Detection of Heart Attack using Cross Wavelet Transformation and Support Vector Machine

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Abstract
Ischemic heart disease is one of the leading causes of death in the world, and includes a wide range of transient forms, including incomplete blood supply to the heart muscle, which cause heart attacks and eventually sudden death. Identifying the main area of the myocardial infarction (MI) is a priority for the treatment of myocardial infarction. Electrocardiogram signal recording is a common method for monitoring cardiac function and widely used for detecting heart attack. In this study, using 10-part sections of the standard 12-lead electrocardiogram signal taken from the PhysioNet database, the diagnosis of the infarction was made possible. First, after removing the electrocardiogram (ECG) signal noises, by applying the Principal Component Analysis (PCA), the dimensions of the 12-lead electrocardiogram signal were reduced. Then the characteristic vector was created using the statistical properties of the wavelet cross spectrum (WCS) and the resulting wavelet coherence (WCOH) by the cross-wavelet transformation (XWT) method. In the next step, using a support vector machine, which is used as a classifier, the location of the heart attack is detected. The results show that the designed system to detect the incidence of MI has a sensitivity of 96.7% and a precision of 99%.

Keywords: Heart attack; Principal Component Analysis; Electrocardiogram signal; Cross-wavelet transformation; Support vector machine

Introduction

Myocardial infarction (MI) is commonly known as a heart attack and occurs when blood flow stops to a part of the heart, causing damage to the heart muscle [1]. Despite the reports on the reduction of myocardial infarction, cardiovascular disease in the world is still one of the leading causes of death. According to the published reports by American Health Association, about 750,000 Americans have a heart attack every year. Therefore, the discovery of new therapies and algorithms for diagnosis and disease prediction has always been vital [1]. There are several methods to determine the location of the myocardial infarction (MI), including angiography, echocardiography and cardiography and so on [2]. The electrocardiogram (ECG) comprises different electrical waveforms such as P, Q, R, S, and T, which representing either depolarization or repolarization of different muscles in the heart [3]. MI characteristics include ST-segment elevation, abnormal Q wave appearance, and T-wave inversion. The ECG signal characteristics change when MI occurs [4]. Fig. 1. shows the samples of normal and MI ECG signals. In the normal ECG, heart is beating in a regular sinus rhythm between 60 - 100 beats per minute but in MI ECG signal, ST interval change and R peak inverse.

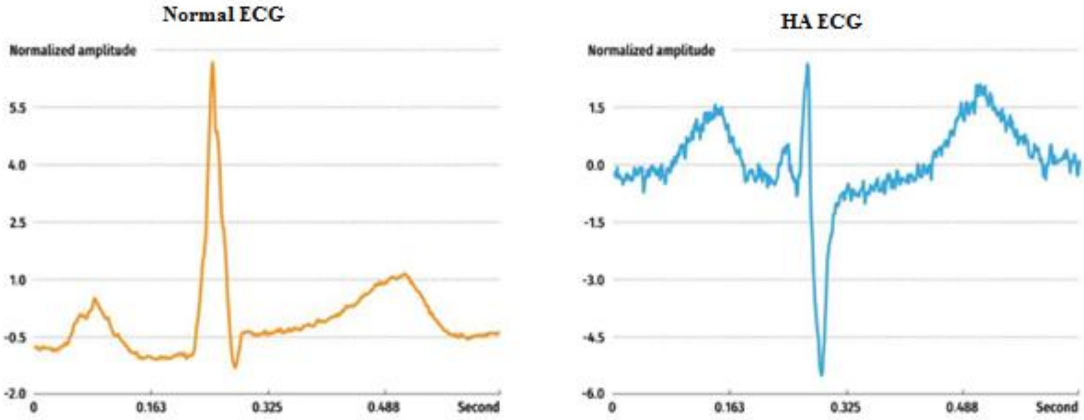


Figure 1. Left for normal and right for MI (Myocardial Infarction) ECG beat

Over the years, several approaches have been proposed to identify HA and improve the accuracy and sensitivity of waveform. Chen et al. [5] extracted the features from the electrocardiogram using time-frequency and frequency-domain algorithms. They used the Perceptron classification method to diagnose arrhythmia. In this method, a feature of the frequency domain is derived from the wavelet algorithm and two features of the time domain have been used. The calculated accuracy of this algorithm is 99.8%.

Arif et al. [6] used the K Nearest Neighbor (K.N.N) method to determine the location of myocardial infarction in data classification. In this study, the features and timing characteristics of the electrocardiogram signal, such as the amplitude of the T wave and Q wave, and the deviation of the ST segment, have been used. These features were extracted from a 12-lead electrocardiogram signal. This research was done in two stages: normal signal separation from the patient and the determination of the injury site. 20,160 electrocardiogram pulses extracted from the available data at the PhysioNet base were used for classifying the test [6].

Singh et al. have used power spectral analysis for extracting some information of heart rate variability [7-11]. In this paper, time-frequency characteristics of the HRV are described by using an adaptive continuous Morlet wavelet transform (ACMWT) method [7]. They also have used a non-invasive diagnosis method to detect cardiac heart disease. In this paper, they extracted 10 non linear feature of HRV signal and used standard database of cardiac heart failure to validate the method [8]. Moreover, they used generalized discriminant analysis (GDA) and the 1-norm linear programming extreme learning machine (1-NLPELM) to detect this disease in the other work [9]. In addition, they have used three methods including adaptive continuous Morlet wavelet transform (ADCMWT), adaptive Stockwell transform (ADST) and adaptive modified Stockwell transform (ADMST) to control cardiovascular in another work [10]. Furthermore, they have used multiscale wavelet packet (MSWP) transform and entropy features to detect the CAD patients using heart rate variability (HRV) signals. In this paper, they extracted 62 features of HRV signals and used extreme learning machine to classify them [11].

Arif et al. [12] used Learning Vector Quantization, which is an echo post-propagation learning network, for diagnosis of myocardial infarction. The characteristic used as input data was the 12-lead electrocardiogram of ST-segment deviation. This study was performed on 769 male patients. Of these, 353 had anterior infarction and 410 patients had lower myocardial infarction. Two class categories were formed, one of which was anterior infarction and the other with lower infarction. The overall accuracy of this test was about 88.6% [12].

Trunk et al. in their study discovered rules for determining the location of the MI associated with the Q, R and S wave to the 17's parts of the heart wall using images obtained from magnetic resonance imaging [13]. Reddy et al. used an artificial neural network-based approach and QRS size for the normal isolation of MI. In this research, the QRS wave amplitude was used as a feature and an artificial neural network was used to classify the MI. The accuracy of this test was approximately 79 % and the specific rate was about 97% [14]. Sharma et al. used the wavelet transform to extract 60 features from the cardiac artery and support vector machine method to identify a myocardial infarction [15].

In a study by Bayasi et al. they initially denoise the signal using high and low pass filter, then by providing an algorithm they identify the points on the ECG, including the QRS complex and the P and T points. They used a naive Bayes classification algorithm in their paper and obtained an accuracy of 84.26 % [16]. Acharya et al. used a convolutional neural network (CNN) algorithm for detection of MI ECG beats with noise and without noise. They achieved an average accuracy of 93.53% and 95.22% using ECG beats with noise and without noise removal respectively [17]. Liu et al. used a 20th order polynomial function (PolyECG-S) for ECG feature extraction and achieved 94.4% accuracy in detecting the (MI) on the test dataset [18]. Baloglu et al. used the convolutional neural network (CNN) on the standard 12-lead ECG signal for the diagnosis of MI. Their proposed architecture yielded impressive accuracy and sensitivity performance over 99.00% for MI diagnosis [19]. Lodhi et al. used a 20-layer convolutional neural network algorithm for detecting the MI. They used a 12-lead signal as input data and achieved a performance of 93.53% in their work [20].

Support vector machines have been used in automated diagnostic systems. In fact, support vector machines are a tool for solving the binary classification problem due to their outstanding performance. The main idea of SVM is to find the maximum margin between educational data and decision-making boundaries [21]. SVM can act as a linear or nonlinear classification according to its core function. A linear kernel function makes SVM a linear classification, and linear core functions such as polynomials and sigmoid make it a nonlinear classification [22-25].

Although these methods accurately analyze ECG signal, the number of features that are required to detect the location of MI increases computation time. Therefore, they are not suitable for portable ambulatory ECG devices. Our main objective of this paper is to provide a suitable method for diagnosing the location of heart attack and have high accuracy and sensitivity performance on ECG lead signals. For this purpose, the features of the ECG signals have been extracted using cross-wavelet and associated properties and SVM has been proposed to detect the location of MI on standard 12-lead ECG data.

Materials and Methods

ECG Database

In order to train and test the method presented here, it is needed that the data be carefully classified by a cardiologist. In this study, the Physiobank (PTB) ECG database is used [26]. The data comprises ECG records of 52 normal subjects and 148 MI patients. In order to access all types of myocardial infarction in these databases, all available data were reviewed and it was observed that all cases of myocardial infarction were classified into ten categories: anterior (A), anterior lateral (AL), anterior septal (AS), inferior (I), inferior lateral (IL), inferior posterior (IP), inferior posterior lateral (IPL), lateral (L), posterior (P) and posterior lateral (PL). That for four of them only one or two cases were recorded and they were ignored (L, P, PL, IP). Of these, 60 records were selected for 60 seconds [27] as follows in Table 1. ECG signal from each lead is digitized at a sampling rate of 1000 Hz. Samples include 43 males and 17 females.

Method

In this study, XWT has been proposed for detecting the location of MI on standard 12-lead ECG data. The studied stages are as follows:

1. Extraction of data (12 -lead Electrocardiographs) from the PTB of PhysioNet database
2. Remove noise from signal
3. Applying Principal Component Analysis(PCA) to reduce the number of signals

4. Obtaining cross-wavelet transform coefficients and wavelet coherence for signals
5. Feature extraction
6. Using support vector machines for classification
7. Evaluate system results based on accuracy and sensitivity and specificity

Table 1. Data number related to each classification class

Rows	Classes	Record number
1	Inferior-lateral(IL)	10
2	Anterior(A)	10
3	Inferior-posterior- lateral(IPL)	10
4	Antero-septal(AS)	10
5	Inferior(I)	10
6	Antero-lateral(AL)	10

A block representation of the method used in this study is given in Fig. 2.

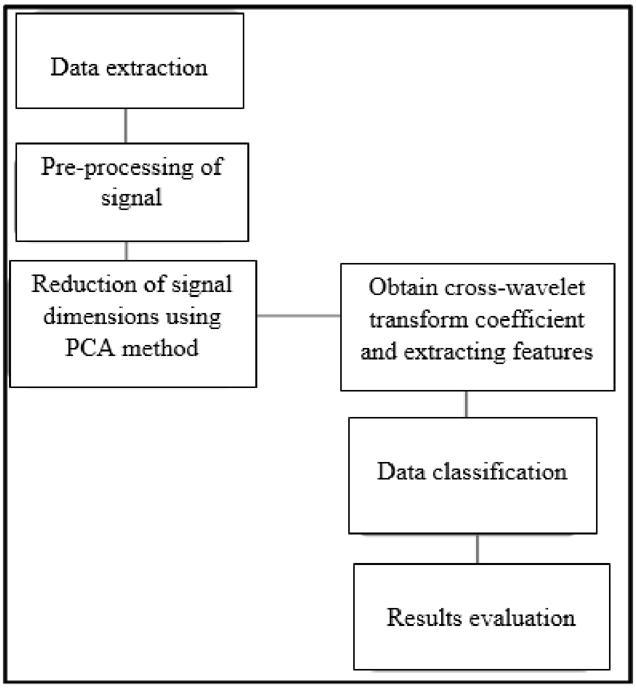


Figure 2. Schematic representation of our proposed method

Preprocessing

A clean signal is essential for heart signal processing. In general, the noise in the electrocardiogram signal includes muscle noise, baseline wanders and power line interference noise [28]. In this study, the use of the wavelet transforms as a feature vector eliminates the noise in the signal. Therefore, noise elimination can improve the heart rate error in subsequent calculations. The baseline and city noise has been removed by cleansing function. To eliminate power line interference a second-order IIR Notch filter has been used. Figures 3 and 4 show a noisy and free-noise of normal ECG.

After noise removal, heart rate variability (HRV) of the signal is extracted. HRV is a physiological signal that indicates changes in heart rate intervals. This signal is extracted from the electrocardiogram and measures the change in the beat-to-beat interval by measuring the time between two successive R peaks. Fig.5 shows the HRV signal obtained from the signal in Fig. 4. The total of this signal, which is 4,000 samples, corresponds to 40 seconds, and in this 40 second, the quality shown in Fig.5 contains

49 beats. The horizontal axis shows the number of beats (from 1 to 48) and the vertical axis shows the distance between the two successive R peaks at in the electrocardiogram.

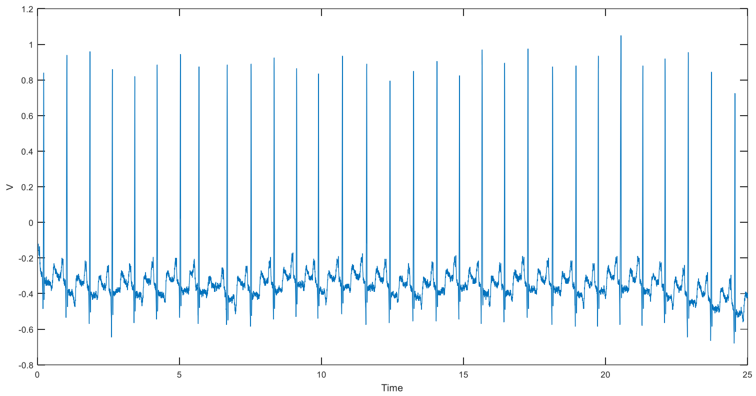


Figure 3. Lead-II of signal before removing noise

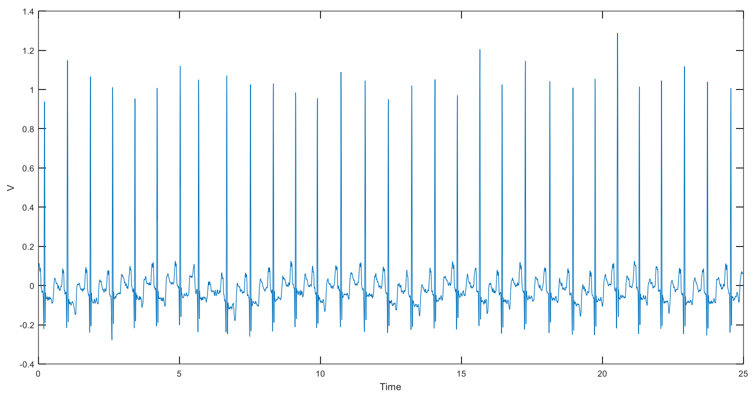


Figure 4. Lead-II of signal after removing noise

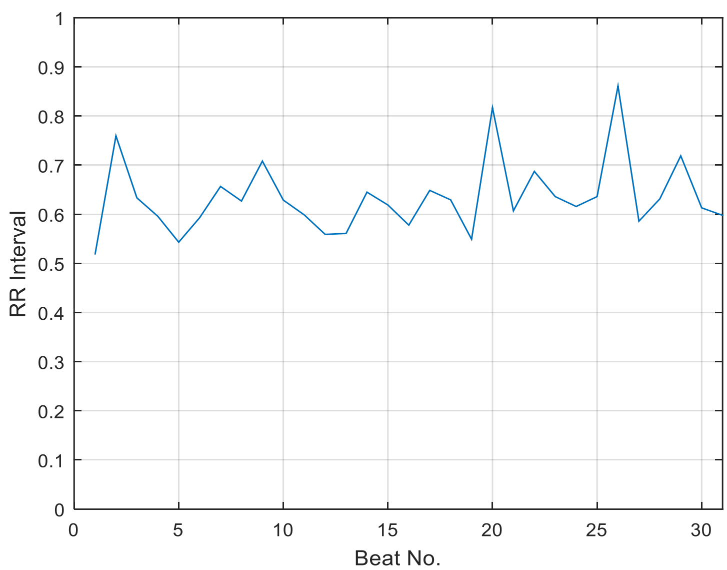


Figure 5. The HRV signal obtained from electrocardiogram shown in Fig 4.

Wavelet Transform

One of the most powerful tools in detecting signals is the wavelet transform. This tool has many applications in the processing of features of signals such as discontinuities, sudden and local changes, energy concentration in a small portion of the signal, and so on. A wavelet transform, like Fourier transform, is a powerful signal processing tool used to transmit signal from one time-space to another. This space is three-dimensional, the dimensions are time, scale, and scope. The significance of this transformation is that the three-dimensional space that this transformation of the signal provides reveals the specific features of the signal that are not accessible to other signal processing tools. On the other hand, there are many natural phenomena that have a transient nature. Discontinuities, sudden and local changes, energy concentration in a small portion of the signal, and many other features that are currently one of the best ways to process them using the wavelet transform [29-30]. In the meantime, the transformation of the wavelet is of more importance, and in this section will be examined.

Cross-Wavelet Transform

Cross wavelet transform (XWT) with x_n and y_n is defined as$W^{XY} = W^X \mathrm{W}^{\mathrm{Y}*}$, where * shows mixed conjugate. In addition, cross wavelet power is $|W^{XY}|$ [31]. Mixed argument $\arg(\mathrm{W}^{\mathrm{XY}})$ can be interpreted as a local relative phase between x_n andy_n. Theoretical distribution of cross wavelet power of two series with a background power spectrum P_K^X and P_K^Y are defined as:

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y} \tag{1}$$

where $Z_v(p)$ is the corresponding confidence level with probability p which is defined with multiplication square root of two distributions X^2. Due to existence a simple cause-and-effect relation between recorded phenomena in time series, we expect constant phase fluctuations [26].

Cross-Wavelet Phase Angle

It is important to obtain the phase difference between the components of the two time-series in a cross-wavelet. Therefore, we need to estimate the mean and confidence intervals of the phase difference, therefore, the mean and confidence interval of the phase difference should be estimated. For this purpose, the circular mean of the phase is used in areas with a statistical significance of over 5%. This method is a useful and general method for calculating the mean of the phase. The circular mean of an angle set (a_i,i=1…n) is defined as:

$$a_m = \arg(X, Y) \quad with \quad X = \sum_{i=1}^{n} \cos(a_i) \quad and \quad Y = \sum_{i=1}^{n} \sin(a_i) \tag{2}$$

Calculation of medium confidence intervals with high reliability is difficult because the phase angles are independent of each other. The number of angles used in the calculation can be increased by increasing the resolution of the scale. However, the dispersion of the angles around the average is also considered. For this purpose, the standard deviation has been been found as follows:

$$s = \sqrt{-2\ln(R/n)} \tag{3}$$

$$R = \sqrt{X^2 + Y^2}$$

The circular standard deviation from this point, which varies from zero to infinity, is similar to linear deviation and its results are similar to the linear deviation when the angles are distributed around an average angle. In some cases, there may be reasons for calculating the average phase angle for each scale [32].

Wavelet Coherence

The power of cross-wavelet power reveals high-power areas. Determining the degree of integrity of the cross-wavelet transform is also a useful measure. The wavelet coherence of two-time series is defined as follows [28].

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)} \tag{4}$$

It should be noted that this definition is similar to the general correlation coefficient definition. Smoothing operator S is written as $S(W) = S_{scale}\left(S_{time}\left(W_n(s)\right)\right)$ where s_{scale} is related to smoothing in wavelet scale axis line and s_{time} is related to smoothing on the time axis. Smoothing operator design, which has same the effect as desired wavelet, is common. In Morlet wavelet, the smoothing operator is proposed as:

$$S_{time}(W)|_s = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)|_s \tag{5}$$

$$S_{time}(W)|_s = (W_n(s) * c_2\Pi(0.6s))|_n$$

where c_1 and c_2 are normalization constants, and Π is a rectangular function. The length of scale correlation reduction for morlet wavelet is 0.6, which is determined as experimental. In practice, both annulations are done discretely, therefore, normalization constants are determined as numeric.

Principal Component Analysis

The principal component analysis is a static technical aimed at reducing the size of the data set. This analysis involves the decomposition of special values of the covariance matrix. The principal component analysis in the mathematical definition is an orthogonal linear transformation that transfers data to a new coordinate system so that the largest data variance of the first coordinate axis is the second-largest variance on the second coordinate axis, and also for the rest. Principal component analysis can be used to reduce the dimension of data, thus preserving components of the data set that have the greatest effect on the variance [33]. In this study, the principal component analysis method was used to 12-lead the electrocardiogram reduction and consequently reduce the dimensions of the system. The function of this method, especially in the first stage of use, is well shown in Fig. 6. As one can see, only the initial signals of the Fig. 6, which outputs the processing of the main components, behave like the electrocardiogram signal, and the rest of the output signal of the processing of the principal components are like the noise. Therefore, it seems that only a few primary signals can be used to process the principal components. It will be explained how many of these components should be selected.

Feature Extraction

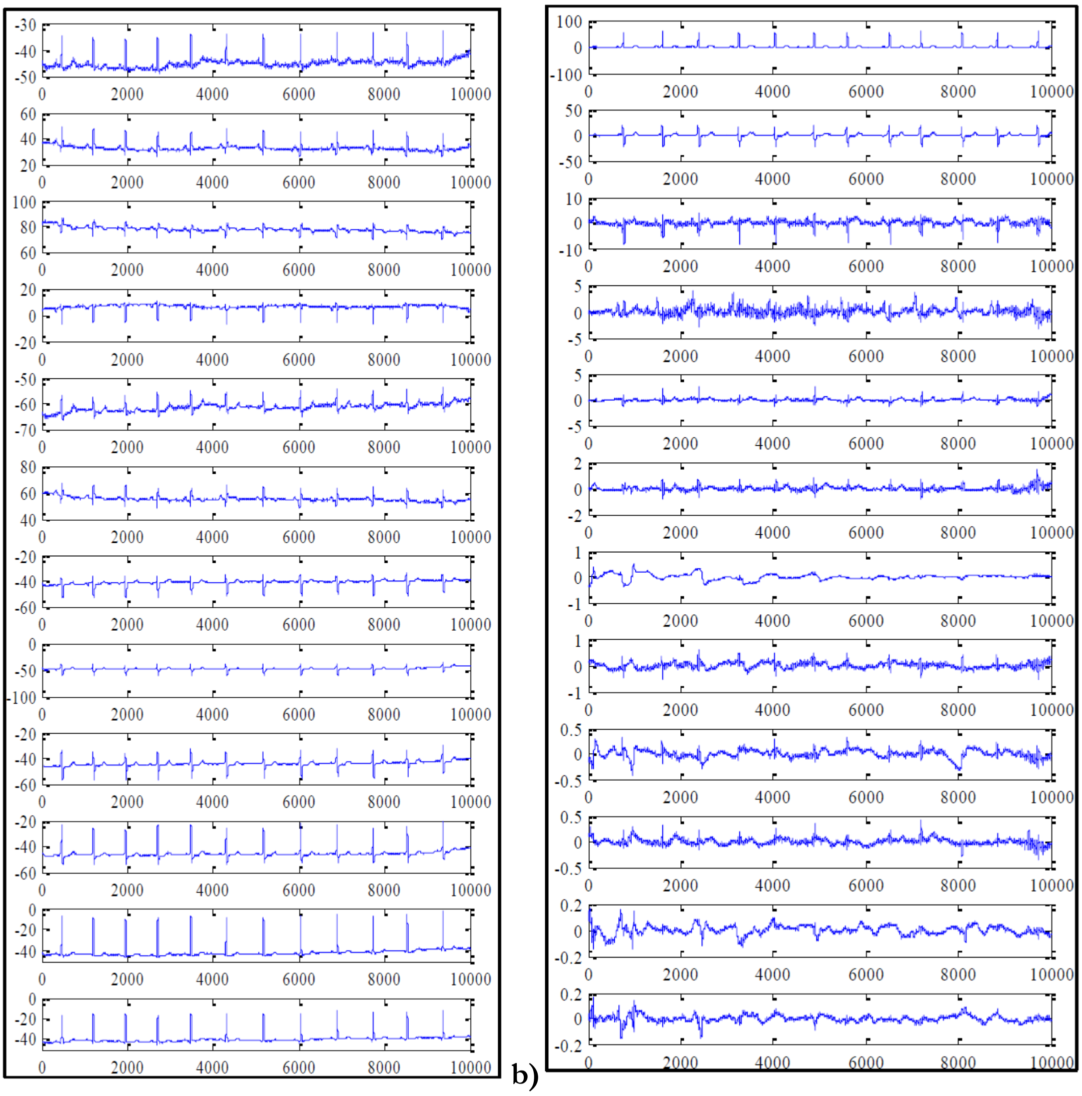
The XWT method is always used to provide the wavelet transform coefficients based on the interaction of two signals on each other. So here the output signals of the principal component analysis method have been prepared in paired with the cross- wavelet function with the Morlet mother-wavelet function, and the outputs were obtained as cross-wavelet coefficients, including the size and angle of the phase of the wavelet cross-spectrum and the wavelet coherence coefficients.

Two examples of the results are shown in Figs. 7 and 8. It is not easy to understand them, and so some parameters must be extracted from the cross- wavelet transforms results as a feature. First, based on cross-wavelet transform results, related signals of phase angle and wavelet coherence are extracted as follows:

$$WCS_{angle(t)} = \sum_{s1}^{s2} WCS(s,t) \tag{6}$$

$$WCOH_{scale(t)} = \sum_{s1}^{s2} WCOH(s,t)$$

where WCS and WCOH are wavelet cross spectrum and the wavelet coherence coefficients respectively. Now several characteristics from each of the above signals will be extracted. Since the statistical features can represent important information of the signal we used some of them in this study for feature extraction. The extracted features are the mean (Mean), standard deviation (SD), skewness (Sk), and kurtosis (Ku), which are related to each of the two above signals. So, after each step, the cross-wavelet has 8 features (2 WCS and WCOH scale, and each of them has 4 features).



a) b)

Figure 6. Reducing the dimensions of the system using the PCA method; **a)** (left image):12-lead of ECG; **b)** (right image): Output of PCA processing

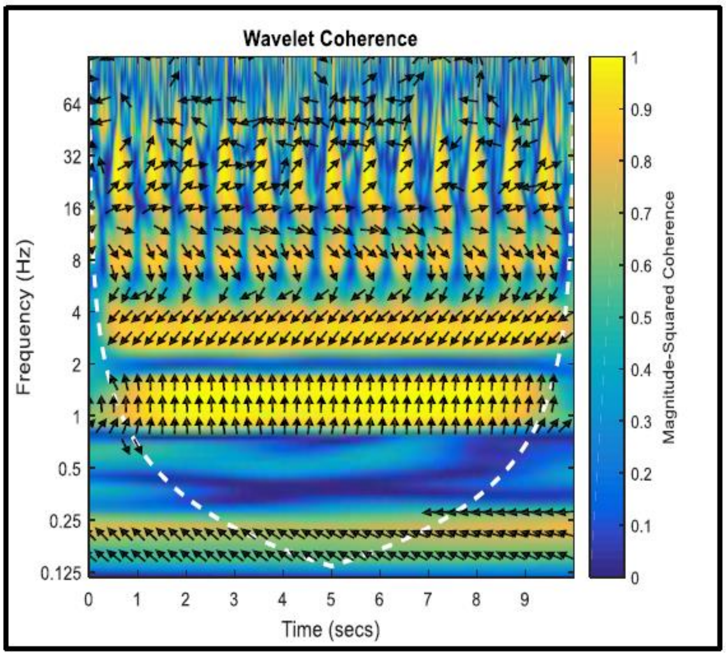


Figure 7. Cross-wavelet transform between the first and second signals of the PCA output

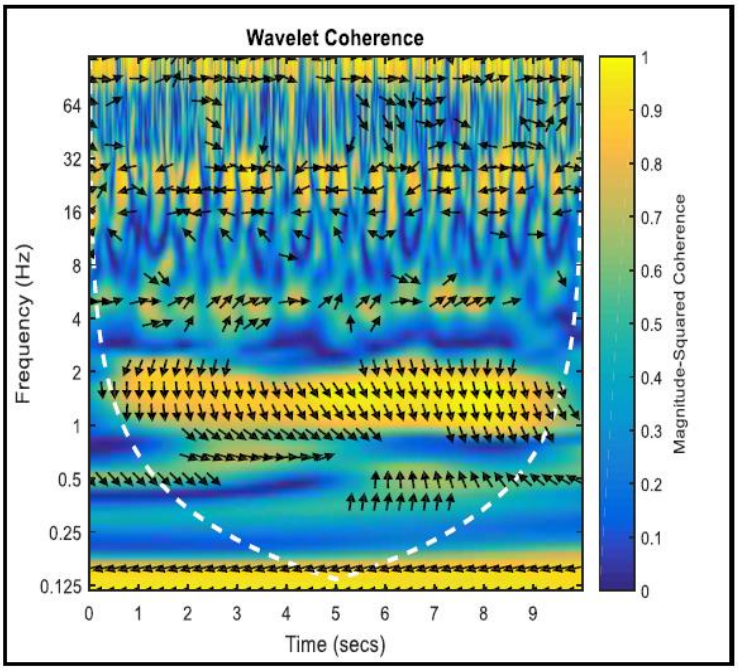


Figure 8. Cross-wavelet transform between the fourth and fifth signals of PCA output

Classification

In this research, a support vector machine (SVM) has been used to classify the data. In today's machine learning applications, SVM is considered one of the most powerful and precise methods among other popular algorithms. SVM is used in various applications such as biomedical signal classification, image classification, text categorization, and bioinformatics.

The SVMs can be considered as a linear or nonlinear classifier as they have different kinds of kernel functions. With a linear kernel function, the SVM becomes a linear classifier, and with a nonlinear kernel functions, such as a polynomial, and a sigmoid function, it becomes a non-linear classifier [34].

Evaluation Parameters

To evaluate the classification system, three parameters are usually used: Sensitivity (SE), Specificity (SP) and Accuracy (AC) [35]. Accuracy is a feature to evaluate the proximity of the obtained results than real results.

$$SE = \frac{TP}{(TP + FN)} \times 100 \tag{7}$$

$$SP = \frac{TN}{(TN+FP)} \times 100 \tag{8}$$

$$AC = \frac{TP+TN}{TN+FP+FN+TP} \times 100 \tag{9}$$

where TP is true positive, TN is true negative, FN is false negative and FP is false positive. In other words:

- FP classified the healthy as patient
- TP classified the patient as patient
- FN classified the patient as healthy
- FN classified the healthy as healthy

It was stated that the principal component analysis was to reduce the dimensions of the system. Now choosing how many principal components of the PCA method to continue research steps needs more investigation. It is assumed that after using the principal component analysis method, the dimensions of the system were reduced to Npc. To perform a cross-wavelet, the pair of signals obtained from the processing of the main components of the wcoherence function must be provided in MATLAB software, which is defined in the transformation of the cross-wavelet. Therefore, the number of 2 compounds of Npc will be chosen.

The minimum value of Npc is equal to 2, because at least 2 signals should be presented to the cross-wavelet. In this study, N_{pc} from 2 to 6 are tested and by using cross-wavelet transforms eight features are obtained.

According to Table 1, it was noted that the number of records is 60 (6 classes and 10 classes each), each record is 60 seconds long. To increase the precision of the results, after the removal of noise and calculating the HRV, the first 5 seconds of the first and last records of each record were deleted and the remaining 50 seconds were divided into 5 10-second sections. Therefore, the total number of data in this case will be 300, with the contribution of each class of 50. To use classifier, data is divided into two the training and testing category that 70% of the each data used for training and 30% of data used for testing the algorithm, that this division is random due to each class of data. Support vector machine with a linear kernel function is used for classification data.

Results

The results are shown in Figures 9 and 10. As is clear in this Figures, afterwards Npc = 4, the percentage of accuracy for training data becomes 100%, and the support vector machine is well trained. However, the accuracy of the test data has been always more important because the final answer is not given to the classifier. Therefore, it is clear that the best mode is Npc=5, and after that, the number of properties increases so that the classification system is mistaken. For this, the characteristic curve diagram of the system performance and the confusion matrix for the test data are shown in Figures 11 and 12, respectively. The confusion matrix is a square matrix N * N, where N is the number of classes in the classification problem, and the element with column i and row j is equal to the number of class i data identified in the diagnosis as j class. It is natural that the best mode is i = j and the optimal mode is when there is only a number on the original diameter of the matrix, but this is impossible in practice, since such systems are never ideal. As shown in Figure 10, the designed system only has an error of about 3 data and has an acceptable 96.7% accuracy. It has already been noted that the accuracy of the system for health education data is 100%, as shown in Figure 12. In total, in this case, the accuracy of the system for all data is 99.0%.

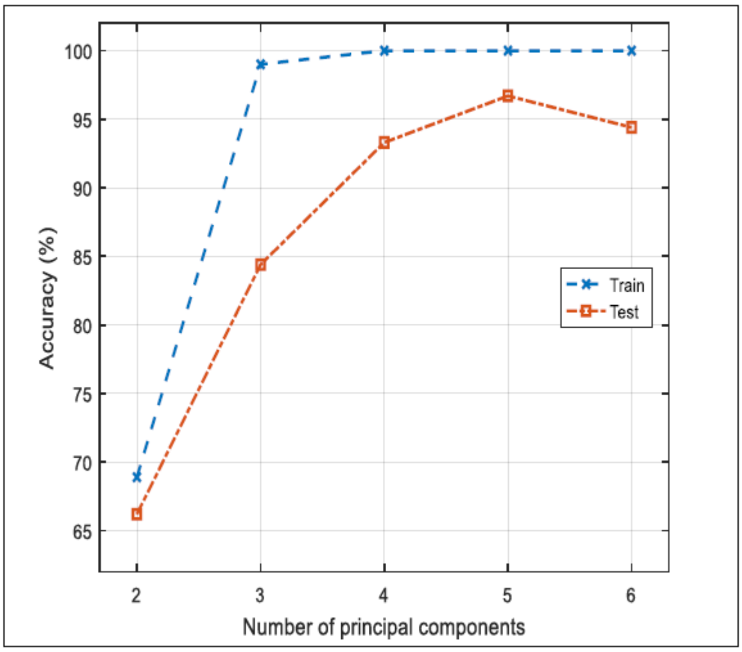


Figure 9. Obtained results for test and train data in different selection of Npc

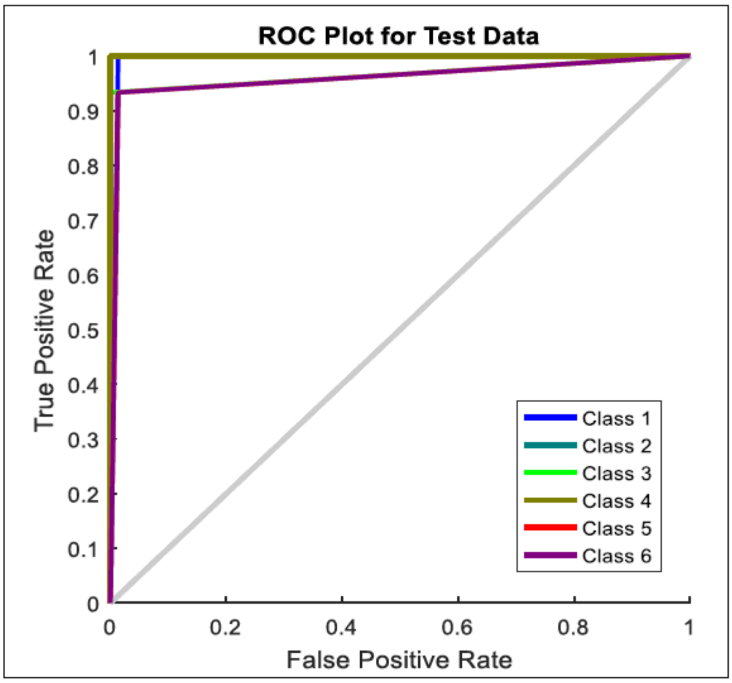


Figure 10. Characteristic curve diagram of system performance for test data for Npc=5

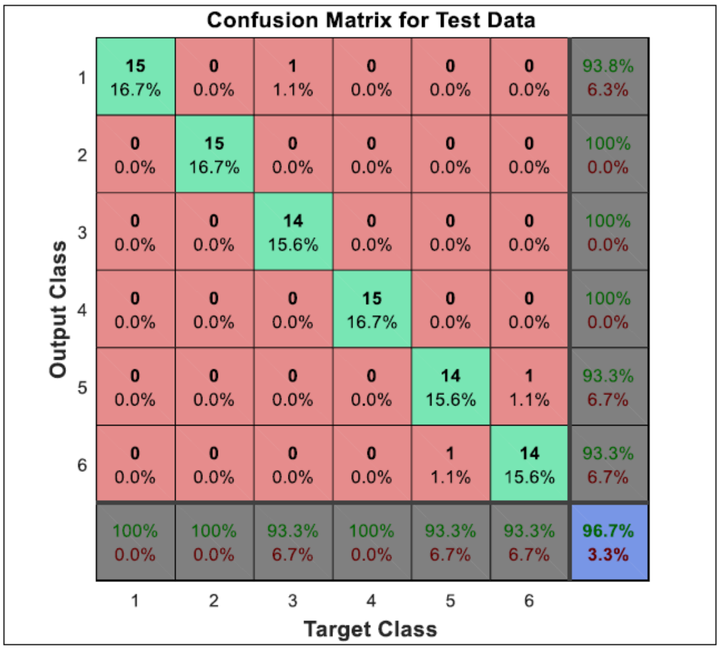


Figure 11. Confusion matrix for data test for Npc=5

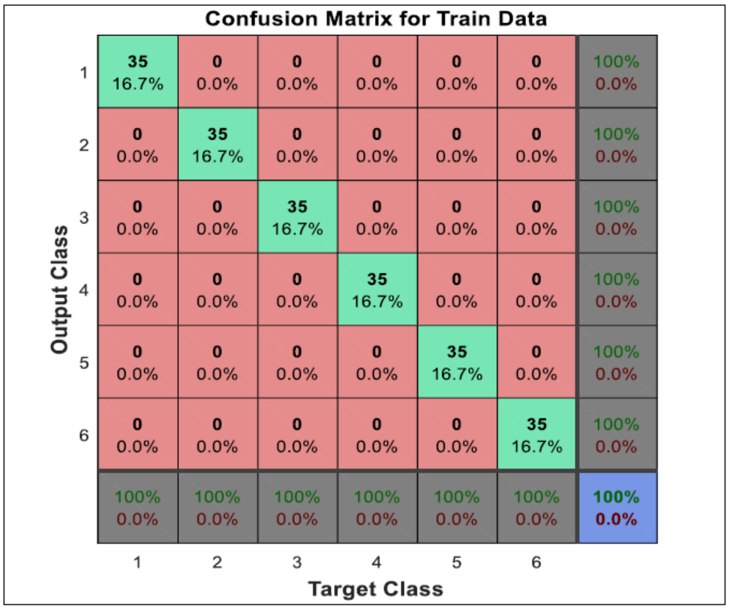


Figure 12. Confusion matrix for training data for Npc=5

Discussion

The paper presents cross-wavelet transformation method to determine HA position. Accordingly, the dimension of electrocardiogram is reduced by PCA algorithm then the extracted characteristics such as Mean, SD, Sk, and Ku of XCW are used in SVM for classification of ECG signal. The results of the assessment show that the accuracy of the proposed system for training, test and total data are 100%, 96.7% and 99 % respectively.

In previous studies in this field, wavelet transform and time-frequency signal parameters are often used as features, and in some cases directly from the standard 12 lead electrocardiogram wavelet coefficients are considered as attributes. But in this study, the characteristics of XWT of the electrocardiogram signal have been used. According to the relatively good accuracy, it can be seen that the use of the XWT method as the main cornerstone of the method for detecting the location of myocardial infarction may be appropriate. The results of this study showed that in a completely emergency situation, the diagnosis of which anatomic region or anatomic site was exposed to the HA of the patient with acute myocardial infarction, in the shortest possible time, using the 12-lead electrocardiogram signal derivation is well done. The identification of the main area of the HA, which may be due to general, partial, or rupture of one or more coronary arteries or blockage of the valve, is very important in the shortest time. The results of this study indicate that the use of 12-lead electrocardiogram signals is usefull to detect the location of MI. In order to complete the discussion, and to pay attention to the importance of the results, the results obtained in this field by other researchers will be discussed. Chen et al., Sadhukhan et al., Trung et al., Sharma et al., Bayasi, et al. and Lodhi et al. recently worked on this issue, which is shown in Table 2. As can be seen in the table, the results of this article are compared to other articles in terms of the number of attributes and results obtained from the PTB database, with very satisfactory results.

In order to extend this study, we intend to use the proposed method in hardware development, especially for wearable sensors.

It should be noted that despite high accuracy of the proposed method, one of the limitations of this research is, needs a lot of time to test the data with respect to the size of data.

Table 2. Comparing the results of this research with the achievements of other researchers

Researchers name and year of research [ref]	Method of work	Number of classes	Results (%)
Chen et al. 2018 [5]	Wavelet and time domain property using perceptron method	2	SE=98.71 AC=98.50
Sadhukhan et al. 2018 [36]	Phase of discrete Fourier transform Logistic regression	6	SE=96.5 AC=95.6
Trung et al. 2013 [8]	Use of cardiovascular signal for extracting 161 features and classification using Regression tree method	8	SE=88.0 AC=89.1
Sharma et al. 2015 [10]	Using wavelet transform to extract features and support vector machines in the classification	6	SE=97.2 AC=98.6
Bayasi et al. 2016 [11]	Use of 7 features of the time domain of heart signal and classification by Bayesian learning method	2	SE=87.3 AC=85.63
Lodhi 2018 [33]	End-to-end Convolutional Neural Network	10	AC=93.53
Present study	Use of cross-wavelet transform to extract features and support vector machine in the classification	6	SE=96.7 AC=99.0

SE = sensitivity; AC = accuracy

In this study, the main objective was to detect the anatomic localisation of the heart attack using support vector machine and cross wavelet transform. Principal component analysis is adopted to reduce the dimensions of 12 lead electrocardiogram signals. The feature vector has been created using statistical features of wavelet cross spectrum (WCS) and wavelet coherence (WCOH) obtained from cross wavelet transform (XWT) method. The proposed method yielded accuracy and sensitivity performance 99% and 96.7% respectively on PTB database.

List of abbreviations

Electrocardiogram, ECG
Principal Component Analysis, PCA
Wavelet coherence, WCOH

Cross-wavelet transformation, XWT
Wavelet cross spectrum, WCS
Myocardial infarction, MI
Heart attack, HA
K Nearest Neighbor, KNN
Convolutional neural network, CNN
Support vector machines, SVM
Physiobank, PTB
Anterior, A
Anterior lateral, AL
Anterior septal, AS
Inferior, I
Inferior lateral, IL
Inferior posterior, IP
Inferior posterior lateral, IPL
Lateral, L
Posterior, P
Posterior lateral, PL
Heart rate variability, HRV
Wavelet transform, WT
Adaptive continuous Morlet wavelet transform, ACMWT
Generalized discriminant analysis, GDA
Adaptive Stockwell transform, ADST
Adaptive modified Stockwell transform, ADMST

Conflict of Interest

The authors declare that they have no conflict of interest.

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