A Neural Network to Identify Human Subjects with Electrocardiogram Signals

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***Abstract*—This paper presents a neural network developed to identify human subjects using electrocardiogram (ECG) signals collected from an "in-house" wearable electrocardiogram (ECG) sensor. In this project, noises were first removed from the raw signals with wavelet filters. ECG cycles were then extracted from the filtered signals and decomposed into wavelet coefficient structures. These coefficient structures were used as input vectors to a 3-layer feedforward neural network that generates the identification results. In the current study, 61 datasets collected from 23 subjects were utilized to train the neural network, which thereafter was tested with 15 new datasets from 15 different subjects. All the 15 subjects in the experiment were successfully identified. The testing results demonstrate that the neural network is effective.**

***Keywords*—Coefficient structure, electrocardiogram, neural network, neural network training, wavelet decomposition**

I. Introduction

In recent years, researchers have recognized the uniqueness of individual's electrocardiogram (ECG) signal, electrical waveforms that origin from the sinus node of the heart causes the heart muscle to pump, and have shown the potential of using ECG as an identification modality [1-4]. For many of these identification methods, extraction of time domain features is required before statistical analysis. These features usually include P-Q interval, Q-T interval, S-T segment etc [2-4]. However, these features may not be always easily obtained due to variations of ECG waveforms from different people [5]. Under these situations, regular statistical classification approaches may be inadequate. Wavelet analysis offers a different view of data than those traditional techniques by presenting information from both time and frequency domains [6]. This information, contained in wavelet coefficient structures, can be used for classification.

Artificial neural networks, working similarly to the human brain's massive parallel distributed processing activities with self-organization, self-learning, and adaptive capacity [7], find applications for this kind of vague and random information. Artificial neural networks can be trained to form arbitrary input-output mapping, making them useful a broad variety of applications. Artificial neural networks have been widely used to solve complex problems and information processing, such as pattern recognition [7-9], signal processing [10], decision-making [11], combinatorial optimization [12] etc. Of these application categories, neural networks demonstrated the greatest potential in pattern recognition and classification [8]. If constructed with the proper architecture and trained with appropriate data, neural networks can tolerate noise and responds correctly for unknown patterns [7]. It has been proven that a three-layer feedforward network is usually sufficient to approximate any mapping function [13].

Since no complicated and unsure time domain feature extraction or classification criteria calculation is needed when neural networks are used, it is natural to consider neural networks for human identification with ECG signals where time domain features are difficult to locate. Thorough literature review shows that no research has been conducted on using neural network pattern classification methods for biometric applications with ECG signals.

In our project, we developed a three-layer feedforward neural network to identify human subjects using signals collected with an "in-house" wearable ECG sensor [14], after the signals were processed with a wavelet decomposition methods [15]. Following this introduction, the data collection and preparation process is first briefly reviewed, after which the neural network identification method is described in detail, including neural network architecture, training, and test. Testing results from our experiment are then summarized and discussed.

II. Method

We collected data with a simple ECG sensor built earlier. More information about the sensor and the data acquisition system can be found in [14]. The data were filtered and decomposed with MATLAB wavelet analysis tools [15]. The wavelet de-noising noisy data technique can usually de-noise a signal without appreciable degradation [6]. The processed data were entered into a three-layer feedforward neural network for classification. This section briefly introduces the data collection and preparation, and emphasizes the neural network design, training, and test.

A) Data Collection and Preparation

A small ECG sensor based on a low power precise instrumentation amplifier was built to collect signal. The raw ECG signal is acquired and stored by a LabVIEW program running on a personal computer through a National Instrument multifunctional input/output card (DAQCard^{TM}-6062E); it is then pre-processed in a MATLAB program. First, individual

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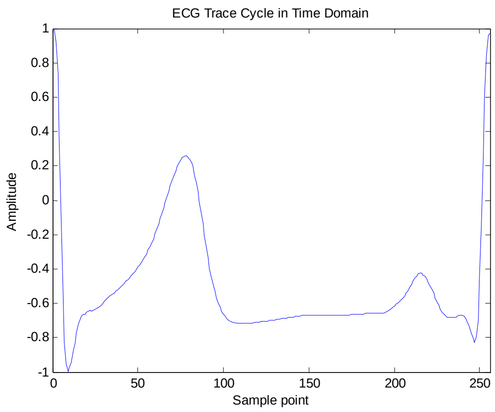
ECG cycles are separated and waveform cycles are interpolated to the same length of 256 points. Although the numbers of ECG cycles of all the dataset vary, 40 cycles are selected from each dataset to further analysis. More information about the process of the 40 cycles can be found in reference [15]. The ECG signal has a time-varying morphology and which is subject to patient physiological variations. There are many sources of noise in a clinical environment that can degrade the ECG signal [16, 17]. In this study, the 40 cycles were reduced to 10 cycles by averaging every 4 cycles to one cycle, to reduce the effects of signal variation effects to identification performance. Therefore, each sample dataset, regardless the original length of the waveform, is reduced to 10 heart beat cycles. Each cycle contains 256 discrete sampling points. The amplitude of all the ECG signal cycles is normalized in to values in the range of [-1 1].

B) Wavelet Decomposition



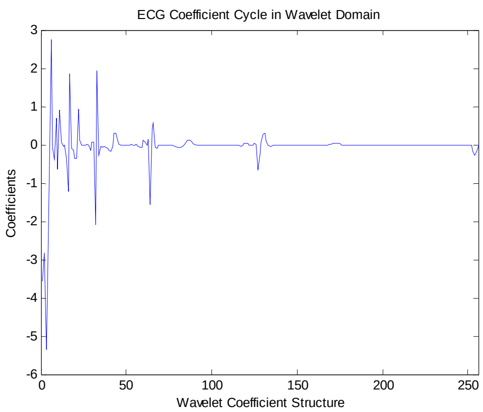


Fig.1. Original ECG cycle in time domain (top) and its wavelet coefficients (bottom).

A ‘bior1.1’wavelet is used after the data preprocess. This family of wavelet exhibits the property of linear phase, which is needed for signal and image reconstruction [6]. With the ‘bior1.1’ wavelet decomposition, the signal cycles were converted into wavelet coefficient structures, in form of vectors with 256 elements. This wavelet transformation is on scale 6; the coefficient structures are composed with 7 parts, in a [4, 4, 8, 16, 32, 64, 128] structure vector. The coefficient structures from ‘bior1.1’ transformation retain a linear relation with the original time domain signal. Each part contains several coefficients that are related with the signal’s time and frequency features in certain frequency region. Fig. 1 shows an original ECG cycle and its coefficients in the structure after the transformation.

C) Network Architecture

Selecting appropriate network architecture and training samples is very important for the performance of a neural network. In our case, a multilayer Backpropagation (BP) neural network is established. The input vector to the neural network includes at least coefficient structure of two different ECG cycles, which come from either the same subject or two different subjects. As described earlier, each cycle’s coefficient structure has 256 coefficients. Thus, the network input layer accepts a 512-element vector as the input vector. The output of the neural network generates the discrimination results which indicate whether the two cycles in the input vector come from the same or two different individuals. If the two wavelet coefficient structures in the input vector belong to the same individual, the network output is +1; otherwise -1. Fig. 2 shows a 3-layers neural network, with a 512-element input vector and a single-element output. The number of neurons in the network is directly related to the number of the input vector elements [18]. In this neural network, 512 elements contain in the input vector. The designed network has an input layer of 64 neurons, a hidden layer of 128 neurons, and an output layer of 1 neuron. Each layer consists of weights, a bias vector, a transfer function, and an output vector. A large number of weights (in this case, 41088) are involved in the network. Note that around half of the elements of the two coefficient structures contained in the input vector are set to zeros after wavelet decomposition. This should significantly reduce the amount of computation required for neural network training and testing.

D) Training Samples Generation

Before a neural network can be used for the discrimination, the network must be trained with enough, comprehensive samples to generate accurate outputs. Due to the large number of weights in the network and the uncertain relationship between the two wavelet coefficient structures in the input vector, a large number of sample-target combinations are needed to ensure the training quality.

To generate enough training samples and their correspond training targets, the following factors are considered: 1) one training sample should have at least two cycles from different sample datasets (each has 10 cycles); 2) the target vector should have about the same number of +1s and -1s. In the default training setting, the MATLAB Neural Network Toolbox uses 60% of the input vectors for training, 20% for validation, and the other 20% for the test. The vectors for training, validation, and test are all randomly chosen from all the available input vectors. It is important to ensure the numbers of targets with +1 and -1 are close for all three steps; 3) an input vector for training combines two 256-element coefficient structures. When the order of the two structures in the vector is swapped, the training target remains the same. We can double the number of training opportunities by swapping the structure order and increase training accuracy.

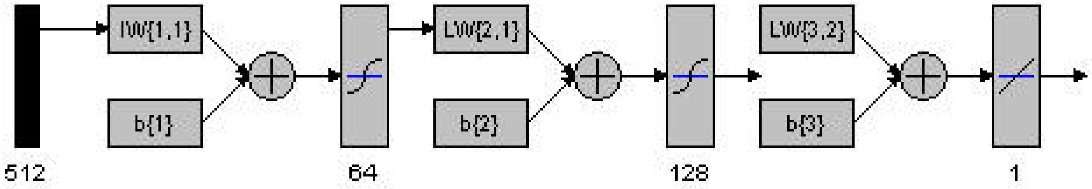


Fig. 2. A 3-layers neural network architecture for ECG signal identification.

E) Neural Network Training

After the network is generated with initialized weights and biases, the network is ready for training. During the training, the weights and biases of the network are iteratively adjusted to decrease a network performance function until it converges to a predefined level. In general, training neural network with a larger training datasets can reduce the recognizing error rate. However, it takes more time to achieve small output errors, especially when the data set contains patterns that are difficult to classify [19]. Based on the MATLAB platform, there are several training algorithms can be used, each of which has its own application fields [8, 20]. The Fletcher-Reeves version of the conjugate gradient (*traincgf*) is used here for network training. This training algorithm is fast, and works well for neural networks with a large number of weights [18]. Fig. 3 shows the network training performance. The curve, representing the sum squared error (SSE) of the network output, gradually converges to the pre-set training goal after a number of epochs. There are several parameters to be setup, including *epochs, show, goal, and learning rate* etc. Totally 3782 sets of data are used as the neural networks training input, the entire training process takes from 2 to 3 hours, depending on the settings.

F) Testing

An ECG signal database with subjects' ECG information has been constructed before testing. Each entry in the database includes an ID number and a wavelet coefficient structure found with the process introduced previously. When a new dataset is to be identified, it is first pre-processed; its wavelet coefficient structures are then obtained for the next testing steps: 1) take one cycle's coefficient structure from those of the ten cycles of the new tested dataset, combining with one coefficient structure from a dataset of a subject in the database. These combinations of two structures make 100 input vectors for the new testing dataset to be tested with a subject in the database; 2) one hundred network discrimination outputs are calculated corresponding to the 100 input combinations; 3) these 100 output values is used to determine whether the two wavelet coefficient structure belong to the same individual or not.

After obtaining an approval from the Internal Research Board, 23 individuals' ECG signals were collected. The subject's characteristics are listed in Table I. All the individuals were sampled twice with an interval of from 5 to 30 days. During each sampling, two or three sets of data collected with an interval of ten minutes between two datasets. Therefore, 4 ~ 6 datasets were sampled a subject has.

TABLE I

TESTING SUBJECT CHARACTERISTICS

Total	Male	Female	Age Range	Race
23	18	5	18~50	Asian, American

III. RESULTS

Fifteen ECG datasets from 15 subjects that had not been used for network training were prepared for verification. The 3-D stem graph in Fig. 4 shows the testing outcome, where the height values in the coordinate is the cumulative score of 100 neural network outputs. A highest score between a testing dataset and an enrolled subject in the database represents a match. The diagonal elements in the coordinate have the largest scores, suggesting that all the 15 individuals' ECG signals are correctly recognized (Both the testing and enrolled subjects are sorted in alphabetic order; therefore, successful matches occur on the diagonal). Fig. 5 illustrates the results in the manner of image gray scale level: a cell with a darker color indicates that the two individuals' heartbeats (horizontal and vertical) match better (Datasets for 23 subjects are enrolled in the database, while the number of testing datasets is 15, so some columns do not have outputs corresponding to subjects in the database). It verified that the neural network output can effectively identify individuals from one another.

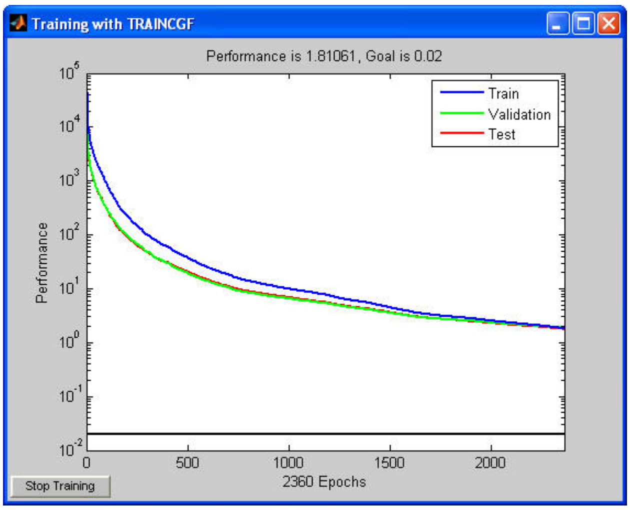


Fig. 3. Convergence of errors during the neural network training.

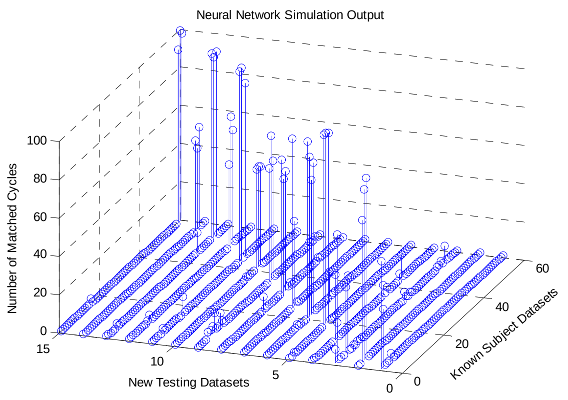


Fig. 4. Identification results for the 15 testing datasets.

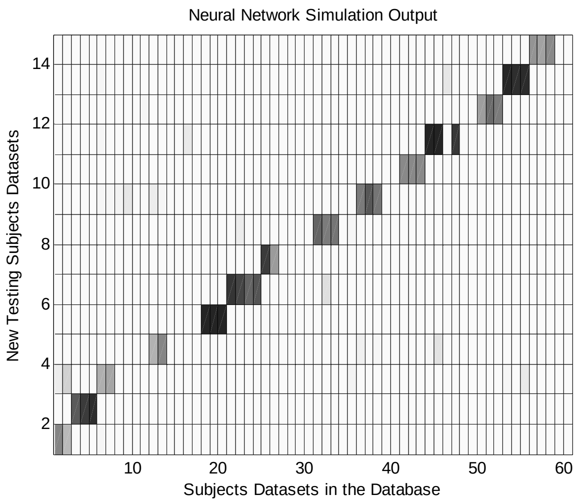


Fig.5. Neural network identification outputs.

IV. CONCLUSION

This paper presented a study on using ECG signals for individual identification. The results from the research demonstrate that a 3-layer BP neural network with wavelet decomposition coefficients as input can effectively identify subjects. Because time and frequency domain information is contained in the wavelet decomposition coefficient structures, and neural networks are suitable for recognition of uncertain relation patterns, the proposed identification approach does not require statistical feature extraction. This method may be used to identify those subjects with poor ECG signals. Future work includes optimization of the neural network architecture to reduce training time and testing its efficacy with a larger number of subjects.

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