CLASSIFICATION OF THE 12-LEAD ELECTROCARDIOGRAM EMPLOYING A FRAMEWORK OF BI-GROUP NEURAL NETWORKS

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Abstract
A framework employing Bi-Group Neural Networks (BGNN) is proposed to classify an unknown 12-lead Electrocardiogram (ECG) into one from a possible six diagnostic classes. The framework was compared with a conventional approach of Neural Network (NN) classification, a decision tree and a classifier based on multiple regression. The proposed approach attained a correct classification level of 80% in comparison with 68%, 66.7% and 68% for the comparative methods respectively.

1.0 Introduction
The electrical signals produced by the heart during its normal operation provide sufficient information to enable diagnosis of a number of cardiac abnormalities. A number of techniques exist which may be employed to acquire and analyse the signals, however, the most commonly employed non-invasive technique is that of 12-lead Electrocardiography. This technique records the sequence of electrical signals of the heart, referred to as the ECG, from various positions on the surface of the patient's body. Hence, it is possible to view the heart from a number of different angles. Each component of the ECG is directly related to the spread of electrical stimulus through a specific region of the heart. Thus by analysing the ECG it is possible to suggest a potential diagnosis.

In an effort to enhance the process of ECG classification, in terms of accuracy, speed, precision and reliability, computerised techniques were introduced. 1957 saw the advent of computerised ECG classification by Pipberger [1]. Since its inception, research techniques in the field have proliferated, with the driving factor being the common goal of enhancing the aforementioned criteria. From the outset it was envisaged that computerised systems would provide more accurate classification of ECGs. Although recent findings indicate that computer based systems provide only comparable results with humans [2], they do, however, offer higher levels of consistency and lower levels of observer variability [3]. It was never considered that the computer would totally replace the expert, however, devoid of their presence, via the computerised system, an intermediate classification may be produced.

2.0 Computerised Classification of the ECG
The classification of the ECG, by computerised techniques, is essentially a pattern recognition task. This may be subdivided into two succinct steps. Firstly a pre-processing stage examines the digitally recorded data, determining boundaries, inter-wave intervals and amplitudes [4]. From this information a 'feature vector' is formed which is considered to describe the morphology of the current recorded signal. Secondly, a stage of classification is employed whereby the feature vector is analysed and the ECG is allocated to one from a set of possible diagnostic classes.

Over the past four decades, much effort has been made in the enhancement of both areas of the pattern recognition problem. With regard to the pre-processing, techniques have begun to reach their limit in pushing forward the accuracy of automated analysis. On the other hand, the problem of the optimum classification algorithm still remains unsolved. Two different approaches to classification have generally been adopted. Firstly, there have been methods of a rule based or decision tree approach and secondly, multivariate statistical analysis techniques have been employed. A major hindrance, however, in the process of classification is the lack of standards currently available to specify rules and criteria required for diagnosis [5]. Thus rule based techniques, where the classification rule set is defined by the human expert, may be considered as disadvantageous since human bias will be introduced into the system. On the other hand, adaptive classifiers, such as statistical approaches avoid this human bias through generation of the classification function/rules during an adaptive training phase. More recently NN have been applied to the problem of ECG classification. Like statistical classifiers, NN may also be considered to be adaptive, hence avoiding human bias in the generation of the classification function.

3.0 Classification of the ECG employing BGNN

In the field of ECG classification, the most commonly employed NN is the Multi-Layered Perceptron (MLP). An MLP is an interconnection of small non-linear processing elements called neurons, in a hierarchical form, yielding a feedforward fully connected structure [6]. An MLP consists of an input layer, an output layer, with the possibility of one or more hidden layers in between. In terms of ECG classification, the feature vector is applied to the input layer and the number of neurons in the output layer is indicative of the number of possible diagnostic classes to which the ECG may be assigned. The NN is trained following iterative exposure to a set of annotated recordings through adjustment of the internal parameters of the network. By varying the number of neurons in the hidden layer(s) and repeating the process of training, it is possible to generate a NN with an optimal level of generalisation following exposure to an unseen set of records.

Although NN have shown promising results in comparison to conventional approaches it is considered that there is still room for improvement. In an effort to further increase performance, a framework based on BGNN has been proposed. By considering an *N*-class classification problem as a family of bi-group classification problems, it is possible to employ a framework of BGNN to provide the same classification abilities as a conventional MLP approach. A BGNN is defined as an MLP with a single neuron in the output layer, specifically trained to identify the presence or absence of a specific diagnostic class. Figure 1 (a) demonstrates the classification abilities of an MLP with 4 output neurons, segregating the classification space into 4 disjoint regions. Figure 1 (b) demonstrates how the same problem can be represented by a framework of 4 BGNN. Each BGNN segregates the classification space into two disjoint regions and in combination can provide the same classification abilities as the conventional MLP approach.

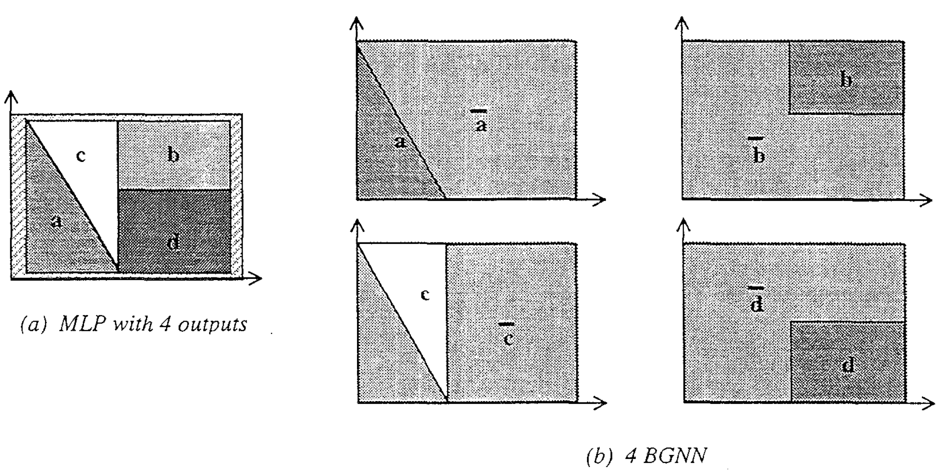

Figure 1 Classification of a 4 class problem employing (a) MLP with 4 output neurons and (b) a combination of 4 BGNN.

By employing BGNN a number of advantages are obtained. Firstly by reducing the complexity of the classification problem, the complexity of the individual BGNN is also reduced. Secondly, more specific feature vectors for each BGNN may be selected, thereby increasing the generalisation of the networks. Finally, a pilot study has indicated such an approach to improve performance in comparison with a conventional MLP [7].

4.0 Results and Conclusions

The framework was formulated to accommodate six diagnostic classes; Inferior Myocardial Infarction (MI), Anterior MI, Combined MI, Left Ventricular Hypertrophy (LVH), a combination of LVH and Combined MI, and Normal. The individual BGNN were trained from a set of 145 records and the entire framework was tested on a set of 75 records. As an additional investigation, various forms of feature vector reduction were performed [8], with the aim of reducing the dimensionality of the vector yet still maintaining sufficient information for discriminatory purposes. Results following testing of the proposed framework, along with additional conventional approaches are given in Table 1.

Classification Method	Performance	Confidence Limits (p=0.05)
BGNN Framework	80%	$\pm$6.79%
Conventional NN	68%	$\pm$7.92%
Decision Tree	66.7%	$\pm$7.98%
Statistical approach	68%	$\pm$7.92%

Table 1 Results following testing various forms of classifiers.

The results from the study clearly indicate the potential advantages of employing NN and indeed the proposed framework of BGNN. It has been demonstrated that by subdividing the classification problem and employing the BGNN framework a significant enhancement in performance has been obtained. Both the conventional MLP approach and the statistical approach attained higher levels of classification in comparison to the rule based approach. The rule based approach is based on an expert Cardiologist's rules and published medical criteria, which has taken many years to compile. However, the formation of the proposed framework has been generated in a much shorter timeframe and has surpassed the performance of the rule based approach. We conclude by suggesting that NN are indeed well suited to the given problem of 12-lead ECG classification and by careful consideration of their structure, considerable enhancements in performance may be obtained.

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