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Stationary Wavelet Transform and Entropy-Based Features for ECG Beat Classification

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Abstract: *In this study, heartbeats are classified as normal, right bundle branch block (Rbbb), paced beat, and left bundle branch block (Lbbb), using the electrocardiography (ECG) signals from the MIT-BIH arrhythmia database. The statistical parameters and entropy of stationary wavelet transform (SWT) coefficients are proposed as the features for the classification. The classification was performed using artificial neural networks. It was observed that both statistical parameters and the entropy features perform better than the time domain, and the discrete time wavelet transform coefficient features. The classification performance of the different wavelet families is also considered.*

Keywords: *ECG beat detection, cardiac arrhythmia, stationary wavelet transform, discrete wavelet transform, Pan Tompkins algorithm, wavelet entropy.*

1. Introduction

Cardiovascular diseases remain the dominant cause of death all over the world. 17.3 million People were estimated to die from cardiovascular diseases in 2008, which accounted for 30% of all global deaths. Furthermore, based on predictions and statistics from the World Health Organization (WHO), 23.6 million people will probably die from these diseases by the year 2030 [1]. Thus, early diagnosis of heart failure is an important mission in health care. Most heart failures start with a few symptoms, such as arrhythmias. Arrhythmia is a cardiac condition caused by the abnormal electrical activity of the heart. The heartbeat may be too fast, too slow, and may be regular or irregular. Since the different mechanisms in the heart generate different arrhythmias, for the correct treatment, the type of the arrhythmia should be diagnosed as early and as accurately as possible.

The electrocardiogram (ECG) is a non-invasive technique which measures the electrical activity of the heart by using probes attached to the human body. It is the most common technique used to detect cardiovascular diseases because of its simplicity and cost. It is tedious and time-consuming to use visual inspection in ECG analysis, even for an expert cardiologist. Therefore, the usage of computer software significantly improves diagnostic accuracy and patient healing outcomes [2].

Classifiers based on ECG morphological features were reported in [3] and [4]. Gradient-based algorithm and time-domain morphology were presented in [5]. Also, [6] described statistical methods of comparison between relative magnitudes of ECG samples and their time-domain slope. In [7], authors presented classification of normal and abnormal signals using R-R interval features of ECG waveform. Owing to the success of representing non-stationary signals in the time-frequency domain, wavelet transform also finds applications in beat classification. In [8], principal components, linear discriminant analysis, and independent component analysis of discrete wavelet transform (DWT) features are used to classify ECG beats from the MIT-BIH arrhythmia database. The statistical features of DWT coefficients are employed in the classification of three classes of arrhythmias in [9]. A comprehensive report on the methods and results of ECG characterization can be found in [10].

Although, DWT is a useful tool for analysing the frequency content of the non-stationary signals changing with time, the down-sampling operation employed in the transform destroys the time-invariance property. Redundant stationary wavelet transform (SWT), however, conserves the time information. In some applications, SWT has been used for denoising [11, 12] and modelling ECG beats [13]. In this paper, SWT was used to extract time-frequency information and to calculate time-frequency entropies, as a contribution to previously developed feature extraction algorithms for beat classification.

Arrhythmia is a heart condition where beats are irregular, too fast or too slow. A bundle branch block implies that the conduction system of the heart is blocked and the electrical impulse cannot travel throughout the heart. Although, bundle branch blocks alone do not have any symptoms or need emergent treatment, they might be dangerous with other heart failures [14]. Also the probability of having a heart condition in the future is increased. Thus, in this study, along with normal heartbeats, left and right bundle branch blocks and paced beats are considered, with the aim of detecting possible heart problems in advance.

In this study the feature sets based on statistical and entropy parameters of stationary wavelet transform (SWT) have been proposed to obtain a new and efficient heartbeat classification system. The four types of ECG waveforms (Normal, Paced, Rbbb and Lbbb) were pre-processed, and R-peak detection was implemented using Pan Tompkins algorithm. An artificial neural network back-propagation algorithm was used for classification. The discrimination performance of the different wavelet families was also investigated. It was observed that SWT-based features outperform the time-domain and discrete time wavelet transform features.

In the following sections, after briefly introducing the classified heartbeats in Section 2, the feature extraction and classification methods are explained in Section 3. The data analysis and results are given in Section 4 and it is followed by the discussion in Section 5.

2. Arrhythmic Heartbeats

The ECG signal is a bioelectrical signal which depicts the cardiac activity of the heart, and it is a technique used primarily as a diagnostic tool for various cardiac diseases because of its simplicity. Different waves and fiducial points of ECG reflect the activity of different parts of the heart, which generate the respective flow of electrical currents. The most important features include the information lying in the P, Q, R, S, and T waves of the ECG signal. QRS complex which is constructed by Q, R and S waves corresponds to the depolarization of the right and left ventricles of the human heart. [15].

Two different arrhythmias, which are not critical in terms of emergent care but important to detect for future cardiac problems, are considered in this study: bundle branch blocks (bbb); and paced beats. When one bundle branch is blocked, the electrical impulse will travel through the intact branch and stimulate the ventricle supplied by that branch. The ventricle affected by a blocked or defective bundle branch is activated indirectly. There is a delay caused by this alternate route and the QRS complex will be longer. The paced beat is the artificial beat from a device called a pacemaker. It can be characterized in ECG by a large peak after the QRS complex. One sample from each beat type is illustrated in Figure1.

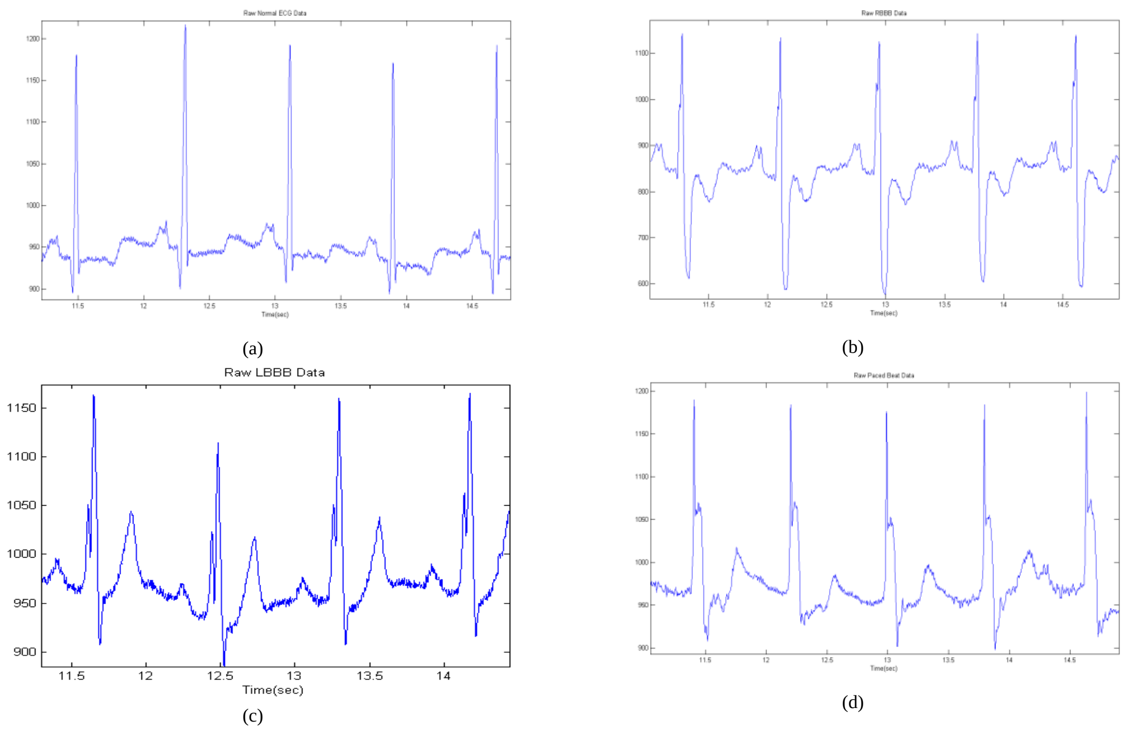

Fig1. *Raw ECG for (a) Normal, (b) Rbbb, (c) Lbbb, and (d) Paced beats from MIT-BIH database*

3. Method

The method used in this work involves data acquisition, pre-processing, feature extraction and classification as the main terms, which are illustrated in Figure 2.

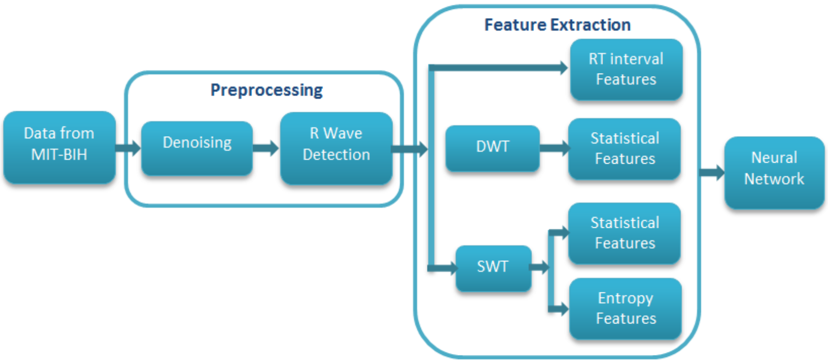

Fig2. *Block diagram of the ECG beat-classification system*

3.1. ECG Database

In this study, the source of the ECG data used for training and testing is the MIT-BIH Arrhythmia database from the Physionet website [16]. The database contains 48 recordings sampled at 360Hz of 30-min durations selected from 24 hr recordings with two channels, obtained from 47 patients [17]. Only one channel of 1 min long data for each record is used in this work.

3.2. Pre-Processing

In order to obtain useful information from a raw signal pre-processing is necessary, including the removal of noise from sources such as electrode contact noise, baseline drift, muscle contraction, power line interference and motion artefacts. The noise-removal stage includes the removal of the mean of the signal. Then, the noise is attenuated by a band-pass filter constructed by a high-pass filter followed by a low-pass filter. Finally, a finite impulse response filter is used to remove the effect of the power line and its harmonics. For the detection of the beats to classify, the QRS stage of the ECG wave should be detected by locating the R-peaks. A well-known and acceptable Pan Tompkins algorithm is employed for this stage [18]. The high slope which distinguishes the QRS wave is detected by differentiation. With the squaring, data is made positive and higher frequencies are removed. Using a moving window integrator covering the QRS area, thresholding is applied to locate R-waves.

3.3. Feature Extraction

In the feature-extraction stage, time domain, DWT and SWT domain features are determined.

3.3.1. R-T Interval Features

200 samples from detected R-peaks were extracted from the R-R interval, which corresponds to the R-T interval which is shown as red rectangles in Figure 3 and this part can characterize the one beat of the ECG signal.

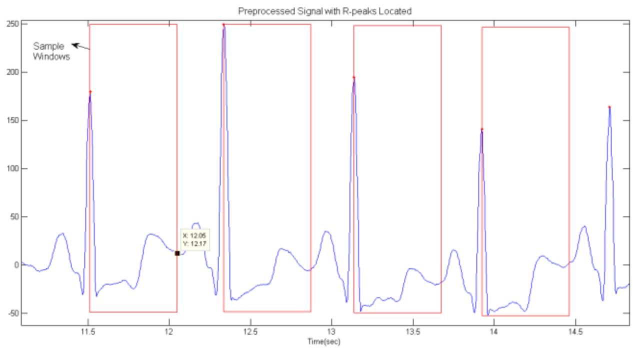

Fig3. *Feature extraction for R-T interval features*

3.3.2. DWT Features

The continuous wavelet transform (CWT) was developed as a method to obtain simultaneous, high-resolution time and frequency information about a signal [19]. The CWT is computed by correlating the signal s (t) with families of time-frequency atoms Ψ(t), and produces a set of coefficients C (a, b) given by:

$$C(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\Psi^{*}\left(\frac{t-b}{a}\right)dt \tag{1}$$

where b is the time location (translation parameter), a is called scale factor and is inversely proportional to the frequency (a>0), *denotes a complex conjugate, and $\Psi(t)$ is the analysing wavelet (mother wavelet).

The Discrete Wavelet Transform (DWT), which is a time-scale representation of the digital signal, is obtained using digital filtering techniques, and is found to yield a fast computation of wavelet transform. DWT can be obtained by

$$C_{mn} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\Psi_{mn}(t)\,dt \tag{2}$$

where the dyadic scaled and translated wavelet is defined as:

$$\Psi_{mn}(t) = 2^{-m/2}\Psi(2^{-m}t - n) \tag{3}$$

The most common wavelets providing the orthogonality properties are Daubechies, Symlets, Coiflets, and Discrete Meyer, in order to provide reconstruction using fast algorithms.

For the extraction of DWT features, DWT is applied to the extracted R-T interval. Different wavelet families are considered to find the best and most suitable wavelet. The level is chosen to cover the frequency range of the normal and abnormal ECG signals. In order to obtain a feature matrix, the statistical parameters, such as mean, median, maximum, minimum, standard deviation, energy and entropy of the approximation, and each level of detail coefficients, is calculated. The final number of samples is reduced from 200 to 77. These features represent the morphological signatures of ECG beats at different resolution levels.

3.3.3. SWT Statistical Features

The stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of DWT. Translation-invariance is achieved by removing the down-samplers and up-samplers in the DWT, and up-sampling the filter coefficients by a factor of $2^{(m-1)}$ in the m^{th} level of the algorithm [20, 21]. The SWT is an inherently redundant scheme, as the output of each level of SWT contains the same number of samples as the input. The major advantage of SWT is the preservation of time information of the original signal sequence at each level [22]. In Section 4, all the entropy calculations are implemented in terms of SWT coefficients.

The procedure for calculating stationary wavelet transform and feature extraction is the same as in discrete wavelet transform, only that in SWT, the level of decomposition is 8 because the length of the signal must be in the form of 2^n, where *n* is the level of decomposition. Therefore, the number of R-T interval samples is 256 instead of 200. The size of the SWT matrix, including detail and approximation coefficients, is 9x256. Then, statistical parameters have been used as SWT features.

3.3.4. SWT Entropy Features

The Shannon entropy [23] gives a useful criterion for analysing and comparing probability distributions. The entropy is the measure of the uncertainty. The wavelet entropy (WE), which is a quantity calculated from wavelet coefficients, appears as a measure of the degree of order/disorder of the signal in the time-frequency plane, so it can provide useful information about the underlying dynamical process associated with the signal. Where an ordered signal with a narrow spectrum has lower entropy, a signal generated by a totally random process will have a wavelet representation with significant contributions from all frequency bands. Thus, entropy will increase.

There are various wavelet entropy measures, such as wavelet energy entropy, wavelet time entropy, wavelet singular entropy, wavelet time-frequency entropy, wavelet average entropy, and wavelet distance entropy. In wavelet entropy, the rate of wavelet energy of a certain wavelet coefficient to the total energy is replaced by the probability in the usual entropy metrics [24]. The wavelet energy in a fixed scale, and time instant is defined by the square magnitude of the corresponding detail coefficients of SWT as

$$E_{mn} = |D_m(n)|^2 \tag{4}$$

where E_{mn} is the wavelet energy spectrum at scale m and time instant n. Therefore, the wavelet energy distribution for M scales and N time instants can be illustrated as in Figure 4.

The total energy covered by the wavelet transform is defined as:

$$E = \sum_m \sum_n E_{mn} \tag{5}$$

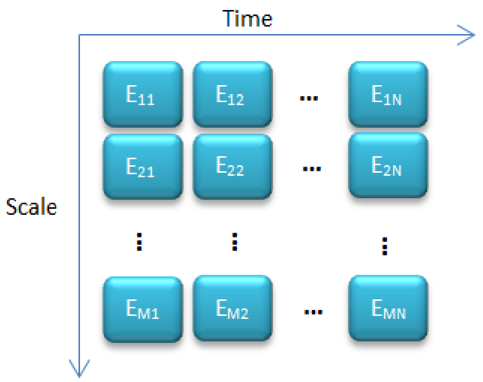

Fig4. *Wavelet energy distribution for M scales and N time instants*

A complexity measure, which demonstrates the complexity of a signal changing with time instants, can be defined by determining the probability as the ratio of the energy of all scales for that time instant to the total energy of the wavelet time entropy, which measures signal complexity changing with time obtained as

$$WTE = -\frac{\sum_m E_{mn}}{E} \log\left(\frac{\sum_m E_{mn}}{E}\right) \tag{6}$$

Similarly, the wavelet frequency entropy is obtained as

$$WFE = -\frac{\sum_n E_{mn}}{E} \log\left(\frac{\sum_n E_{mn}}{E}\right) \tag{7}$$

which measures the complexity of the signal changing with frequency. The wavelet entropy was calculated from the magnitude of SWT coefficients after decomposed with different wavelet families up to 8 levels. For the obtained SWT matrix, the wavelet time entropy WTE and wavelet frequency entropy WFE are calculated to measure the complexity of the signal changing with time and frequency, respectively.

3.4. Classification

For the classification feedforward multilayer perceptron, artificial neural networks have been used. The artificial neural networks (ANN) are structures that mimic the behaviour of learning input-output relations, by using some pre-defined algorithms. One of the most common ANN structures is a multilayer feedforward neural network with back-propagation learning. In this study, ANN with one hidden layer and a Levenberg-Marquardt learning algorithm is employed because of its speed and simplicity. The number of neurons in a hidden layer is selected heuristically [25].

4. Data Analysis and Results

In this paper, 40 ECG records were distributed randomly for classification of normal, paced, rbbb, and lbbb beats. 1,937 ECG beats were fed into artificial neural network, of which 70% was used for training, 15% was used for validation, and 15% for testing. The classification performance is considered in terms of sensitivity, specificity, positive predictive value, negative predictive value, and accuracy [26].

4.1. Performance Analysis of Equivalent R-T Interval Features

200 samples between R-R intervals, which is equivalent to the R-T interval, were extracted as feature values representing ECG classes. The ANN was trained for different numbers of hidden layers, and their testing performances are compared to each other. It is observed that a network with a structure 200:15:4 shows better performance when compared with others.

Table1. *Performance Measures for R-T Interval Features*

ECG Class Beat	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)	Accuracy (%)
Normal	64.86	99.83	99.31	88.22	90.21
Rbbb	98.90	98.24	94.24	99.68	98.39
Paced	98.38	98.55	95.29	99.51	98.51
Lbbb	94.95	87.61	73.93	97.91	89.59
Average	**89.27**	**96.06**	**90.69**	**96.33**	**94.18**

In order to use as a benchmark, the samples extracted from RT intervals were fed into the classifier without applying any transform. The result of the classification in terms of the performance measures is shown in Table 1, where average accuracy is obtained as 94.18%.

4.2. Performance Analysis of DWT Statistical Features

In order to improve the classification accuracy, the R-T interval features were decomposed using DWT as explained before. After the decomposition, statistical parameters such as mean, median, variance, energy, and entropy were extracted, and used as features for ECG classification. The number of neurons in the hidden layer is selected heuristically as 15. After comparing different wavelet families for their recognition rates, it was observed that Db4 wavelet has a better ability to discriminate between ECG beat classes. Then, the performance measures for Db4 wavelet were obtained, as summarized in Table 2. An improvement is clearly seen when compared with classification using R-T interval features.

Table2. *Performance Measures for DWT Features*

ECG Class Beat	Sensitivity (%)	Specificity (%)	Positive Predictive value (%)	Negative Predictive Value (%)	Accuracy (%)
Normal	91.89	98.97	97.14	96.98	97.03
Rbbb	98.35	98.24	94.21	99.51	98.27
Paced	98.92	99.36	97.86	99.68	99.27
Lbbb	92.66	96.94	91.82	97.27	95.79
Average	**95.46**	**98.38**	**95.26**	**98.36**	**97.59**

4.3. Performance of SWT Statistical Features

After calculation of SWT statistical features, the ANN is trained with these features, and as a result of experiments, it was shown that the Db4 wavelet family features with classifier with 15 hidden neurons produce the best results. The system performance indices are summarized in Table 3.

Table3. *Performance Measures For Undecimated Wavelet Transform (SWT)*

ECG Class Beat	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)	Accuracy (%)
Normal	97.75	99.49	98.64	99.15	99.01
Rbbb	95.60	98.24	94.05	98.71	97.65
Paced	98.92	99.36	97.86	99.68	99.26
Lbbb	94.50	98.47	95.81	97.97	97.40
Average	**96.69**	**98.89**	**96.59**	**98.88**	**98.33**

Using SWT, the performance of this proposed system was observed to be successful in terms of classifying ECG class beats. The average sensitivity of the system is 96.69%, while average specificity is 98.89%, compared to 95.86% and 98.80 for DWT.

4.4. Performance of SWT Entropy Features

Wavelet time and wavelet frequency entropies of decomposed signal using SWT were calculated and combined with the statistical parameters of SWT such as mean, median, standard deviation etc., and formed a feature vector of 63x1937 and 63x807 for training and testing, respectively. Tables 4 and 5 summarize the performance measurements of WFE and WTE, respectively.

Table4. *Performance Measures of Wavelet Frequency Entropy*

ECG Class Beat	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)	Accuracy (%)
Normal	95.50	99.32	98.15	98.31	98.27
Rbbb	96.70	97.44	91.67	99.02	97.27
Paced	96.76	98.55	95.21	99.03	98.14
Lbbb	93.58	98.81	96.68	97.65	97.40
Average	**95.64**	**98.53**	**95.43**	**98.50**	**97.77**

Table5. *Performance Measures of Wavelet Time Entropy*

ECG Class Beat	Sensitivity (%)	Specificity (%)	Positive Predictive Value (%)	Negative Predictive Value (%)	Accuracy (%)
Normal	95.55	99.15	97.79	99.83	99.26
Rbbb	94.51	98.40	94.51	98.40	97.52
Paced	98.92	99.20	97.34	99.68	99.13
Lbbb	92.67	98.47	95.73	97.32	96.90
Average	**96.41**	**98.81**	**96.34**	**98.81**	**98.21**

Based on the results obtained after classification with time and frequency entropy algorithms, it was shown that time wavelet time entropy performed better, with an accuracy of 98.21%, which states that the shape of the ECG wave contains more information than the frequency bands.

5. Discussion

The performance results of different feature sets proposed in this study are summarized in Tables 6 and 7.

Table6. *Comparison of Different Methods*

Methods	Sensitivity	Specificity	PPV	NPV	Accuracy
R-T intervals	89.27	96.06	90.69	96.33	94.18
DWT	95.46	98.38	95.26	98.36	97.59
SWT	**96.69**	**98.89**	**96.59**	**98.88**	**98.33**
WTE	96.41	98.81	96.34	98.81	98.21
WFE	95.64	98.53	95.43	98.50	97.77

Among features developed in this study, SWT with statistical features gives the highest accuracy, as shown in Table 6, because of the translation-invariant nature of the stationary wavelet transform. Also, the wavelet time and frequency entropy features produce promising results, using both the time-frequency domain information provided by statistics of SWT and the complexity information provided by the entropy measures, defined in the time-frequency domain.

Table7. *Comparison Between Wavelet Families*

Wavelet Name	**DWT**	**SWT**
	Recognition rate (%)	Recognition rate (%)
Db4	**95.17**	**96.65**
Db10	88.97	94.79
Bior6.8	87.73	92.07
Coif5	94.42	91.08
Sym8	89.71	96.41

When different wavelet families are considered for both discrete wavelet decomposition and its counterpart stationary wavelet decomposition, Db4 shows a higher recognition rate when compared to other families. This indicates that the selection of a suitable wavelet is critical to the success of classification. Also, it is interesting to note that the recognition rates of SWT features for each wavelet family is increased by up to 6.7%, with recognition rates greater than 90%.

6. Conclusion

This paper is an endeavour to address various challenges associated with an automatic beat-classification system. The system proposes a simple, efficient, and robust feature extraction method, which is capable of classifying four ECG beats samples successfully.

Some of the most important steps in ECG analysis are denoising and QRS detection; that is, removing unwanted signal or artefacts that contaminate the signal during recording. In this work, a well-known and acceptable algorithm developed by Pan and Tompkins was used to remove noise and detect QRS complex correctly, for simplicity. After detecting R-peaks, different methods were proposed for feature extraction and classification. An equivalent R-T interval was extracted as 200 samples between two successive R-peaks and then decomposed using DWT and 256 samples for stationary wavelet transform with statistical parameters, calculated in each case as new features. It was concluded that an improvement was recorded when employing stationary wavelet transform, with average sensitivity and average accuracy of 96.69% and 98.33%, respectively. The features calculating the entropy of the wavelet coefficients, along with the statistical parameters, also shows a promising performance, since they include the complexity of the time-frequency space. After designing neural networks with different numbers of hidden layers, 15 neurons are shown to be effective, heuristically. Also, among different wavelet families it was concluded that Db4 shows the best performance. The more the mother wavelet resembles the ECG waveforms, the better the beats are represented.

The aim of this study is to propose a simple, robust, and efficient feature extraction and beat-classification system, which is suitable for portable ECG recorders. The experiments show that pre-processing, SWT statistical feature extraction, and testing per beat takes 5.1ms in a computer with an Intel Core i5-3360M CPU at 2.8GHz and 8GB of RAM, using Matlab R2011b, which is sufficient for online implementation. The integration of the proposed effective ECG beat-classification algorithm into a real-time ECG recorder and arrhythmia detection system is the concern of future works.

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