A UNIVERSAL ECG SIGNAL CLASSIFICATION SYSTEM USING THE WAVELET TRANSFORM

K. Daqrouq[*], *A. Alkhateeb*[*], *W. Ahmad*[†], *E. Khalaf*[*], *M. Awad*[*], *E. Noeth*[‡], *R.A. Alharbey*[§], *A.M. Rushdi*[*]

Abstract: The electrocardiograph (ECG) is one of the most successful medical diagnostic tools. The ECG can show, roughly speaking, all types of heart disorders that appear as ECG signal arrhythmias or problems with the rate or rhythm of the human heartbeat. In this paper, a universal ECG signal arrhythmia classification system is proposed. The proposed system is based on using the wavelet transform in two of its known forms, namely, the discrete wavelet transform (DWT) and the wavelet packet transform (WPT), or a combination thereof. The purpose of the research reported herein is to find out a universal classification system; in the sense of providing a capability for simultaneous classification of all types of known heart arrhythmias. Three algorithms based on the wavelet transform are tested for different wavelet levels, wavelet functions, training and testing ratios, and elapsed times. We rank these algorithms according to the elapsed times needed for their processing over the whole loop of the eight different arrhythmia classes. This ranking nominates the WPT-based algorithm to be the most superior method among the competing methods. A different ranking according to successful recognition rates assigns priority instead to the method combining the WPT and the DWT.

Key words: *ECG, arrhythmia, wavelet transform, energy, elapsed time, recognition rate*

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1. Introduction

Electrocardiography (ECG or EKG) is a commonly-used noninvasive cardiological methodology for testing the existence of disorders in the human heart work, which is

[*]Khaled Daqrouq; Abdulhameed Alkhateeb; Emad Khalaf; Mohamed Awad; Ali Muhammad Rushdi; Department of Electrical and Computer Engineering, King Abdulaziz University, Jeddah 21589, Saudi Arabia.

[†]Waleed Ahmad; University of the Poonch Rawalakot, Rawalakot, Poonch, Azad Jjammu & Kashmir, Pakistan.

[‡]Elmar Noeth; Lehrstuhl für Informatik 5 (Mustererkennung), Martensstr. 3, 91058 Erlangen, Germany.

[§]R.A. Alharbey – Corresponding author; Department of Mathematics, Faculty of Science, King Abdulaziz University, Jeddah 21589, Saudi Arabia, E-mail: rania.math@gmail.com

revealed by electrodes placed on the skin of the patient. The idea behind the ECG is to record the electrical signal that originates from the heart's muscle. The outcome of this methodology is called the electrocardiogram, which is an illustration of the electrical activity of the heart, graphing the voltage signal magnitudes over time [1]. Electrocardiography plays a fundamental role in analyzing various heart diseases including myocardial infarction, ischemia, heart attack, as well as related blockages in arteries and veins. The reason behind that is that any heart arrhythmia presents a particular deformation in the muscle of the heart that causes the sequence of its electrical impulses to experience certain deviations from the standard or normal, which in turn are manifested and illustrated on the ECG [1].

The diagnosis of a specific type of heart disease is a somewhat challenging task and differs from patient to patient. A particular source of difficulty is that a normal or healthy ECG is different for different persons. As a result, diagnosing a specific disease may vary for every individual. Furthermore, in a non-normal ECG, two distinct diseases may have almost the same manifestations [1]. To overcome these obstacles, researchers must think deep and hard to obtain a universal pattern recognition technique. This technique should work regardless of the similarity that occurs in some places in ECG waves with different electrical heart disorders [1–6].

Many ECG arrhythmias may appear as a special pattern called the QRS complex, which is a combination of three graphical deflections, usually constituting the central and most visually obvious part of the ECG tracing. Therefore, many research ideas start from analyzing the QRS complex [7]. One of the techniques that attracted many researchers depends on using various variations of the wavelet transform, and utilizing several kinds of wavelets, including the Haar wavelet [8–10], the Mexican hat wavelet [11, 12], and a combination of different wavelet functions [13]. The authors in [14] presented a wavelet QRS complex detection algorithm based on an ECG signal contaminated with noise, which is comparable to the algorithms given in [15–18]. A different piece of work in [17] introduced the use of the Haar discrete wavelet transform for arrhythmia detection. A classification of seven heartbeat cases (normal beat, bundle branch ectopic beat, supraventricular ectopic beat, normal, and ventricular ectopic beat) was investigated by the Morlet wavelet function and the probabilistic neural network (PNN) [18]. The successful classification rate was up to 100 % for a single arrhythmia but decreased for multiple arrhythmias. The QRS complex was classified by the Haar wavelet and the self organizing map method, which produced improved results in comparison to the fast Fourier transform (FFT) and the cross-correlation methods [10]. In [19], the authors proposed a wavelet transform and an energy based method for atrial fibrillation detection.

The paper assumes that the reader is already familiar with the wavelet transform (WT) and many related concepts such as WT energy, wavelet packet, WP tree, WP tree depth, and feature vectors. Understanding these concepts is not a pre-requisite for appreciating the paper contribution. However, the interested reader might consult some of the pertinent tutorial references such as our references [6–10, 12–14, 16–18, 20, 21].

Before closing this section, we devote this paragraph to stating our contribution to the current state-of-the-art, and highlighting the novelty dimension in our work. We stress that, to the best of our knowledge, earlier attempts at classifying ECG signals were restricted to cases of just one arrhythmia or two arrhythmias, including the normal case. The reason for this restriction is an urge to avoid unnecessary and unwarranted complexity, in particular since the occurrence of a single heart abnormality manifested as a single arrhythmia is more frequent than that of multiple ones. Despite the fact that the appearance of three or more arrhythmias in ECG signals is rather rare indeed, it is still a phenomenon of significant importance, more dreadful consequences, and a non-negligible (albeit small) prevalence. Moreover, this phenomenon signifies a more critical and complicated case of a heart patient that is more challenging to even highly-experienced medical personnel. Therefore, we believe that computer-aided analysis of ECG signals with multiple arrhythmias rather than a single one is even more beneficial to physicians in detecting more complex and less known cardiovascular diseases. Our present contribution is expected to be welcomed by the medical community, since it addresses situations, in which automated analysis well supplement manual human expertise.

In this paper, we introduce and investigate a new universal pattern recognition technique. For this purpose, we develop three different methods of varying levels of sophistication. We employ the probabilistic neural network (PNN) as a classifier. The paper is structured as follows. The first section is the present introduction, followed by Section 2 on the employed methodology and Section 3 on the testing datasets. Section 4 presents the obtained results accompanied by some discussion. Section 5 concludes the paper.

2. Method

In the past twenty years, researchers investigated many methods for ECG arrhythmia classification. However, the previously published methods dealt with only certain specific arrhythmia types. Therefore, a universal classification method that is capable of detecting and handling all kinds of arrhythmia is immensely needed. With this purpose in mind, we present herein three methods, each employing the concept of the wavelet percentage energy, earlier introduced in [22], for modeling almost all types of the known ECG signal clinical features. To calculate the percentage of energy E averaged over all qth WT sub-signals $u_q(t)$, the following equation is reproduced from [21, 22]

$$E(S) = 100 * \sum_{q=1}^{N} \left(u_q(t)\right)^2 / N, \tag{1}$$

$$N = \sum (C^2), \tag{2}$$

where S is the signal and C is the wavelet decomposition vector [22]. For the sake of investigation, the following three methods are studied:

1. Method of percentage energy of the wavelet packet (PEWP): In this method, we extract the features by calculating the percentage of energy for the qth sub-signal $u_q(t)$ of the WP tree, where the length of the feature vector is dependent on the WP tree depth. Therefore, the decomposition wavelet packet level has an immense effect on the classification system performance. The resulting values are used as a feature vector for classification.

(a) Method of percentage energy of the discrete wavelet transform (PEDW): In this method, we calculate the DWT sub-signals for a certain wavelet function for a given depth. The percentage of energy is calculated for several equal frames for each DWT sub-signals, after calculating the average value for each sub-signal. The resulting values are used as a feature vector for classification.

(b) Method of percentage energy of WP of the second level of the DWT (2SPED). In this method, we calculate the second approximation sub-signal of the DWT. For the calculated DWT sub signal, we determine the percentage energy of the WP decomposed from the DWT sub-signal. The length of the feature vector is dependent on the chosen level of the WP tree. The resulting values are used as a feature vector for classification.

Despite the fact that we might currently find several improved versions of the probabilistic neural network (PNN) that can be either more reasonable or have noticeably better performance than the original version, we adopt the original PNN as a classifier for simplicity of exposition. The construction of the used algorithm is as follows:

$$Net = [T, SP, I], \tag{3}$$

where T is the target that is given in the algorithm as a sequence of integers denoting the number of classes, SP is the spread that depicts the standard deviation used in the radial basis function and is usually given as the number 1, unless the numerical data type requires another number, and I is the input feature matrix that contains the training feature vectors as each column contains a feature vector for one signal as follows:

$$I = \begin{bmatrix} F_{11} & F_{12} & \dots & F_{1Tr} \\ F_{21} & F_{22} & \dots & F_{2Tr} \\ \vdots & \vdots & & \vdots \\ F_{N1} & F_{N2} & \dots & F_{NTr} \end{bmatrix}, \tag{4}$$

where Tr is the training vectors' number and T is the target class vector:

$$P = [1, 2, \dots, Tr]. \tag{5}$$

3. Testing dataset

To test the proposed methods, a dataset of an ECG signal of specific disorders was prepared. Nine ECG arrhythmias were extracted from the MIT-BIH arrhythmia database, which is a set of Holter's long-term recordings conducted between years 1975 and 1979 [20,23]. The MIT-BIH arrhythmia database consists of a randomly-chosen sample of 23 ECG records (labeled by non-consecutive numbers from 100 to 124), supplemented by 25 ECG records (labeled by non-consecutive numbers from 200 to 234) selected to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The records are slightly over 30 minutes long and are digitized at a 360-Hz sampling frequency. The subjects were 25 men and 22 women with the men aged 32 to 89 years, and the women aged 23 to 89 years. The testing extracted signals were 10 seconds long, taken from nine ECG arrhythmias. The nine arrhythmia types are shown in Fig. 1. Each type of signal was extracted from several records as seen in Tab. I. The first arrhythmia is Bradycardia (Br), which is the case of an ECG signal that contains long R-R intervals. In other words, the Br signal is a slow ECG signal with the Heart Rate (HR) being less than 60 beats/min. The Br signal occurs during sleep or because of heart weakness. The second type is the second-degree block (SDB), which occurs when the cardiac conduction system of atrial impulse through the

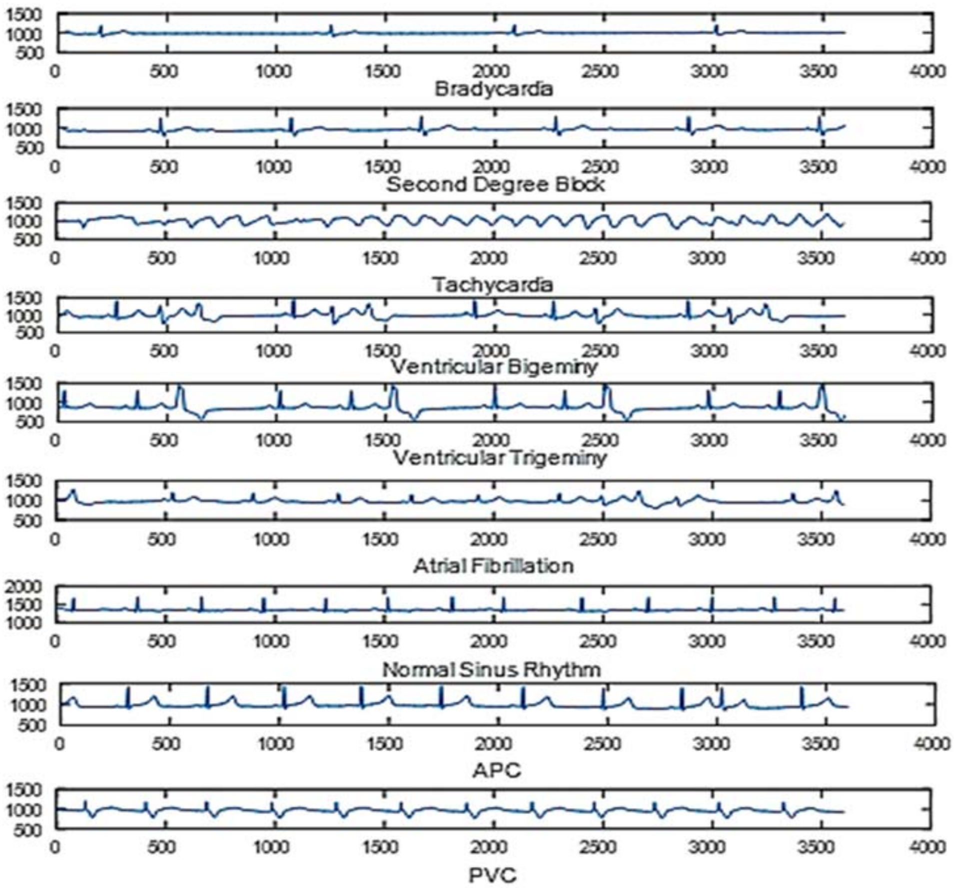

Fig. 1 *The nine ECG arrhythmia patterns contained in the testing database taken from the MIT-BIH database. The vertical axis represents the amplitude, where the units are in mV and can be managed dependent on the scale presented by the numbers from 1 to 2000. The horizontal scale represents the time duration that is dependent on the sampling frequency of 360 Hz. So, the unit will be a second for each 360 samples.*

atrial-ventricular (AV) node and the bundle of His is blocked or delayed. Patients with the SDB disease may be asymptomatic, lightheadedness and syncope. The third arrhythmia illustrated in Fig. 1 is Tachycardia (Tc), which is the ECG arrhythmia of a very fast heart rate that reaches more than 100 beats/min. Mainly, Tc may occur in some typical cases like in fear and during exercise. But in some clinical cases, Tc could be very life threatening, mostly if left without treatment. The fourth arrythmia is Ventricular Bigeminy (VB), which occurs when every normal beat is followed by a ventricular premature beat. The fifth one is Ventricular Trigemini (VT), which happens when two normal beats are followed by one ventricular premature beat. The sixth heart arrhythmia is the Atrial Fibrillation (AF) that occurs when the heart's electrical signal produces a quick contraction of the upper chambers. In this case, the P wave of the electrocardiogram trace may not appear. The AF arrhythmia may lead to a stroke, and in some cases, may cause heart failure. The seventh one is the Normal Sinus Rhythm (NSR). The eighth and ninth cases are the Atrial Premature Complex (APC) and the Premature Atrial Contraction (PAC) that occur when one region in the atria makes a premature beat before the sinoatrial node. On the ECG signal with a PAC arrhythmia, both the T waves and the QRS complexes are seen as very different from their normal readings.

Type	Record
Bradycardia	232
Second-Degree Block	231
Ventricular Tachycardia	106,200,203,205,210,213.214,215,217,221,223,233
Ventricular Trigemini	106,119,124,201,208,214,221,233
Ventricular Bigeminy	106,119,200,207,213,217,223,228
Atrial Fibrillation	201,202,203,210,217,219,221,222
Normal Sinus Rhythm	100, 103
APC	100,101,108,113,118,124,200,201,202,223,220,213
PVC	100,103,112,117,122

Tab. I *The list of the nine classes contained in the testing database and the selected records of the MIT-BIH database.*

4. Results and discussion

In this section, we investigate the performance of the three proposed methods over the ECG signal dataset by testing a big number of arrhythmias. Before starting our analysis, one question arises: What is the motivation behind tackling this massive number of arrhythmia classes, instead of focusing on only one arrhythmia or two arrhythmias as often happened in former research. In fact, the answer to this question points out to the essence of our contribution and motivation behind such sophisticated classification set-up. One of the most critical objectives here is to find out a general and a universal algorithm for classification of almost all ECG arrhythmia types. The investigation system pursued herein will consist of several experiments for exploration of the proposed algorithm over the testing dataset. The study will analyze the recognition rate as evidence about the wavelet function, WT level, training/testing ratio, and the method consuming time. We investigate the proposed methods by comparing their performance as measured by each of these parameters.

The testing data was taken from different records. So, for each arrhythmia 30 signals were prepared. The signals as shown in Fig. 1 are chosen to have only one type of the arrhythmias regardless of the object that the signal belongs to.

At the beginning of our work, the folders of the arrhythmias were prepared. There are nine such folders with each one of them containing 30 different signals or samples of one arrhythmia (.mat type files). The training and testing signals are taken from these 30 signals. For example, the training/testing ratio can be 5/25, 15/15, 20/10, or 25/5. This means that the training data matrix I will have this number of feature vectors for each arrhythmia. So if the ratio is 5/25, it means 5 feature vectors are used for each arrhythmia then the matrix I will have 5×9 columns. And then the remaining 25 signals are tested, and so on.

For testing the proposed methods by the testing dataset, we run the three methods eight times, such that at each time; a different number of arrhythmias is involved. In fact, the performance of the methods is determined for 2, 3, 4, 5, 6, 7, 8, and 9 classes of arrhythmia types separately, as is seen in Tab. II. As it was mentioned before, the purpose of these experiments is to find out a universal system for discrimination among various arrhythmia classes regardless of the numbers of arrhythmias within each of these classes. Therefore, the system used herein is a classification system and not a verification system that uses only two types of classes; a positive class in which some arrhythmias are present, and a negative one, in which all arrhythmias are absent.

At the beginning of our analysis, we used the PEWP method (WP at level 8) as a reference to determine an appropriate wavelet function and an optimal wavelet level. In Tab. II, we present the results of the PEWP performance for different Daubechies wavelet functions. By studying the results tabulated therein, we can

Wav. Fun.	Db1	Db2	Db3	Db4	Db5	Db6	Db7	Db10
Class No. 2	100	100	100	100	100	100	100	100
Class No. 3	93.33	93.33	90	96.66	100	96.66	96.66	93.33
Class No. 4	87.5	87.5	85	90	92.5	90	87.5	85
Class No. 5	80	80	74	76	80	78	72	74
Class No. 6	63.33	63.33	56.66	65	66.66	68.33	56.66	70
Class No. 7	68.57	68.57	62.85	70	71.42	71.42	60	74.28
Class No. 8	62.5	62.5	55	62.5	63.75	61.25	53.75	63.75
Class No. 9	58.88	58.88	56.66	63.33	63.33	58.88	53.33	62.22
Average	76.7638	76.7638	72.5212	77.9363	79.7075	78.0675	72.4875	77.8225

Tab. II *Recognition rates [%] for PEWP versus different wavelet functions.*

notice that Daubechies function type Db5 has the best results compared with other functions, with an average recognition rate that reaches 79.70 %. One observation is very critical here, namely, that the recognition rate of seven arrhythmias is 71.42 %, which is a high number indeed attesting to the success of our current investigation. And that is repetitive for Db6 and Db10. The results in Tab. II are the basic indication for choosing the wavelet function as Db5 for the rest of our experiments.

For evaluating the PEWP performance versus different WP levels, we run the system eight times according to different numbers of arrhythmias. At each time, different WP levels (4, 5, 6, 7, 8, and 9) were utilized, with the coefficients vector length given as follows: 30, 52, 116, 244, 500, and 1012, respectively. The results are reported in Tab. III. The best performance was achieved with level 8 where the result was 79.70 %, and we can see that the result for each iteration was significant.

WP level	4	5	6	7	8	9
Class No. 2	100	100	100	100	100	100
Class No. 3	93.33	96.66	100	96.67	100	93.33
Class No. 4	67.50	87.50	97.5	90	92.5	85
Class No. 5	60	68	72	74	80	70
Class No. 6	53.33	56.71	61.66	61.66	66.66	60
Class No. 7	55.71	55.71	67.14	65	71.42	61.42
Class No. 8	50	48.75	58.75	62.50	63.75	51.25
Class No. 9	45.55	43.33	55.55	61.11	63.33	48.88
Average	65.67	69.58	76.57	67.36	79.70	71.23

Tab. III *Recognition rates for PEWP versus different wavelet levels.*

In Tab. IV, the recognition rate for the PEWP, PEWD, and 2SPED methods versus different Training/Testing ratios is investigated. For this purpose, ratios of 5/25, 15/15, 20/10, and 25/5 for the Training/Testing ratios were tested. We can notice that PEWP and 2SPED have better results than PEWD for the smaller training ratios 5/25 and 15/15, with averages of 40.58 and 69.11, respectively. However, PEWD has better results with the larger training ratios of 20/10, and 25/5 with averages of 82.08 % and 90.39 %, respectively. The average for the 25/5 Training/Testing ratio is 90.39 %, and the recognition rate for nine arrhythmias is 72.5 %. In fact, these results are auspicious and favorable. However, the 2SPED method is immensely competing with the PEWD one, where the average for the 25/5 Training/Testing ratio is 88.94 %, and the recognition rate for nine arrhythmias is again 72.5 %. By contrast, the PEWP method has corresponding values of only 79.16 % and 50 %, respectively.

The elapsed time calculated for the processing of the PEWP, PEWD, and 2SPED methods over the whole loop of the eight different arrhythmia classes (shown in Tab. IV) is investigated in Tab. V. For fair comparison, the three methods were coded similarly in MATLAB, and their codes were implemented on the same platform. We can see that the PEWP method has the best result, while PEWD comes second, and 2SPED ranks third. The reason behind this order is the difference in the level of sophistication for the three methods.

Training/Testing	5/25			15/15		
	PEWP	PEDW	2SPED	PEWP	PEDW	2SPED
Class No. 2	96	51.72	93.10	100	80	96.66
Class No. 3	84	41.37	65.51	97.77	86.66	93.33
Class No. 4	76	39.65	60.34	86.66	80	88.33
Class No. 5	64.8	38.62	46.89	70.66	57.33	69.33
Class No. 7	53.71	39.40	40.39	56.19	59.04	65.71
Class No. 9	45	32.75	34.48	50.83	51.66	62.5
Average	69.91	40.58	56.78	76.10	69.11	79.31
Training/Testing	20/10			25/5		
	PEWP	PEDW	2SPED	PEWP	PEDW	2SPED
Class No. 2	100	100	100	100	100	100
Class No. 3	96.66	100	100	100	100	100
Class No. 4	87.5	90	97.5	85	95	100
Class No. 5	68	70	65	80	92	84
Class No. 7	55.71	70	70	60	82.85	77.14
Class No. 9	48.75	62.5	65	50	72.5	72.5
Average	75.04	82.08	82.91	79.16	90.39	88.94

Tab. IV *Recognition rates for PEWP, PEWD, and 2SPED versus different Training/Testing ratios.*

Method	PEWP	PEDW	2SPED
Elapsed time	55.79 seconds	83.66 seconds	98.48 seconds

Tab. V *Elapsed time calculated for the processing of PEWP, PEWD, and 2SPED over the whole loop of the eight different arrhythmia classes number shown in Tab. III.*

The average for the PEWP method over the three Training/Testing ratios shown in Tab. IV is 75.05 %, for the PEWD method is 70.48 %, and for the 2SPED method is 76.99 %. Tab. V shows the elapsed time in seconds calculated for the processing of PEWP, PEWD, and 2SPED over the whole loop of the eight different arrhythmia classes shown in Tab. III. The results in the table nominate the PEWP method to be the superior method among the three used methods in terms of the consumed time. Meanwhile, the 2SPED method has better results in term of recognition rate with an average that reached 76.99 %. For fair comparison, the three methods were coded similarly in MATLAB 2015a, and their codes were implemented on the same platform. The hardware used was a Surface_Pro_1796 laptop with processor Intel(R) Core(TM) i7-7660U CPU @ 2.50 GHz, 2496 MHz.

In Tab. VI, we compare our proposed method 2SPED to other published methods that are based on the wavelet transforms, such as the method of the average power spectrum density of DWT (WPSD) [19], the method of Shannon entropy with a wavelet packet (WSHE) [24], the method of log energy entropy with a wavelet packet (WLEE) [21] and the method of sure entropy with a wavelet packet (WSE) [22]. An average recognition rate of 76.99 % is achieved by our 2SPED method, whereas the best of its competing methods in Tab. VI (the WPSD method) reached only an average recognition rate of 61.03 %.

Method	Recognition Rate [%]
WPSD	61.03
WSHE	41.34
2SPED	76.99
WSE	58.10

Tab. VI *Results of recognition rates for comparison.*

Our preliminary investigation of classification of error herein simply dealt collectively with error *per se*, without differentiation between the well-known two types of errors. One type of error, called error of type I (error of the first kind or error of false positives) occurs when a healthy person is mistakenly predicted to be a patient inflicted with a specific cardiovascular abnormality or a specific set of abnormalities. Another type of error, called error of type II (error of the second kind or error of false negatives) occurs when a patient inflicted with a specific cardiovascular abnormality or a specific set of abnormalities is mistakenly deemed to be a healthy person [25]. For the problems of heart diseases considered herein, the error of the second type should be given more attention, since it is of more serious and dreadful consequences and ramifications than the error of the first kind. For future work, we strive to treat the problem of ECG-signal classification via a contingency or confusion matrix comprising true positives, false positives, false negatives, and true negatives. Based on this ubiquities matrix, we might derive sets of indicators such as sensitivity, specificity and predictive values, and finally combine these into single metrics such as the Mathew correlation coefficient (MCC), or other means of informedness and markedness [26].

5. Conclusions

In this study, a universal recognition system has been proposed for ECG signal arrhythmia recognition. The challenging task of the present system is to test the possibility to distinguish between a big number of different types of arrhythmias at the same time, which is increased herein to reach the ultimate number of nine. Unlike traditionally known methods that can be used for the classification of just one or two types of arrhythmias only, the proposed study investigates the classification of nine different types of heart disorders with relatively good results. Three wavelets transform-based methods have been investigated by conducting different experimenting with various concepts such as the wavelet functions, the wavelet level, the training/testing systems, and the elapsed time. The results showed that these three methods can distinguish between the nine arrhythmias in a good recognition rate on the average. The average for the PEWP method over the three training/testing systems is 75.05 %, for the PEWD method is 70.48 %, and for the 2SPED is 76.99 %. The elapsed time in seconds calculated for the processing of PEWP, PEWD, and 2SPED over the whole loop of the eight different arrhythmia classes nominates the PEWP method to be the superior method among the three methods in terms of time-consumption. On the other hand, the 2SPED method has better results in terms of the recognition rate.

A natural sequel of the present work is to compare the performance of our automated method to a manual one relying on human judgement. Since we are unaware of any former experiments in which human experts attempted to handle more than two arrhythmias simultaneously, we have to arrange for the conduction of such experiments ourselves. We believe that it is not a really easy task to locate experienced medical personnel who can excel in classifying classes of multiple arrhythmias. Therefore, we preferred to defer to future work the comparison of the performance of our automated method to the manual one relying on human expertise.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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