Error-Rate Analysis for ECG Classification in Diversity Scenario

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***Abstract*— This paper proposes with error-rate for an ECG classifier to support doctors in clinical diagnosis. In particular, ECG signals, which are diversity, may be obtained from various ECG machines on many patients. Therefore, ECG classification has been a critical challenge for scientists in recent years. In the previous studies, the ECG classification produced a promised precision. However, diversity phenomenon on patients had not been considered yet to be able to increase precision. In this paper, a performance of a state-of-art ECG-classifier in diversity scenario will be analyzed using error-rate. In this research, training and testing data are arranged to be different on MIT dataset. Thus, ECG data are separated and then extracted into each heartbeat using a discrete wavelet transform algorithm. Extracted features are trained using a state-of-art neural network method in diversity and non-diversity scenarios. Experimental results demonstrated that the accuracy of the separated data is higher using the ECG classification.**

Keywords*— *MIT ECG dataset, Discrete wavelet transform, Neural Networks, classification accuracy

I. INTRODUCTION

An electrocardiogram (ECG or EKG) is a measuring of how the electrical activity of the heart changes over time as action potentials propagate throughout the heart during each cardiac cycle. The ECG is a graphical representation of the electrical activity of the heart. In addition, an ECG is not only done to find the cause of palpitations or chest pain, dizziness, shortness of breath, but also it has been in use as a non-invasive diagnostic tool. The classification of ECG data is done based on the ECG beat features [1].

The ECG signal contains noise components. In order to have the classification with high precision the ECG signal must be removed noise components by the filter. The algorithms used to remove noise on the ECG signal were wavelet filter, baseline wander, low pass and high pass filter, segmentation of ECG beats or data normalization [2-6]. The most honest signal which preprocessed is used to treatment for the next step.

This classification method extracts some features from the ECG signal as heartbeat temporal features, morphological features, frequency domain features and the coefficients of wavelet transform [7]. After extracting characteristic, ECG signal will be reduced dimension to take training. Dimensionality reduction algorithms such as ICA, PCA, LDA is used to select robust features [8-10]. Some methods such as symmetric uncertainty, FCM, GA (meta-heuristic) were also used for feature selection [11, 12]. ECG signals after dimensionality reduction will be included in the classification to separate the normal and abnormal heart rhythm ties. Algorithms was used to classify the ECG are SVM, SVM classifier with Kernel-Adatron (KA), Modular neural network - MLPNN, Generalized FFNN, Modular neural network, PNN Feed forward, forward neural network with back Cascade propagation [11, 13-16]. The previously studies announced with high precision, but it didn't show clearly how to choose training data and testing data. In this study, the accuracy of the classification in two cases will be investigated.

The paper is organized as follows: Section-2 presents related fundamental knowledge and proposed method. Experimental results and discussion are described in Section-3. The final section shows the conclusion of the article.

II. ECG MATERIALS OVERVIEW

Electrocardiogram is a process that records the electrical activity of the heart over a period of time using the skin electrodes. The standard 12-lead electrocardiogram is a representation of the heart's electrical activity recorded from electrodes on the body surface. ECG signals recorded on grid paper, horizontal axis representing time and vertical axis are voltages, divided into large squares of 5mm size, each large grid consisting of 25 squares small size 1mm as shown in Fig. 1. If all ECG signal rates are 25mm/s constant, then 5 large squares represent the time of 1 second, 300 large squares corresponding to 1 minute, and number of R peaks in 300 major squares. The number of beats per minute. For example, in a lead II heartbeat, there are 1 R peak in every 5 large squares, so 300 large squares have 60 vertices. R, so the patient's heart rate is 60bpm. Fig. 1 also shows how the heart rate is calculated. Therefore, the simple method for calculating heartbeat from ECG signals is: define two peaks R, count the number of squares between two peaks R then take 300 divided by the number of squares between two peaks R. Each ECG beat consist P wave, QRS complex, and T wave. Each peak (P, Q, R, S, T, and U), intervals (PR, RR, QRS, ST, and QT) and segments (PR and ST) of ECG signals have their normal amplitude or duration values. The diagram illustrates ECG waves and intervals is shown in Fig. 2. The origin of the ECG signals in the MIT-BIH database was 4000 long-term Holter signals obtained from 1975 to 1979 at the Beth Israel Heart Attack Laboratory. About 60% of the signals come from inpatients. This data set consists of 23 signals (numbered from 100 to 124 with a number is non-existent numbers (110), and 25 signals (numbered from 200 to 234 and some numbers aren't appeared).

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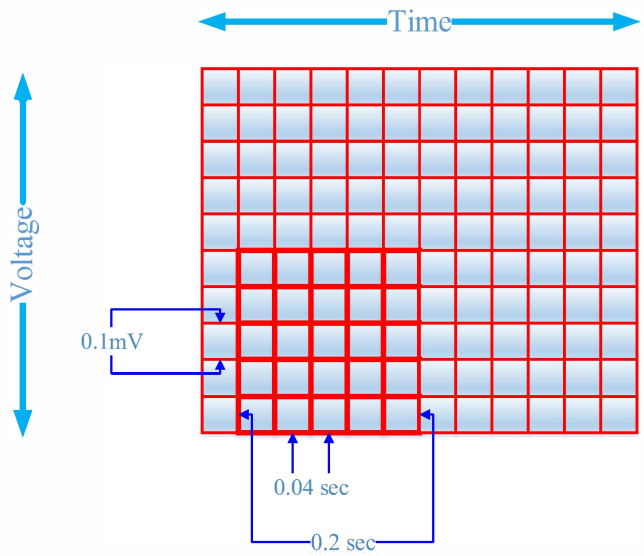

Figure 1. Standard time and voltage measures on the ECG paper

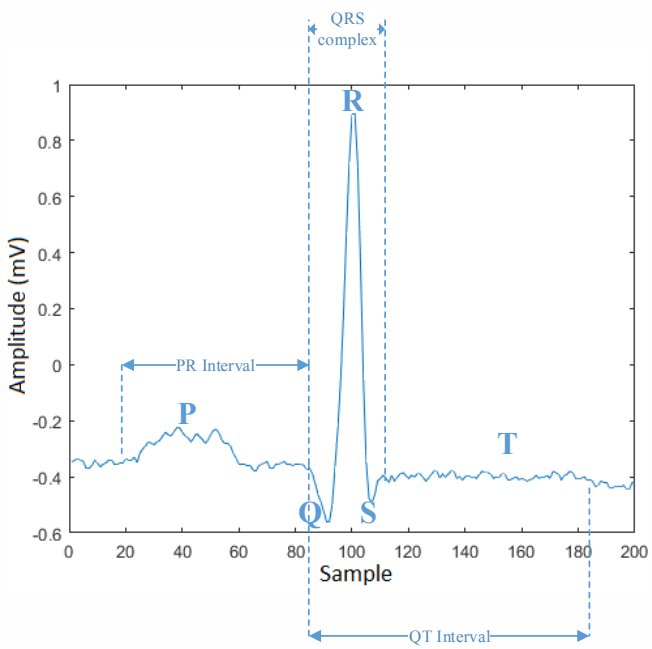

Figure 2. The diagram illustrates ECG waves and intervals

Signals were numbered from 200 to 234 selected from the same set of 23 records (100 to 124) included rare but clinically significant phenomena, though shown randomly and quite small on the Holter. Total 48 signals last over 30 minutes.

After download data we have 144 files with 48 data sets represent for 48 MIT-BIH ARHYTHMIA DATABASE signals. Each data sets were format with MIT format is: *.atr file (MIT annotation files), *.dat file (MIT signal files), *.hea file (MIT header files). MIT signal files are binary files containing samples of digitized signals. These files store the waveforms, but they cannot be interpreted properly without their corresponding header files. They are in the form: RECORDNAME.dat. Header files are short text files that describe the contents of associated signal files. These files are in the form: RECORDNAME.hea. MIT Annotation files are binary files containing annotations (labels that generally refer to specific samples in associated signal files). Annotation files should be read with their associated header files. We have overviewed information about ECG signal, how to calculate ECG rate and database we will use to classify ECG data so next section is the proposed method for classification ECG.

III. PROPOSED METHOD

There are several methods for classification ECG. The following method is the state-of-art method for ECG diagnosis recognition has been proposed in Fig. 3. Block Diagram ECG classification includes three core areas: data preparation, extracted characteristic block and typical classification blocks. ECG after downloading from the available data is taken every heartbeat in the time domain, then the heart rate is converted through DWT domain to easily distinguish minor changes and feature extraction referendum, the data was in dimensionality reduction and classified.

A. Discrete Wavelet Transform

ECG is an important tool in the diagnosis of cardiovascular pathologies arrhythmias and structural abnormalities. To read ECG correctly and fully should have the appropriate approach. Normally or anomaly heart beats depend on the changes on the amplitude and duration of ECG. Characteristic of normal and abnormal heart rhythm are distinguished better in Discrete Wavelet Transform (DWT) domain than in the time domain. Small changes amplitude and duration of the ECG in the time domain is not as clear as in DWT domain [17, 18]. In wavelet analysis, signal characteristics are clearly distinguished through detailed signal level 2, level 3, level 4 and signal approximation level 4. Performing transform wavelet very complex. Continuous wavelet transforms take too much of the original waveform pattern. There are many unnecessary coefficients generated by signal analysis. This redundancy is not a problem in analysis, but it would really be a problem if the application was to restore the original waveform. Restoring the original signal will take a long time. Therefore, for applications requiring two-dimensional transformations, one has to introduce a transformation where the coefficients are created to be at least as fast as possible to restore the original signal. Discrete wavelet transformations do this. Discrete wavelet transform is a special case of wavelet transform. Discrete wavelet transforms provide a close relationship of signal in time and frequency domain and are defined as in (1):

$$W(j,n) = \sum_{j}\sum_{n} s[n] 2^{-\frac{1}{2}} \psi(2^{-\frac{1}{2}} k - n) \qquad (1)$$

Where $W(j,n)$ is the coefficients of the discrete wavelet transform, $s(n)$ is the discrete signal and ψ is the discrete wavelet transform function.

From the definition of discrete wavelet transform in (1). Signals $s(n)$ are analyzed into small components through low pass filters and high pass filters. The wavelet decomposition algorithm is a signal that is analyzed into

different frequency bands by analyzing the signals into coarse approximations and detailed information. The discrete signal $s(n)$ is passed through a low pass filter $h[n]$ and a high pass filter $g[n]$. The output of the low pass filter $h[n]$ produces the approximation (a) that will continue to analyze at a higher level, and the output of the high pass filter $g[n]$ will be the detail component item (d). Here, after passing each filter the bandwidth of the signal was divided by two. This two-component formula is given in (2) and (3).

$$a[k] = \sum_n s(n) f[2k-n] \tag{2}$$

$$d[k] = \sum_n s(n) g[2k-n] \tag{3}$$

When performing the first analysis, the component $a_1[k]$ and $d_1[k]$ is called analytic at level 1. The component $a_1[k]$ continues to be parsed again to produce $a_2[k]$ and $d_2[k]$ are called level 2 analyzes. So this process will be performed to the required level of analysis.

Each of 200 heart signals is split into four levels using wavelet approximation of FIR Mayer ('dmey'). The approximate level-4 coefficient is included the frequency range from 0 Hz to 11.25 Hz, while the level-4 detail coefficient is included the frequency range 11.25 Hz to 22.25Hz. The power spectral density of the different beats of the information is clearly distinguished in these coefficients (coefficient details and approximate level-4). After having criticized characteristic, heart rate can lead to the classification. The classification used in this study is Neural Network algorithm as shown in Fig. 4.

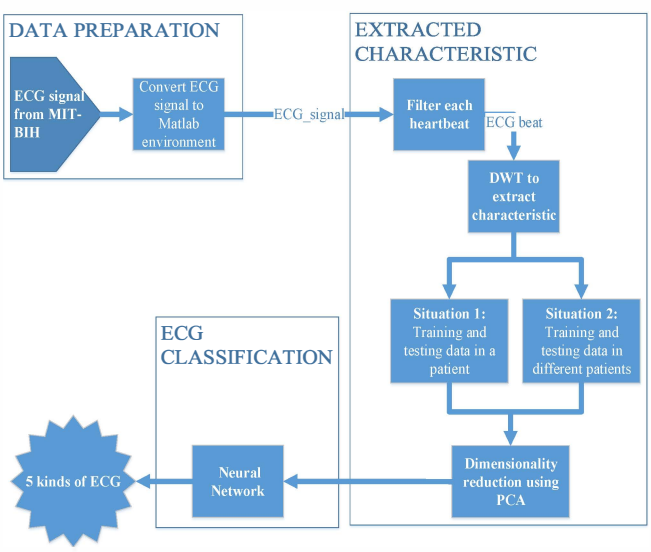

Figure 3. Block diagram of proposed method

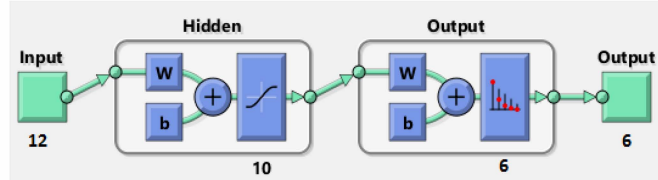

Figure 4. Model Neural Network Classifier

B. Neural Network

In this study, the classification model used is feed-forward neural network. Input layers consists 12 layers corresponding 12 features; a hidden layer include 10 neurons; and an output layer consists 6 neurons represents 6 ECG formats [19]. In addition to this method, the neural network weights are updated using the error back-propagation method. Based on the class label of each model in the training data set, Mean Square Error (MSE) between the desired response and the actual response of the Neural Network is calculated. The weights are updated in the Neural Network until the error value of the MSE reaches below (0.0001). The back-propagation algorithm for training the triple-layer transmission network is summarized as follows.

Step 1: Select the speed $\eta > 0$, choose the maximum error E_{max}.

Step 2: Getting started. Assign the error $E = 0$. Assign the run variable $k = 1$.

Assign the weights: $w_{iq}(k), v_{qj}(k)(i = \overline{1,n}; j = \overline{1,m}; q = \overline{1,l})$ equal to any small random value.

Step 3: (Data transmission) Calculate the output of the network with the input signal $x^{(k)}$:

Hidden layer:

$$net_q(k) = \sum_{j=1}^{m} v_{qj}(k) x_j(k) \qquad (q = \overline{1,l}) \tag{4}$$

$$z_q(k) = a_h\left(net_q(k)\right) \qquad (q = \overline{1,l}) \tag{5}$$

Output layer:

$$net_i(k) = \sum_{q=1}^{l} w_{iq}(k) z_q(k) \qquad (i = \overline{1,n}) \tag{6}$$

$$y_i(k) = a_o\left(net_i(k)\right) \qquad (i = \overline{1,n}) \tag{7}$$

Step 4: (Reverse error) Network weight update:

Output layer:

$$\delta_{oi}(k) = \left[\left(d_i(k) - y_i(k)\right)\right]\left[a'_o\left(net_i(k)\right)\right] \tag{8}$$

$$(i = \overline{1,n})$$

$$w_{iq}(k+1) = w_{iq}(k) + \eta\delta_{oi}(k) z_q(k) \quad (q = \overline{1,l}) \quad (i = \overline{1,n}) \tag{9}$$

Hidden layer:

$$\delta_{hq}(k) = \left[\sum_{i=1}^{n} \delta_{oi}(k) w_{iq}(k)\right]\left[a'_h\left(net_q(k)\right)\right] \quad (q = \overline{1,l}) \tag{10}$$

$$v_{qj}(k+1) = v_{qj}(k) + \eta\delta_{hq}(k) x_j(k) \quad (j = \overline{1,m}) \quad (q = \overline{1,l}) \tag{11}$$

Step 5: Calculate the cumulative error:

$$E = E + \frac{1}{2}\sum_{i=1}^{n}\left(d_i(k) - y_i(k)\right)^2 \tag{12}$$

Step 6: If $k < K$ then assign $k = k+1$ and return to step 3. If $k = K$ then continue to step 7.

Step 7: End a training cycle.

If $E < E_{max}$ then end the learning process.

If $E \geq E_{max}$ then assign $E = 0; k = 1$ and return to step 3 beginning a new training cycle.

The method proposed above is the general method for Neural Network classification, the following section is result and discussion.

IV. RESULTS AND DISCUSSION

In the research, database of MIT-BIH arrhythmia [20] are used for sampling at 360Hz frequency. In this analysis, the author used all the data of the MIT-BIH arrhythmia database as recommended by ANSI / AAMI EC57: 1998. Table 1 shows that the different beats of the MIT-BIH dataset are grouped into six main categories. It means that, the entire data of the database of MIT-BIH arrhythmia were used for making changes of data rates up from 10% to 90% of training data and down from 90% to 10% of testing data. Therefore, the confusion matrix tables obtained are shown in Fig. 5 and Fig. 6, including 10% of the training data and 90% of the testing data. Assume that situation 1 was mixed each heartbeat of all 46 patients together, then divided randomly into two sets of heart rate data: a set of data intended to train and the remaining data to check. However, situation 1 exists the problem a patient having a heart rate in the training data set and test data set.

It can be seen in Fig. 5 that the 95.1% accuracy of the classification is very high. Situation 2 is the opposite case compared with situation 1, particularly randomized patients with heart rates are obtained and separated for training and patients with heart rates for testing. As results, patient's heart rates in training set are different from other rhythms in testing set. Therefore, the classification accuracy is not high compared with the classification of situation 1, only 84.0%.

TABLE I. DIFFERENT BEATS OF THE MIT-BIH DATASET GROUPED INTO SIX CATEGORIES

Serial	Symbol	Detailed name for diseases	The names of the heart beats are classified	Type
1	N	Normal Beat	No Ectopic beat	1
2	L	Left bundle branch block Beat		
3	R	Right Bundle Branch Block Beat		
4	e	Atrial Escape Beat		
5	j	Nodal (junctional) Escape Beat		
6	A	Atrial Premature Beat	Supra-ventricular Ectopic beats	2
7	a	Aberrated Atrial Premature beat		
8	J	Nodal (junctional) Premature Beat		
9	S	Supra-Ventricular Premature Beat		
10	V	Premature Ventricular Contraction Beat	Ventricular ectopic beats	
11	E	Ventricular escape Beat		
12	F	Fusion of Ventricular and Normal Beat	Fusion beat	4
13	/	Paced Beat	Unknown beat	5
14	f	Fusion of paced and normal Beat		
15	Q	Unclassifiable Beat		
16	'!'	Ventricular flutter wave	Non-beat	6
17	'"	N/A		
18	'+'	N/A		
19	'['	N/A		
20	']'	N/A		
21	'x'	N/A		
22	'|'	N/A		
23	'~'	N/A		

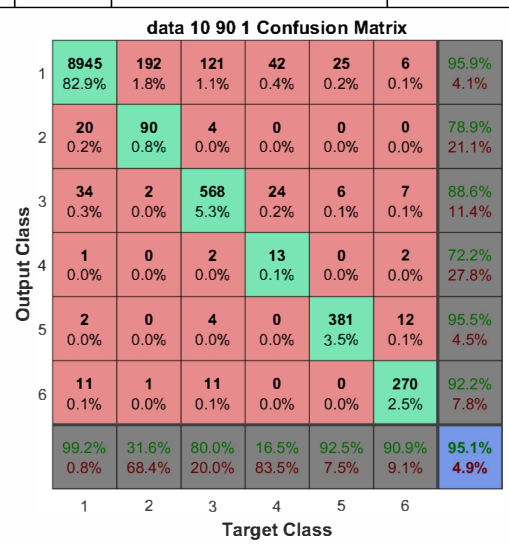

Figure 5. Confusion matrix table situation 10% training data and 90% testing data in the same patient

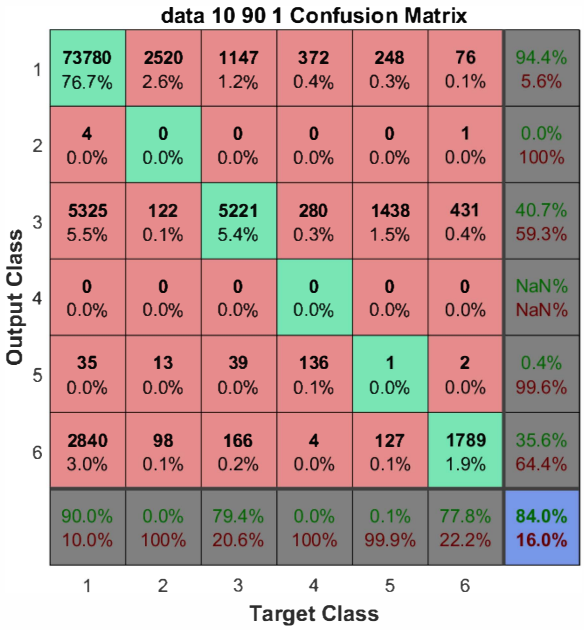

Figure 6. Confusion matrix table situation 10% training data and 90% testing data in the different patients

V. CONCLUSION

An ECG MIT dataset was collected and then built with heart rate features extracted from each dataset. The extracted features were converted into the frequency domain using the DWT method. Moreover, a PCA algorithm for dimensional reduction was applied and the PCA feature data were used for the ECG classification using the Neural Networks. Experimental results show that, the first situation is that the training and testing dataset of patients are the same with the 95.1% accuracy of this proposed approach. The second situation is that the training and testing dataset of patients are separating with the 84.0% accuracy. Therefore, the error-rate of this proposed method in the situation two is higher in the situation one.

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BÀI BÁO KHOA HỌC

THỰC HIỆN CÔNG BỐ THEO QUY CHẾ ĐÀO TẠO THẠC SỸ

Bài báo khoa học của học viên

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