels of interference of pain in everyday functioning. In the second thread of work, focused on investigation of more fine-grained behaviours, there has however only been understanding of the relations of pain behaviours to pain intensity (Keefe and Block 1982; Sullivan et al. 2006) to the exclusion of other psychological factors that underlie physical functioning as shown by the earlier mentioned body of work. The two bodies of work remain disconnected leaving a critical gap that needs to be addressed. The first question addressed in this thesis aims to build a bridge between these two threads by investigating the relationships between bodily motor patterns and pain, MRSE, and emotional distress.

The investigation further aims to inform the development of affect-aware systems that can, thus, provide tailored support for self-managed physical rehabilitation. Although movement behaviour has been pointed to as a cue for assessing pain experience (Sullivan et al. 2006; Keefe and Block 1982), the lack of systematic study of the relationship between movement behaviour and pain experience in the literature makes it difficult to understand what movement behaviours may be of value. Are Keefe and Block's pain behaviours (1982) sufficient? Or as Sullivan (2008) suggests, are there more relevant behaviours, with each pain related state having its own behavioural signature? Although affective computing is moving towards system development that does not require pre-crafting of features but rather uncovers relevant features through mining of raw data, such methods rely on vast amounts of data whereas acquisition of representative data from people with CP is challenging. Further, the methods also do not enable understanding of features in such a way that informs minimisation of the number of sensors used for data capture. This minimisation is important as, in everyday life, it is not possible to capture all aspects of movement behaviour given the need to make the sensing system portable and wearable. This initial question, thus, aims to shed light on how much guarding defines pain and related cognitive and affective states.

The findings of the investigation of RQ1 which showed that guarding is not sufficient to characterise levels of pain, MRSE, and emotional distress, and a more complex combination of lower level movement behaviour descriptions may be at play led to the second question:

> RQ2 (Chapter 6) - *What movement features characterise levels of pain, self-efficacy, emotional distress during physical activity and could enable their automatic detection?*

The question builds on RQ1 by addressing the need to understand what sets of behaviours enable differentiation of levels of the above states and the feasibility of automatic detection of their levels based on these behaviours. It is, thus, composed of two main parts. The first part is on understanding what behaviours contribute to differentiation of the levels of each of the states while the second part of the questions extends this with further investigation of the use of these behaviours for automatic detection. Each of the states is individually investigated by bringing together knowledge from the literature and findings that emerged by working with physiotherapists and from visual inspection of behaviour data from people with CP and healthy participants. Rather than looking at observable movement features alone, movement behaviour was also explored in terms of muscle activity with the aim of having insight to covert motor responses and also contribute to research on this under-explored modality (Huis In ’t Veld, Van Boxtel, and de Gelder 2014a; Huis In ’t Veld, Van Boxtel, and de Gelder 2014b). Feature set optimisation and statistical methods were used to understand the discriminative power of the features.

Beyond investigating the feasibility and limitation of building pain related affect-aware systems based on movement behaviour features, the investigation challenges how pain experience monitoring is currently addressed in affective computing literature and it aimed to signal opportunity for a wider understanding of pain experience and behaviour that goes beyond pain intensity and even beyond the other states explored in this thesis. The investigation also questions current applications of body movement sensing technology in the context of physical rehabilitation as it aimed to provide proof of concept of the possibility of assessing progress (beyond biomechanical metrics typically used in acute conditions) taking into account psychological measures that are relevant for the management of chronic conditions (Olugbade et al., in review; McNaney et al. 2015; Morris 2016; Ayobi et al. 2017).

The understanding of the movement behaviours that enable discrimination between levels of the aforementioned states and the feasibility of automatic detection based on the behaviours led to the further question:

> RQ3 (Chapter 7) - *how can body movement and muscle sensing technology be used to detect levels of pain and related self-efficacy and emotional distress in everyday physical functioning?*

This question is very important as up to now full-body sensing technology for physical rehabilitation has mainly been designed for situated exercising. However, in CP (and other chronic conditions) physical rehabilitation happens during everyday activity and not just during exercises (Singh et al. 2014). On the other hand, wearable devices for fitness and activity level tracking during everyday life (e.g. the Moov Now bracelet (Moov Inc. 2016)) are not suitable for capturing the movement behaviour cues of pain and related cognitive and affective states (Huijnen et al. 2011). The investigation of the question, thus, builds on the understanding of features that emerged from RQ2 with a minimalist design of a wearable network of IMU and sEMG sensors that leads to initial understanding of movement behaviour during functioning. The investigation is composed of two parts. The first part aimed to understand the possibility of using such wearable device for movement behaviour tracking in everyday settings where physical activity is not situated. The second part is groundwork towards understanding the possibility of using the behaviours captured with this set of sensors for automatic detection of the above states in both exercise and functional movements. It is outside the scope of this thesis to investigate fully the usability of the device in everyday settings; however, a partial understanding of what would be a dense examination is provided in the investigation of the question in this thesis.

4.2 Methodology

The approach used to address the research questions is characterised by three main elements: (a) the use of data from people with CP engaged in movements that are generally considered challenging in this population and are constituents of everyday functioning and physical rehabilitation exercise programs; (b) rapid prototyping of wearable body movement sensing devices; and (c) the use of machine learning and statistical analysis to model relations and mapping between movement behaviours and cognitive and affective states. The general aspects of the methodology are described below. Detailed description of the methods used in each study are reported within the specific study chapters.

4.2.1 Datasets

Two sets of data were used in investigating the three questions. One is an existing dataset, EmoPain, while the second, the Ubi-EmoPain dataset, is a new dataset acquired as part of the investigations of this thesis. Both the EmoPain and Ubi-EmoPain datasets comprise real and spontaneous body movement data from people with CP with self-reports of pain intensity and emotional distress. The EmoPain dataset additionally includes data from healthy control participants. Rather than using well-controlled experiments to gather the data, effort was made to gather movement data that better reflect the way people would move if they were self-directing their activity. Hence, little instruction was provided on what would be considered the correct way of executing the movements. This is very important as both the pain literature and the National Health Service pain management program that supported the acquisition of that dataset insisted on the need for the data collection design to be reflective of everyday movement settings where movements are unconstrained.

The EmoPain dataset was used for investigating RQ1 and RQ2. However, it was first extended (as part of this thesis) using an annotation study to obtain annotations for guarding and self-efficacy using physiotherapists. This approach to acquisition of guarding and self-efficacy measures for the EmoPain dataset is based on the findings of Keefe and Block (1982) and Keogh, Griffin, and Spector (1981) that suggest that observer annotation is a reliable means of assessing guarding and MRSE respectively. Physiotherapist annotation of MRSE offers further opportunity to understand how they assess this state and the behavioural cues that they use in making their estimation. The annotation study was, therefore, leveraged to gain understanding of the cues of MRSE so as to inform the investigation of RQ2 given that there have been limited studies in this area, as highlighted in Chapter 3. The EmoPain dataset is described in Section 4.3 and the annotation study that extends it is reported in Chapter 5.

The Ubi-EmoPain dataset was further acquired because of the limitation of the EmoPain dataset that the sensors used to capture its body movement data were expensive and based on a full-body network of sensors (rather than a minimal one) wirelessly controlled by a computer (rather than a portable device such as a phone). RQ3 prompted the need for a dataset based on a reduced set of low-cost sensors so as to investigate the possibility of using such sensors for automatic detection of levels of pain, MRSE, and emotional distress in everyday settings. The acquisition of this dataset is reported in Chapter 7.

For both the annotation study and the data collection study carried out, local and NHS research ethics approval was obtained, and participants gave informed consent. The information sheets and consent forms included as Appendix I.

4.2.2 Rapid Prototyping

A further need that emerged from the review of literature review (in Chapter 3) and is pertinent to the investigation of RQ3 is the need to develop a sensing prototype to acquire body movement data for the Ubi-EmoPain dataset due to lack of readily available integrated low-cost IMU and sEMG sensors. Thus, as part of the investigation of RQ3, a low-cost wearable sensor prototype (named MOVES-PC, for movement sensing prototype for pain and related affect computing) consisting of IMUs and sEMG sensors was developed using iterative rapid prototyping. As the prototype was not intended as a commercially viable system but rather as a rapid prototype to enable investigation of the possibility of using similar sensing systems to detect pain and related states from body movement data in everyday settings, attention was only paid to movement tracking functionality in its design. Placement of the units of the prototype for pain related behaviour tracking were grounded in findings from the investigations of RQ2 based on the EmoPain dataset. Before using the prototype to acquire the Ubi-EmoPain dataset, its efficacy for tracking overt behaviour and muscle activity was validated using healthy participants. The development and validation of the prototype are described in Chapter 7.

4.2.3 Data Analysis

Different types of methods were used to investigate RQ1 and RQs 2-3.

Quantitative data analysis methods were used in investigating RQ1. These include Bayesian modelling techniques and traditional statistical methods. The analyses explored the relationships between guarding and pain and related self-efficacy and emotional distress based on guarding and self-efficacy labels obtained from the earlier mentioned annotation study and self-reports of pain, anxiety, and emotional distress from the EmoPain dataset. The analysis methods used are described in Chapter 5 for convenience. Thematic analysis of the visual cues used by the physiotherapists in estimating MRSE was further done to gain understanding of cues that enable the assessment of the state.

Quantitative analysis methods were also employed in investigating RQ2 and RQ3. Visual inspection, machine learning algorithms, optimisation algorithms, and traditional statistical analysis methods were used to learn the features that enable differentiation between levels of the pain, MRSE, and emotional distress and to understand how the features contribute to automatic detection. This analysis was based on body movement data and self-reports of pain and emotional distress from the EmoPain dataset and physiotherapist ratings of self-efficacy from the annotation study. The machine learning algorithms used in addressing RQ2 and RQ3 are described in Section 4.4 while the other methods are described in Chapters 6 and 7 for the respective studies for the sake of convenience.

4.3 EmoPain Dataset

The EmoPain dataset (pre-existing the work presented in this thesis) is described in this section; study-specific details about subsets of the dataset used for each study are provided in the specific study chapters.

4.3.1 Participants

The EmoPain dataset (Aung et al. 2016) consists of data collected from 28 healthy control participants and 22 people with CP in the lower back, which is the most prevalent CP location (Breivik et al. 2006). The control participants comprised 14 females and 14 males with mean age of 37.1 years. The participants with CP consisted of 15 females and 7 males with mean age of 50.5 years.

4.3.2 Physical Activities

The data was collected while the participants performed two series of physical exercises where each series had similar sets of exercises but differing levels of challenge (Aung et al. 2016).

The investigations of this thesis focus on 3 of the 7 physical exercises performed: Forward Trunk Flexion, Full Trunk Flexion, and Sit-to-Stand. The other four exercises were sitting still, standing still, balance on one leg, and walking. The first two were not considered in this thesis as it has been shown in Watson et al. (1997) that people with CP do not differ from healthy persons in motor patterns during sedentary periods such as sitting or standing still. Forward Trunk Flexion, Full Trunk Flexion, and Sit-to-Stand were chosen over the latter two because of evidence that they are challenging movements for people with low back CP (Watson et al. 1997; Janssen, Bussman, and Stam 2002).

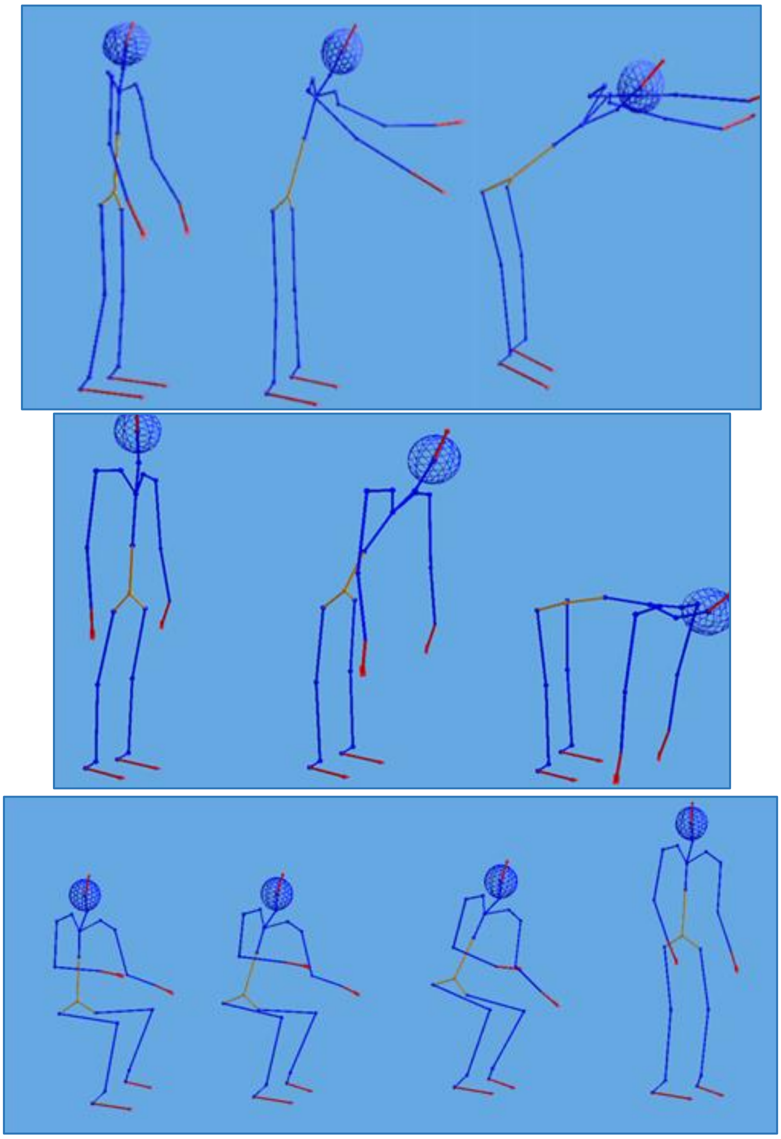


Fig. 4.2. Full body skeleton (reconstructed from motion capture data) of a participant of the EmoPain dataset performing Forward Trunk Flexion (top), Full Trunk Flexion (middle), and Sit-to-Stand (bottom)

Fig. 4.3. Sample video frames showing a participant of the EmoPain dataset performing Forward Trunk Flexion (top), Full Trunk Flexion (middle), and Sit-to-Stand (bottom).

In Forward Trunk Flexion, each participant was instructed to reach with both hands as far forward as he/she could while standing (see Fig. 4.2-top). This simulates functional forward reaching movement such as in reaching for a distant stem in a rose bush while gardening or for a plate on a high kitchen shelf. At the higher challenge level, the participant had to hold a 2-kilogram dumbbell while performing the activity. In Full Trunk Flexion, each participant was instructed to bend to reach towards the toes with his/her hands, starting from standing posture (Fig. 4.2-middle). This also simulates a functional movement, e.g. picking up an item from the floor or bending to tie shoe laces. This activity only had one challenge level. In Sit-to-Stand, each participant had to stand from seated position on a bench (Fig. 4.2-bottom). At the lower challenge level, a participant completed three self-paced sit-to-stand movements, while at the higher challenge level, s/he was required to complete each of three sit-to-stand movements at the prompt of the instructor.

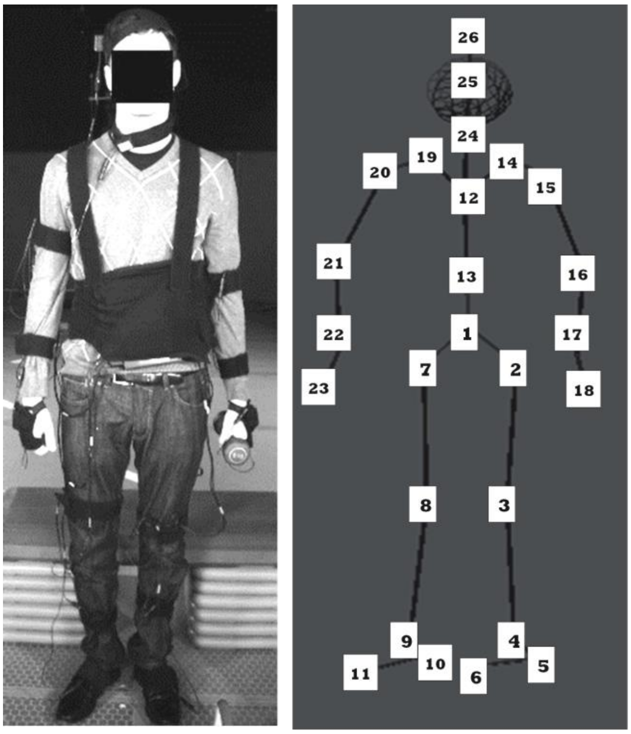


Fig. 4.4. A participant wearing the Animazoo IGS-190 sensor system (Left) and the 26 tracked anatomical joints (labelled from 1 to 26) tracked by the system (Right)

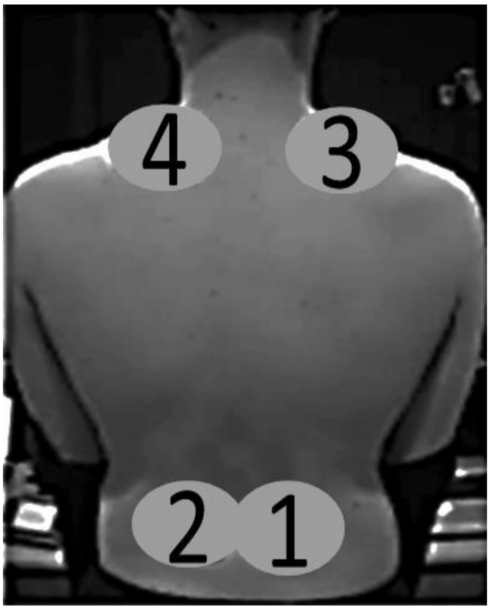


Fig. 4.5. The 4 tracked muscle activity locations

4.3.3 Body Movement Data

Body movement was captured using video cameras, a wearable IMU based motion capture system, and sEMG sensors (Aung et al. 2016). The video cameras captured the ventrolateral view of a participant's movements (see Fig. 4.3) at resolution of 1024 x 1024 pixels and a sampling rate of 58 hertz. The video recordings were used to facilitate labelling of the motion capture data. The motion capture system used is the Animazoo IGS-190, which recorded three-dimensional motion at a rate of 60 hertz. The system comprises 18 gyroscopes attached to the participant using Velcro straps as shown in Fig. 4.4-left: three were placed on each limb while one was placed in the middle of the trunk with another about the pelvis, one on each of the shoulders, and one on the each of the head and the neck. These allowed reconstruction of the three-dimensional positions of 26 anatomical joints (see the labels in Fig. 4.4-right). Muscle activity was captured using the BTS FreeEMG 300 wireless sEMG system, which had 4 sEMG sensors: two were placed bilaterally on the trapezius, the other two on either side of the L4/5 spinal segment as in Fig. 4.5 (Aung et al. 2016). Each sensor recorded muscle activity at 1 kilohertz. The resulting signals were full-wave rectified to single polarity and the upper envelopes of the consequent signal taken to filter out noise.

4.3.4 Affective Measures

There are three measures of the EmoPain dataset that were used in this thesis: Hospital Anxiety and Depression Scale (HADS) scores, pain self-report, and anxiety self-report.

The HADS was completed by both participants with and without CP before performing any of the physical exercises. This scale (Zigmond and Snaith 1983) measures emotional distress (Cosco et al. 2012) (i.e. anxiety and depressed mood) using 14 self-report items each scored between 0 and 3 in increasing order of intensity. One item on the scale, *I can sit at ease and feel relaxed*, was excluded in the use of the HADS in this thesis as this item is thought to be problematic as an emotion measure in people with CP because of its possible somatic interpretations in this population (Pincus et al. 2004; Pallant and Bailey 2005).

Pain self-report was obtained from the people with CP after each exercise type for each of the two series of exercises, using a standard 11-point pain scale (Jensen and Karoly 1992) from 0 for no pain to 10 for extreme pain.

Anxiety self-report was also obtained from these participants after the performance of each exercises using a 0-to-10 scale.

4.4 Modelling approach

The automatic detection of levels of pain, emotional distress, and MRSE were treated as separate modelling tasks in this thesis to gain in-depth understanding of each individual problem. The automatic detection tasks were based on the body movement (motion capture and surface electromyography) data described in Sections 4.3.3 and 7.2. For each of the tasks, body movement features were normalised to address individual differences in lengths of anatomical segments and muscle activity baseline. Details of the normalisation of the features are described in the study chapters. Other individual differences that may affect movement behaviour, such as age, weight, and idiosyncrasies, were accounted for by using leave-one-subject-out cross-validation to evaluate the performance of the detection models.

We approached the building of models as a classification task as each of the states was assumed to comprise a small number of discrete levels based on the requirements for affect-aware CP physical rehabilitation discussed in Chapter 2. As the aim of this thesis is to provide benchmark and proof-of-concept understanding of the feasibility of automatic detection of these states from body movement data as opposed to the investigation of machine learning algorithms, it was considered sufficient to use standard machine learning algorithms for classification. The algorithms used in this thesis are described below. Specific details about hyperparameters used are provided in the study chapters.

4.4.1 Machine Learning Algorithms

As shown in Section 3.3 (see Tables 3.2, 3.3, and 3.4), decision trees, Random Forests (RFs), and Support Vector Machines (SVMs) have been used extensively in pain-related affective computing studies with good classification performance. Thus, these algorithms were chosen for use in the investigations in this thesis. As the focus of this investigation is a proof of concept rather than deployment-ready engineering (and for the sake of easier comparison with general performances in previous studies), the use of more advanced machine learning techniques is left for future work.

A decision tree is a simple classifier built by recursive splits of a feature vector X into subsets (Breiman et al. 1984). A criterion widely used to split the nodes (i.e. feature subsets) is the minimisation of the Gini index of diversity

$$\sum_{i \neq j} p(i \mid m)\, p(j \mid m), \quad i,\ j = 1, 2, \ldots, J$$

which is a measure of the node impurity with respect to J classes, i.e. how much a split does not discriminate between the J classes within a set of observations, where $p(i|m)$ is the probability that an observation of subset X_m Є m of features belongs to class i. This criterion was used for splitting in the decision tree classifiers used in this thesis. Terminal nodes in a tree are assigned a class i based on the rule

$$p(i \mid m) = \max_{j} p(j \mid m) \quad j = 1, 2, \ldots, J$$

A decision tree has the advantage of being able to handle missing data; it does this by optionally storing surrogate splits (for each node) that can be used to classify an observation that is missing the primary feature used to split the node.

In the studies done in this thesis, the MATLAB function *fictree* was used to implement the decision tree and the maximum number *nsplits* of splits was optimised based on grid search.

The RF is an ensemble of decision trees and is defined as:

$$\{h(\boldsymbol{x}, \Theta_k), \quad k = 1, \ldots, K\}$$

where Θ_k is a random vector used to build the kth tree and encodes the randomness in the selection of features for splitting the nodes of the tree or in the selection of observations from the training set $\boldsymbol{x}$ used to build the tree (Breiman 2001). Each tree casts a vote for the classification of an unseen observation. The RF has the advantage of affording use of (multiple) low variance learners (trees) which make the algorithm robust to overfitting (Breiman 2001). In the investigations of this thesis, the MATLAB functions *TreeBagger* and *fitensemble* were used to implement the RF. For the former, the number *ntrees* of trees and the number *nfeats* of randomly selected features used in growing each node were optimised using grid search. In the use of the latter, only the maximum number *nsplits* of splits were optimised (based on grid search).

In contrast to decision tress and RFs, the SVM is a two-class classification algorithm that works by solving for the hyperplane, defined by

$$\boldsymbol{x}'\beta + b = 0$$

that separates observations into either of two classes, *+1* or *-1*, with a maximum margin between the two sets of observations where $\boldsymbol{x}$ is the set of observation and b is a constant (Cortes and Vapnik 1995). The optimal solution of the hyperplane is found by solving for:

$$\arg\max_{\alpha}\left(\sum_{i}^{I}\alpha_i - \tfrac{1}{2}\sum_{i}^{I}\sum_{j}^{I}\alpha_i\alpha_j y_i y_j K(x_i, y_i)\right)$$

where α_i is related to β as

$$\sum_{i}^{I}\alpha_i y_i x_i = \beta$$

with the constraints that

$$\sum_{i}^{I}\alpha_i y_i = 0$$

and

$$0 \le \alpha_i \le C$$

x_i and y_i are the *i*th observation vector and its class respectively while C is the penalty parameter that governs the size of the (soft) margin. A soft margin is necessary as, in reality, observations are usually not fully separable. The margin permits the hyperplane to misclassify some observations; a lower C indicates a stricter permission. $K(\boldsymbol{x}_i, y_i)$ is a kernel function of $\boldsymbol{x}_i$ and y_i; kernel functions are used to map observations into a feature space where they are more linearly separable. The investigations in this thesis explored standard kernel functions, i.e. (1) polynomial kernel

$$K(x_i, y_i) = (x_i^{'} y_i + 1)^d$$

where d is the degree of the polynomial, (2) radial basis function kernel

$$K(x_i, y_i) = e^{\left(\frac{-(x_i - y_i)^{'}(x_i - y_i)}{2\sigma^2}\right)}$$

where σ>1 is the width of the Gaussian function, and (3) hyperbolic-tangent kernel

$$K(x_i, y_i) = \tanh(p_1 x_i x_j^{'} + p_2)$$

where p_1 and p_2 are constants with $p_1 > 0$ and $p_2 < 0$. In the investigations done in this thesis, the MATLAB function *svmtrain* was used to implement the SVM and the optimal $K(\mathbf{x}_i, y_i)$ and C for each model were found using grid search.

4.4.2 Feature Subset Selection Approach

Feature subset selection was done on the feature vectors used for classification. This was done for three main reasons: to understand the contribution of the body movement features investigated in discrimination between levels of the considered states (RQ2), to minimise the number of anatomical segments that need to be tracked for automatic detection (RQ3), and to maximise classification performance (RQ2 and RQ3). Minimising the number of anatomical segments to be tracked enables the number of sensors to be reduced to a minimum and can inform the facilitation of body movement capture for automatic detection in everyday settings. The method used for feature subset selection in the investigations done in this thesis is a wrapper-based approach, which has the advantage of tailoring selection to the specific classification algorithm to be used. Specifically, a breadth-first tree search of the feature vector V was used to find the optimal subset $U^* \subset V$ such that

$$acc_{U^*} = \max_{U} acc_U \quad \forall U \subseteq V$$

where acc_U is the value (i.e. classification performance) of a classification algorithm based on the feature subset U. Rather than an exhaustive search, a method similar to the Branch and Bound algorithm of Narendra and Fukunaga (1977) was used so as to minimise the running time of the search. In the method used in the investigations of this thesis, for any algorithm, a tree node (i.e. feature subset) was visited only if the node is at least as good as its parent based on the assumption that acc_U satisfies monotonicity (and

$$acc_{U_1} > acc_{U_2} > \cdots > acc_{U_m}$$

where $U_1 \subset U_2 \ldots \subset U_m$) and so that the successors of the node will do no better than the node. While this assumption does not always hold true, it allows faster discovery of a feature subset $U \subset V$ where $acc_U \geq acc_V$, which is the objective of feature subset selection in the studies of this thesis. To further reduce the running time of the search, a node was also required to be better than n of its peers (other nodes in the tree whose parents have been visited) to be visited. When the additional criterion was enforced, peer nodes were visited, if they met the criterion, in decreasing order of their values.

4.4.3 Machine Learning Performance Evaluation

As is the standard in affective computing, leave-one-subject-out cross-validation was used to assess classification performance in the investigations done in this thesis because it tests how well a classification model can generalise to observations of unseen subjects. This is particularly important given inter-individual variations in expressions of cognitive and affect states.

4.5 Conclusion

Three main research questions are investigated in this thesis. Each of the investigations is based on data collected from people with CP including an existing dataset extended within this thesis, and a new dataset captured using a custom-built device based on integrated IMU and sEMG sensors. For the first question, Bayesian modelling is the main approach used, while standard machine learning techniques were used in addressing the other two questions. Further details of these and additional methods employed in the investigations are reported, with the findings from them, in the next part of the thesis, Part 3, consisting of Chapters 5, 6, and 7 dedicated to the investigations of the first, second, and third questions respectively.

Part III

Research Studies

5 Exploring The Relationships between Observed Pain Behaviours and Pain and Related Cognitive and Affective States

THE first question investigated by this thesis is: *what is the relationship between observed pain-related behaviour and pain and related self-efficacy and emotional distress?* The review of literature in Chapter 2 points to two main bodies of work in the area of CP related to this question. One set (hereafter referred to as pain theory literature) have focused on understanding the cognitive and affective factors responsible for poor functioning outcomes and the maintenance of the CP condition. The best developed and investigated of these theories is the fear-avoidance theory (Vlaeyen and Linton 2000) which suggests that fear of pain and consequent avoidance behaviour lead to the maintenance of CP and that cognitive appraisal (e.g. catastrophising) mediates the emergence of fear in pain experience. This theory is limited as it is based on studies where fear and avoidance were quantified using broad measures such as the usual level of fear and level of disability respectively. The second body of work has been based on the analysis of more fine-grained behaviours, such as guarding, at the level of individual activities (Keefe and Block 1982; Sullivan et al. 2006). However, they have mostly been focused on pain intensity alone without consideration of related cognitive or affective states. As such these two bodies of work have complementary approaches to gaining understanding of CP; although each part is important in its own right, separately, they fail to uncover important relationships between the relevant factors and behaviour.

The first research question of this thesis was aimed at bringing together these two pain research approaches by modelling the relationship between observed pain behaviour and pain and related cognitive and affective factors grounded on data for specific movement events. To address this question, the existing EmoPain dataset was used to investigate the relationship between measures of pain and cognitive and affective states of people with CP while engaged in physical activities, and pain behaviour accompanying the activities as observed by physiotherapists. To this purpose, the EmoPain dataset was first extended within this thesis by inviting physiotherapists to label pain behaviour observed in videos of the people with CP and of healthy participants during specific activities. Two set of labels were collected: guarding behaviour and MRSE. Guarding was the behaviour targeted as it appears to be the most prevalent and relevant to pain experience of the pain behaviours defined by Keefe and Block

(1982) (Keefe and Block 1982; Tang et al. 2007; Aung et al. 2016). The second label, MRSE, is a cognitive construct, significant to physical functioning in CP (Asghari and Nicholas 2001), that expert observers read from movement behaviour (Keogh, Griffin, and Spector 1981; Singh et al. 2014) but has been ignored in the pain behaviour literature. Given the lack of literature on MRSE, physiotherapists were also asked to report the cues they used in making their estimation. A combination of standard statistical analysis techniques and Bayesian modelling was then used to investigate the relationships between the self-reported affective states (pain intensity, anxiety level, and emotional distress) and observer-rated variables of the extended dataset. Finally, the types of behavioural cues of MRSE reported by the physiotherapists were analysed.

The physiotherapist annotation study is described in Section 5.1 and the methods used to explore the relationships between guarding and pain, anxiety, emotional distress, and MRSE are described in Section 5.2. The results of this analysis and analysis of the MRSE cues are described in Sections 5.3 and 5.4 respectively with low level discussions of these results. In Section 5.5 is a higher level discussion aimed at highlighting the contribution and implication of the findings with respect to the literature. The conclusion of these findings is provided in Section 5.6.

5.1 Physiotherapist Annotation Study

In this section, the methods used in obtaining independent video-based annotations of guarding behaviour and MRSE for the EmoPain dataset from physiotherapists are described.

5.1.1 Rationale for Physiotherapist Annotation

Although the EmoPain dataset originally included guarding behaviour labels, a decision was made to reannotate the dataset for this label because there was low level agreement (Krippendorf's $\alpha < 0.29$) between the ratings in the EmoPain dataset (Aung et al. 2016). This occurred despite the fact that the raters (two physiotherapists and two clinical psychologists) conferred with one another (after independent pilot annotations) to discuss guarding judgements. The low level of agreement was partly due to the high-resolution annotation approach (frame-by-frame annotation) which demanded that the raters not only agree on the occurrence of each guarding event but also on the exact onset and offset of each event. Such fine-grained labelling may be unnecessary for tailoring intervention for CP physical rehabilitation (Keefe and Block 1982) and it may be sufficient to simply detect if a person with CP exhibits guarding at any point during the performance of a movement (e.g. an instance of

Forward Trunk Flexion). Thus, a new annotation study was carried out for this thesis to acquire new guarding ratings per exercise instance (rather than frame by frame) aiming for higher levels of agreement.

Self-efficacy estimations were obtained in the study as self-reports of MRSE were not available in the EmoPain dataset and findings in Keogh, Griffin, and Spector (1981) suggest that expert observer estimation of MRSE is a possible alternative to self-report. The annotation for MRSE also afforded the opportunity to learn how physiotherapists estimate the state. This knowledge is important because it can inform automatic estimation of MRSE.

5.1.2 Method

5.1.2.1 Video Material

There were 421 video clips annotated. Each clip was approximately 1 minute long and showed the performance of Sit-to-Stand, Forward Trunk Flexion, or Full Trunk Flexion in a single challenge level (lower or higher for Sit-to-Stand and Forward Trunk Flexion, and lower alone for Full Trunk Flexion) by a person with low back CP or by a healthy person. Of the clips, 72.7% were of Sit-to-Stand, 19.2% were of Forward Trunk Flexion, and 8.1% were of Full Trunk Flexion. They consisted of 17 people with low back CP (48.2%) and 21 healthy people. The videos from healthy people were included to avoid saturation in the observation of pain behaviour and the labels obtained for these healthy participants were not used in the study as explained in Section 5.2. Persons from either group (CP or healthy) will hereafter be referred to as ‘subjects’ for convenience. The video clips were shown on a laptop with a (diagonal) screen size of 15.5 inches although the video players used did not all allow maximisation to full screen size. Different video players were used as videos in the EmoPain dataset had been recorded using different encodings. All the video clips were shown mute to compel the raters to use visual cues alone.

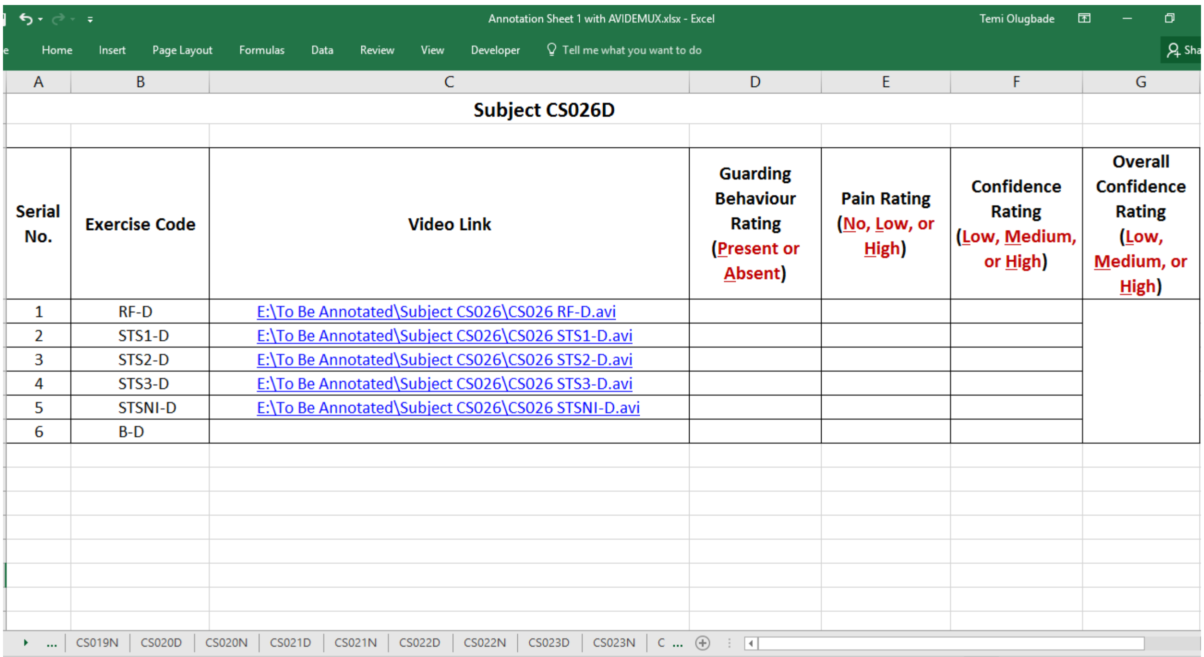
5.1.2.2 Physiotherapists (called raters in the subsequent sections)

The number of physiotherapists used for annotation was based on an estimation of the number of hours needed to have each video clip annotated by 4 physiotherapists. The estimation showed that it would be burdensome (taking about five hours) for one physiotherapist to rate all of the video clips and so a special design was used to assign the video clips to physiotherapists to limit the annotation time for each physiotherapist to one hour. The optimal number of physiotherapists needed to address these constraints was found to be approximately 30. In the design used to assign videos to these physiotherapists, video clips were considered in sets where each set consists of video clips of the three exercises for a single subject in one level of challenge. An hour's worth of video clip sets (approximately 14 sets with 6 video clips per set on average) were then randomly compiled and assigned to each of 30 physiotherapists such that each of the 421 video clips was rated by 4 physiotherapists.

The physiotherapists were recruited from United Kingdom. Their physiotherapy experience ranged from 1 to 36 years (median = 11.5, interquartile range = 12.75); their pain management experience ranged from less than 1 to 32 years (median = 5, interquartile range = 6.75).

5.1.2.3 Annotation Protocol

The raters recorded their annotations in Microsoft Excel Workbooks. Separate Worksheets were used for each video clip set. An example is the Worksheet in Fig. 5.1 which contains hyperlinks to the video clips for the exercise performances of subject CS026 in the difficult challenge level. In the Worksheets, the pain status (CP versus healthy) of the subjects were not made explicit to the raters and the sheets were only marked with codes (e.g. 'CS026D' for the example in Fig. 5.1) to allow the researcher identify them. For each video clip in a Worksheet, the rater were asked to rate:



Subject CS026D

Serial No.	Exercise Code	Video Link	Guarding Behaviour Rating (Present or Absent)	Pain Rating (No, Low, or High)	Confidence Rating (Low, Medium, or High)	Overall Confidence Rating (Low, Medium, or High)
1	RF-D	E:\To Be Annotated\Subject CS026\CS026 RF-D.avi				
2	STS1-D	E:\To Be Annotated\Subject CS026\CS026 STS1-D.avi				
3	STS2-D	E:\To Be Annotated\Subject CS026\CS026 STS2-D.avi				
4	STS3-D	E:\To Be Annotated\Subject CS026\CS026 STS3-D.avi				
5	STSNI-D	E:\To Be Annotated\Subject CS026\CS026 STSNI-D.avi				
6	B-D					

Fig. 5.1. An example of a Worksheet used in the annotation study. Each row in the third column provides a link to the video clip showing the subject (subject CS026) performing the exercise instance labelled in the corresponding row in the second column. Each rater was instructed to provide annotations for each instance in corresponding rows of fourth and seventh columns. (RF = Forward Trunk Flexion, STS = Sit-to-Stand, B = Full Trunk Flexion, D = higher challenge level, NI = Non-Instructed (i.e., a functional movement that the subject was not instructed to perform, but emerged in transitioning between one instructed exercise's end posture and the start posture of the next instructed exercise (Aung et al. 2016))).

1. whether or not they observed **guarding behaviour** in the performance of the exercise shown in the video clip (present or absent). Raters were instructed to use the definition of guarding as "stiff, interrupted or rigid movement while moving from one position to another" (Keefe and Block 1982) (p. 366).

2. their estimation of the **level of pain** (none, low, or high) that the subject in the video clip experienced while performing the exercise. At the time the study was planned, this rating was believed to be of interest for comparison with self-report of pain intensity. However, during the study, a majority of the raters made verbal assertions that they found this a challenging task given the subjectivity of pain experience and, in fact, one rater refused outright to complete pain rating for his set of videos. For this reason, these estimations were not analysed in this thesis.

3. their estimation of the **level of movement related self-efficacy** (low, medium, or high) that the subject in the video clip had in performing the exercise shown. These MRSE levels are similar to those considered in Keogh, Griffin, and Spector (1981). Self-efficacy was referred to as 'confidence' in all instructions given to the raters to foster consistency between their ratings.

The raters were also asked to estimate the overall MRSE (confidence) of the subject shown in the video clips in the Worksheet based on all of the exercise performances seen in the Worksheet. The decision to request this rating emerged from a prior discussion with an experienced physiotherapist who suggested that, in clinical practice, physiotherapists tend to continuously update their judgements about the MRSE levels of a patient as they observe multiple movement performances by the same patient.

5.1.2.4 Rater Profiling

In clinical practice, physiotherapists judge behaviour while the patient is physically present. Given the different observation setting in this study, it was of interest to understand if this difference affected raters' ability to estimate MRSE. Thus, before completing the annotation sheets, raters had to complete a pre-annotation questionnaire where they scored their own levels of confidence (hereafter referred to as 'rater confidence') in evaluating a patient's MSRE using the scale shown in Fig. 5.2. For comparison with their initial self-reports, rater confidence was obtained from the raters again after they completed the annotations. To complement this, the raters were also asked how difficult they found the rating of MRSE. Finally, they were asked to report the cues that informed their estimations of MRSE to understand how these estimations were made. Fig. 5.3 shows the format of the post-annotation questionnaire.

How confident are you that you can detect his/her movement confidence level from a patient’s behaviour?

0	1	2	3	4	5	6
Not At All Confident						Completely Confident

Fig. 5.2. The pre-annotation rater confidence self-report item used in the annotation study

Post-Annotation Questionnaire

	0 Not At All Difficult	1	2	3	4	5	6 Extremely Difficult	0 Not At All Confident	1	2	3	4	5	6 Completel y Confident	What modalities did you use?
Confidence Rating															

Fig. 5.3. The post-annotation questionnaire used in the annotation study

5.1.3 Annotation Study Results

Before investigating the central question of the chapter, the MRSE and guarding annotations obtained were analysed to understand the agreement between the raters and the effect of the study settings on the MRSE estimations. The analysis was important to understand the validity of using this data in the modelling analysis reported in Section 5.2. The results of this preliminary analysis are reported in this section.

5.1.3.1 How Much Do The Raters Agree?

A one-way random, absolute agreement, average measures intraclass correlation (ICC) was computed for the guarding and MRSE ratings to evaluate the level of agreement in the ratings and compare with previous studies. The ICC is a standard method especially with designs, like the one used in this study, where different sets of raters annotate each observation (McGraw and Wong 1996). The ICC variant for absolute agreement was used rather than the variant for consistency which only requires similarity between the rank order of the ratings (Hallgren 2012). The variant chosen instead requires similarity in absolute ratings. A one-way random model was used instead of a two-way random or mixed model as it was assumed that the raters were randomly selected from a larger population (Hallgren 2012).

TABLE 5.1 INTERRATER AGREEMENT

Activity Type	Number of instances	Average Measures ICC	
		Guarding	MRSE
Sit-to-Stand	306	0.72	0.81
Forward Trunk Flexion	81	0.63	0.70
Full Trunk Flexion	34	0.71	0.81
Considering the three movement types (Sit-to-Stand, Forward Trunk Flexion, and Full Trunk Flexion) altogether, for the same challenge level (lower or higher)	73	-	0.76

Guarding

The resulting ICC for the guarding labels was found to be in the good range (Cicchetti 1994) for the three movement types as can be seen in Table 5.1. These values are lower than the level of agreement found in Keefe and Block (1982) (percentage agreement = 0.93). However, the method they used for computing the level of agreement has the limitation of not accounting for the degree of disagreement between raters and agreement due to chance level (Hallgren 2012), so the high value they obtained is likely to be inflated. The values obtained in the study of this thesis were much higher than that of Aung et al. (2016) (Krippendorf's $\alpha < 0.29$) for the EmoPain dataset. This suggests that reduction of the resolution of the ratings provided by raters from rating per frame of exercise instance to rating per exercise instance may have enabled higher level of agreement between raters as intended.

MRSE

The resulting MRSE rating ICCs are shown in Table 5.1: ICC was found to be in the excellent range for two of the movement types and in the good range for the third movement types and for the overall MRSE (Cicchetti 1994). Despite these high values, the levels of agreement are lower than was found in Keogh, Griffin, and Spector (1981). In that study, both the consistency of MRSE ratings made on different occasions by the same raters and concordance between different raters were assessed and so each rater repeated the annotation after a week with access to notes of cues they had reported using in the first round. The level of agreement found within and between raters was ICC = 0.97. The agreement levels may be lower in this thesis because here, unlike in Keogh, Griffin, and Spector (1981), the physical activities performed by the subjects are not part of a (sport) choreography, making the evaluation more subjective. In addition, the instances annotated in Keogh, Griffin, and Spector (1981) had been pre-selected based on initial rating by the researchers although it is not clear what this entailed.

As there were three levels of MRSE considered, the ratings were further analysed using pie charts to understand where there was lack of consensus. The pie charts are shown in Appendix II-A. Lack of consensus was found to mostly occur with adjacent levels of MRSE with the predominant combination being medium and high MRSE levels for the three movement types. 77.9%, 51.7%, and 77.7% of the ratings without a majority vote, for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively, were ties.

5.1.3.2 Did The Study Setting Affect Estimation Abilities?

The self-reports of rater confidence for the MRSE annotation and the levels of difficulty of the annotation reported by the raters were analysed to understand if the use of video in contrast to face-to-face observation typical of clinical settings may have affected their estimation abilities.

29 of the 30 raters provided complete self-reports; Table 5.2 shows the distribution of these reports. A Wilcoxon Signed Rank Test was used to test for difference between the rater confidence scores before and after annotation. The test revealed a statistically significant reduction in rater confidence after rating, z=-2.461, p<0.05, with a medium effect size (r=0.32) although the median rater confidence (median = 4) remained the same. A Spearman Rank Order Correlation test was used to further check for a relationship between the difference in rater confidence and perceived difficulty. A moderately significant correlation was found between the two variables, rho=-0.451, p<.05, suggesting that the perceived difficulty of the annotation may have contributed to the slight decrease in the confidence of the raters in estimating MRSE.

TABLE 5.2 RATER CONFIDENCE AND RATING DIFFICULTY - MRSE

Scale		Number of Raters		
		Rater Confidence		Rating Difficulty
		Pre-Rating	Post-Rating	
not at all	0	0	0	0
	1	0	1	7
	2	0	2	10
	3	2	8	7
	4	16	10	3
	5	10	8	1
completely	6	1	0	1

5.2 Method: Exploring the Relationships between Guarding and Pain, MRSE, and Emotional Distress

The newly collected labels were used to investigate the relationship between guarding behaviour, MRSE, pain intensity, anxiety level, and emotional distress (RQ1). This section presents the method used for that investigation.

5.2.1 Data Preparation

A portion of the dataset annotated in the study described in Section 5.1 was used. This portion consisted of annotations and self-reports for exercise instances for subjects with CP where at least one of the HADS, pain intensity, or anxiety intensity self-reports had been completed. Instances for healthy subjects were not included in the analysis as pain (and anxiety) intensities for these subjects could not be assessed on the same scale as the subjects with CP. Thus, the data used in the analysis consisted of 99 exercise instances of 17 subjects with CP. For each of these instances, the following are the measures of guarding, pain, anxiety, emotional distress, and self-efficacy used:

Guarding: The guarding ratings obtained from the annotation study were recoded numerically with 1 for guarding present and 0 for guarding absent and the sum of the four guarding ratings (each from one of four physiotherapist raters) for each exercise instance was then taken as the guarding score for that instance. The score for each instance was an integer between 0 and 4, both values inclusive. The mean score was 3 with standard deviation of 1.

Pain Intensity: The self-report of pain intensity (between 0 and 10) available in the EmoPain dataset was used. The mean intensity was 5 (standard deviation = 3).

Anxiety Level: The self-report of anxiety intensity (also on a 0-to-10 scale) available in the EmoPain dataset was used. The mean anxiety level was 1, standard deviation was 3.

Emotional distress (fear/anxiety and depressed mood): This was based on the HADS-13 score available in the EmoPain dataset for each subject. The score for a subject was replicated for each exercise instance for the subject. For each instance, the emotional distress score was a value between 0 and 39, both values inclusive. The mean for all the instances was 18 with standard deviation of 7.

Self-Efficacy: A self-efficacy score was computed for each exercise instance as the median of the estimates across its four raters in the annotation study after recoding numerically as 1, 2, and 3 respectively for low, medium, and high. The resulting score for each instance was a value between 1 and 3, both values inclusive. The mean score was 2 (standard deviation = 1).

5.2.2 Analysis Methods

The analysis was focused on providing empirical understanding of the relationships between guarding behaviour and pain and related self-efficacy, anxiety, and emotional distress. Although temporal information (e.g. in terms of behaviour dynamics for each of the different states) could be interesting, this was not the aim of the analyses done in the chapter. Further, such analysis was not possible with the available data.

There were three analysis methods used in the investigation. First, a Spearman's correlation test was carried out (using IBM SPSS Statistics 22) to statistically test for linear relationships between each of pain intensity, anxiety level, emotional distress, and self-efficacy and guarding. Bar charts were then used to further understand the distribution of each of these measures across the guarding scores. Finally, a Bayesian network was used to develop an integrated model that incorporates the pairwise relationships between all of the five states. Although multiple regression based techniques are typically used in such modelling in pain studies, these methods could not be used here because of the lack of independence of the instances in the dataset used. The method used to build the Bayesian network is further described below.

A Bayesian network (G, P) is a graphical model, where G = (V, E) is a directed acyclic graph and P is the joint probability distribution (or the joint probability density in the case of continuous variables, in which case f is instead used) of random variables $X_i \in V$, that satisfies the Markov condition, i.e.

$$\mathrm{P}(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} \mathrm{P}(x_i \mid \pi_i)$$

or

$$f(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} f(x_i \mid \pi_i)$$

π_i denotes the set of parents of X_i (Neapolitan 2004). There are two types of algorithms typically used to learn the structure of a Bayesian network from data: constraint-based algorithms and score-based algorithms (Neapolitan 2004). Constraint-based algorithms learn a Bayesian network using conditional probability tests $X_i \perp X_j \mid S$ (i.e. test of whether X_i is conditionally independent of X_j given a subset of variables $S \subseteq V \setminus \{X_i, X_j\}$) to decide if there should be an edge between each pair of variables X_i and X_j (Koski and Noble 2012). A limitation of constraint-based algorithms is that they assume that there exists a directed acyclic graph G^* that is faithful to the underlying probability distribution P of the data (i.e. that G^* entails all and only conditional independencies in P) and fail when this assumption is not met (Koski and Noble 2012). This class of algorithms also fail when there are interaction effects without main effects between variables (Koski and Noble 2012). Score-based algorithms, on the other hand, search the space of candidate models for an optimal model that maximises a given scoring function. A scoring function commonly used is the Bayesian Information Criterion (BIC) (Schwarz 1978), which is the log likelihood $LL(D; x)$ of a graph D given the data x (a n by d matrix) with a term that penalises for complexity of the graph, i.e.

$$BIC(D;\mathbf{x}) = LL(D;\mathbf{x}) - \frac{\ln n \sum_{i=1}^{d} q_i (k_i - 1)}{2}$$

where q_i is the size of the set of parents of X_i and k_i is the size of the set of values of X_i (Koski and Noble 2012).

$$LL(D;\mathbf{x}) = \sum_{i=1}^{d} \sum_{j=1}^{k_i} \sum_{l=1}^{q_i} count(\pi_i^l x_i^j) \ln \frac{count(\pi_i^l x_i^j)}{count(\pi_i^l)}$$

where count(~) is the number of times the configuration ~ appears in the data (Koski and Noble 2012). While score-based algorithms can return the correct model even if the faithfulness assumption is not met, they, particularly greedy search algorithms, assume compositional property for each subset of vertices (i.e. if $X_i \perp X_j \mid S$ and $X_i \perp X_k \mid S$ then $X_i \perp X_j \cup X_k \mid S$) (Koski and Noble 2012). These algorithms fail if this property is not valid.

In building the Bayesian model for investigation of this thesis, 5-fold cross-validation, with guarding as the dependent variable, was used to choose the optimal structure learning algorithm to model the data. The algorithms considered were two constraint-based algorithms (Grow-Shrink Markov Blanket (Margaritis 2003) and Incremental Association Markov blanket (Tsamardinos, Aliferis, and Statnikov 2003)) and one score-based algorithm (hill-climbing, which is a greedy search algorithm). The *bnlearn* R package (Scutari 2010) which implements these algorithms was used. The data described in the previous section was used to learn the structure of the Bayesian network. Instances with missing values were excluded as the algorithms do not allow missing data; thus, only 84 instances were used for this modelling. Hill-climbing had the best performance (mean squared error = 1.4) in cross-validation and so this algorithm was used to build the Bayesian network.

5.3 Results: Relationships between Guarding and Pain, Anxiety, Emotional Distress, and MRSE

In this section, the results of the Spearman's correlation test (with the visual exploration done) and the Bayesian modelling carried out are reported.

5.3.1 Correlational Models

The correlations found between the variables are shown in Table 5.3. All four cognitive and affective measures (pain intensity, anxiety level, self-efficacy, and emotional distress) were found to be significantly correlated (significance level $p<.0001$) with guarding, and also with one another.

The highest correlation was a negative correlation between guarding and self-efficacy (*rho*=-.86)–note that guarding has 25% higher mean value than self-efficacy but with 25% lower standard deviation value. The strength of this relationship may be influenced by the fact that the two measures were based on observation data provided by the same raters and it indicates that physiotherapists may use their assessment of guarding behaviour of a patient when estimating the self-efficacy level of the patient for the activity. The result also suggests that people with CP with low self-efficacy for a movement are significantly more likely to guard than people with CP with higher levels of self-efficacy while performing the movement.

Marginally strong positive correlation was found between guarding and pain intensity (*rho*=.51), and between guarding and anxiety level (*rho*=.53)–guarding has an 8.3% lower standard deviation value than either pain intensity or anxiety level, but its mean value is 15% higher than that for anxiety level although 15% lower than for pain intensity. The similarity between the correlation of guarding with pain intensity and with anxiety level may be due to the very strong positive correlation found between pain intensity and anxiety level (*rho*=.79)–both pain intensity and anxiety level have the same standard deviation value, however, pain intensity has 40% higher mean value than anxiety level. This high correlation between pain intensity and anxiety level may be a result of them being both self-reported by the participant within temporal proximity to each other. The significance of the relationship of both states with

TABLE 5.3. PAIRWISE SPEARMAN'S CORRELATION COEFFICIENT BETWEEN THE GUARDING AND COGNITIVE AND AFFECTIVE MEASURES

	Guarding	Pain Intensity	Anxiety Level	Emotional Distress	Self-Efficacy
Guarding	-	0.512* (84)	0.534* (84)	0.459* (99)	-0.862* (99)
Pain Intensity		-	0.791* (84)	0.435* (84)	-0.522* (84)
Anxiety Level			-	0.476* (84)	-0.554* (84)
Emotional Distress				-	-0.470* (99)
Self-Efficacy					-

**p* <.0001. Sample size excluding missing values in brackets.

guarding suggests that people with high levels of pain and/or anxiety are more likely to exhibit guarding behaviour than people with lower levels of pain and anxiety.

Correlation of guarding was lowest with the gross emotional distress measure where moderately positive correlation was found (*rho*=.46)–emotional distress has 28.9.1% and 7.1% lower mean and standard deviation values respectively compared to guarding. The correlation indicates that the more distressed a person with CP is about pain and movement, the more likely the person is to exhibit guarding behaviour. The strongest correlation of the emotional distress measure was with anxiety level (*rho*=.48) although this was only marginally higher than its correlation with self-efficacy scores (*rho*=.47), guarding, or pain intensity (*rho*=.44).

Fig. 5.4 provides deeper insight into the relationship between guarding and each of the other measures. The figure contains four bar charts which respectively show the distribution of levels of pain, anxiety, emotional distress, and self-efficacy across the guarding scores. Here, two levels of pain and anxiety were defined as: lower level for <5 on the pain and anxiety scales respectively and higher for ≥5. Two levels of emotional distress were also defined: HADS-13>19 as emotionally distressed and HADS-13≤19 as not. The charts showed that exercise instances judged as definitely not exhibiting guarding behaviour (i.e. instances with guarding scores of 0) were instances where subjects reported lower level pain and anxiety, no emotional

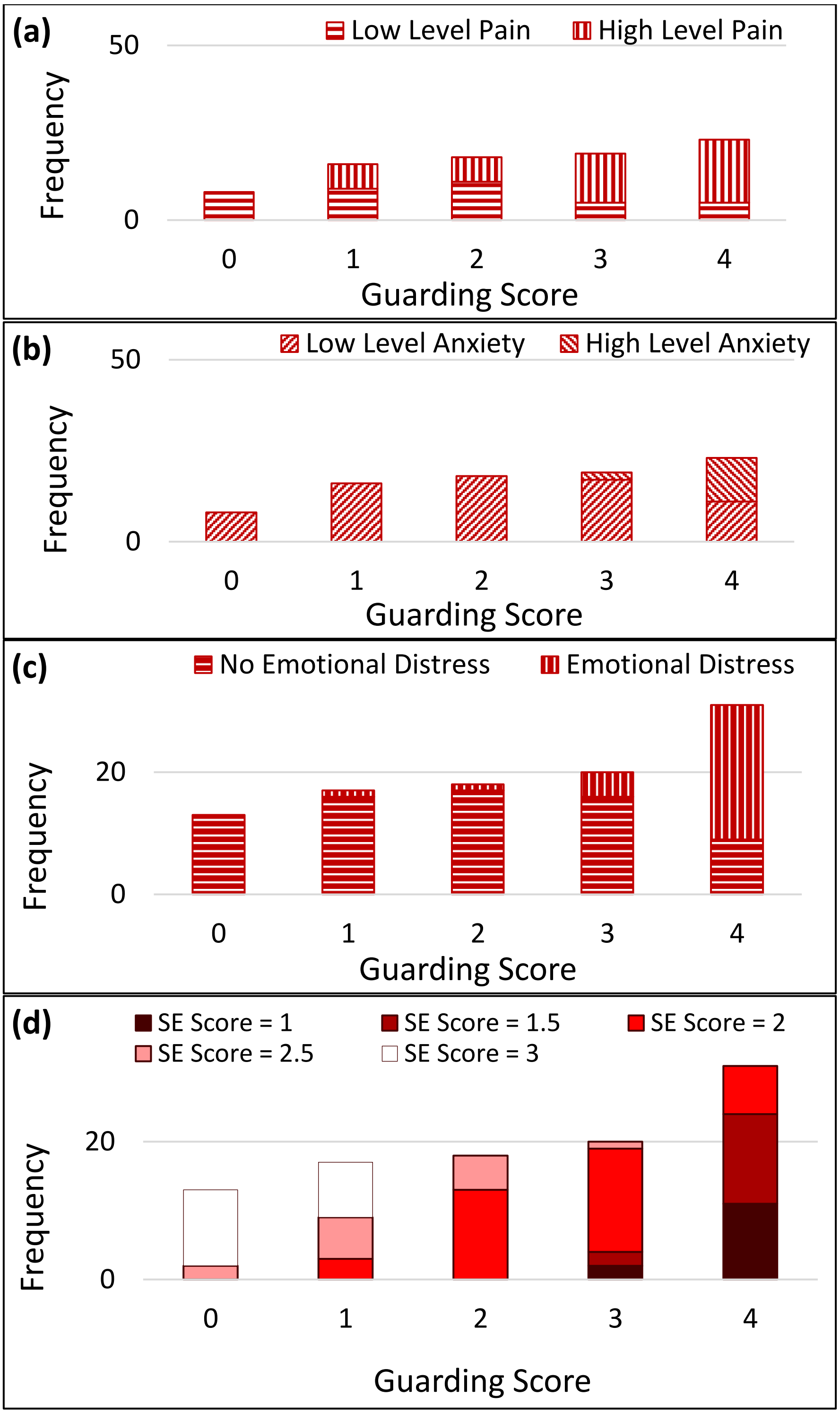


Fig. 5.4. Frequency distribution of guarding scores in people with CP across: (a) pain levels (<5 on the pain scale as lower level and ≥5 as higher), (b) anxiety levels (<5 on the anxiety scale as lower level and ≥5 as higher), (c) emotional distress levels (HADS-13 > 19 as emotionally distressed; HADS-13 ≤ 19 as not), (d) self-efficacy (SE) scores

distress, and were judged to have higher than medium level self-efficacy. However, the exercises instances judged as definitely showing guarding behaviour (i.e. instances with guarding scores of 4) were not isomorphic with respect to the levels of these states, that is, they included instances with different levels of pain, anxiety, emotional distress, and self-efficacy.

5.3.2 Bayesian Model

Fig. 5.5 shows the Bayesian model developed. The number on each edge of the graph represents the decrease in the BIC (i.e. score) of the graph if the edge were removed from the graph. If these numbers are interpreted as the concurrence of the values of two variables and so the ‘strength’ of the relationship between the variables, the strongest relationships are between guarding and self-efficacy (the strongest), and between pain intensity and anxiety level (the second strongest). These findings support the results from the correlational model.

More interestingly, the Bayesian model points to a complex relationship between the five variables. The model suggests that guarding is not directly dependent on pain intensity but that the relationship between the two variables is mediated by anxiety level. This finding is in agreement with the fear-avoidance theory of pain (Vlaeyen and Linton 2000) and it, in the fact, underscores the importance of the affective factors as barriers in engagement in physical activities. However, differently from the fear-avoidance theory, the model suggests that the relation between pain and fear/anxiety may not be mediated by a cognitive construct. A direct relationship between pain and fear/anxiety has indeed been proposed by Pincus et al. (2010) but their theory was not been grounded on data for specific movement events as in this thesis.

Further, the model does not point to a direct relationship between guarding and the gross emotional distress measure. This could be due to the differing nature of assessment of these two measures: guarding was assessed with respect to specific exercise instances whereas emotional distress was assessed with respect to recent state in general. However, it also suggests that depressed mood (which is a component of the emotional distress measure) has a behaviour signature different from fear/anxiety (which is the other component of the emotional distress measure). Indeed, Sullivan (2008) had called for work in this direction, i.e. in disentangling the affective dimensions of pain behaviour. Sullivan suggests that such a distinction has not been considered because the literature on pain behaviour has strongly focused on the protective aspect of pain response. What the Bayesian model suggests is that pain related depressed mood may not evoke fear responses such as those intended to minimise harm. This state may instead lead to clinical depression type of behaviours although Sullivan

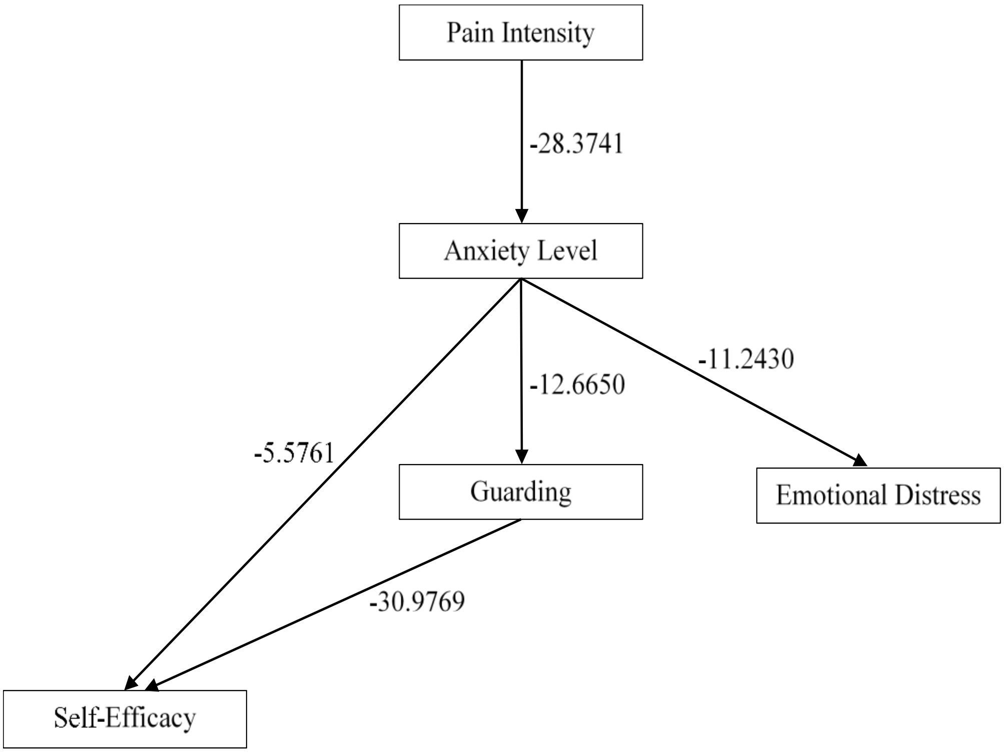


Fig. 5.5. Bayesian network showing the independencies between guarding, pain intensity, anxiety level, emotional distress, and self-efficacy

suggests that affective states in the context of pain may evoke behaviours that would only be found in this context, such as guarding which is only found to be a response to threat in the context of pain (Sullivan 2008).

Finally, the Bayesian model suggests that self-efficacy is also not directly related to pain intensity but that the relationship is again mediated by anxiety level. The model additionally supports the self-efficacy theory (Bandura 1977) in suggesting dependence of self-efficacy on both anxiety level and guarding.

In the next section, the type of behaviour cues the physiotherapist raters reported that they used to estimate this state are analysed. The findings are then discussed together.

5.4 Results: Physiotherapist-Reported Behaviour Cues of MRSE

The cues for estimating MRSE, reported in physiotherapists' own words, were extracted: there were 88 in total. The complete list of cues can be found in Appendix II-B. Thematic analysis was carried out on these cues following the guidelines provided by Braun and Clarke (2006) in order to identify patterns of cues used by physiotherapists in estimating MRSE. The steps taken in this analysis and the results found are described in this section. Extracts from the rater reports are presented in double quotation marks followed by the identification number used to anonymise the rater's identity, written in the format 'R#' where # is a number between 2 and 30, in parenthesis.

5.4.1 Thematic Analysis Method

The thematic analysis consisted of three main steps described here:

5.4.1.1 Step 1 - Removing Exact Duplicates

Most of the cues were reported as single words or phrases such as "speed" (R2). Where cues were reported multiple times with the exact same words across raters, duplicates were removed, resulting in 56 cues. Some of the cues were reported using vague descriptions that were difficult to interpret. For example, "start" (R10), which could mean the starting posture of the subject or the subject's behaviour at the outset of the activity, each with different implications in terms of understanding MRSE cues.

5.4.1.2 Step 2 - Finding Initial Themes in Initial Set of Codes

Each of the remaining 56 cues was coded with no imposed constraints. Five themes emerged from this initial coding: i) the expression modality of the cue, ii) the characteristic described by the cue, iii) the part of the activity where the cue occurred, iv) whether the cue described pacing/timing of phases of the activity, and v) whether the cue described ordering/sequencing of movements in the activity.

5.4.1.3 Step 3 - Removing Semantic Duplicates and Reviewing the Themes

In order to validate the resulting coding such as done in Frith and Gleeson (2004), two other coders (a researcher with expertise in affect detection from body movement and a clinical psychologist and researcher with expertise in pain) additionally coded the cues independently; in this coding iteration, coding was restricted to the initial themes found. For each cue, only codes agreed on by at least two of the three coders were then retained. After this, non-exact duplicates were removed: these were cues that had similar interpretations as another cue although reported using different wording. A cue was marked as a non-exact duplicate of another if the two cues had the same semantic interpretation and had been labelled with the same set of codes by the three coders. For example, "how long they took before they did it" (R18) was judged to be a duplicate of "hesitation on initiating" (R8). Removal of these duplicates resulted in 38 non-duplicate cues. These are shown in Table 5.4. This final set of cues and their codes were then reviewed for themes. Only two of the initial themes remained;

TABLE 5.4. A LIST OF MRSE CUES REPORTED BY RATERS (BOTH LITERAL AND SEMANTIC DUPLICATES HAVE BEEN REMOVED)

	Cue Extracts		Cue Extracts		Cue Extracts
1	speed	14	willingness to move	27	interaction or not with research team
2	speed of starting	15	through sequencing	28	jerky
3	no hesitation	16	balance and alignment	29	compensatory movements
4	hesitation	17	quality of movement	30	facial expression
5	hesitation on initiating	18	global efficiency	31	blink rate
6	smoothness of movement	19	symmetry	32	how present they looked whilst doing it
7	general look of relaxation	20	unusual pattern	33	avertal gaze
8	weight transfer	21	unnatural poses	34	looking down at assesors, equipment
9	ease in which they performed task	22	finish position	35	looking down at themselves - reassurance
10	amplitude of range of movement	23	final posture (if it looked natural to the subject, i.e. if looking comfortable)	36	if they scanned environment around them
11	amount of movement from trunk	24	length of time pose held	37	start
12	guarded behaviour	25	splinting behaviours	38	observing initiation of movement
13	balance saving reactions	26	that they or several participants repeated movements		

TABLE 5.5. THEMES FROM THE MRSE CUES REPORTED BY THE RATERS

Cue Themes	Number of Non-Duplicate Cues	Cue Number in Table 5.4
Expression Modality of Cues		
Body	28	1-21, 23-29
Face	5	7, 27, 30-32
Head and/or eyes	5	27, 33-36
Behaviour Elements of Cues		
Movement behaviour		
movement preparation	2	4-5
movement performance	20	1-3, 6-13, 16-19, 24-26, 28-29
movement conclusion	2	22-23
Engagement behaviour	5	27, 33-36
Facial expressions	1	30

one of the other initial themes became a subtheme while the other themes were not supported by the codes that emerged in the second round of coding.

5.4.2 MRSE Cues Themes

Table 5.5 shows summary statistics of the two themes that emerged: the expression modalities cues and elements of behaviour specified by the cues. The two themes are described below:

5.4.2.1 Expression Modalities of The Cues

This theme highlighted the fact that physiotherapists were using cues from different modalities (body, face, head, eyes) to assess a person's MRSE, and that a few cues (e.g. "start" (R10)) could not be tied to a specific modality. Tables 5.4 and 5.5 show the variety of cues used by the physiotherapists. Bodily cues were the most frequently used, whereas only a few of the physiotherapist raters used facial cues and cues from a combination of the head and eyes. It follows intuition that body is an important modality of MRSE. In addition, the value of bodily expressions (in comparison to other modalities) in affect detection is well established in affect studies (de Gelder 2009; Aviezer, Trope, and Todorov 2012). It is understood that observers tend to assess bodily expressions (more than facial expressions) when the actions (or the readiness to respond to an affective experience), rather than just the mental state, of a subject are to be judged (de Gelder 2009). Furthermore, subjects are predisposed to bodily expressions when they confront feared stimuli as they are motivated towards behaviour that avoids or mitigates perceived harm as shown in Sullivan et al. (2006) where people with CP were found to more likely express bodily pain behaviours when faced with challenging physical activity. This was in contrast to facial and verbal expressions, which were more used to communicate pain to an empathic third party.

5.4.2.2 The Elements of Behaviour Specified by The Cues

Beyond the modality that the cues referred to, patterns were also found to form according to elements of the behaviour that the cues specified. Three main elements of behaviour were described by the reported cues. The majority were movement behaviour cues as can be seen in Table 5.5. The movement behaviour cues extend through all the parts of the movement: 'preparation for movement', 'during movement performance', and 'the conclusion of movement'. However, most of the cues used referred to 'during movement performance'. Another aspect of behaviour that emerged is the engagement behaviour of the subjects. The physiotherapists noted whether the subject looked around the environment, at themselves, or towards or away from the experimenter. The value of the movement and engagement behaviours as cues of MRSE corroborates the finding of Keogh, Griffin, and Spector (1981).

Finally, facial expressions were also reported, although only one rater elaborated on the specific facial expression s/he used: "… grimace" (R10).

5.5 Discussion

The aim of the investigations reported in this chapter was a first step in bridging the gap between two bodies of work in pain literature (pain theories and pain behaviour studies) to understand the relationships between guarding behaviour and pain and related cognitive and affective states. This was important groundwork for understanding how relevant cognitive and affective states can be automatically tracked based on movement behaviour as it addresses the formerly open question of whether these states can be operationalised in terms of guarding behaviour.

To address this problem, the EmoPain dataset was extended with annotations by 30 physiotherapists for guarding behaviour (present versus absent) and MRSE levels (low, medium, or high) in instances of full trunk flexion, forward trunk flexion, and sit-to-stand movements in people with CP. Good to excellent levels of agreement were found between the raters (average of 0.67 and 0.77 for guarding and MRSE respectively), and they were found to report a good level of confidence in their ability to estimate these variables (median of 4 on an increasing scale of 0 to 6), both before and after the annotation, supporting the use of the provided labels as ground truth. The provided labels were then analysed with existing self-reports of anxiety, pain, and emotional distress from the EmoPain dataset, using correlation tests and Bayesian modelling, so as to understand the relationships between guarding behaviour and pain and related cognitive (MRSE) and affective states (anxiety and emotional distress). As expected based on the literature review discussed in Section 2.2), significant correlation was found between each pair of variables. However, it was shown that people may exhibit guarding behaviour despite low levels of pain or anxiety, no emotional distress, and medium MRSE, suggesting a complex relationship between guarding and these states, and, perhaps, the need for behaviour measures of a lower level of granularity. A major finding of the analyses is a novel model (Figure 5.5) of the conditional independence between the variables. This model and its contribution to the understanding of the relationships between guarding and pain and related states are further discussed below (in Section 5.5.1).

As part of the annotation study, the physiotherapists also reported the cues that they used in judging guarding and MRSE. These cues were analysed using thematic analysis, and it was found that the cues were expressions through the body, face, head and eyes, and some could not be described with respect to any specific modality. The body was shown to be the main expression modality used by the raters. It was further found that each cue described movement behaviour, facial expression, or engagement behaviour. A majority of the cues described movement behaviour in terms of preparation, execution, and conclusion of movement. These cues are further discussed below (in Section 5.5.2).

Importantly, these findings suggest that movement behaviour may be a medium for understanding pain, anxiety, emotional distress, and MRSE in the context of CP. The implication of the findings for the main problem of this thesis, i.e. the automatic assessment of pain and related states from body movement, is discussed in Section 5.5.3.

5.5.1 Contribution 1: Updating Pain Theories

A major result of the investigations reported in this chapter is the Bayesian model (of pain and related cognitive and affective states and behaviour) which is a significant contribution to pain research. First, the model provides data-based support to the theory (Vlaeyen and Linton 2000) that fear/anxiety about pain may be a more direct inducement for guarding behaviour than pain itself. This finding is similar to that of Crombez et al. (1999) for amount of movement and of Denison, Asenlof, and Lindberg (2004) for disability.

Secondly, the model provides evidence that suggest limits to the fear-avoidance theory (Vlaeyen and Linton 2000) particularly in the cognitive mediation between pain and fear/anxiety proposed in the theory. This hypothesis of Vlaeyen and Linton (2000) does not fit evolutionary models of pain-fear responses (Williams 2016) and the data-based Bayesian model does indeed suggest that such mediation is not necessary and that there is a more direct relation between pain and fear/anxiety. A possible explanation for the prevailing notion of cognitive factors mediating between pain and anxiety in pain theories is that these theories have been drawn from findings in studies based on broad self-report measures over usual experiences rather than measures for specific events. The contrary finding in the Bayesian model is similar to findings in imaging studies (Ohman 2005) for similar types of threats. This alternative hypothesis was proposed by Pincus et al. (2010) for the context of pain: Pincus et al. postulated that cognitive states (such as catastrophising) may instead modulate pain intensity or fear/anxiety levels themselves.

Finally, the third contribution of the model is that it integrates two theories that have been influential in understanding pain outcomes. The first is the already-discussed fear-avoidance theory (Vlaeyen and Linton 2000). The second is the self-efficacy theory (Bandura 1977) which specifies that self-efficacy influences movement engagement behaviour and that affective responses (such as anxiety) to threat influence self-appraisals of capabilities. Even, though previous studies (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004) have highlighted the relevance of this cognitive construct in the context of pain, the constructed theories of pain have usually overlooked it. While the relation between guarding and self-efficacy may exist partly because they were both judged by the same observers, the direct link between anxiety and self-efficacy suggests that model indeed follows the self-efficacy theory.

5.5.2 Contribution 2: Providing Understanding on MRSE Assessment

The literature review reported in Chapter 3 has shown that, despite the importance of self-efficacy in physical functioning in CP (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004), little attention (Keogh, Griffin, and Spector 1981) has been given to the analysis of bodily behaviour in response to self-efficacy. An important outcome of the analysis of the visual cues of MRSE reported in this chapter is deeper insight into bodily expressions of this state as used by physiotherapists to estimate levels of the states. One of the major findings was that although physiotherapists seem to use cues from a combination of visual modalities to estimate MRSE while observing subjects during physical activity, they rely more on body cues. This is not surprising given the discussion in Chapter 2 of studies (Asghari and Nicholas 2001; Bandura 1977) which indicate influence of MRSE on physical functioning. As mentioned previously, the significance of bodily cues may result from their place as part of adaptive actions (such as in “splinting behaviours” (R25), “compensatory movements” (R28)) intended to protect from pain (de Gelder 2009; Aviezer, Trope, and Todorov 2012; Sullivan et al. 2006). This finding emphasizes the importance of body movement as a modality for automatic affect detection despite the low level of adoption of the modality in the field of affective computing (Kleinsmith and Bianchi-Berthouze 2013). The bodily cues used by the physiotherapists were either a modulation of movement, such as speed and smoothness, or auxiliary to movement, e.g. “general look of relaxation” (R3), “interaction or not with the research team” (R25), similar to the suggestion by Karg et al. (2009) about bodily cues informative for affect detection. However, the majority of the cues were found to be modulations of movement. This is in line with the self-efficacy theory of Bandura (1977); but more importantly, it further suggests that the influence of self-efficacy on performance may go beyond related gross variables such as effort and persistence (Bandura 1977) and may affect lower level elements of performance (such as kinematics, in the case of movement).

Despite body movement cues appearing to be the main focus of the physiotherapists' evaluations, the results show that facial expressions were also found informative in assessing MRSE. While facial expressions are outside of the scope of this thesis for the reasons discussed in Chapter 3, the results suggest the use of multiple modalities could lead to a better assessment of the state of the person. This points to value in in-depth investigation of facial expressions that may be related to MRSE. Although the work on facial expressions of pain such as in the work of Lucey et al. (2011) (and the studies based on the painful face dataset made available through that work) could be relevant, a more extensive analysis of MRSE related expressions may identify a wider facial expression language. It should however be noted that the literature on pain indicates that facial expression in this context is more common in the presence of others (Sullivan et al. 2006). Indeed, Aung et al. (2016) showed that in the collection of the EmoPain dataset where there was a person (the researcher instructing the participants) present with each participant during his/her exercise performances, facial expressions tended to occur at the end of an exercise instance whereas guarding behaviour tended to occur during the exercise. The authors also showed that facial expressions were minimal in the dataset. Facial expressions may become more relevant as avatars and robots (Poggi et al. 2005; Wade, Parnandi, and Matarić 2011) become increasingly adopted as companion or coach. It is reminiscent of the reminder that any assessment, clinical or experimental, is also a social interaction (Schiavenato and Craig 2010) and that some behaviour is cued by the presence of experimenters or clinicians and by their behaviour.

Finally, another category of cues of MRSE found in the study is engagement behaviour. Engagement behaviour was seen as engagement with people present during the exercise sessions and also engagement with the aspects of the surroundings that may affect the exercise (e.g. movement aids such as the chair). Different from the literature on exergaming where motivational engagement (i.e. fun and interest) is investigated (Burke, McNeill, et al. 2009), here, engagement is used to connote attention to environment (people or objects) perhaps as possible sources of support in overcoming (or avoiding) the perceived difficulty of the activity to be performed. Such behaviour was characterised by both head pose and eye gaze. Technology that can detect these modalities could provide information about a person's concerns. In addition, as with facial expressions, in the context of technology based intervention, engagement behaviour could become particularly interesting when an avatar or a robot is used as a coach or companion in physical rehabilitation (e.g. in Wade, Parnandi, Matarić (2011); Poggi et al. (2005)).

5.5.3 Implication for Behaviour Based Modelling of Pain and Related States

The finding that pain, emotional distress, and self-efficacy cannot be simply defined in terms of guarding behaviour (which may be the most prevalent of the overt pain behaviours specified in the pain literature (Keefe and Block 1982; Aung et al. 2016)) suggests that a (larger) set of lower level movement behaviour descriptions is required to assess these states. As discussed in Chapter 2, pain, anxiety, emotional distress, and self-efficacy are important states to consider in tailoring intervention for CP physical rehabilitation (Olugbade et al., in review; Singh et al. 2014; Vlaeyen, Morley, and Crombez 2016; Asghari and Nicholas 2001). Thus, a relevant problem is the need to build a repertoire of movement behaviours that contribute to the automatic estimations of these states, beyond the inadequate taxonomy provided in the pain literature. There has been limited investigation of such collection of pain behaviours. Cook et al. (2013), for example, developed a scale for self-reporting pain behaviours; however, they focused on macro level behaviour (i.e. report of the summary of pain behaviours over a period, e.g. a week) rather than with respect to specific instances of movement (micro level). By contrast, Walsh, Eccleston, and Keogh (2014) investigated the specification of micro level pain expressions based on observer annotations; however, their work is limited to (bodily) expressions of acted pain. The need remains to build a similar collection of movement behaviours for real pain and related cognitive and affective states. The Bayesian model that resulted from the investigation in this chapter suggests the need, in the case of depressed mood, to go beyond protective behaviour (i.e. behaviours intended to minimise harm) which have typically been associated with pain or fear. Affective computing literature already shows the possibility of automatically detecting this state from visual cues, and behavioural studies such as Scherer et al. (2013), Waxer (1974), Lemke (2000), Michalak (2009) provide deep understanding of the behavioural cues that enable this. However, as Sullivan (2008) suggests, the behavioural manifestations that occur in the context of pain may be different.

The aim of the investigation reported in the next chapter was to address this need for an investigation of the movement behaviour cues of these states in the context of pain. In the chapter, an extended analysis of pain, MRSE, and emotional distress behaviours brings together knowledge from pain literature and behaviour studies, the results from analysis of MRSE cues, and further analyses of the EmoPain body movement and muscle activity data. The sensor-based analysis approach is supported by affective computing studies that have shown that body movement sensing technology can provide understanding of fine motor behaviour related to a variety of emotional expressions (for a review see (Kleinsmith and Bianchi-Berthouze 2013)).

For example, Fourati and Pelachaud (2015) used body movement sensor data to provide an understanding of how emotions (anxiety, pride, joy, sadness, panic fear, shame, and anger) are expressed through body movement in (a large set of acted body expressions representing emotionally coloured) everyday activities. Earlier work by Kleinsmith et al. (2011) and Savva et al. (2013) similarly investigated body behaviour cues related to a variety of game-related emotions in physical activity.

5.5.4 Limitation

A limitation of the investigation of the relationships between guarding and pain and related cognitive and affective states is the use of structure learning algorithms to learn the resulting Bayesian model. As mentioned earlier, score-based algorithms like the one used rely on the assumption of compositional property of the variables and may select an incorrect model if the assumption does not hold (Koski and Noble 2012). It has also been widely argued that structure learning algorithms in general cannot be relied on to discover causal models (Koski and Noble 2012). The dilemma for score-based algorithms is that no test of significance of the chosen structure is done (Koski and Noble 2012). In the case of constraint-based algorithms, assuming independence of variables, the problem is that multiple tests of significance are done causing significance level to accumulate to 1 (Koski and Noble 2012). In the analysis of the Bayesian network developed in this thesis, care was taken to address the shortcomings of the structure learning algorithms. First, correlational conclusions made from the model were verified against statistically significant findings of the traditional correlational analysis carried out. In addition, further inferences were grounded in existing theories particularly the fear-avoidance and self-efficacy theories. The resulting model is a starting point for the integration of these variables in a single model and can be further tested using methods that allow model validation. Further work can also build on the model by adding more well-defined behaviours that are used in clinical assessment.

5.6 Conclusion

Despite the understanding in pain research of the influence of self-efficacy and fear/anxiety on broad physical functioning outcomes independently of pain intensity, investigations of pain experience on fine-grained movement behaviours has been focused on pain intensity alone to the exclusion of the states. The investigation reported in this chapter bridges this gap by providing empirical understanding of the relationship between fine-grained movement behaviours (guarding behaviour in particular) and pain intensity, self-efficacy, anxiety, and emotional distress (fear/anxiety and depressed mood). A major outcome of the investigation is a model that provokes new discussion in pain research on the development of pain related fear/anxiety from the experience of pain. The findings of the investigation particularly suggest that multiple pathways may exist between pain and fear/anxiety: one (found within this thesis) is an autonomic fear response to the experience of pain and the second (proposed in the fear-avoidance theory) is the learnt fear response based on negative appraisal of movement and pain such as in catastrophising. Finally, the model informs automatic detection, suggesting the need to consider even lower level measures of movement behaviour (than guarding behaviour), and beyond guarding, to discriminate between expressions of pain, fear/anxiety, and low self-efficacy.

A secondary outcome of the investigation is the extension of the EmoPain dataset with labels of MRSE and new labels of guarding with higher level of agreement between the raters. Further, an understanding of cues used by physiotherapists in assessing MRSE was also provided, particularly showing that movement behaviour during the performance of movements are favoured.

6 AUTOMATIC DETECTION OF LEVELS OF PAIN, SELF-EFFICACY, AND EMOTIONAL DISTRESS BASED ON MOVEMENT BEHAVIOUR CUES

THE second research question of this thesis is the question of *how levels of pain and related self-efficacy and emotional distress can be automatically detected through body movement and muscle activity during physical activity*. It is important to address this problem because, as discussed in Chapters 2 and 3, this functionality will enable technology to provide intervention tailored to these states which underlie reduced engagement in physical activities in people with CP (Vlaeyen, Morley, and Crombez 2016; Asghari and Nicholas 2001). Findings of the investigation reported in Chapter 5 showed that this problem cannot be solved by simply monitoring guarding behaviour (Keefe and Block 1982), which is a major protective behaviour widely considered in pain studies. These findings point to the need to build a collection of finer-grained observable behaviours (beyond behaviours considered 'protective') that contribute to differentiation of levels of these states and understand the feasibility of automatic detection of the states based on such behaviours.

To address the research question, in-depth investigations of body movement cues that enable discrimination between levels of pain and related self-efficacy and emotional distress were carried out. The review of affective computing literature in Chapter 3 showed that a gap still exists in this area as the studies done to investigate automatic detection of these states from body movement during physical activity have been limited and do not address the requirement for tailored technological intervention for CP physical rehabilitation. Emotional distress was investigated as a single factor rather than as fear/anxiety and depressed mood separately because of the unavailability of ground truth for these components. Although anxiety self-reports were included in the EmoPain dataset (Aung et al. 2016), there was underrepresentation of higher level anxiety (anxiety level > 5): mean anxiety level was 1 and standard deviation was 3 based on a 0-to-10 scale. The other relevant ground truth assessment available in the EmoPain dataset (Aung et al. 2016), the HADS, has been shown to inappropriate for measuring anxiety and depressed mood separately in the context of pain (Cosco et al. 2012) even though it was originally designed for this in non-psychiatric populations (Zigmond and Snaith 1983).

The focus of the investigations carried out in this thesis were directed on movement behaviour, first, because of the pertinence of movement behaviour to the context of pain

(Sullivan 2008) as discussed in Chapter 3. In this context, beyond insight into the pain related experiences of people with CP, movement behaviour also shows the coping strategies they use to deal with these experiences. As such, its monitoring can further enrich intervention tailoring by directly indicating behaviours that may need to be disrupted, where relevant, by addressing the underlying pain related cognitive/affective factor. In addition, discussion in the chapter also highlights that body movement (captured using wearable sensors such as IMU and sEMG sensors) is a more practical modality than facial expressions and physiological signals for automatic detection in everyday physical activity settings. Given the complementariness of information from IMU and sEMG sensors, body movement features based on both types of sensors were considered in the investigations carried out. The body movement features investigated are based on pain literature, previous affect studies, discussion with a physiotherapist, the analysis of cues reported in Chapter 5, and visual inspection of movement profiles. These features were analysed using supervised machine learning algorithms, which allow complex combinations of features, in order to understand their contribution to differentiation of levels of pain and related self-efficacy and emotional distress and the feasibility of automatic detection based on them. Traditional statistical methods were also used to understand the individual relevance of the features.

The investigations carried out are reported in this chapter. Section 6.1 provides the notations used in this chapter to describe the body movement data and the features extracted from them. Sections 6.2, 6.3, and 6.4 report the investigations for pain, self-efficacy, and emotional distress respectively. Each of these sections is organised as follows: (1) description of the subset of EmoPain dataset used; (2) discussion of the proposed features and the formulae proposed for computing them from IMU and sEMG data; (3) description of the methods used for features analysis and optimisation; and finally, (4) presentation and discussion of the results of automatic detection, feature set optimisation, and feature relevance. The findings from the three sections are altogether discussed in Section 6.5 at a higher level. The conclusion of these findings is reported in Section 6.6.

6.1 Body Movement Data and Notations

The investigations carried out are based on the extended EmoPain dataset described in Chapters 4 (the EmoPain dataset) and 5 (the extension of the dataset). Each instance in the dataset comprises: 1) a set B of 26 tuples (describing IMU-based anatomical joint movement profiles) $b_k = \left\{ b_{k_t}, \quad \forall t : t = 1, 2, \ldots, T \right\}$, where k = 1, 2, …, 26, corresponding to the labels in Fig. 6.1, b_{k_t} is a three-dimensional vector [$b^x_{k_t}, b^y_{k_t}, b^z_{k_t}$] which describes the position of joint k for that instance in the anterior-posterior, lateral, and vertical axes respectively at time t, *and* T is the duration of the instance in frames; and 2) a set M of 4 sEMG-based muscle activity profiles $m_q = \left\{ m_{q_t}, \quad \forall t : t = 1, 2, ..., T \right\}$, where q = 1, 2, 3, 4, corresponding to the labels in Fig. 6.2.

These notations are used throughout this chapter to describe the extraction of the body movement features analysed with respect to each of the states. A summary of all the features discussed in the following sections (and their computational formulae) is provided in Appendix III. The size of data instances of the EmoPain dataset used will be described in the respective sections for pain, MRSE, and emotional distress as missing labels (whose instances had to be removed) led to different data sizes for the different states.

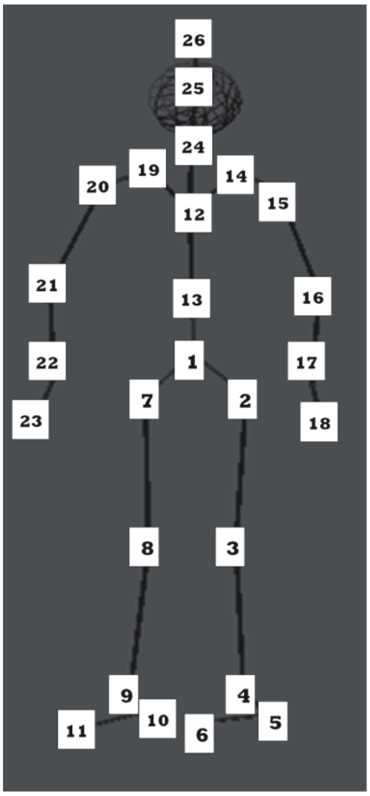


Fig. 6.1. The 26 anatomical joints tracked in the EmoPain dataset (Aung et al. 2016) labelled from 1 to 26

Fig. 6.2. The 4 muscle activity locations tracked in the EmoPain dataset (Aung et al. 2016)

6.2 Pain Level Detection from Body Movement Behaviour

In this section, the investigation of body movement features that contribute to the differentiation between levels of pain is reported.

6.2.1 Data

The part of the EmoPain dataset used for the detection of pain levels consisted of 18, 49, and 104 instances of Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. 66.7%, 61.2%, and 62.5% of these were instances of people with CP respectively for the three movement types. The others were instances of healthy people.

The pain level ground truth was based on the pain self-reports in the EmoPain dataset corresponding to these instances. Due to the limited size of the dataset, all 11 levels of the pain scale used for self-report of pain intensity could not be considered. Instead, two levels of pain were derived from this scale: instances where participants with CP reported pain intensity of 5 or more were classed as higher level pain instances whereas those where pain intensity of less than 5 was reported were classed as instances with lower level pain. Instances for participants without CP were allocated to a third class as these participants are different from people with CP (even those who report zero pain intensity) in terms of pain experience.

6.2.2 Features Investigation and Extraction

The body movement features investigated were based on pain literature, visual inspection of plots of movement profiles in the dataset used, and video based analysis of the movement behaviours of people with CP by an experienced physiotherapist. 13 features were proposed for Full and Forward Trunk Flexion which are similar movement types and 17 features were proposed for Sit-to-Stand. A list of these features is given in Table 6.1. The features and the methods used to extract them from IMU and sEMG data are discussed in this subsection.

TABLE 6.1 FEATURES FOR PAIN LEVEL CLASSIFICATION

Full and Forward Trunk Flexion

ID	Feature	ID	Feature
1	number of peaks in vertical arm displacement profile	7	muscle activity change point amplitude - right lumbar paraspinal
2	time range of peaks in vertical arm displacement profile	8	muscle activity change point time - left lumbar paraspinal
3	mean amplitude of peaks in vertical arm displacement profile	9	muscle activity change point amplitude - left lumbar paraspinal
4	range of trunk flexion	10	muscle activity change point time - right trapezius
5	vertical displacement of the head	11	muscle activity change point amplitude - right trapezius
6	muscle activity change point time - right lumbar paraspinal	12	muscle activity change point time - left trapezius
		13	muscle activity change point amplitude - left trapezius

Sit-to-Stand

ID	Feature	ID	Feature
1	duration	10	muscle activity change point time - right lumbar paraspinal
2	lift speed	11	muscle activity change point time - left lumbar paraspinal
3	vertical displacement of the head	12	muscle activity change point time - right trapezius
4	range of trunk flexion	13	muscle activity change point time - left trapezius
5	range of trunk flexion before lift	14	muscle activity range - right lumbar paraspinal
6	left pelvic angle at lift	15	muscle activity range - left lumbar paraspinal
7	right pelvic angle at lift	16	muscle activity range - right trapezius
8	left knee angle at lift	17	muscle activity range - left trapezius
9	right knee angle at lift		

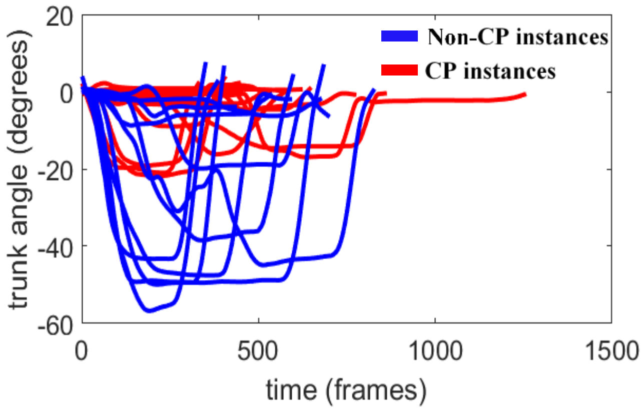
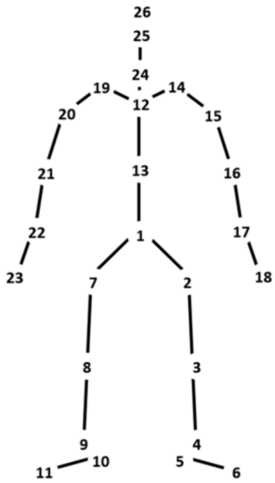


Fig. 6.3. Smoothed trunk angle profiles in the higher level challenge Forward Trunk Flexion, normalised to start at 0°. Negative angles indicate anterior trunk movement

6.2.2.1 Range of Trunk Flexion

Pain studies (Ahern et al. 1988; Watson et al. 1997; Shum, Crosbie, and Lee 2005; Gioftsos and Grieve 1996) point to submaximal flexion of the trunk during Forward and Full Trunk Flexion and Sit-to-Stand as one of the expressions of low back pain. In Watson et al. (1997), this was found in significantly lower EMG recorded at the L4/5 lumbar paraspinal muscle group in people with low back CP compared with healthy controls during forward trunk flexion movement. In Shum, Crosbie, and Lee (2005), it was found in significantly lower range of motion in people with low back pain than in healthy controls while performing sit-to-stand. Gioftsos and Grieve (1996) used this feature with foot forces during sit-to-stand for automatic differentiation of three groups: people with low back CP and healthy controls groups with and without history of back pain. They were able to achieve 0.86 accuracy. Similarly, Ahern et al. (1988) used range of motion, mean of EMG recorded at L3/4 and L4/5 lumbar paraspinal, and a measure of muscle relaxation during forward and full trunk flexion to automatically discriminate people with low back CP from healthy control participants. They also achieved 0.86 accuracy although this performance was based on a single fold of validation.

In line with these findings, visual inspection of plots of the angular displacement of the trunk during Forward Trunk Flexion (shown in Fig. 6.3) shows lower range of trunk flexion in people with CP compared with the healthy controls. Thus, for each of the three movement types, the range of trunk flexion was extracted as a feature. This was based on the computation of trunk flexion angle as the acute angle at the pelvic joint with respect to the thoracic spinal joint and the knee. Analysis of video data from the dataset by a physiotherapist (different from the annotation study reported in Chapter 5) revealed that people with CP may bend the knees instead of flexing the trunk, to execute trunk flexion. As the range of trunk flexion was computed with respect to the knee joints (and a thoracic spinal joint), it was necessary to correct for the use of this strategy. Thus, for Full and Forward Trunk Flexion, for each time *t*, corrective terms c_t^l (for the left side *l* of the body) and c_t^r (for the right side *r* of the body) were added to this computation, i.e.



$$\hat{\theta}_{trunk} = \max(\theta_{trunk}) - \min(\theta_{trunk})$$

where

$$\theta_{trunk} = \left\{ \tan^{-1}\left(\frac{\left\| (b_{12_t} - b_{1_t}) \times (b_{3_t} - b_{1_t}) \right\|}{(b_{12_t} - b_{1_t}) \bullet (b_{3_t} - b_{1_t})} \right) - c_t^l + \tan^{-1}\left(\frac{\left\| (b_{12_t} - b_{1_t}) \times (b_{8_t} - b_{1_t}) \right\|}{(b_{12_t} - b_{1_t}) \bullet (b_{8_t} - b_{1_t})} \right) - c_t^r, \quad \forall t : t = 1, 2, \ldots, T \right\}$$

$$c^l = \begin{cases} \pi - \tan^{-1}\left(\frac{\left\| (b_{2_t} - b_{3_t}) \times (b_{4_t} - b_{3_t}) \right\|}{(b_{2_t} - b_{3_t}) \bullet (b_{4_t} - b_{3_t})} \right) & b_{3_t}^{local} \times b_{13_t}^{local} > 0 \\ 0 & otherwise \end{cases} \qquad \forall t : t = 1, 2, \ldots, T$$

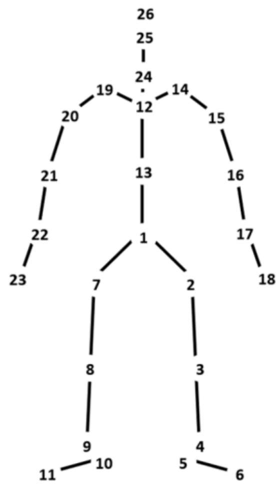
and

$$c^r = \begin{cases} \pi - \tan^{-1}\left(\frac{\left\| (b_{7_t} - b_{8_t}) \times (b_{9_t} - b_{8_t}) \right\|}{(b_{7_t} - b_{8_t}) \bullet (b_{9_t} - b_{8_t})} \right) & b_{3_t}^{local} \times b_{13_t}^{local} > 0 \\ 0 & otherwise \end{cases} \qquad \forall t : t = 1, 2, \ldots, T$$

$b_{k_t}^{local}$ is b_{k_t} transformed such that the pelvic joint (i.e. b_{1_t}) becomes its reference point.

For Sit-to-Stand, range of trunk flexion was computed with respect to the ground rather than the knee because of the large displacement of the knees expected in this movement type (compared with the full or forward trunk flexion), i.e.

$$\hat{\theta}^{g}_{trunk} = \max(\theta^{g}_{trunk}) - \min(\theta^{g}_{trunk})$$

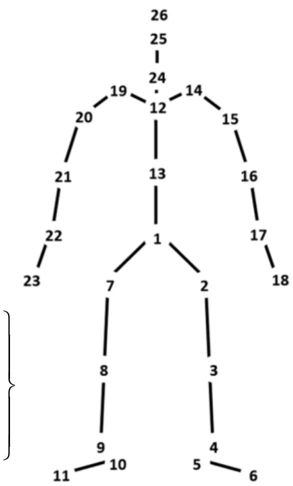


where

$$\theta^{g}_{trunk} = \left\{ \cos^{-1}\left(\frac{\overline{n^{fr}_{t}} \bullet \overline{n^{g}_{t}}}{\left\| \overline{n^{fr}_{t}} \right\| \left\| \overline{n^{g}_{t}} \right\|} \right), \quad \forall t : t = 1, 2, \ldots, T \right\}$$

with $\overline{n^{fr}_{t}}$ = normal vector of the frontal plane (i.e. based on b_{1_t}, b_{14_t}, and b_{19_t}) and $\overline{n^{g}_{t}}$ = normal vector of the traverse plane. The video analysis with the physiotherapist suggested that the range of trunk flexion at the point of buttocks lift could also be informative for discrimination between pain levels. Thus, the range of trunk flexion up till the start of ascension was additionally extracted. This was computed similar to range of trunk flexion computation for Full and Forward Trunk Flexion; however, in this case, the corrective terms were not necessary here since the person remains seated during this period and so the knee bend strategy was not expected to be used. Here, the range of trunk flexion was computed as:

$$\hat{\theta}^{lift}_{trunk} = \max(\theta^{lift}_{trunk}) - \min(\theta^{lift}_{trunk})$$



$$\theta^{lift}_{trunk} = \left\{ \begin{array}{l} \tan^{-1}\left(\frac{\left\| (b_{12_t} - b_{1_t}) \times (b_{3_t} - b_{1_t}) \right\|}{(b_{12_t} - b_{1_t}) \bullet (b_{3_t} - b_{1_t})} \right) + \tan^{-1}\left(\frac{\left\| (b_{12_t} - b_{1_t}) \times (\langle 8 \rangle_t - b_{1_t}) \right\|}{(b_{12_t} - b_{1_t}) \bullet (\langle 8 \rangle_t - b_{1_t})} \right), \\ \forall t : t = 1, 2, \ldots, t^{lift} \end{array} \right\}$$

where t^{lift} is the time the pelvic joint begins ascension.

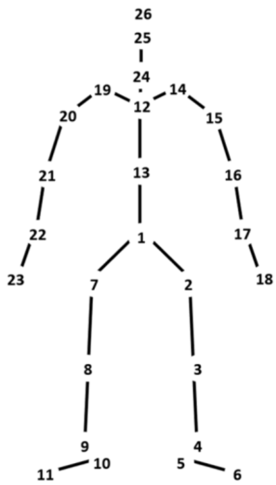
6.2.2.2 Knee and Pelvic Angles at The Point of Lift in Sit-to-Stand

For Sit-to-Stand, the knee and pelvic angles at the point of lift were additionally extracted to characterise the relation between the height of the subject and the height of the seat as this relation can influence the range of trunk flexion (Janssen, Bussman, and Stam 2002). In previous studies on the analysis of sit-to-stand, the influence of the relation between the heights of the subject and the seat on the execution of the movement has usually been addressed by adjusting the seat height to the height of the subject (Jacobs et al. 2011; Shum, Crosbie, and Lee 2009; Christe et al. 2016; Shafizadeh 2016; Tajali et al. 2013; Claeys et al. 2012; Collado-Mateo et al. 2016). However, this was not done in the EmoPain dataset and this is representative of everyday settings where a person will typically sit on seats of a variety of heights (in the bus, at work, at home, on the bed, etc.) as they go about their daily routine.

To account for the relation between the subject and seat heights in the investigation in this thesis, the knee and pelvic angles at the point of buttocks lift were extracted to characterise this relation as these angles provide information about the positions of the foot, which are at that point affected by this relation (Janssen, Bussman, and Stam 2002). However, the positioning of the foot in preparation for ascension may also be influenced by cognitive or affective experiences as was found on further analysis (see Section 6.3). Knee angles at the point of lift were computed similar to trunk flexion angles, as $\theta_{lknee}^{t^{lift}}$ (for the left side of the body) and $\theta_{rknee}^{t^{lift}}$ (for the right side):

$$\theta_{lknee}^{t^{lift}} = \tan^{-1}\left(\frac{\left\|\left(b_{2_{t^{lift}}} - b_{3_{t^{lift}}}\right) \times \left(b_{4_{t^{lift}}} - b_{3_{t^{lift}}}\right)\right\|}{\left(b_{2_{t^{lift}}} - b_{3_{t^{lift}}}\right) \bullet \left(b_{4_{t^{lift}}} - b_{3_{t^{lift}}}\right)}\right)$$

$$\theta_{rknee}^{t^{lift}} = \tan^{-1}\left(\frac{\left\|\left(b_{7_{t^{lift}}} - b_{8_{t^{lift}}}\right) \times \left(b_{9_{t^{lift}}} - b_{8_{t^{lift}}}\right)\right\|}{\left(b_{7_{t^{lift}}} - b_{8_{t^{lift}}}\right) \bullet \left(b_{9_{t^{lift}}} - b_{8_{t^{lift}}}\right)}\right)$$



Similarly, the pelvic angles were computed as $\theta_{ltrunk}^{t^{lift}}$ (for the left side) and $\theta_{rtrunk}^{t^{lift}}$ (for the right side):

$$\theta_{ltrunk}^{t^{lift}} = \tan^{-1}\left(\frac{\left\|\left(b_{12_{t^{lift}}} - b_{1_{t^{lift}}}\right) \times \left(b_{3_{t^{lift}}} - b_{1_{t^{lift}}}\right)\right\|}{\left(b_{12_{t^{lift}}} - b_{1_{t^{lift}}}\right) \bullet \left(b_{3_{t^{lift}}} - b_{1_{t^{lift}}}\right)}\right)$$

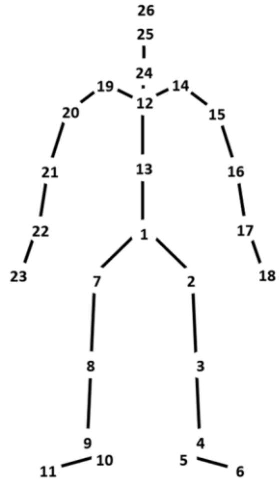
$$\theta_{rtrunk}^{t^{lift}} = \tan^{-1}\left(\frac{\left\|\left(b_{12_{t^{lift}}} - b_{1_{t^{lift}}}\right) \times \left(b_{8_{t^{lift}}} - b_{1_{t^{lift}}}\right)\right\|}{\left(b_{12_{t^{lift}}} - b_{1_{t^{lift}}}\right) \bullet \left(b_{8_{t^{lift}}} - b_{1_{t^{lift}}}\right)}\right)$$

6.2.2.3 Range of Neck Flexion

Visual inspection of plots of vertical displacement of the neck during Forward Trunk Flexion (shown in Fig. 6.4) suggested that there may be less flexion of the head with respect to the trunk in participants with CP compared with healthy participants. Based on the findings, the amount of neck flexion $\hat{z}$ was also extracted for the three movement types:

$$\hat{z} = \max(z) - \min(z)$$

$$z = \left\{ \frac{b_{24_t}^{z} - b_{13_t}^{z}}{\left\| b_{24_{t=1}} - b_{13_{t=1}} \right\|}, \quad \forall t : t = 1, 2, \ldots, T \right\}$$



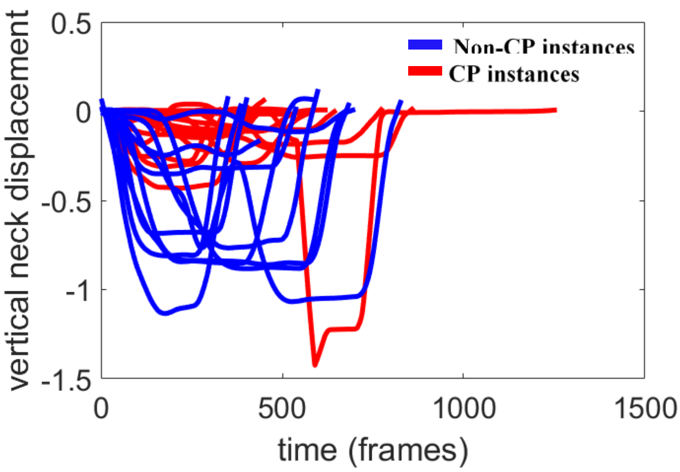
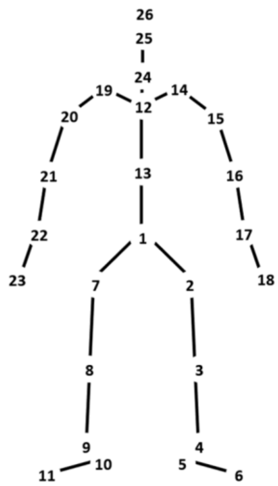


Fig. 6.4. Smoothed vertical neck displacement profiles with respect to the trunk in the higher level challenge Forward Trunk Flexion normalised to individual neck lengths and also normalised to start at 0°. Negative values indicate flexion of the neck

6.2.2.4 Arm Unsteadiness in Full and Forward Trunk Flexion

Further visual inspection also suggested that people with CP with higher level pain may have less arm unsteadiness than those with lower level pain. These findings with the evidence of reduced trunk and neck flexion in people with low back CP (Watson et al. 1997) point to overall stiffness in body movement in this cohort (Keefe and Block 1982).

Thus, for Forward and Full Trunk Flexion, which involve arm movements, unsteadiness in arm movements was characterised, as the number n_p, time range of occurrence $\hat{t}_p$, and mean amplitude $\hat{p}$ of peaks in the smoothed profile $\left\{ b'^{z}_{16_t} - b'^{z}_{15_t}, \quad \forall t : t = 1, 2, \ldots, T \right\}$ of the vertical displacement of the upper arm. Smoothening was done to remove peaks due to noise. This was done using the Savitzky-Golay filter (Savitzky and Golay 1964), which is a standard filter technique. The parameters of the filter (span = 50 frames and order = 1) were decided based on experimentation. The smoothed profile was normalised to different arm lengths by dividing by the distance between the elbow and shoulder joints (i.e. the length of the upper arm).



$$n_p = \sum_{t=1}^{T} g_t$$

where

$$g = \begin{cases} 1 & \left(\left(f_t > f_{t-1}\right) AND \left(f_t \geq f_{t+1}\right)\right) OR \left(\left(f_t \geq f_{t-1}\right) AND \left(f_t > f_{t+1}\right)\right) \\ 0 & otherwise \end{cases}, \quad \forall t : t = 1, 2, \ldots, T$$

$$f = \left\{ \frac{b'^{z}_{16_t} - b'^{z}_{16_t}}{\left\| b'_{16_{t=1}} - b'_{15_{t=1}} \right\|}, \quad \forall t : t = 1, 2, \ldots, T \right\}$$

$\hat{t}_p$ was normalised to the duration of the movement while both $\hat{t}_p$ and $\hat{p}$ were normalised to the range of the upper arm displacement.

$$\hat{t}_p = \frac{\underset{t}{\arg\max}\left(\{g \mid g_t = 1\}\right) - \underset{t}{\arg\min}\left(\{g \mid g_t = 1\}\right)}{T \times (f_{t=T} - f_{t=1})}$$

$$\hat{p} = \frac{\sum_{t=1}^{T}\left(f_t \mid g_t = 1\right)}{n_p \times \left(f_{t=T} - f_{t=1}\right)}$$

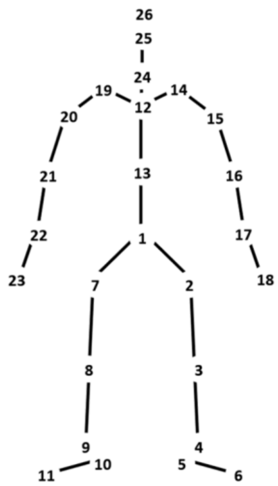
6.2.2.5 Speed of Sit-to-Stand

Slower movement is another body movement feature that has been found to be indicative of pain: Shum, Crosbie, and Lee (2005) found that people with low back pain were significantly slower than healthy controls in performing the sit-to-stand. This finding motivated the extraction of the speed of lift and duration as features for Sit-to-Stand in this study. Duration Δt was computed as:

$$\Delta t = T^* - t_1$$

t_1 is the frame in which either of the shoulders starts motion in the anterior direction (i.e. when the stand movement is initiated) and T^* is the frame in which the pelvic joint reaches maximum vertical displacement (i.e. extension has been completed). Speed of lift $\hat{s}$ was computed as:

$$\hat{s} = \frac{\sum_{t=t_{lift}}^{T^*} s_t}{T}$$



where

$$s = \left\{ b^z_{1_t} - b^z_{1_{t-1}}, \quad \forall t : t = 2, 3, \ldots, T \right\}$$

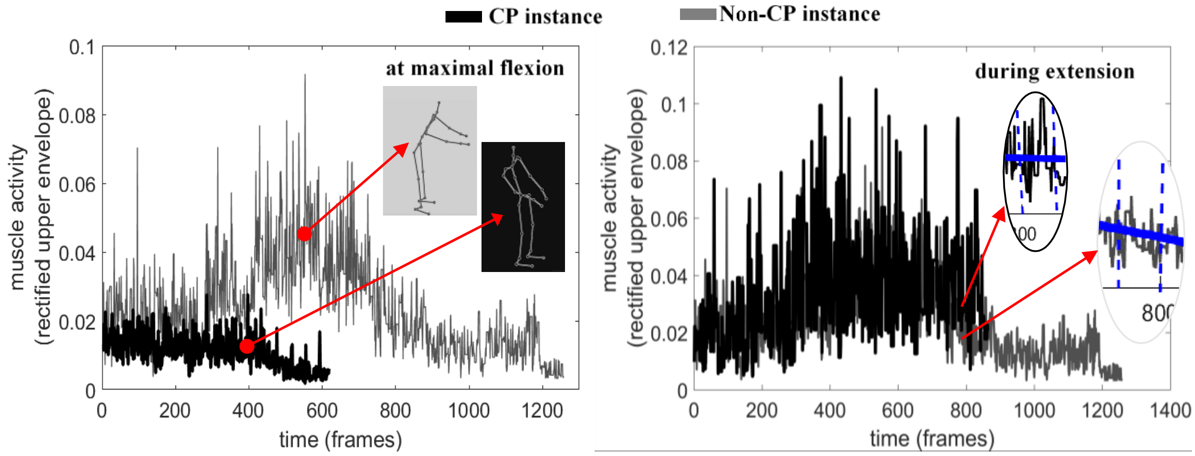


Fig. 6.5. Left - Minimal activity in the right lumbar paraspinal muscle of EmoPain CP participant P24 during Forward Trunk Flexion concomitant with submaximal flexion compared with the healthy pattern during the same physical activity (for EmoPain healthy participant P03). Reconstructed skeletons at the top right show the amount of trunk flexion of P24 (left) and P03 (right) at maximal flexion. Right - Muscle tension in the right lumbar paraspinal muscle of EmoPain CP participant P11 after completing re-extension in Forward Trunk Flexion compared with healthy muscle relaxation in the same phase of the movement (for EmoPain healthy participant P03)

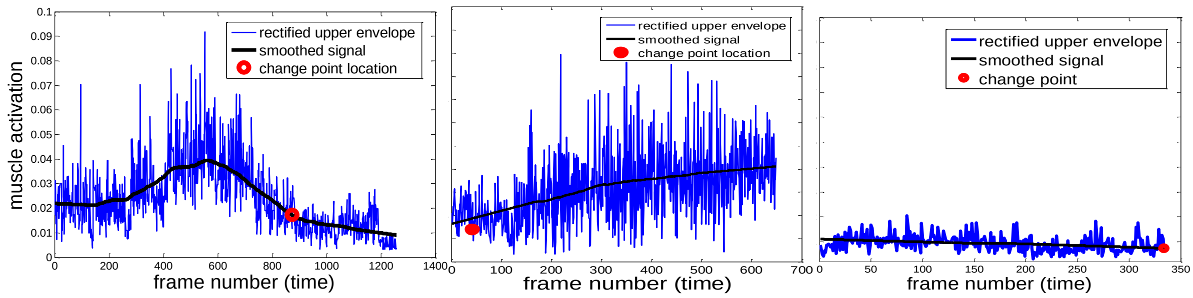


Fig. 6.6. The location of the computed change point for three different patterns of muscle activity during Forward Trunk Flexion

6.2.2.6 *Muscle Tension*

Findings from pain studies (Watson, Booker, and Main 1997; Ahern et al. 1988) further suggest that people with low back CP may have higher lumbar paraspinal muscle activity than healthy participants when fully flexed (typically between 40° and 70° of trunk flexion). During this period, the healthy pattern is muscle relaxation in the lumbar paraspinal as the rest of the flexion is achieved by the pelvic muscles (Watson, Booker, and Main 1997; Ahern et al. 1988). To quantify (the absence of) relaxation during flexion, Ahern et al. (1988) computed the range of lumbar paraspinal muscle activity at maximal flexion. Watson et al. (1997) similarly quantified flexion relaxation as the ratio of the root mean square of the maximal lumbar paraspinal muscle activity during flexion to the root mean square of muscle activity at maximal flexion. Visual inspection of plots of muscle activity during Forward Trunk Flexion indicates that there may also be absence (or rather, delay) of re-extension relaxation in the people with CP who flex their trunk (see Fig. 6.5-right). However, neither Ahern et al. (1988) nor Watson et al. (1997) studied delay in re-extension relaxation.

In the investigation in this thesis, both flexion and re-extension relaxation were characterised by modelling muscle activity change point, i.e. the point where higher muscle activity changes to lower activity, based on the method of Marple-Horvat and Gilbey (1992). The Marple-Horvat-Gilbey (MHG) algorithm uses the difference in mean amplitude within two sliding windows (of span *w*) to locate a change point. Based on experimentation, the MHG algorithm had to be slightly modified by including an odd gap *d* between the two windows to effectively locate the change point in the dataset used. This adapted version was named MHG-v2. Fig. 6.6 shows the computed location of the change point for the three muscle activity patterns (of three different participants) of Fig. 6.5 which were found to be representative of the EmoPain Forward Trunk Flexion data. For Forward and Full Trunk Flexion, two features of the change point were extracted: the time when it occurs $\hat{t}_e$ (normalised to the duration of the signal) and the amount of change in muscle activity that occurs $\hat{e}$ (normalised to the amplitude range of the signal). For the Sit-to-Stand, the time feature of the change point was also extracted with the range of muscle activity.

$$\hat{t}_e = \frac{\underset{t}{\arg\max}\left(\left\{\frac{\sum_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w + (d+1)/2, \ldots, T - \left(w + (d+1)/2\right)\right\}\right)}{T}$$

$$\hat{e} = \frac{\max\left(\left\{\frac{\sum_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w + (d+1)/2, \ldots, T - \left(w + (d+1)/2\right)\right\}\right)}{\max(m_q)}$$

for q = 1, 2, 3, and 4 for the right and left lumbar paraspinal and trapezius muscles respectively.

6.2.3 Features Analysis Methods

The SVM and RF (described in Chapter 4) were used to investigate the efficacy of the features described in the previous section for automatic detection of the three levels of pain. As the SVM is binary classification algorithm, in using it for three-class detection, a two-level hierarchical architecture was used. In this architecture, an SVM (SVM1) was used at the primary level to discriminate between instances of participants with or without CP. A second SVM, SVM2, was used to further differentiate instances of participants with CP as either of lower level or higher level pain. The hyperparameter settings for both SVMs and the RF were based on grid search. For Full Trunk Flexion, SVM1 and SVM2 were linear SVMs with regularisation parameter $C = 10$ and $C = 0.01$ respectively. For Forward Trunk Flexion, SVM1 had a quadratic kernel while SVM2 had a hyperbolic-tangent kernel with coefficients 1 and -1; $C = 1$ for both SVMs. For Sit-to-Stand, SVM1 was a linear SVM with $C = 1$; SVM2 had a Gaussian kernel of width 3.01 and $C = 10$. For the RF: 500 trees and 1 feature to split each node were used for Full Trunk Flexion; for Forward Trunk Flexion, there were 50 trees and the square root of the size of the feature set were used to split each node; for Sit-to-Stand, there were 1000 trees and all the features were used to split each node.

Wrapper-based feature set optimisation was further done using the Branch and Bound method (Narendra and Fukunaga 1977) (also described in Chapter 4) to understand the contribution of the features to the discrimination between the levels of pain. Feature set optimisation was also used to improve classification performance.

In addition, statistical analysis of the features was done to understand the individual relevance of each of the features to differentiation of the pain levels, independent of a learning algorithm. Linear mixed model approach was used as it is the standard method for testing fixed effects in datasets that do not satisfy independence of observations. The analysis was done in IBM SPSS 22. As the dataset also did not satisfy the other general linear model assumptions of normal distribution and heteroscedasticity of variance, as suggested by Field (2013), bootstrapping of the dataset was done in the analysis, with the number of samples set to 1000. A limitation of the bootstrapped linear model analysis in IBM SPSS, however, is that only significance of effect is provided without details of a test statistic and so the test statistic could not be reported.

6.2.4 Results

In this section, the performances of automatic classification, results of analysis of the features using feature set optimisation, and results of the statistical analysis of relevance of the features are presented.

6.2.4.1 Classification Performance

Table 6.2 shows the performance of automatic detection of the three levels of pain using the SVM and RF. Performance was better than chance level classification (0.33 accuracy) for the three movement types with both the SVM and RF. Performances for Full Trunk Flexion were average F1 score of 0.71 and 0.89 respectively for the SVM and RF. These performances were higher than for the other movement types. Full Trunk Flexion requires more trunk flexion than the other two types and the higher level of challenge that this presents may be the reason why it was easier to discriminate between levels of pain in this movement type. However, another plausible reason is that there is lower inter-subject variation due to the relatively small size of the set of Full Trunk Flexion instances. Further tests on a larger dataset will be needed to make any conclusions. Unlike for Full Trunk Flexion, the SVM and RF performed similarly overall for each of Forward Trunk Flexion (average F1 score of 0.53 and 0.52 respectively) and Sit-to-Stand (average F1 score of 0.63 and 0.62 respectively).

TABLE 6.2 PAIN LEVEL CLASSIFICATION PERFORMANCE WITHOUT FEATURE SET OPTIMISATION
(average F1 based on feature set optimisation in bracket to aid comparison)

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	SVM	RF	SVM	RF	SVM	RF
F1 no CP	0.77	**0.83**	0.70	**0.73**	**0.79**	0.66
F1 lower level pain	0.60	**0.92**	**0.48**	0.41	0.44	**0.52**
F1 higher level pain	0.77	**0.91**	0.41	**0.43**	0.67	**0.70**
average F1	0.71 (1.0)	**0.89** (1.0)	**0.53** (0.85)	0.52 (0.64)	**0.63** (0.84)	0.62 (0.68)
accuracy	0.72	**0.89**	**0.55**	**0.55**	**0.65**	0.63

Fig 6.7 shows performance after feature set optimisation. For the three movement types, classification performance improved with both the SVM and the RF. For Full Trunk Flexion, optimisation led to perfect classification (accuracy = 1.0) with both algorithms. For the other two movement types, the SVM outperformed the RF with average F1 scores of 0.85 and 0.64 respectively for Forward Trunk Flexion and average F1 scores of 0.84 and 0.68 respectively for Sit-to-Stand. In Forward Trunk Flexion, both the SVM and RF detected the instances of participants without CP best and performed worst in detecting instances of higher level pain. In Sit-to-Stand, on the other hand, the algorithms both performed best in detecting instances of higher level pain and worst for instances of lower level pain. Table 6.3 shows the confusion matrices for the three movement types using the SVM (which performed at least as good as the RF).

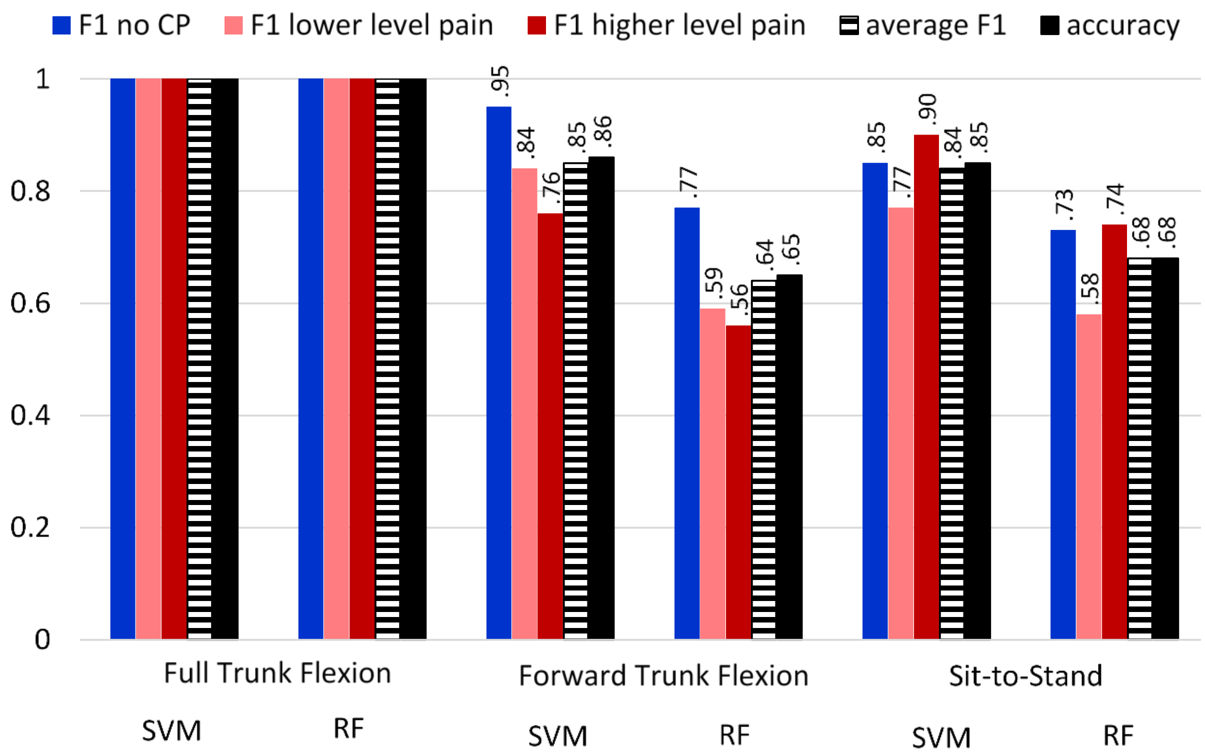


Fig. 6.7. Pain level classification performance with feature set optimisation. 'no CP' refers to healthy people

TABLE 6.3 CONFUSION MATRICES FOR PAIN LEVEL DETECTION WITH FEATURE SET OPTIMISATION FOR THE BEST CLASSIFIER IN FIG. 6.7 (I.E. THE SVM) FOR EACH MOVEMENT TYPE

FULL TRUNK FLEXION (SVM)

		Automatic Detection		
		no CP	lower level pain	higher level pain
Ground Truth	no CP	**6**	0	0
	lower level pain	0	**7**	0
	higher level pain	0	0	**5**

FORWARD TRUNK FLEXION (SVM)

		Automatic Detection		
		no CP	lower level pain	higher level pain
Ground Truth	no CP	**17** (**89.4%**)	1 (5.3%)	1 (5.3%)
	lower level pain	0 (0%)	**13** (**86.7%**)	2 (13.3%)
	higher level pain	0 (0%)	3 (20%)	**12** (**80%**)

SIT-TO-STAND (SVM)

		Automatic Detection		
		no CP	lower level pain	higher level pain
Ground Truth	no CP	**34** (**87.2%**)	3 (7.7%)	2 (5.1%)
	lower level pain	6 (20%)	**22** (**73.3%**)	2 (6.7%)
	higher level pain	1 (2.9%)	2 (5.7%)	**32** (**91.4%**)

6.2.4.2 The Feature Subsets selected for Classification based on Feature Set Optimisation

The analysis of features based on feature set optimisation was done for the SVM, which performed at least as good as the RF for pain level detection for the three movement types.

For Full Trunk Flexion, only one optimal subset was returned for SVM1, this included features 2, 4, 5, 7, 8, 10, 11, 13 in Table 6.1. This suggests that the SVM found arm steadiness, range of trunk and neck flexion, and flexion/extension muscle relaxation useful in discriminating between participants with or without CP. With SVM2, multiple optimal subsets were returned; Fig. 6.8 shows the relative frequency of each feature in these subsets. The amount of muscle relaxation in the lumbar paraspinal appears to be the most important for the SVM to discriminate between levels of pain of people with CP. The only other features that the SVM found useful were the amplitude of peaks in the vertical arm displacement and the time and amount of relaxation of the left trapezius on re-extension.

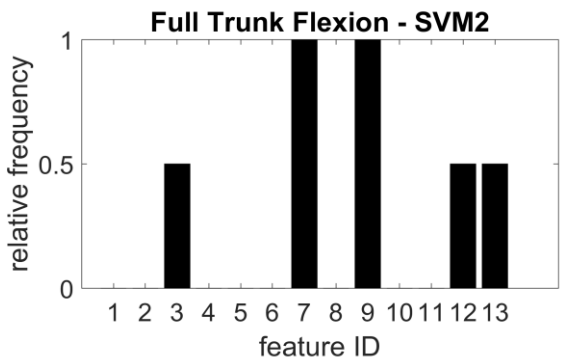


Fig. 6.8. Feature importance for pain level detection based on feature set optimisation. Feature ID follows numbering in Table 6.1 for this movement type (Full Trunk Flexion)

For Forward Trunk Flexion, only one optimal subset was found for SVM1. This included features 1, 4-6, and 8-12 in Table 6.1. This suggests that similar to Full Trunk Flexion, the SVM found arm steadiness, range of trunk and neck flexion, and flexion/extension muscle relaxation useful in discriminating between participants with or without CP. Only one subset was returned for SVM2 also in this movement type and this included features 5, 6, 9, 12 in Table 6.1. This points to the range of head flexion and flexion-extension muscle relaxation features as the only features useful for the SVM in differentiating between levels of pain in people with CP.

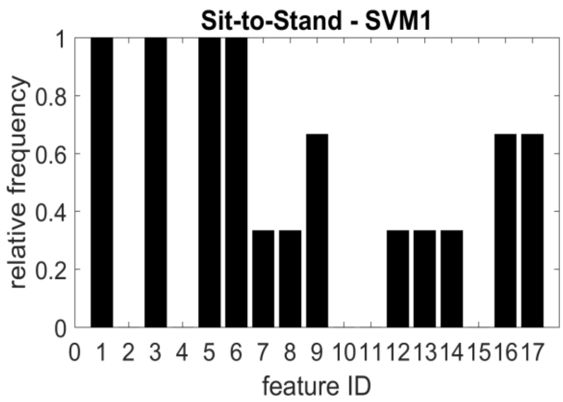


Fig. 6.9. Feature importance for pain level detection based on feature set optimisation. Feature ID follows numbering in Table 6.1 for this movement type (Sit-to-Stand)

For Sit-to-Stand, for SVM1, there were multiple optimal subsets. The relative frequency of each feature in these subsets is shown in Fig. 6.9. The result suggests that, unlike in the Full and Forward Trunk Flexion, the kinematic features (particularly duration, head displacement, range of trunk flexion before lift, and trunk flexion at lift) were the most important for the SVM in discriminating between levels of pain in people with CP. However, the foot positions based on the knee angles and the muscle activity features were also useful to the SVM. For SVM2, only one optimal subset was found. This included features 3-5, 9, 12, 14, 16, and 17 in Table 6.1. This suggests that trunk, neck, and knee angles and muscle activity features were the only features needed by the SVM in discriminating between levels of pain in people with CP.

6.2.4.3 Statistical Relevance of the Features

Tables 6.4 and 6.5 show the features for which effects of pain level were found for Full and Forward Trunk Flexion and Sit-to-Stand respectively. For each feature (in the respective movement type), the means for the three pain groups are ordered according to their magnitudes; where the low level pain group or control group is significantly different from the high level pain group, the ordering is highlighted in bold.

For Full Trunk Flexion, significant difference was only found for the activity change point of the right lumbar paraspinal and trapezius between participants with CP who reported higher level pain and healthy control participants. The result shows that the change point occurred significantly earlier in the lumbar paraspinal for the participants with higher level pain. However, the lower amount of relaxation in this muscle for the participants, although not significant, suggests that their premature relaxation may be due to either suboptimal flexion which enabled early extension and relaxation or suboptimal relaxation with complete relaxation delayed. The amount of relaxation was found to be significantly lower in the trapezius for the participants adding strength to this theory.

For Forward Trunk Flexion, difference was significant for the activity change point for both the left and right lumbar paraspinal and trapezius in addition to the range of trunk and head motion. The result shows that the amount of trunk flexion and the displacement of the head was significantly lowest in participants with higher level pain and highest in healthy control

TABLE 6.4 LINEAR MIXED MODEL ANALYSIS RESULTS FOR PAIN LEVEL IN FULL AND FORWARD TRUNK FLEXION (bootstrapped linear model analysis in IBM SPSS only provides significance of effect without a test statistic and so the test statistic could not be reported - $^{+}p<0.05$, $^{++}p<0.005$ significant difference with H, i.e. higher level pain,)

Feature ID	Feature	Full Trunk Flexion	Forward Trunk Flexion
1	number of peaks in vertical arm displacement profile	L< H<C	H<L<C
2	time range of peaks in vertical arm displacement profile	L<H<C	H<C<L
3	mean amplitude of peaks in vertical arm displacement profile	C<H<L	L<H<C
4	range of trunk flexion	H<L<C	**H<L^{+}<C^{++}**
5	vertical displacement of the head	L<H<C	**H<L^{+}<C^{++}**
6	muscle activity change point time - right lumbar paraspinal	**H<L<C^{+}**	**H<L<C^{+}**
7	muscle activity change point amplitude - right lumbar paraspinal	H<C<L	**H<L<C^{+}**
8	muscle activity change point time - left lumbar paraspinal	C<L<H	H<L<C
9	muscle activity change point amplitude - left lumbar paraspinal	H<C<L	**H<L<C^{++}**
10	muscle activity change point time - right trapezius	H<L<C	H<C<L
11	muscle activity change point amplitude - right trapezius	**H<L<C^{+}**	L<H<C
12	muscle activity change point time - left trapezius	H<L<C	H<C<L
13	muscle activity change point amplitude - left trapezius	H<L<C	**L<H<C^{+}**

H = the feature value for participants with higher level pain, L = the feature value for participants with lower level pain, C = the feature value for healthy control participants.

participants. The findings for the amount of trunk flexion supports earlier findings in Ahern et al. (1988) and Watson et al. (1997) although none of these studies showed a difference within the CP group based on pain levels. The study in this thesis is also the first to show a difference in range of head/neck movements in forward trunk flexion between healthy persons, people with CP with lower level pain, and people with CP with higher level pain. Like in Full Trunk Flexion, activity change point occurred in the right lumbar paraspinal significantly earlier in participants with higher level than in healthy control participants; in this case, the lower amount of change that occurred in participants with higher level pain was significant. These findings make a strong case for the earlier proposed theory although the significantly lower range of trunk flexion in this movement type specifically points to suboptimal flexion as the (perhaps unintentional) strategy that enabled early relaxation. There was also significantly lower relaxation of the left lumbar paraspinal and trapezius for the participants with higher level pain than for the healthy control participants.

The duration, speed of lift, range of trunk flexion, knee angles at lift, and activity features of the left lumbar paraspinal and trapezius were significantly different for the pain levels in Sit-to-Stand. Interestingly, participants with lower level pain significantly had the lowest duration for the movement, lower than for healthy control participants despite healthy control participants significantly having the highest lift and extension speed. The additional finding of significantly higher amount of trunk flexion in the healthy control participants suggests that although participants with lower level pain were slower in lift and extension, lower amount of trunk flexion led to lesser time to prepare for lift and possibly also lesser time to complete extension for them. Participants with higher level pain had significantly higher duration, lower speed, and lower range of trunk flexion than both healthy control participants and participants with lower level pain. This supports findings such as in Shum, Crosbie, and Lee (2005). It was also found that participants with lower level pain had significantly lower left and right knee angles just before lift than participants with higher level pain. This suggests that pain intensity may affect the positioning of the feet for standing up from seated position with those with higher level pain likely to keep their feet as far forward as possible. Another finding was that the activity change point of the left lumbar paraspinal occurred significantly earlier in participants with higher level pain than in participants with lower level pain. As with Forward Trunk Flexion, this may be due to suboptimal flexion of the trunk and as expected, the range of activity of the muscle was also significantly lower in participants with higher level pain than in participants with lower level pain.

TABLE 6.5 LINEAR MIXED MODEL ANALYSIS RESULTS FOR PAIN LEVEL IN SIT-TO-STAND
(bootstrapped linear model analysis in IBM SPSS only provides significance of effect without a test statistic and so the test statistic could not be reported - ^{+}p<0.05, $*p$<0.01, ^{++}p<0.005 significant difference with H, i.e. higher level pain)

Feature ID	Feature	
1	duration	**L^{++}<C^{+}<H**
2	lift speed	**H<L^{++}<C^{++}**
3	vertical displacement of the head	L<H<C
4	range of trunk flexion	**H<L^{++}<C^{++}**
5	range of trunk flexion before lift	L<H<C
6	left pelvic angle at lift	L<C<H
7	right pelvic angle at lift	L<C<H
8	left knee angle at lift	**C<L^{++}<H***
9	right knee angle at lift	**C<L^{+}<H^{++}**
10	muscle activity change point time - right lumbar paraspinal	C<H<L
11	muscle activity change point time - left lumbar paraspinal	**C<H<L^{++}**
12	muscle activity change point time - right trapezius	C<L<H
13	muscle activity change point time - left trapezius	C<H<L
14	muscle activity range - right lumbar paraspinal	H<L<C
15	muscle activity range - left lumbar paraspinal	**H<C<L^{+}**
16	muscle activity range - right trapezius	C<H<L
17	muscle activity range - left trapezius	H<L<C

H = the feature value for participants with higher level pain, L = the feature value for participants with lower level pain, C = the feature value for healthy control participants.

6.3 MRSE Level Detection from Body Movement Behaviour

In this section, the investigation of body movement features that contribute to the differentiation between levels of MRSE is reported.

6.3.1 Data

The ground truth of MRSE for this investigation was based on the MRSE ratings (low, medium, and high MRSE) acquired in the annotation study reported in Chapter 5. To assess the generalisability of the ratings to a single rater and so its reliability as ground truth for automatic detection (Fleiss, Levin, and Paik 1981), a single measures, one-way random, absolute agreement ICC was computed. The resulting ICC was in the poor range (Cicchetti 1994) for Forward Trunk Flexion, ICC = 0.37; for both Full Trunk Flexion and Sit-to-Stand, it was in the fair range (Cicchetti 1994), ICC = 0.55 and ICC = 0.52 respectively. Note that the single measures ICC is a stricter form of the ICC than the average measures ICC computed in Chapter 5 (average measures was used in that chapter to allow for comparison with previous studies) which explains the lower values obtained here in comparison to the values obtained in that chapter. As the single measures ICC values were below optimal (Fleiss, Levin, and Paik 1981), only instances of the annotated dataset without rating ties and ratings with lack of consensus were selected for use in this investigation. ICC was recomputed on this selection to assess the viability of this subset as ground truth for automatic detection. For Sit-to-Stand and Forward Trunk Flexion, the agreement values improved to the good range (Cicchetti 1994), ICC = 0.67 and ICC = 0.66 respectively. It improved to the excellent range for Full Trunk Flexion (Cicchetti 1994), ICC = 0.84. For each instance in this subset, the labels for automatic detection were derived as the median of the ratings for that instance.

The corresponding body movement data (introduced in Section 6.1) were used with these labels. Due to missing data, not all instances of the dataset could be used and so the investigation was based on 20 and 63 instances of Forward Trunk Flexion and Sit-to-Stand respectively; 40% and 61.9% were instances of people with CP for the two movement types respectively. There were only 6 instances of Full Trunk Flexion and so the instances of this movement type were not included in the automatic detection investigation. The distribution of the three levels of MRSE between participants with CP and healthy controls in the other two activity types is shown in Fig. 6.10.

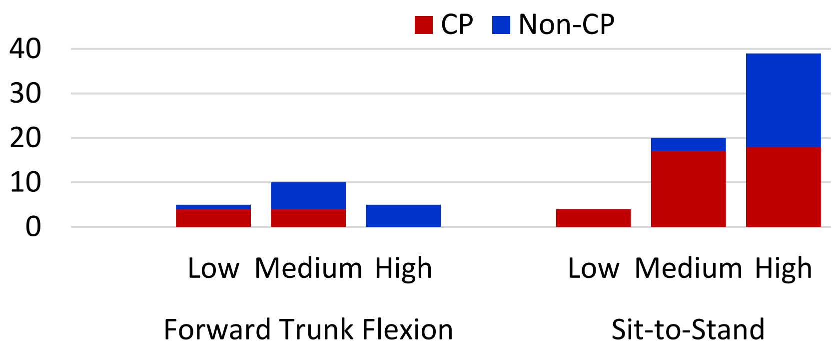


Fig. 6.10. Distribution of the three levels of MRSE between participants with and without CP

6.3.2 Features Investigation and Extraction

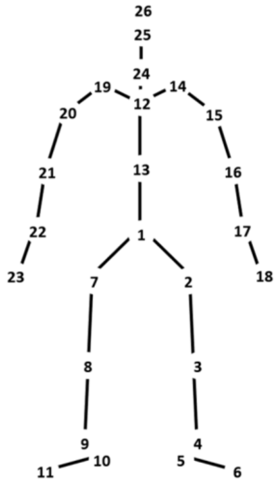
The body movement features investigated were based on the cues revealed from the analysis of cues used by physiotherapists in the annotation study reported in Chapter 5. A finding of the analysis was that physiotherapists use cues in preparation for movement, during movement, and at the conclusion of movement in estimating MRSE. In the investigation reported in this section, only cues expressed during movement were considered as they are more practical for everyday physical activity settings. In clinical settings where physical activities are segmented, i.e. with clear beginning and ending, such as in the annotation study, preparatory and concluding movement behaviours may be relevant. However, in everyday contexts, where the margins between consecutive activities are vaguer and the (automatic) observer has less knowledge of the subject's intention, it is expected that preparatory and concluding movement behaviours would be less useful as cues for MRSE estimation. A list of the features investigated is given in Table 6.6. The features and the methods used to extract them from IMU and sEMG data are discussed in this subsection.

TABLE 6.6 FEATURES FOR MRSE LEVEL CLASSIFICATION

ID	Features
1	speed - hands
2	speed - lower legs
3	speed - upper legs
4	speed - shoulder
5	speed - trunk
6	angle range - pelvic with respect to the head and left foot
7	angle range - pelvic with respect to the head and right foot
8	angle range - pelvic with respect to the trunk and left knee
9	angle range - pelvic with respect to the trunk and right knee
10	angle range - left knee
11	angle range - right knee
12	angle range - left elbow
13	angle range - right elbow
14	angle range - left shoulder (protraction)
15	angle range - right shoulder (protraction)
16	range - left shoulder (abduction/adduction)
17	angle range - right shoulder (abduction/adduction)
18	angle range - neck
19	energy sum
20	dissymmetry
21	right lumbar paraspinal mean activity
22	left lumbar paraspinal mean activity
23	right trapezius mean activity
24	left trapezius mean activity
25	fluidity - hands
26	fluidity - lower legs
27	fluidity - upper legs
28	fluidity - shoulder
29	fluidity - trunk

6.3.2.1 Speed of Movement

Speed of movement $\hat{s}$ was the MRSE cue most frequently reported by the physiotherapists in the annotation study, and so the speed of each of the hands, lower legs, upper legs, shoulder, and trunk were computed, as:



$$\hat{s} = \frac{\sum_{t=2}^{T} s_t}{T}$$

where

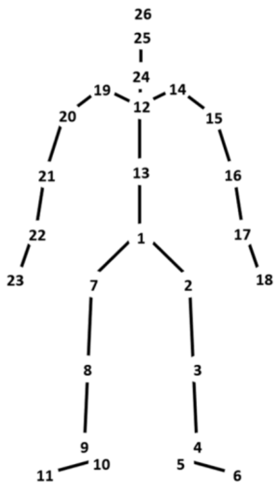
$$s = \left\{ \sqrt{\left(b_{k_t}^{x} - b_{k_{t-1}}^{x}\right)^2 + \left(b_{k_t}^{y} - b_{k_{t-1}}^{y}\right)^2 + \left(b_{k_t}^{z} - b_{k_{t-1}}^{z}\right)^2}, \quad \forall t : t = 2, \ldots, T \right\}$$

k = 17 and 22 for the left and right hands, 3 and 8 for the left and right lower legs, 2 and 7 for the left and right upper legs, 14 for the shoulder, and 13 for the trunk. For the hands, lower legs, and upper legs, the mean s_t for the two sides were taken.

6.3.2.2 Range of Movement

Another cue revealed in the annotation study was range of movement, and so the ranges of 13 full-body joint angles were extracted as in Aung et al. (2016) where the same dataset was used:

$$\hat{\theta} = \max(\theta) - \min(\theta)$$



where

$$\theta = \left\{ \tan^{-1}\left(\frac{\left\| \left(b_{end1_t} - b_{mid_t}\right) \times \left(b_{end2_t} - b_{mid_t}\right) \right\|}{\left(b_{end1_t} - b_{mid_t}\right) \bullet \left(b_{end2_t} - b_{mid_t}\right)} \right), \quad \forall t : t = 1, 2, \ldots, T \right\}$$

with $[\, b_{end1}, b_{mid}, b_{end2} \,]$ = [b_{26}, b_1, b_4], [b_{26}, b_1, b_9], [b_{12}, b_1, b_3], and [b_{12}, b_1, b_8] for pelvic joint angles, [b_2, b_3, b_4] and [b_7, b_8, b_9] for knee angles, [b_{15}, b_{16}, b_{17}] and [b_{20}, b_{21}, b_{22}] for elbow angles, [b_{24}, b_{14}, b_{15}] and [b_{24}, b_{19}, b_{20}] for shoulder angles, [b_{16}, b_{14}, b_{2}] and [b_{21}, b_{19}, b_{7}] for lateral angles for the shoulder, and [b_{26}, b_{24}, b_{13}] for the neck.

6.3.2.3 Guarding

“Guarded behavior" was another cue of MRSE revealed in Chapter 5 and it was taken to mean ‘guarding’ as defined by (Keefe and Block 1982) as significant relations were found between guarding and MRSE in the data modelling reported in the chapter. Previous study by Aung et al. (2016) had investigated the automatic detection of this behaviour in people with CP; in addition to range of joint angles earlier mentioned, the authors used joint energies and mean muscle activity as features. So, the sum of joint energies and the mean muscle activities were extracted. The sum of joint energies for the previously listed 13 joint angles was extracted; energy for each joint was computed, based on Bernhardt and Robinson (2007), as:

$$E = \sum_{t=2}^{T}\left(\theta_t^{'} - \theta_{t-1}^{'}\right)^2$$

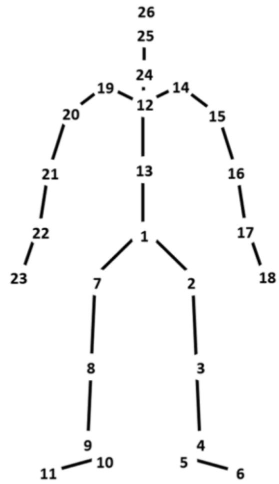
where $\theta^{'}$ is θ smoothed using the Savitzky-Golay filter (Savitzky and Golay 1964). The mean muscle activity was computed for each of the four channels (q =1, 2, 3, 4):

$$\hat{m} = \frac{\sum_{t=1}^{T} m_{q_t}}{T}$$

6.3.2.4 Symmetry

Symmetry was another cue that was revealed in the annotation study and so it was computed as the difference between the left and right shoulders along the anterior and vertical axes, as:

$$\gamma = \frac{\sum_{t=1}^{T}\left(\left\| b_{14_t}^{x} - b_{19_t}^{x} \right\|\right)}{T} + \frac{\sum_{t=1}^{T}\left(\left\| b_{14_t}^{z} - b_{19_t}^{z} \right\|\right)}{T}$$



6.3.2.5 Fluidity/Smoothness of Movement

Fluidity or smoothness of movement was the MRSE cue second most frequently reported by the physiotherapists in the annotation study and so it was also extracted in this investigation. Fluidity was extracted for the hands, lower and upper legs, shoulder, and trunk. To derive fluidity, the method of Balasubramanian et al. (2012) was used to compute the spectral arc length of movement speed profiles as:

$$\alpha = -\sum_{k=1}^{K_c - 1} \sqrt{\left(\frac{1}{K_c - 1}\right)^2 + \left(\Delta \hat{V}_k\right)}$$

where

$$\Delta \hat{V}_k = \hat{V}_k - \hat{V}_{k-1}, \quad k \in [1, K-1]$$

$$\hat{V}_k = \frac{V_k}{V_{k=0}}, \quad V_k = \left| fft(s_{zp}) \right|, \quad k \in [0,\ K-1]$$

$$s_{zp_t} = \begin{cases} s_t, & 0 \le t \le T-1 \\ 0, & T \le t \le K-1 \end{cases}$$

fft(~) is the K-point Fast Fourier Transform, K_C is the discrete time Fourier transform index that corresponded to the cut-off frequency, and $K = 2^{ceil(\log_2 T) + 4}$. For the hands, lower leg, and upper leg, the mean s_t for the left and right sides was used.

6.3.3 Features Analysis Methods

Similar to the investigation of body movement behaviour for pain level detection reported in Section 6.2, three types of analyses were done on the extracted features.

First, the SVM and RF (described in Chapter 4) were used to investigate the efficacy of the features for automatic detection of the three levels of MRSE. Again, as the SVM is binary classification algorithm, in using the SVM for three class detection, a two-level hierarchical architecture was used. At the primary level, SVM1, was used to discriminate between instances high level MRSE and lower level MRSE. A second SVM, SVM2, was used to further differentiate instances of lower level MRSE as either of medium level or low level MRSE. The hyperparameters of both SVMs and for the RF were set based on grid search. For Forward Trunk Flexion, a linear polynomial SVM with regularisation parameter C = 0.01 and 10 for SVM1 and SVM2 respectively was used. C = 10 was the optimal for the two SVMs of Sit-to-Stand; the optimal kernels for this movement type were a polynomial of degree 1 for SVM1 and a polynomial of degree 3 for SVM2. For the RF, 50 trees were used for both Forward Trunk Flexion and Sit-to-Stand and one feature used to split each node for Forward Trunk Flexion but the square root of the size of the feature set for Sit-to-Stand.

Secondly, the Branch and Bound feature set optimisation method (Narendra and Fukunaga 1977) was used to understand the relevance of the features to automatic detection of the three levels of MRSE and to optimise MRSE level detection.

Finally, linear mixed model analysis was used to understand individual relevance of the features to differentiation of the MRSE levels independently of the machine learning algorithm used.

6.3.4 Results

In this section, the performances of automatic classification, results of analysis of the features using feature set optimisation, and results of the statistical analysis of relevance of the features are presented.

TABLE 6.7 MRSE CLASSIFICATION PERFORMANCE WITHOUT FEATURE SET OPTIMISATION
(average F1 based on feature set optimisation in bracket to aid comparison)

	FORWARD TRUNK FLEXION		SIT-TO-STAND	
	RF	SVM	RF	SVM
F1 low	**0.80**	0.73	0.60	**1**
F1 medium	0.63	**0.67**	**0.47**	0.32
F1 high	0.55	**0.73**	**0.79**	0.59
average F1	0.66 (0.79)	**0.71** (0.95)	0.62 (0.70)	**0.64** (0.78)
accuracy	0.65	**0.70**	**0.68**	0.52

6.3.4.1 *Classification Performance*

Classification performance without feature set optimisation is shown in Table 6.7. For both RF and SVM, classification in Forward Trunk Flexion was average F1 score of 0.66 and 0.71 respectively, well above chance level (i.e. accuracy of 0.33). In Sit-to-Stand, classification using the RF (with average F1 score of 0.62) was also better than chance level classification. Although average F1 score of 0.64 for the SVM was also better than chance level classification, the detection of the medium level MRSE was no better than chance using this classification.

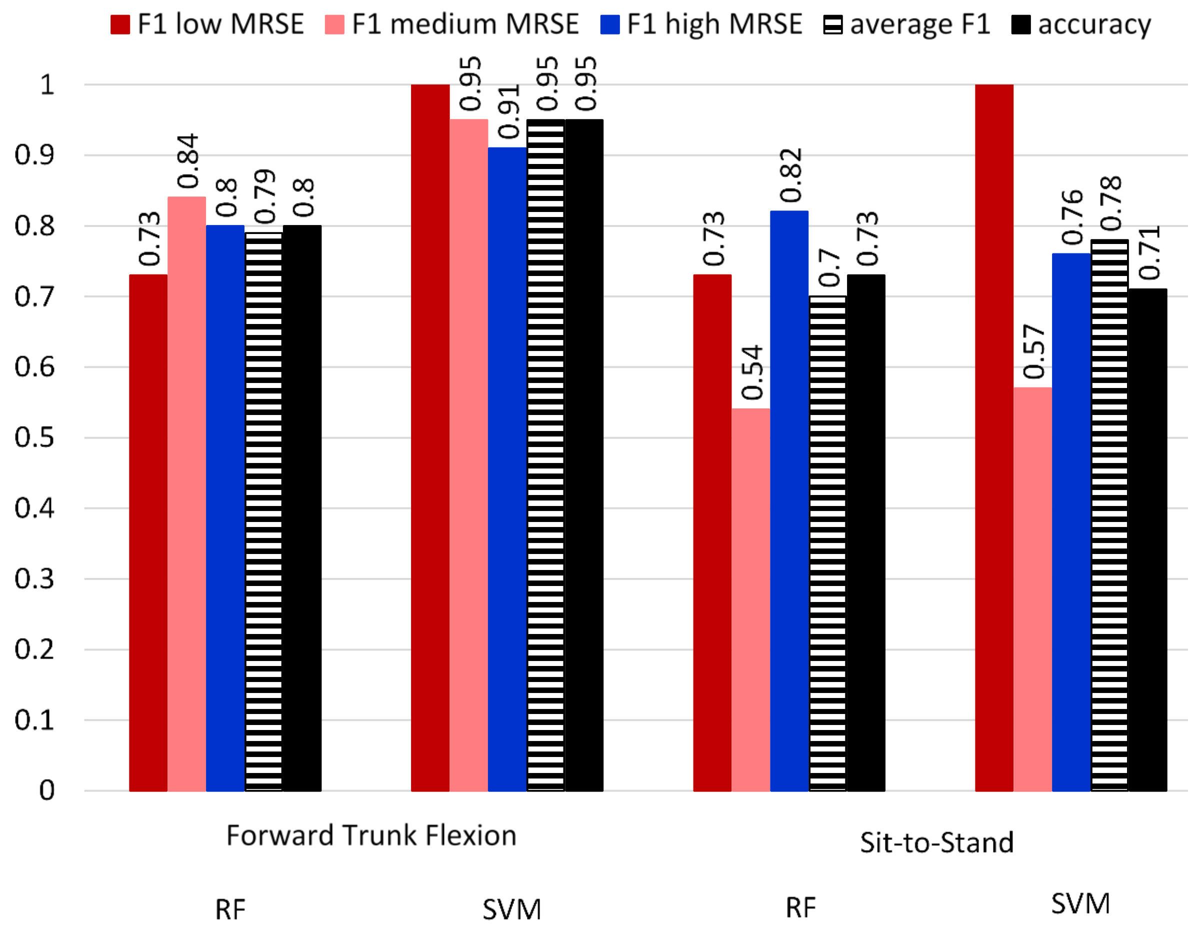


Fig. 6.11. MRSE level classification performance with feature set optimisation

TABLE 6.8 MRSE LEVEL DETECTION CONFUSION MATRICES FOR FORWARD TRUNK FLEXION
(<u>with</u> feature set optimisation)

FORWARD TRUNK FLEXION - RF				
		Automatic Classification		
	MRSE LEVEL	low	medium	high
Ground Truth	low	**4** (**80**%)	1 (20%)	0 (0%)
	medium	1 (10%)	**8** (**8**0%)	1 (10%)
	high	1 (20%)	0 (0%)	**4** (**80**%)
FORWARD TRUNK FLEXION - SVM				
		Automatic Classification		
	MRSE LEVEL	low	medium	high
Ground Truth	low	**5** (**100**%)	0 (0%)	0 (0%)
	medium	0 (0%)	**9** (**90**%)	1 (10%)
	high	0 (0%)	0 (0%)	**5** (**100**%)

TABLE 6.9 MRSE LEVEL DETECTION CONFUSION MATRICES FOR SIT-TO-STAND
(<u>with</u> feature set optimisation)

SIT-TO-STAND - RF				
		Automatic Classification		
	MRSE LEVEL	low	medium	high
Ground Truth	low	**4** (**100**%)	0 (0%)	0 (0%)
	medium	3 (15%)	**10** (**50**%)	7 (35%)
	high	0 (0%)	7 (18%)	**32** (**82**%)
SIT-TO-STAND - SVM				
		Automatic Classification		
	MRSE LEVEL	low	medium	high
Ground Truth	low	**4** (**100**%)	0 (0%)	0 (0%)
	medium	0 (0%)	**12** (**60**%)	8 (40%)
	high	0 (0%)	10 (26%)	**29** (**74**%)

For the two movement types, feature set optimisation resulted in higher classification performance with both RF and SVM as shown in Fig. 6.11. Average F1 score for Forward Trunk Flexion increased to 0.79 and 0.95 for the RF and SVM respectively. For Sit-to-Stand, average F1 score for Sit-to-Stand increased to 0.70 and 0.78 for the two algorithms respectively. The confusion matrices in Tables 6.8 and 6.9 for the Forward Trunk Flexion and Sit-to-Stand respectively show that the SVM perfectly detects low MRSE level for both movement types. This may be due to the lower intra-subject variation resulting from the small size of this class in the dataset. However, this finding is similar to the finding in Chapter 5 that the majority of disagreements in MRSE ratings by physiotherapists in the annotation study reported in the chapter occurred between medium level and high level MRSE.

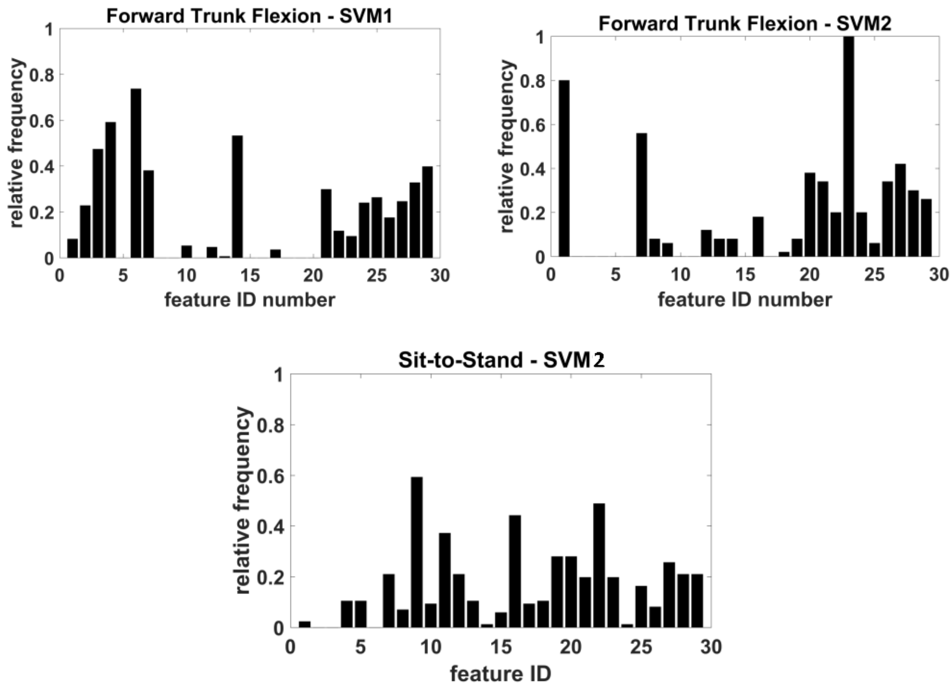


Fig. 6.12. MRSE features importance based on optimisation. Feature ID follows numbering in Table 6.10

6.3.4.2 The Feature Subsets selected for Classification based on Feature Set Optimisation

For Forward Trunk Flexion, selection based on the SVM is reported, as this algorithm performed best in discriminating between the three levels of MRSE in this movement type. Multiple optimal subsets were returned for both SVM1 and SVM2. Fig. 6.12-top-left and Fig. 6.12-top-right show the relative frequencies of each feature in these subsets respectively. The plots show that speed of the limbs, range of angles of the trunk, knee, elbow, and shoulder, muscle activity of the trapezius and lumbar paraspinal, and fluidity of movement were found informative by the SVM in differentiating high MRSE level from lower level MRSE. To further differentiate low MRSE and medium MRSE levels, the SVM found speed of the hand, range of angles of the trunk, elbow, shoulder, energy, and symmetry useful.

For Sit-to-Stand, only one optimal feature combination was found for the RF and it comprised a combination of speed of the trunk, range of angle of the trunk, energy, and activity of the lumbar paraspinal. Only one optimal subset was also returned for SVM1: speed of the upper and lower legs, range of angles of the trunk and shoulder, energy, activity of the trapezius, and fluidity of the movement of the shoulder were found to be informative in differentiating high MRSE level from lower level MRSE. For SVM2, multiple optimal subsets were returned; Fig. 6.12-bottom shows the relative frequencies of the features in these subsets. Only speeds of the upper and lower legs were not found to be useful in discriminating between low and medium MRSE levels.

6.3.4.3 Statistical Relevance of the Features

Tables 6.10 shows the features for which effects of MRSE level were found for Forward Trunk Flexion and Sit-to-Stand. For each feature (in the respective movement type), the means for the three MRSE levels are ordered according to their magnitudes; where the medium MRSE level or high MRSE level is significantly different from low level MRSE, the ordering is highlighted in bold.

For Forward Trunk Flexion, significant difference was found for speed features, range of angles of the trunk and shoulders, energy, and activity of the trapezius. The result shows that participants judged to have lower level MRSE were significantly slower and had significantly lower range of movement of the shoulder and trunk, and energy than those judged as having higher level MRSE. Unsurprisingly, as this may be connected to lower range of movement of the shoulder, it was also found that these participants had significantly lower mean activity in the trapezius than participants judged as having higher level MRSE.

For Sit-to-Stand, significant difference was found for speed features, range of angles of the trunk, knees, left elbow, and neck, energy, symmetry, activity of the trapezius and lumbar paraspinal, and fluidity in the movement of the trunk. The result shows that participants with low MRSE level were significantly slower and had significantly lower range of movement of the trunk and neck. This is similar to the finding for participants with higher level pain in Section 6.2.4. This is not surprising given that the participants judged as having low MRSE level for this movement type reported having higher level pain.

TABLE 6.10 LINEAR MIXED MODEL ANALYSIS RESULTS FOR MRSE

(bootstrapped linear model analysis in IBM SPSS only provides significance of effect without a test statistic and so the test statistic could not be reported - $^{+}p<0.05$, $^{*}p<0.01$, $^{++}p<0.005$, $^{**}p<0.001$, $^{***}p<0.0001$ difference with L, i.e. low MRSE level)

Feature ID	Feature	Forward Trunk Flexion	Sit-to-Stand
1	speed - hands	**L<M<H*****	**L<M<H****
2	speed - lower legs	**L<M**$^{+}$**<H**$^{+}$	**L<M<H**$^{+}$
3	speed - upper legs	**L<M**$^{+}$**<H**$^{+}$	**L<M<H**$^{++}$
4	speed - shoulder	**L<M<H**$^{+}$	**L<M<H**$^{++}$
5	speed - trunk	**L<M<H**$^{+}$	**L<M<H**$^{++}$
6	range - pelvic wrt head & left foot	**L<M**$^{+}$**<H**$^{+}$	L<H<M
7	range - pelvic wrt head & right foot	**L<M*****<H***	**L<H**$^{++}$**<M**
8	range - pelvic wrt trunk & left knee	**L<M<H***	**L<M<H**$^{++}$
9	range - pelvic wrt trunk & right knee	**L<M<H**$^{++}$	**L<M<H**$^{++}$
10	range - left knee	L<M<H	**L<M*****<H***
11	range - right knee	L<M<H	**L<M**$^{+}$**<H**$^{+}$
12	range - left elbow	L<M<H	**L>M*****>H***
13	range - right elbow	L<M<H	L<H<M
14	range - left shoulder (protraction)	**L<M<H***	L<H<M
15	range - right shoulder (protraction)	L<M<H	L<H<M
16	range - left shoulder (abduction/adduction)	**L<M<H***	L>M>H
17	range - right shoulder (abduction/adduction)	**L<M<H***	L>M>H
18	range - neck	**L<M<H**$^{+}$	**H>L>M**$^{+}$
19	energy sum	**L<M<H***	**L<M**$^{++}$**<H**$^{++}$
20	dissymmetry	L<M<H	**L<M<H***
21	right lumbar paraspinal mean activity	L<M<H	**L<M<H**$^{+}$
22	left lumbar paraspinal mean activity	L<M<H	<L<H<M
23	right trapezius mean activity	L<M<H	**L>M>H***
24	left trapezius mean activity	**L<M<H**$^{+}$	**H**$^{++}$**<L<M**$^{++}$
25	fluidity - hands	L<M<H	L>H>M
26	fluidity - lower legs	L<M<H	M<L<H
27	fluidity - upper legs	L<M<H	L>H>M
28	fluidity - shoulder	L<M<H	**L>H**$^{+}$**>M**
29	fluidity - trunk	L<M<H	**L>H**$^{+}$**>M**

range = angle range; wrt = with respect to; L = the feature value for participants with low MRSE level, M = the feature value for participants with medium MRSE level, H = the feature value for participants with high MRSE level.

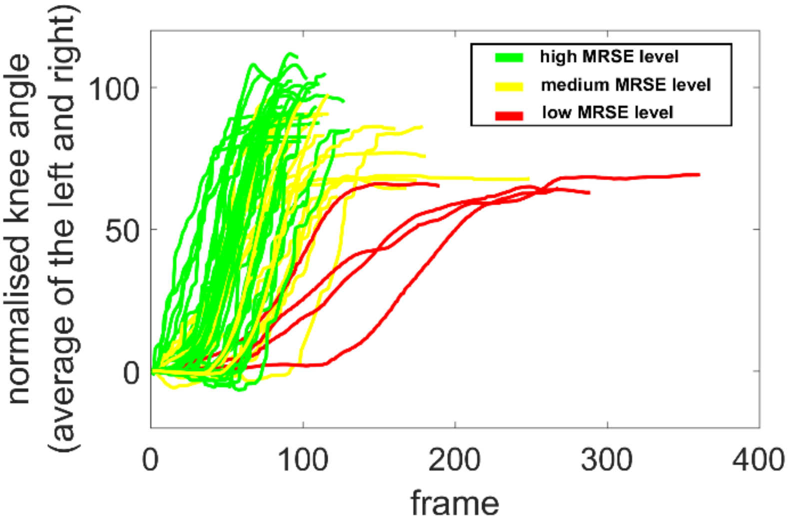


Fig. 6.13. Knee angle profiles (in degrees) during Sit-to-Stand instances performed with high, medium, and low MRSE

It was also found that participants with low MRSE level significantly had the lowest knee angle ranges in Sit-to-Stand while participants with high MRSE level significantly had the highest knee angle ranges and participants with medium MRSE level were in between with significantly higher ranges than those with low MRSE level. This is also similar to the finding for the three pain levels in Section 6.2.4. A plot of the knee angle profiles across the three levels of MRSE is shown in Fig. 6.13. Further analysis of the video of the participants with low MRSE level showed that they indeed kept their feet as far forward as possible as suggested in Section 6.2.4. It is impossible to stand up normally with such foot positioning: the video analysis further showed that all four participants with low MRSE used their hands to either push up for lift or to support lift. This may explain the finding of significantly higher mean activity in the left trapezius in participants with low MRSE level compared with participants with high MRSE level; participants with medium MRSE level had significantly higher mean activity than those with low MRSE level. It may also be connected to the significantly higher range of angles of the left elbow in participants with low MRSE level compared with the other two groups; participants with medium MRSE level had higher ranges than those with high MRSE level.

An additional finding was that participants with low MRSE level had significantly higher range of angle of the neck than participants with medium MRSE level. A surprising finding was that there was significantly more dissymmetry (of the shoulders) in participants with high

MRSE level than in participants with low MRSE level. This may be linked to the similarly unexpected findings for the mean activity of the left and right trapezius. For the right trapezius, mean activity was found to be significantly lower in participants with low MRSE level in contrast to participants with high MRSE level. For the left trapezius, on the other hand, participants with low MRSE level had significantly higher mean activity than those with high MRSE level but significantly lower mean activity than those with medium MRSE level. Another unexpected finding was significantly higher fluidity of the shoulder and trunk in participants with low MRSE level than participants with high MRSE level.

6.4 Emotional Distress Level Detection from Body Movement Behaviour

In this section, the investigation of body movement features that contribute to the differentiation between levels of emotional distress is reported.

6.4.1 Data

The body movement data introduced in Section 6.1 were used in this investigation. Due to missing data, not all instances of the dataset could be used in the investigation and so the investigation was based on 16, 45, and 112 instances of Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. 75%, 66.7%, and 70.5% were instances of people with CP respectively for the three movement types.

Ground truth of emotional distress was based on the HADS-13 scores of corresponding participants in the EmoPain dataset. Due to the limited size of the dataset, all 39 levels of the HADS-13 could not be considered. Instead, two levels of emotional distress were derived from this scale: instances where participants with CP reported HADS-13 score greater than 19 were classed as *distressed* whereas those where HADS-13 score was 19 or less were classed as *not distressed*. There were no healthy control participants in the distressed group, i.e. all of the healthy controls in the dataset had HADS-13 score above 19.

6.4.2 Features Investigation and Extraction

The body movement features investigated were based on previous affect studies. A list of these features is given in Table 6.11. The features and the methods used to extract them from IMU data are discussed in this subsection.

TABLE 6.11 FEATURES FOR EMOTIONAL DISTRESS LEVEL CLASSIFICATION

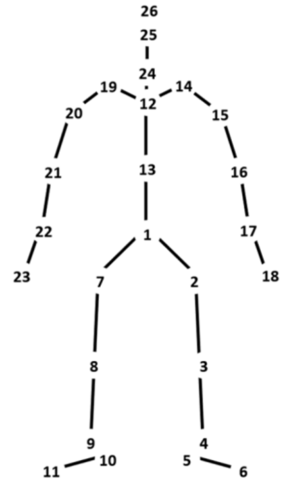
ID	Features
1	shoulder protraction
2	speed - hand
3	speed - lower legs
4	speed - shoulders
5	speed - left shoulder
6	energy - left hand
7	energy - right hand
8	energy - left shank
9	energy - right shank
10	energy - left shoulder
11	energy - right shoulder
12	energy - head
13	minimum head angle
14	duration of minimum head angle
15	minimum hand to thigh distance

6.4.2.1 Head Slump

Head slump is one of the known cues of emotional distress. This was found in a study by Waxer (1974) where observers with background in psychology or counselling rated the angle of the head of psychiatric patients during clinical assessment as one of the nonverbal cues that they used to differentiate the patients with depression and from those without. The observers noted that they specifically judged if a patient had his/her head drooped, looked down, or towards the ground. Scherer et al. (2013) did not find difference in the duration of downward gaze between participants with depressed mood and those without depressed mood significant. However, they found significant difference between distressed (i.e. with anxiety, depression, and/or post-traumatic stress disorder) and non-distressed participants. Further, based on feature set optimisation, Fourati and Pelachaud (2015) showed that the anterior-posterior pose of the head was important for automatic detection of anxiety and sadness in physical activity settings. Using full-body joint kinematics, they obtained accuracy of 0.86 for automatic discrimination between anxiety, neutral, pride, sadness, joy, panic fear, shame, and anger. These findings motivated the extraction of features of head pose in the investigation of this thesis. The features computed were the minimum angle of the head $\theta_{head-trunk}$ (calculated as the average within 10°

of the minimum) and the duration of this angle (range) normalised to the duration of the activity:

$$\theta_{head-trunk} = \frac{\sum_{t=1}^{T} \theta_t \quad iff\ \theta_{\min} <= \theta_t <= \theta_{\min} + 10^\circ}{\sum_{t=1}^{T} 1 \quad iff\ \theta_{\min} <= \theta_t <= \theta_{\min} + 10^\circ}$$



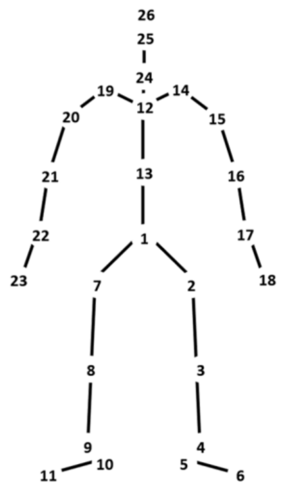
where

$$\theta_{\min} = \min \left\{ \tan^{-1}\left(\frac{\left\| \left(b_{26_t} - b_{24_t}\right) \times \left(b_{12_t} - b_{24_t}\right) \right\|}{\left(b_{26_t} - b_{24_t}\right) \bullet \left(b_{12_t} - b_{24_t}\right)} \right), \forall t : t = 1, 2, \ldots, T \right\}$$

6.4.2.2 Shoulder Protraction

A similar cue of emotional distress is shoulder protraction. For example, do Rosário et al. (2013) found significant strong correlation between usual levels of sadness and shoulder protraction. Similarly, Michalak et al. (2009) found that participants with depression had significantly more slumped posture while walking than those without depression. Thus, this feature was also extracted in the investigation in this thesis. In do Rosário et al., shoulder protraction was computed in a single pose based on measurements taken from photographs. This method cannot be used with IMU data of movement sequences. In Michalak et al., on the other hand, posture was computed as the mean angle between the line connecting the clavicle and the head. Similar to their method, in the investigation in this thesis, shoulder protraction was computed as the minimum angle between the left and right sides of the upper trunk:

$$\theta_{left-right} = \min \left\{ \cos^{-1}\left(\frac{\overline{n_t^l} \bullet \overline{n_t^r}}{\left\|\overline{n_t^l}\right\| \left\|\overline{n_t^r}\right\|} \right), \quad \forall t : t = 1, 2, \ldots, T \right\}$$

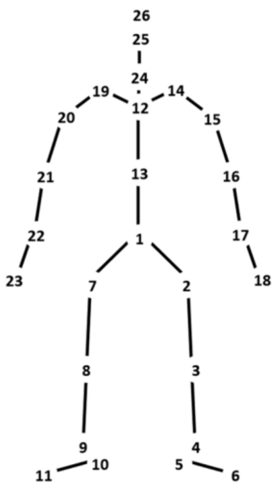


with $\overline{n_t^l}$ = normal vector of the plane of the left hand side of the trunk (i.e. based on b_{12_t}, b_{13_t}, and b_{14_t}) and $\overline{n_t^r}$ = normal vector of the plane of the right hand side of the trunk (i.e. based on b_{12_t}, b_{13_t}, and b_{19_t}).

6.4.2.3 The Use of Self-Adaptors

The use of self-adaptors, i.e. self-touching, has also been associated with emotional distress. Scherer et al. (2013) found that psychiatric patients with depression and/or anxiety significantly used more hand self-adaptors during clinical assessment interviews than those without depression and/or anxiety. The authors also considered head and trunk self-adaptors but differences were not significant with these. In the problem considered in this thesis and the dataset used to investigate it, subjects are engaged in physical activity and these forms of self-adaptors are not likely to occur in this setting. Instead, thigh self-adaptors were considered; to characterise it, the minimum distance between the hands and the thighs was extracted:

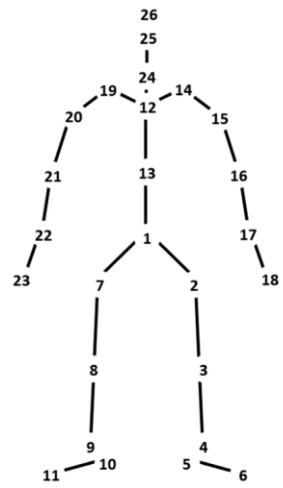
$$d_{\min} = \min\left(\min \left\{ \begin{array}{l} \left(\dfrac{\left\| \left(b_{2_t} - b_{3_t}\right) \times \left(b_{17_t} - b_{3_t}\right) \right\|}{\left(b_{17_t} - b_{3_t}\right)} \right), \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\}, \quad \min \left\{ \begin{array}{l} \left(\dfrac{\left\| \left(b_{7_t} - b_{8_t}\right) \times \left(b_{22_t} - b_{8_t}\right) \right\|}{\left(b_{22_t} - b_{8_t}\right)} \right), \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\} \right)$$



6.4.2.4 Body Sway

Body sway has also emerged as a cue through which emotional distress is expressed. In Michalak et al. (2009), lateral body sway while walking was found to be significantly higher in participants with depression than those without depression. The authors also found that movement (in the arms and head) was significantly less for those with depression. Similarly, Wada, Sunaga, and Nagai (2001) found significant differences between anterior-posterior body sway for anxiety levels. High frequency components were lower and low frequency components were higher for participants with high levels of anxiety. Significant difference was not found for the lateral axis in their study. In the investigation in this thesis, to characterise these cues, the energies of each of the head, trunk, hands, and legs were extracted as the sum of the mean translational and rotational kinetic energies for each segment, assuming unit mass:

$$E = \frac{\sum_{t=2}^{T} {s_t}^2}{2T} + \frac{\sum_{t=2}^{T} {r_t}^2}{2T}$$



$$r_t = \frac{\left\| b_{k_t} \right\|^2}{\left(\cos^{-1}\left(\frac{b_{k_t} \bullet b_{k_{t-1}}}{\left\| b_{k_t} \right\| \left\| b_{k_{t-1}} \right\|} \right) \right)^2}$$

$$s_t = \sqrt{\left(b_{k_t}^x - b_{k_{t-1}}^x \right)^2 + \left(b_{k_t}^y - b_{k_{t-1}}^y \right)^2 + \left(b_{k_t}^z - b_{k_{t-1}}^z \right)^2}$$

where k = 17, 22, 3, 8, 14, 19, 26 for the left and right hand, left and right shank, left and right shoulder, and head respectively. The mean for the left and right sides was used for the hand, shank, and shoulder.

6.4.2.5 Speed of Movement

Movement speed has also been found to differentiate between levels of emotional distress. Michalak et al. (2009), for example, found that participants with depressions walked significantly slower than those without depression. Lemke et al. (2000) also found that those with depression had significantly lower gait speed than healthy controls. This motivated extraction of the speed of the shoulder, hand, and shank (averaged over the left and right sides):

$$\hat{s} = \sum_{t=2}^{T} s_t$$

6.4.3 Features Analysis Methods

Similar to the investigation of body movement behaviour for pain and MRSE level detection reported in Sections 6.2 and 6.3, three types of analyses were done on the extracted features.

First, the SVM and RF (described in Chapter 4) were used to investigate the efficacy of the features for automatic detection of the two levels of emotional distress. The hyperparameters of both SVMs and for the RF were set based on grid search. For Full Trunk Flexion, SVM of regularisation parameter C = 10 and polynomial kernel of degree 7 and RF with 100 trees and the whole feature set used to split each node were used. For Forward Trunk Flexion, SVM with Gaussian kernel of width 25.01 and C = 10 and RF of 50 trees and one feature used to split each node were used. For Sit-to-Stand, SVM with Gaussian kernel of width 12.01 and C = 10 and RF with 1000 trees and the whole feature set used to split each node were used.

Secondly, the Branch and Bound optimisation method (Narendra and Fukunaga 1977) was used to understand the relevance of the features to automatic detection and optimise detection.

Finally, linear mixed model analysis was used to understand individual relevance of the features to differentiation of the emotional distress levels independently of the machine learning algorithm used.

6.4.4 Results

In this section, automatic classification performances, results of features analysis using feature set optimisation, and results of the statistical analysis of relevance of the features are presented.

TABLE 6.12 EMOTIONAL DISTRESS CLASSIFICATION PERFORMANCE - PAIN FEATURES VERSUS EMOTIONAL DISTRESS FEATURES
(without feature set optimisation)

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
Feature Set	Pain	Distress	Pain	Distress	Pain	Distress
F1 distressed	0	**0.57**	0.42	**0.56**	0.39	**0.64**
F1 not distressed	0.90	0.88	0.85	0.85	0.80	**0.90**
average F1	0.45	**0.73**	0.64	**0.71**	0.60	**0.77**
accuracy	0.81	**0.81**	0.76	**0.78**	0.69	**0.84**

6.4.4.1 Classification Performance

Using Pain Features

Initial analysis was done to understand the extent to which pain features (see Section 6.2.2) enable detection of pain related emotional distress levels. This analysis is important because, as Sullivan does theoretically (2008), it questions a unidimensional view of pain behaviour. In the analysis, the pain level features reported in Section 6.2.2 were used for automatic classification of emotional distress levels using the SVM. Table 6.12 shows the result obtained. It was found that while the pain features allowed good detection of *not distressed* instances, they led to worse than chance level detection of the distressed group (F1 = 0, 0.42, and 0.39 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively). The emotional distress, on the other hand, showed much better performance in detecting this group with F1 score better than chance level. This finding suggests that pain related emotional distress has a behaviour signature different from pain intensity's as suggested by the Bayesian model proposed in Chapter 5, and it supports the theory of multidimensionality of pain behaviours (Sullivan 2008).

Using Emotional Distress Features

Classification performance using the emotional distress features without feature set optimisation is shown in Table 6.13 for both the RF and SVM. For both Sit-to-Stand and Forward Trunk Flexion, classification using the RF has average F1 score of 0.80, which is better than chance level (i.e. accuracy of 0.50). Classification using the SVM is lower for both movement types with average F1 score of 0.77 and 0.71 for Sit-to-Stand and Forward Trunk Flexion respectively and the F1 score for the *distressed* class for Forward Trunk Flexion is only marginally better than chance level classification. For Full Trunk Flexion, even though average F1 score for both SVM and RF (0.73 and 0.67 respectively) is better than chance level classification, in the RF, this is only true for the F1 score for the *not distressed* class. Both the SVM and RF perform better in detecting *not distressed* class than the *distressed* class for the three movement types. This finding is not surprising given the dominance of the *not distressed* class in the dataset.

TABLE 6.13 EMOTIONAL DISTRESS CLASSIFICATION PERFORMANCE WITHOUT FEATURE SET OPTIMISATION
(average F1 based on feature set optimisation in bracket to aid comparison)

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	RF	SVM	RF	SVM	RF	SVM
F1 distressed	0.50	**0.57**	**0.67**	0.56	**0.68**	0.64
F1 not distressed	0.83	**0.88**	**0.93**	0.85	**0.92**	0.90
average F1	0.67 (0.67)	**0.73** (0.88)	**0.80** (0.83)	0.71 (0.80)	**0.80** (0.86)	0.77 (0.84)
accuracy	0.75	**0.81**	**0.89**	0.78	**0.87**	0.84

Performance improved with feature set optimisation as can be seen in Fig. 6.14 although the performance of the RF in the Full Trunk Flexion remains the same. The SVM has average F1 score of 0.8 for Full Trunk Flexion. For Forward Trunk Flexion, average F1 score is 0.83 and 0.80 for the RF and SVM respectively. For Sit-to-Stand, average F1 score is 0.86 and 0.84 for the RF and SVM respectively. As can be seen in Table 6.14, for the best classifiers, recall of the distressed class was highest in Sit-to-Stand compared with the other two movement types. This may be due to the higher number of training instances for that class available in this movement type.

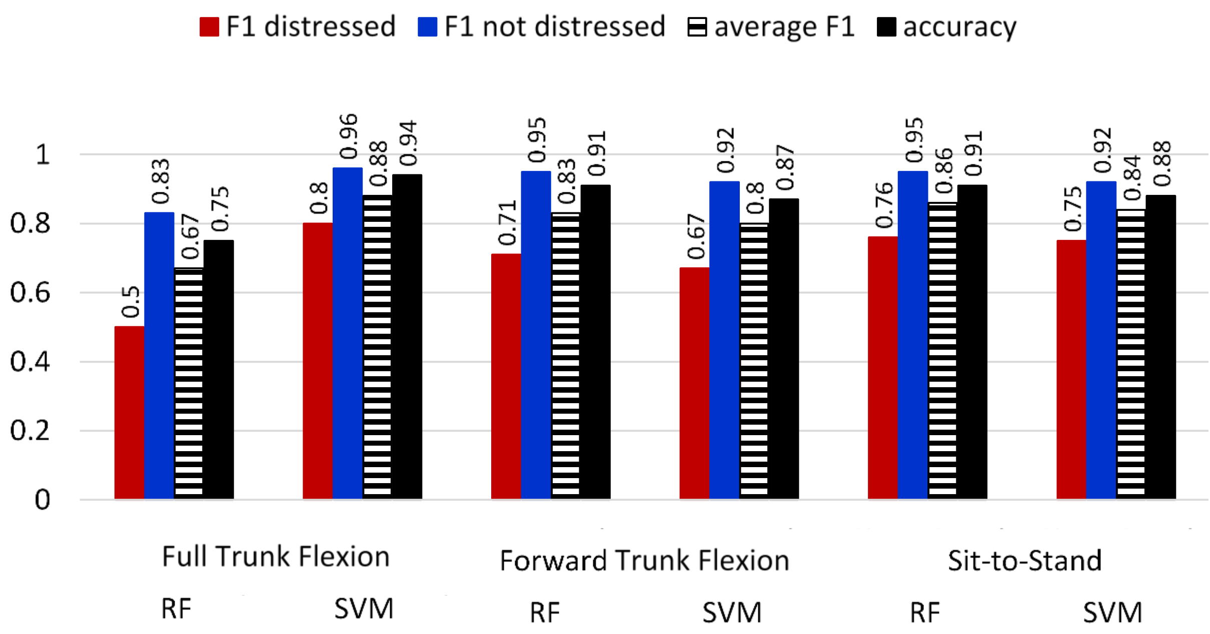


Fig. 6.14. Emotional distress level classification performance with feature set optimisation

TABLE 6.14 EMOTIONAL DISTRESS LEVEL DETECTION CONFUSION MATRICES FOR THE BEST CLASSIFIERS IN FIG. 6.14 (I.E. THE SVM FOR FULL TRUNK FLEXION AND THE RF FOR FORWARD TRUNK FLEXION AND SIT-TO-STAND) FOR EACH MOVEMENT TYPE
(with feature set optimisation)

FULL TRUNK FLEXION - SVM			
		Automatic Classification	
		distressed	not distressed
Ground Truth	distressed	**2** (**66.7**%)	1 (33.3%)
	not distressed	0 (0%)	**13** (**100**%)
FORWARD TRUNK FLEXION - RF			
		Automatic Classification	
		distressed	not distressed
Ground Truth	distressed	**5** (**62.5**%)	3 (37.5%)
	not distressed	1 (2.7%)	**36** (**97.3**%)
SIT-TO-STAND - RF			
		Automatic Classification	
		distressed	not distressed
Ground Truth	distressed	**16** (**72.7**%)	6 (27.3%)
	not distressed	4 (4.4%)	**86** (**95.6**%)

6.4.4.2 The Feature Subsets selected for Classification based on Feature Set Optimisation

For the Full Trunk Flexion, there were multiple subsets returned. Fig. 6.15 shows the relative frequency of each feature in these subsets. The right lower leg energy feature (all energy features were useful), the minimum head angle, and the minimum hand to thigh distance were found to be the most important features for the SVM in this movement type. Further analysis (Fig. 6.16-left) showed that energy of the right lower leg was lower in the distressed group. For the minimum head angle feature, there were more distressed instances with lower values than the *not distressed* instances (Fig. 6.16-middle) suggesting that those distressed tended to slump their heads during execution of this movement type. The importance of this cue in the Full Trunk Flexion but not in the other two movement types may be due to the fact that in contrast to these activity types, the Full Trunk Flexion lends itself to head slump. The distressed group was also found to have lower minimum hand-to-thigh distances than the *not distressed* (Fig. 6.16-right).

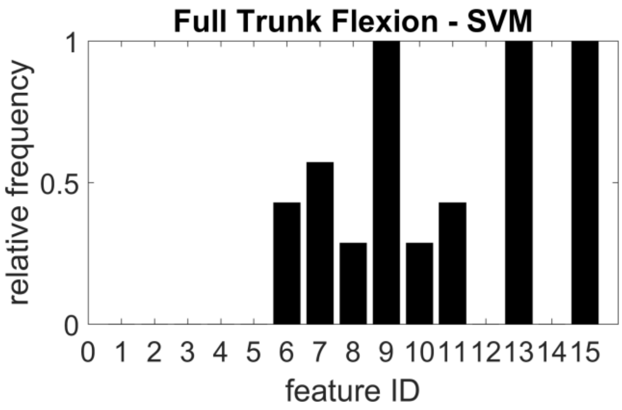


Fig. 6.15. Feature importance for emotional distress detection based on subset selection. The feature ID number follows the numbering in Table 6.15

Fig. 6.16. Left - Right lower leg energies. Middle - Minimum head angles. Right - Minimum hand-thigh distances

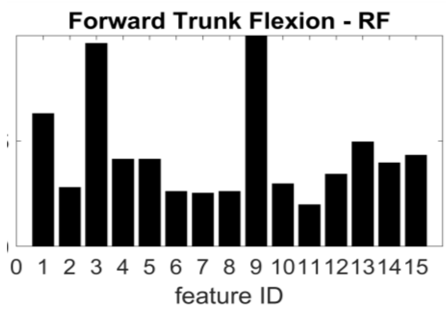


Fig. 6.17. Feature importance for emotional distress detection based on subset selection. The feature ID number follows the numbering in Table 6.15

For Forward Trunk Flexion, multiple optimal subsets were also returned. Fig. 6.17 shows the relative frequency of each feature in these subsets. Unlike the other two movement types, all the extracted features were useful for Forward Trunk Flexion. Similar to Full Trunk Flexion, the right lower leg energy feature was the most important feature in the movement type. The speed of the leg almost matched this feature in importance. It is not clear why the speed of the leg was found to be important here but not in Full Trunk Flexion, which is a similar movement with respect to the legs.

Multiple subsets were also returned for Sit-to-Stand. Fig. 6.18 shows the relative frequency of each feature in these subsets. The minimum hand to thigh distance was the most important feature for this movement type. For this feature, as can be seen in Fig. 6.19, the distressed instances had values similar to about half of the *not distressed* instances. This is not surprising as in Sit-to-Stand, there are reasons other than distress why the hands may be close to the thigh in this movement type (e.g. natural resting of the hands on the thigh at the start of the activity).

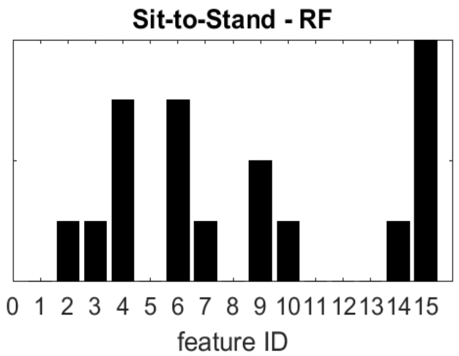


Fig. 6.18. Feature importance for emotional distress detection based on subset selection. The feature ID number follows the numbering in Table 6.15

Fig. 6.19. Minimum hand-thigh distances

TABLE 6.15 LINEAR MIXED MODEL ANALYSIS RESULTS FOR EMOTIONAL DISTRESS
(bootstrapped linear model analysis in IBM SPSS only provides significance of effect without a test statistic and so the test statistic could not be reported - ^{+}p<0.05, $*p$<0.01, ^{++}p<0.005 difference with D, i.e. distressed)

Feature ID	Feature	Full Trunk Flexion	Forward Trunk Flexion	Sit-to-Stand
1	shoulder protraction	D<N	N<D	N<D
2	speed - hand	D<N	**D<N***	**D<N^{++}**
3	speed - lower legs	D<N	**D<N^{+}**	**D<N^{+}**
4	speed - shoulders	D<N	**D<N^{++}**	**D<N^{++}**
5	speed - left shoulder	D<N	**D<N^{++}**	**D<N^{++}**
6	energy - left hand	D<N	D<N	D<N
7	energy - right hand	D<N	**D<N^{+}**	D<N
8	energy - left shank	**D<N^{+}**	**D<N^{+}**	D<N
9	energy - right shank	**D<N^{+}**	**D<N***	D<N
10	energy - left shoulder	D<N	D<N	D<N
11	energy - right shoulder	D<N	D<N	D<N
12	energy - head	D<N	D<N	D<N
13	minimum head angle	D<N	**N^{+}<D**	**N^{+}<D**
14	duration of minimum head angle	D<N	N<D	**N^{+}<D**
15	minimum hand to thigh distance	**D<N***	N<D	**D<N^{++}**

D = the feature value for distressed participants, N = the feature value for participants not distressed.

6.4.4.3 Statistical Relevance of the Features

The results of the linear mixed model analysis are shown in Table 6.15. For each feature (in the respective movement type), the means for the distressed and not distressed groups are ordered according to their magnitudes; where the two groups significantly differ, the ordering is highlighted in bold.

Distressed participants were found to have significantly lower energy of the left and right shank in Full and Forward Trunk Flexion, supporting the finding in Michalak et al. (2009). These participants also had significantly lower minimum hand-to-thigh distance in Full Trunk Flexion and Sit-to-Stand suggesting that they used thigh self-adaptors in these movement types. This adds to the work of Scherer et al. (2013) who only looked at hand, head, and trunk self-adaptors in sedentary settings. As expected from similar studies in Michalak et al. (2009) and Lemke et al. (2000) based on walking activities, the distressed participants were found to be significantly slower in Forward Trunk Flexion and Sit-to-Stand. An unexpected finding was that the distressed had significantly higher minimum head angle in both Forward Trunk Flexion and Sit-to-Stand. It may be that pain related distress lends to rigidity in the movement of the head that masks head slump typical of distress (in non-pain contexts). This is plausible given the findings of limited head movements with higher level of pain and lower level of MRSE in Sections 6.2.4 and 6.3.4 and the finding of significantly higher duration of the minimum head angle in the distressed participants.

6.5 Discussion

The aim of the studies presented in this chapter was to investigate body movement behaviours that contribute to differentiation between levels of pain, MRSE, and emotional distress.

For each of these states, a set of body movement features were proposed (see Appendix III) and in-depth understanding of the relevance of the features to discrimination between levels of each state was developed based on visual exploration, wrapper-based feature subset selection, and linear mixed model analysis. This understanding is further discussed below (in Section 6.5.1). An important finding is that a reduced set of anatomical segments, rather than the full-body (26 joints and 4 back muscles) tracked in the EmoPain dataset, can suffice for automatic detection of these states. This points to the possibility of the use of a minimal sensor network for tracking movement behaviour for this function. This will enable monitoring, and so affect-aware technological intervention, in everyday functioning. The feasibility of such a reduced number of sensor for automatic detection of levels of pain, MRSE, and emotional distress is further investigated in Chapter 7.

The efficacy of the proposed features for automatic detection was investigated using traditional machine learning algorithms (Random Forests and Support Vector Machines). Feature set optimisation led to excellent detection performances. For three-level pain classification, average F1 scores of 1, 0.85, and 0.84 were obtained for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. For three-level MRSE classification, average F1 scores of 0.95 and 0.78 were obtained for Forward Trunk Flexion and Sit-to-Stand respectively while average F1 scores of 0.88, 0.83, and 0.86 were obtained for two-level emotional distress classification for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand. These findings suggest that levels of pain, MRSE, and emotional distress can be reliably (i.e. much better than chance) differentiated from these features. The implication of these findings for affect-aware technological intervention to support people with CP in physical rehabilitation is further discussed below (in Section 6.5.2).

6.5.1 Contribution to Automatic Assessment of Pain, MRSE, and Emotional Distress

A major contribution of the investigations in this chapter is the building of a repertoire of body movement features of pain and related self-efficacy and emotional distress. Literature (Shum, Crosbie, and Lee 2007; Shum, Crosbie, and Lee 2005; Watson et al. 1997; Ahern et al. 1988; Grip et al. 2003; Lai et al. 2009; Gioftsos and Grieve 1996) currently only provide descriptions of movement behaviour that discriminate people with pain from healthy persons. Although Dickey et al. (2002) investigated behaviours that further differentiate people with CP by pain intensity, they focused on vertebral features that are difficult to capture outside clinical settings. Literature on emotional distress has also been limited in that it has often focused on acted expressions (e.g. (Fourati and Pelachaud 2015; Piana et al. 2014; Gunes et al. 2015)), sedentary settings (e.g. (Joshi, Dhall, et al. 2013; Scherer et al. 2013; Rani, Sarkar, and Liu 2005)), and contexts without the compounding effect of pain (e.g. (Lemke et al. 2000; Michalak et al. 2009)). In addition, literature on body movement cues of MRSE is practically non-existent. In this section, the contributions to these areas are discussed highlighting both the contribution of deeper understanding of known cues and the contribution of understanding of new cues. As the low level features describing these cues have already been discussed in the respective sections for each of the three states (Sections 6.2.4 6.3.4, and 6.4.4 respectively), the cues are discussed here as abstractions of these features (rather than using those low level descriptions) to enable easier generalisation and to highlight the overarching themes of the findings.

6.5.1.1 Contribution 1- Deeper Understanding of Known Cues for Pain and Emotional Distress

The investigations done in this thesis contributes to the area of pain behaviour analysis and affective computing by collating relevant cues from several literature sources beyond pain studies and providing deeper understanding of their contribution to the automatic differentiation of levels of pain and emotional distress.

One of these cues is the **tempo of movement execution**. It was shown that this cue provides information about all three states considered in this thesis (pain, MRSE, and emotional distress). Although this may be intuitive, highlighting it in this thesis importantly supports the suggestion of Sullivan (2008) that each pain behaviour may have different cognitive/affective dimensions to it. This is similar to the finding reported in Chapter 5 with guarding behaviour as a description of pain experience. This finding underscores the need to understand which of pain relevant states need to be addressed to facilitate improved movement behaviour. It was further shown in the investigation of this thesis that for pain, the duration of movement execution and movement speed in the ascension phase of a sit-to-stand movement provide different descriptions of this cue. The finding of lower speed in this phase supports previous findings in Coghlin and McFayden (1994) where the phase was found to account for a larger proportion of the movement for people with CP than for healthy participants. It is hypothesized in this thesis that people with CP are able to achieve shorter duration of the movement despite lower speed because of reduced trunk flexion (for ascension initiation) which enables less preparation for ascension and less adjustment to complete the extension phase. It was further shown that beyond differentiation of people with CP from healthy persons found in Grip et al. (2003). Lai et al. (2009), and Shum, Crosbie, and Lee (2005), tempo of movement execution also enables differentiation between lower and higher level pain in CP.

Another cue is the **range of movement of the affected anatomical segment** as a cue of pain. Similar to previous findings such as in Ahern et al. (1988), Gioftsos and Grieve (1996), Grip et al. (2003), and Lai et al. (2009), it was shown that this cue differentiates people with CP from healthy persons. It was further shown that the cue also enables discrimination between levels of pain in people with CP. Range of movement of the affected segment was also shown to be useful in differentiating between levels of MRSE with people with lower level MRSE exhibiting significantly lower range than people with higher level MRSE.

A third cue is **head and shoulder slump** as a cue of emotional distress. Similar to do Rosário et al. (2013) and Michalak et al. (2009), it was shown that shoulder slump is a useful cue of emotional distress. However, the finding in the investigation of this thesis of its relevance in automatic detection in forward trunk flexion alone suggests that this cue may not be universal in physical activity settings and the context of movement may mask it (or make it salient). This finding underscores the fact that cues that are relevant in sedentary settings may not necessarily transfer to physical activity settings. It also points to the relevance of movement context in the case of physical activity. An additionally finding was that head slump is a relevant cue of emotional distress in physical activity settings; this adds to previous findings in sedentary settings in (Waxer 1974; Scherer et al. 2013).

Finally, **body sway** characterised by joint energy was shown to enable discrimination between the presence and absence of emotional distress. However, it is difficult to compare the findings for this cue with findings in previous studies because of differences in emotional distress constructs and the body sway computation methods. This cue was analysed in Michalak et al. (2009) for the depressed mood component of emotional distress and, in their study, (lateral) sway was computed as the difference between the maximum deflection of the shoulders during walking. As no computation formula was given in their paper, it is difficult to understand how their characterisation of sway differs from the approach of this thesis. In Wada, Sunaga, and Nagai (2001), body sway was analysed for the anxiety component of emotional distress and it was computed as the displacement of the centre of gravity while standing. The findings in these studies suggest that lateral body sway increases with depressed mood while anterior-posterior body sway also increases with anxiety but only for low frequency sway with decrease with anxiety for high frequency sway. In the investigation of this thesis, sway characterised by energy was found to significantly decrease with emotional distress (anxiety and depressed mood).

6.5.1.2 Contribution 2 - New Cues for Pain and Emotional Distress

Beyond providing deeper understanding of known cues, data exploration and analyses led to the discovery of six new cues relevant to the automatic discrimination between levels of pain and emotional distress (four and two cues respectively).

It was shown in this thesis that **range of head or neck movement** enables discrimination between levels of pain. Statistically significant effect was only found with forward trunk flexion movement with range of head/neck movement decreasing with pain status (i.e. higher level < lower level < healthy). However, it was found useful for automatic detection of the three pain levels for sit-to-stand and for automatic differentiation between CP and healthy participants for full trunk flexion. Although it was found in the investigation of the thesis that physiotherapists informally use this cue in movement assessment, as far as is known, this thesis is the first to provide evidence of the efficacy of this cue for differentiating levels of pain. Although this cue may be related to guarding behaviour (i.e. stiffness in movement), it should be noted that the head and neck were not the main pain locations of the people with CP (although some of the participants may have had pain in these segments in addition to the low back). This observation is interesting as it suggests that stiffness due to pain experience may generalise beyond the painful segment in people with CP.

Another cue discovered in this thesis was **arm unsteadiness** for discriminating between levels of pain. Although no statistical significance was found, cues of arm unsteadiness were relevant for automatically differentiating people with CP from healthy participants with forward trunk flexion and for automatically detecting the three pain levels in full trunk flexion. Based on findings in visual inspection, it is theorised in this thesis that, similar to the finding with neck movement, pain level results in stiffness of the arm that manifests as reduced unsteadiness of the arm with pain.

It was additionally shown in this thesis that pain leads to atypical **foot positioning** to perform sit-to-stand movement. This cue may already be used informally by physiotherapists; however, as far as is known, this thesis is the first to provide behavioural data evidence of this strategy in people with CP. It was found that people with higher level pain keep their feet as far forward as possible to initiate the movement and use support to lift up in order to execute this biomechanically challenging strategy. Two sub-strategies were found within the sit-to-stand instances where this strategy was used. In one group (all three available instances for P19 and the second and third higher level challenge instances for P24), both hands were used to push up on the bench they were seated on whereas in the second group (all three available instances for P21), one side (usually the right hand side) of the body was raised before the other in ascension and the contralateral hand was used to push up on the bench. There was an instance (the first higher level challenge instance for P24) where both strategies were used: two hands were first used to push up on the bench and then the right hand side of the body was raised further earlier than the left with the left hand kept on the bench during this phase.

Finally for pain level, features of **back muscle relaxation on trunk re-extension** were shown to contribute to discrimination between levels of pain. However, contrary to delayed relaxation on re-extension due to pain as was expected based on visual inspection, people with CP were found to have significantly earlier relaxation than healthy participants in full and forward trunk flexion while people with higher level pain were found to have significantly earlier relaxation than those with lower level pain in sit-to-stand. These findings are theorised to be due to the reduced tension in flexion (in turn due to lower trunk flexion) for people with CP particularly people with higher level pain.

For emotional distress, it was shown in this thesis that the use of **thigh self-adaptors** during physical activity may be a cue of emotional distress. This finding builds on the work of Scherer et al. (2013) that showed that the use of head, hand, and trunk self-adaptors in sedentary settings are cues of emotional distress. In the investigation of this thesis, thigh self-adaptor use was characterised using the minimum distance between the hands and the thighs. This distance was shown to be significantly reduced in those with higher levels of emotional distress.

It was also shown that the **extent (in distance) of head droop** during physical activity may be another cue of emotional distress. It was shown that those with higher levels of emotional distress had significantly less head droop. Although this may seem to contradict findings of head slump in the distressed discussed earlier, the two findings are in fact not antithetical. A valid explanation is that while the distressed keep their head downward for much longer than those not distressed (making head slump a cue of distress), those not distressed move their head farther downward as a result of natural flexibility (as opposed to stiffness) in movement.

6.5.1.3 Contribution 3 - MRSE Cues

The investigations of the thesis also contribute unprecedented understanding of movement cues that enable automatic differentiation of levels of MRSE. This builds on findings in the Chapter 5 of the types of cues used by physiotherapists to estimate MRSE levels. Here, low level descriptions of the cues are referred to where overarching themes of cues were not found.

It was shown that speed, range of joint movement for the pelvic, knee, elbow, and shoulder joints, sum of joint energies, dissymmetry, mean muscle activity, and fluidity of joint movements are relevant cues for discrimination between MRSE levels. **Speed** was found to significantly decrease with decrease in MRSE levels. **Range of movement of the pelvic, knee, and shoulder joints** were also found to significantly decrease with decrease in MRSE levels. Conversely, **range of movement of the elbow** was found to significantly increase with decrease in MRSE levels in sit-to-stand. This finding may be due to tendency for the hands to be used to push up in ascension in lower MRSE levels as was found for higher pain level. A different pattern was found for the **range of head/neck movement** where lower range of movement was found with low level MRSE than was found with high level MRSE in forward trunk flexion. In sit-to-stand, the range of head/neck movement was higher with low level MRSE than with medium level MRSE.

Dissymmetry was found to be significantly lower, in sit-to-stand, in low level MRSE than in high level MRSE. This was an unexpected result as it was hypothesized that there would be larger dissymmetry for people with lower MRSE levels. It may be necessary to investigate simpler dimensions of dissymmetry than was analysed in the investigation of this thesis where an aggregate of the dissymmetry for both the anterior and vertical axes was analysed. Further work may consider these as two separate dissymmetry dimensions for each axis respectively.

Fluidity was also unexpectedly found to be significantly higher in low level MRSE than in high level MRSE in sit-to-stand. The hypothesis in this thesis was that people with lower MRSE levels will be less fluid in their movement than people with higher MRSE levels. It is possible that strategies used in performing the movement enabled people with lower MRSE levels to be more fluid in their movement similar to the finding (in visual inspection) of higher arm steadiness in people with higher level pain. Although fluidity was a cue the physiotherapists in the annotation study reported in Chapter 5 noted as using to estimate MRSE, it is not known in what movement types this cue was found useful and how it was used to assess MRSE levels.

The pattern of **mean muscle activity** across MRSE levels varied with the muscle and the movement type. For sit-to-stand, activity was significantly lower in the right lumbar paraspinal for low level MRSE than for high level MRSE whereas it was significantly higher in the right trapezius for low level MRSE. In this movement type, in the left trapezius, activity was lower for low level MRSE than for medium level MRSE but higher than for high level MRSE. For forward trunk flexion, activity was significant lower in the left trapezius for low level MRSE than for high level MRSE.

6.5.2 Implication for Technological Intervention in CP Physical Rehabilitation

Findings of the feasibility of automatic detection of levels of pain and related self-efficacy and emotional distress during physical activity suggest that technology can be leveraged for personalisation of support and feedback to these states in these settings as needed in CP physical rehabilitation. The performance of automatic pain level classification is comparable with state-of-the-art performance based on facial expressions (e.g. (Werner et al. 2016; Rathee and Ganotra 2016; Roy et al. 2016)). It should however be noted that a fair comparison is difficult as most of the studies in this area focus on the detection of observer rated expressions of pain rather than self-report (which is the clinical standard for assessing pain intensity (Jensen and Karoly 1992)). The automatic emotional distress detection performance outperforms the state-of-the-art performance based on acoustic and facial features (Nasir et al. 2016; Alghowinem et al. 2016) while the performance for automatic MRSE level classification sets the maiden benchmark as it is the first in the area although it (for Forward Trunk Flexion) surpasses findings for epistemic self-efficacy in sedentary learning contexts (McQuiggan, Mott, and Lester 2008; Arroyo et al. 2009; Grafsgaard et al. 2015).

The use of body movement cues for automatic detection of levels of these states in the investigations of this thesis provides the opportunity for richer understanding of the behaviour of a person, and so offers more possibilities to inform interventions in CP, than facial or vocal expressions. This is because bodily cues encode not only information about a person's affective states but also information about the component of the movement that may be perceived as threatening and the action tendency (e.g. guarding, i.e. stiffness in movement) in response to the perceived threat (Vlaeyen and Linton 2000; Sullivan 2008; de Gelder 2009; Alborno et al. 2016). These metadata allow for more targeted real-time feedback or higher-resolution data to guide self-reflection similar to the support provided by clinicians (Singh et al. 2014). For example, if a person with CP is observed to respond to low self-efficacy for a sit-to-stand by first positioning the feet as far forward as possible (an unhelpful strategy that makes the movement more challenging), an automatic observer may suggest raising the level of the seat as a more helpful strategy. Automatic tracking (of these information, i.e. movement behaviour as well as associated affect) is pertinent since, as shown in (Felipe et al. 2015), people with CP are not always aware of the cause of their pain related fears/anxieties and the resulting use of unhelpful strategies. Many physical rehabilitation technologies are already endowed with body movement sensors making them ready to acquire such tracking capabilities. While the focus in this thesis was on the use of wearable IMU and sEMG sensors, the findings of the investigations can easily transfer to other body movement sensor technologies (such as optical based sensors (Jansen-Kosterink et al. 2013; Tang et al. 2015)) used in CP rehabilitation.

6.5.3 Limitation

A limitation of the studies in this chapter is the sizes of the datasets used. This is a challenge that this application area faces as people with CP are unlikely to take part in data collection studies on distressing days (due to pain and related experiences). Further, many people with CP may have underlying conditions (such as hypermobility syndrome) that make everyday living even more challenging and their availability for data collection studies limited. More data with fairer balance across levels of cognitive and affective states is expected to improve classification performance. In addition, more data may allow more fine-grained detection with more levels of pain, emotional distress, and self-efficacy considered. Such data would need to be representative of the levels to be considered; for example, if the 11 levels of the pain self-report scale are to be considered then there should be comparable number of observations for each of the 11 levels. This data would also enable investigation of the dynamics in movement with respect to levels of pain, emotional distress, and self-efficacy. For such analysis, the data would have to include (sensor) observation of movements over extended periods (e.g. hours for pain and emotional distress level analysis) so as to capture changes in the levels of the states and how these changes are reflected in variations in movement execution. Finally, a larger data set will allow the use of deep learning algorithms which are expected to improve classification given that they lead to more complex classification functions than the traditional learning algorithms (such as SVM and RF) allow. Deep learning algorithms may also enable learning of manifolds of IMU and sEMG body movement data that are associated with pain and related states (Goodfellow, Bengio, and Courville 2016).

Given the challenges of data collection in the CP population, it is expedient to investigate portable, low-cost body movement sensors that can facilitate collection in routine functioning similar to methods used by technology companies (e.g. annotation of traffic related data to train Google's self-driving technology based on reCAPTCHA (Hern 2017)) to acquire training data and labels. This need is addressed in the studies reported in the following chapter.

6.6 Conclusion

Addressing the gap in the literature on pain-related affective computing, this study provides understanding of fine-grained movement behaviour that enable discrimination between levels of pain, MRSE, and emotional distress. For pain levels, it was shown that the tempo of movement execution, the range of movement about the pain location, the range of movement of the head, the amount of unsteadiness in the arm, back muscle relaxation on re-extension, and foot positioning (in sit-to-stand) can provide cues that enable discrimination. For MRSE levels, the tempo of movement execution, the range of movement about the pain location, foot positioning (in sit-to-stand), dissymmetry, fluidity, and the average muscle activity were shown to provide cues for discrimination. For pain-related emotional distress, it was shown that the tempo of movement execution, head or shoulder slump, body sway, the use of thigh adaptors, and the extent (in distance) of head droop enable discrimination between its presence and absence. Automatic detection performance based on this taxonomy was shown to be much better than chance level with F1 scores of 0.90, 0.87, and 0.86 for three levels of pain, three levels of MRSE, and two levels of emotional distress respectively. It is important to note that movement type was found to affect the expression of the pain, low MRSE level, and emotional distress: while some expressions are relevant across movement types, movements that are different can have distinct expressions. Advanced techniques such as multilabel classification and transfer learning may be used to learn both variations in movement due to the state of a person with CP and the differences in these variations across movement types. The developed taxonomy contributes to future research in pain-related affective computing and also to the development of affect-aware technology in the context of pain.

7 Towards Ubiquitous Automatic Detection of Levels of Pain and Self-Efficacy in Functional and Exercise Movements

THE findings of the investigations reported in Chapter 6 point to the feasibility of automatic detection of pain and related states from body movement features captured during physical exercises using high fidelity and expensive IMU and sEMG sensors. At the same time, results reported in the chapter suggest that a reduced number of sensors (rather than full-body sensors) may be sufficient for reliable classification. These results have encouraged further investigation of physical activity closer to real life functional activity as a minimal number of sensors enable portability of body movement capture, necessary for non-situated activities typical of everyday settings. This is an important direction as everyday functional activities are an important aspect of physical rehabilitation because they represent valued goals; yet, as discussed in Chapter 2, they do not easily benefit from capabilities gains in situated exercise settings (Singh, Bianchi-Berthouze, and Williams 2017). In addition, as living with CP limits the psychological and physical resources for activities not considered essential (Felipe et al. 2015; Singh et al. 2014), the main setting of physical rehabilitation for people with this condition is valued functional activities rather than exercise sessions outside such activities. In fact, it has been shown that exercising (when found to be of necessary) is interleaved with functional activity (Singh et al. 2014; Zhang et al., in submission), For example, stretching exercise movements are done during breaks while loading the washing machine or walking to work, to prevent muscle stiffness and soreness. Thus, the third research question investigated in this thesis is *how can levels of pain and related self-efficacy and emotional distress be detected in everyday physical functioning based on the body movement behaviours captured using a reduced set of sensors?* A related question that is additionally relevant is of the feasibility of detection across both functional and exercise movement contexts. These questions are investigated in this chapter with the aim of beginning exploration so as to provide initial understanding and motivation for further work in the area by other researchers.

To address these questions, three issues needed to be addressed: 1) the need for a dataset of functional and exercise movements of people with CP captured using a low-cost wearable and portable device; 2) the need to understand the possibility of extracting from this dataset features describing the body movement cues found relevant for automatic detection in Chapter 6; and (3) the feasibility of automatic detection of levels of pain, self-efficacy, and emotional distress based on such a dataset. To deal with the first of these issues, a sensing system prototype (named MOVES-PC) cheaper and more portable than high-fidelity commercial systems such as the Animazoo IGS-190 IMU and the BTS FreeEMG 300 sensors used to acquire the EmoPain dataset was built. This prototype was necessary as at the time, there were no commercially available low-cost alternatives with IMU and sEMG sensor integration. Although the prototype was designed to be easily worn for data capture in functional movement settings, the evaluation of the prototype focused on its functionality alone. However, a discussion of the wearability of the prototype in these settings based on lessons that emerged in the use of it for data collection is given. This discussion can inform the improvements on the design of commercial systems. The prototype developed was used to acquire a new dataset (named Ubi-EmoPain) of body movement data captured from people with CP during both functional movements and physical exercise movements in addition to self-reports of pain, self-efficacy, and emotional distress. This dataset was then analysed using machine learning algorithms to understand the feasibility of automatic detection using such sensor systems. These investigations are reported in this chapter.

The chapter has six main sections. The development and validation of prototype is described in Section 7.1. In Section 7.2, the use of the prototype in collecting the Ubi-EmoPain dataset is described. The methods used to extract the body movement features (resulting from the investigation reported in Chapter 6) from the dataset and analyse them are described in Section 7.3 while the results of the analysis are reported in Section 7.4 with low level discussion of these results. The findings of the investigations are altogether discussed and at a higher level in Section 7.5, and a conclusion is given in Section 7.6.

7.1 Prototype Development

In this section, the development and validation of the MOVES-PC prototype are described.

7.1.1 Development of the Prototype

The MOVES-PC prototype was built to use a variable number of sensing units where each unit comprises an IMU or sEMG sensor connected to an Arduino-based dual in-line package (DIP).

7.1.1.1 The IMU Units

The IMU used in the IMU sensing units (see Fig. 7.1-left) is the MPU-9150 (Invensense Inc 2012), which is an integrated triaxial accelerometer, gyroscope, and magnetometer. The combination of data from the three sensors enables estimation of orientation over time (Kemp, Janssen, and Van Der Kamp 1998; Jasiewicz et al. 2006; Rouhani et al. 2012). The magnetometer gives large errors in the presence of magnetic interference (Kemp, Janssen, and Van Der Kamp 1998; Luinge and Veltink 2005) and so, because the fusion of data from the accelerometer and gyroscope is sufficient for estimation orientation in certain applications (Charry, Umer, and Taylor 2011; Duc et al. 2014; Roan et al. 2012), only data from the accelerometer and gyroscope were fused in this prototype.

The accelerometer can be used on its own to estimate orientation with respect to acceleration due to gravity when acceleration due to motion is negligible (Charry, Umer, and Taylor 2011; Duc et al. 2014; Roan et al. 2012). Orientation can also be independently estimated from the gyroscope, which measures angular velocity; this can be done by integrating angular velocity over time (Luinge and Veltink 2005; Roan et al. 2012). Combining orientation derived from both the accelerometer and gyroscope improve estimation over time (Charry, Umer, and Taylor 2011; Duc et al. 2014; Roan et al. 2012). The complementary filter algorithm (Roan et al. 2012) was used for fusion, computing orientation θ at time t as

$$c\theta_{t_{gyro}} + (1-c)\theta_{t_{acc}}$$

where c is a constant cut-off frequency, which depends on the sampling period T and time constant τ in the relationship

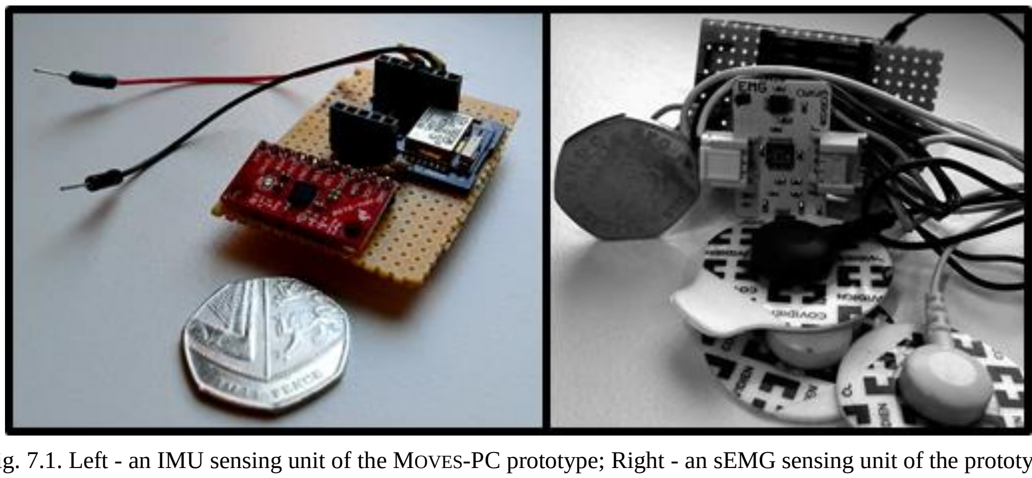


Fig. 7.1. Left - an IMU sensing unit of the MOVES-PC prototype; Right - an sEMG sensing unit of the prototype

$$\tau = T \frac{c}{1-c}$$

This algorithm is simple to implement and has been found to be comparable in performance to other fusion algorithms such as the time-varying complementary filter and the Extended Kalman filter methods (Roan et al. 2012). An open source Arduino implementation of the algorithm (SparkFun Electronics 2016) was used.

7.1.1.2 The sEMG Units

The sEMG sensor used in the sEMG sensing units (Fig. 7.1-right) is the BITalino EMG sensor (Plux 2015) which records muscle activity in the range ±1.65 microvolts for input voltage v_{cc} = 3.3 volts. The sensor uses a bipolar electrode configuration and a reference electrode. The three electrodes were connected to the sensor board using cables of length of 45 centimetres provided by the sensor board manufacturer as an accessory.

7.1.1.3 The Other Components of the Prototype

The DIP used is the RFD22102 (RFduino.com 2013) which consists of a 16 megahertz ARM Cortex-M0 processor with flash memory of 128 kilobits and random access memory (RAM) size of 8 kilobits and a 2.4 gigahertz radio antenna with transmission power of 4 decibel-milliwatt. The transfer functions and filter algorithm used to compute orientation from the IMUs and the transfer function used to derive muscle activity from raw sEMG sensor data were implemented on the DIP for the IMU and sEMG sensing units respectively.

Each sensing unit was powered by a 3.7-volt, 400-milliampere-hour, 0.009-kilogram lithium ion polymer battery and each of IMU and sEMG units weighed 0.052 kilograms and 0.069 kilograms respectively with their batteries and enclosure packaging.

Data was collated from the sensing units via BLE using a custom-built mobile application as master in a star topology with the sensing units as slaves. The application was designed, as shown in the screenshot in Fig. 7.2, to allow: wireless connection of multiple available sensing units, launching of synchronised recording of data with connected sensors, and termination of recording with storage of recorded data.

7.1.2 Validation of the Prototype

The capability of the MOVES-PC prototype to track observable movement and hidden muscle activity was validated before using it to collect the Ubi-EmoPain dataset. This validation was done in two studies with healthy participants. In the first study, only the sEMG sensing units

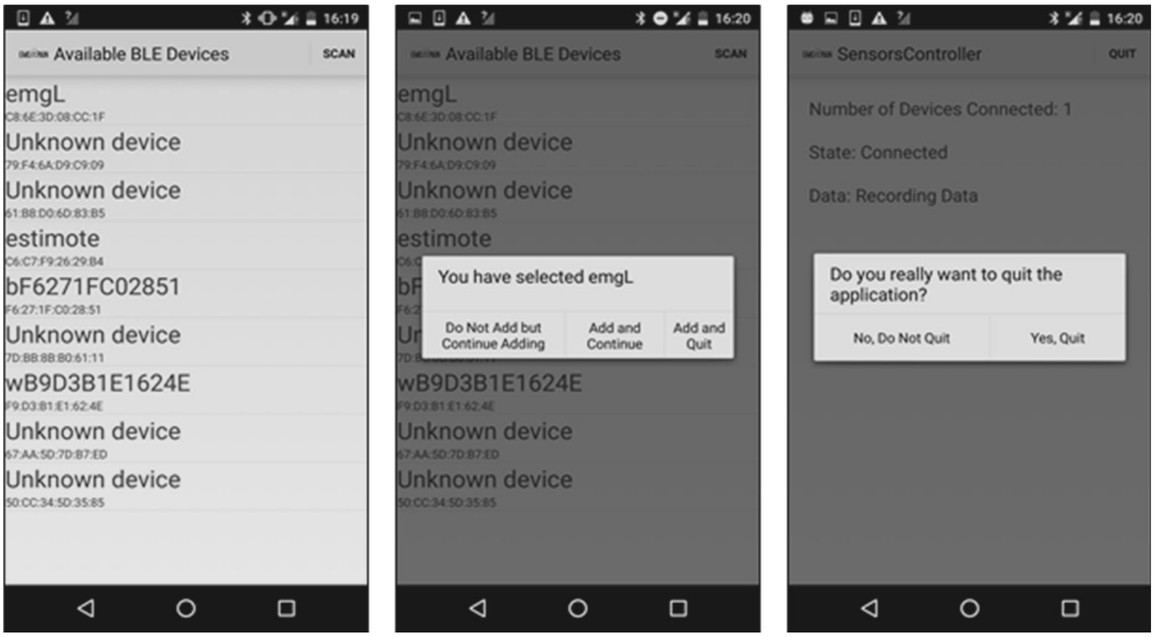


Fig. 7.2. MOVES-PC mobile application screenshots: Left - the list of BLE devices available during a scan; Middle - dialog in connecting to one of the sensing units of the prototype; Right - dialog in terminating a recording session

of the prototype were assessed as, unlike IMU sensors, there has been less understanding of the efficacy of low-cost sEMG sensors and so it was necessary to evaluate their movement capture functionality. Both the sEMG and IMU units of the prototype were together assessed in the second study to understand their efficacy for capture of bodily expression and concomitant muscle activity. The validation activities, sensor placements, participants, and validation tests are described in this section; the results are reported in the next section.

7.1.2.1 Physical Activity

In the two validation studies carried out, the same movement types (Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand) considered in the investigation reported in Chapter 6 were focused on. In the validation studies, the movements were performed in arbitrary order with Sit-to-Stand always performed first followed by Forward Trunk Flexion.

In the Sit-to-Stand activity, each participant was instructed to: sit still for 10 seconds, stand up, and keep standing for 10 seconds. This sequence was repeated once following a stand-to-sit. In the Forward Trunk Flexion, each participant was instructed to: stand for 10 seconds, reach as far forward with the arms as possible, maintain the peak pose for 10 seconds, and then return to standing. The sequence was also repeated once followed by standing for 10 seconds. The Full Trunk Flexion activity was similar to the Forward Trunk Flexion except that the participants were instructed to reach downwards as close to the toes as possible with the arms rather than forwards. Precise timing was not required for the maintenance of the apex poses and so, the timing was done by the participant counting from 1 to 10 out loud or inwards. This timing method was used instead of a clock as it had the advantage of enabling the participants to keep track of the phase of the activity that they were in and so enabled smooth flow between the phases. Instructions were given at the start of each movement type verbally and with demonstrations, and visual aids were placed within the sight of the participant during the movement.

7.1.2.2 Placement of Sensing Units

For the two validation studies, the sensing units used were placed based on the muscle groups and anatomical segments found interesting for the automatic detection of levels of pain, self-efficacy, and emotional distress from body movement in Chapter 6. Two sEMG units were used for both studies with each unit attached to the right trapezius and the right lumbar paraspinal. For both muscle groups, the reference electrodes were placed as recommended by the manufacturer on a bony (i.e. electrically neutral) surface: it was placed on the C7 spinous

Fig. 7.3. Participant P1-2 in Validation Study 2 with 2 sEMG units attached to the lumbar paraspinal and trapezius (with the sensor units held in a waist belt and an arm pouch respectively) and 4 IMU sensors placed on the: head using a visor, trunk using the waist belt, and thigh and shank using a knee sleeve (in yellow)

process for the trapezius and on the lumbar spine for the lumbar paraspinal. In the second study where IMU units were also assessed, IMU units were placed anterior to the head, trunk, thigh, and shank (see Fig. 7.3).

7.1.2.3 Participants

Nine healthy participants were used in the first validation study while three participants were used in the second study.

7.1.2.4 Validation Tests

For the first study, the prototype was validated against a standard sEMG system (the commercial BTS FreeEMG 300) and physical activity ground truth. To enable this, each participant performed each of movement types in two series: the BTS FreeEMG 300 was used in the first series placed as described above (without placement of reference electrodes as these sensors did not have them) and the MOVES-PC was used in the second series at the same electrode positions. Validation analysis was based on visual inspection and traditional statistical tests. In visual inspection, plots of the sEMG data were compared between the BTS FreeEMG 300 sensors and the prototype within each movement type and across the nine participants. The statistical tests further quantitatively evaluated if the prototype enabled differentiation between muscle tension and relaxation. These analyses were found to suffice in providing evidence of the efficacy of the sEMG sensing units of the prototype and so these were the only analyses done in this study.

In the second validation study, the IMU and sEMG sensing units of the prototype were validated against physical activity ground truth and validation analysis was based on visual inspection where plots of the sEMG and IMU data were analysed to assess how concomitant they were and how well they characterised the movements performed. As the trunk flexion-extension data was the easiest to interpret, the analysis reported focuses on the data from the IMU units placed on the trunk.

7.1.3 Results of the Prototype Validation

The results of the validation analysis are presented here. The sEMG data for participants P1 and P7 of the first validation study were not included in the analysis as loss of contact between the sEMG electrodes and the skin led to the capture of noise alone for them.

7.1.3.1 sEMG Units Only in Sit-to-Stand: Visual Inspection

Fig. 7.4-Top shows the raw sEMG signal measured at the lumbar paraspinal of a participant during the Sit-to-Stand activity using the MOVES-PC prototype. The profile shows increasing

muscle activity followed by a decrease in the lumbar paraspinal (accompanying trunk flexion-extension) during both sit-to-stand (STSt) and stand-to-sit (StTS). During sitting and standing, muscle activity remains at baseline. This pattern was the same for the other participants regardless of the sensing system used as can be seen in Fig. 7.5. The pattern for the trapezius in the same activity is similar (see Fig. 7.4-Bottom) except that the maximum amplitude at the apex poses is lower in the trapezius.

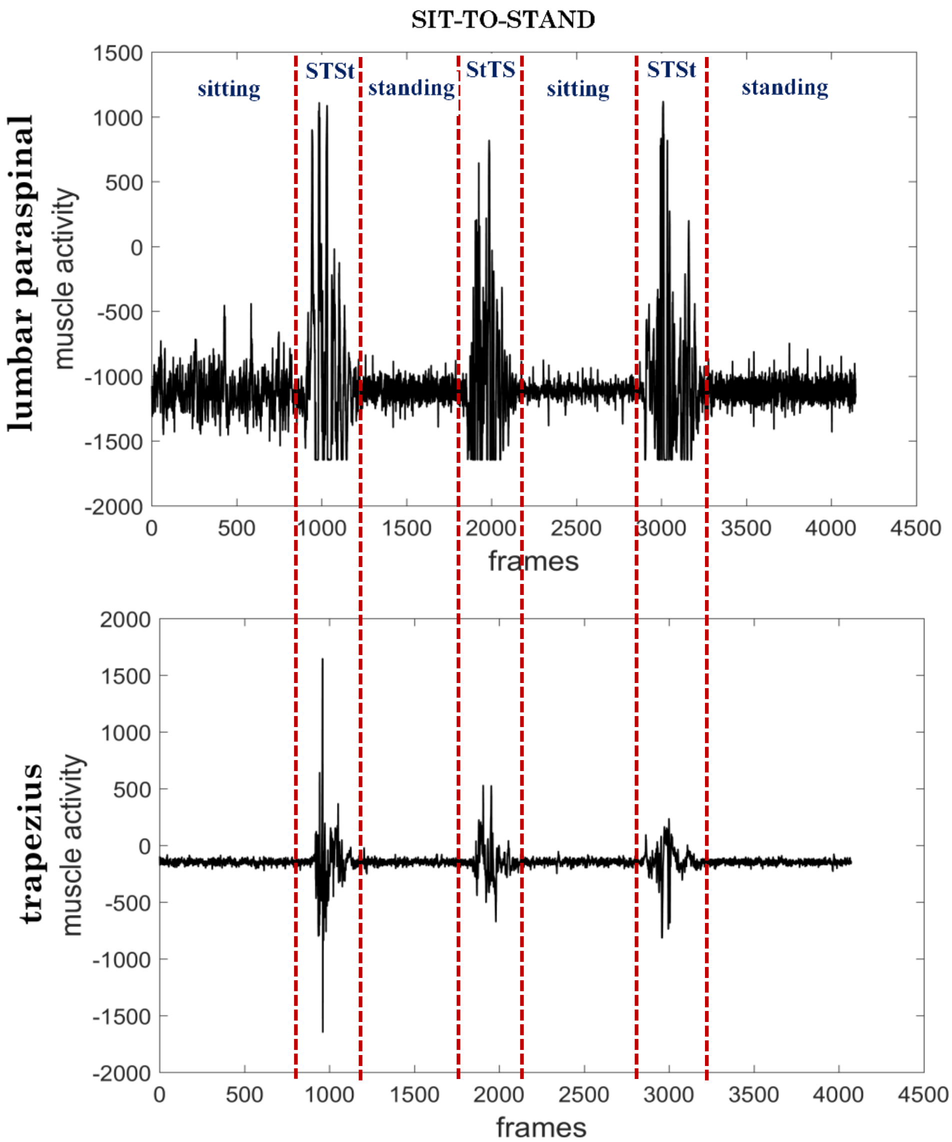


Fig. 7.4. Activity of the lumbar paraspinal (Top) and trapezius (Bottom) of participant P4 captured using the MOVES-PC. *STSt = sit-to-stand, StTS = stand-to-sit*

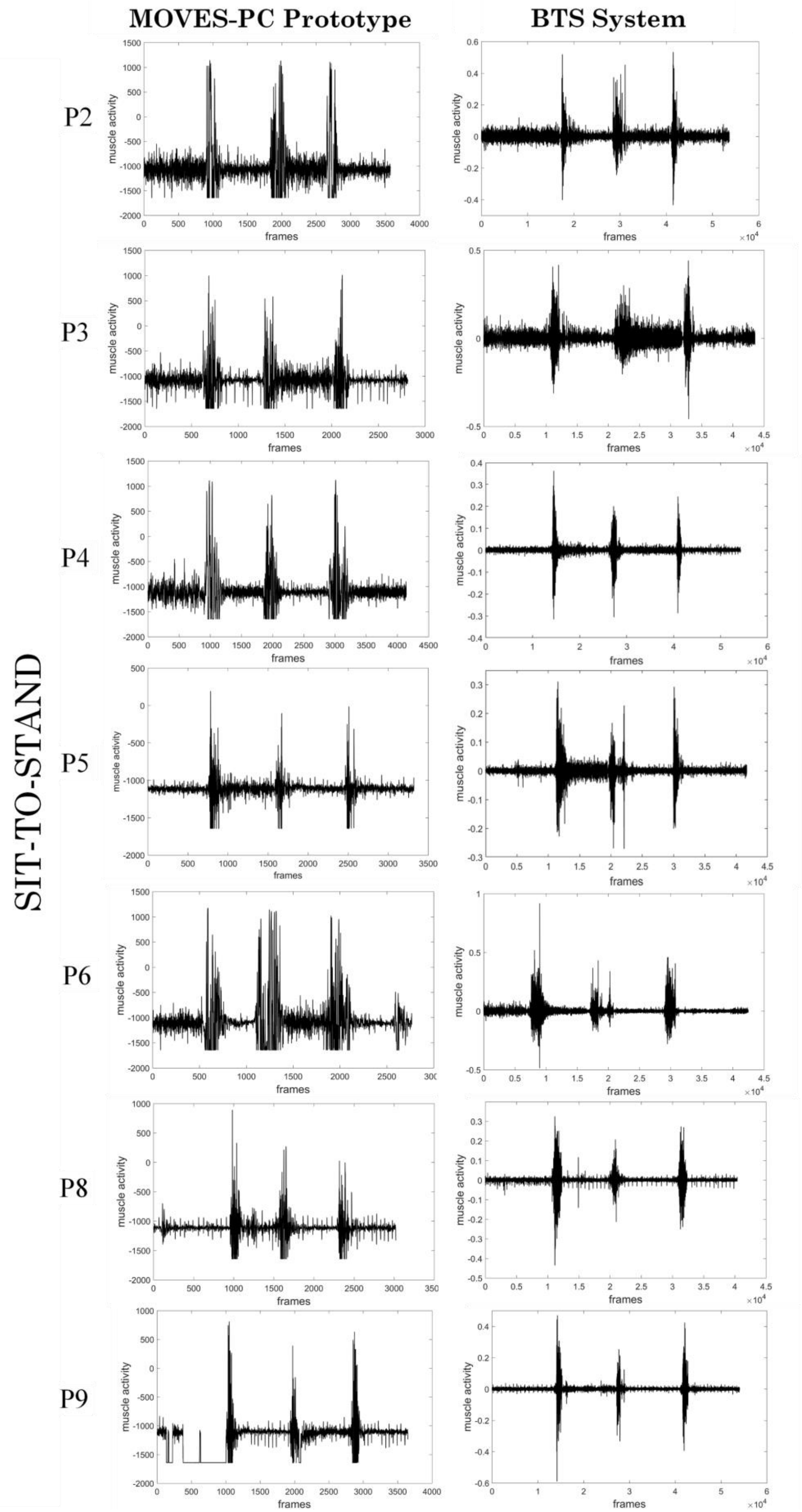


Fig. 7.5. Activity of the lumbar paraspinal of each of 7 participants captured using the low-cost MOVES-PC prototype (Left) and the expensive BTS system (Right)

7.1.3.2 sEMG Units Only in Forward Trunk Flexion: Visual Inspection

A sample of the raw lumbar paraspinal activation profiles captured during the Forward Trunk Flexion activity using the prototype can be seen in Fig. 7.6-top. Similar to the Sit-to-Stand activity, muscle activity remained at baseline while standing and it increased with trunk flexion, and then decreased with re-extension. This is the same pattern for all the participants for both the prototype and the BTS system (see Fig. 7.7). For majority of the participants, high level activity was maintained in the lumbar paraspinal for the length of maximal flexion. There were two deviations, participants P4 and P6, where there was muscle silence during this period. This is the flexion relaxation phenomenon, discussed in Chapter 6, which occurs at large trunk flexion angles (Watson et al. 1997). The exact flexion angle where it starts varies between individuals; however, at this angle, the flexion work is transferred to the pelvic muscles and the back muscles are no more involved. The phenomenon is more common in full trunk flexion where large trunk flexion angles are typically reached. For all the participants, the same pattern was captured by both the prototype and the BTS system. The pattern for the trapezius was similar to the pattern for the lumbar paraspinal as can be seen in Fig. 7.6-bottom.

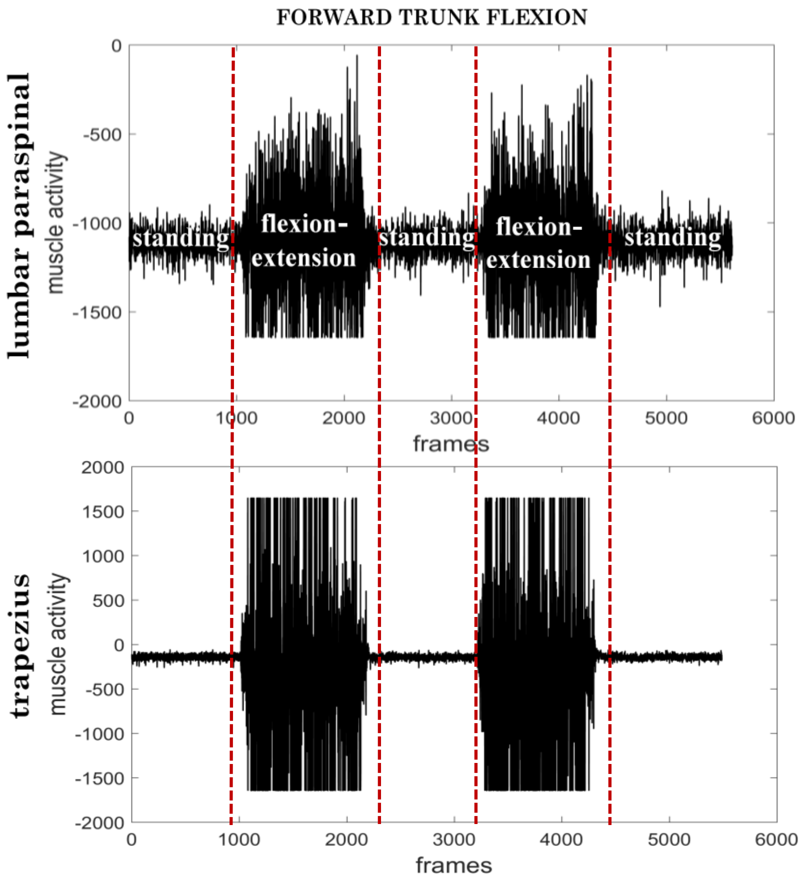


Fig. 7.6. Activity of the lumbar paraspinal (Top) and trapezius (Bottom) of participant P5 captured using the MOVES-PC

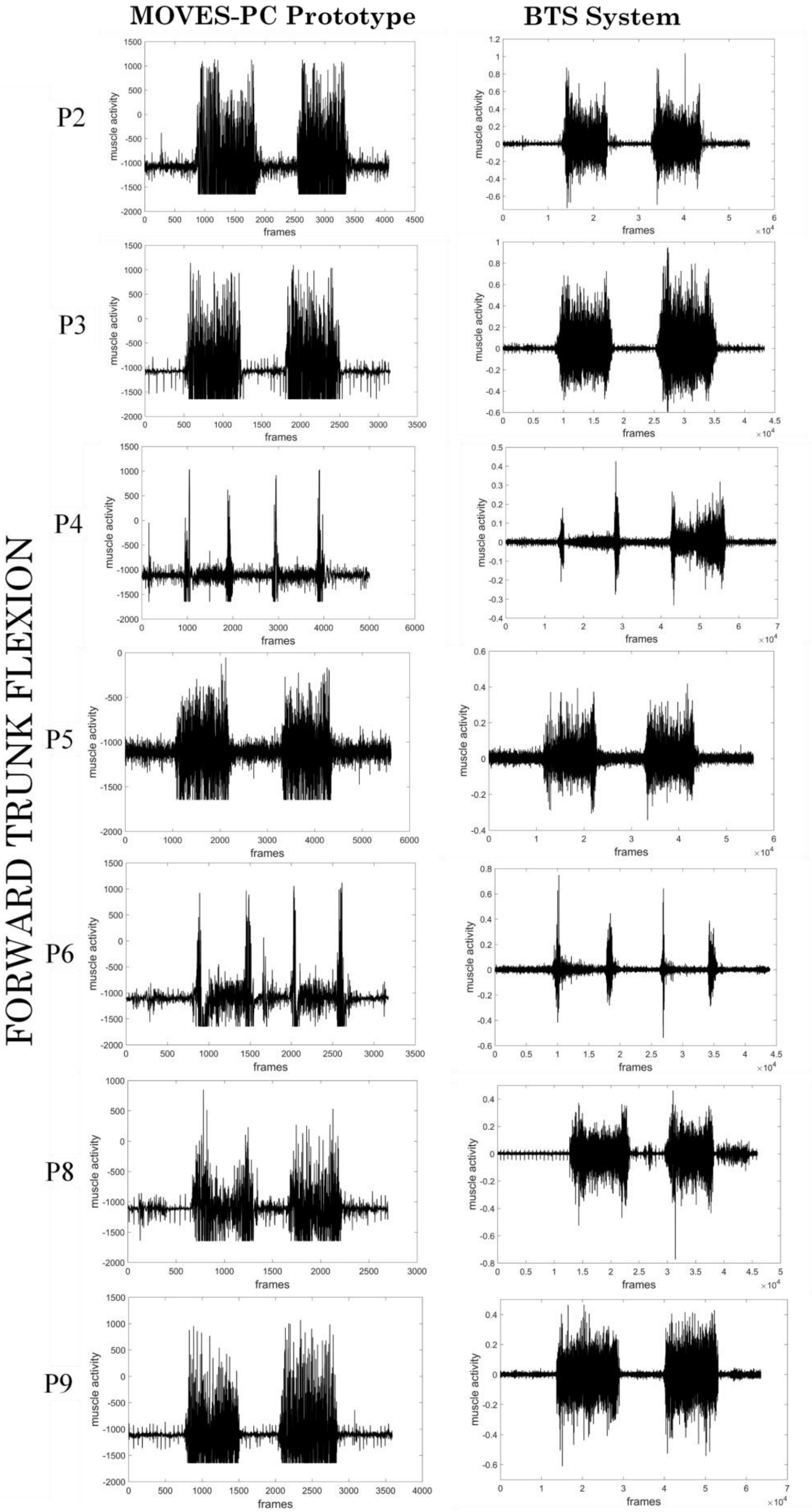


Fig. 7.7. Activity of the lumbar paraspinal of each of 7 participants captured using the low-cost MOVES-PC prototype (Left) and the expensive BTS system (Right)

7.1.3.3 sEMG Units Only in Full Trunk Flexion: Visual Inspection

Fig. 7.8-Top shows the lumbar paraspinal muscle activity pattern of a participant during Full Trunk Flexion measured using the prototype. As expected, there was activity increase with flexion followed by a decrease in activity until muscle silence at maximal flexion due to the flexion relaxation phenomenon; activity re-increased at the beginning of extension followed by a decrease as extension is completed. As shown in Fig. 7.9, this pattern was the same using the BTS system. A similar but less marked pattern was found with the trapezius (see in Fig. 7.8-Bottom).

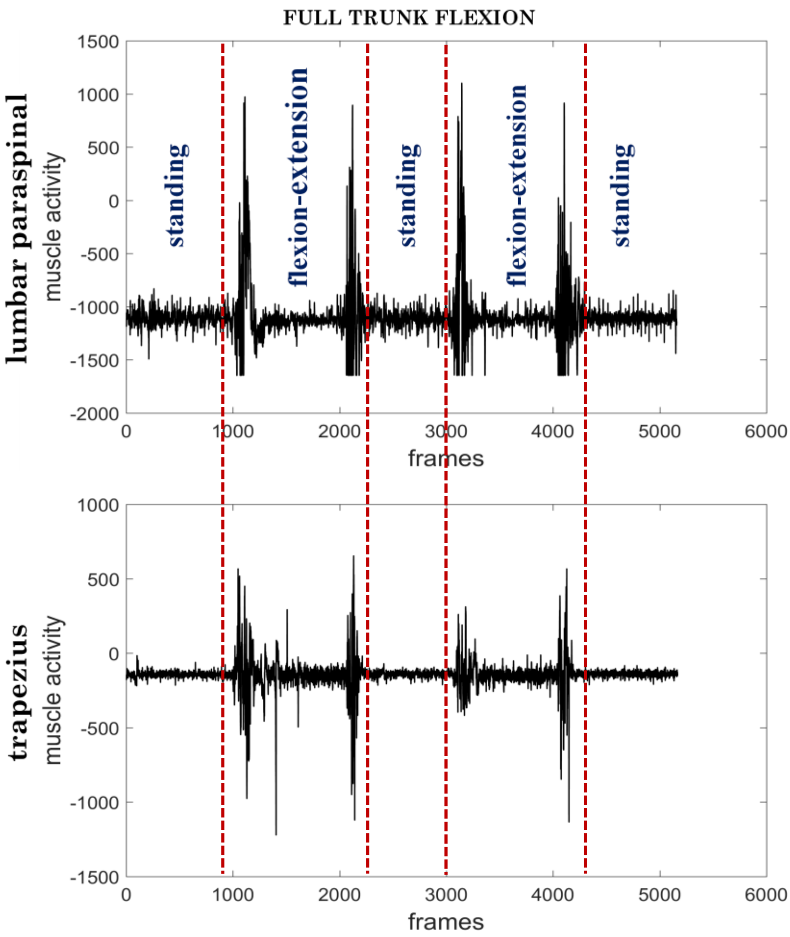


Fig. 7.8. Activity of the lumbar paraspinal (Top) and trapezius (Bottom) of participant P4 captured using the MOVES-PC

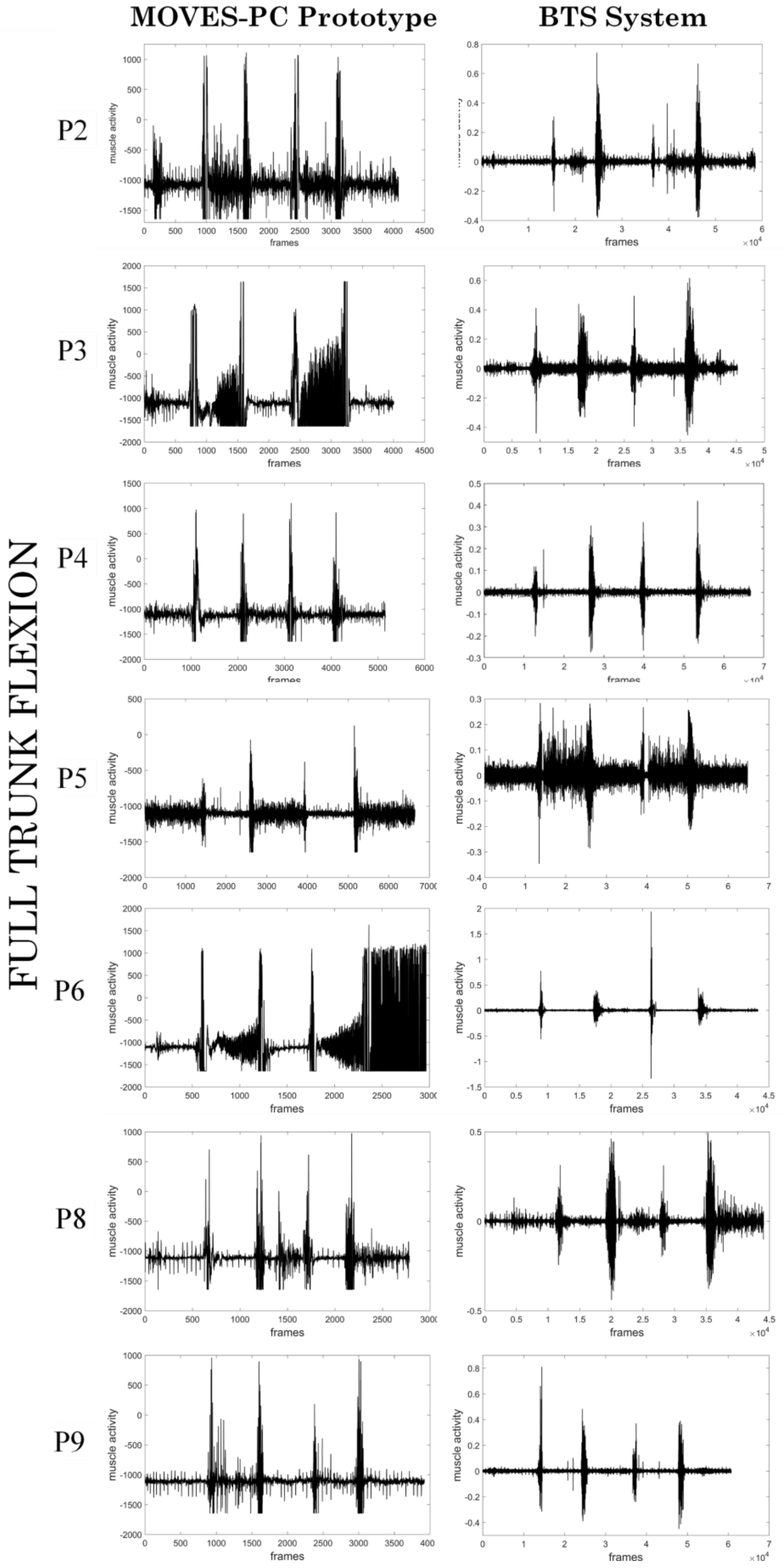


Fig. 7.9. Activity of the lumbar paraspinal of each of 7 participants captured using the low-cost MOVES-PC prototype (Left) and the expensive BTS system (Right)

TABLE 7.1 WILCOXON SIGNED RANK TEST OF DIFFERENCE BETWEEN MUSCLE RELAXATION AND TENSION (FOR BOTH THE MOVES-PC AND THE BTS SYSTEM)

		MEDIAN MUSCLE ACTIVITY	
		MOVES-PC Prototype (mV)	BTS System (V)
		baseline, average maximal	baseline, average maximal
lumbar paraspinal	Sit-to-Stand	-1113.4, 1014.67[a]	0.00004494, 0.358[b]
	Forward Trunk Flexion	-1097.51, 1032.5[a]	0.00003955, 0.4454[b]
	Full Trunk Flexion	-1109.05, 1063[a]	0.00008281, 0.5259[b]
trapezius	Sit-to-Stand	-146.45, 803[b]	-0.00002749, 0.1331[c]
	Forward Trunk Flexion	-147.17, 1646[b]	0.000193, 0.64805[c]
	Full Trunk Flexion	-141.71, 610.5[b]	-0.000010985, 0.088428[c]

[a]z=-2.366, r=0.89, p<.05; [b]z=-2.66, r=0.89, p<.01; [c]z=-2.51, r=0.89, p<.05

7.1.3.4 sEMG Units Only: Statistical Analysis

A Wilcoxon Signed Rank test was done to further test if there was significant difference between baseline muscle activity and maximal activation measured by the prototype (comparing with the BTS FreeEMG 300). Maximal activation was computed for each movement type as the mean of the maximum amplitudes during each flexion-extension in the movement type while baseline was taken to be the mean activation for the first 500 frames in the corresponding muscle activity profile.

Table 7.1 shows the results of the test for the prototype and the BTS FreeEMG 300 system for each of the lumbar paraspinal and trapezius. For the prototype, significant difference was found for both the lumbar paraspinal (z=-2.366, p<.05; with large effect size r=0.89) and the trapezius (z=-2.66, p<.01; with large effect size r=0.89) for the three movement types. This suggests that the prototype allows reliable differentiation of muscle tension from relaxation. This finding was the same for the BTS FreeEMG 300 where there was significant difference for both the lumbar paraspinal (z=-2.66, p<.01; with large effect size r=0.89) and the trapezius (z=-2.51, p<.05; with large effect size r=0.89) for the three movement types.

TABLE 7.2 WILCOXON SIGNED RANK TEST OF DIFFERENCE BETWEEN MUSCLE ACTIVITY CAPTURED FROM THE LUMBAR PARASPINAL AND THE TRAPEZIUS (FOR BOTH THE MOVES-PC AND THE BTS SYSTEM)

	MEDIAN NORMALIZED AVERAGE MAXIMAL ACTIVATION	
	MOVES-PC Prototype (mV)	BTS System (V)
	lumbar paraspinal, trapezius	lumbar paraspinal, trapezius
Sit-to-Stand	2128.07, 950.03[a]	0.357606, 0.133127[b]
Forward Trunk Flexion	2150.6, 1789.35	0.4651, 0.6477
Full Trunk Flexion	2144, 752.74[a]	0.52619, 0.088488[b]

[a]z=-2.366, r=0.89, p<.05; [b]z=-2.66, r=0.89, p<.01

Further analysis was done to test if the difference between the maximal activation of the lumbar paraspinal and the trapezius for Sit-to-Stand and Full Trunk Flexion found on visual inspection (see Fig 7.4 and 7.8 respectively) was significant. This analysis was also done using a Wilcoxon Signed Rank test. Maximal activation was computed as done for the previous test; however, maximal activation was additionally normalised to baseline activity (by subtracting the baseline from the maximal activity) in this test.

Table 7.2 shows results of the test for both the prototype and the BTS FreeEMG 300. For the prototype, significant difference (z=-2.366, p<.05; with large effect size r=0.89) was found for Sit-to-Stand and Full Trunk Flexion. This suggests that higher tension is reached in the lumbar paraspinal than in the trapezius when performing sit-to-stand or full trunk flexion. The finding also provides evidence that the prototype not only enables differentiation between tension and relaxation but that it also allows differentiation between high and low tension. For the Forward Trunk Flexion activity, the difference between the maximal activation of the lumbar paraspinal and trapezius was lower and not significant. This may be because the arms play a more active role in forward trunk flexion than in either of sit-to-stand or full trunk flexion. These findings were the same for the BTS FreeEMG 300 with significant difference (z=-2.66, p<.01; with large effect size r=0.89) found for the Sit-to-Stand and Full Trunk Flexion alone.

7.1.3.5 Both sEMG and IMU Units

To assess how well the sEMG and IMU data concomitantly characterised the flexion-extension movements, the pitch dimension of the two-dimensional IMU data (pitch and yaw) measured at the trunk was plot together with corresponding sEMG data. Each sEMG signal was pre-processed by first normalising to baseline based on subtraction of the mean followed by full-wave rectification. The signal was then converted to volts, and smoothed using the Savitzky-Golay filter (Savitzky and Golay 1964).

Fig. 7.10 to 7.12 show the trunk flexion-extension profiles with corresponding activity of the trapezius captured by the prototype for each of the three participants of the second validation study respectively. Due to noisy data as a result of loss of contact between the sEMG sensor electrodes and the skin, the data for P1-2 in the Full Trunk Flexion activity and for P3-2 in the Sit-to-Stand were excluded from the visual analysis.

As expected, high levels of activity in the trapezius were found to correspond to trunk flexion or extension whereas baseline activity corresponded to resting periods, i.e. sitting (R1) and standing (R2). In addition, trunk flexion was found to be highest in full trunk flexion and lowest in sit-to-stand while maximal activation of the trapezius was highest in the forward trunk flexion and lowest in the sit-to-stand.

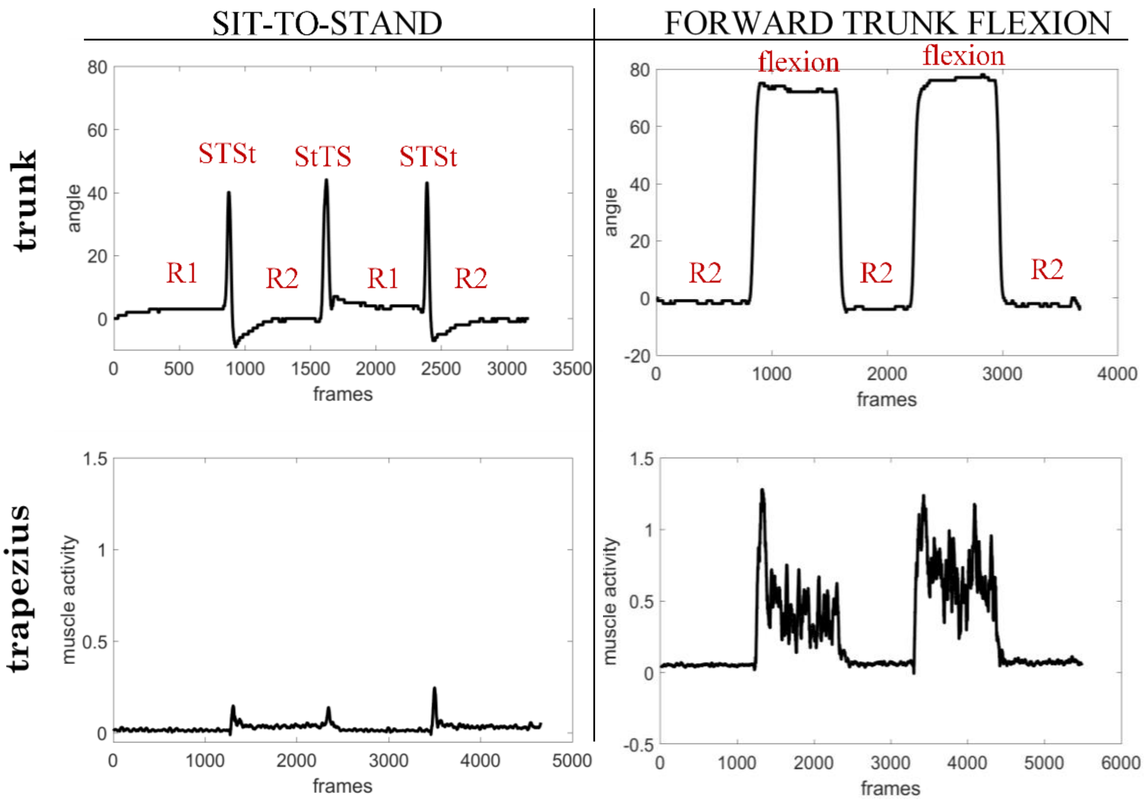


Fig. 7.10. Trunk flexion/extension (Top) and concomitant activity of the trapezius (Bottom) during the Sit-to-Stand (Left) and Forward Trunk Flexion (Right) for participant P1-2. *STSt = sit-to-stand; StTS = stand-to-sit; R1 = sitting; R2 = standing*

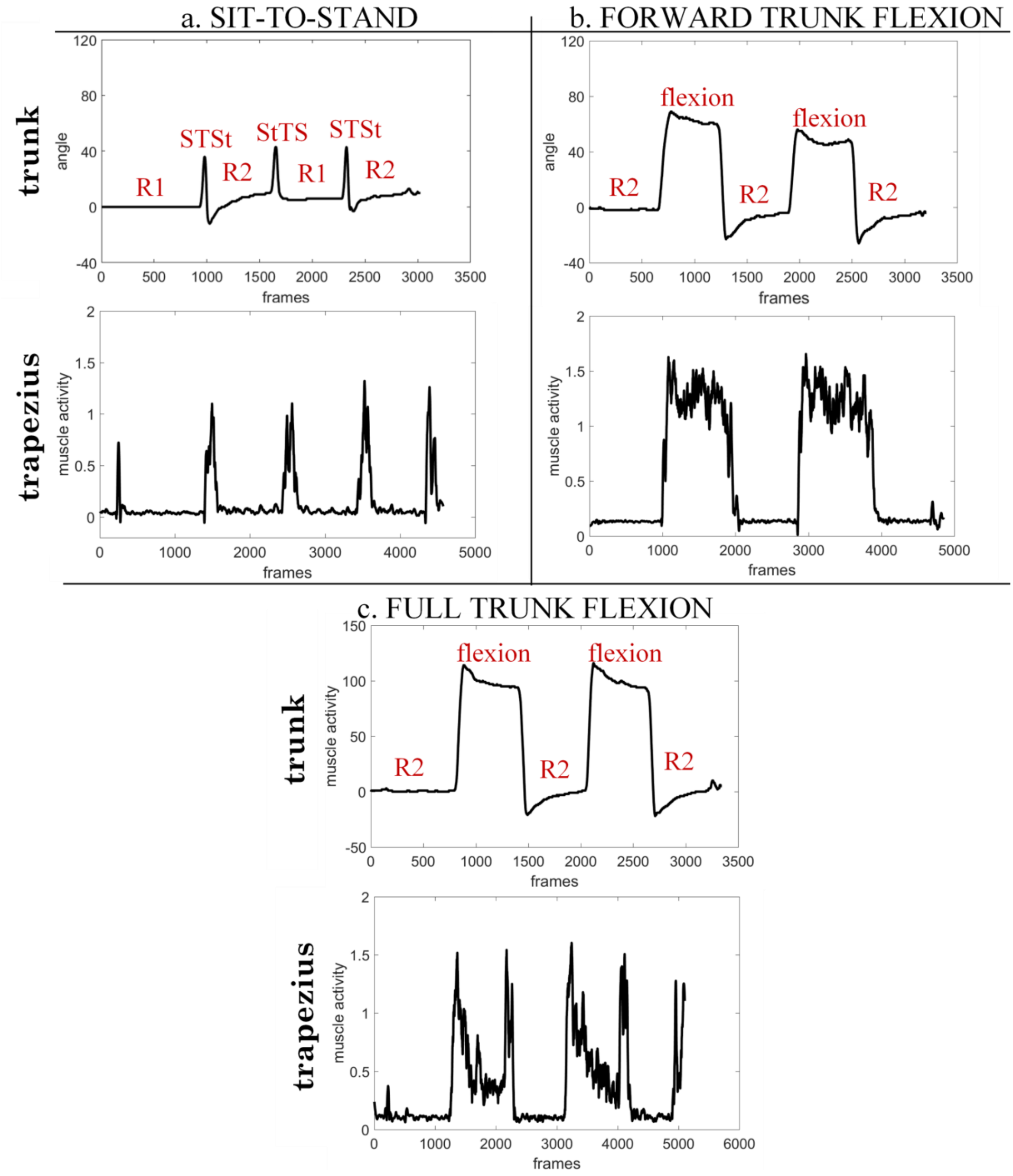


Fig. 7.11. Trunk flexion/extension (Top) and concomitant activity of the trapezius (Bottom) during (a) Sit-to-Stand, (b) Forward Trunk Flexion, and (c) Full Trunk Flexion for participant P2-2. *STSt = sit-to-stand; StTS = stand-to-sit; R1 = sitting; R2 = standing*

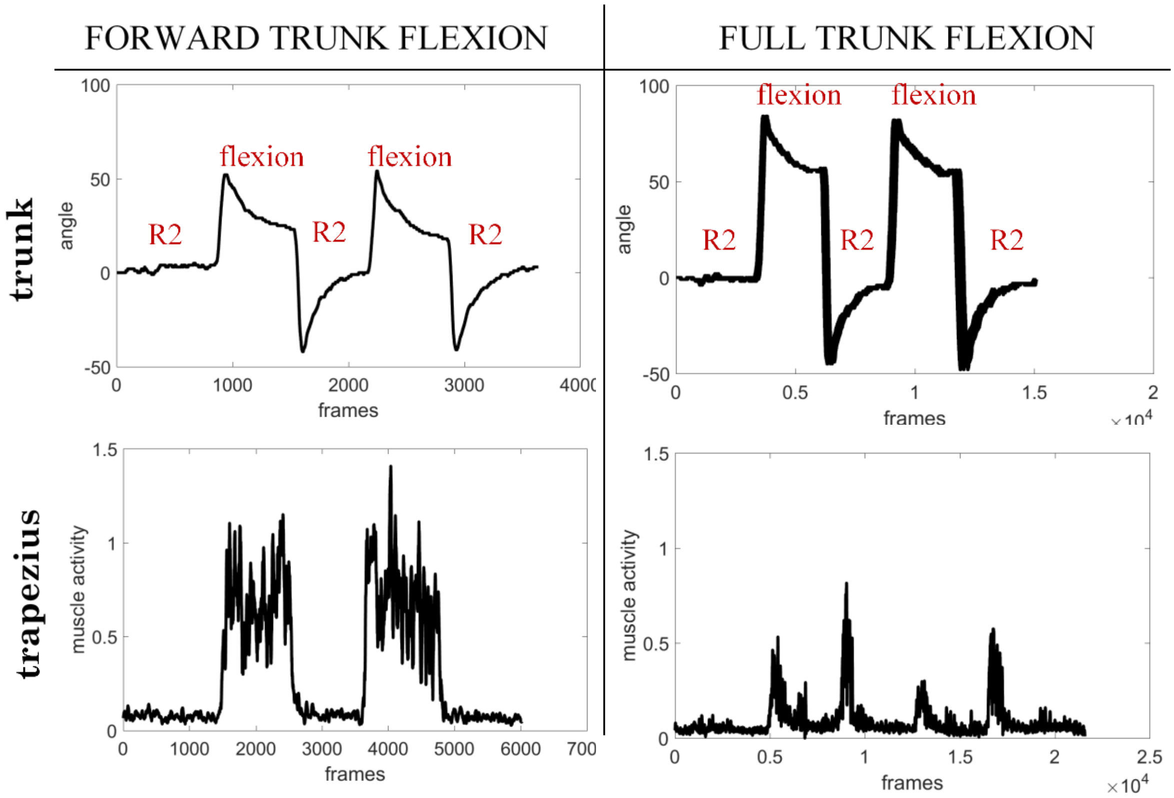


Fig. 7.12. Trunk flexion/extension (Top) and concomitant activity of the trapezius (Bottom) during Full (Left) and Forward Trunk Flexion (Right) for participant P3-2. *R2 = standing*

The overall finding of the two validation studies is that the MOVES-PC enables synchronised, low-cost capture of bodily orientation and concomitant muscle activity information. Although the sEMG sensing units of the prototype suffered signal saturation (e.g. see Fig. 7.6-Bottom), they were found to capture enough information to allow differentiation between muscle tension and relaxation with possibility of further differentiation between two levels of muscle tension. This capability was expected to be adequate for the differentiation between levels of pain and related states and so the prototype was used to acquire the Ubi-EmoPain dataset.

7.2 Data Collection

In this section, the collection of the Ubi-EmoPain dataset using the MOVES-PC is described.

7.2.1 Participants

The participants were 12 people with CP in the lower back. The majority of the participants were recruited through the British College of Osteopathic Medicine (a private institution) and the pain management centre of the National Hospital for Neurology and Neurosurgery (a

National Health Service hospital). A few other participants were recruited outside of these institutions.

The participants comprised 11 females and 1 male with ages ranging between 27 and 77 (median = 51.5). The median number of years of pain for the participants was roughly 28.5 years (interquartile range = 27). Only an estimate can be given as some of the participants were not able to report an exact number of years and only gave an estimate. A more detailed profile of the participants is included in Appendix IV.

For the participants recruited through the college, data collection was carried out in a consulting room provided within the osteopathy clinic of the college while data collection took place in rooms on University College London (UCL) campus for the other participants. The data were collected in controlled environment rather than the participants' homes so as not to put undue stress (e.g. feeling of obligation to prepare their homes for the researcher) on them given the early stage of the work. The next generation of the prototype will be tested in home settings to build on this proof-of-concept phase; however, this next phase is out of the scope of this thesis.

7.2.2 Sensor Placement

Four IMU and two sEMG sensing units were used similar to the second validation study with placements as shown in Fig. 7.13.

To facilitate attachment of the sensing units, customised accessories were designed by the researcher using a sewing machine and other craft resources available at UCL. Although the design of these accessories did not aim to be the final creation, it enabled understanding of the challenges of attaching movement sensor units beyond the typical bracelet designs suitable for the hands alone.

An adjustable visor was used to attach an IMU unit to the head and two IMU units were attached to the thigh and shank respectively using a nonslip knee sleeve fitted with pockets to place the units in. The fourth IMU unit was attached to the trunk using a back-support belt with pockets to hold the unit.

The electrodes of the two sEMG units were attached to the right lumbar paraspinal and trapezius muscles. To prevent dislodging of the electrodes in movement, the rest of the unit attached to the lumbar paraspinal was placed as close as possible to the electrode attachment:

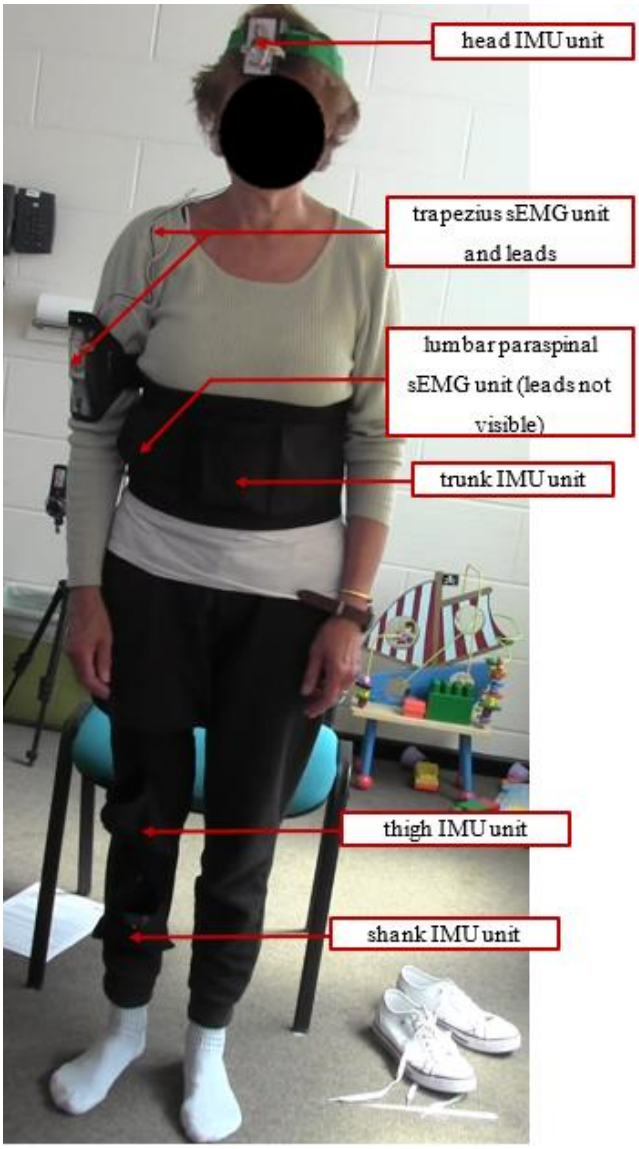
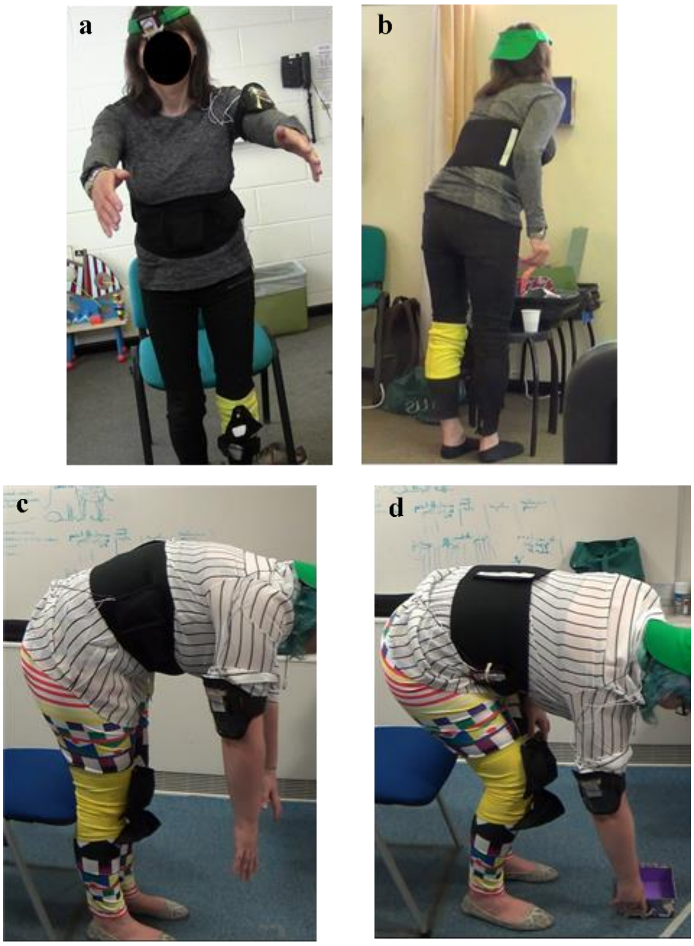


Fig. 7.13. The placement of 4 IMU units and 2 sEMG units of the prototype on participant P4-3 in the data collection study

in an additional pocket on the belt on the trunk. Likewise, the sEMG unit attached to the trapezius was placed in an armband worn on the upper arm.

7.2.3 Physical Activity

After being fitted with the sensing units, each participant performed three repetitions of Sit-to-Stand, Forward Trunk Flexion (i.e. reaching as far forward as possible from standing), and Full Trunk Flexion (i.e. typical movement done to pick an object from the floor) similar to the EmoPain dataset (see Fig. 7.14 a and c). However, here, the exercise movements were randomly interspersed with one repetition of functional forward trunk flexion and functional full trunk flexion. This was done to prevent monotonicity or lack of inter-subject variation due



7.14. **a** and **b**: Ubi-EmoPain participant P2-3 during exercise (in **a**) and during functional (in **b**) forward trunk flexion. **c** and **d**: Ubi-EmoPain participant P6-3 during exercise (in **c**) and during functional (in **d**) full trunk flexion

to repetitiveness when movements of the same type are performed in immediate succession. Thus, other movement types and brief rest breaks occurred between successive performances of the same movement type.

Because of restrictions on possible adaptivity of the locations where the data were collected, everyday functional activities were simulated using furniture and objects available in the rooms. For the functional forward trunk flexion, the participant was asked to pick up a cardboard box affixed to the wall in front of him/her using pressure sensitive adhesive; a barrier was placed between the participant and the wall so that s/he needed to reach forward to complete the task (see Fig. 7.14b). This aimed to reproduce functional forward reaching movement typically used to manipulate an object that is just within reach (e.g. a distant stem in a rose bush while gardening, a cup in a kitchen cupboard, a book on a shelf, a vacuum cleaner) and requires slightly off-balance positioning to get to. In the functional full trunk flexion, the participant was asked to pick a cardboard box from the floor (see Fig. 7.14d) to evoke movement similar to when s/he attempts to manipulate an object on the floor (e.g. shopping bags, a fallen item, shoes).

While the exercise movements simulated routine forward trunk flexion in everyday functioning, the functional movements (taking an object from a wall and picking an object up from the floor) enabled investigation of ‘near-wild’ physical activity settings which is a step closer to everyday scenario. The inclusion of the functional movements in the new dataset is important because, as found in Singh, Bianchi-Berthouze, and Williams (2017), controlled exercise settings do not fully reflect the challenges that people with CP face in everyday functioning. In fact, in Singh et al. (2016), participants reported being more anxious and less confident when performing forward trunk flexion functionally compared to when they performed it in exercise.

It is due to the finding that only one instance of functional movement was requested per movement type in the collection of the Ubi-EmoPain dataset to limit the stress on participants. This is a typical problem when building datasets in delicate circumstances where data collection is limited due to concern about possible stress on the participants and it further points to the need for low-cost body movement sensing systems that allow opportunistic capture of body movement data in everyday settings. The MOVES-PC prototype is a starting point that can inform the development of such systems.

125 movement instances were captured: 46, 45, and 34 were instances of Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively with 26.1%, 22.2%, and 2.9% as functional instances of these movement types respectively. For the instances, sEMG data was recorded at about 65 hertz while IMU data (pitch and yaw) was recorded at approximately 45 hertz. Video was also recorded from three different views: anterior, posterior, and lateral (as can be seen in Fig. 7.14 a, b, and c respectively).

7.2.4 Pain and Related Labels

Similar to the labelling procedure used for the EmoPain dataset, pain related emotional distress was measured using the HADS-13 which participants completed before performing the activities. In addition, for each movement instance, each participant was asked to rate his/her level of confidence of the ability to perform the movement on a scale of 0 to 10 of increasing magnitude before performing the movement as a measure of self-efficacy for the movement. Measure of self-efficacy level before performance is the standard method of efficacy self-report

(Gunter et al. 2003; Treasure, Monson, and Lox 1996) as it is more reliable than post-performance self-report (which is based on reflection) because efficacy is a prediction. The participant was also asked to rate his/her level of pain on a scale of 0 to 10 after completing the movement.

Median HADS-13 score was 12 with standard deviation of 5.6. Only one participant was found to be emotionally distressed (i.e. with HADS-13 > 19). Median pain intensity was 2.5 with standard deviation of 3.3 and there were 36.8% of the movement instances for which higher level pain was reported (i.e. pain intensity >=5). Median MRSE level was 9 with standard deviation of 2.6; lower level MRSE (i.e. MRSE level <=5) was reported for 29.2% of the movement instances.

As with the investigation in Chapter 6, two levels of pain in these participants with CP were considered for automatic detection; pain instances with intensity less than 5 were labelled as lower level pain instances and the other instances were labelled as higher level pain instances. Similarly, two levels of MRSE were considered with MRSE levels greater than 5 labelled as higher level MRSE and others as lower level MRSE. Due to the underrepresentation of the emotionally distressed group in the dataset, analysis for emotional distress was not further done in this investigation.

7.3 Data Analysis Methods

To investigate the feasibility of automatic detection during both functional and exercise movements based on body movement features captured using a minimal set of low-cost wearable sensors, machine learning algorithms were used to explore classification of levels of pain and MRSE based on the sEMG and IMU data of the Ubi-EmoPain dataset. First, the sEMG and IMU data were pre-processed and the body movement features discovered in the investigation reported in Chapter 6 were extracted from them. Due to missing data as a result of technical malfunction (BLE disconnection and interference) or inadequate sizes of the attachment accessories, data imputation was explored for the recovery of missing feature values before modelling. The methods used for pre-processing, feature extraction, data imputation, and modelling are described in this section.

7.3.1 Pre-Processing of Raw sEMG and IMU Data

Each sEMG was pre-processed by first normalising to zero mean and then performing full-wave rectification on the resulting signal; the rectified signal was then smoothed, i.e.

$$e' = f\left(\left\{\left|e_t - \hat{e}\right|, \quad \forall t\right\}\right)$$

where

$$\hat{e} = \frac{\sum_{t=1}^{T} e_t}{T}$$

f is a Savitzky-Golay filter applied over the signal, and $t = 1, 2, ..., T$ the length of the signal in frames. The signal was then converted from millivolts to Volts. Fig. 7.15, for example, shows transformation of the sEMG signal captured at the trapezius of participant P3-3 during Full Trunk Flexion exercise performance. Finally, all pre-processed sEMG signals were resampled to exactly 65 hertz before feature extraction. The IMU data were also resampled to exactly 45 hertz before feature extraction.

7.3.2 Feature Extraction

The features extracted from the pre-processed IMU and sEMG data of the Ubi-EmoPain dataset are based on the features used in the studies in Chapter 6 (based on the full-body EmoPain dataset) where these features were shown to result in good detection performances. However, their computation had to be adapted to the different sensor network used in collecting the Ubi-EmoPain dataset. A summary of the features extracted in this case is given in Table 7.3. The features and their extraction are described in this section.

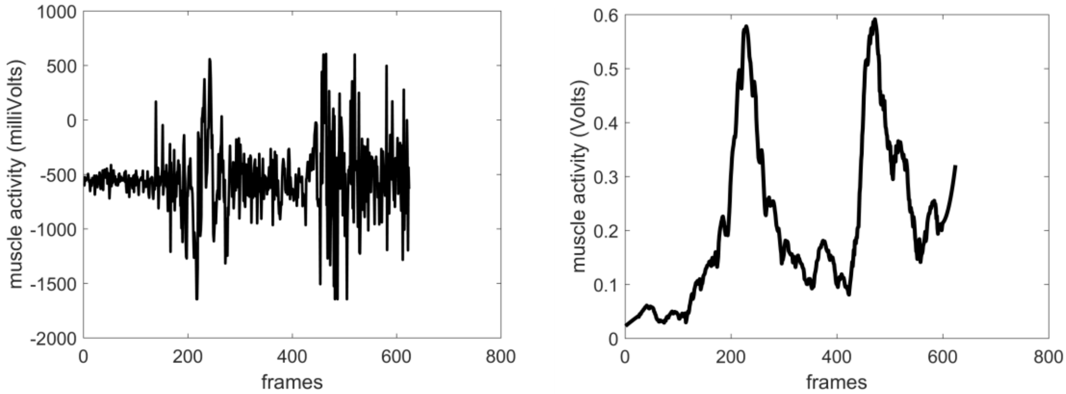


Fig. 7.15. Raw activity (Left) of the trapezius for Ubi-EmoPain participant P3-3, in (Right), the signal has been normalised to zero mean, full-wave rectified, and converted to Volts

TABLE 7.3 FEATURES FOR PAIN AND MRSE LEVEL CLASSIFICATION

	Pain Features	MRSE Features
1	range of trunk flexion	range of trunk flexion
2	range of trunk flexion with compensation for knee bend	range of head flexion
3	range of head flexion	range of thigh flexion
4	lumbar paraspinal activity change point time	range of shank flexion
5	lumbar paraspinal activity change point amount	range of lateral trunk rotation
6	trapezius paraspinal activity change point time	range of lateral head rotation
7	trapezius paraspinal activity change point amount	range of lateral thigh rotation
8	lift speed (for sit-to-stand)	range of lateral shank rotation
9	range of trunk flexion before lift (for sit-to-stand)	trunk speed
10	range of knee flexion post lift (for sit-to-stand)	head speed
11	head extension (for sit-to-stand)	thigh speed
12		shank speed
13		trunk fluidity
14		head fluidity
15		thigh fluidity
16		shank fluidity

7.3.2.1 Pain Level Features

For Full and Forward Trunk Flexion movements, which are similar types of movement in that they both require trunk flexion and movement of the arms, the range of trunk flexion, the range of head movement, and muscle activity change point features were extracted. Since, there was no arm orientation information in the Ubi-EmoPain dataset (due to limitation imposed by BLE interference as is discussed in Section 7.5), the features of arm steadiness used in the investigation in Chapter 6 could not be used here. The range of head and trunk flexion and time of muscle activity change point for the lumbar paraspinal and trapezius were also extracted for Sit-to-Stand. Lift speed, range of trunk before lift, and range of knee flexion post lift were additionally extracted for this movement type. Differently from the feature investigation reported in Chapter 6, the amount of head extension at lift was additionally extracted as new video analysis with physiotherapists showed that this is a cue they use in assessing performance of sit-to-stand. The physiotherapists explained that a strategy used by people with CP to achieve lift in sit-to-stand is to use the head to push up.

Range of Trunk Flexion: Two range of trunk flexion features were computed. For one of them, similar to the method reported in Chapter 6 where knee bends needed to be compensated for in the extraction of this feature because the computation of the trunk angle (from the EmoPain dataset) was dependent on the knee position relative to the hip, compensation for knee bend was done. For the second, no compensation was done as, with the Ubi-EmoPain dataset, trunk orientation information is available independent of the knee information. This range of trunk flexion was computed as:

$$\hat{\theta}^{x}_{trunk} = \max(\theta^{x}_{trunk}) - \min(\theta^{x}_{trunk})$$

where $\theta^{x}_{trunk} = \left\{\theta^{x}_{trunk\ t}, \quad \forall t : t = 1, 2, \ldots, T\right\}$ and $\theta^{x}_{trunk\ t}$ is the pitch orientation (i.e. orientation along the anterior-posterior axis) of the trunk at time t, $1 \leq t \leq T$, $t \in Z$, where T is the number of frames of the movement instance. The knee-corrected range of trunk flexion was computed as:

$$\hat{\theta}^{x}_{trunk-corr} = \max(\theta^{x}_{trunk-corr}) - \min(\theta^{x}_{trunk-corr})$$

where $$\theta^{x}_{trunk-corr} = \begin{cases} \theta^{x}_{trunk\ t} + \left(\theta^{x}_{knee\ t} - \theta^{x}_{knee\ 1}\right) & if \left(\theta^{x}_{knee\ t} - \theta^{x}_{knee\ 1}\right) < 0 \\ \theta^{x}_{trunk\ t} & otherwise \end{cases} \qquad \forall t : t = 1, 2, \ldots, T$$

Range of Neck Flexion: This was computed as:

$$\hat{\theta}^{x}_{head} = \max(\theta^{x}_{head}) - \min(\theta^{x}_{head})$$

where $\theta^{x}_{head} = \left\{\theta^{x}_{head\ t}, \quad \forall t : t = 1, 2, \ldots, T\right\}$ and $\theta^{x}_{head_t}$ is the pitch orientation (i.e. orientation along the anterior-posterior axis) of the head at time t.

Muscle Activity Change Point Time and Amount: The time of muscle activity change $\hat{t}_e$ and the amount of change $\hat{e}$ that occurs at the time, normalised to the duration of the signal and the amplitude range of the signal respectively, were also extracted, based on the same method used in Chapter 6:

$$\hat{t}_e = \frac{\arg\max\limits_{t}\left(\left\{\frac{\sum\limits_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum\limits_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w+\left(d+1\right)/2, \ldots, T-\left(w+\left(d+1\right)/2\right)\right\}\right)}{T}$$

$$\hat{e} = \frac{\max\left(\left\{\frac{\sum\limits_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum\limits_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w+\left(d+1\right)/2, \ldots, T-\left(w+\left(d+1\right)/2\right)\right\}\right)}{\max(m_q)}$$

where w=50 and d=21 are the sliding windows length and gap respectively.

Lift Speed: This was computed as the average speed from the start of ascension to the end of the sit-to-stand movement:

$$s = \frac{\sum\limits_{t=t'+1}^{T}\left(\theta_t - \theta_{t-1}\right)}{T-t'}$$

where $t' = \arg\min\limits_{t}(\theta^x_{trunk})$, $\theta^x_{thigh} = \left\{\theta^x_{thigh_t}, \quad \forall t : t = 1, 2, \ldots, T\right\}$, and $\theta^x_{thigh_t}$ is the pitch orientation (i.e. orientation along the anterior-posterior axis) of the thigh at time t.

Range of Trunk Flexion Before Lift: This was computed as:

$$\hat{\theta}^{x}_{trunk-prelift} = \max(\theta^{x}_{trunk-prelift}) - \min(\theta^{x}_{trunk-prelift})$$

where $\theta^{x}_{trunk-prelift} = \left\{ \theta^{x}_{trunk\ t}, \quad \forall t : t = 1, 2, \ldots, \arg\min_{t} (\theta^{x}_{trunk}) \right\}$.

Range of Knee Flexion Post Lift: This was computed as:

$$\hat{\theta}^{x}_{thigh-postlift} = \max(\theta^{x}_{thigh-postlift}) - \min(\theta^{x}_{thigh-postlift})$$

where $\theta^{x}_{thigh-postlift} = \left\{ \theta^{x}_{thigh_t}, \quad \forall t : t = \arg\min_{t} (\theta^{x}_{trunk}), \ldots, T \right\}$.

Head Extension At Lift: This feature was computed as

$$\hat{\theta}^{x}_{head-prelift} = \max(\theta^{x}_{head-prelift}) - \min(\theta^{x}_{head-prelift})$$

where $\theta^{x}_{head-prelift} = \left\{ \theta^{x}_{head-prelift_t}, \quad \forall t : t = 1, 2, \ldots, \arg\min_{t} (\theta^{x}_{trunk}) \right\}$.

7.3.2.2 MRSE Features

Here, the range of flexion, range of lateral rotation, speed, and fluidity of the head, trunk, thigh, and shank were extracted as features.

Range of Flexion: Here, this was computed as:

$$\hat{\theta}^{x} = \max(\theta^{x}) - \min(\theta^{x})$$

where $\theta^x = \theta^x_{head}, \quad \theta^x_{trunk}, \quad \theta^x_{thigh}, \quad and \quad \theta^x_{shank}$ for the head, trunk, thigh, and shank respectively.

Range of Lateral Rotation: This was computed as:

$$\hat{\theta}^y = \max(\theta^y) - \min(\theta^y)$$

where θ^y is the yaw orientation profile = $\theta^y_{head}, \quad \theta^y_{trunk}, \quad \theta^y_{thigh}, \quad and \quad \theta^y_{shank}$ for the head, trunk, thigh, and shank respectively.

Speed: This feature was computed as:

$$s = \frac{\sum_{t=2}^{T} \sqrt{\left(\theta^x_t - \theta^x_{t-1}\right)^2 + \left(\theta^y_t - \theta^y_{t-1}\right)^2}}{T - 1}$$

where $\theta^x = \theta^x_{head}, \quad \theta^x_{trunk}, \quad \theta^x_{thigh}, \quad and \quad \theta^x_{shank}$ and $\theta^y = \theta^y_{head}, \quad \theta^y_{trunk}, \quad \theta^y_{thigh}, \quad and \quad \theta^y_{shank}$ for the head, trunk, thigh, and shank respectively.

Fluidity: This was computed as the mean jerk (i.e. derivative of acceleration) of the smoothed orientation profiles:

$$f = \frac{\sum_{t=1}^{T-3} j_t}{T}$$

where $j = \sqrt{\left(\frac{d^3\theta^x_{smooth}}{dt^3}\right)^2 + \left(\frac{d^3\theta^y_{smooth}}{dt^3}\right)^2}$

θ^x_{smooth} and θ^y_{smooth} are the smoothed pitch and yaw orientation profiles respectively. Smoothing was done to reduce noise artefacts and it was done using the Savitzky-Golay filter (Savitzky and Golay 1964).

7.3.3 Modelling Methods

The features described in the previous section were used for two-level pain and MRSE classification.

As mentioned earlier, there was missing data in the Ubi-EmoPain dataset: 25.1%, 19.5%, and 24.7% for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Thus, there were missing feature values in the extracted feature set. Two standard approaches (Feelders 1999) for dealing with missing feature values were, therefore, explored for classification modelling:

- **Decision Tree with Surrogate Splits:** One approach was the use of a decision tree with surrogate splits (Breiman et al. 1984), described in Chapter 4, with the incomplete feature set for classification. Hyperparameters were set based on grid search. For pain level detection, the maximum number of splits was set to 7 for Full and Forward Trunk Flexion and 1 for Sit-to-Stand; for MRSE level detection, it was set to 7 for the three movement types.
- **Imputation:** In the second approach, imputation was used to recover missing feature values (Little and Rubin 2014). There are two types of imputation that can be done: single imputation where only one value is imputed for every missing value and multiple imputation where multiple values are imputed for every missing value. The multiple imputation method has the advantage of accounting for uncertainty in imputation by drawing multiple (i.e. M>1) plausible values from a distribution based on the observed values and averaging over these values. In this study, both single and M=5 multiple imputation methods were used. Expectation-maximization is the typical method used for imputation (Little and Rubin 2014); however, it could not be used in here as the Ubi-EmoPain dataset failed the requirement of normality. Regression was instead used for imputation. This was done in IBM SPSS Statistics 22. To build the regression model used for imputation, the order of performance of a movement instance within its movement type (and whether it was exercise or functional), the identification numbers of the participant, the level of reported pain, the HADS-13 score, and the self-report of MRSE were included with the feature vector as predictor variables. In the single imputation approach, three learning algorithms were used for classification: decision tree, RF, and polynomial SVM. Hyperparameter settings was based on grid search:

- For the decision trees: for pain level detection, the maximum number of splits was set to 11 for all three movement types for the imputed datasets; for MRSE level detection, it was set to 7 for the three movement types.
- For the RF: for pain level classification, 50, 100, and 50 trees were used for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively and the maximum number of splits was set to 1; for MRSE level classification, 50, 200, and 50 trees were used for the three movement types respectively and the maximum number of splits was set to 7.
- For the SVM: a linear kernel was used for the three movement types for both pain and MRSE level classification. The regularization parameter was set to 1 for Full and Forward Trunk Flexion in pain level classification and 0.1 for Sit-to-Stand for pain level classification and the three movement types for MRSE level classification.

These three algorithms were used on the single imputation datasets. Feature set optimisation was used to optimise classification performance with these datasets. An adaptation of the Branch and Bound algorithm (Narendra and Fukunaga 1977) (described in Chapter 4) was used for feature set optimisation. Similar to the investigations done in Chapter 6, evaluation for the single imputation datasets was based on leave-one-subject-out cross-validation for reasons discussed in Chapter 4.

With multiple imputation, each imputed set was used to build a decision tree and an ensemble of these trees was used to predict each set of test instances.

7.4 Results

The performances of the classification models for automatic detection of two levels of pain and MRSE using the methods described in the previous section are reported in this section.

7.4.1 Pain Level Classification

7.4.1.1 Non-Imputed Dataset

Classification performance based on the non-imputed dataset is shown in Table 7.4 for the three movement types. Performance for Sit-to-Stand (average F1 score of 0.75) was better than chance level classification (i.e. accuracy of 0.5). However, it was worse than chance level classification for Full and Forward Trunk Flexion with average F1 scores of 0.42 and 0.31 respectively. Table 7.5 shows the confusion matrices for each of these movement types.

TABLE 7.4 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH MISSING VALUES AND DECISION TREES

	FULL TRUNK FLEXION	FORWARD TRUNK FLEXION	SIT-TO-STAND
F1 lower	0.52	0.28	0.82
F1 higher	0.32	0.34	0.67
average F1	0.42	0.31	0.75
accuracy	0.43	0.31	0.76

TABLE 7.5 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH MISSING VALUES AND DECISION TREES

FULL TRUNK FLEXION

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**14**	13
	higher level pain	13	**6**

FORWARD TRUNK FLEXION

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**6**	18
	higher level pain	13	**8**

SIT-TO-STAND

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**18**	5
	higher level pain	3	**8**

7.4.1.2 Imputed Dataset

<u>Single Imputation with Decision Tree</u>: Performance based on the single imputation datasets using decision trees is given in Table 7.6. Classification performance was found to improve with single imputation for the three movement types with average F1 scores of 0.54, 0.64, and 0.79 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Classification for both Forward Trunk Flexion and Sit-to-Stand were better than chance level classification while the performance for Full Trunk Flexion was only marginally better than chance level classification. Feature set optimisation was used to maximise the performances. As shown in Table 7.6, classification for the three movement types improved with feature set optimisation with average F1 scores of 0.67, 0.84, and 0.82 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively with performance much better than chance level. The confusion matrices are shown in Table 7.7.

TABLE 7.6 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND DECISION TREES (WITH AND WITHOUT FEATURE SET OPTIMISATION)

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	Without Optimisation	With Optimisation	Without Optimisation	With Optimisation	Without Optimisation	With Optimisation
F1 lower	0.64	**0.71**	0.68	**0.86**	0.84	**0.86**
F1 higher	0.36	**0.63**	0.60	**0.83**	0.72	**0.75**
average F1	0.50	**0.66**	0.64	**0.85**	0.78	**0.81**
accuracy	0.54	**0.67**	0.64	**0.84**	0.79	**0.82**

TABLE 7.7 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND DECISION TREES WITH FEATURE SET OPTIMISATION

FULL TRUNK FLEXION

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**18**	9
	higher level pain	6	**13**

FORWARD TRUNK FLEXION

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**21**	3
	higher level pain	4	**17**

SIT-TO-STAND

		Automatic Detection	
		lower level pain	higher level pain
Ground Truth	lower level pain	**19**	4
	higher level pain	2	**9**

Single Imputation with RF and SVM: The performance with single imputation using RF and the SVM is shown in Table 7.8. RF performed worse than the decision tree for all three movement types with average F1 scores of 0.45, 0.60, and 0.36 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Only the performance for Forward Trunk Flexion was better than chance level classification.

TABLE 7.8 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND RF AND SVM

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	RF	SVM	RF	SVM	RF	SVM
F1 lower	0.53	**0.67**	0.61	**0.71**	0.55	**0.70**
F1 higher	0.36	**0.46**	0.59	**0.67**	0.17	**0.36**
average F1	0.45	**0.57**	0.60	**0.69**	0.36	**0.53**
accuracy	0.46	**0.59**	0.60	**0.69**	0.41	**0.59**

The SVM performed better than the RF with average F1 scores of 0.57, 0.69, and 0.53 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Despite the overall marginally better than chance level performance for Sit-to-Stand, classification of the high level pain class for this movement type was poor. For Full Trunk Flexion, per class performance was no better than chance level while it was much better than chance level classification for Forward Trunk Flexion. Feature set optimisation was used to maximise the performance of the SVM for these two movement types (Full and Forward Trunk Flexion). Optimisation led to performances much better than chance level: F1 scores of 0.75 and 0.61 for lower and higher level pain respectively and accuracy of 0.70 for Full Trunk Flexion; F1 scores of 0.76 and 0.70 for lower and higher level pain respectively and accuracy of 0.73 for Forward Trunk Flexion.

TABLE 7.9 PAIN LEVEL CLASSIFICATION PERFORMANCE WITH MULTIPLE IMPUTATION AND DECISION TREES

	FULL TRUNK FLEXION	FORWARD TRUNK FLEXION	SIT-TO-STAND
F1 lower	0.42	0.48	0.60
F1 higher	0.28	0.51	0.27
average F1	0.35	0.50	0.44
accuracy	0.36	0.50	0.48

Multiple Imputation with Decision Tree: Performance based on the multiple imputation datasets using decision trees is given in Table 7.9. Multiple imputation worsened performance (compared with the non-imputed dataset) for Full Trunk Flexion and Sit-to-Stand with average F1 scores of 0.35 and 0.44 respectively, both worse than chance level classification. Although average F1 score for Forward Trunk Flexion improved to 0.50, it was still no better than chance level classification.

7.4.2 MRSE Level Classification

7.4.2.1 Non-Imputed Dataset

Classification performance using the non-imputed datasets is shown in Table 7.10. Average F1 scores for the three movement types were 0.44, 0.64, and 0.42 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Per class performance was very poor for Full Trunk Flexion and Sit-to-Stand and no better than chance level classification for Forward Trunk Flexion. Table 7.11 shows the confusion matrices.

TABLE 7.10 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH MISSING VALUES AND DECISION TREES

	FULL TRUNK FLEXION	FORWARD TRUNK FLEXION	SIT-TO-STAND
F1 lower	0.11	0.52	0.19
F1 higher	0.77	0.75	0.64
average F1	0.44	0.64	0.42
accuracy	0.63	0.65	0.50

TABLE 7.11 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH MISSING VALUES AND DECISION TREES

FULL TRUNK FLEXION

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**1**	9
	higher level MRSE	8	**28**

FORWARD TRUNK FLEXION

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**8**	6
	higher level MRSE	9	**22**

SIT-TO-STAND

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**2**	2
	higher level MRSE	15	**15**

7.4.2.2 Imputed Dataset

Single Imputation with Decision Tree: The results of classification using the imputed datasets is given in Table 7.12. For Full and Forward Trunk Flexion, imputation improves classification with average F1 scores of 0.54 and 0.68 respectively; however, per class performance is still poor for Full Trunk Flexion and not much better than chance level for Forward Trunk Flexion. For Sit-to-Stand, average F1 score reduces to 0.40 and there is zero recall of lower level MRSE. With feature set optimisation, performance improves considerably for all three movement types as shown in Table 7.12 with average F1 scores of 077, 0.79, and 0.67 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Performance for Full and Forward Trunk Flexion becomes much better than chance level classification. However, classification of the lower level MRSE for Sit-to-Stand remains worse than chance level classification. The low number of examples of lower level MRSE for this movement type may be the reason for this poor performance. Table 7.13 shows the confusion matrices of these results.

TABLE 7.12 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND DECISION TREES (WITH AND WITHOUT FEATURE SET OPTIMISATION)

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	No Optimisation	Optimisation	No Optimisation	Optimisation	No Optimisation	Optimisation
F1 lower	0.24	**0.63**	0.54	**0.71**	0	**0.46**
F1 higher	0.83	**0.90**	0.81	**0.87**	0.79	**0.87**
average F1	0.54	**0.77**	0.68	**0.79**	0.40	**0.67**
accuracy	0.72	**0.85**	0.73	**0.82**	0.65	**0.79**

TABLE 7.13 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND DECISION TREES (WITH FEATURE SET OPTIMISATION)

FULL TRUNK FLEXION

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**6**	4
	higher level MRSE	3	**33**

FORWARD TRUNK FLEXION

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**10**	4
	higher level MRSE	4	**27**

SIT-TO-STAND

		Automatic Detection	
		lower level MRSE	higher level MRSE
Ground Truth	lower level MRSE	**3**	1
	higher level MRSE	6	**24**

<u>Single Imputation with RF and SVM</u>: The performance with single imputation using RF and the SVM is shown in Table 7.14. RF does not perform much better than the decision tree or chance level for all three movement types with F1 scores of 0.55, 0.54, and 0.45 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively.

TABLE 7.14 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH SINGLE IMPUTATION AND RF AND SVM

	FULL TRUNK FLEXION		FORWARD TRUNK FLEXION		SIT-TO-STAND	
	RF	SVM	RF	SVM	RF	SVM
F1 lower	0.25	**0.30**	0.36	**0.45**	0	**0.27**
F1 higher	**0.84**	0.81	0.71	**0.71**	**0.89**	0.79
average F1	0.55	**0.56**	0.54	**0.58**	0.45	**0.58**
accuracy	**0.74**	0.70	0.60	**0.62**	**0.79**	0.68

The SVM has average F1 score of 0.56, 0.58, and 0.58 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Although marginally better than chance level, per class performance is poor. The SVM performs worse than the decision tree for Full and Forward Trunk Flexion. However, it is better at classifying the lower level MRSE in Sit-to-Stand than either of the decision tree and RF. Feature set optimisation was used to maximise the performance of the SVM for Sit-to-Stand. For the SVM, optimisation led to F1 scores of 0.50 and 0.85 for lower and higher level MRSE respectively and accuracy of 0.76 for Sit-to-Stand. Per class performance is still not much better than chance level.

<u>Multiple Imputation with Decision Tree</u>: The performances based on multiple imputations is shown in Table 7.15. Average F1 score is 0.51, 0.43, and 0.46 for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. Although performance is better for Full Trunk Flexion and Sit-to-Stand (than with the non-imputed datasets), it is no better than chance level classification for all the three movement types.

TABLE 7.15 MRSE LEVEL CLASSIFICATION PERFORMANCE WITH MULTIPLE IMPUTATION AND DECISION TREES

	FULL TRUNK FLEXION	FORWARD TRUNK FLEXION	SIT-TO-STAND
F1 lower	0.28	0.22	0.05
F1 higher	0.74	0.63	0.87
average F1	0.51	0.43	0.46
accuracy	0.62	0.49	0.77

7.4.3 <u>Does Learning in the Classification Models Transfer from Exercise to Functional Instances?</u>

To evaluate classification performance across movement contexts (i.e. exercise and functional movement instances) and so the feasibility of using the same classification models for these two types of movements, a test of the difference between performances for the two contexts was done based on several single imputations. Single imputation was used here as the single imputation dataset had led to better classification performances than the non-imputed dataset and the multiple imputation dataset as reported in the previous two sections. Five additional single imputations were done in addition to the primary one used in the analyses reported in the previous sections and so there were six single imputations used for the test. The evaluation was done with Forward Trunk Flexion instances as classification performance was best for this movement type compared to the other two. The decision tree, which gave the best performance with single imputation earlier, was used for classification. The hyperparameters and optimised feature set of the primary single imputation dataset were used for the additional five single imputation datasets. For each of these six single imputation datasets for Forward Trunk Flexion (each dataset included both exercise and functional instances), leave-one-subject-out cross-validation was done using the aforementioned classification algorithm (decision tree) and hyperparameter settings.

TABLE 7.16 CLASSIFICATION PERFORMANCE FOR EXERCISE AND FUNCTIONAL INSTANCES ACROSS *M*=6 SINGLE IMPUTATIONS
(*N* is the number of instances)

		Accuracy					
	M	0	1	2	3	4	5
Pain	Functional (*N*=10)	0.80	**0.60**	**0.60**	**0.60**	0.30	**0.60**
	Exercise (*N*=35)	**0.86**	0.49	0.49	0.40	**0.54**	0.57
MRSE	Functional (*N*=10)	**0.90**	**0.90**	**0.80**	**0.80**	**0.70**	**0.80**
	Exercise (*N*=35)	0.80	0.83	0.71	0.69	0.63	0.71

Table 7.16 shows the pain and MRSE level classification accuracies for the functional and exercise movement instances for each of the six single imputation datasets for both. For pain level classification, performance was better for the functional instances for four out of the six single imputation datasets; however, for MRSE level classification, performance was better for the functional instances for all six single imputation datasets.

A Wilcoxon Signed Rank test was done to test if the performances for the functional instances was significantly better than the performances for the exercise instances across the six single imputation datasets. For pain level classification, no significant difference was found between the performances for the two movement contexts. However, significant difference was found for MRSE level classification (z=-2.214, p<0.05, with large effect size r=-0.90) with classification accuracies for the functional instances (median=0.80) higher than for the exercise instances (median=0.71). The higher accuracy for the functional instances suggests that, as reported in Singh et al. (2016), low MRSE may have a stronger effect during functional movement making the discrimination between lower and higher MRSE levels clearer in such settings than in controlled exercise settings.

7.5 Discussion

The aim of the studies reported in this chapter was to investigate the possibility of automatic detection of levels of pain and related self-efficacy in functional movements (as well as exercises).

A low-cost wearable prototype based on 2 sEMG (on the left trapezius and lumbar paraspinal) and 4 IMU sensors (on the head, trunk, left upper and lower leg) was built due to the lack of a suitable system. The prototype was then used to acquire a new dataset of functional and exercise movements (full and forward trunk flexion and sit-to-stand); corresponding self-reports of MRSE, pain, and emotional distress were also obtained. The lessons learnt from the use of this prototype and the implication for low-cost body movement sensing in the everyday functioning of people with CP are further discussed below (in Section 7.5.2).

From the acquired dataset, the body movement features investigated in the studies reported in Chapter 6 were extracted, although the computation methods needed to be modified to adapt to the different form of the data here. In addition, a new feature, head extension at lift, was added for pain level detection in the sit-to-stand movements. As a substantial amount of data was missing due to challenges faced in data collection (difficulty in sensor attachment and data transmission), imputation was used to recover missing feature values.

Finally, traditional machine learning methods (decision trees, Random Forests, and Support Vector Machines) were used on the extracted features, with and without (decision trees only) imputation, to understand the feasibility of automatic detection of levels of pain and MRSE based on data captured using a minimal set network. Emotional distress detection could not be investigated as there were few examples of emotional distress in the dataset. The best performances were obtained using single imputation with decision trees and feature set optimisation: average F1 scores of 0.68, 0.85, and 0.81 for two-level pain detection in Full and Forward Trunk Flexion and Sit-to-Stand respectively and 0.77 and 0.79 for two-level MRSE level detection in Full and Forward Trunk Flexion respectively. This suggests the feasibility of automatic detection of these states in functional settings. Further, it was shown that classification models largely trained on exercise instances were significantly at least as good in classifying functional instances as they were in classifying exercise instances. The implication of these findings for CP physical rehabilitation technology is discussed below (in Section 7.5.1).

7.5.1 Implication for Physical Rehabilitation Technology Design

These findings are a first step towards automatic monitoring of the states in everyday physical activity settings. Although the automatic classification performances were not as good as those obtained using the EmoPain dataset (see Chapter 6), they are better than chance level classification and suggest that there is value in further investigation in this direction. The lower performance here is not surprising as the Ubi-EmoPain dataset used here was obtained using a smaller set of low-cost sensors whereas the EmoPain dataset using in the former investigation was acquired using a large set of higher fidelity sensors. The imbalance in the dataset of the two levels of pain and MRSE may have further contributed to this performance.

The use of sensors that are wearable and portable for data capture is a critical contribution of the investigation as these attributes are necessary for capture in ubiquitous settings typical of everyday functioning. Although such capture still has challenges such as those discussed in Section 7.5.2, current trends in sensor technology availability (such as wide adoption of such systems for sports and fitness tracking) provides incentives for these challenges to be addressed in future commercial systems. That the sensors used in the investigation are inexpensive further promises the possibility of mass deployment of physical rehabilitation technology that is able to tailor technological intervention to levels of pain and related cognitive and affective states.

The finding that the models trained with exercise instances were able to classify functional instances with performance as good as or better than exercise instances themselves further points to the possibility of using training sets majorly made up of exercise movements to classify both exercise and functional movements. This has an important implication given the difficulty of obtaining labelled training data in everyday functional settings in that it suggests the possibility of building the training set during exercise sessions where the user can provide self-report labels before and/or after each instance that the system can use as ground truth. Such self-reporting is not practical in everyday functioning as it disrupts functioning. It can also be cognitively burdensome for people with CP (Olugbade et al., in review). In fact, the challenge of self-reporting pain and related states is one of the arguments for the necessity of automatic detection functionality for technology that is to tailor intervention to these states. As exercise settings are more structured and controlled, this problem can be managed in such settings.

How the taxonomy developed within the investigations in Chapter 6 generalise across movement types has been discussed in Sections 6.5 and 6.6; the same understanding applies here although a new challenge emerges. The minimisation of the sensor network used for movement tracking here raises the question of how the proposed sensor configuration may generalise across the variety of movement types that make up everyday functioning. One possible solution, in the deployment of the technology, can be to focus, for each specific user, on a set of movement types that can be tracked using the same sensor configuration and are representative of the movement types found challenging by the specific user. This is similar to the approach taken in this thesis focusing on three movement types generally found challenging by people with low back CP.

7.5.2 Lessons Learnt using the MOVES-PC Prototype

Validation of the MOVES-PC prototype showed that it allowed synchronised capture of IMU and sEMG data that allowed insight into movement behaviour. While the full development of the system is outside the scope of this thesis, in this section, the lessons learnt in developing the prototype are discussed as they can inform progress in commercial sensor design and guide the choice of researchers looking to use low-cost body movement sensors in their studies. Indeed, by the time this thesis was completed, commercial low-cost IMU sensor systems (with mobile application interfaces) have been appearing on the market. While they are more refined and more aesthetically pleasing than the MOVES-PC prototype, they do appear to suffer similar issues.

7.5.2.1 BLE Interference

A major challenge that was faced in the prototype development and data collection with the prototype is BLE interference. Although no formal tests were done in this thesis, this was usually a problem in populated areas and times of the day. Pilot studies showed that this led to BLE visibility and connection becoming extremely difficult to maintain when more than 6 sensing units were turned on.

Interestingly, review of literature in relevant areas leads to wrong assumption that BLE is insusceptible to interference. The argument for this claim is that it is designed to avoid interference with the other wireless technologies (classic Bluetooth, WiFi, and ZigBee) that share the same 2.4GHz band that it operates in. To achieve this, advertising and related transmissions are done over 3 dedicated channels scattered across the band in such a way that they do not coincide with other wireless technologies and data transmission is done using frequency hopping over its remaining 37 channels (Gomez, Oller, and Paradells 2012). Few studies (e.g. (Treurniet et al. 2015)) show evidence of interference within the BLE channels with increasing density of BLE devices.

An observation that was made in the validation and use of the MOVES-PC was that its units were not able to compete with BLE-enabled PCs and phones for visibility. It is possible that these devices use radio antennae with higher transmission power than the DIP used to build the prototype. This points to possible need for a trade-off between transmission power and power consumption especially if the sensing system is expected to always be transmitting. Recent use of Notch (Notch Interfaces Inc. 2016), which is a low-cost commercial IMU-based sensing system, shows that BLE interference may be a problem generally faced albeit hardly documented in the field.

Possible alternatives for short-range communication in power conservative applications like needed for CP physical rehabilitation are WiFi (Harun et al. 2015) and ZigBee although experiments need to be carried out to evaluate the challenge of widespread use of these technologies for low-powered sensing systems.

7.5.2.2 sEMG Electrode Placement

A lesson learnt in the use of the MOVES-PC prototype is that the placement of sEMG electrodes is not trivial. This was especially a challenge because the electrodes needed to be placed in locations that are not within the sight of subject. The lumbar paraspinal placement is particularly difficult to do without assistance. In addition, even though placement on participants was done by a researcher in the validation and data collection studies done, it was a challenge to locate the L4/5 and a neighbouring electrically neutral position for the reference electrode. These experiences highlighted the challenge of using electrode-based sEMG sensors that require placement in posterior locations. Self-management of the CP condition places enormous psychological burden on people with CP (Turk and Okifuji 2002) and so technology that is to support them should itself not be burdensome, and so there is the need for further exploration of sEMG sensor designs that are easier to wear. The sEMG sensor type used to develop the MOVES-PC has the additional disadvantage of depending on disposable electrodes, which add to the cost-in-use of these types of sensors.

Alternatives for muscle activity tracking is becoming increasingly investigated such as in the studies of Gourmelon and Langereis (2006) and Meyer, Lukowicz, and Tröster (2006) although there are still only few low-cost commercial options. One of the commercially available sensors is the Mbody, which is a pair of shorts that allows tracking of muscles around the upper leg particularly the gluteus, quadriceps femoris, biceps femoris, semitendinosus, and semimembranosus (Myontec 2015). The Athos Gear (MAD Apparel Inc 2016) is similar but also includes a top that additionally tracks the pectorals, biceps brachii, and deltoid. Future work can investigate how feasible such sensors are for muscle activity capture in everyday settings for pain and related cognitive and affect detection.

7.5.2.3 IMU Sensor Unit Placement

Another lesson learnt in the use of MOVES-PC was the importance of careful attention to the design of the accessories used to attach the IMU sensing units. In pilot tests, a variety of accessories were experimented with and it was found that their materials needed to be resistant to slip during physical activities, especially for the limbs. It was also important for the materials to be tight-fitting, without causing discomfort, to prevent artefact due to movement of the material. After several experimentations, commercially available non-slip knee sleeves and armbands were used for the lower and upper limbs respectively. Unfortunately, the available sizes did not cater to the range of body shapes of the participants in the data collection. An additional drawback of the knee sleeves is that they were only long enough to allow tracking of the lower thigh and upper shank.

Smart garments like the Heddoko smart garment (Heddeko 2016) are becoming increasingly looked to as a viable solution to the problem of attachment of sensing units to anatomical segments. Studies in related areas have also considered the use of implanted sensors although these have the disadvantage of being highly invasive.

7.5.3 Limitation

A limitation of the automatic detection investigations reported in this chapter is the existence of missing data. This is an unavoidable problem with repeated assessments especially in sensor-based data capture where sensors may be faulty, low on power, or having data transmission difficulties. In the investigation, two main approaches were used to deal with this problem. Although classification on data with missing values has advantage over imputation in that no extra computation is required and it avoids uncertainty of the missing values, it was found to be poorer in classification performance than when imputation is done. This is similar to the finding of Feelders (1999). Single imputation was found to generally yield better results than multiple imputation. This suggests that the variability introduced by the latter may exceed variation between subjects. Further development of an algorithm that models variability in imputation with priority to intra-subject and inter-subject variation over other sources of variation in observed values may allow for a more fitting imputation model for body movement datasets like these.

7.6 Conclusion

Based on a new dataset (Ubi-EmoPain) captured using a custom-built movement sensing prototype (MOVES-PC), it is shown that automatic detection of pain and MRSE during physical activity tracked using a minimal set of (low-cost) sensors is feasible, with F1 score of 0.78 respectively. This points to value in building technology that tailors intervention to people with CP to support everyday physical functioning, on the basis of automatic detection of these states. The performances obtained were based on both exercise and functional movements, with detection for functional movements at least as good as detection for exercise movements in spite of the minority of examples of the former type of movement in the training set used. This suggests possibility of building the automatic detection system with movements captured in exercise settings, where associated pain and MRSE ground truth, necessary to develop such system, are easier to collect. However, based on the use of the MOVES-PC prototype, it is shown that consistent wireless streaming from multiple sensors with low power expenditure and the practicalities of sensor attachment are challenges that still need to be addressed for everyday use of the low-cost sensor by people with CP.

Part IV

Conclusion.

8 OVERALL DISCUSSION AND CONCLUSION

THE aim of this thesis was to address the problem of automatic detection of levels of pain and related self-efficacy, fear/anxiety, and depressed mood during physical activity so as to enable tailoring of CP physical rehabilitation intervention to these states. The import of the states is their significant influence on physical functioning (and so the pursuit of valued goals, e.g. employment and social interactions) in people with CP. To this end, three main research questions (see Fig.8.1 for an overview) were investigated in this thesis.

In the first investigation, the relationship between the observable pain behaviours specified by Keefe and Block (1982) and the aforementioned states was explored to understand the extent to which the states can be operationalised by these behaviours. This was important to investigate as although these behaviours are widely used in pain research for understanding pain experience (Sullivan et al. 2006; Tang et al. 2007; Cook et al. 2013), there has been limited investigation of how they relate to pain related cognitive and affective states. In the exploration done in this thesis, guarding behaviour was focused on as it is more relevant than the other four of Keefe and Block's behaviours (bracing, rubbing, grimacing, and sighing) in the context of physical activity (Keefe and Block 1982; Sullivan et al. 2006; Aung et al. 2016). The results from this study shows a complex relationship between the different states and behaviour and also suggests that these states need to be assessed based on a larger set of lower level behaviours that go beyond behaviours typically associated with pain response.

Following these findings, the second investigation was concerned with the building of a collection of body movement cues (and providing deep(er) understanding of these cues) that enable discrimination between levels of the states. The investigation centred on body movement because of evidence of its significance in the experience of pain (Keefe and Block 1982) and in challenge in physical functioning in this context (Sullivan et al. 2006). Understanding of the feasibility of automatic detection of levels of the states during physical activity based on these cues was further investigated. The investigation as a whole addresses the need for CP physical rehabilitation technology to be affect-aware so as to enable tailoring of intervention and so facilitate engagement in physical activities.

RQ 1 - Chapter 5

What is the relationship between observable pain behaviours and pain, MRSE, and emotional distress?

- EmoPain dataset extension with physiotherapist annotation
- Quantitative exploration of RQ based on extended dataset
- Analysis of MRSE cues reported by physiotherapists in annotation

RQ 2 - Chapter 6

How can levels of pain, self-efficacy, and emotional distress be automatically detected during physical activity based on movement behaviour cues?

- Movement features investigation based on literature, video analysis with physiotherapists, visual inspection of movement data.
- Modelling based on the movement features (from EmoPain dataset) and using machine learning algorithms
- Analysis of feature relevance based on feature set optimisation and statistical methods

RQ 3 - Chapter 7

How can levels of the states be detected in everyday physical functioning based on these behaviours?

- Prototyping of minimal set of low-cost wearable sensors
- Acquisition of Ubi-EmoPain dataset using prototype
- Modelling based on the movement features (from Ubi-EmoPain dataset) and using machine learning algorithms

Fig. 8.1. The research questions investigated in this thesis

The third investigation builds on finding from the previous study that showed that automatic detection of the levels of the states is feasible in physical activity settings based on body movement cues. This third investigation focused on understanding of the feasibility of automatic detection in both functional and exercise movements based on cues captured using a minimal set of low-cost sensors. Such understanding is important due to the need for technological intervention to be available in everyday physical functioning rather than just situated exercises (Singh, Bianchi-Berthouze, and Williams 2017). For such settings, physical rehabilitation technology needs to be wearable, portable, and inexpensive. The investigation was a first step towards affect-aware physical rehabilitation technology in these settings.

In this chapter, the main contributions of these investigations to pain research (Section 8.1) and the field of affective computing (Section 8.2) are discussed, bringing together the main points from the more detailed discussions of the investigation findings in the three study chapters (Chapter 5-7). Future directions of research that these contributions highlight are also discussed in the chapter (in Section 8.3). To close the thesis, a conclusion is further provided at the end of the chapter (Section 8.4).

8.1 Contribution to Pain Research

Consideration of motor behaviours in the investigations of this thesis enabled contribution to pain research where broad behaviour measures (e.g. self-reported summary of pain behaviour over a week) have been prevalent in available understanding of the maintenance of CP (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004). A limitation of broad measures is that they do not allow fine-grained understanding of behaviour. They also do not provide guidance on the needs of a person with CP while engaging in specific movements. The three main contributions to the area of pain research of the investigations of this thesis, based on micro analysis of pain behaviours with pain and related cognitive and affective measures, are discussed in this section.

8.1.1 Empirical Evidence of a Non-Mediated Relation between Pain and Anxiety

The prevailing pain model is the fear-avoidance theory of pain (Vlaeyen and Linton 2000; Vlaeyen, Morley, and Crombez 2016) that proposes that negative cognitive appraisals (particularly catastrophising) related to pain lead to fear/anxiety that evokes behaviours which in the long run and in a recursive way result in disability and the maintenance of pain. The proposed mediation of the relationship between pain and fear/anxiety by catastrophising has been challenged in Pincus et al. (2010) where it is suggested that this cognitive process is instead, like depression, a predisposition towards distress states (such as fear/anxiety) and characterised by low tolerance for pain. Crombez et al. (2012) later also challenged the idea of a cognitive mediator between pain and fear/anxiety; they pointed out three weaknesses of this notion. The first is the problem that the theory as a whole originates from understanding of psychological conditions (such as phobias or anxiety disorders) which are different from pain. The authors further highlight that the tools that have been used in assessing catastrophising also weaken the argument for such a mediator: they suggest that these tools may actually measure the experience of anxiety rather than catastrophising itself. For the authors, a final weakness of the hypothesis is that it does not consider that pain can itself evoke a fear response without appraisal even though it is powerful enough to as has been shown in studies such as Magee and Elwood (2013) with animals (crabs) not capable of cognition.

This thesis contributes evidence that indeed suggests that, similar to other forms of non-pain threats (Ohman 2005), pain and anxiety have a direct relationship without mediation by cognitive processing. It was in fact shown that anxiety may actually be a mediator of the relationship between pain intensity and emotional distress (which includes depressed mood) and between pain intensity and movement related self-efficacy (which is a cognitive appraisal of the ability to execute movement in the face of pain). Importantly, the evidence provided in this thesis is based on assessment of anxiety, pain intensity, and self-efficacy for specific movements rather than within the context of general experiences as has typically been done in pain studies (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004; Eccleston and Crombez 1999) despite its recognised limitation (Pincus et al. 2010).

8.1.2 Micro-Level Behavioural Data Evidence of Significant Influence of Pain, Self-Efficacy, and Emotional Distress on Physical Functioning

As previously mentioned, a limitation of findings in pain studies has been the methods of assessment of the variables analysed. Cognitive and affective variables are usually assessed in terms of general experience rather than for specific movement events (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004; Crombez et al. 1999). Behaviour has also been typically assessed using methods, that summarise self-reported execution of the behaviour over a period (e.g. a week) or that rate tendency towards the behaviour, which lack objectivity and detail about specific movement instances.

In this thesis, behaviour was objectively assessed for specific movement instances and analysed with corresponding measures of pain and related cognitive and affective experiences. Two behaviour assessment methods were considered: expert observer ratings and movement sensor data. The findings from separate analyses using these two behaviour measures supports previous findings that pain, self-efficacy, and emotional distress significantly influence physical functioning. The importance of the finding of this thesis is the objectivity, level of detail, and temporal relevance of the behaviours considered. Extending previous findings (Crombez et al. 1999; Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004), the finding shows that these states pose barriers to individual movement instances. This is similar to the qualitative finding in Olugbade et al. (in review) where people with CP expressed that pain, fear/anxiety, and depressed mood interfere with engagement in individual activities and in different ways.

8.1.3 Evidence-Based Pain Model including Self-Efficacy

Even though it has been shown that self-efficacy plays an important role in engagement in physical activities in CP (Asghari and Nicholas 2001; Denison, Asenlof, and Lindberg 2004), this state has often been overlooked in proposed theories of pain. Perhaps this is due to, as suggested in Crombez et al. (2012), these models originating from psychopathological models for psychiatric disorders, where self-efficacy has not usually featured.

Based on empirical findings, this thesis proposes a model that integrates self-efficacy and typical variables from contemporary models of pain, predominantly pain intensity, fear, emotional distress, and behaviour, such as the fear-avoidance theory of pain (Vlaeyen, Morley, and Crombez 2016). The model is shown in Fig. 8.2. The model is in agreement with the proposal of the fear-avoidance theory that fear/anxiety rather than pain itself leads to pain behaviour (Vlaeyen and Linton 2000). The model further agrees with the self-efficacy theory of relationships between self-efficacy and both anxiety and performance. This model is, however, different from previous theories (e.g. (Vlaeyen and Linton 2000; Pincus et al. 2010)). As earlier mentioned, these theories have largely been theoretical and otherwise based on findings using gross and cumulative measures of behaviour and scales of anxiety with ambiguous items (Pincus et al. 2010). The model proposed in this thesis is instead based on observational assessment of behaviour in specific movement instances (as suggested by Keefe and Block (1982)), single item self-report of pain and anxiety for the same movement instances, and self-efficacy for the same movement instances estimated by expert observers who are reliable assessors of this construct (Keogh, Griffin, and Spector 1981). Even though emotional distress was not assessed for specific instances, it was measured just before the movement events and, given the persistence of depressed mood, it is expected that this measure adequately represents the pain related distress that was experienced during the movement instances.

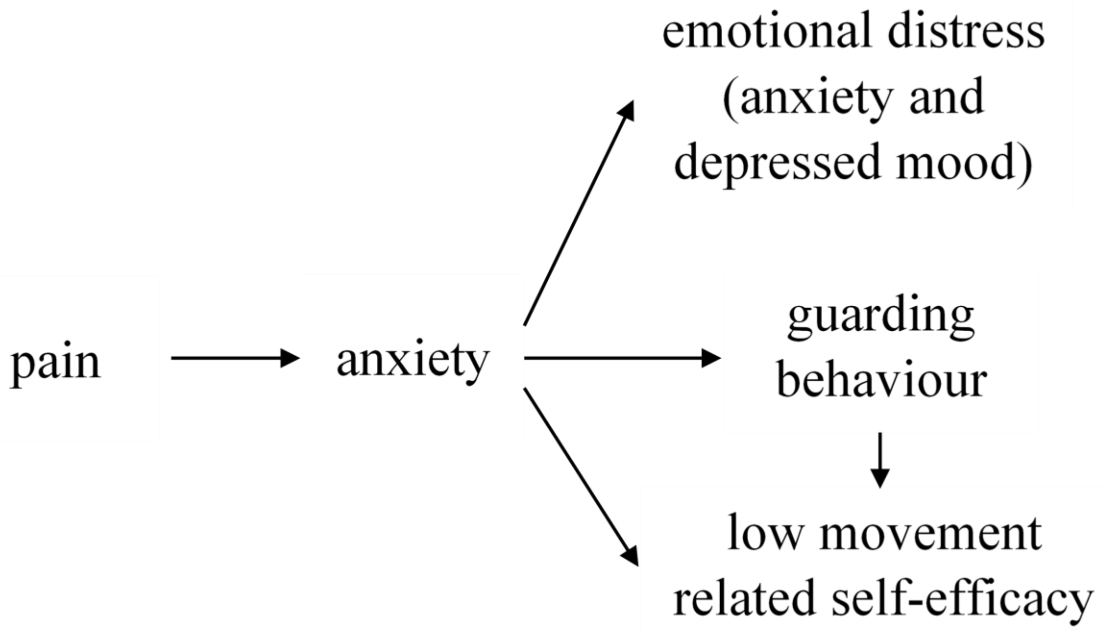


Fig. 8.2. Evidence-based pain model including self-efficacy

The proposed model points to anxiety as the hub of the connection between pain and related cognitive appraisal, affect, and behaviour. Such a relationship has not been previously considered. Further, although previous models (Vlaeyen and Linton 2000; Pincus et al. 2010) have identified fear/anxiety as important, the still prevailing use of the term ‘pain behaviour’ misleadingly implies pain as the cause of the behaviour, and people with CP wrongly see their behaviour as a direct response to actual or anticipated pain levels. Thus, the proposed model, both with its approach (based on behavioural data and microlevel assessment of relevant variables) and the relationships it suggests, can: 1) inspire further debate in the area about the role of fear/anxiety and its place in pain maintenance, 2) inform new types of investigations where more objective and finer grained assessment tools are used, and 3) lead to better understanding of pain.

8.2 Contribution to Affective Computing

Attention in pain related affect computing has been focused on facial expressions of pain based on observer rating (Neshov and Manolova 2015; Zhou et al. 2016; Kaltwang, Rudovic, and Pantic 2012; Rudovic, Pavlovic, and Pantic 2013; Zebarjadi and Alikhani 2016; Roy et al. 2016; Rathee and Ganotra 2016). However, facial expression of pain is likely to have a strong component of communicative function and, therefore, very sensitive to social context, in clinical and in experimental settings. This has not been adequately addressed in studies attempting to quantify facial expression as a sign of pain. This thesis challenges the norm by investigating bodily expressions of self-reported pain, pain related self-efficacy, and pain related emotional distress. The three main contributions of these investigations to the field of affective computing are discussed in this section.

8.2.1 Taxonomy of Bodily Expressed Pain Behaviours

Affective computing based on facial expressions has relied on the Facial Action Coding System (Cohn, Ambadar, and Ekman 2007) (a taxonomy of facially expressed affective behaviours) either in acquiring ground truth (e.g. (Lucey, Cohn, Prkachin, et al. 2011)), deciding features to extract for automatic detection (e.g. (Cohn et al. 2009)), or designing expressions for artificial systems such as avatars and robots (Mazzei et al. 2012). While there have been similar systems for bodily expressions (Huis In 't Veld, Van Boxtel, and de Gelder 2014b; Fourati and Pelachaud 2015)), pain and related states have often not been considered as having significant affective content. The only work that exists in the area is the exploratory work of Walsh, Eccleston, and Keogh (2014) where only acted static bodily expressions were considered.

In this thesis, a taxonomy of observable bodily expressions and muscle activity features was developed for pain, MRSE, and pain related emotional distress (see Appendix III). This taxonomy can facilitate better understanding of pain experience ground truth and can guide the development of expressive artificial systems with pain in their repertoire of affect. Most importantly, the taxonomy can inform automatic detection of the aforementioned states. While recent advances in machine learning particularly deep learning methods have alleviated the need for hand crafting of features for automatic detection, these methods are limited in providing understanding of what types of data to capture in the first place and they rely on the availability of extensive datasets. The traditional feature analysis methods used in this thesis allowed groundwork understanding of the relevance of different anatomical segments, and of the cues that can be garnered from them, to discrimination between levels of the states. Such understanding is particularly important for applications in ubiquitous settings (e.g. CP physical rehabilitation technology) where conservative data capture methods may be necessary. In such settings, it is not possible to capture high fidelity body movement data due to a need to minimise the number of wearable sensors used and the challenge of using camera-based capture methods. The feature understanding can also inform expert acquisition of data that can be used to train deep learning models, which may lead to better detection performance, although they will

TABLE 8.1 SUMMARY OF BODILY CUES OF PAIN AND RELATED STATES CONTRIBUTED TO IN THIS THESIS

Features	Relevant States (understanding provided: *deeper, $^{+}$novel)
Head or shoulder slump	emotional distress*
Body sway	emotional distress*
Tempo of movement execution	pain*, emotional distress*, MRSE^{+}
Range of movement about the pain location	pain*, MRSE^{+}
Thigh self-adaptors	emotional distress^{+}
Extent (in distance) of head droop	emotional distress^{+}
Range of neck/head movement	pain^{+}
Arm unsteadiness	pain^{+}
Back muscle relaxation on re-extension	pain^{+}
Foot Positioning in sit-to-stand	pain^{+}, MRSE^{+}
Dissymmetry	MRSE^{+}
Fluidity	MRSE^{+}
Mean muscle activity	MRSE^{+}

require vast amounts of data which may also result in better detection performances with parsimonious models such as SVM- or RF-based models.

In this thesis, bodily cues were classified according to pain level, emotional distress, and MRSE (see Table 8.1 for a summary). First, deeper understanding of known bodily cues of pain and emotional distress were provided. Novel bodily expressions of these states were further proposed and analysed. Finally, novel understanding of bodily expressions of MRSE was also provided. The focus on bodily features is based on the function of bodily behaviours in how a person deals with the experience of pain. Pain literature has previously only pointed to the protective or fear-response role of such behaviours, i.e. the intent to minimise harm from perceived threat (Sullivan et al. 2006), such as reduced range of motion and stiffness in movement. In this thesis, it was shown that some of these behaviours (e.g. atypical foot positioning to execute sit-to-stand) may additionally be used to cope with the challenge faced in executing a task or situation. It was further shown that these functions may not explain all of the behaviours observed in the context of pain and that some of these behaviours are similar to those found in non-pain distress contexts (such as slumped posture and the use of self-adaptors) suggesting that they are behaviours (unconsciously) used to manage distress (Ekman and Friesen 1969; Waxer 1974). Computational methods for extracting these cues from IMU and sEMG data were proposed in this thesis. Further, a library of extraction functions (Olugbade 2017) has been made available open source to support future work in the area. The computational methods and library provide the opportunity of leveraging recent advances in sensing technology to reduce reliance on expertise and time intensive coding for bodily behaviour analysis that has been necessary in the prevalent observational method of Keefe and Block (1982).

8.2.2 Understanding of the Feasibility of Pain and Related Affect Detection in Physical Activity Settings

The computing of pain, self-efficacy, and emotional distress has largely been limited to the acted expressions (for anxiety), sedentary settings (for depressed mood and self-efficacy), and facial expressions (for pain). In this thesis, the feasibility of the detection of these states based on spontaneous expressions in movement behaviour in physical activity settings was shown. This feasibility suggests the possibility of a wider range of affective computing applications. It particularly points to opportunities for affect-awareness in settings that go beyond largely static contexts and pervades during real (as opposed to posed) physical functioning. As was the aim of the thesis, this functionality addresses the need in CP physical rehabilitation for technology to be aware of pain level (especially low versus high), anxiety, depressed mood, or self-efficacy (low versus higher levels) in relation to engagement in physical activities or movement (Olugbade et al., in review). These capabilities enable the possibility of providing technological intervention that addresses the barriers that these states pose to engagement in physical activities. The feasibility of affect detection based on bodily features is critical in this application as this modality further informs personalisation of intervention (Sullivan 2008) because, as discussed in the previous section, bodily expressions represent coping strategies and action tendencies (Sullivan et al. 2006; de Gelder 2009) that may need to be disrupted. In addition, bodily features are already a primary modality in physical rehabilitation technology given their centrality to measurement of physical capability.

In this thesis, average F1 scores of 1, 0.85, and 0.84 were obtained for three-level pain classification in Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand movement types respectively. For three-level MRSE classification, the average F1 scores were 0.95 and 0.78 for Forward Trunk Flexion and Sit-to-Stand respectively while average F1 scores of 0.88, 0.83, and 0.86 were obtained for two-level emotional distress classification for Full Trunk Flexion, Forward Trunk Flexion, and Sit-to-Stand respectively. These results highlight opportunities for affect-awareness in technology-supported physical rehabilitation.

8.2.3 A First Step Towards Pain and Related Affect Detection in Everyday Functional Activity Settings

In this thesis, further moves were made to push pain and related affect detection beyond the sedentary and posed settings which generalise rather poorly to everyday life. To this end, it was shown that pain and MRSE levels can be detected in functional movements with worst performance as good as detection in exercise movements even when the classifier is largely trained on exercise movements. This is an important finding as it suggests the feasibility of building detection systems for everyday settings based on data captured in more controlled settings for the sake of convenience and cleaner data. It was further shown that detection of the states in both movement contexts is possible based on a minimal set of low-cost movement sensors. Average F1 scores of 0.68, 0.85, and 0.81 were obtained for two-level pain detection in Full and Forward Trunk Flexion and Sit-to-Stand movement types respectively while average F1 scores of 0.77 and 0.79 were obtained for two-level MRSE level detection in Full and Forward Trunk Flexion movement types respectively.

A discussion of the challenges that need to be addressed to enable low-cost sensing of body movement behaviours based on integration of IMUs and sEMG sensors was additionally provided in the thesis. This discussion can inform advance in sensing technology design and development (especially for application in CP physical rehabilitation) on one hand, and it can also provide understanding that can guide researchers interested in low-cost body movement sensing.

8.3 Potential Future Directions

The contributions of the thesis point to the potential for more work in the area. In this section, four possible directions for further work that build on this thesis are discussed:

8.3.1 Direction 1 - Going Beyond Pain, MRSE, Fear/Anxiety, and Depressed Mood

Although the literature on pain point to the states investigated in this thesis (pain, self-efficacy, fear/anxiety, and depressed mood) as critical states to address to promote engagement in physical functioning in people with CP, other states may also play a role in how these people cope with pain and the challenge of everyday functioning in this condition.

For example, (Trost et al. 2012) suggest that anger, which may result from frustration with barriers to the achievement of valued goals such as everyday functioning, can lead to lack of adherence to helpful coping strategies. It has also been shown that pain related anger additionally fuels other pain related negative affect such as depressed mood (Okifuji, Turk, and Curran 1999) which influence engagement in physical activities (Olugbade et al., in review). Pain catastrophising, which is the cognitive appraisal of pain as a threat associated with hypervigilance on pain (Sullivan et al. 2001), has also been found to contribute to worsened pain and disability in people with CP (Velly et al. 2011). These findings point to the need for attention of physical rehabilitation technology on these other states so that they can be addressed, to further enable engagement in physical activities.

Automatic monitoring of the states provides the opportunity for such technology to tailor intervention to them. However, as shown with the review discussed in Chapter 2, it is important to first better understand how they pose barriers and the forms of intervention that may address these barriers. Such understanding can inform affective computing design including the affect monitoring settings to plan for (e.g. sedentary versus exercise versus functional), the most useful modalities to consider (e.g. body movement, face, biosignals), and the level of detail that technology needs to understand of the states (e.g. the object/subject of anger, the degrees of catastrophising). Informed design will ensure relevance of the developed technology.

8.3.2 Direction 2 - Extending Available Pain Datasets for Additional Analysis

The only dataset of body movement expressions in people with CP was the EmoPain dataset (Aung et al. 2016) which was used in this thesis. Due to the challenges of behavioural data collection in this population as discussed in Chapters 6 and 7, the size of the data available in the dataset is limited compared to other data mining areas. This size limitation restricts the types of analysis that can be done on the data. Deep learning methods are, for example, challenging to leverage with such data sizes. It is important to consider deep learning methods as they can lead to better detection models because they enable more complex functions of a feature space (Goodfellow, Bengio, and Courville 2016). Another challenge of a limited data size is the difficulty of developing comprehensive data-based models of pain (for example, including behaviour variables other than guarding in the proposed model discussed in Section 8.1.3) due to the problem that the order of dimensions is then the same as that of the data size. Such extended models can be important in informing the design of integrated automatic detection of pain and related states, for example, using transfer learning methods (Romera-Paredes et al. 2013) or multilabel classification algorithms (Sucar et al. 2014). It is, thus, an important direction to extend this existing dataset to enable these forms of analysis that require large data sizes.

In this thesis, a new CP exercise and functional movement dataset (Ubi-EmoPain) was acquired, based on low-cost sensors. Unlike the EmoPain dataset, this dataset enables investigation of settings close to the real world where movements go beyond exercises to functional activity for which the barriers for a person with CP may be different from those faced in exercising (Singh, Bianchi-Berthouze, and Williams 2017) and where there may be constraints on the number of sensors that can worn without restricting movement. It is, thus, important to also extend this dataset beyond the 125 instances that were collected in the investigation of this thesis. As with the EmoPain dataset, a larger dataset can enable better detection performances. For this direction of work, it is important to understand the problems of data collection with low-cost wearable motion capture and muscle activity sensors. Partial understanding of these problems was provided in this thesis: it was shown that attention needs to be paid to the data transmission methods to be used and the challenge of ensuring adequate placement of the necessary sensors for effective acquisition of such data.

8.3.3 Direction 3 - Designing Low-Cost Body Movement Sensing Devices for Affect-Aware CP Physical Rehabilitation

These highlighted challenges of current low-cost options can also be addressed in future work. It is, for example, important to understand which wireless transmission method can be an effective alternative to BLE which may suffer interference. Possible choices are WiFi and ZigBee, but there is limited understanding of the efficacies of these methods with multiple transmitting units in dense communication settings (i.e. where there are high numbers of networks) where interference is likely. Thus, future work can investigate these transmission methods with a focus on the capture of the pain related movement cues that have been proposed in this thesis. Findings from such investigation can inform the design of affect-aware CP physical rehabilitation systems.

It is also important to further investigate the possibility of low-cost IMU and sEMG sensors (accessories) that can be worn on anatomical segments beyond the bracelet designs popular in fitness tracking (e.g. (Moov Inc. 2016)). As has been shown in this thesis, the bodily cues important for understanding intervention needs in CP physical rehabilitation may (depending on the pain location) require tracking of back muscles which are difficult to self-access, and the head, trunk, and legs which are not typical anatomical segments where accessories are worn. Although there are several emerging designs to cater to similarly unusual bodily segments (e.g. (Notch Interfaces Inc. 2016; Heddeko 2016)), there is limited understanding of the usability of these sensors (or sensor accessories). For affect-awareness to be integrated into commercially available CP physical rehabilitation technology, such understanding will need to be explored.

8.3.4 Direction 4 - Venturing into Physical Activity in Real World Settings

The findings of this thesis point to the possibility of automatic detection of levels of pain, MRSE, and emotional distress in functional movements based on low-cost sensors. This calls for further work considering functional movements captured in real world settings rather than the laboratory settings where the data used in this thesis were captured. This direction is important as this setting is where physical rehabilitation takes place. As discussed earlier, the barriers that people with CP face in controlled and partially-controlled settings are different from the challenges that they face in less controlled environments typical of everyday functional activities (Singh, Bianchi-Berthouze, and Williams 2017). The work of this thesis on functional movements is necessary groundwork that can inform further investigation of real settings. In particular, the thesis provides understanding of the bodily cues to focus on capturing in such settings and the challenges of capturing these cues in those settings.

Availability of low-cost commercial sensing systems, such as those suggested in Section 8.3.3, will enable work in this direction as such sensors will facilitate data collection. The use of such sensors in real settings can also further inform tailoring of their design for usability in these settings.

8.4 Conclusion

The aim of this thesis was to address the problem of automatic detection of levels of pain, self-efficacy, fear/anxiety, and emotional distress for tailored technological intervention in CP physical rehabilitation.

This problem was addressed with three main investigations. First, the relationship between observable bodily pain behaviour and these states was explored to gain understanding of how such behaviours can be used to define the states. Secondly, an in-depth investigation of the bodily cues that enable automatic discrimination of the states was carried out to inform automatic detection of the levels of the states. Thirdly, an investigation of the possibility of such detection in functional movements and based on low-cost sensors was done.

The findings of the thesis point to the feasibility of automatic detection of levels of these states in exercise movements using IMU and sEMG sensors that enable high fidelity data capture and also in exercise and functional movements using lower cost sensors that are more practical in real settings. More importantly, the thesis provides a taxonomy of bodily cues that can be used for automatic detection of the levels of these states. This taxonomy can be used in the design of affect-aware physical rehabilitation technology, for further understanding of intervention needs, and in the design of embodied artificial agents that need to be able to express pain and related states.

The findings of the thesis further contribute to the literature on pain by: 1) providing evidence that challenges the theory of a cognitive mediator between pain and related anxiety and places anxiety centrally in determining behavioural engagement; 2) grounding previous understanding of the influence of pain and related states on physical functioning on behavioural data; and 3) proposing a pain model that includes self-efficacy, a construct that contributes to the challenge of engagement in physical activity in people with CP.

This thesis also contributes a new dataset of people with CP in exercise and functional movements based on low-cost IMU and sEMG sensors. This dataset will be made available to other researchers in the area to enable further work. The existing EmoPain dataset was additionally extended in the investigations of the thesis with annotations for guarding behaviour and MRSE; these annotations will also be made publicly available when the EmoPain dataset is made open. Further, an open source library of the bodily cue extraction methods used in the investigations of the thesis is also now available for researchers in the area to access. Finally, preliminary understanding of the challenges of low-cost sensing of the bodily cues is provided in the thesis.

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Appendices

APPENDIX I

A. Information Sheet – UCL Research Ethics Committee

Title of Project: **Emotion & Pain Project**

This study has been approved by the UCL Research Ethics Committee [Project ID Number]: ***UCLIC/1516/012/Staff Berthouze/Singh***

Name, Address and Contact Details of Investigators:

Prof. Nadia Bianchi-Berthouze
University College London Interaction Centre
2nd Floor, 66-72 Gower Street
London WC1E 6EA, United Kingdom
+44 (0)20 3108 7067

We would like to invite you to participate in this research project. You should only participate if you want to; choosing not to take part will not disadvantage you in any way. Before you decide whether you want to take part, it is important for you to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or you would like more information.

This project aims develop technology to help patients with chronic pain by providing tailored feedback and support for movements performed as part of self-directed rehabilitation.

We will interview you about the needs and uses for such technology. We will ask your opinion of current prototypes we have developed. We will ask you to do everyday activities, exercise or play computer games while wearing movement sensors and/or biosensors; you may also receive multimodal feedback, such as sound, while doing these activities, o inform you about your movement. The activities will be recorded using these sensors, thermal cameras, and video/audio recording. We will also ask you to complete pain questions or movement-related questionnaires.

All data will be handled according to the Data Protection Act 1998 and will be kept anonymous. Researchers working with Prof. Berthouze will analyze the data collected. The information gathered will be used to understand requirements for chronic pain physical rehabilitation technology.

With your permission, we would like to use extracts of the video and audio recordings to demonstrate to people with chronic pain how assistive technology can be used for the management of their condition. If you are not happy for your face to be visible, we will show videos with your face obscured.

With your permission, we would also like to use extracts of the video and audio recordings for teaching, conferences, presentations, publications, and/or thesis work. Please note that these presentations may be recorded by individuals without our knowledge and displayed on social media.

It is up to you to decide whether or not to take part. If you choose not to participate, it will involve no penalty or loss of benefits to which you are otherwise entitled. If you decide to take part, you will be given this information sheet to keep and be asked to sign a consent form. If you decide to take part, you are still free to withdraw at any time and without giving a reason.

B. Consent Form – UCL Research Ethics Committee

Title of Project: **Emotion & Pain Project**
This study has been approved by the UCL Research Ethics Committee [Project ID Number]:
UCLIC/1516/012/Staff Berthouze/Singh

Participant's Statement

I ……………………………………….....................................

agree that I have

- read the information sheet and/or the project has been explained to me orally;
- had the opportunity to ask questions and discuss the study;
- read the guidelines on the use of computer game that may be used in the study;
- received satisfactory answers to all my questions or have been advised of an individual to contact for answers to pertinent questions about the research and my rights as a participant and whom to contact in the event of a research-related injury.
- I understand that my participation will be taped/video/sensors recorded and I am aware of and consent to the analysis of the recordings;
- I understand that I must not take part if I am not physically able to do the tasks;
- I agree to be invited in the future by UCL researchers to participate in follow-up studies.

For the following, please circle "Yes" or "No" and initial each point.

____I agree for the videotape to be used by the researchers in this project in further research studies YES / NO

____I agree for the videotape to be used by the researchers to demonstrate assistive technology to people with chronic pain and clinicians YES / NO

____I agree for the videotape to be used by the researchers for teaching, conferences, presentations, publications, and/or thesis work. I understand that these presentations may be recorded without the knowledge of the researchers by media or other individuals/researchers YES / NO

____ I agree for the videotape to be used in other projects by members of this research group YES / NO

____I agree for the videotape to be shared with researchers who are not involved in this project YES / NO

I understand that I am free to withdraw from the study without penalty if I so wish and I consent to the processing of my personal information for the purposes of this study only and that it will not be used for any other purpose. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998.

Signed: Date:

Investigator's Statement

I ………………………………………………………………………..

confirm that I have carefully explained the purpose of the study to the participant and outlined any reasonably foreseeable risks or benefits (where applicable).

Signed: Date:

C. Information Sheet – NHS Research Ethics Committee

University College London Hospitals **NHS**
NHS Foundation Trust

Reference: IS-Evaluation-CP
UCL Project ID number: 10/0514
REC number:
Form version: 1.0
Date: 14/12/2011

1. Study title

Automated psychological & physical feedback for chronic pain rehabilitation

2. Invitation paragraph

You are being invited to take part in a research study. Before you decide, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

3. What is the purpose of the study?

The influence of pain on everyday life can be considerable. Pain is a complex and intense experience affecting the way we feel, move and approach different situations. This project aims to develop a technology to encourage people with chronic pain to do more physical activity and give feedback on the activity. In order to evaluate the effectiveness of the technology in giving feedback, we need people with chronic pain to try the technology and tell us how they experience it.

4. Why have I been invited?

We are asking people with chronic low back pain to volunteer for this study.

5. Do I have to take part?

It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and you will be asked to sign a consent form. If you decide to take part you are still free to withdraw at any time and without giving a reason. A decision to withdraw at any time, or a decision not to take part, will not affect the care you receive.

6. What is involved in the study?

This project aims develop healthcare technology to help patients with chronic pain by providing feedback on their movement performance and psychological support during self-directed rehabilitation.

You will be introduced to the technology and given an introduction and demonstration of the technology. You can then try the technology if you wish for a maximum duration of 5 minutes at a time. This will involve doing physical activity like bending, stretching, and walking. The duration of physical activity will not exceed 30 minutes. A researcher will always be present with you. You may be asked to wear some motion sensors, heart rate monitor or EMG sensors (sensors to measure muscle activity). These sensors will not do any harm and are often used in therapy. If at any stage of the activity you feel uncomfortable, you can withdraw from the study. After the evaluation session, there will be a short interview to discuss your experience with the technology. You will be video recorded during the activity session and audio recorded during the interview. All data will be held in accordance with the data protection act.

7. What are the possible benefits of taking part?

There is no direct benefit to you from taking part in this study: we are asking you to do it to help design a technology to support and motivate physical activity in people with chronic pain.

8. How will Information be kept?

A unique research ID number will be assigned to the information we collect from you, and any personal identifiable information, such as your name and data of birth, will be in a separate file and not linked directly with the rest of the information.

All the information collected will be treated according with the Data Protection Act 1998 and UCL Data Protection Act Policy 2000 (http://www.ucl.ac.uk/efd/recordsoffice/data-protection/). Paper records will be stored in locked filing cabinets. Digital information (e.g. your movement data and the video recording which will be encrypted) will be stored in password protected and secure computers to be used by researchers involved in the project.

9. What if something goes wrong?

Every care will be taken in the course of this study. However, if you wish to complain, or have any concerns about any aspect of the way you have been approached or treated by members of staff or about any side effects (adverse events) you may have experienced due to your participation in the study, the normal National Health Service complaints mechanisms are available to you. Please ask to a member of the research team if you would like more information on this. Details can also be obtained from the Department of Health website: http://www.dh.gov.uk

10. What will happen to the results of the research study?

This research project is 4 years long, and we would hope to publish and disseminate the results, or to present them at conferences, during and after the project. During the dissemination process no patients' names will be disclosed either in publications or in conferences. If you would like us to send you a summary of our findings, please give us a mailing or e-mail address so that we can do so.

11. Who is organising and funding the research?

The research is funded by The Engineering and Physical Sciences Research Council (EPSRC) grant to Dr Berthouze at UCL.

12. Withdrawal from the project

Your participation in this study is entirely voluntary. You are free to decline to enter or to withdraw from the study any time without having to give a reason. If you choose not to enter the trial, or to withdraw once entered, this will in no way affect your future medical care. All information provided will be treated as strictly confidential and will only be used for medical purposes. Participation in this study will in no way affect your legal rights.

13. Who has reviewed the study?

The study has been reviewed and passed by the UCLH Research Ethics Committee and the Engineering and Physical Sciences Research Council (EPSRC).

14. Contact for further information

If you want any further information about the study, please contact:

Dr Nadia Berthouze 020 7679 0690 n.berthouze@ucl.ac.uk

Dr Amanda Williams 020 7679 1608 amanda.williams@ucl.ac.uk

Aneesha Singh 020 7679 0683 (x30683) aneesha.singh.10@ucl.ac.uk

Or visit the project website: http://www.emo-pain.ac.uk

Thank you for taking the time to read this information sheet and considering taking part in the study.

D.Consent Form – NHS Research Ethics Committee

Reference: CF-Evaluation-CP
Centre Number:
Participant Identification Number for this study:
UCLH Project ID number: 10/0514
Form version: 2.0
Date: 14/12/2012

Consent Form for Evaluation of Technology

Title of project: **Automated psychological & physical feedback for chronic pain rehabilitation**
Name of Principal Investigator: Dr Nadia Berthouze

Please initial box

1.	I …….................……………….......confirm that I have read and understood the information sheet dated *14/12/2011 (version1.0)* for the above study and have had the opportunity to ask questions.	
2.	I confirm that I have had sufficient time to consider whether or not I want to take part in the study	
3.	I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my medical care or legal rights being affected.	
4.	I agree that my evaluation session can be video taped YES/NO	
5.	I agree for the video recording to be used during the study for this research study ONLY YES / NO	
6.	I agree for the video recording to be used by the researchers of this study ONLY YES / NO	
7.	I agree that my interview can be audio-recorded YES/NO	
8.	I agree for the interview transcript to be used during the study for this research study ONLY YES / NO	
9.	I agree for the interview transcript to be used by the researchers of this study ONLY YES / NO	
10.	I agree to take part in the above study	

Participant: ____________________________ Date ________ Signature ______________________

Person taking consent: ______________________ Date ________ Signature__________________

Dr Nadia Berthouze Date ____________ Signature _________________________
Researcher (to be contacted
if there are any problems)

Comments or concerns during the study

If you have any comments or concerns you may discuss these with the investigator. If you wish to go further and complain about any aspect of the way you have been approached or treated during the course of the study, you should write or get in touch with the Complaints Manager, UCL hospitals. Please quote the UCLH project number at the top this consent form.

Reference: CF-Video
Centre Number:
Participant Identification Number for this study:
UCLH Project ID number: 11/0514
Form version: 1.0
Date: 14/12/2011

Consent form for video recording evaluation (CF-Video)

Title of project: **Automated psychological & physical feedback for chronic pain rehabilitation**
Name of Principal Investigator: Dr Nadia Berthouze

Please initial box

1.	I agree for the videotape to be used by the researchers for teaching or conference presentations YES / NO	
2.	I agree for the videotape to be used in other projects by members of this research group YES / NO	
3.	I agree for the videotape to be shared with researchers who are not involved in this project YES / NO	

Participant: ___________________ Date ____________ Signature _________________

Person taking consent: _________________________ Date __________ Signature_____________

Dr Nadia Berthouze Date ____________ Signature _________________________
Researcher (to be contacted
if there are any problems)

Comments or concerns during the study

If you have any comments or concerns you may discuss these with the investigator. If you wish to go further and complain about any aspect of the way you have been approached or treated during the course of the study, you should write or get in touch with the Complaints Manager, UCL hospitals. Please quote the UCLH project number at the top this consent form.

UCL HOSPITALS

UCL Hospitals is an NHS Foundation Trust incorporating the Eastman Dental Hospital, Elizabeth Garrett Anderson & Obstetric Hospital, The Heart Hospital, Hospital for Tropical Diseases, National Hospital for Neurology & Neurosurgery, The Royal London Homoeopathic Hospital and University College Hospital.

THE NATIONAL HOSPITAL FOR NEUROLOGY AND NEUROSURGERY

APPENDIX II

A. Pie Charts showing the Frequencies of the Three Levels of MRSE in Instances of Full Trunk Flexion, Forward Trunk Flexion, and Sit-To-Stand with Disagreements between the Ratings provided in The Annotation Study.

Full Trunk Flexion

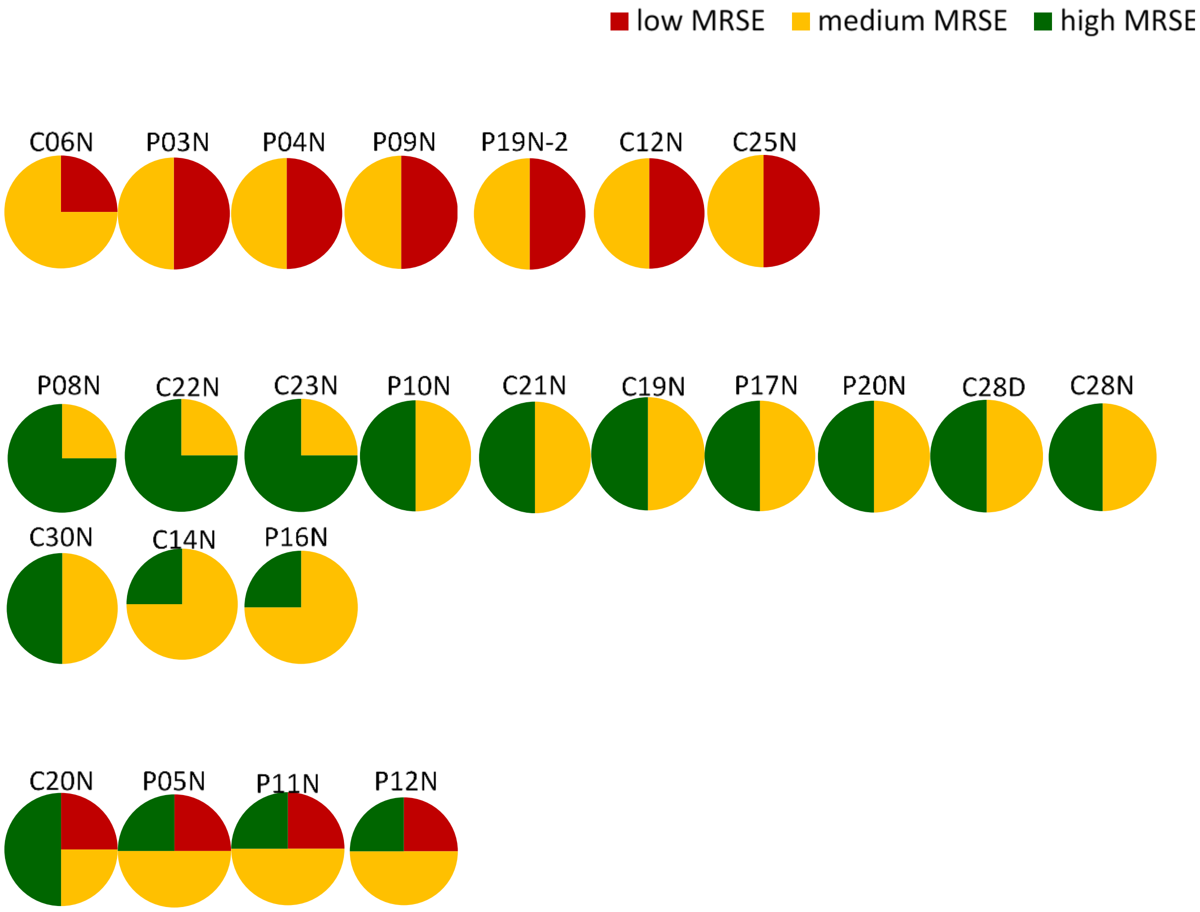


Fig. II-A1. Each pie chart indicates the frequency of the three MRSE labels in the rating for a Full Trunk Flexion instance where there was lack of consensus among the four raters for that instance. The pie chart titles refer to the instance ID with ‘P’ and ‘C’ for a participant with CP and a healthy control respectively and ‘N’ and ‘D’ for lower and higher level challenge of the movement type respectively

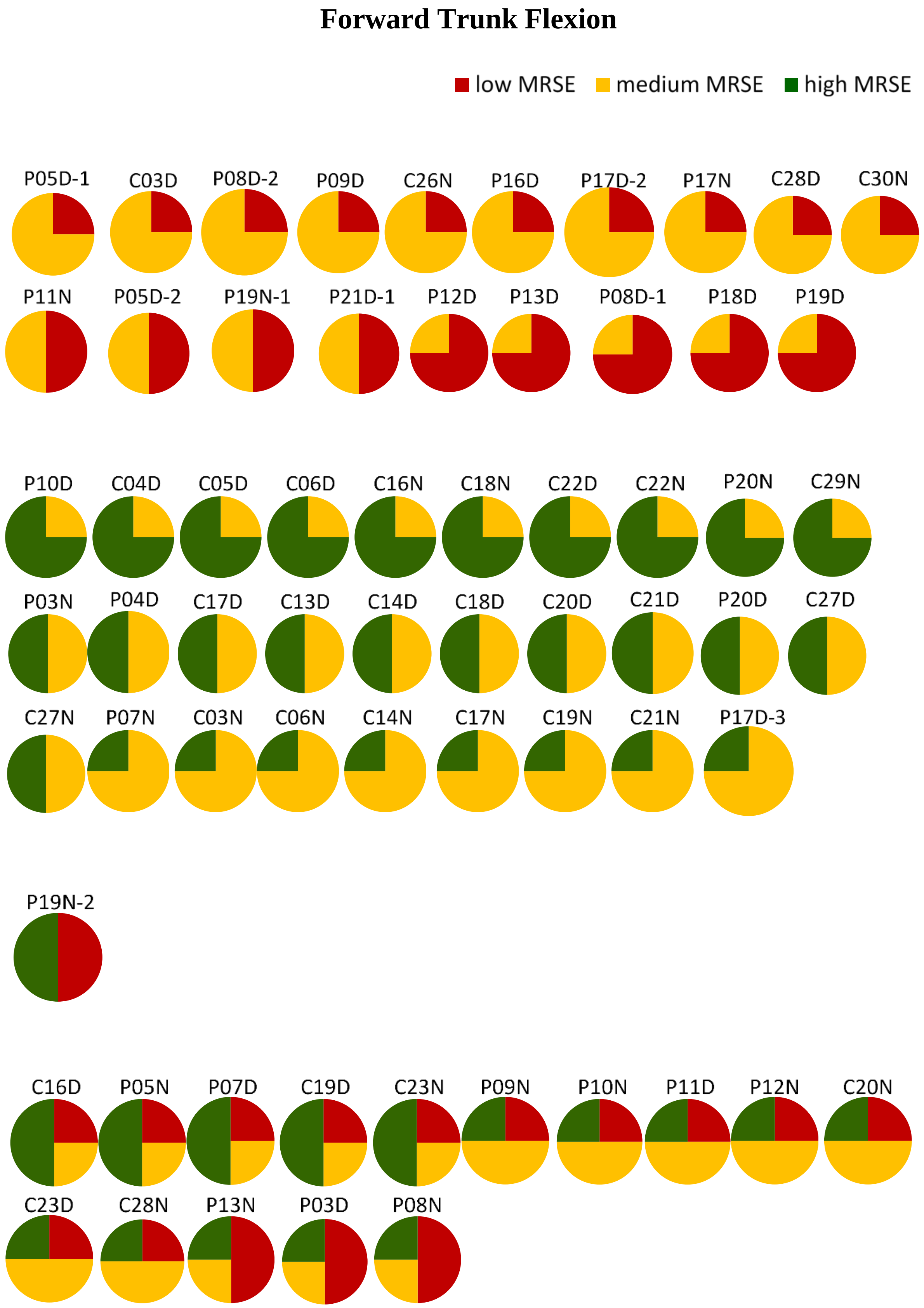


Fig. II-A2. Each pie chart indicates the frequency of the three MRSE labels in the rating for a Forward Trunk Flexion instance where there was lack of consensus among the four raters for that instance. The pie chart titles refer to the instance ID with ‘P’ and ‘C’ for a participant with CP and a healthy control respectively and ‘N’ and ‘D’ for lower and higher level challenge of the movement type respectively

Sit-to-Stand I - Low versus Medium MRSE

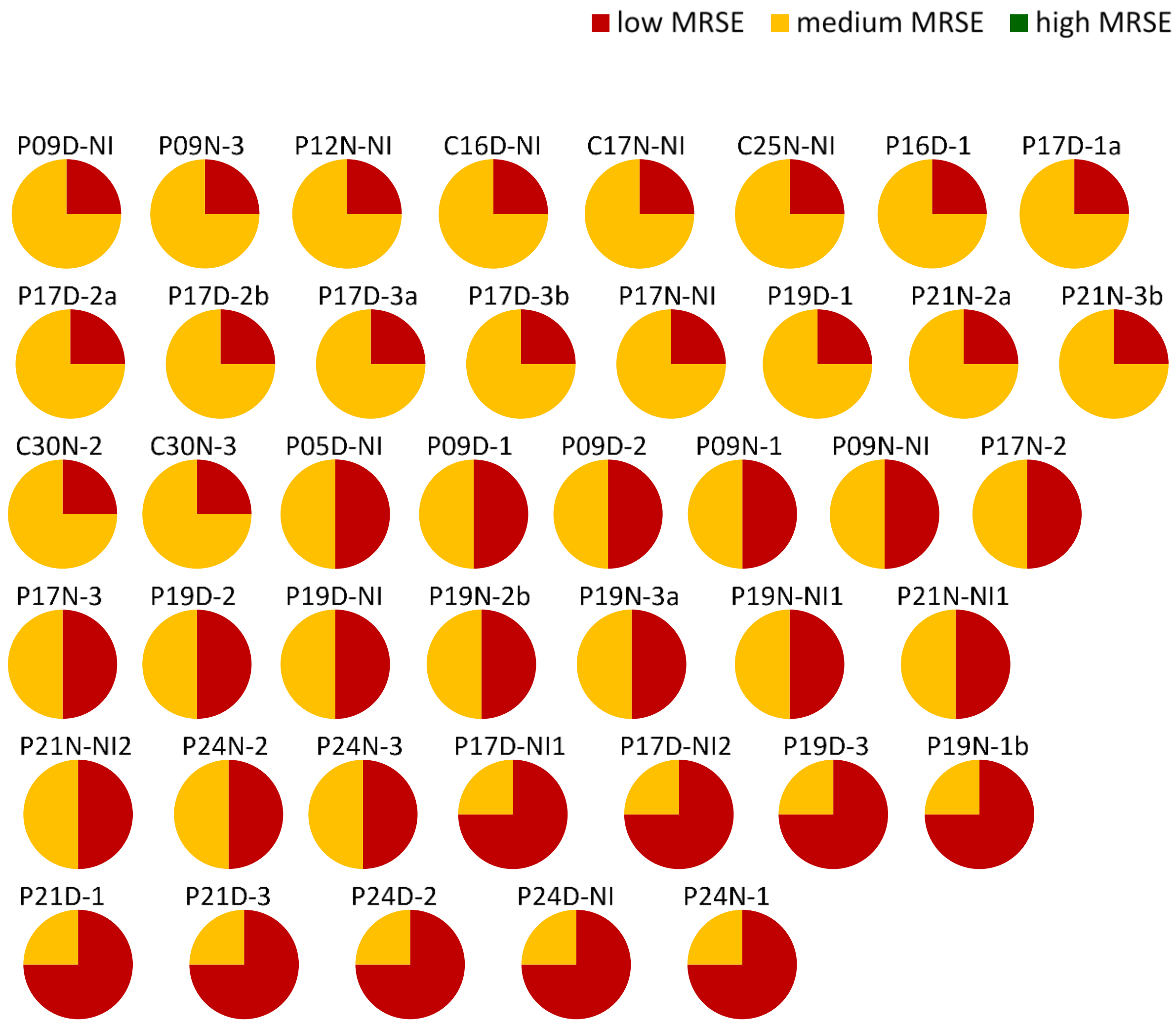


Fig. II-A3a. Each pie chart indicates the frequency of the three MRSE labels in the rating for a Sit-to-Stand instance where there was disagreement between low and medium MRSE. The pie chart titles refer to the instance ID with 'P' and 'C' for a participant with CP and a healthy control respectively and 'N' and 'D' for lower and higher level challenge of the movement type respectively

Sit-to-Stand II - Medium versus High MRSE

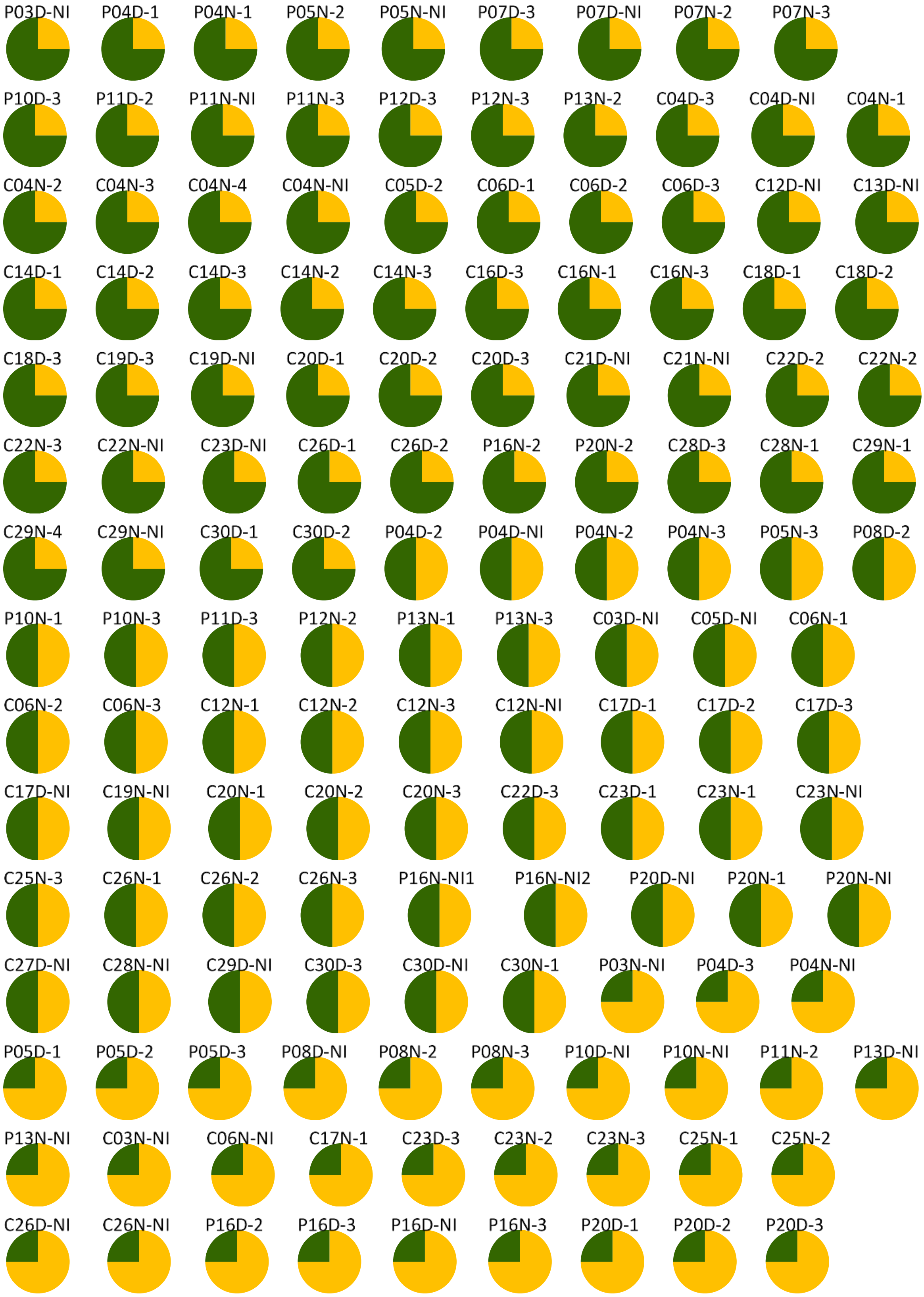


Fig. II-A3b. See Fig. II-A3a

Sit-to-Stand III – Low or Low and Medium versus High MRSE

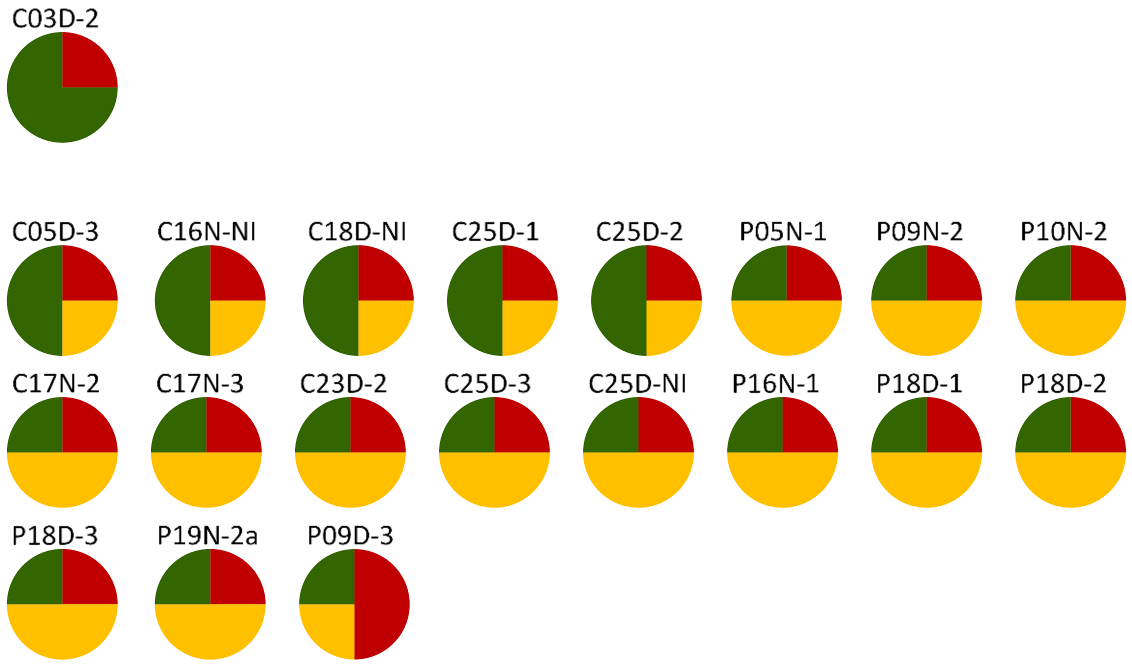


Fig. II-A3c. See Fig. II-A3a.

B. Cues Physiotherapists Reported Using in Estimating Self-Efficacy in The Annotation Study Presented in Chapter 5

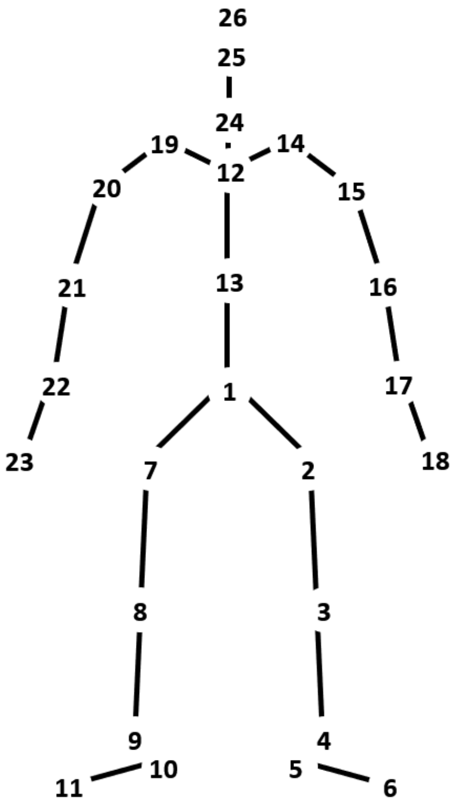
Rater ID	Cues (Extracts)	Rater ID	Cues (Extracts)
R2	speed	R14	speed of movement
R2	hesitation	R14	through sequencing
R3	facial expression	R14	range of lumbar flexion/extension
R3	speed	R14	balance and alignment
R3	smoothness of movement	R15	speed of starting
R3	start	R16	looking down at assessors, equipment
R3	finish position	R16	looking down at themselves - reassurance
R3	general look of relaxation	R16	hesitation
R4	speed	R16	facial expression
R4	weight transfer	R17	speed
R4	fluidity of movement	R17	quality of movement
R5	speed of movement	R17	facial expression
R6	ease in which they performed task	R18	how long they took before they did it
R6	speed	R19	global efficiency
R7	speed	R19	seamless transition
R7	expression on face	R20	speed
R8	hesitation on initiating	R20	fluidity of movement
R8	observing initiation of movement	R21	speed
R8	amplitude of range of movement	R21	subtle facial expression
R8	speed	R21	symmetry
R8	fluidity of movement	R21	fluency of movement - pause etc
R8	facial expression	R21	unusual pattern
R9	guarded behaviour	R22	how fluid movement looked
R9	speed of movement	R22	how present they looked whilst doing it
R9	facial expression	R23	facial expression
R10	balance saving reactions	R23	smoothness of movement
R10	blink rate	R23	unnatural poses
R10	facial expression grimace	R23	final posture (if it looked natural to the subject, i.e. if looking comfortable)
R10	avertal gaze	R24	speed
R10	start	R24	length of time pose held
R10	end positions	R24	delay with movement
R11	speed	R25	facial expressions
R11	willingness to move	R25	splinting behaviours
R12	amount of movement from trunk	R25	flow
R12	speed of movement	R25	that they or several participants repeated movements
R13	how quickly they are performing the movement	R25	interaction or not with research team

Rater ID	Cues (Extracts)
R25	if they scanned environment around them
R26	speed
R26	quality of movement
R26	facial cues
R27	ease of movement
R27	willingness
R27	no hesitation
R28	jerky
R28	quality of movement
R28	speed of movement
R28	compensatory movements
R28	facial expressions
R29	smoothness of movement
R29	facial expression
R30	speed
R30	fluidity of movement

APPENDIX III

Movement Features Investigated

Notation



- $t = 1, \ldots, T$ where T = duration in frames
- $b_k = \left\{ b_{k_t}, \quad \forall t : t = 1, 2, \ldots, T \right\}$, where $k = 1, \ldots, 26$, corresponding to the labels in the figure,
- b_{k_t} = three-dimensional vector $[\, b_{k_t}^x, b_{k_t}^y, b_{k_t}^z \,]$ describing position of joint k in the anterior-posterior, lateral, and vertical axes respectively at time t
- $m_q = \left\{ m_{q_t}, \quad \forall t : t = 1, 2, \ldots, T \right\}$, where $q = 1, 2, 3, 4$ for the right and left lumbar paraspinal and trapezius respectively

A. Pain Level Detection

Feature	Formula
Number of peaks in the vertical displacement of the upper arm (n_p)	$n_p = \sum_{t=1}^{T} g_t$ where $g = \begin{cases} 1 & ((f_t > f_{t-1})\ AND\ (f_t \geq f_{t+1}))\ OR\ ((f_t \geq f_{t-1})\ AND\ (f_t > f_{t+1})) \\ 0 & otherwise \end{cases}, \quad \forall t : t = 1, 2, \ldots, T$ $f = \left\{ \dfrac{b'^{z}_{16_t} - b'^{z}_{16_t}}{\left\| b'_{16_{t=1}} - b'_{15_{t=1}} \right\|}, \quad \forall t : t = 1, 2, \ldots, T \right\}$
Range of peaks in the vertical displacement of the upper arm	$\hat{t}_p = \dfrac{\underset{t}{\arg\max}\left(\{g \mid g_t = 1\}\right) - \underset{t}{\arg\min}\left(\{g \mid g_t = 1\}\right)}{T \times (f_{t=T} - f_{t=1})}$ where g is same as in above
Mean height of peaks in the vertical displacement of the upper arm	$\hat{p} = \dfrac{\sum_{t=1}^{T}(f_t \mid g_t = 1)}{n_p \times (f_{t=T} - f_{t=1})}$ where f and g are same as in above
Range of head flexion	$\hat{z} = \max(z) - \min(z)$ $z = \left\{ \dfrac{b^{z}_{24_t} - b^{z}_{13_t}}{\left\| b_{24_{t=1}} - b_{13_{t=1}} \right\|}, \quad \forall t : t = 1, 2, \ldots, T \right\}$
Range of trunk flexion	$\hat{\theta}_{trunk} = \max(\theta_{trunk}) - \min(\theta_{trunk})$ where $\theta_{trunk} = \left\{ \begin{array}{l} \tan^{-1}\left(\dfrac{\left\|(b_{12t} - b_{1t}) \times (b_{3t} - b_{1t})\right\|}{(b_{12t} - b_{1t}) \bullet (b_{3t} - b_{1t})} \right) - c^{l}_{t} + \\ \tan^{-1}\left(\dfrac{\left\|(b_{12t} - b_{1t}) \times (b_{8t} - b_{1t})\right\|}{(b_{12t} - b_{1t}) \bullet (b_{8t} - b_{1t})} \right) - c^{r}_{t}, \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\}$ $c^{l} = \begin{cases} \pi - \tan^{-1}\left(\dfrac{\left\|(b_{2_t} - b_{3_t}) \times (b_{4_t} - b_{3_t})\right\|}{(b_{2_t} - b_{3_t}) \bullet (b_{4_t} - b_{3_t})} \right) & b^{local}_{3_t} \times b^{local}_{13_t} > 0 \\ 0 & otherwise \end{cases} \quad \forall t : t = 1, 2, \ldots, T$ and $c^{r} = \begin{cases} \pi - \tan^{-1}\left(\dfrac{\left\|(b_{7_t} - b_{8_t}) \times (b_{9_t} - b_{8_t})\right\|}{(b_{7_t} - b_{8_t}) \bullet (b_{9_t} - b_{8_t})} \right) & b^{local}_{3_t} \times b^{local}_{13_t} > 0 \\ 0 & otherwise \end{cases} \quad \forall t : t = 1, 2, \ldots, T$ $b^{local}_{k_t} = b_{k_t}$ transformed such that. b_{1_t} becomes its reference point.

Feature	Formula
Range of trunk flexion (with respect to the ground)	$\hat{\theta}^{g}_{trunk} = \max(\theta^{g}_{trunk}) - \min(\theta^{g}_{trunk})$ where $\theta^{g}_{trunk} = \left\{ \cos^{-1}\left(\frac{\overline{n^{fr}_t} \bullet \overline{n^{g}_t}}{\left\Vert \overline{n^{fr}_t} \right\Vert \left\Vert \overline{n^{g}_t} \right\Vert} \right), \quad \forall t : t = 1, 2, \ldots, T \right\}$ with $\overline{n^{fr}_t}$ = normal vector of plane with b_{1_t}, b_{14_t}, b_{19_t} $\overline{n^{g}_t}$ = normal vector of the traverse plane
Range of trunk flexion before lift (for sit-to-stand)	$\hat{\theta}^{lift}_{trunk} = \max(\theta^{lift}_{trunk}) - \min(\theta^{lift}_{trunk})$ $\theta^{lift}_{trunk} = \left\{ \begin{array}{l} \tan^{-1}\left(\frac{\left\Vert (b_{12t} - b_{1t}) \times (b_{3t} - b_{1t}) \right\Vert}{(b_{12t} - b_{1t}) \bullet (b_{3t} - b_{1t})} \right) + \tan^{-1}\left(\frac{\left\Vert (b_{12t} - b_{1t}) \times (\langle 8 \rangle_t - b_{1t}) \right\Vert}{(b_{12t} - b_{1t}) \bullet (\langle 8 \rangle_t - b_{1t})} \right), \\ \forall t : t = 1, 2, \ldots, t^{lift} \end{array} \right\}$ where t^{lift} is the time the pelvic joint begins ascension.
Duration (for sit-to-stand)	$\Delta t = T^{*} - t_1$ where T^{*} = frame where the pelvic joint reaches maximum vertical displacement
Average lift speed (for sit-to-stand)	$\hat{s} = \frac{\sum_{t=t^{lift}}^{T^{*}} s_t}{T}$ where $s = \left\{ b^{z}_{1_t} - b^{z}_{1_{t-1}}, \quad \forall t : t = 2, 3, \ldots, T \right\}$
Pelvis angle at lift (for sit-to-stand, $k = 3$ for left and right respectively)	$\theta^{t^{lift}}_{trunk} = \tan^{-1}\left(\frac{\left\Vert (b_{12_{t^{lift}}} - b_{1_{t^{lift}}}) \times (b_{k_{t^{lift}}} - b_{1_{t^{lift}}}) \right\Vert}{(b_{12_{t^{lift}}} - b_{1_{t^{lift}}}) \bullet (b_{k_{t^{lift}}} - b_{1_{t^{lift}}})} \right)$
Left knee angle at lift (for sit-to-stand)	$\theta^{t^{lift}}_{lknee} = \tan^{-1}\left(\frac{\left\Vert (b_{2_{t^{lift}}} - b_{3_{t^{lift}}}) \times (b_{4_{t^{lift}}} - b_{3_{t^{lift}}}) \right\Vert}{(b_{2_{t^{lift}}} - b_{3_{t^{lift}}}) \bullet (b_{4_{t^{lift}}} - b_{3_{t^{lift}}})} \right)$
Right knee angle at lift (for sit-to-stand)	$\theta^{t^{lift}}_{rknee} = \tan^{-1}\left(\frac{\left\Vert (b_{7_{t^{lift}}} - b_{8_{t^{lift}}}) \times (b_{9_{t^{lift}}} - b_{8_{t^{lift}}}) \right\Vert}{(b_{7_{t^{lift}}} - b_{8_{t^{lift}}}) \bullet (b_{9_{t^{lift}}} - b_{8_{t^{lift}}})} \right)$
Muscle relaxation change point (for each muscle q)	$\hat{t}_e = \frac{\underset{t}{\arg\max}\left(\left\{ \frac{\sum_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w + (d+1)/2, \ldots, T - \left(w + (d+1)/2\right) \right\} \right)}{T}$
Muscle relaxation magnitude (for each muscle q)	$\hat{e} = \frac{\max\left(\left\{ \frac{\sum_{i=t-\left(w+d/2\right)}^{t-d/2} m_{q_i}}{w} - \frac{\sum_{i=t+d/2}^{t+\left(w+d/2\right)} m_{q_i}}{w}, \quad \forall t : t = w + (d+1)/2, \ldots, T - \left(w + (d+1)/2\right) \right\} \right)}{\max(m_q)}$

B. Self-Efficacy Level Detection

Feature	Formulae
Speed (for k = 17, 22, 3, 8, 14, 19, 26 respectively. For bilateral joints, the mean for the left and right was used)	$\hat{s} = \frac{\sum_{t=2}^{T} s_t}{T}$ where $s = \left\{ \begin{array}{l} \sqrt{\left(b_{k_t}^{x} - b_{k_{t-1}}^{x}\right)^2 + \left(b_{k_t}^{y} - b_{k_{t-1}}^{y}\right)^2 + \left(b_{k_t}^{z} - b_{k_{t-1}}^{z}\right)^2}, \\ \forall t : t = 2, \ldots, T \end{array} \right\}$
Joint angle range ([b_{end1}, b_{mid}, b_{end2}] = [b_{26}, b_1, b_4], [b_{26}, b_1, b_9], [b_{12}, b_1, b_3], and [b_{12}, b_1, b_8] for pelvic joint angles, [b_2, b_3, b_4] and [b_7, b_8, b_9] for knee angles, [b_{15}, b_{16}, b_{17}] and [b_{20}, b_{21}, b_{22}] for elbow angles, [b_{24}, b_{14}, b_{15}] and [b_{24}, b_{19}, b_{20}] for shoulder angles, [b_{16}, b_{14}, b_2] and [b_{21}, b_{19}, b_7] for lateral angles for the shoulder, and [b_{26}, b_{24}, b_{13}] for the neck)	$\hat{\theta} = \max(\theta) - \min(\theta)$ where $\theta = \left\{ \begin{array}{l} \tan^{-1}\left(\frac{\left\| \left(b_{end1t} - b_{midt}\right) \times \left(b_{end2t} - b_{midt}\right) \right\|}{\left(b_{end1t} - b_{midt}\right) \bullet \left(b_{end2t} - b_{midt}\right)} \right), \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\}$
Sum of energies	$E = \sum_{t=2}^{T} \left(\theta_t^{'} - \theta_{t-1}^{'}\right)^2$
Symmetry	$\gamma = \frac{\sum_{t=1}^{T} \left(\left\| b_{14_t}^{x} - b_{19_t}^{x} \right\| \right)}{T} + \frac{\sum_{t=1}^{T} \left(\left\| b_{14_t}^{z} - b_{19_t}^{z} \right\| \right)}{T}$
Mean muscle activity	$\hat{m} = \frac{\sum_{t=1}^{T} m_{q_t}}{T}$
Joint fluidity (Balasubramanian, Melendez-Calderon, and Burdet 2012)	$\alpha = -\sum_{k=1}^{K_c - 1} \sqrt{\left(\frac{1}{K_c - 1}\right)^2 + \left(\Delta\hat{V}_k\right)}$ where $\Delta\hat{V}_k = \hat{V}_k - \hat{V}_{k-1}, \quad k \in [1, K-1]$ $\hat{V}_k = \frac{V_k}{V_{k=0}}, \quad V_k = \left| fft(s_{zp}) \right|, \quad k \in [0, K-1]$ $s_{zp_t} = \begin{cases} s_t, & 0 \le t \le T-1 \\ 0, & T \le t \le K-1 \end{cases}$ $fft(\sim)$ is the K-point Fast Fourier Transform, K_C is the discrete time Fourier transform index that corresponded to the cut-off frequency, and $K = 2^{ceil(\log_2 T) + 4}$

C. Emotional Distress Level Detection

Feature	Formula
Shoulder protraction	$\theta_{l-r} = \min \left\{ \cos^{-1}\left(\frac{\overline{n_t^l} \bullet \overline{n_t^r}}{\left\| \overline{n_t^l} \right\| \left\| \overline{n_t^r} \right\|} \right), \quad \forall t : t = 1, 2, \ldots, T \right\}$ where $\overline{n_t^l}$ = normal vector of the plane with b_{12_t}, b_{13_t}, b_{14_t} $\overline{n_t^r}$ = normal vector of the plane with b_{12_t}, b_{13_t}, b_{19_t}
Speed (for k = 17, 22, 3, 8, 14, 19, 26 respectively. For bilateral joints, the mean for the left and right was used)	$\hat{s} = \sum_{t=2}^{T} s_t$ $s_t = \sqrt{\left(b_{k_t}^x - b_{k_{t-1}}^x\right)^2 + \left(b_{k_t}^y - b_{k_{t-1}}^y\right)^2 + \left(b_{k_t}^z - b_{k_{t-1}}^z\right)^2}$
Energy	$r_t = \frac{\left\| b_{k\,t} \right\|^2}{\left(\cos^{-1}\left(\frac{b_{k\,t} \bullet b_{k\,t-1}}{\left\| b_{k\,t} \right\| \left\| b_{k\,t-1} \right\|} \right) \right)^2}$ $E = \frac{\sum_{t=2}^{T} s_t^{\,2}}{2T} + \frac{\sum_{t=2}^{T} r_t^{\,2}}{2T}$ where s_t and k are the same as in above
Minimum head angle (the duration of θ_{min}±10° was also extracted)	$\theta_{head-trunk} = \frac{\sum_{t=1}^{T} \theta_t \quad iff\ \theta_{\min} <= \theta_t <= \theta_{\min} + 10^\circ}{\sum_{t=1}^{T} 1 \quad iff\ \theta_{\min} <= \theta_t <= \theta_{\min} + 10^\circ}$ where $\theta_{\min} = \min \left\{ \tan^{-1}\left(\frac{\left\| \left(b_{26_t} - b_{24_t}\right) \times \left(b_{12_t} - b_{24_t}\right) \right\|}{\left(b_{26_t} - b_{24_t}\right) \bullet \left(b_{12_t} - b_{24_t}\right)} \right), \forall t : t = 1, 2, \ldots, T \right\}$
Minimum distance of the hand to the thigh	$d_{\min} = \min \left(\begin{array}{l} \min \left\{ \begin{array}{l} \left(\frac{\left\| \left(b_{2t} - b_{3t}\right) \times \left(b_{17t} - b_{3t}\right) \right\|}{\left(b_{17t} - b_{3t}\right)} \right), \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\}, \\ \min \left\{ \begin{array}{l} \left(\frac{\left\| \left(b_{7t} - b_{8t}\right) \times \left(b_{22t} - b_{8t}\right) \right\|}{\left(b_{22t} - b_{8t}\right)} \right), \\ \forall t : t = 1, 2, \ldots, T \end{array} \right\} \end{array} \right)$

APPENDIX IV

A.Ubi-EmoPain Dataset Participant Profile: Demographics

ID	Gender	Age	Occupation	Number of years of pain
P01	Female	77	Retired	14
P02	Female	58	Retired (due to health and pain)	10
P03	Female	66	Counsellor-Therapist	40+
P04	Female	66	-	50
P05	Female	50	Marketing	10
P06	Female	27	Artist	10
P07	Female	60	Full-time carer to disabled family member	35
P08	Female	36	Economist	approximately 12
P09	Female	44	Teaching assistant	30
P10	Male	27	Not working due to health	27
P11	Female	44	Paediatric occupational therapist	38
P12	Female	53	Self-employed	53

B. Ubi-EmoPain Dataset Participant Profile: Pain Related Self-Report

ID	Usually Pain Intensity (0-10)	Usually Pain Distress (0-10)	Current Pain Intensity (0-10)	Current Pain Distress (0-10)	Pain Locations
P01	3	0	3	0	lower back and neck
P02	10	10	8	8	all over the body
P03	4	4	3	3	lower back (right side) and left leg
P04	7	7	2	2	lower back (right side)
P05	7	8	8	6	lower back and left knee
P06	7	5	6	4	lower back, waist, knees, legs, shoulders
P07	8	7	0	2	lower back
P08	4	6	3	4	lower and upper back, wrists, left knee and ankle, and neck
P09	4	4	5	3	lower back, elbows, shoulders, knees, ankles, and neck
P10	8	7	8	6	lower and upper back, legs, shoulders, hands, waist, and legs
P11	7	7	5	4	lower and upper back, shoulders, wrists, knees, ankles, hips, left side of trunk
P12	5	3	6	3	lower and upper back, hands, legs, hips, elbows, shoulders, neck, and head

C. Ubi-EmoPain Dataset Participant Profile: Movement Self-Report

ID	Exercise Frequency	Sit-to-Stand Avoidance	Forward Trunk Flexion Avoidance	Full Trunk Flexion Avoidance	Use to support physical activity
P01	Daily	Never	Never	Often	-
P02	Several times a day	Often	Often	Always	stretching exercise, pain diary
P03	Daily	A few times	Often	A few times	-
P04	Couple of times a week	Never	Never	A few times	-
P05	Couple of times a week	Never	A few times	Never	Diary, apps, kinesiology tape
P06	Rarely	Always	Always	Always	Power assist manual chair
P07	Daily	A few times	A few times	A few times	-
P08	Couple of times a week	Never	Never	Never	-
P09	Couple of times a week	Never	Often	A few times	-
P10	Couple of times a week	Never	Never	Never	Hand and wrist splint, orthopaedic insole for shoes
P11	Couple of times a week	A few times	Never	Never	apps
P12	Several times a day	A few times	A few times	A few times	Write down plans