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INNOVATION

Detection of cardiac ischaemia using bispectral analysis approach

Amjed Al-Fahoum*[1], Ausilah Al-Fraihat[2], and Aseel Al-Araida[3]

[1]Biomedical Systems and Informatics Engineering Department, Hijjawi Faculty for Engineering Technology, Irbid 21163, Jordan, [2]Biomedical Engineering dept., Hashmite University, Zarqa, Jordan, and [3]Industrial Engineering dept., Jordan University of Science and Technology, Irbid, Jordan

Abstract

This paper highlights a new detection method based on higher spectral analysis techniques to distinguish the Electrocardiogram (ECG) of normal healthy subjects from that with a cardiac ischaemia (CI) patient. Higher spectral analysis techniques provide in-depth information other than available conventional spectral analysis techniques usually used with ECG analysis. They provide information within frequency parts and information regarding phase associations. Bispectral analysis- Bispectrum and Quadratic Phase Coupling techniques are utilized to detect as well as to characterize phase combined harmonics in ECG. The work is developed, tested and validated using Normal Sinus Rhythm Data from the MIT-BIH Database and CI data from the ST Petersburg European ST-T Database. The results validate the efficacy of the introduced method by maintaining 100% sensitivity and achieving 93.33% positive predictive accuracy. The simplicity and robustness of the proposed method makes it feasible to be used within available ECG systems.

Keywords

Bispectral, detection, ECG, ischaemia, phase coupling, time domain analysis

History

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1. Introduction

Cardiac ischaemia (CI) is the most frequent type of heart failure arrhythmia. CI is a result of narrowing of arterial blood vessels which results in a lower amount of oxygenated blood reaching the heart muscle. This condition may lead to heart attack without having prior warning [1].

Cardiac ischaemia is one of the frequent fatal diseases in the industrialized countries. It happens because of thickening and hardening of the artery wall (arteriosclerosis) [2,3]. In more than 90% of cases, ischaemia is developed in larger arteries and causes most cases of coronary artery diseases. Moreover, ischaemia may produce changes in ECG electrocardiography (ECG) signal that may generate ventricular tachycardia/fibrillation and repolarization abnormalities [4,5].

The global burden of ischaemic heart disease (IHD) increased by 29 million disability-adjusted life-years (29% increase) between 1990–2010 [6]. Heart failure ischaemia is a heart problem which is caused by a partial or complete blockage of heart arteries causing less oxygenated blood to reach the heart muscle. When the coronary arterial blood vessels are unable to source adequate oxygen-rich body towards the heart, symptoms of CI can take place. This particular disease may result in heart attack with no forewarning as well as without pain. CI is also called myocardial ischaemia that can cause damage to heart muscles as well as cutting down their power to push blood efficiently. Myocardial ischaemia might cause critical abnormal heart rhythms. These sorts of events are most often initiated with symptoms like shortness of breath, chronic coughing or perhaps wheezing. In order to prevent these cardiac problems, there must be an early, fast and reliable detection method. During myocardial ischaemia, the damaged cardiac tissue does not depolarize as healthy tissue, where abnormal electrical activity produces additional depolarization waves that appear during the ST segment and also may affect the shape of the T wave when the damage is intensive [7]. Therefore, the research studies are focused on having a fast and reliable discovery to the trusted and regular detection of ischaemia events from ECG, because ECG is certainly and normally a recorded signal during the patient check-up as well as the examination process. Inside the electrocardiographic (ECG) signal, ischaemia is indicated as slow moving alterations of the ST segment and/or the actual T wave [8–12], as shown in Figure 1.

Many detection algorithms of cardiac ischaemia are developed based on direct measurement of ST segment shift. Various studies revealed that myocardial ischaemia is associated with a noticeable ST deviation. In these studies, the magnitude and the direction of ST shifts indicate the position and the size of the damage [13–16]. Moreover, QRS slopes are also good indicators of cardiac ischaemia. In previous studies [17,18] it was found that myocardial ischaemia can be detected by measuring upward and downward amplitude of QRS slopes. The results showed that QRS slopes are less steep during cardiac occlusion. Furthermore, Wavelet transform is used in the detection of ischaemia events by identifying the ischaemic episode from the characteristic

*Corresponding author. Email: afahoum@yu.edu.jo

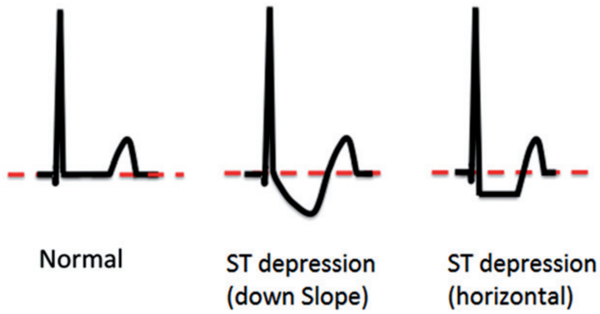

Figure 1. Normal and ischaemic ST segment.

point of the ECG signal [19,20]. However, some of the existing methods use neural networks in ischaemia detection. A combination between neural networks with another technique like principal component analysis, various transforms and fuzzy logic improves the sensitivity of the detection [9,21]. Cardiac imaging is also utilized for ischaemia detection by analysing the changes in 3D image of the heart using mathematical equations [22,23].

The objective of this paper is to propose a new detection method based on higher order spectral analysis techniques for fast and reliable ischaemia detection. The proposed method will be assessed and compared with many available methods in the literature that are applied for detection of a healthy person ECG from a patient ECG who is suffering from a cardiac ischaemia. The conventional individual ECG data is extracted from MIT-BIH NSR databases. On the other hand, ischaemia data is extracted from European ST-T databases. The bispectrum of the obtained data was performed. The bispectral analysis showed obvious differences on the phase coupling domain for the different data, leading to a very simple and practical classification scheme in comparison with all cited works that handle this problem.

2. Methodology

Figure 2 demonstrates the proposed ECG analysis scheme. Within the pre-processing phase the mean is taken off the data, so that the DC Level can be taken away. The Butterworth high pass filter is used to eliminate base-line drift if it exists. A notch filter at 50/60 Hz is also used to eliminate power line interference.

2.1 Bispectrum

Bispectrum of a signal is defined as the second order Fourier transform with the third order cumulants of the signal. It is provided by:

$$S_2^x(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty} C_3^x(\tau_1,\tau_2)\ \exp[-j(\omega_1\ \tau_1 + \omega_2\ \tau_2)] \tag{1}$$

where $S_2^x(\omega_1,\omega_2)$ is second-order Fourier Transform; $C_3^x(\tau_1,\tau_2)$, is third-order cumulants, which is the expectation operator; ω_1 and ω_2 are Radian frequency components; τ_1 and τ_2 are time delay; and $\omega_1=2\pi f_1$.

The bispectrum is a function of two-frequency variables ω_1 and ω_2. The bispectrum analyses the frequency components at ω_1, ω_2, $\omega_1+\omega_2$ $(\omega_1-\omega_2)$ [24,25].

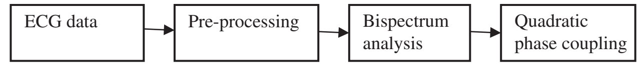

Figure 2. Block diagram of proposed method.

Table 1. Bifrequency triplets and their corresponding phases.

Bifrequencey	$f_1, f_2, 2\,f_1$	$f_1, f_2, f_1 + f_2$	$f_1, f_2, f_1 - f_2$
Phase	$\Phi_1,\ \Phi_2,\ 2\ \Phi_1$	$\Phi_1,\ \Phi_2,\ \Phi_1 + \Phi_2$	$\Phi_1,\ \Phi_2,\ \Phi_1 - \Phi_2$

2.2 Quadratic phase coupling

In a non-linear technique, an interaction involving two harmonic parts will cause a contribution to the power due to either the total or the change of its frequencies. Quadratic phase coupling takes place when two waves work together non-linearly and produce another wave having a frequency equal to the sum or difference of the previous frequencies of the two waves. The bispectrum is effective at detecting and characterizing quadratic stage coupling. Harmonically associated peaks within the power spectrum are essential conditions to the occurrence of quadratic non-linearities within the data. The bispectrum preserves phase and is used to extract phase information quantitatively. The quantitative measure of phase coupling is the bicoherence [24]. Squaring the bicoherence may be interpreted as the proportion of signal energy at the frequency (f_1+f_2) which is coupled with the spectral components at the frequencies f_1 and f_2. For more details, bifrequency triplets and the corresponding phases are illustrated in Table 1.

The phase coupling can be quantitatively identified by what is called the phase coherency spectrum, which is the normalized bispectrum, and it is defined as:

$$s(f_1,f_2) = \lim_{T\to\infty}\left[\frac{1}{T}\frac{|S_2(f_1,f_2)|}{p(f_1),p(f_2)p(f_1+f_2)}\right] \tag{2}$$

where $p(f_i)$ is the power spectrum of the signal at frequency f_i. Theoretically, the value of $s(f_1, f_2)$ will be very close to unity when there exists a high degree of coherency. That is, when a quadratic spectral interaction exists. On the other hand, phase coupling between spectral components is lost when the value of $s(f_1, f_2)$ is very close to zero. This means that the components at f_1 f_2 and f_1+f_2 are not quadratically coupled. To enhance the resolution capability of the bispectrum in distinguishing closely spaced peaks, a parametric model can be used. The model is driven by a non-Gaussian white noise generator. This model is based on the third order recursion (TOR) method [25]. Details of obtaining the bispectrum and biocoherence are discussed in Al-Fahoum and Khadra [24] and Khadra et al. [25].

The bicoherence has values between [0;1]. If the bicoherence has values other than zero, then a phase coupling at some pair of frequencies exists and, if it is zero, then there is no phase coupling. Bispectrum analysis is followed by estimating contours for bicoherence (phase coupling) and calculating the ratio energy of the analysed signals. Figure 3 and Table 2 depict the flowchart of the cardiac ischaemic detection scheme and summarizes the cardiac ischaemic detection process, respectively.

3. Results and discussion

During normal sinus rhythm, phase coupling between the various frequency components of the ECG signal takes place. This phase coupling reduces during cardiac ischaemia [25]. Due to the fact that the bispectrum preserves the phase coupling information of the ECG signals, it is expected to have differences in bispectrum between normal and abnormal ECG signals. The pre-processed signals obtained from the aforementioned databases were analysed using the bispectrum method.

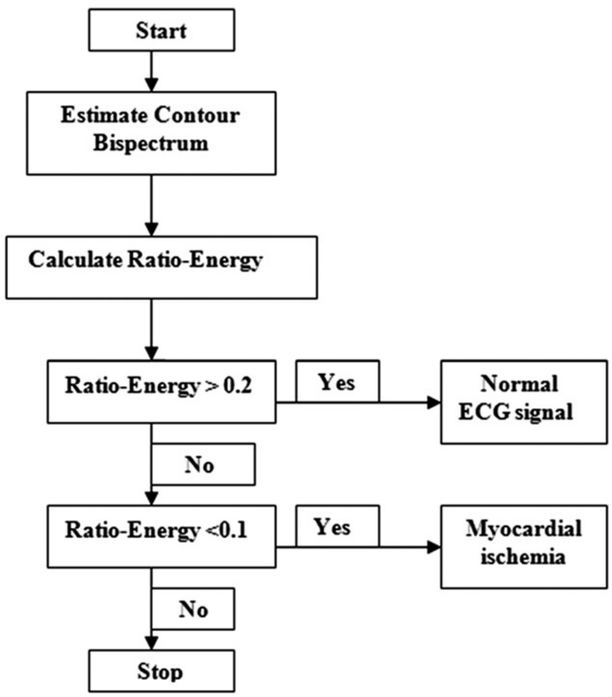

Figure 3. Flowchart showing the principle of the cardiac ischaemic detection scheme.

Table 2. Summary of cardiac ischaemic detection process.

Cardiac ischemic detectionIF	
IF	[Ratio/Energy] >0.2
THEN	ECG Signal is Normal
IF	[Ratio/Energy] <0.1
THEN	ECG Signal is Myocardial
ELSE	STOP (Neither Ischaemic Nor Normal)

From Figure 4 it can be observed that the area of the projected bispectrum is considerably larger for normal ECG signals compared to ischaemic ECG signals. This means that, for healthy subjects, bispectrum will span wider ranges of both f_1 and f_2. On the other hand, sharpness of the contour peaks indicates the presence of quadratic phase-coupling. Three-dimensional plots of bispectrum contents for both normal and ischaemic ECG signals are shown in Figure 5. Due to symmetry properties, in this study we will focus only on the region $f_1 \geq 0$ and $f_2 \geq 0$.

As shown in Figure 5, the base of the peak of a normal ECG signal is wider than that of an ischaemic ECG signal. This means that the energy contents of the bispectrum of the maximum values for both f_1 and f_2 must be greater for normal ECG signals when it is compared with the same parameters of ischaemic ECG signals. To make it more obvious, QPC is represented as a contour peak in a contour map. Figure 6 displays the contour maps for normal and ischaemic ECG signals.

The total energy of a specific region of the map (E-region) is also calculated in order to find (Ratio-Energy) where (Ratio-Energy) = ((E-region)/(E-total)) of every ECG signal in this study. To distinguish between normal and ischaemic ECG signal depending on (Ratio-Energy), the position and the size of the region used in calculating (E-region) was changed frequently until a significant difference in (Ratio-Energy) between normal and ischaemic ECG signals is obtained. It was noticed that the best results are achieved in the region $f_1 \leq 10$ Hz and $f_2 \geq 10$ Hz.

From Figure 6, it is obvious that the Ratio-Energy of normal and ischaemic signals is different. It is obvious that the Ratio-Energy for healthy ECG signals is considerably higher than the ratio of ischaemic signals. Ratio-Energy values for normal ECG signals are *higher than 0.2*, while the Ratio-Energy value for ischaemic ECG signals is

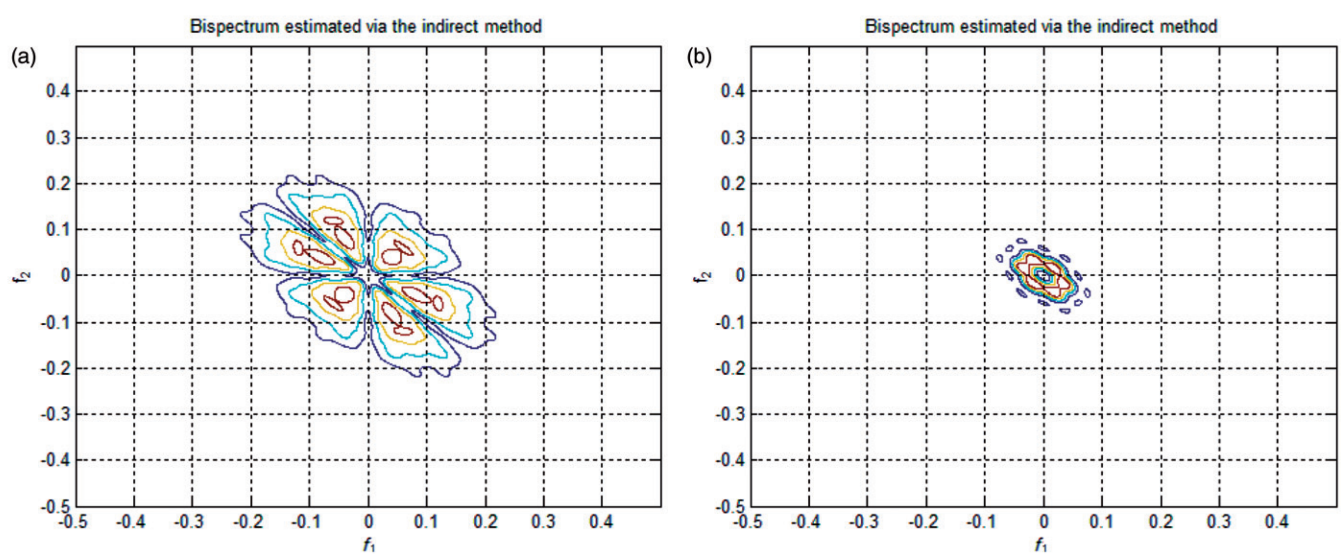

Figure 4. (a) Bispectrum contour plot of normal ECG signal, (b) Bispectrum contour plot of ischaemic ECG signal.

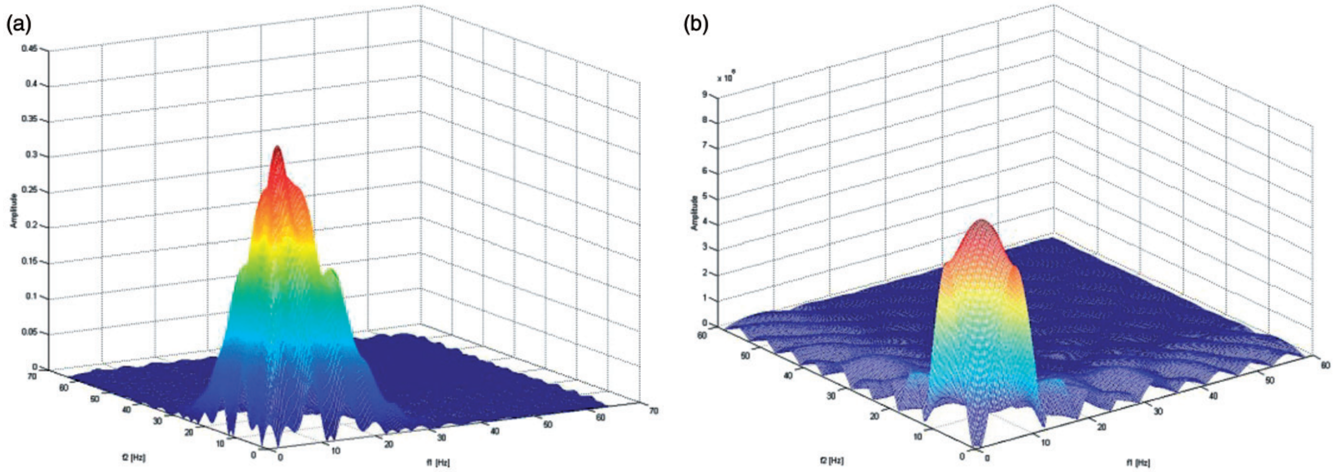

Figure 5. 3D plot of bispectrum for (a) Normal ECG signal and (b) Ischaemic ECG signal.

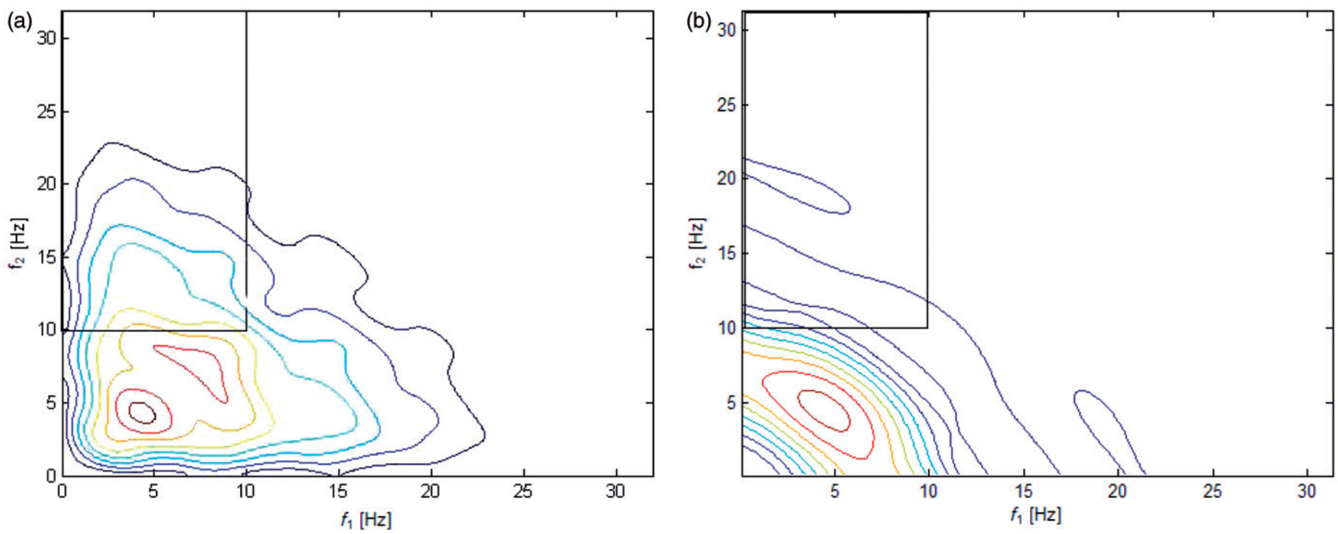

Figure 6. Contour maps for (a) Normal ECG signal, and (b) Ischaemic ECG signal.

lower than 0.1. Therefore, 0.1 and 0.2 are selected as classification thresholds. The sensitivity of the training set using these thresholds is maintained itself at 100% and the positive accuracy was also 100%. Accordingly, the two thresholds are used for testing and validating the algorithm. These results are shown in Figure 4, which illustrates the contour maps of the studied ECG signals. The contour lines appear denser for normal ECG signals in the specified region when it is compared to ischaemic ECG signals. The flow chart in Figure 3 outlines the classification procedure.

The performance of this method is validated by choosing 14 random ischaemic ECG records from the European ST-T database and 24 random normal ECG signals from the MIT-BIH database. The database contains the data of 90 double channel 2-h ECG signals with a sampling rate of 250 Hz. For a fair comparison with other published methods, the selected data from the ST-T database represent all the records that have ischaemic disease only. Other data that has mixed disease is excluded. On the other hand the number of normal records is huge; therefore, a reasonable number of records are selected randomly. The effectiveness is tested in terms of sensitivity (Se) and positive predictive accuracy (PPA).

Table 3 shows the values of Ratio-Energy for 10 normal and 10 ischaemic ECG signals. These signals are used to validate the obtained sensitivity and accuracy of the classification algorithm. It is worth mentioning that the 7th normal signal has a Ratio-Energy within the range of ischaemic signals. This signal was responsible for reducing the positive accuracy to 93.33%.

The sensitivity measures the ability to detect ischaemic signals, whereas positive predictive accuracy provides estimation likelihood that a detected signal is a true ischaemic signal.

$$Se\,(\%) = \frac{TP}{TP + FN} \times 100 \tag{3}$$

$$PPA\,(\%) = \frac{TP}{TP + FP} \times 100 \tag{4}$$

where $TP = 14$ correctly identified ischaemic signals; $TN = 23$ correctly rejected (normal signals); $FP = 1$

Table 3. Ratio-energy of normal and ischaemic ECG signals that were used in validating the classification algorithm.

Normal ECG signal	Ischaemic ECG signal
0.509 07	0.029 56
0.235 04	0.055 06
0.483 66	0.028 99
0.277 72	0.027 43
0.231 54	0.066 16
0.321 68	0.094 63
0.021 62	0.017 31
0.281 65	0.029 65
0.257 46	0.010 83
0.578 91	0.054 27

Table 4. Comparison of performance of developed methods for ischaemia.

Reference	Method	SE	PPA
Exarchos et al. [26]	Rule mining based	87	93
Dranca et al. [27]	Decision Trees	89.89	70.03
García et al. [28]	RMS method	85	86
Andreao et al. [29]	HMM	89	85
Goletsis et al. [30]	GA and Multi criteria	91	91
	HySMID	91	93
Ranjith et al. [19]	Wavelet Transform	92	86
Papaloukas et al. [31]	Parametric modelling	81	84
Papaloukas et al. [32]	Set of Rules	70	63
Papadimitriou et al. [33]	SOM	74.9	73.7
	SOM and RBF	79.5	77.6
	SOM and SVM	82.8	82.4
Jager et al. [9]	PCA	87	88
Maglaveras et al. [34]	Back propagation Network	89	78.38
Stamkopoulos et al. [35]	PCA and ANN	90	93
Silipo and Marchesi [36]	Recurrent ANN	77	85
	Knowledge learning ANN	71	66
Vila et al. [37]	Fuzzy logic	83	75
Taddei et al. [38]	Geometric method	84	81
Polak et al. [39]	Adaptive Logic Network	72	66
	Adaptive Network	88.62	100
	Discriminant method	62	66

incorrectly identified (normal but classified as ischaemic); and $FN = 0$ incorrectly rejected (ischaemia classified as normal).

The purpose of the new method is to detect ischaemic signals, then FN represents an 'incorrectly rejected' signal which means 'the number of ischaemic signals that are rejected from their correct category and classified as normal'. All the 14 ischaemic signals are classified correctly. If no ischaemic signal is classified as normal then $FN = 0$. The result of the 7th signal shown in Table 3 affects the accuracy and produces $FP = 1$. This value represents 'incorrectly identified', which means 'normal ECG record, but it is classified as ischaemic'.

The average sensitivity and average positive predictive accuracy were found to be 100% and 93.33%, respectively, by randomly choosing 14 records from the European ST-T database and 24 records from the MIT-BIH database. To compare the results obtained by this method with available detection methods from the literature, a quantitative performance analysis using the same database is provided in Table. It is obvious that the sensitivity and the positive predictive accuracy of the proposed methods do better than all the methods presented in Table 4. Moreover, what makes this method very suitable is its simplicity and technical feasibility.

4. Conclusion

In this work, a new method for cardiac ischaemic detection based on higher order spectral analysis techniques is introduced. The bispectrum and bicoherence showed a strong correlation with the number of sources that generate cardiac arrhythmias. It is shown in Al-Fahoum and Khadra [24] that multiple sources that are individually coherent will emit their electrical impulses at the instant of arrhythmia. The ECG signal will be the result of all responses of these incoherent sources. Analysing the non-linear activities of the ECG rhythm under ischaemic conditions showed the ability of the high order statistic techniques in simplifying the presence of these hidden details to appear more focused and sharp in specific frequency regions. During normal sinus rhythm, phase coupling between the various frequencies of the ECG signal is kept. At the instant of ischaemia, such phase coupling will not be maintained at the same level, rather it will reduce significantly. These observations simply enable the capability of the technique to properly detect ischaemic events and further localize them. This localization property is easily expressed in obtaining an energy ratio parameter to distinguish among normal and ischaemic patients. The effectiveness of the proposed method was validated using the European ST-T database. This database is made of 90 ECG recordings with an annotated ischaemic ECG signal. The performance measurement parameters, sensitivity (Se) and positive predictive accuracy (PPA) are calculated to detect ischaemic ECG signals. The results indicate the usefulness of the proposed method in detection of ischaemia, providing excellent sensitivity and positive predictive accuracy of 100% and 93.33%, respectively. The classification scheme is very simple, depending only on one parameter which doesn't require complex segmentation or huge processing requirements. Moreover, the method can be easily integrated within an ECG instrumentation system as an early detection scheme in primary healthcare facilities.

Declaration of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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