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ECG ARRHYTHMIA RECOGNITION IMPROVEMENT USING RESPIRATION INFORMATION

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Abstract. Electrocardiogram (ECG) and respiration signals are two basic but important biomedical signals. They provide good source of information used to determine the patient’s conditions, where the earlier is more popular. The difficulty is the ECG signals are usually of small amplitude and are susceptible to various noises such as: the 50 Hz grid noise, poor electrodes’ contacts with the patient's skin, the patient’s emotional variations, the respiration and movements (including the breathing movements) of the patient, etc. In this paper we propose two ways to improve the accuracy of ECG signal recognition by filtering out the effect of the respiration in the ECG signal and by using the information of breathing stage as features in ECG signal classification. These approaches can improve the reliability and accuracy of the arrhythmia classification. As the classifier we use the modified neuro-fuzzy TSK network. The proposed solution will be tested with data from the MIT-BIH and the MGH/MF databases.

Keywords: ECG signal recognition, arrhythmia recognition, respiration, neurofuzzy network, intelligent classifier.

Classification numbers: 4.2.3; 4.7.3; 4.7.4.

1. INTRODUCTION

Despite the rapid development of medical technologies, the electrocardiogram (ECG) remains one of the main tool used by the doctors to detect the health conditions of the patients. The ECG signal is still collected by measuring the voltage difference between two electrodes attached to the patient [1]. Since there is still no perfect ECG signal analysis and classification algorithm, actually there are many research actively being performed to increase as high as possible the accuracy and the reliability of the results. One of the sources of difficulty in classifying ECG signals is the influence of the patient’s movements, among which there are the unavoidable respiration movements.

When the patient breathes, the relative positions of the electrodes vary and also the contacting impedance between the electrodes and the skins change to affect the quality of the ECG signal registered [2, 3, 4, 5, 6]. At the same time, it’s known that during inhaling period, the heart rate accelerates and during the exhaling period, the heart rate slows down. These factors (and not only) lead to changes in the ECG signal [7]. An ECG signal, as the superposition of a number of electrical events in the heart, consists of characteristic points as shown in Fig. 1.

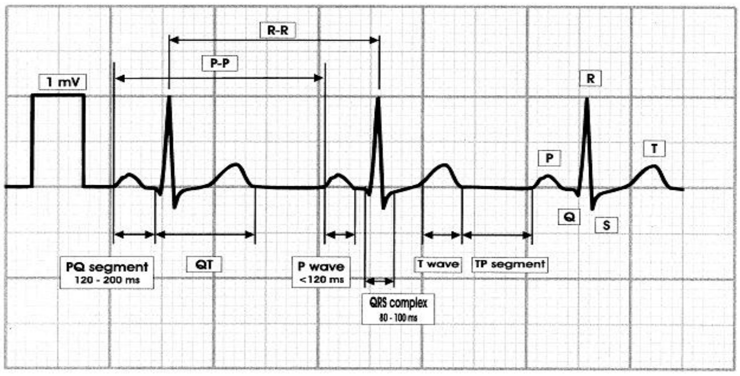


Figure 1. Example of ECG signal and its characteristic points.

The respiration is a vital activity of living. Performed in the lung's cells, it provides oxygen for the blood and withdraws back the carbon dioxide. Studies such as in [5, 6] have shown that respiratory activities lead to electrocardiographic signal changes.

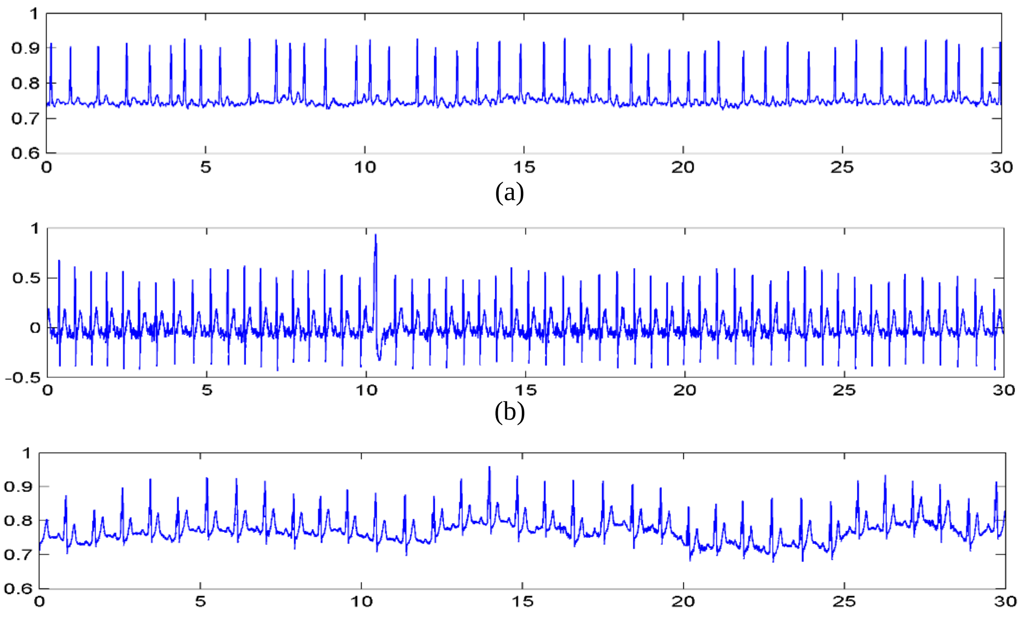


Figure 2. Examples of ECG signals affected by: a) sinus arrhythmia with R-R intervals changed, b) amplitude modulated, and c) baseline drift.

The respiration activity may affect the ECG signal and cause the so called sinus arrhythmias, amplitude modulation and baseline drift.

- Sinus arrhythmias: Sinus arrhythmia is a phenomenon in which the RR interval of an ECG signal is altered by the rhythm, i.e. during inhaling period, the heart rate accelerates and during the exhaling period, the heart rate slows down as shown in Figure 2a.

Many research use this RR interval as one of the important features for ECG classification [4], so changing the RR cycle will adversely affect the quality of the ECG signal classification.

- Amplitude modulation effect: Because during the breathing process, the volume of the thoracic cavity changes, resulting in changes in the thoracic impedance [5] and changing the angle of the cardiac vector compared to the reference vector, this makes the amplitude of the R peak modulated according to the rhythm [6] as shown in Figure 2b.

  Since the peak amplitude is also an important feature [9], then the modulation of the R peak of the ECG signal also affects the results of classification.

- The baseline drift: The breathing process moves the skin resulting in a change of contact impedance between the electrodes and the skin surface, which causes a baseline drift in the ECG signal [2] is illustrated in Fig. 2c.

From the above analysis, the effect of breathing on the ECG signal is indirect and nonlinear [7] and leads to the quality decrease in ECG signal classification. The purpose of the paper is to propose a solution to reduce those effects.

The quality of the classification can be evaluated on the basis of following factors: the number of misclassification cases, number of false-negative cases, number of false positives. The model is considered to be better when the errors are small, in which the most important is the FN index since this is the case that can have the worst impact on the patient.

2. METHODS FOR REDUCTION OF THE EFFECTS OF BREATHING IN THE ECG SIGNALS

2.1. A short review of methods for breathing effects reduction for ECG signals

There has been a number of studies suggesting to remove respiratory effects in ECG signals [7, 8, 10]. It can be a simple task of counting the respiration rate for apnea checking of the patients like in [11], where an accelerometer was used to count the number of breaths simultaneously with the ECG measuring process.

Various research has proposed a filter application to eliminate the effect of breathing on ECG signals. Classical methods include high-pass filtering because the breathing frequency varies in the range of 0.05 Hz to 1 Hz. Alste proposed in [12] the use of a 255th order Kaiser high-pass filter at cutoff frequency 0.8 Hz. In [13] the authors proposed using the FIR filter (Finite Impulse Response) and the IIR (Infinite Impulse Response) with cutoff frequency of 0.5 Hz. Test results for FIR Kaiser, Hanning, Hamming, Blackman filters and 2nd order Butterworth IIR filters showed that the second-order Butterworth filter has a lowest PRD (Percentage Root Mean Squared Difference) of the signals before and after removing the effect (32.77 %).

Not only the static filters, adaptive filters are also proposed by various authors as the Least Mean Squares (LMS) adaptive algorithm in [14]; Kalman adaptive filter in [15] or a combination of FIR filter with LMS adaptive algorithm as in [10] to eliminate the effects of respiration in the ECG signal. However, the method of adaptive filtering has the disadvantage of requiring a real respiration signal or an ECG signal for reference to update the filter coefficients, resulting in a high calculation efforts.

In [16, 17], it is proposed to use the Principal Component Analysis (PCA) method. In [17] PCA was used to determine the rhythm in the ECG signal characteristic such as QRS complex, P wave or T wave by finding the direction with the highest variance. To overcome this hypothesis, in [16] a generalized case of PCA, the so-called kPCA (Kernel PCA) method was used. Experimental results on the Fantasia Database show that the effect of kPCA removal is better than PCA. The disadvantage of PCA method is the number of Principle components is dynamic and unknown in advance for each clients.

In [18] the Short-Time Fourier Transform (STFT) was proposed to estimate the heart signal to be extracted. This method has the disadvantage of having to choose the size of the window length in accordance with the ECG signal. The STFT was also used in [19], in which the work evaluated of the recognition algorithms for the supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), atrial fibrillation (AF), and ventricular fibrillation (VF). Fast Fourier transform (FFT) and an MLP (Multilayer Perceptron) were selected for the detection algorithms. The results showed that the proposed integrated algorithm can achieve good accuracy in comparison with other previous studies.

In [20] it proposed the Modulation Morphological Filtering (MMF) to eliminate respiratory effects in the ECG signal, but it also affects the characteristics of the ECG signal.

In [21], the authors used the Empirical Mode Decomposition (EMD) method to decompose the ECG signals into a number of IMFs (Intrinsic Mode Functions). Experimental results in the MIT-BIH database and in the actual patient showed that the EMD method has little effects only on the ECG characteristic features. The EMD method was also used in [22] in combination with the discrete wavelet transform (DWT) to detect R-peaks and QRS complex. The Probabilistic neural network (PNN) and radial basis function neural network (RBF-NN) were used to recognize the arrhythmia beats. The solution achieved 99.7 % accuracy in detecting the QRS complex.

The article [23] proposed the so called maximum margin clustering method with immune evolution (IEMMC) to classify the features vector extracted from the QRS complexes. The authors also used the wavelet transform for R peak detection. Compared with K-means and iterSVR algorithms, the IEMMC algorithm showed better performance in classification.

The features vector may be more sophisticated in preparing, such as in [8], where the feature vectors of an ECG signal consisted of both linear and nonlinear features were used to improve the classification of ECG data containing five types of arrhythmias: non-ectopic beats (N), supra-ventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F) and unclassifiable and paced beats (U). As nonlinear features, the authors proposed high order statistics and cumulants, as linear features, the principal component analysis of discrete wavelet transform coefficients was used. The method was able to classify the N, S, V, F and U arrhythmia classes with high accuracy (98.91 %) using a combined support vector machine and radial basis function neural network.

Most of the methods analyze and classify the ECG signal beat-by-beat, but in [24], the authors proposed a method to recognize segments of ECG signal containing a number of heartbeats. The method used the temporal features (i.e., the dynamics) from ECG patterns. As the classifier, an RBF neural network was trained and tested with the accuracy about 90 %.

2.2. The proposed solutions

As shown in studies, the effect of respiration in ECG signals in terms of signal is nonlinear [6] with frequency spectrum in the range of [0.05 ÷ 1] Hz. Wavelet analysis is a common method for analyzing dynamic signals such as ECG signals. As mentioned above, many studies have proposed wavelet transform to eliminate the effects of general noise and breathing in particular in ECG signals with different wavelet family and levels. In this paper, we will re-test them with the concentration on the frequency range given above to select the configuration which give the highest improvement to the results. For databases when there are also the record of the patient respiration process, we extract from the record 2 features to include into the inputs of the classifier: the instantaneous amplitude of the respiration signal and the average of 10 last durations of peak-to-peak period from the respirational signal. These recommendations are intended to address the effect of arrhythmia, as these effects can not be overcome by the wavelet filter. The instantaneous amplitude of the respiration signal will help determine whether the R-R spacing (used in ECG identification) is altered by breathing or by pathology. Similarly, the average pulse of the last 10 spikes also provides information about the patient's movement status, thereby adjusting the conclusions of the ECG signal. The ideas of using more than one biomedical signals to support the analysis of ECG signal was already considered, for example the research in [25] proposes a multimodal data association method that used also features extracted from blood pressure (BP) and electroencephalogram (EEG) to support the ECG signal classification when the signals are strongly noised. The proposed method got an overall score (on the testing set) better than the typical method using QRS detector and BP detector from PhysioNet. But the use of respiration signal as in this paper is novel.

For comparison, we will compare the performance of ECG signal classification in 3 scenarios:

1. The base case, we use the results from [9], where the ECG signal is characterized by a vector of 18 features: 16 coefficients when decomposing the QRS complex of the given rhythm into the first 16 Hermite functions, the last R-R durations and the average of 10 last R-R durations.
2. The 2nd case: the same ECG signals as in the base case are filtered using the wavelet based filters. After that, the same algorithm of features vector generation is used (with 18 components) and also a new TSK network is trained for recognizing those new features vectors.
3. The 3rd case: when the respiration process is also recorded, the feature vectors contain 20 components: the 18 components as above and 2 more features: the instantaneous amplitude of the respiration signal and the average of 10 last durations of peak-to-peak period from the respirational signal. Again a TSK network will be trained to recognize the feature vectors to classify the actual beat. The numerical results will show that 2nd and 3rd cases will have better results than the base case.

As the nonlinear classifier, the modified TSK neurofuzzy network as in Fig. 3 is proposed. This network has a modified membership function defined as:

$$\mu_i(\mathbf{x}) = \frac{1}{1+\left(\frac{\|\mathbf{x}-\mathbf{c}_i\|}{\sigma_i}\right)^{2b_i}} \tag{1}$$

which helps to reduce the number of nonlinear parameters almost 3 times [26].

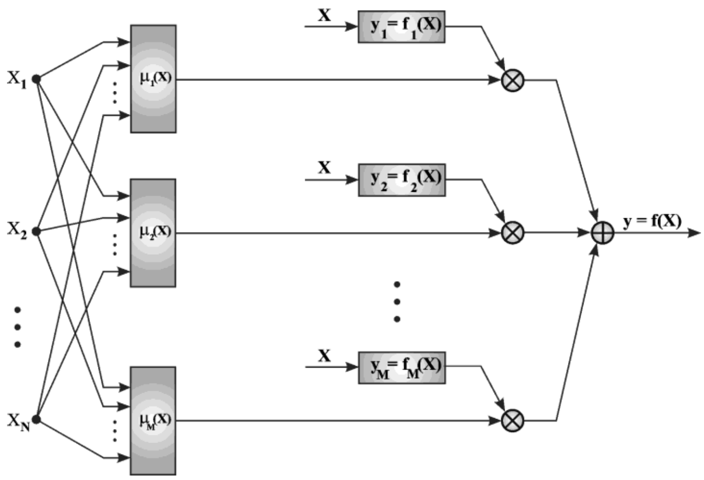


Figure 3. The structure of a modified TSK network.

The network is trained by a hybrid gradient-based algorithm [26] to process these feature vectors to make the classification.

3. THE TRAINING AND TESTING DATA SETS

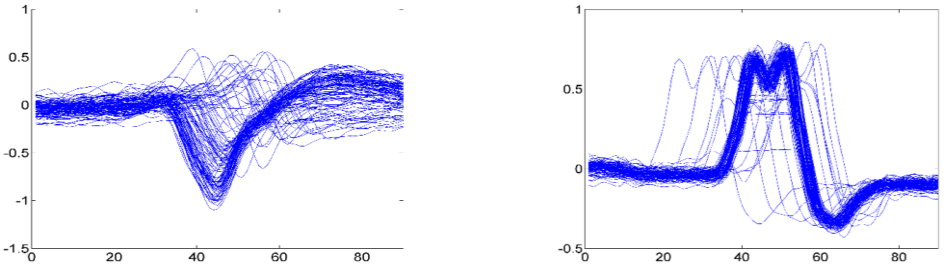
To test the proposed solution, we use two databases: the first is the MIT-BIH database with ECG signals only and the later is the MGH/MF database with both ECG and respiration signals measured at them same time.

The database of MIT-BIH arrhythmias [27] was created at the Boston's Beth Israel Hospital from 1975 to 1979. It consisted of 48 records collected from 47 participants, including 25 men aged 32 to 89 and 22 women aged 23 to 89 (records 201 and 202 were collected from the same person). All records were digitized at 360 Hz and each record has at least two independent cardiologists marking the specimens, marked at the R-peak of each heartbeat.

With the MIT-BIH database, this paper uses 16 records (16 patients) with 7 different rhythm types: Normal sinus rhythm (denoted as type N), left bundle branch block (type L), Right Bundle Branch Block Beat (type R), Premature Atrial Contractions (type A), Premature Ventricular Contraction (type V), Ventricular flutter wave (type I) and Ventricular escape beat (type E). We extracted totally 3577 QRS samples, which we further randomly divided two sets: 2385 samples (about 2/3) of 16 patients for learning, the remaining 1192 samples are used for testing. The total number and the number of sample pieces taken from the records and divided into the dataset and the test are shown in Table 1a. The ratio between number of samples used for training and testing was chosen within the range used by other authors, varying from 50 % - 50 % to 80 % - 20 %. Since there is no recommended ratio, the more important thing is we should use the same data sets to make the comparison between methods more reliable. On the other side, since the range of the output signal from a TSK network is not limited by 1 as the sigmoid neurons, therefore we decided to encode the desired corresponding output for the ECG signals in the following simple way: the N-type rhythms had the output equal 1, the L-type rhythms had the output equal 2, etc. and the E-type rhythms had the output equal 6.

The MGH/MF database [27] includes not only the ECG signals but also the respiratory and blood pressure of the patient. It consists of 250 records from 250 patients at Massachusetts

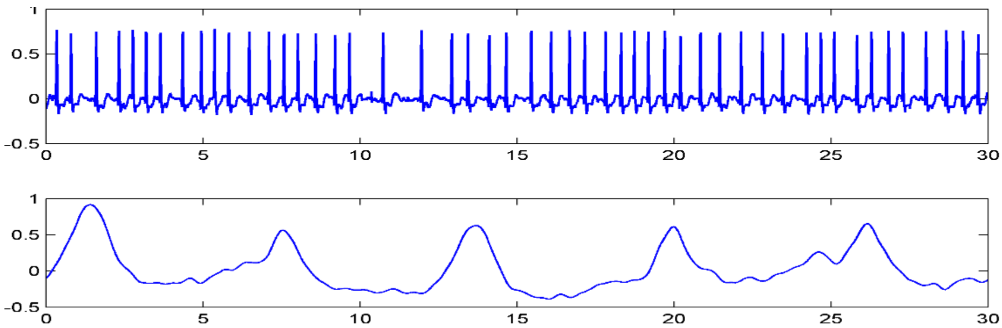
General Hospital. In this database, the most popular rhythms are of the normal sinus type, the Premature Ventricular Contraction (type V), and the supraventricular premature beat (denoted as type S). We have extracted from 20 records a total 4500 samples. Details of the number of samples taken from the records are summarized in Table 2. The procedures for generating feature vectors and the output vectors are similar to that of the MIT-BIH database. For the outputs, we used the similar encoding method as above: the N-type rhythms had the output equal 1, the V-type rhythms had the output equal 2, and the S-type rhythms had the output equal 3.



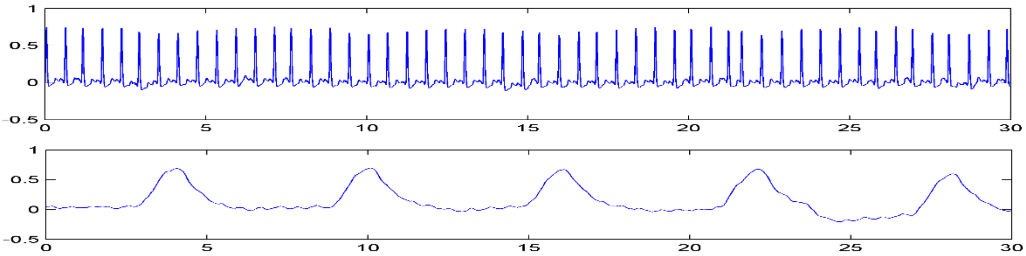
V: Premature ventricular contraction S:Supraventricular premature beat

Figure 4. Example of QRS segments for S and V arrhythmia types.

Figure 4 shows the examples of QRS segments for both V and S arrhythmias. It can be seen that in pathological cases, the ECG signal in general and the QRS segment in particular has signal variations strong in both amplitude and shape. In Fig. 5, there are some example segments of the ECG signals along with the respiration signal measured simultaneously from the MGH/MF database. The segments also show the effect of R-R variation and the modulation of the R peak amplitudes.



(a)



(b)

Figure 5. Examples (from the MGH/MF database) of ECG signals and their corresponding patient respiration signal: a) sinus arrhythmia with R-R intervals changed, b) amplitude modulated.

Table 1. Detail numbers of rhythm types selected from the MIT-BIH and MGH/MF databases.

Rhythm type	*Total number*	*Learning samples*	*Testing samples*
N	1000	667	333
L	500	333	167
R	500	333	167
A	500	334	166
V	500	333	167
I	472	315	157
E	105	70	35
Total	**3577**	**2385**	**1192**

Table 2. Detail numbers of rhythm types selected from the MGH/MH database.

Rhythm type	*Total number*	*Learning samples*	*Testing samples*
N	2700	1800	900
S	675	450	225
V	1125	750	375
Total	**4500**	**3000**	**1500**

4. NUMERICAL RESULTS

This section will present the ECG signal classifications results of trials in different 5 scenarios:

- Test No. 1: Classifying the ECG signals from MIT-BIH without using wavelet filtering (and no respiration signals were available)
- Test No. 2: Classifying the ECG signals from MIT-BIH with wavelet filtering (and no respiration signals were available)
- Test No. 3: Classifying the ECG signals from MGH/MH without using wavelet filtering and no respiration signals were used.
- Test No. 4: Classifying the ECG signals from MGH/MH with wavelet filtering (no respiration signals were used).
- Test No. 5: Classifying the ECG signals from MGH/MH with wavelet filtering and with the using respiration signal.

By trial-and-error method, it’s found out that the Coiflet level 4 has the best performance on our datasets. And with the frequency range around 0.5 Hz, the 360 Hz sampling frequency of the ECG signals, the A_8 component is removed as the wavelet filtering procedure.

As the classifying model for all scenarios, this paper uses the TSK neurofuzzy network [26]. The reliability of the identification model is assessed on the basis of the 4 measures mentioned in Section I.

4.1. Results for tests with data from MIT-BIH

The TSK network is built with 18 inputs corresponding to 18 components of the feature vectors, 7 binary outputs corresponding to 7 types of N, A, E, L, R, I and V. The number of fuzzy inference rules was tried from 1 to 20, and the results show that for the 17 rules the lowest testing results were achieved. To facilitate the calculation of test errors, the number of FN cases, FP cases, statistic parameters,..., we constructed the confusion matrix as shown in Tables 3 and 4 in which, columns are destinations and rows are network outputs. The main diagonal of the matrix represents the correct classifications, other positions are the errors.

Table 3. Testing results for test No. 1.

	N	***A***	***E***	***I***	***L***	***R***	***V***
N	324	12	1	0	0	0	2
A	8	151	0	0	1	1	1
E	0	0	34	0	0	0	0
I	0	0	0	156	0	0	2
L	0	0	0	0	165	0	1
R	1	3	0	0	1	166	0
V	0	0	0	1	0	0	161
Total	***333***	***166***	***35***	***157***	***167***	***167***	***167***

Table 4. Testing results for test No. 2.

	N	***A***	***E***	***I***	***L***	***R***	***V***
N	325	8	1	0	0	0	1
A	6	156	0	0	1	3	0
E	0	0	33	1	0	0	0
I	1	0	1	155	0	0	2
L	0	0	0	1	166	0	1
R	1	1	0	0	0	164	1
V	0	1	0	0	0	0	162
Total	***333***	***166***	***35***	***157***	***167***	***167***	***167***

Table 5. Performance comparison between tests No. 1 and 2.

	Test No. 1	*Test No. 2*
Testing total error	35	31
FN	15	10
FP	9	8

The tests showed that, when applying a wavelet filtering process (removing the A_8 component in Coiflet wavelet decomposition), the performance of the TSK classifier was improved. The total testing error was reduced from 35 to 31, and especially the FN cases was reduced from 15 to 10.

4.2. Results for tests with data from MGH/MF

These tests use a set of 20 records to build a set of data and test data sets for the identification model. Because the MGH/MF database contains breath measurements simultaneously with the ECG signal. Similar to experiments with the MIT-BIH database to facilitate the calculation of test errors, FN cases, FP cases, etc.

From the output of the TSK network we summarize the results of Tests 3, 4 and 5 as shown in Table 6.

Table 6. Performance comparison between tests No. 3, 4 and 5.

	Test No. 3	*Test No. 4*	*Test No. 5*
Testing total error	62	55	51
FN	30	26	23
FP	16	14	11

The tests showed that, when applying a wavelet filtering process (test No. 4) the performance of the classifier was improved, and when using both solutions, the achievement is further improved. The total testing error was reduced from 62 to 51, and especially the FN cases was reduced from 30 to 23.

5. CONCLUSIONS

The paper presented the two approaches to improve the quality of the ECG arrhythmia classification, which are the wavelet filtering the frequency range from 0.05 to 1 Hz and the use of 2 features based on the respiration signals. The numerical results have shown that each approach helps to improve the classification results not only in reducing the total error but also in important measures such as False Negative cases and Sensitivities.

The method can be further explored with new features from the respiration signals.

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