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A Preliminary Investigation of the Effect of Force Variation for Myoelectric Control of Hand Prosthesis

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Abstract— **The myoelectric control of prostheses has been an important area of research for the past 40 years. Significant advances have been achieved with Pattern Recognition (PR) systems regarding the number of movements to be classified with high accuracy. However, practical robustness still needs further research. This paper focuses on investigating the effect of the change in force levels by transradial amputee persons on the performance of PR systems. Two below-elbow amputee persons participated in the study. Three levels of forces (low, medium, and high) were recorded for different hand grips with the help of visual feedback from the Electromyography (EMG) signals. Results showed that changing the force level degraded the performance of the myoelectric control system by up to 60% with 12 EMG channels for 4 hand grips and a rest position. We investigated different EMG feature sets in combination with a Linear Discriminant Analysis (LDA) classifier. The performance was slightly better with Time Domain (TD) features compared to Auto Regression (AR) coefficients and Root Mean Square (RMS) features. Finally, the error of the classification was considerably reduced to approximately 17% when the PR system was trained with all force levels.**

I. Introduction

MYOELECTRIC control refers to the control of a prosthetic limb via the Electromyography (EMG) signals (also known as myoelectric signals) which are recorded non- invasively via one or more surface electrodes fitted inside the socket of the prosthetic limb. Identification of the user's intended motion caused by muscle contraction is the main objective of myoelectric control [1]. The EMG signal has played an important role in rehabilitation because of its non-invasive nature when recorded from the skin. In addition to its role in prosthetic control, it plays an important role in Functional Electric Stimulation (FES) and assistive device control such as exoskeleton devices [2].

Research during the past four decades has focused on the control of prosthetic limbs with Pattern Recognition (PR) of EMG signals to identify muscle patterns to control multi-functional upper-limb prosthesis. It is a very promising approach since it offers an intuitive control for the hand prostheses with the ability to control multiple Degrees of Freedom (DOF). However, prostheses with PR systems are not yet commercially available or implemented for clinical use.

Improvement of the system robustness towards practical problems is important since solving these problems would help to make the PR systems a clinically available option. There have been some recent attempts to address the potential problems associated with PR systems to improve the practical robustness such as variation in limb position [3], signal non-stationarity [4], force change [5], the dexterity [6] and electrode shift [7]. However, the effect of force change on the performance for the amputee persons needs more attention.

Scheme and Englehart [5] studied in their review the effect of force level variation on the performance of PR-based EMG control. EMG data were collected from 8 bipolar channels from normal subjects who performed 9 classes of hand motions. The force level was varied from 20% to 80% of the strongest contraction which the participant felt comfortable with. Time Domain (TD) features and a Linear Discriminant Analysis (LDA) classifier were used for classification. To test the ability of the PR system to handle new forces, the classifier was trained at each force level and then tested with all force levels. The error rates were between (32 to 44%) for the classifiers compared to (8-19%) when training and testing with the same force level. However, it must be noted that the experiment in their study was conducted on intact-limbed subjects who benefited from the visual feedback from the limb [5]. In real life, an amputee person lacks the visual feedback because of the loss of the limb after the amputation process. More importantly, it is not known if these findings can be generalized to amputee persons since they have a different muscle structure after amputation. Also, muscle atrophy might occur due to the lack of use of the stump for long time after the amputation process.

To sum up, the current training strategy of PR systems is able to identify single level of force and the PR systems are usually trained with examples of patterns with that predefined force level. However, there is little evidence about what will happen to the performance of the amputee person if the force level changes. To address these limitations, two amputees were recruited in this study, which investigates the effect of changing the force level on the PR system's performance for the transradial amputees. We also propose a training strategy to help to decrease the effect of force change for the amputee persons.

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II. METHODOLOGY

A. The Participants

Two below-elbow amputee persons (A_1 and A_2) with unilateral amputation participated in the study. The 1st amputee person (A_1) age was 32 years old and he had the amputation 5 years ago, while amputee person (A_2) age was 29 years and he had the hand amputated when he was 2 years old. None of the amputee persons use a myoelectric prosthesis due to non-availability. The amputee persons' data were collected at the Artificial Limbs and Rehabilitation Centers in Baghdad and Babylon, Iraq. The study was approved by the Human Ethics Committee of the Faculty of Science and Technology at Plymouth University and both amputee persons gave their written informed consent to participate in the study.

B. Electrode locations

The skin of the subjects was cleaned with alcohol and abrasive skin preparation gel (NuPrep®, D.O. Waver and Company, USA) was applied.

Twelve pairs of Ag/AgCl electrodes (Tyco healthcare, Germany) connected to a differential amplifier were placed around the left stump in 2 rows. Fig. 1 shows the electrode locations for A_1. European recommendations for sEMG (SENIAM) [8] were followed for placing the surface electrodes and the elbow joint was used as reference to mark the electrode locations.

Figure1. Surface electrodes locations for amputee person A_1.

C. Signal acquisition

The signals were acquired with a custom-built multi-channel EMG amplifier with a gain factor of 1000 per channel. The signals were sampled at a rate of 2000 Hz with 16-bit resolution data acquisition (USB-6210, National Instruments) and bands-pass filtered (20-450) Hz. Also, a notch filter (centered at 50 Hz) was implemented for reducing power line noise. Virtual Instrument (VI) implemented in LABVIEW (National Instruments, USA) was used for signal acquisition and display. A screen shot of the VI developed in Labview is shown in Fig. 2.

D. Experimental Protocol

Four different grip patterns were investigated in this work: 1) Fine pinch with thumb and index fingers; 2) Tripod grip with thumb, index and middle fingers; 3) Power grip (hook or snap); 4) Spherical grip. There was an additional no-movement class added to the dataset.

To examine the effect of force variation on the performance of EMG-based PR systems, the following experimental protocol was used. After placing the electrodes, each amputee person is asked to examine the 12 EMG signals on the screen in real-time and to change the force of contraction for different type of grips. The objective was to see how the amplitude is changing according to the force (see Fig.2). They are given couple of minutes to explore that. For each grip, the amputee persons produced the following force levels:

1) Moderate Force

To record the EMG with different forces, each amputee person is asked to produce the constant non-fatiguing contraction with moderate force and hold the position for a period of 8 seconds for each movement which constitute a trial. Six trials were recorded for each movement.

2) Low Force

It is very challenging for the amputee person to produce a different force of contraction for a given movement because of the loss of visual feedback from the hand after the amputation. Our aim was to record a lower level of force and higher level than the moderate force. The reason for that is to simulate the daily life scenario when the signal force varies with the everyday use.

The amputee persons used their intact-hand to help them to imagine the needed movement with the proper force. Also, they were using the visual feedback from the Labview screen to see the EMG channels which helped them to produce the needed force.

The participants were asked to produce a lower force level than the moderate level and hold it for 8 seconds. Six trials were recorded for the low force level for each gesture for each amputee person. It is worth mentioning that the amputee persons found the visual feedback very helpful because it was challenging for them to produce a low level of contraction.

3) High Force

A higher force level than the moderate force was produced by the amputee persons with the help of visual feedback and the intact-hand as well. They were instructed to produce the high force level at a comfortable level to them and to hold the contraction for 8 seconds. The Maximum Voluntary Contraction (MVC) was avoided since it might cause fatigue due to the non-use of the muscle for long time. Preliminary investigation with some amputee persons to produce MVC for a given movement caused some pain and fatigue. For that reason, MVC was not included in the recording protocol.

Producing the high force level was difficult for the amputee persons as they have not used the remaining muscles in the stump for long time. Furthermore, the high force of contraction produced tremor in some occasions when holding during performing the trial. The amputee subjects produced 6 trials for each gesture with the high force.

E. EMG Pattern Recognition Analysis

The MATLAB® 2011a software (Mathworks, USA) was used to perform the analysis in this study. Overlapped segmentation scheme was used with 160 ms segment length and 40 ms segment overlap. Two feature extraction methods were investigated. The first one was the Time Domain (TD)

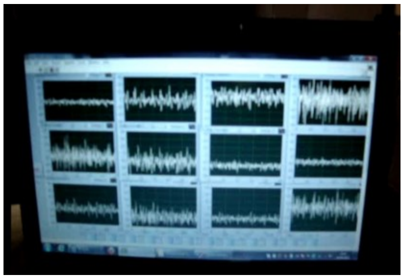

Figure. 2. Screen shot of the Labview VI showing the 12 EMG channels which were used as a feedback to help the amputee persons to produce the correct level of force.

features [5] which contain the following features: integral absolute value, waveform length, zero crossings, slop sign changes and kurtosis. Recent work showed that kurtosis is a good measure to characterize the force level changes based on the analysis of the probability density function (PDF) of the EMG signal [9]. For that reason, kurtosis was added to TD feature set.

The second feature set consisted of the coefficients of the 4^{th} order Auto Regression (AR) model and the Root Mean Square (RMS) value feature as previously used in the literature since the 4^{th} AR model was reported to have a good tradeoff between performance and order [10, 11].

Linear Discriminant Analysis (LDA) was used to perform the classification since it is simple and proven to show good results for myoelectric control [12]. Furthermore, it avoids iterative training giving less problems with under- and over-fitting [13].

To test the classification performance, the following classifier experimental Schemes were explored:

1) Training the classifier with a single force level and testing it with the same level of force.
2) Training the classifier with single force level and testing it with the untrained (unseen) 2 force levels.

In these two experimental schemes, the signals from the first 3 trials were combined to produce the training set while the last 3 trials were combined to produce the testing set, which was used to evaluate the accuracy of the classification.

3) Training the classifier with the 3 levels of force and testing it with a single level of force at a time.

In this experimental scheme, the signals from the first 3 trials for all force levels were concatenated to produce the training set. As for the testing set, the last 3 trials for each force level were used to the classifier performance.

III. Results and Discussion

Fig. 3 displays the classification errors for the 2 amputee persons when training and testing the classifier with the same force (Experimental Scheme 1) with 2 feature sets, i.e. TD and AR+RMS.

It can be noticed that the performance for the 2 amputee persons was different for each feature set and force level. For instance, A_1 was better than A_2 for the training and testing with low force and TD features outperformed slightly the AR+RMS features. On the other hand, A_2 was better than A_1 when training and testing with high force with TD features also outperforming AR+RMS. For training and testing the classifier with medium force, there was variability in the performance with different features where the error for A_1 was much lower with AR+RMS features compared to TD features. However, for A_2, the TD feature set was better than AR+RMS features. In general, TD features slightly outperformed AR+RMS features in most cases.

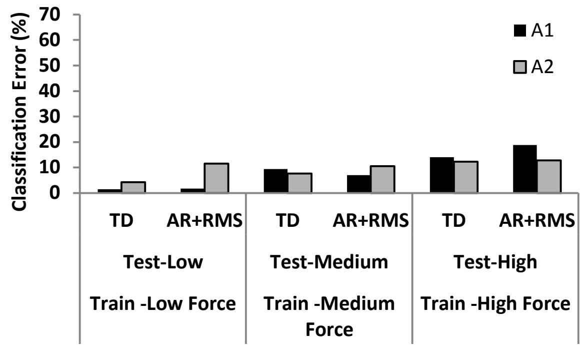

Figure. 3. Classification errors for the amputee persons when training and testing the classifier with the same force level (Experimental Scheme 1) with 2 feature sets (TD and AR+RMS)

Fig. 4 shows the error rates for the classification when the classifier is trained with single level of force and tested with the unseen force levels (Experimental Scheme 2). Clearly, the error rates are much higher than when training and testing with the same level of force as shown in Fig. 3. These high error rates (>50%) might occur during the daily life usage of the prosthesis when the amputee person might change the force level.

Fig.3 and Fig.4 suggest that the performance for the amputee persons was variable. Such variability in the results between the subjects may be due to different level of amputation for each amputee person.

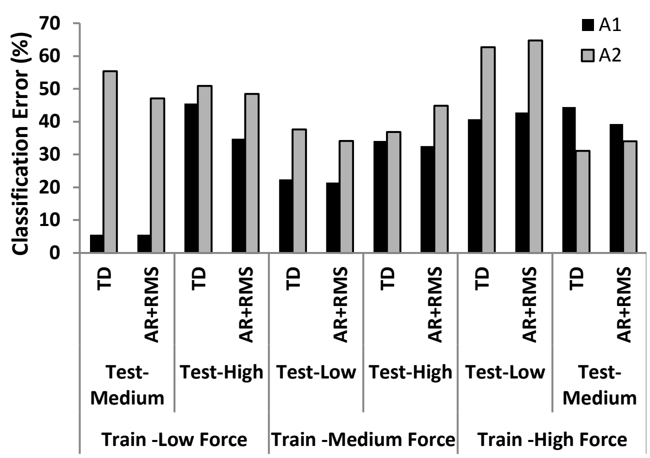

Figure. 4 Classification errors of the amputee subjects when training the classifier with one force and performing the testing with unseen force levels

Fig.5 presents the results for training the classifiers with the 3 force levels (low, medium, and high) and testing the classifier with a single level of force at a time (Experimental Scheme 3). It can be noticed that the error rates dropped significantly from those displayed in Fig. 4 for the case of unseen forces. The error rates are approximately 17%, which is still below the accepted error level for a usable system (the error rates for a usable system should be less than 10%) [5]. When training will all forces, TD features outperformed slightly AR+RMS features in all cases apart from the case for A_1 for training will all forces and testing with the medium force. These results could be improved by training the subject with the appropriate feedback over many sessions to minimize the error rates for a usable system and to produce the needed grasp with the correct force level.

In Fig. 5, the error rates for the high forces were much higher than the low and medium forces for both amputee participants. Generally speaking, the high force is difficult to perform for an amputee person since it requires a lot of effort from them. Additionally, producing a high force level and maintaining it for long time might produce fatigue since the amputee persons have not used their stump muscles for long time. This might explain why the error rates were much higher for the high force levels than the low and medium levels of force.

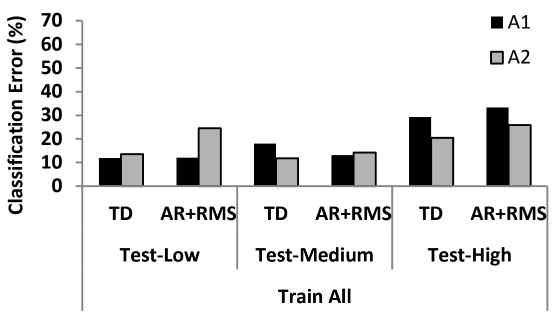

Figure. 5. Classification errors when training with all force levels and testing the classifier with each level of the three forces.

Ideally, a system must be robust enough so that its performance when training with all forces and testing with different forces would better, or at least equal to, the performance that would be obtained when training and testing with forces individually. Therefore, the main recommendation of this study, which was conducted for the first time on real amputee persons, is that it is important to take into account the effect of force change on the performance of multi-functional upper-limb prosthesis controlled by the EMG. This effect is important for non-amputee control subjects and even more important for the amputee persons since many factors are changed after the amputation process, such as the loss of visual feedback and the loss of part of the muscle structure. This study is a part of larger project to examine and to improve the performance of PR systems for the amputee persons. Work is in progress to recruit more amputees to take into account the inter-subject variability on a large scale. Furthermore, more gestures are being added to the current set to examine the force change with for PR- based myoelectric control.

IV. Conclusion

In this paper, we draw the attention to a serious real-life problem that the amputee persons might face in their everyday life. It would be very difficult for them to control multiple forces for many gestures without the proper adequate planned training to make them exert the correct pattern. Results showed that the performance of the myoelectric control system is degraded by up to 60% when the force level varied and that TD features outperformed AR and RMS features. These results suggest that it is possible to improve the system's robustness against force change with the use of TD features and training will all force examples.

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