

Original Article

Detection and classification of cardiac ischemia using vectorcardiogram signal via neural network

Ali Reza Mehri Dehnavi^a, Iman Farahabadi^{*a}, Hossain Rabbanif^a,
Amin Farahabadi^a, Mohamad Parsa Mahjoob^b, Nasser Rajabi Dehnavif^c

Abstract

BACKGROUND: Various techniques are used in diagnosing cardiac diseases. The electrocardiogram is one of these tools in common use. In this study vectorcardiogram (VCG) signals are used as a tool for detection of cardiac ischemia.

METHODS: VCG signals used in this study were obtained from 60 patients suspected to have ischemia disease and 10 normal candidates. Verification of the ischemia had done by the cardiologist during strain test by the evaluation of electrocardiogram (ECG) records and patient's clinical history. The recorder device was Cardiax digital recorder system. The VCG signals were recorded in Frank lead configuration system.

RESULTS: Extracted ischemia VCG signals have been configured with 22 features. Feature dimensionalities were reduced by the use of Independent Components Analysis and Principal Component Analysis tools. Results obtained from strain test indicated that among 60 subjects, 50 had negative results and 10 had positive results. Ischemia detection of neural network using VCG parameters indicates 86% accuracy. Classification result on neural network using ECG ischemia detection parameters is 73% accurate. Accumulative evaluation including VCG analysis and strain test indicates 90% consistency.

CONCLUSIONS: Regarding the obtained results in this study, VCG has higher accuracy than ECG, so that in cases which ECG signal cannot provide certain diagnosis of existence or non-existence of ischemia, VCG signal can help in a wider range. We suggest the use of VCG as an auxiliary low cost tool in ischemia detection.

KEYWORDS: Vectorcardiography, Myocardial Ischemia, Neural Networks.

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Coronary atherosclerosis based on vascular stenosis level and blood circulation blockage of myocardium and thrombosis formation cause some symptoms and consequences. Decreasing blood circulation is progressive and by delivering non-sufficient blood, myocardium cells are deprived of blood combinations necessary for their survival. This condition is called ischemia. ECG is a common diagnostic tool used in surviving cardiovascular system.¹ Although ECG signal is used as a general method in cardiac performance evalua-

tion, the main and major objective of ECG is the experience dependency of cardiologist in interpretation of the registered samples.² Typical method for ECG interpretation is mainly based on wave shape rather than vectorial concepts and information content. Generally using ECG signal analysis in spite of some advantages such as availability in medical centers has a main problem which is lack of accurate and detailed information representation of cardiac electric activity.³

Another surface potential registration system

^a Department of Medical Physics and Engineering, School of Medical, Isfahan University of Medical Sciences, Isfahan, Iran.

^b School of Medicine, Jahrom University of Medical Sciences, Jahrom, Iran.

^c Saeed Hospital, Isfahan University of Medical Sciences, Isfahan, Iran.

* Corresponding Author

E-mail: eiman237@yahoo.com

with high amount of electrodes (100-500 electrodes) can provide more transparent view of the cardiac electrical activity, but the main problem with this method is hardware complication. In the VCG method only 6 electrodes are used with special arrangements known as Frank. In recent decades many of researchers concentrated on the VCG field.⁴⁻⁷ These studies were mostly focused on cardiac diseases diagnostic, education development on VCG and comparison with ECG performance.^{8,9} Extensive studies have been done recently on animals and considering cardiac ischemia in animals using VCG algorithm.¹⁰⁻¹² Other applications of VCG signal are in arrhythmias classification^{13,14} and fetus movement survival.¹⁵ One of the VCG advantages is its similarity to Three Dimensions view of patient electrocardiogram signal via a 3 dimensional (3D) model of human heart. Commonly extracted features used in VCG are 22 in number (Table 1).⁴⁻⁹ In cases which the number of features are big in comparison to the number of samples the use of nonlinear classifiers such as Neural Network classifiers are recommended.^{16,17}

The VCG curve is based on an approximate bipolar model of cardiac electric activity which is a common concept used in ECG interpretation. On the other hand, electrocardiography may not show sufficient signs of electrical activity in specific sites of heart, while in VCG, better approximation of cardiac activity can be obtained, especially in back region of the heart. Some ischemic diseases are related to malfunctioning of regions on the back of the heart.^{18,19}

This study attempts to obtain a deeper aspect of cardiac activity by various processing on vector cardiogram signals of normal and abnormal candidates. In this work two and three dimensional coordinate axis are used to display VCG. The 2D plane display is the selection of either dual combination of three local axis on XYZ space. In 3D space, it is necessary that all three registered leads are displayed simultaneously against each other. In VCG registration 4 leads are used for chest derivations

registration and 2 leads are used for heart back derivations registration. Planer and spatial VCG demo are retrieved and displayed for normal and suspected cardiac ischemic candidates. This mode of representation allows physicians to diagnose cardiac diseases better and more accurate than conventional ECG.

Methods

In this study 60 patients with chest pain, who were suspected to have ischemia and referred to emergency department of Saeed hospital in Khomayneh were examined. Patients were in average age of 55 ± 3 years old. 32 patients were male. At the first stage of admission, ECG and VCG signals of all subjects were obtained in rest state. Patients were treated by drug and hospitalization to gain a stable condition. All subjects performed exercise test 6 weeks after releasing from hospital, and results of ECG and VCG signals were compared with results of exercise test. Patient's records including ECG, VCG and exercise test's results were analyzed by cardiologists. Exclusion criteria were having non-sinus rhythm, Bundle Branch block, use of anti ischemic medication and disability to perform exercise tests.

Electrocardiogram Signal

ECG signals were recorded on the base of the 12 standard leads. Ischemia was defined based on ST segment downward deviation or changes of T wave in the form of negative (greater than 3 mm in depth) or biphasic T wave. The examination results of ECG signals showed that 21 patients had ischemic symptoms and the rest of them were normal.

Vector Cardiogram Signal

Frank arrangement was used for VCG extraction by the use of Cardiac digital recorder. According to the system user manual useful leads for VCG information are available on leads (if four lead from right to left and two back leads named from up to down). Secondary signals such as X, Y, and Z, are extracted from Frank leads using following equations:

$$X = 0.78 \times (0.78 \times A + 0.22 \times C - I)$$

$$Y = 0.35 \times M + 0.65 \times F - H$$

$$Z = 0.78 \times (-0.15 \times A + 0.85 \times M - 0.30 \times I - 0.43 \times E - 0.27 \times C)$$

Table 1. Extracted features of current data (mean value ± STD)

Num	Feature	VCG (normal)	VCG (ischemia)
1	VCG Azimuth	-1.52 ± 0.0041	1.23 ± 0.0039
2	VCG Elevation	1.12 ± 0.0028	-0.59 ± 0.0017
3	QRS _{AF} [†]	46.65 ± 2.146	78.68 ± 3.128
4	QRS _{AS} ^{††}	79.50 ± 4.012	-53.15 ± 3.605
5	QRS _{AH} ^{†††}	32.10 ± 1.209	-18.67 ± 1.023
6	T _{AF}	-86.12 ± 2.87	-86.56 ± 2.45
7	T _{AS}	61.19 ± 3.125	35.65 ± 3.301
8	T _{AH}	-23.50 ± 2.13	-2.64 ± 1.084
9	QRS_T _{Ratio AF}	-0.54 ± 0.0036	-0.90 ± 0.0042
10	QRS_T _{Ratio AS}	1.29 ± 0.0036	1.49 ± 0.0041
11	QRS_T _{Ratio AH}	-1.36 ± 0.0047	7.07 ± 0.042
12	max QRS_T _{AF}	104.15 ± 3.27	0.66 ± 0.0035
13	max QRS_T _{AS}	62.97 ± 2.65	28.66 ± 3.013
14	max QRS_T _{AH}	2.21 ± 0.71	69.28 ± 4.029
15	MA*	104.15 ± 4.72	69.28 ± 3.16
16	RMMV**	1.68 ± 0.0067	2.35 ± 0.0021
17	DEA***	4.69 ± 0.083	3.45 ± 0.0712
18	T _{Loop Length}	131 ± 2.903	148 ± 1.98
19	QRS _{Loop Length}	45 ± 2.701	50 ± 2.019
20	T _{Loop Area}	4.03e-004 ± 0.0064	7.72e-004 ± 0.00302
21	QRS _{Loop Area}	0.0012 ± 0.000102	-0.0011 ± 0.000204
22	QRS_T _{Ratio Area}	2.9854 ± 0.0046	1.4313 ± 0.0028

† Angle in frontal

†† Angle in sagittal

††† Angle in horizontal

* Maximum angle between QRS and T loop axes

** Ratio of maximum to mean T vector magnitudes

*** Difference of angle in azimuth and elevation

Exercise Test

Strain test was performed according to the Bruce protocol accompanied with heart rate and blood pressure monitoring. The ECG signals were recorded before, during and after the test.

Noise Removal and Filtering

Prior to the process, acquired VCG data should be filtered from high frequency and power line noise. To get rid of noise, a sixth order Butterworth low pass filter with cut frequency of 50 HZ is used. Some sample results of this filter and its effect on the produced loops in each

plan are shown in figure 1. At upper row of the figure 1, 2D views of the original captured VCG signals and at the lower row filtered 2D views of VCG signals are shown.

Feature Extraction

For classification of the data there should be number of features available from data samples to apply on the different type of classifiers. Feature selection for discrimination of healthy from patients is a big challenge to this type of work. We used 22 features of the VCG that were most commonly used in previous studies.

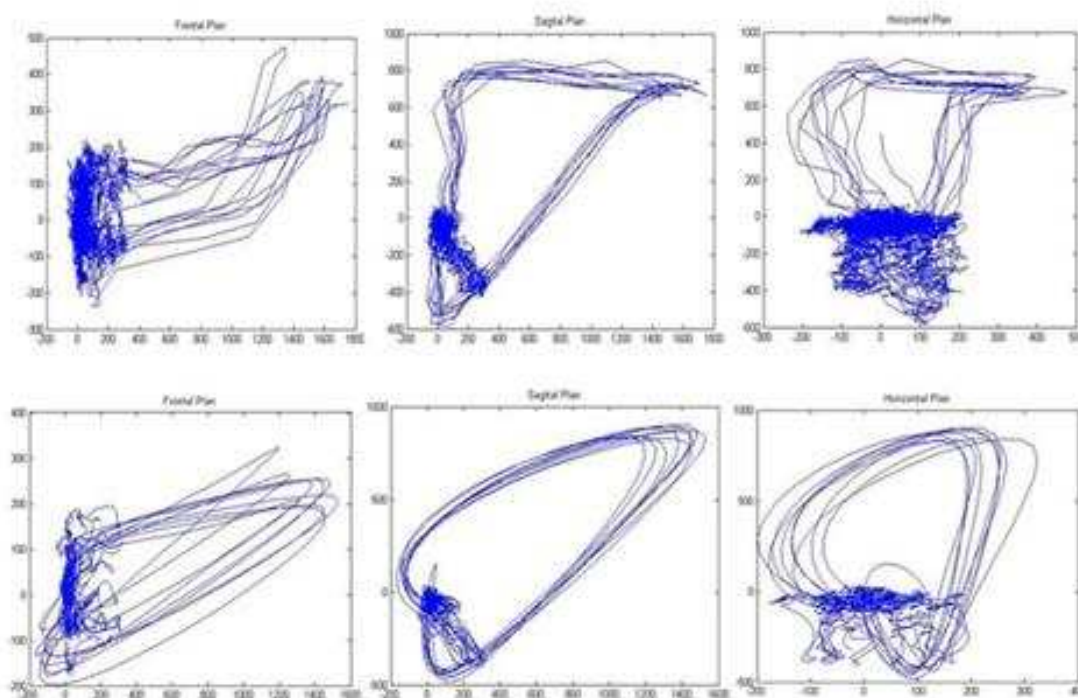


Figure 1. Upper row original and Lower row filtered VCG 2D views

Feature Reduction

It should be mentioned that because of high amount of extracted parameters there is an over complexity for classifiers. Therefore before application of the data to classifiers, data dimensionality should be reduced. The Principal Component Analysis and Independent Components Analysis methods are used in data dimensionality reduction.

Principal Component Analysis

The extracted components of all subjects are applied on Principal Component Analysis (PCA) algorithm and then on the base of eigenvector and eigenvalues priority, components are ranked.²⁰ In this method, by removing less significant coordinates, the data dimensionality is reduced. Extracted features from PCA are applied on neural networks with different input nodes based on the number of selected features for each trail and one hidden layer with two hidden nodes and output layer with two nodes for healthy and suspected patients. The best classification result is obtained with five input features. Therefore data dimension from 22 coordinates reduced to 5 coordinates.

Independent Components Analysis

Independent components analysis technique uses high order statistical features of the data. This technique is often used in various applications including arrays processing, communication, medical signals and speech processing.²¹ Independent Components Analysis (ICA) is a statistical model which process multivariable data from a large sample space. Variable independency is not important and each variable may be a linear or nonlinear combination of different independent hidden variables. Hidden variables usually are non-Gaussian and mutually independent, that each one of them are effects of an independent source component. Therefore ICA can be regarded as a generalization of principal component analysis or factors analysis. By the application of ICA on the data there would be a linear projection of the data space to new data coordinate system. In spite of the PCA in which the resulted coordinates are orthogonal to each other, in the ICA new data coordinates are not necessarily orthogonal. In the ICA we try to find a transfer function which converts a random vector X to linear independent components. The aim of

this method is maximization of the transfer function. The data dimensionality reduction in this stage was similar to the procedure in PCA.

Data Classification and Analysis

After data dimensionality reduction data should be classified. Thus proper neural network with 5 input nodes, a hidden layer with 2 nodes and output layer with two nodes was used. One of the output nodes were dedicated to class of the healthy cases and the second one to patients with positive ischemia exercise test. The available data set is randomly divided to two sets of train and test. For generalization aspect this procedure is repeated for several neural networks with random initialization values. In the train set there were 23 samples including 20 data from suspected subjects and 3 from healthy ones and the remaining 47 cases were used as a test set. The training of the network was stopped on base of minimal training Root Mean Square (RMS) error. By cross validation test on different combination of the train and test sets using neural network classifiers, classification results are obtained. Classification results are analyzed by the help of SPSS-16 software and different statistical parameters of the classification results such as sensitivity, specificity and p value were computed.

Results

All recorded VCG data including healthy and suspected ones were analyzed and their features were extracted (Table 1). Dimensionality of the data is reduced to five by means of the PCA. Their mean values are calculated for two groups of healthy and ischemia suspects (Table

2). Reduced data dimension mean values of ICA dimensionality reducers for two groups of data are also given in table 3. Classification results of neural network on three test samples are shown in table 4.

During ECG data analysis we found that among 60 candidates there was 21 ischemic suspects. Also with VCG signal examination we found that among 60 patients, 14 candidates were ischemic suspect. During exercise test it was determined that 50 patient had negative test and 10 had positive test, which confirmed ischemic heart disease. ECG and VCG analytical results were compared with exercise test results. Among 14 patients with positive VCG, seven had positive exercise test and seven had negative exercise test. Among patients with negative VCG, three of them had positive exercise test. Moreover among 21 patients with positive ECG, six of them had positive exercise test and 15 had negative exercise test; among patients with negative ECG four patients exercise test showed positive. The sensitivity, specificity and other statistical parameters of the ECG and the VCG are calculated for ischemia evaluation (Table 5). The ECG sensitivities and specificities for the ischemia evaluation are 60 and 70 percent and for VCG are 70 and 86 respectively. Kappa coefficient index and p value for VCG is 0.483 and 0.001 and for ECG is 0.208 and 0.069 respectively. Negative predictive value (NPV) and Positive predictive value (PPV) for ECG is 89.7 and 28.6 percent and for VCG is 93.5 and 50 percent. False Negative Ratio (FNR) and False Positive Ratio (FPR) for ECG is 40% and 30% and for VCG is 30% and 14% respectively.

Table 2. Output of PCA algorithm for two groups

Group	PCA output				
Normal	57.675	-74.823	71.156	-3.881	-215.054
Ischemia	-24.893	3.511	-110.182	28.373	-355.620

Table 3. Output of ICA algorithm for two groups

Group	ICA output				
Normal	-0.3187	-0.3598	2.5273	2.7662	0.5672
Ischemia	-0.3486	-1.0791	-1.0559	0.6253	0.4196

Table 4. Result of neural network on three sample test data

Case	Neural network output		Results
1	0.8922	0.1062	+ (true)
2	0.1037	0.8977	- (true)
3	0.9623	0.0448	+ (true)

Table 5. Result of calculation of statistical features

	Sensitivity	Specificity	Kapa	P value	NPV*	PPV**	FNR [†]	FPR ^{††}
ECG	60%	70%	0.208	0.069	89.7%	28.6%	40%	30%
VCG	70%	86%	0.483	0.001	93.5%	50%	30%	14%

* Negative predictive value

** Positive predictive value

† False negative ratio

†† False positive ratio

Discussion

As previous studies shown the VCG has higher sensitivity and accuracy than ECG for other diseases. Hurd et al had shown 82% and 34% sensitivity for VCG and ECG on patients suffering from myocardial infarction.¹⁸ Also Eriksson et al studied patients with left and right Bundle Branch Block in order to diagnose myocardial infarction. They found that sensitivity of VCG in patients with right and left Bundle Branch Block is 71% and 78% respectively.¹⁹ In our study the negative predictive value (NPV) and positive predictive value (PPV) for ECG is 89.7, 28.6 percent and for VCG is 93.5 and 50 percent respectively. False Negative Ratio (FNR) and False Positive Ratio (FPR) for ECG are 40% and 30% and for VCG

are 30% and 14% respectively. Our study came to conclusion of previous studies with higher accuracy.

Conclusions

As results of this study shows VCG is more sensitive than ECG, so in cases that ECG signal of a patient suspected to ischemia is without any signs for commenting about existence or non-existence of ischemia, vector cardiogram signal can be used. We used stress testing as a standard reference test. Further study is needed to compare ECG and VCG or other diagnostic methods such as cardiac scan and angiography in order to extend preference of VCG and 3D findings over surface ECG more accurately.

Conflict of Interests

Authors have no conflict of interests.

Authors' Contributions

ARMD carried out the design and coordinated the study and had contribution in preparing the manuscript. IF participated in most data acquisition and analysing of the data and contributed in manuscript writing. AF had contribution in manuscript preparing and data analysing. HR had contribution in data acquisition and analysing. MPM had contribution in clinical data evaluation. NRD had contribution in patient selection, data acquisition and clinical data evaluation. All authors have read and approved the content of the manuscript.

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