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A System for the Visual Detection and Analysis of Obsessive Compulsive Disorder

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed. I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

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Signed: Conor Cameron

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Contents

Abstract

Computer vision is a burgeoning field that lends itself to a diverse range of challenging problems. Recent advances in computing power and algorithmic sophistication have prompted a renaissance in the literature of this field, as previously computationally expensive applications have come to the fore. As a result, researchers have begun applying computer vision techniques especially prominently to the analysis of human actions, in an increasingly advanced manner. Chief among the potential applications of such human action analyses are: human surveillance, crowd analysis, gait analysis and health informatics. Even more recently, researchers have begun to realise the potential of computer vision techniques, occasionally in conjunction with other computational approaches, to enhance the quality of life for people living with mental illness. Much of this research has focused on enhancing the existing, traditionally psychiatric, treatment plans for such individuals. Conventionally, these treatment plans have involved a mental health professional taking a face-to-face approach and relying significantly on subjective feedback from the individual, regarding their current condition and progress. However, recent computational methods have focused on augmenting such approaches with objective, e.g. visual, monitoring and feedback on an individual's condition over time. Of these approaches, most have focused on depression, bipolar disorder, dementia, or some form of anxiety. However, none of the approaches described in the literature has been aimed directly at addressing the issues inherent to patients with Obsessive Compulsive Disorder.

Motivated by this, the proposed thesis comprises the design and implementation of a system that is capable of detecting and analysing the compulsive behaviours exhibited by individuals with Obsessive Compulsive Disorder. This is accomplished with the aim of assisting mental health professionals in their treatment of such patients. We achieved the aforementioned via a three-pronged approach, which is represented by the three core chapters of this thesis. Firstly, we created a system for the detection of general repetitive (compulsive) behaviours indicative of Obsessive Compulsive Disorder. This was achieved via the use of a combination of optical flow detection and thresholding, an image matching algorithm, and a set of repetition parameters.

Via this approach, we achieved good results across a set of three tested videos. Secondly, we proposed a system capable of classifying behaviour as either compulsive or non-compulsive based on the differences in the repetition intensity patterns across a set of behavioural examples. We achieved this via a form of motion history image, which we call a 'Temporal Motion Heat Map' (TMHM). We produced one such heat map per behavioural example and then reduced its dimensionality using histogram-based pixel intensity frequencies, before feeding the result into a Neural Network. This approach achieved a high classification accuracy on the set of 40 tested behavioural examples, thus demonstrating its ability to accurately differentiate between compulsive and non-compulsive behaviours, as compared to a set of existing approaches. Finally, we built a system that is capable of categorising different types of behaviour, both compulsive and non-compulsive, and then assessing them for relative approximate anxiety levels over time. We achieve this using a combination of Speeded-Up Robust Features (SURF) descriptors for behaviour classification and statistical measures for determining the relative anxiety of a given compulsion. This system is also able to achieve a good accuracy when compared with other approaches.

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List of Abbreviations

ASD Autism Spectrum Disorder

CBT Cognitive Behavioural Therapy

CFS Correlation-based Feature Selection

DBS Deep Brain Stimulation

ERP Exposure and Response Prevention Therapy

MEI Motion Energy Image

MHI Motion History Image

MoSIFT Motion Scale-Invariant Feature Transform

OCD Obsessive Compulsive Disorder

PAM Personalised Ambient Monitoring

PCA Principal Component Analysis

RTMHM Reduced Temporal Motion Heat Map

STIP Spatio-Temporal Interest Points

SURF Speeded-Up Robust Features

SVM Support Vector Machine

TMHM Temporal Motion Heat Map

Y-BOCS Yale-Brown Obsessive Compulsive Inventory

Publications from this Thesis

C. Cameron, I. Khalil, D. Castle. “A System for Detecting Compulsive Behaviours in Obsessive Compulsive Disorder”. *[To be submitted]*

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Chapter 1

Introduction

Over the last few decades there has been a considerable increase in interest in the application of computational approaches to analysing many information-rich aspects of human behaviour [1, 2, 3, 4, 5, 6, 7, 8]. Much of this research has been prompted by the recent increases in computing power and algorithmic sophistication that have allowed computer vision and similar techniques to be used to analyse large quantities of data in a reasonable period of time. In particular, video-based human activity analysis has seen notable growth in areas including: crowd behaviour dynamics [9, 10], ambient assisted living [11, 12], and automated human behaviour surveillance [13, 14]. Among these, a very promising field has emerged, which focuses on the manner in which human behaviour analysis can be used as a means of psychiatric monitoring, assistance and intervention. Many promising approaches have been proposed in this field, which together have covered a variety of mental health issues, including: Anxiety [15], Depression [16, 17], Bipolar Disorder [18], and Autism Spectrum Disorder (ASD) [19]. The benefits of such computational approaches to the analysis of behaviours endemic to various mental health issues is manifold. Namely, these approaches provide not only the ability to assist mental health professionals in their early diagnosis of an individual with a mental illness, but also more prominently in their ability to individualise and enhance the existing treatment plans available to individuals with mental health issues.

In this vein, we opted to produce a system for the detection, analysis and interpretation of specific types of behaviours endemic to Obsessive Compulsive Disorder (OCD); a condition which has, from the computational perspective, been hitherto under-appreciated in the literature. Moreover, OCD tends to manifest in a manner that is amenable to computer-vision-based behavioural monitoring. This is a result of the anxiety-based repetitive behavioural symptoms, known as 'compulsions', that are exhibited by most individuals suffering from the disorder. It is the visual detection and analysis of these compulsive behaviours, as well as the determination of that which visually separates these behaviours from non-compulsive behaviours that constitute the core of this thesis. We believe that the tripartite system contained in this thesis has demonstrated the ability to efficaciously monitor and analyse these OCD compulsions for the purpose of augmenting existing treatment plans. Furthermore, while the direct integration of the proposed system into existing mental health treatment plans is beyond the scope of this thesis, we nevertheless believe that this system yields good future potential for real-world implementation, as demonstrated by the results detailed herein.

1.1 Motivation

The motivations for directing this research specifically towards OCD, are as follows. As previously mentioned, there is a dearth of research in the computing literature on the subject of automated systems designed to detect, analyse and define compulsive OCD behaviours. Thus, it is currently an area of significant research potential, as well as for potential improvements in patient understanding and outcomes. Moreover, it is important to consider that OCD is not only an illness of considerable burden to both the sufferer and their family, but also constitutes a significant cost to the healthcare system, comparable with depression [20, 21]. Existing methods of assessing OCD and monitoring the progress of its treatment have tended to rely on subjective assessments, such as self-reports, questionnaires and patient interviews [22, 23, 24]. Systems such as that proposed in this thesis hold future potential to augment existing treatment plans by providing a greater depth of information to mental health professionals than would otherwise be available.

1.2 Existing Research

Regarding the literature on computational approaches to mental health issues, the most common approaches have tended to be those dealing with depressive disorders [25, 26, 27], one of the most common mental illnesses. These approaches often make use of accelerometers, computer vision, and self-reporting techniques in order to provide comprehensive insight into the behaviour of a given individual. Moreover, these approaches commonly look for the absence of normal behaviour, rather than the presence of abnormal behaviour. Such behavioural examples include lethargy, a general lack of daily movement, and a reduction in facial expressions from what would otherwise be considered normal for the individual. Additional approaches have considered bipolar disorder, which is a psychiatric disorder characterised by alternating bouts of anxiety and depression. Approaches designed to address this disorder, such as that proposed by Amor et al., have tended to rely on monitoring similar cues to those of depression [28]. Yet other approaches have looked into ASD, with the aim of analysing the stereotypical movements characteristic of the disorder [29]. These innovative and insightful systems demonstrate not only the considerable interest of the research community in taking a computational approach to psychiatric intervention, but also the viability of such an approach. Regardless, none of the approaches in the existing literature have focused specifically on OCD, thus indicating a void which holds great potential for future research applications.

From the opposing angle, a few computational behaviour analysis approaches have looked at the use of repetitive behaviour cues for a variety of different applications. For example, Lu et al. looked at detecting and classifying repetitive behaviour for the purposes of ergonomic benefits [30]; Endeshaw et al. and Jansohn et al. both looked into analysing repetitive motions in video content for the purposes of detecting sexually explicit material [31, 32]; and Fan et al. looked at repetitive sequential movements in an attempt to detect fraud at retail check-out stations [33]. However, none of these approaches is designed to handle the compulsions inherent to OCD, nor to consider a psychiatric perspective. Regardless, the overall body of research on repetitive behaviour detection and analysis is still quite scant, and no research that we yet have discovered focuses specifically on detecting or analysing the compulsive behaviours inherent to OCD. Due to this lack of attention, in conjunction with the distinct potential for enhancing the existing knowledge and treatment of the condition, we sought to build a system which could serve as a demonstration of the value of such research, by looking to detect and analyse the visible manifestations of OCD and use them as cues for treatment.

1.3 Our Contributions

This thesis comprises a number of contributions, partially technical, but mostly application and systems based. Our contributions include the following:

- **Provided a system that is capable of automatically detecting compulsive behaviours:** The first core chapter of this thesis is geared towards providing a system that can detect compulsive behaviours by exploiting their repetitive nature. More specifically, we use a combination of optical flow mechanisms, in conjunction with an image similarity algorithm and repetition thresholds in order to establish a baseline for unduly repetitive behaviour. The implementation of this portion of the thesis indicates good potential for detecting many of the general behavioural compulsions characteristic of OCD.

- **Presented an efficient representation for capturing compulsive behaviours:** In the second core chapter of this thesis, we present a method of capturing compulsive OCD behaviours, of variable duration and dynamism, in a reduced form that is suitable for both storage and classification. We achieve this via a type of Motion History Image, which we call a TMHM. TMHMs are a product of the frequency with which an optical flow vector moves across a given coordinate on a 2D video axis across time. We further reduce each TMHM into a histogram-based representation called a 'Reduced Temporal Motion Heat Map' (RTMHM). RTMHMs are an efficient format for storing compulsive and non-compulsive behaviours, whilst still preserving their degree of repetitiveness across time.

- **Provided a system that is capable of differentiating between compulsive and non-compulsive examples of the same type of behaviour:** In the second core chapter of this thesis, we provide an additional system for further differentiating between compulsive and non-compulsive behaviours. This is achieved through a combination of the aforementioned RTMHMs, Correlation-based Feature Selection (CFS), and a Multilayer Perceptron classification component. Our implementation of this portion of the thesis has demonstrated a high degree of accuracy in differentiating the compulsive and non-compulsive behaviours on which it has been tested.

- **Provided a system that is capable of differentiating between global degrees of behaviour compulsivity:** In the second segment of the second core chapter, we demonstrate that the aforementioned system is also capable of accurately differentiating between varying degrees of compulsivity among behaviours. This kind of 'global' compulsivity grading could provide valuable information to a mental health professional about the general lower, intermediate, and upper degrees of a given individual's compulsions and thus could potentially be helpful in assessing the general severity of said compulsions. We achieved this via the use of the system proposed in the first segment of the second core chapter, with some minor modifications made to the multilayer perceptron.

- **Demonstrated a method capable of successfully classifying different patterns of behaviour:** In the third core chapter of this thesis, we proffer a system that is capable of accurately clustering behaviour types that are typical of OCD, based on visual similarity. This is achieved by deriving SURF descriptors from TMHMs of compulsive behaviour from the second core chapter of this thesis. The SURF descriptors are then used to classify various labelled instances of compulsive and non-compulsive behaviour using a bag of words model and a Support Vector Machine (SVM) classifier with 4-fold cross-validation. This results in a robust system that is scale and translation invariant and requires only a basic set of manually labelled behaviour instances to be trained.

- **Presented a method of estimating the relative anxiety associated with an individual's compulsive behaviours:** In the third core chapter of this thesis, we also provided a method that could, for example, be used by mental health professionals to quickly and easily view the relative anxiety of an individual's compulsions. We achieved this by deriving a baseline average (mean) for each compulsive TMHM in a given behaviour cluster and then used this to compare each compulsive example of behaviour to the baseline for that cluster. This is valuable in that it could be used to compare compulsive behaviours both across time and within a given time period to establish whether any given example of compulsive behaviour is more or less anxiety-driven than usual for an individual.

1.4 Thesis Structure

The remainder of this thesis is organised in the following manner: *Chapter 2* provides foundational background material on OCD and how it connects to the proposed research. *Chapter 3* details our research on producing a system for the detection of OCD. *Chapter 4* explains the second phase of our research, which differentiates compulsive from non-compulsive behaviour by looking at inter-behavioural differences. *Chapter 5* discusses our work on providing a system for grouping behaviours, with the aim of determining the relative anxiety of a given behaviour. Finally, *Chapter 6* provides concluding remarks, which recapitulate the research that we have undertaken for this thesis, our results, their implications, any limitations of our research, and future research directions.

1.4.1 Background

The background chapter of this thesis provides an essential introduction to the fundamentals of OCD and how they relate to this thesis. It is thus recommended that the reader begin here in order to fully appreciate the content of the chapters that follow. Specifically, this chapter provides a general background on OCD, the motivations for the system proposed herein, and the current methods used to treat OCD and how they relate to this research.

1.4.2 Chapter 1

The first core chapter of this thesis delves into motion detection and analysis; a field that has witnessed significant research interest over the last decade. One of most intriguing recent developments in this field has been its potential application to assisting mental health professionals in their treatment of patients with a variety of mental health issues. In this first chapter we propose just such a novel system for patients with OCD, based on the repetitive nature of their compulsive behaviours. More specifically, we focus on the integration of optical flow algorithms with image similarity metrics and novel repetitive motion thresholds in order to automatically and accurately detect simulated compulsive behaviours from a set of video clips. The general novelty of this system lies in its ability to detect these compulsive OCD behaviours, based solely on their motion cues, repeat rates and visual similarities. In achieving this, we don't rely on any prior training methods, specialist equipment, predefined human models, or action restrictions, thus increasing efficiency and reducing overall system complexity. The experimental simulations conducted for this first core chapter indicate that the proposed system is able to detect an average of 87% of simulated compulsive behaviour repetitions in the tested videos and overall was able to successfully recognise all tested compulsive behaviours.

1.4.3 Chapter 2

The second core chapter of this thesis addresses a similar issue to the first, but from a different perspective, namely that of distinguishing groups of compulsive and non-compulsive behaviour as a whole. However, unlike the first chapter, this chapter instead presents a detection method based on the differences *between*, rather than *within*, characteristic compulsive and non-compulsive behaviours. In other words, *inter-behavioural* variation, rather than *intra-behavioural* variation. For this purpose, we propose the use of a simple optical flow matrix summation technique that is able to efficiently capture compulsive and non-compulsive behavioural elements based on their degree of repetitiveness. For the sake of simplicity, we refer to this representation as a TMHM. Each TMHM is then translated into a frequency-based representation that we herein refer to as an RTMHM. We then demonstrate how these RTMHMs can be used to train a Multilayer Perceptron classifier to distinguish between compulsive and non-compulsive behaviours with a high degree of accuracy. In addition to this, we employ the same feature selection and classification model to classify various behaviours into categories of either *low*, *medium* or *high* compulsivity. Based on our experimental simulations for the compulsive vs. non-compulsive behaviour classification, the system proposed in this second chapter is able to achieve an overall classification accuracy of 92.5% when tested on multiple types of simulated compulsive and non-compulsive behaviours. Furthermore, when tested on the same behaviours, labelled as either 'low', 'medium', or 'high' compulsivity, the proposed system is able to classify said behaviours with an overall accuracy of 83%.

1.4.4 Chapter 3

In the third and final core chapter of this thesis, we combine two mechanisms to establish a system for the determination of anxiety, based on the visual appearance of behavioural compulsions. In order to achieve this, we first demonstrate the efficacy of SURF descriptors on the TMHM representation of behaviours used in the last chapter of this thesis. This is used in conjunction with a bag of words model and an SVM to classify different examples of both compulsive and non-compulsive behaviour. The behaviours in this case are not classified based on whether or not they are compulsive, as in the previous chapter, but are instead classified based on their morphological type, e.g. 'walking back and forth', 'reading', 'opening a drawer'. The purpose of this is to provide a means of classifying TMHM behaviours such that each behaviour can then be analysed within the context of its group. This then allows for the second section of this chapter, which presents a basic statistical method for approximating a relative measure of anxiety for behaviours. This measure is based on how the TMHM of a given behaviour compares in intensity to other examples within the same behavioural class. This provides us with an approximate assessment of anxiety that can be compared to normal non-compulsive baselines of the same type of behaviour, based on compulsive/non-compulsive labels that could be provided by the second core chapter of this thesis. Experimental results demonstrate that the system proposed in the first section of this core chapter is able to correctly classify different types of behaviour 82% of the time, with almost all misclassifications occurring when two behaviours are highly visually similar and thus difficult to distinguish. The second section of this core chapter was presented to a mental health professional who deemed it an acceptable approximation of the level of anxiety that an individual may be experiencing (with the caveat that, especially during treatment, the compulsivity of a behaviour will not necessarily reflect precise internal anxiety, but nevertheless can be used as a rough guide in general).

1.4.5 Conclusion

The final chapter of this thesis recapitulates the central arguments, contributions and results of each of the core chapters in order to provide a side-by-side comparative overview of the research. Finally, future work, based on the current research, is presented in closing.

Chapter 2

Background

In order for the reader to better understand the subsequent sections of this thesis, which revolve around specific behavioural elements endemic to OCD, and to an extent, the associated obsessions, it is essential that some background material on the condition first be provided. As such, this section is dedicated to detailing many of the fundamental elements of OCD with which the reader should become acquainted in order to understand how the proposed system could be of assistance in treating this condition.

2.1 An Overview of OCD

Obsessive Compulsive Disorder is a psychiatric disorder that is characterised by recurrent behavioural abnormalities known as 'obsessions' and 'compulsions' [35, 36].

- **Obsessions** are repetitive and persistent distressing thoughts, images, and/or urges. These are not the same as excessive worries that normal individuals experience as a result of real life issues. The individual experiencing the obsessions will either try to ignore, suppress or neutralise the obsessions with some other thought or action, often with a compulsion.
- **Compulsions** are repetitive behaviours and/or mental acts that are typically performed in an attempt to neutralise the obsessions. Usually, compulsions will follow rigid rules and can involve any number of activities. They are aimed at reducing or preventing distress or some perceived dreaded event [37].

The connection between these obsessions and compulsions, as well as the manner in which they tend to feed into each other, is illustrated in Figure 2.1. It is important to note that, while most individuals demonstrate both obsessions and compulsions, some individuals may only demonstrate one or the other. For example, some individuals suffer from what is sometimes known as "Pure Obsession" OCD, in which there are no outward compulsions involved in the disorder [38]. Nevertheless, physical compulsions are a very common component of OCD and thus can be used as a proxy for the level of distress being experienced in many cases.

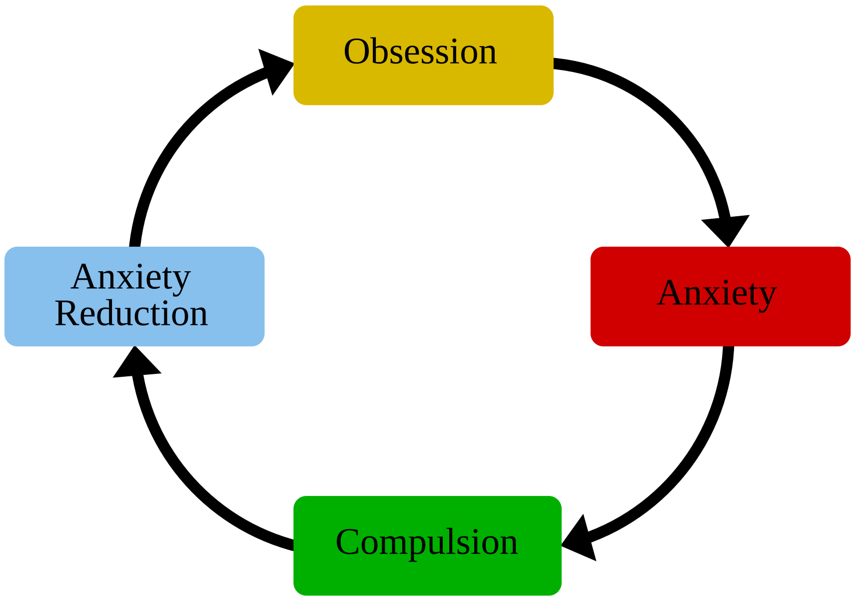

Figure 2.1: *A typical representation of the nature of OCD, in which the directional arrows indicate the cyclical and perpetual quality of the condition.*

Examples of mental obsessions include:

- Fear of contamination from germs, dirt, poisons, and other physical and environmental substances.
- Excessive concern with symmetry, exactness and orderliness.
- Excessive concerns about illness, religious issues or morality. [39].
- Fear of being responsible for something terrible happening (e.g. a fire or burglary) [40].

Examples of physical compulsions include:

- Repeatedly walking back and forth through a doorway.
- Touching, tapping or moving in a particular way or a certain number of times.
- Repeating routine activities and actions such as reading, writing, walking, picking up something or opening a door [39].
- Washing ones hands (and/or body) an excessive number of times, even to the point of causing significant skin damage and/or pain [40].

Two simulated examples of such compulsive behaviours can be seen in Figure 2.2. One element that compulsive behaviours share in common is that they tend to involve unduly repetitive cycles of behaviour. Unlike normal behaviours, these behaviours are not directed towards a goal that would typically be considered an inherent function of the behaviour itself, but instead are directed towards alleviating internal anxiety. In other words, these behaviours do not result in the completion of any meaningful task, nor are they inherently enjoyable for the individual [41]. Furthermore, an individual with OCD is usually aware of the senselessness of the behaviour, with most acknowledging that their obsessions and compulsions are, at a minimum, somewhat unrealistic, though the degree of insight among individuals varies [42, 43]. Nevertheless, the urge to perform such behaviours can be so strong that the individual will carry them out against their own rational inclinations, as doing so will typically allow them to regain some temporary peace of mind [44].

In general, behaviour is considered compulsive when it is persistent and has no correlation with what would otherwise be the functional goal of such behaviour, typically leading to undesirable consequences [45]. In an associated manner, the mechanism underlying such compulsive behaviours may represent a disruption in the normal processes of goal-directed action control, in combination with a reliance on habit formation [46]. Regardless, such behaviours are merely ritualistic acts that are repeated either a specific number of pre-determined times, or an indeterminate number of times in an attempt to lessen the associated anxiety. Thus, it is essentially this discrepancy between the known functional goal of a given behaviour and the behaviour being performed in a manner that fails to achieve this goal, or achieves it repeatedly, with no additional benefit, that defines OCD behaviours as abnormal and compulsive.

Naturally, it would be desirable to differentiate OCD compulsions from non-compulsive behaviours based on their goals. However, as these goals are psychological in nature, it would be very difficult to gain access to them. Moreover, in order for an algorithm to understand

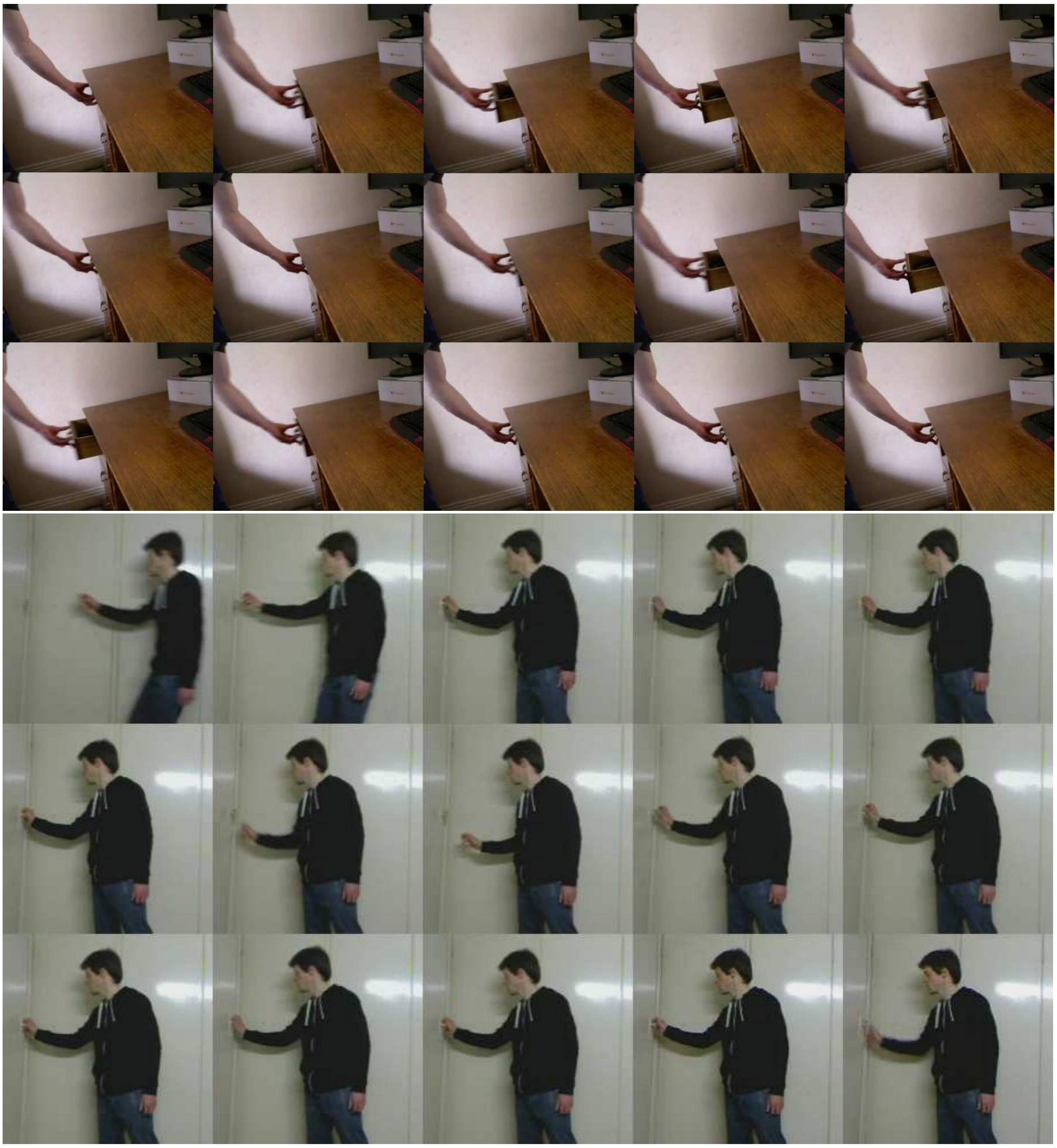

Figure 2.2: *Two simulated examples of compulsive behaviour. The top sequence demonstrates a drawer being continually opened and closed unnecessarily. The bottom sequence depicts a compulsion involving repeatedly checking whether or not a door is locked. Repeating such routine behaviours is common among individuals with OCD.*

what the goal of a given human behaviour is, it would typically need to either be exposed to a substantial dataset of normal human behaviour, to learn the difference between normal goals and compulsive goals, or be provided with a large, pre-defined database of correlations between various behaviours and goals. Indeed, this is the foundation for much of the research in machine learning and classification tasks, in which, intuitively, larger datasets tend to allow one to achieve better performance [47]. This is doubly true for cases in which the classes are highly similar and thus more difficult to separate, such as would be the case with most examples of repetitive non-compulsive behaviour vs. repetitive compulsive behaviour.

Similarly, human beings are able to learn associations between various concepts and goals through processes of 'knowledge acquisition' and 'skill refinement' [48]. The knowledge of these associations is acquired and refined through years of experience, which machine learning algorithms rarely, if ever, have access to. As a result it would be a considerable task for any machine learning algorithm to recognise a substantial enough set of behaviour-goal associations to know what was considered normal and what was considered compulsive behaviour. Thus, we regarded doing so as beyond the scope of the current thesis and instead opted for an alternative that was less time and resource intensive.

2.2 Prevalence and Burden of OCD

OCD is considered to be a relatively common psychiatric disorder, and while estimates of its prevalence vary, most studies put the value for the general population at between 1% and 3% [49, 50, 51, 52]. Moreover, the negative impact that OCD has on the healthcare system and the quality of life for sufferers and their families is known to be considerable [53, 54, 55]. Much of the severity of OCD comes from the debilitating nature of the condition, the associated stigma, and the considerable amount of time that individuals lose to the condition. For example, it has been estimated that OCD-related behaviours consume a daily average of 5.9 and 4.6 hours for obsessions and compulsions respectively [50]. OCD has even been ranked by the World Health Organization as one of the top 20 causes of disability among 15-44-year-olds [56]. Thus, it can be seen that although OCD is not the most prevalent psychiatric disorder, its severity nevertheless makes it an essential target for continued research as well as for innovations in treatments. Furthermore, technology has been slow to adapt to the needs of the psychiatric community and very little computer science research has been directed towards OCD. In fact, no research that we have yet encountered addresses the issue of video-based detection and analysis of compulsive behaviours in individuals with OCD. Thus, the research proposed in this thesis could serve as a valuable tool to help mental health professionals determine the efficacy of a given psychiatric treatment, while gaining new insight into the condition of their patients.

Regardless, certain mental disorders besides OCD also involve the production of repetitive behaviours. Notable among these is ASD [57, 58], as well as various types of dementia [59, 60]. Importantly, the repetitive behaviours exhibited in ASD also hold the potential to be responsive to various interventions, further highlighting the value of monitoring systems for such disorders [61]. Due to the fact that these disorders often share the characteristic element of repetitive behaviours, a system, such as that proposed in this thesis, could potentially be adapted in future research to address similar issues among these other mental health disorders. This further illustrates a tremendous need for systems that are capable of detecting repetitive behaviour across various mental health disorders for timely diagnosis and treatment. Regardless, this thesis will focus specifically on OCD and, as such, is only designed to capture the compulsive behaviours inherent to this condition.

With this in mind, we will first note a few limitations of the proposed system. Firstly, in order for compulsions to visually register in an accurate manner, they must be clearly visible, rather than occluded, or barely detectable. In other words, because the system is motion-based, it works best with gross bodily motions and physical movements, which encompass typical OCD behaviours. The proposed system is not designed to effectively capture very small or obscure movements such as ticks, or small twitch-like movements. Due to their additional complexity, we leave the solutions to these problems to future research. Moreover, it is worth noting that, as previously mentioned, some individuals with OCD will only have obsessions as symptoms, i.e. they won't exhibit any visible compulsions. Naturally, such cases cannot be captured by a video-based system. Regardless, most cases usually involve both obsessions and compulsions [62]. Thus, this is not a significant issue.

2.3 Diagnosing OCD

The diagnosis of OCD is made via a clinical interview with a mental health professional based primarily on foundational diagnostic texts, such as the World Health Organization's International Classification of Diseases and the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders [37, 63]. While these texts may differ slightly in the nuances of their diagnostic criteria, the key characteristics that identify the disorder remain the same, namely that the individual experiences either obsessions, compulsions, or both, and that these obsessions and/or compulsions interfere significantly with daily living, for example, by being time consuming, or causing marked distress [63]. Furthermore, in establishing a baseline for an individual's symptom severity, standardised rating scales such as the Yale-Brown Obsessive Compulsive Scale, and patient behaviour estimates, are often used [64]. These rating systems are typically also drawn upon during treatment, in order to assess a patient's progress. More recently, additional insights are being provided via neuroimaging studies, which are capable of mapping structural changes and abnormal patterns of activity in the brains of individuals with OCD [65, 66, 67]. As a result, these studies are edging towards providing more definitive objective markers to complement existing OCD diagnoses [68].

2.4 Current Treatments for OCD

Traditionally, the treatment for OCD has focused on a combination of Cognitive Behavioural Therapy (CBT), self-reporting and, in certain cases, pharmacological interventions [69, 37, 70]. Additional treatments, such as Deep Brain Stimulation (DBS) are also beginning to gain exposure as effective methods of treating refractory cases [71, 72]. Pharmacological interventions tend to involve the use of Selective Serotonin Reuptake Inhibitors, D-Cycloserine, and in refractory cases, anti-psychotics [73, 74]. The decision of whether or not to use various therapies is typically informed by the severity of the case in question and the outcomes any prior treatments. Furthermore, the effectiveness of each method can often be enhanced if complemented by another therapy, such as CBT with pharmacological agents. However, the precise effectiveness of any given treatment method may depend on a number of individual factors, including the severity of the individual case [75]. Consequently, most typical treatment plans for OCD will involve the use of CBT, often Exposure and Response Prevention Therapy (ERP), sometimes in combination with pharmaceuticals, or in the most refractory cases, surgery or DBS [76].

Exposure and Response Prevention Therapy is a form of CBT that is frequently used in cases of OCD due to its high efficacy regarding the disorder [77, 78]. ERP seeks to reduce an individual's compulsions and their associated anxiety over time by exposing the individual to an anxiety-provoking stimulus while requesting that they resist the urge to commit compulsive behaviours in response [79]. As this is accomplished in manageable increments across time, it has the effect of habituating the patient to not performing the behaviour, while simultaneously reducing anxiety. While ERP has shown considerable success, it nevertheless involves relapse for some patients, with some cases proving highly intractable [80]. Thus, in determining the progress of a patient's treatment over time, a computational behavioural monitoring approach that could automatically detect and analyse the patient's compulsive behaviours could certainly prove beneficial.

Thus, systems such as that proposed herein may be able to increase the chances of an efficient recovery for an individual with OCD, while potentially reducing the chances of more severe relapses due to the potential to catch regression early. On the event that a relapse does occur, a computational approach could provide a visual documentation of the patient's condition leading up to the relapse and could also allow for a more comprehensive understanding of what went wrong, where the patient's own explanation may not be able to present the full picture. Much of this has to do with the fact that self-reporting is a subjective measure and, as such, is subject not only to a number of biases, but also to false reporting and general memories of error [81, 82]. Moreover, many existing diagnostic tools, whether the rating is provided by the clinician themselves, as in the Yale-Brown Obsessive Compulsive Inventory (Y-BOCS) [83], or the patient, as in the Obsessive-Compulsive Inventory [22] and Obsessive Belief Questionnaire [23], only attempt to ascertain very general details and thus cannot offer the same degree of fine-grained detail that a system such as that proposed herein is capable of achieving.

This is important to note, because, in initially assessing an individual suspected of having OCD, a combination of interviews, self-assessments and psychiatric evaluations are most often used. Typically this will involve the use of a diagnostic tool, such as the aforementioned Y-BOCS, as well as a full psychological assessment performed by a mental health professional [84, 24]. These assessments provide mental health professionals with information, such as the current severity of an individual case, that can then be used to determine the most likely effective treatment. However, as the severity of OCD tends to wax and wane to some extent over time, it is necessary for the patient to be monitored and re-assessed at regular intervals throughout a given course of treatment, in order to determine the efficacy of the current treatment plan [85]. As a result, it is essential that the progress of any given treatment plan be closely monitored in the most objective manner possible in order to provide the most efficacious and timely treatment, as well as to reduce undue anxiety for the patient. Such requirements naturally lend themselves to computational interventions, which are able to provide an enhanced level of monitoring of a patient's condition over time, above and beyond that of self-reporting and discussion.

Chapter 3

Overall Methodology

This chapter is designed to provide the reader with a better understanding of how the components of this thesis fit together and further aims to adumbrate the underlying principles behind the proposed system. Thus, in the sections comprising this chapter, we outline the structure of the proposed system in a potential real-world implementation, then discuss the general experimental setup of the proposed system and its limitations.

3.1 Proposed System Structure

Figure 3.1 is a schematic of the overall proposed system as it would be implemented in practice. This figure is used to illustrate how the components of the proposed system are designed to cooperate, as well as the overall idea behind the system and how it could be used pragmatically to the benefit of mental health professionals and their patients. As can be seen in the figure, the proposed system is comprised of the three core chapters. The first core chapter establishes the automatic compulsion detection component; the second core chapter details the compulsion classification component, including both the compulsive vs. non-compulsive element and the global degree of compulsivity element that considers whether a behaviour is of low, medium, or high compulsivity. Finally, the third core chapter concerns the behaviour classification and anxiety metrics that together present a picture of the relative anxiety level of various behaviours.

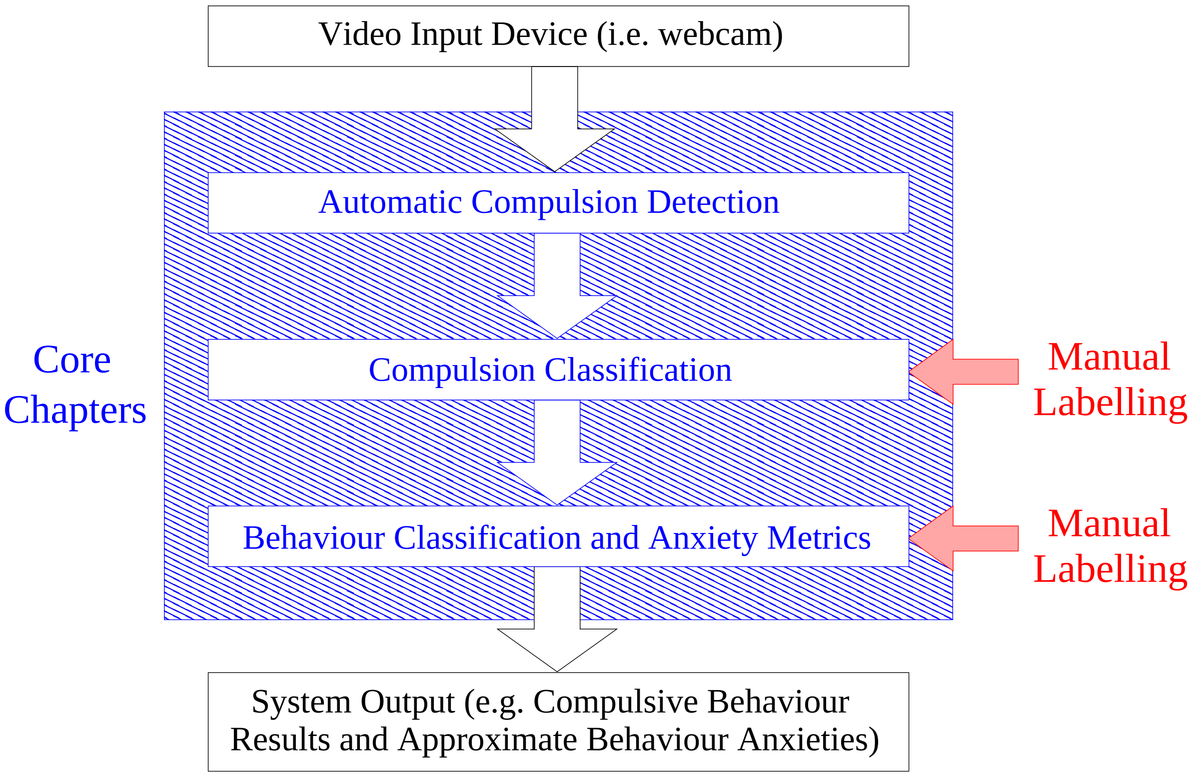

Figure 3.1: *A schematic overview of the implementation of the proposed system*

3.2 General Experimental Setup

The experiments designed to test the proposed system were run on a single Desktop PC with 8GB of RAM, and an 8-core processor running at 3.40 GHz. All coding for the three chapters contained herein was produced in the MATLAB technical computing software suite. The behaviours comprising the video-based data sets for each chapter were simulated by the same individual, namely, the author. The limitations of using such an approach are discussed in Section 3.4. The experiments for the first chapter were conducted on a set of three videos, each simulating a single compulsive behaviour. The second chapter was tested on a set of 40 videos, comprising five simulated compulsive behaviours. Each of the five behaviours was represented by 8 videos, with each video varying the degree of compulsiveness of the behaviour, as well as the clothing and lighting conditions. The complete details of each of the experimental simulations will be discussed in their respective chapters.

3.3 Implementing the Proposed System in a Real-World Scenario

The setup of the system proposed in this thesis entailed the use of video clips designed to simulate the behavioural aspects of OCD compulsions. As previously mentioned, these simulated compulsions were verified with a mental health professional in order to establish that they represent plausible examples of real-world OCD compulsions. The proposed system was designed in this manner due to time and resource constraints. Nevertheless, we consider the results of the proposed system to be a good approximation of how the system would function under clinical conditions with real patients. The precise accuracy of the system under such circumstances however remains an open question that had to be left for future research.

Regardless, to provide an example, the hypothetical setup of the proposed system in practice would entail the use of a single, inexpensive webcam placed in an optimal location in at least one room of a patient's house. The specifics of this setup would be based on a determination of the least invasive location in the patient's house that would still allow a good coverage of their compulsions to be established. This location would need to be determined via a discussion with both the patient and the mental health professional. Thus, future work would be orientated towards the implementation of such a system. This would include conducting clinical trials to determine the efficacy of the system in a sample of patients with OCD. This real-world integration would also require connecting the aforementioned system to a data store, from which a mental health professional could then access the data produced by the system, ideally via a front-end application. Although this future work is not implemented herein, it is nevertheless mentioned in order to give the reader a more comprehensive picture of how the proposed system could effectively be implemented in practice.

3.4 Limitations of the Proposed System

In the interest of transparency, it is important to note that the purpose of this thesis is to provide a comprehensive and effective system for detecting and analysing compulsive behaviour in OCD, with the aim of future implementation. However, due to time and resource constraints, we limited the dataset used throughout this work to a set of simulated behaviours performed by an individual, namely the author of this thesis, who does not have OCD. These simulations were based on a thorough reading of the psychiatric literature, as well as online forum and discussion posts from individuals who actually have the condition. Regardless, in order to reduce bias and verify the behaviours performed, the types of compulsions performed were shown to, and discussed with, a psychiatrist who specialises in treating individuals with OCD. The psychiatrist was satisfied that the behaviours represent realistic examples of what an individual with OCD may exhibit.[1]

Moreover, while no two individuals with OCD are necessarily going to demonstrate the exact same behaviours, certain categories of behaviours and movements are nevertheless stereotypical and recognised as part of the condition. Chief among these elements is that compulsive behaviours are consistently repetitive. This is typically the result of an attempt to nullify distressing thoughts, or 'obsessions', that the individual typically experiences in conjunction with the compulsions, often triggering the onset of the compulsion. Regardless, not all cases of OCD compulsions focus on strictly repetitive behaviours, with some individuals instead needing to perform actions in a predefined sequence, or in a certain number of chunks. However, this is not considered a significant drawback, as the great majority of OCD compulsions are of the repetitive type that the proposed system is designed to capture.

Additionally, OCD compulsions can typically be grouped into categories, with some of the most common being: checking behaviours, washing and/or cleaning behaviours, repeating routine activities and counting behaviours. Most of the behaviours we simulated for this thesis would

[1] Professor David Castle has corroborated that the proposed system possesses both psychiatric novelty and value and that the behaviours performed represent accurate examples of compulsions manifested by individuals with OCD.

be classified as either checking behaviours, or behaviours that involved repeating routine activities, which together constitute a large portion of OCD behaviours. As a result, we do not attempt to catch all behaviours, but merely provide a foundation for future research. Due to the aforementioned limitations, a real-world implementation of the proposed thesis would require fine-tuning. Nevertheless, we believe that, based on the experimental results detailed in this thesis, a real-world implementation of the proposed system would prove effective. Lastly, as with any situation involving the observation of a human being, the individual in question may modify their behaviour in response to their being observed, often to appear in a more positive light. This is known as the Hawthorne (or observer) effect, and is not considered a serious issue for the purposes of this research [34]. Nonetheless, it is noted as a potential limitation of the proposed system.

Finally, it is important to note that our focus was centred on the unduly repetitive nature of compulsive behaviours. By only considering behaviours with a high number of repetitions, we eliminated the need to learn human behaviours one by one and were instead able to design a system that could catch many common OCD behaviours with minimal-to-no training. Naturally, one distinct drawback of this approach is that some normal behaviours, such as exercise, involve a high number of repetitions that can appear similar to certain OCD compulsions. However, as the system proposed in this thesis is intended, in a real-life implementation, to be set up in the residence of an individual who already has OCD, the false positives generated by behaviours such as exercise would be considered minimal and could be ignored upon inspection by a mental health professional. Furthermore, the location of the camera could be strategically placed in a location that would typically encounter little-to-no exercise or similar repetitive but non-compulsive behaviours. The individual could be further instructed to avoid exercise, and similar behaviours, in the monitored room, where possible.

Chapter 4

Detecting Compulsive Behaviours Based on Similarity and Repetition Thresholding

4.1 Introduction

Due to advances made in both video recording technology and computational processing power over the last few decades, the field of human motion detection and analysis has recently seen a significant amount of interest [86, 87, 88, 31, 30, 89, 90, 91, 92]. As a result, the use of various forms of computational, especially visual, monitoring technology as a means of assisting mental health professionals in treating their patients, has also begun to flourish [18, 26, 28, 93, 94]. Among the mental health conditions capable of benefiting from this kind of technology, OCD has received comparatively little attention, despite its considerable prevalence and severity [95, 96]. OCD is an anxiety disorder characterised primarily by two symptoms, namely, intrusive thoughts known as 'obsessions', and repetitive physical behaviours known as 'compulsions' [35, 42]. Importantly, as the latter of these two symptoms, the compulsions, represent visible, albeit indirect, manifestations of anxiety, they hold the potential to be analysed algorithmically via video footage. It is this potential that the proposed system attempts to capitalise on.

Existing methods of treating patients with OCD tend to rely on self-report measures in conjunction with Cognitive Behavioural Therapy and, in some cases, medication [69]. However, there are notable drawbacks inherent to self-report measures, including: a reliance upon human memory, which is notoriously unreliable, as well as biases that may be imposed by the patient, such as the desire to view themselves, or to be seen, in a more positive light [97, 82]. Conversely, the proposed system has the ability to measure a patient's progress objectively, based on the severity of their compulsions. This could then be used to enhance a mental health professional's chosen treatment plan. The proposed system could thus prove highly valuable to mental health professionals wishing to track the progress and efficacy of a chosen treatment plan. We believe that existing human motion detection systems cannot adequately or appropriately distinguish, or assess, the specific characteristics of OCD in a manner sufficient enough to beneficially supplement existing treatment plans. Thus, the proposed system represents a valuable and novel potential enhancement to existing OCD treatment plans, via its ability to fill a void that has hitherto not been addressed. This is despite the great potential that such a system holds in advancing the treatment and understanding of OCD.

Existing applications of motion detection and analysis have often focused on accurately classifying generic pre-set action sequences, such as walking, running and jumping [98, 87, 99, 100]. Some approaches have also focused on motion detection and activity recognition in the workplace for ergonomic purposes [30, 101]. However, existing pre-defined motion and action classification systems are not apt for the purposes of the proposed system. This is because our focus lies more specifically on whether or not an exhibited action is unduly repetitive, or compulsive, in general, rather than whether or not it characterises a specific action pattern. Other approaches require some form of human model representation in order to recognise motion cues and/or actions [102, 103]. Such models can resist adaptation to different body morphologies due to their typical use of distinct bodily points of interest that often differ across individuals. Moreover, the demands of such models are generally higher in computational complexity and thus less efficient than is desirable for the proposed system. Because most OCD compulsions are characterised primarily by unduly repetitive motion [37], it is beneficial to focus solely on the motion cues themselves, thus enhancing the efficiency and pliability of the proposed system.

Additional approaches have focused on accurate motion estimation, and even repetitive actions, in cases such as ergonomics and preventing fraud [30, 33]. However, such approaches are often high in complexity and are not designed to address the compulsive motions exhibited by individuals with OCD, nor the variable number of possible repetitions. We are not aware of any video-based technique currently being used to automatically detect the compulsive behaviours exhibited by individuals with OCD. The proposed system could thus be of considerable benefit to patients and mental health professionals alike. This could allow for a transition beyond the traditional self-report measures, which, although fairly reliable, are nevertheless irrevocably subject to the same drawbacks of subjectivity, memory unreliability and potential bias of the patient, in addition to being unable to provide the same level of fine-grained detail that a computer-vision-based system is able to achieve.

In developing the proposed system, the authors have provided the following contributions:

- **Successfully detected repetitive motions characteristic of OCD:** The proposed system is able to detect any repeated gross bodily motion that may occur as a result of OCD. This was primarily achieved using optical flow, without reliance upon any prior human model or activity set. These motions were characterised by their unduly repetitive nature. This is the linchpin of the system and provides a significant benefit in that it allows the actual compulsive behaviours characteristic of OCD to be detected. This information could then theoretically be sent to a given mental health professional to monitor and evaluate the progress of their patient. Although this is beyond the scope of the current work.

- **Successfully maintained a high repetitive action detection ratio:** The proposed system was able to detect an average of 87% of the repetitive movements exhibited, while also maintaining a low number of false-positives. This was achieved via the use of a dense optical flow field, drawing comparisons between points of repetition across video frames, and setting a minimum threshold of repetitions required for a behaviour to be considered unduly repetitive, or 'compulsive'. This is important, as the system needed to be able to detect the majority of compulsive behaviours exhibited by an individual in order to prove effective.

- **Provided an objective method of detecting compulsions that could be easily combined with existing OCD treatment plans:** The proposed system is designed in such a way that a mental health professional could easily integrate its output electronically with existing self-report measures and treatments. This is possible due to the fact that most patient data is already stored in an electronic form, which the proposed system could simply augment with its own output data. This is an incidental benefit and means that a given mental health professional wishing to retrieve data from the proposed system could have such data sent, for example, by email, or by secure line, to a medical database. The potential consequences of this, however, are currently theoretical, though may be implemented in future work.

The remainder of this chapter is organised as follows: Section 4.2 provides background material relating to the proposed system, in order for the reader to better understand the subject matter that follows. This includes a brief explanation of optical flow. Section 4.3 offers an in-depth explanation of the proposed system, its components and how they function in an integrated manner. Section 4.4 explains the set-up, details and parameters used in our experiments. Section 4.5 discusses the experiments that were conducted and explores the implications of their results. Section 4.6 briefly discusses the related and pertinent literature and Section 4.7 summarises our findings, as well as the benefits and limitations of the system proposed in this first core chapter.

4.2 Background

In order to provide the reader with a contextual understanding of the content that follows, the optical flow technique implemented in the proposed system is briefly touched upon in Section 4.2.1.

4.2.1 Optical Flow

Optical flow is a concept that was originally developed for the field of psychology in order to explain the apparent visual motion that occurs as a result of relative motion between an observer and a scene [104]. It has since been successfully applied, in various forms, to computer vision problems as a method of detecting and interpreting motion occurring in a scene [105, 106, 107, 108, 109]. One of the primary benefits of using optical flow in the proposed system is that it is relatively straightforward to implement and is known to be successful and reliable in a variety of circumstances. Additionally, optical flow, as implemented in the proposed system, doesn't require any prior training to take place, which would otherwise be computationally expensive and time intensive.

Although much research has been conducted in computer-vision-based optical flow, two of the most influential, and still commonly used, techniques of the field are the Horn-Schunck and Lucas-Kanade methods [105, 106]. The Horn-Schunck method is a global optical flow method. Generally, global methods are useful when more dense optical flow vectors are needed, which can be useful in situations where high motion precision is key. However, the main disadvantage of such approaches is that they are generally more sensitive to noise than local optical flow methods, such as the Lucas-Kanade. Conversely, the Lucas-Kanade method is a local optical flow method and thus generally provides less dense motion fields than, for example, the Horn-Schunck method. However, local methods can be beneficial for situations that require reduced noise in the motion vector and thus are more suitable for other applications [110]. Because the proposed system is designed for indoor use and involves stable camera locations, we considered noise less of an issue than precision and thus were thus more concerned with deriving the

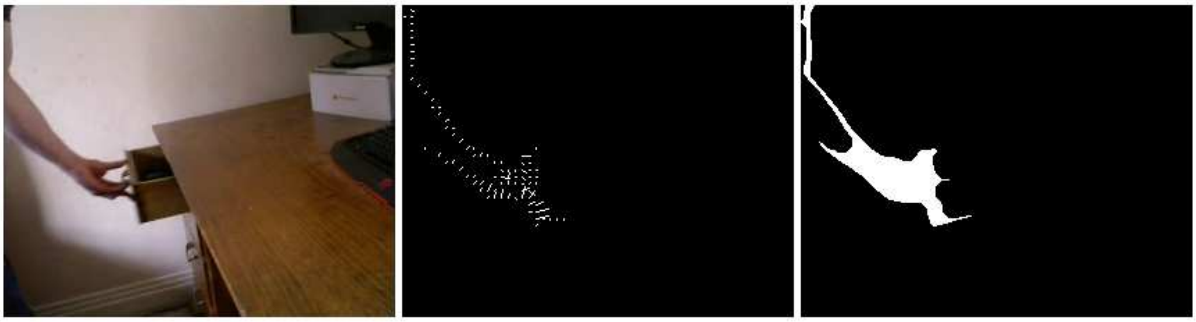

Figure 4.1: *An example of the aforementioned techniques in practice. The original video footage of a simulated compulsive behaviour can be seen in the leftmost image, followed by the optical flow motion vectors and finally the expanded outline of the moving figure, which we refer to as the 'figure image'.*

dense optical flow vectors needed for accurately detecting bodily movements. As a result, We considered the Horn-Schunck method to be more appropriate for the proposed system. Moreover, although the Horn-Schunck method produces slightly more noise among the motion vectors, this had little impact on the proposed system's effectiveness.

4.3 Methodology

This section introduces the methodology of the proposed system and is organised as follows: Section 4.3.1 provides an overall description of the system and explains how its various components fit together. Section 4.3.2 details how the optical flow measure was implemented. Section 4.3.3 describes the image similarity metric that was employed and how it was used to determine repeated behaviour matches. Finally, Section 4.3.4 expounds upon the use of compulsion thresholds and parameters to clarify how the proposed system defines compulsive behaviour in OCD.

4.3.1 An Overview

The proposed system comprises three primary elements:

- **An optical flow algorithm:** This is the aforementioned Horn-Schunck method, which is used to locate a moving individual in a given video. In doing so, it produces several sets of motion vectors, which are then used to generate respective 'figure images' for subsequent behaviour comparisons.

- **An image similarity metric:** This is Pearson's product-moment correlation coefficient, which can be used to determine the correlation between two variables. When extended to a 2D form, it can be used to determine the similarity between two 2D image matrices. This is discussed in greater detail below, along with the other image similarity metrics that were tested in our preliminary experiments.

- **A set of repetitive behaviour thresholding parameters:** This element is used in conjunction with the image similarity metric in order to differentiate between unduly repetitive, or compulsive, behaviour and non-compulsive behaviour. Specifically, these parameters are: The *maximum delay between repeats*, *the minimum required number of repeats* and *the maximum allowable variation in the repeat speed/rate.*

The proposed system's overall operation on a given video proceeds as follows:

Firstly, each video is de-constructed into a series of consecutive RGB frames, or images. Each RGB image is then converted into a respective greyscale image. This was required in order for the optical flow method to function. Regardless, this is immaterial, as, in this case, colour information merely adds processing time and complexity without being essential for accurate motion detection. In using MATLAB, each greyscale frame is interpreted as an M-by-N matrix, where M and N are the respective width and height dimensions of a given image. These M-by-N matrices are then fed into the Horn-Schunck optical flow algorithm, which produces a set of motion vectors. Next, the motion vectors are overlaid as white segments onto a black background to produce a binary image. The gaps between the representative motion vectors in the binary image are then filled in order to create a semi-solid motion figure within the binary image. This semi-solid figure represents the moving individual and is henceforth referred to as the *figure image.* The aforementioned steps are illustrated in Figure 4.1.

As the system produces each figure image in turn, it is compared to every prior figure image within a given *window size* in order to detect any viable matches. The window size is a variable parameter that indicates the number of antecedent figure images to be considered during image comparisons. Note, however, that an image does not necessarily need to be compared with every antecedent figure image unless the frame rate of the video is low. This is because human motion tends to progress at a much slower rate than most standard video capture frame rates. Thus, the system should nevertheless be able to maintain a respectable accuracy if each figure image were instead compared with, for example, every fifth frame that preceded it, rather than every sequential frame. This would equate, in a 25 FPS video, to comparing frames at a rate of five per second. Nevertheless, we opted to use every preceding frame within the window size for comparisons, as, under this condition, the proposed system was still able to proceed at a desirable speed.

Regardless, because the image comparison process is costly, we needed to implement an image similarity algorithm that was both efficient and accurate. In order to achieve this, we evaluated three well-known image similarity metrics. These metrics were: *Euclidean Distance*, *Hamming Distance* and the *Pearson product-moment correlation coefficient* (AKA Pearson's r). Each of these metrics were used to compare two 2-Dimensional figure images at a time in order to determine their degree of similarity. More specifically, this was accomplished by comparing the respective vectors across the two image matrices. The detailed process involved for each image comparison method is explained in Subsection 4.3.3. Simply put, in order for two figure images to be considered a match, they must possess a similarity greater than an elected threshold. This threshold is detailed in Section 4.4.

Finally, if enough matches are detected within a sequence of behaviour then the behaviour in question is considered compulsive. The minimum required number of matches is determined by the *Minimum Number of Repetitions* parameter, which is detailed in Subsection 4.3.4. It is also important to note that these behaviours must be detected within a given time frame of each other. This is designed to prevent normal behaviours that are naturally repeated over an extended time period, like hand-washing and turning on a light switch, from being erroneously classed as compulsive. Conversely, while these same behaviours may be compulsively performed in some individuals with OCD, in such circumstances, the behaviours are usually repeated in comparatively short succession, with little, if any break in between, hence highlighting the temporal importance of the behaviours. This compulsive temporal boundary is represented by the *Repeat Rate* parameter. While this entire process may seem rather simple, it is nevertheless effective for the previously described purposes of this research, as demonstrated in Section 4.5.

All of the aforementioned elements are illustrated in pseudocode in *Algorithm 3.1* as they are implemented in the proposed system.

4.3.2 Detecting Motion in Videos

As previously mentioned, the proposed system uses the Horn-Schunck method of optical flow, which computes an estimate of the velocity field, $[u\ v]^T$, that minimises the Equation 4.1. As an optical flow method, Horn-Schunck is capable of processing a given video in order to obtain motion vectors across frames.

$$E = \iint (I_x u + I_y v + I_t)^2 dxdy \ \alpha \iint \{(\frac{\partial u}{\partial x})^2 + (\frac{\partial u}{\partial y})^2 + (\frac{\partial v}{\partial x})^2 + (\frac{\partial v}{\partial x})^2\} dxdy \tag{4.1}$$

Where:

- $(\frac{\partial u}{\partial x})$ and $(\frac{\partial u}{\partial y})$ are the spatial derivatives of the optical velocity component u
- α scales the global smoothness term
- *Ix*, *Iy*, and *It* are the spatiotemporal image brightness derivatives

---

```
// A video involving one repetitive behaviour
video = repBehav1.avi;

for each frame in video
{
   matchCount = 0;
   repBehavsCount = 0;

   greyFrame = rgb2grey(frame);

   // Calculate optical flow motion vectors
   flowVectors = calcOptFlow(greyFrame);

   // Fill in motion vector gaps to create an
   // outline of the detected individual
   figImage = fillGaps(flowVectors);


   while(1)
   {

      if(matchDetected)
         framesToComp =
            distBetweenMatch+(distBetweenMatch*percentDiff);
      else
         framesTocomp = winsize;

      // Take each figure image preceding the
      // current one for comparison, but only up
      // to a maximum of the window size
      for each priorFigImage within framesToComp
      {
         // Compare current figure image with previous
         // figure images within window size using
         // Pearson's r
```

```
        simResult = getSim(figImage, priorFigImage);

        if(simResult > simThresh)
        {
            printf("Match detected\n");



            // Add the matching frame to the vector for
            // potentially repetitive behaviour
            matchFrames[matchCount] = simThresh or figImage;

            if(matchFrames[matchCount].numReps > minReps)
            {
                printf("Repetitive behaviour detected\n");

                // Add newly detected repetitive behaviour to
                // list of repetitive behaviours
                repBehavs[repBehavsCount] =
                    matchFrames[matchCount];

                repBehavsCount++;
            }
            matchCount++;

            break;
        }

        // If we have not detected another repeat of the
        // behaviour before the maximum delay elapses, then
        // we assume that the behaviour has been stopped
        if(elapsedFrames > maxDelay)
            resetMatchFrames(matchFrames, matchCount);
    }
  }

}
```

Algorithm 3.1: An overview of the proposed system

These motion vectors were the basis for determining where an individual was located within a given frame. The decision to use the Horn-Schunck method was based on its known reliability and efficacy. During preliminary tests, we compared the Horn-Schunck method to the Lucas-Kanade method and found it to demonstrate superior results for the purposes of the proposed system. These Horn-Schunck motion vectors then provided the basis from which we derived the previously mentioned figure images. Based on our preliminary tests, these figure images allowed for a higher degree of accuracy than using the motion vectors alone. This is likely because the motion vectors themselves are more sensitive and rigid, and thus express notable noise, and so can benefit from being approximated somewhat.

In using optical flow as our method of choice for motion detection, a few assumptions were applied to the videos being processed. Firstly, it was assumed, for the sake of simplicity, that only one individual would ever be present in view of the camera during the video. Secondly, it was assumed that there would be very little movement from other objects within the video, during the monitoring process, as this can distract from the individual being observed. This limitation was considered acceptable because all video footage for the proposed system is expected to be obtained from a static viewpoint, in an indoor location, and thus little movement from anything other than the human in question is expected. Additionally, as the setting was indoors, we expected little variation in lighting, which could otherwise disrupt the optical flow process if a compulsive behaviour were to be performed during significant lighting changes. Finally, as the system uses a single, view-invariant camera, motions that proceed along the camera's depth axis e.g. walking directly towards the camera, cannot be detected very accurately and thus were excluded from testing. However, this can be ameliorated by having the camera placed in a high corner of the room, where actions directly in line with the camera's viewing plane would be rare, or difficult to achieve.

4.3.3 Image Similarity and Repetitions

In order to detect the compulsive behaviours exhibited by an individual with OCD, we needed to take the figure image, as retrieved from the motion vectors from the previous steps, and compare it to other figure images to check for high similarities. Using this method, the proposed system is able to pinpoint two similar images depicting separate repetitions of the same specific compulsive behaviour. This is effective because repetitive compulsions are naturally cyclical. For example, when an individual opens and closes a drawer, the entire process tends to look very similar when repeated. Thus, if an image of an individual opening a drawer is compared to the same individual shortly thereafter opening the drawer a second time, the second image will tend to look very similar to the first.

Before carrying out the image comparison process, appropriate similarity measures had to be chosen. To this end, we tested three primary methods, namely 2D Euclidean Distance, 2D Hamming Distance, and 2D Pearson's r due to their good potential fit for the task. Each of these methods uses comparative calculations that are based on 2D matrices. In this context, each figure image is viewed as a 2D binary matrix, in which each pixel is represented by a binary value of either 0 (black) or 1 (white).

Our chosen method, Pearson's r, is a simple method of calculating the correlation coefficient between points in 2D space. We used Pearson's r to determine whether two given figure images possessed a 2D pixel similarity above a pre-set similarity threshold. As previously mentioned, the maximum allowable distance between two frames to consider them a match was also a pre-set parameter. The formula for Pearson's r, as well as the formulas for the specific variants of the 2D Euclidean and Hamming distances, are illustrated below:

Pearson's r:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}}$$

where $\bar{A}$ = is the 2D mean of matrix A and $\bar{B}$ is the 2D mean of matrix B

2D Hamming Distance:

$$n = mean(mean(a \ \oplus \ b) * z)$$

where z is the ratio of 0s to 1s in the line and XOR is an exclusive OR operation

2D Euclidean Distance:

$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2}$$

During preliminary tests Pearson's r showed the most promising results and thus was chosen as the image similarity metric for the proposed system. An example of a match being detected by the proposed system using this metric is depicted in Figure 4.2.

4.3.4 Demarcating Compulsive Behaviour

In order to determine whether any set of figure image matches, as indicated by the previously described image similarity metric, could be considered 'compulsive', we first had to define the boundaries of what constituted compulsive behaviour in OCD. Due to the large variety in potential speed, dynamism, delay and number of repetitions that characterise a compulsion, no single method can capture all behaviours perfectly. Regardless, to afford the largest degree of flexibility while still maintaining accuracy, it was necessary to define a number of parameters for compulsive behaviours. These are the: *Repetition Window Size*; *Minimum Similarity Threshold*; *Minimum Number of Repetitions* and *Repeat Rate*. Each of these parameters is explained in detail below. As a rule of thumb, the parameters can be loosened to automatically capture more examples of an individual's compulsive behaviours, but typically with the upshot that a greater

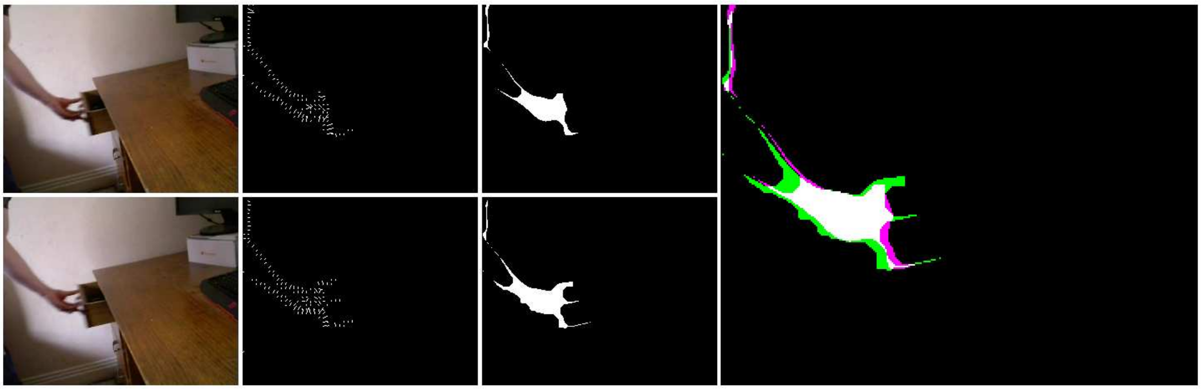

Figure 4.2: *An example of two frames that have been detected as a match by the proposed system. The first three images in the top of the figure (left to right) depict the original representation of the 39th frame of a test video, followed by its optical flow representation and finally, its representation as a 'figure image'. The first three frames in the bottom of the figure (left to right) depict the same representations, but instead for the 76th frame of the test video. The final, larger frame on the right depicts the differences between the two figure images (in which: green represents components only from the 39th frame, magenta represents only those from the 76th frame and white represents their crossover) in which a similarity accuracy of 72.97% was found*

number false positives will be incurred. Conversely, the parameters can also be tightened, which would result in fewer compulsive behaviours being captured i.e. some compulsive behaviours may be missed as false negatives, but with the consequence of fewer false positives. The specific details of how the system would initially be configured for a given individual in practice would depend on the degree and variety of the patient's compulsions and would be informed by input from a mental health professional.

- **Repetition Window Size:** This represents the maximum permissible delay (measured in number of frames) between two frames that contain repeated actions. This is designed to prevent any behaviour that is repeated after a sufficiently extended duration from being deemed repetitive. This functionality is required for a number of reasons. Firstly, many different types of behaviours are eventually repeated after a significant period of time, such as turning a light switch on and off, standing up and sitting down and walking back and forth through a doorway. It is of course normal to repeat these behaviours over extended periods of time, but not to do so excessively over a short duration. Nearly all OCD compulsions involve an action that is repeated almost immediately after it is finished, as the individual feels compelled to repeat the behaviour until they are freed from the associated anxiety (typically an intrusive thought). The maximum permissible delay between repeats of a given behaviour will enforce this characteristic of OCD in order to differentiate compulsive from non-compulsive behaviour.

- **Minimum Similarity Threshold:** The minimum similarity threshold defines how similar two figure images must be, as determined by the image similarity metric, in order to be considered a behaviour or action repeat. This threshold will need to be set lower for compulsive behaviours that have a low similarity among repetitions and higher for behaviours that have a high similarity among repetitions. As an example, the threshold could be left at 50% similarity for all compulsive behaviours. However, this would engender the drawback that for high similarity behaviours, the proposed system would likely, in some cases, overestimate the number of repeats, thus producing false positives. In general, the higher the similarity threshold is set, the fewer false positives there will be, but the less likely the system will be to detect dissimilar repeats of a compulsive behaviour. This parameter could initially be established through discussions with a mental health professional based on prior knowledge of the individual with OCD.

- **Minimum Number of Repetitions:** The minimum number of repetitions parameter defines the number of times that a given cycle of behaviour must be repeated in order to qualify as abnormally repetitive i.e. compulsive. To illustrate, opening and closing a

Table 4.1: *Parameters Used in Experiments*

Video	Window Size	Min Similarity Threshold	Repeat Rate
1 - Tapping on a Table	50	0.55	1.5
2 - Opening and Closing a Drawer	50	0.6	4.0
3 - Walking Back and Forth	50	0.52	4.0

drawer could be considered a distinct action or behaviour cycle and as such would represent one behaviour. A repeat of this behaviour would be to open and close the drawer again, which would then constitute two behaviour cycles i.e. one repeat of the behaviour. If the individual then proceeds to open and close the drawer an additional five times, within a short time frame, this would be considered excessive, as the behaviour pattern has been repeated an undue number of times. This is a fundamental characteristic of many compulsive behaviours in OCD; that they are repeated an unnecessary, or abnormal, number of times.

- **Repeat Rate:** The rate at which a repeated behaviour can vary in terms of duration per behaviour cycle. Simply put, this parameter is used to relax the temporal constraints on how fast, or slow, a behaviour must be performed in order to be considered a repeat of the previous behaviour. For example, if a behaviour (e.g. opening and closing a drawer) takes five seconds to complete and the repeat rate is set at 2.0, then the time frame in which the next repeat of the behaviour can be considered a match is 10 seconds. Thus, if the individual then opens and closes the drawer a second time, within 10 seconds, it will still be considered a repeat of the first behaviour, as it still conforms to the *Initial Time Frame * Repeat Rate* formula.

4.4 Experimental Details

This section describes the system configuration, test videos and metrics used in conducting our experiments. It is organised in the following manner: Subsection 4.4.1 presents an overview of the system configuration that was used in our experiments. Subsection 4.4.2 provides information about the set of videos used to test the proposed system. Finally, subsection 4.4.3 details the metrics used to evaluate the performance of the proposed system.

Video	Duration (seconds)	Number of Frames
1 - Tapping on a Table	22	555
2 - Opening and Closing a Drawer	26	659
3 - Walking Back and Forth	38	961

Table 4.2: *Details of the videos used in testing*

4.4.1 System Configuration

All of our analyses and experiments took place in the MATLAB technical computing software suite. The MATLAB software was executed on a single PC running Windows 7, with 8GB of RAM and an 8-core processor running at 3.40 GHz. The version of MATLAB used was the 64-bit R2012b. The Horn-Schunck optical flow algorithm used in the proposed system came from the MATLAB Computer Vision System Toolbox. The implementation of Pearson's r came from the MATLAB Image Processing Toolbox function *corr2*. As discussed in Subsection 4.3.4 we also implemented the following compulsive behaviour thresholds: *Repetition Window Size*; *Minimum Similarity Threshold*; *Repeat Rate* and *Minimum Number of Repetitions*, with the values detailed in Table 4.1.

4.4.2 Video Data

Three videos were used in testing the proposed system, each depicted in Figure 4.3 with their details displayed in Table 4.2. All three videos were of the AVI format, with a resolution of 400(W) x 226(H) @ 25 FPS. Each video of a simulated OCD compulsion was created by the authors, based on the existing body of mental health knowledge. The videos were designed to be as accurate and as close to reality as possible, whilst still providing clear and precise examples of compulsive behaviour. Each video involves one individual performing repetitive/compulsive actions from a stable webcam viewpoint, however different angles were used for each behaviour in order to demonstrate the proposed system's efficacy at different set-up points. Nevertheless, in reality the camera would only be set-up at one such viewpoint per individual case and all behaviours would then be captured from that perspective. Additionally, the total number of repetitions, their speed, and any brief breaking periods i.e. the periods between repeats, were varied in order to provide the sense of variety seen in natural, real-world compulsions, whilst still exhibiting clear compulsive tendencies.

The parameters and content of each video are described below.:

Figure 4.3: *Left to right: Video 1 - Tapping on a Table; Video 2 - Opening and Closing a Drawer; Video 3 - Walking Back and Forth*

Video 1 - Tapping on a Table:
This video simulates a compulsion of repeatedly tapping on a tabletop. The tapping act is repeated several times in a row, before a brief pause occurs, after which the tapping is repeated. The pausing was designed to break up the compulsive behaviour slightly in order to test if the proposed system could still detect the repetitions after such pauses. This provided a more natural example of compulsive behaviour, as an individual will not always perform the entirety of a repetitive behaviour without a single pause.

Video 2 - Opening and Closing a Drawer:
This video simulated a compulsion involving opening and closing a drawer repeatedly. This is a form of checking behaviour i.e. repeatedly making sure something is or isn't in the drawer. The opening and closing of the drawer is repeated across varied periods of time, with occasional brief pauses before starting the process again. Checking behaviours are often a source of considerable distress for individuals with OCD.

Video 3 - Walking Back and Forth:
This video simulates a compulsion involving walking back and forth. The individual moves slightly different distances each time and the amount of time per repetition is similar, but varied. Again, this is done to simulate natural compulsive behaviour. Like most OCD compulsions, this behaviour is unproductive, but often relieves anxiety for the affected individual. This could occur, for example, when the individual gets stuck in a mental obsession while walking past a certain location, or simply taking a step. Repeating such routine behaviours is common among individuals with OCD, especially when a cycle of anxiety is triggered.

4.4.3 Performance Metrics

In determining the efficacy of the proposed system, we first considered its accuracy regarding the number of behavioural repetitions that it was able to detect and secondly, the number of false positives it produced in the process. An additional potential metric that was not chosen, was the accuracy of the system in determining whether a detected repetitive behaviour is characteristic of OCD or not. Because of the near-endless variety of compulsive behaviours possible in OCD and the high level of complexity in separating them from normal repetitive behaviours (such as skipping), we left this problem for future research. Thus, the proposed system will detect highly repetitive behaviours whether they are indicative of OCD or not. However, as the proposed system is intended to be placed in an optimal location within the residence of a patient already known to have OCD, this is not considered to be an issue.

Regarding accuracy, the key for the proposed system is only to detect whether or not a potential compulsive behaviour has actually been performed, based on its general repetitive nature. Consequently, while it is optimal for every repetition of a given behaviour to be detected, it is nevertheless typically not necessary in order to detect a behaviour as being compulsive, so long as the accuracy is nevertheless high. In determining the accuracy of the proposed system, each video was first manually scrutinised in order to determine the true number of repetitions of a given compulsive behaviour. This was then compared with the number of repetitions that the proposed system was able to detect in order to provide an overall accuracy for each sequence of behaviour.

4.5 Experimental Results and Analysis

This section documents the results of our experiments and provides an interpretation and explanation of said results.

In Figures 4.4-4.6, repetitions are plotted based on the frame in which they are detected. Note that green lines (repetitions manually detected by a human viewer i.e. 'actual repetitions') and blue lines (repetitions detected by the proposed system) need not overlap perfectly. The manual detection method, in this case, counted repeated cycles of behaviour from a point at the beginning of the cycle. For example, in a video of hand tapping, the entire tapping behaviour consists of the hand being slightly raised (at the wrist) above the table, and then being lowered again, in quick succession. This results in a tapping motion, which is repeated. When considering manually detected repetitions, the chosen comparison point to match occurs during the

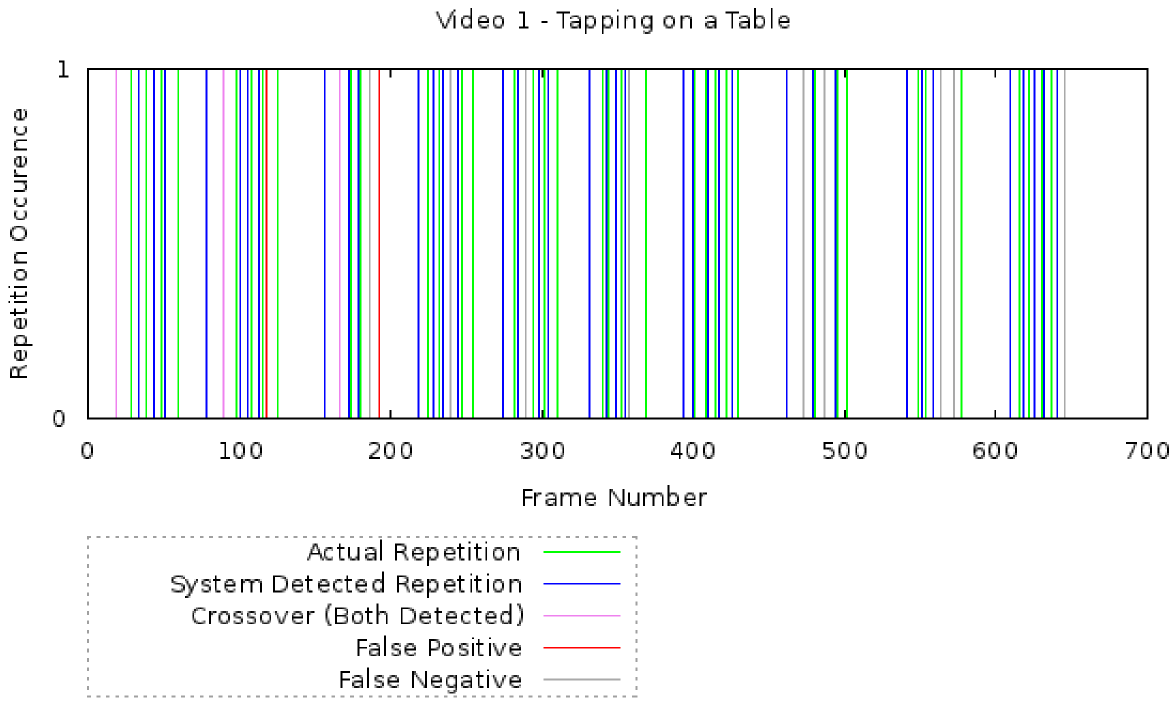

Figure 4.4: *Graphical Results for Video 1: Tapping on a Table*

raising of the hand (the beginning of the behaviour). When the hand is next raised in the same manner, it will be considered a repeat. On the other hand, the proposed system automatically detects repetitions based on the first detected match point in the behaviour cycle that is above the nominated similarity threshold. Depending on the behaviour this will sometimes occur before and sometimes after the manually detected match point. On less common occasions, the manually detected and system detected points will overlap completely, or crossover. Thus, if perfect accuracy were achieved, the graph would show one blue line for every green line, meaning that every manually detected repetition would also have been detected by the proposed system. Purple lines have additionally been used in some of the graphs for clarity. The purple lines represent situations in which both manual detection and the proposed system have found a match on the exact same frame i.e. a crossover, meaning that only one of the two colours (green or blue) would otherwise be seen.

Finally, red lines are used to indicate situations in which the proposed system has incorrectly detected a repetition where one doesn't actually exist, usually by detecting a repetition more than once within the same behaviour cycle. These are known as *false positives.* False positives tend to occur when the repetition is detected in both the up and down or back and forward phase of a behaviour. Additionally, in highly symmetrical behaviours i.e. behaviours that look nearly-identical in both the forward/backward (or up/down) directions the proposed system

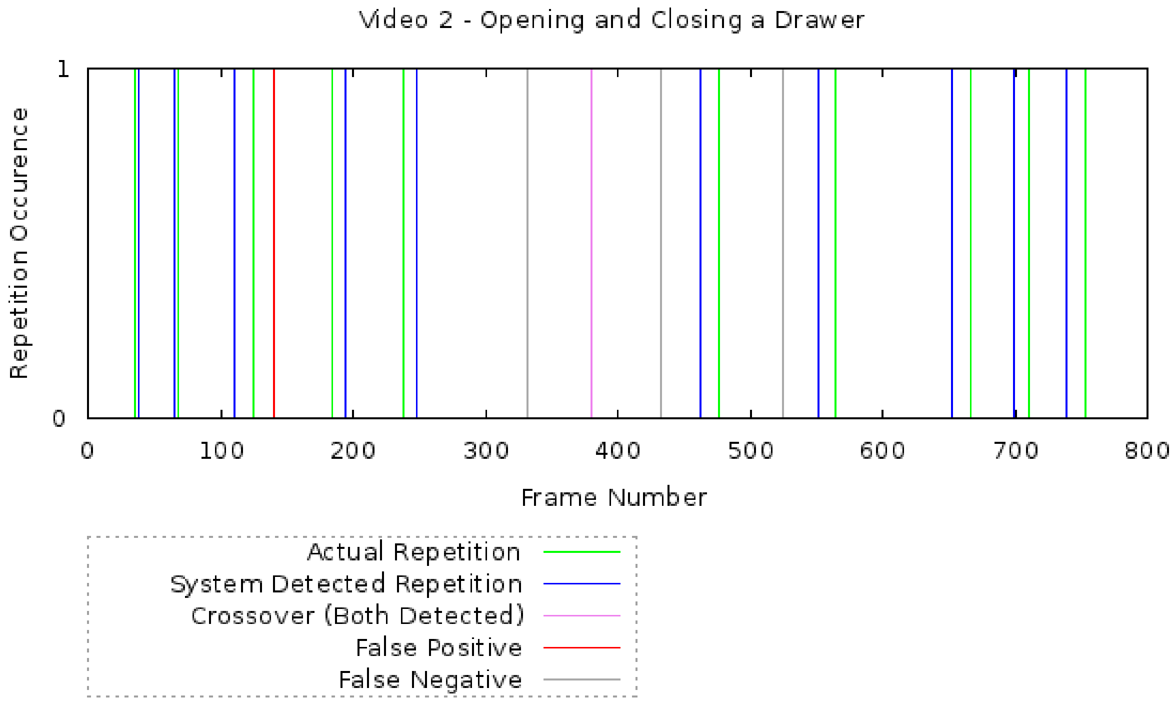

Figure 4.5: *Graphical Results for Video 2: Opening and Closing a Drawer*

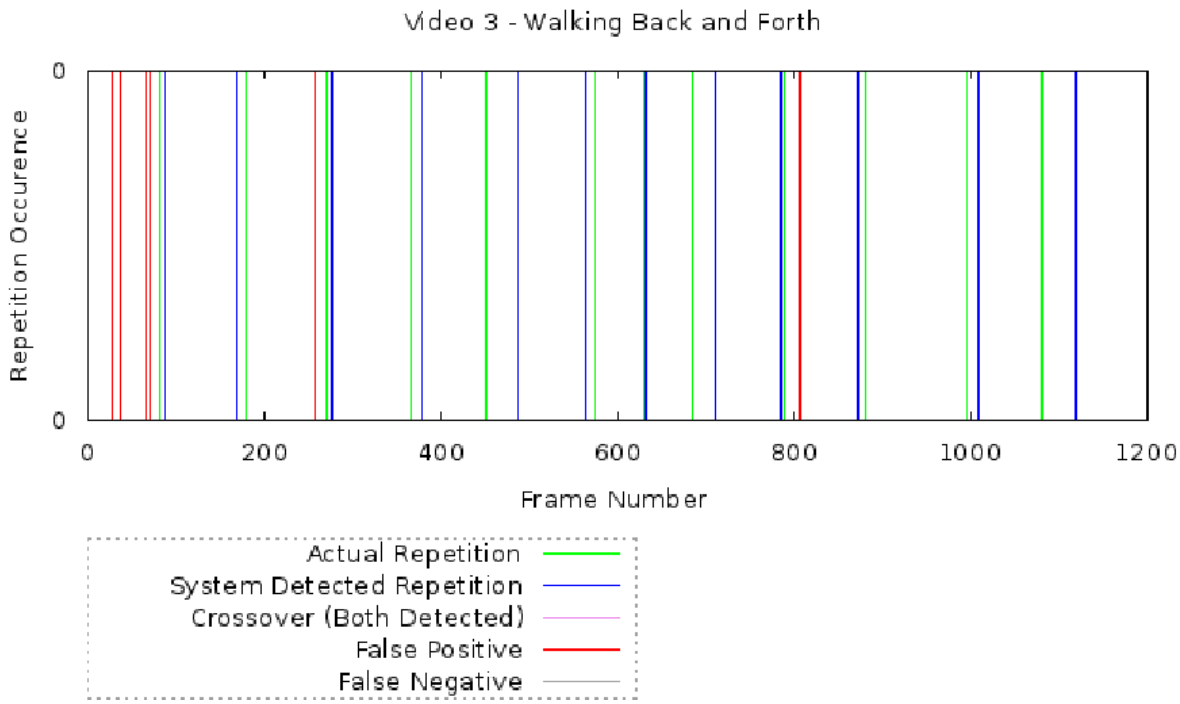

Figure 4.6: *Graphical Results for Video 3: Walking Back and Forth*

may exaggerate the rate of true repetitions. However, as this end-user information is intended for mental health professionals to evaluate, false positives are less of an issue than *false negatives*, which can result in potentially missing compulsive behaviour patterns. Regardless, if the *Minimum Number of Repetitions* threshold is set high enough, then normal, non-compulsive behaviours would rarely produce enough false positives to be erroneously identified as compulsive behaviour. In cases where normal behaviours are incorrectly identified as compulsive, they can simply be ignored by a mental health professional reviewing the data. Again, however, these would be uncommon.

It can be seen from the results in Figure 4.4 that the proposed system is quite good at detecting repetitions in the video stream without producing too many false positives. This is evidenced by the close fit between the number of green and blue lines. Interestingly, we can also determine the frequency of clustered repetitions in this video by looking at the green, blue and purple lines as a group. These lines appear to be bunched together. This is because the tapping behaviour in the video consists of a series of taps before the tapping motion stops and subsequently repeats again. This produces the characteristic bunched appearance of the detected repetitions.

Figure 4.5 consists of fewer repetitions than Figure 4.4 and thus is a bit more visually demonstrative of the accuracy of the proposed system. It can be seen that the manually detected repetitions and system detected repetitions fall very near to each other, with many even being matched quite closely in pairs. This demonstrates a good correlation between the actual repetitions and those that the system is detecting. This again reinforces the fact that the proposed system is able to detect the actual repetitions quite accurately.

As demonstrated in Figure 4.6 the proposed system produces more false positives on Video 3 than on any other video, but also achieves the highest overall accuracy in terms of detected repetitions. The high number of false positives is likely due to the proposed system detecting multiple similar movements within a behaviour cycle which aren't actually full repetitions of behaviours, but merely similar close movements in a sequence. This could likely be avoided by raising the required similarity threshold, at some cost to the overall accuracy of the system. However, we do not consider this necessary as the false positives are still at a fairly acceptable level and do not otherwise detract from the efficacy of the proposed system in accurately detecting the compulsive behaviour. Additionally, setting the *Minimum Number of Repetitions* parameter to a reasonable value would likely further neutralise this type of issue.

As shown in Table 4.3, of the three videos that the experimental simulations were run on, Video 3 received the highest overall accuracy, but at the cost of also incurring the greatest number of false positives. Video 1 also received a high accuracy and managed to do so with very few false

Video	Actual Repetitions	Detected Repetitions	Precision	Recall
Video 1	50	41	95.35%	82%
Video 2	14	11	91.67%	78.57%
Video 3	12	12	66.67%	100%

Table 4.3: *The accuracy of the proposed system on the three test videos. We consider the accuracy of the proposed system to be most aptly reflected by its recall. Note that false positives are not included in the detected repetitions count.*

positives. Video 2 received a similarly high accuracy to Video 1, also with few false positives.

Although the *Minimum Number of Repetitions* parameter was not explicitly implemented in the experimental simulations, as it would make no difference to the presented results, it is nevertheless useful to explain the part it plays in the proposed system. In attempting to detect the behavioural repetitions in Video 1, the proposed system was able to detect four consecutive repetitions before it considered the repetitive behaviour terminated. In reality, however, the repetitive behaviour continued. This premature termination can occur as a result of a few repetitions being missed and thus the window being terminated due to a time-out, thus prompting the search for a new, subsequent sequence of repetitive behaviour. It can also occur due to the repetitive behaviour changing in form so that it no longer looks sufficiently similar to the previous repeated cycles of that behaviour. Both of the previous two are a result of the *Repetition Window Size* and *Repeat Rate* parameters causing a time-out. This is designed to prevent the system being held up after a compulsive behaviour has terminated and also to ensure that continued repetitions of a compulsive behaviour are captured even if the behaviour begins to look dissimilar to previous cycles of the same behaviour. This is thus achieved by terminating the search for the current pattern of behaviour after the pre-elected delay so as to begin the search again for a new repetitive behaviour cycle, including a changed form of the same behaviour.

After the previously mentioned termination after four repeats of the behaviour, the system went on to detect another 39 consecutive repetitions, which included two false positives. Assuming that the Minimum Number of Repetitions parameter was set to five, the first sequence of repetitive behaviour would not be considered indicative of OCD, but the second sequence would. This means that the behaviour in Video 1 would be considered overall to be compulsive behaviour indicative of OCD, which is correct.

Regarding Video 2, the proposed system detected two separate sequences, the first of which contained two repetitions and the second of which contained 10 repetitions, one of which was a false positive. Again, assuming a Minimum Repetition threshold of five, only the second sequence would be considered repetitive, which would again be considered a success as the proposed system detected the overall behaviour pattern as compulsive. When tested on Video 3, the proposed system detected a total of five sequences, the first three of which contained one repetition each. These repetitions were false positives. Assuming the same five repetition minimum threshold, none of these would be considered compulsive OCD behaviour. The fourth sequence contained two repetitions, and would also not be considered repetitive. The fifth and final sequence contained twelve repetitions, two of which were false positives. This final sequence would be considered compulsive behaviour. Thus, Video 3 would also be classified as exhibiting compulsive behaviour characteristic of OCD, which is again, correct.

These results demonstrate that not only can the proposed system detect simple compulsive behaviours typically characteristic of OCD, but it can also detect the number of repetitions in these behaviours with a high degree of accuracy. Based on the graphical results and overall accuracy of the proposed system on the test videos, we believe that the proposed system has demonstrated good potential, not only for future research, but also for possible future implementation in a clinical context.

4.6 Related Work

Lu et al. proposed a multi-dimensional segmentation model in conjunction with classification techniques with the aim of detecting repetitive movements for ergonomic benefits [30]. Although their system shares a fundamental similarity with ours it does not deal with individuals possessing any kind of mental disorder, nor does it analyse movements in the context of repetitive behaviour generalised enough to catch OCD behaviours. Furthermore, the system proposed by Lu et al. is not designed to account for the conceptual elements of typical OCD compulsions, such as behavioural repeat rates and repeat thresholds, nor is their system intended to serve this purpose. Conversely, our system is tailored to OCD compulsions, while remaining generalised enough to capture many different possible OCD compulsions. These elements of the proposed system could provide insight into the efficacy of a mental health professional's chosen treatment plan.

Fan et al. proffered a novel framework for detecting and recognising sequential repetitive tasks performed by human actors [33]. However, due to the authors' focus on the unique nature of sequential events, they impose strict spatial and temporal constraints on the actions to be performed. This would not likely adapt well to the kind of behaviours indicative of OCD. Moreover, it would not be generalised enough to catch the wide range of possible compulsions, with varying speed and dynamism. Finally, the authors also focus on a potential overlapping of actions, as when two actions in a sequence are performed simultaneously. This doesn't tend to occur very often in OCD compulsions, as the behaviour itself is repeated in cycles until the anxiety is relieved. Thus, our focus, in contradistinction, is on atomic behaviours that repeat themselves.

Endeshaw et al. and Jansohn et al. both proposed systems to analyse repetitive motions for the purposes of detecting sexually indecent video content [31, 32]. Like the proposed system, Endeshaw et al. use the adjacency in time and space of motion vectors to determine repetitive behaviour. However, their system is intentionally limited to the frequency band of repetitive movements that indicate indecent content. This wouldn't be effective for the proposed system, as compulsive behaviours differ and are more general. Thus, the proposed system was designed to be free enough to detect general repetitive behaviours indicative of OCD, yet restrictive enough to be matched against the same behaviour when repeated. Alternatively, Jansohn et al. combine both image features and MPEG-4 motion vectors to detect pornographic content online. Although effective, this technique is not specific enough to address our needs, as it does not threshold repetitive behaviour, nor concern itself with an excessive number of repetitions, as is the case in the proposed system. Additionally, their system relies on MPEG-4 motions vectors, which are not as widely applicable as optical flow techniques due to their dependency on MPEG-4 format video content.

Sarel et al. proposed a method of separating transparent layers in scene dynamics [111]. In achieving this they assume that one of the layers includes repetitive dynamics, while the other layer can include any arbitrary non-rigid dynamics. The approach can take both video and audio data into account. While interesting, this approach makes the inherent assumption that there is already repetitive behaviour in one of the layers and thus is more concerned with layer separation than detecting repetitive behaviour. Because of this, the system does not focus on the number of repetitions, nor their similarity, nor does it focus on detecting repetitive behaviours characteristic of OCD. Overall, the system proffered by Sarel et al. uses similar principles to ours and has similar aims, but is directed towards a different overall objective. Ultimately, we require a system that can automatically detect the repetitive behaviours once they surpass a certain number of repetitions. Because of this, the system proposed by Sarel et al. wouldn't be appropriate for our purposes and objectives.

Goodwin et al. proposed the use of accelerometers combined with pattern recognition in order to identify behaviours indicative of ASD, such as hand flapping and body rocking [112]. More specifically, three pertinent points of interest, the left wrist, right wrist and torso were used as placement locations for the accelerometers. The output data of the accelerometers was labelled as one of three classes of known autistic behaviour and then fed into a C4.5 decision tree, which was used to classify the instances with promising results. As in our case, the researchers noted how invaluable this kind of data could prove to be to mental health professionals. Regardless, the system proposed by Goodwin et al. is tied to accelerometer use and is thus restricted to that domain. This technology, though useful, would not likely be able to discern the same range and dynamicity of behaviours in many cases as could simply be observed through video analysis. Furthermore, as the system is built for ASD, it is naturally not designed to capture OCD compulsions, many of which can be more visually-based than acceleration-based and can occur via different body parts. Regardless, the use of accelerometers in this kind of research is an interesting direction and could perhaps even serve as some form of complement to future compulsive behaviour analysis systems.

Hashemi et al. designed a comprehensive computer-vision-based system for the early detection of ASD in children based on four primary criteria: Sharing Interest, Visual Tracking, Disengagement of Attention and Atypical Motor Behaviour [113]. These activities were all assessed using an automated video-based system in order to provide a clinician with in-depth information about the child's condition. Perhaps most interestingly to our research, is the atypical motor behaviour element. While this element often contains repetitive movements, the authors chose to focus primarily on the sub-aspect of an asymmetrical gait. The authors achieved this using a combination of models to produce articulated 2D stick men, which were able to represent and track the toddler. The stick-man is comprised of segments that represent the separate limbs and torso of the individual and can be used to calculate joint angles during limb movements throughout the video. By determining the joint angles across time, the authors are able to detect asymmetric behaviours characteristic of ASD. While highly interesting, this study did not directly consider repetitive behaviours and thus would need to be adapted if it were used for OCD. Conversely, as our system is designed specifically to detect and analyse repetitive compulsions, rather than an asymmetric gait, it is able to solve problems directly attributable to OCD. Hashemi et al. also note the importance of automated systems for the early diagnosis and analysis of mental health issues.

Mugica et al. proposed a system for the monitoring and analysis of patients with major depressive disorder during their first year of depression [26]. The researchers noted the value of consistent patient monitoring during treatment to determine the success of a given psychiatric treatment. Regardless, there are notable contrasts between the research of Mugica et al. and our own. Firstly, our research focuses on OCD and compulsive behaviour, whereas theirs focused on a number of factors including questionnaires and sensors that recorded sleep and movement patterns. However, none of these elements were related to the idea of compulsive behaviour or the consequent anxiety endemic to OCD.

Amor et al. proposed a very interesting monitoring system for patients with Bipolar Disorder using Personalised Ambient Monitoring (PAM) [28]. Their system used multiple sensors, both environmental and wearable, that assisted in calculating underlying patterns of behaviour. However, their system does not capture specific behaviours and is more focused on gross patient locations and general behaviours. Additionally, although their system could be extrapolated to detect the progress of a treatment on an individual's general behaviour over time, it nevertheless does not detect repetitive behaviour, nor does it apply to individuals with OCD. Conversely, we required a system that would specifically cater to individuals with OCD.

Pediaditis et al. produced a novel system for the detection of stress and anxiety from human faces [114]. Their system used multiple features taken from multiples aspects in order to detect the anxiety. The features included: Region of Interest detection, head motion estimation, facial colour for heart rate estimation, eye-related features such as blinking and eye opening, and mouth-related features. When combined these features were then used fed into an Artificial Neural Network for classification. While valuable, this type of system would not be sufficient for anxiety detection based on compulsive behaviour due to its specific focus on the head, as many OCD cues are instead observed in bodily movements. The steep requirements in terms of the number of features would further make OCD behaviour classification difficult, due to high dimensionality and complexity. Regardless, the use of such a system to complement compulsive behaviour detection is a plausible future area of interest.

4.7 Conclusion

The proposed system has demonstrated that it can accurately identify simulated compulsive behaviours indicative of OCD. It achieves this through a combination of optical flow, an image similarity metric and repetition thresholds. Results gathered from experimental simulations demonstrate that the proposed system has good future potential to assist in analysing the success of various treatments for OCD, based on the prevalence and severity of various exhibited behaviours. Moreover, the proposed system holds future potential for comfortable integration with existing electronic patient data to provide a synergistic benefit to the patient and mental health professional. This is further beneficial because the proposed system doesn't interfere with existing treatment paradigms, nor the patient-doctor relationship. Systems such as that proposed herein thus offer the ability not only to increase a mental health professional's general understanding of OCD, but also their success in treating their patient's specific and unique issues.

An additional benefit of the proposed system is that it detects rather general compulsive behaviour, which provides it with the potential to adapt well to the repetitive behaviours that characterise ASD, since many of these behaviours share similarities with OCD compulsions. This may yield further benefits to mental health professionals in assisting such patients. The generalised nature of the proposed system, along with its lack of dependency on predefined human models and classification means that it is also efficient and relatively low in complexity, compared to more elaborate methods. We believe that the novelty of the proposed system, through its potential to act as a new measure in OCD patient treatment, is palpable and worth substantial future research to further refine and enhance the benefits of the system.

Despite the benefits of the proposed system, it also possesses some drawbacks. Namely, the system assumes that only one individual will be present and in view of the camera. If this assumption is not met, then motion from other individuals could potentially interfere with the monitoring of the individual with OCD. Additionally, many behaviours exhibited by normal individuals under certain circumstances (e.g. skipping, drying dishes, and certain exercises) possess very similar characteristics to repetitive OCD compulsions. Human beings can typically differentiate these behaviours by knowing how many repetitions of a general behaviour is necessary to produce a desired effect or goal. However, in order for a system to know this, common, yet normal, repetitive behaviours would likely have to be 'blacklisted' in order to single out behaviours that are unduly repetitive. Nonetheless, how one would go about achieving this is a question for ongoing and future research.

The research presented in the next core chapter focuses on more advanced methods of further detecting and analysing the differences between repetitive compulsions and similar, but non-compulsive behaviours.

Chapter 5

Distinguishing Compulsive from Non-Compulsive Behaviours in Obsessive Compulsive Disorder

5.1 Introduction

Recent advances in motion description and analysis techniques, in conjunction with continued improvements in computing power, have resulted in a burgeoning of interest in the field of human activity analysis [115, 92, 116, 117, 118, 119, 120, 121]. Moreover, researchers have only just begun to realise the considerable potential that behaviour monitoring systems hold in their ability to inform mental health professionals and complement existing mental health treatment plans [122, 123, 93, 124, 125]. Despite this, very little such research has focused specifically on the repetitive behaviour patterns that are characteristic of multiple mental health conditions, including ASD and OCD. Furthermore, no research that we are aware of has visually targeted the repetitive behaviours (compulsions) of OCD in an attempt to assist mental health professionals in treating patients with this prevalent and debilitating disorder. In order to fill this niche and thus provide a valuable enhancement to traditional OCD treatment plans, we proffer a system specifically aimed at detecting the compulsive patterns of behaviour characteristic of individuals suffering from OCD. Thus, the aim of the proposed system is to allow mental health professionals to both better understand their patient's unique condition and to treat it on a more individual level.

Current methods of treating OCD typically involve the application of a targeted psychological intervention, such as Cognitive Behavioural Therapy, in conjunction with patient self-report progress measures and, in some cases, medication [69, 126]. While such approaches have been demonstrated to work rather well for many patients, there are nevertheless drawbacks inherent to their use. One notable example is the potential lack of reliability of self-report measures. This can be due not only to the limitations of human memory, which itself can be rather unreliable [97, 127], but also to the subjective biases of the individual in question [128]. As a result of the aforementioned issues, we developed a system with the potential to be later employed as an enhancement to existing treatment plans. This would be accomplished in such a manner as to allow objective information to be automatically gathered, analysed and then utilised by a mental health professional as an effective supplement to their existing knowledge of a patient's condition and progress. Ultimately, this would allow the mental health professional to make more informed decisions about the most effective treatment plan for their patient at any given time.

Previous approaches to activity analysis have often focused on generic human action datasets, either self-produced or well-known, such as the KTH dataset. These datasets tend to demonstrate behaviourally normal human action sequences, such as walking, jogging, pushing and hand waving [129, 130, 100, 131]. Additional research has focused on repetitive behaviour analysis for the purposes of ergonomics [30, 132] and fraud prevention [33]. However, the aforementioned research does not attempt to take psychologically abnormal behaviours into account, such as the compulsive behaviours exhibited by individuals with OCD. As such, the existing corpus of research does not lend itself readily to detecting the distinct behavioural patterns characteristic of OCD compulsions, nor to comparing compulsive behaviours with non-compulsive behaviours. Other researchers have begun focusing on the application of various algorithmic techniques to particular mental health conditions, however, none of these approaches have specifically focused on OCD or its general bodily compulsions [133, 26, 134, 122, 135]. No research that we are aware of has sought to develop a system for the analysis of compulsive behaviours in individuals with OCD. It is these behaviours that the proposed system is specifically designed to distinguish.

In developing the proposed system, we have provided the following core contributions:

- **Presented an efficient representation for capturing compulsive behaviours:** Herein we proffer a method of capturing compulsive OCD behaviours, of variable duration and dynamism, in a reduced form that is suitable for both storage and classification. We achieve this via a type of Motion History Image, which we call a TMHM. TMHMs are a product of the frequency with which an optical flow vector moves across a given coordinate on a 2D video axis across time. We further reduce each TMHM into a histogram-based representation called an RTMHM. RTMHMs are an efficient format for storing compulsive and non-compulsive behaviours, whilst still preserving their degree of repetitiveness across time.

- **Provided a system that is capable of differentiating between compulsive and non-compulsive examples of the same type of behaviour:** The proposed system is able to efficiently differentiate between compulsive and non-compulsive behaviours via a number of techniques. Namely, we combined the aforementioned RTMHMs, CFS, and a Multilayer Perceptron classification component. Our implementation of this portion of the thesis has demonstrated a high degree of accuracy in differentiating the compulsive and non-compulsive behaviours on which it has been tested, achieving an overall classification accuracy of 92.5% on the tested dataset.

- **Provided a system that is capable of differentiating between global degrees of behaviour compulsivity:** In the second segment of this second core chapter, we demonstrate that the aforementioned system is also capable of accurately differentiating between varying degrees of compulsivity among behaviours. This kind of 'global' compulsivity grading could provide valuable information to a mental health professional about the general lower, intermediate, and upper degrees of a given individual's compulsions and thus could potentially be helpful in assessing the general severity of said compulsions. We achieved this via the use of the system proposed in the first segment of this core chapter, with some minor modifications made to the multilayer perceptron.

The remainder of this chapter is structured in the following manner: Section 5.2, presents background material on the Multilayer Perceptron classification algorithm so that the reader may better understand the integration of the classification aspect of the system. Some brief background material is also presented on the CFS algorithm, which is used to pare down the original set of attributes. Section 5.3 discusses the elements that comprise the proposed system and how they function together to distinguish compulsive from non-compulsive behaviour. Section 5.4 explains the parameters and setup that were used in our experiments. Section 5.5 details our experimental results and explores their implications. Section 5.6 discusses the related literature and finally, Section 5.7 discusses our findings, the benefits and limitations of the proposed system and our future research.

5.2 Background

This section provides some brief background material on the both the CFS algorithm and the Multilayer Perceptron used in the proposed system. Thus, Subsection 5.2.1 discusses the Correlation-based Feature Selection algorithm and why it was chosen for the proposed system, whereas Subsection 5.2.2 discusses the Multilayer Perceptron, its application to classification problems and why it was chosen for the proposed system.

5.2.1 Correlation-based Feature Selection

Correlation-based Feature Selection is a method of deriving a subset of predictive features from an initial dataset by determining which features have a high correlation with the class, yet are uncorrelated with each other [136]. This can be formalised as follows:

$$r_{zc} = \frac{k\overline{r_{zi}}}{\sqrt{k + k(k-1)\overline{r_{ii}}}}$$

in which:

- r_{zc} is the correlation of the summed components and a given outside variable
- k is the number of components
- $\overline{r_{zi}}$ is the average of the correlations between the components and the outside variable, and
- $\overline{r_{ii}}$ is the average inter-correlation between components [136].

The entropy measure can then be calculated as follows:

$$H(Y|X) = -\sum_{x \in X} p(x) \sum_{y \in Y} p(y|x) log_2(p(y|x))$$

followed by the dependency (correlation measure) of y on x:

$$C(Y|X) = \frac{H(Y) - H(Y|X)}{H(Y)}$$

As with feature selection in general, this typically has the benefit of allowing for more efficient classification and can additionally help to avoid overfitting on the training data [137]. CFS was chosen due to its efficiency and ability to derive a representative, yet concise set of unique features for the classification stage of the proposed system. The resultant set of features has a typical predictive accuracy similar to prominent methods. Indeed, in our preliminary tests involving a Naive Bayes classifier, a Multilayer Perceptron, and a Support Vector Machine, CFS produced a feature set with an accuracy comparable to the prominent method of Principal Component Analysis (PCA), but in a much shorter time frame. Considering our initial dataset began with over 900 features per instance, as the number of instances increases into the hundreds, as could perhaps be expected under real-life circumstances, the dimensionality begins to increase substantially, and with it the speed of the feature selection method begins to fall. Thus, in such circumstances, the efficiency of the feature selection method becomes crucial. Along with the accuracy, this was one of our primary reasons for choosing CFS.

5.2.2 Multilayer Perceptron

A Multilayer Perceptron is a type of multilayer feed-forward neural network, which is designed to detect complex patterns for the purpose of classification [138]. It has demonstrated considerable predictive accuracy across a number of fields [139, 140, 141], typically being coupled with the error back-propagation algorithm in order to adjust the response of the network to hew more closely to the desired network output [142]. The Multilayer Perceptron was chosen for the proposed system due to its ability to provide not only a high degree of accuracy, as demonstrated in preliminary results, but also due to its reasonable efficiency and ability to adapt to the nuanced complexity that may occur when trying to distinguish more fine-grained examples of low, medium, and high compulsivity behaviours. More specifically, when compared in our initial testing with Naive Bayes and a Support Vector Machine, the Multilayer Perceptron was able to equal or outperform both algorithms by a small margin when classifying compulsive vs. non-compulsive behaviour examples, as well as the global degree of compulsivity of the behaviours.

5.3 Methodology

This section expounds the structure and functionality of the proposed system and is organised as follows: Subsection 5.3.1 offers a high-level description of the system. Subsection 5.3.2 explains the RTMHMs that the proposed system uses to describe and classify patterns of compulsive behaviour. Subsection 5.3.3 details how a Multilayer Perceptron is used to separate the compulsive from non-compulsive RTMHMs and briefly details why it was chosen over comparable approaches. Finally, Subsection 5.3.4 explains how the Multilayer Perceptron was also used to classify behaviour examples into low, medium, and high degrees of anxiety.

5.3.1 An Overview

The proposed system is composed of three primary elements:

- **RTMHMs:**
  This is the storage format used in the proposed system to describe both compulsive and non-compulsive behaviours of variable duration. Specifically, each RTMHM depicts a single, information-rich example of behaviour in a manner that retains the behaviour's degree of repetitiveness. This is a crucial element for determining whether a behaviour is likely to be compulsive or not.

- **Compulsive Behaviour Classification:**
  The proposed system can use either manually or automatically generated labels to describe the aforementioned RTMHMs. For the sake of accurately testing the system's efficacy, manually generated (known) labels were used in all experiments. More specifically, these labels were used in the training and classification phase, where they were fed into a Neural Network. In the proposed system, the Multilayer Perceptron can be trained on any set of compulsive and non-compulsive behaviours in the RTMHM form. For the purpose of pragmatism, we retrieved the RTMHMs from isolated, video-based, limited-duration compulsive behaviour simulations, rather than from a constant video stream.

- **Compulsion Severity Classification:**
  As an additional enhancement to this chapter, the proposed system is also capable of distinguishing between varying global degrees of compulsivity in behaviour. In order to demonstrate this effect, we separate our dataset into three groups, based on their degree of compulsivity, and label them accordingly, namely: low compulsivity, medium compulsivity and high compulsivity. After applying CFS, we are able to train an artificial neural network to recognise the three aforementioned degrees of behavioural compulsivity with an accuracy of 85%.

The general functionality of the proposed system proceeds as follows: opaque silhouettes (referred to as 'figure images') for each compulsive behaviour are derived from optical flow vectors

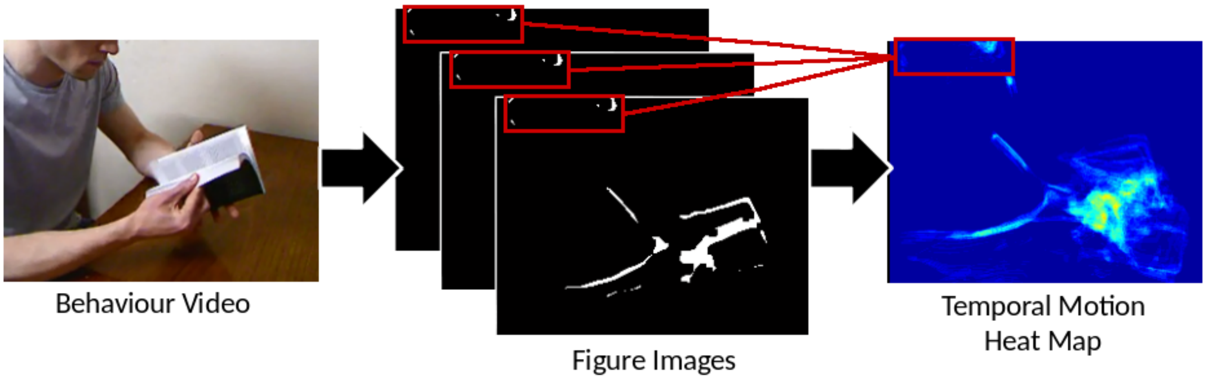

Figure 5.1: *An example video of a simulated compulsive reading behaviour in its original format (leftmost); as a set of figure images extracted from the video's optical flow motion vectors (centre); and, as a TMHM (right). Note that the optical flow components are taken from the first core chapter, whereas the TMHM is part of the proposed system. Note also that the TMHM has not yet been reduced to its constituent pixel intensity frequencies, hence it is displayed here as a TMHM rather than as an RTMHM.*

and have been extracted from our prior research. These figure images are combined across time to produce a single 2D additive matrix, which we herein refer to as a TMHM. This process is illustrated in Figure 5.1. This additive process for a given pixel location within the TMHM is represented by the following formula:

$$\textbf{AddPixLoc} = \sum_{x}^{N} Rx(yz)$$

Where;

- R is the running total;
- x is a 2D image matrix;
- and yz represents a given 2D pixel location;

Each TMHM is then distilled into an efficient, frequency-based representation for training and classification. We refer to this compact representation as an *RTMHM*. Once the RTMHMs have been generated, they need to be labelled. In order to accomplish this, there are two options: *manual labelling*, performed by a human, or *automatic labelling*, performed by our system from core chapter 1. As previously noted, we opted to manually label the RTMHMs used in training and classification so as to isolate the results of the proposed system and gain an accurate appraisal of its efficacy. Moreover, in practice, the proposed system would need only one initial set of manually labelled images, per individual case, in order to be effectively trained.

Regardless of whether the RTMHMs are manually or automatically labelled, the optical flow derived figure images from the first core chapter are nevertheless required to generate the initial TMHMs. From that point on, the proposed system can then theoretically train itself on the basis of future classification results. This would continue as more examples of compulsive and non-compulsive behaviour continued to accumulate. Naturally, this process will be most effective if

```
// The set of all test videos
vs = getVideoSet

// Open a figure image stream using our previous system to
// each video in turn
for every video in vs
{
    fis = getFigImageStream(video);

    // Create a new TMHM
    TMHM = newTMHM();

    for each figImage in fis
    {
        // Add the next binary figure image to the current
        // running total which is our TMHM
        TMHM = TMHM + figImage;
    }

    // Create an RTMHM
    RTMHM = getFreqValues(TMHM);

    // Produce class label for RTMHM
    currClass = video.getClass;
    RTMHM.class = currClass;

    // Append the current RTMHM to training/test data file
    appendToFile(RTMHM, dataFile);
}

// Feature Selection
ApplyCFStoFile(reducedFeats, dataFile);

// Classify dataFile using a Multilayer Perceptron with 10-fold
// cross-validation
crossVal(reducedFeats, NeuralNet);
```

Algorithm 4.1: An overview of the proposed system the system is initially given a large set of manually labelled training images informed by expert domain knowledge. However, this is not necessary in order for the proposed system to perform accurately, as our system from the first core chapter can already differentiate compulsive from non-compulsive behaviour at a more rudimentary, intra-behavioural level. Once the RTMHMs have been labelled, Correlation-based feature selection is then applied to reduce the overall number of features to a more efficient, yet representative set. A Multilayer Perceptron is then trained on this reduced feature set. Once the classification model is built, it can then be fed new examples of compulsive and non-compulsive behaviour to predict, based on the labelled RTMHMs used to initially train the model. For the purpose of clarity, the functionality of this compulsive vs. non-compulsive behaviour component of the proposed system has also been detailed in *Algorithm 4.1.* Additionally, the original RTMHM dataset was alternatively labelled to highlight the severity of the compulsivity of each of the behaviour examples i.e. low, medium, and high compulsivity. This dataset is also then reduced through CFS and used to train a Multilayer Perceptron to predict the degree of behavioural severity. This process is essentially the same as that depicted in *Algorithm 4.1.*

5.3.2 RTMHMs

The RTMHM is a data format that can be used to efficiently and accurately represent compulsive behaviour for the purposes of storage and classification. In the first core chapter of this thesis, we used the Horn-Schunck optical flow algorithm to derive motion vectors from video footage. These motion vectors can then be harnessed to produce opaque silhouettes that we refer to as 'figure images'. In the proposed system, these figure images are taken across the complete duration of a given behaviour and stacked upon one another, in order to produce what we refer to as a TMHM. This involves the summation of the separate binary figure images, thus producing a single 2D TMHM matrix, which represents the relative pixel intensities at any given x,y coordinate for a given behaviour. Simply put, the more frequently a set of pixels is traversed by an individual in the original video footage, the higher the intensity values for those pixels in the TMHM. Thus, the TMHM, in essence, preserves the degree of repetitiveness of a given behaviour across time. This technique distinctly lends itself to compulsive behaviour analysis, as locations within the TMHM that are of a higher intensity have repeatedly been traversed more times than areas with a lower intensity. Furthermore, the more repetitive a behaviour is, the more times that behaviour is likely to cycle across the same visual area, thus producing distinct heat map signatures for compulsive and non-compulsive behaviours. This effect can be seen in Figure 5.2, which details a very 'cool' blue heat map produced by a non-compulsive behaviour, as compared to the 'warm' red/orange/yellow heat map produced by the same behaviour in a

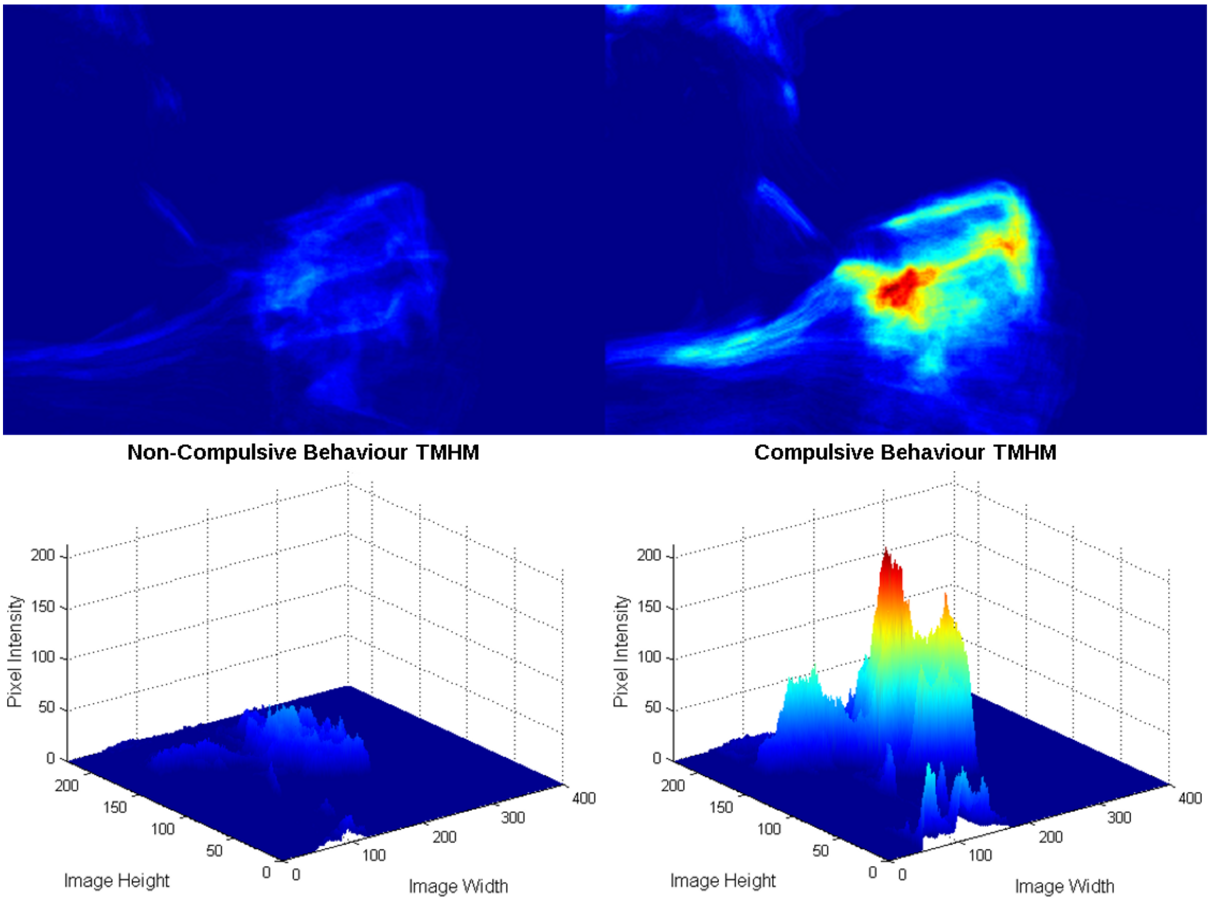

Figure 5.2: *An example of the pixel intensity across a TMHM. In the top images, the 2D TMHMs can be seen, depicting both a non-compulsive reading behaviour (left) as well as a compulsive version of the same behaviour (right). In the bottom two images, a 3D graphical representation of the same two TMHMs is illustrated, showing a clear difference in pixel frequencies intensities between the compulsive and non-compulsive behaviours. These pixel intensity frequencies are a good indication of the degree of repeated motion throughout a captured behaviour.*

compulsive form.

Once we have the TMHM, we then need to reduce its dimensionality while still preserving its degree of repetitiveness. The purpose of this is to make the processing and machine learning phases more efficient, as well as to preserve space in terms of storage. In order to achieve this, we used a simple frequency histogram conversion. This allowed us to preserve the relative frequency of pixel intensity values across a given TMHM, whilst reducing the overall size and dimensionality of the data. It's important to note that we were only concerned with the degree to which a behaviour was repetitive, such that we could distinguish varying degrees of compulsive behaviour from non-compulsive behaviour. We did not otherwise need to preserve the structure of the behaviour, nor its relative size, as these factors were not relevant to the relative compulsiveness or non-compulsiveness of the behaviours. A comparison between compulsive and non-compulsive RTMHM histograms is depicted in Figure 5.3. One can clearly see, mostly notably in the lowest 50 pixel intensities, that the non-compulsive behaviour has a much greater frequency of pixel intensities below 10, before essentially bottoming-out completely. This is because most pixels are traversed very few times in non-compulsive (i.e. normal, non-repetitive) behaviours and thus there are very few pixel intensities above the lower intensities. Contrast this with the compulsive behaviour, in which the frequency of pixel intensities remains notable until it reaches an intensity of about 50, at which point it too peters out, but nevertheless remains slightly above the non-compulsive behaviour.

In formulaic terms, for each pixel (x,y) coordinate in a flattened (i.e. 1D) TMHM, we take a frequency, and count all pixels containing it, which can be formalised as follows:

Given a set:

$$S = \{x \mid P(x) = f\}$$

In which;
x = a pixel location in an array
$P(x)$ = the value at that pixel location
f = a given frequency value

Then, for each S, we increment the count for the given f by one. When we tally such a count for each f, the resulting array is the RTMHM.

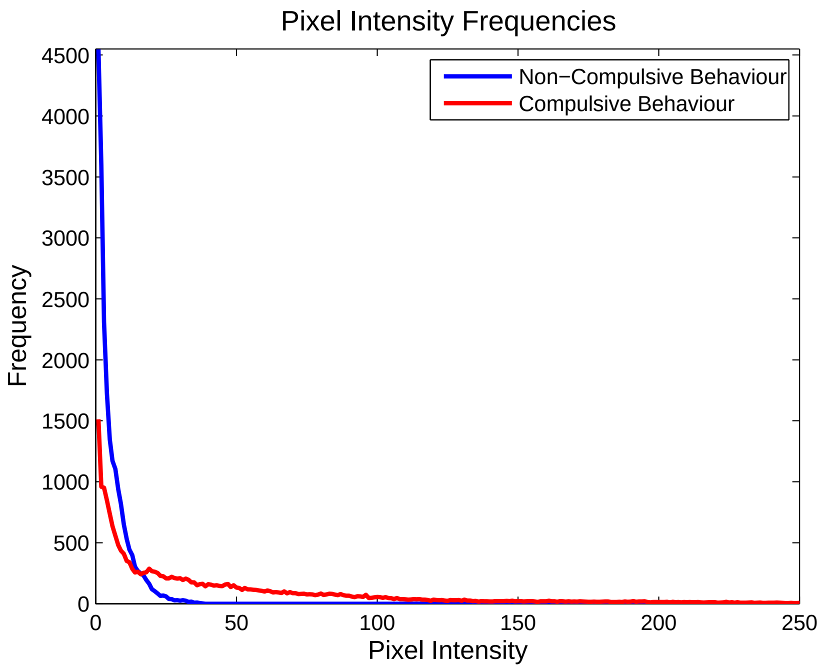

Figure 5.3: *A comparison between the frequency of various pixel intensities in an RTMHM of a compulsive and non-compulsive behaviour. Higher pixel intensities indicate that a given pixel has been traversed more frequently over a given period of time, whereas lower pixel intensities have seen little, if any, traversal.*

5.3.3 Compulsive Behaviour Classification

In order to accurately classify the RTMHMs, we had to first label each training and test instance and then extract the most relevant features. When applying CFS, we used the relative pixel intensity frequencies as the features, which were then distilled down to a reduced set of the most pertinent pixel intensity frequencies. This firstly involved binning the frequencies at every integral value increase in pixel intensity in order to create the initial frequencies. Thus, the minimum pixel intensity value was 0, representing no motion whatsoever. This then continued up to a maximum value, which was represented by the highest pixel intensity seen across all RTMHM examples in the test dataset.

It is noteworthy that this method thus initially employs a sparse feature set, as it represents all empty pixel intensity values for a given RTMHM with the placeholder '0'. This will predominantly occur when an RTMHM doesn't have many high intensity pixel values, due to a low degree of repetitive actions in the original video. Because such RTMHMs will still be stan-

Classification Technique	Accuracy
Multilayer Perceptron	92.5%
Naive Bayes	90%
Support Vector Machine	90%

Table 5.1: *A comparison of three prominent classification techniques, used on our dataset of 40 instances, for compulsive behaviour classification*

dardised to the same pixel intensity length as the longest RTMHM in the dataset, as will all RTMHMs in the data set, they will tend to have a tail of pixel intensities at the lower end which are all 0s. Naturally, this sparse approach can result in a substantial number of features, thus creating issues of dimensionality. For example, the sparse approach resulted in a total of 938 features across all instances. Thus, in order to increase efficiency and reduce the dimensionality of the dataset, we applied CFS, which then reduced the dataset to a total of 11 pertinent features.

Regarding our chosen classification method, a Multilayer Perceptron, we initially conducted preliminary testing to determine the efficacy of three different algorithms on our dataset. Notably, we tested a Multilayer Perceptron, Naive Bayes and an SVM. The parameters were tuned for each model in turn in order to achieve optimal results on the dataset. Ten-fold cross-validation was used for all three classification models and the dataset provided to each method was identical. The results of these preliminary experiments are detailed in Table 5.1. It can be seen that, while all three techniques performed rather well, the Multilayer Perceptron was able to outperform the other two methods on the tested dataset. As a result, we chose the Multilayer Perceptron as the classification method for the proposed system.

As previously noted, we used manual labelling for all RTMHM behaviour instances in our experiments. Regardless, there is also the potential for automatic labelling to be used, as derived from system proposed in the first core chapter of this thesis. In total, this process resulted in 20 examples being manually labelled as compulsive behaviour and 20 examples being manually labelled as non-compulsive behaviour. With the features selected and the instances labelled, we opted to use 10-fold cross validation, as in the preliminary testing, during classification, due to the relatively small size of our data set. This allowed us to get a better overall estimate of the efficacy of the proposed system and get more out of the dataset.

Classification Technique	Accuracy
Multilayer Perceptron	83.3%
Naive Bayes	76.7%
Support Vector Machine	66.7%

Table 5.2: *A comparison of three prominent classification algorithms, used on our dataset of 30 instances, for classifying different levels of compulsivity*

5.3.4 Comparing the Degree of Compulsivity across Behaviours

In addition to the aforementioned compulsive behaviour classification, we also classified behaviours based on their general degree of compulsivity. The aim of this was to provide an objective overview of the degree of compulsivity of an individual's behaviours, to a mental health professional, as a loose guide to understanding the severity and circumstances of the patient's condition. In order to accomplish this, we manually labelled 30 instances of behaviour as one of three classes, namely, *low*, *medium* or *high* compulsivity. The definitions of these classes were as follows:

- **Low:** 1-2 repetitions of the behaviour (non-compulsive)
- **Medium:** 15-20 repetitions of the behaviour (compulsive)
- **High:** 20-25 repetitions of the behaviour (compulsive)

Note that in the low repetition condition, such behaviours would not generally be considered compulsive due to their low repeat count. Regardless, they were used to demonstrate the ability of the system to discern compulsivity even in conditions of very low compulsivity. Regarding the feature set, CFS was used in order to derive a set of 19 features, per instance, for classification. Once the features had been selected, a Multilayer Perceptron was chosen, having again demonstrated a good accuracy on the dataset as compared to other approaches, as detailed in Table 5.2. The parameter values chosen for the Multilayer Perceptron were then optimised for the data in order to produce the final classification model.

5.4 Experimental Details

This section describes the parameters used in carrying out our experiments. It is organised as follows: Subsection 5.4.1 provides information on the general setup that was used for the experiments. Subsection 5.4.2 details the videos used in testing the proposed system.

5.4.1 System Configuration

All of our experiments were executed on a single PC, running Windows 7, with 8GB of RAM and an 8-core processor clocked at 3.40GHz. In order to create the optical flow system and the RTMHMs, we used the 64-bit R2012b version of the MATLAB technical computing software suite. We then flat-packed the RTMHMs into CSV files in order to ferry them to the WEKA machine learning software suite for building, training and testing a Multilayer Perceptron classifier. As previously mentioned, because we had a fairly small dataset, we used 10-fold cross validation when training the Multilayer Perceptron in order to get a more accurate prediction of the overall classification accuracy.

5.4.2 Video Data

During analysis and classification for the first set of experiments, we used a total of 40 videos, which were designed to simulate five different types of OCD behaviour. The videos used various types of clothing and lighting conditions. These variations were designed to test the robustness of the system. Furthermore, while every example of a given behaviour was filmed from a single, fixed camera angle, multiple angles were used across the five different behaviours. While in practice the camera is intended to remain in a fixed location, this element was designed to demonstrate the proposed system's ability to function effectively despite the camera's initial placement. Additionally, 20, of the total 40, behaviours were designed to be compulsive while the other twenty were non-compulsive examples of the same behaviours.

Finally, among the compulsive behaviours, both a moderately repetitive and a highly repetitive condition were simulated. This was an important element for the second set of experiments. As previously noted, this involved performing between 10 and 15 behaviour repetitions in the moderately repetitive condition and between 20 and 25 behaviour repetitions in the highly repetitive condition. This aspect was also designed to test the robustness of the system, as different individuals with OCD will tend to perform different numbers of repetitions, depending on the severity and particulars of their condition. Thus, some individuals may perform compulsive acts with only mildly, or moderately, repetitive behaviours, whereas others may perform highly repetitive compulsions, or even get stuck in a repeating compulsion cycle. In conducting the second set of experiments, the original set of 40 videos needed to be pruned down to 30. This was done in order to avoid class bias during training, such that only two, of the total four, examples of non-compulsive behaviour were used for the low compulsivity condition. We then split the four examples of compulsive behaviour between two examples of medium compulsivity and two examples of high compulsivity behaviour. This meant that a total of 10 instances were removed from the dataset, two from each of the five behaviour classes, for a total of 30 behaviour examples.

The five different types of behaviour were as follows:

- **Video Group 1 - Checking DVD**:
  This video group depicts an individual repeatedly picking up, looking at and replacing a DVD case. This type of behaviour is considered to be a 'checking' behaviour, or an example of repeating a routine activity, and is an attempt to make sure that everything is as expected, or to purge an associated obsession. The time between the individual picking up and putting down the DVD, across the video examples, is similar, but arbitrary and is designed to be as close to typical compulsive behaviour as possible. This type of behaviour can carry on repeatedly until the individual feels certain that the behaviour has been performed correctly and/or that the associated mental obsession has been cleansed. Like other OCD behaviours, this ritualism is designed to alleviate the anxiety associated with negative intrusive thoughts.
- **Video Group 2 - Opening and Closing a Drawer**:
  This video group depicts an individual repeatedly opening and closing a drawer. This is also a form of checking, or repeating of a routine behaviour, and in this case could involve making sure something is or isn't in the drawer, or simply getting stuck in the behavioural cycle because an intrusive thought occurred when the individual was initially opening or closing the drawer. The drawer opening and closing behaviour is repeated across varied periods of time, with occasional brief pauses before the process is restarted.
- **Video Group 3 - Lock Checking**:
  This video group depicts an individual repeatedly checking whether a door is locked by turning the door knob. This is another common form of checking behaviour usually related to a combination of security concerns and anxiety. Again, the behaviour is repeated across varied periods of time, with no strict timing in order to simulate natural compulsivity.

Video Group	Duration Range (seconds)
Checking DVD	4 – 96
Opening and Closing a Drawer	2 – 39
Lock Checking	4 – 77
Reading	12 – 126
Walking Back and Forth	4 – 102

Table 5.3: *Details of the video groups used to test the proposed system*

- **Video Group 4 - Reading**:
  This video group depicts an individual picking up a book, reading a passage from the book, and then setting the book back down, before repeating the process a number of times. This is an example of repeating a routine activity and is repeated with natural variations in timing.
- **Video Group 5 - Walking Back and Forth**:
  This video group depicts an individual repeatedly walking back and forth. The individual moves slightly different distances each time and the time that passes per repetition is similar, but varied. Again, this is designed to simulate natural compulsive behaviour. As is typical of OCD compulsions, this behaviour is unproductive, but often relieves anxiety for the individual in question. This type of behaviour may occur when the individual gets stuck in a mental obsession while walking past a certain location, or even just taking a step.

For further details on the videos used in the experiments, see Table 5.3.

5.4.3 Performance Metrics

In order to establish the accuracy of the proposed system, the metrics used were: the rate of *false positives*, *false negatives*, the *precision*, the *recall*, and the *overall classification accuracy.* In order for the proposed system to be considered effective it had to demonstrate a high classification accuracy, while still maintaining a low false negative and low false positive rate. A low false positive rate, in particular, is crucial, as this metric demonstrates the degree to which a non-compulsive behaviour is erroneously classified as a compulsive behaviour. These were more of a concern than false negatives, as they could theoretically cause non-compulsive behaviours to eventually become misclassified as compulsive behaviours as the number of false positives grows. In rare cases, this could lead to the proposed system recognising both highly repetitive and low-to-non repetitive behaviours as compulsive, leading to an inability of the proposed system to discriminate accurately between the two. However, this is not a serious concern, as it would require the number of false positives to consistently outstrip the number of true positives in order to have any major effect. Results gleaned from the proposed system indicate that this is a very unlikely scenario.

5.5 Experimental Results and Analysis

The results from our experiments indicate that the proposed system is capable of achieving an overall accuracy of 92.5% when classifying compulsive vs. non-compulsive behaviours. More specifically, of the 40 simulated behaviours, both compulsive and non-compulsive, used for classification, 37 were classified correctly and three were classified incorrectly. Of the misclassifications, two occurred when compulsive behaviours were mistakenly classified as non-compulsive behaviours (false negative) and the other occurred when a non-compulsive behaviour was mistakenly classified as a compulsive behaviour (false positive). These results suggest that the proposed system is fairly balanced in its ability to classify both compulsive and non-compulsive behaviours and that it is able to do so with a high degree of accuracy. The errors in this case have likely occurred on the one hand as a result of non-compulsive behaviours that are more repetitive than usual and, on the other, as a result of compulsive behaviours that are less repetitive than usual.

Regarding the misclassified behaviours, behaviour instances 13 and 21 were the compulsive behaviours that were misclassified as non-compulsive, whereas behaviour 28 was the non-compulsive behaviour that was misclassified as compulsive. Considering instance 13 in greater detail, Figure 5.4 serves as a visual illustration of why the behaviour may have been misclassified as it was. From the top graph in the figure it can be seen that the misclassified (comparison) instance resembles elements of both compulsive and non-compulsive behaviour. However, the instance bottoms-out noticeably faster than the average compulsive behaviour and thus begins to more closely resemble non-compulsive behaviour thereafter. This indicates that while the average compulsive behaviour typically comprises many pixels in the higher intensity range, this behaviour instead possesses relatively few, thus causing it to be misclassified as non-compulsive behaviour. This likely occurred because this particular type of compulsive behaviour (drawer opening) involved very little gross bodily movement and instead involved only restricted movement of the arm. Thus, under certain circumstances, this behaviour seems to be more likely

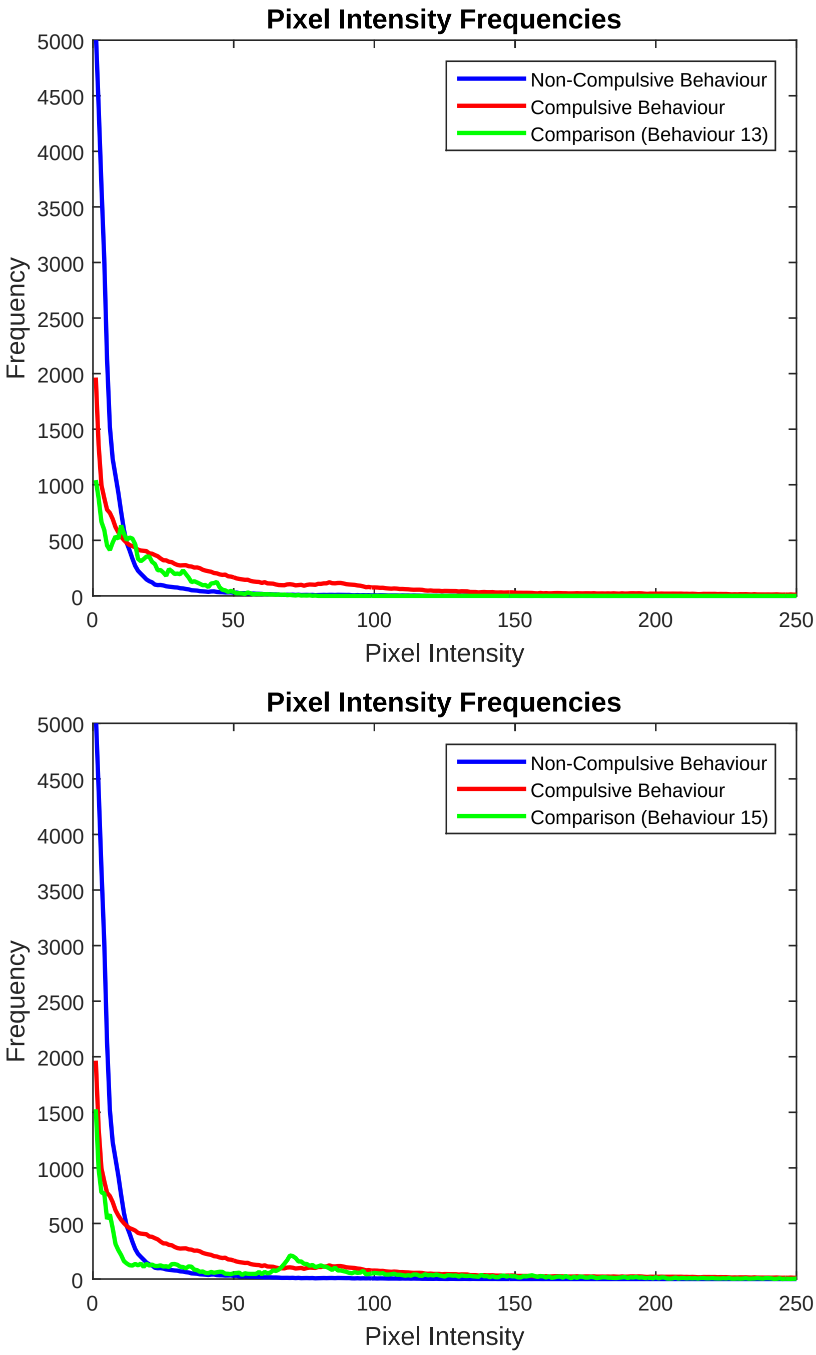

Figure 5.4: *A comparison between a misclassified example (top) of a compulsive behaviour (instance 13) and a correctly classified example (bottom) of compulsive behaviour (instance 15). Both figures demonstrate the example in question (green), as compared to the median-based average of both all compulsive (red) and all non-compulsive (blue) behaviours.*

	TP Rate	FP Rate	Precision	Recall
Non-Compulsive	0.95	0.1	0.905	0.95
Compulsive	0.9	0.05	0.947	0.9
weighted average	0.925	0.075	0.926	0.925

Table 5.4: *Classification accuracy on the test video set*

to be misconstrued as non-compulsive than other types of compulsive behaviours. Regardless, the very same type of compulsive behaviour was classified correctly as compulsive in its other three examples; it was only this particular example that was erroneously considered to be non-compulsive behaviour. Moving on to the bottom graph in the figure, another example of the same type of compulsive behaviour (drawer opening), can be seen to adhere more closely to the typical compulsive behaviour pattern. This is illustrated especially prominently by the tail of the (comparison) behaviour line remaining higher, and thus more characteristic of typical compulsive behaviour for longer, indicating that the TMHM of this behaviour example comprises more higher pixel intensity values, as compared to the graph of the previously mentioned misclassified example above.

Consider now behaviour 28, another example of misclassified behaviour. Figure 5.5 demonstrates this misclassification in comparison to a correctly classified instance. In the top graph of the figure we can see that the non-compulsive behaviour actually follows the pattern of typical compulsive behaviour fairly closely. This is likely because the behaviour in question (reading) naturally involved minor movements back and forth, such as when the individual moved the book or turned a page, which tend to show up as more pronounced on a heat map. This is because such movements can understandably be interpreted as compulsive movements. This issue could be resolved simply by setting the threshold for movement dynamism higher (in the system proposed in core chapter 1) so that such instances don't get passed on to the TMHM element of the system. Alternatively, such instances could be better classified if more labelled examples of that same type of non-compulsive behaviour were available for comparison during classification. However, our test set of videos for the proposed system was limited to 4 examples of this type of behaviour (in its non-compulsive form) due to time and resource constraints. Note that the bottom graph in the figure is another example of a non-compulsive reading behaviour, but one which wasn't misclassified as compulsive. This is likely because it follows the non-compulsive behaviour more closely and can be seen to drop off at the tail (right) end of the graph, just as non-compulsive behaviours tend to.

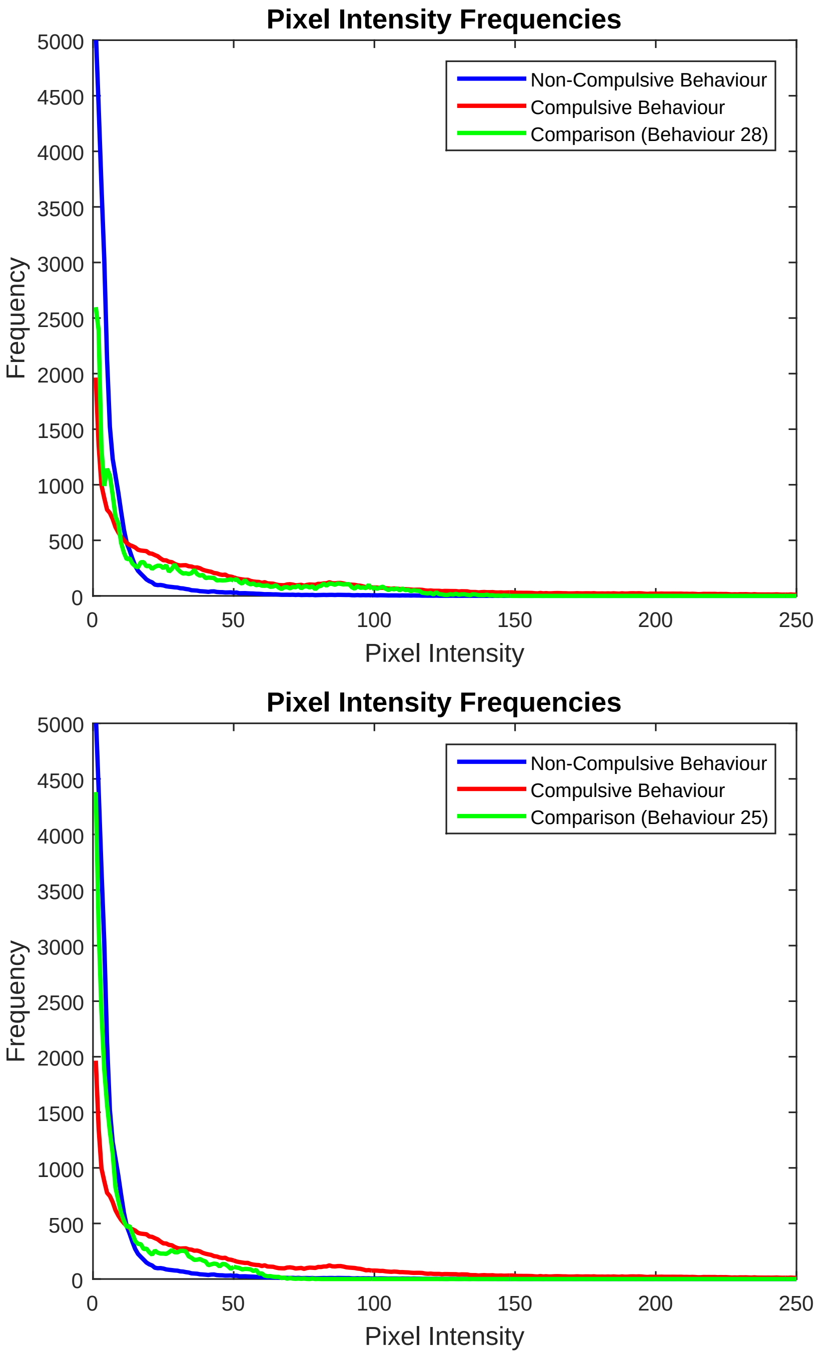

Figure 5.5: *A comparison between misclassified example (top) of a non-compulsive behaviour (instance 28) and a correctly classified example (bottom) of non-compulsive behaviour (instance 25). Both figures demonstrate the example in question (green), as compared to the median-based average of both all compulsive (red) and all non-compulsive (blue) behaviours.*

Classified as $\Rightarrow$	**Non-Compulsive**	**Compulsive**
Non-Compulsive	19	1
Compulsive	2	18

Table 5.5: *Confusion matrix of experimental results*

	TP Rate	**FP Rate**	**Precision**	**Recall**
Low Compulsivity	0.9	0.1	0.818	0.9
Medium Compulsivity	0.8	0.1	0.8	0.8
High Compulsivity	0.8	0.05	0.889	0.8
weighted average	0.833	0.083	0.836	0.833

Table 5.6: *Classification accuracy on the test video set*

Finally, considering the results in greater depth, the proposed system has a weighted average *True Positive Rate* of 0.925 and a weighted average *False Positive Rate* of 0.075. These results indicate that the proposed system is able to classify behaviours as either compulsive or non-compulsive with a high degree of accuracy. This is important, because, as previously mentioned, the ratio of the true positives of a class, compared to all instances classified as that class, known as the 'precision' should be high, in order to reduce the likelihood of false positives skewing the prediction model for compulsive behaviour. In this case, the weighted average *precision* is 0.926, which indicates that the proposed system is able to accurately sift out compulsive behaviours with a high degree of accuracy, without producing many false positives in the process. Finally, the 'recall' of the proposed system is also noteworthy, as it essentially tells us how many of the compulsive behaviours were correctly recognised as such. In this case the weighted average *recall* was 0.925, indicating that the proposed system is very good at finding compulsive behaviours without missing many. For these results in detail, see Tables 5.4 and 5.5. Taking all of this together, the proposed system demonstrates good potential to be an effective tool for the classification of the compulsive vs. non-compulsive behaviours exhibited by individuals with OCD.

The results from the second part of this chapter are detailed in Tables 5.6 and 5.7. These results indicate that the proposed system is also able to achieve a high accuracy when classifying these data from the perspective of the degree of compulsivity. Naturally, this problem will be slightly more difficult than that proposed in the first part of this chapter and, as such, the accuracy is

Classified as ⇒	**Low Compulsivity**	**Medium Compulsivity**	**High Compulsivity**
Low Compulsivity	9	1	0
Medium Compulsivity	1	8	1
High Compulsivity	1	1	8

Table 5.7: *Confusion matrix of the second set of experimental results*

expected to decline somewhat. This is likely a result of the problem being similar at its core to distinguishing between compulsive and non-compulsive behaviour, but with a larger number of classes and potentially more subtle boundaries between the degrees of compulsivity. Thus, a problem such as this will typically require an advanced method such as a Multilayer Perceptron to provide a fine-grained classification ability. Further analysing the results, it can be seen that the Multilayer Perceptron has been able to classify the dataset with fairly even accuracy across the three classes, with the low compulsivity class demonstrating the highest accuracy of 90% and both the medium and high compulsivity classes demonstrating an accuracy of 80%. Finally, considering Table 5.6, the *true positive* and *false positive* rate, along with the *precision* and *recall*, further reinforce the efficacy and accuracy of the proposed system across the examples.

Overall, these results indicate that the proposed system holds considerable potential for classifying compulsive behaviours indicative of Obsessive Compulsive Disorder. It would be interesting to further confirm these results on larger datasets, however, for the purposes of the current research, we were restricted to the current dataset due to time and resource constraints. Nevertheless, due to its ability to distinguish complex patterns, including in non-linearly separable data, the Multilayer Perceptron would be expected to perform admirably on larger datasets as well. A higher accuracy may even be expected due to the greater number of training instances that would inevitably accompany such a dataset. Regardless, a more comprehensive dataset from real patient trails would be a very interesting and informative direction for future research.

5.6 Related Work

Bobick et al. performed some interesting foundational work using Motion Energy Images (MEI) and Motion History Images (MHI) for the recognition of human activities [143]. For the purposes of their research, Bobick et al. used aerobic exercise as the test activity. MEIs and MHIs are generated for each of the aerobic activities and Hu moments are then used to match an example exercise against prior examples of various types of exercise in order to determine its type. The research by Bobick et al. thus is not specifically focused on repetitive, or compulsive, behaviour. Moreover, Bobick et al. focus specifically on the structural integrity of an image in order to match the exercise classes. Conversely, our research benefits from the dimensionality reduction of our MHI-like heat maps via frequency reductions and CFS, and is focused on the problem of classifying compulsive vs. non-compulsive behaviours, regardless of the behaviour type. Nevertheless, the work of Bobick et al. provides an essential and foundational insight into the recognition of human action types.

Han et al. proposed the use of thermal infrared imagery for the use of repetitive human activity detection, noting its value regardless of background imagery and colour properties [144]. The researchers used a similar type of motion history image to ours, in stacking binary images, however, they obtained their binary images from infrared imagery and background subtraction, whereas we obtained ours from optical flow motion vectors derived from standard webcam footage. This, however, is where the similarities end. Where Han et al. used PCA for finding a reduced set of points, we used a histogram-based reduction of frequencies, combined with CFS. We didn't require morphological structure to be preserved for our compulsive behaviours, but Han et al. did, as they were concerned with gait analysis and thus the morphological appearance of the individual's gait was imperative. The system proposed by Han et al. was only designed for the analysis of walking and running gait and thus was only tested as such, whereas our system was designed for general compulsive behaviour, exemplified through repetitive actions.

Hu et al. provided a unique method for incrementally learning human gait [87]. As in our system, their system uses optical flow as a basis, but then builds upon this using Local Binary Patterns to describe motion as a static representation. Hu et al. then supplement this with Hidden Markov Models to further represent the gait dynamics of an individual. We instead opted to use RTMHMs to describe the patterns of compulsive and non-compulsive behaviour for our system. Furthermore, while the system developed by Hu et al. provides an effective method of describing averaged human gaits, it is nevertheless a specialised system and does not take repetitive patterns of behaviour into account, nor is it designed to consider patterns of behaviour characteristic of OCD. Conversely, our system is designed specifically with repetitive patterns of behaviour in mind, which allows us to determine the compulsivity of a given behaviour.

Zelnik et al. offered an approach to analyse dynamic motion, for capturing different behaviours, using a type of motion history image [145]. This was then represented as a distribution of spatio-temporal points for each action. Their system is able to detect and classify these actions against others based on the similarity of their spatio-temporal signature, regardless of the video length and number of behavioural repetitions. Nevertheless, while this system is well-designed and effective, it is not built to focus on the number of repetitions in a behaviour, as it is only concerned with the behavioural signature of an action, regardless of the number of repetitions performed. Furthermore, while the system proffered by Zelnik et al. does take temporal differences into account, it nevertheless considers actions that are separated by a notable temporal distance to be distinct. Conversely, our system is designed to classify behaviour similarities based specifically on their respective degrees of compulsivity. Thus, in our system, so long as two behaviours exhibit a similar pixel intensity signature, they will be matched, regardless of their spatial and temporal differences.

Patsadu et al. used a Kinect-based skeleton point system to compare the recognition accuracy of various data mining methods [146]. In order to achieve this, they gathered a total of 20 body joint positions, obtained from the Kinect Software Development Kit. Using this set of points Patsadu et al. compared a set of four different classification approaches for analysis. The approaches used were: a Neural Network, a Support Vector Machine, a Decision Tree and Naive Bayes. The authors found all approaches to demonstrate a high accuracy on their set of points for the three tested behaviours. More specifically, the authors found the back propagation neural network to perform the most effectively. Regardless, the three tested behaviours, namely: standing, sitting down and lying down, are not very complex. Furthermore, as the behaviours are not repetitive, it is likely that the system would have to be adapted if it were to attempt to classify compulsive behaviours. Finally, the authors had some issues with classification approaches such as Naive Bayes, primarily because the large set of precise points were different for tall and short subjects, thus making it difficult to provide any strong independence assumptions. Regardless, as we use a Neural Network for the proposed system, and are dealing with different, more complex behaviours, we don't consider any of this to be an issue and, rather, consider it to reinforce our proposed system.

Uhrikova et al. proposed a system for the detection of repetitive behaviours typical of individuals with dementia [147]. They achieved this using a single ceiling-mounted camera to monitor an individual's bodily trajectory across time. Using this approach, a pattern, based on an individual's movements, can be traced across the floor and certain of these patterns can be recognised as repetitive. The primary difference between the approach of Uhrikova et al. and our approach is that our camera perspective assumes a typically lateral (or frontal) view of the individual. This is because our system is designed to provide a view of the compulsive movements of various aspects of the body, both on a smaller scale, such as in compulsive limb movements, and at a larger scale, such as in compulsive walking behaviours. Thus, our system is not concerned with general bodily trajectory over time, more indicative of dementia, and is instead concerned with sequential repeats of, typically simple, atomic behaviours, usually indicative of OCD.

Coronato et al. demonstrated a method of using an accelerometer to detect stereotypic behaviours in patients with ASD [148]. This system is similar in principle to that of Goodwin et al. [112] in that it primarily uses the output of an accelerometer, worn on the body, to detect repetitive, i.e. stereotypic, patterns of behaviour. It achieves this by analysing certain features in the signal output of the accelerometer and then applying a neural network to identify the stereotypic behaviours based on their recognisable patterns. The core difference between this system and our own is that ours is designed to work on visual data, which we consider to be more telling of various compulsion-based behaviours. Furthermore, the system proposed by Coronato et al. is only designed to work with hand gestures, which are typical of ASD, as the accelerometer is worn on the wrist and is primarily designed to detect hand movements along a 3D-axis relating to that point of reference. Regardless, we don't discount the possibility that, in general, accelerometers could be an interesting supplement to a system such as ours in potentially catching certain indications of some compulsive behaviours.

Wang et al. proposed an interesting method for detecting neuropsychiatric disorders such as schizophrenia, based on facial cues [149]. In order to accomplish this, the authors devised an automated system to detect and track various facial features in videos so that these could then be used as inputs to facial expressions classifiers. A profile was then built in order to establish normal baselines for various emotions such as happiness, sadness, and anger. This was then compared to emotional examples from patients with psychiatric conditions such as schizophrenia and Asperger's syndrome. While effective, the system proposed by Wang et al. considers only facial cues, rather than bodily cues, and thus would likely encounter difficulty if attempting to pick up compulsive behaviour cues. Furthermore, the system is primarily designed to detect emotionally abnormal states, such as flattened affect, rather than compulsion-based anxiety. Thus, the facial expressions picked up by the authors aren't intended to relate specifically to anxiety, but more directly to emotions in general. Regardless, with some modifications, the system proffered by Wang et al. could potentially be used to monitor some variant of facial anxiety and used as a complement to a bodily compulsion detection system.

Finally, Galna et al. ran experiments using a 3D Kinect-based system to determine the ability of the Kinect to measure various behaviours in Parkinson's Disease [150]. The authors demonstrated that the Kinect was able to determine the timing of repeated behaviours with good accuracy, but was not able to detect spatial elements of the behaviours as successfully. Torres et al. proposed a similar system, also for Parkinson's Disease, but for detecting motion abnormalities [151]. This falls in line with other studies that have noted the potential value of the Kinect for motion and behaviour analysis, including for mental disorders. However, it also urges more caution before such systems are ready to accurately and robustly accommodate these behaviours.

5.7 Conclusion

The system proposed in this second core chapter has demonstrated its ability to distinguish compulsive from non-compulsive behaviours efficiently and with a high-degree of accuracy. This indicates that the proposed system has good potential for effectively detecting compulsive behaviours indicative of OCD. Furthermore, the proposed system has also demonstrated a strong ability to distinguish different degrees of behavioural compulsivity, namely, low, medium and high. Thus, the proposed system has future potential for adoption by mental health professionals for the clinical analysis of compulsive behaviours typical of their OCD patients, so as to gain a more individual understanding of their patients' ongoing issues. Additionally, the proposed system could potentially aid mental health professionals in achieving this with only minimal input on their end. This is a result of the proposed system's ability to accurately detect and isolate only the instances from the footage that are examples of compulsive behaviour.

The primary benefit of the proposed system is thus its ability to analyse and assess compulsive behaviour patterns objectively as they occur across time. In future work, this could provide a mental health professional with an entirely new dimension of understanding, thus potentially allowing for more effective and expedient treatment of patients with OCD. An additional benefit of the proposed system is that, due to the its ability to detect repetitive behaviour patterns in general, it would likely be highly adaptable to detecting similar behaviour patterns in individuals with ASD, who also often display characteristic repetitive behaviour patterns. Further benefits include the proposed system's ability to detect different degrees of behavioural compulsivity as low, medium, or high. This is highly useful information that can be used to further understand the nature of an individual's compulsions. Thus, we believe the novelty of the proposed system, through its ability to efficiently and accurately distinguish compulsive from non-compulsive behaviour, represents a considerable benefit to mental health professionals which will, in the future, hopefully allow for the advancement of treatments for individuals suffering from OCD and stimulate further research in this burgeoning field at the nexus between technology and psychiatric intervention.

Despite the aforementioned benefits, the proposed system still has some limitations. Namely, if the system misclassifies too many instances over time, the rate of misclassifications may naturally begin to accumulate in a sort of feedback loop. To avoid this runaway effect, the system could either be supplemented at regular intervals with new examples of manually labelled compulsive behaviour, or simply periodically restarted with new examples of compulsive behaviour, either from the system proposed in the first core chapter, or, again, manually labelled. Moreover, as the proposed system does not distinguish between 'normal' repetitive behaviours (such as skipping, jogging on the spot, etc.) and compulsive repetitive behaviours, some repetitive (but non-compulsive) behaviours may be classified as compulsive. This should not distinctly affect the accuracy of the proposed system, as the focus is on repetitive behaviour patterns, which these behaviours still describe. However, these examples of behaviour can be circumvented to some extent by strategic camera placement and filtering by a mental health professional or system user in future implementations.

While this second core chapter has focused on compulsive behaviour vs. non-compulsive behaviour, our final core chapter will turn the focus to grouping, analysing and calculating the related degree of anxiety associated with different types of compulsive behaviour, based on their appearance. Thus, while this chapter considered 'global' compulsivity, the next chapter will focus on the compulsivity of behaviours relative to other behaviours of the same type. This is an important feature to take into account when considering how indicative of anxiety a compulsive behaviour may be. This will further yield future potential to assist mental health professionals in understanding their patients' unique case of OCD, whilst still requiring little direct input on behalf of the mental health professional.

Chapter 6

Determining Anxiety through Behavioural Clustering and the Variation in Repetition Intensity

6.1 Introduction

Computer-vision-based behaviour analysis and classification is a topic that has been of interest to researchers for some time now [87, 152, 153, 154, 155, 156, 157, 158]. Much of this interest stems from the wide variety of applications available to researchers studying the topic, from crowd analysis [159], to security-based surveillance and anomaly detection [160, 161], to gait recognition [162, 163], assisted living [164, 165], emotion recognition [166] and more recently, mental health applications [167, 168]. Arguably one of the most valuable applications of late, computer-vision-based mental health analysis has relied upon increases in computing power and algorithmic sophistication that have only relatively recently allowed researchers to discern the subtle behavioural cues that can be observed in everything from stress [169] to depression [170, 93], dementia [171], bipolar disorder [28] and ASD [172]. Despite this keen interest, little has been done to exploit the naturally visible behavioural compulsions evident in OCD. As these behavioural manifestations are related to the level of anxiety that an individual is experiencing at a given time, we see strong potential in such research regarding its value to mental health professionals in more deeply understanding their patients' needs [173].

Conventional approaches to treating and understanding patients with OCD have tended to focus on a combination of therapeutic interventions, such as CBT, and self-report measures.

While such approaches have been demonstrated to be quite successful, they nevertheless entail multiple drawbacks. Arguably chief among these drawbacks is the fact that patient feedback relies on human memory, which is not only highly subjective, but is also known to be quite volatile [97, 128]. Conversely, the aim of the proposed system is to analyse the behavioural compulsions of individuals with OCD in an objective manner that can be used by mental health professionals to not only better understand their patients' individual compulsions, but also to better understand the nature of the physical signs of the condition in greater depth. The proposed system aims to achieve this by grouping different physical compulsions together based on their visual similarity and then ascribing an approximate anxiety level to each behaviour in turn, based on the intensity of its visual repetitiveness. Through this novel method of visually analysing and understanding OCD compulsions and their related anxiety, we believe that the proposed system demonstrates the viability of computer-vision-based OCD monitoring to aid mental health professionals in improving their understanding and treatment of their individual patients.

Traditional applications of visual behavioural analysis have focused on a wide-variety of behaviours, with many of these being common human behaviours, for such applications as surveillance, workplace ergonomics, assisted living, detecting emotional states, and driver vigilance [14, 174, 175, 176, 177]. However, only relatively recently has the analysis of abnormal behaviours characteristic of mental illness become a topic of considerable research interest. Of this body of research, the primary focus has been on both the detection and analysis of behaviours characteristic of specific disorders. Much of this research has been driven by an attempt to understand the current progress and severity of the disorder, as well as to assist mental health professionals in early diagnosis or determination of the most effective treatment strategies.

For example, MADRIM, proposed by Mugica et al., was designed to monitor patients with Major Depressive Disorder and analyse their progress during treatment [26]. Additionally, Goodwin et al. used accelerometers and pattern recognition techniques to detect behaviours typical of individuals with ASD [112]. Amor et al. proposed a system for analysing individuals with Bipolar Disorder using PAM [28]. Finally, multiple computer-vision approaches have been proposed to address the increasing burden of dementia, most prominently Alzheimer's Disease [147, 178]. Despite this notable interest in computational psychiatric interventions, no research that we have yet encountered has focused specifically on OCD and its associated anxiety-driven physical compulsions. Furthermore, no research has focused on using visual compulsion detection and analysis to produce anxiety ratings, which could be of great value to mental health professionals. These points are what the research presented herein is designed to address.

In total, the proposed system comprises the following contributions:

- **Demonstrated a method capable of successfully classifying different patterns of behaviour:** In the third core chapter of this thesis, we proffer a system that is capable of accurately clustering behaviour types that are typical of OCD, based on visual similarity. This is achieved by deriving SURF descriptors from TMHMs of compulsive behaviour from the second core chapter of this thesis. The SURF descriptors are then used to classify various labelled instances of compulsive and non-compulsive behaviour using a bag of words model and an SVM classifier with 4-fold cross-validation. This results in a robust system that is scale and translation invariant and requires only a basic set of manually labelled behaviour instances to be trained.

- **Presented a method of estimating the relative anxiety associated with an individual's compulsive behaviours:** In the third core chapter of this thesis, we also provided a method that could, for example, be used by mental health professionals to quickly and easily view the relative anxiety of an individual's compulsions. We achieved this by deriving a baseline average (mean) for each compulsive TMHM in a given behaviour cluster and then used this to compare each compulsive example of behaviour to the baseline for that cluster. This is valuable in that it could be used to compare compulsive behaviours both across time and within a given time period to establish whether any given example of compulsive behaviour is more or less anxiety-driven than usual for an individual.

The remainder of this chapter is organised as follows: Section 6.2 presents essential background material that the reader should become acquainted with before moving on to subsequent sections. Section 6.3 provides an in-depth explanation of the proposed system and its components. Section 6.4 explains how the experiments were set up and executed as well as the parameters that were used. Section 6.5 presents the results from our experiments and discusses their implications vis-a-vis the value and effectiveness of the proposed system. Section 6.6 provides a brief discussion of the pertinent literature and Section 6.7 recapitulates our findings, as well as the benefits and limitations of the proposed system, before briefly mentioning future research that we plan to undertake.

6.2 Background

This section provides a brief overview of the foundational material that is needed to understand the information in subsequent sections. It includes subsection 6.2.1, which describes SURF descriptors and how they have been integrated within the proposed system to provide robust compulsive behaviour classification.

6.2.1 SURF descriptors

SURF is a scale and rotation-invariant feature detector and descriptor, which is designed to be highly robust and efficient [179]. It achieves these goals via a simplified Hessian-based matrix measure. Simply put, in deriving SURF features from an image, a set of representative, orientation-invariant feature descriptors will be created, which can then be compared for similarity with other descriptors from other images. The efficiency and general orientation invariance of SURF make it highly useful when applied to certain problems in computer vision, including object recognition and tracking. The need for such an algorithm was to fill a void in the ability to detect individuals at different scales and slightly different positions during compulsive behaviours. For example, an individual may move closer to or further from the camera during the same compulsion performed at different times. By making the system scale invariant, it is better able to recognise similar behaviours regardless of scale, among other qualities. This is why SURF was a valuable asset, as it is able to perform at a similar level of accuracy to a Scale-Invariant Feature Transform, but with more efficiency, thus making it apt for the proposed system. The formula for SURF is detailed below:

$$I\Sigma(x, y) = \sum_{i<x} i = 0 \sum_{i<y, j=0} I(i, j)$$

The aforementioned benefits of SURF indicated that it could be implemented in the proposed system to produce a set of robust feature descriptors from our dataset of TMHMs. These descriptors were then clustered into a vocabulary of visual words in a bag of words model and the results of this process were then classified into different behaviour groups via an SVM. For the purposes of this research, MATLAB's implementations of SURF, bag of words model, and SVM were used [180].

6.3 Methodology

This section presents the methodology of the proposed system and is organised in the following manner: Subsection 6.3.1 gives a general picture of the proposed system so that the reader can understand how its components fit together. Subsection 6.3.2 details how we used a combination of TMHMs, SURF descriptors, a bag of visual words model, and an SVM to train a classifier to recognise different groups of labelled compulsive behaviours. Subsection 6.3.3 describes the metrics that we used to derive anxiety approximations from the classified examples of compulsive behaviour.

6.3.1 An Overview

The proposed system is composed of two primary components:

- **A behaviour classification algorithm:**
  This is a set of MATLAB-based SURF descriptors translated into a bag of visual words model, used to represent the features. An SVM was then applied to classify the behaviours based on these features. This step was necessary in order to group future behaviour automatically, before using it for baseline anxiety comparisons.

- **An anxiety correlation algorithm:**
  This is a set of statistical measures designed to compare new examples of compulsive behaviour to averages of the same behaviour, exhibited by the same individual, in the past. This approach requires some prior grouping of the behaviour examples to have been appropriately established. In this case, this would be achieved by the aforementioned classification algorithm.

The overall operation of the proposed system proceeds as follows:

To begin with, we took a set of 40 TMHMs from the second core chapter of this thesis, which comprised eight examples of five different simulated compulsive behaviours. An example of these TMHMs can be seen in Figure 6.1. We then labelled the 40 behaviours manually and fed them into a MATLAB implementation of a bag of SURF features classification model. Due to the small size of our dataset, we modified the approach to use 4-fold cross validation. This resulted in each fold comprising ten behavioural examples, which could then be compared against the examples in every other fold. The behaviours were evenly distributed amongst the folds i.e.

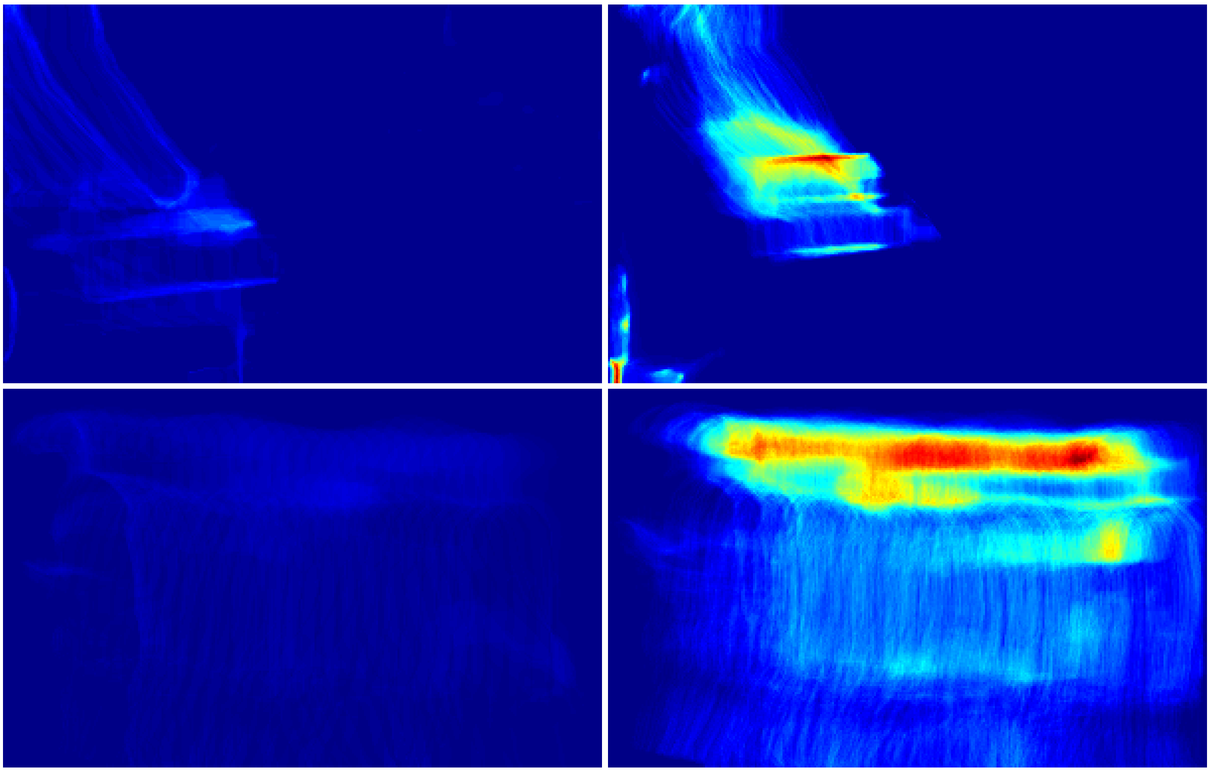

Figure 6.1: *Four TMHMs are depicted demonstrating two different behaviours. Moving clockwise from top-left: a 'cold', low-intensity, non-compulsive example of a drawer opening behaviour; a 'hot', high-intensity, compulsive example of a drawer opening behaviour; a 'hot', high-intensity, compulsive example of a back-and-forth walking behaviour; a 'cold', low-intensity, non-compulsive example of a walking behaviour.*

two examples of each behaviour per fold, in order to ensure that an even balance of behaviour types were being trained and tested.

As previously mentioned, in addition to training a classifier to recognise different behaviour groups, an anxiety algorithm was also used to ascribe an approximate anxiety level to each compulsive behaviour. This was achieved by comparing the individual anxiety calculation for each compulsive behaviour to the average for the same type of compulsive behaviour, in order to place it within an anxiety distribution. This is based on a sample standard deviation calculation for the compulsive behaviour group, which could then be used to establish how far from average anxiety a given level of compulsivity in a behaviour is for an individual. In other words, any new example of a previously seen compulsive behaviour could be assessed automatically in order to determine how aberrant it is in terms of repetitiveness for that individual. This could prove immensely valuable to mental health professionals, as it could give them, at a glance, objective, statistical measures of where any given example of compulsive behaviour exhibited by an individual would fit into said individual's normal patterns of behaviour.

Additionally, the proposed anxiety algorithm also takes into account the frequency of compulsive behaviours in general, over a given time period. For the purposes of the proposed system, 24 hours was decided upon as an appropriate time frame within which to count behavioural frequency. However, any chosen value in hours can be substituted for the 24 hours in a day. Thus, not only is the intensity of each compulsive behaviour taken into account in comparison to its norms, but the number of compulsive behaviours of any type, exhibited over a period of 24 hours, is also proposed as part of the anxiety algorithm. Consequently, during times of high anxiety, an individual's increased compulsive behaviour frequency could be captured by the system as an objective indicator of their anxiety. Information of this type could potentially be used by mental health professionals to better understand the condition and progress of their patients in the future.

For the purpose of clarity, the aforementioned system components are also detailed in Algorithms 5.1 and 5.2. Additionally, the manner in which the system components connect together is depicted in a flowchart in Figure 6.2.

```
// Get set of TMHMs
tmhm_set = getTMHMs();
numFolds = 4;

// Get SURF descriptors for each TMHM
```

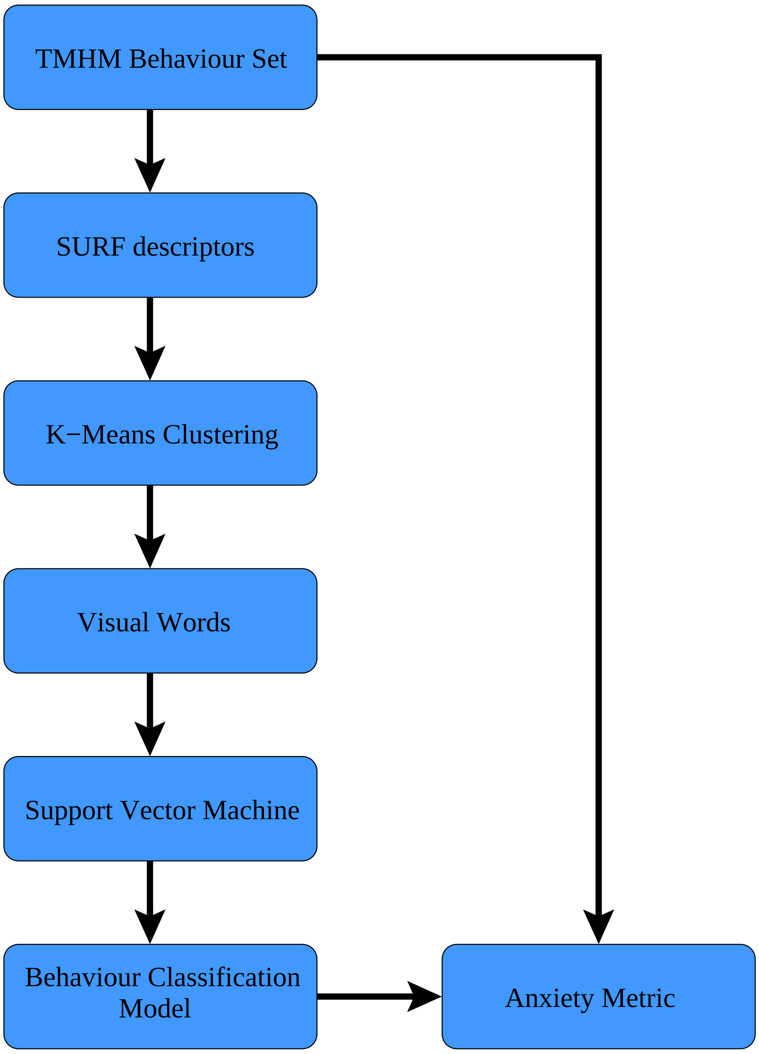

Figure 6.2: *A flowchart illustrating how the system components fit together*

```
tmhm_surf = getSURFDescs(tmhm_set);

// Divide set of TMHMs into four folds (ten examples per
// fold), whilst preserving a relatively equal number of
// compulsive behaviours per fold
for( i = 0; i < numFolds; i++)
   fold(i) = createBalancedFold(tmhm_surf,10);

for ( i = 0; i < numFolds; i++)
{
   // Get every fold besides this one
   trainData = getOtherFolds(i);
   testData = fold(i);

   // Build a bag of visual words from SURF descriptors
   visWordsTrain = BagVisWords(trainData);
   visWordsTest = BagVisWords(testData);

   // Classify data using an SVM
   resultTrain[i] = trainSVM(visWordsTrain);
   resultTest[i] = testSVM(visWordsTest);
}

// Derive an overall accuracy from the separate runs
resTest = mergeResults(resultTest);
```

Algorithm 5.1: Behaviour classification

```
// Get set of TMHMs
tmhm_set = getTMHMs();

for every tmhm in tmhm_set
   anxMet = mean(tmhm);

// Produce population standard deviation from the current
// sample of anxiety points
anxStdDev = calcPopStdDev(anxMet);

// Compare new points with the existing distribution
// to see where they fall in terms of anxiety
for every tmhm in new_tmhm
{
   newAnxMet = mean(tmhm);
   anxVal = comparePoints(newAnxMet,anxStdDev);
}

// Combine anxiety values for all compulsive behaviours over
// 24 hours to produce a single anxiety rating
anxRating = sum(anxVals)/24;
```

Algorithm 5.2: The anxiety algorithm

6.3.2 Behaviour Clustering

In order to determine the level of anxiety that an individual is experiencing relative to their own typical behaviour patterns, a baseline first needs to be established for the same type of behaviour, or a very similar type of behaviour. This enables the proposed system to ascribe an average degree of anxiety, based on behavioural compulsivity, for that specific behaviour, as exhibited by that individual. In order to achieve this, we first separated the test dataset of 40 TMHMs into their constituent five sets of behaviour. Note that half of all examples were of compulsive behaviour, while the other half were of non-compulsive behaviour. Thus, for each of the five types of behaviour, four examples of said behaviour were compulsive and four examples of the same behaviour were non-compulsive.

Each example was then manually labelled with its behaviour type so that a k-means clustering algorithm could be used to create a bag of visual words based on the centroids of the set of TMHM-derived SURF descriptors. We chose not to use the rotation-invariant principle of the SURF descriptors when they were being derived from the TMHMs, as it weakened the overall accuracy of the system, likely due to a greater potential for confusion of the SURF points among the classes. A bag of 500 visual words were used for each behaviour instance, with 30 behaviour instances being used in total (10 were held out for testing). Once the bag of visual words had been computed based on the cluster centroids, an SVM with a linear kernel was then used to train and classify the instances. In order to optimise this process, we tuned the SVM cost parameter to a reasonable value, of 0.1, which was low enough to avoid overfitting issues while still retaining a considerable overall classification accuracy. In the process of training and testing the SVM classifier, the dataset was manually split into four folds, each comprising 10 examples, with each fold having two examples of all five behaviours. Once the folds were created, SURF descriptors were derived from each TMHM image. An example of this process can be seen in Figure 6.3. This process allowed four-fold cross validation to be performed when training and testing the SVM classifier on the dataset.

Thus, the SVM model was trained to predict previously unseen examples of known behaviours, hence no longer requiring manual labelling, except in the case of new types of behaviour. Separating the behaviours in this way is of great value, as it allows each behaviour group to be viewed in isolation, which could then be used to gain a better understanding of the nature of such patterns of compulsive behaviour. Perhaps more importantly, as previously noted, separating compulsive behaviours into distinct groups allows direct comparisons to be made within behaviour groups, especially as new examples of that same behaviour come to light. This can be beneficial not only for determining a patient's progress over time, but also for establishing

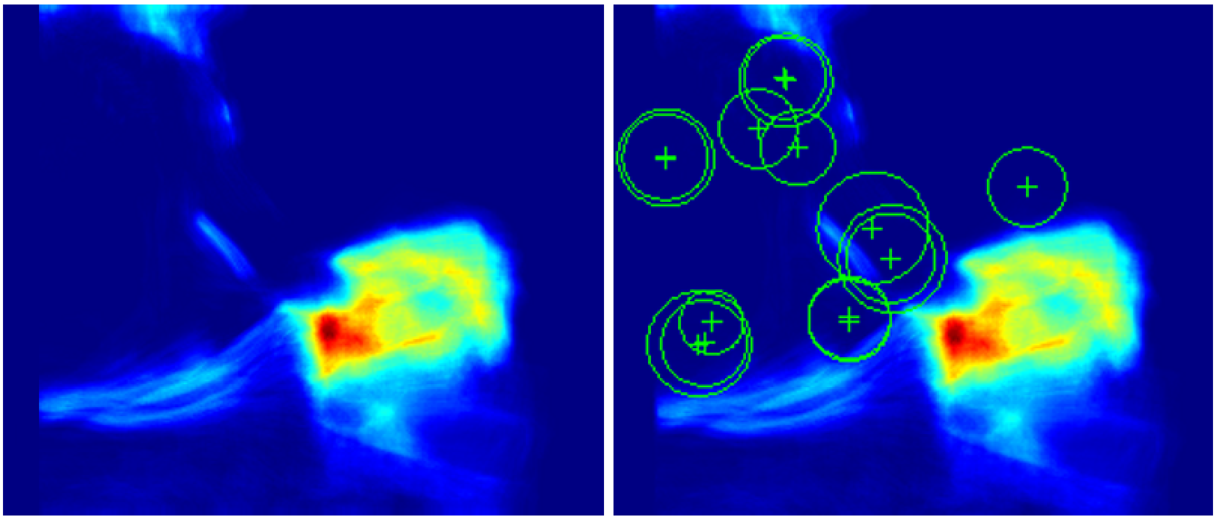

Figure 6.3: *An example of a TMHM of a reading behaviour (left), along with its set of strongest interest points (right).*

normal degrees of anxiety and compulsivity for a given set of behaviours and an individual.

6.3.3 Anxiety Metrics

Once the behaviours have been classified into distinct groups, an algorithm is then needed to ascribe anxiety levels to individual behaviour examples and the behaviour groups. In considering this, two general directions present themselves, which will be referred to as *global* and *relative* anxiety metrics. A global anxiety metric can be thought of as providing an objective, universal measure of anxiety for any given behaviour in isolation, based on its overall level of repetitiveness. The main drawback of this approach is that individuals will naturally differ in both how compulsive and dynamic their behaviours typically are under a given level of anxiety. Conversely, a relative anxiety metric would consider an example of a given behaviour, as manifested by a specific individual, in comparison to what is typical for that individual. For the purposes of this research, a relative anxiety metric was deemed more appropriate, as it not only provides a more fitting assessment for the individual, but could also potentially be effective in informing a mental health professional of the change in an individual's compulsions across time.

Note that in order to isolate the results for the two components of the proposed system, the behavioural clustering and the anxiety metric, and thus provide a more accurate appraisal of each, the original labelled dataset of behaviours, i.e. the pre-classified set of behaviours, was used rather than the output of the behaviour classification system. To begin with, the mean of

Compulsive Behaviour	Mean	Sample Standard Deviation
Checking DVD	22.45	9.40
Opening and Closing a Drawer	7.84	4.57
Lock Checking	14.64	9.72
Reading	34.03	22.59
Walking Back and Forth	30.84	19.08

Table 6.1: *Details of the video groups used in testing the proposed system*

each labelled TMHM in a given behaviour group was calculated. A sample standard deviation was then calculated from the mean values of the compulsive examples of the given behaviour type. This can be formalised as follows:

$$\mathbf{AnxI} = S(\sum_{n=1}^{N} mean(ImC(n)))$$

where;
S = the sample deviation
ImC = a given image class

The sample standard deviation was chosen because it took into account the fact that the given set of behaviours were only a small representative sample of how the patient's compulsions may appear overall for that type of behaviour. Once the standard deviation had been calculated for the distribution, each example could then be compared to the mean of all examples based on where it fell within the distribution. Naturally, all example data points falling within one standard deviation of the mean would be considered normal, all falling between one and two standard deviations above and below the mean would be considered indications of higher and lower than normal levels of anxiety, while everything greater than two standard deviations would be seen as considerably higher or lower anxiety than normal. An example of this approach can be seen in Figure 6.4. The overall mean and sample standard deviation for each tested behaviour class is also depicted in Table 6.1.

To compare the proposed system with a manual approach, a mental health professional would need to view large quantities of recorded data of a patient and then assess their anxiety using

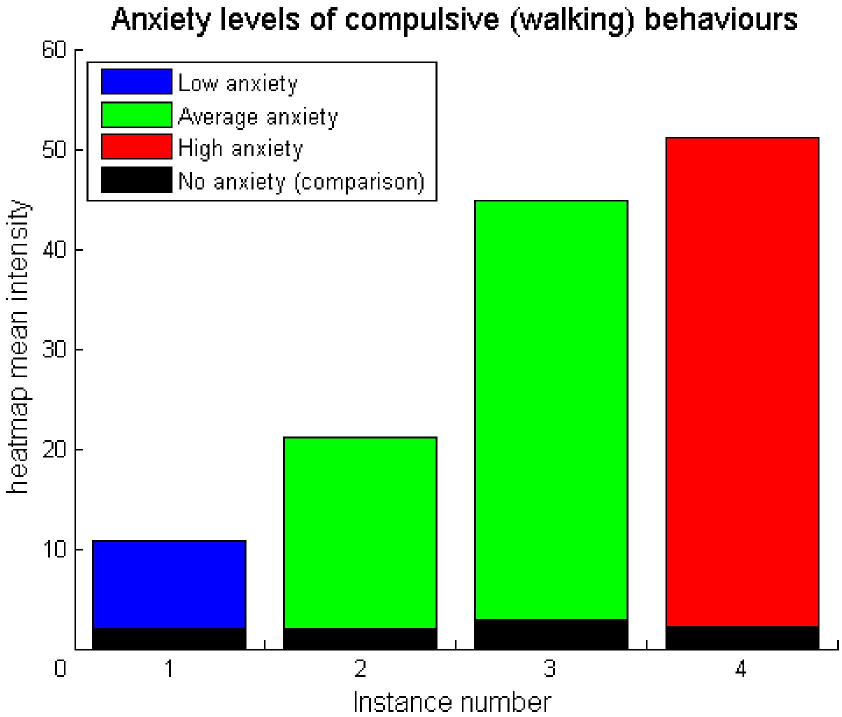

Figure 6.4: *An example of the relative anxiety metric as applied to the set of walking behaviours*

their own statistical metrics. Instead, the proposed system is able to produce this metric from the grouped TMHMs automatically. This has the potential to allow mental health professionals to see aspects of their patients' compulsions in a new light. Note, however, that the current research is only concerned with producing a viable 'proof of concept' simulation of OCD compulsion analysis. Any direct use of the proposed system by mental health professionals in a clinical context is beyond the scope of the current work and is planned for future work. Finally, all compulsive behaviours are then considered as a whole and viewed in terms of frequency over a period of 24 hours.

During the course of treatment, an individual may be experiencing more anxiety than can be detected via their compulsions as they instead try to deal with their anxiety without visible compulsion responses. This is to be expected. However, overall, as the individual is treated, not only should their compulsions fall, but so too should the associated anxiety. Concordantly, if a new spike in compulsive behaviour is detected during the patient treatment, it may indicate that the patient has relapsed and is again experiencing a high degree of anxiety. Without the proposed system, in terms of gathering a solid and objective measure of an individual's relative and global anxiety, a mental health professional would need to view large quantities of recorded data from a patient and then assess the anxiety using their own statistical metrics. The proposed system is instead able to produce this metric from the grouped TMHMs automatically and this data could thus be used to effectively and objectively inform mental health professionals about their patients' progress. This could allow mental health professionals to see aspects of their patients' compulsions in ways they likely never have before.

6.4 Experimental Details

This section explains how the proposed system was configured, as well as the parameters that were used during the experimental simulations. It includes the following subsections: Subsection 6.4.1 details the system setup and the applications that were used to run the experiments, while Subsection 6.4.2 describes the video dataset that was used in the experiments. Finally, Subsection 6.4.3 details the performance metrics used in validating the proposed system.

6.4.1 System Configuration

All of our experiments were run within the MATLAB technical computing suite, on a single desktop computer with an 8-core processor running at 3.5GHz, with 8GB of RAM. The version of MATLAB used was the 64-bit R2015a. The SURF algorithm, bag of visual words model and SVM were part of a set of MATLAB functions included in the Computer Vision System Toolbox.

6.4.2 Video Data

The images used during all experiments were TMHMs obtained from our previously mentioned set of 40 initial videos. These 40 videos were distinct, simulated examples of OCD compulsions obtained from different camera angles, under various lighting conditions. Each TMHM, derived from the second core chapter, represents one video and thus one example of compulsive behaviour in a single image that preserves the degree of compulsivity. This representation was considered apt for the purposes of the proposed system and thus the 40 behavioural TMHMs were retained in testing the proposed system.

The 40 examples of compulsive behaviour can be subdivided into five distinct classes of behaviour, which are as follows:

- **TMHM Behaviour Set 1 - Checking DVD**:
  This behaviour consisted of repeatedly picking up and replacing a DVD on a table. This

type of behaviour would typically be considered a *checking* behaviour, or an example of repeating a routine activity.

- **TMHM Behaviour Set 2 - Opening and Closing a Drawer**:
  This behaviour consisted of repeatedly opening and closing a drawer. This is another form of checking behaviour, or repeating a routine activity.

- **TMHM Behaviour Set 3 - Lock Checking**:
  This behaviour consisted of repeatedly checking if a door was locked by turning the doorknob. This type of compulsion can be common among individuals with security fears, in which a lack of certainty can cause the behaviour to continue excessively.

- **TMHM Behaviour Set 4 - Reading**:
  This behaviour entailed reading a passage from a book before replacing the book and picking it up again repeatedly. This type of behaviour would typically be considered an example of repeating a routine behaviour.

- **TMHM Behaviour Set 5 - Walking Back and Forth**:
  This behaviour involved walking back and forth repeatedly over the same location. This type of behaviour can occur when an individual gets stuck in a rumination and can't rid themselves of the intrusive thought. Behaviours such as these are good demonstrations of how OCD can end up consuming such a large amount of time out of an individual's day.

Each of the above five behaviour classes contained four compulsive examples of the behaviour and four non-compulsive examples for comparison. This video set was the same as that used in the previous core chapter, more specific details of which are listed in Table 5.3.

6.4.3 Performance Metrics

In determining the accuracy of the behaviour clustering aspect of the proposed system, we performed 4-fold cross validation on the model five times and averaged the result. This was done to avoid biasing the results, as the examples placed in the folds were chosen at random, though this was achieved whilst preserving relative behaviour distributions. From this, a confusion matrix was produced. Furthermore, the overall accuracy of the proposed system was determined by tallying the total number of correct results across all behaviours. The average precision and recall are also noted as additional indicators of the performance of the proposed system.

Regarding the performance of the anxiety metrics, naturally an evaluation of the proposed method of ascribing anxiety can only be made by a mental health professional based on its

Run number	**Accuracy (%)**
1	85
2	80
3	85
4	82.5
5	77.5
Average:	82%

Table 6.2: *Average accuracy for each experimental run*

utility to their profession. This is because this research exists at the nexus of computer science and psychiatric evaluation. With this in mind, we presented the proposed anxiety algorithm to a mental health professional who noted that while, as previously mentioned, compulsions are not always perfectly correlated with anxiety, they are nevertheless sufficiently closely connected enough to confirm the proposed system's utility and validity within the context of OCD compulsion analysis.

6.5 Experimental Results and Analysis

Across five runs, shuffling the instances contained in the folds, an average accuracy of 82% was obtained across all instances. The accuracy for each of the five runs can be seen in Table 6.2. Across the five runs, the accuracy hit a low of 77.5% and reached a high of 85%. These results indicate a decent accuracy on the tested data, especially when we take into account that most of the inaccuracies are the result of strong visual similarities between the chosen compulsive behaviours. If we tease apart from a different perspective, we get the results detailed in Table 6.3. This confusion matrix considers the accuracy from the perspective of each of the five behaviour classes, in which the rows indicate the actual class of the behaviour and the columns indicate what the behaviour was classified as. Finally, Table 6.4 presents the Sensitivity, Specificity, Positive Predictive Value and Negative Predictive Value for the classification results overall.

When we consider the deficiencies in the overall accuracy from this perspective, we can see that they occurred primarily across one specific behaviour class, namely *Behaviour Group 3*. This behaviour group involved a compulsive door lock checking behaviour, which was notably confused with a behaviour group involving walking back and forth. On closer inspection, the

Classified as (%) ⇒	**Behaviour 1**	**Behaviour 2**	**Behaviour 3**	**Behaviour 4**	**Behaviour 5**
Behaviour 1	**85**	10	2.5	2.5	0
Behaviour 2	2.5	**90**	0	0	7.5
Behaviour 3	0	0	**37.5**	0	62.5
Behaviour 4	0	0	0	**97.5**	2.5
Behaviour 5	0	0	0	0	**100**

Table 6.3: *Confusion Matrix of experimental results for classifying the five behaviours*

Metric	**Result**
True Positive Rate (Sensitivity)	82%
True Negative Rate (Specificity)	95.5%
Positive Predictive Value	87.27%
Negative Predictive Value	95.93%

Table 6.4: *Overall experimental results*

reasons for this become clear, the Lock Checking and Walking behaviours both contain a brief walking movement back and forth along the same axial plane. Both behaviours also look, in many ways, similar when one inspects their TMHMs, as can be seen in Figure 6.5. Thus, while these two behaviour examples don't look identical, their distinct visual similarities mean that, for certain such behavioural examples, there is likely close to as much intraclass variation as there is interclass variation vis-a-vis these two specific classes. This is further exemplified by Figure 6.6 in which a notable difference can be seen between this same behaviour type at a low repetition rate and a higher repetition rate. Specifically, most of the cases of misclassifications occurred when the very low repetition, non-compulsive lock checking behaviours were misclassified as walking behaviours. Again, the proposed system is most likely classifying these separate behaviours as the same behaviour type because they appear visually quite similar to each other. Remedying this primarily low-repetition issue is an open question for future research, but is not a significant issue, as it only occurs in highly visually similar behaviour classes.

Regardless, the other three behaviour groups performed very well, with behaviour groups 1, 2, 4, and 5, being classified with respective accuracies of 85%, 90% 97.5% and 100%. These behaviours, DVD checking, Drawer Opening, Reading, and Walking back and forth, respectively, tended to involve behaviour examples that were very similar within each class i.e. low intraclass variation, thus demonstrating a more distinct class cohesion. These behaviours were also notably less likely to be confused with other behaviours. It is interesting, however, that certain of these behaviours experienced asymmetrical class confusion, that is, behaviour group 3 was confused with behaviour group 5, but not vice-versa. This is likely a result of the aforementioned higher class cohesion within class 5, meaning that many behaviour examples were probably more similar to each other than to behaviour examples in class 3. Conversely, the same was probably not true for Behaviour group 3, where its results instead indicate that many of its examples were considered to be somewhat more similar to behaviour group 5 than to their own class.

As we are primarily concerned with using grouped behaviours to produce a baseline level of anxiety, it is not critical that the grouped behaviours are identical, just similar. Furthermore, not all examples of a given behaviour are going to be visually identical, so some leeway and a somewhat wide distribution of pixel intensities across a behaviour group is to be expected. Finally, if the proposed system were to be implemented in general practice, a confusion of two visually similar behaviours would likely not pose any issue to a mental health professional viewing the anxiety results of the various classes of compulsive behaviours. Regardless, ideally the proposed system would still be able to separate most such behaviours and thus we regard the overall accuracy of 82% to indicate quite good accuracy given the circumstances, but with the noted drawbacks.

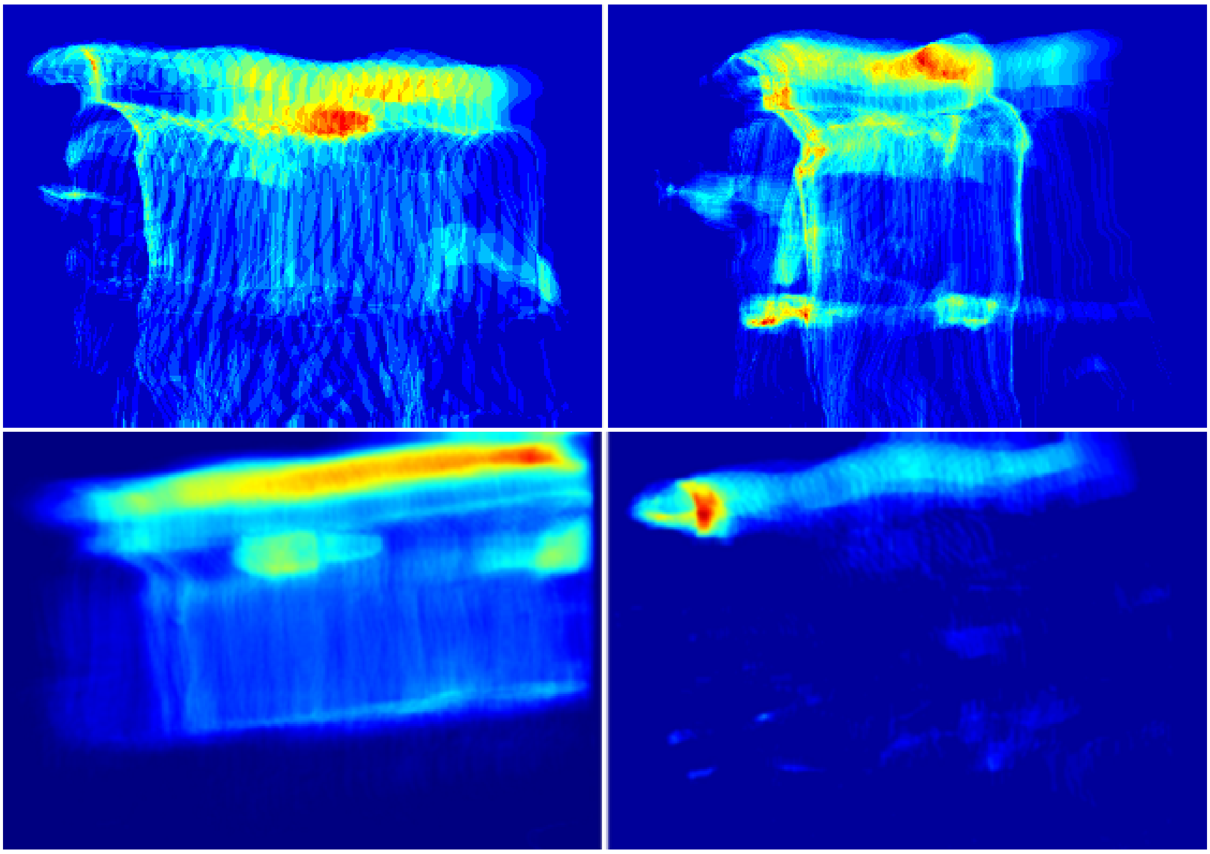

Figure 6.5: *Two examples of a walking behaviour (left - top and bottom) compared to two examples of a lock checking behaviour (right - top and bottom). It can been seen that despite the different behaviours, their appearance in this case can be quite similar. This has to do with the movement towards the door in the lock checking behaviour. Note that the lack of bodily definition in some TMHMs is a result of the way different lighting conditions interact with certain colours of low contrast clothing.*

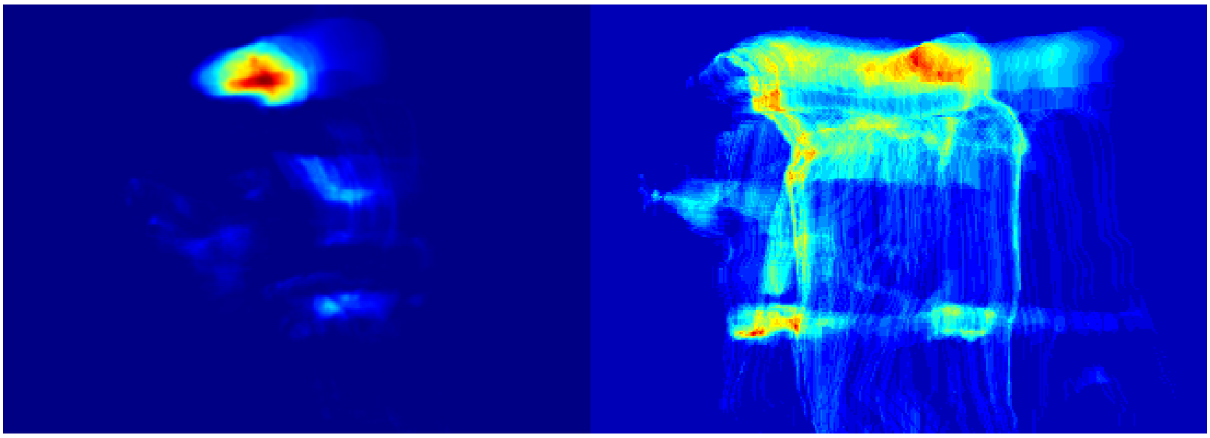

Figure 6.6: *An example of the variation between two instances of the same behaviour (lock checking). Despite being the same type of behaviour, these two behaviours appear visually to be somewhat different, giving this type of behaviour a high-class intra-class variation.*

6.6 Related Work

Ouanane et al. demonstrated the use of SURF descriptors, combined with PCA and an SVM, to classify aggressive and non-aggressive behaviours [181]. These behaviours are compared by first extracting a set of interest points using known algorithms. SURF is used for feature description in order to make the system robust and efficient. Once the features have been matched across images of different types of behaviour, the dimensionality of the matches is then reduced using PCA. These reduced points are then used to represent aggressive and non-aggressive behaviour classes when an SVM classifier is subsequently applied. The research of Ouanane et al. shares some similarities with ours, such as the use of SURF descriptors and an SVM for modelling different behaviours. However, the input used to generate the SURF descriptors for our system is a set of TMHMs, as opposed to the use of raw images by Ouanane et al. Furthermore, we classify behaviour classes based on their behaviour type, which is a multi-class problem, as opposed to the binary classification problem of aggression vs. non-aggression. Finally, this first component of our system is used to inform an anxiety rating in the second component, whereas the system proposed by Ouanane et al. is not concerned with anxiety.

Karaman et al. introduced a wearable video system for human activity indexing in patients with dementia [182]. In order to achieve this, the system employs motion based temporal segmentation, SURF descriptors for image localisation, and MPEG colour information for determining information about the patient's environment. These elements are then used in a Hierarchical Hidden Markov Model for activity representation. The research of Karaman et al. further exemplifies the recent interest in video-based interventions capable of providing objective information and analyses of the outcomes of patients with mental health issues. While this system uses some similar techniques to ours, such as SURF for image description and localisation, it doesn't use any form of motion history image or heat map for this purpose, nor does it look towards any determination of anxiety based on the patient. Conversely, our system derives SURF descriptors from our TMHMs for the purpose of analysing distinct actions from individual images. Our system also provides a method of ascribing an approximate anxiety to behaviours based on the repetition intensity of the behaviours exhibited.

Nievas et al. looked into testing the interesting idea of violence detection in video clips [120]. They achieved this using a bag of words model combined with an SVM classifier, using various kernels, and compared Spatio-Temporal Interest Points (STIP) detectors and the Motion Scale-Invariant Feature Transform (MoSIFT) algorithm. When testing their system on two video datasets, they achieved similar performance for all three descriptor-SVM kernel combinations on the first dataset, whereas for the second the MoSIFT + Histogram Intersection Kernel combination was the most accurate. While these results are slightly inconclusive, the authors argued that they nevertheless demonstrate the viability of motion descriptors and the bag of words model for the purpose of violence detection in videos, due to the relatively high overall accuracy of the technique across both datasets. Although the approach of Nievas et al. uses some comparable elements to ours, such as a bag of words model and an SVM, we use SURF descriptors with our TMHMs, rather than MoSIFT or STIP, as SURF has demonstrated good performance across activity classification while being scale invariant. Moreover, the system proposed in core chapter 3 is designed to detect anxiety, whereas the system of Nievas et al. is designed to detect only violence and thus does not implement or compare the TMHM elements that our system is based upon.

Han et al. produced a system for detecting unsafe behaviours in construction work using computer vision techniques [183]. They achieved this through the use of predefined 3D skeleton models to represent known dangerous behaviours, which were compared to 3D camera data from construction sites in order to identify unsafe behaviours in practice. While robust, the system does not take the degree of repetitiveness of behaviours into account and thus could not be used to specify anxiety based on such a degree of repetition, as is the aim of our system. Moreover, while effective, the 3D camera approach necessarily requires additional calculations which would inherently slow the system and add complexity. We instead prefer to take a simpler 2D approach, which nevertheless proves effective for capturing the tested OCD behaviours and can simultaneously establish an approximate anxiety level of a behaviour. Regardless, perhaps an approach such as that proposed by Han et al. could be integrated into future work on repetitive behaviour detection, with modifications in place.

Sivalingam et al. proposed an interesting system for the purpose of tracking children for early indications of mental disorders [29]. The primary benefit of this is that the early diagnoses enabled by such systems could allow mental health professionals to provide effective treatments sooner rather than later. The authors detail the benefits of automated systems for addressing such tasks and note that mental health professionals often don't have the time or access to data that would enable them to perform such tasks themselves. Like the proposed system, the system by Sivalingam et al. is designed to analyse behaviour in individuals with mental illnesses such as ASD, however, their system is primarily designed for tracking children in a classroom setting, whereas ours is designed for analysing the behaviour of, typically adult, individuals in their own home. Moreover, our system is designed to differentiate behaviour clusters characteristic of OCD and to produce associated anxiety levels. Whereas the system by Sivalingam et al. is designed primarily for tracking children across a room, handling occlusions and managing tracking hand-offs between multiple different cameras.

Girard et al. proffered a system for the video-based analysis of various facial cues for indicators of depression [27]. They undertook this research while patients were treated, over time, in clinical sessions, with a mental health professional. As with our system, the system proposed by Girard et al. looks for characteristics indicative of an individual's mental health and uses these as markers of times when the individual is experiencing a greater severity of symptoms. In the research of Girard et al., these characteristics were, fewer affiliative facial expressions and decreased head motion. In the case of our system, this was the distinction between different compulsive sets of behaviour, as well the designation of an associated anxiety level. Thus, while both systems use video-based behaviour detection and analysis, the primary difference between the research of Girard et al. and ours is that we focus on an anxiety disorder, namely OCD, and its compulsive characteristics, whereas Girard et al. focus on depression and its typical manifestations. Nevertheless, the system proposed by Girard et al. takes into account more minutia in expression, notably facial expression, than does our system, which indicates that it could also act, with some modifications, as a complement to our system. This could enhance our system by involving certain facial cues in OCD detection and analysis, in addition to the more distinct bodily cues.

Joshi et al. also proposed a system for the visual analysis of behavioural cues in individuals with depression [25]. They achieved this by calculating space-time interest points of upper body movements, in addition to capturing intra-facial muscle movement for facial expressions. As in our system, behavioural analysis is performed to avoid the subjectivity normally inherent to self-report measures and opinion. Additionally, cues of behaviour indicative of the mental illness are used as markers for the severity of the patient's condition. Regardless, this system is again related to depression rather than anxiety, but the research is nevertheless interesting and has potential points of application regarding OCD facial recognition, with adaptation, in the future.

Pavlidis et al. pioneered some early work on anxiety detection using thermal imagery in order to detect changes primarily in facial temperature [184]. This was used as a means to detect suspects engaged in illegal and potentially harmful activities. Pavlidis et al. achieved this by mapping various facial areas, such as the forehead, cheeks, nose, chin and neck, in order to calculate the average thermal activity within these areas across time. This thermal activity could then be viewed for changes which may indicate anxiety in the individual being monitored. While a very interesting and original approach, it nevertheless requires specialised thermal camera equipment and is designed, as such, to primarily detect changes in body temperature. Conversely, our system focuses specifically on repetitive behaviours, as these are the hallmark of compulsions, and thus serve as an indicator of OCD. Moreover, not all anxiety experiences, even for an individual with OCD, are associated with compulsions. Regardless, if economically feasible, the use of systems such as that of Pavlidis et al., with some modifications applied, may yet prove potentially useful for detecting some of the changes associated with anxiety, and may even prove useful for gauging some of the aspects of certain anxiety disorders.

Fasching et al. proposed a system for the classification of motor stereotypies, which relate to Autism [185]. While interesting and valuable, the research of Fasching et al. is oriented more towards Autism stereotypies rather than the compulsions inherent to OCD. Regardless, the paper does take into account an example of compulsive handwashing behaviour, which is common in OCD. However, this is only one type of compulsive behaviour and thus the research of Fasching et al. does not attempt to produce a general classification system, with an anxiety assessment, such as that proposed herein. Furthermore, our research had also begun more than a year prior to the publication of that of Fasching et al. Finally, even more recently, Fasching et al. proposed an additional system for the automated coding of handwashing activities in OCD [186]. While this system shares some similarities with ours, it again only takes into account the analysis of handwashing behaviours, whereas our system is designed to detect a variety of typical OCD compulsions, based on their repetitive nature, and to then assign them an approximate anxiety rating. Nevertheless, the interesting research of Fasching et al. demonstrates the value, and increasing need, of computational approaches to the understanding and analysis of OCD behaviours.

6.7 Conclusion

In this third and final core chapter, we have proposed a system that is capable not only of being trained to recognise and group behaviours into specific clusters, but also of providing a relative anxiety metric which can be used to objectively approximate the severity of an individual's OCD compulsions at a given point in time. The proposed system also holds the potential to help mental health professionals understand their patients' progress across time, while they're being treated, though the exact implementation of this clinical aspect is beyond the scope of the current research. The aforementioned contributions were achieved, on the one hand, through a combination of TMHM-derived SURF descriptors, a visual bag of words model, and an SVM as a behaviour classifier and, on the other, through a combination of metrics for an approximate anxiety level. As a result of the aforementioned contributions, we believe that the proposed system has the potential to open up new avenues of insight for mental health professionals in understanding their patients' unique compulsions and anxiety.

The primary benefit of the proposed system is its ability to provide an objective determination of the anxiety associated with an individual's behaviours across time. This could give mental health professionals access to a fine-grained understanding of their patient's particular compulsions and how those compulsions have evolved across time. This could prove highly useful in assessing how various treatment plans play out, as well as how effective various behavioural interventions, such as Exposure and Response Prevention Therapy, prove to be on the patient and their individual compulsions. However, the deployment of the proposed system in a specific form appropriate for a mental health professional as the end-user is still a subject for future research. Herein, we believe we have laid the bedrock necessary for this to take place.

Despite the value of the proposed system, there are still some notable drawbacks. Namely, the proposed system requires manual labelling in order for the behaviour classification process to function. Naturally, this is only necessary in so far as it teaches the classifier new compulsions that an individual exhibits. However, as most individuals with OCD don't develop new compulsions very often and instead tend to maintain the same set of compulsions, we don't consider this to be a serious issue. Furthermore, as the proposed system only seeks to create loose categories of compulsive behaviours, it is not essential that the compulsive behaviour groups be rigorously defined, so long as they are similar enough that their TMHM signatures don't differ significantly and thus potentially throw off the anxiety baselines. This means that the proposed system will likely still function adequately even if walking and lock checking behaviours, for example, get put in the same class, as they are likely to produce similar anxiety signatures regardless.

Future work will focus on providing a direct algorithmic approach to analysing, and objectively documenting, a patient's progress across time as a function of their treatment. We furthermore plan to extend the existing system to provide a real clinical implementation which could be used by mental health professionals in cooperation with their patients.

Chapter 7

Conclusion

In this thesis, we presented novel research into the creation and application of a system for the detection, classification and analysis of behaviours typical of Obsessive Compulsive Disorder. We also provided a mechanism to determine the approximate anxiety for such compulsions. Our primary contributions were thus broken down into three core chapters, consisting of: detecting OCD behaviours, classifying OCD behaviours, and analysing and determining an approximate anxiety level for compulsive behaviours.

7.1 Detecting OCD Behaviours

The first core chapter of this thesis presented a novel system for the detection of general compulsive OCD behaviours, based on their repetitive nature. The system was able to achieve this via the use of an optical flow algorithm, in conjunction with a set of repetition thresholding metrics, and an image similarity algorithm. Our experimental results demonstrate that the proposed system is capable of achieving a high accuracy on the tested simulated compulsive behaviour examples. More precisely, the system achieved an overall average accuracy of 87% across the three tested videos. Furthermore, the results demonstrated that each example of compulsive behaviour was recognised as being compulsive, thus indicating a 100% recognition accuracy. This is the most important aspect of the system, as it defines whether or not a compulsive behaviour will be detected as such in the first place. Finally, the system was capable of achieving the aforementioned while maintaining a low number of false positives within each video. Thus, the number of repetitions per video was rarely overestimated to any notable extent.

Despite the effectiveness of the system proposed in the first core chapter, some limitations must also be noted. Firstly, the system is only designed to handle non-intricate compulsions, as opposed to complex, multi-faceted compulsions. While this is fine for most general OCD compulsions, it may result in less desirable accuracies for more sophisticated compulsions, such as hand washing. A slightly more complex compulsion behaviour recognition system, designed for static behaviour examples rather than real-time detection, was explored in the second core chapter specifically to address this point, which could either complement the system from the first core chapter, or act as a stand-alone system. Additionally, as previously mentioned, repetitive, but non-compulsive behaviour, such as exercise, was not considered in the production of this research due to time and resource constraints, and thus was left for future research. Finally, it was assumed that only one individual at most would be in the room in any given video clip and that that individual was the intended target of the monitoring. It was further assumed that there would be few, if any, moving objects in the room. These assumptions also apply to the other two core chapters. We consider these assumptions to be reasonable and necessary based on our time and resource constraints. We made these assumptions based on the fact that the camera setup was expected to be restricted to a room that was typically frequented by just the one person, and that this individual would be the only person at home the majority of the time. Overall, we believe that the system proposed in the first core chapter demonstrates good potential for future testing and real-world implementation for general compulsive behaviours.

7.2 Classifying OCD Behaviours

The second core chapter of this thesis presented a novel system designed to differentiate compulsive from non-compulsive behaviour, based on their pixel intensity signatures. These signatures were created via a combination of a type of motion history image that we referred to as a TMHM. The dimensionality of these TMHMs was then reduced using a histogram-based-representation in order to produce a set of final RTMHMs. These were then manually labelled as examples of either 'compulsive' or 'non-compulsive' behaviour classes and fed into a Neural Network, which was trained before being used to classify the examples. Overall, the system proposed in the second core chapter proved to be highly effective, achieving an overall classification accuracy of 92.5% when it was tested on a set of 40 simulated behaviour examples, both compulsive and non-compulsive. This efficacy also held when classifying behaviours into different global degrees of compulsivity, namely: 'low', 'medium' and 'high' compulsivity. In this case, the system proposed in the second core chapter was able to achieve an overall accuracy of 83%.

Regardless, there are some noteworthy limitations of the system proposed in the second core chapter. Firstly, the RTMHM instances must be labelled beforehand in order to first train the system. Secondly, once the system is trained, it can naturally begin to accumulate misclassifications over time as it occasionally encounters ambiguous instances. As a result, the system would likely need to be periodically retrained in order to avoid a potential bias developing in some cases. Moreover, as with the last chapter, examples of highly repetitive behaviour are assumed to be compulsive and thus non-compulsive but highly repetitive behaviours may be misclassified by the system. However, these are not very common and, as previously mentioned, can be ignored manually by a mental health professional using the system. Regardless, the system proposed in the second core chapter performs well overall and is able to classify the great majority of instances correctly as either compulsive or non-compulsive behaviours.

7.3 Determining Approximate Anxiety Levels

The third and final core chapter of this thesis contained two primary components. Firstly, it comprised a system designed to group both compulsive and non-compulsive behaviours together by labelled behaviour type. In order to achieve this, a set of SURF features was derived from the TMHMs of the previous chapter. An SVM was then used to classify each behaviour example, both compulsive and non-compulsive, into a respective labelled behaviour classes. The second component of the third core chapter comprised an algorithm designed to derive an approximate anxiety level for each behaviour example, based on a relative intensity comparison to other behaviours of the same type. This was achieved by utilising the behaviour classes produced by the first component in order to derive the aforementioned anxiety level from each behaviour example by comparing it to the averages of its behaviour class. As with the previous core chapter, the first component of the third core chapter demonstrated a good degree of efficacy and reliability, achieving an overall accuracy of 82%. Regarding the second component, because the anxiety algorithm involved a subjective result, it was instead verified with an independent mental health professional who deemed the algorithm's basis to be sound. Thus, the result for the second component of the final chapter was also favourable.

However, despite the benefits of the system proposed in the third core chapter, there were also some drawbacks. Firstly, due to the visual similarities between some behaviours, certain classes could, on occasion, be confused resulting in somewhat of a reduction in overall accuracy. This was especially notable when two behaviour classes were highly visually similar, such as 'lock checking' and 'walking back and forth'. Nevertheless, these issues are fairly minor and only apply to certain very similar behaviour examples. Arguably, such examples could nevertheless be classified into the same behaviour group and still achieve good results for the subsequent anxiety metrics. Moreover, as with the previous core chapter, the behaviour examples must be manually labelled by an expert, at least when considering the initial set of examples and the initialisation of the system. Additionally, the system is not designed to classify unseen types of behaviour, which means that such examples would simply fall into the class with the most visually similar behaviours. Thus, if a new class needed to be added, new labelled behaviour examples of that class would need to be added, on which the system could then be trained. Finally, as with most classification systems, a larger set of behaviour examples with a large variety of behaviour classes will tend to produce more accurate results than smaller data sets.

7.4 Implications of this Research

Having summarised the contributions of the core chapters of this research, it is beneficial to expound upon the implications that this research has not only in the field of computer vision, but also for OCD research and mental health practitioners in general. To begin with computer vision research, the primary contribution of this thesis is its application to the novel domain of detecting and analysing compulsive patterns of behaviour in OCD. Namely, this thesis demonstrates that, through a combination of visual detection, image processing, and machine learning techniques, a system can be developed that has the potential to detect the characteristic compulsive elements of OCD behaviour. This potential is encouraging and will hopefully stoke further research into the same, and similar domains in mental health with regards to innovative methods of detecting and analysing similar, visually detectable behaviours.

Regarding OCD research, hitherto the primary perspective has naturally been psychiatric, though the application of computational systems to similar mental health issues has been steadily burgeoning. Importantly, this shift from traditional methods of assessing and understanding OCD shows great potential, which will likely only increase as the pertinent algorithms and technologies become more advanced. Notably, as OCD has a strong visual component, the repetitive behavioural compulsions, it naturally lends itself to automated visual behaviour tracking systems. This makes it a prime candidature for future computational research that is capable of augmenting the existing treatment plans provided by clinicians. This is especially notable when a patient can benefit from multiple modalities of tracking the progress of that treatment, which is often the case. Thus, tasks that a clinician wouldn't normally be able to reasonably accomplish, such as reviewing hours of patient video footage to determine any potential reduction in compulsion severity, now have the potential to be automated by future systems, similar to that proposed herein.

Finally, the primary value of this research for mental health practitioners is the insight they would gain from access to the additional data provided by a system such as that proposed herein. While the current system is only a proof of concept, through future research, we hope to establish a real-world implementation with the aid of clinical trails in order to further substantiate the efficacy of such approaches to the treatment of mental health issues.

7.5 Future Work

Future work will be orientated towards priority goals that were beyond the scope of the current research effort, due to time or resource constraints. Firstly, tracking elements could be implemented into the overall system so as to determine which individual in the room is the one that the system is intending to follow. This would require removing noise that results from other inconsequential individuals and objects. Additionally, facial recognition would likely be required in order to ensure a positive match when selecting from among multiple individuals in the same room at the same time. Joint and/or silhouette matching across frames would likely also be needed for continued monitoring of that individual. Such tracking elements would be of benefit in ensuring that the system could maintain knowledge of a key individual across time, for more accurate behaviour comparisons. This would be useful because, for the purposes of this system, an individual's compulsions are only intended to be compared to their own prior compulsions and not to those of others. Such changes would further allow the system to function optimally in high-traffic indoor areas.

Another key area of future research would be eliminating false positives from repetitive behaviours that are not of a compulsive nature. One example of such behaviours would be exercise, which is a non-compulsive activity that manifests in many ways similarly to compulsive behaviours. This could potentially be achieved through more advanced training, involving comparisons with a large number of normal exercise behaviours. However, even using such an approach, it may still be difficult to distinguish compulsions from exercise-like behaviours, as some compulsions can even involve exercise, with the only difference arguably being the psychological intention of the individual rather than the visual manifestation of the behaviour. Nevertheless, this would be an interesting and valuable area for future research, as effectively removing behaviours of this kind would lead to a reduction in false positives and a more robust system overall.

Finally, testing and implementing the system with actual OCD patients would be a key priority in demonstrating the system's potential for real-world application and benefit. This would involve negotiating clinical trials with a mental health professional, as well as using webcams to receive real-time visual feedback on patients before, during, and after standard psychiatric treatments. An easy-to-use front-end interface would also be beneficial for mental health professionals wishing to access the data from their patients.

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