CLASSIFICATION OF EMG SIGNALS USING WAVELET FEATURES AND FUZZY LOGIC CLASSIFIERS

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Summary

This project involves the design of fuzzy classifiers targeted for a two-class EMG classification problem. One of the main objectives of this project is to prove the performance efficiency of the designed fuzzy classifiers, which are developed using both type-1 and type-2 fuzzy logic systems (FLS).

Given a collection of EMG data for simple human arm motions such as hand close-open and forearm pronation-supination, we shall use a subset of them to create a rule-based classifier (RBC) using fuzzy logic. We have developed both type-1 and type-2 fuzzy classifiers and also compared them to see which classifier provides the best performance in terms of classification accuracy.

The most important step is to extract appropriate features from the EMG signals under study. We have used the EMG data obtained from 2 subjects, a healthy and a post stroke subject. Using Continuous Wavelet Transform (CWT), we obtain the wavelet coefficients of EMG signals, which are the features for the fuzzy classification system. The maximum absolute value of the wavelet coefficients at each scale were extracted as features for the classifier.

The uncertainties involved in EMG signals suggest that it is more appropriate to model each input measurement as a type-2 fuzzy set. An interval type-2 non-singleton type-2 FLS model is appropriate for the case where there is non-stationary additive noise like EMG signal measurements.

Finally, a FLS contains many design parameters whose values must be set by the designer. After the tuning of each FL RBC is completed, these classifiers are tested on the remaining unused data. Its classification accuracy is the performance measure that is used to evaluate it and to compare it against the other classifiers.

We have designed the following five FL RBCs: singleton type-1 FL RBC, non-singleton type-1 FL RBC, interval singleton type-2 FL RBC, interval type-1 non-singleton type-2 FL RBC, and interval type-2 non-singleton type-2 FL RBC. All the five designs used the totally independent approach in which all of the parameters were tuned independently for each design.

We have given comparisons between type-1 and type-2 fuzzy logic classifiers for both the singleton as well as the non-singleton case. The results show how the steepest descent tuning procedure affects the performance of the classifiers. In addition, we have also analyzed the classification accuracy when only the dominant muscles are chosen as the input features.

We used a back-propagation algorithm for tuning, in which each element of the training set is used only one time, and the FLS parameters are updated using an error function. Training occurs for only one epoch.

From the results, we take note of the following key points. Coiflet wavelets has proved to work out well for the EMG data under study. Type-2 FLS outperform the type-1 FLS. The interval type-2 non-singleton type-2 FLS performs the best and the interval type-1 non-singleton type-2 FLS also gives comparable results. Out-of-product classification results have been summarized which is very useful for real-time EMG classification purposes. Finally, we have also tested the versatility of the fuzzy classifiers.

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Chapter 1

Introduction

Many researchers working on exoskeletons and assistive devices have been using Electro Myo Gram(EMG) signals to control the torque required at the human joints [1,2,3]. As we know the human body is a typical fuzzy system. EMG is the measurement of the muscle activity and measuring these signals on the skin surface identifies the intention of the user. These signals are also fuzzy. Researchers have proposed neuro-Fuzzy controllers for this purpose. They use Fuzzy sets to represent the uncertainty and neural networks for adaptive learning ability. In this thesis, I will present in detail a better option to handle the uncertainties [4] involved in EMG signals.

Measurement of EMG signal is corrupted by additive noise [5] whose signal-to-noise ratio (SNR) varies in an unknown manner. Research on type-2 Fuzzy Logic System (FLS) [6,7] show that a type-2 Fuzzy model is appropriate in modeling measurements such as EMG signals.

I propose to implement Type-2 FLS [8,9] as well as the normal Type-1 for the classification of EMG signals, which can be used later for control of assistive devices. Based on the subjects' simple motion patterns such as hand close-open and forearm pronation-supination motions obtained from pre-experiment, IF-THEN rules for the fuzzy system can be obtained. The results of all these fuzzy classifiers with and without tuning have been summarized.

The entire project could broadly be broken down into four important phases, (1) the EMG signal measurement and signal processing phase- the signal capturing phase alone was done by Prof. Ted Milner and his group in Simon Fraser University (2) feature extraction and selection phase (3) fuzzy classifiers, classification algorithms development phase and (4) strategies for classifiers' performance improvement phase.

The thesis consists of eight chapters and brief descriptions of these are:

Chapter 1 Introduction – The scope of the thesis is presented here. Some background information on the topic is provided in this chapter.

Chapter 2 Literature Review – In this chapter, related works from other researchers are discussed, reviewing the current state of technology and general approach in this field of research.

Chapter 3 EMG signals – The important details related to EMG measurement and signal processing are explained in this chapter.

Chapter 4 Feature extraction – The time and frequency domain approaches, their relative advantages and disadvantages, and the reasons for choosing Continuous Wavelet transform for EMG feature extraction are presented in this chapter.

Chapter 5 Fuzzy approach to EMG classification – In this chapter, the proposed fuzzy logic systems will be discussed. Details of type-1 and type-2 FLS, both singleton and non-singleton systems are presented.

Chapter 6 Design of fuzzy classifiers for EMG classification – The structure and algorithm of the five fuzzy classifiers used for EMG classification will be presented in the chapter.

Chapter 7 Simulation results – Experiments are done on the EMG signals to classify them. The relative performance of all the fuzzy classifiers will be discussed in this chapter.

Chapter 8 Conclusions and Recommendations – In this chapter, conclusions drawn from this work are summarized and some recommendations for further investigation in this topic are also provided.

Chapter 2

Literature Review

A good and computationally efficient means of classifying EMG signal patterns has been the subject of research in recent years. Important research works and valuable lessons learnt from them are shared among the research community through publications in journals and Conferences. In this chapter, we give a brief survey of some of the research works that are related to our work in this thesis.

2.1. EMG signal detection and processing

The study of EMG signal and its classification is an interesting topic, which has lots of scope for research. The EMG signal has been detected for various reasons in the past [10]. This area of research has been vastly explored in the last few decades. Researchers and clinicians had great difficulties [11, 12] in converting the raw EMG signal into usable signals that can provide sufficient information about the subject. This is primarily due to the fact that technology at that time, especially in terms of hardware and software, was still unable to handle the uncertainties involved in the measurement of the myosignals. Different methods to decrease the range of pick-up and thereby potential crosstalk have been proposed. Some of them include using electrodes of smaller surface area, choosing smaller bipolar spacing and employing mathematical differentiation.

The interest in EMG research did not stop at research centers and universities; Commercial companies also took up the challenge in research. Groups like Noraxon, Matlab [13,14], etc., resorted to work on building hardware systems and software packages for the processing of raw EMG signals. Analyzing the EMG signal using pattern recognition techniques can perform human gesture recognition. However, the EMG signals generated by specific gestures and motion patterns are subject dependent.

2.2. Algorithms for EMG classification

Control of assistive devices and exoskeletons using EMG signals has been the focus for many researchers. Given the complexity of EMG signals for specific motion tasks, motion detection and EMG classification is a challenging task. Many approaches to achieve efficient control using EMG signal classification had been considered, and they could generally be classified into the following main categories: (1) Neural Network (2) Fuzzy logic (3) Hybrid Fuzzy-Neural approaches and (4) Wavelet based.

2.2.1. Neural Network approach

In 1990, Kelly et al.,[15] described some early work done to explore the application of neural networks to myoelectric signal analysis. Hopfield algorithm was used to compute the time series parameters of the moving average signal model. The performance of two algorithms, namely the Hopfield and Sequential Least Squares algorithm were compared and it was concluded that Hopfield was two to three times faster than the latter based on a typical EMG data. Some additional results such as the use of perceptrons in future myoelectric signal analysis were also discussed.

In 1991, Nishikawa and Kuribayashi[16] used neural network to discriminate hand motions for EMG-Controlled Prostheses. Here the neural network was used to learn the relation between EMG signal's power spectrum and the motion task desired by the handicapped subject.

Hudgins et al., [17] analyzed the EMG signals for controlling multifunction prosthesis. Features were extracted from several time segments of the myoelectric signal to preserve pattern structure. These features were then classified using an artificial neural network. They observed that the performance of their system enhanced due to the neural network's ability to adapt to small changes in the control patterns.

The application of neural networks for the classification of myoelectric signals [18] and further in the control of the assistive devices based on these signals has been an interesting research.

2.2.2 Fuzzy approach

There have been many works on applying the fuzzy approach to EMG classification and control of assistive devices. Fuzzy logic has the ability to deal with imprecise, uncertain and imperfect information. The strength of fuzzy logic lies in the fact that it is based on the reasoning inspired by human decision-making. This fuzzy logic is used to handle the vagueness intrinsic to many problems by representing them mathematically. We have listed some of the prominent research in this field.

Some research groups have validated the use of fuzzy system for EMG classification and control of exoskeletons [19]. Fuzzy logic has demonstrated a good result in terms of higher recognition rate, insensitivity to training and consistent outputs. EMG signals and the force measured during elbow motion have been used as input information to fuzzy controllers. The input variables are the Waveform Length of biceps and triceps EMG signals, and the force measured at the subject's wrist. The torque command for the exoskeletal robot joint was obtained as the output from this controller.

Kiguchi et al. developed a fuzzy controller to control the elbow and shoulder joint angles of the exoskeleton based on the moving average value of EMG signals from arm and shoulder muscles and the generated wrist force [20]. Nearly 50 fuzzy IF-THEN control rules were designed based on the analyzed human subject's elbow and shoulder motion patterns in the pre-experiment.

In 2003, the same group proposed an improved version known as the fuzzy-neuro controller and implemented a back-propagation learning algorithm for the controller adaptation. Desired joint angle and impedance of the exoskeletal system were outputs from this controller.

Fuzzy logic was also used to detect the onset of EMG and to classify user intention in a multifunction prosthesis controller [1]. The fuzzy logic system did the EMG classification and based on the classification results, the controller executed the corresponding prosthesis functions. Ajiboye and Weir [3] proposed a heuristic fuzzy logic approach for multiple EMG pattern recognition in a multifunctional prosthesis control. Basic signal statistics such as mean and standard deviation were used for membership function construction. The rule base construction was done by a fuzzy c-means data clustering method. This system discriminated between four EMG patterns for subjects with intact limbs, and between three patterns for limb-deficient subjects. Overall classification rates ranged from 94% to 99%. This heuristic fuzzy algorithm also demonstrated success in real-time classification, both during steady state motions and motion state transitioning. This kind of functionality is necessary for the control of multiple degrees-of-freedom in a multifunctional prosthesis.

2.2.3 Hybrid Fuzzy-Neural approaches

Apart from using neural networks and fuzzy logic, researchers also tried their combination called neuro-fuzzy or fuzzy-neural systems for EMG classification and assistive devices control. Fuzzy systems have a reasoning capability similar to that of human beings. In addition, their combination with neural networks gives adaptive learning and self-organization capabilities to these hybrid systems.

In order to help everyday life of physically weak people, exoskeletal robots were developed for human motion support. In [21], the authors proposed controllers that can control the angular position and impedance of the exoskeletal robot system based on skin surface electromyogram (EMG) signals and the wrist force during the elbow motion. In order to make the robot flexible enough to deal with vague biological signal such as EMG, fuzzy neuro control has been applied to such controllers. While executing the controller, they consider the generated wrist force is more reliable when the subject activates the muscles little, and the EMG signals are more reliable when the subject activates the muscles a lot.

2.2.4 Wavelet based methods

Feature extraction is an important step for EMG classification. Time domain and frequency domain parameters were chosen as representative features for EMG signals. In this thesis, we have adopted the Wavelet transform and wavelet coefficients to represent the EMG signals. We have listed down some of the works, which demonstrated an encouraging level of results by identifying human intention and thereby controlling assistive devices.

The properties of wavelet transform turned out to be suitable for non-stationary EMG signals. Wavelet transform in combination with artificial neural network technique was used for the classification of EMG signals [22]. Neural network architecture with three layers in feed-forward fashion was designed using back propagation algorithm. After training the network with wavelet coefficients, it was able to classify four forearm motions with an average accuracy of 90%. The wavelet transform proves to be a powerful tool for real time preprocessing of EMG signals prior to classification.

An improvement to the previous work was the use of a wavelet-based feature set, reduced in dimension by principal components analysis [23]. It was demonstrated that exceptionally accurate performance was possible using the steady-state myoelectric signal. Exploiting these successes, a robust online classifier was constructed, which made online decisions on a continuous stream of EMG. Although in its preliminary stages of development, this online scheme promised a more natural way of myoelectric control than one based on discrete, transient bursts of activity.

Later in the year 2002, a wavelet based neuro-fuzzy approach [24] was proposed to classify EMG signals for movement recognition. EMG signals were analyzed with wavelet transform, and feature vectors were constructed by Singular Value Decomposition transform from wavelet coefficients for further movement recognition. It has been shown that proper feature selection and clustering techniques would improve the performance of the system.

In another study by Subasi et al. [25], feed-forward artificial neural networks and wavelet neural networks based classifiers were developed for EMG classification and they were compared with respect to their classification accuracy. In these methods, they used an autoregressive model of EMG signals as input to classification system. EMG obtained from 7 normal subjects, 7 subjects with myopathy and 13 subjects with neurogenic disease were analyzed in this work. The success rate for the wavelet system was 90.7% and for the neural network was 88%. The superiority of the wavelet-based systems over the traditional neural network systems was demonstrated for EMG classification of a specific dataset.

2.3. Type-1 and Type-2 fuzzy logic system (FLS) applications

In the previous sections, we were discussing many different approaches to EMG classification and how they can be used to control assistive devices. In this section, we will discuss some type-1 and type-2 FLS applications that have shown convincing results when used for applications analogous to EMG signal classification. These typical examples will substantiate why we have opted to develop fuzzy classifiers using both type-1 and type-2 fuzzy systems for our EMG classification in this thesis.

A typical rule-based fuzzy logic system (FLS) consists of three basic units- a fuzzifier, an inference mechanism and an output processor. A FLS that utilizes type-1 fuzzy sets is called a type-1 FLS. On the other hand, a FLS that utilizes at least one type-2 fuzzy set is called a type-2

FLS. Type-1 fuzzy sets are certain; hence uncertainties in the fuzzy logic rules cannot be modeled using type-1 FLS. As an improvement, type-2 fuzzy sets were used. In this case, the membership function is described by more design parameters compared to type-1 fuzzy sets. The output processor unit for a type-1 FLS contains only a defuzzifier that converts type-1 fuzzy set into a crisp number. In a type-2 FLS, the output processor is composed of a type-reducer, followed by a defuzzifier.

Type-1 FLS have been in use for many decades in engineering applications. Type-2 FLS [26] and its applications have been developed recently and in the last few years researchers have started exploring this field. In particular, we will see in these applications that the Type-2 fuzzy classifiers prove to be more robust in the presence of noise.

It was demonstrated with experiments in 1999 [27] that type-2 FLS can outperform a type-1 FLS for one-step prediction of a Mackey-Glass chaotic time series. This time series is obtained by solving a delayed non-linear differential equation known as the Mackey-Glass equation. These measurements were also corrupted by additive noise. In this paper the main focus was on model-based statistical signal processing and how some problems that are associated with it can be solved using fuzzy logic. Type-2 FLS have proven that they can handle linguistic and numerical uncertainties better than type-1.

A new approach for MPEG variable bit rate (VBR) video modeling and classification using type-2 fuzzy techniques was presented by Liang and Mendel [28]. They identified that a Gaussian membership function with uncertain variance (uncertain standard deviation) was the most appropriate choice to model the log-value of I/P/B frame sizes in MPEG VBR video. Fuzzy c-means method was used to obtain the mean and standard deviation of the input dataset. Type-1, type-2 fuzzy classifiers and a Bayesian classifier were designed for video traffic classification and fuzzy classifiers were compared with the Bayesian classifier. Simulation results show that the type-2 classifier performs the best in out-of-product classification.

In another experiment [29], Hani Hagras used indoor and outdoor robots navigating in unstructured environments to test the real time performance of type-2 Fuzzy Logic Controllers (FLC). Different robot behaviors like edge following, obstacle avoidance and goal seeking were tested. In these experiments, the type-2 FLC also outperformed the performance of the type-I FLC. One advantage of using type-2 fuzzy sets to represent the FLC inputs and outputs is that it will result in the reduction of the rule base when compared to using type-1 fuzzy sets.

In 2005, Herman, et al. [30] examined the potential of the type-2 FLS in devising an EEG based brain-computer interface. The designed type-2

FLS was required to classify imaginary left and right hand movements based on time-frequency information extracted from the EEG with the short time Fourier transform. Their challenge was to assign the examined EEG signals to classes of the associated mental tasks. The Type-2 fuzzy classifier proved to be more robust in the presence of noise and also compared favorably to a linear discriminant analysis classifier in terms of classification accuracy.

Another relevant work by National University of Singapore [31] assessed the feasibility of using a type-2 fuzzy system for ECG arrhythmic beat classification. Three types of ECG (Electrocardiograph) signals, namely the normal sinus rhythm (NSR), ventricular fibrillation (VF) and ventricular tachycardia (VT), were considered. The inputs to the fuzzy classifier were the average period and the pulse width, two features that are commonly used for computer-assisted arrhythmia recognition. Tests using data from the MIT-BIH Arrhythmia Database show that the type-2 fuzzy classifier yields an accuracy of 90.91% for VT events, 84% for VF events and 100% for NSR events. These results are superior when compared to type-1 system, neural network using self-organizing map and fuzzy rule-based methods.

Type-2 FLS have also been applied to classification of battlefield ground vehicles based on acoustic features [32]. In this paper, three fuzzy logic rule based classifiers were proposed and experiments were conducted to evaluate the performances of these architectures, and then they were compared to a Bayesian classifier. All the fuzzy classifiers performed substantially better than the Bayesian classifier and they achieved higher than the acceptable 80% classification accuracy. It is interesting to note that Interval type-2 fuzzy classifiers perform better than their type-1 counterpart, although sometimes not by much.

In this chapter, our main focus is to convince the readers why we have opted to design wavelet based type-1 and type-2 fuzzy classifiers for EMG classification. To support our claim we have given a brief literature assessment of some important research works in the field of EMG classification using neural networks and fuzzy approaches, and some relevant applications of type-1 and type-2 fuzzy systems. This chapter also identifies several applications where type-2 FLS have been chosen instead of the traditional type-1 FLS because of its comparative advantages.

The classifier model and the features used in that classifier have to be chosen appropriately with sufficient care. We should bear in mind that the performance of any classifier varies widely with different choice of dataset, training algorithm, feature selection, etc. In a pattern recognition problem, there should be a negotiation between the various available choices. A very strong classifier can perform poorly if the choice of features is not good. The reverse is also true: a carefully chosen feature set can classify well even if a weak classifier is used.

Chapter 3

Electromyographic Signals

When a muscle contracts, the neuromuscular activities associated with that muscle results in myoelectric signals being generated which we call as EMG. It is a common practice to measure the skin surface EMG signals in order to identify the intention of an individual [12]. For example if we want to build any prosthetic or orthotic device, we will need to know the intention of the users. One solution is to use EMG signals. There are various factors involved in the development, recording and analysis of myoelectric signals, which we will discuss later in this chapter.

Measurement of EMG signal is corrupted by additive noise whose signal-to-noise ratio (SNR) varies in an unknown manner [33]. Unlike the classical Neurological EMG, where an artificial muscle response due to external electrical stimulation is analyzed under static conditions, the focus of Kinesiological EMG can be described as the study of the neuromuscular activation of muscles within postural tasks, functional movements, work conditions and treatment/training regimes [34]. The EMG is considered as a reasonable reflection of the muscle activity [35], which indicates the firing rate of motor neurons.

Each individual has his own style of using his muscles for a certain motion and one muscle is associated with more than one motion task [36]. This fuzzy behavior of biological signals such as EMG has been noted many years back [37]. Analysis of EMG data can be done using raw signal (prior to any processing) or using processed signal. The raw data is not very useful for classification purposes. Hence, it is usually processed and used for further analyses.

3.1. Raw EMG

The use of EMG has many benefits - it measures muscular performance, helps us to record treatment and training regime for future use, helps subjects with disabilities to train their muscles. However, there are some difficulties in the measurement and processing of these signals [38]. One such aspect is the choice of sampling frequency for EMG measurement. The sampling rate of Analog/Digital kit must be at least twice as high as the maximum probable frequency of the signal. This is in accordance with Nyquist's sampling theorem. If the sampling frequency is too low then it might lead to aliasing effects.

The band setting for EMG amplifiers should be chosen carefully. Usually the lower limit is 2 Hz or less and the upper limit is 10 kHz or higher [39]. This means to ensure that the signal is not lost, a sampling frequency of at least 20 kHz or more is recommended.

Although, the measurement and processing of EMG signal [40,41] is a difficult task, the evolution of many computational tools and other software has made it easier to convert the raw EMG signals to usable form.

3.1.1. Details of subjects, EMG recordings

The following five are the important factors to be considered before recording EMG signals [40-42].

1. Choice of electrodes;
2. Skin preparation technique;
3. Electrode dimensions;
4. Appropriate electrode placement and location of muscles, and;
5. Inter-electrode distance (There is very little clue to find a standard inter-electrode distance).

The quality of any EMG measurement strongly depends on a proper skin preparation and electrode positioning. The key factor in skin preparation is to establish stable electrode contact and low skin impedance. Most modern EMG-amplifiers are designed for skin impedance levels between 5 and 50 kOhm (between pairs of electrodes). Usually it is necessary to perform some skin preparation before the electrodes can be applied. There are no general rules for this and there are several possibilities to reach a good skin condition for EMG-measurements [33].

The following procedures may be considered as the key steps to prepare the skin:

1) Removing the hair

2) Cleaning the skin – Using conductive cleaning pastes, sand paper or alcohol to perform soft rubbing on the skin. A light red color on the skin is an indication of good skin impedance. For surface electrodes, silver or silver chloride (pre-gelled) electrodes are most commonly used.

For certain cases, a simple alcohol cleaning may be sufficient for skin preparation.

3.1.2. EMG recordings and Signal Processing techniques

The EMG data used in this study were obtained from experiments done at Neuromuscular Control Laboratory, Simon Fraser University [43,44]. The experiment started in May 2007 and was completed in July 2007.

Two subjects were chosen as given below:

1. Post-stroke subject: Right handed male, 63 years old with right hemiplegia.
2. Healthy subject: male, 61 years old.

The following key points are crucial during the EMG signal capture and the subsequent signal processing steps.

- Skin cleaning and surface electrode positioning
- Filter bandwidth
- Sampling rate
- Acquisition card

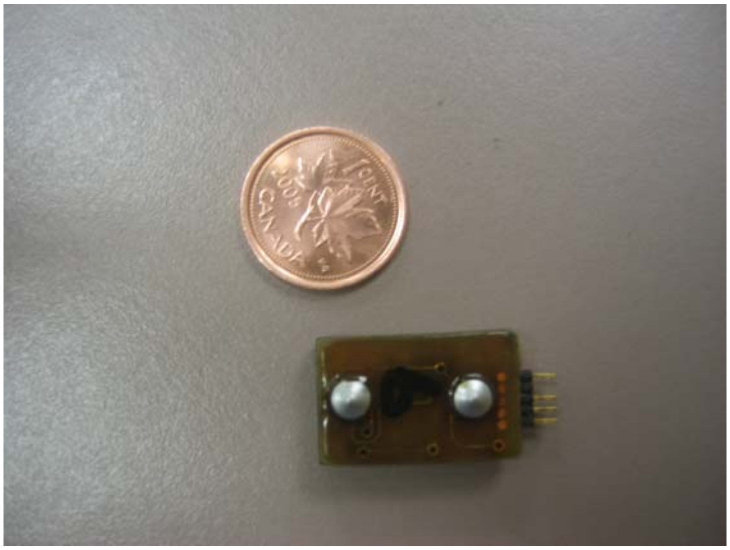

Fig.3.1 Bipolar surface electrodes used for EMG recording

For skin preparation, the skin was cleansed with alcohol. Custom-built active bipolar electrodes (surface electrode) with variable gain as shown in Fig.3.1 were used and filtered in 30 Hz and 500 Hz bandwidth range. The sampling rate for the EMG measurements was 2 kHz, keeping in mind the Nyquist's sampling theorem. A data acquisition card with 16 channels was used to acquire the data in the SFU laboratory (only 9 channels were used, as they recorded from 9 muscle sites). The 9 muscle sites from the arms are the Extensor carpi radialis (ECR) muscle, the Extensor digitorum communis (EDC) muscle, the Flexor carpi ulnaris (FCU) muscle, the Flexor digitorum superficialis (FDS) muscle, the Peroneus tertius (PT) muscle, the Biceps (BI), the First dorsal interosseous (IDI) muscle, the Abductor Pollicis Brevis (APB) and the Abductor digiti minimi (ADM) muscle as in Fig. 3.2.

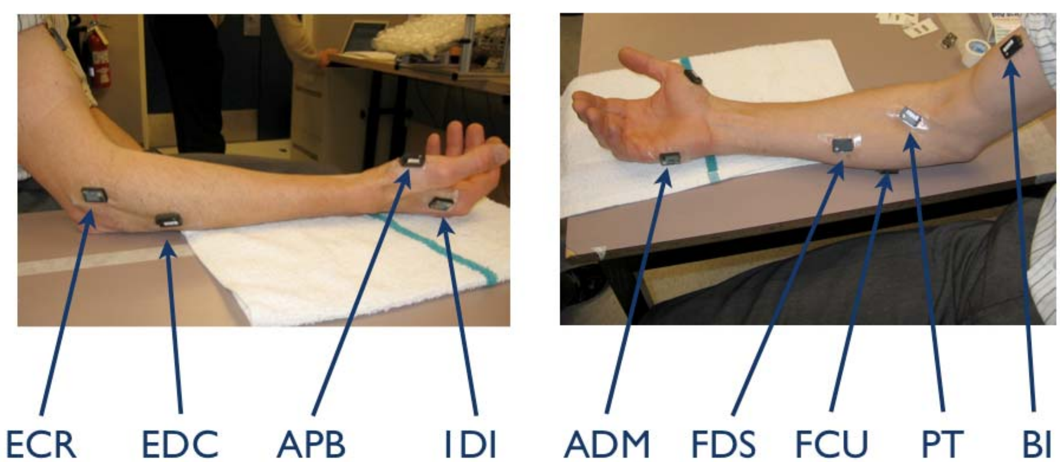

Fig.3.2 Surface EMG electrode sites on the subject

EMG signals vary widely when the detection condition varies such as changes in subjects, small changes in electrode locations, and day-to-day measurements of the same muscle site. Normalization eliminates this problem and signals are now scaled to a percentage of reference value. This allows a direct quantitative comparison of EMG findings between subjects. Fig. 3.3 shows the EMG signals of a subject both before and after normalization. Normalization [45] is done for comparing EMG parameters across different muscles or for different subjects. We do this by dividing the measured EMG value by the Maximum voluntary contraction (MVC) [10] that is likely to reflect the differences in the conditions of the recording. The MVC procedure is done for each of the 9 muscle sites separately. We notice that this normalization changes only the amplitude and does not affect the shape of EMG signals. The raw signals obtained from these muscles were already filtered in the bandwidth of 30 Hz to 500 Hz. The next step is offset removal. DC offset is simply the mean amplitude of the signal; by subtracting the mean amplitude from each sample we can remove this offset.

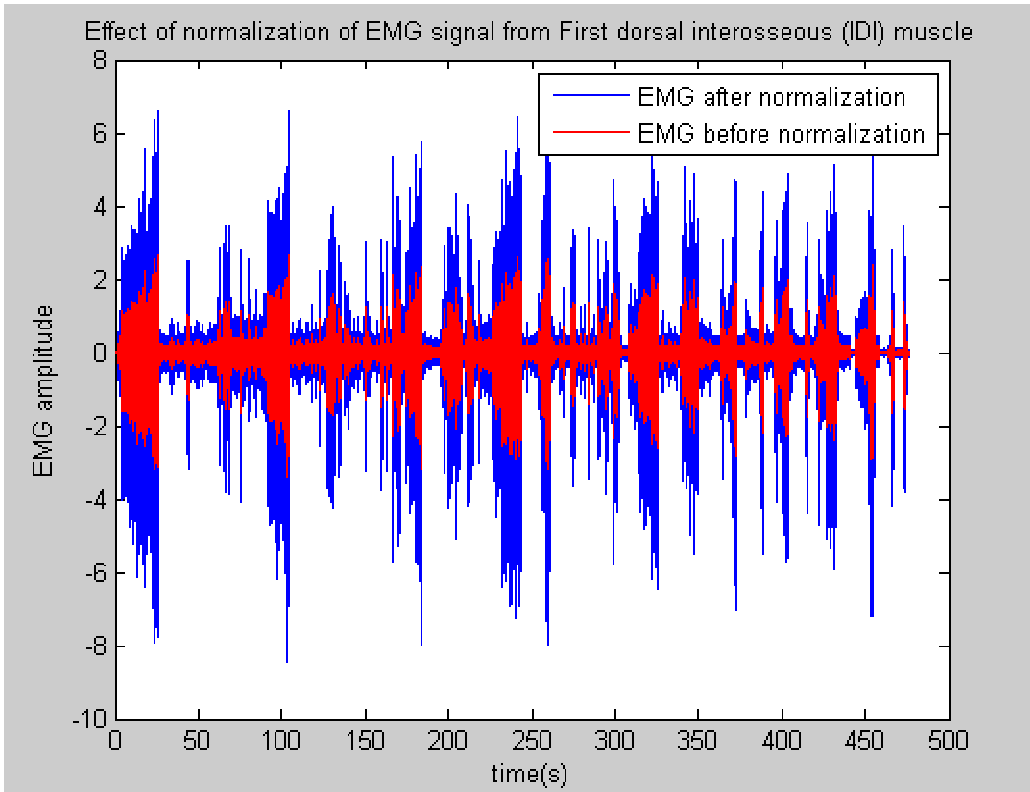

Fig.3.3 EMG signals of patient before and after normalization

3.2. Kinds of motion

Each subject generated two different types of motion: hand close-open and pronation-supination of the forearm. The contraction levels were assumed to be arbitrary as long as they are reasonably consistent. It was also ensured that the level of contraction was comfortable enough for the subjects to perform these motions without any fatigue.

The number of trials depends on the subject, i.e. if he was tired or experienced pain, the session was limited. In the EMG dataset that we are using, the two subjects have performed 10 trials per set. They rested for 2 minutes between subsequent sets. The duration for the whole experiment for the subject with hemiplegia lasted for nearly 2 months. To summarize, the complete experiment comprised of 16 sessions (days), each session is composed of 2 or 3 sets and each set consists of 10 trials. The raw EMG signal is not very useful to us. We will have to process the EMG signals using a sequence of steps.

In our study, we used the EMG signals when the two subjects performed simple, but very common hand motion tasks. The healthy subject's EMG levels were measured as well in order to compare them with that of the post-stroke subject.

The main objective of the experiment done at Simon Fraser University was to develop robotic tools for the rehabilitation of hand functions after stroke [43,44]. In order to analyze further, the EMG of post-stroke patient both before and after rehabilitation training were also measured.

The subjects performed two specific motions such as hand close-open and forearm pronation-supination as shown in Fig 3.4 and 3.5. These were the functions that the post-stroke subjects wanted to recover so that it would help them in their daily activities such as knob manipulation, handwriting practice, etc., [46]

Fig.3.4 Post-stroke subject performing hand close-open motion with robotic device

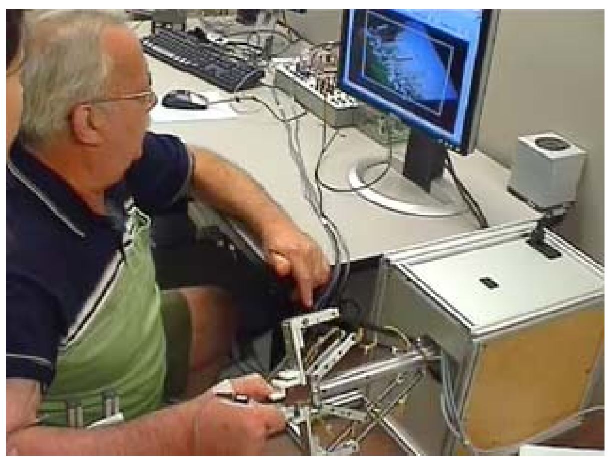

Fig.3.5 Post-stroke subject performing forearm pronation-supination motion with robotic device

The details of the robotic devices for opening and closing of hand, haptic knob and robotic interface for handwriting rehabilitation are not described here as we focus only on the EMG classification using fuzzy approaches.

Chapter 4

Feature Extraction

Any classifier's performance is based on numerous factors. One such factor is the most appropriate choice of the feature set. The way in which we represent the EMG signals for classification is very important. In this chapter, we focus on the representation of EMG signals so that the designed fuzzy classifiers can clearly distinguish between human arm motions.

In addition, we have discussed the various approaches to extract useful features from signals. In particular, we have summarized the time domain and frequency domain features; their relative advantages and disadvantages. We know that EMG signals can be represented in both time domain and frequency domain [47]. Hence, for signal classification, the signal's energy depicted in a dual representation has been used by Englehart, et al., [48].

For the EMG signals under study, we have chosen a dual representation using Continuous wavelet transforms (CWT) which characterizes these signals in terms of time and scale information.

Time-frequency representations of signals have been used in various classification applications such as recognition of speech signals [49,50], radar imaging and signal analysis [51], underwater acoustic and geo-acoustic signals [52].

For signal classification applications, the signals are represented using different transformation methods. Due to their complexity in nature for most of these methods, we resort to only Continuous Wavelet Transform for our work. The first mention of wavelets appeared in an appendix to the thesis of A.Haar in 1909. One property of this Haar wavelet, named so after its inventor, is that it has compact support, meaning it vanishes outside of a finite interval. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Many other fields also make use of the concept of wavelets such as in astronomy, acoustics, signal and image processing, earthquake-prediction, nuclear engineering, sub-band coding, music, magnetic resonance imaging, speech discrimination, optics, radar.

4.1. Time domain features

Many raw signals have been represented in their time domain, which is nothing but simple amplitude versus time representation of the signals. Signal processing applications require additional information that is not present in the time domain representation. For this reason, signals were analyzed in their frequency domain also.

Myoelectric patterns can be represented by the following features [17]: Mean absolute value, mean absolute value slope, zero crossings, slope sign changes and waveform length are some of the ways of feature representation for EMG signals. Although the variance in the time structure of these signals is high, waveform statistics may be stable enough to allow pattern recognition.

4.2. Frequency domain features

The frequency spectrum of any signal tells us what frequencies exist in that signal. The plot of the quantity of signal with respect to the frequency is called as frequency spectrum. Such a representation of a signal is known as frequency domain representation. Fourier transform (FT) and Short time Fourier transform (STFT) are discussed under this section. The problem of STFT is overcome by using Wavelet Transform for our EMG signal analysis.

4.2.1. Fourier Transform (FT)

FT decomposes a signal into complex exponential functions of different frequencies. If the FT of a signal in the time domain is taken, the frequency-amplitude representation of that signal is obtained. The way it does this is defined by the following two equations:

$$X(f) = \int_{-\infty}^{+\infty} x(t).e^{-2j\pi ft}\,dt \tag{4.1}$$

$$x(t) = \int_{-\infty}^{+\infty} X(f).e^{2j\pi ft}\,df \tag{4.2}$$

Equations 4.1 and 4.2 are the expressions for Fourier transform and inverse Fourier transform, respectively. In the above equations, *t* and *f* stand for time and frequency, respectively. *x* and X denote the signals in the time domain and frequency domain, respectively.

Using this simple expression of FT, it is possible to easily find out whether a particular frequency component is a major component of the signal or not. The main outcome of FT is that it tells us what are the frequency components existing in the signal under study. In certain specific applications, we may want to know when in time these frequencies occur in the signal. This feature is not available in the FT and is one major disadvantage of the FT. In short, FT is very useful for stationary signals where we are not concerned with when the different frequency components appear in the signal. In Fourier transform, we can include a finite measurement time window, which is known as the windowed Fourier transform.

Many biological signals are non-stationary. To name a few are ECG (Electrocardiograph), EEG (Electroencephalograph), and EMG (Electromyogram).

4.2.2. Short Time Fourier Transform (STFT)

We notice only a minor difference between STFT and FT. In STFT, the signal is divided into small segments, and each segment of the signal can be assumed to be stationary. Thus, the signal is interpreted as a piecewise-stationary signal. In biomedical signal processing, choosing a proper segmentation for the signals has to be done with care. The signals have to be studied prior to choosing the stationary segments. We need to ensure if the signals are highly non-stationary signals or if they are signals with wide stationary segments.

We multiply the signal $x(t)$ by a window function $\omega(t-t')$. The resulting transform gives the frequency content of the signal near $t=t'$. Usually, the width of the window function is equal to the stationary segment of the signal.

$$X_{STFT} = \int_t [x(t).\omega(t-t')].e^{-2j\pi ft}dt \tag{4.3}$$

The STFT of the signal as shown in Eq.4.3 is nothing but the FT of the signal multiplied by a window function.

The problem with STFT is the choice of a proper window function. If we choose a small narrow window, we get a good time resolution but a poor frequency resolution. Narrow windows abide by the rule of stationary signals. Another option is to choose a wide window size. In this case, the time resolution gets poorer and the frequency resolution is better than the former case. We have to make a compromise in choosing the window function for the STFT. When the window size is too large, the STFT becomes the normal FT. The choice of window function is application dependent. Once, we choose the window size and then it remains fixed. Hence, we face the resolution problem. To overcome this, CWT was developed. This will be discussed in detail in the next section.

4.2.3. Continuous Wavelet Transform (CWT)

The wavelet transform is performed in the same manner as STFT. We multiply the signal x(t) by a wavelet function instead of a window function as in Eq.4.3. As we discussed in the previous section, the resolution problem can be resolved using CWT which uses a different approach called Multi Resolution Analysis. This method of analysis makes more sense for biological signals like EMG, ECG, etc., where there are high frequency signal components for short time intervals and low frequency signal components for long time intervals in such signals. Hence the Multi Resolution Analysis when applied to EMG signals computes the transform for the signals segment-by-segment individually with different resolutions for each segment based on the nature of the signal. The expression to compute the CWT of a signal x is given as follows.

$$X_{CWT} = \frac{1}{\sqrt{|s|}} \int x(t) \psi^* \left(\frac{t - \tau}{s} \right) dt \qquad (4.4)$$

In the case of FT as in Eq.4.1, we notice that the signals in time domain are represented in their frequency domain, whereas in Eq.4.4, there is a scaling parameter s instead of frequency f. This scaling parameter s is the reciprocal of frequency f. We also notice that the window function is being translated along the time axis using the parameter τ. The function ψ is called the wavelet basis function or mother wavelet, where the asterisk in the superscript denotes complex conjugate. It serves as a source function to generate many other wavelets. It is called as the mother wavelet as we can derive daughter wavelets by obtaining scaled and translated versions of this wavelet. The significance of the scale s in the computation of CWT is to either compress or expand the signal x(t). We usually calculate the CWT for a finite interval of values of s, starting from 1 to 25 for our EMG signals here. Thus, the CWT is computed for the EMG signals by incrementing the values of τ and s. The plot of CWT can be shown in either a two-dimensional or three-dimensional graph. It is usually represented on a time-scale axis. The magnitude of the CWT can be represented by a gray-scale colour graph with time on the horizontal axis and scale on the vertical axis.

4.3. EMG feature extraction using Continuous Wavelet transforms

Fast Fourier Transform and other frequency transformations assume that the EMG signal when measured during a motion task remains stable. Continuous Wavelet Transform, which was selected for this research, gives a time-scale view of signals [53]. This makes the identification of muscle motions easier. The wavelet type and the decomposition level were chosen after some initial trials on the available EMG data. There is no standard procedure to choose the most appropriate type of wavelet and the decomposition level that will best suit the available data. It is purely application dependent.

4.3.1. Choice of mother wavelet

The choice of mother wavelet can be done from the following families: Beylkin [54], Spline, Daubechies, Mexican hat and Morlet [55,56]. Researchers have already checked the suitability of various mother wavelets for myoelectric signal analysis. It has been shown that the features obtained using Wavelet Transform with Coiflet-4 as the mother wavelet, yielded the lowest classification error on a transient EMG dataset [23].

In this thesis, we have also chosen the same Coiflet-4 mother wavelet. Here the number next to the wavelet's name represents the number of vanishing moments and is associated with the number of wavelet coefficients. This wavelet family has good de-noising effects and they work well for signal analysis [57] and in financial trends.

The wavelet function $\psi(x)$ and the scaling function $\varphi(x)$ for the Coiflet wavelets should satisfy the following conditions:

$$\int dx \;\; x^j \psi(x) = 0, \qquad \text{and} \tag{4.5}$$

$$\int dx \;\; \varphi(x) = 1, \qquad \int dx \;\; x^j \varphi(x) = 0, \qquad j = 0,1,\dots,N-1 \tag{4.6}$$

The following are the characteristics of Coiflet wavelet [56]:

1. The Coiflet wavelets are both orthogonal and biorthogonal [58] in nature. Orthogonal wavelets are those that satisfy the condition that the inner product of the scaled and translated mother wavelet is an impulse function. The associated wavelet transform of biorthogonal wavelets is

invertible but not necessarily orthogonal. Biorthogonal wavelets can be used to construct symmetric wavelet functions.

2. They are compactly supported wavelets.

3. The order of this wavelet ranges from 1 to 10. We have chosen the wavelet of order 4 for our work.

4. The length of the filter is usually six times the order of the wavelet.

5. Coiflets are wavelet functions that are more symmetrical compared to Daubechies wavelets.

In addition, the Coiflets are those wavelets with the highest number of vanishing moments for a given support width. The Coiflet wavelet is different from the Daubechies wavelet in the sense that it was constructed with vanishing moments for both the wavelet function and scaling function. In signal analysis the Coiflets are desirable due to their symmetry property.

4.3.2. Wavelet Coefficients

The continuous wavelet transform analysis of the signal involves the estimation of some constant numbers called as wavelet coefficients. These coefficients refer to the closeness of the signal to the wavelet at the current scale.

For example, if the EMG signal measured from one muscle has a major frequency component at a particular value of scale, then the wavelet at that value of scale will be similar or almost close to that muscle's signal.

Therefore, the CWT coefficient computed at this point will be a relatively large number. Similarly, a small value of the wavelet transform coefficient indicates that the EMG signal pattern is far different from the wavelet at that particular value of scale. In short, the wavelet coefficients obtained using Eq.4.4 shows the correlation between the chosen wavelet and the signal under study, at various values of scales.

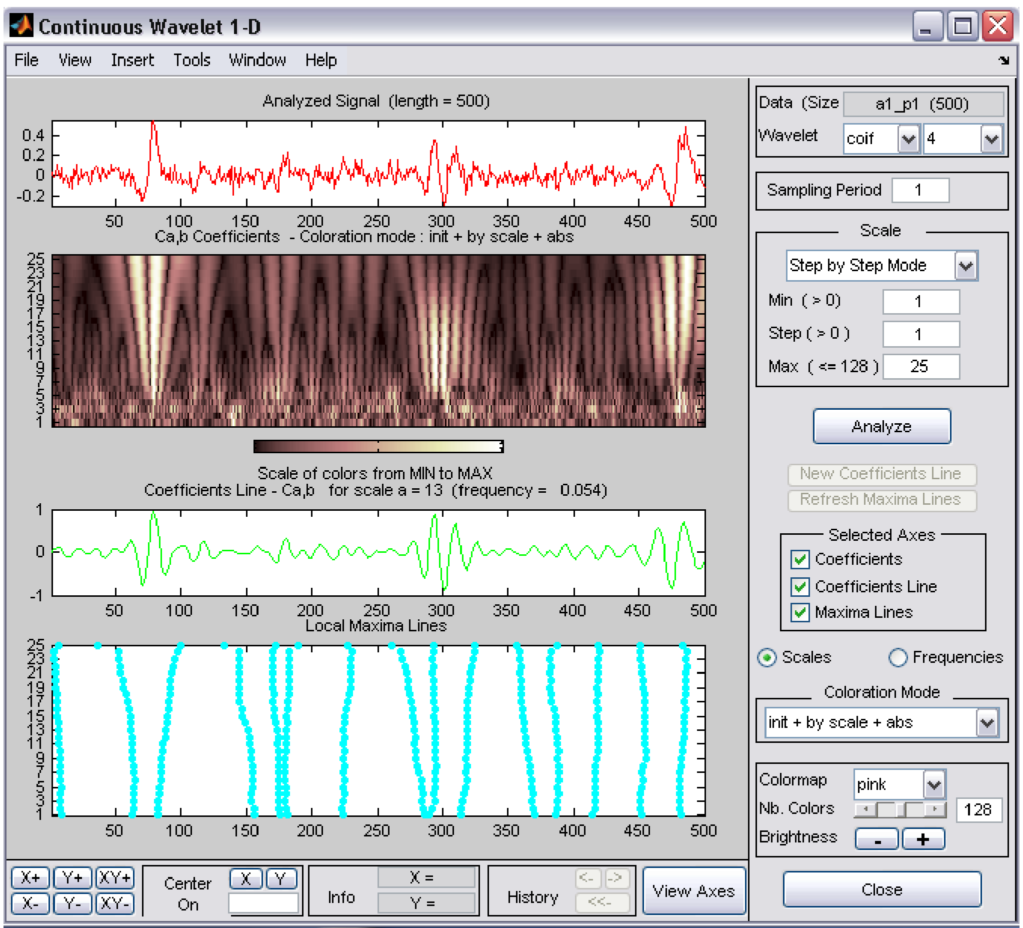

Fig. 4.1 Computation of CWT coefficients using Matlab toolbox

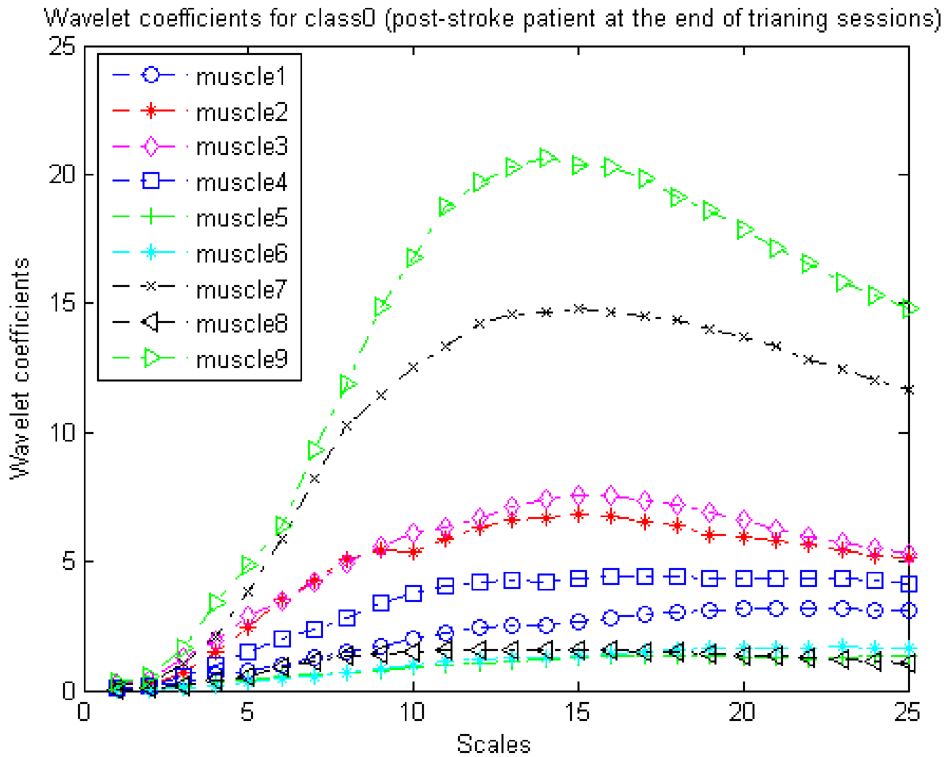

Fig. 4.2 Coiflet Wavelet coefficients of post-stroke subject for class 0

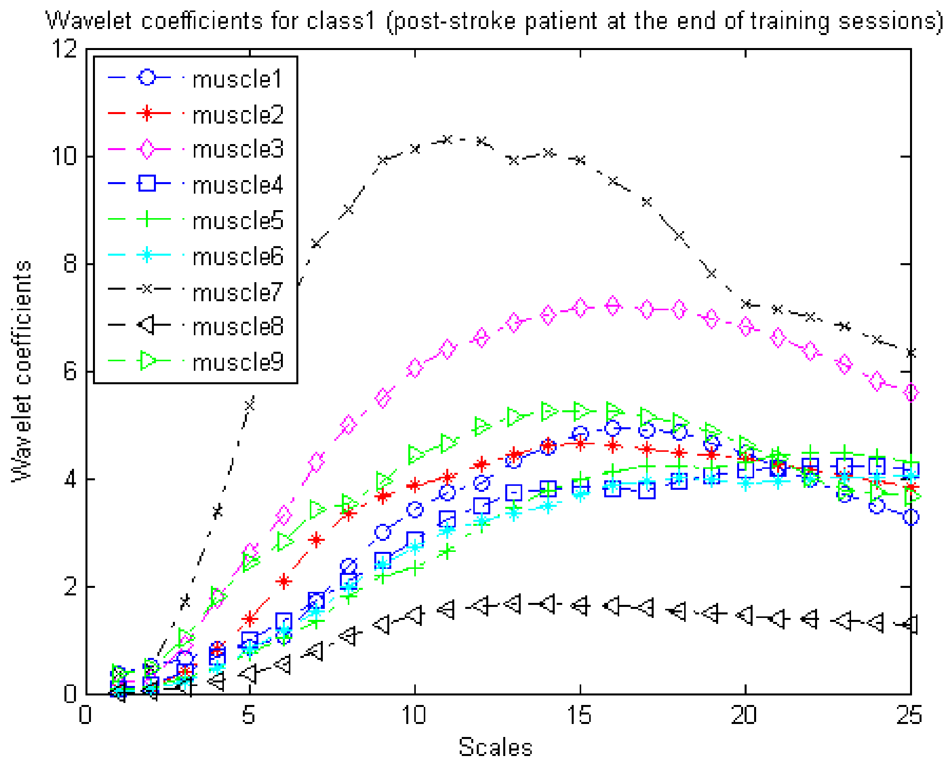

Fig.4.3 Coiflet Wavelet coefficients of post-stroke subject for class 1

Using the wavelet toolbox in Matlab, we were able to obtain the wavelet coefficients for EMG signals by choosing coiflet-4 as the mother wavelet. As we have discussed in the previous section, the number of scales is chosen randomly as a reasonable number since we are not concerned with the reconstruction of these EMG signals. We have chosen the scales from 1 to 25 and the scale increment is done using a “step-by-step” mode. Fig. 4.1 shows a snapshot of the Matlab wavelet toolbox that plots the wavelet coefficients.

Using the above method, we have obtained the wavelet coefficients corresponding to all the nine muscles for the post-stroke subject. Figs. 4.2 and 4.3 show the plots of wavelet coefficients with respect to the scales. We will be using these wavelet coefficients as features for EMG signal representation.

4.3.3. Proper selection of features

Another consideration is the need to choose the appropriate features that serve as a good replication of the signals' characteristics. Feature selection methods will determine the best subset within the original feature set. Feature selection is performed here using the criterion from another research work [22].

The maximum absolute value of the wavelet coefficients at each scale was extracted as features for the classifier. We choose the maximum 25 coefficients corresponding to 25 scales. Once the data sets are extracted from the subjects, and proper feature selection is done, we then obtain the antecedent membership functions and the input fuzzy sets using statistical approaches in Microsoft Office Excel. We arrive at 4 rules, 2 for each class. Further details of the fuzzy system are described in the subsequent chapters.

Chapter 5

Fuzzy Approach to EMG Classification

In year 2000, Chan et al [19] worked on fuzzy EMG classification for the control of prosthesis. They used a fuzzy approach called ISO-FUZ, which is initialized with the basic Isodata algorithm and trained with the back-propagation algorithm. The fuzzy approach was compared with an Artificial Neural Network and it was superior to the latter in many aspects such as higher recognition rate, insensitivity to overtraining and consistent outputs demonstrating higher reliability.

In this chapter, we will discuss type-1 and type-2 FLS, their relative advantages and disadvantages. In order to search for an improved solution to the EMG classification problem, we have proposed to compare both type-1 and type-2 FLS. We will also briefly describe Singleton and Non-singleton fuzzy systems. As we are concerned with rule-based fuzzy classifiers, we should first construct the structure for the fuzzy rules based on the available dataset. The EMG data obtained from the healthy and post-stroke subjects are inputs to the fuzzy classifiers. They appear in the antecedents of the rules. Using CWT, we obtained the wavelet coefficients as representative features for these EMG signals. These coefficients serve as antecedents to the fuzzy rules and the consequent is either ‘0’ or ‘1’ each indicating either of the two motion tasks under study. When the consequent is ‘0’ it indicates hand open-close motion and when the consequent is ‘1’ it indicates forearm pronation-supination motion tasks.

Fuzzy technology has the potential to tackle the uncertainties that exists during arm movement changes. Hence, we have chosen a rule-based fuzzy system design for our EMG classification problem. In this chapter, we will discuss the major components in a fuzzy system, type-1 and type-2 FLS, the fuzzy rules and the classification of the fuzzy systems into singleton and non-singleton.

5.1. Fuzzy Logic System (FLS)

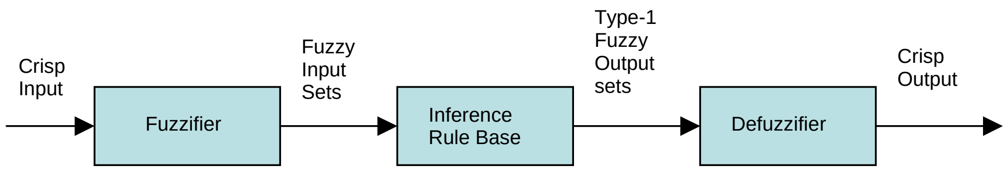

Fig. 5.1 Schematic representation of a fuzzy logic system (FLS)

A FLS is depicted in Fig.5.1. It contains the following major components- inference rule base; input processor called fuzzifier, and output processor called defuzzifier. The inference engine maps each rule's fuzzy input sets into each rule's fuzzy output set. Rules are very important for a FLS. Each rule can be thought of as a subsystem and it has one to many membership functions (fuzzy sets) associated with it. The rules come into action only when the inputs are applied to them.

The fuzzy rules are nothing but a simple mapping from the inputs to the outputs and this mapping can be expressed quantitatively as y = f(x). This kind of FLS is very common and widely used in many engineering applications of FL, such as in FL controllers and signal processors. It is also known as a fuzzy controller, fuzzy system, fuzzy expert system, or fuzzy model.

There are a number of possibilities for a FLS. The design degrees of freedom that control the accuracy of a FLS are the number of inputs, the number of rules, and the number of fuzzy sets for each input variable.

We are free to choose the membership function for our design of fuzzy classifiers. This choice can also be done based on an estimate of the kind and quantity of noise present. We make sure that this function is symmetric about its mean based on the assumption that noise effect is most likely to be equivalent on all points.

Examples of such membership functions are:

Gaussian: $$\mu(x) = \exp[-(x - x')^2 / 2\sigma^2], \tag{5.1}$$

Triangular: $$\mu(x) = \max(0, 1 - |(x - x') / c|), \tag{5.2}$$

Some other membership functions such as:

$$\mu(x) = 1/(1 + |(x - x') / c|^n), \tag{5.3}$$

where x' is the center value of the fuzzy sets, standard deviation σ and c are values that represent the spread of these sets. Larger values of the spread for these membership functions imply that more noise is anticipated to exist in the data.

Finally, a FLS contains many design parameters whose values must be set by us before we work with the FLS. There are many ways to do this, and all these methods make use of a set of data, usually called the training set. This set consists of input-output pairs for the FLS, and, if these pairs are measured signals, then they are uncertain as the measurements excite the FLS. We should first set the values for the design parameters in the FLS. This can be done using the training dataset, which is a prototype of the entire data to be analyzed.

In this chapter, so far we have discussed the structure and qualities of a fuzzy logic system in general. In the remaining chapter, we will briefly discuss the properties of type-1 and type-2 FLS, differences between a singleton and non-singleton fuzzifier and the different methods of extracting fuzzy rules from the data in hand.

5.1.1. Type-1 and Type-2 FLS

Type-2 FLS in general are described by type-2 membership functions that are characterized by more design parameters than a type-1 membership function. The difference in the structure of a type-2 FLS can be seen in Fig.5.2.

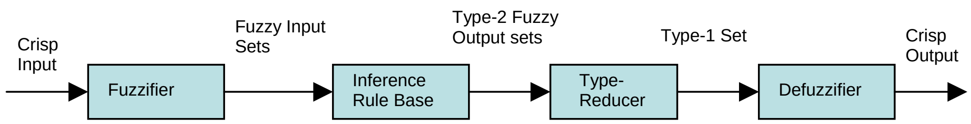

Fig. 5.2 Schematic representation of a type-2 fuzzy logic system (FLS)

The main difference between a type-1 and type-2 fuzzy set lies in the membership function. For a type-1 fuzzy set, membership function is a two dimensional function and it is constrained to be between 0 and 1, whereas for a type-2 fuzzy set, it is three-dimensional. There are uncertainties involved when we use data such as EMG signals in our fuzzy system design. These uncertainties appear in the fuzzy rules as well as in the EMG measurements, which are used as inputs to the fuzzy classifiers. When we design the type-1 and type-2 FLS, we are optimizing the parameters of the membership function using some training data.

The type-1 fuzzy sets that we choose are precise membership functions. There is no room for modeling the uncertainties in type-1 fuzzy sets. Such precise functions do not have the ability to handle the uncertainties involved in the measurements and rules. Type-2 FLS is a better option when we are unable to arrive at an exact membership function for a fuzzy set. Hence, they can be used to handle rule uncertainties and even measurement uncertainties.

It is difficult to visualize the plot of the type-2 fuzzy sets in three dimensions. One easy way is to plot the two-dimensional domain of the type-2 fuzzy sets called as footprint of uncertainty (FOU). An example of such FOU is shown in Fig.5.3. This plot shows a type-2 Gaussian membership function whose mean varies from 4.5 to 5.5 (i.e. the mean is uncertain) and whose standard deviation is perfect. The space between the two Gaussian curves in Fig.5.3 represents weighting. If the weighting is assumed to be uniform then such a type-2 fuzzy set is called an interval type-2 fuzzy set. In this study, we have used only interval type-2 FLS [59], as the computations are easier and well established.

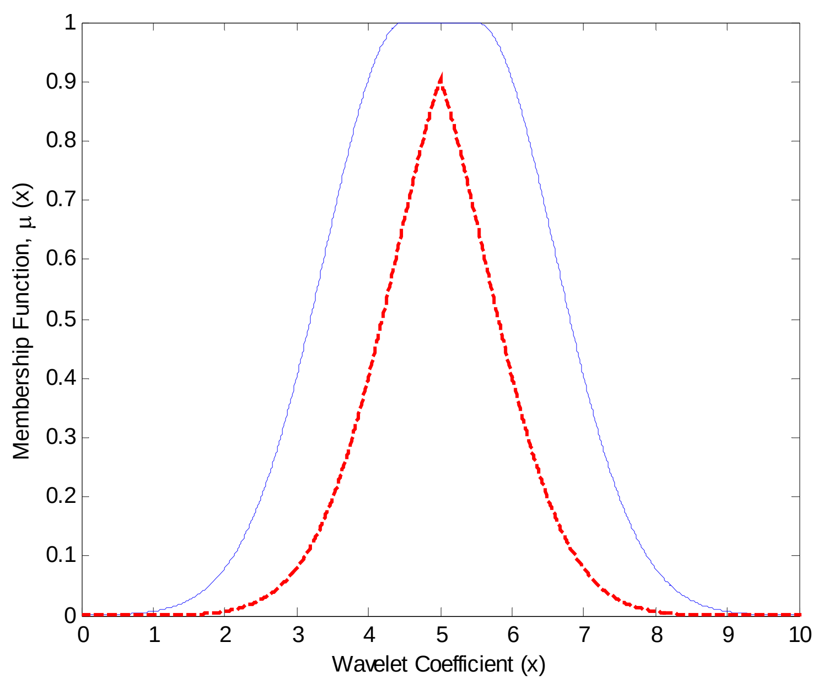

Fig. 5.3 FOU for Gaussian membership function with uncertain mean.

A Gaussian primary membership function with uncertain mean can be expressed as

$$\mu_k^l(x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - m_k^l}{\sigma_k^l}\right)^2\right] \qquad m_k^l \in [m_{k1}^l, m_{k2}^l] \qquad (5.4)$$

where k=1,…,a (the number of antecedents) and l=1,…,R (the number of rules).

Let us assume that $G(m_{k1}^l, \sigma_{k1}^l; x_k) = \exp\left[-\frac{1}{2}\left(\frac{x_k - m_{k1}^l}{\sigma_{k1}^l}\right)^2\right]$

The upper membership function, $\overline{\mu}_k^l(x_k)$ is

$$\overline{\mu}_k^l(x_k) = \begin{cases} G(m_{k1}^l, \sigma_k^l; x_k) & x_k < m_{k1}^l \\ 1 & m_{k1}^l \le x_k \le m_{k2}^l \\ G(m_{k2}^l, \sigma_k^l; x_k) & x_k > m_{k2}^l \end{cases} \qquad (5.5)$$

and the lower membership function, $\underline{\mu}_k^l(x_k)$ is

$$\underline{\mu}_k^l(x_k) = \begin{cases} G(m_{k2}^l, \sigma_k^l; x_k) & x_k \le \frac{m_{k1}^l + m_{k2}^l}{2} \\ G(m_{k1}^l, \sigma_k^l; x_k) & x_k > \frac{m_{k1}^l + m_{k2}^l}{2} \end{cases} \qquad (5.6)$$

Because of the additional features (in terms of more degrees of freedom) in the type-2 fuzzy sets, a type-2 FLS can give better results when compared to a type-1 FLS. This has not yet been proved mathematically. However, in most of the applications to which Mendel has applied type-2 FLS, he always observed that better performance is obtained using a type-2 FLS than is obtained using a type-1 FLS [28, 32].

According to Mendel's works on type-1 and type-2 FLS performance, the following are some cases in which he observed that type-2 FLS are more appropriate than the type-1 FLS:

- Case 1: When the non-stationary nature of the measurement noise cannot be expressed mathematically beforehand (cases where the measurements are corrupted by variable signal-to-noise ratio).

- Case 2: When the non-stationary nature of the features obtained from our measurements cannot be expressed mathematically beforehand (one typical example is the video traffic classification).

- Case 3: When the time-varying nature of the data-generating mechanism cannot be expressed mathematically beforehand (in non-linear and time-varying digital communication channels where co-channel interference need to be reduced).

- Case 4: When IF-THEN questionnaires are used for experts knowledge mining (examples such as traffic control for ATM system).

Our work on classification of EMG signals is identical to a rule-based video traffic classification problem.

5.1.2. Fuzzy Rules for EMG classification

In order to establish the fuzzy rules for a fuzzy logic system, we start with the training dataset. To begin, we choose a certain number of input-output training pairs. Our next step is to convert the training dataset into a set of fuzzy rules (IF-THEN, IF-THEN-ELSE, etc.). In this work, we use only IF-THEN fuzzy rules, which is the most simple and very common rule type. All fuzzy sets in the rules are represented by Gaussian membership functions.

We have N input-output numerical data training pairs, $(x^1 : y^1), (x^2 : y^2), ..., (x^N : y^N),$ where x is the input and y is the output of a FLS. Our goal is to completely specify the FLS using the training data.

The design methods that we adopt usually determine the values of the parameters in the antecedent and consequent membership functions based on the training dataset. The maximum number of rules we can arrive at is equal to the number of training pairs that we choose. This is the simple case when there is no tuning involved in the FLS. Tuning determines an optimal system that provides the best fit to the input-output pairs, with respect to a cost function. Tuning further reduces the number of rules.

The following are some methods to extract rules from the numerical training data:

- The centers of the fuzzy sets in the antecedents and consequents of the rules are obtained directly from the training data.

- Assume fuzzy sets for the antecedents and consequents ahead of time and then relate the data with these fuzzy sets.

- The FLS is first designed and then all its design parameters are optimized using the training data.

Extraction of rules from the data is the first method and it is explained in detail below as we use a similar approach for our EMG classification.

A rule is of the form:

Rule1: IF x_1 is F_1 and x_2 is F_2……………and x_p is F_p, THEN y is G (5.7)

Here F_1, F_2 , ……F_p fuzzy sets whose membership function is centered at the measured value of x_1 , x_2 , …. and x_p.

In this method, the centers of the antecedent and consequent membership function are completely determined by the training data. In this method, the numerical training data are used just one time to obtain all the rules. Hence, this can be called one-pass method.

In 1992, the idea of tuning the design parameters in a FLS using the numerical training data was introduced for the first time. After this work, many similar research works were published on adaptive training procedures.

Another important aspect is the weighting for the rules [60]. All the rules in a rule base will fire to a particular degree. Some rules are more reliable than the others. We should assign larger weight to such rules than the less reliable rules. For a multi-class pattern classification, such rule weighting has shown improved results [61,62]. In cases where the boundaries between classes are clearly defined, the rules can be assigned equal weighting. Here for our application, we give equal weighting to all our rules in order to make the computations easier.

Type-2 FLS also use rules similar to type-1 FLS. The structure of rules does not change as we go from type-1 to type-2 FLS. In a type-2 FLS at least one of the antecedent or consequent membership function will be type-2 fuzzy sets instead of all type-1 fuzzy sets. Hence a FLS becomes type-1 or type-2 based on how we model the fuzzy sets in the rules' antecedents and consequents.

5.2. Singleton vs. Non-singleton fuzzy classifiers

Fuzzy classifiers can be of either singleton or non-singleton type. The choice of the fuzzifier depends on how we quantify the uncertainties present in the system. The fuzzifier maps a crisp point $x \in X$ into a fuzzy set F_X in X.

Singleton fuzzifier

The singleton fuzzifier is the most widely used fuzzifier. Given below is the definition for a fuzzy singleton.

F_X is a fuzzy singleton with support $\bar{x}$ if $\mu_{F_X}(x) = 1$ for $x = \bar{x}$ and $\mu_{F_X}(x) = 0$ for all other $x \in X$ with $x \neq \bar{x}$

We can infer from the above definition that each of the separable components of $\mu_{F_X}(x)$ is a fuzzy singleton. We shall assume that $\mu_{X_i}(\bar{x}_i) = 1$ for $x_i = \bar{x}$ and $\mu_{X_i}(\bar{x}_i) = 0$ for all values of $x_i \in X_i$ and $x_i \neq \bar{x}_i$.

Non-singleton fuzzifier

In non-singleton fuzzification, any measurement $x = \overline{x}$ is mapped into a fuzzy number. Hence, there is a membership function for each measured value. Given below is the definition for a non-singleton fuzzifier for a better understanding of this concept.

A non-singleton fuzzifier is one for which $\mu_X(\overline{x}) = 1$ $(i = 1, ..., p)$ and $\mu_X(\overline{x})$ decreases from one as x moves away from $\overline{x}$.

The non-singleton fuzzifier is commonly used when the input is corrupted by noise. This fuzzifier implies that the given measured value of input has the highest possibility to be the correct value when compared to all other inputs in its immediate neighborhood. However, because the input is corrupted by noise, neighboring input measurements are also likely to be the correct value, but to a lesser degree.

The possible combinations of fuzzy systems that we can choose from are listed below. We will be using all these different cases to classify the human hand EMG signals.

Case I: Singleton type-1

- No uncertainties.
- All the fuzzy sets are type-1 sets.

- Measurements are perfect and treated as crisp values.

Case II: Non-singleton type-1

- Inputs are type-1 fuzzy numbers.

- Can handle the uncertainties when measurements are noisy.

Case III: Singleton type-2.

When any one of the antecedent or consequent sets is a type-2 fuzzy set, then such a system is called a type-2 FLS.

- Can account for the uncertainties of the antecedents or consequents in rules

- Cannot explicitly account for input measurement uncertainties as it uses singleton fuzzification.

Case IV: Non-singleton type-2

- Can account for all kinds of uncertainties that were mentioned above.

Chapter 6

Design of fuzzy classifiers

Pattern recognition, in simple terms means the classification of a dataset based on the features that represent the data. These features are obtained using feature selection (extracting features that characterize the given dataset). Pattern recognition can be done in many ways of modeling such as deterministic, statistical, neural network, and rule-based methods. In this thesis, we have adopted the rule-based approach to the EMG classification problem. We have used the Fuzzy Logic Software developed by Mendel et al., [9,63] for the design of type-1 and type-2 FLS. All the concepts discussed in this chapter are very important, as they have been used in the design of the rule-based fuzzy classifiers.

In this chapter, we shall design the following five Fuzzy Logic Rule Based Classifiers (FL RBC): singleton type-1 FL RBC, non-singleton type-1 FL RBC, interval singleton type-2 FL RBC, interval type-1 non-singleton type-2 FL RBC, and interval type-2 non-singleton type-2 FL RBC. By choosing these classifiers, we aim to study the difference in the performance of type-1 versus type-2 FLS and singleton versus non-singleton fuzzifiers. All the five designs are using the totally independent approach in which all the parameters are tuned independently for each design.

Given a collection of EMG data for simple human arm motions such as hand close-open and forearm pronation-supination, we shall use a subset of them to create a rule-based classifier (RBC) using fuzzy logic. The first few milliseconds of the EMG from arm motions will be used in order to design the classifier. We have developed type-1 and type-2 fuzzy classifiers and also compared them to see which classifier provides the best performance in terms of classification accuracy.

We must decide on the following important factors before we begin our design of fuzzy classifiers.

1. Type of fuzzification, whether it is singleton or non-singleton.
2. Shape of the membership function, whether it is a Gaussian function, triangular or trapezoidal function.
3. Whether the design parameters in the membership function are fixed ahead of time or tuned during the training.

Our overall approach is listed below.

Step 1: Choose features that represent the data and use them as the antecedents in fuzzy rules.

Step 2: Obtain the FOU for the EMG training dataset.

Step 3: Form fuzzy rules using the selected features.

Step 4: Optimize all the design parameters using steepest descent algorithm.

Step 5: Apply the available data to all the designed fuzzy classifiers and compare them in terms of classification accuracy.

We give a short introduction to the rule-based classifier in the subsequent paragraphs and will show how the typical rules look like. This knowledge is very essential before we proceed further to the design of fuzzy classifiers.

Rules for a RBC of EMG signals use the selected muscle signal features as their antecedents and have one consequent. This type of rule that we use is a special case of a Mamdani FLS, where the consequent is a singleton. The antecedents are the muscles' maximum absolute values of wavelet coefficients. The consequent is either 0 or 1. It is 0 if the EMG signal corresponds to hand close-open motion or 1 if the EMG signal corresponds to forearm pronation-supination motion. There is nothing fuzzy about the consequent in the rules. The rule consequent is assigned a numerical value, 0 or 1. Each rule in a type-1 FL RBC looks like this:

IF a_1 is F_1 and a_2 is F_2 and ………and a_9 is F_9, THEN the product is motion1 (consequent $y^l = 0$) or motion2 (consequent $y^l = 1$).

For a type-2 FL RBC the rule looks like:

IF a_1 is $\tilde{F}_1$ and a_2 is $\tilde{F}_2$ and ………and a_9 is $\tilde{F}_9$, THEN the product is motion1 (consequent y^l =0) or motion2 (consequent y^l = 1)

Here the suffix 1 to 9 in the antecedent part of the rule represents the features obtained from the nine muscles. These rules that we have adopted are from the Mamdani FLS [9] where a typical rule consequent is characterized as a singleton.

A natural way to handle the uncertainties in EMG measurement is by using fuzzy logic. The problem here is to choose the right membership function. Choice of different membership functions will lead to different results. Under some reasonable assumptions, Gaussian functions are considered to be the most adequate choice of the membership functions for representing uncertainty in measurements [64-66]. In our work, the shapes of all the membership functions are fixed to be Gaussian functions. The shape of the input measurement's membership function is fixed but not the parameters. To ensure that the input measurement parameters adapt to the training data, we use the training data itself to tune the parameters of the input measurement membership functions in our work. Our tuning algorithm is described below.

6.1. Back-Propagation (Steepest descent) algorithm

All the antecedent and consequent parameters are tuned using the back-propagation method.

Given an input-output training pair (x^i, y^i), we want to design the FLS [9] as below. The output of the FLS is given by

$$f(x^i) = \sum_{l=1}^{R} y^l \phi_l(x^i) = \frac{\sum_{l=1}^{R} y^l \prod_{m=1}^{a} \exp\left(-\frac{(x_m^i - m_m^i)^2}{2(\sigma_m^i)^2} \right)}{\sum_{l=1}^{R} \prod_{m=1}^{a} \exp\left(-\frac{(x_m^i - m_m^i)^2}{2(\sigma_m^i)^2} \right)} \tag{6.1}$$

$i = 1, \ldots, N$

where a indicates the number of antecedents, R is the number of rules and i is the iteration count.

The difference between the computed fuzzy logic system output $f(x^i)$ and the actual output y^i obtained from training dataset is used to compute the error function. We wish to design the FLS such that the following error function is minimized.

$$e^i = \frac{1}{2}\left[f(x^i) - y^i \right]^2$$

$$i = 1, \ldots, N \qquad (6.2)$$

From Eq.6.1, we notice that f is completely characterized by $\bar{y}^l$, m_m^i and σ_m^i (l=1,…,R and m=1,…,a).

In the steepest descent algorithm we try to minimize this error function and update all the design parameters of the FLS (m=1,…,a, l=1,…,R and i=0,1,…).

$$m_m^i(i+1) = m_m^i(i) - \alpha_m [f(x^i) - y^i]\left[\bar{y}_l(i) - f(x^i)\right] \times \frac{\left[x_m^i - m_m^i(i)\right]}{(\sigma_m^i(i))^2} \phi_l(x^i) \qquad (6.3)$$

$$\bar{y}_l(i+1) = \bar{y}_l(i) - \alpha_y [f(x^i) - y^i]\phi_l(x^i) \qquad (6.4)$$

$$\sigma_m^i(i+1) = \sigma_m^i(i) - \alpha_\sigma [f(x^i) - y^i]\left[\bar{y}_l(i) - f(x^i)\right] \times \frac{\left[x_m^i - m_m^i(i)\right]^2}{(\sigma_m^i(i))^3} \phi_l(x^i) \qquad (6.5)$$

It is easy to initialize the values for m(0), y(0) and $\sigma(0)$ in Eqs. 6.3 to 6.5 [9] since these design parameters are associated with the antecedent and consequent membership functions of values such as physical measurements. If we choose these parameters in a random manner, then in such a case the back-propagation algorithm will converge very slowly. Choosing them with some care and knowledge of the training data will cause this algorithm to converge much faster. In this work, we have chosen the wavelet coefficients (obtained from Continuous Wavelet transform) of the EMG signals for each of the nine muscles. We will derive the antecedent membership functions from these features. The mean of the Gaussian membership function is located at the maximum absolute value of the wavelet coefficients corresponding to scales from 1 to 25 and the standard deviation is obtained similarly by measuring the deviation of these coefficients from the mean value.

This will yield 25 rules for each motion task, thereby giving 50 rules. We simply choose only 4 rules, 2 for each motion task. This is done by special inspection of the rule base and choosing fewer representative rules, which will result in simpler computation.

The learning parameters, α_m, α_y and α_σ also should be chosen appropriately. Usually, we choose the same value α. Choosing a small value for α will take long time to converge whereas a large value for α will cause the algorithm not to converge at all.

In this algorithm each element of the training set is used only once, and the FLS parameters are updated using an error function, that depends only on one data point at a time. Training is done for only one epoch.

After training using the back-propagation method, the FLS is fixed. Its performance is then evaluated with the percentage of data correctly classified, which is nothing but the classification accuracy.

6.2. Classification algorithm for type-1 Fuzzy classifier

In this section, we will provide some important formulas for type-1 FL RBC. As we know, two motion tasks have been considered here. One is close-open motion of the hand and the other is the pronation-supination of the forearm. The rule consequent, y^l, is treated as a crisp set; i.e. $y^l = 0$ for motion class 1, and $y^l = 1$ for motion class 2.

The membership function for the rule consequent can be given as below:

$$\mu_{con^l}(y) = \begin{cases} 1 & y = y^l \\ 0 & otherwise \end{cases} \quad \text{where l=1,…,R.} \tag{6.6}$$

The membership function for the fired rule can be expressed as

$$\mu_{rule^L}(y) = \mu_{con^L}(y) * [\sup_{x_1 \in X_1} \mu_{X_1}(x_1) * \mu_{F_1^1}(x_1)] * [\sup_{x_2 \in X_2} \mu_{X_2}(x_2) * \mu_{F_2^1}(x_2)] * ......$$
$$* [\sup_{x_a \in X_a} \mu_{X_a}(x_a) * \mu_{F_a^1}(x_a)]$$

(6.7)

$$\mu_{rule^l}(y)=\begin{cases}\begin{cases}[\sup_{x_1\in X_1}\mu_{X_1}(x_1)*\mu_{F_1^1}(x_1)]*[\sup_{x_2\in X_2}\mu_{X_2}(x_2)*\mu_{F_2^1}(x_2)]*\ldots. \\ *[\sup_{x_a\in X_a}\mu_{X_a}(x_a)*\mu_{F_a^1}(x_a)]\end{cases} & y=y^l \\ 0 & y\neq y^l\end{cases}$$

(6.8)

For a singleton type-1 FL RBC, Eq.6.8 simplifies to

$$\mu_{rule^l}(y)=\begin{cases}T_{m=1}^{a}\mu_{F_m^l}(x_m^i) \\ 0\end{cases}=\begin{cases}f^l & y=y^l \\ 0 & y\neq y^l\end{cases} \tag{6.9}$$

For a non-singleton type-1 FL RBC, Eq.6.8 simplifies to

$$\mu_{rule^l}(y)=\begin{cases}T_{m=1}^{a}\sup_{x_m\in X_m}[\mu_{X_m}(x_m)*\mu_{F_m^L}(x_m)] & y=y^l \\ 0 & y\neq y^l\end{cases} \tag{6.10}$$

There are many methods to obtain the defuzzified output from the type-1 fuzzy set. We have shown a typical height defuzzifier. The output of a type-1 RB FLC in this case can be expressed as

$$y_1(x)=\frac{\sum_{l=1}^{R}f^l y^l}{\sum_{l=1}^{R}f^l} \tag{6.11}$$

In the above equation, $y^l=0$ or $y^l=1$. We make a final decision that the EMG measurements correspond to hand close-open motion (class 0) or forearm pronation-supination motion (class 1) based on the magnitude of the defuzzified output.

IF $y_1(x) < 0.5$, decide motion1

IF $y_1(x) \geq 0.5$, decide motion2 (6.12)

The normalization operation does not change the sign of $y_1(x)$. Hence for two-class classification problem, we can also simplify Eq.6.11 to obtain the unnormalized output for the FLS as

$$y_1(x) = \sum_{l=1}^{R} f^l y^l \tag{6.13}$$

For the type-1 FL RBCs, each antecedent's membership function has two design parameters, its mean and standard deviation. Hence, there are 2x9=18 design parameters per rule.

For the type-2 FL RBCs each antecedent's membership function has three design parameters, two means and one standard deviation parameter; hence, there are 3x9=27 design parameters per rule. As we have mentioned earlier, there is no uncertainty about the consequent. It is either a 0 or 1, so it is a singleton.

We can have one or two additional design parameters depending on how we model the input measurements. Tuning is done using the steepest descent algorithm, which will determine the optimum values for all design parameters.

6.2.1. Singleton versus Non-singleton type-1 FLS

We move over to a non-singleton FLS when we have a set of noisy input-output numerical data training pairs. What is new for a non-singleton type-1 FLS is the need for the designer to choose membership function for the input measurements. This is not needed for a singleton type-1 FLS as the measurements are considered to be perfect without any uncertainty. We need to specify the mean and standard deviation for each input's Gaussian membership function. These two design parameters in each rule will give additional new possibilities for a non-singleton type-1 FLS.

We will see later in the results that there will be some improvement in results as we move on from singleton to non-singleton FLS, but the improvement in performance is not so significant. The reason is that we have not accounted for all of the uncertainties as they should be accounted for (as in type-2 FLS). The training data are noisy, but there is no way to account for this in the antecedent membership function (type-1 fuzzy set) of a type-1 FLS.

6.3. Classification algorithm for type-2 Fuzzy classifier

A FLS is type-2 as long as one of its antecedents or consequents sets is a type-2 fuzzy set. When no uncertainties are present, then singleton type-1 FLSs can provide excellent results.

A type-2 fuzzy set $\tilde{A}$ is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u)$, which can be represented as below.

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u) \big/ x,u \tag{6.14}$$

where $\iint$ denotes union over all admissible x and u. Also, $0 \le \mu_{\tilde{A}}(x,u) \le 1$ is called the secondary membership function and $J_x \subseteq [0,1]$ is the primary membership of x.

Consider a type-2 FLS having 'a' inputs $x_1 \in X_1, ..., x_a \in X_a$ and one output $y \in Y$. The number of rules is R as in the type-1 systems. In the type-2 case any rule has the form of a type-2 relation between the input space $X_1 \times ... \times X_a$, and the output space, Y, of the type-2 FLS.

IF x_1 is $\tilde{F}_1^l$ and … and x_a is $\tilde{F}_a^l$, THEN y is $\tilde{G}^l$ $\quad l = 1,..., R$ (6.15)

A general type-2 FLS is too complicated as there are computational difficulties involved. We have chosen to use interval type-2 fuzzy sets in order to simplify our approach. It is easy to compute the meet, join operations and perform type-reduction when interval type-2 fuzzy sets are used. Using interval sets for secondary membership functions also resolves the problem of choosing appropriate secondary membership functions. The uncertainties in the interval sets are evenly distributed among all admissible primary memberships.

Another important step is the choice of appropriate Footprint of Uncertainty (FOU) for the type-2 FLS. It is done by first analyzing the available training dataset using statistical techniques and examining the variations of the appropriate statistics. It is a pure statistical approach.

To begin, let us see how to express the secondary membership function of each a-antecedent fired rule [9].

$$\mu_{rule^l}(y) = \mu_{con^l}(y) \cap \{[\bigcup_{x_1 \in X_1} \mu_{\tilde{X}_1}(x_1) \cap \mu_{\tilde{F}_1^l}(x_1)] \cap [\bigcup_{x_2 \in X_2} \mu_{\tilde{X}_2}(x_2) \cap \mu_{\tilde{F}_2^l}(x_2)] \cap \ldots\ldots$$

$$\ldots\ldots\ldots \cap [\bigcup_{x_a \in X_a} \mu_{\tilde{X}_a}(x_a) \cap \mu_{\tilde{F}_a^l}(x_a)] \qquad y \in Y \tag{6.16}$$

This is the input-output relation for the inference engine. The input is a type-2 fuzzy set that is given to excite a rule in the inference engine and the output is again a type-2 fuzzy set. We assume that $\mu_{\tilde{X}_a}(x_a) \cap \mu_{\tilde{F}_a^l}(x_a)$ is only a function of x_a. This implies that the join operation is done over a scalar variable.

Applying the general equation from Eq.6.6 to 6.16, we obtain

$$\mu_{rule^l}(y) = \begin{cases} \mu_{con^l}(y) \cap \{[\bigcup_{x_1 \in X_1} \mu_{\tilde{X}_1}(x_1) \cap \mu_{\tilde{F}_1^l}(x_1)] \cap [\bigcup_{x_2 \in X_2} \mu_{\tilde{X}_2}(x_2) \cap \mu_{\tilde{F}_2^l}(x_2)] \cap \ldots\ldots \\ \qquad \ldots\ldots\ldots \cap [\bigcup_{x_a \in X_a} \mu_{\tilde{X}_a}(x_a) \cap \mu_{\tilde{F}_a^l}(x_a)] & y = y^l \\ 0 & y \neq y^l \end{cases}$$

(6.17)

This can be expressed in simple terms as below.

$$\mu_{con^l}(y) = \begin{cases} F^l(x') & y = y^l \\ 0 & y \neq y^l \end{cases} \tag{6.18}$$

These equations apply for the case when the input and antecedent sets are interval type-2 fuzzy sets.

$F(x')$ is an interval type-1 fuzzy set which is denoted as follows[9].

$$F(x') = [f_{lower}(x'), f_{upper}(x')] \tag{6.19}$$

where

$$f_{lower}(x') = \sup_x \int_{x_1 \in X_1} \int_{x_2 \in X_2} \int_{x_3 \in X_3} [\mu_{lower\,\tilde{X}_1}(x_1) * \mu_{lower\,\tilde{F}_1^l}(x_1)] * [\mu_{lower\,\tilde{X}_2}(x_2) * \mu_{lower\,\tilde{F}_2^l}(x_2)] * \ldots$$
$$\ldots\ldots\ldots\ldots * [\mu_{lower\,\tilde{X}_a}(x_a) * \mu_{lower\,\tilde{F}_a^l}(x_a)] / x \tag{6.20}$$

$$f_{upper}(x') = \sup_x \int_{x_1 \in X_1} \int_{x_2 \in X_2} \int_{x_3 \in X_3} [\mu_{upper\,\tilde{X}_1}(x_1) * \mu_{upper\,\tilde{F}_1^l}(x_1)] * [\mu_{upper\,\tilde{X}_2}(x_2) * \mu_{upper\,\tilde{F}_2^l}(x_2)] * \ldots$$

$$\ldots\ldots\ldots\ldots * [\mu_{upper\,\tilde{X}_a}(x_a) * \mu_{upper\,\tilde{F}_a^l}(x_a)] / x \tag{6.21}$$

The supremum for the above 2 equations is attained when each term inside the square bracket attains its supremum.

Applying the extension principle [9] to Eq.6.13, we obtain the extended output of a type-2 FL RBC as

$$Y_2(x') = [y_l, y_r] = \int_{f^l \in [f_{lower}{}^l,\, f_{upper}{}^l]} \ldots\ldots\ldots \int_{f^M \in [f_{lower}{}^R,\, f_{upper}{}^R]} 1 \Big/ \sum_{i=1}^{R} f^i y^i \tag{6.22}$$

Here $f^i \in F^i = [f_{lower}{}^i, f_{upper}{}^i]$ and y^i is a crisp value.

We obtain the values for the end limits as below.

Left limit, $y_l = \sum_{i=1}^{R} f_{lower}{}^i y^i$ (6.23)

Right limit, $y_r = \sum_{i=1}^{R} f_{upper}{}^i y^i$ (6.24)

The defuzzified output of the type-2 FL RBC is

$$Y_2(x') = (y_l + y_r)/2 = \sum_{i=1}^{R} y^i \left(f_{lower}{}^{i} + f_{upper}{}^{i} \right)/2 \tag{6.25}$$

We use this value in the decision rule as given in Eq.6.12 similar to the type-1 FL RBC.

6.3.1. Singleton type-2 FLS

The singleton type-2 FLS accounts for the uncertainties in the rule antecedents and consequents, but does not explicitly account for input measurement uncertainties. In this design the parameters of the interval singleton type-2 FLS are initialized independently. This means that we have tuned all the parameters of the interval type-2 FLS without using any information from the previous type-1 design.

For the interval singleton type-2 FLS, we initially set the intervals of uncertainty for the means (Gaussian function with uncertain mean) of each of the antecedent's fuzzy sets based on the knowledge from the training samples.

Although the interval singleton type-2 FLS has incorporated the uncertainties that are in the training data into its rules, it still does not account for the input measurement uncertainties because it is using singleton fuzzification. We move on to develop non-singleton type-2 FLS which can account for all the uncertainties that are present in the classification problem.

We should interpret the training data as a collection of IF-THEN rules. Each rule consists of interval type-2 fuzzy sets. They are associated with the elements of input training pairs and are described by primary membership function. We have chosen Gaussian function with uncertain mean as our primary membership function.

The consequent sets are also described by Gaussian primary membership function with uncertain mean and interval secondary membership functions given by

$$\mu^j(y) = \exp\left[-\frac{1}{2}\left(\frac{y-m^j}{\sigma^j}\right)^2\right] \qquad m^j \in [m_1^j, m_2^j] \qquad j = 1,\ldots,R \qquad (6.26)$$

Note that the centroid of each $\mu^j(y)$ is an interval type-1 set

$$C = [y_l^j, y_r^j] \qquad\qquad j = 1,\ldots,R \qquad (6.27)$$

In addition, the inputs are now type-2 fuzzy numbers whose primary membership functions are Gaussian functions and whose secondary membership functions are interval sets. The design method that we adopt will specify all the parameters of the membership functions using the input-output training pairs.

The number of rules in the type-2 FLS depends on the design method that is used to construct it. If we do not tune the FLS parameters, then the number of rules is the same as the number of training pairs. If tuning is done, then we use fewer rules.

Let us discuss the possible number of design parameters in our fuzzy classifiers:

- Antecedent parameters: The total number of design parameters in the antecedent for R rules is 3aR. This is because every rule has ‘a’ antecedents and each antecedent has 3 design parameters (2 means and a standard deviation parameter).
- Consequent parameters: A total of 2R parameters since there is only one consequent per rule.
- Measurement parameters: A total of 2a parameters since there are 2 standard deviation parameters in each input and there are ‘a’ inputs. If each input measurement has the same standard deviation parameters, there will only be 2 additional parameters instead of 2a.

So the maximum number of design parameters is 3aR+2R+2a.

When we tune the parameters of interval singleton type-2 FLS, we notice that it is different from the tuning in a singleton type-1 FLS. We need to determine the active upper and lower antecedent membership functions for the endpoints of the output. As the parameters change, due to their tuning, the dependency of the left and right endpoints on these parameters also changes. This is not the case in a type-1 FLS.

Table.6.1 Design parameters to be tuned in each of the five fuzzy classifiers

Type of Fuzzy logic system	Number of parameters in one input set	Number of parameters in one antecedent	Number of parameters in consequent	Total number of design parameters
Singleton type-1 FLS	N/A	m_{F^i}, σ_{F^i}	$\bar{y}^i$	$2aR + R$
Non-singleton type-1 FLS	σ_{X_k}	m_{F^i}, σ_{F^i}	$\bar{y}^i$	$2aR + R + a$
Interval singleton type-2 FLS	N/A	$m_{k1}^i, m_{k2}^i, \sigma_k^i$	y_l^i, y_r^i	$3aR + 2R$
Interval type-1 non-singleton type-2 FLS	σ_{X_k}	$m_{k1}^i, m_{k2}^i, \sigma_k^i$	y_l^i, y_r^i	$3aR + 2R + a$
Interval type-2 non-singleton type-2 FLS	σ_{k1}, σ_{k2}	$m_{k1}^i, m_{k2}^i, \sigma_k^i$	y_l^i, y_r^i	$3aR + 2R + 2a$

R-Number of rules; a-Number of antecedents in each rule; suffix ‘l’ and ‘r’ indicate left and right endpoints, respectively; N/A-not applicable.

6.3.2. Interval Non-singleton type-2 FLS

Type-2 FLS whose inputs are modeled as type-1 fuzzy numbers are named as type-1 non-singleton type-2 FLS whereas type-2 FLS whose inputs are modeled as type-2 fuzzy numbers are named as type-2 non-singleton type-2 FLS. An interval type-2 non-singleton type-2 FLS model is appropriate for the case where there is non-stationary additive noise like EMG signal measurements.

The rules of a type-2 non-singleton type-2 FLS are the same as those for a type-1 non-singleton type-2 FLS, which are the same as those for a singleton type-2 FLS. The only difference in this case is the fuzzifier. It treats the inputs as type-2 fuzzy sets, and consequently this effect is seen on the inference block.

What is new for a type-2 non-singleton FLS is the need for the designer to choose type-2 membership functions for the input measurements; this step is not necessary for a type-1 non-singleton type-2 FLS. As mentioned earlier we have chosen a Gaussian primary membership function with uncertain mean for the input, then an interval for the mean (uncertain) needs to be specified for that function. The interval end-points represent the additional new possibilities for a type-2 non-singleton type-2 FLS.

Chapter 7

Simulation results

In this section, we will present our results, and some analysis of the designed rule-based fuzzy classifiers based on the results obtained. Five fuzzy classifiers have been tested for EMG classification. They are

1. Singleton type-1 FLS;
2. Non-singleton type-1 FLS;
3. Interval singleton type-2 FLS;
4. Interval type-1 non-singleton type-2 FLS in cases where the antecedent membership functions are Gaussian primary membership functions with uncertain means and the input sets are type-1 Gaussian, and;
5. Interval type-2 non-singleton type-2 FLS in cases where the antecedent membership functions are Gaussian primary membership functions with uncertain means and the input membership functions are Gaussian primary membership functions with uncertain standard deviations.

7.1. Comparison of type-1 and type-2 FLS performance

We have compared the performance of the designed type-1 and type-2 fuzzy EMG classifiers on the basis of their classification accuracy throughout this thesis. We are mainly concerned with EMG classification for human arm motions.

Table 7.1 given below suggests that the choice of Coiflet 4 wavelet proves to be more efficient than the Daubichies (db-4) wavelet. This shows the comparison results for a one of the post-stroke subject data that we have.

Table 7.1 Comparison of Coiflet vs. Daubichies wavelet

Classifier type	Classification Accuracy	
	Coiflet4	Daubichies 4
Singleton type-1 FLS	96%	56%
Non-singleton type-1 FLS	94%	88%
Interval singleton type-2 FLS	96%	61%
Interval type-1 non-singleton type-2 FLS	87%	72%
Interval type-2 non-singleton type-2 FLS	95%	67%
Linear classifier	88%	70%

7.1.1. Tuning the design parameters

We tested the dataset with the following fuzzy classifiers and their corresponding results are tabulated below. We also tuned the design parameters to see how it affects the classification accuracies. We used a steepest descent algorithm to tune these parameters. After tuning is done by varying the step size (alpha), we fix these parameters to test them. The details of parameter tuning are given in the tabulation below for a specific dataset of a healthy subject.

Table 7.2.Details of design parameter tuning for the fuzzy classifiers

Type of Classifier	Parameters that we tune	Value of step size (alpha)
Singleton type-1 FLS	M, sigma,c0	alpha=0.001
Non-singleton type-1 FLS	M, sigma, sn, c0	alpha=0.01
Interval singleton type-2 FLS	M1, M2, sigma, c1, c2,	alpha=0.01
Interval type-1 non-singleton type-2 FLS	M1, M2, sigma, c1, c2, sn	alpha=0.01
Interval type-2 non-singleton type-2 FLS	M1, M2, sigma, c1, c2, sn1, sn2	alpha=0.01

Table 7.3 Results for type-1 and type-2 fuzzy classifiers before and after tuning

Type of Classifier	Patient dataset1	Patient dataset2	Healthy subject dataset1	Healthy subject dataset2	Healthy subject dataset3
Singleton type-1 FLS	86% (89%)	96% (96%)	95% (95%)	96% (96%)	95% (95%)
Non-singleton type-1 FLS	94% (83%)	94%(96%)	90% (93%)	91% (95%)	88% (95%)
Interval singleton type-2 FLS	86% (86%)	96% (96%)	95% (97%)	96% (96%)	94% (94%)
Interval type-1 non-singleton type-2 FLS	84%(85%)	87% (96%)	89% (97%)	91% (95%)	74% (94%)
Interval type-2 non-singleton type-2 FLS	91% (89%)	95% (96%)	94% (97%)	95% (95%)	88% (93%)

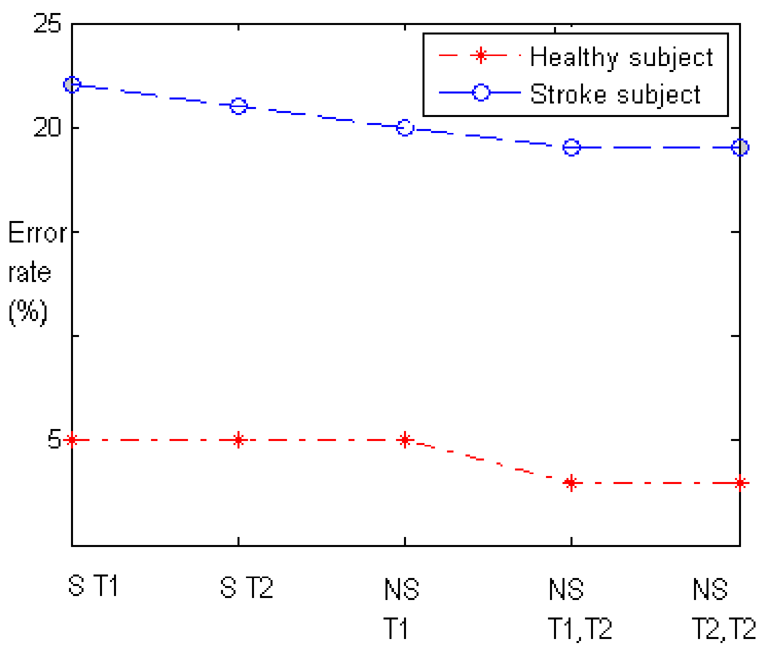

Fig.7.1 Error rate for Healthy and Post-stroke subjects.

In real time applications, the EMG classifier has to deal with unseen data most of the time. We will focus on one set of results called out-of-product classification in the next section.

7.1.2. Out-of-product EMG classification

"Out-of-product" means that we use only a few seconds of the total SEMG recording to establish the rules and we optimize (tune) the resulting classifiers based on this dataset. We do the testing with the unseen dataset to validate the actual classification accuracies of these classifiers.

Table 7.4 Out-of-product classification results for the fuzzy classifiers

Type of Classifier	Patient dataset1	Patient dataset2	Healthy subject dataset1	Healthy subject dataset2	Healthy subject dataset3
Singleton type-1 FLS	90.63%	97.92%	96.88%	97.92%	95.83%
Non-singleton type-1 FLS	87.5%	97.92%	96.88%	96.88%	95.83%
Interval singleton type-2 FLS	87.5%	97.92%	96.88%	97.92%	95.83%
Interval type-1 non-singleton type-2 FLS	86.46%	97.92%	96.88%	96.88%	95.83%
Interval type-2 non-singleton type-2 FLS	91.67%	97.92%	98.96%	96.88%	94.79%

7.2. Choosing only dominant muscles as features

Neglecting unimportant muscles, choosing the most dominant muscles is the next development. We did not choose these 9 muscles as EMG sites in a random manner for motion detection. These were the muscles, which demonstrated a significant electrical activity during specific hand motions.

We analyzed the EMG of all these 9 muscles in detail and found some redundancies among them. We observed that the muscles 1, 4 and 5 were redundant for both the types of motion tasks (close-open and pronation-supination) and their contribution was not so significant compared to the other muscles. So we tried to analyze the classifiers by neglecting these 3 muscles.

The results remained almost unchanged in some cases, and in others, there was a significant improvement in the classification accuracies obtained from our fuzzy classifiers when we chose only the most dominant muscle features as inputs. These are the results that we obtained. We observe from Table 7.5 that for both the patient and the healthy subject, the performance of all five fuzzy classifiers has improved in many cases.

Table 7.5 Results for the fuzzy classifiers after choosing only dominant muscles.

Type of Classifier	Patient dataset1	Patient dataset2	Healthy subject dataset1	Healthy subject dataset2	Healthy subject dataset3
Singleton type-1 FLS	91 (86%)*	95 (96%)	96 (95%)	90 (96%)	96 (95%)
Non-singleton type-1 FLS	93 (94%)	95 (94%)	96 (90%)	91 (91%)	96 (88%)
Interval singleton type-2 FLS	91 (86%)	96 (96%)	96 (95%)	89 (96%)	96 (94%)
Interval type-1 non-singleton type-2 FLS	93 (84%)	96 (87%)	96 (89%)	92 (91%)	96 (74%)
Interval type-2 non-singleton type-2 FLS	95 (91%)	96 (95%)	96 (94%)	91 (95%)	96 (88%)

* The values within the bracket indicate the classification accuracies obtained with all the 9 muscles.

The only exception is healthy subject dataset2 where there is no significant improvement. Actually, the performance has reduced. This shows that there is a trade off in the choice of the dominant muscles for signal classification applications. The more the number of muscle sites, the computations becomes more complex and the speed is reduced. Whereas if the number of muscle sites are reduced by neglecting the so called less significant muscles, the computation speed seems to be fast, but we have a disadvantage of loosing some muscle behaviors that might reduce the accuracy to some extent.

7.3. Testing adaptability of the designed fuzzy classifiers

We checked the versatility of the fuzzy classifiers that we designed by training them with healthy dataset1 and then testing them with all the other unseen dataset, i.e. healthy dataset1, healthy dataset2, healthy dataset3, patient dataset1 and patient dataset2.

Table 7.6 Classification results when healthy subject dataset1 is used for training

Type of Classifier	Healthy subject dataset1	Healthy subject dataset2	Healthy subject dataset3	Patient dataset1	Patient dataset2
Singleton type-1 FLS	95%	94%	93%	69%	78%
Non-singleton type-1 FLS	95%	94%	95%	69%	80%
Interval singleton type-2 FLS	95%	94%	94%	69%	79%
Interval type-1 non-singleton type-2 FLS	97%	95%	95%	70%	81%
Interval type-2 non-singleton type-2 FLS	97%	95%	95%	70%	81%

From table 7.6, we observe that since we have trained the classifiers with data from a healthy subject, the classification accuracies for healthy subjects is very high; whereas the classification accuracies for post-stroke subject dataset is comparatively low. We are not surprised to note that Interval type-1 non-singleton type-2 FLS and Interval type-2 non-singleton type-2 FLS perform the best in all the cases as claimed by Mendel in his works [28, 32].

We did not stop at this point. We wanted to check the versatility of the fuzzy classifiers further. So we trained them with data from one patient dataset and then tested them with another patient dataset. The following table gives the details.

This result is quite surprising; the classification accuracy in the 2nd column is too low around 50%. Almost all the close-open motions (in our case “class0”) have been wrongly classified as pronation-supination motions (in our case “class1”). The main source of this distinctive error comes from the overlapping electrical activity in the adjacent electrode sites during the EMG measurement stage.

We make the following observations from Table 7.7. Type-2 FLS outperform the type-1 FLS. The interval type-2 non-singleton type-2 FLS performs the best and the interval type-1 non-singleton type-2 FLS also gives very good results. The reason for the latter is because the interval type-1 non-singleton type-2 FLS used σ_n as the initial value for the standard deviation of its input measurement membership functions, and this value of σ_n gives a good approximation to the average value of the standard deviation of the uniform noise.

Table 7.7 EMG Classification results to check versatility of the classifiers

Classifier Type	Train with patient dataset1 & test with patient dataset2 (Before rehabilitation training)	Train with patient dataset2 & test with patient dataset1 (Before rehabilitation training)	Train with patient dataset1 & test with patient dataset2 (After rehabilitation training)	Train with patient dataset2 & test with patient dataset1 (After rehabilitation training)
Singleton type-1 FLS	77%	50%	65%	88%
Non-singleton type-1 FLS	77%	50%	65%	88%
Interval singleton type-2 FLS	76%	50%	65%	87%
Interval type-1 non-singleton type-2 FLS	77%	50%	65%	89%
Interval type-2 non-singleton type-2 FLS	80%	53%	79%	92%

During our experiments, while tuning the fuzzy classifiers, we noticed that type-2 FLS achieve close to their optimal performance almost at the first epoch of tuning. This shows that type-2 FLS (as compared to type-1 FLS) are very promising for real-time signal processing where more than one epoch of tuning is not possible.

Chapter 8

Conclusions and Recommendations

8.1. Conclusions

The entire project could broadly be broken down into four important phases, (1) the EMG signal measurement and signal processing phase, (2) feature extraction and selection phase, (3) fuzzy classifiers, classification algorithms development phase and (4) strategies for classifiers' performance improvement phase.

We have mentioned in the previous chapter that the classification accuracy shows significant improvement when we choose only the most significant muscles by neglecting those muscles that do not contribute much to the specific motion tasks. The post-stroke subject is a hemiplegic who has lost his ability to manipulate his right limbs. We have observed that after rehabilitation training, the results are much better than before training.

Through this project, different fuzzy classifiers were designed and their performances were verified. Different arm motions, which were preferred by the post-stroke subjects such as hand close-open and forearm pronation-supination, were measured and classified based on the appropriate extracted features. We have shown that the five fuzzy classifiers achieve relatively good results, in particular, after neglecting some less important inputs, which are the wavelet coefficients of unimportant muscles' EMG in this experiment.

The approach of using continuous wavelet transform for analysis and classification of EMG signals using rule based fuzzy logic classifiers has proved to be efficient and successful. These results can be used directly in the design of real-time EMG classifiers for rehabilitation and assitive devices.

Our type-2 RB FLC classifiers did not give very good results. We can make a superficial conclusion that a type-1 FL RBC is sufficient for applications, which do not make use of linguistic uncertainties. Further in-depth research has to be done to explore the effects of both type-1 and type-2 FL RBC in the presence of linguistic uncertainties and also knowledge mining. This will help in the field of rehabilitation in cases where it is difficult to take EMG signal measurements.

8.2. Recommendations

The results raise a few questions, which needs further analysis.

- Why our fuzzy classifiers were unable to differentiate between the different kinds of motions with 100% accuracy?
- Why is it that in most of the cases hand close-open motion is wrongly classified as forearm pronation-supination motion? In other words, why is it that comparatively class0 is more wrongly classified than class1?
- How can we further improve the classification accuracy?

Answering these questions is beyond the scope of our work; yet we will address these issues in the point of view of improving the fuzzy classifiers' efficiency with our previous observation. Let's try to answer these questions without going into too much detail of the biomechanics of human limbs.

The approach of tuning the design parameters using other new tuning algorithms could be further investigated to achieve better results. Choice of the value for step size (alpha) when tuning the fuzzy classifiers has to be done. The best choice of membership function is still an open question whether it should be Gaussian, Triangular or any other function.

Another issue that could be further worked on is the investigation of how much uncertainty be present in a problem so that it is worthy of choosing the interval type-2 FLS for a better performance compared to type-1 FLS. It is also essential to clearly identify in which sense type-2 are expected to outperform type-1; whether it is in terms of classification error rate, generalization or robustness of the two designs. Some issues discussed here need further analysis and provides a scope for future researchers.

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Appendix A

Comparison of EMG signals before and after training

In order to analyze the post-stroke subject's motions before and after the rehabilitation training sessions, we do the following. We analyze the muscles behavior of the stroke patient before and after the training sessions. We notice that initially before any training, the patient tried to use a certain muscle (specifically the biceps), which appears to be the most active and dominant muscle for performing both the motions. The amplitude of EMG measured at this muscle site is very high before rehabilitation training and suddenly it reduces tremendously (one-tenth) after the subject undergoes training exercises. Fig.A.1. shows this effect of training on the biceps muscle. In our experiment, we see that the healthy individual does not use the biceps prominently to perform the two classes of motion when compared to other muscle sites. After sufficient rehabilitation training with a robotic device (allows the patient to support his arms on the table and perform these motions with an assistance), we observe that the muscle activity at the biceps is greatly reduced.

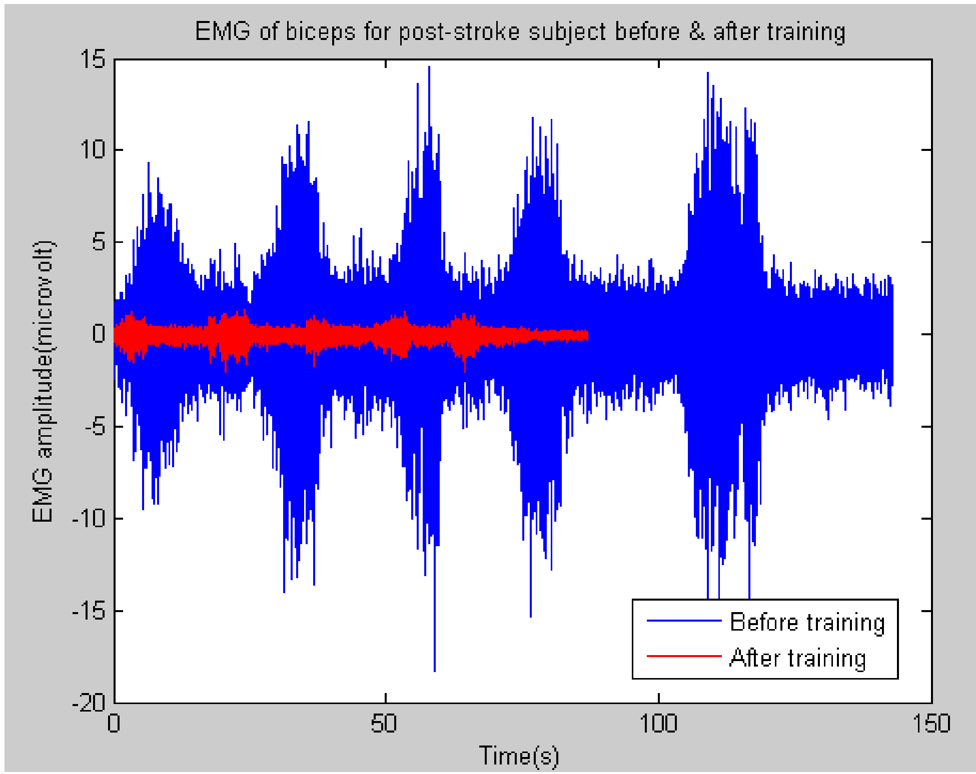

Fig.A.1. Effect of training on the biceps muscle for forearm pronation-supination motion

The Pronator Teres electrode site has almost the same level of muscle activity for both the motions (before as well as after training). Hence, we conclude that the contribution from this muscle is very minimal to be the input for the fuzzy classifiers. We look for more contrasting characteristics among the muscles so that our resultant features remain more distinct for fuzzy classification. Choice of the most dominant, appropriate muscles from all the available muscles for the fuzzy classifiers will be discussed in the forthcoming chapters.

The patient has learnt during the training sessions to make use of the correct set of muscles for specific motion tasks, so that he can provide less effort and perform the motions with ease.

Even after rehabilitation training, the post-stroke subject takes more time than that taken by the healthy individual to perform 10 trials of the motions. This shows that it is not logical to just directly compare (without any compromise) the healthy subject with the post-stroke subject, even after sufficient rehabilitation training.

By carefully analyzing the muscle behaviors, we gain an insight into the patients' difficulties in manipulating a particular muscle and how he misuses his muscles. After training, the patient has sufficiently trained his muscles and learned to use the correct combination of muscles.

We would like to mention again that the post-stroke subject we considered here is a hemiplegic. He has lost his ability to move his right limbs. He is quite unsure of the muscles that he should employ for performing these motions.

The subject used the same combination of muscles with a similar level of activity for both the hand motions. There is no clear distinction between the two motion tasks. This is clearly evident from the observation of the

RMS values of each muscle before any rehabilitation training. After rehabilitation training, the motion patterns are better than before training.