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Protocol for Site Selection and Movement Assessment for the Myoelectric Control of a Multi-Functional Upper-Limb Prosthesis

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***Abstract*-Although there have been many advances in electromyography (EMG) signal processing and pattern recognition (PR) for the control of multi-functional upper-limb prostheses, some the outstanding problems need to be solved before practical PR-based prostheses can be put into service. Some of these are the lack of training and deployment protocols and the provision of the tools required. Therefore, we present a preliminary procedure to personalize the prosthesis deployment. In the first step, we record the demographic information of each individual amputee person and their background. In the second step of the protocol, the EMG signals are acquired. PR algorithms and parameters will be chosen in the 3rd step of the protocol. In the 4th step, the best number of EMG sensors to achieve the maximal performance with a full set of gestures is identified. The final step involves finding the best set of movements that the amputee person can produce with an accuracy > 95% as well as identifying the movements with the worst performance, which would require further training. This proposed approach is validated with 2 transradial amputees.**

I. INTRODUCTION

THE human hand and arm are essential for a person to perform many daily life activities, including communication and interaction [1]. The loss of hand and wrist function after upper-limb amputation leads to significant disability [2].

There have been many advances in multi-functional upper-limb prosthesis control, specifically using Pattern Recognition (PR) based systems since they offer intuitive control and the ability to control multiple movements compared to the conventional myoelectric control which offers a limited set of actions. However, upper-limb prostheses controlled with PR systems are not commercially available yet, due to a number of outstanding problems, such as force change, signal non-stationarity, electrode movement and arm position [3]. In this paper, we deal with the problem of tuning the PR system to the needs and capabilities of each individual amputee. The development of appropriate protocols will allow clinical professionals (i.e., the occupational therapists and the prosthetists) to provide amputee people with effective configuration, training, and maintenance of PR-based automated prostheses [3].

Each amputee person is affected differently by the level of amputation, muscle structure left after amputation, time since amputation, training state, and the presence of nerve injury. Treating each amputee person as an individual rather than grouping the amputees together is important because each amputee person might be able to perform some movements with a higher performance than other amputees. The number of electromyography (EMG) channels needed to achieve maximal performance, as well as their locations, may well be different for each individual due to the different muscle structure after amputation. Therefore, each individual amputee's needs should be addressed by optimizing the number of channels and the movements with maximal performance. This would be a vital development for the future deployment of PR-based EMG controlled multi-functional upper-limb prosthesis. Having a reliable movement subset is important for a usable system (error rates should be <10%) [3]. Generally speaking, if the performance for 10-movement-class classification problem is 80%, there would be 2 wrong movements in each 10, which may be unacceptable. Thus, finding the best movements that each individual amputee can perform is an important challenge.

A subject–oriented approach was presented by Troncossi *et al.* [4] to guide the mechanical design of the high level upper-limb prosthesis. In a later study, they suggested a procedure [5] to guide the design of an actuated shoulder articulation for externally powered prostheses. However, the approach was for high-level amputation. No approach is proposed yet for transradial amputee people to guide the process of selecting the EMG sensor locations and the best movement subset.

The current protocol for determining the control site to fit commercially available myoelectric prostheses involves looking for a superficial muscle for easy access of the myoelectric signal of the wrist flexor and extensor muscles responsible for hand opening and closing. The amputee person should have enough strength for activating the control systems as well as being able to voluntarily control the contraction and relaxation independently from other muscles. By moving the test electrode around in a medial-lateral plane while observing the signal strength with a Myoelectric tester device, the clinical professional assesses the selection of the site [6]. However, the drawback is that, if

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the subject cannot control one muscle independently from a second one, only one muscle control is feasible. Furthermore, it is difficult to apply such protocol to PR based systems since they offer ways to control multiple myoelectric sites (usually > 4) and they utilize feature extraction combined with multi-dimensional classifiers for the separation of multiple classes.

In this paper, we propose a novel protocol for myoelectric site selection and movement analysis designed to optimize the performance for a set of movements performed by the amputee persons. For each individual, the number of EMG channels is tuned. Then, we then analyze each participant separately to find the movements with accuracy above 95%. Two transradial amputees were recruited in this study in order to validate the protocol and to examine the ability of the protocol for individual amputees.

II. METHODOLOGY

The steps for the proposed protocol for the myoelectric site selection and movement analysis and is shown in Fig.1. The protocol involves the following steps.

A. Step1: Demographic information for the amputee persons

This step involves acquiring the demographic information for each amputee person. The data recorded by the expert are: 1) Type of amputation; 2) Cause of amputation; 3) Which hand is missing; 4) Dominant hand; 5) Dimensions of the stump and intact-hand; 6) Time since amputation; 7) Type of prosthesis used; and 8) Previous and/or current job.

As a proof of concept, two transradial amputee persons (A_1 and A_2) with unilateral amputation participated in the study. The 1st amputee person (A_1) age was 26 years old while amputee person (A_2) age was 24 years. Both amputee persons had the amputation of the left hand 3 years ago as a result of electrical shock with right hand being the dominant hand. None of the amputee persons use a myoelectric prosthesis due to non-availability. It is worth mention that this step can help to decide the number of channels for each amputee according to the stump length of the amputee. 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. The amputee persons' data were collected at the Artificial Limbs and Rehabilitation Centers in Baghdad and Babylon, Iraq.

B. Step 2: Signal acquisition and experimental protocol

This step comprises the signal acquisition and recording experimental protocol. First, 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 for A_1. A_2 has a short stump; therefore, only 10 pairs of electrodes were placed around the stump as suggested by the data collected in *Step 1*. Fig.2 shows the stump of A_1. European recommendations for EMG (SENIAM) [7] were followed to place the surface electrodes and the elbow joint was used as reference to mark the electrode locations. The ground reference electrode was placed on the Olecranon process of the Ulna for both amputee participants.

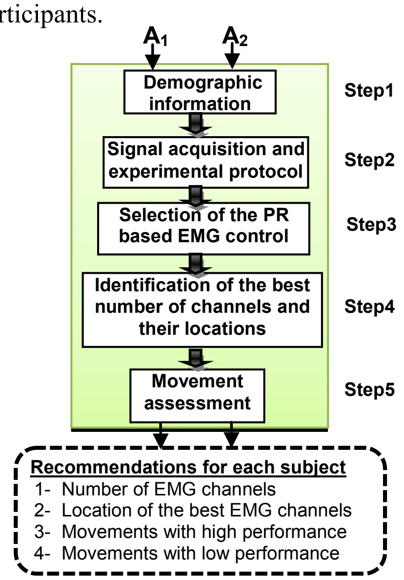

Figure 1. The proposed diagram of the protocol for the amputee persons.

Figure 2. A picture showing the stump for the 1st amputee (A_1).

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 noise reduction. LABVIEW software (National Instruments, USA) was used for signal acquisition and display.

Six movement classes were investigated in this study and there was an additional no-movement class which was added to the dataset. The movements are: Thumb Flexion (Th. F.), Index Flexion (Ind. F.), Fine Pinch (Fine P.), Tripod Grip, Hook Grip, and Spherical Grip (Sph. G.)

The amputees were asked to produce a constant, non-fatiguing contraction with moderate force and hold the position for 8 seconds for each movement. Six trails were recorded for each movement. Trials 1-3 were used for the training whereas trials 4-6 were combined to produce the testing set which was used evaluate the classification accuracy.

C. Step 3: Selection of the PR based EMG control

The MATLAB® 2011a software (Mathworks, USA) is used to perform PR analysis in this study. An overlapped segmentation scheme is used with 160 ms segment length and 50 ms segment overlap. Time Domain (TD) features [3] are used for feature extraction (mean absolute value, waveform length, zero crossings and slope sign changes). A Support Vector Machine (SVM) [8] classifier is used since it is a state-of-the-art technique that works well in high dimensional spaces by searching for a hyper-plane with the largest margin to classify different datasets [9]. It also supports multiclass classification using the "one versus one" procedure to perform the classification

D. Step 4: Identification of the best number of channels and their location

Channel optimization is applied empirically [10-12] to find the best subset of EMG channels that achieve maximal performance for each individual amputee. This finds out which subset of channels provides the best trade-off between accuracy and number of channels for each participant. For every iteration of the channel optimization, the classification accuracy is calculated after eliminating one EMG channel at a time. Afterward, the channel that has the least effect on the performance is removed. This approach is applied for 2 transradial amputees who performed 7 movement classes.

E. Step 5: Movements' assessment

The movement assessment involves performing the classification of all movements with the best EMG channels identified from *Step 4* of the protocol for a particular amputee person. The objective is to find the best set of movements that each amputee can achieve with the lowest error. This is defined as an acceptable level of error. For a proof of concept, the error level of (<5%) is adopted in this study.

Several iterations are performed to find the best set of movements. The classification accuracy is calculated for all movements in each step. Then, the errors for all movements are examined individually. The movement with the highest level of error is identified and removed from the set of movements. This procedure is repeated until a set of movements with an average error below a predefined acceptable threshold is obtained.

F. The recommendations

After *step 5* of the optimization, a set of recommendations is concluded for each amputee person with the objective of helping the clinical professional to fit the prosthesis. The set of recommendations contains the following:

1) The number of the best EMG channels' subset.
2) The location for those EMG channels.
3) The movements that can be achieved with an error *lower* the acceptable error.
4) The movements that could be achieved with an error *higher* the acceptable error.

III. Results and Discussion

Fig. 3 displays the results of *step 4* of the protocol for amputee person A_2 showing the best number of channels. Five channels gave same performance as the whole set of ten EMG channels. Fig. 4 illustrates the location of the optimal 5 channels' subset for the same amputee person (shown in black).

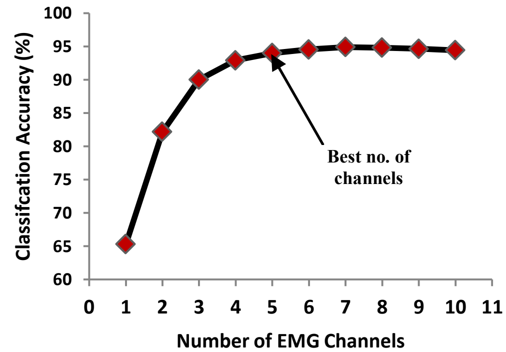

Figure. 3. The results of A_2 for *step 4* of the protocol, it shows the classification accuracy for different number of EMG channels.

As for A_1, the performance was different. Seven channels was the best subset that gave a similar performance to the whole set of 12 channels.

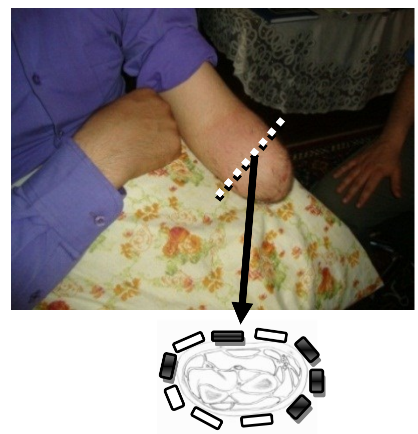

Figure 4. The optimal 5 EMG channel locations for amputee person A_2 (shown in black).

In Fig.5, the classification accuracy for different iterations is presented for the 5th step of the proposed protocol. As it can be seen, three iterations were performed for A_1 while only 2 iterations of *step 5* were needed for A_2 to achieve an overall error of less than 5%.

An important advantage of this step is that it identifies the movements with the lowest performance for each individual amputee person. This will help the rehabilitation personnel to perform the rehabilitation process on these movements and to deliver a subject-specific movement rehabilitation scheme for the amputee person.

An example of the 5th step of movement assessment for the 2nd amputee (A_2) is shown in Fig. 6. The figure displays the confusion matrix for iteration 1 of the optimization process. In that iteration, index flexion was the movement with the highest error (11.6%). Therefore, it was discarded. The overall accuracy for the second iteration was 95.8% after removing index flexion from the movement set.

A summary of the recommendations of the protocol for control site selection and movement assessment for 2 amputee persons is shown in Table 1.

Unlike Troncossi *et al.*[4], whose approach can be used to determine a limited selection of prosthesis architectures sutiable to meet the amputee's needs with high level of amputation, we presented a protocol which can be used to tune the EMG channels as well as best movement subset based on each individual transradial amputee. In addition, this approach was validated on 2 transdarail amputees whereas Troncossi *et al.*[4] did not valdiate their protocol on high-level amputes.

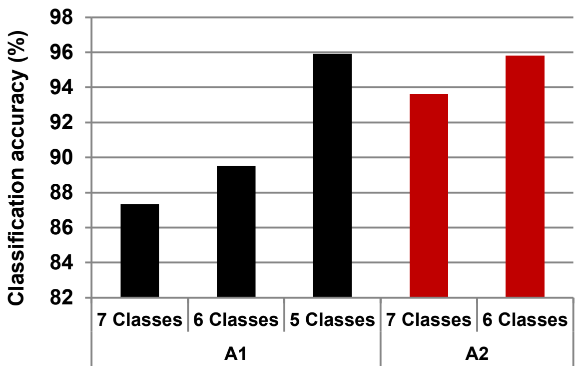

Figure 5. Classification accuracy for each iteration of *step 5* of the protocol for the 2 amputee participants (A_1, shown in black and A_2, shown in red).

Table 1. Summary of recommendations of the protocol for A_1 and A_2.

Amputee Person ID	Whole set of channels	Optima l subset	Movements with high accuracy
A_1	12	7	Th. F., Fine P., Tripod G. and Hook G.
A_2	10	5	Th. F., Fine P., Tripod G., Hook G. and Sph. G.

In Conclusion, we have presented a proof-of-concept procedure for a subject-specific protocol for control site selection and movement assessment with PR systems. It optimizes the performance for a set of movements done by the amputee persons. For each individual, the number of EMG channels is tuned. We then analyze each participant separately to find the movements with accuracy above 95%. The results showed that each amputee is different, in terms of the number of EMG channels that achieved the optimal performance and the number of movements that could be classified with an error less than 5%. Despite this challenge, the results suggest that the proposed procedure might be a very valuable methodological approach to help in the personalization of upper-limb prostheses. The inter-subject variability on a large scale will be explored in a future work.

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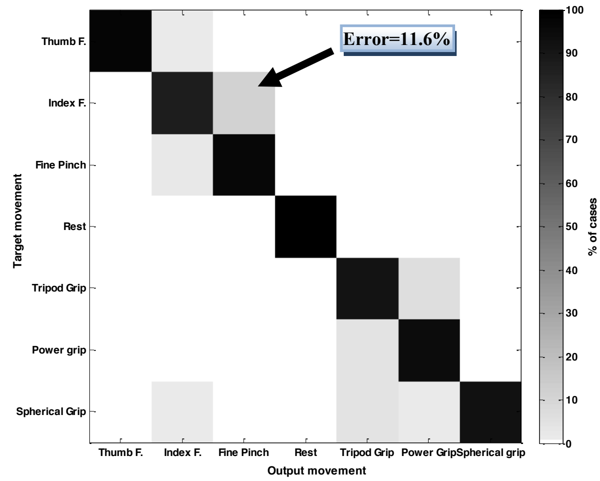

Figure 6. Confusion matrix for A_2 participant for iteration 1 of step 5of the protocol. The overall accuracy for 7 movement classes was accuracy 93.6%.

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