Wearable Sensor Technologies Applied for Post-Stroke Rehabilitation

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/project 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.

Zhe Zhang

24th July 2015

In dedication to my parents who have been providing me unwavering supports in the past 27 years.

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; and, any editorial work, paid or unpaid, carried out by a third party is acknowledged.

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ABBREVIATIONS

ADL	: Activities of Daily Living
ARAT	: Action Research Arm Test
BAN	: Body Area Network
DALYs	: Disability-Adjusted Life-Years
IS	: Ischemic Stroke
ICH	: Intracerebral Haemorrhage
TR	: Telerehabilitation
IMU	: Inertial Measurement Unit
PCA	: Principal Component Analysis
ICA	: Independent Component Analysis
FIS	: Fuzzy Inference System
ANFIS	: Adaptive Neural Fuzzy Inference System
WHO	: World Health Organization
ICF	: International Classification of Functioning, Disability and Health
IS	: Ischemic stroke
ICH	: Intracerebral Haemorrhage
ESD	: Early Supported Discharge
LOS	: Length of Stay
ADL	: Activities of Daily Living
MI	: Motricity Index
FMA	: Fugl Meyer Assessment
ROM	: Range of Motion
PROM	: Passive Range of Motion
AAROM	: Assistive Active Range of Motion
AROM	: Active Range of Motion

WMFT	: Wolf Motor Function Test
FAS	: Functional Ability Scale
NIHSS	: Nation Institute of Health Stroke Scale
ECG	: Electrocardiography
EMG	: Electromyography
sEMG	: Surface Electromyography
LOO	: Leave One Out
SUBCL	: Subtractive Clustering
SVM	: Support Vector Machine
CART	: Classification and Regression Tree
LDA	: Linear Discriminant Analysis
QDA	: Quadratic Discriminant Analysis
PNN	: Probabilistic Neural Network
PSD	: Power Spectral Density
FFT	: Fast Fourier Transform
DWT	: Discrete Wavelet Transform
DTW	: Dynamic Time Warping
FKC	: Fuzzy Kernel Classifier
LPC	: Linear Prediction Coefficient
ZC	: Zero Crossing
TKEO	: Teager-Kaiser Energy Operator
MF	: Membership Function
MEMS	: Microelectromechanical Systems
MS	: Multiple Sclerosis
LoRS	: Level of Rehabilitation Scale
BI	: Barthel Index
PPG	: Photoplethysmograph

PCG	: Phonocardiogram
PD	: Parkinson’s Disease
CP	: Cerebral Palsy
COPD	: Chronic obstructive pulmonary disease
CIMT	: Constraint Induced Movement Therapy
RBF	: Radial Basis Function
PPV	: Positive Predictive Value
UPDRS	: Unified Parkinson’s Disease Rating Scale

ABSTRACT

Stroke is a common cerebrovascular disease that is recognized as one of the leading causes of death and ongoing disability around the globe. Stroke can lead to losses of various body functions depending on the affected area of the brain and leave significant impacts to the victim's daily life. Post-stroke rehabilitation plays an important role in improving the life quality of stroke survivors. Properly designed rehabilitation training programs can not only prevent further functional deterioration, but also helps patients gradually regain their body functionalities. However, the delivery of rehabilitation service can be a complex and labour intensive task. In conventional rehabilitation systems, the chart-based ordinal scales are considered the dominant tools for impairment assessment and the administration of the scales primarily relies on the doctor's manual observation. Measuring instruments such as strain gauge and force platforms can sometimes be used to collect quantitative evidence for some of the body functions such as grip strength and balance. However, the evaluation of the patients' impairment level using ordinal scales still depend on the human interpretation of the data which can be both subjective and inefficient. The preferred scale and evaluation standard also vary among institutions across different regions which make the comparison of data difficult and sometimes unreliable. Furthermore, the intensive manual supervision and support required in rehabilitation training session limits the accessibility of the service as the regular visit to qualified hospital can be onerous for many patients and the associated cost can impose an enormous financial burden on both the government and the households. The situation can be even more challenging in developing countries due to higher growing rate of stroke population and more limited medical resources.

The works presented in this thesis are focused on exploring the possibilities of integrating wearable sensor and pattern recognition techniques to improve the efficiency and the effectiveness of post-stroke rehabilitation by addressing the abovementioned issues. The study was initiated by a comprehensive literature review on the latest motion tracking technologies and non-visual based Inertia Measurement Unit (IMU) had been selected as the most suitable candidate for motion sensing in unsupervised training environment due to its low-cost and easy-to-operate characteristics. Following the design and construction of the 6-axis IMU based Body Area Network (BAN), a series of stroke patient motion data collection experiments had been conducted in conjunction with the Jiaxing 2nd Hospital Rehabilitation Centre in Zhejiang province, China. The collected motion samples were then investigated using various signal processing algorithms and pattern recognition techniques to achieve the

three major objectives: automatic impairment level classification for reducing human effort involved in regular clinical assessment, single-index based limb mobility evaluation for providing objective evidence to support unified body function assessment standards, and training motion classification for enabling home or community based rehabilitation training with reduced supervision. At last, the study has been further expanded by incorporating surface Electromyography (sEMG) signal sampled during rehabilitation exercises as an alternative input to enhance accurate impairment level classification. The outcome of the investigations demonstrate that the wearable technology can play an important role within a tele-rehabilitation system by providing objective, accurate and often realtime indications of the recovery process as well as the assistance for training management.

LIST OF PUBLICATION

Following is the list of papers that have been submitted or accepted during the candidature period:

- **Z. Zhang**, L. Liparulo, M. Panella, X. Gu, Q. Fang, "A Fuzzy Kernel Motion Classifier for Autonomous Stroke Rehabilitation", Biomedical and Health Informatics, IEEE Journal of , vol.PP, no.99, pp.1,1, 2015.
- **Z. Zhang**, Q. Fang, and X. Gu, "Fuzzy inference system based automatic Brunnstrom stage classification for upper-extremity rehabilitation," Expert Systems with Applications, vol. 41, pp. 1973-1980, 2014.
- **Z. Zhang**, Q. Fang, and F. Ferry, "Upper limb motion capturing and classification for unsupervised stroke rehabilitation," in IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society, 2011.
- **Z. Zhang**, Q. Fang, L. Wang, and P. Barrett. "Template matching based motion classification for unsupervised post-stroke rehabilitation." In Bioelectronics and Bioinformatics (ISBB), International Symposium on, 2011.
- **Z. Zhang**, F. Ferry, Q. Fang, and X. Gu, "Robotic arm for unsupervised stroke rehabilitation: A pilot study using PID controller," in Orange Technologies (ICOT), 2013 International Conference on, 2013.
- **Z. Zhang**, Q. Fang, X. Gu, "Objective Assessment of Limb Mobility for Post-stroke Rehabilitation", IEEE Transactions on Biomedical Engineering, Submitted 2014.
- L. Liparulo, **Z. Zhang**, M. Panella, X. Gu, Q. Fang, "A Novel Fuzzy Approach for Automatic Brunnstrom Stage Classification using Surface Electromyography", IEEE Transaction on Neural Systems and Rehabilitation Engineering, submitted 2014,
- Q.Fang, **Z. Zhang**, Y.Tu,"Application of Gait Analysis for Hemiplegic Patients using Six-axis Wearable Inertia Sensors" , IEEE IECON - 40th Annual Conference on IEEE Industrial Electronics Society, 2014.

Chapter 1

INTRODUCTION

1.1 RESEARCH MOTIVATION

Stroke is an acute cerebrovascular disease caused by haemorrhage or blockage in brain blood vessels. The cerebral ischemia as a direct consequence of stroke can lead to severe neurological damage and depending on the region affected, a number of impairment including muscle weakness, sensory loss, aphasia, cognitive problem and visuospatial dysfunction [1]. Stroke is known as one of the leading causes of death and ongoing disability in the world [2]. According to statistics, approximately 17 million people worldwide had a new or recurrent stroke incident in 2010, and 5.9 million deaths during the year were stroke related [3]. By 2010, there were also 33 million stroke survivors in the world and many of them are still suffering from stroke impairments and unable to live independently. This problem remains significant challenge for health care and rehabilitation institutes around the world.

Post-stroke rehabilitation has been proven to be essential and effective in helping stroke patients to gradually regain part of their body functionality in numerous researches [4]. However, the influence of stroke is continuously rising with the aging population and the amount of health care expenditure contributes to stroke-related programs is also growing proportionately. In Australia, the average first-year cost per case for first-time Ischemic Stroke (IS) and Intracerebral Haemorrhage (ICH) stroke patients in 2004 were AU$6,022 and AU$3,977 respectively. The lifetime cost per case for IS and ICH were estimated to be AU$57,106 and AU$49,995, which adds up to AU$1.7 billion and AU$232 million for the entire nation. It is also worth noting that the inpatient rehabilitation expenses have contributed 28.7% and 27.9% to the overall cost for each type of stroke [5].

In recent years, home-based and community-based Telerehabilitation (TR) training programs have attracted substantial amount of research attentions not only for cost reduction but also to improve rehabilitation outcome. Early Supported Discharge (ESD) is a widely recognized program which aims to accelerate discharge by providing comprehensive support for the patients to continue rehabilitation training in community or home setting [6-9]. ESD allows patients to train in a more familiar environment where they are going to perform Activities of Daily Living (ADL) and create a smoother transition [7]. However, how to maintain the intensity and quality of rehabilitation training in the environment with no or reduced supervision is one of the primary issues that must be addressed to ensure the best rehabilitation outcome.

Apart from improving efficiency and accessibility, another challenge to be addressed in post-stroke rehabilitation is on improving the reliability and feasibility of the clinical assessments. The evaluation of patients' body functioning such as motor function is considered as a crucial process in any post-stroke rehabilitation program. The deterioration of motor function can impact patient's ability of independent living in various forms in addition to the reduction of muscle strength and dexterity. The rehabilitation intervention for each patient needs to be customized to target different type of impairments effectively [10, 11]. By conducting motor function assessments throughout a rehabilitation program, clinicians can track their patients' recovery progress and acquire evidence for improving individualized training prescriptions to ultimately optimize rehabilitation outcome. Conventionally, clinical evaluations have been manually performed by experienced clinicians using various chart-based ordinal scales such as Brunnstrom stage of recovery [12, 13], Fugl-Meyer Assessment (FMA) [14], Barthel Index (BI) [15], and National Institutes of Health Stroke Scale [16]. Apart from the shortcoming of inefficiency, the lack of consensus also limits the usefulness of the conventional evaluation methods, which makes the comparison of patient's data across different institutes and regions very difficult. In 2001, World Health Organization (WHO) presented the International Classification of Functioning Disability and Health (ICF) to serve as a comprehensive assessment framework that is designed to be used uniformly around the world. However, the implementation of ICF is also hindered by the subjective nature of the conventional methods as the evaluation standard can vary between occasions [17]. Therefore to truly improve the efficiency and reliability of limb mobility evaluation in rehabilitation and realize unified classification standards, objective and quantitative assessment methods are required.

1.2 RESEARCH QUESTIONS

The primary objective of the research in this thesis was to develop automatic and quantitative solutions to facilitate objective motor function assessment and unsupervised post-stroke rehabilitation using data collected with wearable sensors. In order to achieve optimal performance and feasibility for each application, various inputs including kinematic and physiological signals were investigated and analysed with specifically designed pattern recognition techniques. The detailed research questions, which were addressed in this thesis, are as follow:

1. *"Can widely-used and subjective 'chart-based' clinical assessments be replaced by objective and automatic approaches?"*

Conventional clinical assessments are heavily based on human experience that can be both inefficient and subjective. In order to solve these issues, a reliable computerized solution for objective motion quality assessment and impairment level classification is required. The expected solution should be able to automatically classify stroke patients' impairment level based on widely used ordinal scales such as Brunnstrom stages of recovery. The system is expected to be low-cost and easy to operate to suit unsupervised rehabilitation settings. In order to prove the validity of the system, the automatic classification result should be checked against the rehabilitation expert's manual assessment.

2. *"Can stroke patients' limb mobility be assessed quantitatively using kinematic data collected during rehabilitation training?"*

The assessment of stroke patients' limb mobility is also essential due to its close relationship with the ability of performing ADL. It can provide important evidences for individualizing rehabilitation interventions, which would ultimately maximize the training outcome. A mobility assessment system can also be substantially beneficial to routine training sessions by providing feedback on the patient's motion quality and thus give additional drive and guidance to the patient. However, the subjective nature of manual assessment process and the lack of consistent evaluation measure have significantly limited the usefulness of the result. The ordinal scale based evaluation methods which are designed for impairment level classification are labour intensive to implement and insensitive to the subtle changes in motor function. Therefore, they are not suitable to be applied in regular rehabilitation training sessions for providing feedback and tracking recovery progress. In order to realize a unified assessment standard and provide efficient and reliable evaluation of stroke patient's limb mobility, a quantitative and objective metric system must be established.

3. *"Can post-stroke rehabilitation training motions be classified accurately using an automatic system to facilitate unsupervised training?"*

The development of home and community-based telerehabilitation systems can be the key to counter the ever-increasing hospital healthcare expenditure. It also frees up medical and human resources and make rehabilitation service available to those who have difficulties to visit hospitals regularly. The efficiency of the system can be boosted further if the automatic monitoring and assessment techniques are integrated to replace the human supervision. However, one challenge must be dealt with first is how to identify the patient's motion adequately during a training session. The accuracy of the identification process is critical as most of the automatic evaluation techniques rely on it for database matching where a wrongly classified motion will certainly lead to misleading analysis and thus counterproductive feedback. The low-level supervision environment also requires the hardware setup of the monitoring system to be as simple as possible, yet robust to operate.

4. *"Does surface Electromyography recordings correlate with stroke patients' motor impairment level that it can be used for automatic impairment classification?"*

Due to its non-invasive characteristic, in contrast to intramuscular electromyography (EMG), sEMG based system has been increasingly involved in the clinical process of evaluating motor function and detecting neuromuscular disorders. As an indicator of voluntary intention, sEMG is also frequently implemented in rehabilitation programs to evaluate patient's recovery progress especially at the early stages when voluntary motions are hard to detect due to high flaccidity. In rehabilitation applications, sEMG measurements are conventionally taken and analysed by rehabilitation experts manually. In order to be integrated with unsupervised post-stroke rehabilitation systems, the relationship between sEMG features and stroke recovery progress must be investigated and an automatic method is needed to be developed to perform classification based on widely recognized clinical scales, such as Brunnstrom stage of recovery.

1.3 SUMMARY OF CONTRIBUTIONS

In pursuance of the answer to the aforementioned research questions, consecutive investigations on data sampling and analysis techniques have been carried out for each topic. Experiments with stroke patients at various recovery stages have also been conducted to validate the performance of the proposed solutions. The list presented below is a highlight of the major contributions of the studies discussed in this thesis.

- The study of objective clinical scale assessment
  - A low-cost inertial measurement based wearable sensor network was developed to collect stroke patient's upper-limb motion data.
  - Kinematic features that are related to Brunnstrom stages of recovery were extracted and investigated.
  - An Artificial Neural Fuzzy Inference System (ANFIS) was trained to automatically classify patient's recovery progress in term of Brunnstrom stages.
  - The performance of the system was demonstrated in a cross-validation test with 200 motion data sets sampled from stroke patients whose Brunnstrom stages were evaluated by expert panel in prior to the experiment.

- The study of quantitative limb mobility evaluation
  - A single index based metric system has been developed to quantitatively evaluate stroke patient's upper-limb mobility based on the motion data collected during rehabilitation training.
  - The evaluation result can be used as a motion quality indicator to provide real-time feedback to the patients during training. At the same time, it can also give additional information to the clinician regarding patient's training performance and adherence.
  - The mobility index is not only useful to reflect the quality of the motion but also found to be highly correlated with recovery progress. Therefore, the evaluation result can serve as a quantitative evidence to realize standardized stroke impairment assessment.

    - The proposed index has demonstrated promising potential as input feature for automatic Brunnstrom stage classification in a test involving 21 stroke patients with various degrees of impairments.

- The study of automatic training motion identification
    - Six prevalent upper limb post-stroke rehabilitation training exercises have been compared and studied.
    - Kinematic features extracted from motion data have been ranked and selected based on their contribution to motion classification.
    - A fuzzy kernel motion classifier was specifically developed to achieve optimized classification performance.
    - The proposed motion classifier has demonstrated superior accuracy compared to other popular methods in a cross-validation test involving 531 training motion data collected from 14 stroke patients with various degrees of impairment.
- The study of sEMG based impairment level assessment
    - The single-channel sEMG sampled from stroke patient’s lateral deltoid during shoulder training exercise has been investigated.
    - The correlation between sEMG features from both time and frequency domain and stroke-induced impairment have been studied.
    - A fuzzy kernel classifier based on geometrically unconstrained membership function was specifically developed to automatically classify Brunnstrom stages based on the sEMG features.
    - A cross-validation test has been carried out with nine stroke patients. The result has demonstrated that the proposed sEMG approach can produce competitive result compared to kinematic data based methods. It also has the advantage of being able to classify patients with severe impairment whose motion feature cannot be adequately captured using inertia sensors.

1.4 THESIS ORGANIZATION

The rest of the thesis is organized as follows:

Chapter 2, Literature Review will provide a brief overview of current stroke rehabilitation systems, motion monitoring methods, and pattern recognition algorithms.

Chapter 3, Automatic Impairment Level Classification will introduce a fuzzy inference system based method which automatically classifies stroke patient's upper-limb impairment based on Brunnstrom stages of recovery.

Chapter 4, Quantitative Limb Mobility Evaluation will present a single-index based metric system that measures stroke patient's upper limb mobility in accordance with the level of impairment.

Chapter 5, Training Motion Classification for Unsupervised Rehabilitation will present a fuzzy kernel motion classifier which can accurately classify various rehabilitation training motions performed by the stroke patients.

Chapter 6, Impairment Classification Using Surface Electromyography will present an alternative approach which utilizes sEMG signal instead of kinematic measurement of the stroke patient during rehabilitation training to classify the level of impairment automatically.

Chapter 7, Conclusion will summarize the research contributions and discuss the future work.

Chapter 2

LITERATURE REVIEW

2.1 STROKE AND REHABILITATION: A MEDICAL PERSPECTIVE

2.1.1 STROKE

Stroke or "brain attack" is a common acute cerebrovascular disease that is caused by haemorrhage or infarction induced cerebral blood supply interruption. In Figure 2-1, an illustration of the two major types of stroke is presented. Ischemic stroke, as depicted in the left drawing, is a result of artery blockage mainly due to the formation of thrombosis or emboli. The other less common but more deadly type of stroke is due to spontaneous bleeding inside the brain as illustrated in the drawing on the right. During a stroke onset, the depression of cerebral circulation, increased intracranial pressure, and toxic effects of the released blood can cause severe damage to the brain tissues [18]. Due to its abrupt nature and serious consequences, stroke is considered as a medical emergency and requires immediate treatment of medications or neurosurgeries [4, 19-22]. Despite the consistent

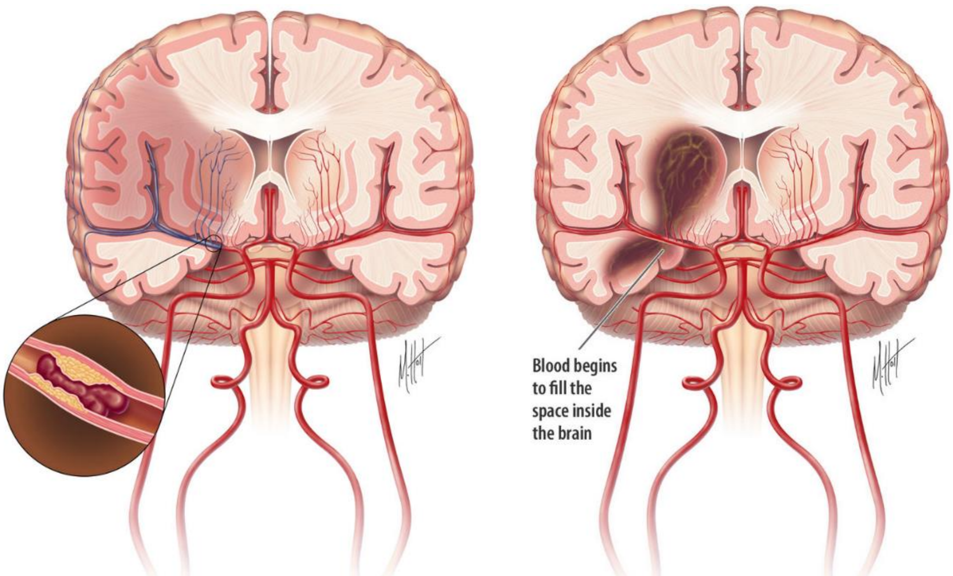


Figure 2-1. The illustrations of ischemic and haemorrhagic stroke (from: The internet stroke centre, www.strokecenter.org/patients/about-stroke, access Dec 2014)

decrease of the mortality rate over the last decades, stroke is still one of the leading causes of death and ongoing disabilities [23]. Epidemiological studies have shown that stroke is the second most common cause of death after ischaemic heart disease which accounts for 9% of the overall deaths around the world [24-26]. It is also the third most common cause of disability-adjusted life-years (DALYs) [27]. By 2010, there were 17 million people with the first stroke incident and 5.9 million stroke-related deaths [25]. In total, the number of stroke survivors worldwide have exceeded 62 million, in which 55%-75% of them suffer from various degrees of body functioning impairment [28, 29]. The amount of health care expenditure associated with stroke is also rising rapidly due to the ever-growing stroke population. In industrialized countries, more than 4% of direct healthcare expenses are stroke related. In Australia alone, the average first-year cost per case for first-time Ischemic Stroke (IS) and intracerebral haemorrhage (ICH) stroke patients in 2004 were AU$6,022 and AU$3,977 respectively. The lifetime cost per case for IS and ICH were estimated to be AU$57,106 and AU$49,995 which add up to AU$1.7 billion and AU$232 million for the entire nation. It is also worth noting that the inpatient rehabilitation expenses have contributed 28.7% and 27.9% to the overall cost for each type of stroke [5].

In developing countries like China, the economic development has brought significant changes to the peoples' lifestyle. However, a substantial increase of stroke risk factors such as physical inactivity, obesity, hypertension, and diabetes have also taken place [30]. The lack of prevention and control policy, insufficient stroke care and rehabilitation resources, and relatively low personal income have created further challenges on stroke prevention and management [31]. In 2004, the average fee for stroke admission in China was 6,356 RMB (approx. AU$1,060), which was two times the average annual income of rural residents. The healthcare expenditure associated with stroke in public hospitals alone was 1.17 billion RMB (approx. AU$195 million) in 2003. The number is still rapidly growing at a rate of 117% per year and had reached 8.19 billion RMB by 2009 which imposed significant financial burdens to both the healthcare systems and societies [30-32].

Most of the stroke survivors suffer from some degrees of long-term disabilities which reduces their overall quality of life. The impairment of central nervous system will suppress cerebral electrical activity and thus result in loss of various body functions from muscle weakness to cognitive deficits depending on the location of the lesions [2, 3, 18]. One of the most common types of stroke induced disability is motor function impairments including hemiparesis, incoordination and muscle spasticity [33] and it is also the focus of the study discussed in this thesis. The motor function impairments can affect stroke patient's motion on more than just muscle strength and dexterity. The upper motor neuron lesion can lead to imbalanced excitatory and inhibitory input to alpha motor neurons and cause abnormal muscle excitability or spasticity which can impose a significant limitation on patient's motion [34]. An obligatory synergy pattern caused by neurological disorder can also be observed when stroke patients struggle to perform voluntary isolated joint movements [35]. As a result, motor impairment can greatly jeopardise stroke survivors' ability of independent living.

2.1.2 Post-Stroke Rehabilitation

Post-stroke rehabilitation is the procedure that aims at inducing positive changes to the neurological reformation process after stroke through active or passive exercises [4, 6, 8]. Despite the irreversible damage in the brain tissue, it is possible to partially regain the body functions via brain's ability of reorganizing itself in response to intrinsic or extrinsic stimuli [36]. Post-stroke rehabilitation plays an important role in shaping the neurological changes during this remodelling process and maximize the positive outcomes [18, 37]. From a neuropsychology perspective, the rehabilitation process involves retraining the neural pathways or enabling new neural pathways to regain or improve neurological functioning that has been impaired in stroke incident [18]. In this section, the current understanding of the neurological process of post-stroke rehabilitation and techniques to improve recovery gains will be reviewed.

2.1.2.1 Neuroplasticity

Neuroplasticity is referring to the brain's ability of "reorganizing its structure, function and connection… in respond to intrinsic or extrinsic stimuli" [36]. The ability of the brain to change or remodel itself based on experience forms the basis of the brain's capacity to retain memory and improve functions. It is also proven to be the underlying mechanism of the post-stroke recovery process [38]. The potential of neural plastic reform can vary based on a number of factors including the nature and the severity of the stroke, time after stroke, motivation, mood, levels of stress environment, and viable brain networks with plasticity capacity. Most patients can benefit from this process to subsequently recover part of their body functions. Substantial amount of researches have been dedicated to investigating this plastic phenomena [39-42]. Despite the governing rules of the neural network reconnectivity being mostly unknown, it has been discovered that the post-injury behavioural experience is considered "one of the most potent modulators of cortical structure and function…(and it is) critical to the reassembly of adaptive modules" [41, 43]. It is also believed that the rewiring process can be constantly shaped by repetitive behaviours and temporal coincidence [41, 44]. The behavioural experience can be classified into two major types depending on whether it is focused on the repetition of motor activity or skill acquisition. The neural plasticity associated are often referred as activity-dependent plasticity and learning dependent plasticity [18, 45]. The activity-dependent plasticity can be achieved through constant practice of motor activity while learning-dependent plasticity required task-orientated training [45]. Both types of plasticity are considered essential in post-stroke recovery, and different rehabilitation training programs are developed to apply specific interventions as well as to facilitate the neural plasticity [37, 46-48].

2.1.2.2 Intensive Rehabilitation

A number of studies have demonstrated that post-stroke motor recovery can benefit from intensified motor therapy [7, 49-52]. The result of a meta-analysis carried out by Kwakkel et al. [50], which involved twenty studies and 2686 stroke patients suggested that intensive rehabilitation therapy with more dedicated treatment time can lead to an enhanced and faster improvement of motor recovery, especially at the early stage of rehabilitation. Similar conclusion was reached in [51]: a study investigated the influence of therapy intensity in stroke rehabilitation as measured by Length of Stay (LOS) and functional independence. The result indicates that higher therapy intensity is associated with improved rehabilitation outcomes. The importance of repetitive voluntary movement based training has also been verified in many literatures [52-54] as the efficacy of post-stroke rehabilitation can be improved by engaging patients in repetitive exercises. A study conducted by De Wit et al has reported that the stroke patients in the German and Swiss rehabilitation centres tend to recover better compared to the patients in UK despite similar staff number and efficiency [55]. The analysis had shown that the difference was caused by the consistent delivery of more intense therapy in German and Swiss rehabilitation centres. Based on these findings, it can be concluded that the training intensity is correlated with the rehabilitation outcome. However, in order to ensure the high-intensity rehabilitation, more demanding management, and human supervision may be required which can potentially increase the cost.

2.1.2.3 Early Support Discharge (ESD)

The discharge planning and outpatient rehabilitation support also play an important role in rehabilitation programs that affects both the training efficiency and effectiveness. Unnecessarily prolonged hospital stay can increase the cost of rehabilitation and occupy additional medical resources [56]. ESD is a program that accelerates the discharge process and allowing patients to continue rehabilitation in the community and home settings [9, 57-59]. Comprehensive interdisciplinary support must also be included in the program to ensure that the intensity and the quality of the rehabilitation training are at the required level. Some of the obvious advantages of ESD includes cost reduction, freeing up hospital beds, and lowering the burden for caregivers [59]. Compared to the standard care, ESD can also improve patients' ability to perform ADLs, achieve better satisfaction of services and accelerates the process of community reintegration [60, 61]. Reports can also be found in some studies that suggest ESD can also improve the functional recovery and reduce the risk of death by providing a smoother transition between acute care and rehabilitation [7, 61, 62].

2.1.3 *TELEREHABILITATION*

In order to facilitate ESD and to provide support for home and community-based rehabilitation, telerehabilitation (TR) systems have been considered as a viable solution and attracted substantial amount of research attentions. The primary advantage of TR is being able to expand the coverage of the rehabilitation services and making the services accessible for patients who have difficulties to travel [63]. Many TR systems are developed on computer platforms that can be conveniently integrated with computer-aided systems to more efficient data management and service delivery [64, 65]. Moreover, TR systems can also enable one-to-many supervision that allows multiple patients to receive services from a single rehabilitation expert simultaneously and hence it significantly lowers the cost and improve the efficiency [66]. The idea of incorporating telecommunication technologies to deliver rehabilitation services outside hospital is not new to the field of rehabilitation medicine. Currently, the majority of the systems are implemented using audio and video link technologies in which the communications between patients and medical staffs are established using conventional telephone or video-conference modules [64, 67-70]. In [68], a conventional TR system adopted for pressure ulceration management in patients with spinal cord injuries was described. A still-image videophone was used for communication between doctors, caregivers and patients. The doctor can provide remote direction to the caregivers in positioning the camera for taking adequate images of the patient for assessment.

In order to improve the efficiency of supervision and data management, sensor and software aided systems have been introduced in recent years [71-73]. Figure 2-2 illustrated an example of the modern TR system that integrates wireless wearable sensor, video link, training management and data mining software systems. By implementing various sensing devices, patients' physical or physiological parameters can be collected in real-time during rehabilitation services and be accessed by the rehabilitation experts remotely for evaluation. As a result, the rehabilitation experts can have better understanding of patient's progress and adjust training scheme accordingly to optimize the outcome. In [71], an artificial sensory system using wearable garments integrated with electroactive polymeric material were proposed to facilitate TR. The device was designed to perform strain sensing as well as mechanical actuation to support upper extremity rehabilitation outside hospital. In [74-76], Virtual Reality (VR) technologies were implemented in post-stroke TR systems to improve the training efficiency and patient's participation. The systems consisted only a PC with real-world controller and video-camera. The patient was requested to complete motion tasks related to upper-extremity training in the virtual environment where the patient's movements were animated and the therapists can supervise the training in real-time over a high-speed internet connection. The experiments were conducted to verify patient's upper-extremity motor function improvement after the TR training and the results demonstrated significant gains as measured by clinical tests. Wearable inertia sensor and pressure sensor are also popular candidate in modern TR systems. In [77], a shoe-based sensing device that integrates accelerometer and pressure sensors is proposed to be used in TR systems for measuring stroke patient's activity. By processing the kinematic and kinetic data collected by the two types of the sensors, the system is able to differentiate patient's posture. The recorded data is used to reflect patient's activity level and provide behavioural enhance feedback as part of a TR intervention. A more detailed review on the state-of-art TR systems with integrated wearable technology will be presented in the 2nd section of the chapter.

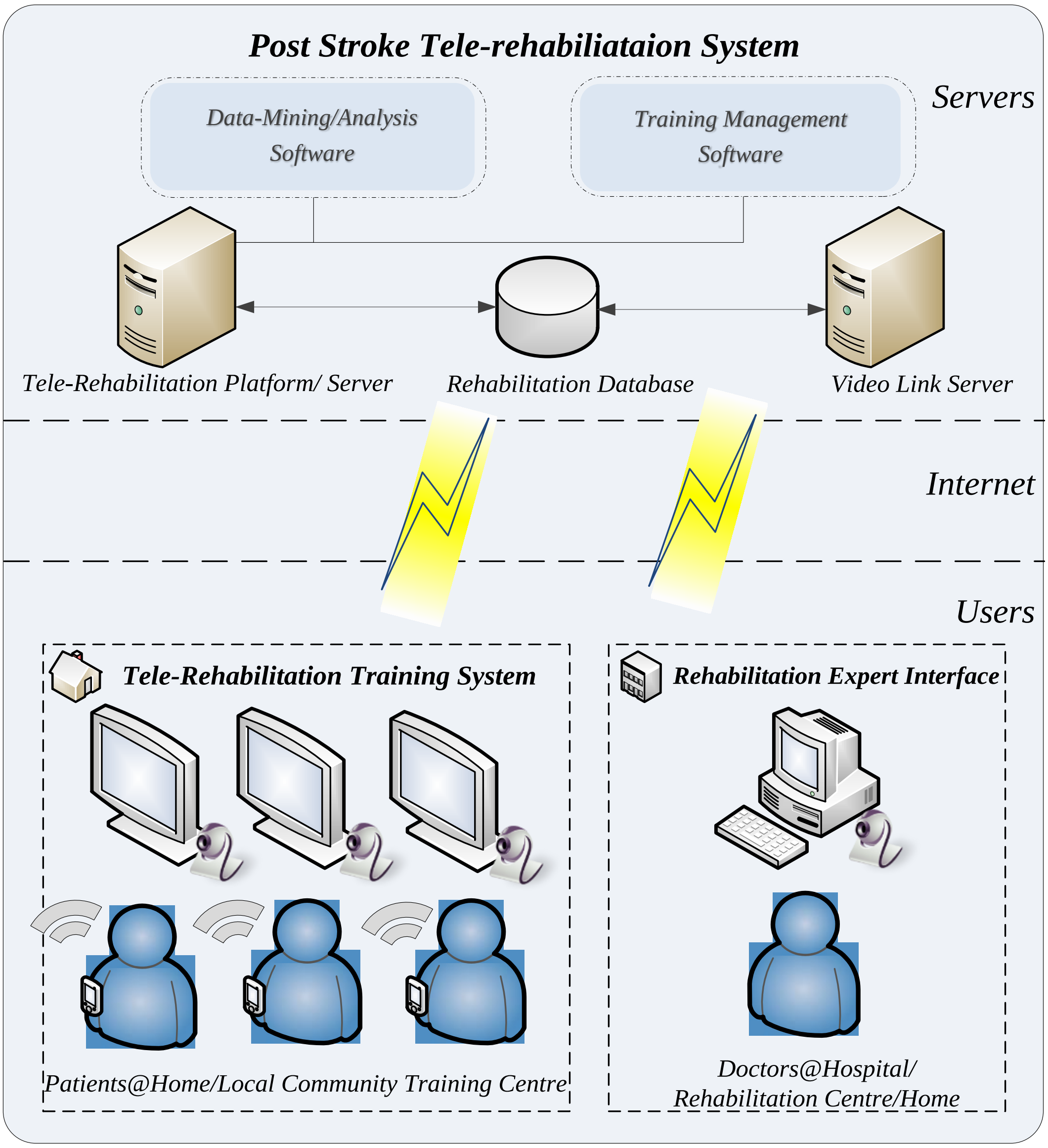


Figure 2-2. An illustration of wearable sensor integrated TR system

2.1.4 *Clinical Assessment Scales*

The clinical assessment of body function has been an important part of post-stroke rehabilitation. By conducting body function assessments throughout a rehabilitation program, the clinicians can track the patients' recovery progress and customize the training prescriptions for optimal rehabilitation outcome. Conventionally, the assessments are performed manually by experienced rehabilitation experts using chart-based ordinal scales including Brunnstrom stage of recovery [12, 13], Fugl-Meyer Assessment(FMA) [14], Barthel Index [15] and National Institutes of Health Stroke Scale (NIHSS) [16]. Some scale measures disease and disability from a different aspect compared to the others and therefore utilize different assessment settings and procedures. A brief summary of popular assessment scales that are commonly used in stroke rehabilitation programs is provided below.

2.1.3.1 Brunnstrom Approach

Brunnstrom approach, as originally introduced in [12, 13], is a well-known measure for modelling the recovery process following stroke-induced hemiplegia. The method emphasizes on the progressive development of the motion synergic pattern during the rehabilitation process and divides the motor recovery process into six stages from the period of complete flaccidity which begins immediately after stroke to the disappearance of spasticity when the patient can perform near-normal to normal movement as presented in Table 2-1.

Brunnstrom stages are very commonly adopted clinically to classify stroke patient's rehabilitation progress due to its simplicity and validity [78-83]. Compared with other conventional measures with complex scoring systems that cover every detailed aspect of the patients' condition such as Fugl-Meyer Assessment [84], the six-stage classification system of Brunnstrom approach is focused on the key factors closely associated with the rehabilitation progression including the degree of spasticity and synergies. The simplicity not only makes Brunnstrom classification one of the most favourable measures as a repetitive follow-up test during rehabilitation program, but also helps to improve the communication efficiency with patients by allowing them to effortlessly understand their recovery progress. The effectiveness of Brunnstrom approach has also been proven by many studies. In [85], Brunnstrom recovery stages were compared with spasticity measurement using Modified

Modified Ashworth Scale (MMAS) during an experiment involving 30 stroke patients, and the result showed a strong correlation between the Brunnstrom recovery stages and the MMAS scores. In [86], 46 stroke patients were monitored during a rehabilitation program, and Brunnstrom recovery stage was found highly sensitive to changes in patient's rehabilitation outcome and well correlated with measured Motricity Index (MI). Stroke patients are usually examined for Brunnstrom stages regularly since they are admitted to the rehabilitation facility in order to track their recovery progress. Currently, the classification process can only be performed by experienced physicians. The conclusion is derived directly by observing the amount of spasticity, synergy pattern and voluntary motion from the movements performed by patients. Such process is often inefficient and subject to human error, especially when the patient’s condition is near the boundary between the two Brunnstrom stages. The classification results are also vague and lack of quantification. In order to overcome such shortcomings, the possibility of introducing automated solution for objective classification of Brunnstrom Stages is investigated in this study.

TABLE 2-1 BRUNNSTROM STAGES OF RECOVERY

Stage	**Description**
Stage I	Immediately after stroke onset; complete flaccidity; no voluntary movement.
Stage II	Initial stage of recovery; spasticity and obligatory synergies appear.
Stage III	Increased spasticity and synergy patterns; voluntary control of affected limb is possible but with limited range.
Stage IV	Spasticity and synergy patterns begin to decline; improved movement range.
Stage V	Further decline of spasticity; isolated joint movement without synergy pattern become possible
Stage VI	No apparent spasticity; near-normal to normal movement and coordination.

2.1.3.2 Fugl-Meyer Assessment (FMA)

FMA scale, as first introduced by Fugl Meyer et al. in 1975, is another evaluation system which utilize cumulative numerical score to reflect stroke patient's physical performance [87]. The FMA scale was developed largely based on the Twitchell and Brunnstrom's multi-stage model of post-stroke motor recovery [13, 14, 88]. Similar to Brunnstrom approach, Fugl Meyer's method also stresses on the synergies developed during the post-stroke recovery process rather than solely rely on the conventional testing of muscle strength. However, FMA provides a more comprehensive evaluation scheme of patient's overall impairment that consists of multiple independent assessment modules, including upper and lower extremity motor function, body balance, sensation qualities, passive range of motion and joint pain. The modules are further divided into items corresponding to specific body functions and each item is evaluated using a 3-point ordinal scale: 0 for complete loss of function, 1 for partial loss of function and 2 for fully functional. Overall, there are 266 points possible, and an increase in total score can be seen as an indicator for partial or overall body function improvement during rehabilitation. An example of the FMA score sheet as introduced in Sanfor et al.'s paper [89] is shown in Figure 2-3.

The assessment of FMA score usually involves a stroke patient performing a series of pre-defined tasks under the supervision of a professionally trained physical therapist and then the numerical scores for each item is given based on the therapist's observation. Different assessment tasks are designed to demonstrate various aspects of patient's body function. Different muscle groups are first elicited to test reflex activities. Volitional extension and flexion movements for multiple joints are then performed to exam motor functions. The patients are also required to perform fast-paced motions and to maintain certain postures to show their coordination and balance. The sensation scores are measured in two forms: the first one is to examine patient's ability to sense light touches on various body parts, and the second one is to test if patient can sense the position of various joints without the help of another sensory input e.g. visual. At last, range of motion (ROM) is tested on different joints and the occurrence of pain is recorded [87].

FMA scale has also been widely used in both clinical and research settings for decades and a number of researches have been carried out to investigate the reliability and validity of the method [14, 89, 90]. In the original work conducted by Fugl Meyer et al, 28 patients with stroke and hemiplegia were included in a clinical trial to evaluate the validity of FMA and 15 patients remained to be followed through at least half a year. All patients' body functions were evaluated using a selective FMA scale at the beginning of the study, and then they were re-examined at a regular interval subsequently. The result of the study showed that all remaining patients in the follow-up study had demonstrated some degree of positive progress reflected on FMA score despite some disturbance caused by undercurrent complications that had jeopardized the recovery of some individuals. The multi-stage development observed from the long term FMA result also matches the findings of Twitchell [88] and Brunnstrom, which supports the validity of the method. The author also believes that the 3-point scale together with rigidly standardized procedure had minimized the chance of error and thus ensured high reliability [13]. In another research conducted by Wood-Dauphinee et al., FMA scale was compared with a neurologic status scale, a stroke severity scale, the Barthel index (BI) and the Level of Rehabilitation Scale (LoRS) using the data from a clinical trial with 167 stroke patients [90]. The result demonstrated a significant correlation between the outcome of different measures and between subscale scores and the total scores of FMA. However, it is also suggested that FMA has a high coefficient of variation compared to BI, which makes it less efficient as more subjects would be required. In a review written by Gladstone et al. [14], the sensitivity, reliability, validity and responsiveness have been thoroughly discussed. By summarizing the result from a number of clinical studies, the author has drawn the conclusion that despite the shortcomings such as the inclusion of subjective items in sensation measurement, overweighted upper extremity score, lack of finger movement assessment, and the redundancy in the joint pain measurement, FMA is still a feasible and important clinical and research tool for evaluating changes in post-stroke motor impairment.

Patient's Name ______ Patient No. ______

Therapist's Name ______ Date ______

UPPER EXTREMITY

A. Shoulder/Elbow/Forearm

I. Reflex activity

Flexors —Biceps	☐
—Finger flexors	☐
Extensors—Triceps	☐

II. a. Flexor synergy

Shoulder—Retraction	☐
—Elevation	☐
—Abduction	☐
—Outward rotation	☐
Elbow —Flexion	☐
Forearm —Supination	☐
b. Extensor synergy	
Shoulder—Adduction/inward rotation	☐
Elbow —Extension	☐
Forearm —Pronation	☐

III. Hand to lumbar spine

Hand —Move to lumbar spine	☐
Shoulder —Flexion 0°–90°	☐
Elbow 90° —Pronation/supination	☐
IV. Shoulder —Abduction 0°–90°	☐
—Flexion 90°–180°	☐
Elbow 0° —Pronation/supination	☐
V. Normal reflex activity	☐
Total—Shoulder/Elbow/Forearm	☐

B. Wrist

Elbow 90°—Wrist stability	☐
Elbow 90°—Wrist flexion/extension	☐
Elbow 0° —Wrist stability	☐
Elbow 0° —Wrist flexion/extension	☐
Circumduction	☐
Total—Wrist	☐

C. Hand

Fingers mass flexion	☐
Fingers mass extension	☐
Grasp a	☐
Grasp b	☐
Grasp c	☐
Grasp d	☐
Grasp e	☐
Total—Hand	☐

D. Coordination/Speed

Tremor	☐
Dysmetria	☐
Speed	☐
Total—Coordination/Speed	☐
Total Motor Score for the Upper Extremity	☐

LOWER EXTREMITY

E. Hip/Knee/Ankle

I. Reflex activity

Flexors —Hamstrings	☐
—Achilles	☐
Extensors—Patellar	☐

II. a. Flexor synergy

Hip —Flexion	☐
Knee—Flexion	☐
Ankle—Dorsiflexion	☐
b. Extensor synergy	
Hip —Extension	☐
—Adduction	☐
Knee—Extension	☐
Ankle—Plantar flexion	☐
III. Knee—Flexion	☐
Ankle—Dorsiflexion	☐
IV. Knee—Flexion	☐
Ankle—Dorsiflexion	☐
V. Normal reflex activity	
Flexors —Hamstrings	☐
—Achilles	☐
Extensors—Patellar	☐
Total—Hip/Knee/Ankle	☐

F. Coordination/Speed

Tremor	☐
Dysmetria	☐
Speed	☐
Total—Coordination/Speed	☐
Total Motor Score for the Lower Extremity	☐

G. Balance

Sit without support	☐
Parachute reaction, nonaffected side	☐
Parachute reaction, affected side	☐
Supported standing	☐
Standing without support	☐
Stand on nonaffected leg	☐
Stand on affected leg	☐
Total Score—Balance	☐

H. Sensation

a. Light touch

Arm	☐
Palm	☐
Leg	☐
Plantar	☐

(continued)

b. Position

Shoulder	☐
Elbow	☐
Wrist	☐
Thumb (interphalangeal)	☐
Hip	☐
Knee	☐
Ankle	☐
Great toe	☐
Total Score—Sensation	☐

I. Passive Joint Motion/Joint Pain

		Motion	Pain
Shoulder	Flexion	☐	☐
	Abduction >90°	☐	☐
	Outward rotation	☐	☐
	Inward rotation	☐	☐
Elbow	Flexion	☐	☐
	Extension	☐	☐
Forearm	Pronation	☐	☐
	Supination	☐	☐
Wrist	Flexion	☐	☐
	Extension	☐	☐
Fingers	Flexion	☐	☐
	Extension	☐	☐
Hip	Flexion	☐	☐
	Abduction	☐	☐
	Outward rotation	☐	☐
	Inward rotation	☐	☐
Knee	Flexion	☐	☐
	Extension	☐	☐
Ankle	Dorsiflexion	☐	☐
	Plantar flexion	☐	☐
Foot	Pronation	☐	☐
	Supination	☐	☐
Total Score—Passive Joint Motion/Joint Pain		☐	☐

SUMMARY

A. Shoulder/Elbow/Forearm	☐
B. Wrist	☐
C. Hand	☐
D. Coordination/Speed	☐
Total Upper Extremity	☐
E. Hip/Knee/Ankle	☐
F. Coordination/Speed	☐
Total Lower Extremity	☐
G. Balance	☐
H. Sensation	☐
I. Passive Joint Motion/Joint Pain	☐ M ☐ P
TOTAL SCORE	☐

Figure 2-3. FMA score sheet (Sanford et al, 1993)

2.1.3.3 Barthel Index (BI)

Different from Brunnstrom stages and FMA scale, Barthel scale or BI is an ordinal scale that is focused on measuring patient's performance and independence in ADL such as dressing and cleaning. As originally introduced in [15], BI is comprised of 10 variables or items that are individually assessed based on the patient's ability on performing ten different activities. The evaluation of the BI is observation based, and each item is graded into three different levels: inability to complete the task, completion with assistance, and completion without assistance. The relatively simplistic scoring system of the original BI provides low training and implementation complexity to ensure a high inter-rater reliability and repeatability [91-93]. However, this design is considered ineffective to detect small changes in functional independence [94]. The lack of sensitivity issue is addressed in the modified versions of BI where multi-point scoring systems are adopted [93-95]. The items included in BI are listed below:

- Personal hygiene/grooming
- Bathing
- Feeding
- Toilet use
- Stair climbing
- Dressing
- Bowel control
- Bladder control
- Mobility
- Wheelchair/chair to bed transfer

BI and its modified versions are widely recognized as the most reliable and the most frequently cited ADL assessment tools [92, 93, 96]. Apart from assisting clinical decision-making, BI is also often adopted to evaluate the efficacy of medical treatments and rehabilitation programs [97-99]. The validity and reliability of BI are investigated in a number of researches [91, 100-102]. Collin et al. conducted a research comparing the BI score obtained using four different rating methods including self-report from the patient or relative, report from nurse after at least one shift, direct observation from a trained nurse and an occupational therapist [91]. The result showed a statistically significant coefficient of concordance between scoring results from different rating method and all four methods can produce reliable results. Therefore, it is suggested that BI can be obtained efficiently and reliably by querying informed nurse and patient's relative. However, the usage of BI is not without pitfalls. In Collin's study, the author also pointed out that discrepancies exist when evaluating individual items as a result of different interpretation of the evaluation criteria which has not been uniformly standardised. In a review study conducted by Geert et al., the lack of consensus on the clinical relevance of the BI total score is believed to be a major problem which can hinder the design, the interpretation, and the comparison of the acute stroke trials [102]. Another limitation of BI is that the environment factor can dramatically affect the evaluation result, and it often varies between cases [15]. Therefore, the BI results from different trials may not always be comparable. It has also been reported that BI produces extraordinarily high internal consistency which might be an indication of redundancy within items e.g. personal hygiene and bathing [103].

Overall, BI is a reliable and valid ADL scale that can be implemented efficiently. The relatively short assessment time and administration simplicity makes BI suitable to be repetitively tested during a rehabilitation program, and thus it is considered a suitable tool for tracking the patient's recovery progress over time [95]. The BI's advantage of maintaining reasonable reliability even when it is conducted through patient's self-report or phone interview also makes it particularly useful in clinical or research situations when direct follow-up assessment is not applicable [91]. However, the ambiguous assessment criteria and the absence of the environment factor correction can reduce its reliability in settings with independent raters and varying environments like multicentre clinical trials.

2.1.3.4 National Institute of Health Stroke Scale (NIHSS)

NIHSS is another widely used stroke scale that measures the patient's impairment from neurological functioning perspective. There are 11 key items covered in a standard NIHSS examination i.e. level of consciousness, gaze (extraocular movement), visual fields, facial palsy, upper and lower extremity motor function, limb ataxia (coordination), sensory function, language (aphasia), speech (dysarthria) and inattention (neglect). Each item can be assigned a score up to 4 to reflect the degree of impairment and the total maximum score is 42 (or 31 in the modified version) which represents the most severe level of stroke or a comatose state [104]. The assessment of the scale is designed to be conducted only through direct observation/examination by trained professionals. Compared to BI, NIHSS provides more comprehensive and detailed guidelines on assessment protocol e.g. specific questions to be asked for measuring the level of consciousness and naming sheet/picture to be used for evaluating aphasia. Video training and certification are also available to improve the standardization of the procedure [105]. The clinical relevance of the NIHSS score is well established, and the total NIHSS score has been successfully implemented to derive stroke acuity, lesion size and prognostic information in several researches [106-108].

The rigorous assessment criteria of NIHSS ensures its excellent reliability and validity, which makes it a popular candidate for various clinical and research applications. First of all, it is considered as a sensitive tool for tracking post-stroke neurological changes. In Young et al.'s work [109], NIHSS is proven to be more sensitive than BI and modified Rankin Scale in measuring a simulated treatment effect and it allows smaller sample sizes or greater statistical power. NIHSS is considered as an important intervention evaluation tool especially in studies related to thrombolytic therapy [110]. In the t-PA study conducted by National Institute of Neurological Disorders and Stroke (NINDS) [111, 112], a random control trial of recombinant tissue plasminogen activator (rt-PA) for patients with acute ischemic stroke, NIHSS was adopted to evaluate the efficacy of the treatment. A change of 2 points or more on the total score of NIHSS was used as an indicator of a clinically relevant change of patient's condition [110]. NIHSS also has great value as a predictor of post-stroke hospital disposition [113]. It is believed that NIHSS score can provide prognosis information even at early stage of admission of acute stroke patient where BI usually fails to perform due to the floor effect of its scoring criteria [110]. As observed in [113], patients with NIHSS lower than 5 are most likely to be discharged home after acute care whereas a score greater than 13 at the time of admission suggest a greater chance that long-term care in nursing facilities will be required. However, NIHSS has lower sensitivity on single function items such as limb motor function and requires the aid of function assessment or ADL scales to measure the outcome of post-stroke rehabilitation comprehensively.

2.1.3.5 Wolf Motor Functional Test

Wolf Motor Functional Test (WMFT) is another assessment of upper extremity motor ability that is commonly implemented in stroke and traumatic brain injury rehabilitation applications [114, 115]. However, in contrast to the other manual inspection or interview based assessments, WMFT utilizes timed task to evaluated stroke patients' upper limb function quantitatively. The original version of WMFT consisted of 21 items, which was reduced to 17 in the widely used modified version. It mainly tests three aspects of stroke patients' motor function: dexterity, functional ability and strength. The examiners always test the less affected upper extremity followed by the most affected side for comparison purpose. The Wolf system uses a six-point ordinal scale where a 0 indicates no voluntary intention detected for completing the tasks, and a 5 indicates normal arm function. The assessment has a maximum score of 75 where the lower scores suggests lower functioning levels.

The validity of WMFT is verified in a number of researches. In one of the original researches conducted by Wolf et al [115], WMFT and upper extremity FMA were evaluated for 19 stroke patients and 19 age-matched healthy participants by 2 random raters. The assessment result demonstrated high interrater reliability and significant correlation can be observed from the two scales. In [114], Morris et al, investigated the test-retest reliability of WMFT in addition to interrater reliability in an experiment involving 24 stroke subjects. The 15 functional tasks were performed by each subject in two tests with a 2-week interval, the scoring was carried out at a later time by blinded therapists based on the video recordings. The results have proven that WMFT has adequate test-retest reliability and interrater reliability in all three domains. Overall, WMFT is a reliable assessment tool, which also has relatively high sensitivity to upper extremity function changes. However, the performance of WMFT require dedicated testing tasks and setup, and thus it is difficult to be integrated into routine training sessions using automatic assessment systems.

2.1.3.6 International Classification of Functioning, Disability and Health (ICF)

Despite various guidelines that have been published by local and international organizations as an effort to standardise stroke impairment assessment and to provide recommendation on different aspects of rehabilitation process, a unified framework which can be applied across different region, discipline, and perspectives is still lacking [6, 8, 116-118]. The WHO International Classification of Functioning, Disability and Health (ICF) was created to fulfil the gap and serves the purpose of being a universal 'language' that can be understood by health professionals, researchers, policy makers, patients and patient organizations.

ICF is a classification tool which considers human health and well-being in a broad picture that covers various perspectives of functional status from body structure to living environment instead of solely focusing on a certain health condition [119]. As a comprehensive framework, ICF consists of two major parts: Functioning and disability, and Contextual Factors. The first part covers the aspects of body functionality and structure as well as the subject's ability to conduct daily activities and to be involved in different life situations. An ICF assessment will investigate not only the level of impairment to patient's body, but also the restrictions and the limitations that affect patient's life quality. The second part of ICF discusses the contextual factors including the environmental and personal factors that may either facilitate or obstruct patient's performance in daily activities or life situations. ICF can be further broken down into lower level components as illustrated in Figure 2-4. For each detailed 1st to 4th level components, one or more qualifiers can be assigned to describe the severity of impairment or the extent of influence, therefore, the comparison of data across subjects, disciplines and regions becomes possible. ICF also provides a coding system based on the hierarchical structure by combining the part prefix, category code and the qualifiers that can be used in health informatics systems.

To apply the ICF assessment in clinical environments, WHO has also published supporting practical instruments such as WHO Disability Assessment Schedule (WHODAS) and ICF checklist. However, the comprehensive ICF includes over 1400 categories which can be very time-consuming to complete. To improve the clinical practicability, ICF core sets have been developed to cover smaller groups of categories which are relevant to certain health condition such as stroke and thus greatly reduce the amount of time required to conduct an assessment. The ICF core set for stroke was developed in 2004 by conducting a Delphi method based consensus process with international experts from different backgrounds [120]. Altogether, 166 2nd level categories were included in the current version (extended version) with 59 categories from the component body function, 11 from body structures, 59 from activities and participation and 37 from environmental factors [121]. Despite its relatively small size, the selection of categories has a very comprehensive coverage of the typical problems that could be involved from post-stroke body function impairment to attitudes of society and surrounding individuals. After years of development and validation, the ICF core set for stroke started to become a multi-professional assessment standard and its feasibility has been validated and acknowledged in a number of researches [122-125].

However, the implementation of ICF is also hindered by the subjective nature of the human experienced based assessment. The reliability of the ICF qualifier evaluation has been questioned in a number of literatures due to the lack of unified evaluation standard [17, 126, 127]. Therefore, an automatic and quantitative standard evaluation method is much needed.

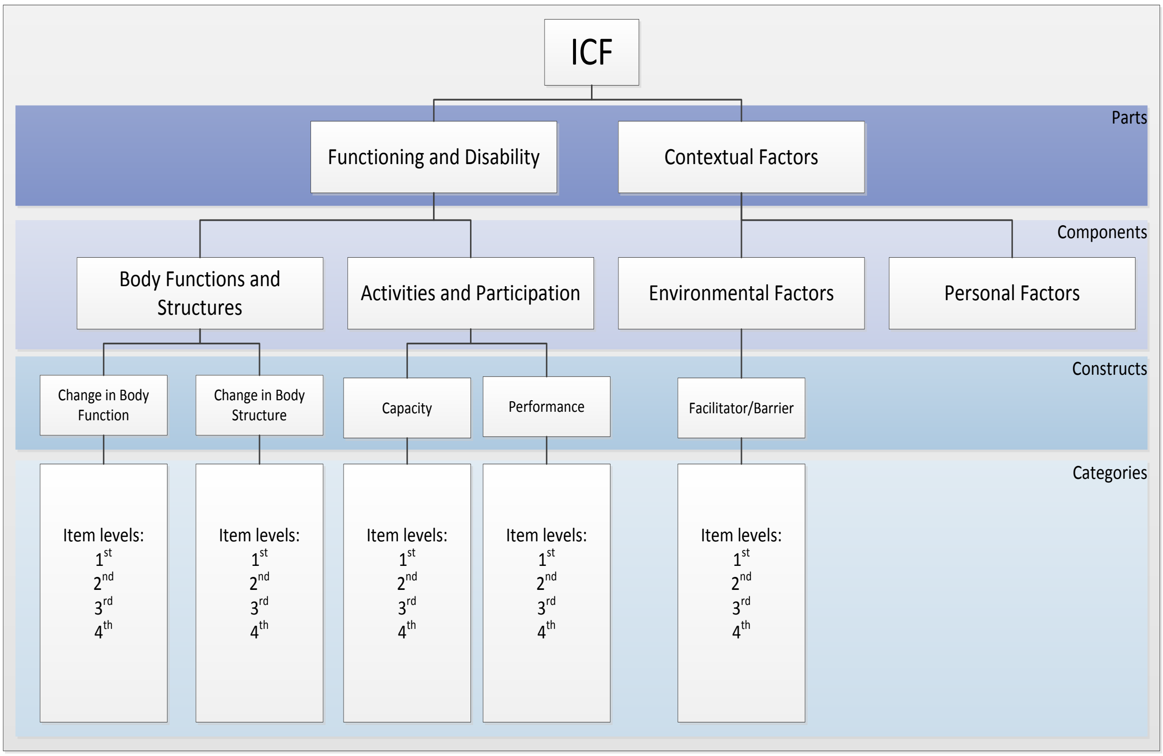


Figure 2-4. Structure of ICF

2.1.3.7 Clinical Assessment Scales Summary

For decades, the chart-based assessment scales are the primary tools for post-stroke impairment assessment. However, the conventional human experience based methods are not only inefficient, but are also lacking in consensus between assessors, which results in relatively low interrater reliability. The discrepancies in the selection of clinical scale is another limiting factor that increases the difficulty of comparing of patient's data across different institutes and regions. There are a large amount of different body function assessment scales in addition to the ones introduced in this thesis. As summaries by Rehabilitation Measure Database [128], there are over 300 assessment processes current used in rehabilitation programs around the globe. In Table 2-2, a list of commonly used assessment scale is presented for comparison. Although most of the assessment scales varies in evaluation methods, nevertheless, they still largely overlap in feature and scope. ICF has been developed as a unified standard to address the issue of inconsistency in clinical assessment. However, it still relies heavily on manual examination and questionnaires. As a result, the assessment result will inevitably subject to human error and inconsistent evaluation standards. In order to improve the efficiency and reliability of motor function assessment in post-stroke rehabilitation, automatic and objective assessment methods are required.

TABLE 2-2 LIST OF COMMON CHART-BASED SCALES FOR POST-STROKE REHABILITATION

Title of Scale	Assessment Scope	Application	Assessment Type / Complexity
Brunnstrom Stages of Recovery	Motor recovery	Stroke	Professional inspection / Low complexity – 6-grade scale for upper and lower extremities
FMA	ADL; motor recovery; balance; sensation; pain	Stroke	Professional inspection / High complexity – 3-grade scales with 155 items across 5 domains
BI	ADL	Brain injury; geriatrics; stroke	Self-report or interview / Low complexity – 3-grade scales for 10 ADL items
NIHSS	Comprehensive (body functioning impairments)	Stroke	Professional inspection / High complexity – multi-grade (up to 5), 11 items
Glasgow Coma Scale	Consciousness	Conditions involve coma (brain injury; stroke)	Interview / Low complexity – 6-grade scale for 3 domains
Ashworth Scale	Muscle spasticity	Cerebral Palsy (CP); Multiple Sclerosis (MS); brain injury; stroke	Inspection / Low complexity – 6-grade scale for each affected muscle/joint
Functional Assessment Measure	ADL	Brain Injury; geriatrics; MS； stroke	Professional Inspection / High complexity – 7-grade scale with 30 items
Wolf Motor Function Test	Upper extremity motor function (dexterity and strength)	Stroke; brain injury	Professional Inspection (timed tasks) / High complexity – 6-grade scale with 21 items across 3 domains
ICF	Comprehensive (body impairments and contexture factors)	Comprehensive (disease, disability and other health related conditions)	Professional Inspection / High complexity – multi-grade scale with over 1400 categories (Comprehensive set, core sets available for some conditions)

2.1.5 Clinical Assessment Tools

In addition to visual inspection and interview, quantitative measurements such as stride length, joint range of motion, and time for completing specific task are also commonly adopted to improve the reliability and validity of clinical assessments and support medical decisions. Apart from generic tools like ruler, goniometer, and stopwatch, specifically designed biomechanical instruments such as grip dynamometer and balance board are often required for measuring specific body function parameters. In this section, some of the clinical assessment tools that are widely implement in post-stroke rehabilitation are reviewed.

2.1.5.1 Strain gauge and dynamometer

Figure 2-5. A Jammer grip dynamometer
(http://www.prohealthcareproducts.com/jamar-plus-digital-hand-dynamometer/)

Strain gauge and dynamometer are instruments for force and power measurement. In post-stroke rehabilitation, the muscle strength is a critical parameter to be monitored and trained as it can significantly affect the quality of ADL performance such as walking and dressing. One of the most frequently used force measurement tool is a hand dynamometer as shown in Figure 2-5. It quantifies the patient's grip strength by measuring the maximum force that the user can apply by gripping the handle and the result can facilitate hand function related clinical assessments. In a post-stroke rehabilitation related study conducted by Bohannon [129], the adequacy of hand dynamometer for characterizing upper extremity strength during stroke recovery was investigated. A Jamar grip dynamometer was used to collect grip strength data from 26 stroke patients. The elbow flexion and shoulder abduction strength was also measured for comparison using MicroFET dynamometer. The result suggested that the grip strength measured was statistically adequate for characterizing the limb strength in post-stroke patients and significant correlation was found between force measurements at the different parts of the limb. The grip dynamometer are also used for analysing hand muscle atrophy. In a research conducted by Triandafilou et al. [130], the index finger musculature of 25 stroke survivors and 10 age-matched healthy control subjects were studied and compared to find quantified evidence for atrophy. The maximum voluntary power grip force of the stroke patients were quantitatively assessed using a Jammer hand dynamometer to determine their hand strength deficits and ultrasonography was used to measure the muscle thickness and cross section area during the experiment. The result showed that the muscle size in the paretic hand of stroke patients was significantly reduced with respect to the muscle size in the non-paretic hand. Another significant implementation of dynamometries in post-stroke rehabilitation is to assess the amount of muscle spasticity. In [131], Pierce et al. investigated the test-retest reliability of isokinetic dynamometry in knee flexor and knee extensor muscle spasticity assessment for CP patients. The peak resistive torque and work were measured for each subjects using an isokinetic dynamometer, and acceptable relative test-retest reliability was obtained by calculating intraclass correlation coefficient. Similar study was conducted by Cetin et al. [132] and the test-retest reliability was verified for wrist spasticity assessment in stroke patients using an isokinetic dynamometer. The experiment involved 21 chronic stroke patients with 20 age-matched healthy control subjects. The spasticity was assessed using the Ashworth Scale and a computerized dynamometer was adopted to measure the subjects' resistance produced during wrist flexion and extension movement. The result showed a significant correlation between Ashworth scale grades, dynamometric scores, and calculated torque. Intra-class correlation coefficient was also obtained, and it indicated that the dynamometric approach can provide relatively high reproducibility when used as a spasticity assessment tool for post-stroke rehabilitation.

2.1.5.2 Balance board

Balance is an important quality in post stroke rehabilitation. The loss of balance is a common stroke impairment and it has severe impact on the stroke patient's life quality and independence as it limits their ability of performing critical ADL including bathing, dressing, and toileting and walking. Balance is also a major domain of post-stroke assessment which is covered in dedicated scales like Berg balance scale and comprehensive scales like FMA and ICF. Specialized tools are sometimes adopted in clinical assessment to measure balance quantitatively and also provide feedback for rehabilitation trainings. One of the most common balance measurement tools is a balance board. As shown in Figure 2-6, balance board is a standing platform that can measure the user's weight distribution and centre of gravity, which can provide valuable information about the user's posture. In [133], Clark et al. conducted a research to investigate the validity and reliability of Wii balance board, a low-cost commercial balance board as can be seen in Figure 2-6, as an assessment tool for measuring standing balance. The Wii balance board was used to examine single and double leg standing balance for 30 subjects, and its performance is compared with laboratory-grade force platform. The experiment result demonstrated that Wii balance board was a valid and reliable tool for clinical assessment of standing balance. The Wii balance board was implemented for post-stroke static and dynamic balance assessment in [134]. Thirty stroke patients were examined for static standing balance, weight distribution and dynamic mediolateral weight shifting using the balance board. The result was compared with conventional clinical tests including 10-metre walk test and step test, and strong correlation was found between mediolateral weight shifting and step test. Intraclass correlation

Figure 2-6. A commercial balance board “Wii Fit” by Nintendo
(http://scopeblog.stanford.edu/2010/01/26/wii_fit_board_f/)

coefficient calculation also proved that the balance board test was highly reliable between testing occasions.

2.1.5.3 Gait Analysis Systems

In post-stroke rehabilitation, gait analysis detects the walking pattern and posture that is unique to hemiplegic patients at different recovery stage and it is another area in clinical assessment that often require specialized tool for quantitative data acquisition. In contrast to the strength and balance test, gait analysis requires more comprehensive kinematics data and it is not uncommon that multiple types of measurement are used in conjunction. As demonstrated in Figure 2-7. Pressure plates based system is also commonly adopted in gait analysis. However, more precise pressure distribution is required compared to balance test and the measurement generally covers a certain walking distance which requires a pressure sensing mat. Another system that is often used in gait analysis is visual based motion tracking systems. Instead of directly sensing the weight transfer, the optical systems captures the walking pattern and posture using multiple cameras with visual marker as illustrated in Figure 2-8. By combining the two approach, both kinetic and kinematic data can be collected at the same time to construct a comprehensive record of the patient’s waking pattern. In a research conducted by Bensoussan et al. [135], pressure plate based sensing device and visual-based motion sensing system are used together to investigate the motion and force asymmetries in stroke patient's gait initiation pattern. A 6-camera optoelectronic system was used to sample the kinematic information at 100Hz and the kinetic information was recorded using two strain gauge based force plate at 500 Hz. By analysing the multiple gait features captured by the two systems including stride and step length, phase duration, force, weight transfer, and joint motion range, the researchers were able to determine how asymmetrical adaptive posture-motor strategies were developed in stroke patients to compensate for the impairment.

2.1.5.4 Clinical Assessment Tools Summary

By taking quantitative measurement using specialized tools, the reliability and validity of human inspection based clinical assessments can be improved. However, the tools, as introduced in this section, is not without drawback. First of all, most of these instruments can only provide measure specific parameters of certain body function, the evaluation of the scale still require human experience based interpretation. Secondly, the assessment tools generally require repetitive manual operation and are too obtrusive to be integrated into continuous monitoring system for long time tracking applications. In addition, complex measurement instruments such as the visual-based motion tracking system are costly and require professional installation and operation. In recent year, wearable sensors with low-cost and unobtrusive design are increasingly involved in clinical assessment especially for automatic systems designed to collect data continuously for a relatively long period. More comparison and discussion about wearable sensing technology will be introduced in the next section of the chapter.

Figure 2-7. Pressure plate based gait analysis system (http://www.sensorprod.com/foot-plate-pressure-sensor.php)

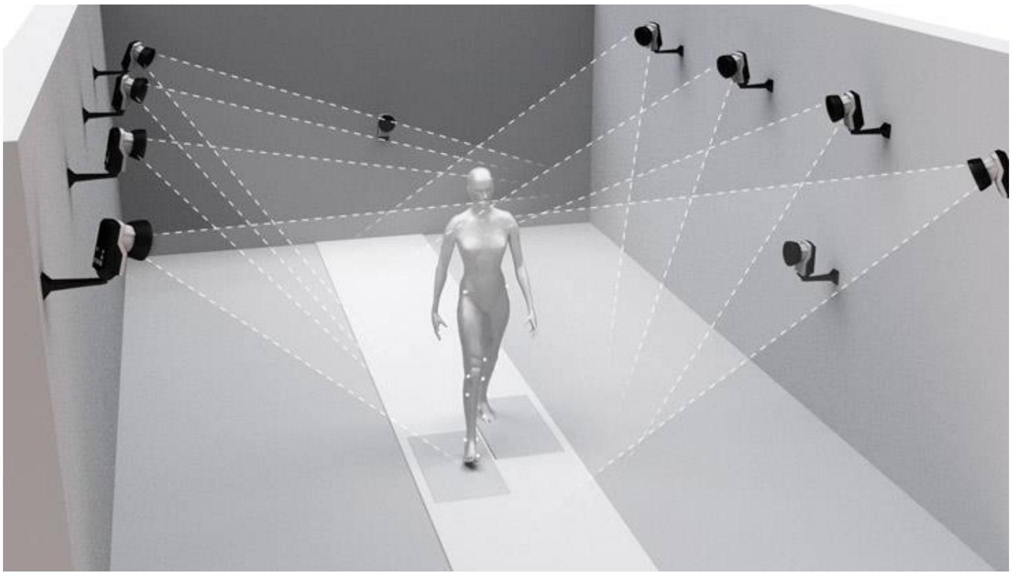


Figure 2-8. An illustration of gait analysis using visual based motion tracking system (Qualisys: http://www.qualisys.com/applications/biomechanics/gait-analysis-and-rehabilitation/)

2.2 Wearable Sensor in Rehabilitation: An Engineering Perspective

Along with the recent rapid development of mobile computing and miniature devices, an increasing amounts of wearable sensor based products can be found in clinical applications [136]. The unobtrusive and relatively low cost nature of wearable devices has a substantial potential on transforming the conventional rehabilitation practice as it provides the capability for gathering quality and quantitative data from patients efficiently even in non-clinical settings like home or outdoor environment [137]. As demonstrated in Table 2-3, wearable sensors can be applied to collect a large range of signals from physiological to physical. Specifically designed body sensor networks can be integrated into clothing, accessories, and living environments to continuously collect various types of signals and parameters during patient's daily activities [138]. As a result, the rehabilitation experts can follow patient's performance and adherence during training programs more closely and conduct objective assessment on patient's impairment level and recovery progress based on the data that are automatically collected using wearable sensors. An example is the wearable health care system based on knitted integrated sensors proposed in [139] as shown in Figure 2-9. The system is designed to continuously record physiological signals including respiration, ECG, physical activity, and temperature. By integrating sensors, electrodes, and connections in fabric form, the system is capable of performing long-term patient monitoring in a non-invasive and unobtrusive way.

The major current research challenges of wearable sensor technology fall into three key areas [137]. The first one is the development of various types of wearable sensor units. In general two main types of data are of interest in clinical rehabilitation applications namely the physical motion data such as linear and angular acceleration [140], and the physiological data such as Electrocardiography (ECG) and EMG [141]. Substantial amount of researches has been carried out to refine the sensor design to record these data with improved reliability while remaining unobtrusive. Secondly, the system integration and implementation of wearable sensor network is also an important topic. In order to fulfil the requirement of different clinical applications in various settings, the sensor combination, communication method and data infrastructure have to be thoroughly investigated to achieve optimal performance and efficiency. At last, after gathering patient data with wearable sensor networks, another major challenge is on how to extract clinically meaningful information from the enormous amount of data. In this section, the state-of-art research outcomes from these areas will be reviewed.

TABLE 2-3 THE TYPES OF WEARABLE SENSOR

Type of signals	Type of Sensors	Description of measured data
ECG	Skin electrodes	Electrical activity of the heart
EMG	Skin electrodes	Electrical activity of the skeletal muscle
EEG	Scalp electrodes	Electrical activity of the brain
Blood pressure	Cuff-based/ Photoplethysmogram (PPG)	Pressure exerted by circulating blood upon blood vessel
Body temperature	Skin patch/ temperature probe	Temperature at the skin surface
Respiration rate	Piezoelectric/Piezoresistive sensor	Chest expansion and contraction
Oxygen saturation	Pulse oximeter	Oxygenation of the blood
Heart rate	Pulse oximeter/skin electrodes	Frequency of the cardiac cycle
Skin conductivity	Galvanic skin response	Electrical conductance of skin (indication of sweating)
Phonocardiogram(PCG)	Phonocardiograph	Sound of the heart
Blood Glucose	Strip-base glucose meter	Glucose in the blood
Body Motion	Accelerometer / IMU	Kinematic data of human body

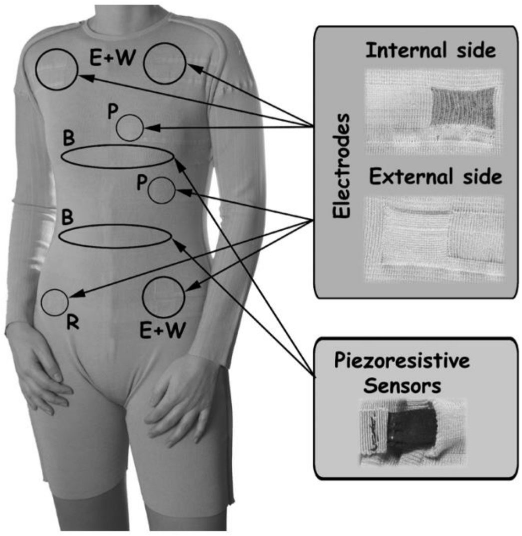


Figure 2-9. A prototype wearable sensor garment designed by Paradiso et al. (R. Paradiso et al. 2005)

2.2.1 Wearable Sensors

In the field of rehabilitation medicine, wearable sensors are developed to collect a great range of physical or physiological signals including body movement, gait pattern, ECG, EMG, EEG Blood pressure and Respiration rate. Different design approaches have been taken to suit various applications such as mobility assessment, fall detection, location tracking, activity tracking, medical status and medication intake monitoring. The scope of this thesis is focused on the assessment of stroke induced motor function impairment. For this reason, this review will be limited to the sensors designed for motion sensing and mobility evaluation applications.

One of the important types of wearable sensor is the motion sensor which is designed to collect real-time data that dynamically represent the human body movement and posture changes [142]. The current available human motion tracking solutions can be divided into two major categories: visual based and non-visual based systems. Visual based systems utilize optical sensor such as cameras and visual marker to record human movements, and they can usually provide highly accurate result. Therefore, they are extensively used in research labs to study human kinematics for sports and rehabilitation applications. For example, VICON is a commercially available visual based motion tracking system that utilizes high resolution and high frame rate infrared camera array to provide 3D spatial displacement tracking. In [143], the VICON system was adopted together with ground reaction force and EMG measurement in a study that investigated the human gait dynamics involved in walking up and down a hill. In another research by McIntosh et al., a VICON system was utilized to prove the effectiveness of ankle-foot orthosis on hemiparetic gait [143]. In a recent study related to stroke rehabilitation, the 3d motion trajectories of stroke patients were sampled using a similar visual-based system Qualisys Oqus 300 to verify the effectiveness of a home training program involving sEMG biofeedback [144]. However, most of the studies involving visual-based system for rehabilitation applications are still in the preliminary stage or designed to be operated only in major hospitals and research centres. One of the largest obstacles which prevent visual-based systems to be widely implemented in practical clinical application especially in home and community settings is the vast cost and operation complexity. The multiple camera setups also require relatively large space without obstruction which is often unavailable in patient's home and community training centres.

On the other hand, the non-visual-based systems, especially inertia sensors based on microelectromechanical systems (MEMS), are attracting increasing interest in the field of physical medicine and rehabilitation due to their significantly lower cost and compact size [136, 137, 145]. Inertia sensors including accelerometers, gyroscopes and sometimes magnetometers are often combined as Inertia Measurement Units (IMU). They can be attached to various parts of human body and form a wearable sensor network to simultaneously record kinematic data during rehabilitation training. The sampled data can be used to assess various properties of the training movement including motion type, frequency, intensity, duration and quality. IMU based sensing systems are often considered as a suitable candidate for providing TR services as they are relatively easy to setup and operate, and required no additional space. A number of researches have been carried out to investigate dedicated IMU based sensing systems to be used in non-clinical settings. Zhou et al. has proposed an upper-limb motion tracking system to support home-based rehabilitation. The design is capable of providing relatively accurate estimation of wrist, elbow and shoulder positions using only a pair of accelerometers [146]. In a preliminary study conducted by Yang et al., the researchers explored the possibility of using simple inertia sensor network setup to assess hemiparetic gait pattern in terms of walking speed and temporal gait symmetry [147]. Strommen et al. performed an early mobilisation study with a similar setup using accelerometers to quantitatively measure and compare acute and transient ischemic stroke patient's pattern of physical activity [148]. The low cost and non-invasive setup can be expanded to non-clinical setting for long-term physical activity analysis.

In addition to the kinematic input based systems, Surface Electromyography (sEMG) has also attracted growing interest in the field of rehabilitation engineering. sEMG records the electrical activities produced by skeletal muscle groups using electrodes attached to the skin surface. Surface EMG signal can provide rich information about muscle activation and function from neuro-electrophysiology perspective. It is commonly adopted in clinical settings when repetitive assessment of general muscle activation is needed due to the relatively simple and non-invasive procedure compared to intramuscular EMG [149, 150]. Due to the ability of reflecting critical neural activities such as the motor unit recruitment and synchronisation, surface EMG has already been proven effective for detecting neuromuscular abnormalities, fatigue and voluntary motion intention [151-153]. The implementation of sEMG analysis can also be found in post-stroke rehabilitation applications [154, 155]. After a stroke incident, the upper motor neuron lesion can lead to imbalanced excitatory and inhibitory input to alpha motor neurons and cause abnormal muscle excitability or spasticity which eventually results in significant limitation on patient's motion [34]. Therefore, by investigating the abnormalities in sEMG signal, valuable information about stroke patient's motor function impairment can be obtained. In [155], high-density surface EMG with 89 channel recordings was used for classifying different training motions performed by stroke patients. A Hidden Markov Multivariate Autoregressive (HMM-mAR) network based approach for bisectional stroke impairment classification had been introduced in [154]. However, in order to replace the current human experience based motor function assessment, multi-level stroke impairment classification has to be investigated.

2.2.2 Wearable Sensor Based Rehabilitation systems

In order to utilize the benefit of advanced wearable sensor technology, computer-aided rehabilitation systems for various clinical applications are also being developed and experimented [142, 156]. A brief list of state-of-art rehabilitation systems and research projects that take advantage of wearable sensor technology is presented in Table 2-4. Although most of these systems are targeting different medical conditions, they can be subsumed under two main categories based on their functional application: supervision and assessment. Supervision includes monitoring patient's daily activity, record training intensity, and identifying emergency events such as fall and seizure. Assessment includes evaluating patient's body function impairment and tracking rehabilitation progress. The latest technological development for both applications will be reviewed in the following sections.

2.2.2.1 Wearable Sensor for Patient Supervision

One of the most common forms of supervision enhancements using wearable sensor based system is the automatic emergency event detection. This type of system continuously monitors patient's physical or biological signal through wearable sensor network and searches for special patterns that may indicate an emergency event such as a fall or a seizure. Such system can improve supervision reliability and efficiency in hospital-based rehabilitation programs and is considered a necessity for ensuring the safety in home or community-based rehabilitation programs where professional human supervision may be lacking.

Fall detection is an important safety feature that applies to a wide range of conditions from general eldercare to hemiplegia rehabilitation. Inertia measurement based systems are often adopted in such application to detect the kinematic features that indicates a possible falling motion, which is then used to trigger medical alert immediately. Although IMU-based motion sensing and data processing technology is relatively mature, techniques that improve the accuracy of distinguishing a fall from intentional ADLs are still being investigated [157, 158]. In a study conducted by Kangas et al. [157], the accelerometer placement and classification algorithm for fall detection were investigated. Three tri-axial accelerometers with a sampling rate of 400 Hz were attached to subject's non-dominant wrist, waist, and forehand. Raw acceleration data were first processed with a 50 Hz down-sampling and median filter for noise reduction. Four different parameters were extracted for fall detection: a mixture of dynamic and static acceleration components on all axis were first summed together to obtain a 'total sum vector'. The dynamic and vertical acceleration components were then separated from the sum before the maximum difference in acceleration within a 0.6s sliding window was calculated to capture the fast changes. The parameter thresholds were adjusted in the experiment to minimise the chance of false alarms from ADLs. The experiment involves two voluntary subjects performing intentional fall and a series of ADLs. The result suggests that the waist and forehead measurements are most suitable for differentiating falls from ADLs where 100% sensitivity can be achieved. A different approach, which focuses on the transition of postures, was proposed in [158]. In Li et al.'s design, two IMUs attached to the subject's chest and thigh were used to measure both linear and angular acceleration. Four different postures: standing, bending, sitting and lying were defined by setting the thresholds for IMU inclination angles. A three phase decision making process was then proposed to distinguish falls from ADLs. Firstly, a condition check was performed on the sum of acceleration to determine if the subject was at a static posture or during a dynamic transition. If a static posture was identified, the type of the posture was then recognized using the inclination thresholds. Finally, if a lying posture was recognized, the dynamic motion before the posture would be analysed to determine if it was unintentional and thereby a fall. Three volunteers were involved in the experiment by performing intentional falls and ADLs. The experiment result shows that the posture transition focused design is capable of correctly responding to some of the complex cases such as fast sit down and fall on stairs. However improvements are still needed as these systems are not able to perform in perplexing situations such as jumping into bed or falling against wall.

TABLE 2-4 A SUMMARY OF RECENT WEARABLE SENSOR APPLICATION IN REHABILITATION

Research group	Type of Condition	Description of wearable sensor configuration
Kangas et al. [157]	Fall Detection	Triaxial accelerometric measurement at waist, wrist and head to distinguish fall from ADL
Li et al. [158]	Fall Detection	Two IMUs to monitor subjects posture and to detect falls using a combination of IF-THEN rules
Nijsen et al. [159-161]	Epilepsy	Accelerometer/ extracted feature for myoclonic epileptic seizure detection
Pitta et al. [162]	Chronic obstructive pulmonary disease (COPD)	Accelerometer armband to measure COPD patient's physical activity and find its correlation with pulmonary function impairment
Patel et al. [163]	COPD	Wireless wearable sensor network to monitor COPD patient's activity
Manson et al. [164]	Parkinson's disease (PD)	Single accelerometer on shoulder to monitor the dyskinesia severity of PD patient
Thielgen et al. [165]	PD	Accelerometer output to quantify tremor severity scores
Huang et al. [166]	Stroke	Multiple inertia sensor for reconstructing 3D upper limb movement and evaluating impairment
Uswatte et al. [167]	Stroke	Accelerometer to provide objective information about upper limb activity for patient with sub-acute stroke
Prajapati et al. [168]	Stroke	Accelerometer sensor network to monitor the quantity and quality of stroke patient's gait pattern
Del Din et al. [169]	Stroke	Inertia-based wearable sensors to collect kinematic data from stroke patients during WMFT tasks and automatically evaluate FMA scores
Carpinella et al. [170]	Multiple Sclerosis (MS)	A single wrist-mounted IMU to evaluate MS patients upper limb function based on ARAT rating

Another significant application of wearable sensor in patient supervision is the detection of epilepsy seizures. Identifying seizure accurately in a timely manner is important for patient care and antiepileptic drug delivery management [159]. Conventionally, the most reliable seizure detection approach is performed by combining a direct visual inspection and a manual electroencephalogram signal screening (EEG), which can be excessively labour intensive, especially during night time. The EEG system also restricts the possibility of performing seizure detection in home-based environments. In order to provide additional patient supervisions when human resource is limited, audio-triggered automatic alarm systems are currently widely implemented despite their poor sensitivity and Positive Predictive Value (PPV) [171]. A novel approach which utilizes wearable accelerometers to detect motor features that may indicate epilepsy seizure was introduced in [159]. In the proposed design, wearable sensor nodes were constructed with two Analog Devices ADXL202E 2D accelerometer that were mounted at perpendicular angle to enable a 3D measurement. The motion data were collected from all four limbs as well as from chest, together with ECG, EEG, and video recording for a comparison purpose. A 36 hours clinical trial was performed with 18 patients who suffer from severe epilepsy. The result has demonstrated that the accelerometer setup can detect 48% of the total seizures and 100% for 10 out of the 18 patients. In two of the follow-up researches [160, 161], 80% detection sensitivity was achieved with accelerometer-based system. However, the PPV remains low which indicates a large number of false alarm. Based on evidence, it is clear that accelerometer data can be used as a complementary input in addition to the EEG approach, but as an independent measure, more development is still required especially for reducing the false-positive rate.

Wearable sensor systems that measure kinematic information are also used for monitoring the activity level of patients with Chronic Obstructive Pulmonary Disease (COPD) and estimate their daily energy expenditure. Physical inactivity is commonly observed from COPD victims after the acute exacerbations, and it can result in a number of comorbidities such as muscle atrophy and decrement in quality of life [172]. Increasing physical activity is considered one of the objectives for COPD treatment and developing accurate energy expenditure tracking systems is important for measuring the outcome of pulmonary rehabilitation programs and improve clinical intervention [173, 174]. The conventional activity measurement methods include direct observation, self-reporting, radioisotope water techniques and gaseous composition measurement and they are either time-consuming, unreliable or require complex setup to implement [173]. In one of the pioneer studies [175], an experiment conducted by Wong et al. demonstrated how an accelerometer can be used for physical activity level measurement. The result has shown that a wearable sensor based measurement is linearly correlated to the conventional oxygen consumption based measurement. Along with the recent development of miniature IMUs, an increasing number of motion sensing wearable sensor based systems has been developed for this application [162, 172, 176-178]. In [173], the validity of activity measurement using accelerometer was further proven by evaluating its correlation with testing subjects' exercise capacity, pulmonary impairment level, self-report on dyspnea and self-efficacy. 47 subjects were involved in a 3-day experiment with a single accelerometer attached to the non-dominant side of the waist. The result has shown a high correlation between measures in general. The test-retest reliability of the setup was also tested with a repeated 6-minute walk where a high intraclass correlation coefficient was scored. In a series of researches conducted by Pitta [162, 172, 178], the relationship between physical activities, pulmonary function impairment and hospitality after exacerbation was studied with the aid of wearable accelerometers. In [162], an accelerometer integrated armband was used to monitor the physical activity of 40 COPD patients over 2 days. The result has shown that patient's maximal voluntary ventilation is better correlated with patient's activity level than forced expiratory volume and inspiratory capacity. In a more recent study conducted by Patel et al. [163], a different activity monitoring approach was proposed. A wearable sensor network that consists of 10 wireless IMU nodes was used to collect the motion data from different parts of the body and classification tests were performed to identify ADLs. Experiments have been conducted with 15 COPD patients performing a selection of 11 different ADLs and exercises. Six different classifiers including nearest neighbour, Naïve Bayes, J48 decision tree, Random Forest and Support Vector Machine (SVM) were implemented and compared in both a 10-fold and Leave-One-Out cross-validation tests. The results have shown that the best error rate was achieved by SVM where 88% of the ADLs can be correctly identified.

2.2.2.2 Wearable Sensor for Clinical Assessment

Automatic clinical assessment is another important application of wearable sensor system in rehabilitation settings. Clinical assessment may include the quantification of certain body function such as limb mobility or objectively examine the severity of certain conditions such as motor fluctuation in Parkinson Disease (PD). By adopting wearable sensor technology, an automatic system can be built to facilitate the clinical assessment process of a wide range of conditions, from PD to stroke, by improving its reliability and efficiency, as well as providing quantitative feedback to support both patient's rehabilitation training and doctor's decision making. In contrast to patient supervision applications, where threshold finding and template matching techniques are dominant, in clinical assessment applications, advanced classification algorithms are often required to relate feature parameters to clinically meaningful measures such as Brunnstrom Stages of Recovery for stroke or Unified Parkinson's Disease Rating Scale (UPDRS) for PD. It is also considered as a more challenging problem as the evaluation of certain conditions involves a large number of factors and the conventional assessment tools are usually designed to suit experience based human decision making which may not be easy to fully comply with using automatic systems.

One of the most widely investigated clinical assessment system is gait analysis [179]. Gait analysis involves a quantification of various dynamic features and an identification of pathological gait patterns that may be related to certain conditions. Gait analysis is extensively used in stroke rehabilitation as hemiplegic gait patterns have unique features that can be related to the recovery progress, and stroke patients' walking ability can greatly affect their life quality. In a research conducted by Prajapati et al. [180], wearable accelerometers were placed above stroke patient's ankle for eight continuous hours to study the characteristic of patient's daily walking pattern. Correlation analysis was then conducted for motor impairment measured in Chedoke McMaster Stroke Assessment (CMSA) scale to gait parameters including bout duration and walking speed. The result revealed that a statistically significant increase of gait asymmetry can be observed between daily walking and laboratory assessment. In a follow-up study [168], similar setup was adopted with additional heart rate monitor to prove that cardiorespiratory workload is unlikely to limit walking participation and the patients were intentionally walking at speed below the level which may provide health benefits. In a research carried out by Luinge et al. [181], a Kalman filter based sensor fusion method was used to reduce the integration drift and to ultimately improve the accuracy of IMU based human kinematic measurement. In [182], the relationship between cognition impairment and gait variability and stability in geriatric patients was investigated using single accelerometer data and extracted features such as walking speed, trunk acceleration, stride variability and regularity. However, these methods produced indirect outcomes that can only be referenced by professionals, implying that the conclusive evaluation still depends on subjective judgments. In order to obtain a self-generated benchmark that is used as feedback to benefit the rehabilitation process, more objective and intuitive scoring system are required.

IMU-based wearable sensors are also frequently used for evaluating motor fluctuation and levodopa-induced dyskinesia in PD. In [164], shoulder mounted accelerometer was used to perform dyskinesia assessment for PD patients. The accelerometer output were compared with established clinical dyskinesia scales including modified Abnormal Involuntary Movement and Goetz scales, and strong correlation was observed for both scales. In another study conducted by Thielgen et al. [165], an IMU-based system, which is capable of automatic tremor severity assessment, was proposed. The 4-channel accelerometer based approach was tested with 30 patients with PD, and the system was capable of detecting evident changes in tremor severity after specific treatment. In [183], a wearable sensor based home monitoring system for patients with PD was proposed. An IMU-based wireless body sensor network was adopted to collect patient's motion data during the performance of motor tasks defined in UPDRS and the system was capable of capturing the severity of tremor, bradykinesia and dyskinesia based on the sensor reading, and estimating UPDRS scores using a Support Vector Regression based method.

Upper limb motor mobility evaluation is considered more difficult compared to gait analysis due to higher variability and complexity [184]. By applying biomechanical models such as Fitts' Law, it is possible to calculate a 'performance index' for each motion based on the angular speed, accuracy and amplitude measured by optical sensors [185-187]. However, when dealing with stroke patients' motion evaluation, the problem becomes even more complex for several reasons. Firstly, stroke patients' motion cannot be fairly evaluated solely based on basic physical parameters such as amplitude and speed. Patients' age, fitness level, and other health conditions may limit the limb flexibility and strength and thus greatly affect those physical parameters. Moreover, due to cognitive problem, many stroke patients are not able to follow the guidance precisely, therefore, the evaluation cannot be done by simply matching the motion trajectory. In order to address these difficulties, a more sophisticated and robust classification system is required.

In recent years, a few studies have been carried out on implementing motion evaluation techniques for stroke rehabilitation applications. One example is a sensorized garments used in self-administered post-stroke physical rehabilitation system introduced by Giorgino [188]. The system was constructed with strain sensors to measure patients' upper extremity motion during rehabilitation training sessions. A template matching classifier based on Dynamic Time Warping (DTW) algorithm was adopted to identify the type of the motion and to produce real-time feedback according to the similarity between the sample and template. The classifier is effective for the purpose of motion pattern recognition due to its nature of eliminating influence introduced by distortion or phase shift when comparing two sequences. However, the system itself is not designed for differentiating different stages of stroke impairment. In order to produce comparable classification results that match doctors' evaluation, the system design, including both sampling procedure and classifier training method, has to be sensitive to the features that are pertinent to the post-stroke recovery process e.g. synergy pattern development and symptoms of muscle spasticity.

A micro-sensor based upper limb rehabilitation system which can perform motor impairment evaluation was introduced in [166]. A range of inertial measurement sensors, including tri-axial accelerometers, gyroscopes and magnetometers, were utilized in this system as motion capture units. The kinetic data, sampled by the motion capture units, enabled the reconstruction of the 3-dimensional movement performed by patients and the evaluation process was based on Active Range of Motion (AROM) and Motor Feature Indices (MFI) extracted from the reconstructed motion data. This type of the systems can usually provide intuitive feedback and it can also allow physicians to observe patient's training activity remotely in real time. However, the use of multiple types of inertial sensor will greatly increase the cost and computation complexity. The feature selection technique used was based on the observation of the statistical difference between the data sampled from stroke patients and healthy individuals. The design was also unsuitable for body function impairment classification as some features that can be used to identify stroke patients may be misleading when used to evaluate stroke recovery progress. For example, significant statistical difference often appears in features like motion speed when comparing healthy participant with stroke patients. However, it is not always true that the faster moments indicate better recovery as it may also be the sign of high spasticity and a lack of muscle control.

In a research conducted by Uswatte et al. [167], the reliability and validity of a wearable accelerometer based system as a rehabilitation outcome evaluation method were investigated. A system consisted of four accelerometers was attached to stroke patient's limbs and chest for long-term measurement of patient's daily activity. The objective of the experiment was to evaluate the effectiveness of constraint-induced movement therapy (CIMT) in post-stroke rehabilitation and the data sampling was conducted in a 3-day period before and after CIMT. The accelerometer output were summed over an epoch of 2 seconds as a feature to reflect the amount of activity performed by the patient. The patients' activity is also rated using Motor Activity Log (MAL), an interview based assessment. The experiment result showed that the data collected by the accelerometer based system supported the hypothesis that CIMT can improves the stroke patient's body function and activity level. The test-retest reliability of the system was adequate and a significant correlation between the measurement and MAL was observed, which suggests that the accelerometer based method is a valid tool for evaluating rehabilitation outcome.

A computerized motor-skill analyser for visuo-motor skilled motion evaluation was introduced in [189]. The user of the system was required to move a traced object/marker on a two-dimensional plan and followed a figure-of-eight pattern shown on a display. The lap time and the accumulated trajectory error were recorded as references for evaluation. The experiment outcome demonstrated that the trajectory error had a negative correlation with Brunnstrom stage. However, the motion tracking scheme was not sensitive enough to detect the presence of spasticity and the synergic patterns and thus the system was not capable of differentiating stroke patients at different Brunnstrom stages.

In a study conducted by Del Din et al. [190], IMU-based wearable sensors were utilized to collect acceleration data from stroke patients during a Wolf Motor Function Test (WMFT) and the features extracted from the data were used for FMA estimation. Motion data were sampled from twenty-four stroke survivors, and eight WMFT motor tasks were performed by each participant. A random forest was used for pattern recognition, and the result has demonstrated that the proposed system can estimate FMA score based on motion recorded from the WMFT tests with low RMS error. However, the system was developed around WMFT which is a functional test designed specifically for impairment evaluation and requires extensive professional supervision. As a result, the automatic assessment feature cannot be integrated into the routine rehabilitation training and the implementation of the system in an unsupervised environment will be relatively difficult.

Similar quantitative assessment approach can also be expanded to other upper extremity motor function impairment. In [170], IMU was used to assess upper limb motor function in patients with multiple sclerosis. A functional task-based clinical assessment tool named Action Research Arm Test (ARAT) was used to evaluate patients' ability to handle objects and the objective was to develop an automatic assessment method which can overcome the drawbacks of the conventional assessment including subjectivity and low sensitive to mild impairment. The experiment was conducted with 12 healthy participants and 21 patients, and the motion data was sampled using a single wrist-mounted IMU. Basic features such as movement duration and a jerk index which measures motion smoothness were adopted, and correlation between feature value and clinical scores were investigated. The result shows that the features are strongly correlated to ARAT rating and Nine-Hole Peg test score, and the motor performance measured in jerk and duration for patients with different level of impairment are significantly different. However, only statistical analysis was conducted in this study and specifically tuned classifier may be needed to replace manual classification process of the clinical scales.

2.2.3 Pattern Recognition in Rehabilitation

In addition to the sensor design and the data acquisition techniques, another significant challenge in implementing wearable sensor network in rehabilitation systems is how to process the enormous amount of data that are collected during continuous patient monitoring and to extract the patterns which can provide valuable and accurate information to assist rehabilitation professional's decision-making. Most of the automatic features provided in wearable sensor based rehabilitation systems such as training motion identification and objective mobility assessment also require advanced machine learning and data mining techniques.

Pattern recognition is considered as an efficient machine learning method for strafing data with various size and types by assigning labels to each data instance with or without supervision. The classification process may be performed by measuring similarities on the basis of a chosen number of extracted features that represents the original data. The application of pattern recognition extends across in a wide spectrum of science and engineering topics. In the field of medicine and biomedical engineering, pattern recognition plays a prominent role in bioinformatics, computer-aided medical diagnosis and cognitive science [191]. The performance of most of the pattern recognition techniques varies significantly between applications. Depending on the type and structure of the data, the noise level, the output expectation and the environmental factors, the researcher often has to investigate a list of algorithms before finally choosing one with the highest performance for a particular application. It is often necessary to fine tune the algorithm using model validation techniques such as cross-validation in order to achieve the optimal performance. Ensemble methods or highly customized systems may also be developed to suit certain requirements of the application. In this section, some of the state-of-the-art rehabilitation medicine related implementation of pattern recognition techniques will be reviewed.

2.2.3.1 Linear Regression Models

One of the simplest forms of pattern recognition is the use of linear regression models where its output is a sum of weighted attribute values. Linear models are often applied to binary classification problems such as separating paretic samples from healthy samples. However, they cannot adapt to the different shapes of clusters, hence, often perform poorly when there is a complex separating surface between clusters. As a result, regression methods are often used alongside statistical analysis in trials to identify a potential pattern rather than building classifiers to assist decision-making in clinical applications. For example, in a study conducted by Sprigle et al., linear regression were adopted for analysing the relationship between the pelvic tilt data of patient sitting in a wheelchair measured using two different systems [192]. In [193], Moy et al. conducted a study to evaluate the performance of a wearable activity tracking system for COPD patient which is based on counting walking steps using uniaxial accelerometer. A linear progression model was used to identify predictors for the percentage of correctly captured step counts in various settings. Similar technique was also adopted in Zollo et al.'s series of studies involving robot-assisted chronic stroke rehabilitation [194, 195]. A linear regression analysis was utilized for deriving quantitative indicators from kinematic data collected from InMotion2 robotic therapy system and a handheld accelerometer to represent biomechanical motor performance and investigate their correlation with conventional clinical scale namely FMA.

2.2.3.2 Decision Trees

A more common approach adopted in solving classification problems is Decision Tree, which is a "divide and conquer" type rule-based classifier that grows tree shape structured patterns by learning training instances [196]. Each node in the tree is associated with a condition that is tested against a particular attribute of the inputs and the input instances will travel through a certain path decided by the testing results from the root to the leaf node where it will receive a label as classification output. Decision trees are relatively easy to tune and are capable of solving classification problems with nonlinear separating surface. However, larger decision trees are prone to overfitting and they require additional pruning process to remove the branches that provides fewer classification advantages or is generated from noise or incorrect data. An ensemble of trees are often grown together through a bagging process where multiple subsets are created by randomly select samples from the original training dataset, and the final classification output is decided based on a majority vote. The ensemble approach, or "random forester", produces classification models with reduced variance and improves classification accuracy, therefore it is often preferred in practical applications [197].

Decision tree method was extensively used in the series of researches conducted by Patel et al., regarding wearable sensor based post-stroke rehabilitation monitoring [190, 198]. In [198], decision trees were adopted to estimate FAS using patient's motion data sampled with accelerometers during the performance of selected Wolf Motor Function Test tasks. Twenty features extracted from the sensor data were selected using ReliefF algorithm and Davies-Bouldin cluster validity index to remove features that contribute less for separating classes. A bagging with replacement process was performed to generate multiple subsets of samples for growing random forest, and the splitting of the nodes on each tree was based on a subset of features. The accuracy of the model was further improved with a percentage error reduction based pruning process. A similar approach was adopted in [190] where random forests are constructed to estimate FMA using the same motion dataset, but only with single Wolf Motor Function Test item.

2.2.3.3 Instance-Based Learning

Instance-based learning algorithm such as K-nearest neighbour (KNN) is another common type of techniques that are used to address the motion classification problem [199-204]. Unlike many other pattern recognition techniques, instance-based method retains the original input instances for classification without a learning process to generalized data into a set of inference rules. This type of the learning strategy is generally referred as lazy learning, as most of the work is delayed until the evaluation stage when the query is made. As a result, the classification process can become too cumbersome and impractical for many applications. When instance-based methods are implemented with template matching algorithms for multinomial motion classification, the classifier performance could be further damaged as the heavy querying process may be repeated multiple times to locate the optimal match. In order to be integrated into regular rehabilitation training, the classification process must be computationally inexpensive to perform even with a large number of motion types. Therefore, despite the classification performance, instance-based learning is not considered as the most suitable candidate for many practical applications.

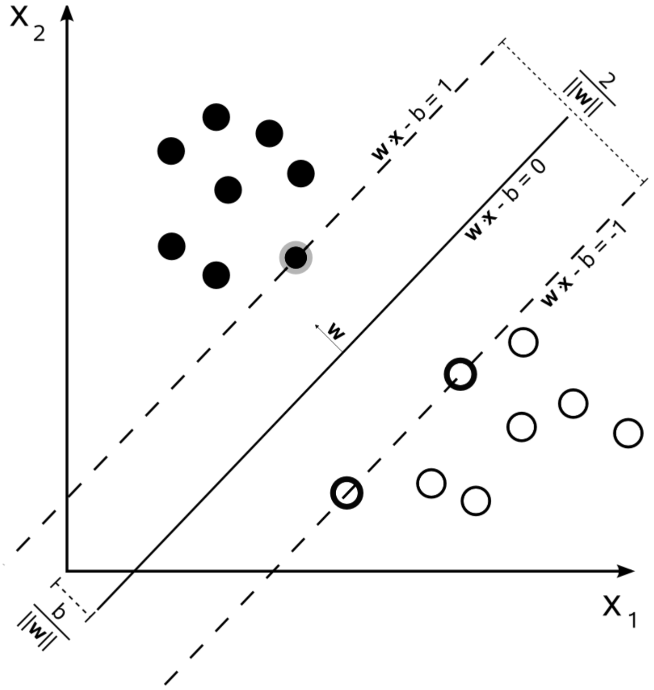
In a research investigating fatigue level during ADL using sEMG [204], a KNN classifier was trained to grade the sEMG samples collected from extensor carpi redialis muscle during repeating palm flexion-extension movements into four different physiological states based on the level of fatigue. The classification was obtained by placing the input sample into the training data space and performing a majority vote using the class labels of the four nearest samples. KNN algorithm is also tested in a four-class brain computer interface problem by Schlogl et al. [203]. The objective was to classify EEG data recorded with 60 electrodes from 5 subjects into 4 groups of different motor-imagery tasks. KNN with various number of k values was compared with other methods that include Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). However, its accuracy appeared to be significantly inferior to the other two despite the relatively fast processing time.

2.2.3.4 Support Vector Machine (SVM)

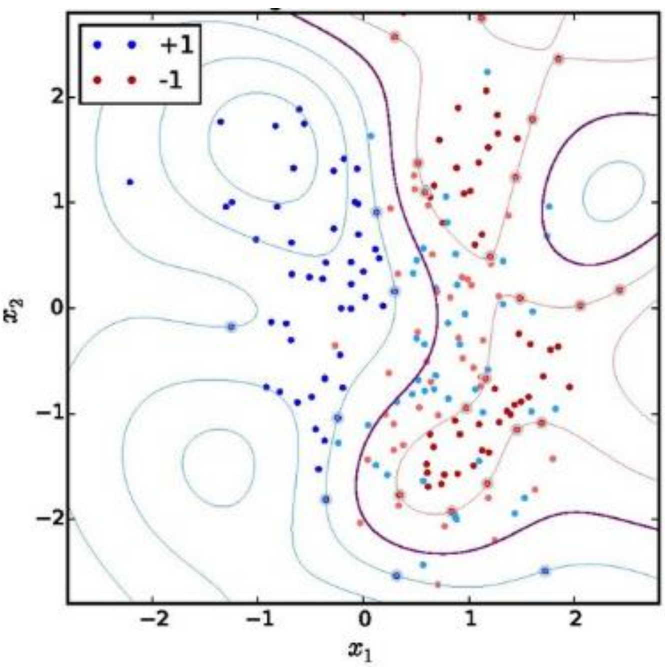
SVM is a powerful pattern recognition tool with high generalization ability that is designed for complex binary classification problems as originally proposed in [205, 206]. SVM separates samples from different classes by constructing a linear discriminant function based on the critical boundary samples called 'support vectors' and maximizes the gap of separation between them. However, contrary to regular linear models, SVM is capable of solving linearly non-separable data by incorporating kernel function to create nonlinear separating surface from high-dimensional space. Multiple binary SVM can also be combined to extend its capability for solving multiclass classification problems[207]. An illustration of SVM is presented in Figure 2-10. As depicted in both figures, 2D space is formed by feature x_1 and x_2. In Figure 2-10a, the two classes are linearly separable and a separating surface can be found using equation $w \cdot x - b = 0$ where x represents the sample vector, w is the normal vector to the surface and b determines how far the surface offsets from the origin along w. The support vectors on the boundary are highlighted. In Figure 2-10b, a Gaussian kernel is implemented to construct a high-dimensional separating surface and a soft margin is used as errors within the margin are allowed. An additional soft margin coefficient C, which governs the penalty associated with the misclassification rate, is introduced as a tuning parameter and a trade-off between margin sizes and he error penalty must be considered to improve the optimization process of the SVM.

In the field of biomedical engineering, SVM is a common candidate for biosignal pattern recognition applications such as body motion identification or EEG/EMG-based event recognition [208-211]. However, the performance of SVM is highly dependent on the choice of the kernel function and the tuning of penalty and kernel parameters. The computation complexity, which increases rapidly as the size of the dataset grows, can also be a limiting factor that hinders its performance.

In a study of EEG analysis for seizure prediction conducted by Subasi et al. [209], an SVM with Radial Basis Function (RBF) kernel was implemented to detect epileptic seizure. Discrete Wavelet Transform (DWT) was used to decompose the original EEG signal and extract its features. Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) were then applied to reduce and to optimize the feature set. The SVM parameters were tuned within a 10-fold cross-validation process. The final testing result showed that a combination of LDA and SVM produced the best classification result. In another study investigating the feasibility of using wearable accelerometer data to estimate the severity of Parkinson Disease [210], SVM with three different kernel functions: polynomial, exponential, and RBF, were tested and compared. Based on the testing results, polynomial kernel is considered the most suitable for the application as it can help to achieve higher accuracy in general and take less influence from low penalty parameter value. In Schlogl's brain-computer interface study[203], SVM demonstrated superior accuracy compared to KNN and LDA in a Leave-One-Out cross-validation test. However, it also required the longest processing time.



a)



b)

Figure 2-10. A demonstration of SVM: a) SVM with a clear linear separation surface. b) SVM with soft margin when perfect separation is not applicable. (http://en.wikipedia.org/wiki/Support_vector_machine, date accessed: 9 Jan 2015)

2.2.3.5 Fuzzy Approaches

Fuzzy approaches refer to the classification methods that utilize fuzzy logic or Fuzzy Inference System (FIS). Same as the other inference engines, FIS can perform input-output mapping based on a knowledge base. As the name suggests, FIS allows fuzzy reasoning and defines a variable with a degree of membership which is usually a range between 0 and 1. In pattern recognition, this characteristic allows FIS-based algorithms to take uncertainties into account and create a more precise configuration of label assignment. On the other hand, the conventional crisp algorithms are unable to tolerate the overlapping of the classes because the model permits only a binary decision which assigns each input pattern a single class. Compared to the conventional inference systems, FIS is more similar to human logic where it describes the value of attributes as a degree of likelihood. This characteristic gives FIS an advantage in dealing with vagueness and uncertainties which are often encountered in fields such as disease diagnosis, and thereby it is widely implemented in medical applications [212]. The input and output of FIS are linked by a set of conditional statements called fuzzy rules, which usually require the aid of automatic algorithms for modeling complex systems. Adaptive Neuro-Fuzzy Inference System (ANFIS) is an integration of Artificial Neural Network (ANN) and FIS, and it is a widely adopted approach relative to the fuzzy rule tuning. ANFIS based classifiers are specialized in dealing with highly nonlinear systems [213]. A good example is [214] where an ANFIS classifier with five layer back-propagation ANN and generalized bell-shaped membership function was implemented to detect a heart valve disorder based on recorded Doppler heart sounds. Wavelet transform and short-time Fourier Transform were used for feature extraction and LDA was used for feature reduction. The result has shown that the ANFIS based approach can achieve higher sensitivity and specificity compared to SVM based approach and greater specificity than Fuzzy C-Mean based approach. In another study that involves vigilance level estimation using EEG recording [215], Gaussian curve membership function based ANFIS classifiers were employed in a similar setting where the features were extracted using DWT decomposition and Shannon entropy was used to rank and select features. The classification accuracy has also been found to be higher than ANN model based methods.

Chapter 3

AUTOMATIC IMPAIRMENT LEVEL CLASSIFICATION

Impairment level classification is an important process in a post-stroke rehabilitation and it has to be repetitively performed throughout the program to track the patient's recovery progress and to adjust the training scheme accordingly. Conventionally, chart-based manual assessments are commonly adopted in practice. The efficiency and reliability of these procedures were limited due to the lack of unified classification standard and automatic assessment tool. In this chapter, a novel approach for impairment level classification based on Brunnstrom stages of recovery is presented. Brunnstrom stage classification is one of the most common measures of stroke patients' rehabilitation progress and usually it can only be performed by experienced clinicians. The proposed method employs a hybrid algorithm based on Principal Component Analysis (PCA) and fuzzy inference system as depicted in Figure 3-1. Kinematic data is collected using a low-cost IMU based Body Area Network (BAN) system and a set of features reflecting the subjects' motion characteristic are extracted from the filtered sensor output. PCA is applied to reduce the dimensionality of the feature space and to derive the principal components that are closely related to patients' motion quality and motor functional limitation. A Fuzzy Inference System (FIS) is then constructed based on the extracted information before getting tuned and trained using ANFIS for automatic Brunnstrom stage classification. Experiments have been conducted using motion sampled from 21 stroke patients and three healthy participants. The result of cross-validation test has demonstrated that the system is capable of classifying Brunnstrom stage of recovery with 87.5% of accuracy when verified against rehabilitation expert's decision.

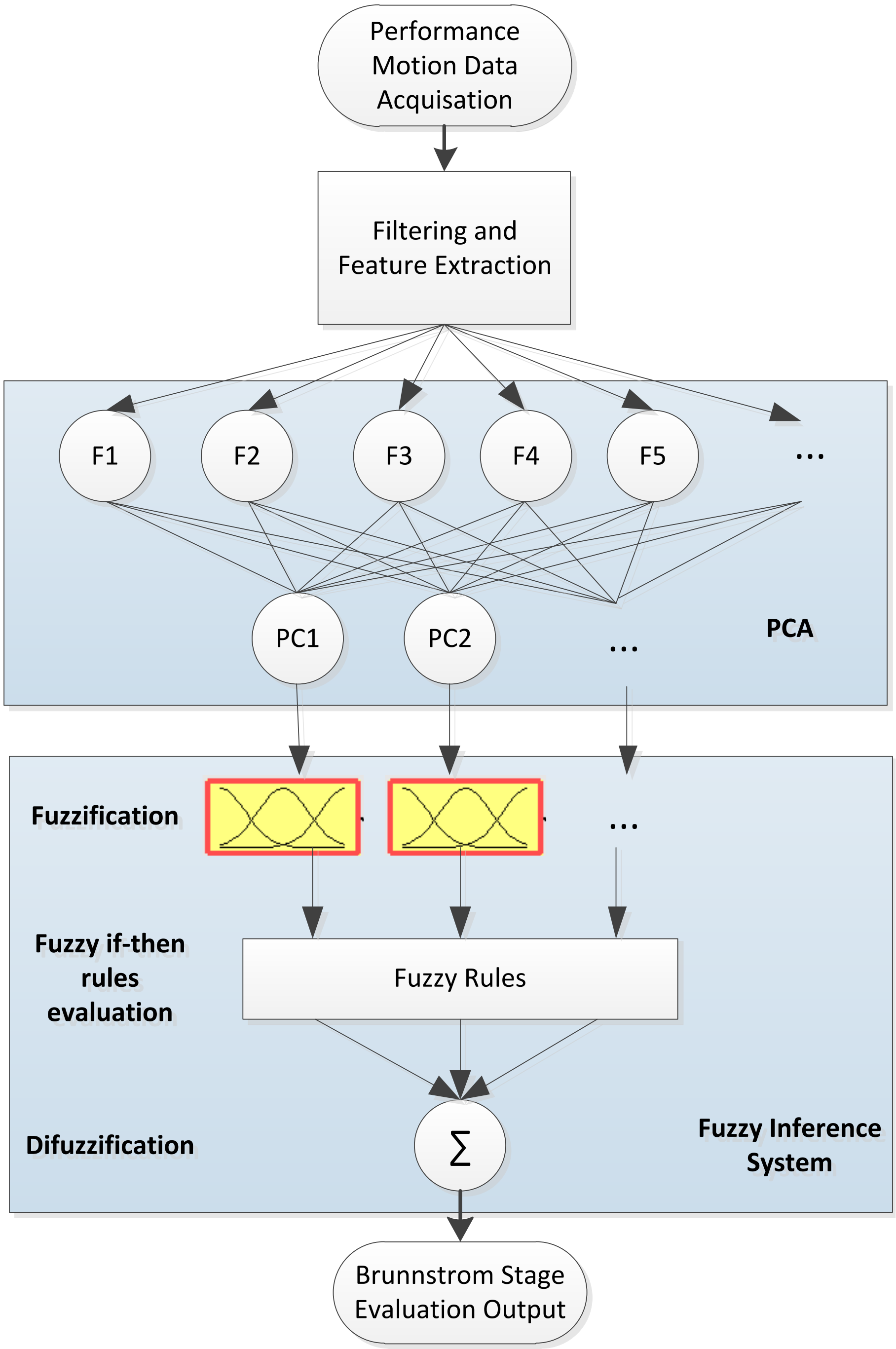


Figure 3-1 The system diagram of the proposed Brunnstrom Stage classifier

3.1 METHODOLOGY

3.1.1 IMU BAN

A low-cost non-visual based motion tracking BAN had been developed for sampling motion data from subjects. The wireless sensor node used in the experiments consists of a 3-axis accelerometer (Analog Devices ADXL335), which captures acceleration information up to 30m/s^{2,} and a low power Zig-Bee based communication module, powered by a 3.7V, 1000mAh Polymer Lithium Ion battery. There are no secondary sensors, such as a gyroscope used in the system for the size and cost reduction of each sensor node. The sensor samples the motion at 20Hz and outputs a signal mixture of dynamic acceleration caused by linear motion and vibration, and static acceleration caused by angular motion respect to the direction of gravity. In the experiment, two sensor nodes were required to be attached to the subjects' arm, on the wrist, and in the middle of the biceps brachii muscle belly as shown in Figure 3-2, in order to track the isolated joint motion which is crucial for Brunnstrom stage classification.

Figure 3-2 The mounting positions of the inertia sensors

3.1.2 Principal Component Analysis

PCA is a simple and powerful statistical tool and it is well-known for its ability to reduce the spatial redundancy from a set of data by applying orthogonal linear transformation and extracting principal components with maximized variance from a large group of variables. By performing a feature extraction, the implementation of PCA can significantly increase a classifier's performance as proven in [216] and it has been adopted in various engineering problems for signal decomposition and dimension reduction [209, 217, 218]. The process of PCA starts with obtaining covariance matrix of the input feature matrix. An orthogonal transformation of the input matrix need to be carried out with optimized eigenvectors which ensure the new components produced will meet following properties [219]:

1. The new components are uncorrelated.
2. The new components will have sequentially maximum possible variances.
3. The mean-squared error in the representation of the original inputs by the principal components is minimal.

The principal components are sorted in descending order of the eigenvalues to represent the importance of each component. In the proposed system, PCA is utilized to extract principal eigenvectors that represent the trend of stroke rehabilitation process which can produce input for the fuzzy inference system by projecting motion data onto the principal component coordinate. During the experiment, a total number of 27 different features have been extracted in order to cover as much information from the data as possible and direct observation of these variables for trends and connections is complicated and sometimes confusing. However, by studying the actual patients' upper-limb motion, we know that some unique patterns are presented at different Brunnstrom stages. For example, at stage III, the patients have just regained the ability to move their limb voluntarily, and the motions are usually weak with significantly limited range. The high muscle spasticity also stops them from relaxing the muscle and completing the movement. At higher recovery stages like stage IV, the patient's muscle strength and endurance have significantly increased in most of the cases and a better muscle control allows them to complete the exercise at much higher standards with some consistency although the synergy pattern is still observable up to stage VI. In order to unveil these inherent patterns from observed attributes and provide a clearer image of how these patterns can be related to stroke recovery progress in terms of Brunnstrom stages, PCA is adopted as a matching solution in our application.

3.1.3 Fuzzy Inference System

Same as the other inference engines, fuzzy inference system can perform input-output mapping based on a knowledge base. Compared to conventional inference systems, FIS is more similar to human logic, in which it describes values of attributes as a degree of likelihood. This nature gives FIS an advantage in dealing with vagueness and uncertainties which are often encountered in fields such as disease diagnosis. That is the reason why it is widely implemented in medical applications [212]. Since the proposed system is aiming at replacing human diagnosis of Brunnstrom stage, FIS is considered as a proper tool for decision-making.

As demonstrated in Figure 3-1, in a fuzzy inference system, the inputs are first transformed into degrees of membership in a process called fuzzification, which is done by projecting the input numerical values into a set of membership functions (MF) with predefined fuzzy sets. The degree of membership obtained is a fuzzy representation of the extent that the linguistic value has reached and it is used as a premise for decision-making based on fuzzy rules. Fuzzy if-then rules are conditional expressions that link premise and consequent fuzzy sets. Depending on the type of fuzzy if-then rules employed, fuzzy inference systems can be classified into different types [220]. The one used in the proposed system is called Takagi-Sugeno fuzzy inference or simply type-3 fuzzy inference system [221]. Different from type-1 and type-2 systems, where it utilizes projected value on an output MF as the fuzzy rule evaluation output, type-3 systems use a linear combination of input variables with an additional constant term as the output and the overall system output is a weighted average of the output from each rule. The operation of a zero-order type-3 system is demonstrated as follows:

If the system has two inputs x_1 and x_2, the output z_i for each fuzzy rules is evaluated as:

$$z_i = ax_1 + bx_2 + c_i \tag{1}$$

However, for a zero-order system, the first order terms can be omitted and the function will only yield the constant c_i for the i^{th} rule: $z_i = c_i$. Each output is also weighted by a firing strength w_i. For an AND rule, w_i can be calculated as:

$$w_i = FuzzyAND(A_1(x_1), A_2(x_2)) \tag{2}$$

where A_1, A_2 are the input MFs, and the final output y can then be obtained as:

$$y = \sum_i \overline{w}_i z_i = \frac{\sum_{i=1}^{N} w_i c_i}{\sum_{i=1}^{N} w_i} \tag{3}$$

where N is the number of the fuzzy rules.

The fuzzy inference system structure of the proposed system is shown in Figure 3-3. The two inputs are the 1st and 2nd principal components extracted during PCA. Each input is associated with three different MFs which define different range of the input value. Nine fuzzy if-then rules and nine corresponding output MFs, which are constants related to Brunnstrom stages in this case, construct the framework that is required for the decision-making process. The output of this structure will be a numerical value that represents the patients' recovery progress on the scale of Brunnstrom approach. However, in order to evaluate the classification system performance, the classification output are rounded to the nearest integer during the experiment e.g. for all output value $4.5 \leq y < 5.5$, the subject will be classified as Brunnstrom stage V.

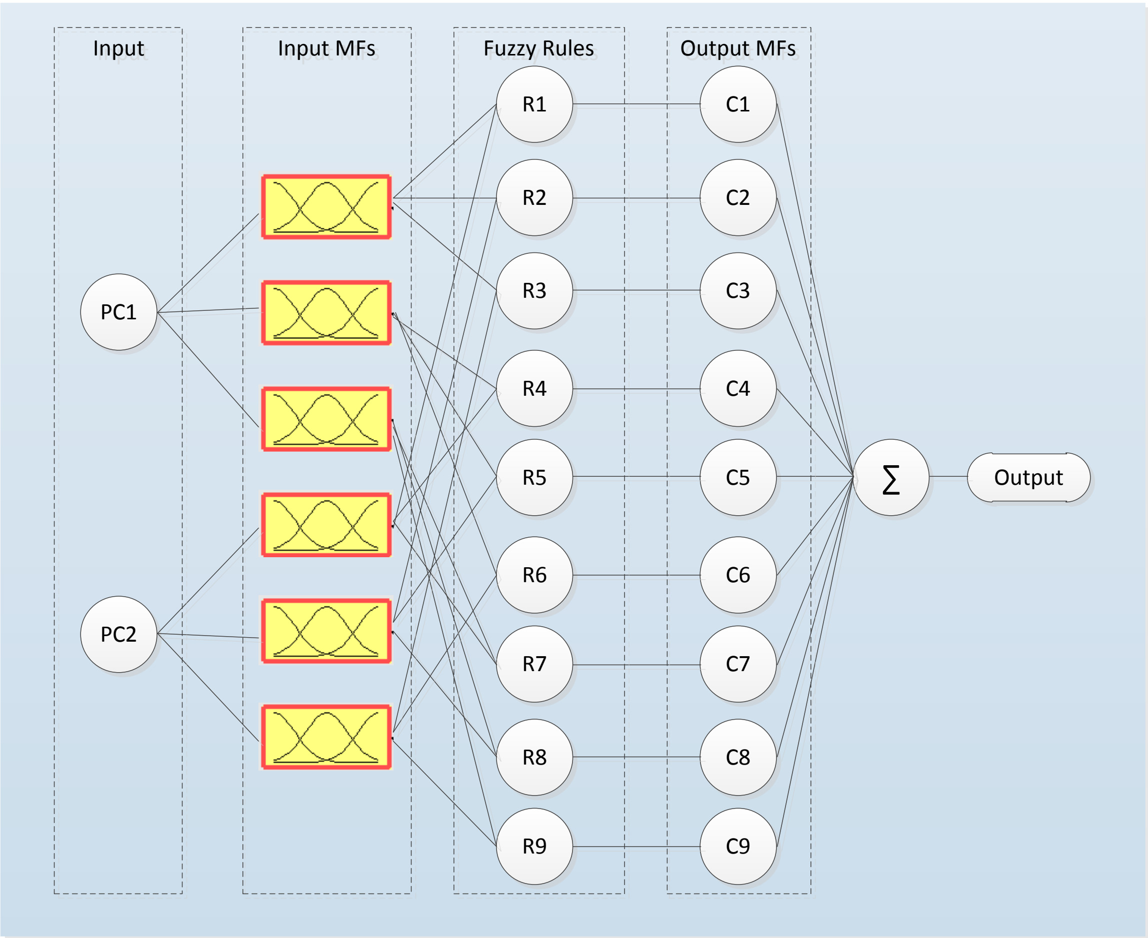


Figure 3-3. Fuzzy inference system structure for proposed classification system

3.1.4 ANFIS

In this study, ANFIS method was adopted to model the system and to train the fuzzy inference system. Since it was first introduced in [222], ANFIS has been widely implemented as an effective tuning tool for fuzzy inference systems in many areas [212, 223]. As an adaptive network architecture, it provides an automatic solution for transforming human knowledge or experiences into fuzzy rules and subsequently tuning the MFs within the fuzzy inference system for minimum output error and maximum performance [27]. ANFIS adopts a hybrid learning algorithm which combines least squares estimation and backpropagation for parameters tuning. Such hybrid algorithm has been proven to be highly efficient with superior speed and accuracy compared to many Artificial Neural Network based methods [27]. The basic structure of a type-3 ANFIS is shown in Figure 3-4. As can be seen, after fuzzification process, fire strength and its normalized form are generated through the two layers of nodes in the middle of the structure. The overall output is produced in the same way as described in equation (2) and (3).

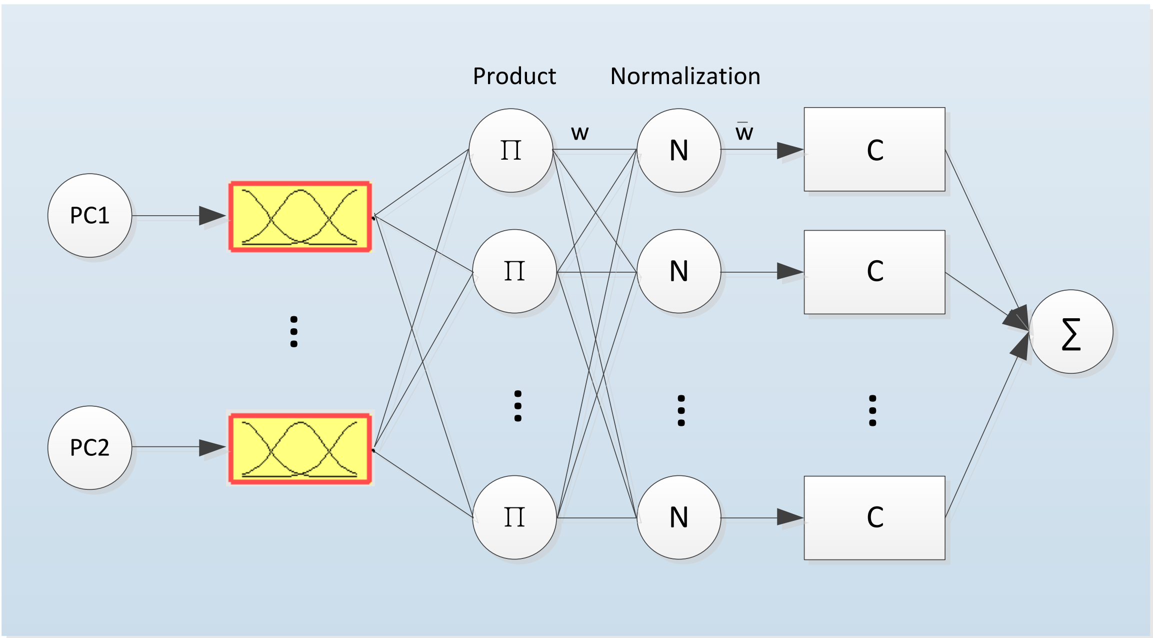


Figure 3-4. The basic structure of Type-3 ANFIS

3.1.5 EXPERIMENT PROTOCOL

The experiments in this research were conducted in collaboration with the Rehabilitation Medical Centre of the 2nd Hospital of Jiaxing in China. The subjects involved in the experiment included both the stroke patients and the healthy participants from the hospital and over 200 motion data recordings were collected from 21 selected patients and three healthy participants.

The patient subjects were chosen from the patients with a Brunnstrom stage ranging from III to V. The patients from stage I and II are excluded from the experiment because the patient's condition could still be unstable during the early recovery stages and they usually have difficulties performing any voluntary upper limb movements that are identifiable by IMU-based system. Patients at stage VI are also omitted as their limb mobility is similar to healthy people as defined in Brunnstrom Approach and usually they do not require supervised training services provided in the hospital rehabilitation centre. Therefore, healthy staff members were chosen to form the stage VI group in the experiment. The patients participated in the experiment consisted of 12 men and 9 women with an average age of 58.7 and a range of 45 to 78 years old. During the selection process, the patients with severe cognitive, perceptual or communication problem, or any other health condition that is not suitable for the experiment were excluded. All the patient subjects were examined by experienced physicians for Brunnstrom stages prior to the experiment, the human observation based results were used to examine the validity of the proposed approach.

A shoulder touching exercise was selected to be performed by every subject for motion sampling purpose. The exercise movement involved lifting the impaired arm forward to a 90-degree angle, and then moving it horizontally until the hand reaches the shoulder on the other side before returning to the starting position. The motion is commonly used in stroke rehabilitation as an upper extremity Active Assistive Range of Motion (AAROM) exercise, which means the patient is encouraged to actively drive the muscle surrounding the shoulder and elbow joints with only necessary amount of assistive support. However, in order to test patient's actual body function, the movement was performed as an Active Range of Motion (AROM) in the experiment and all the participants have to carry out the exercise without any assistance. In order to execute the movement, voluntary muscle contraction is required from multiple muscle groups. The extension and flexion movements of the arm can demonstrate the level of spasticity and the presence of synergy patterns. In order to smoothly complete the motion, muscle strength and joint flexibility will also be tested. Therefore, this exercise is considered as a benchmark that covers most of the attributes of upper limb motor function required for Brunnstrom Classification.

During the sampling experiment, the subjects were initially ordered to rest at general sitting position for two minutes. Before the beginning of the sampling process, they were guided to perform the exercise several times with the assistance from a trained physician until they were familiar with it. They were then required to complete five valid repetitions of the exercise individually which were tracked by the IMU sensors. A valid repetition must be a coherent movement without interruption, and each repetition is required to be completed within a 10 seconds timing window. The sampled motion data were fed into the software signal processing module with a 50Hz low-pass filter to prevent aliasing. Twenty-seven feature variables were then extracted before the PCA can be applied for further analysis.

TABLE 3-1 LIST OF KINEMATIC FEATURES FOR BRUNNSTROM CLASSIFICATION

Feature type	**Feature name**	**Feature description**
Maximum Magnitude	AMP_X1,AMP_X2,AMP_Y1 AMP_Y2,AMP_Z1,AMP_Z2	The maximum magnitude found for the data sequences of each axis from two sensor node. They are calculated by simply taking the average of the maximum value from 5 movement repetitions.
Quadratic Mean	RMS_X1,RMS_X2,RMS_Y1 RMS_Y2,RMS_Z1,RMS_Z2	The quadratic mean found for the data sequences of each axis. They are calculated by averaging the RMS value of 5 movement repetition for each axis.
Energy ratio	ENE_X,ENE_Y,ENE_Z	The ratio of two average signal waveform energies measured from two sensor nodes. Each waveform energy component is defined in (4)
Acceleration	ACC_X,ACC_Y,ACC_Z	The summation of the difference found between two adjacent samples on each axis to reflect the high frequency component in the movement.
Consistency	CONSIST_X,CONSIST_Y,CONSIST_Z	The measure of consistency which is the maximum value found in cross-correlation sequences computed between every two movement repetitions.
Duration	DUR	The active motion duration which is the length of the data where the magnitude is higher than the RMS value.
Variance	VAR_1,VAR_2	The average variances of DUR which is another measure of consistency.
Synergy Coefficient	SYN_X,SYN_Y,SYN_Z	The feature for evaluating independency between forearm and upper arm. It is Calculated by summating the normalized cross-correlation result of the data sequences from two sensors, as defined in (5) and (6).

3.2 RESULT AND DISCUSSION

In Figure 3-5, a comparison of motion data sampled from stroke patients at Brunnstrom stage III and V is shown. As can be clearly observed, the subject at stage V demonstrates a significantly better capability of performing isolated joint movement consistently with controlled speed and extensive reach. In contrast, the motion sample of stage III subject shows very limited moving range and a strong synchronized pattern caused by obligatory synergies, which is a signature symptom during the stage III of the recovery process. It can also be observed that the stage III subject was struggling to complete the exercise naturally by returning the limb to the starting position through a controlled trajectory as the high spasticity was restricting the elbow joint extension.

The loading plot in Figure 3-6a and Table 3-1 listed all the feature variables extracted from the motion data samples and their contribution to the principal components obtained from PCA.

AMP_X1, AMP_X2, AMP_Y1, AMP_Y2, AMP_Z1, AMP_Z2 are the maximum magnitude found for the data sequences of each axis from two sensor nodes. They are calculated by simply taking the average of the maximum value from the five movement repetitions. RMS_X1, RMS_X2, RMS_Y1, RMS_Y2, RMS_Z1, RMS_Z2 are the quadratic mean found for the data sequences of each axis. They are calculated by averaging the RMS value of the five movement repetition for each axis. ENE_X, ENE_Y, ENE_Z are the ratio between the average energy stored in the waveform that measure from two sensor nodes. The energy stored in each data sequence is calculated by:

$$ENE = \sum_{n=1}^{N} \left| x[n] \right|^2 \tag{4}$$

where N is the length of the data sequence.

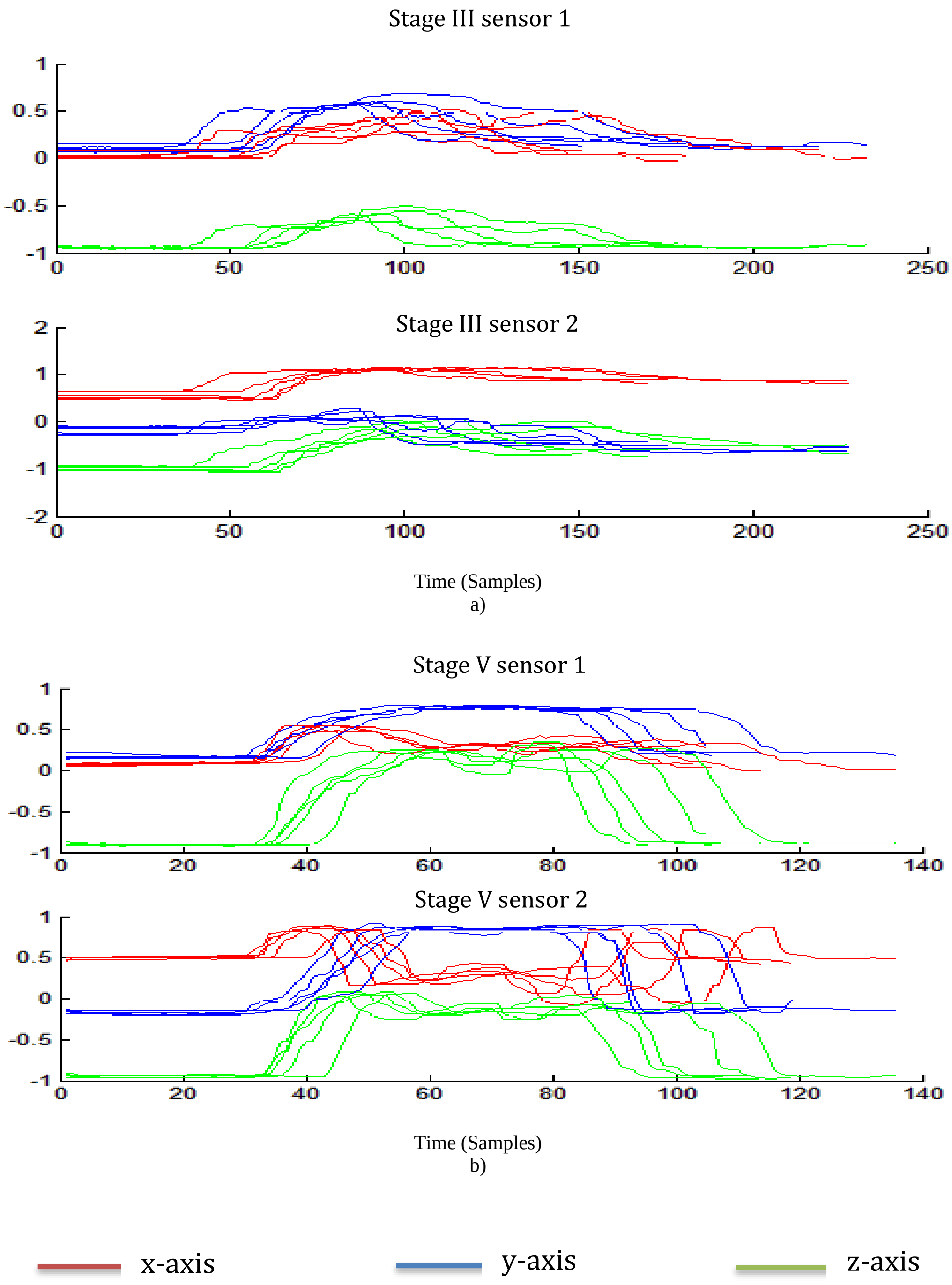


Figure 3-5. A comparison between the 3-axis motion data recorded from stage III stroke patient (a) and stage V stroke patient (b). The plots are the superposition of the data from 5 movement repetitions in order to demonstrate the motion consistency.

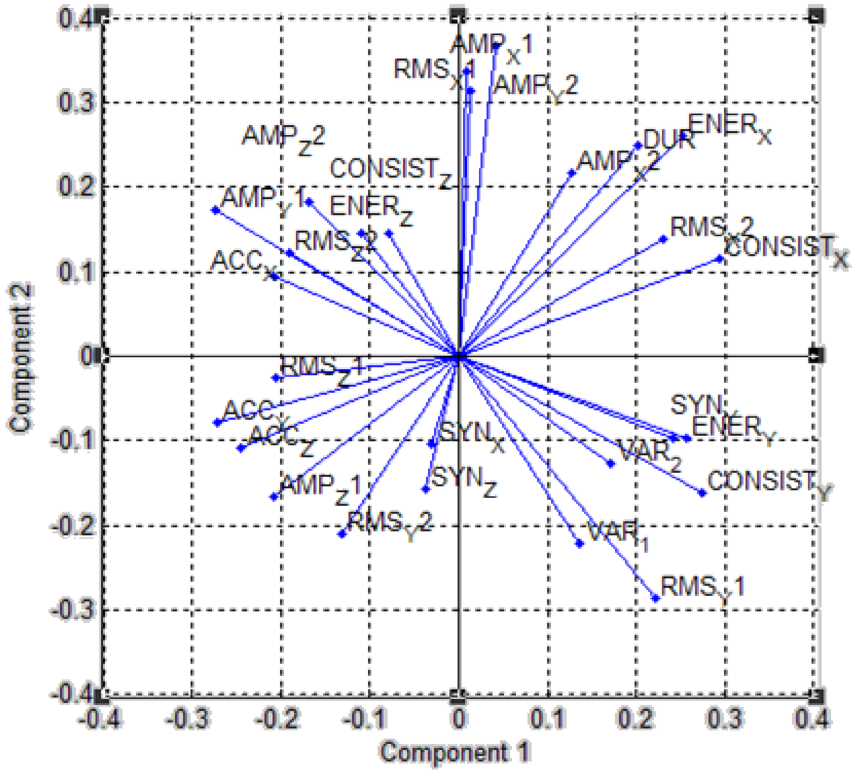
ACC_X, ACC_Y, ACC_Z are the added maximum difference found between two adjacent samples on each axis to reflect the high-frequency component in the movement. CONSIST_X, CONSIST_Y, CONSIST_Z are the measurement of consistency which are the maximum value found in cross-correlation sequences computed between every two movement repetitions. DUR is the active motion duration which is the duration of the data when the magnitude is higher than the RMS value, and VAR_1 and VAR_2 are the averaged variance of DUR which is another measure of consistency. SYN_X, SYN_Y, SYN_Z are the features for evaluating the independence between forearm and upper arm. It is calculated by summating the normalized cross-correlation result of the data sequences from two sensors, as in

$$SYN = \sum_{n=1}^{N} \frac{R_{x_1 x_2}[n]}{\sigma_{x_1}\sigma_{x_2}} \tag{5}$$

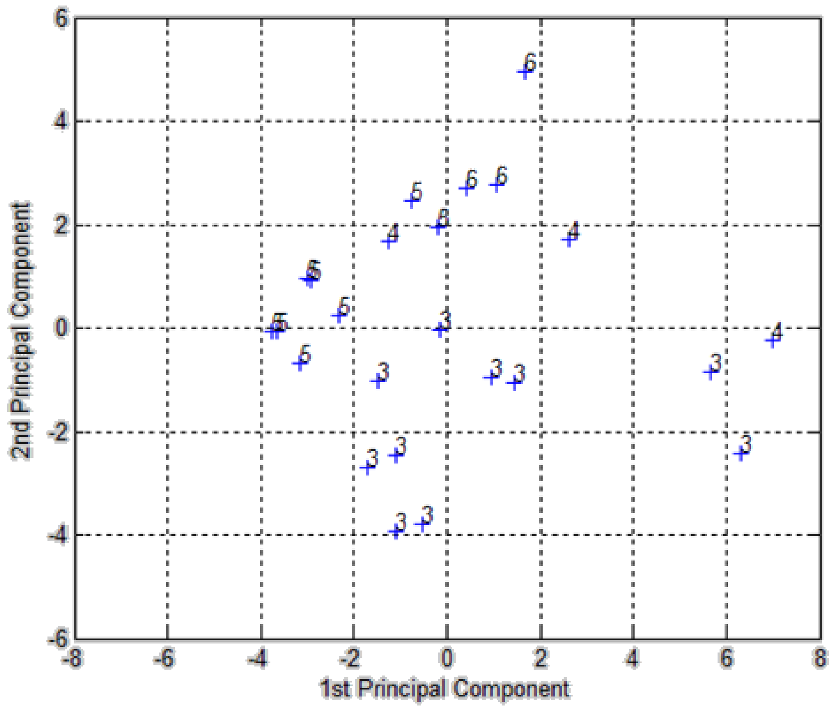
$$R_{x_1 x_2}[n] = \sum_{i=1}^{N} (x_1[i] - \bar{x}_1)(x_2[i+n] - \bar{x}_2) \tag{6}$$

where σx1 and σx2 are the standard deviations of the data sequences from two sensors.

As can be seen clearly from Figure 3-6a, the projected data is following the trend of Brunnstrom model along the 2nd principal coordinate since most of the stage III data are projected at the bottom of the plot whereas the ones at higher recovery stages can be found at the top. The correlation between the 2nd principal component and the Brunnstrom stage can also be observed from Figure 3-6a. The feature variables such as SYN and VAR exhibit clear negative contributions to the loading plot which indicates that the motion samples with less isolated joint movement and consistency would have a lower score after projection. This agrees with the Brunnstrom approach's primary principle of focusing on synergies and voluntary movement. In contrary, features such as AMP_X1 and RMS_X1 are positioned in the opposite direction of the 2nd principal coordinate which shows a high positive correlation with stroke recovery progress. This is because the most difficult part of the



a)



b)

Figure 3-6. a) Loading plot of all the feature variables. b) Observation projection on the plane of principal component 1 and 2 labelled with Brunnstrom stage.

sampled exercise movement is the horizontal shoulder reaching motion along the sensor's x-axis. It involves biceps contraction and requires certain strength and flexibility to hold the elbow in the air during the entire motion. The patients in the early stage of stroke recovery will encounter great difficulty to complete this part of the movement due to the severe spasticity. Therefore, the subjects, who completed the motion with a greater magnitude on sensor's x-axis, will generally be classified as higher recovery stage. On the other hand, the 1st principal component can be seen as a measure of force and control. It can be seen that many attributes related to control, including consistency (CONSIST) and duration (DUR), have strong contributions to the positive side of the 1st principal coordinate, whereas other features such as acceleration (ACC) have negative correlations to the principal component. This shows that the motion samples located at the right side of the coordinate have lower speed and amplitude which could indicate the lack of strength. However, this is sometimes resulted from factors other than impairments such as age, gender, and attitude. At the same time, the samples located at the left side demonstrate a stronger motion. However, it can also be due to the excessive body swing or the sudden falling motion which happens when the patient is unable to complete the exercise as a result of lack of muscle endurance or flexibility. It is also interesting to see that, although the 1st principal component axis cannot represent the patients' recovery progress in general, it is very effective in separating the patients at stage IV or V, which is a difficult task even for experienced physicians. The reduced influence of spasticity in stage V patients gives them more movement range, strength, and confidence in performing the exercise. It can also help some patients to achieve greater motion speed and magnitude. Another significant difference is the disappearance of synergy patterns especially in Y-axis, which indicates the patient's ability of flexing the elbow without lifting the entire upper arm in order to touch the shoulder. This feature is also greatly associated with the 1st principal component axis.

After PCA, the data projected onto 1st and 2nd principal components were used as the input to the fuzzy inference system and were fuzzified with predefined MFs. Figure 3-7 demonstrates the MFs for both inputs optimized by ANFIS. It can be seen that the three MFs which correspond to three fuzzy sets are defined for each input and Gaussian curve MF is selected due to its smooth and symmetrical shape, which is given by:

$$f(x;\sigma,c)=e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{7}$$

The surface plot in Figure 3-8 shows the relationship between the input and the output of the inference system which is defined by the fuzzy if-then rules. As can be seen, the shape of the surface matches the observation projection plot in Figure 3-6. The highest score was recorded when the value of the 1st principal component was 'medium' and the value of the 2nd principal component was 'high'. As a result, the subject who had average strength and endurance but can perform highly isolated joint movement was classified with the highest Brunnstrom stage. On the other hand, fast motion speed, strong force or long endurance with no enough control and independent joint movement was given in a lower score.

The result of system performance test is presented in Table 3-2. In order to ensure an unbiased validation, Leave-One-Out (LOO) cross-validation method was employed during the experiment. The testing result has been compared with the judgment made by a group of three rehabilitation experts with more than 20 years of experience. As can be seen, the classification results for stage III and VI are almost perfectly matched with the doctor's evaluation. However, the unequal size of the sample groups for different Brunnstrom stages, especially the lack of samples for stage IV patients, jeopardized the classification accuracy. This effect was amplified under LOO cross-validation test because when a testing sample is drawn from a smaller Brunnstrom stage group, the training data set will be unbalanced. Overall, an accuracy of 87.5% was achieved in this experiment which is quite promising. PCA is known for its 2nd order statistics nature and its performance improves when more observation data for each group can be evenly added to the system to form a near Gaussian distribution. Therefore, classification accuracy is expected to increase with the growth of the collected patient data.

TABLE 3-2 BRUNNSTROM STAGE CLASSIFCATION RESULT

	Brunnstrom Groups				Total
	Stage III	*Stage IV*	*Stage V*	*Stage VI*	
Actual No. of patients	10	3	8	3	24
Correct count	9	2	7	3	21
Correct rate	90%	66.7%	87.5%	100%	87.5%

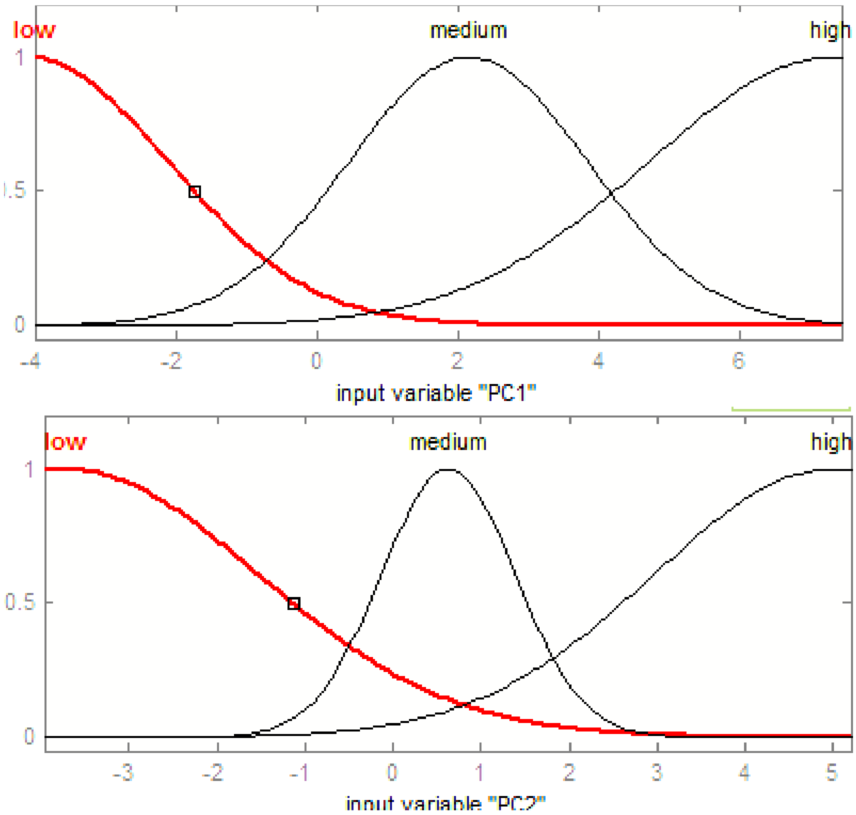


Figure 3-7.Input MFs for Principal component 1 and 2

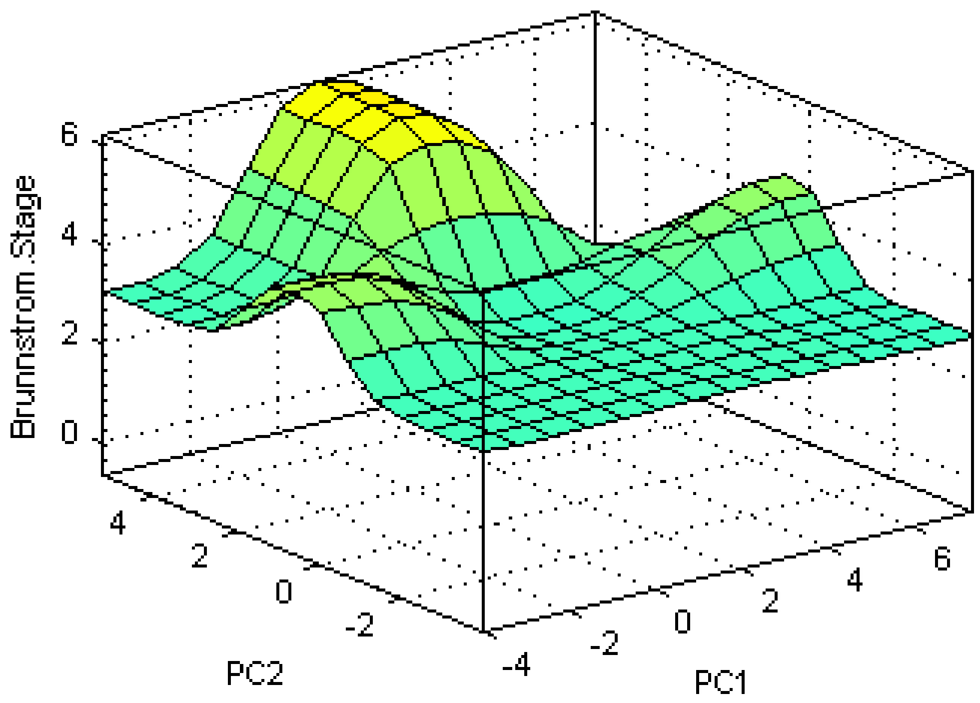


Figure 3-8. Input-output Surface plot: principal components 1 and 2 vs. Brunnstrom recovery stage

3.3 SUMMARY

In this chapter, a novel approach for objective Brunnstrom stage classification has been proposed. In the experiment, over 200 motion samples were collected and tested for Brunnstrom stage classification from 24 subjects, including 21 actual stroke patients. An overall 87.5% of the classification results agreed with the doctors' assessment while 90%, 87.5%, and 100% accuracies were achieved for identifying patients at Brunnstrom stage III, V and VI, respectively. Based on the outcome of the experiment, the PCA and fuzzy inference system based approach is capable of producing valid and quantitative result that evaluates stroke patient's recovery progress and it can be implemented as an alternative to the conventional human-based process of Brunnstrom recovery stage classification.

Chapter 4

QUANTITATIVE LIMB MOBILITY EVALUATION

In this chapter, a novel single-index based assessment system for quantitative evaluation of upper extremity mobility in post-stroke rehabilitation will be presented. The proposed measure can serve as a reliable evidence for unified body function classification to improve individualized rehabilitation training or as an intuitive feedback to facilitate patient's rehabilitation training in both supervised and unsupervised environment. The evaluation process employs a constrained Dynamic Time Warping (DTW) based technique to generate objective and consistent quantitative results to reflect patient's motion quality in relation to predefined templates and thus manifest limb mobility. The process is also designed to be inexpensive to perform, both financially and computationally. Therefore, the proposed method utilizes 20Hz 3-axis accelerometer data collected using a single IMU attached to the patients' wrist. The evaluation of the mobility index involves a normalization process that only requires the lower bound distance calculation which is also used for indexing DTW [224] and the upper bound distance which can be calculated in $O(n)$. The validity and reliability of the proposed assessment index have been tested with 120 motion samples collected from 21 stroke patients and three healthy participants. The patients' limb function impairment levels are classified using Brunnstrom stages of recovery by an expert panel. The statistical difference in the evaluation results for the patients with different impairment level, and the correlation between the proposed metric index and Brunnstrom stages are investigated. A classification experiment has also been conducted using K-NN classifier to test the proposed index score's feasibility as a feature for automatic impairment level classification.

4.1 METHODOLOGY

The implementation of the proposed assessment system is illustrated in Figure 4-1. The training motion samples are first collected from both rehabilitation professionals and stroke patients using a wireless IMU. A 5th order median filter is utilized to remove the transient spikes in the signal caused by random shocks without distorting the waveform. Training motion templates are generated by averaging motion samples collected from rehabilitation experts. Constrained DTW is used as templates matching method in order to cope with the non-stationary and nonlinear variations caused by non-pathological features in each motion sample. The DTW distance computed is then normalized to produce an index for the proposed mobility evaluation metric system. In the experiment, a classification test using three different classifier, namely K-Nearest-Neighbour (KNN), Quadratic Discriminant Analysis (QDA), and Naïve Bayes (NB) classifier, have been performed to demonstrate the proposed assessment index's validity and feasibility as a feature for objective Brunnstrom stage classification. The detail of the experiment setup and methods are explained in the following sections.

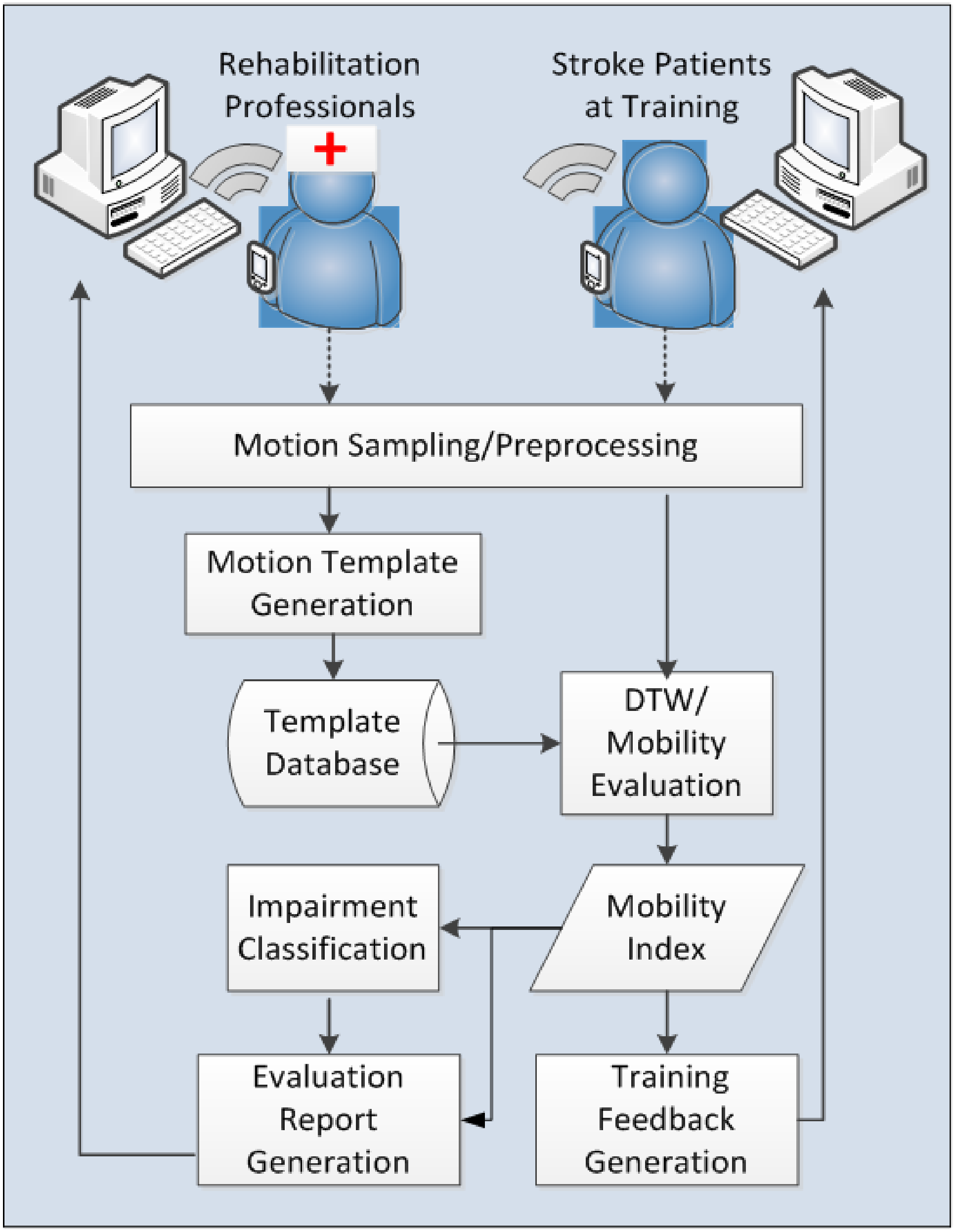


Figure 4-1. The implementation of the proposed assessment system for limb mobility evaluation

4.1.1 *DYNAMIC TIME WARPING*

DTW is a dynamic programming algorithm that is commonly used for temporal sequences similarity measurement in template matching application. It is well known for its non-linear time normalization effect which can compensate the timing differences between two temporal sequences by warping the time axis before calculating the minimized residue distance [225]. Compared to Euclidean distance or cross-correlation based template matching algorithms, DTW is more flexible and robust due to its ability to accommodate both phase and speed variations and it has been widely implemented in automatic speech recognition [225] and biomedical signal analysis applications such as Electrocardiography (ECG) [226, 227] and Photoplethysmograph (PPG) [228]. To compute DTW distance for two time series $\mathrm{S} = \{\mathrm{S_i} | \mathrm{i} = 1,2, \dots, \mathrm{n}\}$ and $\mathrm{T} = \{\mathrm{T_i} | \mathrm{i} = 1,2, \dots, \mathrm{m}\}$, a $\mathrm{n} \times \mathrm{m}$ distance matrix D is first constructed where the (i^{th}, j^{th}) element of D is the Euclidian distance between the two matching points from the original time-series: $\mathrm{D(i,j)} = \sqrt{(\mathrm{S_i} - \mathrm{T_j})^2}$. The warping path $\mathrm{w} = \{\mathrm{w_k} | \mathrm{k} = 1,2, \dots, \mathrm{K}\}$ which represents the possible alignments between the two original time series can then be defined as each element of w is a pair of mapped points from S and T: $\mathrm{w_k} = (\mathrm{i_k}, \mathrm{j_k})$ with following conditions:

- Monotonic conditions: $\mathrm{i_{k-1}} \le \mathrm{i_k}$ and $\mathrm{j_{k-1}} \le \mathrm{j_k}$.
- Continuity conditions: $\mathrm{i_k} - \mathrm{i_{k-1}} \le 1$ and $\mathrm{j_k} - \mathrm{j_{k-1}} \le 1$.
- Boundary conditions: $\mathrm{i_1} = \mathrm{j_1} = 1, \mathrm{i_K} = \mathrm{n}, \mathrm{j_K} = \mathrm{m}$.

To avoid warping path with excessive timing difference and to ultimately improve computation efficiency, an additional locality constraint can be added: $|i_k - j_k| \le r$ where r is a positive integer which can be tuned according to the length of the input time series[225]. Finally, the DTW distance D_{dtw} can be calculated by accumulating the distance along the optimal warping path W which covers the least distance:

$$\mathrm{D}_{dtw} = \sum_{i=1}^{K} D(W_i) \tag{7}$$

and it can be implemented using the dynamic programming:

$$d_{i,j} = \mathrm{D}_{i,j} + \min \begin{cases} d_{i-1,j} \\ d_{i,j-1} \\ d_{i-1,j-1} \end{cases} \tag{8}$$

and

$$\mathrm{D}_{dtw} = \mathrm{d}(\mathrm{W}_K) = \mathrm{d}_{n,m}. \tag{9}$$

A demonstration of DTW distance calculation is presented in Figure 4-2. As can be seen, the obvious dissimilarity in motion speed between the candidate motion sample and the template is compensated by realigning the two data sequences and resulted in an optimal match. The distance matrix between the two sequences is visualized in Figure 4-2c. The darker area surrounding the diagonal line indicates warping paths with small distance and the red line shows the optimal path which can lead to shortest DTW distance. The locality constraint can be seen in Figure 4-2d. When DTW is implemented in our study, 25% of the data length of the longer candidate sequence is used as locality constraint. However, in accordance with the boundary condition of DTW, the length difference between the two data sequences will be used as a constraint if its value is greater than the calculated constraint as shown in (10).

$$\mathrm{r} = \max \begin{cases} \mathrm{Round}(0.25 * \max(\mathrm{m}, \mathrm{n})) \\ \mathrm{m} - \mathrm{n} \end{cases} \tag{10}$$

DTW has a computational complexity of $O(nm)$, hence, it can be difficult to compute efficiently when used with high-resolution samples or large sample size and due to that DTW distance does not obey the triangular inequality and cannot be easily indexed as Euclidean distance [229]. To address this issue, a number of researchers have proposed techniques to fast compute an exact lower bound distance for DTW that satisfies the triangular inequality and eventually enables exact indexing to reduce the computation time without allowing false dismissals [224, 230, 231]. The lower bound distance introduced in [224] will also be used to normalize the DTW distance and generate the mobility index in the proposed system.

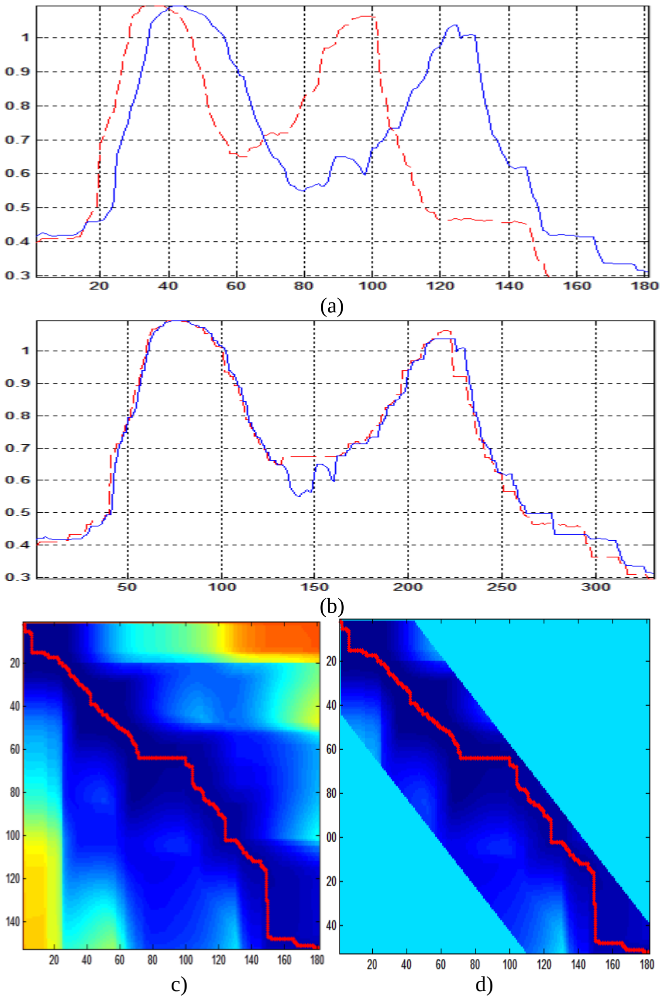


Figure 4-2. A demonstration of DTW distance calculation on sampled motion data. a) Original x-axis candidate data (red dotted) and template(blue) b) Warped candidate date(red dotted) and template(blue) c) Unconstrained DTW d) DTW with locality constraint of 25% data size

4.1.2 EXPERIMENT PROTOCOL

The motion sampling experiment was conducted in collaboration with the rehabilitation medical centre of the 2nd Hospital of Jiaxing in Jiaxing, China and was approved by the ethic committees of RMIT University and the 2nd Hospital of Jiaxing. Overall, 21 patients (12 males, 9 females, mean age 58.7 ±19.3 years) and 3 rehabilitation doctors as healthy subjects participated. The patient subject selection was based on the following inclusion criteria: 1) the participant must have no hemodynamic instability, 2) no severe cognitive impairments, 3) no dementia, 4) no major post-stroke complication, 5) able and willing to give consent, 6) Due to the reason that the patients at Brunnstrom stage I and II are unable to perform unsupported upper extremity voluntary movement which can be captured using the IMU sensor, only patients at stage III and above will be included in the experiment. All patient subjects were examined by an expert panel for Brunnstrom stages prior to the sampling experiment. The panel members are selected from rehabilitation doctors who have 1) extensive clinical experience with stroke patients and stroke rehabilitation, 2) experienced in conducting stroke rehabilitation related medical research. The healthy participants were grouped as Brunnstrom stage VI in the experiment based on the definition of Brunnstrom Approach.

A shoulder touching exercise was selected as the sample training motion to examine subject's limb mobility in the experiment. The motion starts with raising the impaired arm to horizontal level, and then adducting the elbow to touch the opposite shoulder with hand before gently lowering the arm to the starting position. This movement is commonly practiced as a rehabilitation training exercise and was performed as an Active Range of Motion (AROM) during the experiment where all the participants have to complete the exercise without any assistance to reflect their actual body functioning. Voluntary muscle contraction from multiple muscle groups can be observed during completion of the movement. The extension and flexion motion of the elbow joint can demonstrate the level of spasticity and the presence of synergy patterns. In order to complete the motion smoothly, muscle strength, and joint flexibility were also tested. Therefore, this exercise is considered as a benchmark to reflect stroke patient's limb mobility in general and body function impairment level.

During the sampling experiment, the subjects were initially asked to rest at general sitting position for two minutes. Before the sampling began, they had been requested to perform the exercise several times with the guidance of a trained physician until the motions were familiarized. Then they were required to complete five valid repetitions of the exercise individually and were tracked by a wireless IMU. A valid repetition must be a coherent movement without interruption, and each repetition was required to be completed during a 10s timing window. An instruction video is looped during the sampling process to help the motion synchronization.

A single low-cost IMU was adopted in this study for sampling motion data from subjects. Non-visual based wearable IMU motion tracking devices are commonly utilized in rehabilitation training supervision applications, especially in home or community-based training environments, where resources are limited [140, 232-234]. Compared to visually based systems, IMU devices are relatively cheaper, more compact, and are easier to setup and operate. The wireless sensor node used in the experiments mainly consisted of a 3-axis accelerometer that has a capability of capturing acceleration information up to 30 m/s^2 and a low power Zig-Bee based communication module powered by a 3.7 V, 1000 mAh Polymer Lithium Ion battery. The sensor samples the motion at 20 Hz to principally capture the slow varying static acceleration that indicates tilting angle and the low sampling rate can help to reduce the computational cost of DTW. The placement of the sensor nodes in the experiment is shown in Figure 4-3.

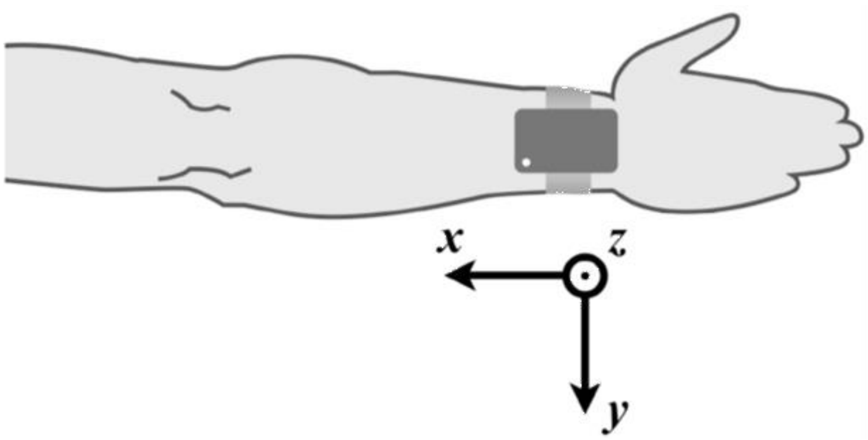


Figure 4-3 .The placement of the IMU for quantitative limb mobility evaluation

4.1.3 Mobility Index

As introduced in the previous section, DTW technique can effectively reject dissimilarities/influences caused by motion speed and delay. However, it is very sensitive to amplitude difference as minimal changes in motion magnitude can significantly affect the output distance. Despite the fact that the motion magnitude can be considered as an important aspect of motion quality, it is only able to partially reflect patient's limb mobility when other patient conditions and attributes are comparable. When assessing a patient's body function and mobility in stroke rehabilitation application, it is also important to examine the patient's ability of completing exercise motion with correct trajectory which can help to detect muscle flaccidity, spasticity and synergy patterns. Therefore, in the proposed approach, a mobility index obtained by normalizing DTW distance with estimated upper and lower bound is used to evaluate patient's limb mobility. The normalization process scales the unbounded output distance down to a defined range in relation to the theoretical extrema which makes the results more comparable and reduces the sensitive to general motion magnitude variation. As a result, the mobility index is more suitable as an assessment score to facilitate post-stroke rehabilitation training and generate more accurate result when adopted as input feature for automatic body function impairment classification. The benefit of the proposed mobility index will be further demonstrated in section 4.2 and 4.3.

Let $S = \{S_i | i = 1,2, \ldots, n\}$ be the candidate training motion data sequence and $T = \{T_i | i = 1,2, \ldots, m\}$ is the motion template sequence. The mobility index is defined as:

$$Q_{mobility}(S,T) = 1 - \frac{D_{dtw}(S,T) - D_{lb}(S,T)}{D_{ub}(S,T) - D_{lb}(S,T)} \tag{11}$$

with

$$D_{lb}(S,T) = \max \begin{cases} |First(S) - First(T)| \\ |Last(S) - Last(T)| \\ |max(S) - max(T)| \\ |min(S) - min(T)| \end{cases} \tag{12}$$

$$D_{ub}(S,T) = max(m,n) * \max \begin{cases} |max(S) - \min(T)| \\ |min(S) - max(T)| \end{cases} \quad (13)$$

where $Q_{mobility}$ is the proposed mobility index. $D_{dtw}(S,T)$ is the DTW distance between candidate sequence S and Template T. $D_{lb}(S,T)$ is the lower bound distance for $D_{dtw}(S,T)$ as introduced in [224] which is originally designed for exact indexing DTW. D_{ub} is the estimated upper bound distance for $D_{dtw}(S,T)$ which is calculated by multiplying the maximum distance with the length of the diagonal path. It is assumed that the distance between the two data sequences is the largest when they are uniformly separated by the maximum possible distance and no warping action will occur. The dynamic range of Q_{motion} is (0, 1]. The maximum quality 1 is achieved when $D_{dtw}(S,T)$ is equal to the lower bound distance $D_{lb}(S,T)$ or the candidate sequence matches the template exactly. As the difference between the two sequences increases, the mobility index keeps reducing and approaching 0. In practical situation, when the training motion in the template is performed by the candidate voluntarily and recorded using the proposed device and setting, the mobility index will generally range from 0.65 to 0.98.

4.2 EXPERIMENT RESULT

Figure 4-4 shows a comparison between motion samples. The motion template generated by averaging the DTW warped motion data sampled from 3 different rehabilitation doctors is shown in Figure 4-4a. The motion samples collected from a Brunnstrom stage VI subject and a stage III subject are presented in Figure 4-4b and Figure 4-4c respectively. It is clear from the images that the stage VI subjects are generally able to follow the predefined motion trajectory more accurately and consistently with controlled speed, whereas the stage III samples tend to be jerky and inconsistent which are signs of lack of strength, stability and dexterity. It can be seen that the stage III patient also has difficulty reaching the target position as the motions always terminate earlier due to the limitation of joint flexibility and excessive muscle spasticity. The dissimilarities in the motion trajectory can clearly reflect the limitations of the subject's upper limb mobility.

The mobility evaluation results including the medians, 25th and 75th percentiles and non-outliner ranges of both the DTW distance and mobility index calculated for each impairment groups and individuals are presented in Table 4-1. The 24 subjects are classified into four impairment groups based on their Brunnstrom stage evaluated by the expert panel prior to the experiment. Stage III subjects suffer from severe motor function impairment and their limb mobility is considerably limited due to excessive spastic hypertonia. Both the DTW distance and mobility index suggest that stage III subjects' motion quality is relatively poor and inconsistent. Although some individuals, such as S8, are capable of achieving single motion mobility index as high as 0.880, a large fluctuation in performance can be observed which indicates disadvantaged limb control and endurance. Stage IV and stage V subjects were affected by mild to moderate impairment. The declining muscle spasticity and obligatory synergy motion patterns enable the patients to perform more isolated voluntary limb motions and complete the exercise motion with higher precision. This improvement is clearly verified in the mobility evaluation result as the group DTW distance median dropped 45% from 58.2 to 32.0 and the mobility index median increased by 10.7% from 0.782 to 0.866. However, due to stroke-induced pain and impaired muscles control, some subjects such as S21 at this stage also tend to perform with even wider range of motion quality due

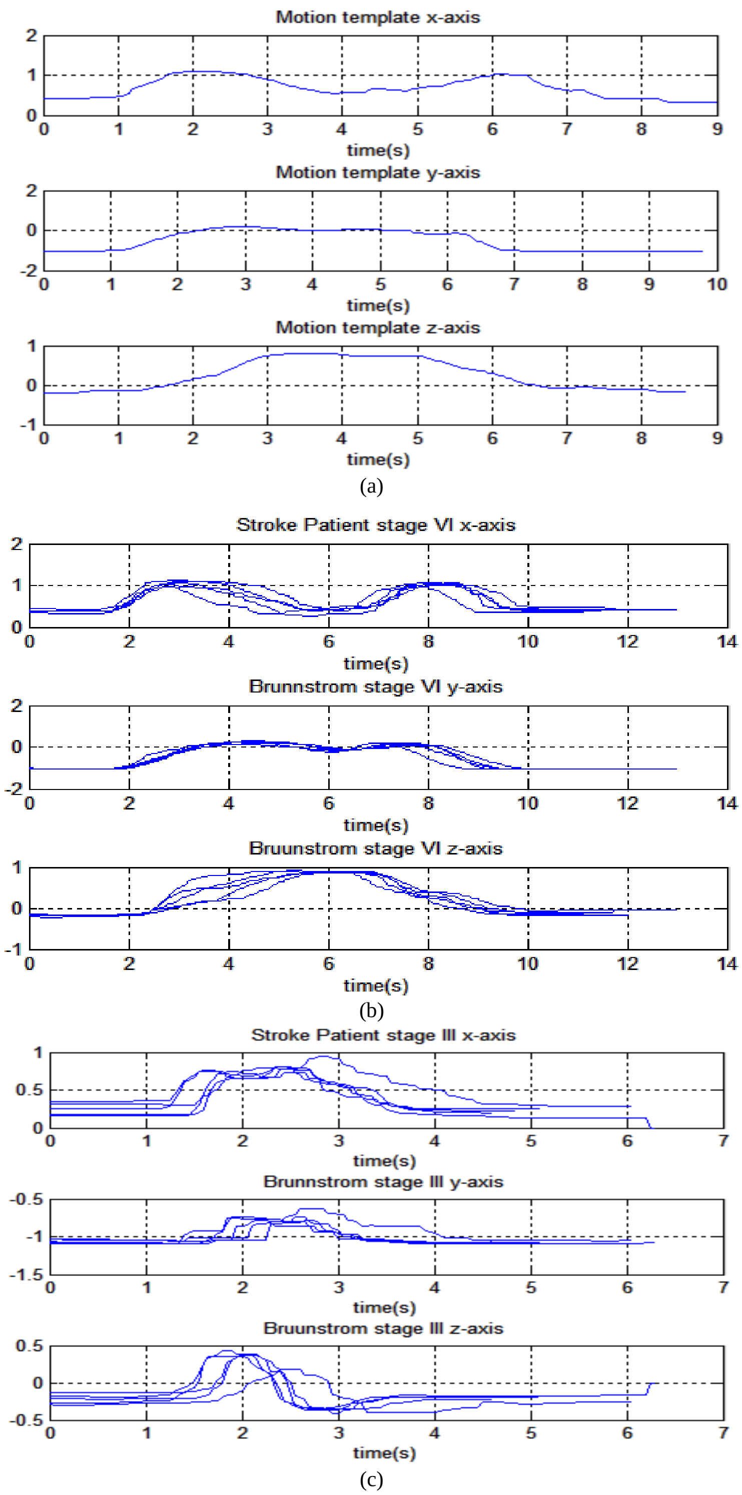


Figure 4-4.a) The 3-axis motion template for shoulder touching exercise. b) Five exercise motion samples collected from a stage VI subject. c) Five exercise motion samples collected from a stage III subject.

TABLE 4-1 LIMB MOBILITY EVALUATION RESULTS

Group	SUBJECT	No. of Samples	DTW Distance			Mobility Index		
			Median	**25^{th} -75^{th} Percentile**	**Min-Max Range**	**Median**	**25^{th} -75^{th} Percentile**	**Min-Max Range**
Stage III Severe Impairment	*S1*	*5*	*49.3*		*12.4 (45.9-58.3)*	*0.782*		*0.074 (0.747-0.821)*
	S2	*5*	*60.8*		*15.2 (58.1-73.2)*	*0.769*		*0.054 (0.735-0.789)*
	S3	*5*	*57.4*		*16.8 (45.1-61.9)*	*0.850*		*0.050 (0.822-0.872)*
	S4	*5*	*69.8*		*10.9 (68.9-79.9)*	*0.751*		*0.045 (0.715-0.759)*
	S5	*5*	*46.4*		*19.5 (42.6-62.1)*	*0.782*		*0.019 (0.778-0.797)*
	S6	*5*	*37.9*		*13.8 (27.5-41.2)*	*0.836*		*0.044 (0.829-0.872)*
	S7	*5*	*48.1*		*14.0 (40.9-54.8)*	*0.802*		*0.059 (0.761-0.820)*
	S8	*5*	*39.1*		*13.5 (33.6-47.1)*	*0.838*		*0.074 (0.806-0.880)*
	S9	*5*	*87.8*		*14.9 (83.0-98.0)*	*0.743*		*0.039 (0.719-0.758)*
	S10	*5*	*82.6*		*20.4 (71.9-92.3)*	*0.770*		*0.060 (0.754-0.814)*
	S11	*5*	*114.5*		*16.1 (102.6-118.7)*	*0.769*		*0.025 (0.757-0.782)*
	Group Result	***55***	***58.2***	***33.9 (45.3-79.2)***	***91.3 (27.4-118.7)***	***0.782***	***0.063 (0.759-0.822)***	***0.165 (0.715-0.880)***
Stage IV Moderate Impairment	*S12*	*5*	*26.5*		*9.6 (20.8-30.4)*	*0.875*		*0.030 (0.857-0.887)*
	S13	*5*	*20.7*		*15.0 (17.2-32.3)*	*0.907*		*0.032 (0.887-0.919)*
	S14	*5*	*35.1*		*17.1 (18.4-35.5)*	*0.876*		*0.056 (0.873-0.929)*
	S15	*5*	*43.4*		*6.4 (39.9-46.2)*	*0.796*		*0.054 (0.780-0.835)*
	S16	*5*	*45.9*		*37.9 (25.6-63.5)*	*0.885*		*0.068 (0.844-0.912)*
	Group Result	***25***	***32.9***	***15.3 (25.5-40.8)***	***48.3 (17.2-65.5)***	***0.866***	***0.042 (0.848-0.890)***	***0.133 (0.796-0.929)***
Stage V Mild Impairment	*S17*	*5*	*24.5*		*9.0 (22.5-31.5)*	*0.880*		*0.056 (0.843-0.898)*
	S18	*5*	*29.3*		*2.9 (27.9-30.7)*	*0.875*		*0.013 (0.869-0.883)*
	S19	*5*	*19.6*		*4.4 (15.5-19.9)*	*0.912*		*0.030 (0.905-0.935)*
	S20	*5*	*19.4*		*5.8 (15.0-20.8)*	*0.918*		*0.011 (0.916-0.927)*
	S21	*5*	*25.6*		*25.7 (11.8-37.5)*	*0.868*		*0.094 (0.841-0.935)*
	Group Result	***25***	***22.5***	***8.5 (19.6-28.1)***	***25.7 (11.8-37.5)***	***0.897***	***0.044 (0.874-0.918)***	***0.095 (0.840-0.935)***
Stage VI No Impairment	*S22*	*5*	*8.3*		*4.7 (5.8-10.5)*	*0.966*		*0.021 (0.957-0.978)*
	S23	*5*	*10.1*		*2.4 (8.8-11.2)*	*0.960*		*0.010 (0.959-0.969)*
	S24	*5*	*6.7*		*1.3 (5.7-7.0)*	*0.969*		*0.007 (0.965-0.972)*
	Group Result	***15***	***8.3***	***3.6 (6.4-10.0)***	***5.5 (5.7-11.2)***	***0.966***	***0.009 (0.960-0.969)***	***0.021 (0.957-0.978)***
Summary		***120***	***37.7***	***37 (20.7-57.7)***	***113 (5.7-118.7)***	***0.857***	***0.124 (0.782-0.906)***	***0.263 (0.715-0.978)***

to few underperformed motion samples. Stage VI subjects in this experiment are healthy participants and a significant leap in motion quality can be observed in the result compared to stroke patient subjects. The subjects in this group are not only able to complete training motions with remarkably high quality but also retain very high consistency. The difference between subjects is also relatively smaller as all health participants do not suffer from any limitation in limb mobility and can precisely adhere to the predefined motion trajectory. It is worth noting that the proposed mobility index has exhibited superior ability to suppress excessive influences of motion magnitude difference and reduce the variance within each group compared to the original DTW distance. For instance, S11 is considered as an extreme case in stage III group due to the large DTW distance. The subject failed to raise the elbow to the required height voluntarily during the first stage of the motion therefore caused a significant dissimilarity in signal magnitude despite the ability to complete the motion reasonably well on the horizontal axis. However, when the subject was evaluated using the proposed mobility index, the influence of magnitude difference was suppressed and thus the result can correctly reflect the patient's performance.

The evaluation results are visualized in Figure 4-5. Significant difference can be observed on the mobility index of subjects from different Brunnstrom stage groups ($p<0.001$, 95% CI: 16.5, 23.7, two-tailed Welch t-test) and a strong correlation can be found between the mobility index and the subject's Brunnstrom stage ($r=0.8523$, $p<0.001$) which is an improvement from the correlation estimated using the original DTW distance ($r=-0.7669$, $p<0.001$). By observing the difference in the distribution of the DTW distance and mobility index in Figure 4-5c and Figure 4-5f, it can be seen that the mobility index was able to better differentiate the different impairment groups especially for groups at stage III and VI, and their medians as indicated using red markers are more evenly and sparsely separated to help reducing class overlapping in classification applications.

The computation speed test was performed on a workstation with Intel Core i5-2467M 1.6GHz CPU with 4 GB RAM using MATLAB® in Windows environment. Each operation was executed for 360 times to estimate the average performance. The average time consumed for computing DTW distance is 8 milliseconds or 3.6 milliseconds with 25% constraint. The average time consumed for mobility index estimation is 3.8 milliseconds.

In order to prove the applicability of the proposed assessment system, a series of Brunnstrom stage classification tests have been conducted with proposed limb mobility index as input features. Table VII, VIII, IX shows the confusion matrix for the LOO classification test. The maximum overall classification accuracy 85.83% is achieved when using KNN classifier with k=3. It can be seen that the obvious difference in limb mobility evaluation result between healthy and stroke patients has ensured that stage VI group can always be classified with 100% accuracy and sensitivity. Relatively low class sensitivity is presented for stage IV and V patients in all three classification methods. According to the definition of Brunnstrom stages [12, 13], the major difference between the two groups is the development of synergy pattern and isolated joint movements which can be unapparent when measured using single IMU. Additional features are required to further distinguish the specific motion patterns in each group.

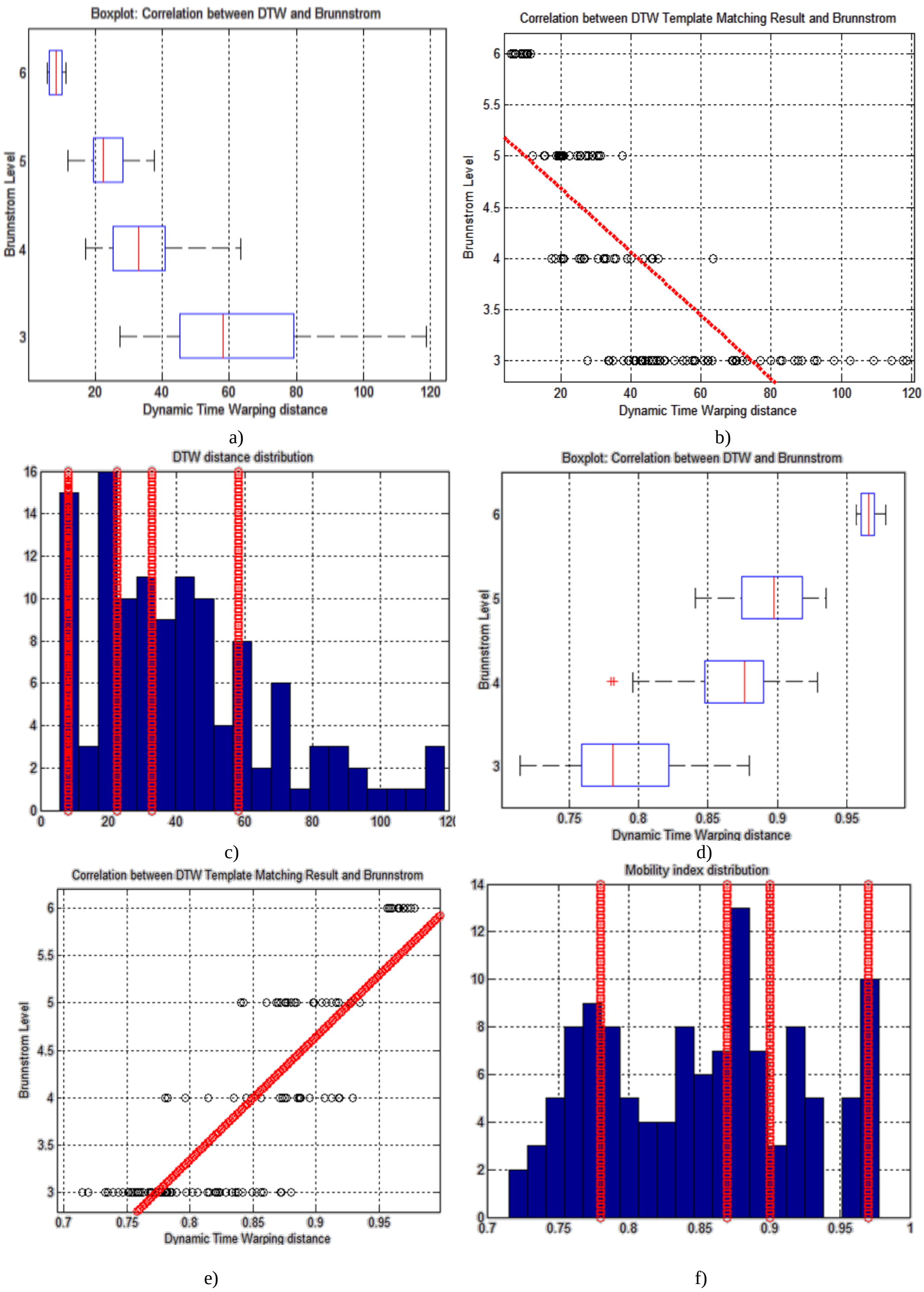


Figure 4-5. A comparison of the DTW distance and the mobility index a) comparison of DTW distance evaluated for subjects from different impairment groups b) correlation between DTW distance and Brunnstrom stage c) the distribution of DTW distance d) comparison of mobility index evaluated for subjects from different impairment groups e) correlation between proposed mobility index and Brunnstrom stage f) the distribution of mobility index

TABLE 4-2 CONFUSION MATRIX OF BRUNNSTROM CLASSIFICATION (NAIVE BAYES)

	Stage III	Stage IV	Stage V	Stage VI	Classified Sum
Stage III	47	5	1	0	53
Stage IV	6	9	8	0	23
Stage V	2	11	16	0	29
Stage VI	0	0	0	15	15
No. of Sample	55	25	25	15	
Sensitivity/ Accuracy	85.5%	36%	64%	100%	72.5%

TABLE 4-3 CONFUSION MATRIX OF BRUNNSTROM CLASSIFICATION (QUADRATIC DISCRIMINANT ANALYSIS)

	Stage III	Stage IV	Stage V	Stage VI	Classified Sum
Stage III	47	5	1	0	53
Stage IV	4	13	3	0	20
Stage V	4	7	21	0	32
Stage VI	0	0	0	15	15
No. of Sample	55	25	25	15	
Sensitivity/ Accuracy	85.5%	52%	84%	100%	80%

TABLE 4-4 CONFUSION MATRIX OF BRUNNSTROM CLASSIFICATION (KNN)

	Stage III	Stage IV	Stage V	Stage VI	Classified Sum
Stage III	51	6	2	0	59
Stage IV	3	15	1	0	19
Stage V	1	4	22	0	27
Stage VI	0	0	0	15	15
No. of Sample	55	25	25	15	
Sensitivity/ Accuracy	92.7%	60%	88%	100%	85.8%

4.3 DISCUSSION

In the study presented here, a novel single index based metric system for limb mobility evaluation in post-stroke rehabilitation has been developed and its validity has been tested against Brunnstrom stages of recovery which is an example of widely used conventional clinical ordinal scale.

The proposed method utilizes motion data that are sampled from stroke patients during rehabilitation training using low-cost IMU. The relatively low sampling rate and small data size has ensured the practicality of the proposed algorithm without sacrificing its validity and sensitivity, as demonstrated in the experiment. The experimental result suggests that the proposed method is consistent with the general sequential development of motor recovery after stroke. In addition, the high correlation with Brunnstrom stages of recovery has revealed its feasibility as input feature for automatic body function impairment classification.

Template matching based algorithms have been successfully used for differentiating training movements in post-stroke rehabilitation training [199, 200]. However, the Euclidean distance and cross-correlation based methods are not sufficient for evaluating patients' mobility as they are unable to adapt to various motion speeds. In order to overcome this problem, DTW distance is employed in this study. A novel mobility index has also been generated to further improve the validity and efficacy of objective mobility evaluation without adding significant computation load. The experimental result has demonstrated that the proposed mobility index produces superior performance on multiple aspects, compared to the original DTW distance.

After the discovery of the high correlation between the proposed mobility index and Brunnstrom stages of recovery, a series of classification experiments have been conducted to further examine the applicability of the proposed method. Various types of classifiers have been applied including NB classifier, QDA and KNN. The mobility indexes on three motion axis are used as the only input features and the performance is evaluated by conducting a LOO based validation test to ensure repeatable result. Highly promising results have been obtained with maximum 85.83% overall classification accuracy and 92.7% and 100% single class sensitivity for stage III and stage VI groups. Compared to specifically designed Brunnstrom classification method as in [235], the assessment method proposed in this paper can achieve similar result with much lower complexity in both hardware and software.

The proposed limb mobility evaluation method is also versatile when being applied in post-stroke rehabilitation training. It generates normalized quantitative results which can be easily comprehended by stroke patients and recorded by software systems. Therefore, it is also a feasible solution for enhancing supervision in TR programs other than providing training feedback and evidence for unified body function assessment in general clinical settings.

4.4 SUMMARY

In this chapter, a novel metric system for limb mobility evaluation for post-stroke rehabilitation has been proposed. The contribution of this study is to provide an objective, efficient, and reliable solution for quantitative limb mobility assessment. It can serve not only as an intuitive feedback to facilitate patients' rehabilitation training in both supervised and unsupervised environment, but also as a reliable evidence for improving individualized rehabilitation training and hence realizing post-stroke body function assessment standardization. The experimental results have demonstrated that the proposed index is capable of reflecting the difference in movement quality for patients from different impairment groups. A strong correlation with widely used Brunnstrom scale and high accuracy in the classification test are also indications of its ability as a unified scale for body function impairment level assessment. The evaluation process of the proposed index is designed to be practical to perform with low financial and computational cost and it can be integrated into rehabilitation training systems as an intuitive feedback to guide the patients for maintaining high standard training quality. It can also help the clinician to track patient's training effort and recovery progress without having to attend entire training session.

Chapter 5

TRAINING MOTION CLASSIFICATION FOR UNSUPERVISED REHABILITATION

In the previous chapters, two novel approaches have been introduced to address the two major challenges for realizing unified objective motor function assessment: automatic impairment level classification and quantitative mobility evaluation. The aforementioned techniques can be integrated into everyday rehabilitation training sessions and substantially boost the quality and efficiency of the rehabilitation program by making the patient's recovery progress traceable with quantitative results without an increase of required human effort. However, in order to successfully implement these techniques in an environment with no or reduced supervision, an automatic motion classification method is also required. The patient's movement during rehabilitation training must be monitored automatically to detect the pre-defined motions that can be used for assessment. By identifying the exercise motions performed during each training session, the patient's training effort and adherence can also be tracked effectively. The reliability of the motion identification process is essential in this application as any misclassification can not only result in false assessment score, but also provide misleading feedbacks on patient's performance and potentially induce negative influence to the doctor's decision.

In this chapter, a fuzzy kernel motion classifier specifically designed for unsupervised rehabilitation is introduced. In order to minimize the cost and operational complexity, the combination of non-visual based inertia sensing devices and pattern recognition algorithms are often considered more suitable in such applications. However, the high motion irregularity due to stroke patients' body function impairment has significantly increased the classification difficulty. A novel fuzzy kernel motion classifier specifically designed for stroke patient's rehabilitation training motion classification is adopted as a solution to the problem. The proposed classifier utilizes geometrically unconstrained fuzzy membership functions to address the motion classification even with defective motion samples. In order to validate the performance of the classifier, experiments have been conducted using real motion data sampled from stroke patients with a broad range of impairment level and the results have demonstrated that the proposed classifier is superior in terms of error rate compared to other popular algorithms.

5.1 POST-STROKE REHABILITATION EXERCISES

The aim of post-stroke rehabilitation is to improve the life quality of the stroke victims and to help their participation and reintegration into the community [4]. One of the greatest impact of stroke is the chronic motor deficit including muscle weakness and spasticity, which can greatly limits stroke patients' performance of ADLs and thus jeopardise their ability of independent living. Rehabilitation training exercises are designed to address the stroke-induced limitations by practicing and improving specific body functions. Some of the major objectives that limb motor function training targets are [236]:

- Promoting flexibility and relaxation of muscles
- Decrease pain and stiffness
- Reduce spasm with fatigue and stress
- Improve balance and endurance
- Maintain and improve range of motion
- Improve coordination and speed for completing fine motor tasks

Different forms of rehabilitation trainings are implemented at the different stages of post-stroke recovery to optimize the efficacy. During the initial period after acute stroke incident including Brunnstrom stage I & II, the patients suffer from severer flaccidity and struggle to perform voluntary movements. In order to provide rehabilitation training to the patients at the early recovery stages, Passive Range of Motion (PRM) exercises, which involves moving the paretic limbs using only external force, are extensively applied. PRM is also crucial for maintaining joint flexibility and preventing contracture. When the patients have partially regained motor function, but are still experiencing difficulty to achieve the full range of the exercise movement, Assistive Active Range of Motion (AAROM) exercises are used. AAROM training encourages patients to actively drive their limb to perform the exercise, but external assistance is also allowed to help the patients further extending their range of motion. For patients who are mildly affected by stroke or at a higher recovery stage such as Brunnstrom V & VI, Active Range of Motion (AROM) exercises are generally incorporated into training. AROM occurs when patients can complete the exercise without any external assistance and it is an effective mean to improve the muscle strength and endurance. Resistance trainings, which applies additional load to the muscle, are sometimes used to further develop the patients' strength. It is worth noting that, patients who can perform most of the exercises in AROM form are more suitable to unsupervised training due to less dependence to external support. However, some of the exercises can be performed as PROM or AAROM by introducing self-assistance. Therefore, patients from Brunnstrom III or IV can also train in unsupervised environment with the aid of a reliable automatic monitoring system.

The study presented in this chapter is to investigate how to automatically identify different exercise motions in a regular rehabilitation training session. Therefore, in order to prove the validity of the solution, six classic training exercises that are widely adopted in clinical applications are selected for the experiments: Bobath handshake, straight arm palm press, shoulder horizontal flexion and extension, forehead reaching with elbow, shoulder touching, and wrist turn. The description of each exercise is presented here.

Bobath handshake is a PROM exercise that is commonly used to improve the flexibility of the upper extremity and shoulder. In the experiment, it is performed in a sitting position. As demonstrated in Figure 5-1, the exercise involves clasping hands together in front of the body and raising both hands up straight towards the ceiling. The unaffected side hand can provide assistance to life the paretic side hand. Therefore, this exercise can be

Figure 5-1. A demonstration of the Bobath handshake exercise

completed even the patient is at early stage and suffers severer muscle weakness. However, the high spasticity developed during the recovery process or other limiting factor to the range of motion such as joint contracture can greatly affect the motion quality.

Straight arm palm press is another self-assisted PROM that can helps to improve upper extremity flexibility. As demonstrated in Figure 5-2, the exercise starts by pressing the affected side hand against a flat surface next to the body with the palm facing down. The unaffected side hand is placed over the affected side elbow and the then whole body can lean towards the affected side to stretch the wrist joint. The magnitude of this movement is relatively smaller compared to other exercises, but it can be difficult to perform for the patients with stiff forearm flexors and hands.

Shoulder horizontal flexion and extension is usually performed as an AAROM exercise, which helps to improve not only the upper extremity flexibility, but also the strength and endurance of deltoid muscles. The exercise motion is demonstrated in Figure 5-3. It starts when the affected side arm is held horizontally and fully stretched with the fingers pointing the unaffected side. The arm then slowly swings towards the other side while keeping the elbow joint extended. This exercise is considered difficult without external assistance due to the amount of shoulder strength and endurance required. However, in order to test the classification performance in unsupervised environment, this exercise is performed as AROM where no external assistance was provided.

Figure 5-2 A demonstration of the straight arm palm press exercise

Figure 5-3. A demonstration of the shoulder horizontal flexion and extension exercise

Forehead reaching with elbow is an AROM exercise which tests the strength and flexibility of the shoulder. As demonstrated in Figure 5-4, the patients are required to place the affected side hand on the opposite side shoulder, and then try to reach the forehand using the elbow while keeping the fingers on the shoulder and head straight. The movement can be performed at least partially without assistance by most of the patients from Brunnstrom stage III and above. However, the patients, who suffer from high plasticity, may have difficulty placing the hand on top of the opposite side shoulder and thus deform the posture and thus making the automatic identification of the movement more difficult.

Figure 5-4. A demonstration of the forehead reaching with elbow exercise

Figure 5-5. A demonstration of the shoulder touching exercise

Shoulder touching is the same exercise that is adopted in the automatic impairment classifcation and mobility assessment studies that are disucessed previous two chapter. The movement involves lifting the affected side arm to horizontal position then flexing the elbow to reach the opposite shoulder with hand. It is also an common AAROM exercise and, similar to shoulder horizontal flexion and extension, it requires high strengh and endurance from anterior deltoid mucsle to be performed as AROM without assisstance. The elbow joint also has to be fexible enough for the hand to successfully reach the opposite side shoulder. For testing the motion classifcation in unsupervised environment, this exercise is also required to be performed as AROM in the experiment.

Figure 5-6. A demonstration of the wrist turn exercise

Wrist turn is the last exercise included in the experiment. Similar to the palm press exercise, it mainly targets the stiffness of the forearm muscle groups and it is usually performed as a self-assisted PROM or AAROM exercise. The exercise requires simply flipping the paretic hand on a flat surface with the assistance of the unaffected side hand. It is considered relatively simple as a PROM exercise and it can be completed by the patients from the early stages of recovery.

The objective of this study is to investigate a robust and reliable method to classify the six movements when they are performed as AROM exercise during rehabilitation training sessions. The detailed methodology and experiment design is presented in the next section.

5.2 METHODOLOGY

5.2.1 DATA SAMPLING

The overview of the fuzzy kernel classification system is shown in Figure 5-7. The motion data were sampled at 400Hz using the accelerometer and gyroscope from an Xsens IMU module (MTi-300). The sensor node was attached to the patient's forearm with the positive direction of the x-axis pointing the elbow as illustrated in Figure 4-3. The node was aligned with the centre line of the back of the hand and was mounted as close to the wrist joint as possible to ensure that it is not affected by any wrist movements. The raw data collected were then fed through a sequence of pre-processing procedures. A median filter was first applied to remove spikes in the signal caused by electrical noise or signal drop-off without distortion to the waveform. In practical situations, it needs to be taken into account that the patients may have different side of the body affected by stroke. Therefore, during the pre-processing stage, data collected from the left hand impaired patients had the Y-axis of accelerometer data and X and Z-axis of gyroscope data inverted in order to rectify the difference. After the axis inversion, the 3-axis accelerometer reading was purified by removing the static offset caused by the gravity, and it was then integrated into velocity. However, the raw accelerometer measurement was kept in separated data sequences in order to retain the information of static acceleration. The 3-axis angular velocity measured by gyroscope was also integrated into orientation. Therefore, after the pre-processing, 9 data sequences (velocity, raw acceleration and orientation) were ready for the feature extraction process. In total, 63 features were used as shown in Table 5-1 and PCA process was applied after the first normalization process, which scales the input features in a range between 0 and 1, in order to reduce the data complexity before the classifier training. As illustrated in Figure 5-7, the processed data was partitioned for classifier training and testing, and a ten-fold cross-validation process was adopted to rotate the datasets. For classifier training, a fuzzy classifier which is based on unconstraint fuzzy membership function was constructed with the normalized principle components as input features. The number of principle components and the adjustable parameters in the classifier was determined by performing a grid search in the cross-validation process, where the value of the parameters were determined based on the classification performance.

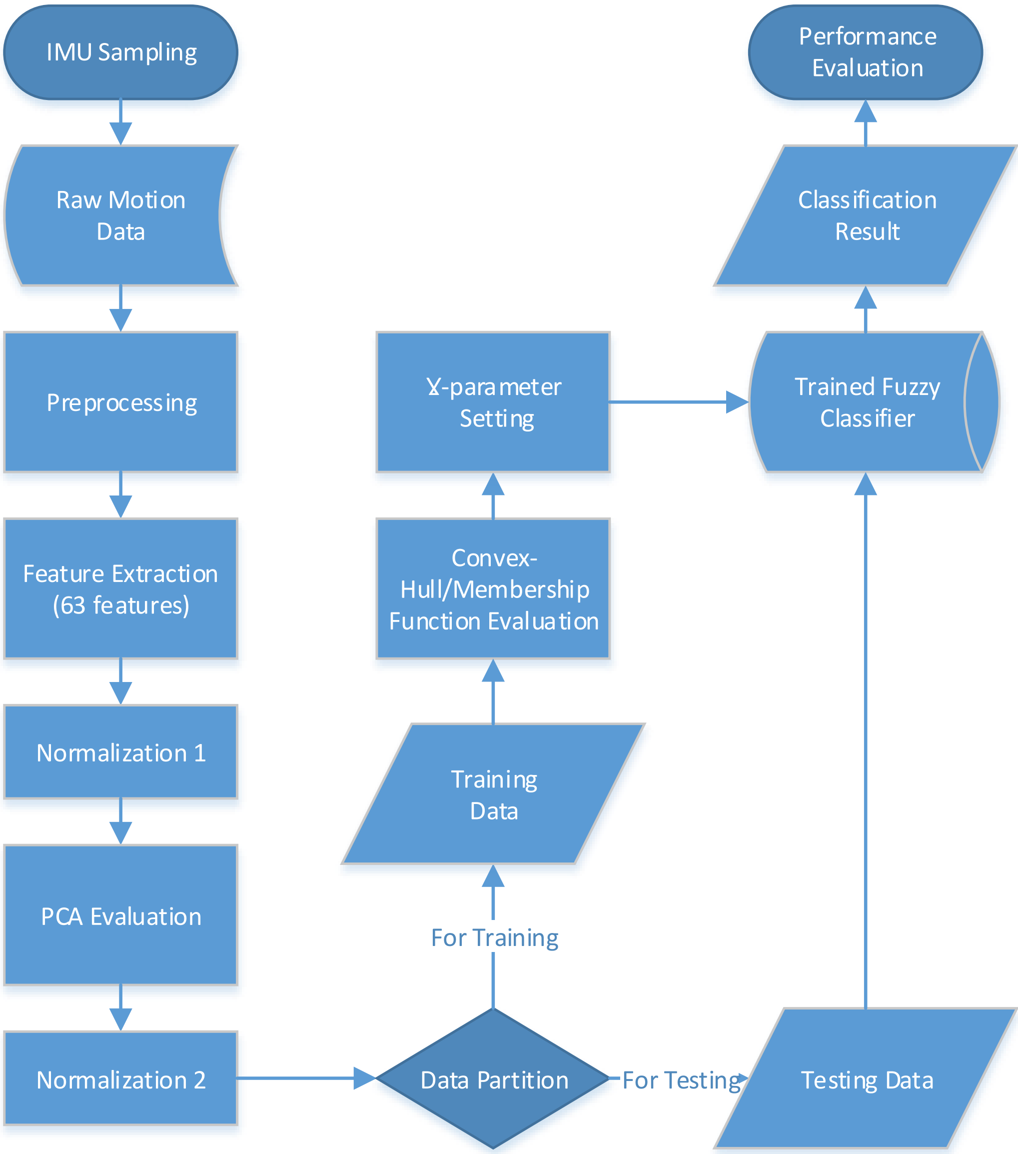


Figure 5-7. Flow chart of the proposed motion classifier for post-stroke rehabilitation training

5.2.2 *CLASSIFIER ARCHITECTURE*

The upper limb motions classification problem in post-stroke patients has been solved using the proposed model shown in Figure 5-8, which will be referred as Fuzzy Kernel Classifier (FKC) in this thesis. After data normalization, the classifier evaluates a label vector L vector, for any pattern x:

$$\mathrm{L} = \left[\mu_{(1)}(\mathrm{x}), \mu_{(2)}(\mathrm{x}), \ldots\ \mu_{(K)}(\mathrm{x})\right], \tag{14}$$

where the k^{th} element of L represents the fuzzy MF of the pattern to the k^{th} class. We adopt the Winner-Takes-All (WTA) criterion for decision-making. Therefore, we chose the maximum value in the L vector, and we assign the final accordingly crisp label representing the estimated motion class for pattern x.

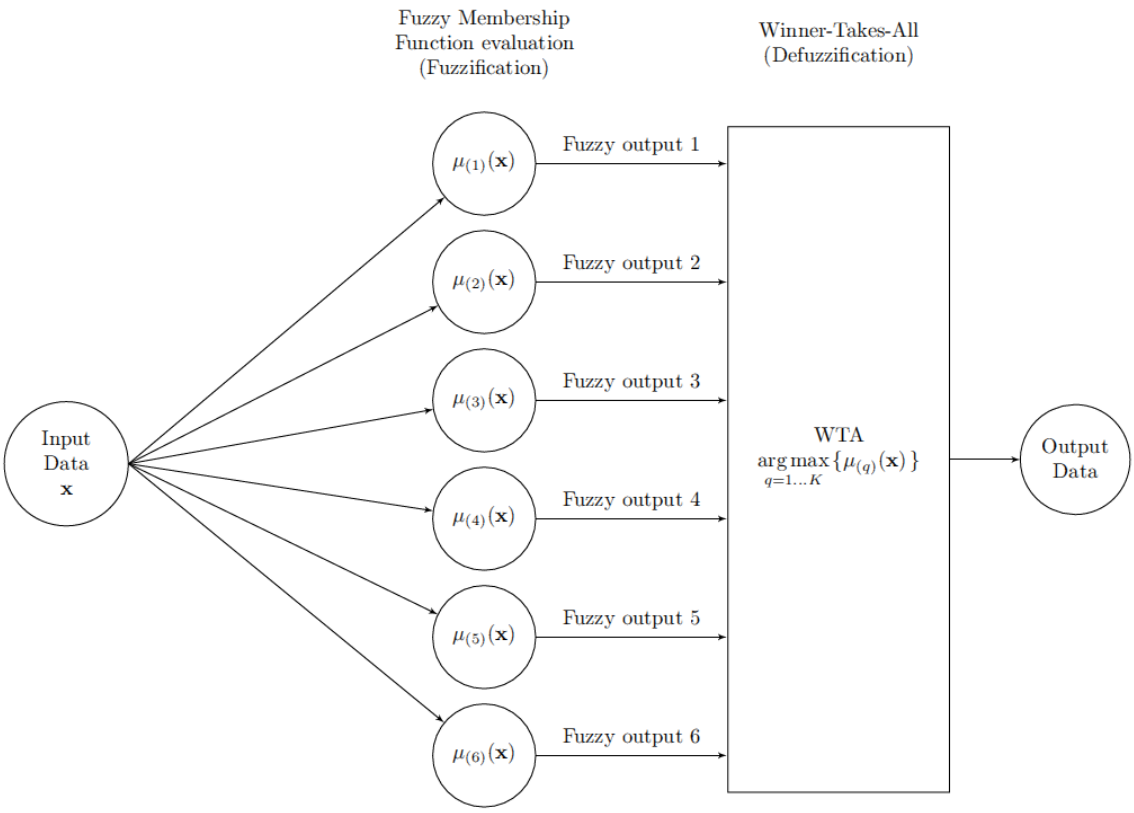


Figure 5-8. The structure of the proposed FKC

Before the classifier training, a pre-processing step of data normalization must be taken to merge all data feature space will be merged into a range between 0 and 1. Let M be the number of patterns of the dataset $D = \{x_1, x_1, \dots, x_M\}$ and N be the number of features. Each pattern of the dataset can be represented by a N-tuple of real numbers:

$$x_m = [x_{m1}, x_{m2}, \dots x_{mN}], \mathrm{m} = 1 \dots \mathrm{M}. \tag{15}$$

Since the features are completely heterogeneous, the patterns are normalized within each column:

$$x_{mj} \leftarrow \frac{x_{mj}-b_j}{a_j-b_j}, m = 1 \dots M, j = 1 \dots N, \tag{16}$$

where $a_j = arg \max_{m=1\dots M}\{x_{mj}\}\ and\ b_j = arg \min_{m=1\dots M}\{x_{mj}\}$.

Once the normalization is completed, the training set will need to be determined as a matrix where each row represents a vector of features to be used for the model learning. The proposed classifier establishes a set of fuzzy MFs to associate the patterns of each motion to the corresponding class. The used MFs, based on data geometrical representation and point-to-polygon distance evaluation, is as presented in [237]. These MFs are constructed by taking regular polygons that cover all the patterns of each class and H kernel functions on both the vertices and the centroid of the corresponding polygon. The mathematical representation of the process is shown as follows:

$$\mu^{(cone)}(x) = \max\left[0, 1 - \frac{\gamma}{\sqrt{N}} d_2(x, c)\right] + \sum_{i=1}^{H} \max\left[0,1 - \frac{\gamma}{\sqrt{N}} d_2(x, v_i)\right], \tag{17}$$

where N is the number of dimensions/features N, $d_2(x, c)$is the point-to-centroid Euclidean distance, $d_2(x, v_i)$ is the point-to-ith-vertex Euclidean distance and γ is the parameter that define the slope of the MF.

In the large amount of data analysis, if the number of dimensions increases, the identification of all the vertices of a polytope requires high computational costs. The convex hull of a set of points is the smallest convex set that contains the points [238] and it is considered as an effective solution for real-time polygon boundary evaluation in many scientific disciplines [239-242]. As demonstrated in Figure 5-10, we used this mathematical algorithm for the evaluation of the vertices in which it is possible to place the linear function during the MFs construction [242]. The unconstrained convex shape of the MF can be clearly observed in Figure 5-11, where two MF examples, computed using 10 randomly selected points from the [0,1] space, are visualized in 2D planes.

The γ parameter represents the skewness of the MF: the greater the value of γ the faster the function goes to zero, as revealed in Figure 5-9. The optimization of this parameter helps the correct estimation of the pattern membership to each class. An excessively small value might result in a critical class overlapping while a large value may also cause indetermination as the area covered by MFs will be too small and the degree of membership to all the known classes could be very close to zero.

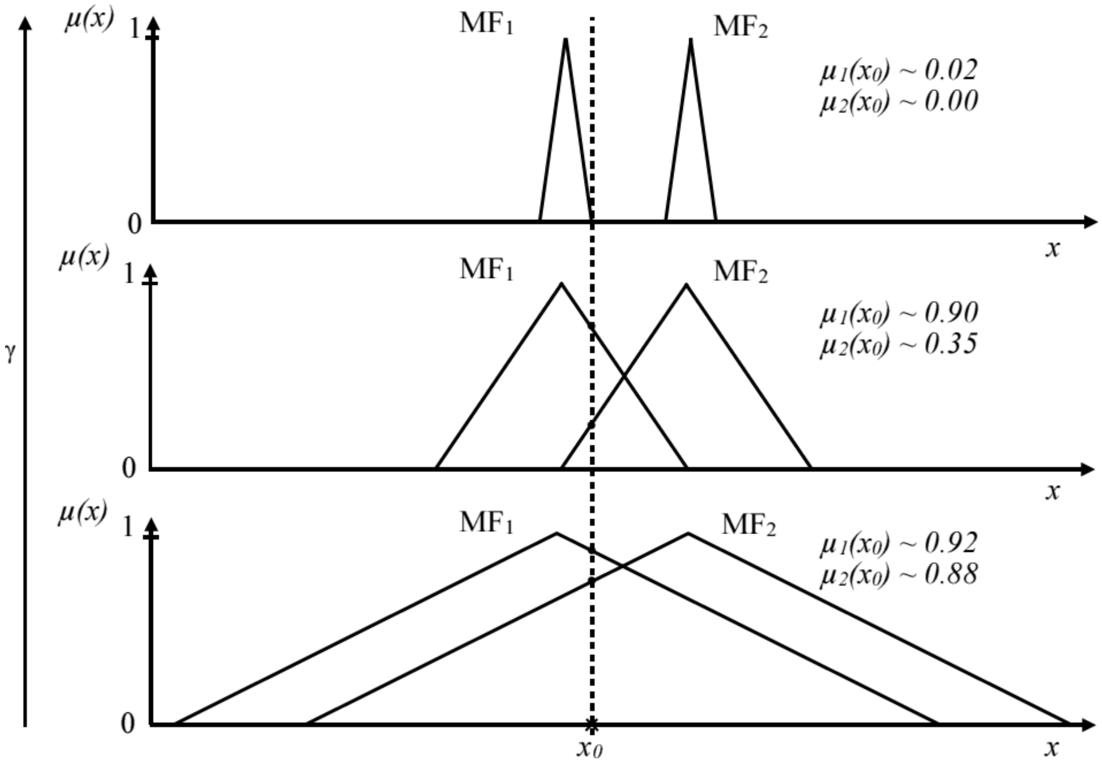


Figure 5-9. Fuzzy MF evaluation with the γ parameter varying

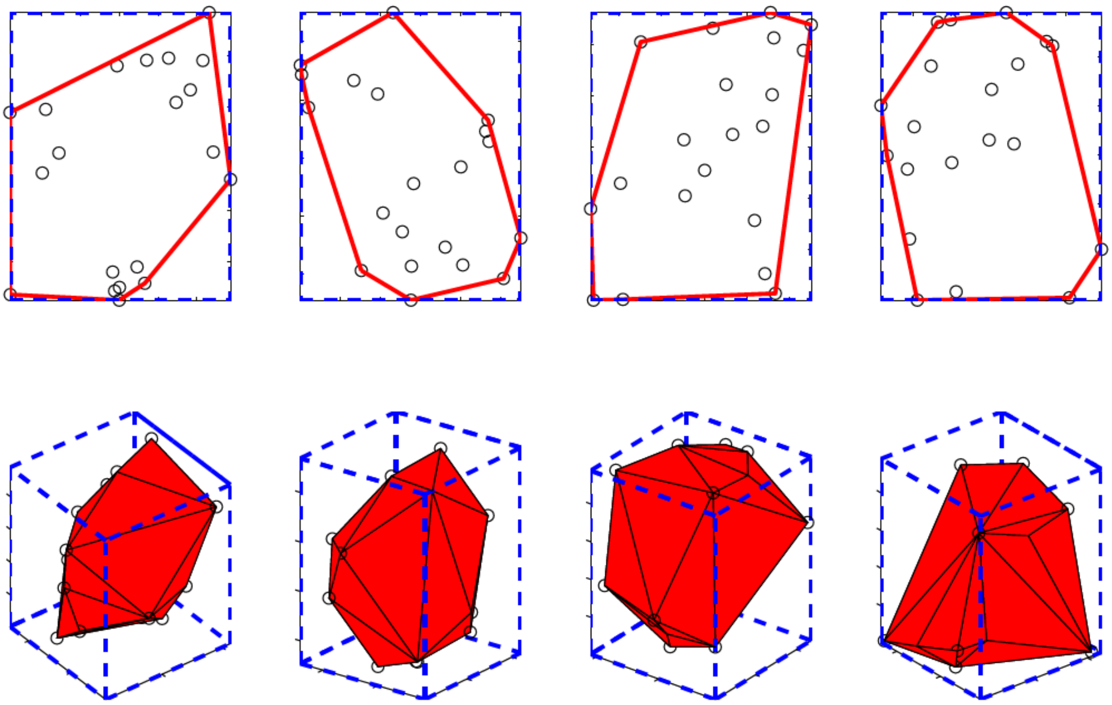


Figure 5-10. Convex Hull Example in 2-D and 3-D

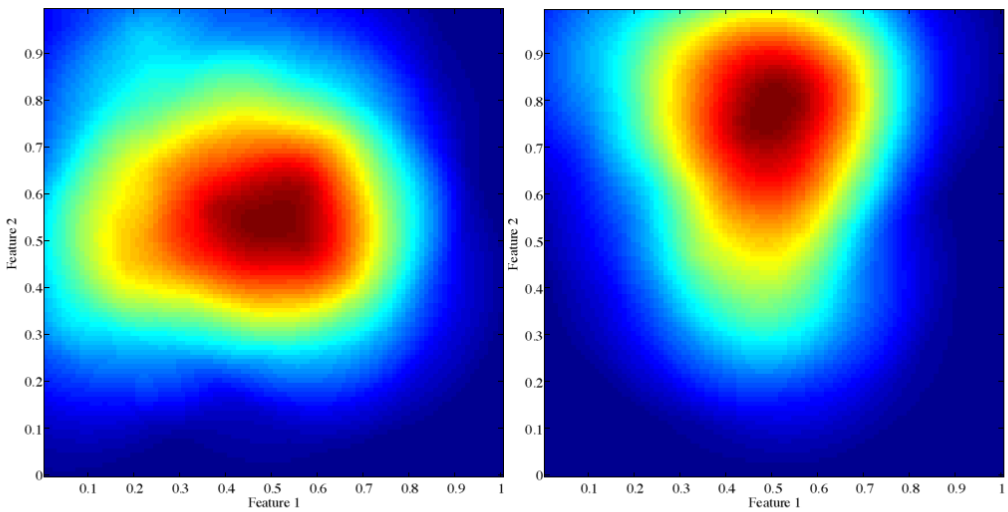


Figure 5-11. Examples of the adopted MF visualized in 2-D plane with two different sets of randomly selected samples

TABLE 5-1 LIST OF FEATURES FOR FUZZY MOTION CLASSIFIER

Feature type	Feature names	Feature description
Mean	MeanACCX, MeanACCY, MeanACCZ, MeanANGX, MeanANGY, MeanANGZ	Mean magnitude calculated for acceleration, angular position and velocity data sequence.
Standard Deviation	StdACCX, StdACCY, StdACCZ, StdANGX, StdANGY, StdANGZ, StdVELX, StdVELY, StdVELZ	Standard deviation calculated for acceleration, angular position and velocity data sequence.
Duration	DurACCX, DurACCY, DurACCZ, DurANGX, DurANGY, DurANGZ,	Effective duration calculated by counting the number of continues samples with absolute magnitude greater than the 20th percentile for each data sequence.
Energy	EneANGX, EneANGY, EneANGZ, EneANGX, EneANGY, EneANGZ, EneVELX, EneVELY, EneVELZ,	Signal energy calculated by taking the sum of squared magnitude for each data sequence.
Dominant Frequency Power	PowACCX, PowACCY, PowACCZ, PowANGX, PowANGY, PowANGZ, PowVELX, PowVELY, PowVELZ,	Power Spectral Density (PSD) at dominant frequency calculated for each data sequence after time-frequency domain conversion using Fast-Fourier-Transform (FFT).
Dominant Frequency	FreqACCX, FreqACCY, FreqACCZ, FreqANGX, FreqANGY, FreqANGZ, FreqVELX, FreqVELY, FreqVELZ,	Dominant frequency calculated by locating the peak PSD for each data sequence after FFT.
Mean Power	AvePowACCX, AvePowACCY, AvePowACCZ, AvePowANGX, AvePowANGY, AvePowANGZ, AvePowVELX, AvePowVELY, AvePowVELZ	Average power of the power spectrum calculated for each data sequence after FFT.

5.2.3 *Experiment Protocol*

The experiments were conducted in collaboration with the Rehabilitation Medical Centre of the 2^{nd} Hospital of Jiaxing in China. All the experiment procedures and data access were approved by the ethics committees of the hospital and the university. After the informed consent and selection process, 14 stroke patients from the centre, including 10 males and 4 females with an average age of 60.3 (ranged from 32-78), participated in this research with a total of 531 motion data sets collected. The patient subjects were selected with a broad range of impairment level (Brunnstrom stage I-V) to test if the system was suitable for various stages of rehabilitation training. During the selection process, the participants were examined by experienced doctors and the ones with severe cognitive, perceptual or communication problem or any other health conditions that could have been not suitable for the experiment, have been carefully excluded.

The motion sampling process utilized the six classical upper extremity rehabilitation exercises that are introduced in the beginning of the chapter: Bobath handshake, straight arm palm press, shoulder horizontal flexion and extension, forehead reaching with elbow, shoulder touching, and wrist turn. The motions are selected as they are the most frequently performed exercises in the hospital which are familiar to the patients and they are also able to cover the different perspectives of patients' motion impairments including multiple joint flexibility, muscle strength, and spasticity. The patients were asked to follow a video demonstration that repeats ten times for each exercise and no additional assistance was provided except for safety reasons. The participants were encouraged to attempt all six motions. However, due to the difference in impairment severity, most of the patients at low Brunnstrom stage (I-III) were not able to complete every exercise. Despite some motions being badly performed, every complete motion samples from all the 14 patients were included in the dataset to ensure the validity of the test result. However, six patients who had better performance during the exercise were selected to form a separate dataset in order to demonstrate the influence of motion quality of classification result.

5.3 RESULT AND DISCUSSION

The classification accuracy is represented by the error rate as is the percentage of incorrectly classified motions evaluated in a test set which is never used during the training phase. The classification error is evaluated while changing the γ value in a practically computable range between 0.2 and 20 with a 0.2 step. Any further increase above the range will result in the separation of the kernel functions within the MF evaluation, and therefore it jeopardizes the performance of the classifier. The performance evaluation has the scope of investigating the behaviour of the proposed method with a consideration of both the most advantageous and the most disadvantageous situations. To realize that, ten different partitions of the whole dataset into training and test sets are considered, and the performance is evaluated in terms of the averaged accuracy on the ten different test sets for every value of γ.

Two datasets with different groups of patients involved were used in the performance evaluation in order to demonstrate the influence of motion quality on classification accuracy:

• Group with six patients (6P): The dataset consists of motion samples from 6 patients at higher Brunnstrom stages who can perform all the six motions with relatively high quality. The dataset includes 360 patterns with 60 in each of the six motion classes.

• Group with 14 patients (14P): The dataset consists of motion samples from all 14 patients with significant variation in motion quality due to the difference in impairment severity. The dataset includes 531 patterns with different number of samples in each of the six motion classes as some patients at low Brunnstrom stages have difficulties in completing certain movements.

The PCA analysis transforms all of the 63 features into principal components that are subsequently ranked based on their percentage of contribution in terms of describing data variance. Theoretically, the motion classifier can work with any number of principal components as the more components are included the more information from the original dataset will be covered. However, most of the variance is explained by the first few principal components and by adding extra components, the required computation resources will rise significantly.

The error rate versus γ value plots with different number of patients and principal components are presented in Figure 5-12 and Figure 5-13. It can be seen that the error rate drops significantly while more information are recovered by adding extra principal component for both dataset. A 0% error rate was finally achieved using seven principal components, which captures 72.3% of the variance, and when $\gamma^*=8.2$. In the case of 14P dataset, as shown in Figure 5-13, where the low-quality motion samples are introduced, some performance deterioration can be observed compared to 6P group although less than 1% error rate was also achieved with the same number of principal components. The γ value for the best result was slightly shifted to 10.2, which indicates that the shape of the MF boundary is optimized to be steeper to accommodate the additional class overlapping due to the increase of uncertainties. The detailed classification results for 14P dataset using $\gamma^*=10.2$ can be found in the confusion matrix listed in Table 5-2, which shows for each row the number of patterns of every real motion (M1, M2, . . . , M6) that are assigned to the estimated outcome.

TABLE 5-2 CONFUSION MATRIX FOR 14 PATIENTS TEST

		Estimated outcome					
		M1	M2	M3	M4	M5	M6
Actual value	M1	141	0	0	0	0	0
	M2	0	80	0	0	0	0
	M3	0	0	90	0	0	0
	M4	1	0	1	58	0	0
	M5	0	0	1	0	79	0
	M6	0	0	0	0	0	80

A group of commonly used classification algorithms, trained in the Matlab™ software (version R2013a), have also been tested for comparison in order to test if superior classification performance in terms of error rate could be obtained using the proposed fuzzy approach. The ten-fold cross validation process was applied to all classifiers for parameter optimization and fair comparison. First of all, a neuro-fuzzy classifier whose parameters were adapted using the scaled conjugate gradient method was tested [243]. The Classification and Regression Tree (CART) [244] as a classic approach was also implemented as well as the widely adopted Support Vector Machine (SVM) that was optimized with a Radial Basis Function (RBF) kernel and Sequential Minimal Optimization (SMO) method. Moreover, the probabilistic classifiers have also been involved in the comparison including the Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) [245], Naive Bayes classifier [246], and the feedforward Probabilistic Neural Network (PNN) [247]. The exact same datasets, preprocessing techniques, and experimental procedure were used for generating the results as listed in Table 5-3. It can be seen from the result that the proposed FKC has a distinct advantage over other popular methods in terms of accuracy for post-stroke motion classification application. SVM that has been widely adopted in motion tracking application can be treated as a benchmark [208], [211] and a near 1% error rate was achieved after tuning an RBF kernel SVM. Despite the high accuracy, the implementation of SVM in this application can be limited since the choice of kernel can dramatically affect the performance. The computation time, which multiplies rapidly as the size of the dataset increases, is another factor that hinders its implementation [205]. On the other hand, the proposed FKC requires only a single γ parameter to be tuned in the validation phase, and the computation time is relatively quicker especially in testing phase once the convex set is determined.

It is also worth noting that as an instance-based learning algorithm, K-nearest neighbour (KNN) has been previously proposed to address the motion classification problem and it is also included in this experiment [13] [14]. Unlike many other pattern recognition techniques, an instance-based method retains the original input instances for classification without a learning process to generalized data into a set of inference rules. This type of learning strategy is generally referred as “lazy learning”, because most of the work is not started until the evaluation stage, when the query is made, and, as a result, the classification process can become too cumbersome and impractical for many applications. When it is combined template matching based approach for multinomial motion classification, the situation is worsened as the heavy querying process may be repeated multiple times to locate the optimal match. In order to be integrated into regular rehabilitation training, the classification process must be computationally inexpensive to perform even with a large number of motion types. Therefore, despite the classification performance, instance-based learning is not considered as the most suitable candidate for this application.

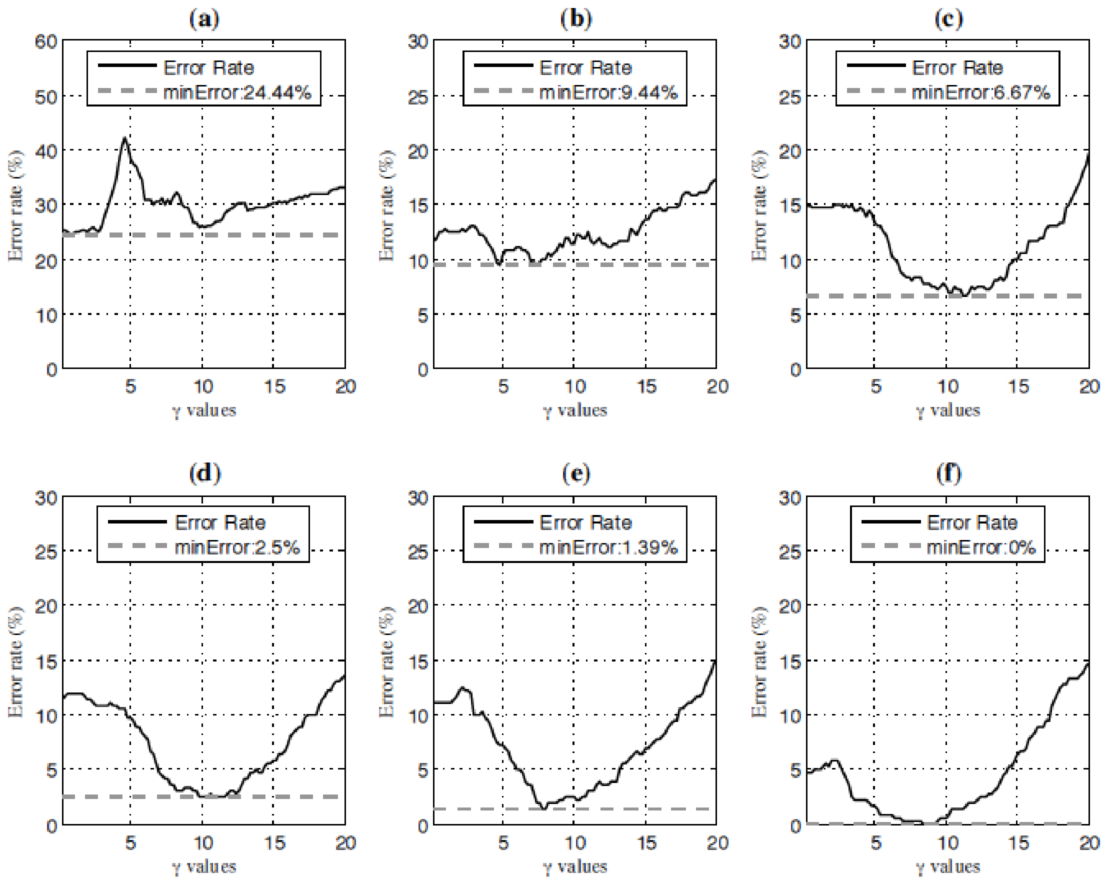


Figure 5-12. Six Patients classification. Error rate obtained by varying γ from 0.2 to 20 with a step of 0.2. Different number of principal components used: a-2, b-3, c-4, d-5, e-6 and f-7.

TABLE 5-3 ERROR RATE COMPARISON - MOTION CLASSIFICATION

Algorithm	6 Patient	14 Patient
Fuzzy Kernel Classifier	0.00	0.56 (±0.64)
Neuro-fuzzy Classifier	1.67 (±1.32)	1.70 (±1.10)
Classification Tree (CART)	5.28 (±2.31)	4.90 (±1.84)
Support Vector Machine (SVM)	1.32 (±1.18)	1.11 (±0.89)
K-Nearest Neighbour (KNN)	1.32 (±1.18)	0.56 (±0.64)
Linear Discriminant Analysis	1.67 (±1.32)	8.35 (±2.35)
Quadratic Discriminant Analysis	0.56 (±0.77)	1.32 (±0.97)
Naive Bayes	3.06 (±1.78)	6.03 (±2.02)
Probabilistic Neural Network (PNN)	11.11 (±3.25)	67.23 (±4.00)

All the error rates are expressed in (%) with 95% confidence error bounds

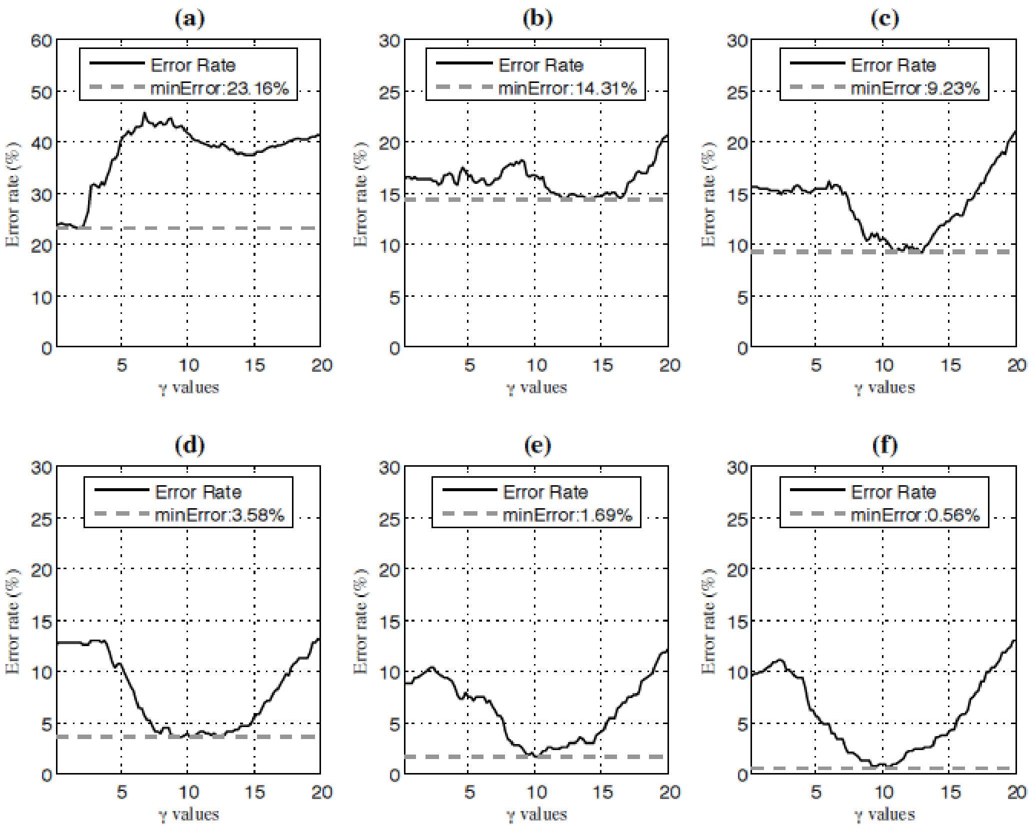


Figure 5-13.14 Patients classification: Error rate obtained by varying γ from 0.2 to 20 with a step of 0.2. Different number of principal components used: a-2, b-3, c-4, d-5, e-6 and f-7.

5.4 SUMMARY

In this chapter, a novel fuzzy kernel motion classifier that was specifically designed for autonomous stroke rehabilitation applications has been presented. The system is capable of accurately identifying common rehabilitation exercise movements during a stroke patient’s routine training session using the kinetic data collected through an IMU attached to patient’s wrist. By implementing the proposed motion classifier in a TR training system, doctors will be able to track patient's training performance remotely without having to follow through the entire session. The optimized geometrically unconstrained MFs adopted in the classifier can effectively manage the motion class overlapping issue, which is one of the major obstacles in classification problems, especially when dealing with irregular motion samples performed by stroke patients with various degree of body functionality impairments. The proposed classifier has also undergone a series of validation experiments, and the results have demonstrated superior performances compared to other popular pattern recognition algorithms. When including no less than seven features as input, extracted by means of PCA, the fuzzy kernel motion classifier can achieve 0% error rate for low impairment level patient group and 0.56% for all patients.

Chapter 6

IMPAIRMENT CLASSIFICATION USING SURFACE ELECTROMYOGRAPHY

In addition to kinematic information, sEMG signal can also be sampled conveniently using wearable devices. Compared to IMU-based approach, sEMG has the advantage of being able to detect voluntary motion and intention from patients with high flaccidity in the early recovery stages. The correlation between sEMG features and Brunnstrom stages of recovery and the possibility of adopting sEMG measurement as an alternative input for impairment level classification is investigated here. In this chapter, a novel fuzzy kernel based approach which automatically classifies stroke patients motor function impairment based on Brunnstrom scale using surface EMG signal is presented. The system is designed to be efficient and practical to implement in rehabilitation training settings. The validity of the proposed method has been tested with 93 surface EMG samples collected from 9 stroke patients. The participating patients motor function impairment levels are classified based on the Brunnstrom stage of recovery by an expert panel prior to the experiment and the automatic classification results are generated by the proposed system is compared with the expert's judgement. Both 10 Fold and Leave-One-Out (LOO) cross validation method has been adopted to ensure repeatable results.

6.1 sEMG AND MOTOR RECOVERY

In post-stroke rehabilitation, sEMG is considered as a popular method for detecting muscle activation and providing biofeedback to facilitate rehabilitation training. However, little is known regarding how muscle activation coordination patterns are related to the post-stroke functional recovery process. In a healthy neuromuscular system, skeletal muscles are voluntarily activated by the electrical messages that delivered from the brain through the upper and lower motor neuron, and finally arrives muscle fibres via the neuromuscular junction as illustrated in Figure 6-1 and the electrical activities that triggers muscle contraction can be monitored via EMG devices. However, after a stroke incident, brain tissues are damaged due to either the interruption of cerebral circulation, or the increased intracranial pressure and toxic effects from the released blood in the case of haemorrhagic stroke. Consequently, the neuromuscular pathway is impaired and, similar to other cortical, subcortical or spinal cord lesions, Upper Motor Neuron Syndrome (UMNS) can occur. Depending on the severity and location of the damage, the upper motor neuron lesion can lead to imbalanced excitatory and inhibitory input to alpha motor neurons and cause abnormal muscle excitability which results in significant limitation of patient’s motion including pathological changes to muscle strength, tone (hypotonia and hypertonia) and control. Many post-stroke body functional impairments are results of the abnormity of neuromuscular activity. For example, it is believed that the spasticity, which can be universally observed in stroke patients from the stage II or above of Brunnstrom stage of recovery, is a result of co-contraction of the flexors and extensors. These pathological electrical activities can be observed via EMG. However, how the post-stroke functional recovery process is related to the pathological EMG patterns is still debatable. In [248, 249], Buurke et al suggested that the functional gait improvement after stroke is the result of the compensatory strategies in muscle activation of the unaffected leg and other biomechanical rather than the changes in the muscle coordination of the impaired leg. In the research conducted by Tang et al. [250], no co-contraction was found in antagonistic muscles of the paretic limb after investigating 17 stroke patients’ sEMG recording of the elbow flexor muscle during isometric contraction. On the other hand, Hammond et al.[251] found that significant increment in co-contraction ratio of antagonist activity to agonist and antagonist combined activity can be observed in the wrist flexor and extensor muscle of stroke patients using EMG.

In this study, the sEMG signal measured from stroke patient from various recovery stages will be compared, and the relationship between the features of stroke patients' sEMG patterns and their recovery progress will be investigated. An automatic Brunnstrom stage classifier is also developed to demonstrate how sEMG measurements can be adopted to aid post-stroke clinical assessments.

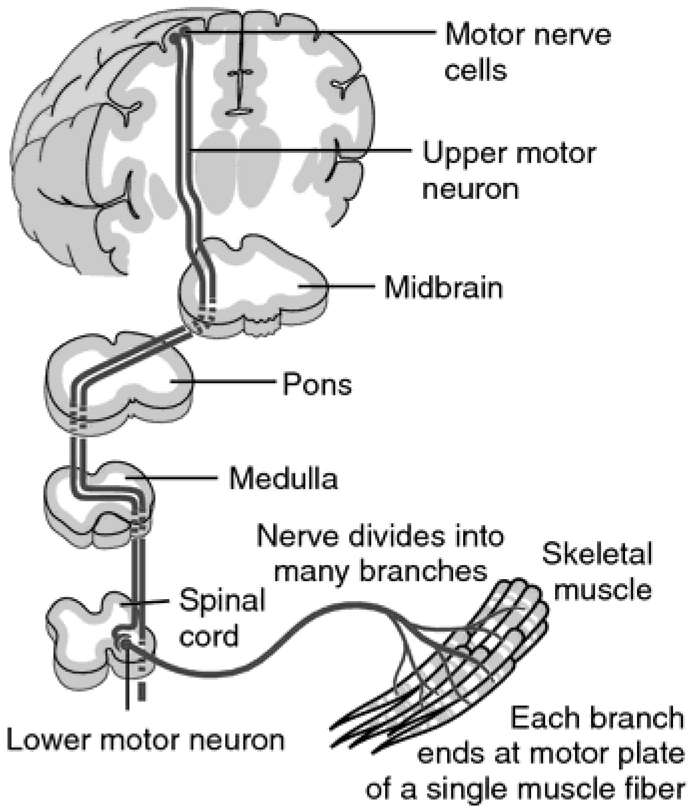


Figure 6-1. An illustration of motor signal pathway
(http://medical-dictionary.thefreedictionary.com/motor+neuron)

6.2 METHODOLOGY

The high level view of the proposed motion classifier system is shown in Figure 6-2. The sEMG signal is first sampled from stroke patients' lateral deltoid muscle during a repetitive rehabilitation training exercise using a single channel sEMG module at 3 kHz. The raw data is fed through a band-pass filter for pre-processing and ten different features from both time and frequency domain are then extracted for pattern recognition. A normalization step is performed before classifier training in order to accommodate every feature of the data space in the range between 0 and 1. Similar to the process flow introduced in chapter 5, the data are petition into different groups for classifier training and testing, and both LOO and ten-fold cross-validation were implemented in this study to ensure the generalizability of the classifier. During each cross-validation test, the data are separated into three groups: the training, validation, and testing dataset. The classifier is first trained and validated using the training and validation set in order to optimize the internal parameter, and then the performance of the system is examined using the testing data.

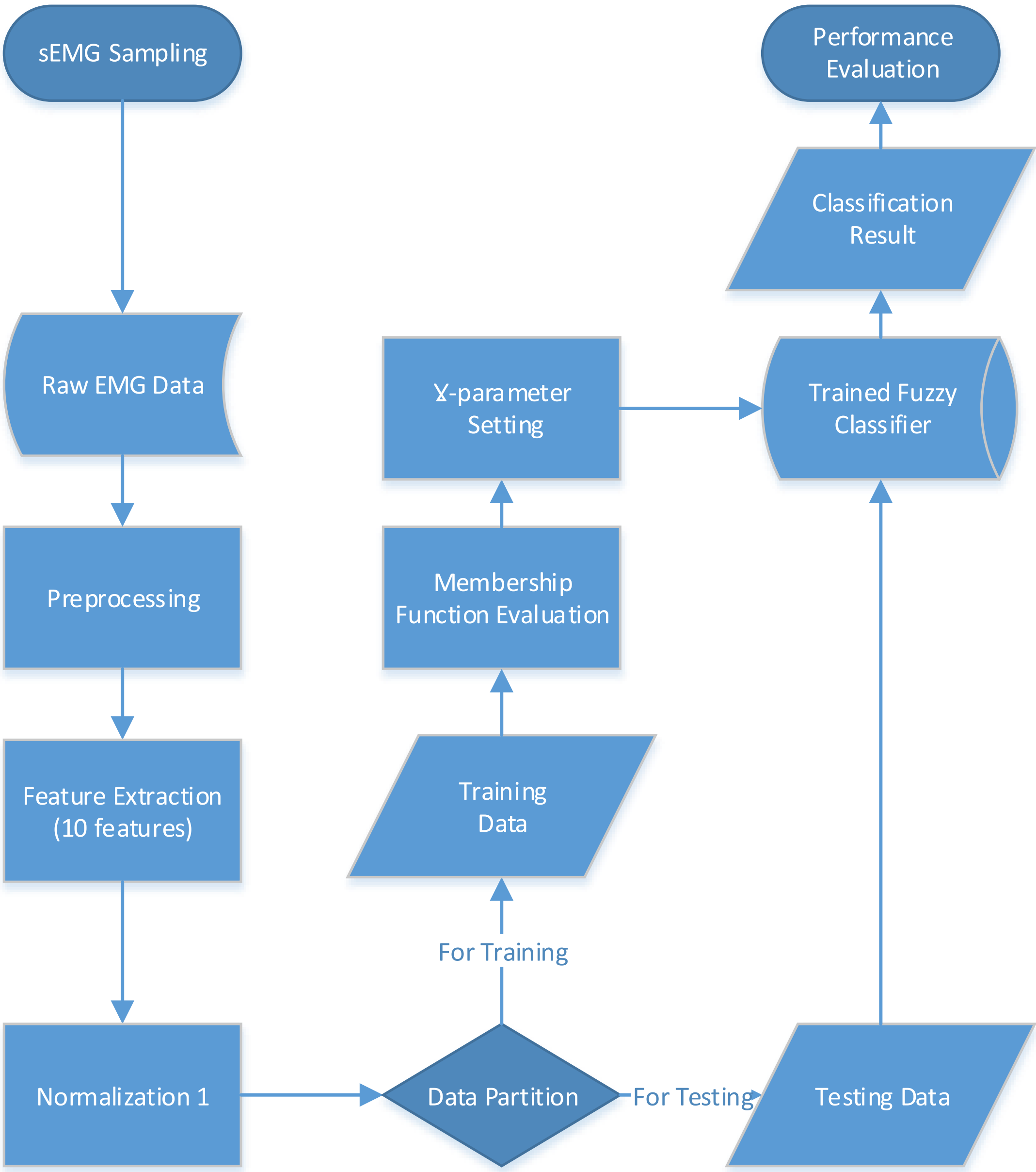


Figure 6-2: System flow chart of the proposed sEMG based automatic impairment classification system

6.2.1 FUZZY MEMBERSHIP FUNCTION

A flexible and computationally affordable MF is adopted in the proposed study to deal with complex shaped data clusters and to improve the classification performance. An MF is constructed by combining cone-shaped linear kernels evaluated for each pattern based on point-to-boundary distance. As a result, it does not have the constraints derived from particular geometrical structures such as hypercubes, hyperspheres, and regular polytopes. Instead, it adapts its shape based on the structure of data clusters. This approach was originally introduced by Liparulo et al. [237], in which the results have proven that the unconstrained MF is effective and feasible when dealing with complex clustering tasks. In this approach, each linear kernel is associated with an MF represented by a number L of points corresponding to the patterns belonging to that class. The evaluation of the MF is inversely related to the distance between pattern and cluster boundaries. This method exploits the superposition of an appropriate number of functions for building the MF of each cluster. Let L × N be a matrix V, where N is the number of data features:

$$\mathrm{V} = \begin{bmatrix} v_1 \\ \vdots \\ v_L \end{bmatrix} = \begin{bmatrix} v_{11} & \cdots & v_{1N} \\ \vdots & \ddots & \vdots \\ v_{L1} & \cdots & v_{LN} \end{bmatrix}. \tag{18}$$

Let x be the pattern whose MF to the class must be computed, the MF can be represented as:

$$\mu(\mathrm{X}) = \sum_{i=1}^{L} \max\left[0,1 - \frac{\gamma}{\delta} d_2(x, v_i)\right], \tag{19}$$

where $d_2(x, v_i)$, i=1…L, is the pattern-to-i^{th}-point Euclidean distance and δ is the maximum distance that can occur between the two patterns. This value can be determined simply based on the total number of features using the following expression:

$$\delta = \sqrt{N}. \tag{20}$$

An example of cone-based MF is illustrated in Figure 6-1. It is based on a toy example with a single class composed of 12 randomly generated patterns. The graphical representation of the MF is obtained by taking the summation of the 12 overlapped kernel functions constructed over each pattern within the class. The MF is normalized within a range from 0 to 1.

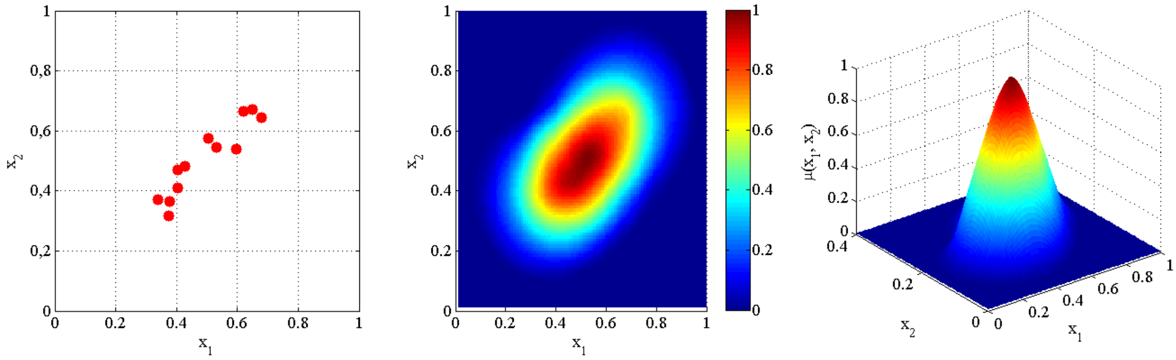


Figure 6-1: MF computation for a simple 2-D example, cone-shaped kernels are placed at each point within the class

6.2.2 PROPOSED FUZZY CLASSIFIER

The design of the proposed fuzzy classifier is presented in Figure 6-2. After acquiring the normalized input dataset, a label vector L vector for any pattern x, is evaluated as:

$$\mathrm{L} = [\mu_1(\mathrm{x}), \mu_2(\mathrm{x}), \ldots, \mu_K(\mathrm{x})]. \tag{21}$$

where the k^{th} element of L represents the fuzzy MF of the pattern to the k^{th} class. The fuzzified input is then directly passed to a Winner-Takes-All (WTA) process for decision-making and the corresponding crisp label of the largest value in the L vector will be chosen as classification for pattern x.

The original data pool is first divided into training and validation sets for determining the optimal parameters for the model learning. By applying the aforementioned method in equation (19), the proposed classifier can then establish a set of fuzzy MFs to classify input patterns to the corresponding Brunnstrom level. The γ is the only parameter that is required to be optimized in the training phase. It defines the skewness of the MF: the greater the value of γ, the faster the function falls to zero as the distance increases, and vice versa, as revealed in Figure 6-3. The optimization process is critical for achieving the best estimation of the clusters. An excessively small value might result in unwanted class overlapping while a large value may cause indeterminable clusters as the area covered by MFs will be insufficient and the degree of membership to all the known classes could be very close to zero.

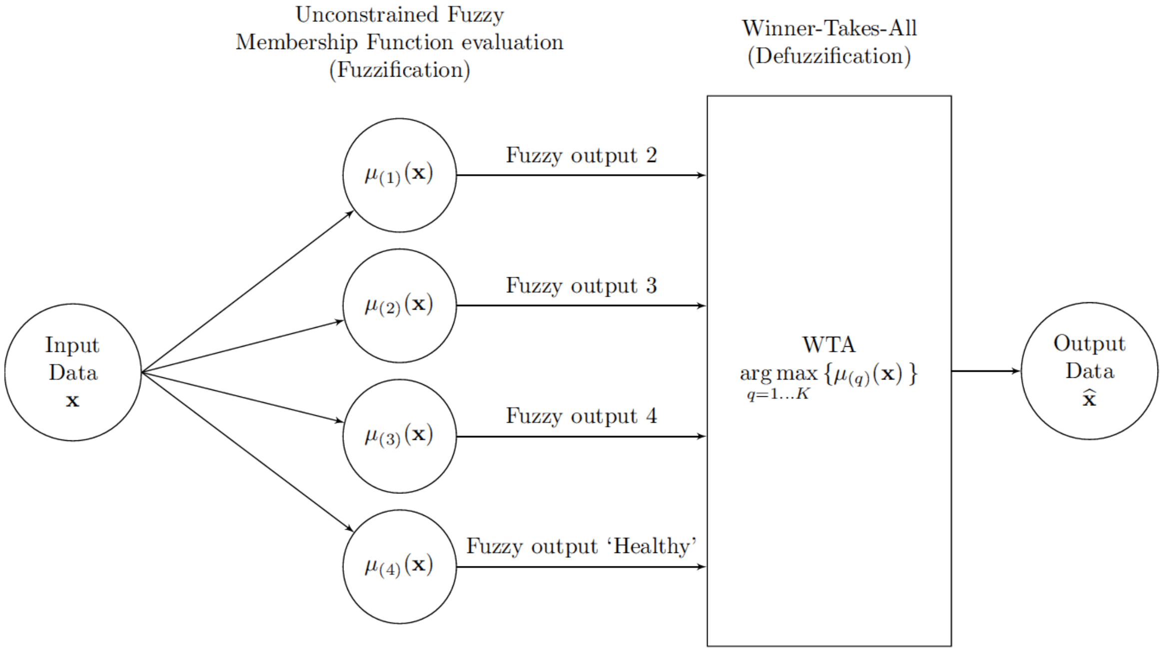


Figure 6-2: The structure of the proposed sEMG Fuzzy Classifier

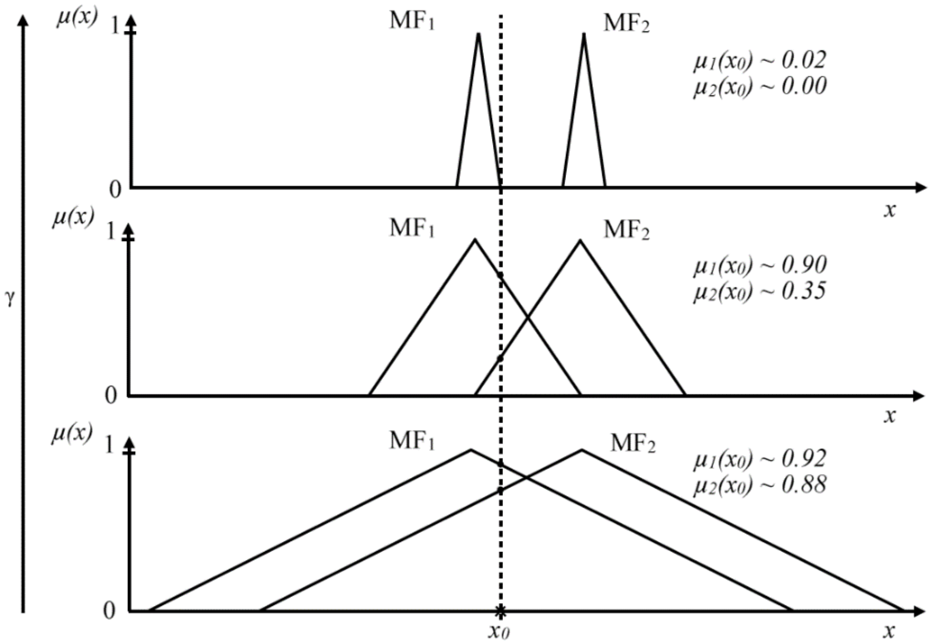


Figure 6-3: Fuzzy MF evaluation with various γ values

6.2.3 *EXPERIMENT PROTOCOL*

In order to examine the performance of the proposed system, an experiment, with data being sampled from actual stroke patients, has been conducted. The sEMG data samples are collected from the stroke patients in the Jiaxing 2nd hospital rehabilitation centre, Zhejiang, China. The data access and experiments have been approved by the ethic committees of RMIT University and Jiaxing 2nd hospital. Nine stroke patients (three males, six females, mean age 67.2 ± 29.2) with various level of body function impairment (Brunnstrom stage II to IV) have participated the experiment. The patient subjects were verified to be within the phase of stroke recovery using Computer Tomography (CT) or Magnetic Resonance Imaging (MRI). In order to meet safety and ethics requirements, the following inclusion criteria were imposed:

1. No hemodynamic instability;
2. No severe cognitive impairments;
3. No dementia;
4. No major post-stroke complication;
5. Able and willing to give consent.

Although sEMG based approach can effectively detect voluntary motion intention for stroke patients even at very early stage of recovery, no stage I patients were involved in the experiment due to unstable condition and high risk of complications. All patient subjects were examined by an expert panel for Brunnstrom stages prior to the sampling experiment. The panel members were selected from rehabilitation doctors who have:

1. Extensive clinical experience with stroke patients and stroke rehabilitation;
2. Experience in conducting stroke rehabilitation related medical research.

Overall, 93 sEMG data have been collected using a Noraxon TeleMyo DTS 2400 system with Ag/AgCl surface electrodes and a sampling rate of 3kHz. An arm abduction and adduction movement were used during the sampling experiment, and the sEMG data were sampled from middle deltoid muscle. The movement starts with both arms being relaxed at side of the body with fingers pointing down naturally. The patient then smoothly raises the arm which is sampled sideways to reach the maximum angle possible before slowly lowering it back to the starting position and getting ready for the next repetition. At the beginning of the data sampling process, the experiment procedure and involved exercise movements are first explained to the participating patients. Enough time was given to the patients for practice and rest before the actual sEMG sampling. The surface electrodes were placed on the muscle belly with an interval of 2cm. The reference electrode is placed at a spot where no muscle activation can be detected during the movement. The skin surface was prepared with gauze and alcohol to remove dead skins and also to clean the excess oils before electrodes placement. During each recording, no more than five repetitions of the movement are performed by each patient to reduce the influence of muscle fatigue which may significantly affect the sample quality for early recovery stage or elderly patients. The sampling process was repeated between 2 to 3 times for each patient with new electrodes and re-initialized setup which gives the patients enough time to rest and also introduces variability such as the change in skin impedance. The sEMG data were collected from patients' limbs on both the affected and the healthy side of the body for comparison.

6.2.4 Feature Extraction

The surface EMG signals sampled at 3kHz were first fed through a 10^{th} order digital ellipse bandpass filter with a passband from 20 to 500Hz and 30dB attenuation on stop-bands for noise reduction. The filtered samples were also rectified for activation detection using Root-Mean-Square (RMS) method with a sliding Hamming window as presented below.

Let x be the filtered EMG input signal and s be the rectified output signal. The rectification process can be written as:

$$s(\mathrm{n}) = \sqrt{\frac{1}{L}\sum_{k=n}^{n+L-1}(x(k)\,w(k))^2}, 1 \leq \mathrm{n} \leq \mathrm{N} \qquad (22)$$

where N is the number of windowed segments, L is the window length, w(k) is the Hamming window function defined as:

$$w(k) = 0.54 - 0.46\cos\left(2\pi\frac{k}{M-1}\right), 1 \leq k < L \tag{23}$$

The muscle activations were then automatically localized by setting a threshold in relation to signal magnitude. The segmentation process of a sEMG signal sampled from a stage-3 patient is illustrated in Figure 6-4. It can be seen that rectangular windows are applied over the detected movement onsets. The window length is calculated to be 20% larger than the activation period determined by an amplitude threshold to cover the complete movement. The activation periods which are too close to the beginning or the end of the sample sequences are disposed to avoid the inclusion of unintended or incomplete movements.

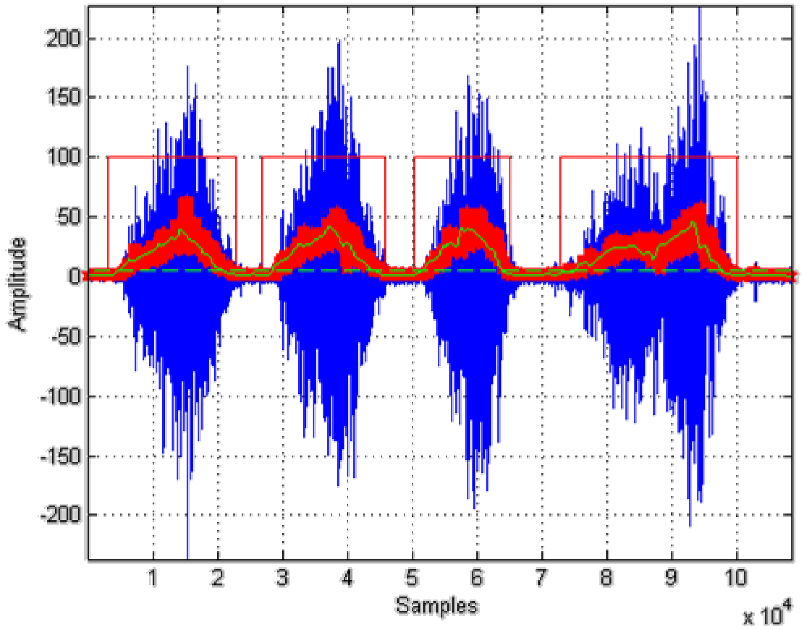


Figure 6-4: the segmentation of the sEMG signal sampled from a stage 3 patients. The high-frequency blue waveform in the background is the original filtered sEMG signal. The slow varying green thin line is the rectified signal obtained using a 2048 points Hamming window. The horizontal dash line indicates the amplitude threshold for activation detection which is set to be 40% of the signal median. The red rectangular are the windows for signal segmentation.

Ten features on both time and frequency domain were extracted from the segmented sEMG samples before classification. The details of each feature are presented below:

- **Maximum Amplitude**: The maximum amplitude reached in the rectified signal.
- **Mean Amplitude**: The mean amplitude of the rectified signal.
- **Activation duration**: The length of data segment which represents the duration of the muscle activation as illustrated in fig?
- **Signal Energy**: The energy estimated using Teager Kaiser Energy Operator (TKEO) during muscle activation. The TKEO in discrete form is given in [252, 253] as:

$$\psi[x(n)] = x(n)^2 - x(n+1)x(n-1) \tag{24}$$

where x(n) is the sEMG data sequence. The signal energy can then be calculated as:

$$\text{ENE} = \sum_{n=1}^{N} \psi[x(n)] \tag{25}$$

- **Maximum changing rate**: the peak value in the first derivative of the rectified sEMG signal
- **The 2nd and 3rd Linear Prediction Coefficient (LPC)**: The 2nd and 3rd LPC are computed by constructing a 2nd order forward linear predictor of the sEMG sample signal and minimizing the prediction error with least-squares method using the ‘lpc’ function in MATLAB.
- **Average Zero Crossing (ZC) rate**: the ZC rate is calculated by counting the zero crossing events of the original sEMG signal within a window which is defined as:

$$\text{C(n)} = \frac{1}{L}\sum_{k=n}^{n+L-1} sgn(x(k)x(k+1)) \tag{26}$$

where L is the window length and x is the original sEMG signal. The average ZC rate is computed as:

$$\text{AZC} = \frac{1}{N}\sum_{n=1}^{N} C(n) \tag{27}$$

- **Mean Power Frequency (MPF):** The MPF is the centroid frequency of the signal power spectrum defined as:

$$\text{MPF} = \frac{\sum_{n=1}^{N} P(n)f(n)}{\sum_{n=1}^{N} P(n)} \tag{28}$$

Where P is the power spectrum estimated using Welch's modified periodogram method and f is the normalized frequency vector.

- **Median Frequency:** Median Frequency is the frequency which divides the sEMG power spectrum into two equal portions with same accumulated power. It can be defined as:

$$\sum_{n=1}^{MF} P(n) = \sum_{n=MF}^{N} P(n) = \frac{1}{2}\sum_{n=1}^{N} P(n) \tag{29}$$

6.3 RESULT AND DISCUSSION

The dataset used is a M × N matrix, where M = 93 is the number of the motions performed by 9 patients with various level of body function impairment (Brunnstrom stage II to IV) and N = 10 is the number of data features. Table 6-1 shows the labels used as output in the classification stage.

The extracted features are first tested against Brunnstrom stages of recovery to investigate the correlation between sEMG signal attributes and the progression of post-stroke recovery. Different evaluation methods including InfoGain, ReliefF and Pearson correlation coefficient are adopted in order to analyse the contribution, correlation strength and statistical significance of the selected features. InfoGain measures the contribution of each feature in terms of the information gain with respect to the labels. It is evaluated by subtracting joint entropy of the feature and class from the entropy of the feature. On the other hand, ReliefF [254] can examine how relevant the features are to the classification problem by implementing an instance based nearest neighbour search. The labels of randomly selected samples are compared to the samples nearby and a large number of neighbours with different labels on a single axis can indicate an irrelevant feature. The Pearson correlation coefficients [255] and the p-values are also calculated to demonstrate the strength and the significance of the correlation between the features and the Brunnstrom stages. The complete result is shown in Table 6-1. InfoGain and ReliefF are implemented using WEKA data mining workbench and the result listed is the ranker output.

By comparing the results, it can be seen that most of features are strongly correlated to the Brunnstrom stages especially amplitude, changing rate and frequency domain features. Some of the results are visualized in Figure 6-5 and Figure 6-6. Mean amplitude and Median frequency both exhibit strong correlation with the recovery progress and contribute significant information gain which can benefit the classification performance. As depicted in Figure 6-5, the sEMG samples from paretic and non-paretic group can almost be separated using only the two features and the overlapping is relatively mild. It can be observed that the signal sampled from unaffected limb usually has higher median frequency and stronger average amplitude. The strong linear correlation between median frequency and Brunnstrom stages is also demonstrated in Figure 6-6. As a result, the classification of stroke impaired and unaffected samples as performed in [256], [257] can be achieved with sEMG features without too much difficulty. However, the automatic classification of stroke patients at different impairment level or recovery stage has significantly greater value than the binary classification of healthy and stroke impaired subjects which is obvious and unnecessary in most clinical settings. Brunnstrom stage classification is comparatively more challenging and it cannot be achieved with individual features due to the noticeable class overlapping presented within the recovering stages. Therefore, in order to achieve class separation, multiple features must be combined using more sophisticated classification method.

TABLE 6-1 SEMG FEATURE COMPARISON

Feature	InfoGain	ReliefF	Pearson r	Significance
Maximum Amplitude	1.017	0.130	0.71	P<0.001
Mean Amplitude	1.201	0.149	0.73	P<0.001
Activation Duration	0.286	0.036	-0.36	P<0.001
Signal Energy	1.231	0.042	0.57	P<0.001
Maximum Changing Rate	0.677	0.117	0.73	P<0.001
2nd LPC	0.548	0.076	0.32	P<0.001
3rd LPC	0.228	0.086	-0.03	P=0.388
Average Zero Crossing Rate	0.386	0.047	0.50	P<0.001
MPF	0.652	0.091	0.60	P<0.001
Median Frequency	0.641	0.091	0.64	P<0.001

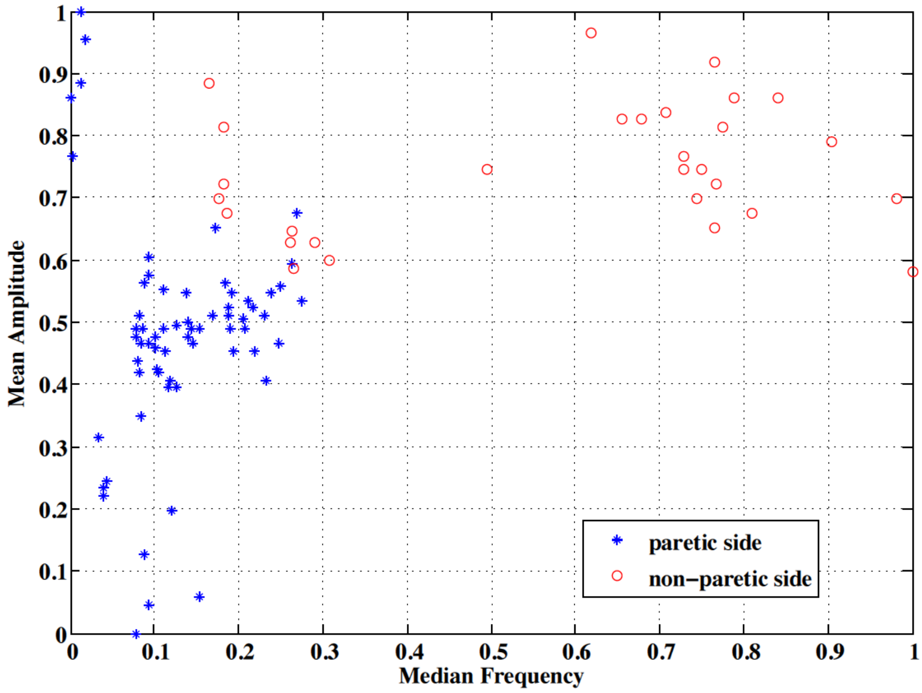


Figure 6-5: Comparison of sEMG samples from paretic and non-paretic side

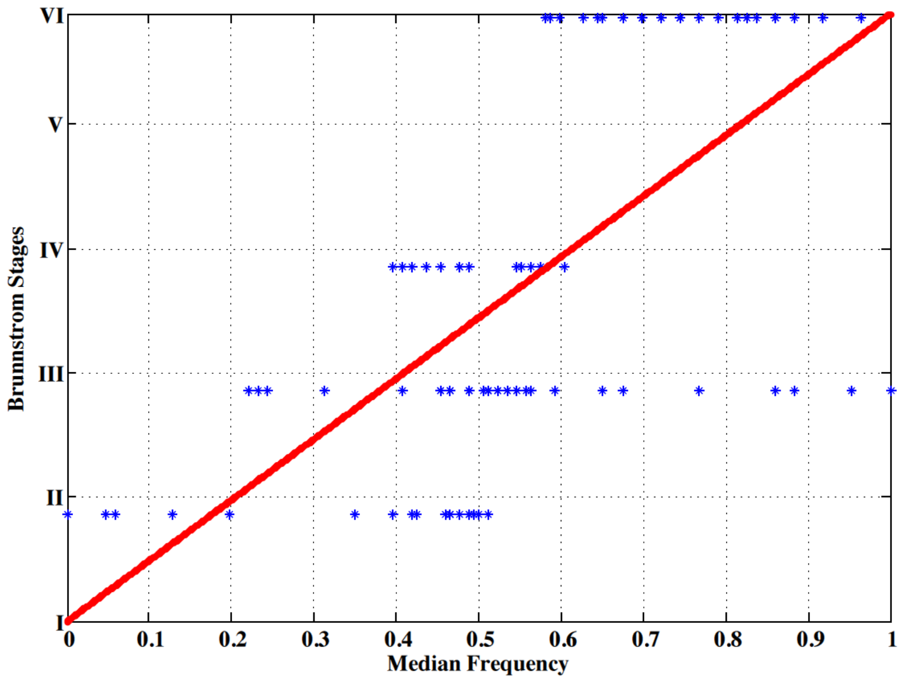


Figure 6-6: Correlation between Median Frequency and Brunnstrom stages. The linear regression is plotted using the red line.

Figure 6-7 demonstrates how the proposed fuzzy kernel classifier is tuned with cross-validation to realize accurate Brunnstrom stage classification. The learning phase has been performed by evaluating the classification error while changing the value in a computable range between 2 and 10 with a step of 0.1 as depicted in the graph. Therefore, the γ^*chosen for the testing phase is the minimum value in correspondence of the best error rate that is calculated from a suited validation set. Both 10-Fold and LOO cross-validation, have been performed to ensure the generalizability of the classifier. The performance is evaluated as the averaged accuracy, which is the number of correctly classified data divided by the total number of data in percentage, calculated for each data partition.

In order to demonstrate that the proposed method can obtain smaller error rate, different classification algorithms, trained in the Matlab™ software (version R2013a), have also been tested for comparison. They are described as follows:

- A Fuzzy Inference System (FIS) with both Mamdani [258] and Sugeno type [221] trained using the Subtractive Clustering (SUBCL) method [259] and a Neuro-Fuzzy Classifier whose parameters are adapted using the scaled conjugate gradient method [243] are included as fuzzy approaches.
- Support Vector Machine (SVM) [206] and Classification And Regression Tree (CART) [244] are included as hard/crisp approaches.
- Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) [245], Naive Bayes classifier [246] and the feedforward Probabilistic Neural Network (PNN) [247] are included as probabilistic classifiers.

TABLE 6-2 CLASSIFIER PERFORMANCE COMPAIRSON

Algorithm	Error rate for 10-Fold Test	Error rate for LOO
Proposed Fuzzy Kernel Classifier	**7.53 (±5.36)**	**8.60 (±5.70)**
FIS Classifier (Sugeno)	9.68 (±6.01)	11.83 (±6.56)
FIS Classifier (Mamdani)	9.68 (±6.01)	11.83 (±6.56)
Neuro-Fuzzy Classifier	11.83 (±6.56)	17.20 (±7.67)
LDA	30.11 (±9.32)	31.18 (±9.41)
QDA	17.20 (±7.67)	19.35 (±8.03)
Naive Bayes Classifier	24.73 (±8.77)	23.66 (±8.64)
SVM	24.73 (±8.77)	22.58 (±8.50)
CART	16.13 (±7.48)	15.05 (±7.27)
PNN	45.16 (±10.11)	46.24 (±10.13)

All the error rates are expressed in (%) with 95% confidence error bounds

In Table 6-2, the final results over the test set are shown. As expected, all the tested fuzzy methods achieve better performance compared to the others and the proposed fuzzy classifier attains the minimum error rate and the best performance in terms of accuracy. The detailed performance result of the proposed fuzzy classifier using 10-Fold cross validation is presented in Table 6-3 in the form of a confusion matrix. High single class sensitivity can be observed in stage II, III, and the healthy group. The classification of impairment level based on clinical scales using solely the sEMG is still a difficult task. Features that are targeted in Brunnstrom classification such as synergy pattern development can be hard to capture on single channel sEMG and the relatively small sample number for stage IV group may also have hindered the performance. Nevertheless, the performance of the proposed approach is highly competitive to many current state-of-art inertia or optical measurement based classification methods [166, 198, 235, 260] and it proves that, alone with kinematic and physiological inputs, single channel sEMG sampled during the dynamic exercise can also be treated as valid evidence for post-stroke impairment level classification.

TABLE 6-3 CONFUSION MATRIX FOR THE PROPOSED CLASSIFIER

		Classified Outcome					
		Stage II	Stage III	Stage IV	Healthy	Total	Accuracy
Actual Value	Stage II	17	0	1	0	18	94.44%
	Stage III	0	30	2	0	32	93.75%
	Stage IV	3	0	11	0	14	78.57%
	Healthy	0	0	1	28	29	96.55%
	Total	20	30	14	28		92.47%

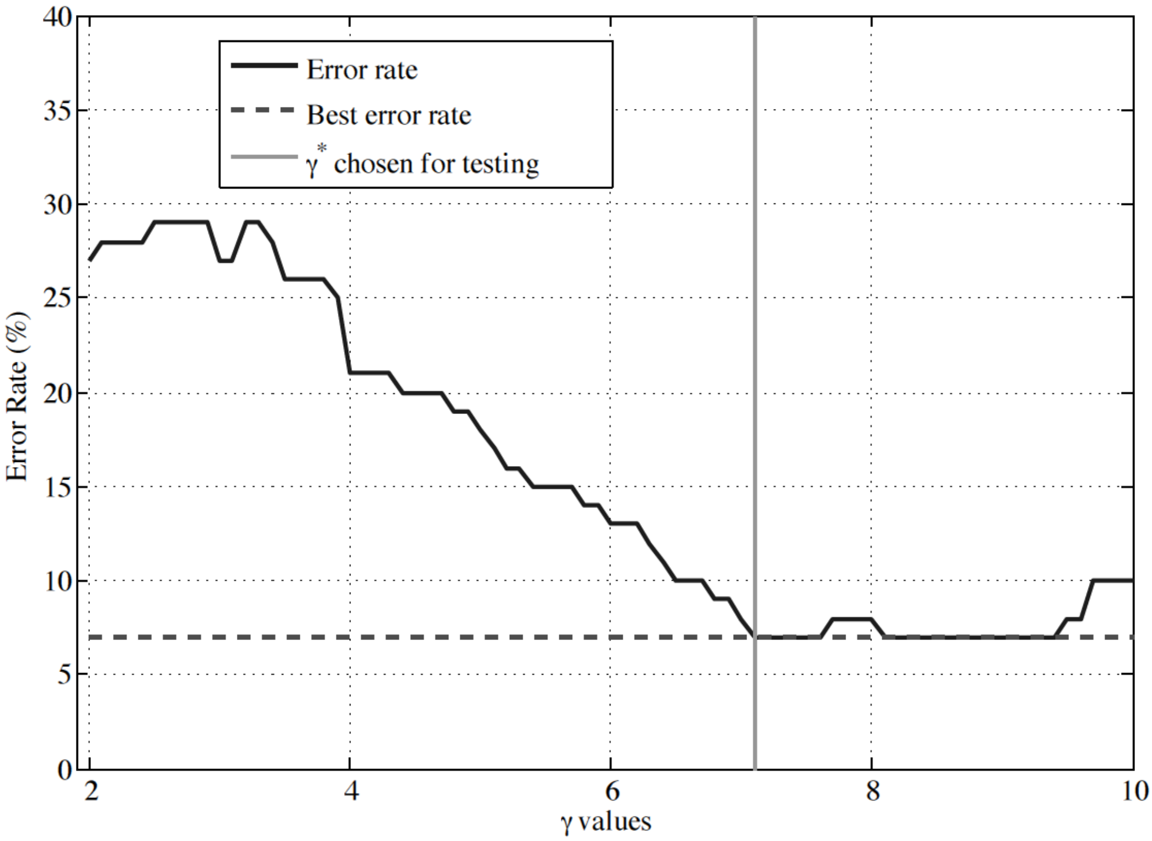


Figure 6-7: An example of the optimization process of γ^* during the validation phase.

6.4 SUMMARY

In this chapter, a novel fuzzy approach for automatic Brunnstrom classification using sEMG has been proposed. After investigating the sEMG data on time and frequency domain, a strong correlation between the extracted features and the stroke patients' recovery progress has been be observed. By implementing specifically designed fuzzy kernel classifier, the system is capable of automatically performing objective and reliable assessment of stroke patients' motor impairment and produces highly accurate classification outcomes that agree with human expert's decision as demonstrated in the experimental results. The automatic classification system can be integrated into post-stroke rehabilitation training programs to reduce the human effort involved in the repetitive clinical assessment especially in a training environment with reduced supervision, such as committee or home-based rehabilitation programs. The objective process can also serve as a supplementary evidence for human observation based assessment and as a help to create unified evaluation standards for more reliable data comparison across different institutions.

Chapter 7

CONCLUSION AND FUTURE WORKS

7.1 OVERVIEW

The primary objective of this investigation is to research on novel wearable sensor-based approaches that can offer automatic assessment and supervision in post-stroke rehabilitation training applications. The research presented in this thesis mainly focuses on addressing the existing issues of the conventional rehabilitation systems:

1. **Subjectiveness**: The conventional manual assessment methods rely heavily on the experience of the assessor and the evaluation standards can differ significantly among different institutes or regions. As a result, the reliability and consistency of the assessment result are compromised.
2. **Insensitivity**: Many popular clinical assessment scales are based on nominal or ordinal measurement which is not able to capture the relative degree of difference between two grades. Therefore, such systems cannot be used to detect minor progressive changes of patient's body function during rehabilitation program.
3. **Inefficiency**: Due to the dependencies of human supervision, conventional rehabilitation programs can be very labour intensive. This disadvantage not only increases the amount of financial cost and occupied resources but also hinders the development of home and community-based rehabilitation systems.

In order to optimize the efficiency and effectiveness, different combination of techniques was implemented to provide solutions for various tasks in rehabilitation programs. While taking unsupervised rehabilitation settings into consideration, the solutions are developed to be inexpensive to perform both financially and computationally. The highlights of the research findings will be summarized in the next section.

7.2 Major Research Findings

The study discussed in this thesis can be summarized into the following four major findings:

- **Stroke patients' impairment level measured in Brunnstrom stages of recovery can be automatically classified using kinematic data that are collected by wearable sensors.**

  As discussed in **Chapter 3**, a fuzzy inference system based automatic Brunnstrom stage classification method was developed for upper-limb rehabilitation. The classifier utilizes the patient motion data sampled during rehabilitation training using two wireless IMUs. The experimental results have demonstrated that the system can produce quantified results which match rehabilitation experts' evaluation with high accuracy.

- **Stoke patient's limb mobility can be assessed quantitatively and automatically during rehabilitation training using a single-index metric system**

  As discussed in **Chapter 4**, a novel single index based metric system for limb mobility evaluation during post-stroke rehabilitation training was developed. The mobility index generated can serve as an intuitive feedback to facilitate rehabilitation training and also provide objective and reliable evidence for setting individualized training prescription. The strong correlation with Brunnstrom stage of recovery and high accuracy when used as classifier input have both indicated its potential as a unified scale for body function impairment level assessment.

- **The post-stroke rehabilitation training session can be supervised using an automatic motion classifier system which can accurately differentiate rehabilitation training motions**

  As discussed in **Chapter 5**, a fuzzy kernel motion classifier for unsupervised post-stroke rehabilitation training was developed. The system utilizes only single IMU input and is capable of classifying predefined upper-limb rehabilitation training movements accurately and efficiently even when the movements were performed poorly or inconsistently. The experimental results have demonstrated that the proposed system can provide reliable results to facilitate other unsupervised training features such as automatic impairment classification and limb mobility assessment.

- **The patient's motor impairment level can also be evaluated by using a single channel sEMG that is sampled during rehabilitation training exercise.**

  As discussed in **Chapter 6**, the relationship between the single channel sEMG signal sampled from middle deltoid muscle during shoulder training exercise and stroke patient's impairment level measured in Brunnstrom stage of recovery was investigated. In order to automatically evaluate stroke-induced motor impairment, various sEMG features in both time and frequency domain had been studied and a specifically designed fuzzy kernel classifier was developed to tackle the challenges in discriminating data classes with complex separating surfaces. The experimental results have demonstrated that the sEMG based method can produce very competitive classification outcome that can facilitate unsupervised rehabilitation training.

The significance of the work presented in this thesis can be summarised as follow:

- The quantitative mobility evaluation system can realize unified impairment level classification by providing reliable, consistent and quantitative evaluation of stroke patient's limb mobility.
- The automatic impairment classification process can significantly reduce the human efforts involved in repetitive clinical assessments.
- The mobility index proposed for limb-mobility assessment is more sensitive to fine changes of motor functions during post-stroke recovery.
- The assessment process is designed to be implemented with routine rehabilitation training as the result can be obtained while patient performing general exercise movements.
- The computerized process and the quantitative output can be easily integrated with health informatics systems to facilitate customized training programs or rehabilitation medicine research

- The low cost, low operation complexity design is suitable for home or community-based rehabilitation training programs
- The motion assessment feature can provide real-time feedback based on patient's motion quality during a training session which encourages patients to dedicate more effort and thus achieve better training outcome.

7.3 FUTURE WORK

The primary objective of this research is to utilize the advantages of wearable sensor technology and to search for a solution to replace the conventional inefficient, insensitive and subjective clinical assessment process used in the current rehabilitation systems. To reach the answer, a number of challenges must be overcome first. In this section, the path of investigation throughout the candidate's Ph.D research is reviewed and the possible future development is then discussed.

First of all, before researching for a new assessment approach, an established clinical scale must be chosen as a benchmark to ensure that the concurrent validity of any new system can be demonstrated by showing its accordance with the widely recognised standard. The conventional clinical scales are created to suit experience-based human decision maker rather than objective classification machines. Therefore, the selection process must consider if the scale matches the characteristic of automatic assessment system in addition to the reliability and popularity. In wearable sensor based systems, the subjectivity and the variability of the user are already minimized, and the high efficiency and quantitative property should be fully utilized to improve assessment frequency and sensitivity. Popular scales such as BI is known for high internal reliability and repeatability. However, it can be reliably assessed by taking quick query and it is designed to examine patients' independence and their ability to perform ADL rather than motor function. Therefore, wearable sensor based systems do not have significant advantage over human observer. The comprehensive scales such as ICF and NIHSS both includes multiple items for motor impairment assessment. However, these scales are developed with maximized reliability to be used in multi-centre clinical trials and thus only minimum number of grades for each item is allowed: an approach to avoid interrater variability and human errors at the cost of sensitivity. In the research presented in this thesis, Brunnstrom Stage of Recovery, a six-stage scale which models the sequential development of post-stroke motor function recovery, is chosen as the benchmark. The advantage of choosing Brunnstrom approach is that it puts an emphasis on limb mobility features that can be conveniently captured using IMU or sEMG based wearable sensors. The multi-grade structure also provides relatively high sensitivity, and the clearly defined assessment criteria can benefit from the quantitative assessment supported by the wearable sensors.

Compared to the other generic body function scales, Brunnstrom stages of recovery is specialised in motor function impairment evaluation and specific motor function characteristics are clearly defined for each stages. Therefore, the design of the classification system must follow these features in order to ensure the validity and the efficiency. A two-IMU design that samples the upper arm and the forearm movement separately was proposed for the aforementioned reason. In addition to capturing the magnitude and speed, the two sensor design has the advantage of being able to record the elbow joint flexibility and the ratio of synergy motions which are key features defined in Brunnstrom approach. The expected result was validated in the PCA test as the obvious trends of motor function recovery can be observed on the principal components. The features representing motion magnitude and synergy movement are captured by the 1st and 2nd principal components respectively. A transition pattern can also be observed where the samples with the less synergy movement and averaged motion magnitude usually have a higher Brunnstrom stage. By implementing ANFIS, the pattern is formulated into fuzzy if-then rules and applied as Brunnstrom stage classifier which its validity was further proven in a LOO cross-validation test.

By successfully creating an automatic system for Brunnstrom stage classification, it has been proven that the idea of using motion sensing wearable sensor to assess upper-limb motor function is valid. However, as mentioned previously, the conventional clinical scales are subject to limitations of human observation based evaluation method. Despite having more variability than other scales, Brunnstrom stages are still not sensitive enough to track small development of motor function taken place in daily rehabilitation training. To fully extend the advantage of quantitative assessment and enables highly sensitive feedback which can support rehabilitation training and decision-making, a single-index based metric system for limb mobility assessment is proposed. The new index is normalized to a range of 0 to 1 where 1 indicates perfect motion quality and it provides an intuitive representation of patient’s motion quality and mobility limitation. While the proposed index can reflect much more detailed variations in limb motor function than conventional scales, the validity of the index is guaranteed by its strong correlation with Brunnstrom stages of recovery.

The proposed Brunnstrom stage classifier and limb mobility metric system are both automatic processes which are designed to be implemented with minimal human supervision. However, the correct operation of both design require the motion samples of a specific pre-defined movement and this requirement cannot be guaranteed in an unsupervised environment as random motions from the user can appear during the sampling time. Therefore, to make the first two solutions work, a reliable patient motion identification system is required. Compared to clinical assessment, the patient monitoring applications possess a different set of requirements including much higher classification accuracy and faster processing speed. In chapter 5, a fuzzy classifier based approach was proposed and it was capable of identifying six different predefined exercise movement with near perfect accuracy using the measurement from only a single IMU.

In summary, the intention of this research is to explore the possibility of using current wearable sensor technology to transform the conventional form of clinical assessment. The outcome of the investigations suggest that wearable technology can contribute significantly to TR systems and rehabilitation programs in general by enabling the automatic and objective clinical assessment and the unobtrusive patient supervision. It is expected in the future that by introducing the automatic approaches, the post-stroke motor function assessments can be made more accessible and efficient so that more patients can benefit from highly individualized rehabilitation interventions including those who train at home or community rehabilitation centre. The new assessment process can also enable a new generation of clinical scale which has unified assessment criteria to ensure high reliability for data comparison and multi-centre research without having to reduce the sensitivity, which is important to track short term progress and optimize intervention.

A number of ideas on how future studies can be conducted based on the research findings acquired from this research are presented below:

- **Developing automatic impairment classification techniques for various popular clinical scales.**

  A large number of stroke assessment scales are currently used around the globe. Depending on the local regulation and the focused area, different assessment scales may be preferred by different institutions and multiple scales may be used at the same time. Therefore, it can be beneficial to modify the current systems to comply with various assessment scales and standards.

- **Developing automatic impairment classification techniques for lower-limb exercise and gait analysis.**

  The lower limb functioning also has considerable influence on stroke patient's life quality. While different feature extraction strategies may be required, similar design and experiment approaches may be implemented to develop the impairment classification and limb mobility assessment systems for lower body movements.

- **Designing a comprehensive post-stroke telerehabilitation system that integrates automatic assessment and supervision using multichannel hybrid inputs.**

  By combining the techniques developed in this study, an unsupervised post-rehabilitation training system can be developed to support home or community-based rehabilitation training. Multi-channel kinematic and physiological signals can be integrated to further improve the classification accuracy. For clinical implementation, an information management system and integrated user interface will also be required. The objective of the study will be testing the efficacy of the system against the conventional training systems in a long-term clinical evaluation.

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