ANALYSIS OF HAND FORCE BY EMG MEASUREMENTS

by

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ABSTRACT

This project investigates the use of myoelectric signals to predict wrist orientation and torque in healthy volunteers and seniors. Surface electromyography (sEMG) signals from forearm muscles were recorded while the volunteers were exerting wrist torque on a custom-made force-sensing platform. Multi-class support vector machines (SVM) were used for classification and regression. The obtained experimental results showed that the SVM method worked well especially in the case of cross-session validation. The proposed sEMG processing scheme enabled classifying wrist torque direction with accuracy higher than 98% for healthy volunteers and 92% for seniors and estimate wrist torque intensity with an average mean square error (MSE) less than 0.08 for regression. The results obtained from the classification and regression showed that the pattern recognition and estimation of sEMG of the forearm muscles is feasible.

Keywords: surface electromyography (sEMG); pattern recognition; support vector machines (SVM).

To my Parents

ACKNOWLEDGEMENTS

I would like to thank Dr. Carlo Menon for his guidance and support throughout this project work. He has given me a tremendous amount of feedback for improving on the work. I also would like to thank Dr. Cormac Sheridan for helping on the collection and analysis of the data for the case study 2, Mr. Amirreza Ziai for helping in the design of the custom rig and Mr. Zhen Gang Xiao for helping in the data collection.

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CHAPTER 1 INTRODUCTION

1.1 Motivation and Objectives

A compelling research goal of particular interest to our society is to improve independent living of seniors and maintenance of their normal functional autonomy while aging. In fact, everyday simple operations such as turning a tap handle or closing the screw cap of a bottle or a jar can be challenging for the seniors.

The design of an assistive device, which could improve independent living of seniors, requires a good understanding of the physiology and functions of the hand. The main focus of this project was on the development of a surface EMG (sEMG) pattern recognition system for the movement of the wrist, in terms of direction and force that could be used in assistive devices. Many researchers have worked on pattern recognition to predict hand gestures using sEMG signals but only few studies have considered the amount of force applied by the user. sEMG data was collected from volunteers and Support Vector Machines (SVM) was used for their classification and regression. The objectives of this project were as follows:

a) Identifying the forearm muscles that can be used for predicting wrist movements.
b) Extracting suitable features from sEMG of the forearm muscles for classification and regression.
c) Collecting experimental data for classification and regression methodologies.
d) Implementing the classification and prediction system and assessing its performance.

1.2 Organization

The motivation and objective for this project have been discussed. The remaining chapters of the project are organized as follows:

Chapter 2 presents a background for the sEMG signals and its applications along with a brief overview of the literature related to different techniques of sEMG pattern recognition.

Chapter 3 presents the first experiment (Case study 1) related to the pattern recognition for estimation of wrist torque based on forearm surface electromyography signals. It starts with the experimental setup, the software used and the protocol followed to acquire data from volunteers. The techniques used for feature extraction, classification and regression are presented followed by the results obtained from the study.

Chapter 4 presents the second experiment (Case study 2) for the detection and analysis of grasping force and wrist torque intention by EMG measurements and PCA analysis. It starts with the experimental setup, software used, the protocol followed to acquire data from volunteers, filters applied to remove movement artifacts and unwanted noise and post-processing applied to raw data. The PCA technique used for dimensionality reduction, classification and regression is presented followed by the results obtained from the study.

Chapter 5 presents the third and last experiment (Case study 3) for the classification of surface electromyography signals in seniors. It starts with the experimental setup and the protocol followed to acquire data from volunteers. The techniques used for feature extraction and classification are presented followed by the results obtained from the study.

Chapter 6 discusses results from the three case studies and presents a discussion of the possible future work.

CHAPTER 2 BACKGROUND

The sEMG signal is composed of the action potentials from groups of muscle fibers. This signal reflects the functional status of nerves and muscles [1]. It measures electrical currents generated in muscles during their contraction and can be detected with electrodes placed on the surface of the skin. Accurate estimation of force from observation of the sEMG can potentially provide a reliable tool for controlling assistive devices [2, 3]. An assistive device that can provide an additional force for movement of the hand could be used to assist activities of daily living [3, 4] and train muscles at the same time.

At present, there are few studies of the EMG amplitudes of the muscles of the forearm in relation to everyday complex contractions of the whole hand. Simple contractions involving just one or two fingers have shown co-contraction of all the muscles associated with these fingers [5-7].

The ultimate goal of the research performed at Simon Fraser University is the design of a device that would assist seniors, to perform simple everyday tasks such as opening a door or a jar containing food. It will be controlled by the EMG signals of the forearm. Similarly to the assistive devices which have been developed in recent years [8-16], it will have an exoskeleton configuration [17-18]. The device will interpret the EMG signals to detect the intention of the user automatically, and will then assist with that movement.

Machine learning techniques have been successfully employed for identification of hand gestures in which different features to detect hand postures in volunteers have been explored [19, 20]. For example, AR model coefficients, slope sign changes and mean absolute value have been proposed in [21] to determine with high accuracy (96%) different hand postures. Similarly, the use of average sEMG amplitude and cepstrum using SVM was proposed in [22] and an accuracy of about 90% was obtained. Also different classification techniques have been proposed such as SVM, neural networks [23], multilayer perceptron [24] and fuzzy classifier [25]. In this project we focus on the prediction of the intensity of force exerted by the young volunteers and seniors. SVM [26, 27] and feature extraction [28] are used to achieve this objective.

With increasing age, the skeletal muscles tend to lose their strength and this is identified as an important topic in aging [29]. The human hand is the most used part of our musculoskeletal system and hence it needs to be kept strong with exercise and appropriate use. A major challenge in the design of an assistive device is to acquire input signals that could provide information regarding the intention of the user such that the perceived delay by the user in the movement of the hand is minimized. This intuitively suggests that acquiring the input signals from neurological activity of the user would suite the application.

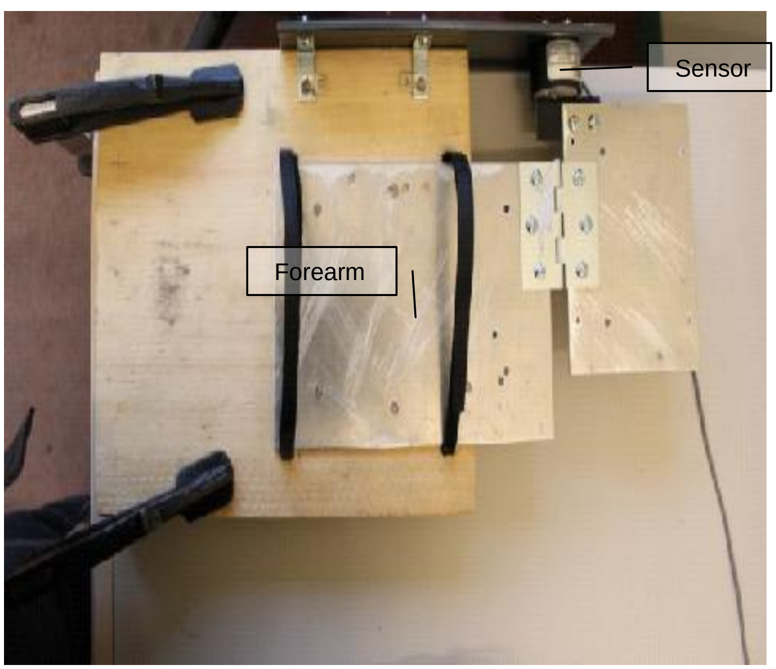
Although identification of different postures in young volunteers through sEMG have been successful, there is a need to investigate the same techniques on seniors as there are many physical and neurological changes occurring in humans over the course of age. This project focuses on hand postures of both the youngest and of seniors and assesses if age hinders the identification of seniors' hand postures by using sEMG signals. It is well known that aging reduces grip and pinch strength [30]. This project therefore investigates the effect of applying forces at different orientations and finger pinching, and classifying the corresponding sEMG signals of the seniors.

CHAPTER 3 Case study 1: pattern recognition for estimating wrist torque.

3.1 Experimental Setup

Two young volunteers participated in this study. A custom rig, shown in Figure 3-1, was developed to record the amount of force/torque applied by each volunteer. The volunteers could comfortably hold the rig with one hand; the rig's force sensor recorded the amount of torque exerted by the wrist of the volunteer. The rig allowed recording torque applied both in wrist flexion/extension and radial/ulnar deviation.

EMG electrodes were fixed to the volunteers' right forearms by using medical adhesive bands applied with appropriate force to make sure that the electrodes' active faces were tightly adhering the forearm skin. The output signal was used for the sEMG pattern recognition and regression. Figure 3-2 illustrates each electrode's position on the forearm. Table 3-1 represents the name of muscles used in this experiment.



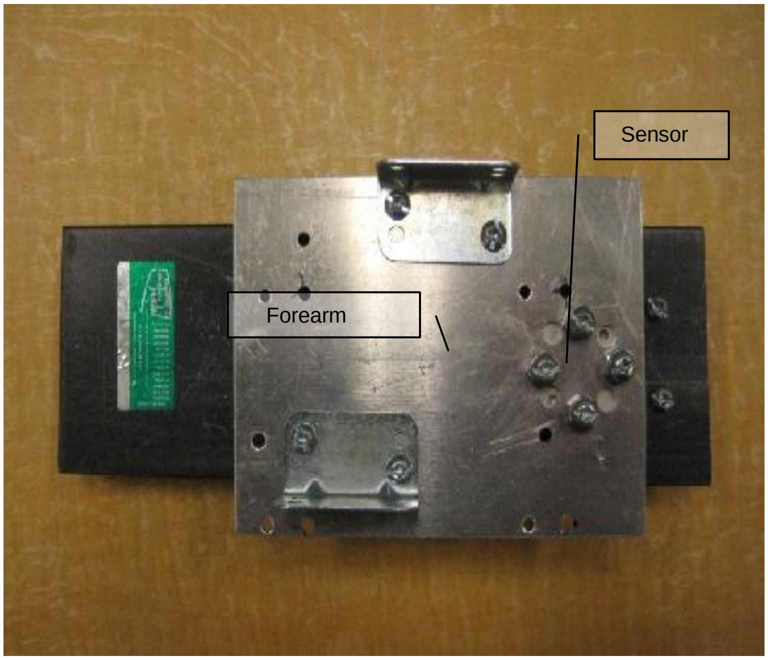


Figure 3- 1: Custom rig

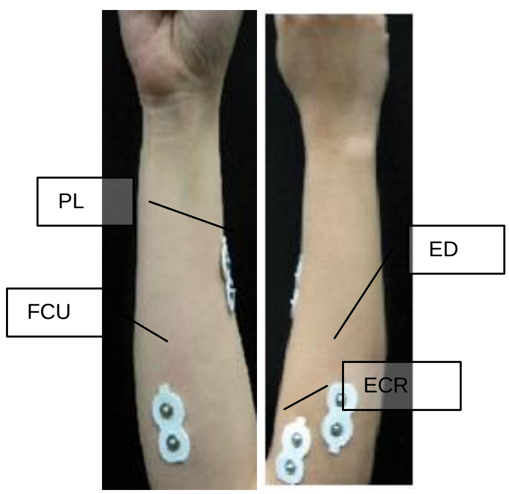


Figure 3- 2: Location of Surface Electrodes on the Forearm

This study was approved by the Office of Research Ethics, Simon Fraser University and each of the subjects signed a written consent form. sEMG signals from four forearm muscles of the volunteer were therefore recorded along with the force/torque. A commercial sEMG acquisition system (Noraxon Myosystem 1400L) was used to record the data. Several muscles in the forearm are involved in the movement of the wrist, details of which can be found in [31].

Table 3- 1: Muscles

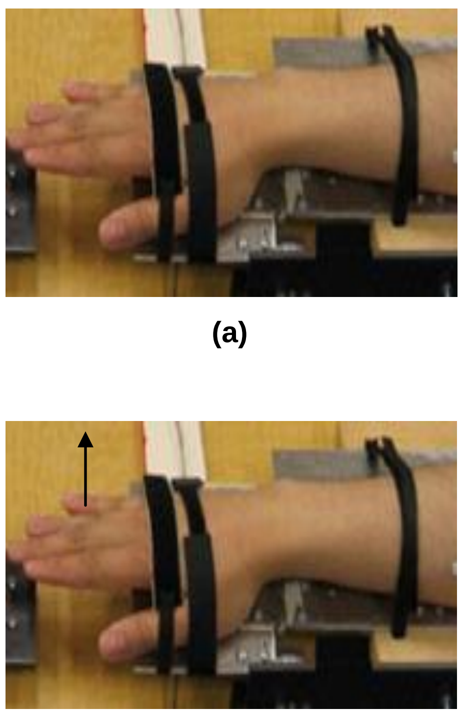
Muscle
Flexor Carpi Ulnaris (FCU)
Palmaris Longus (PL)
Extensor Digitorum (ED)
Extensor Carpi Radialis (ECR)

3.2 Software

We used LabVIEW software for the sEMG signal and the data was acquired at a sampling frequency of 1024 samples per second and saved in the form of text files for later analysis. Library for SVM (LIBSVM) [32] tool in the Matlab environment provides an implementation for SVM, which we utilized to test the classification and regression accuracy for our study.

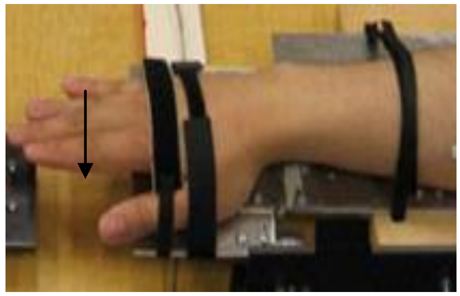
3.3 Protocols for Data Collection

A set of eight protocols, presented in Table 3-2, was followed in order to collect the data from the volunteers. Each volunteer started at rest position as shown in Figure 3-3-a. In the first protocol, the volunteer was asked to apply her/his maximum torque during flexion while placing the hand on the custom rig as shown in Figure 3-3-c. This protocol was repeated three times - the output of the torque sensor is shown in Figure 3-4-a. The EMG amplitude recorded for this maximum value of torque was regarded as the maximum voluntary contraction (MVC) and a percentage of this torque was used to follow other protocols. MVC was also used to normalize EMG amplitudes. Similarly, in protocol 2 the volunteer applied maximum torque during wrist extension as shown in Figure 3-3-b - the output of the torque sensor is shown in Figure 3-4-b. Note that the value of the torque obtained in this case is in negative direction. Protocol 3 was used to gather actual data to perform classification and regression. The volunteer was asked to start from rest and then continuously increase her/his torque till 50% of MVC torque was reached. The duration of the ramp was around 10 seconds. This process was also repeated three times - the output of the torque sensor is shown in Figure 3-4-c. Similarly, protocol 4 was used to gather the data for wrist extension. Again the volunteer started from rest and gradually increased the torque to 50% of MVC - the output of the sensor is shown in Figure 3-4-d. Protocols 5 to 8 followed the same pattern as protocols 1 to 4 with flexion replaced by radial deviation as shown in Figure 3-3-e and extension by ulnar deviation as shown in Figure 3-3-d. The output graphs were also similar and are not shown.



(a)

(b)



(c)

(d)

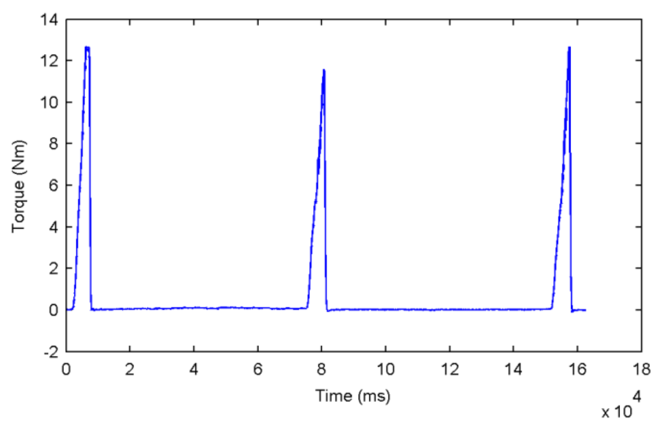
(e)

Figure 3- 3: Hand gestures and motions chosen for classification and regression

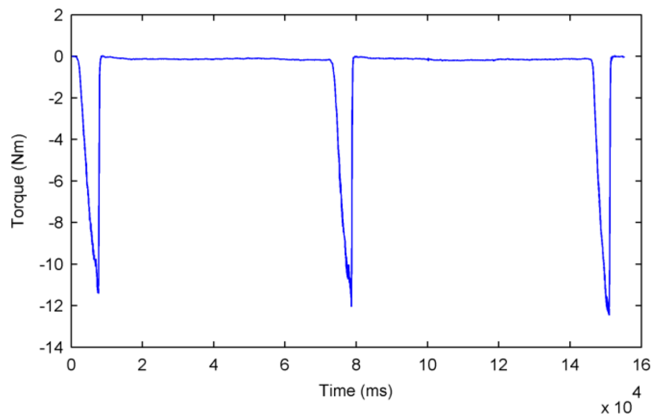
(a) rest, (b) extension, (c) flexion (d) ulnar deviation (e) radial deviation

Table 3- 2: Protocols and definitions

Protocols	Definitions
Protocol 1	Apply maximum torque for wrist flexion three times with an interval of 30 seconds.
Protocol 2	Apply maximum torque for wrist extension three times with an interval of 30 seconds.
Protocol 3	Start from rest and increase torque for wrist flexion gradually until 50% of MVC is reached. Repeat three times.
Protocol 4	Start from rest and increase torque for wrist extension gradually until 50% of MVC is reached. Repeat three times.
Protocol 5	Apply maximum torque for wrist radial deviation three times with an interval of 30 seconds.
Protocol 6	Apply maximum torque for wrist ulnar deviation three times with an interval of 30 seconds.
Protocol 7	Start from rest and increase torque for wrist radial deviation gradually until 50% of MVC is reached. Repeat three times.
Protocol 8	Start from rest and increase torque for wrist ulnar deviation gradually until 50% of MVC is reached. Repeat three times.



(a)



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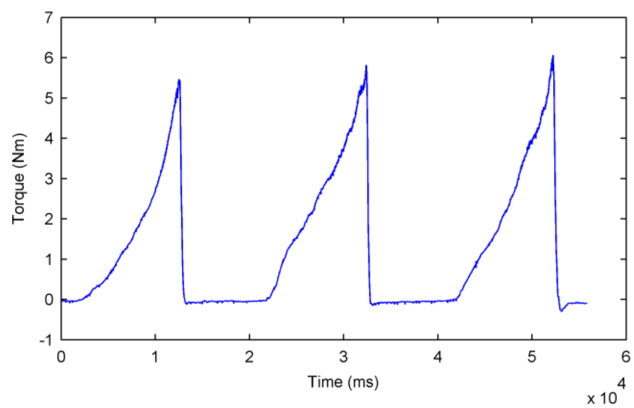

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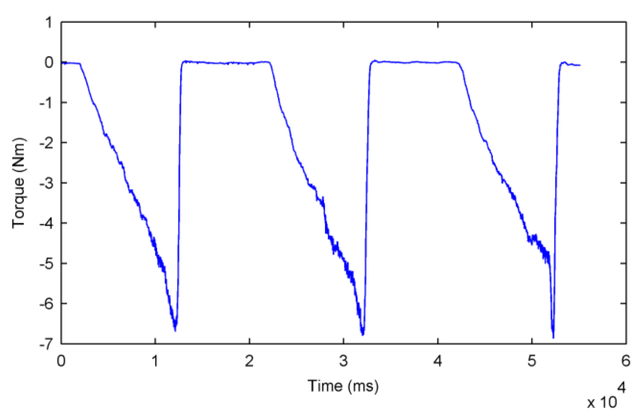


(d)

Figure 3- 4: Different torques representing different protocols

(a) protocol 1, (b) protocol 2, (c) protocol 3 and (d) protocol 4

3.4 Feature Extraction

Matlab software was used to extract features from the raw sEMG signals. Extracting features from each sample of the raw sEMG signal does not provide any useful information, as the structural detail of the signal is lost. For this reason researchers have used the technique of extracting features from a window of predetermined length.

The first step to extract features from the recorded data was segmenting the signal into 250 ms intervals corresponding to 256 samples in each segment. Using each segment, features were extracted and then the segment window was incremented by 125 ms including 128 samples for the next feature. Three types of features were extracted from each segment of the data.

The first feature was based on AR models. AR models are used for time-series analysis and can be defined as a linear combination of previous samples and noise. Mathematical representation is given in (1):

$$y_n = \sum_{i=1}^{p} a_i^p y_{n-i} + w_n \qquad (1)$$

where {*a* for *i* = 1,. . . , *p* } are AR model coefficients and *w* is the additive noise. We used the AR model coefficients as the features with a model order of four, generating four features for each channel of sEMG.

The second feature was the waveform length, which is defined as a measure of the waveform complexity in each segment. Waveform length is mathematically defined by (2):

$$z = \sum_{k-1}^{N} |\Delta y_k| = \sum_{k-1}^{N} |y_k - y_{k-1}| \qquad (2)$$

The third feature used was the time windowed RMS value of the raw sEMG signal. RMS value basically provides information regarding the amplitude of the signal and is given by (3):

$$emg_{rms} = \sqrt{\frac{emg_1^2 + emg_2^2 + \ldots + emg_n^2}{n}} \qquad (3)$$

where emg_i is the amplitude of the i^{th} sample in the time domain, and n is the number of samples. Extracting the explained three types of features from each channel of sEMG provided us with a 24 dimensional feature vector from each segment.

3.5 Classification/Regression

SVM [33-36] was chosen as the classifier and regressor [37-38] for the obtained feature vector (a brief description of SVM can be found in Appendix A). Figure 3-5 details our proposed sEMG signal classification scheme.

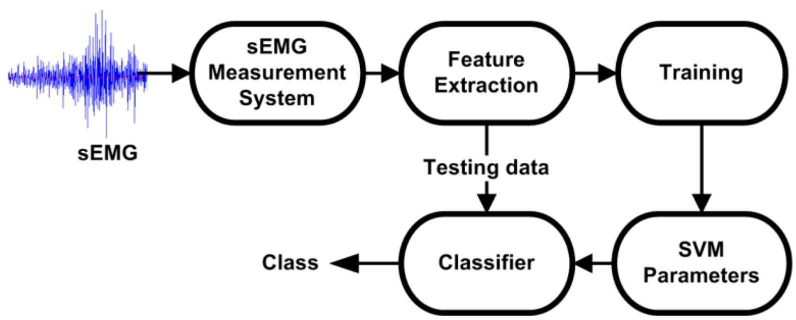


Figure 3- 5: Block diagram of the proposed sEMG signal classification scheme

The appropriate values of ε and γ and *c* were selected during training to ensure good generalization performance on test data. Table 3-4, 3-5, 3-6 shows the values of ε, γ and *c* which performed reasonably well and provided the good cross-validation accuracy in our experiment.

RBF kernel was used as the kernel function in our study. This type of kernel is suitable when the relation between class labels and attributes is nonlinear. The RBF kernel nonlinearly maps samples into a higher dimensional space. Consequently we were able to perform the linear classification in this space.

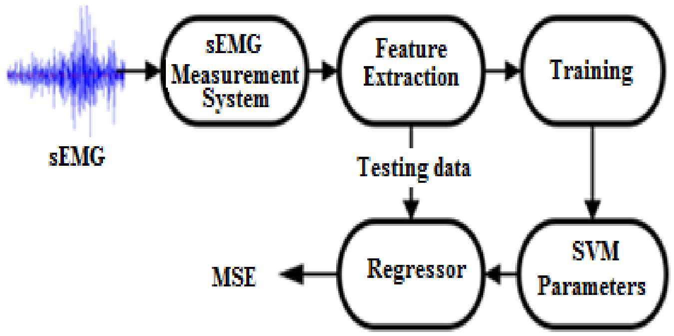


Figure 3- 6: Block diagram of the proposed sEMG signal regression scheme

Table 3- 3: Class definition

Class Number	Class definition
1	Rest
2	Wrist flexion
3	Wrist extension
4	Wrist radial deviation
5	Wrist ulnar deviation

Table 3-3 represents the different classes of this study. The gathered data was divided into training and testing data. Ten seconds of data per protocol was extracted for each class. Out of these, 90% of data were used as training data and 10% of data were used as testing data. The user applied the torque according to description of different classes and 5 classes were trained from the training data. The SVM model was then used to predict the results on the testing data. Figure 3-6 details our proposed sEMG signal regression scheme.

3.6 Results

Table 3-4, Table 3-5 and Table 3-6 show the classification and regression accuracy for participants obtained using the optimal SVM parameters in hand force estimation and classification. It was observed that the accuracy was high. The trained data was used to precisely distinguish between different force levels of hand

and estimate the force applied by the participant. It was demonstrated that the Multi-class SVM is able to estimate and classify the different sets of the sEMG patterns produced by the forearm muscles. Multi-class SVM was adapted very well while testing the untrained data and as a result the overall accuracy of correct classification was 100%.

Table 3- 4: Results for classification

Volunteer	Classification			
	C	γ	Cross Validation Accuracy	Testing Accuracy
Volunteer # 1	4	2	99.37	100
Volunteer # 2	2	0.25	100	100

Table 3- 5: Results for regression on flexion/extension

Volunteer	Regression for flexion/extension				
	C	γ	ε	Cross Validation MSE	Testing MSE
Volunteer # 1	32	0.5	0.0625	0.0409	0.024
Volunteer # 2	16	0.5	0.0625	0.0328	0.01096

Table 3- 6: Results for regression on radial/ulnar deviation

Volunteer	Regression for ulnar/radial deviation				
	C	γ	ε	Cross Validation MSE	Testing MSE
Volunteer # 1	32	1	0.125	0.1513	0.254572
Volunteer # 2	8	0.5	0.0625	0.0583	0.028093

CHAPTER 4 Case study 2: detection of grasping force and wrist torque through PCA analysis

4.1 Experimental Setup

Force and torque measurements were obtained by using a purpose-built rig (see Figure 4-1) capable to both measure grasping force and wrist torque in radial–ulnar deviation and flexion–extension directions. A force sensor (Futek Advanced Sensor Technologies, Inc, Irvine, CA, USA, model LLB350 miniature load button) was mounted between two semi-circular aluminum discs, one fixed and one moveable, that the volunteers grip during the experiments. A torque transducer (Transducer Techniques, Temecula, CA, USA, model TRT-100) was mounted underneath the gripping handle. During the experiments, the rig was clamped to a table to keep it steady. The volunteers could comfortably hold the rig with one hand; the rig's force sensor recorded the amount of torque exerted by the wrist of the volunteer.

Experiments were conducted on right handed 18 volunteers (11 males, 7 females, mean age 35.2 ± 17 years), none of whom had a serious hand injury or surgery in the past five years, except one male volunteer. This volunteer had a forearm injury from which he had fully recovered and was recruited to test the hypothesis that for healthy volunteers, a similar pattern should be present in terms of their muscle recruitment. Volunteers were randomly selected from the campus at Simon Fraser University.

Electromyography (EMG) is a well-established technique for measuring the electrical activity of muscles of the human body [4]. Surface EMG (EMG) is easy to prepare and the risk of infection is very low, but it measures a large area of multiple fibres and is most suitable for muscles of the superficial layer (the layer of muscle nearest the skin). EMG amplitude increases with the level of contraction but other factors, such as proximity of the probe to the muscle, or the sweat becoming trapped between the skin and the probe, can also affect the reading amplitude. Surface EMG were used in this study as they are suitable for being embedded on a non-invasive portable assistive device.

EMG electrodes were fixed to the volunteers' right forearms by using medical adhesive bands applied with appropriate force to make sure that the electrodes' active faces were tightly adhering the forearm skin. The output signal was used for the sEMG pattern recognition. Figure 4-2 illustrates each electrode's position on the forearm. Table 4-1 represents the muscles used in this study.

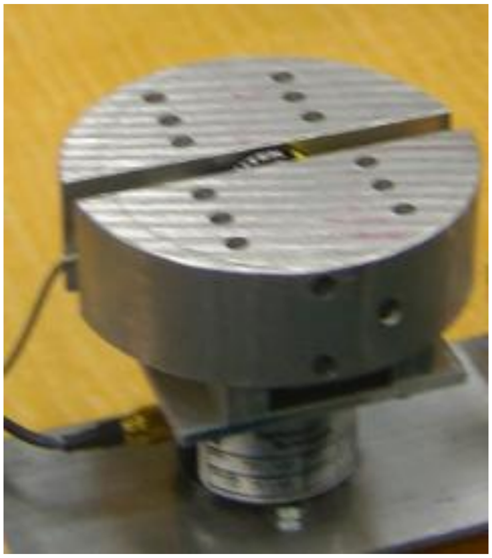


Figure 4- 1: Custom rig

Figure 4- 2: Location of Surface Electrodes on the Forearm

This study was approved by the Office of Research Ethics, Simon Fraser University and each of the subjects signed a written consent form. sEMG signals from forearm muscles of the volunteer were therefore recorded along with the force/torque. A commercial sEMG acquisition system (Noraxon Myosystem 1400L) was used to record the data.

Table 4- 1: Muscles

Muscle
First Dorsal Interossei (FDI)
Abductor Digiti Minimi (ADM)
Abductor Pollicis Longus (APL)
Extensor Carpi Radialis longus (ECR)
Extensor Carpi Ulnaris (ECU)
Flexor Carpi Radialis (FCR)

4.2 Software

We used LabVIEW software for the sEMG signal and the data was acquired at a sampling frequency of 1024 samples per second and saved in the form of text files for later analysis. Library for SVM (LIBSVM) tool in the Matlab environment provides an implementation for SVM, which we utilized to test the classification and regression accuracy for our study.

4.3 Protocol for data collection

A set of three protocols, presented in Table 4-2, was followed in order to collect the data from the volunteers. Volunteers were asked to complete three protocols. The volunteers were seated facing a table with the measurement device in front of their right shoulder. When recording began, the volunteer first rested their hand on the device without exerting force or torque in order to gain EMG signals at rest. The following three protocols, repeated three times each, were performed by the volunteers:

1. Gradual twist clockwise until maximum torque clockwise is reached as shown in figure 4-3-a and the output of the sensor is shown in Figure 4-4-a
2. Gradual twist counter-clockwise until maximum torque counter-clockwise is reached as shown in figure 4-3-b and the output of the sensor is shown in Figure 4-4-b
3. Gradual increase of grasp until maximum force (F) is reached as shown in figure 4-3-c and the output of the sensor is shown in Figure 4-4-c

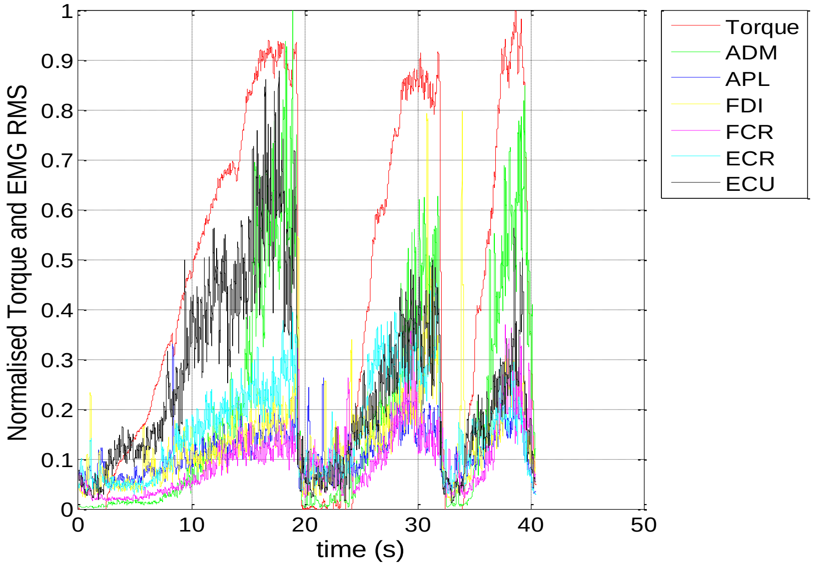
(a)

(b)

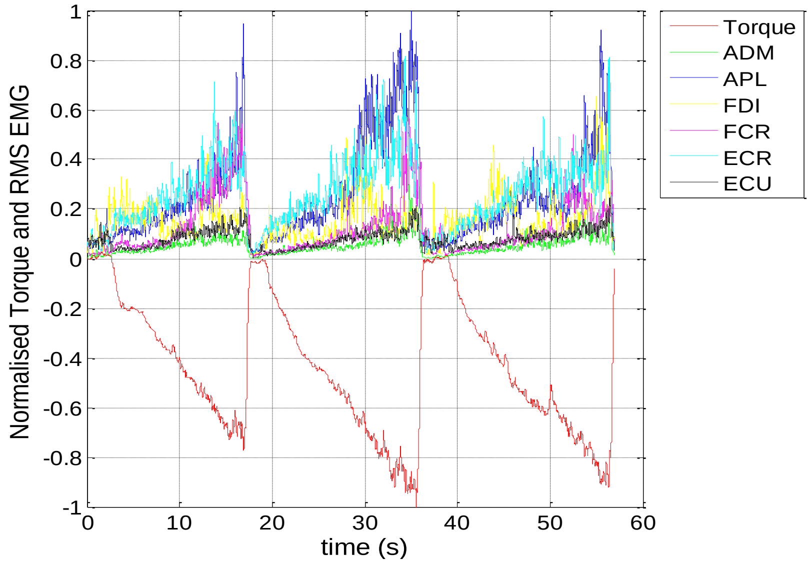
(c)

Figure 4- 3: Hand gestures chosen for classification and regression

(a) clockwise; (b) counter-clockwise; (c) grasp



(a)



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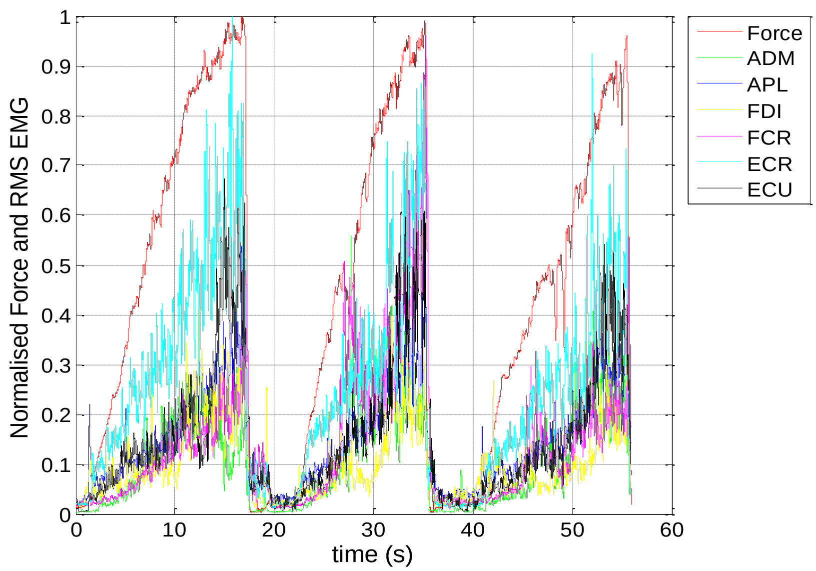


(c)

Figure 4- 4: Different forces and torques representing different protocols

(a) protocol 1; (b) protocol 2; (c) protocol 3

Table 4- 2: Protocols and definitions

Protocols	Definitions
Protocol 1	Gradual twist clockwise until maximum torque clockwise is reached.
Protocol 2	Gradual twist counter-clockwise until maximum torque counter-clockwise is reached.
Protocol 3	Gradual increase of grasp until maximum force (F) is reached.

4.4 Filters

From the three protocols, a set of six EMG measurements were recorded from each volunteer. After recording, the EMG signals were stored for post-processing. A band pass filter to the signals between 20 Hz and 500 Hz was used; the 20 Hz lower limit was applied to remove movement artifacts; the upper 500 Hz limit was used to remove unwanted noise. This band pass filter was suitable to record muscle activity as muscle fibers typically fire in the 50 – 120 Hz range. The EMG signals were also filtered with a stop-band at 60 Hz to remove noise generated by the local electrical equipment, lights, and supply, etc. A second order Butterworth filter was used in both cases.

4.5 Data Post-processing

The raw EMG signals were processed in several steps. The first involved calculating the root-mean-square (RMS) value of the surface EMG recorded from each muscle using the following equation:

$$EMG_{iRMS}(t) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(EMG_i(t)\right)^2}, i = 1 \ldots 6 \quad (4)$$

where $EMG_i(t)$ is the recorded EMG signal at time t for muscle i, T is the length of the averaging window – in this case, value of T = 100 ms was chosen – and $EMG_{iRMS}(t)$ is the RMS value of the raw EMG signal at time t for muscle i. The RMS values for EMG are then normalized to allow for results from different users to be compared directly. Normalization is used to account for differences in volunteer strength, probe placement, and other factors. In this case, the largest RMS value for each muscle is found and used as in (5)

$$EMG_{iNORM}(t) = \frac{EMG_{iRMS}(t)}{\max(EMG_{iRMS})}, i = 1 \dots 6 \quad (5)$$

where EMG_{iNORM} is the normalized EMG for muscle i and $\max(EMG_{iRMS})$ is the maximum value for the RMS EMG for muscle i.

4.6 PCA

Principal Component Analysis (PCA) [39] is a commonly used technique for grouping non-linearly separable data sets. It provides a method of input array dimension reduction and can help eliminate redundancy in the input dataset. Thus, it reduces the number of inputs that are needed for classification. In addition, by using PCA to reduce the dimensionality of the results from 6 dimensions to 3 dimensions, it will make it easier to visualise and interpret any pattern present in the data. By doing so, it also helps to reduce problems with the “Curse of Dimensionality” [40]. This is a problem whereby it is difficult to gather enough data because higher dimension problems typically have a very high number of potential solutions. The process, as applied to this work, involves a number of steps. The first step is to find the average value for each muscle, as follows in (6):

$$\overline{EMG} = \frac{1}{N}\sum_{t=0}^{N-1} EMG_{NORM}(t) \quad (6)$$

where N is the total number of samples recorded and $\overline{EMG}$ is the average for all muscles. From this, the deviation vectors ($\overrightarrow{EMG_{DEV}}(t)$) can be calculated (7).

$$\overrightarrow{EMG_{DEV}}(t) = EMG_{NORM}(t) - \overline{EMG} \quad (7)$$

The deviation vectors are the zero-mean of the normalized EMG values and are arranged into a matrix as follows:

$$D = \left\{\overrightarrow{EMG_{DEV}}(0)\ \overrightarrow{EMG_{DEV}}(1) \dots \overrightarrow{EMG_{DEV}}(N-1)\right\} \quad (8)$$

The covariance matrix of EMG_{NORM} can then be calculated using (9):

$$C = D^T D \qquad (9)$$

The n eigenvalues (λ_i) and eigenvectors (q_i) (in this case n = 6), of the $n \times n$ symmetric covariance matrix C can then be calculated. The eigenvalues are ranked such that $\lambda_i > \lambda_j$ for $i < j$. The magnitude of the eigenvalues (λ_i) is equal to the variance in the dataset spanned by its corresponding eigenvector (q_i), as in (10).

$$\lambda_i = \sigma^2 = \frac{1}{N}\sum_{x=0}^{N-1} \overrightarrow{EMG_{DEV}}(x) q_i \qquad (10)$$

The eigenvectors of the covariance matrix C define n possible unit vectors q_i. There are, therefore, n possible projections of $\overrightarrow{EMG_{DEV}}(x)$ by q_i:

$$a_j = q_j^T \overrightarrow{EMG_{DEV}}(x) = \overrightarrow{EMG_{DEV}}(x)^T q_i, \quad j = 1,2,\dots,n \qquad (11)$$

a_j are the projections of $\overrightarrow{EMG_{DEV}}(x)$ by q_i and are called the principal components (PCs). Dimensionality reduction is obtained using (12):

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} q_1^T \\ q_2^T \\ \vdots \\ q_l^T \end{bmatrix} \overrightarrow{EMG_{DEV}}(x), \quad l \leq n \qquad (12)$$

In this case, n = 6 and values of l = 3 were used. Figure 4-5 shows the data collected for all volunteers for the three protocols. There is a large degree of overlap between the results for the three protocols making this data very difficult to classify accurately.

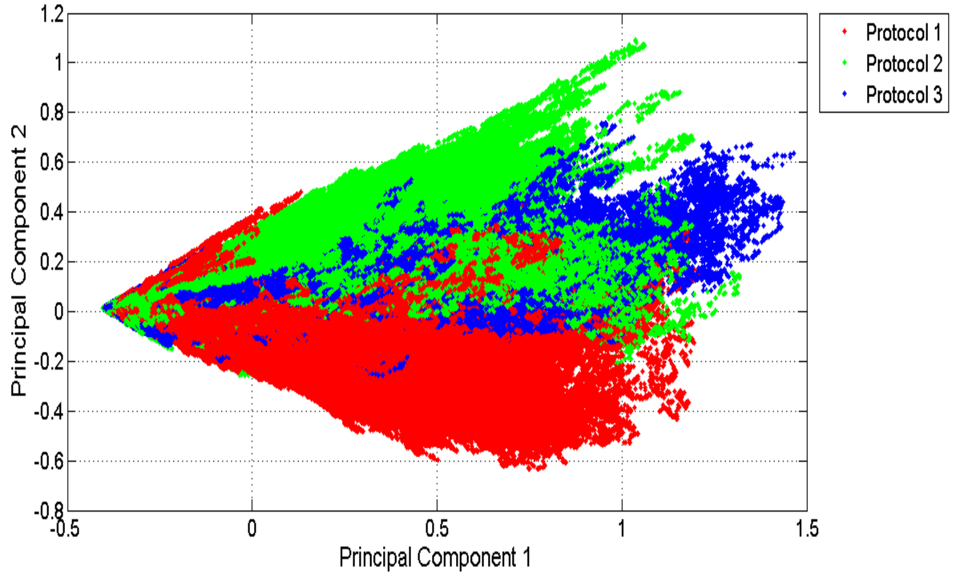
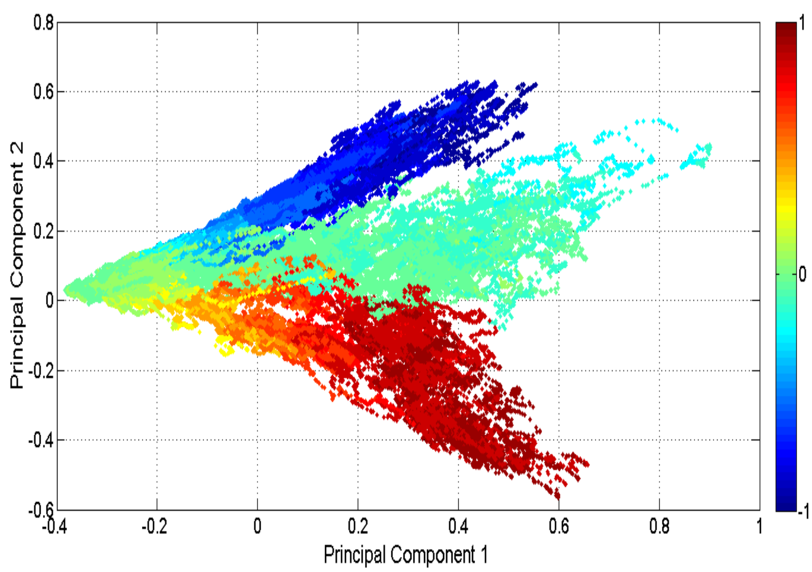
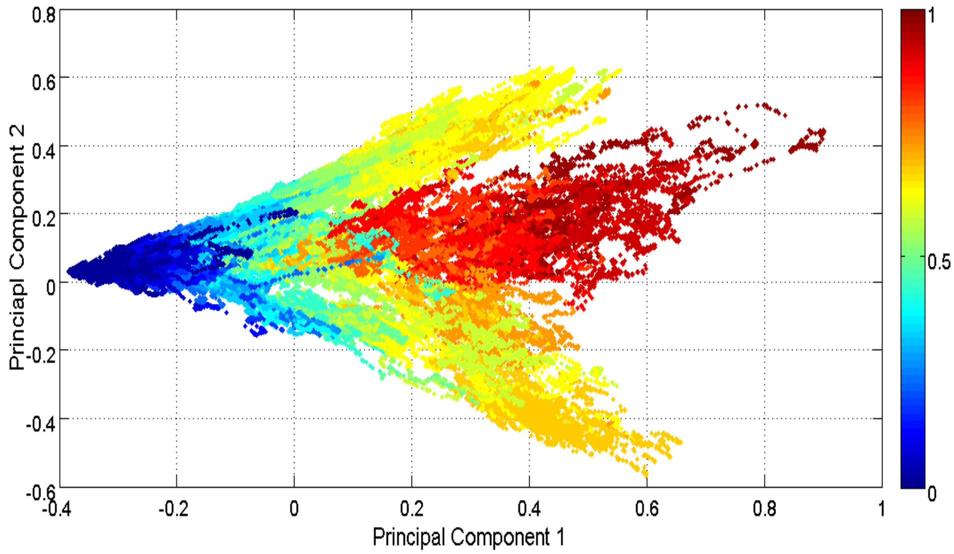


Figure 4- 5: PCs for all protocols

Figure 4-6 present the normalized torque and force applied by each volunteer for the first three protocols.

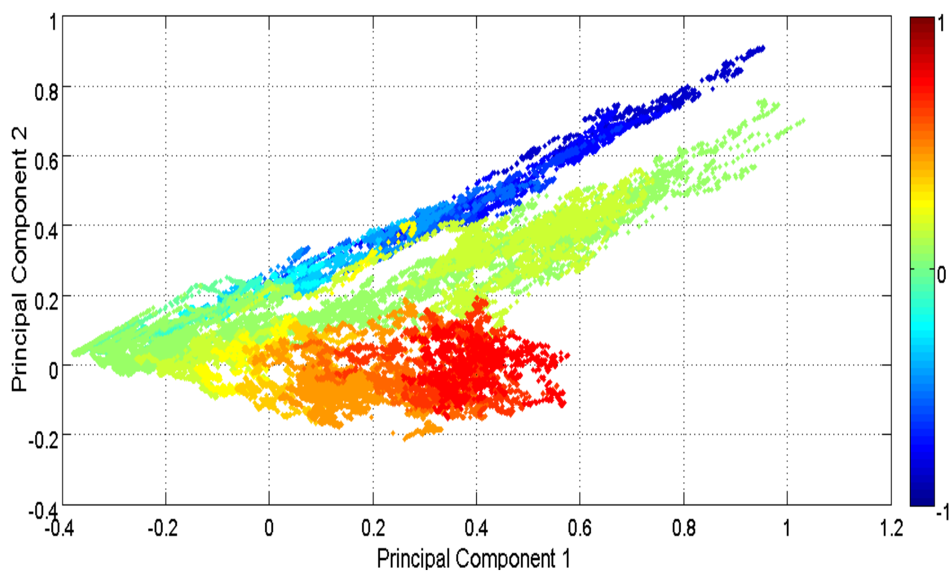


(a)



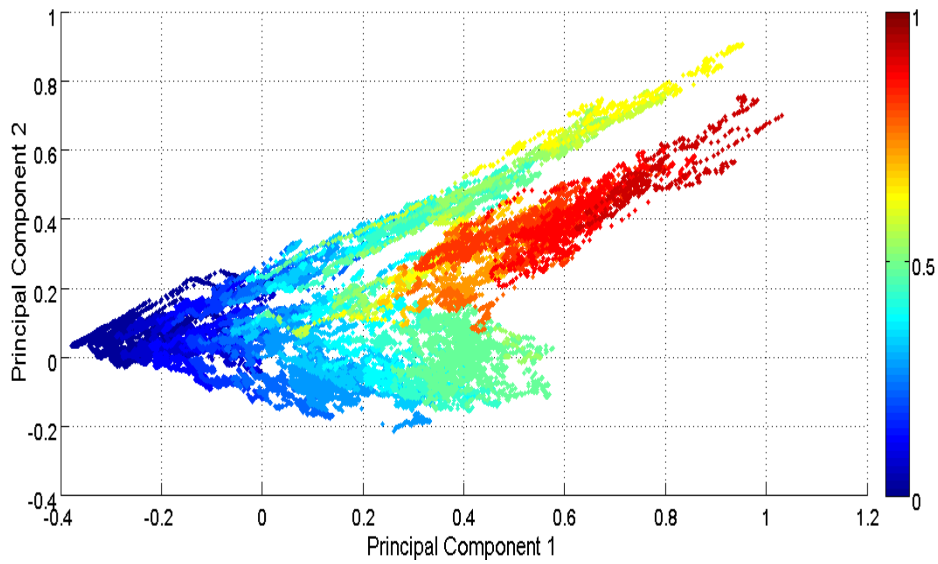
Principal Component 1
Principapl Component 2
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
0.5
0

(b)



Principal Component 1
Principal Component 2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
1.2
1
0
-1

(c)


Principal Component 2
Principal Component 1
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.4
-0.2
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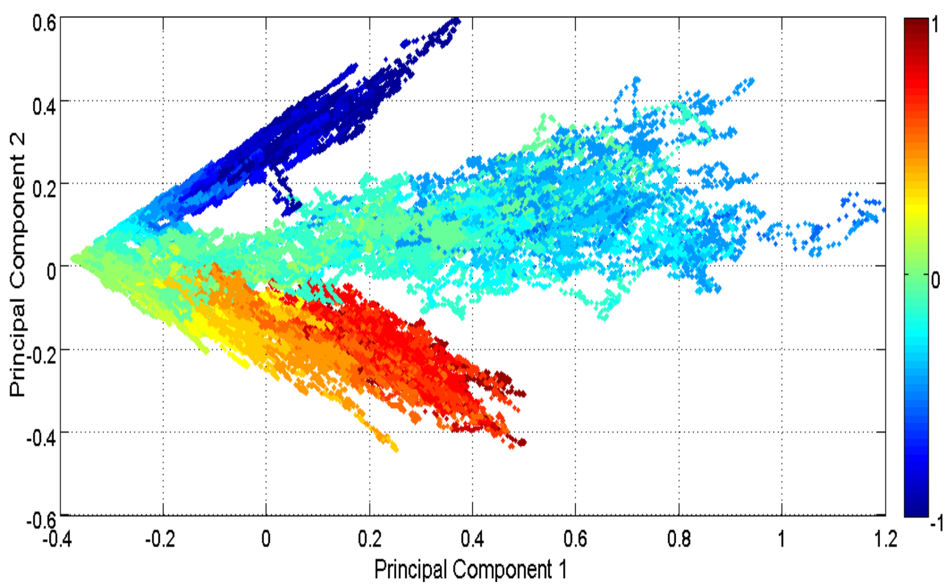
0.2
0.4
0.6
0.8
1
1.2
1
0.5
0

(d)


Principal Component 2
Principal Component 1
0.6
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-0.2
-0.4
-0.6
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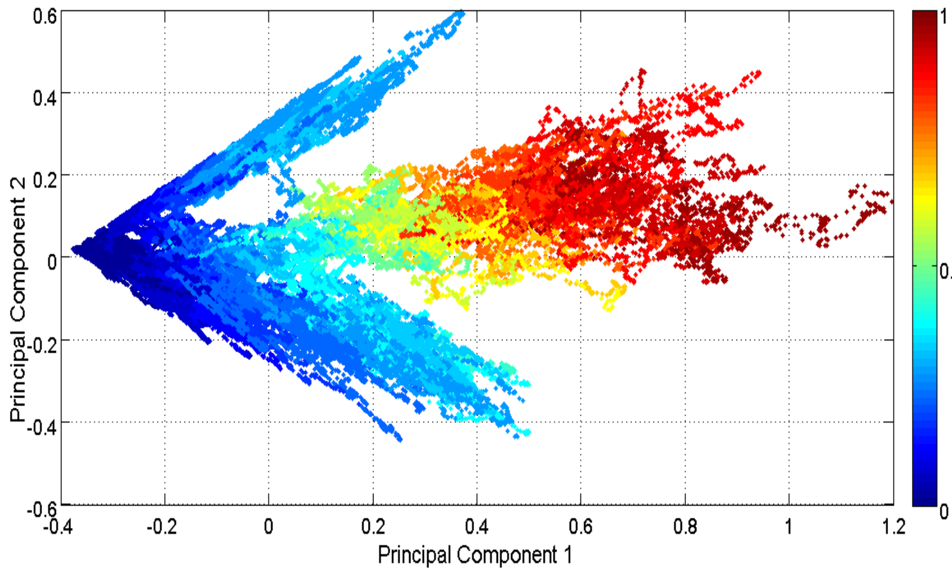
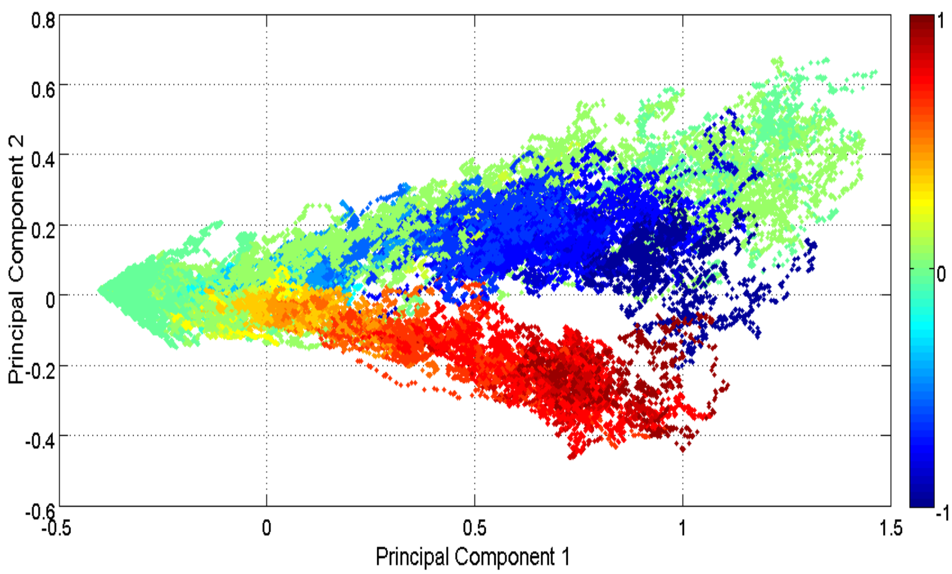
0.4
0.6
0.8
1
1.2
1
0
-1

(e)



(f)



(g)

Figure 4- 6: Principal Components of Protocols 1, 2, and 3, plotted using the Force measured to color the data for interpretation

(a) Volunteer 1 – Torque; (b) Volunteer 1 – Force; (c) Volunteer 6 – Torque; (d) Volunteer 6 – Force; (e) Volunteer 7 – Torque; (f) Volunteer 7 – Force; (g) Volunteer 18 – Torque

4.7 Classification/Regression

The LibSVM tool was used in the Matlab environment. LibSVM has an implementation for multi class SVM (a brief description of SVM can be found in Appendix A).The appropriate values of ε and σ and *c* were selected during training to ensure good generalization performance on test data. Table 4-4 and Table 4-5 and Table 4-6 shows the values of ε, σ and *c* which performed reasonably well and provided the good cross-validation accuracy in our experiment. Figure 3-5 and Figure 3-6 details our proposed sEMG signal classification and regression scheme.

Table 4- 3: Class definition

Class Number	Class definition
1	Clockwise twist
2	Counter-clockwise twist
3	Grasp

The gathered data was divided into training and testing data. Ten seconds of data per protocol was extracted for each class. Out of these, 90% of data were used as training data and 10% of data were used as testing data. The user applied the torque according to description of different classes and 3 classes were trained from the training data. The SVM model was then used to predict the results on the testing data. Table 4-3 represents the different classes of this study.

4.8 RESULTS

Table 4-4, 4-5 and 4-6 show the classification and regression accuracy for participants obtained using the optimal SVM parameters in hand force estimation and classification. It was observed that the accuracy was high. The trained data was used to precisely distinguish between different force levels of hand and estimate the force applied by the participant. It was demonstrated that the Multi-class SVM is able to estimate and classify the different sets of the sEMG patterns produced by the forearm muscles. Multi-class SVM was adapted very well while testing the untrained data. The proposed sEMG processing scheme enabled classifying wrist torque direction with 98.4% accuracy and estimate wrist torque intensity with an average mean square error (MSE) of 0.035.

Table 4- 4: Results for classification of the three protocols

Volunteer	Classification		
	C , γ	**Cross Validation Accuracy**	**Testing Accuracy**
Volunteer # 1	40, 0.2	100	100
Volunteer # 2	40, 0.2	100	100
Volunteer # 3	55, 1	100	100
Volunteer # 4	40, 0.5	100	100
Volunteer # 5	40, 0.2	100	100
Volunteer # 6	40, 0.2	100	100
Volunteer # 7	40, 0.2	100	100
Volunteer # 8	40, 0.7	100	100
Volunteer # 9	90, 1	95.1852	100
Volunteer # 10	40, 0.2	100	100
Volunteer # 11	75, 1	100	100
Volunteer # 12	40, 0.2	99.5556	98
Volunteer # 13	60, 1	99.3333	93.33
Volunteer # 14	40, 0.2	100	100
Volunteer #15	45, 1	100	100
Volunteer # 16	75, 1	99.7778	93.33
Volunteer # 17	40, 0.2	100	100
Volunteer # 18	40, 0.9	99.8519	86.66

Table 4- 5: Results for regression on torque-right direction

Volunteer	Regression on torque-right direction		
	c , γ, ε	**Cross Validation MSE**	**Testing MSE**
Volunteer # 1	256, 8, 0.0625	0.0107	0.027906
Volunteer # 2	256, 8, 0.0625	0.0025	0.00414671
Volunteer # 3	256, 8, 0.0625	0.0015	0.00600973
Volunteer # 4	256, 8, 0.0625	0.0015	0.00148856
Volunteer # 5	256, 8, 0.0625	0.0016	0.0123437
Volunteer # 6	128, 8, 0.0625	0.0115	0.00964194
Volunteer # 7	256, 8, 0.0625	0.0031	0.0207856
Volunteer # 8	256, 8, 0.0625	0.0017	0.00153481
Volunteer # 9	256, 8, 0.0625	0.0017	0.000965356
Volunteer # 10	256, 8, 0.0625	0.0021	0.00420353
Volunteer # 11	256, 8, 0.0625	0.0036	0.0624723
Volunteer # 12	256, 8, 0.0625	0.0035	0.101655
Volunteer # 13	256, 4, 0.0625	0.0019	0.0190663
Volunteer # 14	256, 8, 0.0625	0.0021	0.0126201
Volunteer # 15	256, 8, 0.0625	0.0043	0.124212
Volunteer # 16	256, 8, 0.0625	0.0048	0.0188893
Volunteer # 17	256, 8, 0.0625	0.0092	0.0516616
Volunteer # 18	256, 8, 0.0625	0.0075	0.0363234

Table 4- 6: Results for regression on torque-left direction

Volunteer	Regression on torque-left		
	c, γ, ε	Cross Validation MSE	Testing MSE
Volunteer # 1	256, 8, 0.0625	0.0189	0.197743
Volunteer # 2	256, 8, 0.0625	0.0018	0.0182339
Volunteer # 3	256, 8, 0.0625	0.0074	0.00511358
Volunteer # 4	256, 8, 0.0625	0.0083	0.0117953
Volunteer # 5	256, 8, 0.0625	0.0024	0.00199683
Volunteer # 6	256, 8, 0.0625	0.0078	0.109492
Volunteer # 7	256, 8, 0.0625	0.0023	0.00240562
Volunteer # 8	256, 8, 0.0625	0.0104	0.0744344
Volunteer # 9	256, 8, 0.0625	0.0010	0.081339
Volunteer # 10	256, 8, 0.0625	0.0028	0.00953446
Volunteer # 11	256, 8, 0.0625	0.0056	0.0167816
Volunteer # 12	256, 8, 0.0625	0.0049	0.0299364
Volunteer # 13	256, 8, 0.0625	0.0039	0.00684606
Volunteer # 14	256, 8, 0.0625	0.0079	0.0418601
Volunteer # 15	256, 8, 0.0625	0.0026	0.0502815
Volunteer # 16	256, 8, 0.0625	0.0054	0.0120277
Volunteer # 17	256, 8, 0.0625	0.0032	0.0285208
Volunteer # 18	256, 8, 0.0625	0.0239	0.0420893

CHAPTER 5 Case study 3: classification of surface electromyography signals in seniors - a preliminary investigation

5.1 Experimental Setup

A total of fifteen seniors (average age of 70) volunteered to participate in this study. The study was approved from the Office of Research Ethics, Simon Fraser University and each of the seniors signed a written consent form. A custom rig was developed to record the amount of force/torque applied by the volunteer. The rig consisted of two plastic halves with a force sensor (Futek LCM-300) in between them. These two plastic structures form a sort of a semi-sphere, which a person can comfortably hold with his hand and the force sensor can record the amount of force exerted by the volunteer during squeezing. This plastic structure is connected to a metallic platform through a torque sensor (Transducer Techniques TRT-100) so that if a volunteer performs ulnar or radial deviation while holding the plastic structure, the torque sensor can record the amount of torque produced by the volunteer. A picture of the custom rig is shown in Figure 5-1.

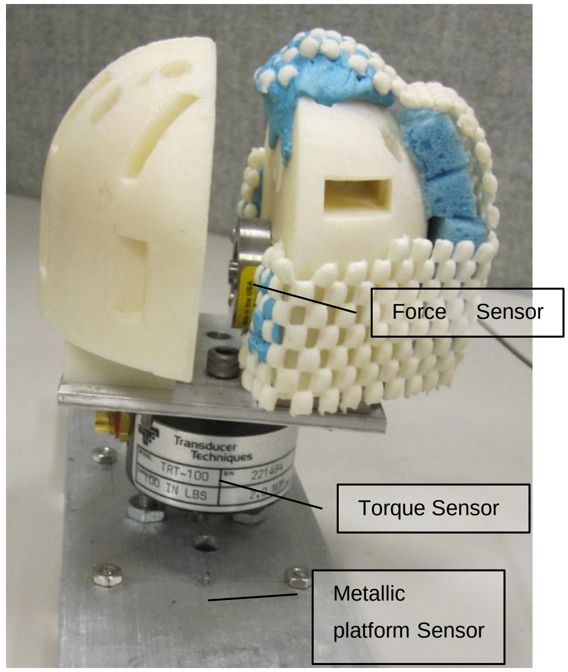


Figure 5- 1: Custom rig

sEMG signals from forearm muscles of the volunteer were also recorded along with the force/torque while the volunteer was performing the predefined protocols which are explained in the next section. A commercial sEMG acquisition system (Noraxon Myosystem 1400L) was used to record the data along with Noraxon's dual electrodes. Figure 5-2 shows the location of surface electrodes on the forearm. The chosen muscles are presented in Table 5-1.

In order to synchronize the data obtained from the custom rig with sEMG signals a data acquisition board from National Instruments (USB-6289) was used. An application was developed using LabVIEW software for acquisition of the data. This application had a graphical interface which the volunteer used to see the amount of force/torque applied in real-time and to have a visual feedback for timing which was critical to follow specific protocols. The data was acquired at a sampling frequency of 1024 samples per second and saved in the form of text files for later analysis.

5.2 Protocols for Data Collection

Five protocols were defined to collect data corresponding to different actions. These actions are presented in Figure 5-2 while the protocols are summarized in

Table 5-1. The volunteer was asked to squeeze (see Figure 5-2-a) the custom rig twice with maximum force in protocol A. This force was regarded as the maximum voluntary contraction (MVC) for squeezing. The output obtained from the force sensor for one of the volunteers during this protocol is shown in Figure 5-3-a. In protocol B, the volunteer was asked to perform ulnar deviation (see Figure 5-2-b) twice with maximum torque and then radial deviation (see Figure 5-2-c) twice with maximum torque. These values were regarded as MVC for ulnar and radial deviation. The output of the torque sensor for one of the volunteers following this protocol is shown in Figure 5-3-b. The volunteer was asked to perform protocols C and D at 50 % of MVC so as not to over exert their muscles. In protocol C, the volunteer was asked to squeeze the custom rig for about 5 seconds. The timing and the force exerted by the volunteer was visible on the graphical interface of the developed application. This squeezing action was repeated three times and a representative output of the force sensor is shown in Figure 5-3-c. Similarly in protocol D, the volunteer was asked to alternate between radial and ulnar deviation for 5 seconds repeating the process three times. A representative output of the torque sensor is shown in Figure 5-3-d. Protocol E asked the volunteer to pinch the force sensor two times first by using thumb and index finger (see Figure 5-2-e), then two times using thumb and middle finger (see Figure 5-2-f), then two times using thumb and ring finger (see Figure 5-2-g) and finally two times using thumb and little finger (see Figure 5-2-h). The output of the force sensor for one of the volunteers is presented in Figure 5-3-e. Protocols C, D and E were used to extract data for classification purposes.

Table 5- 1: Protocols and Definitions

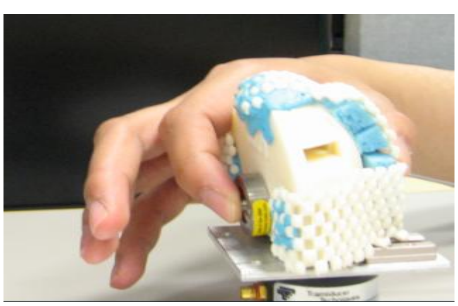
Protocols	Definitions
Protocol A	Apply maximum force by squeezing the custom rig two times.
Protocol B	Apply maximum torque for radial deviation two times and then apply maximum torque for ulnar deviation two times.
Protocol C	Apply 50 % MVC force while squeezing for three seconds. Repeat for three times.
Protocol D	Apply 50 % MVC torque for alternate radial and ulnar deviation for three seconds. Repeat for three times.
Protocol E	Pinch two times with a comfortable force using thumb and index finger, then two times using thumb and middle finger, then two times using thumb and ring finger and finally two times using thumb and little finger.

(a)

(b)

(c)

(d)



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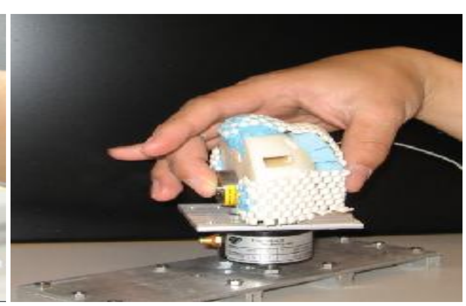

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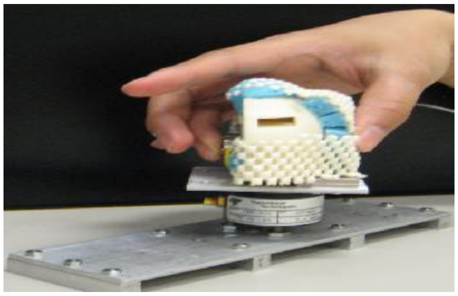
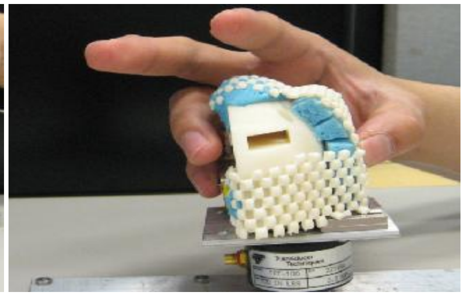
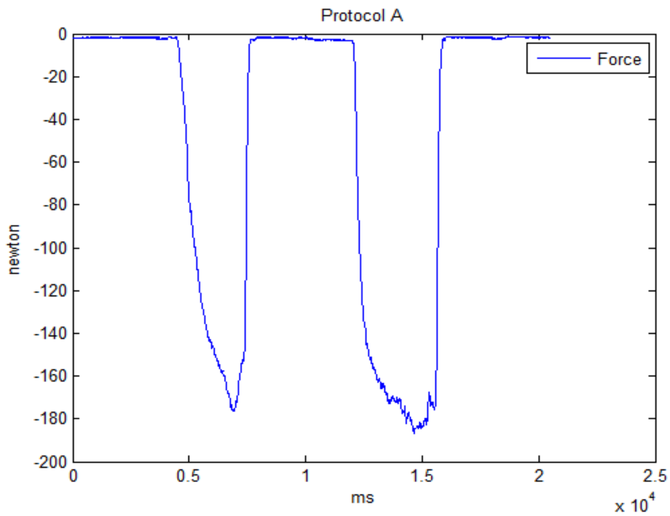




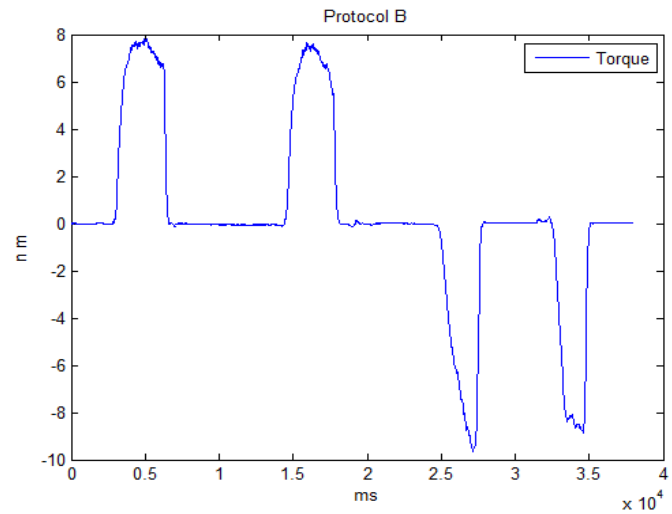
(g) **(h)**

Figure 5- 2: Different hand gestures and motions chosen for classification

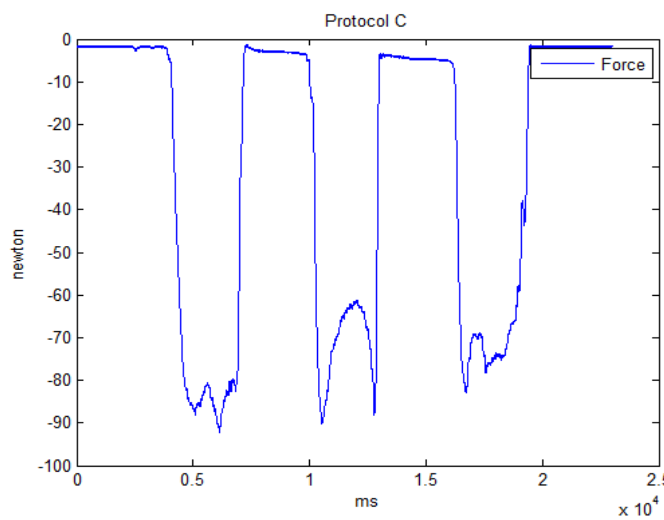
(a) Grasp; (b) Ulnar deviation; (c) Radial deviation; (d) Rest; (e) Index finger pinching; (f) Middle finger pinching; (g) Ring finger pinching; (h) Little finger pinching



(a)



(b)



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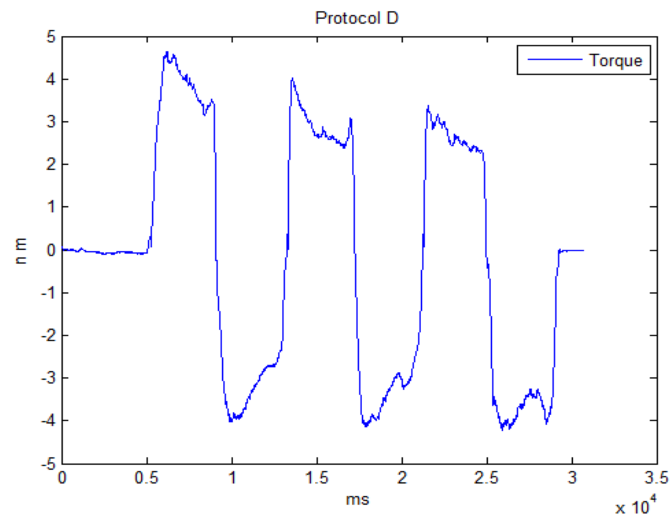

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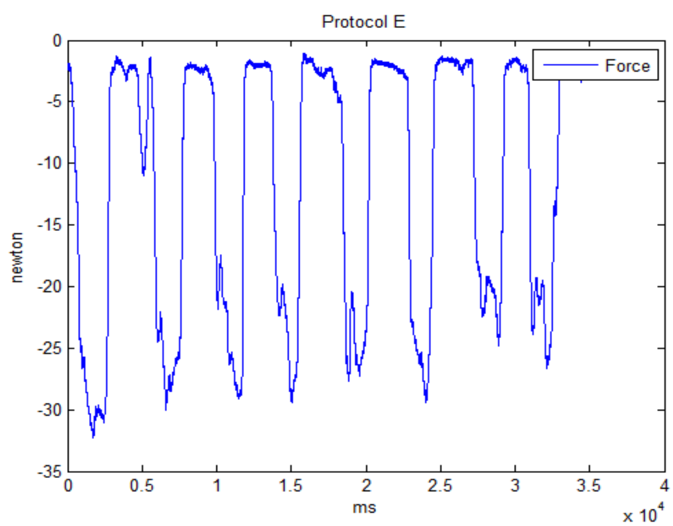

(e)

Figure 5- 3: Different forces and torques representing different protocols

(a) Protocol A; (b) Protocol B; (c) Protocol C; (d) Protocol D; (e) Protocol E

5.3 Feature Extraction

We used Matlab software to extract features from the raw sEMG signals. The first step to extract features from the recorded data was segmenting the signal into

250 ms intervals corresponding to 256 samples in each segment. Using each segment, features were extracted and then the segment window was incremented by 125 ms including 128 samples for the next feature.

Three types of features were extracted from each segment of the data. The first feature used was the time windowed RMS value of the raw sEMG signal that is computed by (3).

The second feature used was based on AR models. AR models are used for time-series analysis and can be defined as a linear combination of previous samples and noise. Mathematical representation is given in (1). We used the AR model coefficients as the features with a model order of four, generating four features for each channel of sEMG.

The third feature was the waveform length, which is defined as a measure of the waveform complexity in each segment. Waveform length is mathematically defined by (2).

Extracting the explained three types of features from each channel of sEMG provided us with a 24 dimensional feature vector from each segment. After extracting the features any pattern recognition algorithm can be utilized for classification.

5.4 Classification

The gathered data was divided into training and testing data. Ten seconds of data per protocol was extracted for each class. Out of these, 90% of data were used as training data and 10% of data were used as testing data. The user applied the torque according to description of different classes and 8 classes were trained from the training data. The SVM model was then used to predict the results on the testing data (a brief description of SVM can be found in Appendix A). Table 5-2 represents the different classes of this study.

Table 5- 2: Class Definition

Class Number	Class definition
1	Rest
2	Grasp
3	Radial deviation
4	Ulnar deviation
5	Finger pinching – index finger
6	Finger pinching – middle finger
7	Finger pinching – ring finger
8	Finger pinching – little finger

In our study we used a grid search on classifier parameters. Various values were tried and the one with the higher accuracy was selected. Trying exponentially growing sequences of parameters is a practical method to find the suitable parameters. After finding the suitable parameters, the whole training set was trained again to generate the final result. Figure 3-5 details our proposed sEMG signal classification scheme.

5.5 Results

The trained data was used to precisely distinguish between different motions and gestures of hand. It was demonstrated that the multi-class SVM is able to classify the different sets of the sEMG patterns produced of the forearm muscle. Multi-class SVM was adapted very well while testing the untrained data and as the result the overall rate of correct class identifying was 92%.

Table 5-3 shows the classification accuracy for fifteen participants obtained using the optimal SVM parameters in hand motion and gesture classification. It was observed that the classification accuracy for some participants was higher than the others. The reason is that these seniors were good at controlling the hand functions and were able to follow the protocols quite accurately and as a result sEMG signal patterns were easily classified.

Table 5- 3: The SVM classification accuracy – the selected c and γ result by grid search for each participant

Participant	Accuracy Percentage	***c***, γ
A	100	40, 0.4
B	92	40, 0.2
C	83	65, 0.2
D	83	40, 0.2
F	92	40, 0.2
I	83	70, 0.6
K	92	40, 0.4
L	75	40, 0.5
M	100	40, 0.2
N	100	40, 0.2
O	92	40, 0.2
P	83	40, 0.2
Q	100	40, 0.2
R	100	40, 0.6
S	100	40, 0.2

CHAPTER 6 Conclusions and future work

6.1 Project summary and conclusions

In the case study 1, a method for classification of wrist torque direction and estimation of wrist torque intensity by using forearm sEMG was presented. The methodology to extract suitable signal features was discussed and results were presented for the two healthy participants volunteering in this study. A SVM with radial basis kernels was used. The average accuracy of 100% was obtained for the classification of wrist torque direction and an average MSE of 0.07% in prediction was obtained for the estimation of torque intensity.

In the case study 2, a different method was investigated. Specifically, we used the PCA technique for reducing the dimension of the problem. In this case, eighteen healthy volunteers participated in the study. Similarly to the previous case study, wrist torque direction and intensity was estimated by analyzing sEMG data. The obtained results showed that it was possible to use EMG readings to determine the amount of torque the volunteers applied to the force/torque measurement system which was employed. The isometric experiments, which were performed, provided a model describing how torque applied by the wrist and hand of a volunteer interact. The results show that there exists a repeatable pattern of muscle engagement that corresponds roughly to the amount of torque being generated by the muscles of the forearm for volunteers who are healthy, have no musculoskeletal conditions, and are of a similar age and background. The average accuracy of 98.4% was obtained for the classification of wrist torque direction and an average MSE of 0.035% in prediction was obtained for the estimation of torque intensity.

In the last study (case study 3), fifteen seniors participated. A method to accurately classify the different hand gestures and motions for seniors using the multi-class SVM is proposed. This method used two phases for the hand motion estimation: the first phase was extracting different features of the recorded sEMG signal: three types of features were extracted namely sEMG RMS values, AR model coefficients and waveform length. The second phase was the hand motion classification of the extracted features with the multi-class SVM. The accuracy of 92% was obtained for the classification of different hand gestures.

Results obtained for the three analyzed cases proved that the patterns of the sEMG of the forearm in seniors are suitable for classification purposes and the use of these signals for control of an assistive device may be feasible. Independently from the experimental setup, PCA, extracted features and volunteers' age, the proposed method based on SVM proved to be potentially suitable for driving a future force controlled wrist assistive device.

6.2 Future Research

The ultimate goal of this research is to improve the autonomy of the users and help train their muscles so that they could easily perform activities of daily living. Future research will focus on improving our classifiers and hardware used to detect sEMG. Specifically, in the performed study we used isometric cases, which might not be suited for practical applications; a model based approach to predict dynamic motions may be employed to improve performance of our system. In addition, portability is another important factor in the development of a suitable assistive device. The equipment that was used in this study for detecting sEMG is however not portable – a portable sEMG measurement system should therefore be developed. The following tasks are therefore foreseen for our future research:

1. The classification and regression techniques need to be modified in order to be used during dynamic hand movements.
2. sEMG system needs to be improved to become portable
3. An assistive device should be developed to enable validation of our software.

APPENDICES

Appendix A: Support Vector Machines

SVMs are a set of supervised learning methods used for classification and regression. SVM works well in high dimensional spaces. SVM has also recently been successfully applied to bio-information signals for pattern recognition [41, 42]. Based on the recorded data, SVM produces a model which predicts the target values of the unseen data given only the unseen data attributes. SVM searches for a hyper-plane with the largest margin to classify different data sets. In a general form, SVM requires solving the following optimization problem presented by (13):

$$\min \quad \frac{1}{2}\|w\|^2 + C\sum_{n=1}^{N}\xi_n$$

$$\text{subject to} \quad \begin{array}{ll} t_n k(\mathbf{x}_n) \geq 1 - \xi_n, & n = 1, \ldots, N \\ \xi_n \geq 0 & \end{array} \qquad (13)$$

where n is the number of data points, x_n is the vector representing a data point, t_n is the label associated with a data point, k is the learned model, w is the vector representing adaptive model parameters, ξ_n is the slack variable and $c>0$ is the penalty factor.

The regressor minimizes a bound on the expected error for future test data. Considering the linear SVM regression, given by (14):

$$f(X) = z^T x + b \qquad (14)$$

where x is the input vector and z is the model parameter and b is a scalar bias. The SVM regression optimization problem finds a linear function that predicts outputs almost equal to y value with no more than epsilon error. This function approximates the data within an epsilon-tube of sensitivity. The following constrained cost function is minimized by (15):

$$min \ \frac{1}{2} z^T z$$

$$subject\ to \ \begin{cases} f(x)_t - < z, x_t > -b \leq \varepsilon \\ < z, x_t > +b - f(x)_t \leq \varepsilon \end{cases} \quad \forall t \tag{15}$$

where x is the input vector and z is the model parameter, b is a scalar bias and ε controls the size of the insensitivity tube over the regression line. The function is the inner product of the input vector x with a model parameter w plus the scalar bias b. The optimization algorithm for regression is governed by the same three parameters presented above. The parameter ε, however, receives a special meaning as it governs the size of the ε-insensitive tube over the regression line.

Library for Support Vector Machines (LIBSVM) tool in the Matlab environment provides an implementation for SVM which we utilized to test the classification accuracy for our study. The LIBSVM supports multiclass classification and uses "one versus one" algorithm in order to classify. For the "one versus one" algorithm, classification is done using a maximum wins voting strategy, in which every classifier assigns the data to one of the two classes, then the vote for the assigned class is increased by one vote. In this algorithm the class that is most classified is selected as the final class. Considering N as the number of classes, this approach involves building N (N-1)/2 classifiers. In fact the time for training classifiers decreases, since the training data set for each classifier is smaller. LIBSVM supports four kernels to extend SVM for non-linear classification and are presented in Table A-1 (where *a, b,* β and *d* are kernel parameters. $\vec{x}_i$ and $\vec{x}_j$ are training vectors).

Table A- 1: Kernels in LIBSVM

Function	Equation
Linear	$y(\vec{x}_i, \vec{x}_j) = \vec{x}_i \vec{x}_j$
Polynomial	$y(\vec{x}_i, \vec{x}_j) = (a\vec{x}_i \vec{x}_j + b)^d$
Radial Basis	$y(\vec{x}_i, \vec{x}_j) = \exp(-\beta \left\| \vec{x}_i - \vec{x}_j \right\|^2$
Sigmoid	$y(\vec{x}_i, \vec{x}_j) = \tanh(a\vec{x}_i \vec{x}_j + b)$

Radial Basis Function (RBF) Kernel

RBF kernel was used as the kernel function in our study. This type of kernel is suitable when the relation between class labels and attributes is nonlinear. The RBF kernel nonlinearly maps samples into a higher dimensional space. Consequently we were able to perform the linear classification in this space.

Algorithm parameters

The algorithm is governed by three parameters:

1. The parameter *c* controls the trade-off between allowing some training errors and forcing rigid margins. Increasing the value of *c* increases the cost of misclassifications but may result in models that do not generalize well to points outside the training set.
2. The parameter ε controls the width of the ε-insensitive zone, used to fit the training data. The value of ε can affect the number of support vectors used to construct the regression function. The bigger ε, the fewer support vectors are selected and the solution becomes more sparse. On the other hand, increasing the ε-value by too much will result in less accurate models.

3. The parameter γ is the convergence tolerance. It is the criterion for completing the training process

Cross-validation and grid-search

We had three parameters for an RBF kernel: *c,* ε and γ. The goal was to find the suitable *c*, ε and γ so that the classifier can accurately predict the test data. Using 8-fold cross-validation, we divided the training set into 8 equal subsets of data. Then one subset was tested using the classifier trained on the remaining 7 subsets. Each instance of the whole training data was classified once and the cross validation accuracy was the percentage of correctly classified data. Using cross-validation procedure, we can prevent the over-fitting problem. We chose the parameters that did not over-fit data and gave better cross-validation and testing accuracy.

In our study we used a grid search on classifier parameters. Various values were tried and the one with the higher accuracy was selected. Trying exponentially growing sequences of parameters is a practical method to find the suitable parameters. After finding the suitable parameters, the whole training set was trained again to generate the final result.

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