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Review Article

ISCHEMIC BEATS DETECTION USING BISPECTRUM ANALYSIS OF THE ISCHEMIC EPISODES IN HEART RATE VARIABILITY

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ABSTRACT
In this paper, a new method for early and non-invasive diagnosis of myocardial ischemia is presented. Generally, clinical methods based on exercise tolerance test and angiography which is performed by feeding specific material in heart arteries is used for myocardial ischemia diagnosis. These methods are very invasive. Besides, morphological diagnosis of ST segment and T wave is very important and also difficult in Holter recording which is a long term electrocardiogram signal recording. In this survey automatic diagnosis of ischemia sections in long term ECG signal is done with bispectrum analysis of heart rate variability (HRV) signal which can be extracted from ECG signal and the bispectrum is obtained in episode time of 36 seconds. In this paper, 120 and 110 ischemia and normal episodes are investigated, respectively. Then, phase coupling in HF, LF and VLF bands are investigated. Average, variance and sum of bispectrum power in different bands of HRV signal are considered as input feature vector to the neural network. After that, classification is performed by KNN, PNN and SVM classifiers and by using leave one out cross validation method which has 85.09 % sensitivity, 91.74 % specificity and 88.35 % total accuracy.

Keywords: *Ischemia; Bispectrum; Heart Rate Variability; Neural Networks*

INTRODUCTION
Myocardial ischemia is one of the most prevalent heart diseases which is occurred due to revascularization reduction to the heart muscles. Blood flow is usually reduced due to obstruction of coronary vessels, obstruction by a thrombus, and sometimes because of the narrowing of the capillaries and small blood vessels within the heart, which leads to stroke, and sometimes death (Goletsis *et al.*, 2004). Therefore, early diagnosis and treatment are important in the treatment of this disease. Conventional clinical diagnostic methods like exercise tolerance test and coronary angiography is associated with the injection of certain materials (Didvania *et al.,* 2001).
Invasive clinical procedures are very risky and with high cost, thus providing a non-invasive method is so important. Most non-invasive methods presented are based on ECG signal analysis. Myocardial ischemia will influence in the ST segment and T wave of the ECG signal that will result in elevation or depression in the ST segment and T-wave inversion. In many of these cases, the features of time, frequency and time-frequency are derived from the signal and are diagnosed by neural network and fuzzy logic. In (William *et al.,* 2002) Jackknife network is used for early diagnosis of patients with chest ache where considering derived features like elevation or depression of ST segment and T wave, 88 % of ischemic beats and 86.2 % of non-ischemic beats are diagnosed correctly.
In (Exarchos *et al.*, 2006) the association rule is used to detect ischemia. The investigations (Juger *et al.*, 2009) through morphological feature extraction method from Karhunen–Loève method in time domain have been used. In (8) semi-hidden Markov model is used to detect ischemia through dynamic analysis of time series extracted from the ECG signal. In (Faganeli *et al.,* 2006) with the extraction of features such as the heart rate, the parameters of morphology (William *et al.*, 2003) and determination of the parameters of Legendre polynomial within 20 seconds of starting the events of ischemia and 20 seconds at the time of the toughest events in ischemia, 77.9 % of the ischemic beats are diagnosed correctly. In (Cahn *et al.*, 2013) a method for analyzing biological signal quality in real time is used where the signal to noise ratio (SNR) as

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ST segment deviation is shown. In (Cheng *et al.*, 2013), the discrete wavelet transform to extract the six features of the fifth level of this transform is used.

In addition to changes in the ST segment and T wave, it is shown that the frequency bands power of HRV changes during ischemia. In the paper (Wang *et al.*, 2007) the method of time-frequency analysis, Smooth Pseudo Wigner Ville Distribution is used for analyzing HRV during ischemia before and after it. Also fisher linear discriminant analysis is used to find the sensitive parameters for ischemia detection. In the paper (Petterson *et al.*, 1996) the analysis of HRV with time variable- frequency band is used with considering the breathing frequency and frequency analysis method is used for signal analysis in the frequency domain.

In (14) time frequency analysis method is used on HRV signal to determine the ST segment of ischemia like (Wang *et al.*, 2007) with the difference that time-frequency distribution method is used for calculating the power in HF, LF and VLF bands. In (Tan *et al.*, 2003), wavelet analysis is used to investigate the changes in power of frequency bands for heart rate variability at 30 minutes before the shift of ST segment. In this survey low frequency band power of HRV, 10 and 5 minutes before the ST segment change and high frequency band power in 4 minutes before ST segment change is increased. In (Lanza *et al.*, 1996) and (Kop *et al.*, 2001) the HRV power spectrum is used for cardiac ischemia patients.

In power spectrum estimation of frequency bands, it is assumed that the signal is minimum phase and it is obtained from a linear process in a way its frequency components are unrelated and only its frequency components are estimated while phase information between different frequencies are neglected. As the HRV signal is obtained from a non-linear process, it has to be derived from the combination of various sinusoidal non-linear components that each of them has a different separated frequency and their non-linear combination would produce components in the summed and differentiated frequency. These features are not completely shown in the power spectrum estimation of the signal (Nikias *et al.*, 1993). As the HRV signal has these features, it is expected this problem can be solved with bispectrum analysis. Frequency components with phase coupling are illustrated in bispectrum analysis. Therefore, this method would give useful information by phase coupling analysis in ischemic events and bispectrum pattern related to the ischemic beats can be extracted and they can be used for discrimination and classification between ischemic and non-ischemic beats.

Bispectrum Analysis

The power spectrum distribution is estimated at different frequencies.

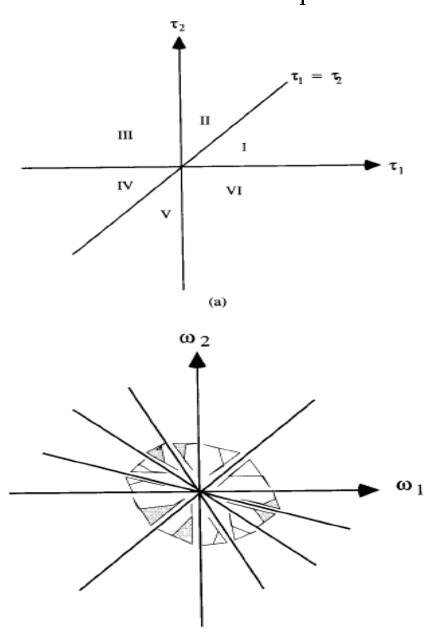

Figure 1: (a) Symmetry in third order Cmolent, (b) Symmetric sections in bispectrum

Therefore the relation between frequencies combinations would be lost in power spectrum while this information is maintained in bispectrum analysis because high order spectrum has information about signal phase, non-linearity of signal and its non-Gaussian feature and it has the ability to diagnose and reproduce the non-minimum phase signals (18).

Third order cumulant for a discrete and non-Gaussian signal with zero average is obtained by:

$$C(m,n) = E[x(k)x(k+m)x(k+n)] \qquad (1)$$

So that, E is expected value and x(k) is the signal samples. Third order cumulant is a symmetric function of 6 parts shown in Figure 1. Bispectrum is achieved by third order cumulant Fourier transforms as follows.

$$B(w_1, w_2) = \sum_{m=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} C(m,n).\exp[-j2\pi(mw_1 + nw_2)] \qquad (2)$$

In a way we have: $|w_1|,|w_2| \leq \pi$

Like third order cumulant, bispectrum should have a symmetric function. As shown in Figure 1, bispectrum contains 12 symmetric sections for a real process where the entire spectrum is obtained by triangular sections $w_1 \geq 0, w_1 \geq w_2, w_1 + w_2 \leq \pi$

One of the advantages of bispectrum is in Gaussian signals. For Gaussian signals, all high order cumulant spectrums above 2 are zero. As a result, if a non-Gaussian signal is associated with Gaussian noise, the high order spectrum would eliminate the noise (Nikias *et al.*, 1993). One of the other advantages of high order spectrum is its high signal to noise ratio (SNR). This makes possible that recognition, estimation or even reproduction of the signal is doable. Generally, high order spectrum analysis is useful in applications with non-linear process, non-minimum phase signals and Gaussian signal with noise and non-Gaussian signals (Nikias *et al.*, 1993).

I. Automatic detection algorithm of myocardial ischemia in signal

This survey contains five stages:

- Providing a database
- Preprocessing
- Features extraction
- Features selection
- Classification

A. Providing Database

In this survey Long Term ST database is used (Jager *et al.*, 2003). In this database, ECG signal episodes are classified into two group of ischemic and normal.

In this database cardiac ischemia is measured and maintained based on three protocols A, B and C which protocol A is utilized in this research (Jager *et al.*, 2003).

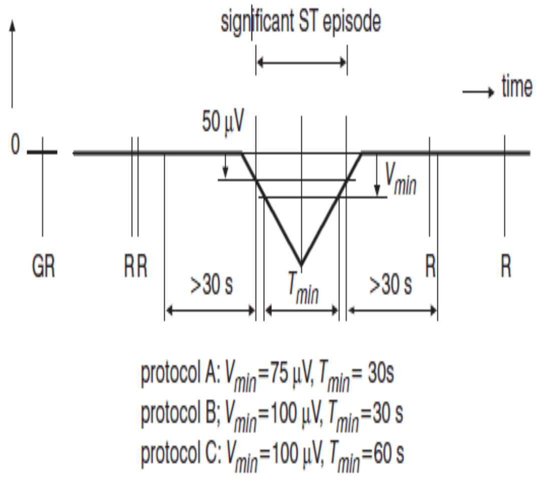

Figure 2: Protocol and diagnosis of ischemic events

As shown in Figure 2, ischemic episodes are started when the ST level difference with reference value is higher than 50μV. In this condition, this level difference has to reach $V_{\min} = 75\mu v$ and has to last 30 seconds and it has to be finished when this level difference is lower than 50μV. Bedsides, in this database HRV signal can be extracted like any ischemic and normal episodes.

B. Preprocessing

Considering Figure 3, HRV signal has ectopic and noisy beats. So preprocessing has to be done at first. Preprocessing is included of two stages where in the first stage ectopic and noisy beats are recognized and in the second stage beats are replaced (Aubert *et al.*, 1999).

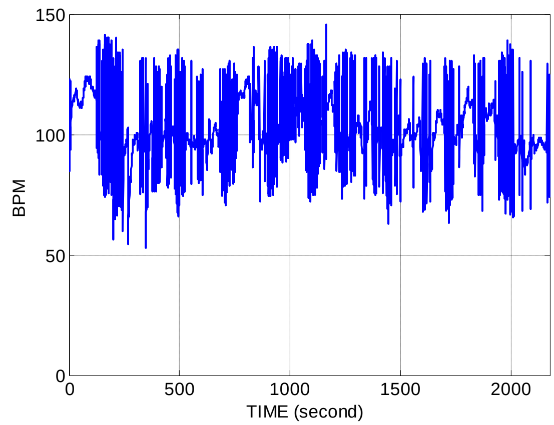

Figure 3: HRV signal in ischemic events with noisy and ectopic beats

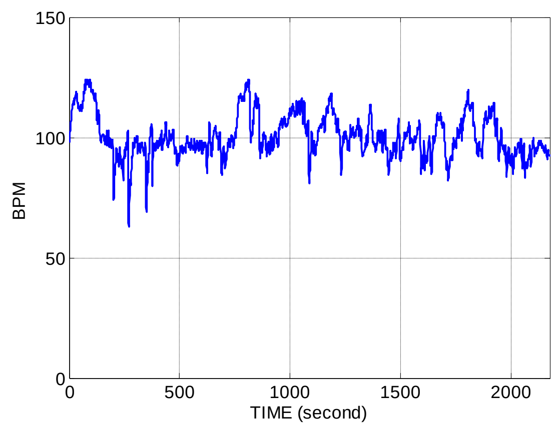

Figure 4: HRV signal after preprocessing

In order to recognize the ectopic beats two methods can be used percentage filter method and standard deviation filter method. In the first method, interval variation percentage with respect to the previous interval should not be higher than the defined percentage (often 20 %). In the standard deviation filter, standard deviation value should not be higher than the determined value (often 3). At last, Cubic spline interpolation method is used in order to replace the beats. Figures 3 and 4 show the diagram before and after preprocessing, respectively (Auber *et al.*, 1993).

C. Features Extraction

After extraction of HRV signal from the ECG signal, episodes of 36 seconds from normal and ischemic regions are separated in the HRV signal. Then bispectrum of each episode is calculated. Figures 5 and 6 show a typical HRV signal and its bispectrum in the normal episodes.Figures 7 and 8 show an example of HRV signal and its bispectrum on ischemic periods.

In order to extract the features of the bispectrum, the power of bispectrum is derived in the three frequency bands, very low frequency (VLF) (0 to 0.05 Hz), low frequency (LF) (0.05 to 0.15 Hz), high frequency

(HF) (0.15 to 0.5 Hz). In this study, mean, variance, and summation of phase coupling in interval VLF-VLF, VLF-LF, VLF-HF, LF-VLF, LF-LF, LF-HF, HF-VLF, HF-LF, HF-HF has been calculated in the first and fourth quarter where because of the symmetry that exists in the second and third quarter, calculating the characteristics of this part is neglected. Thus, a total of 54 features were extracted from the bispectrum HRV signal.

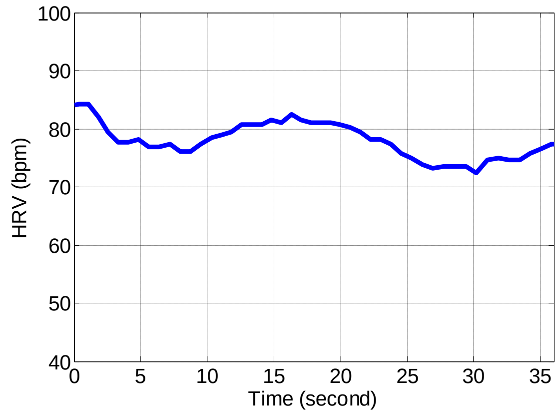

Figure 5: Normal HRV signal

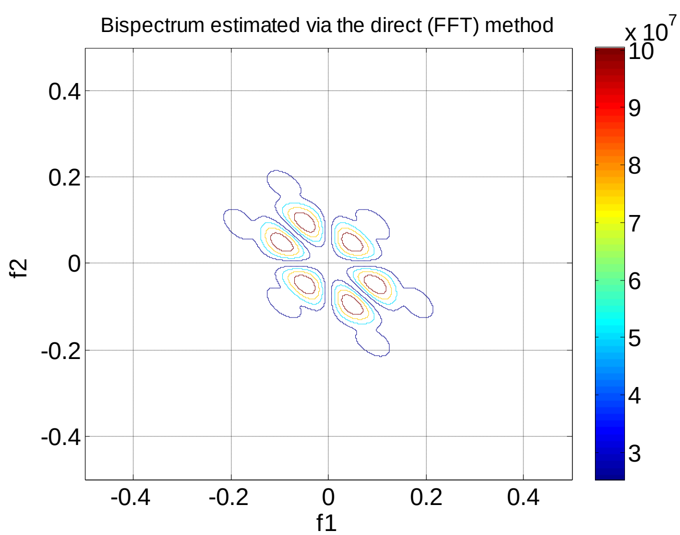

Figure 6: Bispectrum analysis of normal HRV signal

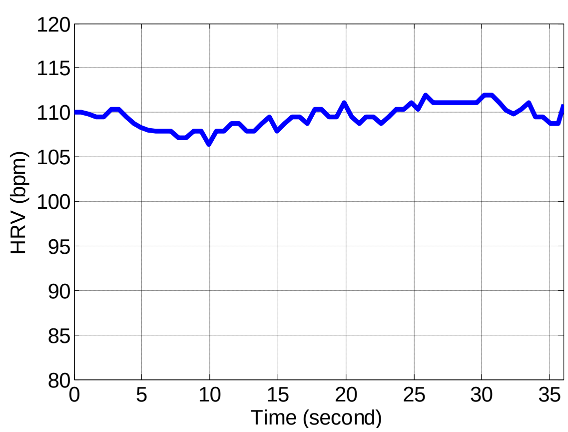

Figure 7: Ischemic HRV signal

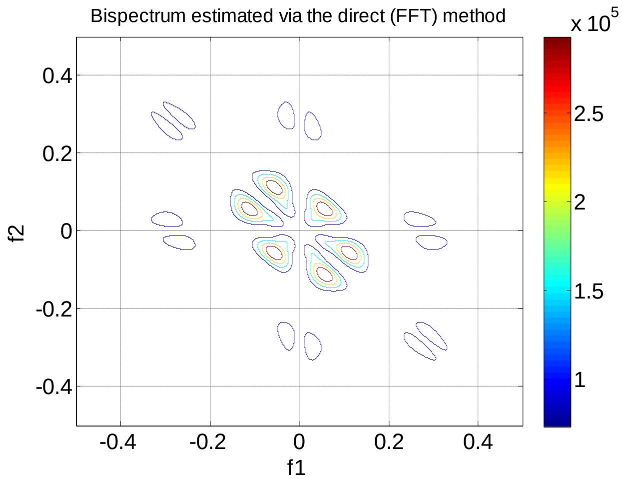

Figure 8: Bispectrum analysis of ischemic HRV

D. Features Selection

In order to reduce redundancy in the extracted feature vector in the previous stage, the features with more mutual information and objective class are selected by mutual information theory. Mutual information between two random variables x and y is defined in terms of the probability density function as follows (20):

$$I(x,y) = \iint p(x,y)\log\frac{p(x,y)}{p(x)p(y)}dxdy$$

Therefore, based on the mutual information theory 32 features is selected and applied as input to the classifier.

E. Classification

In order to classify the normal and ischemic episodes based on the features of bispectrum, the K nearest neighbor classifier (KNN) with a value of K = 7, support vector machine (SVM) with RBF kernel and probabilistic neural network (PNN) which are a network under supervision are used. In order to evaluate the results of classifiers Leave one out cross validation method is used. The results are classified according to sensitivity criterion (a measure of correct diagnosis of ischemic episodes), specificity criterion (correct diagnosis criteria of normal episodes) and total accuracy (measure of accuracy diagnosis of ischemic and normal episode).

Leave out one algorithm performs in a way that in any time of classifier training, all data are used except one data and that data is utilized for testing the classifier (classifier test). This continues until all the data are once examined as test data.

CONCLUSION

Table I shows the classification results of the HRV episodes based on the features of bispectrum. Table I shows that among these three classifiers, SVM and PNN have maximum value of the sensitivity to the 85.96 % and on the other side KNN has largest percentage of the specificity and total accuracy to the value of 91.74 % and 88.35 %.

Discussion and Conclusion

The aim of this paper is to diagnose the myocardial ischemia using bispectrum analysis in HRV signal derived from ECG signal. The proposed method is a non-invasive and simple method so that only the features of bispectrum are analyzed and there is no need to extract time or frequency features of the HRV signal frequency-time spectrum. In the bispectrum, phase coupling between signal frequency components is recognized. The results of this survey show that phase coupling in ischemic episodes of the signal is different from its normal signal. Therefore, bispectrum analysis can be used for diagnosis of ischemic sections in long term ECG signal and as a result ischemia diagnosis would be easier for the medic.

Table 1: Classification results

Classifier	Result		
	Sensitivity (%)	***Specificity (%)***	***Total Accuracy (%)***
KNN	85.09	91.74	88.35
SVM	85.96	84.40	85.20
PNN	85.96	86.24	86.10

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