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Development of a Control Strategy for a Multifunctional Myoelectric Prosthesis

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Abstract: The number of people who have lost limbs due to amputation has increased due to various accidents and diseases. Numerous attempts have been made to provide these people with prosthetic devices. These devices are often controlled using myoelectric signals. Although the success of fitting myoelectric signals (EMG) for single device control is apparent, extension of this control to more than one device has been difficult. The lack of success can be attributed to inadequate multifunctional control strategies. Therefore, the objective of this study was to develop multifunctional myoelectric control strategies that can generate a number of output control signals. We demonstrated the feasibility of a neural network classification control method that could generate 12 functions using three EMG channels. The results of evaluating this control strategy suggested that the neural network pattern classification method could be a potential control method to support reliability and convenience in operation. In order to make this artificial neural network control technique a successful control scheme for each amputee who may have different conditions, more investigation of a careful selection of the number of EMG channels, pre-determined contractile motions, and feature values that are estimated from the EMG signals is needed.

Key words: Artificial arm, Myoelectric control, Neural network pattern classfication, Prosthesis

INTRODUCTION

Not only because of congenital defect disorders but also because of diseases and industrial accidents, the number of people with limb amputations has been increasing every year [1]. In order to replace their loss of function, many attempts have been made to develop powered prosthetic devices [2], and electromyographic signals (EMG) from a body's intact musculature have been widely used as control signals for those powered prosthetic devices [3]. Although the success of using the EMG signal is apparent in some commercial prosthetic devices[4, 5], these devices are generally limited to accomplishing rather simple functions such as finger gripping and hand opening motions. The obstacles to development of a practical multifunctional prosthesis has been mainly attributed to difficulties in implementing a multifunctional EMG control strategy. In order to control multifunctional prostheses using EMG signals, it is necessary to produce more control outputs. If the number of control outputs per EMG channel is limited to only one or two as is seen with conventional EMG control methods, an attempt to provide more control outputs consequently requires more channels per EMG signals and more electrodes located on the various muscle sites are needed. However, this technique is remarkably impractical for isolating the required number of contracting muscles in amputees [6]. In order to overcome such a problem, many research groups have attempted to extract more control information from each channel of the EMG signal or multichannel system, so that that the number of control outputs can be greater than the number of EMG channels. Dorcas and Scott proposed a three-state control method to extract three different control signals from a single EMG channel [7]. A statistical analysis of the EMG signals corresponding to various contractile motions has also been reported [8, 9] and pattern recognition methods have been developed based on statistical analysis to identify EMG signals obtained from the subjects' musculature [10, 11]. In addition, Hudgins et al. proposed a new approach to classifying EMG signal patterns using an artificial neural network [12].

In a previous study using an artificial neural network as a pattern recognition algorithm, they demonstrated the capability of classifying four

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contractile motions from the EMG signals recorded from two EMG channels [12]. This implies that it is possible to generate four different output functions using two paired electrodes located on the skin. A more recent study also used a neural network classifier, and they demonstrated that they could classify six types of motion when four EMG channels were used [13]. Although the classification accuracy of their controller was high, it was affected by the number of EMG channels; the accuracy was shown to decrease as the number of EMG channels were decreased. Therefore, as more output functions are required for controlling more dexterous prostheses, more EMG channels may be needed. However, there has always been concern about how many EMG channels are necessary for practical use of a multifunctional prosthesis. Therefore, there is still an obvious motivation to extract more control information from a single EMG channel or from a combined multi-EMG channel. In this study, we employed the previously proposed EMG control scheme (pattern recognition using an artificial neural network) with the goal of generating more control outputs than previous studies using the pattern recognition strategy. For the purpose of usability of the system, we also restricted the number of channels of the EMG signal used in this study to three.

From the results of our study, we reaffirmed the feasibility of an algorithm using a multifunctional EMG control method using artificial neural network pattern recognition and demonstrated that the classification accuracy of a controller is significantly dependent on choosing the proper configuration of pre-determined contractile motions and also on choosing the proper feature values estimated from the EMG signals.

METHOD

The concept of the control scheme is illustrated in Figure 1. In this study, we used a three-channel EMG configuration to extract as many as 12 different control signals. Subjects contracted their muscles with one of the 12 pre-classified motions. The 12 classes of arm motion were defined from all possible simultaneous combinations of six primitive motions including; arm depression and elevation, humeral rotation in and out, and elbow flexion and extension as shown in Figure 2. The EMG signals produced by muscle contraction combined with one of the classified motions were fed into the calculation part of the control scheme. Some feature values such as variance and integrated waveform length were calculated and given to the discrimination part. The discrimination part was responsible for classifying the features values into one of the specific patterns that had been initially defined for each of the 12 classes. The classified patterns were then used as specific control signals to actuate electrically powered prostheses. The neural network theory, which may be suitable for classifying myoelectric signals [14], was chosen as the classifier in this study. The structure of the neural network used in our control method was a multiplayer perception feed-forward network including a single hidden layer. All the input nodes were connected with the hidden layer, which was then connected with the output nodes corresponding to the output pattern classes. The relationship between inputs and outputs was strengthened by the neural network's learning theory. Upon strengthening the relationship, users would be able to control a prosthesis by performing a muscle contraction with one of the defined composite motions.

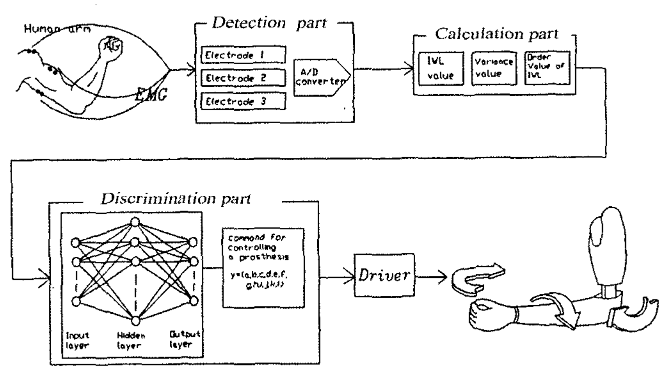

Fig. 1. The overall scheme of the control method tested in this study. When muscles are contracted at one of the 12 pre-classified motions, EMG signals are acquired from three pairs of electrodes. From the EMG signals, statistical feature values are calculated. The calculated values are then given to the inputs of the artificial neural network in the discrimination part in which desired outputs are classified. The different classified outputs are used

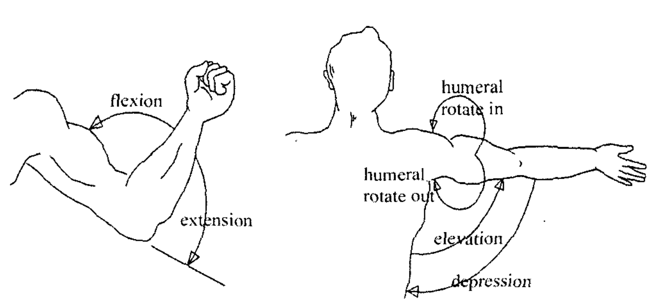

Fig. 2. Six primitive motions are illustrated; elbow flexion and extension, arm depression and elevation, and humeral rotation in and out. The simultaneous combinations in these motions result in the 12 composite motions discussed herein.

Table 1. The 12 classified composite motions are defined from the combination of arm, humeral and elbow primitive motions. The symbol "o" is marked for each individual active primitive motion required to produce the composite motions listed in the first column.

Classified Motion	ARM		HUMERAL		ELBOW	
	Depression	Elevation	Rotate In	Rotate Out	Flexion	Extension
D-E	o					o
D-F	o				o	
DIF	o		o		o	
DOF	o			o	o	
DIE	o		o			o
DOE	o			o		o
E-E		o				o
E-F		o			o	
EIF		o	o		o	
EOF		o		o	o	
EIE		o	o			o
EOE		o		o		o

In our experiments, three differential electrodes were attached to three distinct muscle sites, which included the long head of the biceps, triceps, and deltoid, respectively. The EMG signals were sampled at 10 kHz for 500 milliseconds through an amplifier (1000 fold gain) [10] with a 60 Hz notch filter and a 5-1000 Hz band pass filter. Seven male subjects, whose ages were between 25 and 30, participated in the evaluation of our control system. For each subject, EMG signals from three channels were recorded in response to 12 different composite motions, and each set was defined as one collected data set. This one set of collected data was repeated 12 times per subject for three days and 4 sets of data were recorded each day. Thus, a total of 12 sets of data were collected from a single subject. After signal collection was completed, statistical analysis involving the study of zero crossings, slope sign changes, integrated waveform length, variance, and Fast Fourier Transforms were performed based on the acquired EMG signals. Among these statistically calculated values, we chose the integrated waveform length and variance as input features to the input nodes for the neural network. The integrated waveform length (IWL equation) was given by $IWL = \sum_{k=1}^{N} |\Delta \hat{x}_k|$ where, N = the number of samplings, and $\Delta \hat{x}_k = \hat{x}_k - \hat{x}_{k-1}$. The variance equation was given by $\sigma_i^2 = \frac{1}{N-1}\sum_{k=1}^{N}(\hat{x}_k - X_i)^2$. In addition to IWL and variance, we created one more feature value (the ranking value) in order to increase the probability of accurate classification. This value was also given to the input nodes for the neural network. The ranking value was set between -1.0 and 1.0 according to the order of magnitude of IWL as shown in Table 2. For instance, if the IWL value obtained from the deltoid is greater than those from any other muscle site, and also if the IWL value from the triceps is the lowest, the ranking value is determined as +1.0.

Table 2. The ranking value as determined by the order of magnitude of IWL. The right three columns show the order of magnitude of IWL, and the far left column indicates the ranking value depending on the orders.

The Ranking Value	he order of magnitude of IWL		
	Biceps	Triceps	Deltoid
+1.0	2	3	1
+0.6	1	3	2
+0.2	1	2	3
-0.2	2	1	3
-0.6	3	1	2
-1.0	3	2	1

Because the EMG signals were obtained from three channels, we calculated three sets of IWL values, three sets of variance, and one ranking value obtained from comparison of IWLs from different channels. Accordingly, the neural network used in this study had a total of seven input nodes corresponding to inputs of the three values of IWL and variance respectively, and the ranking value. Before these values were given to the nodes of the neural network, the values were normalized by linear interpolation so that all the values were between −1.0 and +1.0. The structure of the neural network consisted of 12 output nodes corresponding to the 12 classes of motion patterns and a single hidden layer containing 30 nodes. The network was trained using a standard back propagation algorithm [15]. This algorithm was selected because of its extensive use in pattern recognition literature and its reliability. When the number of hidden layers was less than 20 or greater than 30, pilot testing showed that the rate of pattern recognition decreased. For the training, the 12 output values corresponding to each composite motion were defined as 1.0, and the output function was written as y = (a, b, c, d, e, f, g, h, i, j, k, l) where a, b, c, e, d, f, g, h, i, j, k, and l represent each classified class respectively. The relationship between input and output features was written as $\vec{y}_p = \vec{x}_{pji}$ where p is the pattern number (p = 1, ..., 12), j is the total number of the data set (j = 1, ..., 9), i is the input node number (i = 1, ..., 7), $\vec{x}_{pji}$ is the input values, and $\vec{y}_p$ is the desired output values. In order to end the neural network training stage, the error was defined as $Error = \sum_{p=1}^{12}\sum_{j=1}^{n}\sum_{i=1}^{12} | y_p - o_{pji} |$ where y_p is the desired output value corresponding to the pattern p, and o_{pji} is the calculated output value given at the corresponding input value x_{pji}. The training stage was successfully terminated when the error value converged to less than 0.01. The evaluation testing of our control method was performed according to the following procedures. For each subject case, the neural network relationship was strengthened using 9 randomly selected data sets from the pool of 12 data sets. The remaining three data sets were used for evaluating the performance of the already trained neural network system. Thus, the rate of correct pattern recognition was tested three times for each subject.

RESULTS

The results of the evaluation testing are shown in Figure 3. The bars and numbers describe the Classifica -tion performance (percentage of correct classification rate). They were averaged over 7 subjects. The average correct classification rate over 12

classified motions was 64.7% ± 15.4%. The best performance (85.7%) was observed in the E-E motion (arm elevation and elbow extension) while the DOF (arm depression, humeral rotate out, and elbow flexion) motion showed the poorest performance (28.6%).

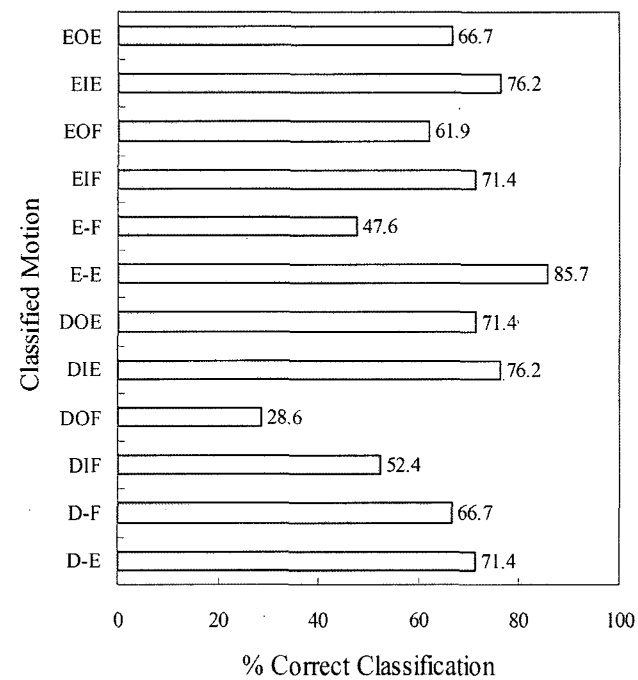

Fig. 3. Classification results for 12 classes.

In order to better characterize the classification performance associated with contractile motions, we investigated the incorrectly classified patterns from our testing. Table 3 shows the incorrect recognition rates for various cases. For instance, when D-F was given as the input, the incorrect recognition rate that was recognized as either DIF or DOF was 4.8% and 23.7% respectively, and the incorrect recognition rate that recognized as other classifications was 4.8%. The incorrect recognition rate, recognized as D-F and DOF for a given DIF, was 19% and 14.3% respectively, and the incorrect rate that was recognized as D-F and DIF, when DOF was given, was 33.3% and 33.3%. The observation of incorrect classification suggests that the incorrect recognition induced by the humeral in and out motions were generally greater than that induced by other motions, such as arm depression and elevation or elbow flexion and extension.

Table 3. Incorrect classification rates for 12 classes. The first column of each table represents the input pattern, and the first row of each table represents the incorrectly resultant pattern. All values are percentages.

Classified Motion	D-F	DIF	DOF	Other
D-F	N/A	4.8	23.7	4.8
DIF	19	N/A	14.3	14.3
DOF	33.3	33.3	N/A	4.8

Classified Motion	E-F	EIF	EOF	Other
E-F	N/A	19	23.8	9.6
EIF	14.3	N/A	9.5	0
EOF	19	4.8	N/A	19.1

Classified Motion	D-E	DIE	DOE	Other
D-E	N/A	4.8	23.8	0
DIE	14.2	N/A	4.8	4.8
DOE	23.8	0	N/A	4.8

Classified Motion	E-E	EIE	EOE	Other
E-E	N/A	14.3	0	0
EIE	23.8	N/A	0	0
EOE	4.8	4.8	N/A	28.5

Since most errors came from the motion of humeral in and out, we excluded the humeral in and out motions from the 12 pre-determined contractile motions and then performed the evaluation testing. The overall recognition rate significantly increased up to 92.0% at the cost of the reduction of the number of classes from 12 to 4 (Table 4).

Table4. The correct classification rate using four classes after the humeral motions were excluded from the contractile motions that had been initially determined.

Classified Motion	% Correct Classification
D F	92.0
D E	96.8
E F	88.8
E E	90.5

DISCUSSION

The electromyographic signal (EMG) has been a good candidate for the control of powered upper limb prostheses. However, it has been a difficult task to extract a number of control signals from only a few EMG channels in order to provide more dexterous control for powered prostheses. Therefore, it is always desired to produce a greater number of control signals from the EMG signals. To overcome this problem, an approach using a neural network pattern recognition technique has been proposed and studied [12, 13]. In such an approach, EMG signals are acquired from a single channel or a few channels at a time for certain contractile motions that have been initially pre-determined. Then, a pattern recognition algorithm classifies the contractile motions based on some feature values calculated from the EMG signals and generates different control outputs. This, in turn, allows for control of a prosthetic device according to different contractile motions. Such a pattern recognition control scheme has numerous advantages over the conventional EMG control including the following: 1) For conventional myoelectric control, the EMG signal that is detected on the skin through electrodes must be rectified because the voltage level is used as a trigger signal like an "on and off" control, and the voltage level is generally proportional to the intensity of the muscle contraction. This may cause muscle fatigue during long-term use. On the other hand, the pattern recognition control method does not need to require users to contract their muscles hard under any circumstances because it only needs some feature values that can be estimated from raw EMG signals for classification. 2) Increasing the number of output control signals is not necessarily limited by the number of EMG channels (electrodes) attached to the skin. With the pattern recognition control method, it is possible to easily increase the number of output patterns as long as the recognition accuracy can be ensured by determining a proper configuration of pre-determined contractile motions and choosing the proper feature set values.

A previous study using a neural network pattern classifier technique demonstrated the ability to discriminate between four types of limb motion [12], and a more recent study showed that as many as 6 different pre-determined contractile motions can be accurately classified using four channels of EMG signal [13]. Although these results are encouraging, it is always desired to have more output functions in order to control a powered prosthesis with more dexterity and in a natural way. Therefore, the motivation of this study was to increase the number of output control signals while, for the purpose of usability, limiting the number of EMG channels that was used. We employed 12 different contractile motions and the EMG signals were acquired from three bipolar electrodes. The number of EMG channels can influence the accuracy of classification, and it appears that a multiple channel configuration improves accuracy [13]. However, it is impractical to attach too many EMG channels on the skin. From our pilot experiment, using less than three channels appeared not to be sufficient to classify twelve motions. Thus, in this study, we used a maximum of three EMG channels. We focused on the feasibility of a neural network pattern classifier with as many as twelve output patterns. Thus, the experimental procedure and evaluation testing was designed with the intention of having normal bodied subjects participate.

The results of this study showed that the pattern classification of our model could correctly classify around 65% of the twelve different patterns after an initial training of the neural network. It was observed that most of the errors in classification occurred between DOF and either D-F or DIF, between DIF and D-F, and between E-F and either EOF or EIF (table 3). This suggests that the humeral rotation motions (in, out, and neutral) played a negligible role in producing peculiar pattern features. However, humeral rotation played a relatively larger role when that rotation was conducted simultaneously with both arm elevation and elbow extension (EOE, EIE, and E-E). This suggests that determination of contractile motions can significantly affect the classification performance. As a means of improving the correct recognition rate, we decided to make no separation between DOE and D-E, D-F and DOF, and E-F and EOF. This will increase the overall correct recognition rate up to about 76 %. However, at the expense of the increase in the correct recognition rate, the total number of output patterns was reduced from 12 to 9. When the humeral motion was completely excluded from contractile motions, the overall correct recognition rate was increased up to 92%. However, this reduced the number of output patterns to four.

There could be several other factors that may have affected the overall classification rate in our evaluation testing. First, the important innate characteristics of the EMG signal may have been corrupted due to signal noise. Prior to testing, subjects were asked to perform motions and contract their muscle as consistently as possible throughout the testing period. Nevertheless, there remained concerns regarding this consistency. Inconsistency in motion and muscle tension may have weakened the pattern characteristics. If the evaluation testing was performed with a single subject with more data sets, we expect that the recognition rate could have increased because the consistency could have been secured. Additionally, the classification performance is significantly affected by the choice of feature values that are given as inputs to an artificial neural network [16]. We can calculate many statistical values from EMG signals; however, only simple time domain feature values were used in this study. The classification performance can be favorably affected by using the feature values that are calculated from time-frequency statistical analysis such as wavelet-based analysis [13]. However, in order to get a substantial benefit from any advanced time-frequency analyzed feature values, it should be done under the assumption that each channel of EMG signals from amputees is acquired from relatively separable independent muscle groups. In general, however, the acquired EMG signals from amputees may represent compound muscle activity resulting from various muscle groups that are less likely to contribute to pre-determined contractile motions or the EMG signals can be contaminated with unknown artifacts due to particular skin or muscular conditions of amputees. Considering these perspectives, in this study, we placed electrodes onto muscle groups that are not necessarily dominant in carrying out the 12 pre-determined contractile motions. Accordingly, we used feature values calculated from simple time domain statistical analysis.

Although this study demonstrated the ability to generate many more outputs than previous studies using a similar control scheme, the accuracy performance of our control model may be very different when applied to amputees. It would be unavoidable to consider the different configuration of pre-determined contractile motions, different locations for electrodes, and different muscle tensions than the testing setup used in this study. Therefore, every aspect regarding input features and output features should be determined based on the condition and needs of the individual. In a previous study that accurately classified six types of hand motions [13], four-channel EMG electrodes were placed onto muscle groups in the forearm that dominantly contribute to each different pre-determined limb motion. Accordingly, there might be an advantage to using feature values estimated from time-frequency analysis. However, when applied to amputees, it may be difficult to accurately locate the muscle groups that are directly responsible for the pre-determined contractile motions. In this study, we employed 12 different contractile motions, and all the motions did not physiologically originate from muscle groups where we chose to place the electrodes. This gave us a stronger reason to use an artificial neural network pattern recognition technique. Although the input modality may not be directly associated with output modality, a great advantage of using an artificial neural network lies in the fact that it supports a stronger relationship between the input and output of a system as more training procedures are involved. In addition, if a certain user is targeted using our control model, more detailed information on muscle remnants and available contractile motions can be collected and a more reliable neural network system can be created. Thus, the accuracy of performance can be increased with individual settings. However, it can be difficult to find as many contractile motions as are needed to control multiple functions, and we may need to compromise between the number of output functions and accuracy for its practical applications.

This study demonstrated the feasibility of a neural network classification control method that could generate twelve functions using three EMG channels. Although such a control method has great potential for a multifunctional prosthetic device, more investigation is needed to better classify input contractile motions. The various conditions of each amputee may cause different performances, but a careful selection of the number of EMG channels and estimated feature values can make this artificial neural network control technique a successful control scheme for multi-functional prosthetic devices.

REFERENCES

[1] A. Esquenazi, *"Amputation rehabilitation and prosthetic restoration. From surgery to community reintegration"*, Disabil Rehabil, Vol. 26, pp. 831-6, 2004.

[2] P. A. Parker and R. N. Scott, *"Myoelectric control of prostheses"*, Critical Reviews in Biomedical Engineering, Vol. 13, pp. 283-310, 1986.

[3] R. N. Scott and P. A. Parker, *"Myoelectric prostheses: state of the art"*, Journal of Medical Engineering & Technology, Vol. 12, pp. 143-51, 1988.

[4] S. C. Jacobsen, D. F. Knutti, R. T. Johnson, and H. H. Sears, *"Development of the Utah artificial arm"*, IEEE Transactions on Biomedical Engineering, Vol. 29, pp. 249-69, 1982.

[5] T. W. Williams, 3rd, *"Practical methods for controlling powered upper-extremity prostheses"*, Assistive Technology, Vol. 2, pp. 3-18, 1990.

[6] P. J. Cordo, *"Controlling multiple degree of freedom powered prostheses"*, Proc. IEEE Conf. Frontiers of Eng. and Comp. In Health Care, Columbus, OH, pp. 1.5.1-1.5.5, 1983.

[7] D. S. Dorcas and R. N. Scott, *"A three-state myoelectirc control"*, Med. Biol. Eng., Vol. 4, pp. 367-370, 1966.

[8] D. Graupe, J. Salahi, and K. H. Kohn, *"Multifunction prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals"*, J. Biomed. Eng., Vol. 4, pp. 17-22, 1982.

[9] G. N. Saridis and M. A. Newman, *"Upper limb EMG statistical analysis"*, Vol. Proc. MIDCON '79, Chicago, IL, 1979.

[10] G. N. Saridis and T. P. Gootee, *"EMG pattern analysis and classification for a prosthetic arm"*, IEEE Transactions on Biomedical Engineering, Vol. 29, pp. 403-12, 1982.

[11] R. W. Wirta, D. R. Taylor, and F. R. Finley, *"Pattern-recognition arm prosthesis: a historical perspective-a final report"*, Bulletin of Prosthetics Research, pp. 8-35, 1978.

[12] B. Hudgins, P. Parker, and R. N. Scott, *"A new strategy for multifunction myoelectric control"*, IEEE Transactions on Biomedical Engineering, Vol. 40, pp. 82-94, 1993.

[13] K. Englehart, B. Hudgins, and P. A. Parker, *"A wavelet-based continuous classification scheme for multifunction myoelectric control"*, IEEE Trans Biomed Eng, Vol. 48, pp. 302-11, 2001.

[14] R. P. Lippmann, *"An introduction to computing with neural nets"*, IEEE ASSP Mag., pp. 4-22, 1987.

[15] W. T. Miller, R. S. Sutton, and P. J. Werbos, Neural networks for control: The MIT press, 1990.

[16] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, *"Classification of the myoelectric signal using time-frequency based representations"*, Med Eng Phys, Vol. 21, pp. 431-8, 1999.