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A NOVEL TECHNIQUE FOR CLASSIFICATION OF MYOELECTRIC SIGNALS FOR PROSTHESIS

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Abstract: This paper presents an investigation into classifying myoelectric signals using a new fuzzy clustering neural network architecture for control of multifunction prostheses. Moreover, a comparative study of the classification accuracy of myoelectric signals using multi-layer perceptron with back-propagation algorithm, and the new fuzzy clustering neural network (FCNN) is presented. The myoelectric signals considered are used to classify four upper-limb movements, which are elbow flexion, elbow extension, wrist pronation and wrist supination, grasp, and resting. The results suggest that FCNN can generalise better than the multi-layer perceptron without requiring extra computational effort. The proposed neural network algorithm allows the user to learn better and faster. *Copyright © 2002 IFAC*

Keywords: Fuzzy clustering, neural network, myoelectric signal, pattern recognition.

1. INTRODUCTION

In prosthesis control applications, the identification of various myoelectric signals is used to control the movement of prostheses. The control strategy of prostheses is based on generating a set of repeatable muscle contraction patterns and classifying these patterns in a suitable manner. In conventional methods, this strategy is slow and not reliable when the muscle contraction is different from the ordinary arm function. The information extracted from the myoelectric signal, represented in a feature vector, is chosen to minimise the control error. To achieve this a feature set, which maximally separates the desired output classes must be chosen. The need for fast response of the prosthesis limits the period over which these features can be extracted. The recognition of the signal characteristics can be accomplished with various soft-computing approaches, such as neural networks and fuzzy logic. For example, Chaiyaratana *et al*. (1996) used two different types of radial basis function (RBF) neural networks, Kelly *et al*. (1990), Ito *et al*. (1991), and Karlik *et al*. (1994) have used different multi-layer perceptron (MLP) neural network structures, Hudgins *et al*. (1993) have used Hopfield and ART, and later FIRNN, Englehart *et al*. (1995), Del Boca and Park (1994), and Seker (1995) have used different kinds of fuzzy classification techniques. Most of the research has been carried out with using MLP neural networks (NNs) containing one hidden layer in conjunction with the back-propagation algorithm. However, the work reported by Costa and Gander (1993), incorporates an MLP NN with two hidden layers.

Myoelectric signals can be drawn from various locations on a subject's body. This is an application dependent criterion. For example, the signals from flexor digitorium superficialis are used in the classification of finger movements (Hiraiwa *et al.*, 1989), and the signals from biceps and triceps branchii are used to determine the arm movements (Hudgins *et al.*, 1993; Ito *et al.*, 1991; Kuruganti *et al.*, 1995). The control signal can be derived from a single myoelectric channel (Costa and Gander, 1993; Hudgins *et al.*, 1993; Karlik *et al.*, 1994; Kelly *et al.*, 1990), or from multi channels, such as two channels (Kuruganti *et al.*, 1995; Yeh *et al.*, 1993), four channels (Ito *et al.*, 1991), or five channels (Doerschuk *et al.*, 1983). Using a single channel myoelectric signal would result in less complexity in the NN structure. However, the positions of electrodes can become less critical and the classification accuracy can be increased with multi-channel signals (Kuruganti *et al.*, 1995).

Most of the previous research is concerned with the classification task of arm movements. The experiments are usually carried out in two possible ways: by exposing the subject's arm movements to a weight constraint (Costa and Gander, 1993) or by allowing the subject to perform the movement naturally (Hudgins *et al.*, 1993; Kuruganti *et al.*, 1995). The control schemes, on the other hand, have been based almost entirely upon a discriminate approach to pattern recognition, in which each pattern is described by a set of features. Feature sets can be obtained using various methods. For example, the parameters of some stochastic models such as an autoregressive (AR) model or autoregressive moving average (ARMA) model can be used as a feature set. A number of researches have accordingly utilised AR models (Doerschuk *et al.*, 1983; Graupe *et al.*, 1985; Karlik *et al.*, 1994; Kelly *et al.*, 1990; Kiryu *et al.*, 1994; Merletti and Lo Conte, 1995; Zardoshti-Kermani *et al.*, 1995, Chaiyaratana *et al.*, 1996). All these have been based upon the research work of Graupe and Kline (1975), which involves modelling myoelectric signals as ARMA models. Later research has shown that an AR model is sufficient for modelling myoelectric signals. Graupe *et al.* (1985) has proved that a myoelectric signal within a period of 0.2-0.3 seconds can be modelled as a 4th order AR model. Different arm movements are considered in studying the muscle contraction. AR parameters of myoelectric signals received from the muscles for these different movements are used as features to classify the signals with an NN model (Kelly *et al.*, 1990; Karlik and Ozbay, 1996; Karlik *et al.*, 1994).

The classification problem may be divided into the stages of feature extraction, dimensionality reduction, and pattern recognition. Englehart *et al.* (2001) have solved this problem using a wavelet packet based feature set, which is shown to outperform all other forms of signal representation except that reported by Karlik (1999).

In the study reported in this paper the AR model parameters and their signal power are used as features using PARCOR methods for the feature sets. The feature sets are clustered for different arm movements using the fuzzy C-means algorithm, and the cluster sets are used as input to an NN. Moreover, the paper presents a comparative study of the classification accuracy of myoelectric signals using MLP NN using the back-propagation algorithm and a fuzzy clustering neural network. The results of classification accuracy are shown to be better than that reported by other researchers.

2. DETERMINATION ON MLP STRUCTURE

In this study a three-layered feed-forward neural network is used and trained with the error back-propagation algorithm. Figure 1 shows a general structure of the neural network. The back propagation training through generalised delta rule of learning is an iterative gradient algorithm designed to minimise the root mean square error between the actual output of the multi-layer feed-forward NN and the desired output. Each layer is fully connected to the previous layer, and has no other connection. The cost function of the MLP is given as

$$\varepsilon(n) = \frac{1}{2}\sum_{k=1}^{N_o} e_k^2(n) \qquad (1)$$

where $\varepsilon(n)$ is the instantaneous cost function at iteration n, $e_k(n)$ is the error from output node k at iteration n and N_o is the number of output nodes.

The error from each output node can be defined as

$$e_k(n) = d_k(n) - y_k(n) \qquad (2)$$

where $d_k(n)$ is the desired response of output node k at iteration n and $y_k(n)$ is the output of the output node k at iteration n.

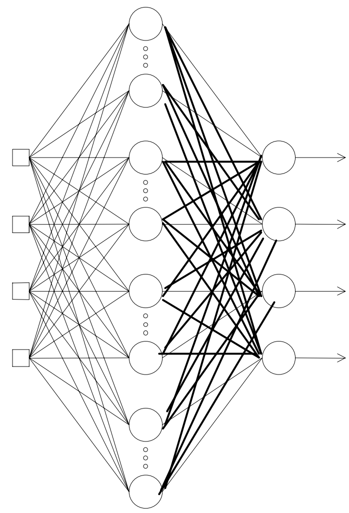

Fig. 1. General structure of MLP neural network.

Haykin (1994) gives a summary of the back-propagation algorithm as follows:

1. *Initialisation.* Set all the weights and threshold levels of the network to small random numbers that are uniformly distributed.

2. *Forward computation.* Let a training example be denoted by [**x**(n), **d**(n)], with the input vector **x**(n) applied to the input layer and the desired response vector **d**(n) presented to the output layer. The net internal activity level $v_j^{(l)}(n)$ for neurone j in layer l is given by

$$v_j^{(l)}(n) = \sum_{i=0}^{p} w_{ji}^{(l)}(n) y_i^{(l-1)}(n) \qquad (3)$$

where $y_i^{(l-1)}(n)$ is the signal from neurone i in the previous layer l-1 at iteration n and $w_{ji}^{(l)}(n)$ is the weight of neurone j in layer l that is connected to neurone i in layer l-1 at iteration n. For $i = 0$

$$y_0^{(l-1)} = -1 \qquad (4)$$

and

$$w_{j0}^{(l)}(n) = \theta_j^{(l)}(n) \qquad (5)$$

where $\theta_j^{(l)}(n)$ is the threshold applied to neurone j in layer l. With the use of a logistic function for the sigmoidal non-linearity, the output of neurone j in layer l is given by

$$y_j^{(l)}(n) = \frac{1}{1+\exp(-v_j^{(l)}(n))} \qquad (6)$$

If neuron j is in the first hidden layer (i.e., l = 1), set

$$y_j^{(0)}(n) = x_j(n) \qquad (7)$$

where $x_j(n)$ is the jth element of input vector **x**(n). If neurone j is in the output layer (i.e., $l = L$), set

$$y_j^{(L)}(n) = o_j(n) \qquad (8)$$

The error can be computed as

$$e_j(n) = d_j(n) - o_j(n) \qquad (9)$$

where $d_j(n)$ is the jth element of the desired response vector **d**(n).

3. *Backward computation.* Compute the local gradients (δ) of the network by progressing backward, layer-by-layer. For neurone j in output layer L, the local gradient is given by

$$\delta_j^{(L)}(n) = e_j^{(L)}(n) o_j(n) \left[1 - o_j(n)\right] \qquad (10)$$

For neurone j in hidden layer l, the local gradient is given by

$$\delta_j^{(l)}(n) = y_j^{(l)}(n)\left[1 - y^{(l)}(n)\right] \sum_k \delta_k^{(l+1)}(n) w_{kj}^{(l+1)}(n) \qquad (11)$$

The weight of the network in layer l can be adjusted according to the generalised delta rule as,

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left[w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)\right] + \eta \delta_j^{(l)}(n) y_i^{(l-1)}(n) \qquad (12)$$

where η is the learning rate parameter and α is the momentum constant. In this study, the learning rate parameter is chosen to be 0.95. The number of hidden nodes is determined experimentally. Experimental results show that the optimum number of hidden nodes is 7 with the highest classification accuracy of 97% for 2000 iterations.

3. DETERMINATION OF THE FUZZY CLUSTERING NEURAL NETWORK STRUCTURE

Structure identification of fuzzy systems is possible by constructing enough rules with the appropriate input and output membership functions. The identified model can accordingly be used to describe the behaviour of the target system as well as for prediction and control purposes.

The idea of fuzzy clustering is to divide the data into fuzzy partitions, which overlap with each other. Therefore, the containment of each data to each cluster is defined by a membership grade in [0,1]. In formal words, clustering in unlabeled data X={x_1, x_2, …, x_N} $\subset \Re^h$, where N is the number of data networks and h is the dimension of each data vector, is the assignment of c number of partition labels to the vectors in X. c-Partition of X are sets of (c.N) membership values {u_{ik}} that can be conveniently arrayed as a (cxN) matrix U=[u_{ik}]. The problem of fuzzy clustering is to find the optimum membership matrix U. The most widely used objective function for fuzzy clustering in X is the weighted within-groups sum of squared errors objective function J_m which is used to define the following constrained optimisation problem (Bezdek, 1993):

$$\underline{\min_{U,V}} \left\{ J_m(\mathrm{U}, \mathrm{V}; \mathrm{X}) = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \left\| x_k - v_i \right\|_A^2 \right\} \qquad (13)$$

where,

$$U \in M_{fcn} = \left\{ U \in \Re^{cN} \left| \begin{array}{l} 0 \le u_{ik} \le 1 \quad \forall ik \,\&\, \forall k, u_{ik} > 0 \,\exists \mathrm{i} \\ 0 < \sum_{\mathrm{k}=1}^{\mathrm{N}} u_{ik} < n \,\forall_{\mathrm{i}} \;\&\; \sum_{\mathrm{i}=1}^{c} u_{ik} = 1 \;\forall \mathrm{k} \end{array} \right. \right\}$$

$V=\{v_1, v_2, \ldots, v_c\}$ is a vector of (unknown) cluster centres, and $\|x\|_A = \sqrt{x^T Ax}$ is an inner product norm. A is an hxh positive definite matrix, which specifies the shape of the clusters. The matrix A commonly selected as the identity matrix, leading to the definition of Euclidean distance, and consequently to spherical clusters. Fuzzy partitions are carried out by the fuzzy C-means (FCM) algorithm through an iterative optimisation of equation (16) according to the following steps (Emami *et al.* 1996):

Step-1: Choose the number of clusters (c), weighting exponent (m), iteration limit (iter), termination criterion (ε >0), and the norm for error $= \|V_t - V_{t-1}\|$.

Step-2: Guess initial position of the cluster centres: $V_0 = \{v_{1,0}, v_{2,0}, \ldots, v_{c,0}\} \subset \Re^{ch}$.

Step-3: Iterate for t = 1 iter; Calculate

$$u_{ik,t} = \left[\sum_{j=1}^{c} \left(\frac{\|X_k - V_{i,t-1}\|_A}{\|X_k - V_{j,t-1}\|_A} \right)^{\frac{2}{m-1}} \right]^{-1} \qquad (14)$$

and

$$V_{i,t} = \frac{\sum_{k=1}^{N} (u_{ik,t})^m x_k}{\sum_{k=1}^{N} (u_{ik,t})^m} \qquad (15)$$

IF error $= \|V_t - V_{t-1}\| \le \varepsilon$, THEN stop, and put $(U_f, V_f) = (U_t, V_t)$ NEXT t.

In this paper, a clustering-based approach is adopted for four AR parameters and their signal power used as input to the NN. Six clusters with a total data size of 6x5 for each movement is used. This corresponds to half the size of the real data, which is 6x12 for each movement. Table 1 shows the recognition rates for the six arm movements achieved after 2000 iterations. As noted the recognition rates vary between 93% and 100%, with average recognition accuracy of 98 %.

For example, 6 test patterns belonging to elbow flexion were recognized successively. Recognition rates 97% were found for one of them, 98% for both of them, and 99% for the others.

Table 1. Recognition rates for the six arm movements

	93 %	95 %	96 %	97 %	98 %	99 %	100 %
Resting					2	2	2
Wrist Sup.	1		1	1	2	1	
Grasp		1			2	3	
Wrist Pro.				1		1	4
Elbow Ext.		1		2	1	1	1
Elbow Flex				1	2	3	
Total	1	2	1	5	9	11	7

4. RESULTS AND DISCUSSION

Two different training and test sets were used. All samples were trained and tested using MLP and fuzzy clustering neural network (FCNN). The results for the generalised case in terms of different convergence rates for the six arm movements are given in Table 2.

Figure 2 shows the classification rate of both methods as a function of number of iterations. As can be seen, with both methods, the classification rate decreased with an increase in the number of iterations.

The results show that the FCNN converges to a determined error goal at lower training epochs than the MLP. Moreover, The FCNN gives much better results than the MLP in most cases with respect to correct classification rate, which was found as 98.3%. This is the best result compared to those reported previously; Karlik (1999) found 96.1% classification rate, and Englehart *et. al*. (1999) found 93.7% classification rate.

Table 2. Comparing two methods

	MLP	FCNN
Classification rate	97 %	98 %
Iteration Number	2000	2000

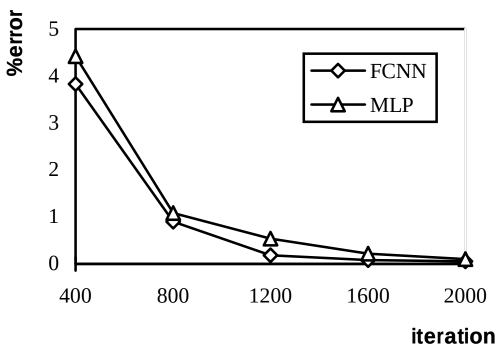

Fig. 2. Classification rate of MLP and CFNN.

5. CONCLUSION

A new technique based on fuzzy clustering neural networks has been proposed for classification of myoelectric signals. A comparative study of the proposed technique has been carried out with the MLP neural networks and it has been demonstrated that the FCNN method outperforms the MLP NN. Moreover, it has been shown that the FCNN method gives better classification rates than other previously reported techniques.

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