Surface Electromyography Signal for Control of Myoelectric Prosthesis of the Upper-Limb Using Independent Component Analysis

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***Abstract*—An electromyography signal that was taken from the surface of the stump-muscle of an amputee is used to control over the myoelectric prosthesis. We present a method of acquiring these signals over the surface of the skin by using a surface-EMG electrode connected to it. In this study, a five fingered prosthetic hand, actuated by five motors, one motor for each finger was used to simulate some of the hand action movements and assess its capability of giving control over each hand action movement. The study was concerned with the signal acquisition that controls the myoelectric prosthesis. ICA was applied to separate mutually independent components that are the result of surface electromyography signals which provided a promising method in the classification of hand action movement based on each level of muscle contraction. The study determined the pattern of each hand action based on the correlation between estimated percent Muscle Voluntary Contraction (%MVC) vs. degree of movement of the motor, and the correlation between the motor frequencies vs. the degree of movement of the motor.**

***Index Terms*—electromyography, independent component analysis, percent muscle voluntary contraction, motor, microcontroller**

I. Introduction

Electromyography signals are the ample effects due to muscle contraction. It detects the electrical potential generated by the muscle cells when these cells are electrically or neurologically activated. It is adapted and used in myoelectric prosthesis of upper limb. Patient with amputated arm may choose from cosmetic prosthesis, body action prosthesis, myoelectric prosthesis, hybrid prosthesis, or specific prosthesis and according to [1] depending on the type of amputation, a myoelectric prosthesis can then be provided to the person after identifying the level of amputation.

Electromyography (EMG) and ultrasonography have been widely used for skeletal muscle assessment. It was demonstrated that the muscle thickness change collected by ultrasound during contraction, namely sonomyography (SMG), can also be used for assessment of muscles and has the potential for prosthetic control [2].

The control of shoulder disarticulation prostheses remains a challenging problem. A novel method, using targeted muscle reinnervation to develop additional myoelectric control sites, has improved the control of myoelectric upper limb prosthesis in a patient with bilateral amputations at the shoulder disarticulation level. Encouraged by this achievement [3], high density surface electromyogram (EMG) signals from the patient's reinnervated muscles were recorded as he actuated a variety of different movements.

Design and testing of these devices is currently performed using function generators or the healthy EMG signals of the tester. However, these methods of testing either do not provide data representative of the intended usage or are inconvenient to the tester [4]. Recent work [5] at UCLA approached the multifunctional (MF) control problem using a large number of electrodes, though still considering only a limited part of the EMG spectrum. The present approach is based on earlier work of [6] in 1975, which required a far smaller number of electrode locations because it permitted identification and discrimination even where correlations between the measured signal and the prosthesis control functions are very weak.

In this study, a simple and portable prototype device was used to simulate the surface EMG signal in order to control a myoelectric prosthesis. The objective of the

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study is to acquire necessary control signal. The acquired signal through muscle contraction will be used as the basis for a particular hand action movement. The method known as Independent Component Analysis will be used to separate independent component by simultaneously taking its median values from five distinct signals. Each mutually independent component will be classified as Grip ( ), Hold ( ), Pick ( ), Open ( ), and Close ( ) position for the myoelectric prosthesis.

II. Prosthesis Testing

Relative control sites were identified in order to acquire necessary data from the surface of the skin through muscle contraction. Each contraction of muscle must give specific signal combination for each movement. The input signal coming from the surface of the skin was considered as mixed signal and appropriate algorithm was used to determine the pattern for a particular hand movement.

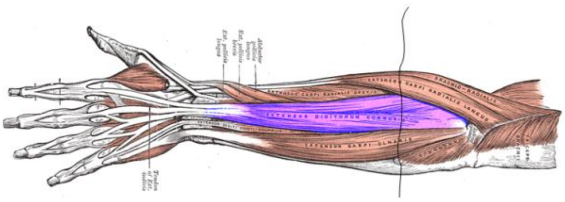

Figure 1. Relative control sites

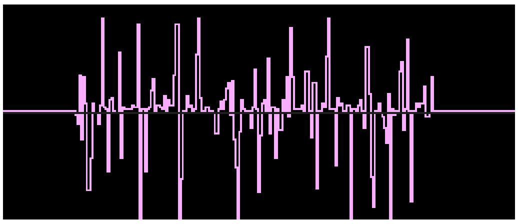

Figure 2. Raw EMG recorded from a muscle surface

Fig. 1 shows a complex set of muscle wherein relative control sites are considered. Extensor carpi radialis (ECR), Extensor digitorumcomunis (EDC), Extensor carpi ulnaris (ECU), Flexor palmarislongus (FPL) are some of the muscle group that is considered in the study.

An sEMG signal was taken from the interfaced between the muscle surface and the prosthesis through an electrodes. A raw EMG is shown in Fig. 2. The same sets of signal were generated using the electrode placed on the surface of the skin but with different level of precision. Different EMG signal will be analyzed after acquiring signal from twenty participants. This is large enough to conduct the testing procedure and to determine the percent error and difference using the least square methods.

In this study, the major part of the prosthesis was made using servo motors. The impact of the design depends on the design of the prosthesis and the muscle contraction level. Both of these are the parameters that need to be tested for linear correlation. The study used simple linear regression and correlation coefficient determination [7] to determine whether there is a linear relationship between muscle contraction measured in percent muscle voluntary contraction (%MVC) and motor frequency for each hand action movement or degree of movements:

$$y = b_0 + b_1 x \tag{1}$$

where b_0 is the intercept and can be considered as the parameter estimates between shifts, and can be set as constant for each segment being analyzed. Each segment may correspond to each hand action movement (e.g. Open ( ) → Pick ( ) through Pick ( ) → Open ( ) where b_0 can be found equal or constant for each shift), b1 is the slope of the linear relationship.

A force estimate was applied to determine the percent maximum voluntary contraction (%MVC) to move the servo motor to its specific hand movement or the expected action performed. The PWM of servo motor movement relative to its high time at specified frequency. For 0ms – 2.3ms → right to left (0 °– 180 °), and 1.2ms → halfway (90 °). Based on previous studies, the amplitude of the sEMG signal is proportional to the force produced by the muscle [8]. The table for force estimate of %MVC is shown in Table I and the corresponding action to be performed. For the 25% MVC or 0 °- 45 °, the expected action movement may vary from 0 to 0.6ms to accomplish a Pick( ) movement, a time varying constant is expected as long as the task for Pick( ) is not yet done, then the next action is performed.

TABLE I. %MVC Estimate and Expected Action Performed

Maximum Voluntary Contraction (%MVC)	Degree of Movements	Expected Action Performed
0%	0 °	Hand Open( )
25%	0 °- 45 °	Pick ( )
0%	45 °- 0 °	Hand Open( )
50%	0 °- 90 °	Hold( )
0%	90 °- 0 °	Hand Open( )
100%	0 °- 180 °	Grip( )
0%	180 °- 0 °	Hand Open( )

Fig. 3 shows the signal analysis by least square method. The parameter shifts are the equivalent transition states of each hand action movement. The least square method was used to interpret the signals under each situation. The contraction level can be achieved until certain movement was performed.

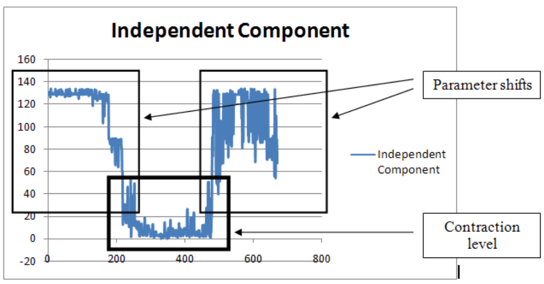

Figure 3. Signal analysis by least square methods

Fig. 4 shows the correlation between the two variables in this study. The correlation coefficient ***R*** in Table II indicates that correlation between the Force Estimate for %MVC is sufficient in measuring the force exerted from the muscle. The correlation coefficient R^2 is 100% significant indicating that the degree movement is due to the frequency produced by muscle contraction. The standard error in this case measured the variability of the actual degree of movements from the expected hand action movement.

The Hand Open( ) is set as the base movement and has a degree of movements equal to 0 where the %MVC is also zero, which implies that the Accuracy is 100% and has no error which was computed using the formula for %Error in equation 2.

$$\%Error = abs\left(\frac{(Degreerelatedto\,\%MVC - \%MVC)}{\%MVC}\right)x\,100 \quad (2)$$

The Linear Regression Test for determining the correlation between servo motor frequency and the degree of movement is described as follows: The test was based on the total number of observations as dictated by the interval of frequency.

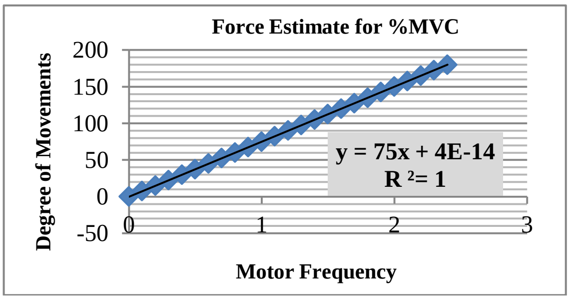

Figure 4. Correlation between motor frequency and degree of movements

The linear regression equation from this test is:

$$y = 75x + 4E - 14$$

$$R^2 = 1$$

The equation was used to predict the change of frequency that resulted from the degree of movement relative to the muscle force.

$$4E - 14 = 75\,(0) + 4E - 14$$

Thus, a 4E-14% increase in the average motor frequency will result in 4E-14 degree of movement relative to the muscle force or muscle contraction.

TABLE II. REGRESSION STATISTICS

Multiple R	1
R Square	1
Adjusted R Square	0.956521739
Standard Error	1.64102E-16
Observations	24

The correlation coefficient (R^2) = 1 and the coefficient of determination (Adjusted R) R= 0.956521739 suggest that there is a strong correlation between the two variables being compared.

The Linear Regression Test for determining the correlation between %MVC and degree of movement is described as follows: The same test was performed in determining the correlation between the %MVC and the degree of movements. The correlation ***R*** as shown in table 3 indicates a significant correlation between the degrees of movement and the exerted force or the %MVC. The correlation coefficient $\boldsymbol{R^2}$ shows 100% significance indicating that the degree movement is due to the %MVC. The standard error in this case measured the variability of the %MVC from the expected hand action movement. The number of observation is the same as the previous test done for degree of movements and motor frequency shown in Fig. 5. The linear regression equation from this test is as follows:

$$y = 1.800x + 0.004$$

$$R^2 = 1$$

The equation can be used to predict in determining the change in the degree of movements with %MVC.

0.004 =1.800(0) + 0.004

Thus, a 0.004% increase results in %MVC for each degree of movements.

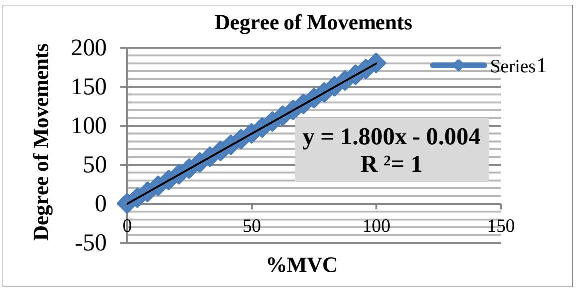

Figure 5. Correlation between %MVC and degree of movements

TABLE III. REGRESSION STATISTICS

Multiple R	1
RSquare	1
Adjusted R Square	1
Standard Error	0.02776
Observations	24

The correlation coefficient (R^2)=1, and the coefficient of determination (Adjusted R^2)=1 which suggest that the two variable being compared has a strong correlation.

III. DATA GATHERING AND EMG ANALYSIS

The accuracy test used the following sequence of 0%, 25%, 0%, 50%, 0%, 100%, and 0% MVC. The first test was performed for the Open ( ) position and the percent error and accuracy were taken using the formula stated in equations 2 and 3.

$$Accuracy = 100\% - \%Error \quad (3)$$

The following are sample signals acquired from surface of the skin: the mixed input signals and their corresponding independent components taken as sample set performed by 20 participants and is captured using FASTICA Algorithm in MATLAB.

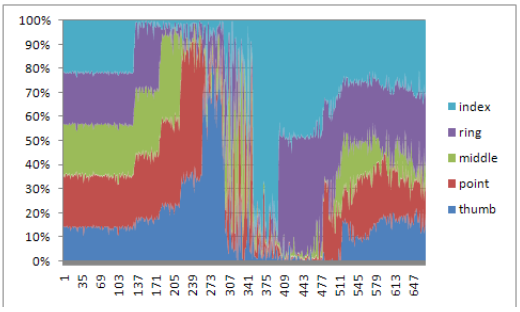

Figure 6. Mixed input signal from Hold( ) position of tester 1

The mixed input signal from tester 1 is shown in Fig. 6 and is acquired from muscle that makes the index, ring, middle, point and thumb finger to perform the Hold( ) position.

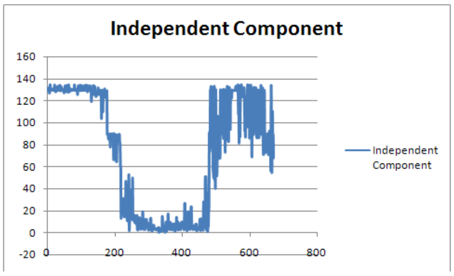

Figure 7. Independent component from Hold( ) position of tester 1

The independent components from the Hold ( ) position of tester 1 is shown in Fig. 7.

TABLE IV. MEAN ERROR AND ACCURACY TEST

Number of Participants	Maximum Voluntary Contraction (%MVC)	Degree of Movements	Expected Action Performed	%Error	Accuracy
	0%	0°	Open( )	2.18%	97.2%
20	25%	0°- 45°	Pick ( )	26.04%	73.96%
20	50%	0°- 90°	Hold( )	34.72%	65.28%
20	100%	0°- 180°	Grip( )	37.38%	62.62%

Table IV shows the Mean Error and Accuracy measures of the hand movement performed by twenty participants. The following set of EMG signal was used to classify each hand action movement generated during a specified muscle contraction, where each participant used for a preselected %MVC pattern for testing the designed myoelectric prosthesis.

TABLE V. EXPECTED HAND MOVEMENT

Expected Hand Movement	%MVC	Best-Fit Line Equation	Correlation Coefficient R^2	Coefficient Determination R
Hand Open( )	0%	-0.0026x + 176.94	0.0388	0.1970
Pick ( )	25%	-0.1747x + 108.26	0.5308	0.7286
Hold( )	50%	-0.5104x + 167.85	0.8174	0.9041
Grip( )	100%	-0.554x + 167.32	0.8298	0.9109

Table V shows the expected hand movement together with the correlation coefficient.

IV. APPLICATION OF INDEPENDENT COMPONENT ANALYSIS

The observed linear mixture x from five electrodes of n independent components

$$x_j = a_{j1}s_1 + a_{j2}s_2 + ... + s_{jn}s_n, \ for\ all\ j. \quad (7)$$

was converted into matrix format to process it using MatLab. The statistical model

$$x = As \quad (8)$$

is called independent component analysis, or ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_j [9]. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. All the observed signals are random vector x, and must estimate both A and s using the observed signal x.

V. RESULTS AND DISCUSSION

Surface electromyography signal is sensitive in nature and can be easily influenced by external noise and artifacts. External noise and artifacts that contaminates sEMG signals can be classified into electrode noise, motion artifacts, ambient noise and inherent noise from other electrical and electronic components.

In the analysis of data signal of various EMG test particular to each hand movement, the accuracy test used the following sequence: 0%, 25%, 0%, 50%, 0%, 100%, and 0% MVC. Table 3.16 shows the percent error for each hand action movement for all participants using the formula stated in equation 3.2. The hand action movement for Hand Open ( ) position gave a mean error of 2.18%, while the Hand Pick position 26.04%. The Hold and Grip position showed a relatively close percent mean error of 34.72% and 37.38%, respectively, since the two hand action movement is almost equivalent in specified movement.

For the expected hand action movement in table 3.17, the best fit line equation of the Hand Open ( ) position y= -0.0026x + 176.94, Hand Pick ( ) is y = -0.1747x + 108.26, Hand Hold ( ) is y = -0.5104x + 167.85 and for Hand Grip ( ) is y = -0.554x + 167.32. The intercepts are 176.94°, 108.26°, 167.85°, and 167.32°which was considered in this study as the parameter estimates between shifts, and set as constant for each set of data (e.g. control signals from each finger flexion). The correlation coefficients of the expected hand action movements were as follows: for Open( ) position, 3% of the data points (control signals) were utilized since it is at the starting position or at 180°(servo motor position), 53% of data points were utilized by the Pick( ) to accomplish a simple pick routine (at specified time given for the tester), 82% were utilized by the Hold( ) position and 83% were utilized by the Grip( ) position since both Hold( ) and Grip( ) position may perform the same movement at the same given instance.

The Independent component analysis was applied for the entire signal of the mixed input variables using FASTICA in MatLab.

VI. Conclusions and Future Works

This study is concerned with the signal acquisition to control the myoelectric prosthesis, the signal acquired from the five mixing inputs of five electrodes connected through the surface of the skin was analyzed and found out that based on the median values of each of the 670 data points within the contraction level it is evident that independent components can be extracted from the mixing signal matrix through the application of independent component analysis.

The independent component that is extracted from the mixing signal matrix could be develop as a new perceptual input signal that could generate a smooth transition between shift (from one hand action to the next) and the parameter estimates between shifts.

Designing a myoelectric prosthesis for a person with transradial amputation requires a unique power source for each motor and utilizes small amount of power. It should be lightweight and a pre-amplifier module must occupy less space in the overall design of the prosthesis. The electrodes must be capable of rejecting noise, so that for each muscle contraction, an accurate signal pattern is acquired before it reaches the instrumentation amplifier. With the parameter shifts too high for this study, it is recommended that the electrodes which act as sensors should be replaced with another sensing device so that it can generate increasing and decreasing values in connection with the applied muscle force.

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