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A Vectorcardiogram-based Classification System for the Detection of Myocardial Infarction

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Abstract—**Myocardial infarction (MI), generally known as a heart attack, is one of the top leading causes of mortality in the world. In clinical diagnosis, cardiologists generally utilize 12-lead ECG system to classify patients into MI symptoms: 1. ST segment elevation, 2. ST segment depression or T wave inversion. However unstable ischemic syndromes have rapidly changing supply versus demand characteristics that is one of the several limitations of 12-lead ECG system for MI detection. In addition, the ECG sensor placements of 12-lead system is not easily donned and doffed for tele-healthcare monitoring at home. Vectorcardiogram (VCG) system in clinic is another type of diagnosis plot which represents the magnitude and direction of the electrical potential in the form of a vector loop during cardiac electric activity. The VCG system can easily acquire three ECG waves from X, Y, Z directions to composite vector signal in space and the VCG signals can be transferred to 12-lead ECG signal through Dower transformation and vice versa. Hence, this study attempts to develop a VCG-based classification system for the detection of Myocardial infarction. In the experiment results, the proposed system can select the proper ECG features based on cardiologist's knowledge and proposed principal moments of QRS complex. The classification performance of MI detection can be reached to 99.89% of sensitivity, 92.51% of specificity, 95.35% of positive predictive value, and 96.96% overall accuracy with maximum-likelihood classifier (MLC).**

Keywords: myocardial infarction, ECG, vectorcardiogram, classification, 12-lead ECG system, machine learning

I. Introduction

Myocardial infarction (MI), generally known as a heart attack, is the interruption of blood supply to a part of heart, causing heart cells to die [1, 2]. In general, MI can take place in different portions of heart, such as anterior, inferior, posterior, inferior-lateral, anteriorseptal, posterior-lateral, and the traid of MI is ischemia, lesion and infarction [1, 2]. Among the diagnostic tests available to detect heart muscle damage are an electrocardiogram (ECG), echocardiography, and various blood tests, such as aspartate aminotransferase, creatine kinase, myoglobin, and tropnin-T etc. [3].

The ECG signals are vital to investigate human's health, and have been used as a common tool to assist to detect the abnormal cardiac electrical activities for a long time. The most commonly used clinical ECG-system, the 12-lead ECG system, consists of the following 12 leads, which are I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5[4]. The diagnosis of different types of MI in the standard clinical 12-lead ECG has different diagnostic key observations, for example, T waveforms invert, ST-elevation, and pathological Q waveforms [1, 5, 6]. However, the key characteristics of MI are too hard to capture from one perspective view of the 3 dimension heart electrical activities for each one lead ECG signal. Recent advances in computer graphics and wireless technologies have renewed interest in three Frank orthogonal leads vectorcardiogram (VCG), X, Y, Z lead, that use fewer leads than the conventional 12-lead ECG signals for medical diagnostic applications[7]. In the signal process aspect, VCG has a linear transformation with 12-lead ECG [7-9], and emerges as a natural option for 3-dimensional graphical and visualization systems, as seen in Figure 1, for detecting and monitoring cardiac disorders, such as various types of myocardial infarction and atrial fibrillation (AF) [7]. In home care aspect, wearing 3-lead Frank VCG device is easier and more convenient than 12-lead ECG device for users.

In clinical, Starr et al. [5] proposed three diagnostic criteria of inferior myocardial infarction by the frontal plane of VCG signals, and there are i) time from the 0 point to leftward X intercept and distance from the 0 point to leftward X intercept, ii) A maximal frontal plane QRS vector, and iii) A maximal superior deviation and a ratio of maximal superior deviation to maximal inferior deviation. Bortolan and Christov [10] also presented three indices to detect MI, there are i) maximum angle between QRS and T loop axes, ii) T axis elevation and azimuth angle difference, iii) ratio of maximum to mean T vector magnitudes. With the development of technology and signal processing techniques, there are different sophisticated computer-based interpretations in time, frequency or phase domain to capture the significant distinguishable features

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from bio-signals [1, 2, 11, 12], for example, Ge [13] proposed that using the coefficients from multivariate autoregressive model via VCG signals to distinguish normal case, acute MI, sub-acute MI.

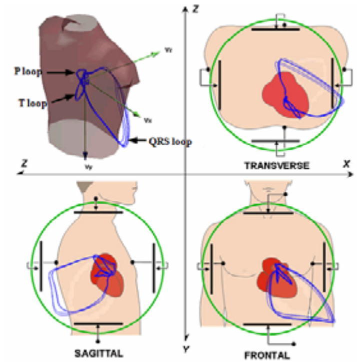

Fig 1. VCG signals from different views of human torso showing various coordinate axes [1, 4].

In practice, features of these references have their own characteristics, and therefore, all of these features have been considered as the features to detect MI. In this study, we combine these features from clinical, signal process and some features we proposed, which construct some signification diagnostic and underling hidden characteristics in the measured VCG loop between healthy and MI recordings, as the feature sets and propose a classification system with some different types of classification methodology to identify normal (healthy) and abnormal (MI) subjects.

II. VCG Feature Extractions

The MI detection of classification system requires feature extractions of VCG signals. A good recognition algorithm depends on the proper feature set representing the VCG signals, such as the difference of VCG waveforms between normal and abnormal VCG signals. This study presents some different features, which extracted by VCG signals, to identify MI or healthy subjects. As follow, some reference feature extractions have been briefly introduced as following:

First, there are three types' characteristic indices to detect myocardial infarction obtained from T-wave morphology of VCG signals, which had presented by Bortolan and Christov [10]. These features are i) maximum angle between QRS and T loop axes (RT angle), ii) T axis elevation and azimuth angle difference (EDA), and iii) Ratio of maximum to mean T vector magnitudes (RMMVt), respectively.

Second, there are three diagnostic criteria of inferior myocardial infarction, which are obtained from the frontal plane of VCG signals, will be the feature set. These are i) Time from the 0 point to leftward X intercept and distance from the 0 point to leftward X intercept (XL), ii) A maximal frontal plane QRS vector (AM), and iii) A maximal superior deviation and a ratio of maximal superior deviation to maximal inferior deviation (Ratio of SD to ID) [5].

Third, the multivariate autoregressive (AR) model has been extensively applied for bio-signal modeling [13, 14]. Hence, multivariate AR coefficients will be including as VCG features. VCG signals for each subject can be represented by p×M2 multivariable AR coefficients, where p is the order of an M-channel multivariable AR model. According to the suggestions of [13], the AR model order of four had been selected. Hence, in this study 4×32=36 multivariable AR coefficient via 3-dimension VCG leads, hereinafter called AR coefficients.

For understanding the process of heart rhythm on QRS complex and T waveform of VCG signals, third order moment (skewness coefficient) and fourth order moment (kurtosis coefficient) are proposed, and correlation coefficient of T wave and an upper semicircle curve is proposed as the degree of the inverse T wave. R-R interval (RRI) and Q-S interval (QSI) also are the important indices to describe the heart rhythm. Hence, the average and variance of RRI and QSI from a 6sec signal are considering as the features in this study. Table 1 is a simple description to understand the extractions of feature in this study.

TABLE I

Feature extractions from VCG signals

Signal source		Feature extraction
VCG signal		Multivariable AR coefficients [13]
		Ratio of maximum QRS vector magnitudes to T vector magnitudes RMMV [10]: 1. QRS vector magnitudes 2. T vector magnitudes
		Degree of the inverse T wave
X-lead	QRS complex T wave	3st principal moment 4st principal moment (above features are proposed in this study)
Y-lead		
Z-lead		
Transverse plane (XZ)		R-T peak angle [10]
left sagittal plane (YZ)		
VCG (XYZ)		
Frontal plane (XY plane)		R-T peak angle [10]
		EDA [10]
		AM [5]
		Ratio of SD to ID [5]
		XL [5]
Temporal domain		Mean of RR interval (6 sec) Mean of QS interval (6 sec) Variance of RR interval (6 sec) Variance of QS interval (6 sec)

III. Proposed Classification System

In this study, we propose a classification system to detect MI via VCG signals. In this system, first segmented 6 seconds signals from the collected VCG signals, and then detection of QRS and T is implemented. From the results of QRS and T detection, extracting the features, which have introduce in section II, as the input data for classifiers. According to the feature extractions, 64 features have been extracted. However, not all of features are significant useful in the classifier. Sequential forward (FFS) and backward (BFS) feature selection algorithms are applying to select the important features in feature selection. Finally, the classification evolution is implemented. Figure 2 is the proposed classification system flowchart.

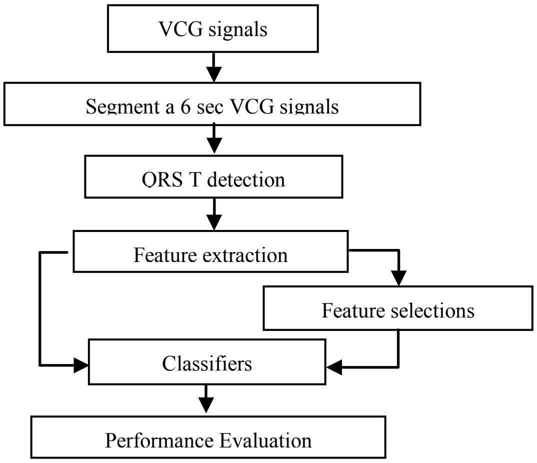

Fig. 2 the flowchart of the VCG classification system

There are four different types of classifier, two parametric and two nonparametric classifiers are applying to identify normal and abnormal subjects. Two parametric classifiers are maximum-likelihood classifier (MLC) and general linear model (GLM), respectively, and other two nonparametric classifiers are k nearest neighbor (k-NN) and support vector machine (SVM).

MLC [15] is made up by maximum a posteriori (MAP) and assuming the samples following the multivariate normal distribution with mean vector $\boldsymbol{\mu}_i$ and covariance matrix Σ_i of each class ω_i , $\forall i = 1,2$. The decision of MLC can be expressed as equation (1):

$$\omega_{MAP}^{MLC} = \arg\min_{i=\{1,2\}} \left\{ -2\ln p_i + \ln\left|\Sigma_i\right| + (\mathbf{x}-\boldsymbol{\mu}_i)^{-1} \Sigma_i^{-1} (\mathbf{x}-\boldsymbol{\mu}_i) \right\} \quad (1)$$

where p_i is the priori probability of class ω_i.

GLM [15] is a statistical parameter model based on estimating the coefficient set β of the linear model, and the model can be expressed as

$$y = \mathbf{x}\boldsymbol{\beta} = \beta_0 + \beta_1 x_1 + \ldots + \beta_d x_d \quad (2)$$

where y is the observe response and $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, \ldots, \beta_d]^{\mathrm{T}}$ is the estimator of coefficient of the linear model, which is estimated from training data and least square method.

The conception of k-NN [15] is to find the set of k nearest neighbor in the training set for an input sample, and assign this sample to the most frequent class among this training set.

SVM [16] is a binary classifier, and learning a separating hyperplane $\mathbf{w}$ from support vectors in the feature space, also called Hilbert space, to maximize margins between two different classes, and it's implementing by a kernel function.

IV. Experimental Data and Designs

In his study, we adopted the benchmark VCG dataset in PTB database from PhysioNet (2006 QT Challenge) [17]. There are 448 VCG available recordings, including 80 Healthy Controls (HCs) and 369 MIs. In this study, all VCG signals would be collected a segment 6 seconds signals, and feature extractions are implemented via these 6 seconds signals. For avoiding the incomplete heart loop in these 6 seconds VCG signals, we removed first and end heart loop.

For investigating the influence of different size of HCs, two datasets with different sizes of HC case are presented. One includes 369 MIs and 80 HCs, and the other one includes 369 MIs and 240 HCs, which are resampling three times from different sections in 30 seconds VCG recording. Now making a brief summary about feature sets and classifications as follows:

There are six feature sets and four classifiers were employed in the experiments. Six feature sets extracted from the references [10], [5], and [13], all of features from references and we proposed (simply named ALF), and the features selected from FFS and BFS, respectively. Four classifiers are MLC, k-NN, GLM, and SVM, respectively.

For the investigation of classification performance evaluation, k-fold cross validation (k=10) and random subsampling methods were employed in this experiments. For each combination of the experiment, k-fold cross validation will repeat 100 times by the random subsampling methods to obtain the classification performance. The classification performances are evaluated based on four evaluation indices, which are sensitivity, specificity, positive predictive value (PPV), and overall accuracy, and the average and standard deviation of each index would be displayed.

TABLE II
EXPERIMENTAL DESIGNS

PTB Dataset	Feature sets	Classifiers
Dataset1 :	Reference [10]	MLC
368 MIs and 80 HCs	Reference [5]	*k*-NN
Dataset 2:	Reference [13]	GLM
368 MIs and 240 HCs	ALF, FFS, BFS	SVM

V. Experimental Results and Discussions

With combinations of experimental design, there are 48 combinations. For a convenient reason, we only display the highest classification performance for each feature set and datasets. Table 3 and 4 are shown these results for dataset 1 and 2, respectively. Note that shadow part and bold type indicates the best performance of each evaluation index. The number in bracket is the standard deviation.

The following are some findings based on these results:

1. According to the overall accuracy, the highest performance of all combinations is BFS+MLC, no matter in dataset 1 or dataset 2.
2. The data size between MIs and HCs is a large imbalance (369:80) in dataset1, and hence, some classifiers can't explicitly distinguish the difference between MIs and HCs precisely in training step. As the HC sample size increase, the classification performance represent ascending tendencies.
3. The feature set, ALF, includes all the features. This feature set not only retains the advantages from references [5], [10], and [13], but also contains other different significant features. Hence, the performance from ALF is always

overcome other feature sets from reference.

4. The BFS is implemented by the feature set, ALF. The advantage of BFS is a useful and significant portion of feature was reserved, and removing some trivial and insignificant portion of feature. From experiments, show that the features obtain from BFS can capture the higher performance.

TABLE III
THE BEST CLASSIFICATION PERFORMANCE OF EACH FEATURE SET WITH THE ASSOCIATED CLASSIFIER FOR DATASET 1.

	Sensitivity	Specificity	PPV	Accuracy
Reference 1+ MLC	87.19 (0.50)	71.58 (2.17)	93.38 (0.48)	84.40 (0.59)
Reference 2+ SVM	51.09 (0.53)	73.51 (1.34)	89.87(0.47)	55.10 (0.51)
Reference 3+ SVM	90.22 (0.98)	**78.10 (1.80)**	**95.03 (0.41)**	88.07 (0.95)
ALF+ SVM	96.46 (0.41)	70.76 (1.93)	93.88 (0.37)	91.91 (0.37)
FFS+SVM	96.29 (0.37)	71.01 (1.83)	93.92 (0.36)	91.82 (0.45)
BFS+MLC	**99.21 (0.20)**	66.84 (3.31)	93.29 (0.63)	**93.48 (0.69)**

TABLE IV
THE BEST CLASSIFICATION PERFORMANCE OF EACH FEATURE SET WITH THE ASSOCIATED CLASSIFIER FOR DATASET 2.

	Sensitivity	Specificity	PPV	Accuracy
Reference 1+ SVM	78.66 (0.71)	88.75 (0.78)	91.47 (0.55)	82.64 (0.54)
Reference 2+ *k*-NN	64.04 (1.16)	62.88 (1.73)	72.58 (1.01)	63.59 (1.01)
Reference 3+ SVM	90.95 (0.87)	**97.87 (0.50)**	**98.49 (0.36)**	93.68 (0.68)
ALF+ GLM	99.56 (0.15)	88.56 (1.57)	93.05 (0.89)	95.22 (0.61)
FFS+MLC	97.49(0.36)	94.98 (0.59)	96.76 (0.37)	96.50 (0.36)
BFS+MLC	**99.89 (0.14)**	92.51 (1.81)	95.35 (1.07)	**96.96 (0.70)**
BFS+MLC	**99.89 (0.14)**	92.51 (1.81)	95.35 (1.07)	**96.96 (0.70)**

VI. CONCLUSIONS

This study proposed a classification system and a suit feature set to classify MI patterns. In order to measure the effectiveness of the feature sets, four classifiers are applying to identify the HCs and MIs. The experiments show the features selected from BFS with MLC provides a relatively high sensitivity 99.89% and standard deviation (0.14%) with a compromise of specificity 92.51% and standard deviation (1.81%), and the overall accuracy attain a high performance 96.96% with small standard deviation 0.70%. In the future, more significant features have been surveyed for the classification system to detect heart diseases.

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