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A Study of the Effect of Force Control on the Performance of a Myoelectric Finger Flexion Recognition Algorithm

Ali H.. Ali Al-Timemy[1], Guido Bugmann[1] and Nicholas Outram[2]

***Abstract*— This paper demonstrates the effect of changing the force of contraction and finger range of motion on the performance of the myoelectric movement recognition algorithm. Two sets of Surface Electromyography (sEMG) signals were collected from the right forearm of five healthy subjects. The first set was measured by subjects who were asked to flex their finger to a moderate level of force and range of motion. For the second set of data the subjects used VarGrip finger force with their flexion movement. The VarGrip springs were set to exert light force for all fingers to ensure that all fingers are flexed to the same extent with same force and range of motion. The algorithm was Auto Regression (AR) features combined with a Linear Discriminant Analysis (LDA) classifier to recognize the flexion movement for the little, ring, middle and index fingers from eight channel sEMG recordings. Results showed that multi channel sEMG system combined with VarGrip finger exerciser will improve classification performance by 8% compared to unconstrained flexion of fingers (91.65% versus 84% for unconstrained force).**

***Keywords*- Myoelectric Prosthesis, Dexterous Hand, Surface EMG Signal, Finger Flexion, AR Features and LDA Classifier.**

I. INTRODUCTION

IN the forearm, there are many muscles responsible for finger and hand movements located in the anterior (flexor) and posterior (extensor) compartments within three layers which are deep, intermediate and superficial layers. Each muscle controls one movement or many movements at the same time. Some particular finger or hand movements are performed by the contraction of more than one muscle [1].

It has been reported that EMG recorded from the amputee forearm muscles after hand amputation are similar to EMG of healthy subjects [2, 3]. Therefore, there is still an EMG signal when the amputee intends to perform a movement.

This fact inspired researchers to develop EMG signal processing algorithms for the control of a myoelectric hand.

Myoelectric control algorithms focus on the control of a prosthetic limb with surface EMG recorded non- invasively by two surface electrodes in minimum that could be fitted inside the socket of the prosthetic limb. Identification of the user's intended motion caused by muscle contraction and the implementation of the specific movement are the main objectives of myoelectic control [4].

Surface EMG signals have been used by many researchers to control a prosthetic hand with three hand movements (open-close and rotation). However, Identification of finger movements is a challenging task since it is very difficult to recognize finger flexions and extensions from a finite number of control signals [5]. There are two causes for this difficulty. The first one is that surface EMG signals for finger flexions are generally small in amplitude compared to hand movement EMG. The second cause is that the location of the two muscles controlling the four finger flexions (flat muscles with finger specific compartment) lies in the intermediate and deep layer of the forearm. Both causes will make it difficult and complicated to record high amplitude EMG with a good class separation.

There is a current need for a dexterous hand device with the proper myoelectric control that could be used skillfully with adroitness providing a movement with dexterity as well as ease of operation by the user and multi degree of freedom movements [6, 7]. This in turn will give the potential for myoelectric controlled hand with more movements to be performed and with flexibility in handling those movements [5].

Two muscles in the anterior compartment of the forearm are responsible for the flexion of little, ring, middle and index fingers. Flexor Digitorum Superficialis (FDS) that lies in the intermediate layer while Flexor Digitorum Profundus (FDP) sitting in the deep layer of the anterior compartment of the forearm. Fig.1 shows the intermediate and deep layers of the anterior (flexor) compartment of the forearm.

There are a few researches in the area of identification of finger movement discrimination and control. An early reported research for finger movement identification was published by Uchida *et al.* [8]. The objective of the work was to identify five single and combination finger

Ali H. Ali Al-Timemy and Guido Bugmann are with Centre for Robotics and Neural Systems (CRNS), Phone: (+44) 7551059424, (Email:ali.ali@plymouth.ac.uk, email: gbugmann@plymouth.ac.uk)

Nicholas Outram is with Signal Processing and Multimedia Communication (SPMC) research group, Phone: (+44) 1752 586257, (Email: nicholas.outram@plymouth.ac.uk)

School of Computing and Mathematics, University of Plymouth PL4 8AA, United Kingdom

movements. These movements were flexion of all fingers, index flexion, middle flexion, thumb flexion and relaxation of all fingers. Two pairs of surface EMG electrodes (active and ground electrodes) placed on FDS and the extensor digitorum were used in their study. The signals were processed by Fast Fourier Transform (FFT) with 10 frequency bands. The FFT frequency bands were introduced to an Artificial Neural Network (ANN) trained with a Back-Propagation algorithm (BP) with one hidden layer of 7 neurons. A recognition rate of 86% was achieved with the 2 pairs of electrodes used compared to 67% recognition rate when using only one pair of electrodes placed on the FDS.

Another attempt was reported by a research group led by Jiang *et al.* [5] to recognize flexion and extension for thumb, index and middle finger (six moevemnts) by using two and four EMG electrodes. The aim of the research was to demonstrate the difference between the use of two and four electrodes with multi resolution analysis and artificial neural networks for the proper finger motion recognition. Variance, mean, maximum and mean of absolute value of the Wavelet Transform (WT) decomposition were used as input features to the classifier. An ANN trained with BP algorithm was used for the classification. The results showed that a higher percentage of finger recognition accuracy could be achieved with the use of 4 electrodes rather than two electrodes. For the case of using four electrodes, an average accuracy of 87% of all six finger motions was obtained. However, for the case of two electrodes, an overall accuracy of 75% was obtained.

A later attempt was presented by Singh and Kumar [9] in which identification of flexions for four fingers were proposed. Only one electrode was placed on the FDS muscle with a reference electrode which was placed near the elbow joint. WT and continuous WT were used for feature extraction. A simple thresholding technique was applied to the feature vectors to reduce their dimension and the classification was done by support vector machine.

Practically, there are many difficulties when recording EMG signals from the subjects for the purpose of myoelectric control. These difficulties are the inability to achieve the same range of motion for all movement and the invariability in applying the same amount of force when performing a movement by the same subject [10].This difficulty in controlling the force of contraction for a finger movement may result in an increase in the classification error of a particular control system and reduce system accuracy.

This paper proposes a finger discrimination algorithm based on multi channel surface recordings. The objective of this work lies in two parts. The first one is to introduce a simple control algorithm for discriminating four independent finger motions with the use of multi channel surface EMG electrodes and a simple pattern recognition system. The second objective is to investigate the effect of controlling the force of contraction of finger flexion on the system accuracy.

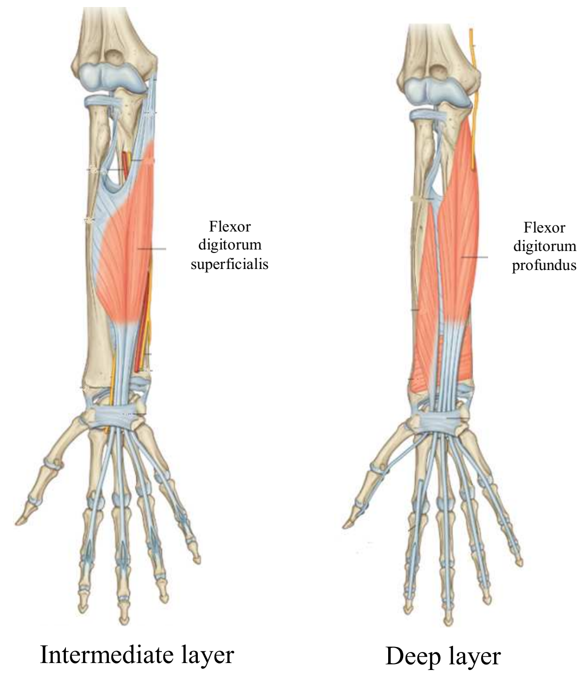

Fig 1. Intermediate and deep layers of the anterior compartment of forearm muscles. Adapted from [1].

II. Methodology

An EMG signal was recorded from the forearm muscles of five male subjects (age 28-40 years) volunteered for the study with the use of 8 surface electrodes. The subjects were asked to read the participant information sheet and to give their written consent for the agreement to perform the experiment. The proposed protocol for EMG recording has been approved by the Human Ethics Committee of the Faculty of Science and Technology at University of Plymouth, UK.

The signals were recorded by Multi Channel EMG/Evoked Potential system from (Nehon Kohden /Japan) at the Neurophysiology department, Derriford hospital, Plymouth. Eight self adhesive surface EMG electrodes from VIASYS Healthcare /Germany were placed in the upper part of the forearm. It is difficult to place surface electrodes over any muscle unless dissected. The best surface location that could be achieved was placed on the forearm locations that lay above the location finger flexor muscles mentioned above. The reference electrode was placed on the olecranon process of the unla while the ground electrode was placed 6 cm away from the wrist.

Two sets of EMG signals were collected from the right hand of five healthy subjects. Each set of recording consists of 4 sec recording of Little Flexion (LF), Ring Flexion (RF), Middle Flexion (MF) and Index Flexion (IF) with 4 sec rest period which was introduced after the finish of RF resulting in a total time length of 20 sec for the set. The first set was when the subjects were asked to flex their finger to a moderate level of force and range of motion. The second set of data when the subjects used VarGrip finger force with their flexion movement. The VarGrip device has a four spring stiffness starting from light, intermediate, heavy and too heavy force. The VarGrip springs were set to exert a light force for all fingers as shown in fig 2. This was to ensure that all fingers are flexed to the same extent with the same force and range of motion.

The signals are windowed with a window size 300ms with a step size 64ms for the training and testing data set.

To reduce the dimensionality of the input time domain EMG signals, AR coefficients (first five numbers) and root mean square value represented the input feature vector as recommended in [11].

The training set for the system consisted of three sets of recordings (60 second total length of the training data) while two sets of recordings were used as a testing data.

Classification is performed with an LDA classifier since the problem of training iteratively could be avoided with the use of LDA giving a low chance of under and over training [11].

Fig. 2. Varigrip Variable Tension Finger Exerciser with the index finger flexion

III. Results and Discussion

The classification accuracies were calculated with the application of majority voting. Majority vote is a type of post processing suggested by [12] that will improve recognition accuracy by a small percentage. These small percentages are useful specially when looking at the small variation between the EMG signals for finger movements.

Majority-vote post processing (Fig. 3) employs the eight previous classification results with the present one. The analysis window size was 300 ms with a step size of 64 ms. The classification results then are judged on the basis of the common class which appeared in each window. The process will reject the false misclassification and ensure a smooth operation[11].

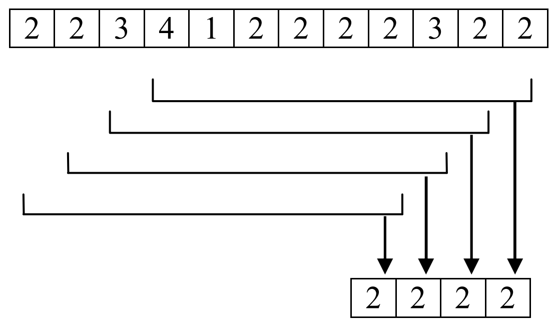

Fig. 3 Majority Vote post processing

An overall classification accuracy of **91.6%** for five subjects was achieved with controlling the force. Whereas for the case of uncontrolled force, an overall accuracy of **83.96%** was recorded. The confusion matrices for the case of uncontrolled force and controlled one are shown in Table.1 and Table 2. respectively. Classifications output for uncontrolled and controlled force are shown in Fig. 4 and Fig. 5 respectively.

For the case of controlled force (with the use of VarGrip), subject 1 achieved the highest classification accuracy of 92.45% with the application of majority vote post processing while subject 4 achieved the lowest classification accuracy of 90%. A sample of classification output with the 8 channel EMG is shown in Fig 6.

From the above results, there is an 8 % difference in classification accuracy across the subjects between uncontrolled force and controlling the force with the use of VarGrip.

Table 1 Confusion matrix for 5 subjects of finger flexions including rest without the use of VarGrip finger exerciser.

		Actual finger class				
		LF	**RF**	**Rest**	**MF**	**IF**
Predicted finger class	**LF**	113	3	0	4	7
	RF	7	107	0	14	0
	Rest	2	1	115	8	2
	MF	10	0	0	91	27
	IF	4	0	0	13	108

Table 2 Confusion matrix for 5 subjects of finger flexions including rest with the use of VarGrip finger exerciser.

		Actual finger class				
		LF	**RF**	**Rest**	**MF**	**IF**
Predicted finger class	**LF**	116	0	0	4	6
	RF	4	114	1	8	0
	Rest	0	3	122	1	2
	MF	0	0	2	106	21
	IF	0	0	0	1	125

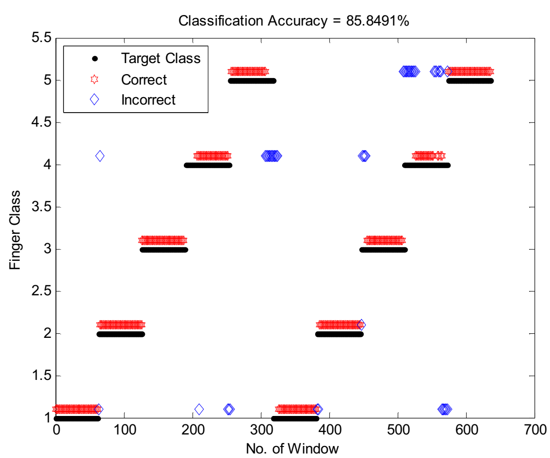

Fig. 4. Classification results of uncontrolled force for subject 2

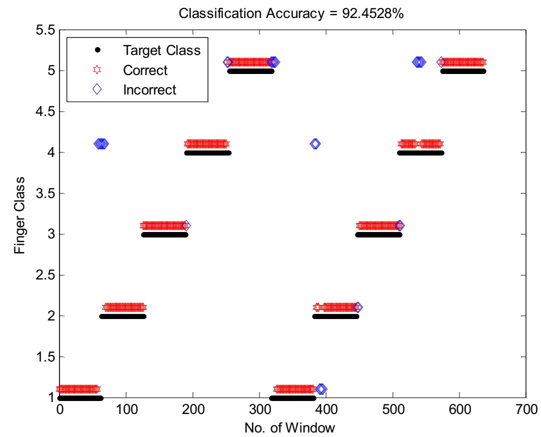

Fig. 5. Classification results of controlled force with Vargrip exerciser for subject 1

IV. Conclusion

The effect of changing the force of contraction and finger range of motion on the performance of the myoelectric motion recognition algorthim was proposed. The algorithm uses AR features combined with an LDA classifier to recognize the flexion movement for the little, ring, middle and index fingers from eight channel EMG recordings. Two sets of EMG signals were collected from the right forearm of five healthy subjects. The first set of data was collected when the subjects were asked to flex their fingers to a moderate level of force and range of motion**.**

The other set was as collected with the use of VarGrip finger exerciser in which VarGrip springs are set to exert light force for all fingers to ensure that all fingers are flexed to the same extent with same force and range of motion.

The results suggested that a multi channel EMG system combined with the VarGrip finger exerciser will improve classifier output by 8 % compared to unconstrained flexion of fingers (91.65% versus 84% for unconstrained force).

Additional data collection, using different forces of the VarGrip finger exerciser, is being done to study the influence of applying a different force of contraction on the system accuracy and to predict the force of the finger flexion movement performed.

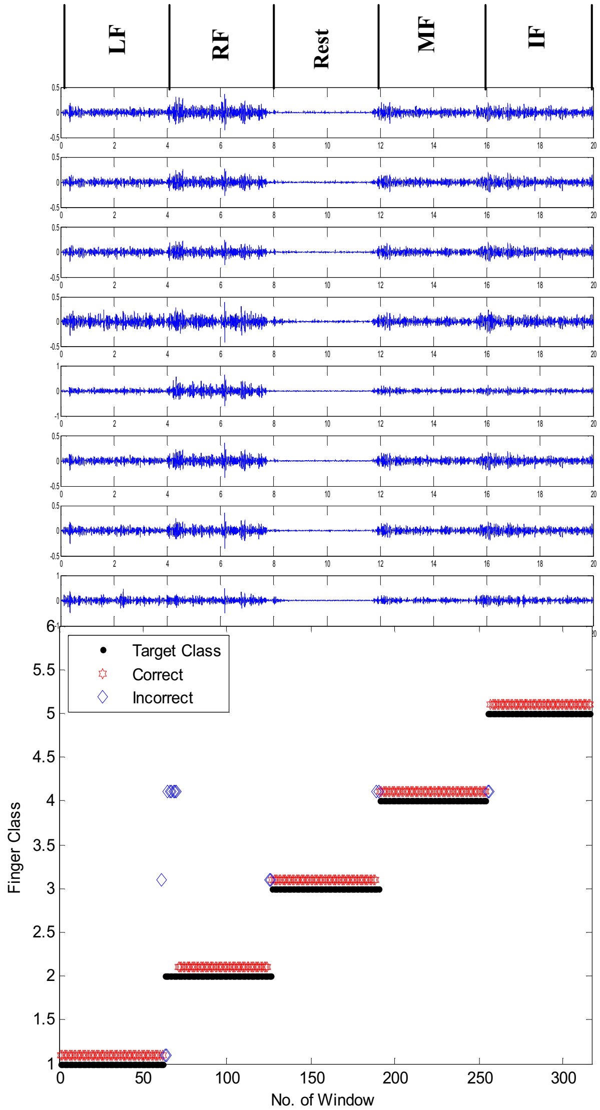

Fig. 6. A Sample of 20 sec classification output of force controlled movement for subject 3

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