MYOELECTRIC SIGNAL CLASSIFICATION USING EVOLUTIONARY HYBRID RBF-MLP NETWORKS

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Abstract- This paper introduces a hybrid neural structure using radial-basis function (RBF) and multilayer perceptron (MLP) networks. The hybrid network is composed of one RBF network and a number of MLPs, and is trained using a combined genetic/unsupervised/supervised learning algorithm. The genetic and unsupervised learning algorithms are used to locate the centres of the RBF part in the hybrid network. In addition, the supervised learning algorithm, based on a back-propagation algorithm, is used to train the connection weights of the MLP part in the hybrid network. Performances of the hybrid network are initially tested using a two-spiral benchmark problem. Several simulation results are reported for applying the algorithm in the classification of myoelectric or electromyographic (EMG) signals where the GA-based network proved most efficient.

1 Introduction

Artificial intelligence has been successfully utilised in various applications, where it has proved to outperform other conventional methods or can be used to solve a problem in a more efficient way. In some cases however, the use of a single type of artificial intelligence to solve a particular problem is difficult or inefficient, and the use of a hybrid structure is one possible way of improving performances. Combining different types of neural network is a good starting point for achieving a hybrid structure, with genetic algorithms used to optimise the connection weights, the topology, or the connection weights and topology of the network once the network architecture is chosen.

One good example of how to use a genetic algorithm to optimise the neural network topology is given in Robbins et al. (1993). In this case, a genetic algorithm is used to find the optimal number of hidden layers and hidden nodes for a multilayer perceptron. In the case that the network topology has been defined before hand, genetic algorithms can be used to optimise the connection weights of the whole network in one go (Thierens et al., 1993; Whitley et al., 1990) or to optimise the connection weights layer by layer (Park and Park, 1993).

Genetic algorithms have also been used to optimise both the network topology and the connection weights simultaneously. Chromosomes are used to represent both network connections and weights. Examples of works of this kind are given in Dasgupta and McGregor (1992), Hintz and Spofford (1990), and White and Ligomenides (1993). A simple genetic algorithm is used to optimise the topology and connection weights in a multilayer perceptron in Dasgupta and McGregor (1992) while in White and Ligomenides (1993), a distributed genetic algorithm is used instead. The topology and connection weights in a recurrent network are optimised using a genetic algorithm in Hintz and Spofford (1990).

In the case where the computer memory limitation or hardware implementation of a neural network is the major consideration, using a sparsely connected neural network would be more appropriated than using a fully connected one. A genetic algorithm can be used to search the space of the network construction rules which will result in a construction of a sparsely connected network (Saha and Christensen, 1994) or to prune a fully connected network where the chromosome will represent the present and absent of connection links (Smuda and KrishnaKumar, 1995; Whitley et al., 1990).

In this paper, a hybrid radial-basis function-multilayer perceptron (RBF-MLP) network is used to demonstrate the idea of a hybrid network. A combined algorithm, comprised of genetic, supervised learning and unsupervised learning algorithms, is used to train the network. The genetic and unsupervised learning algorithms are used to achieve the locations of the centres in the RBF part of the network while the supervised learning algorithm is used to obtain the connection weights in the MLP part. Since a genetic algorithm is used to achieve a set of optimal locations of the RBF centres, this work is fallen into the case of using a genetic algorithm to optimise connection weight category. The learning capability of the hybrid RBF-MLP network will be demonstrated via the use of a two-spiral benchmark problem.

The hybrid RBF-MLP network is then used in a pattern recognition task where the input patterns are extracted from bio-electric signals called myoelectric or electromyographic (EMG) signals. Characteristics of myoelectric signals can be used to identify patterns of extremity movements, such as elbow flexion or elbow extension. In summary, a hybrid RBF-MLP network will be used as a pattern classifier where the function mapping will be between myoelectric signals

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and types of extremity movement. Comparative analysis between the use of a hybrid RBF-MLP network for this classification task and a previous work in the same area of biomedical research is also given in this paper.

The organisation of this paper can be described as follows. In section 2, the architecture of the hybrid RBF-MLP network is explained. Then the supervised learning algorithm is discussed in section 3, while the unsupervised learning algorithm is explained in section 4. In addition, the contribution of a genetic algorithm in the combined learning algorithm is given in section 5. In section 6, the overall learning capability of the hybrid network is demonstrated via the use of the two-spiral benchmark problem. In section 7, the overview of the myoelectric signal pattern recognition application is given. The experiments and the results obtained from using the hybrid network as the myoelectric signal classifier are illustrated in section 8. Discussions on the results are given in section 9. Finally, the conclusions are drawn in section 10.

2 Architecture of the Hybrid RBF-MLP Network

The structure of the hybrid RBF-MLP network is illustrated in Figure 1.

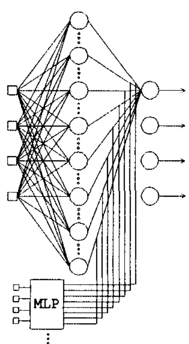

Figure 1: Schematic diagram of the hybrid RBF-MLP network

In Figure 1, the hybrid RBF-MLP network is composed of one radial-basis function network and one or more multilayer perceptrons. The input nodes in both the RBF and MLP parts will receive the same input signal, while the output from the hybrid network is obtained from the output nodes of the RBF part. The centres of the radial-basis functions are unsupervisedly trained using unsupervised and genetic algorithms. The connection weights in the RBF part, which are connected to the same output node of the radial-basis function network are the output from one of the multilayer perceptron networks. Consequently, the number of multilayer perceptron networks is equal to the number of output nodes in the radial-basis function network. This also leads to equality between the number of output nodes in each multilayer perceptron and the number of Gaussian functions in the radial-basis function network. Note that the connection weights within each multilayer perceptron are supervisedly trained using back-propagation algorithm.

With this structure, the learning algorithm will contain both supervised and unsupervised learning. A supervised learning algorithm will be used to train the connection weights in the MLP part while an unsupervised learning algorithm and a genetic algorithm will be used to arrange the location of the centres in the RBF part. The supervised learning algorithm will be discussed in section 3, while the unsupervised learning algorithm will be explained in section 4. In addition, the genetic algorithm part will be discussed in section 5.

3 Supervised Learning Algorithm for Training the Connection Weights in the MLP Part

Generally, a supervised learning algorithm is developed by firstly defining a cost function of a training error which the neural network has to minimise. Then a partial derivative of this function with respect to a parameter of the neural network, which requires the training, is obtained. This partial derivative is then subsequently used in the delta learning rule for updating the parameter of the network. In the case of the hybrid RBF-MLP network, the cost function for the development of the supervised learning procedure is given by

$$\varepsilon(n) = \frac{1}{2}\sum_{i=1}^{q} e_i^2(n) \qquad (1)$$

where $\varepsilon(n)$ is the instantaneous cost function at iteration n of training, $e_i(n)$ is the error from output node i of the RBF part at iteration n and q is the number of output nodes in the RBF part. The error from each output node is defined as

$$e_i(n) = d_i(n) - \sum_{j=1}^{M} w_{ij}(n) G(\|\mathbf{x}(n) - \mathbf{t}_j\|^2), \quad i = 1, 2, \ldots, q \qquad (2)$$

where $d_i(n)$ is the desired output of output node i at iteration n, $w_{ij}(n)$ is the connection weight between output node i and Gaussian function j, $\mathbf{x}(n)$ is the input pattern presented to the network, $\mathbf{t}_j$ is the centre of the Gaussian function j, M is the number of Gaussian functions in the network and $G(.)$ is the jth Gaussian function of the network. The partial derivative of the cost function given in (1), with respect to the connection weight, is given by

$$\frac{\partial\varepsilon(n)}{\partial w_{ij}(n)} = -e_i(n) G(\|\mathbf{x}(n) - \mathbf{t}_j\|^2),$$
$$i = 1, 2, \ldots, q; j = 1, 2, \ldots, M \qquad (3)$$

where $\frac{\partial\varepsilon(n)}{\partial w_{ij}(n)}$ represents the partial derivative of the cost function $\varepsilon(n)$ with respect to the connection weight $w_{ij}(n)$ at iteration n. Using the delta learning rule, a formula for adapting the connection weights in the radial-basis function network is given by

$$w_{ij}(n+1) = w_{ij}(n) - \eta \frac{\partial\varepsilon(n)}{\partial w_{ij}(n)} \qquad (4)$$

where η is the learning rate parameter.

As stated earlier in section 2, the connection weights in the RBF part of the hybrid network is the output from the MLP part. From equation (4), it can be seen that the desired output from the MLP part is represented by the connection weights after adaptation ($w_{ij}(n+1)$), while the actual output from the MLP part is given by the connection weights before adaptation ($w_{ij}(n)$). This implies that the training error which will back-propagate through the multilayer perceptrons will be equivalent to the term $-\eta \frac{\partial \varepsilon(n)}{\partial w_{ij}(n)}$ in (4). Since the value of the connection weights in the neural network can lie outside the range of 0 and 1, the logistic function which is usually used as the activation function in the multilayer perceptron is removed from the output neurons in the MLP part and is replaced by a linear function. In other words, the output from each neuron in the output layer of the MLP part will be a linear combination of the signals from the hidden layer in the corresponding multilayer perceptron network. With this modification to the output layer of the MLP part, in order to maintain the same level of non-linearity as in a normal multilayer perceptron that contains one hidden layer and uses a logistic function as the activation function in all the neurons, two hidden layers which contain neurons with the logistic activation function were used in each multilayer perceptron network in the hybrid structure.

The two-spiral problem is used to compare performances between a radial-basis function network, using a least mean square algorithm, and the hybrid RBF-MLP network. The number of training epochs required by the network for its mean squared error over one training epoch to converge to a pre-set level is used as its performance index. The locations of the centres of radial-basis function and hybrid RBF-MLP networks are fixed along the spirals' path. In the hybrid RBF-MLP network, five hidden nodes are presented in each hidden layer of each multilayer perceptron network. The benchmark results between the radial-basis function network and the hybrid RBF-MLP network are shown in Table 1.

Number of Centres	Number of Epochs Required	
	RBF	RBF-MLP
122	60	50
110	90	70
98	170	130
86	450	350
74	1,500	700

Table 1: Benchmark results between the RBF and hybrid RBF-MLP networks

As the number of centres is reduced, the difference between the numbers of training epochs required by the radial-basis function and hybrid RBF-MLP networks to reduce mean squared error over one training epoch to the pre-set level becomes more apparent. It can be seen that the number of training epochs required by the hybrid RBF-MLP network is smaller than that required by the radial-basis function network in all five cases. Hence it can be said that the training error of the hybrid RBF-MLP network converges faster than that of the radial-basis function network.

4 Unsupervised Learning Algorithm for the Selection of Centres in the RBF Part

In section 3, the supervised learning part of the combined learning algorithm has been discussed. In this section, the unsupervised learning algorithm will be explained. Based on early literature, the most commonly used strategy for training the centres of the radial-basis function is to use an unsupervised learning rule (Moody and Darken, 1989). The unsupervised learning algorithm which will be discussed next is based on an algorithm devised by Fritzke (1994). In summary, the algorithm allows the network size to increase gradually by incrementing a new centre into the network where it is required. At any given time during the training cycle, the unsupervised learning algorithm will force the centres of the radial-basis function to be located where the arrangement of the centres in the input space will produce the best convergence of the training input data. If in one particular area of the input space during the training cycle there are not enough centres to cover the input patterns, a new centre will be put into this particular area. Similar to the unsupervised learning rule described by Moody and Darken (1989), during the training, the centre in the network which is the nearest centre to the input pattern which is being presented to the network will move towards this

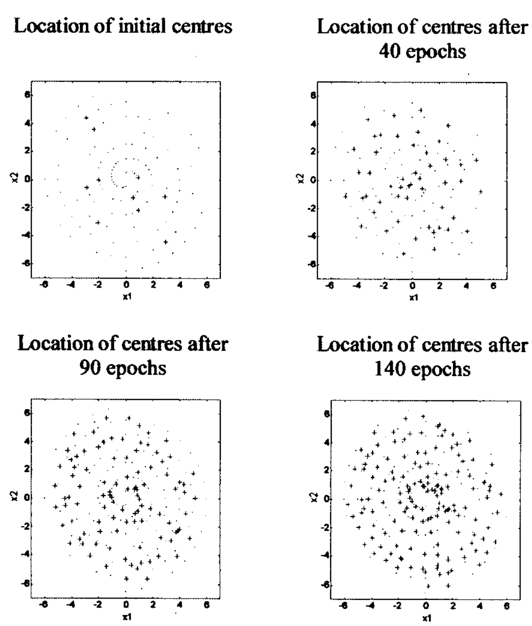

Figure 2: Location of the centres of the radial-basis functions during unsupervised learning

particular pattern. However, the difference is that the neighbour centres to this particular centre will also move toward this input pattern, with a lesser degree of movement.

The two-spiral problem is used to demonstrate this algorithm, with ten randomly chosen training patterns are used to initialise the algorithm. Examples of the locations of the centres during training a network to solve the two-spiral problem are given in Figure 2. In Figure 2, as the training progresses, the algorithm tries to produce the best coverage of training patterns in the input space using the available centres during each training epoch. This attempt can be clearly seen as early as after 40 epochs of unsupervised learning. This proves the effectiveness of this unsupervised learning rule.

5 Genetic Algorithm Part of the Combined Learning Algorithm

In section 4, the unsupervised learning rule has been used to identify the location of centres in the input space during training. In summary, a genetic algorithm will be used to enhance the performance of the unsupervised learning rule. A population of centres of the radial-basis functions are unsupervisedly trained in parallel. Genetic operators are then applied to the population in order for a new population with a better arrangement for the location of the centres to emerge after the algorithm run. The genetic operators used are discussed as follows.

5.1 Fitness Calculation Method

The fitness measurement of individual networks in this case is based on the spread of the centres in the input space. The radial-basis function network can generally perform a good input-output mapping if there is at least one centre in the vicinity of each data sample in the input space. In other words, the centres of the radial-basis functions are said to be well spread in the input space if the minimum distances between each data sample and its nearest centre are approximately the same. This is reflected in the fitness function used, where it is based on the standard deviation of the distances between the training pattern and its nearest centre over the set of training patterns. Using this fitness function, a fit individual will have a small standard deviation which means that the shortest distance between each training pattern and its nearest centre is very close to its mean value.

5.2 Selection Method

The roulette wheel selection is used for the demonstration of the hybrid RBF-MLP network using the two-spiral problem. However, later on in this paper, when the framework is used in the myoelectric signal pattern recognition application, the stochastic universal sampling (Baker, 1989)is used instead for the purpose of reducing the selection bias. Nevertheless, this change in selection method does not effect the functionality of the hybrid network. Although the roulette wheel selection method is inferior to the stochastic universal sampling selection method, the indication of improvement when a genetic algorithm is used should still be noticeable in the case of the two-spiral problem. Note that the elitist strategy used throughout the genetic algorithm run when either the roulette wheel selection or stochastic universal sampling is used is to select the two fittest networks from the population and then pass them on to the next generation without crossover or mutation.

5.3 Crossover and Mutation Methods

Although in general, crossover and mutation operations will be applied to the chromosome of the individuals, in this paper no chromosome coding mechanism is implemented. Instead, crossover and mutation operations are achieved entirely in the input pattern space; these two operations are explained as follows.

For the crossover method, two parent networks are randomly picked from the selected population for one crossover. A randomly generated hyper-plane in input space is created and is used to separate the set of centres into two sections. This hyper-plane will always pass through the centre of mass of the centres in one of the parent networks. The crossover operation is illustrated in Figure 3. Since the number of centres in each offspring from the same parents after crossover may not be equal, the centres are selected at random from the offspring which has a higher number of centres and then passed on to the other offspring.

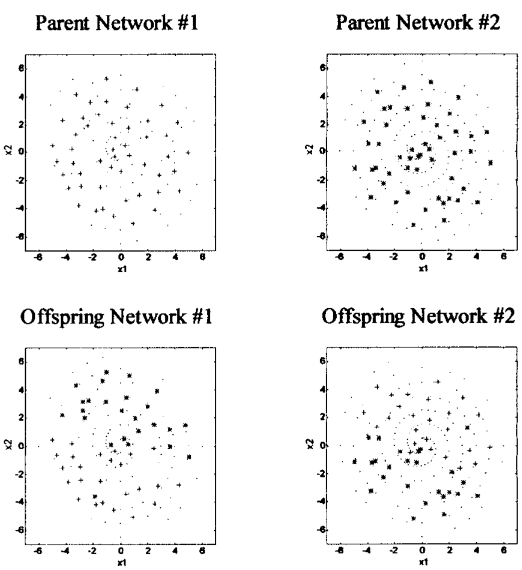

Figure 3: Crossover operation in the input space

Moving onto the mutation method: since the locations of the centres are changing from one iteration to the next, according to the unsupervised learning rule, the mutation effect has already been achieved within the unsupervised learning part. Therefore, no extra mutation method is required in the genetic algorithm part. The parameter settings for the genetic algorithm are summarised in Table 2.

Parameter	Value
Crossover probability	0.8
Mutation probability	0
Population size	30
Number of elitist individuals	2

Table 2: Parameter settings for the genetic algorithm

6 Combined Learning Algorithm and the Network Learning Capability

In the previous sections, the neural network and genetic algorithm contributions to the proposed hybrid structure has been explained. Both parts of the structure have been combined together in the following manner. A pool of networks which contain only the RBF part of the hybrid network are trained using the unsupervised learning algorithm as explained earlier. During this training, the genetic algorithm is applied at constant intervals to readjust the location of the centres of the radial-basis functions. Once both the unsupervised learning and genetic algorithm run are finished, the fittest network from this network pool, containing the best arrangement of centres for the radial-basis functions, is picked out. Then the MLP part of the complete hybrid network, which contains the best set of centres in the RBF part, is trained using the supervised learning algorithm. The combined learning algorithm can be summarised as follows.

1. Initialise the networks in the population with centres which are randomly drawn from the training patterns.
2. Unsupervisedly train the centres of each network for n epochs.
3. Perform g generations of genetic algorithm.
4. Repeat steps 2 to 3 until the required network size is reached.
5. Supervisedly train the connection weights in the MLP part of the fittest network.

The two-spiral problem is used here to validate the hybrid network and its combined learning algorithm. Two simulations were carried out for this purpose. In the first simulation, the unsupervised and the supervised learning algorithms are used to train the hybrid RBF-MLP network. In the second simulation, the combined learning algorithm is used. For a fair comparison between these two simulations, a pool of networks which contained only the RBF part of the hybrid network are trained in parallel in the first simulation. The size of the network pool is equal to the size of population in the second simulation. The best network from this pool, determined by using the fitness criterion described in the genetic algorithm part of the combined algorithm, is then connected to the MLP part which is trained using the supervised learning. The resulting hybrid network is then compared with the best individual from the second simulation.

The simulation results are given as follows. Figure 4 shows the final sets of centres in the two networks, one without the use of the genetic algorithm and the other with. Figure 5 shows the decision boundaries produced by the two networks, one without the use of genetic algorithm and the other with. From Figure 4, it can be seen that the location of the centres of the radial-basis functions is much improved when the genetic algorithm is used. Without the use of the genetic algorithm, the centres tend to lump together around the inner circles of the spirals' path. This observation is confirmed in Figure 5, where the decision boundary produced by the hybrid network is much poorer when the genetic algorithm is not used. The results emphasise the importance of the genetic algorithm in improving the location of the centres of the radial-basis function network in the input space.

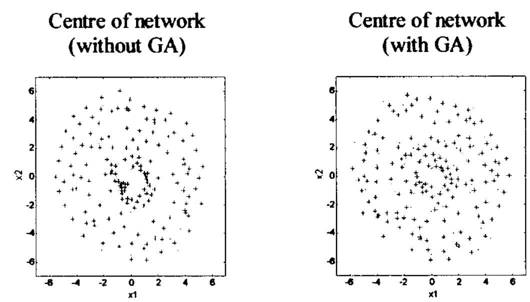

Figure 4: Centres for the radial-basis functions in the hybrid networks after training

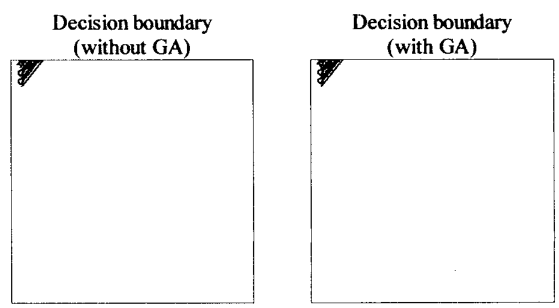

Figure 5: Decision boundaries produced by the hybrid RBF-MLP networks

7 Myoelectric Signal Pattern Recognition Application

Myoelectric signals are the signals which are generated by muscles when they contract. They have been used in various aspects of medical and biomedical applications. For example, they are used for the diagnosis of neuromuscular disease such as polymyositis (Kumaravel and Kavitha, 1994). One of the most common uses of myoelectric signals, which is the main issue of this paper, is for controlling prosthesis manipulators (Scott and Parker, 1988). Each myoelectric signal, generated by the muscle in performing different tasks, has a unique pattern. This pattern contains information about the direction of movement and the speed of the action. To be able to control a prosthesis successfully, the microprocessor, which is a part of the prosthesis, must be able to classify these patterns accurately; this results in a pattern recognition problem.

Myoelectric signals can be drawn from various locations on a human body depending on the type of movement in which a prosthesis device is required to achieve. In this paper, the movement of a human arm is under consideration. This leads to the experiment set-up which involves the use of myoelectric signals measured from biceps and triceps branchii. The control signal for a prosthesis device can be derived from a single myoelectric channel or from multiple channels. Using a single channel myoelectric signal would result in a less complex input structure to the classifier. However, using multi-channel signals makes the positions of the electrodes on the human subject become less critical to the experiment and increase the classification accuracy (Kuruganti et al., 1995). For this reason, two-channel signals are used in this study.

The myoelectric signal is essentially a one-dimensional pattern. The methods and algorithms which have been developed for one-dimensional pattern recognition can therefore be applied to this analysis. 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. Furthermore, the need for a fast response of the prosthesis limits the period over which these features can be extracted. A feature extraction method developed by Hudgin et al. (1993) has proved to be an efficient method in achieving a well-defined feature set from a short burst of myoelectric signals. This method is chosen for use in the feature extraction process.

The task of pattern recognition always involves the use of a pattern classifier. For the application of myoelectric signal pattern recognition, the majority of research in this area focuses on the use of multilayer perceptron with one hidden layer as the pattern classifier. In this paper, a comparison between the multilayer perceptron and the hybrid RBF-MLP network on pattern recognition task will also be discussed.

8 Experimentation and Results

As mentioned earlier, arm movements are the main interest in this experiment. Myoelectric signals are measured from biceps and triceps branchii since these two muscle groups are directly responsible for the arm movements of interest. Four movement patterns - elbow flexion, elbow extension, wrist pronation and wrist supination are the four classes of pattern which can be identified from the signals measured from these two muscle groups. Thus, these four movement patterns will also be the output classes in which the classifier must be able to classify from the input feature. Myoelectric signals are measured by means of using two pairs of surfaced differential electrodes placed on the biceps and triceps. A schematic diagram of the locations of electrodes on the subject's arm is given in Figure 6. Electrodes were placed on these specific locations for the reason that it has been proved to be the best locations for obtaining two-channel myoelectric signals for identifying these types of movement (Kuruganti et al., 1995). The data are then collected through a myoelectric signal measurement part of a system called the ELITE system. Details on this measurement system can be found in Ferrigno and Pedotti (1985).

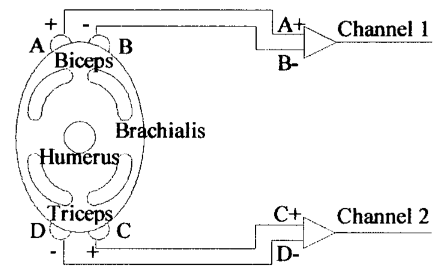

Figure 6: Location of electrodes on the subject's arm

Since the interested types of contraction can be paired up into two distinct groups - elbow flexion/extension and wrist pronation/supination, the human subject was asked to produced a number of sets of continuous movements which contain either alternating elbow flexion and extension or alternating wrist pronation and supination. The corresponding sets of continuous contraction were separated into a number of single contraction periods by means of thresholding. Then the initial part of each single contraction period is extracted from the raw signal where the signal features are subsequently obtained from the extracted section. Samples of raw myoelectric signals which were collected in this continuous contraction arrangement are displayed in Figure 7. In Figure 7, it can be seen that for one set of contraction data, there are either alternating pairs of signal representing elbow flexion and extension or alternating pairs of signal representing wrist pronation and supination.

Once the required section of the signal is obtained, the signal section can be segmented into a number of multiple non-overlapping consecutive segments where the signal features can be extracted from each segment. Since the data section in this experiment contains synchronous signals from two channels, the segmentation is also needed to be done synchronously on the data from both channels. After segmenting the signal, five signal features as recommended by Hudgin et al. (1993) can be extracted from the myoelectric signal: the mean absolute value, the mean absolute value slope, the zero crossings, the slope sign changes and the wave-form length. Note that these features will be used as input to the neural networks.

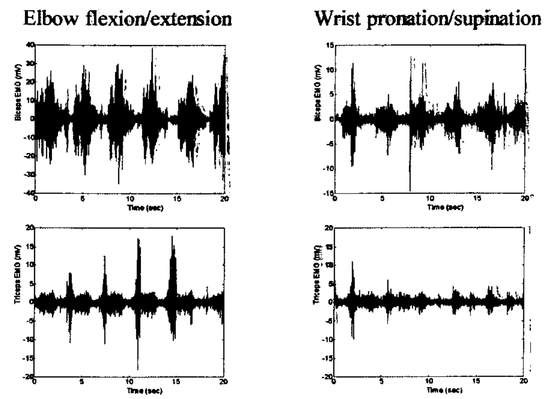

Figure 7: Samples of raw myoelectric signals

Four separate test cases are considered here. Each test case involves a different number of signal segments used in the classification process. The number of signal segments considered in the experiment are one, two, four and five segments. The classification accuracy of the hybrid RBF-MLP network and the multilayer perceptron is illustrated in Figure 8.

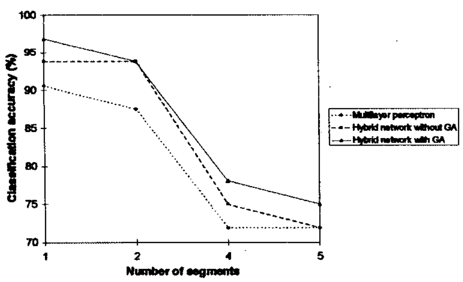

Figure 8: Classification accuracy of the networks from four test cases

9 Discussions

After training the multilayer perceptron and hybrid RBF-MLP networks with the same training patterns and testing the networks with the same testing patterns, the results indicate that the hybrid RBF-MLP network which uses the genetic algorithm as part of combined learning algorithm can generalise better than the multilayer perceptron in all four test cases. It is also noticeable that the upper and lower bounds of classification accuracy of the hybrid network which does not utilise the genetic algorithm are the classification accuracy of its counterpart which uses the genetic algorithm and that of the multilayer perceptron, respectively. Nevertheless, all four test cases are used to find the number of segments in the myoelectric signal, which gives the highest classification accuracy and the simulation results indicate that the test case with one signal segment gives the best result. For the first test case, approximately a 3 % improvement in classification accuracy can be obtained by using the hybrid RBF-MLP network without the use of the genetic algorithm in comparison with the multilayer perceptron. Approximately, a 3 % improvement can be gained when the genetic algorithm is also in use. This helps to prove the validity of using this neural structure for myoelectric signal pattern recognition.

The previous work in the same area of myoelectric signal pattern recognition which can be closely identified with the work presented in this paper is discussed in Kuruganti et al. (1995). However, there are some differences between the experiment described in Kuruganti et al. (1995) and the one presented here. For example, the experiment by Kuruganti et al. (1995) uses a sampling period of 1 ms during raw data collection process and the length of signal samples which is used for classification task is 240 ms. However, the sampling period used in the experiment presented in this paper is 2 ms and the considered length of signal samples is 200 ms. Furthermore, Kuruganti et al. (1995) do not use slope sign changes as the input feature to the multilayer perceptron. In other words, only the mean absolute value, mean absolute value slope, zero crossings and wave-form length were used as the input features in their case. Nevertheless, Kuruganti et al. (1995) also use two-channel myoelectric signals, which are collected from the same position on the subject's arm. Also, a multilayer perceptron with one hidden layer is used as the pattern classifier in their experiment. These similarities make the following direct comparison possible.

Kuruganti et al. (1995) have shown that with the signal partitioned into six segments, the average classification accuracy of the multilayer perceptron using two features - mean absolute error and zero crossings - as the input, is 95.6 %, while when four features are used, the average classification accuracy is 93.7 %. These figures are slightly lower than the classification performance of the hybrid RBF-MLP network with the use of a genetic algorithm. This means that a higher classification accuracy than the one presented in Kuruganti et al. (1995) can be achieved with half the sampling frequency and with a shorter time required for collecting the raw signals. The final neural network will be implemented into a microprocessor which is embedded in the prosthesis device. Therefore, a faster response will be very much desirable in a real-time implementation.

10 Conclusions

This paper reported a stage in the concept of evolutionary hybrid neural networks. The proposed hybrid structure was composed of a hybrid RBF-MLP network and combined supervised/unsupervised/genetic learning algorithm. The radial-basis function (RBF) part of the network is responsible for the way the function mapping between the input and output of the network is achieved. In contrast, the multilayer perceptron (MLP) part is used to improve the tracking error convergence rate during supervised learning. In summary, the process of teaching the hybrid RBF-MLP network can be divided into two main parts: the training of the centres in the RBF part and the training of the connection weights in the MLP part. An unsupervised learning algorithm, based on that described in Fritzke (1994), and a genetic algorithm are used to locate the centres of the radial-basis functions in input space. A supervised learning algorithm, based on the back-propagation algorithm, is used to train the connection weights in the MLP part. Using the two-spiral benchmark problem, the hybrid RBF-MLP network proved to be an efficient neural structure which can be used in an application such as pattern recognition.

The hybrid RBF-MLP network was then subsequently used in a biomedical application which involves the task of pattern classification. The aim of this application was to classify the types of upper arm movement, such as elbow flexion or extension, using a bio-electric signal called a myoelectric signal. Myoelectric signals can be measured from muscle groups which are responsible for the specific extremity movements. The time domain characteristics of these signals are extracted from raw myoelectric signals and are used as the input to the neural classifier. The simulation results suggest that the classification accuracy of the hybrid RBF-MLP network is approximately six percent higher than that of a multilayer perceptron. This proves that although the multilayer perceptron is widely used in this particular area of biomedical research, there exists other types of classifier which are superior to the multilayer perceptron in terms of the classification accuracy. Other benefits gained by using a hybrid RBF-MLP network instead of a multilayer perceptron have been given in discussions section within this paper. This also includes a comparison with a previous work in the same area; this utilised the same methods of signal collection and feature extraction.

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