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Differentiating Type of Muscle Movement via AR Modeling and Neural Network Classification

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Abstract

The aim of this study is to classify electromyogram (EMG) signals for controlling multifunction proshetic devices. An artificial neural network (ANN) implementation was used for this purpose. Autoregressive (AR) parameters of a_1, a_2, a_3, a_4 *and their signal power obtained from different arm muscle motions were applied to the input of ANN, which is a multilayer perceptron. At the output layer, for 5000 iterations, six movements were distinguished at a high accuracy of 97.6%.*

Key words: *Myoelectric signals, artificial neural networks, classification*

1. Introduction

The analysis of muscle dynamics has been employed for a variety of applications, including prosthesis control and discrimination of movements. Control of a multifunctional prosthesis can be implemented by using myoelectric signals obtained from a couple of surface electrodes. This is particularly evident in cases where the patient has lost his/her arm at a point distal to his/her elbow. The control strategy used in the work evaluates the set of parameters of each movement via myoelectric signals obtained from almost identical muscle contractions. The prosthesis is assumed to do six different movements. These are elbow flexion and extention, wrist supination and pronation and finally grasp and resting. By using these parameters, it is possible to classify different muscle contractions. Each class of muscle contraction is used to trigger a particular function inteh prosthetic device. It is made sure that muscle contraction produces the right signals for the required movement.

D. Graupe has first shown that muscle contraction could be defined from EMG signals [1,2]. He has suggested the idea of using a time series model of EMG signals to identify a control strategy [3]. G. N. Saridis and T. P. Gooteee have done statistical analysis of EMG signals occurring in the biceps and triceps of patients with amputated or paralyzed arms [4]. Other multifunction prostheses have been developed using several channels of amplitude coding [5]. These require the existence of several electrode sites that are usually difficult if not impossible to locate on high level amputees. The Swedish hand and Utah arm have been used with some success in combination with an electric hand, but this has required the use of a mechanical switching arrangement or a switch-based quick co-contraction to select which of the two devices is to be controlled [6,7]. More elaborate multifunction prostheses have been attempted, but the result is that training the user to isolate the required number of control muscles is impractical, if not impossible [8].

Kelly et al. have suggested a multifunctional control design based on EMG signal classification by using different type of artificial neural networks (ANN) and utilizing Graupe's work [9]. Their success rate for classification was arount 90% for four movements. Later Hudgins et al. implemented a multifunctional myoelectric control [10] based on Kelly et al.'s work, with a success rate of 92% for classification of the four movements using ART 2.

In this study, multilayer perceptron network classification of the six movements was done using the time series model parameters of the signals obtained from the biceps and triceps at an average success rate of 97.6% for 5000 iterations.

2. Background

2.1. The Autoregressive (AR) Method

In order to obtain the complete linear information content of the EMG signals, it is essential that data reduction be employed as far as possible to reduce the dimensions the problem without loss of information. This is achieved, in our approach, by means of first employing signal identification. Noting that the recorded EMG signal represents a time series that is essentially stochastic, our algorithm consists of identifying the parameters of the time series that is recorded in terms of an autoregressive (AR) model, given by

$$S_k = -\sum_{i=1}^{p} a_i S_{k-i} + e_k \tag{1}$$

S_k denoting the recorder signal (k^{th} discrete time), a_i being the AR parameters, p being the order of the AR model, and e_k being white noise.

The use of an AR model in this problem has several advantages. It can be proven that a stationary time series can be represented by an AR model as above [11]. Although the EMG signal is not fully stationary, it is sufficiently stationary for each limb function considered, to yield AR parameters whose range of variations with time are small enough to facilitate discrimination between limb functions.

The linear AR model is fully optimal only if S_k is Gaussian, and is otherwise only linearly optimal, i.e., the best linear model for S_k. Hence, in the non-Gaussian case, a non-linear signal model would be required for full optimality [11]. However, without prior parameter knowledge, which is not available in our problem, no identification of an optimal model is possible in the general case, and if it were possible it would be too lengthy and too complex from a computational point of view to be of use in a concrete prosthesis application. Furthermore, one can show that the EMG signal can be considered as a n outcome of a sequence of impulses with independent Poisson-distributed intervals passed through a linear filter. Since the muscles involved are usually (in the biceps or triceps) actuated by a large number (several hundred, for example) of motor units, the average interspike interval is small compared with the dominant time constant of the linear filter involved. Assuming the practical average interspike interval concerned is of the order of t=0.1s, and assuming that N=200 motor units are involved in the muscle contraction, the Poisson rate is λ=N/t=2000. This Poisson rate implies that the EMG signal involved closely fits a Gaussian process. In this study, the partial autocorrelation (PARCOR) algorithm is used in order to obtain AR parameters [12, 14].

2.2. Artificial Neural Networks (ANN)

Recently, it has been shown that neural networks are able to solve various complex problems [13]. On the other hand, multilayered feed-forward networks have a better ability to learn the correspondence between input patterns and teaching values from many sample data by the error back-propagation algorithm [14]. Therefore, in this paper we used a three-layered feedforward neural network and trained it by error back-propagation. The neural network's software was written by the investigators and we employed back-propagation in a supervised learning paradigm in which the generalized delta rule was used in adjusting the weight values. Figure 1 shows a general structure of a neural network. Each layer is fully connected to the previous layer, and has no other connection. The output O_j of each unit j is defined by

$$O_j = f(net_j), net_j = \sum_i w_{ji} O_i + \theta_j \quad (i \in \text{preceding layer}) \tag{2}$$

where O_i is the output of unit i, w_{ij} is the weight of the connection from unit i to unit j, θ_j is the bias of unit j, $\sum_i$ is a summation over every unit i whose output flows into unit j, and $f(x)$ is a monotonously increasing function. In practice, a logistic activation function (sigmoid function) $f(x)$=1/(1+exp(-x)) is used.

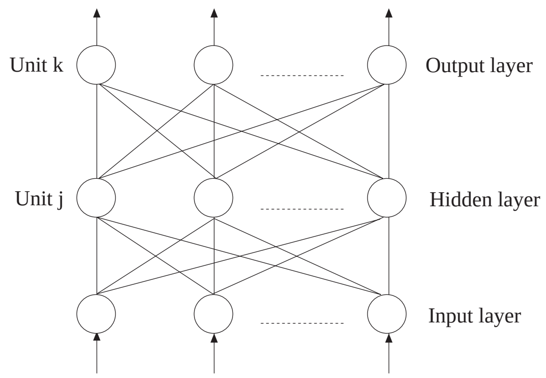

Figure 1. Ordinary type neural network

When the set of m-dimensional input patterns $\{i_p = (i_{p1}, i_{p2}, \ldots, i_{pm}); p \in P\}$ where P denotes set of presented patterns, and their corresponding desired n-dimensional output patterns $\{t_p(t_{p1}, t_{p2}, \ldots, t_{pm}); p \in P\}$ are provided, the neural network is trained to output ideal patterns as follows. The squared error function E_p for a pattern p is defined by

$$E_p = \frac{1}{2}\left[\sum_{j \in output} (t_{pj} - o_{pj})^2\right] \tag{3}$$

t_{pj}: target (desired) value, o_{pj}: actual network output value.

The purpose is to make $E = \sum_p E_p$ small enough by choosing appropriate w_{ij} and θ_{ij}. To realize this purpose, a pattern $p \in P$ is chosen successively and randomly, and then w_{ij} and θ_j are changed by

$$\Delta_p w_{ji} = -\epsilon(\partial E_p / \partial w_{ji}) \tag{4}$$

$$\Delta_p \theta_j = -\epsilon(\partial E_p / \partial \theta_j) \tag{5}$$

where ϵ is a small positive constant. By calculating the right hand side of (4) and (5), it follows that

$$\Delta_p w_{ji} = \epsilon \delta_{pj} O_{pi} \quad (6)$$

$$\Delta_p \theta_j = \epsilon \delta_{pj} \quad (7)$$

where

$$\delta_{pj} = \begin{cases} f'(net_j)(t_{pj} - O_{pj})(\text{when j belongs to the output layer.}) \\ f'(net_j) \sum_k w_{kj} \delta_{pk} (\text{otherwise}) \end{cases} \quad (8)$$

Note that k in the above summation represents every unit k in the layer following the layer of j (unit j). In order to accelerate the computation, the momentum terms are added in (6-7),

$$\Delta_p w_{ji}(n+1) = \epsilon \delta_{pj} O_{pi} + \alpha \Delta_p w_{ji}(n) \quad (9)$$

$$\Delta_p \theta_j(n+1) = \epsilon \delta_{pj} + \alpha \Delta_p \theta_j(n) \quad (10)$$

where n represents the number of learning cycles, and α is a small positive value. In this study, by trial and error the optimum α and ϵ constant values were determined to be: α=0.1, ϵ=4.

3. Methods and Results

This work aims at evaluating a logical strategy to drive the motors of the prosthesis. This strategy is obtained via EMG signals extracted from the biceps and triceps muscles of the arm. The control design used to obtain the strategy is presented in Fig. 2. As can be seen in the figure, controller design comprises the phases (steps) of initial signal processing, characterization, classification, and decision making. In the first phase, the EMG signal is detected using a pair of surface Ag-AgCl electrodes. The electrodes are placed on fat biceps 3 cm distant from each other and behind the triceps. The EMG signal obtained from the electrodes is amplified and passed through a low-pass filter to be sent to the level determining circuit. In the second phase, A/D conversion, data recording, and AR modeling are done. At the last stage, the decision is made by classifying the AR parameters using ANN.

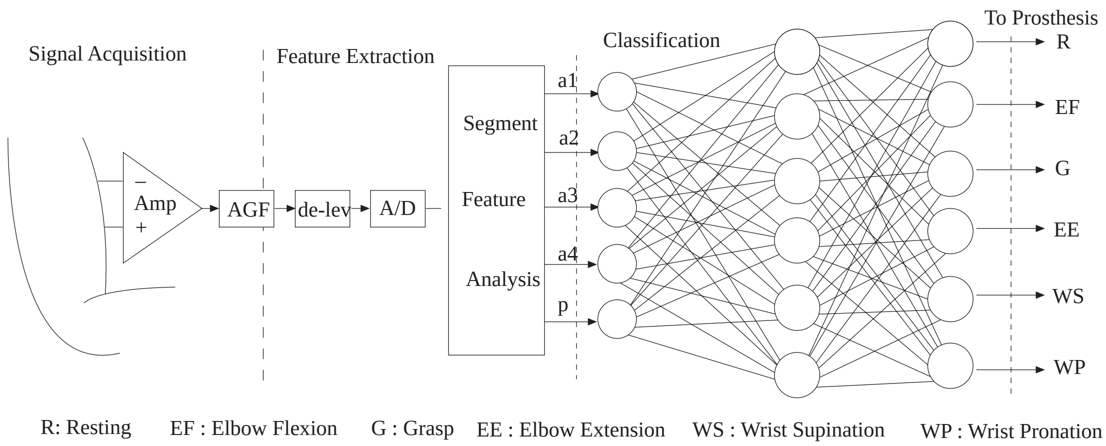

Figure 2. Myoelectric Control of a Multifunction Prosthesis

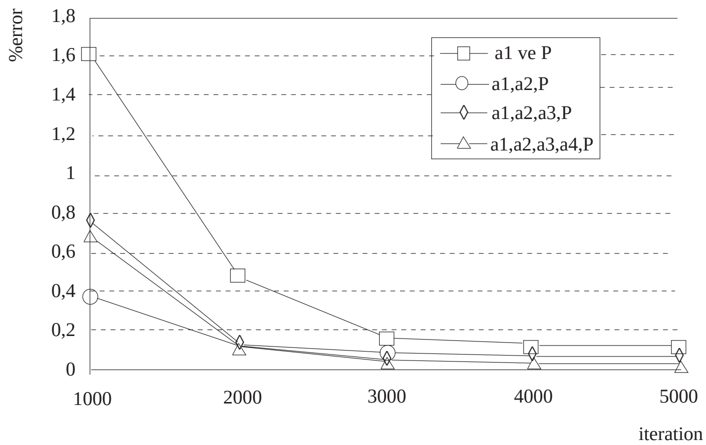

Figure 3. The effect of AR parameters on error rate

EMG signals were obtained from a 26-year-old healthy man for elbow flexion and extension, wrist supination and flexion and grasp and resting. Each movement was repeated 6 times and for each movement 4800 samples were taken within 1 second. Some data at the beginning and at the end of the data of 4800 were extracted in order for the rest to be linearized. During the experiment, great care was taken to use the same muscle each time for the same arm movement. When the EMG signals were processed, they were normalized and the DC levels were found. By subtracting the DC level from each sample the signals were made to have a mean value of zero. Samples of 4800 were split into 12 segments of 400 samples (80 ms). Each segment was multiplied with a Blackman type window function to perform windowing. Typical AR model parameters obtained from recording EMG signals from two movements are given in Tables 1 and 2 [15]. AR parameters of a_1, a_2, a_3, a_4 and their signal power were applied to the input of ANN, which is a multi-layer feed-forward perceptron. Training was done by back-propagation algorithm. During network training, the controller collects 12 sample feature sets for each contraction. This group of training feature sets is presented to the neural network with corresponding class outputs. The back-propagation algorithm then adjusts the network weights from preset random values to reduce the output error to some specified value. The desired output was set to 0.9 if it was the largest network output, and to 0.1 otherwise. The error between the actual network output and desired output is used to update the network weights, which are being continually modified by the most recent patterns presented to the classifier. The learning rate for the back-propagation rule is kept small so that the long-term trends in the generated patterns produce the desired weight adaptation.

Table 3 shows how many of the 12 patterns given are recognized by all movements. Six movements are included: resting (R), elbow flexion (EF), elbow extension (EE), wrist supination (WS), wrist pronation (WP) and grasp (G). For 100 iterations, all patterns of resting and elbow flexion are recognized where as none of the patterns of wrist supination and grasp are recognized. Four of the wrist pronation and 5 of the elbow extensions can be identified. On the other hand, the patterns of 2 wrist pronations, 2 elbow extensions and 7 elbow flexions are wrongly recognized. For 500 iterations, elbow extension movement is recognized for all patterns and this is achieved for wrist pronation and grasp for 600 iterations. After 2000 iterations all patterns are recognized. This is because the values of wrist supination and grasp are close to each other.

The recognition percentage was found to be 96.1% for 3000 iterations, and 97.6% for 5000 iterations assuming gain (learning rate) ϵ=4, and a momentum coefficient of α=0.1. The ANN programming language is Turbo Pascal, and a PC with a Pentium 90 processor was used for the calculations.

Table 1. AR parameters of elbow extension

a_1	a_2	a_3	a_4
-2.2914128854E+00	1.4157880401E+00	1.5643946565E-01	-2.7576257484E-01
-2.2236665563E+00	1.1925184658E+00	3.7804077194E-01	-3.4387288667E-01
-2.5605990742E+00	2.1284516167E+00	-4.7985836909E-01	-8.5217132090E-02
-2.1855094142E+00	1.1668151587E+00	3.5497629656E-01	-3.0421272700E-01
-2.1335049591E+00	1.0162656173E+00	4.8782226231E+01	-3.6814453276A+01
-2.3205685494E+00	1.3983241604E+00	2.496231425E-01	-3.2406063327E-01
-2.2736460701E+00	1.3090069187E+00	3.0759887510E-01	-3.4078144846E-01
-2.1544811453E+00	1.0935288607E+00	3.894865289E-01	-3.2407480865E-01
-2.2177809049E+00	1.1889682963E+00	4.0943813260E-01	-3.7655125553E-01
-2.3595552024E+00	1.5141832312E+00	1.3451033751E-01	-2.8448465373E-01
-2.3105310227E+00	1.4117335132E+00	2.0540127137E-01	-3.044298559E-01
-2.0866797895E+00	9.1354732122E-01	5.1311636760E-01	-3.3697516577E-01

Table 2. AR parameters of elbow flexion

a_1	a_2	a_3	a_4
-2.3542062185E+00	1.4851184597E+00	1.4528583345E-01	-2.7379972680E-01
-2.4726544348E+00	1.8385442000E+00	-2.0527237386E-01	-1.5744447000E-01
-2.4573193843E+00	1.7527869504E+00	-8.63436033770E-02	-2.0686584583E-01
-2.3926002892E+00	1.6307035562E+00	9.9958495213E-03	-2.4512770954E-01
-2.3730717435E+00	1.5655434941E+00	3.6312152113E-02	-2.2689045467E-01
-2.2351576581E+00	1.2796459202E+00	2.7017863040E-01	-3.1305935123E-01
-2.4544280426E+00	1.7943195752E+00	-1.2409796096E-01	-2.1258192259E-01
-2.6320357985E+00	2.2931298851E+00	-6.1287175187E-01	-4.5692505305E-02
-2.5094879915E+00	1.9042301538+00	-2.0069102896E-01	-1.9150689238E-01
-2.3592941518E+00	1.5443889449E+00	7.4672604464E+02	-2.5650593923E-01
-2.5892689199E+00	2.1397847674E+00	-4.3889054107E-01	-1.1007795451E-01
-2.4751362659E+00	1.8528491083E+00	-2.1320267626E-01	-1.8249904129E-01

Table 3. Testing results of six arm movements as a function of iteration

Iteration number	Resting (R)	WristS. (WS)	Grasp (G)	WristP. (WP)	ElbowE x(EE)	Elbow Fl(EF)	Movements of False Recognition
100	12	0	0	4	5	12	2WP,3EE,7EF
200	12	0	0	6	8	12	8WP,4EE,4EF
300	12	1	1	8	9	12	5G,2WS,4EE,3EF
400	12	1	6	9	11	12	10G,2WS,3EE,1E
500	12	1	6	11	12	12	11G,1WP,1EE
600	12	1	11	12	12	12	11G
800	12	1	12	12	12	12	11G
1000	12	2	12	12	12	12	10G
1200	12	3	12	12	12	12	9G
1500	12	8	12	12	12	12	4G
1800	12	11	12	12	12	12	1G
2000	12	12	12	12	12	12	0

4. Conclusion

This work was done concerning the classification of myoelectric signals by a multilayer neural network which has a stable feature. Previous studies have required high iteration of patient training for good-distinction of myoelectric signals. In practice, neural network classifiers are well-suited for reducing the amount of patient training required. It also has the feature that the commands concerning the desired movement are received directly. For that reason, in this method, the network can easily adapt itself to the special types of signals which are produced by the patient. For example, when a different elbow-extension signal is sent by the patient, the neural network decides on the similarity of this to the trained elbow-extension signal, and then the elbow-extension state must be 0.9 (logical 1) and the others must be 0.1 (logical 0), at the output. This process is carried out easily and very fast (i.e., for real-time application) in the test phase of an ANN program which we modified.

In this work, input values of neural network data were received from the patient, and there was no loss of data. Values were rounded to three decimal places. The values aliasing from the AR parameters of the six different movements were also taken into account. If they are distinguished, then it is clear that the training percentage will rise more. Although Kelly *et al.* have claimed that it is sufficient to use only the parameter a_1 and that the other parameters have no real effect on the learning rate, in the present study it has been shown that the AR parameters, such as a_2, a_3 and a_4, affect the learning the rate. As can be seen from Figure 3, if the number of AR parameters is increased in the input of neural network, the error rate of calssification is reduced. In another words, it is better to differentiate the learning rates of the types of muscle movement. In addition, the first time, in this work, six movements were distinguished at a high accuracyy rate, 96.1% for 3000 iterations. As mentioned in the introduction, the previous highest recognition rate was 92% for four movements, also at about 3000 iterations.

In the future, this experimentally implemented work can be performed by engineers and medical doctors in cooperation. The six basic movements can be investigated more specifically with the aid of developments in computers and other technological fields (electrodes, interfacing, etc.). For example, patients can also be trained to perform some extra movements, such as slow, middle, and fast elbow flexion. This kind of myoelectrically controlled prosthesis is mounted to extensor and flexor muscles if the patient has lost his/her arm somewhere under his/her elbow, and to the biceps, triceps and deltoid muscles if the patient has lost of his/her arm somewhere above his/her elbow (as we had for this study). According to the patient's level of amputation, one, two, or all of the muscles (biceps, triceps, and deltoid) can be used.

References

[1] D. Graupe, "Functional Separation of EMG Signals via ARMA Identification Methods for Prosthesis Control Purposes", IEEE Trans. Syst. Man Cybern., SMC-5, (1975), 252-259.

[2] D. Graupe, J. Magnuses, and A. Beex, "Microprocessor System for Multifunctional Control of Upper-Limbs Prostheses", IEEE Trans. Automat. Control., AC-23, Aug. (1978), 538-544.

[3] 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., 4, (1982), 17-22.

[4] George N. Saridis and Thomas Gotee, "EMG Pattern Analysis and Classification for a Prosthetic Arm", IEEE Trans. Biomed. Eng., BME-29 no: 6, June (1982), 403-412.

[5] H. Schmeild, "The I.N.A.I.L. Experience Fitting Upper-Limb dysmelia Patients With Myoelectric Control", Bull. Prosth. Res., BPR 10-27, (1997), 17-42.

[6] C. Almstrom, P. Herbets, and L. Korner, "Experiences With Swedish Multifunction Prosthetic Hands Controlled by Pattern Recognition of Multiple Myoelectric Signals", Int. Orthopased, 5, (1981), 15-21.

[7] S. C. Jacobsen, D. F. Knutti, R. T. Johnson, H. H. Sears, "Development of The Utah Artifical Arm", IEEE Trans. Biomed. Eng., BME-29, April (1982), 249.

[8] P. J. Cardo, "Controlling Multiple Degree of Freedo Powered Prosthesis", in Proc. IEEE Conf. Frontiers of Eng. and Comp. in Health Care, Columbus, OH, (1983), 151-155.

[9] M. Kelly, P. Parker, and R. N. Scott, "The Application of Neural Networks to Myoelectric Signal Analysis: a Preliminary Study", IEEE Trans. Biom. Eng., BME-37, (1990), 221-227.

[10] B. Hudgins, P. Parker, R. N. Scott, "A New Strategy for Multifunction Myoelectric Control", IEEE Trans. Biomedical Eng., 40, no: 1, January, (1993), 82-94.

[11] A. Kohen, "Biomedical Signal Processing", vol. 1, (CRC Press, 1986), p. 3-5, 81-89.

[12] B. Karlık, H. Pastacı, M. Korürek, "Myoelectric Neural Networks Signal Analysis", in Proc. IEEE 7th. Melecon'94, Antalya, Turkey, 1, April (1994), 262-264.

[13] T. J. Sejnowski, C. Rosenberg, "Parallel Networks That Learn to Pronounce English Text", Complex Syst., 1, (1987), 145-168b

[14] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Parallel Distributed Processing Explorations in the Microstructures of Cognition", vol.1, (Eds.) D. E. Rumelhant and J. L. Mc Clalland, (MA: MIT Press, Cambridge 1986), p. 318-362.

[15] B. Karlık, "Myoelectric Control of Multifunction Prosthesis by Using Artificial Neural Networks", Ph.D. Thesis, Department of Electrical Eng., Institute of Science, Yıldız Technical University, Istanbul, Turkey, 1994.