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ECG Biometric Using Multilayer Perceptron and Radial Basis Function Neural Networks

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Abstract— **This paper proposes a new method to identify people using Electrocardiogram (ECG), particularly the QRS complex which has been proven to be stable against heart rate variability and convenient to be used alone as a biometric feature. 324 QRS complexes are extracted from ECGs of 18 subjects in Physionet's MIT-BIH Normal Sinus Rhythm Database (NSRDB). Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are used to classify those QRS complexes. If the training data are chosen carefully to cover a wide range of input values (i.e. QRS complexes), then the classification accuracy rates can reach above 98% using MLP and 97% using RBF.**

I. INTRODUCTION

The electrocardiogram (ECG) (Fig. 1) is a biological signal which has recently attracted attention of researchers as a new way to identify a person [1]-[2]. ECG is difficult to falsify and possesses many discriminative features such as the three major waves: P wave, QRS complex and T wave. These differences derive from anatomical structure of each person's heart and many physiological conditions [1]. Biel

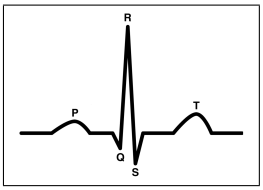

Fig. 1 – ECG Waveform

et al. [3] were among the first researchers who proved the capability of ECG as a new biometric. They used a diagnostic ECG device to record 12-lead resting ECGs which could be a limitation of their work. Resting ECG signals do not accurately reflect changes in heart rates of people as they experience different physical and emotional conditions in their real lives.

Sufi et al. [4] progressed a step further to propose a new patient authentication technique from compressed ECG. As the lengths of compressed ECG segments are substantially smaller than plain text ECG segments, the authentication process will be speeded up, enabling faster diagnosis and treatment of emergency cardiac patients in wireless telecardiology applications. However, data used in their experiment were from public ECG databases where each person has one record. Some parts from this record were used for learning and other parts were used for testing. Moreover these databases often do not contain ECGs with changed heart rate for each person as they include only resting ECG signals.

So far as we know, most of the research works on ECG biometric either collect data from multiple subjects across multiple sessions as in [5], [6] or use ECG data from public ECG databases as in [4], [2]. In the latter case, they have to show that ECG features used in their work are stable against heart rate variability to avoid the above mentioned limitations. Tawfik et al. [6] collected ECG data from 22 healthy males and females with a relatively wide range of heart rates for each person at different test sessions to simulate different conditions occurring in real life. One of their conclusions was that the QRS complex showed great stability with changes in heart rate, while both T and P waves vary according to different heart rates.

The above conclusion has given us a strong reason to use QRS complex which is proved to be stable against heart rate variability. Additionally, we utilize two of the most popular types of neural networks as classifiers. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks have their remarkable abilities to derive meaning from complicated or imprecise data, and can be used to extract patterns and detect complex trends.

The rest of the paper is organized as follows. Section II discusses how we collected, pre-processed and arranged ECG data (i.e. QRS complexes) into input and output matrices. Next, in section III, we discuss architectures of MLP and RBF neural networks used in out experiments. In section IV we discuss how the proposed system was implemented and results of our experiments. Finally, section V concludes the paper.

II. DATA PREPARATION

A. Collecting Data

We randomly collected 324 QRS complexes from 18 subjects in MIT-BIH Normal Sinus Rhythm Database (NSRDB), which is available on Physionet website [7]. Each QRS complex was represented by 23 points from p1 to p23 in millivolts. Fig. 2 shows an overview of our data. Fig. 3 shows the graph of one QRS complex taken from subject s16265. 12 QRS complexes of each subject were plotted and placed next to each other in Fig. 4. These plots show clearly the differences between QRS complexes of 18 subjects used in this experiment.

B. Pre-processing Data

Our training dataset contained 216 QRS complexes of 18 subjects. Each subject had 12 QRS complexes that were inputs applied to our neural networks. The subjects that those networks predicted (i.e. outputs) would be compared to

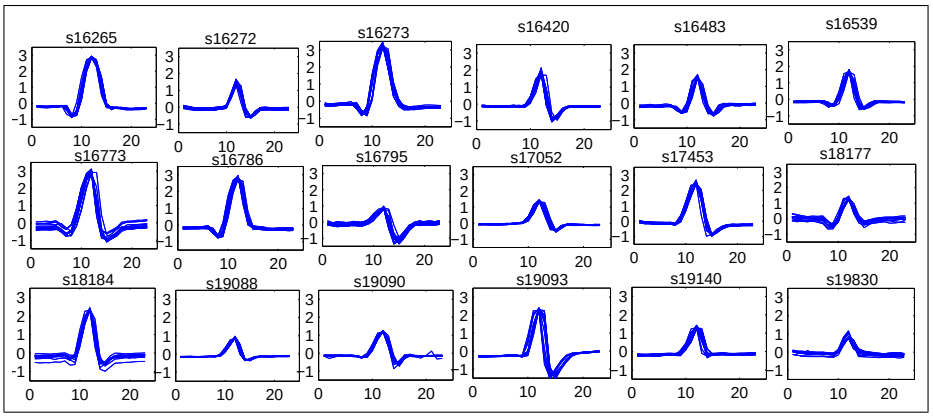

Fig. 4 – Differences between QRS complexes of the 18 subjects used in this experiment

	p1	p2	p3	. . .	p22	p23	subject
324 QRS complexes	-0.175	-0.195	-0.175	. . .	-0.315	-0.305	s16265
	0.005	-0.025	-0.095	. . .	-0.025	-0.065	s16272
	-0.265	-0.255	-0.275	. . .	-0.455	-0.475	s16273
	. . .	. . .	. . .	. . .	. . .	. . .	. . .
	. . .	. . .	. . .	. . .	. . .	. . .	. . .
	-0.185	-0.165	-0.195	. . .	-0.125	-0.105	s19140
	-0.055	-0.115	-0.135	. . .	-0.225	-0.225	s19830
	23 points						18 subjects

Fig. 2 – Overview of the data used in this experiment

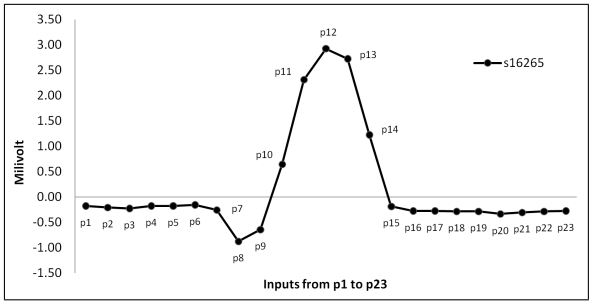

Fig. 3 – A QRS complex taken from subject s16265

the known subjects (i.e. targets). Many learning algorithms can be used during this leaning stage to adjust network parameters such as weights and biases to move the outputs closer to the targets.

We carefully chose training data so that it includes all the data points close to decision boundaries defining a subject. For each subject, the training dataset would include QRS complexes that have minimum and maximum R peak amplitudes among all QRS complexes of that subject, while the test set would only include QRS complexes with R peak amplitudes within this range. Although neural networks can be trained to generalize well within the range of inputs in training datasets (i.e. interpolation), they have limited abilities to accurately extrapolate beyond this range [8].

The input matrix had 23 rows and 216 columns as shown in Fig. 5. Each column contained the data of a QRS complex. The number of rows was equal to the number of points we used to plot a QRS complex. The target matrix in Fig .6 stored all known subjects of QRS complexes in the

	QRS1	QRS2	QRS3		QRS215	QRS216	
p1	-0.175	0.005	-0.265	. . .	-0.185	-0.055	23 rows
p2	-0.195	-0.025	-0.255	. . .	-0.165	-0.115	
p3	-0.175	-0.095	-0.275	. . .	-0.195	-0.135	
. . .	. . .	. . .	. . .	. . .	. . .	. . .	
p22	-0.315	-0.025	-0.455	. . .	-0.125	-0.225	
p23	-0.305	-0.065	-0.475	. . .	-0.105	-0.225	
	216 columns						

Fig. 5 – Overview of the input matrix

input matrix. Each of its columns represented one known subject and corresponded to one column of the input matrix. Therefore, the target matrix also had 216 columns. There were 18 distinct subjects so the target matrix had 18 rows from a1 to a18. Elements of target matrix are 1s and 0s only. Each subject was different from another by the position of the only element 1 in that column while other elements were 0s. Fig. 6 shows an overview of the target matrix.

	s16265		s16272		s19140		s19830	
a1	1	. . .	0	. . .	0	. . .	0	18 rows
a2	0	. . .	1	. . .	0	. . .	0	
a3	0	. . .	0	. . .	0	. . .	0	
	. .	. . .	. . .	. . .	. . .	. . .		
a17	0	. . .	0	. . .	1	. . .	0	
a18	0	. . .	0	. . .	0	. . .	1	
	216 columns							

Fig. 6 – Overview of the target matrix

The test dataset contained 108 QRS complexes of 18 subjects. Each subject had 6 QRS complexes. The test set was used to determine the classification accuracy rate, and to measure and compare the performance of MLP and RBF. The test set was also represented by input and target matrices. Their formats were very similar to those shown in Fig. 5 and Fig. 6.

III. SYSTEM ARCHITECTURES

The building blocks of neural networks are many artificial neurons connected together to produce a combined effect. For each type of neural network, we will start by describing the architecture of each neuron followed by the overall description of the network.

A. MLP Neural Network Architecture

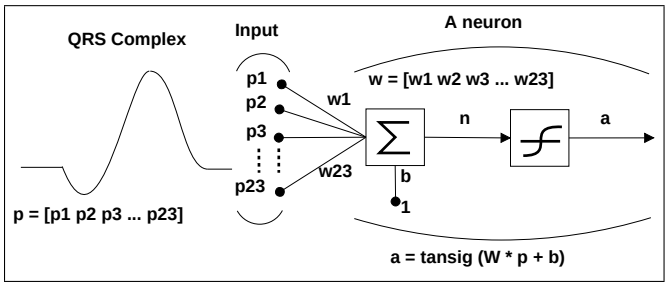

Fig. 7 – Structure of a neuron used in MLP neural network

MLP neural network is a network of many neurons organized into layers called hidden and output layers. Fig. 7 shows the structure of one of the neurons we used to build our MLP network. Each QRS complex is represented by 23-element column vector p. Each element of the input vector is conceptually connected to each neuron through a weight matrix W. The dot product in equation (1) is performed to obtain a weighted input $W \bullet p$.

$$W \bullet p = W_1 p_1 + W_2 p_2 + W_3 p_3 + ... + W_{23} p_{23} \quad (1)$$

The results is then added to the bias b to obtain the net input n which is passed through the Tan-Sigmoid transfer function (Fig. 8a) [9] to produce the output a. Equation (2) summarizes this process.

$$a = \text{tansig}(W \bullet p + b) = \text{tansig}(n) \quad (2)$$

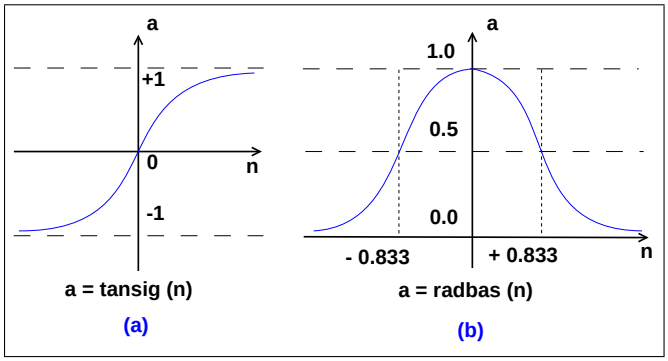

Fig. 8 – Graphs of Tan-Sigmoid transfer function (a) [9] and Radial Basis transfer function (b) [10]

In this experiment, we used a two-layer MLP neural network with 35 neurons in the hidden layer and log-sigmoid transfer functions for the hidden and output neurons as shown in Fig. 9. We selected the number of neurons in the hidden layers manually so that it was enough for the network to converge while making sure that overfitting did not occur. [11]. The number of neurons in the output layer is equal to the number of distinct classes [11]. Hence, we used 18 neurons in the output layer.

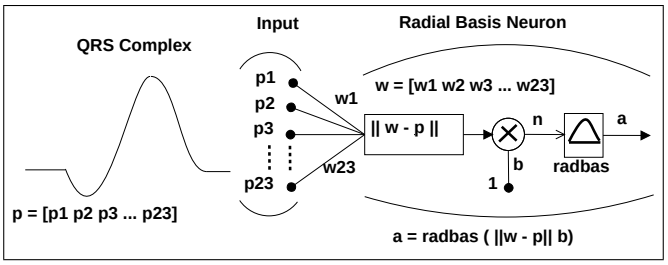

Fig. 10 – Structure of a radial basis neuron. (The $\|w - p\|$ box in this figure accepts the input vector p and the single row input weight matrix W, and produces the Euclidean distance of the two)

B. RBF Neural Network Architecture

Radial basis networks require more neurons than standard feedforward backpropagation networks, but can often be designed in a fraction of the time it takes to train standard feedforward networks. Fig. 10 shows the structure of a typical radial basis neuron. Here the Euclidean distance between p and W is calculated using Equation (3).

$$d(W,p) = \sqrt{(W_1 - p_1)^2 + (W_2 - p_2)^2 + ... + (W_{23} - p_{23})^2} \quad (3)$$

The results is then multiplied by the bias b to obtain the net input n which is passed through the radbas transfer function (Fig. 8b) [10] to produce the output a. Equation (4) summarizes this process.

$$a = \text{radbas}(\|w - p\| b) = \text{radbas}(n) \quad (4)$$

In this experiment, we used a two-layer RBF neural network as shown in Fig. 11. The number of radbas neurons in the hidden layer was 216 which was equal to the number of QRS complexes in the training dataset. This is also the drawback of this type of RBF because the number of hidden neurons is determined by the number of input vectors [12]. There were 18 neurons in the output layer. Competitive transfer functions [13] were used in the output layers.

IV. IMPLEMENTATION AND RESULTS

In MATLAB environment, we used the training dataset to train the MLP neural network in Fig. 9 several times. This helped the network to start with different initial conditions (i.e. initial values of input weights and biases) before each training cycle [11]. Finally, after several training cycles, the mean square error dropped to an acceptable value which was below 3.56×10^{-3} in our experiment. The trained MLP network was then tested with the testing dataset. Final results are shown in Table I. Also in MATLAB, the RBF neural network in Fig 11 was initialized and tested using the training and testing dataset respectively. Final results are shown in Table I.

Using Weka, we combined the training with the testing dataset into one dataset which had 324 QRS complexes. Both MLP and RBF neural networks were used with 10-fold cross validation to classify those QRS complexes. When working with RBF network, 18 clusters were used because there were 18 distinct subjects. Final results are shown in Table II.

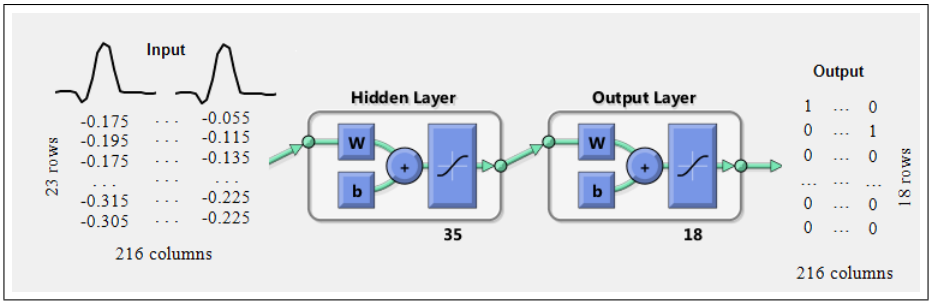

Fig. 9 – Architecture of the MLP neural network used in this experiment

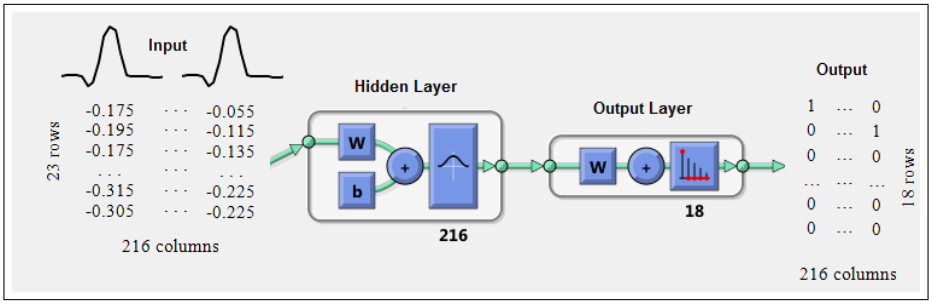

Fig. 11 – Architecture of the RBF neural network used in this experiment

	MLP	RBF
Correctly Classified Instances	106	107
Incorrectly Classified Instances	2	1
Accuracy rate	98.15%	99.07%

TABLE I – Classfication results obtained using MLP and RBF neural networks in MATLAB environment over 108 QRS complexes of 18 subjects

	MLP	RBF
Correctly Classified Instances	323	316
Incorrectly Classified Instances	1	8
Accuracy rate	99.69%	97.53%

TABLE II – Classification results obtained using MLP and RBF neural networks in Weka environment over 324 QRS complexes of 18 subjects

V. CONCLUSION

The results have shown a high level of accuracy when using QRS complexes to identify people. Multilayer Perceptron and Radial Basis Function neural networks have also shown their usefulness in this classification task. After training, these networks can be reused multiple times for those distinct 18 subjects. Multilayer neural networks can be trained to generalize well within the range of inputs for which they have been trained. However, they do not have the ability to accurately extrapolate beyond this range. Therefore, the training data should be chosen carefully to cover a wide range of input values to the neural networks to obtain the highest level of accuracy.

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