EMG Denoising and Feature Optimization for Forearm Movement Classification

Angkoon Phinyomark

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Author Mr.Angkoon Phinyomark
Major Program Electrical Engineering

Major Advisor :

....
(Assoc.Prof. Dr. Chusak Limsakul)

Co-advisor :

....
(Asst.Prof. Dr. Pornchai Phukpattaranont)

Examining Committee :

....Chairperson
(Assoc.Prof. Dr. Montri Karnjanadecha)

....
(Assoc.Prof. Dr. Chusak Limsakul)

....
(Asst.Prof. Dr. Pornchai Phukpattaranont)

....
(Assoc.Prof. Dr. Chuchart Pintavirooj)

The Graduate School, Prince of Songkla University, has approved this thesis as partial fulfillment of the requirements for the Doctor of Philosophy Degree in Electrical Engineering.

....
(Prof. Dr. Amornrat Phongdara)
Dean of Graduate School

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Author Mr.Angkoon Phinyomark
Major Program Electrical Engineering
Academic Year 2011

ABSTRACT

Surface electromyography (sEMG) signal is one of the most significant biomedical signals that are widely applied in both medical and engineering applications. As many disabled and elder people have difficulty accessing current assistive devices which have a traditional user interface, such as joysticks and keyboards, more advanced hands-free human-machine interfaces (HMIs) are necessary. The study presented in this thesis was aimed to use the sEMG signals during upper-limb movements from the forearm muscles for the control of assistive devices, as known the multifunction myoelectric control system. Four main components have been more carefully considered. Firstly, pre-processing stage based on wavelet denoising algorithms was evaluated and the optimal parameters were presented. The system with this pre-processing stage improved both classification accuracy and robustness. Secondly, existing EMG feature extraction methods were evaluated and new EMG features based on fractal analysis were proposed. The optimal feature vector which consists of time-domain features i.e. Willison amplitude, waveform length and root mean square, as well as fractal features i.e. detrended fluctuation analysis and critical exponent analysis was suggested. Thirdly, the use of extended versions of linear discriminant analysis (LDA) method i.e. uncorrelated LDA, orthogonal LDA and orthogonal fuzzy neighborhood discriminant analysis were not only reducing the computational time but also increasing the accuracy of the system. Finally, the LDA classifier was used due to a robustness property. In this study, the proposed systems not only improve the classification accuracy but also increase the robustness and decrease the complexity. The major applications of the proposed systems are prosthesis and electric power wheelchair. Recent and future trends of both applications have also been presented.

ชื่อวิทยานิพนธ์	การลดสัญญาณรบกวนในสัญญาณไฟฟ้ากล้ามเนื้อ และการหาลักษณะเด่นที่เหมาะสม สำหรับการจำแนกรูปแบบการเคลื่อนไหวของแขนท่อนล่าง
ผู้เขียน	นายอังกูร ภิญโญมารค
สาขาวิชา	วิศวกรรมไฟฟ้า
ปีการศึกษา	2554

บทคัดย่อ

สัญญาณไฟฟ้ากล้ามเนื้อชนิดพื้นผิว เป็นหนึ่งในสัญญาณทางชีวการแพทย์ที่สำคัญ ซึ่งถูกนำไปประยุกต์ใช้อย่างแพร่หลายทั้งทางด้านการแพทย์และวิศวกรรม เนื่องจากการใช้งานอุปกรณ์ช่วยเหลือของผู้พิการและผู้สูงอายุ โดยการใช้ส่วนเชื่อมต่อแบบเดิม เช่น คันบังคับและแป้นพิมพ์ มีความยากลำบาก ดังนั้นส่วนเชื่อมต่อระหว่างอุปกรณ์กับผู้ใช้ที่มีประสิทธิภาพและง่ายจึงมีความจำเป็น การศึกษานี้มีวัตถุประสงค์ในการประยุกต์ใช้สัญญาณไฟฟ้ากล้ามเนื้อชนิดพื้นผิว จากกล้ามเนื้อแขนท่อนล่าง ในท่าทางการเคลื่อนไหวแขน เพื่อควบคุมอุปกรณ์ช่วยเหลือ หรือที่เรียกว่า ระบบควบคุมที่ใช้สัญญาณไฟฟ้ากล้ามเนื้อหลายฟังก์ชัน โดย 4 องค์ประกอบหลักที่สำคัญของระบบควบคุมดังกล่าวถูกศึกษา ซึ่งประกอบด้วย (1) ขั้นตอนการประมวลผลเบื้องต้น โดยการกำจัดสัญญาณรบกวนด้วยวิธีการเวฟเล็ต ซึ่งพารามิเตอร์ที่เหมาะสมได้ถูกนำเสนอ จากผลการทดลองพบว่า ระบบควบคุมซึ่งมีการประมวลผลเบื้องต้น สามารถปรับปรุงประสิทธิภาพของระบบ ทั้งด้านความแม่นยำและการทนต่อสัญญาณรบกวน (2) วิธีการคัดเลือกลักษณะเด่นของสัญญาณไฟฟ้ากล้ามเนื้อที่มีการใช้งานอยู่ ได้ถูกนำมาประเมินหาวิธีที่เหมาะสมที่สุด และมีการนำเสนอวิธีการคัดเลือกลักษณะเด่นของสัญญาณวิธีใหม่ โดยการใช้การวิเคราะห์แฟลกทัล จากผลการทดลอง ได้มีการแนะนำวิธีการคัดเลือกลักษณะเด่นที่เหมาะสม ซึ่งประกอบด้วย วิธีการในโดเมนเวลา เช่น วิธีการหาแอมพลิจูดของวิลลิสัน วิธีการหาค่าความยาวของรูปแบบคลื่น วิธีการหาค่ารากของค่าเฉลี่ยกำลังสองของสัญญาณ และวิธีการแบบแฟลกทัล เช่น วิธีการวิเคราะห์ความแปรปรวนด้วยการกำจัดแนวโน้ม วิธีการวิเคราะห์หาค่ายกกำลังของจุดวิกฤต (3) การลดขนาดของข้อมูลด้วยวิธีการประยุกต์ของการวิเคราะห์การจำแนกแบบเชิงเส้น ถูกแนะนำให้ใช้กับระบบ เช่น วิธีการประยุกต์แบบตั้งฉาก วิธีการประยุกต์แบบไม่มีความสัมพันธ์ โดยนอกจากจะลดเวลาในการคำนวณลงแล้ว ยังสามารถเพิ่มความแม่นยำของระบบด้วย (4) ตัวจำแนกด้วยวิธีการวิเคราะห์การจำแนกแบบเชิงเส้น ถูกนำมาใช้ เนื่องจากคุณสมบัติการทนต่อสัญญาณรบกวน กล่าวโดยสรุป ระบบควบคุมที่ใช้สัญญาณไฟฟ้ากล้ามเนื้อหลายฟังก์ชันในการศึกษานี้ ได้ปรับปรุงทั้งเรื่องของความแม่นยำในการคัดแยก การทนต่อสัญญาณรบกวน และความซับซ้อนของระบบ ซึ่ง

สามารถนำไปการประยุกต์ได้หลักๆ กับ 2 อุปกรณ์ คือ อวัยวะเทียม และรถเข็นไฟฟ้า โดยที่แนวโน้มของการพัฒนาอุปกรณ์ทั้งสองได้ถูกนำเสนอด้วยในรายงานฉบับนี้

CONTENTS

CONTENTS (CONT.)

CONTENTS (CONT.)

LIST OF FIGURES

LIST OF FIGURES (CONT.)

LIST OF ABBREVIATIONS

2D CC	2D cross-correlation
A/D	Analog-to-digital
ACO	Ant colony optimization
ANFIS	Adaptive neuro-fuzzy inference systems
AR	Auto-regressive coefficients

ARTMAP	Fuzzy ARTMAP neural network
BB	Biceps brachii
BPNN	Back propagation neural networks
CC	Cepstrum coefficients
CMRR	Common mode rejection ratio
ECRL	Extensor carpi radialis longus
ECU	Extensor carpi ulnaris
ED	Extensor digitorum
EDC	Extensor digitorum communis
EE	Elbow extension
EEG	Electroencephalography
EF	Elbow flexion
EOG	Electrooculography
FCNN	Fuzzy clustering neural network
FCR	Flexor carpi radialis
FCU	Flexor carpi ulnaris
FFT	Fast Fourier transform
FIS	Fuzzy inference systems
FL	Fuzzy logic-based classifier
FMMNN	Fuzzy min-max neural networks
FP, M1	Forearm pronation
FS, M2	Forearm supination
FT	Fourier transforms
GA	Genetic algorithm
GDA	Generalized discriminant analysis

LIST OF ABBREVIATIONS (CONT.)

GMM	Gaussian mixture model
GMP	Gabor matching pursuit
HC, M8	Hand close
HIST	Histograms
HMIs	Human-machine interfaces

HMM	Hidden Markov model
HO, M7	Hand open
HOS	Higher-order statistics
ICA	Independent component analysis
IEMG	Integrated EMG
KNN	*k*-nearest neighbor
LDA	Linear discriminant analysis
LVQ	Learning vector quantization
MAV	Mean absolute value
M5	Wrist radial deviation
M6	Wrist ulnar deviation
MDF	Median frequency
MMCSs	Multifunction myoelectric control systems
MNF	Mean frequency
NN	Neural networks
OFNDA	Orthogonal fuzzy neighborhood discriminant analysis
PCA	Principle component analysis
PL	Palmaris longus
PSO	Particle swarm optimization
PSD	Power spectral density
R	Rest state
RBF	Radial basis function
RC	Regression coefficients
RMS	Root mean square
SBS	Sequential backward selection

LIST OF ABBREVIATIONS (CONT.)

sEMG	Surface electromyography
SFS	Sequential forward selection
SNR	Signal-to-noise ratio
SOFM	Self-organizing feature map
SSC	Slope sign change

STFT	Short-time Fourier transforms
SVM	Support vector machines
TB	Triceps brachii
TDNN	Time-delay neural network
TE	Thumb extension
TF	Thumb flexion
TS	Tabu search
VAR	Variance
WAMP	Willison amplitude
WE, M3	Wrist extension
WF, M4	Wrist flexion
WL	Waveform length
WPT	Wavelet packet transform
WT	Wavelet transform
WVD	Wigner-Ville distribution
ZC	Zero crossing

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CHAPTER 1

Introduction

1.1 Background and Rationale

Surface electromyography (sEMG) signal is one of the most significant biomedical signals. During the last two decades, the sEMG signals are widely studied and applied in both medical and engineering applications [1, 2]. This is owing to the fact that the use of sEMG signals is very easy, fast and convenient [3]. In other words, the sEMG signals have better properties than other biomedical signals including electrooculography (EOG) signal and electroencephalography (EEG) signal by virtue of their higher signal-to-noise ratio (SNR) [4]. In control applications, the sEMG signals are known as the "myoelectric signal". Myoelectric control, hence, refers to as the process of controlling an external device by utilizing myoelectric, or sEMG, signals from the human muscles [2]. Additionally, the external devices commonly refer to as prosthesis, an electric wheelchair, a robot arm, or any other assistive and rehabilitation devices. As many disabled people have difficulty accessing current assistive and rehabilitation devices, which have a traditional user interface, such as joysticks and keyboards, more advanced hands-free human-machine interfaces (HMIs) are necessary. Hence, more attention should be paid to the development of myoelectric control.

In multifunction myoelectric control systems (MMCSs), different patterns of sEMG signals are recognized and matched with the control commands. For instance, in Fig. 1, the sEMG signals obtained from six upper-limb movements of a forearm muscle show that different patterns of sEMG signals can be observed. Normally, MMCSs consist of three main modules [2, 5]. The first module includes two sub-modules: sEMG signal acquisition and data pre-processing. The second module is an important module. Different patterns of sEMG signals are recognized and matched with the control commands in this module which is known as the pattern recognition. This module can be divided into three main sub-modules that consist of feature extraction, dimensionality reduction, and classification methods [5, 6]. The third module is a control system. It serves as an interface between software and hardware. In other words, the output commands are sent to control the

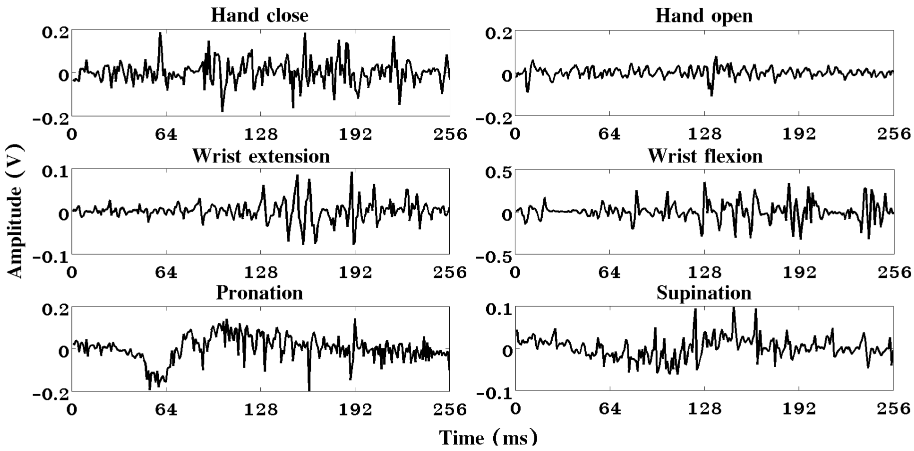


Fig. 1 SEMG signals obtained from six movements of the flexor carpi radialis muscle.

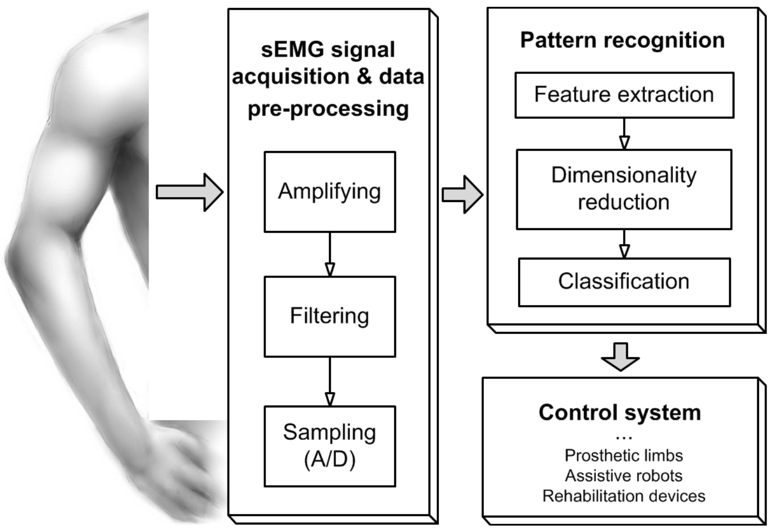


Fig. 2 The procedure of multifunction myoelectric control systems.

external devices. The procedure of all MMCS modules is shown in Fig. 2. More attention has been paid to all MMCS modules in this research. The main focus, however, is aimed to improve the performance of sEMG pattern classification, the second module. More details of all modules are described in the following.

The first module is sEMG signal acquisition and data pre-processing. The sEMG signals are acquired from surface electrodes placed over the muscles. Usually, the acquisition process is performed together with pre-processing sEMG signals in order to reduce the effect of noises and improve spectral components of sEMG signals. This module commonly consists of three significant sub-modules: amplifying, sampling, and filtering [5]. Hence, most of recent sEMG acquisition systems can conduct all three sub-modules. Due to the small amplitude of sEMG signals, firstly sEMG signals are amplified with the gain of the amplifier set normally to 60dB. After amplifying process, continuous sEMG signals are sampled using an analog-to-digital (A/D) converter. As a result, discrete sEMG signals are obtained from this process. Typically sEMG signals are sampled at 1000 Hz or 1024 Hz, due to the fact that the dominant energy of sEMG signals is concentrated in the range of 20-500 Hz [2] and the approximately double-rate requirement is a consequence of the Nyquist theorem. Subsequently, filtering sEMG signals are conducted using a band-pass filter with a high CMRR to reduce motion artifact and sEMG signal inherent instability, below 20 Hz, and other high-frequency random noises, over 500 Hz. In addition, a notch filter at 50 or 60 Hz is implemented. To this end, a discrete-time signal has already to be used in the next module, the pattern recognition.

The second module is the recognition of sEMG patterns. The different patterns of sEMG signals are classified into the control commands. This module consists of three sub-modules: feature extraction, dimensionality reduction, and classification methods [6]. However, in some systems, the second sub-module can be leapt because of the small size of a feature vector [7]. Firstly, features are extracted from raw sEMG data in order to emphasize the pertinent structures in sEMG signals and reject noises and irrelevant signal [8]. After extraction, the feature vector is formed and sent to the classifier, or the classification method. However, the increasing of feature dimensions can cause a big problem for the classifier in computation [9]; therefore, reducing the dimensions of a feature vector can be conducted by using the dimensionality reduction method, before sent it to the classifier. A reduction of computational times in the classifier is an advantage while getting the similar classification accuracy by using a few features [10].

The third module is the control systems. The control commands are generated based on the decisions in the pattern recognition module. A wide variety of potential applications have been presented during the last two decades such as prosthetic limbs, assistive robots, electric wheelchairs, and virtual interfaces [2, 3]. Additionally to improve the quality of control, post-processing and feedback are performed. A majority voting, a popular post-processing method is often applied to make a smooth output and increase the classification accuracy [10]. In addition, the low-level and high-level feedbacks are used to improve the quality of user's control and dexterity. The low-level feedback is a sensory feedback such as the obstacle avoidance and the high-level feedback is visual information such as command display [11].

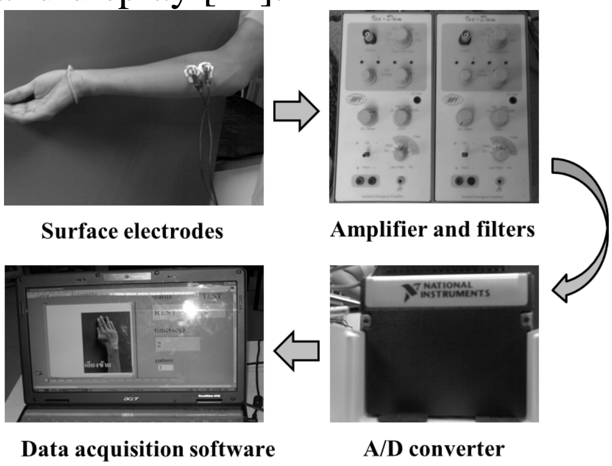


Fig. 3 SEMG signal acquisition and data pre-processing system.

1.2 Literature Review

During the past two decades, various researches have conducted in the analysis of sEMG signals for measurement and classification of human muscle movements. An extensive review of the researches during recent decades has been presented and discussed in detail, in this section, in order to clarify the state-of-the-art in MMCSs. The review covers three main modules as mentioned in the previous section.

1.2.1 EMG Signal Acquisition and Data Pre-processing

1.2.1.1 Data Acquisition

An overall process of sEMG signal acquisition and data pre-processing system is shown in Fig. 3. An overview of data acquisition and pre-processing was described in Section 1.1. In this sub-section, the recommendation and the specification of data acquisition and pre-processing from the literature are presented as the following in detail.

- Surface electrode: A number of important properties of sEMG sensors are discussed. It is very clear that a bipolar electrode configuration has been used most frequently. Monopolar and array electrodes have been reported in a few studies. Further, for the bipolar sensor configuration, it is clear that the Ag/AgCl electrode is preferred [12]. An Ag/AgCl electrode is very stable electrically; as a result, it makes a small noise. The general recommendation of electrode size and inter-electrode distance in sEMG measurement is 10 mm and 20 mm, respectively [12]. Throughout the literature, the most popular electrode size, however, is 6 mm diameter, while the most popular inter-electrode distance is 20 mm. A circular, or disc, electrode is routinely used to measure sEMG signals. Moreover, the user's skin should be thoroughly cleaned with alcohol.
- Detection mode and amplification: Two detection modes, generally, can be configured: monopolar and differential. As has been noted above that the amplitude of sEMG signals is very small and can range from 0 to 10 mV (peak-to-peak). Thus, it is necessary to amplify the sEMG signal amplitude. For the forearm muscle system, a differential amplifier with a gain of 1000 has been used often [11]. Differential amplifiers with a gain from 1000 to 5000 have been employed for the muscles on or around the shoulder [13, 14]. Normally a differential amplifier with a 60dB gain is recommended. The specification

of input impedance and common mode rejection ratio (CMRR) have been reported based on types of the sEMG instruments. To maximize its performance the amplifier must have a high input impedance and a high CMRR. Moreover, in some systems, high resolution data is sampled and converted from analog into digital data, A/D, instead of using a high gain amplifier [7].

- Sampling sEMG signals into the computer: The usable energy of sEMG signals is limited to a frequency range of 0 to 500 Hz and based on the Nyquist Theorem which states that the sampling frequency should not be less than twice the frequency of the sample [15], the minimum sampling frequency should be set at 1000 or 1024 Hz [16]. A higher sampling rate is preferred to improve both data resolution and accuracy. However, in some studies, lower rates of sampling were employed such as 128, 256, and 512 Hz [17, 18].
- Filtering of raw sEMG signals: Different kinds of noise may interfere the signal and may arise from various sources. Generally, noises in sEMG signals can be divided into four main types: inherent noise in electronic components used in detection and recording equipment, ambient noise, motion artifacts and the inherent instability of the sEMG signals [19, 20]. Noise originated from electrodes can be reduced by using Ag/AgCl electrode type. For other noises, sEMG signals are passed through a high-pass filter with a cutoff frequency of 20 Hz to remove motion artifacts and the inherent instability of the sEMG signals [21]. A low-pass filter is used to remove signals with unwanted frequencies above 450 or 500 Hz [22], and a notch filter is used to remove the ambient noise, i.e. power-line interference, which arises at the 50 or 60 Hz frequency [23].

1.2.1.2 Experiment Setup

In the experiment setup, the role of five issues including sensor location, number of sensors, movement types, number of movements, and number of participants should be

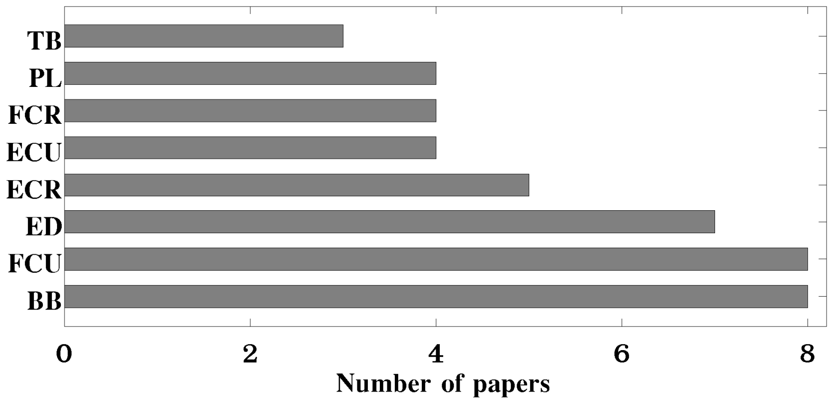


Fig. 4 The summary of sensor locations reported in the review. It should be noted that the muscles that have been used in less than three research papers are not shown in the figure.

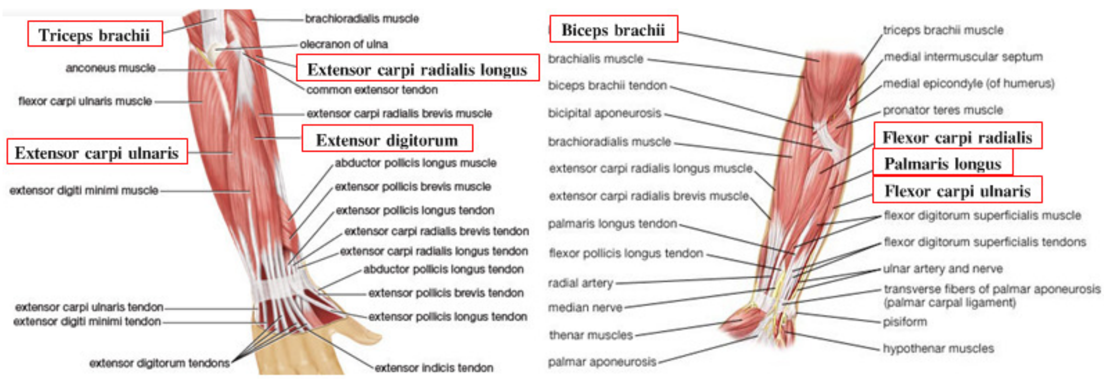


Fig. 5 The physiological representation of the upper-arm and forearm muscles [24, 25].

emphasized. Firstly, sensor location, the literature presents many different muscle locations for sensors notably on the head, forehead, face, neck, back, shoulder, upper-arm, forearm, and hand. The location is dependent on the disability of the target user. For instance, if the target user is a person with a C4 spinal cord injury, sensor locations on the hand, forearm, and upper-arm are not possible. In addition, the location is also selected based on physiology and anatomy basis. More attention, however, has been paid to human upper-limb movements. Therefore, most popular locations in the literature are forearm muscles. The summary of the sensor locations, or muscle positions, is shown in Fig. 4. From this figure, the popular upper-arm muscles are biceps brachii (BB) and triceps brachii (TB) muscles, and the popular forearm muscles are flexor carpi ulnaris (FCU), extensor digitorum (ED), extensor carpi radialis longus (ECR), extensor carpi ulnaris (ECU), flexor carpi radialis (FCR) and palmaris longus (PL) muscles. In order to obtain

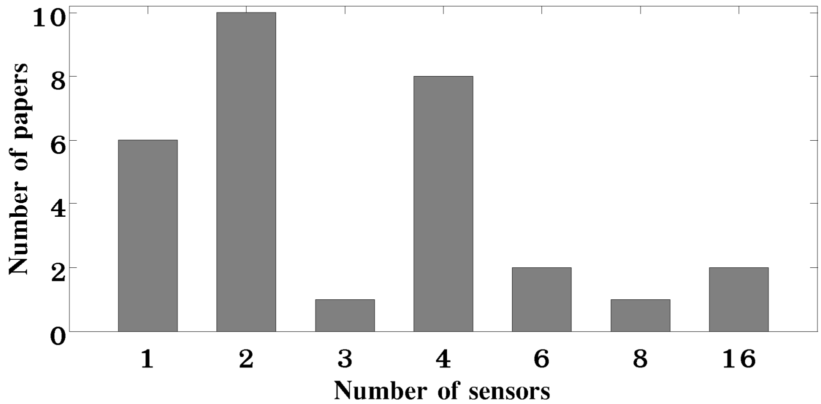


Fig. 6 The summary of the number of sensors reported in the review.

information from both flexor and extensor, the FCU and ED muscles may be useful for classifying upper-limb movements. The physiological representation of the upper-arm and forearm muscles is presented in Fig. 5. Further, reference electrodes are essential for furnishing a common reference for the differential inputs from the pre-amplifier in the sensor electrodes. To this end, the reference electrodes should be located as far away as possible from the sensors and on electrically neutral tissue. The reference electrode is usually placed on the wrist, for forearm and upper-arm locations, and other reference electrodes are placed on the neck and the middle of the forearm. It should be noted that the summary in Fig. 4 is based on sixty-one research papers [6, 8, 26-84]. In addition, Figs. 6-7 and Figs. 10-15, are also summarized from sixty-one research papers [6, 8, 26-84]. However, there are some papers originated from the same research group, in that case if the researchers implemented the same condition it will be counted only one time in a summary.

Secondly, another important issue to be considered is the number of sensors. The number of sensors is dependent on types of the application. As shown in Fig. 6, one, two, three, four, six, eight, and sixteen channels have been used. Most MMCS studies used two and four channels in basic to increase the classification accuracy. MMCSs that used more than four channels are not recommended because their computational complexity will be expensive. In MMCS, researchers have tried to reduce the number of sensors as far as possible. Therefore, a single channel is suggested to be used and developed in future studies. However, a single channel may not be complex enough and high accuracy may not be achieved in recent classification algorithm.

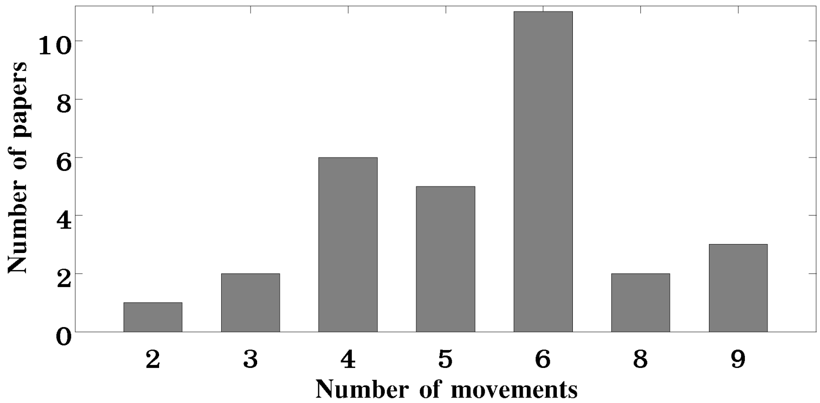


Fig. 7 The summary of the number of movements reported in the review.

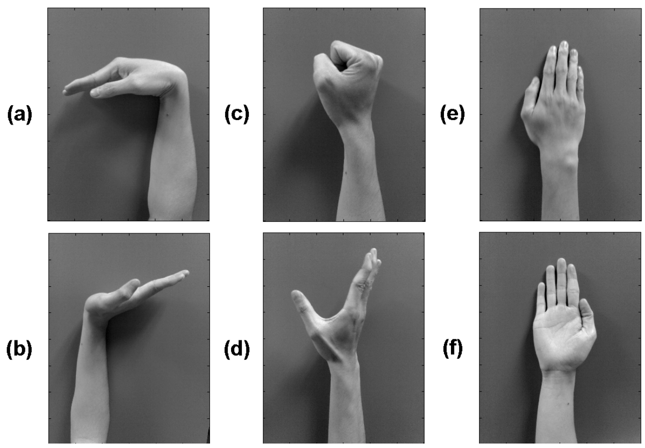


Fig. 8 Six different upper-limb movements: (a) wrist flexion, WF, (b) wrist extension, WE, (c) hand close, HC, (d) hand open, HO, (e) forearm pronation, FP, and (f) forearm supination, FS, as performed by participants [P24].

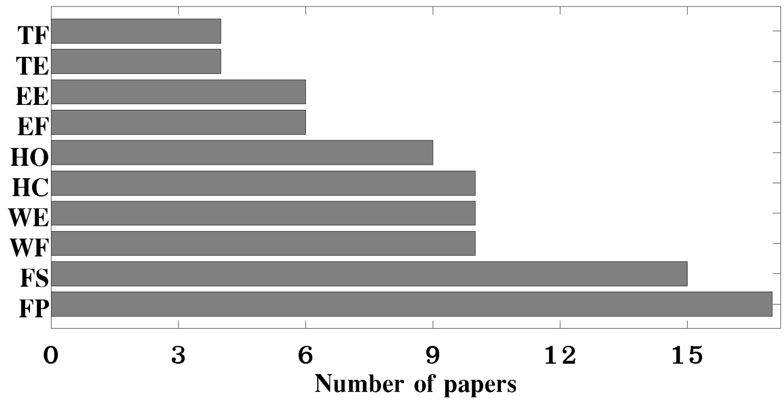


Fig. 9 The summary of movement types reported in the review. Note that TF is thumb flexion. TE is thumb extension. EE is elbow extension. EF is elbow flexion.

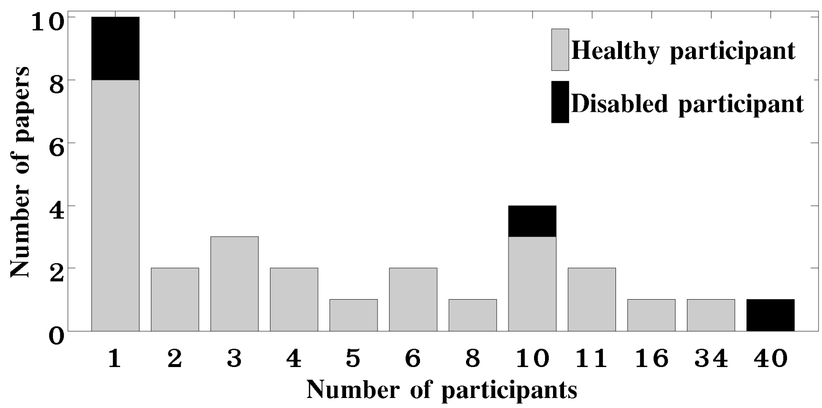


Fig. 10 The summary of the number of participants in the experiment reported in review.

The third and the fourth issues are the number of movements and movement types. The number of movements possible is directly dependent on the location and number of sensors, as discussed in two previous paragraphs, and the control commands are also directly dependent on the number of user's movements. Hence, researchers have tried to increase the number of movements. However, the classification accuracy of a high number of movements is normally less than the classification accuracy of a low number of movements. The literature records the number of movements varying from as few as one to as many as nine movements as shown in Fig. 7. The popular number of commands is six. These different upper-limb movements as shown in Fig. 8 were used as the protocol to record sEMG signals from the participant most frequently, as can be observed in Fig. 9. They consist of hand close (HC), hand open (HO), wrist extension (WE), wrist flexion (WF), forearm pronation (FP) and forearm supination (FS). In general, human movements are extension and flexion of the body joints such as thumb joint, wrist joint, and elbow joint. Other movements are open, close, pronation, supination and deviation as shown in Fig. 9. The control commands of MMCSs are generally four directions and stop or rest command, thus the movements corresponding to those five commands are used most frequently. However, a trade-off between classification accuracy and number of control commands is still a challenge for researchers.

Finally, the number of participants in the experiment should be considered. As can be seen from Fig. 10, the number of participants used in the experiments was reported and from whom data was acquired, varied considerably. In the maximum case, forty participants took part in the study and the experimental findings can therefore be regarded as reliable. However, many studies employ only a small, particularly a single subject, and often insufficient number of participants. Generally, in studies of sEMG pattern recognition reported in the literature, around ten subjects have been employed which is sufficient for the results to be meaningful [54, 70].

1.2.2 Pattern Recognition

Numerous classification methods have been reported by researchers which have been successfully employed in MMCSs [31, 61, 65, 68, 70, 79]. Before movement patterns can be recognized, the data must be segmented, and this is one of the most important pre-processing stages. A segment is a sequence of data which is used to estimate the features it contains. If the duration of the segments is too short, this can result in bias and variance in the feature estimation. However, long duration segments impose high computational costs and are probably not appropriate for the real-time operation. The literature reveals that all the sEMG data segments employed in the real-time operation were less than 300 ms [31, 70]. Segment lengths of 64, 128, and 256 ms, for instance, were examined. For all segment lengths, disjoint and overlapped segmentations can be applied [31, 70].

1.2.2.1 Feature Extraction

Raw sEMG signals acquired from a number of electrodes positioned on the muscles contain a huge amount of data but little information. If these raw sEMG data are used as inputs in the classification process, the classification accuracy will be low and the computational time will be high. Therefore, in pattern recognition, raw sEMG data needs to be transformed into a reduced representative set of features. If the extracted features are carefully selected, a feature vector will contain effective and relevant information drawn from the whole set of raw data which can be used to represent the desired tasks. Generally in the sEMG signal analysis, feature extractions can be divided into three main sets: time-domain features, frequency-domain features, and time-frequency or time-scale features. Definitions of all EMG features extracted and mentioned in the literature as being used in MMCSs are included in [P11-P15, P24, P27, P30].

In MMCSs [2], time-domain and time-scale features have commonly been successful in recognizing muscle activities, but frequency-domain features have been more useful in determining muscle fatigue. From the point of view of class separation, time-scale features are better than features in time-domain. However, as can be seen from Fig. 11, time-domain features have been proposed for widely used in MMCSs since a disadvantage of time-scale features is that they are more complex to compute compared to time-domain

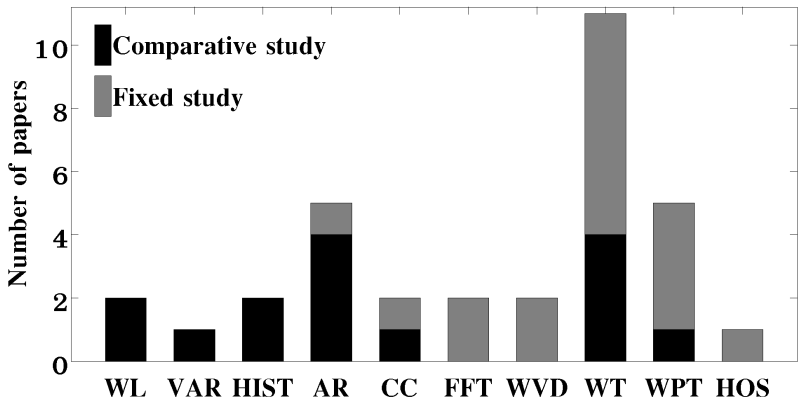


Fig. 11 The summary of single feature in the review. Note that HOS is higher-order statistics. Comparative study refers to the best method compared to other methods which were evaluated in the paper, and fixed study refers to only selected method which was evaluated in the paper.

and frequency-domain features, and are therefore not suitable for mobility devices. The problem is what a high quality feature is. Overall, a high quality sEMG feature space should have three following properties [8, 66]:

- Maximum class separability: This ensures that the resulting classification accuracy will be as high as possible. There are two major approaches to quantifying the suitability of feature spaces: (1) an estimation of the classification rate by a classifier, and (2) using the separability measures i.e. the Davies-Bouldin index.
- Robustness: This ensures that the resulting classification accuracy will be preserved in a noisy environment as much as possible.
- Complexity: This ensures that the proposed method can be implemented with reasonable hardware and in a real-time manner.

Because of their computational simplicity, time-domain features are the most popular in MMCSs. Two well-known time-domain features are mean absolute value (MAV) and root mean square (RMS) [2, 5]. However, the best time-domain features reported in literature are variance (VAR), histograms

(HIST), waveform length (WL), auto-regressive coefficients (AR) and Cepstrum coefficients (CC) as shown in Fig. 11. Other commonly used time-domain features are integrated EMG (IEMG), zero crossing (ZC), slope sign change (SSC), Willison amplitude (WAMP), and regression coefficients (RC). The pioneers in the sEMG time-domain analysis are Hudgin et al. [85]. Hudgin et al. proposed multiple time-domain features that the classification accuracy obtained was roughly 90% for two sEMG channels and four upper-limb movements [85]. Even so time-domain features are limitedly successful because these methods assumed that the sEMG signals are stationary, while the sEMG signals are non-stationary [86-87]. In addition, most time-domain features are sensitive to noises [8]. However, only one feature per EMG channel can be obtained from most time-domain features. Therefore, for a more powerful feature vector, this feature can be combined with other advanced sEMG features, i.e. time-scale and non-linear features, in future studies. Subsequently, information contained in frequency-domain is used. Some characteristic variables in power spectral density (PSD) are employed as a feature such as mean frequency (MNF) and median frequency (MDF) [2] where PSD is obtained from the traditional Fourier transforms (FT) or the fast Fourier transform (FFT). Afterwards, time-frequency and time-scale representations that correspond both time and frequency are proposed such as short-time Fourier transforms (STFT) and Wigner-Ville distribution (WVD) [26, 84]. STFT is help in characterizing sEMG signals in different frequency bands. Other two successful time-scale features are wavelet transform (WT) and wavelet packet transform (WPT) [66, 70]. Advantages of WT and WPT are that features can perform local analysis of sEMG signals. Moreover, they contain useful information in both of frequency content and time domain, and expose the trends of sEMG signals. WT and WPT decompose original sEMG signals into some multi-resolution components according to a basis function called "mother wavelet or wavelet function".

However, a high computational complexity is a major problem of time-frequency and time-scale features. The dimensionality reduction technique is investigated to solve this problem. It will be discussed in the next sub-section.

From Fig. 11, the most popular single feature is WT, followed closely by WPT. Both features are time-scale features. The most popular time-domain feature is AR, followed closely by WL. However, in [31], for a single feature, WL outperforms the others including AR, and with respect to the computational time required for WT, WPT and AR, multiple time-domain features is recommended. As shown in Fig. 12, the second-order of auto-regressive model (AR2) and RMS are proposed two times by the different researches. Other multiple feature sets are only introduced in each literature. The popular multiple time-domain features consist of MAV, WL, ZC and SSC, or TD set in Fig. 12 that is introduced by Hudgin et al. [85]. In future research, more attention should be paid to the evaluation of multiple sEMG features.

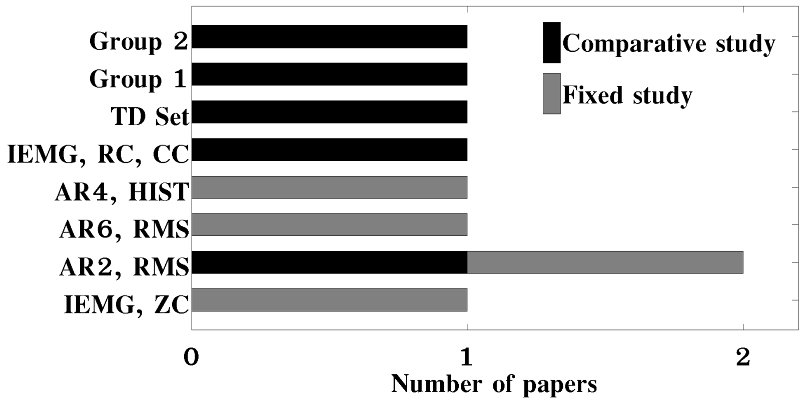


Fig. 12 The summary of multiple features reported in the review. Note that TD set is MAV, WL, ZC, and SSC. Group 1 is IEMG, VAR, WL, WAMP, ZC, and AR2. Group2 is IEMG, SSC, VAR, WL, WAMP, ZC, and AR2.

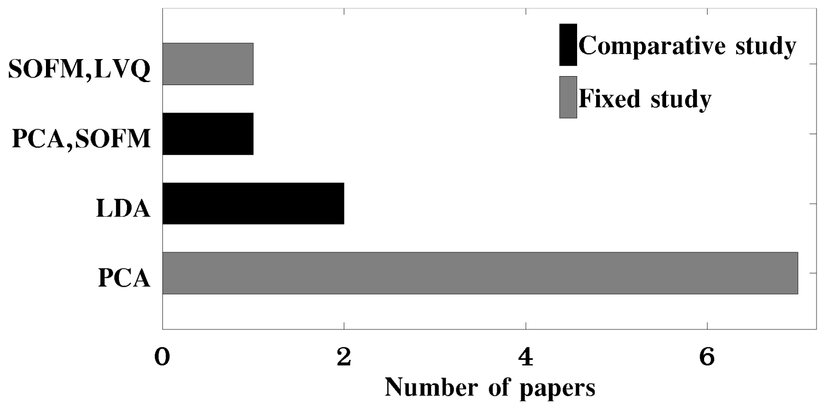


Fig. 13 The summary of feature projection techniques reported in the review. Note that LVQ is learning vector quantization.

1.2.2.2 Dimensionality Reduction

In order to support the future development of embedded processor systems, many researchers have proposed an optional component, dimensionality reduction, which also supports a more complex implementation of the time-scale feature method and new, more advanced classifiers that have been proposed for use with MMCSs in a last few years. Dimensionality reduction is used to enhance the performance of MMCSs because of an increasing use of vector space features, especially when time-scale features including WT and WPT are used. Dimensionality reduction is used to reduce a lot of features in vector spaces. The most popular feature reduction method is principle component analysis (PCA) as shown in Fig. 13. In this method, a linear-nonlinear feature reduction composed of a

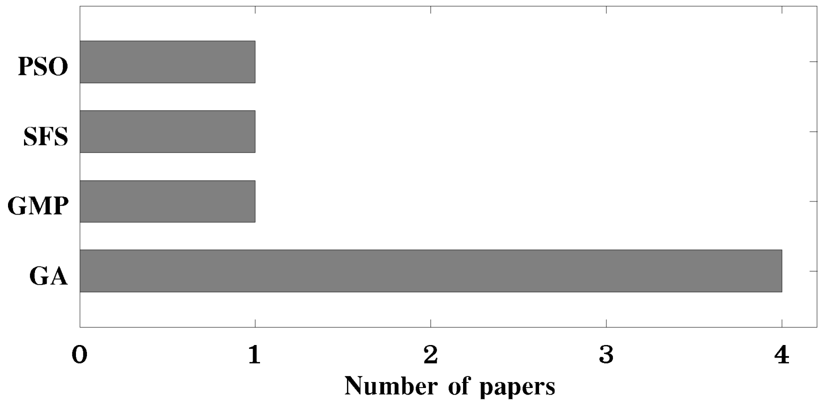


Fig. 14 The summary of feature selection techniques reported in the review.

PCA and a self-organizing feature map (SOFM) is utilized to increase the classification accuracy and reduce the computational time [56]. Alternatively, the linear supervised feature reduction method employs linear discriminant analysis (LDA) and its performance is said to be better than other feature-reduction methods including PCA and SOFM [54]. Finally, non-linear and fuzzy extension versions of LDA can be incorporated by introducing kernel learning and fuzzy techniques into the traditional LDA, methods known as generalized discriminant analysis (GDA) and orthogonal fuzzy neighborhood discriminant analysis (OFNDA), respectively [88-89]. Using these methods, the computational time is reduced and the classification accuracy may also be improved. The methods mentioned above is dimensionality reduction method based on feature projection technique.

There is another technique for reduction of feature dimension known as the feature selection. The simple explanation about the difference between feature projection and feature selection is a reduced feature set. A reduced feature set based on feature selection technique is obtained from the best features in the original feature set, same values but some selected features. On the other hand, instead of searching the best subset, feature projection tries to determine the best combination of the original feature set to form a new feature set, different values. Normally, size of new feature set is smaller than the original feature set for both feature projection and selection techniques. In feature selection techniques, the Euclidean distance is an easy technique that is first implemented and compared with PCA [6, 70]. After that many different distance techniques have been evaluated and applied in the search strategy approaches. In recent, the important distance criterion and search strategy method are respectively Davies-Bouldin's index and genetic algorithm (GA), as shown in Fig. 14. Other search strategy methods that have been evaluated are sequential forward selection (SFS), sequential backward selection (SBS), Gabor matching pursuit (GMP), and Tabu search (TS) [68, 90]. Currently, some powerful selection methods have presented a better performance over popular method, GA, such as particle swarm optimization (PSO), and ant colony optimization (ACO) [34].

1.2.2.3 Classification Methods

The classification algorithm or classifier is the final module in sEMG pattern recognition. Feature extraction in vector form is sent to classifier and is classified into unique classes. The selection of classifier is important stage because the varying patterns over time of sEMG signals decrease the classification performance. The optimal classifier should be able to deal with varying patterns, prevent over fitting, and meet real-time constraint. Several different kinds of classifier have been mentioned in the literature as demonstrating effective performance in a variety of sEMG applications. Examples of successful types of the classifier in sEMG pattern recognition are: neural networks (NN), fuzzy logic-based classifier (FL), the neuro-fuzzy approach, the probabilistic approach, LDA and support vector machines (SVM). Numerous literatures firstly focus on the success of NN in sEMG pattern recognition, particularly back propagation neural networks (BPNN) [85] as shown in Fig. 15. The advantage of NN is its capability to represent both linear and non-linear relationships. Moreover, it learns those relationships to create models directly from input features. NN can meet for the real-time constraint. Many literatures used BPNN as a standard classifier when researchers would like to compare the performance of a novel classifier. Other types of NN architectures have been used in the field of MMCS such as LVQ neural network [48], radial basis function (RBF) neural network [83], and dynamic neural network i.e. time-delay neural network (TDNN) [91]. Other commonly classifier is FL, notably fuzzy inference systems (FIS) [49]. The advantages of FL are the robustness and able to discover sEMG patterns that is not easily detectable. Afterwards, the combination of NN and FL is attended as known the neuro-fuzzy approach. Some neuro-fuzzy approaches are presented i.e. fuzzy ARTMAP neural network (ARTMAP) [53], fuzzy clustering neural network (FCNN) [61], fuzzy min-max neural networks (FMMNN) [13], and adaptive neuro-fuzzy inference systems (ANFIS) [68].

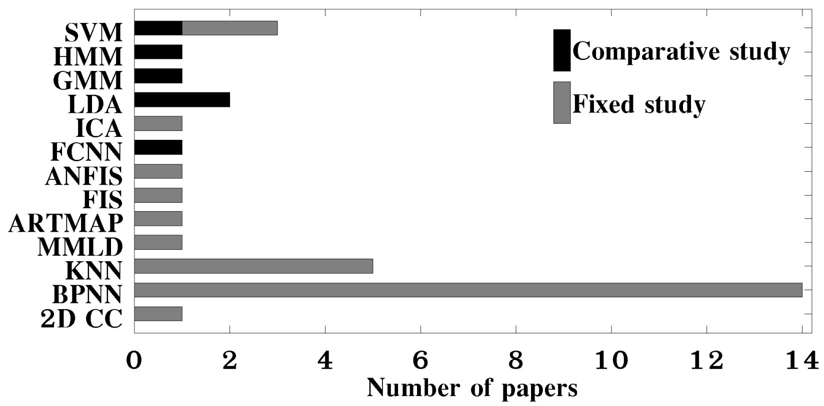


Fig. 15 The summary of classifiers reported in the review. Note that 2D CC is 2D cross-correlation and ICA is independent component analysis.

Recently, other two classifiers, LDA [9] and SVM [31] are becoming significant in sEMG pattern recognition. The good performance in classification and the suitability for real-time myoelectric control are the main reasons that LDA and SVM are becoming the important classification techniques today. LDA and SVM have been successful in a great number of sEMG pattern recognition such as upper-limb and lower-limb prosthesis control, and MUAP classification. The main drawback of LDA is its linearity. On the other hand, simple SVM is based on linear decision boundaries, but SVM can create non-linear decision boundaries by using kernel functions [31]. However, both classifiers have better performance than NN [31, 70], and in a recent study [92], LDA showed that it is the most robust classifier compared to other commonly used classifiers. Other classifiers in EMG pattern recognition are the probabilistic classifiers such as hidden Markov model (HMM) [79, 80] and Gaussian mixture model (GMM) [65], and nearest neighbor classifiers such as *k*-nearest neighbor (KNN) [8] and modified maximum likelihood distance (MMLD) [78]. A summary of all classifiers reported in the review is presented in Fig. 15.

1.2.3 Control System

The first generation of sEMG control system often offers ON/OFF control schemes or only open/close hand control. Today, sEMG signals can control multifunction system. MMCS can control six to nine movements from one to four EMG channels and the performance accuracy is also higher than 90%. The most important application of MMCSs is the prosthesis. It is only commercial application of MMCSs available today. Otto Bock Arm is currently available myoelectric prostheses. Attention in most of literature during last 20 years has paid to develop the upper-limb prosthesis [5, 8, 28, 62, 63]. In addition, a number of publications have shown other potential applications for MMCSs such as electric power wheelchair control [4, 11, 17, 18], cursor mouse control [93, 94], industrial robot arm [95, 96], and virtual reality [97, 98], as shown in Fig. 16.

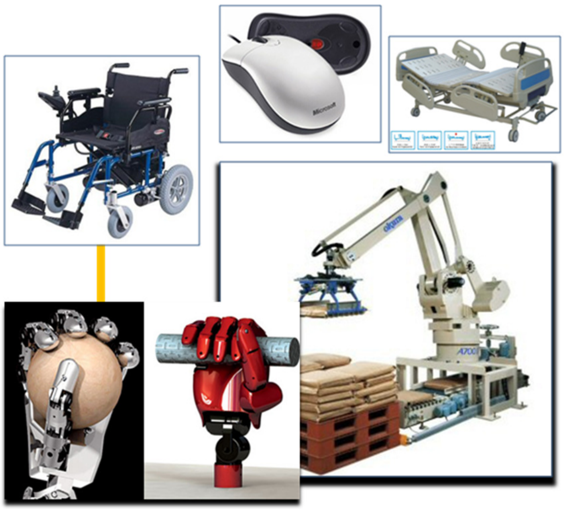


Fig. 16 An example of MMCS applications.

CHAPTER 2

Objectives

2.1 Research Objectives

The main aim of this research is to investigate all classification techniques for identification of upper-limb movements using forearm muscles recording of sEMG signals. The objectives of this research work are to:

2.1.1 study, analyse, and develop a pre-processing sEMG signal technique based on the wavelet analysis;

2.1.2 study and evaluate the existing sEMG features, as a measure of muscle activity particularly in robustness and redundancy point of views, and develop the class separation index for evaluating sEMG features;

2.1.3 study and analyse the new fractal features, as a measure of low-level and equal muscle activity, and to modify the existing frequency-domain features, as a robust measure of muscle activity against noise; and

2.1.4 study and analyse the dimensionality reduction and classification methods for the classification of muscle activity related to sEMG signal.

2.2 Research Scopes

2.2.1 Analysis and development of the wavelet denoising analysis techniques are based on denoising and estimation sEMG signal viewpoints.

2.2.2 Evaluation of the existing sEMG features is based on three main criteria: maximum class separability, robustness, and complexity.

2.2.3 Analysis and modification of the new fractal features and the existing sEMG features are based on two criteria: maximum class separability and robustness.

2.2.4 Development of the class separation index is for evaluating the existing sEMG features and for finding the relationship between the proposed class separation index and the popular classifier.

2.2.5 Analysis and development of the dimensionality reduction methods are for feature based on wavelet transform.

2.2.6 Developments of dimensionality reduction and classification methods are based on maximum class separability and complexity.

2.2.7 EMG signals are recorded from forearm muscles and upper-limb movements.

2.2.8 EMG signals are recorded from young subjects between the age of 20 and 30.

2.2.9 The performance of all techniques is evaluated using the computer simulation.

2.3 Research Advantages

The main advantages of using the new techniques in four main cascade components including pre-processing sEMG signals based on the wavelet analysis, feature extraction, dimensionality reduction, and classification methods of sEMG signals in the classification of upper-limb movements from forearm muscles are

2.3.1 improving the control accuracy of prosthesis and electric power wheelchair,

2.3.2 less sensitive to various kinds of noise and thus long term usage, and

2.3.3 able to identify the small changes in the low-level and equal power muscle activation.

CHAPTER 3

Experiments and EMG Data Acquisition

In this chapter, our experimental procedures for recording the sEMG data are described. Three different datasets are used as the representative sEMG signals in the research. All datasets have some differences in the experimental setup, for instance, sensor locations, the number of sensors, movement types, the number of movements, the number of participants, and the specification of sEMG signal acquisition system. However, all studies in this research are evaluated and investigated based on these three datasets. To easily understand all sEMG data used in each study, or paper, more details in each dataset are described in the following sections, as the Dataset I-III.

3.1 Dataset I

The representative sEMG signals used in this set were acquired from six commonly used upper-limb movements as mentioned in Section 1.2.1.2. Six movements consist of HC, HO, WE, WF, FP and FS as shown in Fig. 8. This dataset was used frequently in the preliminary studies. Only one subject volunteered to participate in this experiment. The volunteer was asked to perform a short dynamic movement. Two forearm muscles were selected: the FCR and ECR muscles. Both muscles are the popular muscles, as clearly shown in Fig. 4. The sEMG signals were recorded from the right forearm of the volunteer by two pairs of surface electrodes (3M red dot 25 mm foam solid gel). The electrodes were separated from each other by 20 mm. A band-pass filter of 10-500 Hz bandwidth and an amplifier with 60 dB gain were used. A sampling frequency was set at 1000 Hz using a 16-bit A/D converter (National Instruments, DAQCard-6024E). In the experiment, 10 datasets were recorded for each movement. In total, 60 datasets with duration of 256 ms, or 256 samples, were collected. Examples of measured sEMG signals for six movements and two muscles, FCR and ECR, are respectively shown in Fig. 1 and Fig. 17. The differences between patterns of all movements and muscles are clearly observed from such figures.

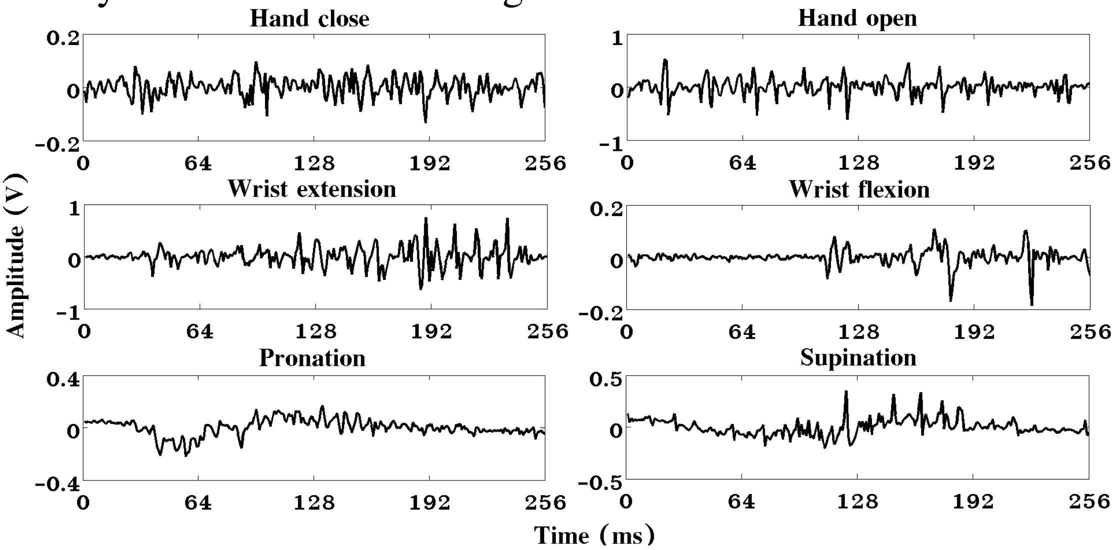


Fig. 17 EMG signals obtained from six movements of the ECR muscle.

3.2 Dataset II

The second dataset was used to confirm the preliminary results. This dataset was acquired by Dr. Adrian D. C. Chan at the Carleton University in Canada [10]. Six movement types used in Dataset I were also used in this experiment, but the number of sensor locations increases from two to eight, and the number of participants in the experiment also increases from one to thirty. Eight sensor locations were on the seven forearm positions, 1-7, and the upper-arm position, 8, using the Duo-trode Ag-AgCl electrodes (Myotronics, 6140) as shown in Fig. 18. A common ground reference was placed on the wrist using Ag-AgCl Red-Dot electrode (3M, 2237). Each movement was performed four times throughout a trial. For every subject, there are four sessions and six trials in each session. In all, there are

96 data (4 sessions×6 trials×4 times) for each movement. Additionally, each motion is subjected to a duration of three seconds. A band-pass filter of 1-1000 Hz bandwidth and an amplifier with 60 dB gains (Grass Telefactor, Model 15) were set for the acquisition system. These signals were sampled at 3000 Hz (National Instruments, PCI-6071E) with a sampling duration of 120 s. In order to reduce time in recognition, sEMG data were down-sampled to 1000 Hz. More details of experiment and data acquisition are described in [10]. The sample of measured sEMG signals for one trial from muscle position 1 was shown in Fig. 19. The difference between patterns of all movements is also observed from this figure similar as in Dataset I.

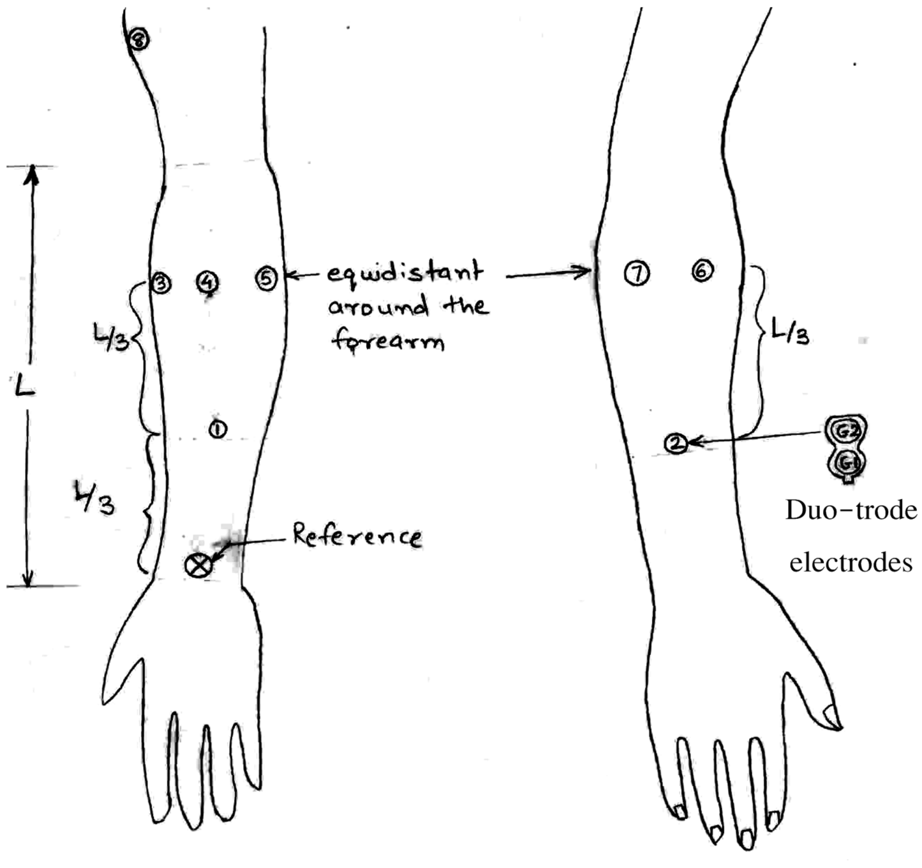


Fig. 18 The electrode placement used in the eight-channel sEMG data acquisition. Eight bipolar electrode pairs were used with a reference at the wrist [10].

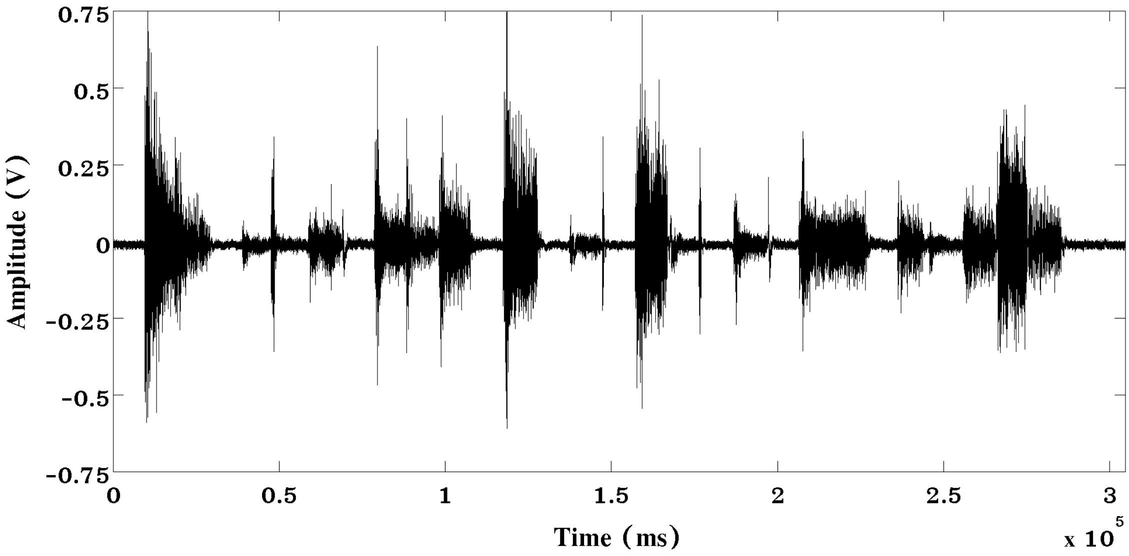


Fig. 19 EMG signals obtained from six upper-limb movements of muscle position 1 for four times.

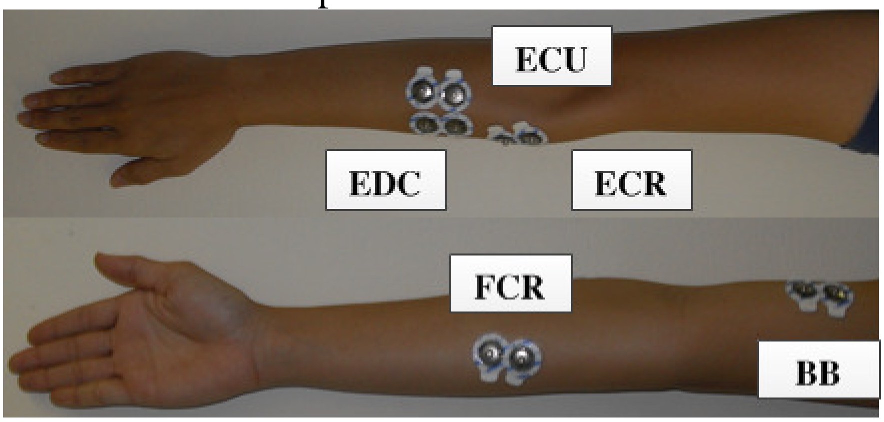


Fig. 20 The electrode placement used in the five-channel sEMG data acquisition [P16].

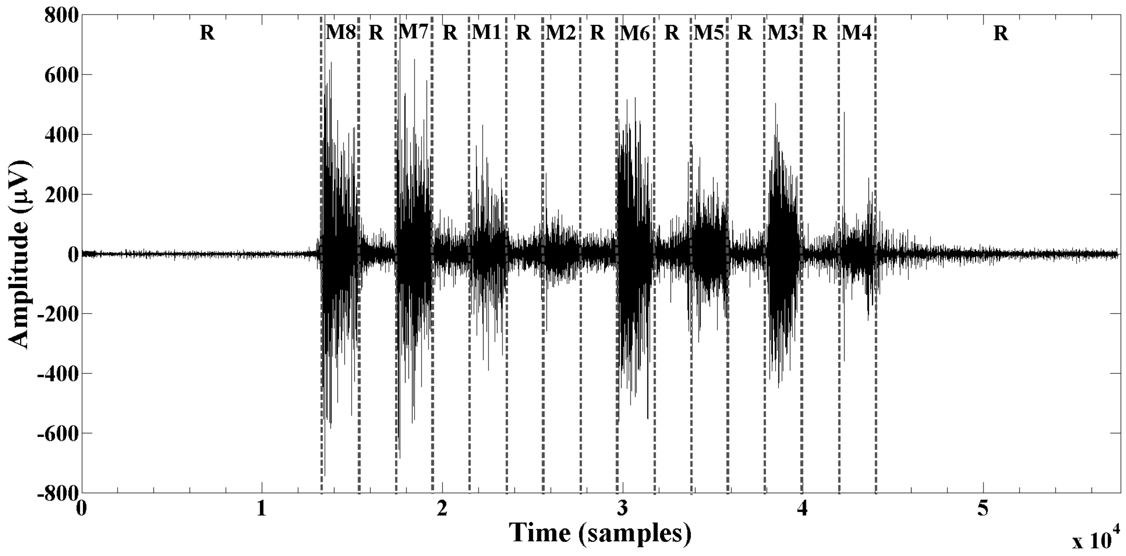
3.3 Dataset III

The third dataset was used to improve the performance of sEMG pattern recognition from six to eight movements, or six to eight output commands. The sEMG data were collected from 20 normal young subjects, 10 males and 10 females. The mean (and the standard deviation in brackets) of the age, height, weight and body mass index of the male samples were 21.5 years (0.97 years), 169.7 cm (3.72 cm), 61.0 kg (8.08 kg), 21.12

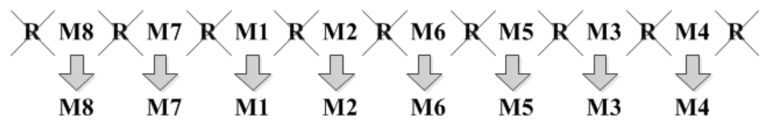
kg/m^2 (2.10 kg/m^2). For the female samples these were 21.2 years (0.79 years), 157.8 cm (6.25 cm), 48.8 kg (4.37 kg), 19.63 kg/m^2 (1.76 kg/m^2), respectively. All subjects are dexterous with their right hands.

The sEMG data were collected from five muscle positions on the right arm using the bipolar Ag/AgCl electrodes (Kendal ARBO, H124SG). Five pairs of disposable pre-gelled self-adhesive surface electrodes of 24 mm diameter (circular) were applied to the subjects at an inter-electrode distance of 20 mm after suitable preparation of the skin with alcohol. The five muscle positions used in this experiment were: ECR, ECU, FCR, BB, and extensor digitorum communis (EDC) muscles, as shown in Fig. 20. An Ag/AgCl electrode (Red Dot 2223, 3M Health Care) was placed on the wrist to provide a common ground reference. It was also a disposable pre-gelled self-adhesive surface electrode but its diameter was 43.1 mm.

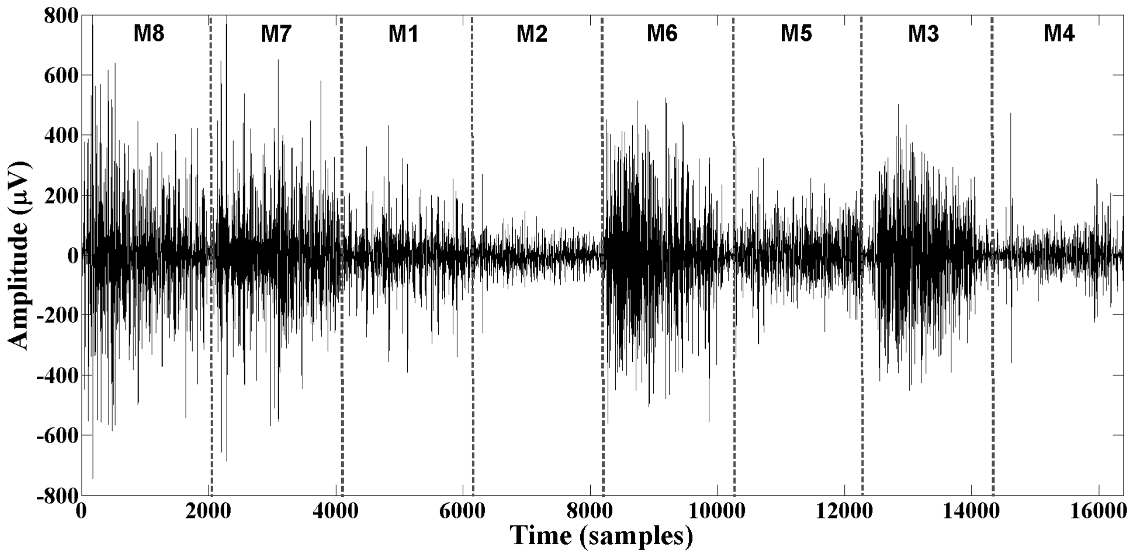
The sEMG signals were amplified and sampled by a commercial wireless sEMG measurement system (Mobi6-6b, TMS International B.V.). These signals were amplified with a gain of 19.5x and bandwidths of 20 to 500 Hz. Signals were sampled at 1024 Hz



(a)



(b)



(c)

Fig. 21 (a) The example EMG data of 56 seconds in length (b) The movements order and the procedure of the removed rest state (c) The final removed EMG data of 16 seconds in length. Note that the example data is from the fourth trial of the first session in the first day of Subject 1 with the ECR muscle [P16].

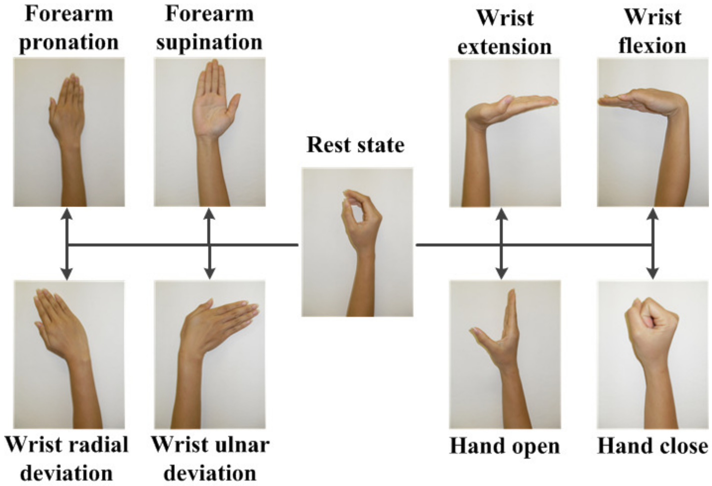


Fig. 22 Eight upper-limb movements and a rest state [P16].

with a high resolution of 24 bits. The raw EMG signals were less likely to be contaminated by all kinds of noises, i.e., movement artifacts, powerline interferences, and electrical noises from electronic equipments as we can observe in Fig. 21(a).

The sEMG data were collected as the volunteers performed eight commonly used distinct upper-limb movements including forearm pronation (M1), forearm supination (M2), wrist extension (M3), wrist flexion (M4), wrist radial deviation (M5), wrist ulnar deviation (M6), hand open (M7), and hand close (M8) as shown in Fig. 22. Within each trial, the subject maintained each movement for two seconds in duration and separated each movement by a two-second period rest state (R) to avoid a transitional stage (i.e., during movement changes). Moreover, thirteen-second rest periods were also introduced at the start and the end of each trial to give a preparation time for the subject and to avoid any incomplete data recording that could be cutoff before an action is finished. Thus each trial contains a 56-second period in length. Each day, each subject completed three sessions, with five trials in each session. The order of movements was randomized in each session. Moreover, to study the fluctuation of the sEMG signal, these three sessions per day were employed on four separate days. In total, 60 datasets with duration of two seconds were collected for each movement from each subject. However, to render easier processing all rest states were removed before an extraction step was performed. This is presented in Fig. 21(b). Hence, each trial comprised 16 seconds or 16,384 samples in length, as shown in Fig. 21(c).

CHAPTER 4

Results and Discussion

This thesis is based on the papers, which are referred to in the text by P letter and their Arabic numerals. The study presented in this thesis was aimed to classify the sEMG signals during upper-limb movements for the control of assistive devices, notably prosthesis and intelligent wheelchair. The research study can be divided into four main components:

4.1 Pre-processing sEMG Signals Using Wavelet Analysis

The sEMG signals that originate in various muscles and activities are definitely contaminated by various kinds of noise. This becomes a major problem to extract certain features and thus the reach to high accurate recognition. Therefore, in the last decade, many researchers have an interest in developing the better techniques and improving the existing methods to reduce noises and estimate the useful sEMG information. In this research, the denoising and estimation of sEMG signals are based on wavelet analysis. Throughout the extensive reviews, most wavelet-based denoising methods have been proposed and evaluated for the sEMG signals in signal denoising viewpoint [P1, P2]. The application of wavelet-based denoising methods requires the selection of five processing parameters.

The suggestion of five wavelet denoising parameters in a compromise between two points of view, signal denoising and signal estimation, is presented in the following.

(1) The type of wavelet basis function [P3-P6]: Daubechies2, Daubechies7, Symlets2, Symlets5, Coiflet4, BiorSplines5.5 and ReverseBior2.2.

(2) The decomposition level j [P3-P6]: 4.

(3) The threshold rescaling method [P7]: Level dependent for N (wavelet coefficient length) and first-level/level dependent for σ (standard deviation of noise).

(4) The threshold selection rule [P7, P10]:

- Global scale modified universal method ($THR = 2^{-J/2}\sigma\sqrt{2\log(N)}$), and

- Weighted universal method ($THR = w\sigma\sqrt{2\log(N)}$) at $w = 0.55$.

(5) The thresholding function [P8-P9]: Adaptive denoising shrinkage method ($cD_j = cD_j - THR_j + \frac{2THR_j}{1+e^{2.1cD_j/THR_j}}$, where cD is the wavelet's detail coefficients).

4.2 Evaluations of Commonly Used EMG Feature Extraction

To be successful in classification and recognition of sEMG signals, three main cascaded modules should be carefully considered that consist of data pre-processing, feature extraction, and classification methods, particularly the selection of an optimal feature vector. Feature extraction is a method to extract the useful information that is hidden in sEMG signals and remove the unwanted sEMG parts and interferences. Appropriate features will directly approach high classification accuracy. Three properties have been suggested to be used in the quantitative comparisons of their capabilities that consist of maximum class separability, robustness, and complexity. Although many researches have mainly tried to explore and examine an appropriate feature vector for numerous specific sEMG signal applications, there have a few works which make deeply quantitative comparisons of their qualities, particularly in robustness and redundancy points of view. In this research, both viewpoints are focused. A number of features are robust across different kinds of noise, thus intensive data pre-processing methods shall be avoided to be implemented [P11-P12]; and most of time-domain and frequency-domain features are superfluity and redundancy, thus the reduction of computational time caused by redundant features can be achieved [P13]. However, evaluating sEMG features in class separability viewpoint is still done using the modification of class separation index, namely RES index [P14-P15].

The suggestion of the optimal features based on three viewpoints is presented in the following.

(1) Maximum class separability without feature redundancy [P13-P15]: Mean absolute value (MAV) from energy information method, waveform length (WL) from complexity information method, Willison amplitude (WAMP) and slope sign change (SSC) from frequency information method, auto-regressive (AR) coefficients from prediction model method, and multiple trapezoidal windows (MTW) from segmenting method. All features are calculated in the time-domain. EMG features based on frequency domain are not recommended in the sEMG signal classification.

(2) Robustness [P11-P12]: WAMP, SSC, root mean square (RMS) and mean frequency (MNF) for the tolerance of white Gaussian noise and power-line interference.

(3) Complexity: All time domain features or time-scale features with dimensionality reduction technique.

4.3 Investigations of Novel and Modified EMG Feature Extraction

Major properties of sEMG signals are complexity, randomness, non-stationarity and non-linearity. However, most of traditional and existing sEMG features, consisting of time domain, frequency domain, and time-frequency/time-scale domain introduced above, are calculated based on linear or statistical analysis. Hence, such methods cannot extract the real hidden information in the sEMG data. From these limitations and disadvantages, in this research, an extraction of the properties that is hidden in the complexity of the sEMG signals by using the non-linear analysis is gaining an interest. Two fractal analysis methods, namely the detrended fluctuation analysis (DFA) [P16-P18] and the critical exponent analysis (CEA) [P19-P21], have been proposed as the useful sEMG features. Both fractal features are better than other existing nonlinear methods, including the Higuchi's method. On the other hand, some traditional sEMG features are modified in order to improve a robustness performance, particularly for frequency-domain features [P22-P23]. However, their classification performance is poor. Therefore, these features are not recommended to be used in the optimal feature vector.

The suggestion of the optimal parameters for each feature is presented in the following.

(1) DFA method: the minimum box size is approximately four, the maximum box size is one-tenth of the signal length, the box size increment is based on a power of two, and the quadratic polynomial fits is used in the fitting procedure.

(2) CEA method: the step size of the moment exponent is 0.01.

4.4 Dimensionality Reduction and Classification Methods

Two last important components in the procedure of sEMG signal classification are dimensionality reduction and classification methods. For dimensionality reduction, attention has been paid to the application of wavelet coefficient features [P24-P25]. The usefulness of extraction of the EMG features from multiple-level wavelet decomposition of the EMG signal is investigated. The results show that most of the EMG features extracted from reconstructed sEMG signals of the first-level and the second-level detail coefficients yield the improvement of class separability in feature space. For classification methods, only linear discriminant analysis (LDA) classifier is focused due to a robustness property.

CHAPTER 5

Concluding Remarks

5.1 Conclusions

Noises contaminated in the sEMG signals are an unavoidable problem during recording data. Moreover, noises are a main problem in the analysis of sEMG signal both in clinical and engineering applications. Random noises that have their frequency components fall in the energy band of the sEMG signal are the major problem. Conventional filters do not effectively remove random noises but the wavelet denoising algorithm is not problematical in this way. Hence, numerous wavelet denoising methods have been proposed during the last decade [P1-P2]. Five wavelet denoising parameters that were optimized [P3-P10] can be useful to apply for many sEMG applications. The pre-processing stage based on the wavelet denoising algorithm is recommended to be implemented in the analysis of sEMG signal, especially in multifunction myoelectric control system.

After the pre-processing stage, the selection of an optimal feature vector is an important one to be successful in classification of sEMG signals. Appropriate features will directly approach high classification accuracy. Three properties have been used in the quantitative comparisons of their capabilities. The optimal features based on one of three criteria are presented i.e. waveform length (WL) and auto-regressive (AR) coefficients in maximum class separability viewpoint [P13-P15] or Willison amplitude (WAMP) in robustness viewpoint [P11-P12]. However, the optimal feature vector should be selected for the specific application. Furthermore, the modification of class separation index, namely RES index is recommended to be used in the evaluating EMG features [P14-P15].

However, most of traditional and existing sEMG features are calculated based on linear or statistical analysis, whereas major properties of sEMG signals are complexity, randomness, non-stationarity and non-linearity. Therefore, such methods cannot extract the real hidden information in the sEMG data. Two fractal analysis methods, namely the detrended fluctuation analysis (DFA) [P16-P18] and the critical exponent analysis (CEA) [P19-P21], have been recommended to combine with other recommended time-domain features such as WL, AR and WAMP in order to make a more powerful feature vector. Both DFA and CEA extract the properties that are hidden in the complexity of the sEMG signals. Moreover, modified mean and median frequency (MMNF and MMDF) are useful frequency-domain features that can be added into the feature vector in order to improve a robustness performance [P22-P23].

For dimensionality reduction, if the wavelet coefficients are used as the EMG features, only features extract from the reconstructed sEMG signals of the first-level and the second-level detail coefficients are suggested instead of extract from all wavelet coefficients [P24-P25]. On the other hand, if all wavelet coefficients were used, feature projection method should be applied before performing classification. For classification method, linear discriminant analysis (LDA) is recommended to be used as a classifier due to the high performance in classification of the sEMG signal, the robustness in a long-term effect usage, and the low computational cost [P7-P10, P13, P16, P22].

5.2 Recommendations for Future Study

5.2.1 Pre-processing sEMG Signals Using Wavelet Analysis

(1) Developing a new robust wavelet denoising method which the performance does not depend on the distribution of sEMG signals and noises should be done. It should be noted that, at low-level movements, the sEMG signals have the

Laplace distribution, whereas at high-level movements, the sEMG signals have the Gaussian distribution [99].

(2) In the analysis of intramuscular EMG signal, the re-evaluating wavelet denoising parameters should be done because the purpose in interpretation is different [100].

5.2.2 Evaluations of Commonly Used EMG Feature Extraction

(1) The evaluation of EMG features in the classification of sEMG signals obtained from the elderly or the disabled peoples should be done. The optimal feature vector may be changed due to the low-level of sEMG signals (different distribution and noises) [101].

(2) The evaluation of EMG features in the classification of sEMG signals recorded from the subject on many consecutive days (i.e. 21 days [92]) should be done. The optimal feature vector may be changed due to the fluctuation of sEMG signals.

(3) The evaluation of EMG features in robustness viewpoint should be re-tested with the mixed noises (such as the combination between white Gaussian noise and power-line interference). In addition, other kinds of noise i.e. movement artifacts should be used in the evaluating robust EMG features.

5.2.3 Investigations of Novel and Modified EMG Feature Extraction

(1) DFA should be better in the classification of sEMG signals from bi-functional movements (i.e. forearm pronation and supination) of low-level and equal power as compared to other successful and commonly used EMG features based on magnitude and other fractal techniques (More details in Appendix A).

(2) Variance fractal dimension (VFD) is one of the most significant fractal analysis methods that can be implemented for real-time systems. VFD should be tested its performance in the classification of sEMG signals. It can be applied not only for the

feature classification but can be applied as a segmentation method and a signal-to-noise ratio (SNR) estimator (More details in Appendix B).

5.2.4 Dimensionality Reduction and Classification Methods

(1) The extended versions of LDA i.e. uncorrelated linear discriminant analysis (ULDA), orthogonal linear discriminant analysis (OLDA) and orthogonal fuzzy neighborhood discriminant analysis (UFNDA) should be evaluated their performance compared with a baseline system (without feature projection) and principle component analysis (PCA), the most popular used EMG feature projection (More details in Appendix C). In addition, a combination between advanced linear and non-linear methods should be done.

(2) For classification method, the LDA classifier should be employed as a classification method due to a robustness property, notably in the long-term use of sEMG pattern classification (More details in Appendix D). Most of related works on the sEMG signal classification focus on the improving accuracy. On the other hand, several researches focus on increasing the number of classified movements and reducing the number of electrode placements. However, for realizing practical applications of MMCS, the effect of long-term usage or reusability is one of the challenging issues that should be more carefully considered, whereas only a few works have been investigated this effect in recent.

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VITAE

Name Angkoon Phinyomark
Student ID 5110130012
Educational Attainment

Degree	Name of Institution	Year of Graduation
Bachelor of Engineering in Computer Engineering (First Class Honors)	Prince of Songkla University	2007
Doctor of Philosophy in Electrical Engineering	Prince of Songkla University	2011

Scholarship Awards during Enrolment

Ph.D. Scholarship from Thailand Research Fund through the Royal Golden Jubilee Ph.D. Program, 2008-2012

Ph.D. Research Scholarship from Graduate School, Prince of Songkla University, Thailand, 2010-2011

Visiting Research Scholarship from University of Murcia, Spain, 2007

B.Eng. Scholarship from Faculty of Engineering, Prince of Songkla University, Thailand, 2004-2008

List of Publication and Proceeding

1. International Journal Publications

1.1 A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Fractal Analysis Features for Weak and Single-channel Upper-limb EMG Signal," *Expert Syst. Appl.*, 2012.

1.2 A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7420-7431, June 2012.

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1.4 S. Aungsakun, A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Development of robust EOG-based human-computer interface controlled by eight-directional eye movements," *Int. J. Phys. Sci.*, vol. 7, 2012.

1.5 A. Phinyomark, M. Phothisonothai, P. Phukpattaranont, and C. Limsakul, "Critical exponent analysis applied to surface electromyography (EMG) signals for gesture recognition," *Metrol. Meas. Syst.*, vol. 18, no. 4, pp. 645-658, 2011.

1.6 A. Phinyomark, M. Phothisonothai, P. Phukpattaranont, and C. Limsakul, "Evaluation of movement types and electrode positions for EMG pattern classification based on linear and nonlinear features," *Eur. J. Sci. Res.*, vol. 62, no. 1, pp. 24-34, Oct. 2011.

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1.12 A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "A novel feature extraction for robust EMG pattern recognition," *J. Comput.*, vol. 1, no. 1, pp. 71-80, Dec. 2009.

2. Book Chapter and Book Series Publications

2.1 A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "The usefulness of wavelet transform to reduce noise in the SEMG signal," in *EMG Methods for Evaluating Muscle and Nerve Function*, M. Schwartz, Ed. Rijeka: InTech, 2012, pp. 107-132.

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4. International Conference Proceedings Publications

4.1 A. Phinyomark, S. Jitaree, P. Phukpattaranont, and P. Boonyapiphat, “Texture analysis of breast cancer cells in microscopic images using critical exponent analysis method,” in *Proc. 3rd Int. Science, Social-Science, Engineering and Energy Conf.*, Nakhon Pathom, 2012.

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4.6 A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “EMG signal denoising via adaptive wavelet shrinkage for multifunction upper-limb prosthesis,” in *Proc. 3rd Biomedical Engineering Int. Conf.*, Kyoto, 2010, pp. 35-41.

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6. Other Publications

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6.2 C. Limsakul, A. Phinyomark, and P. Phukpattaranont, “Feature extraction of EMG signal,” in *Proc. 3rd Int. Symp. Biomedical Engineering*, 2008, pp. 8-11.