

WAVELET BASED ANALYSIS OF ECG SIGNAL FOR THE DETECTION OF MYOCARDIAL INFARCTION USING SVM CLASSIFIER

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ABSTRACT

This paper introduce a new technique for automatic and accurate detection of heart attack which is also known as Myocardial Infarction. The ECG signals may be corrupted with different types of noises. So an efficient noise removal technique is inevitable. In this paper, we use a denoising technique using wavelet transform which aims to estimate the signal of interest from the composite signal. Features are extracted using polynomial fitting algorithm and classification of ECG beats is done by using an SVM (support vector machine) classifier. The proposed algorithm is capable for automatic detection of heart attack and also improves the classification quality.

KEYWORDS: Myocardial Infarction, Wavelet Transform, Polynomial Fitting, Support Vector Machine

INTRODUCTION

Electrocardiogram (ECG) is a graphical representation graphical representation A typical ECG waveform is shown in Figure 1 consist of P, QRS and T waves. In 24 hours, an ECG can record over one lakh heartbeats for a single patient. Analysis of these signals manually is a difficult thing for the diagnosis of certain cardiac diseases. So automated analysis of long term ECG can help physicians to understand a patient's physiological state. Automated tools are needed for cardiologists to analyze ECG data accurately. In clinical application, automated classification of long duration ECG signal is essential. Previous methods to tackle this issue were supervised learning approaches[2]-[3], that adapts some supervised methods. In [8], the analysis is based on the extracted features such as Hermite coefficients and neural network based methods are used for classification. ECG recordings can be processed by using these supervised learning methods[3] but they do not yield good quality results. These techniques only take the difference between labels of the entire ECGs but not consider the difference between the labels of heart beats within the ECG. Semi supervised Learning(SSL) strategies[4]-[6] are introduced to address this problem. This approach will select a subset of heartbeats from the training set of ECG data, manually labeled by cardiologists and at last work classifiers on them.

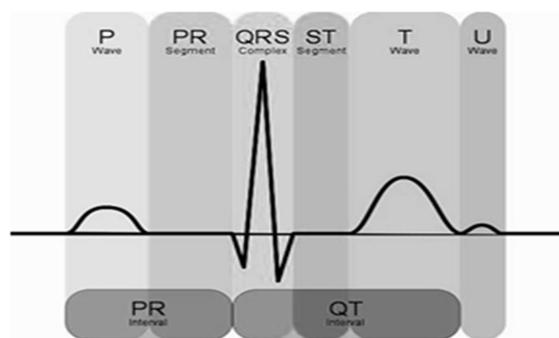


Figure 1: A Typical Electrocardiogram

A multiple instance learning strategy for ECG classification is proposed in [1]. This method is more complex for the analysis of long term ECG data[7]. In this paper, we propose an efficient classification system that improves the quality of Multiple instance learning. An efficient wavelet based filtering methods and SVM classification is used. The proposed algorithm achieves good performance on classification of ECGs related to Myocardial Infarction.

The reminder of this paper is organized as follows. Section II briefly describes about myocardial infarction. Section III describes the methodology. Section IV gives the simulation results and finally section V presents conclusions and gives directions for future work.

MYOCARDIAL INFARCTION

In recent years, Myocardial Infarction(MI) is one of the heart diseases causing very high death rates. So it is essential to recognize and locate MI in ECGs. One of the major indications of myocardial infarction is the elevation in the ST segment which is shown in Figure 2. Our main task in this paper is to detect MI from ECG. MI occurs when blood flow stops to part of the heart causing damage to the heart muscle.

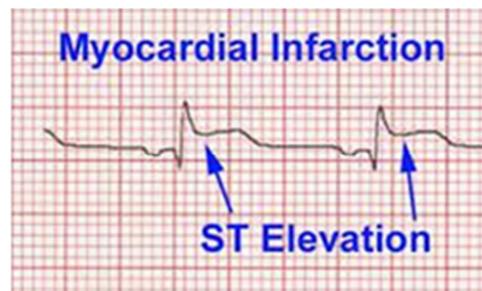


Figure 2: Indication of MI from Patient's ECG

METHODOLOGY

Our proposed system contains three main phases: ECG filtering (Preprocessing), Feature extraction and classification. The methodology used in this paper is shown in Figure 3

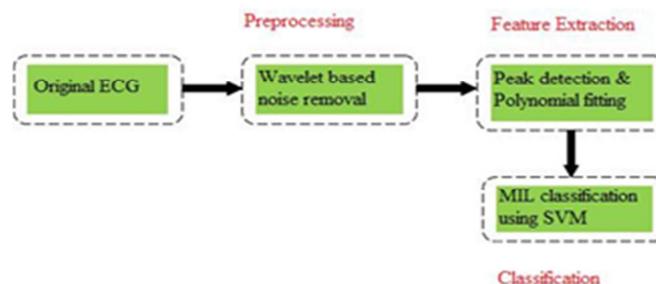


Figure 3: Block Diagram

ECG Filtering

The aim of this paper is to classify heartbeats. Before performing this task, several preprocessing steps were performed on the ECG raw data. Skin electrodes are used for capturing ECG signal. They are prone to contamination by various types of artifacts or noise. Usually two principal sources of ECG signal can be distinguished. One is due to physical parameters of the recording equipment and the second one is the baseline wander. ECG is a nonstationary

biosignal corrupted by noise. . It is proved that Wavelet Transform[9] can be used as an efficient tool for denoising such signals.

The aim of this denoising process based on wavelet trans-form is to estimate the signal of interest $s(i)$ from the com-posite signal $f(i)$ by eliminating the noise $e(i)$ given that the composite signal $f(i) = s(i) + e(i)$. The noisy signal decom-position is done by using discrete wavelet transform(DWT) using the Daubechies wavelet. The obtained coefficients are passing through a threshold[10] and setting certain values to zero. The denoised signal is recovered by taking the inversediscrete wavelet transform(IDWT). By zeroing the scaling coefficients of DWT, the baseline drift also can be removed. This is equivalent to filtering the ECG signal with a high pass filter having a cut-off frequency of 2.8 Hz.

Feature Extraction

MI is usually indicated by the ST segment of ECG signal. Peak detection algorithm[11] is used to detect the characteristic points such as R, S and T points. After ST segment is extracted from the ECG signal, polynomial fitting algorithm on the ST segment is applied for extracting features from it. The fitted curves are similar to the original ST segments, so the information in the ST segments such as width, shape etc., are expressed by a few polynomial coefficients. Usually $n+1$ coefficients are there for n order fitting. The elevation in QRS peak is also an indication for myocardial infarction. So the height of QRS peak is also included as a feature for the classification.

Classification

A frame work of classification is shown in Figure 4. All beats in the training set is first grouped into different clus-ters by using k-means clustering algorithm. This algorithm utilizes the swarm intelligence algorithm particle swarm opti-mizer(PSO)[5] to find a set of optimal variable weights.

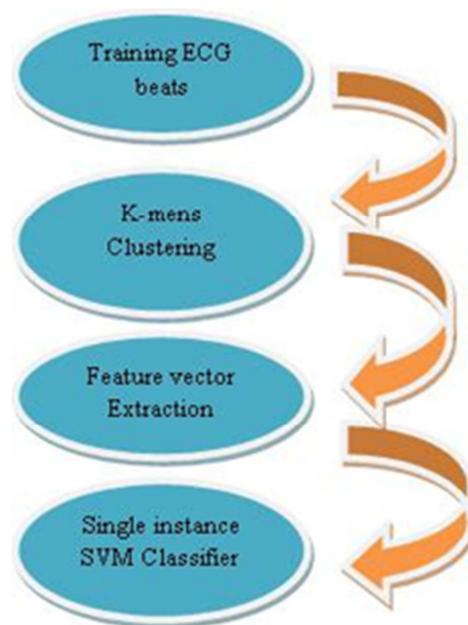


Figure 4: Block Diagram for Classification

Each cluster is characterized by a Gaussian kernel

$$\text{RBF}_l = \exp \left[-\frac{(x - \mu_l)^2}{2\sigma_l^2} \right] \quad (1)$$

where μ_l is the center of the l th cluster, determined by taking the mean value of heartbeats in the cluster

$$\sigma_l = \mu \frac{\sum_{i=1}^l \text{dist}(\mu_i - \mu_l)}{l-1} \quad (2)$$

where μ is the user-defined scale factor. Feature vectors are extracted by analyzing the cluster over heartbeats and finally single instance classifier such as support vector machine classifier (SVM)[9] is used for classification.

SIMULATION RESULTS

To illustrate the performance of the proposed system, we conducted a series of experiments on the PTB diagnostic ECG database. First in the pre-processing stage, the input ECG signal is filtered by using a wavelet based filter. Compared with conventional filtering methods, this wavelet-based filter has advantages because of less mean square error value.

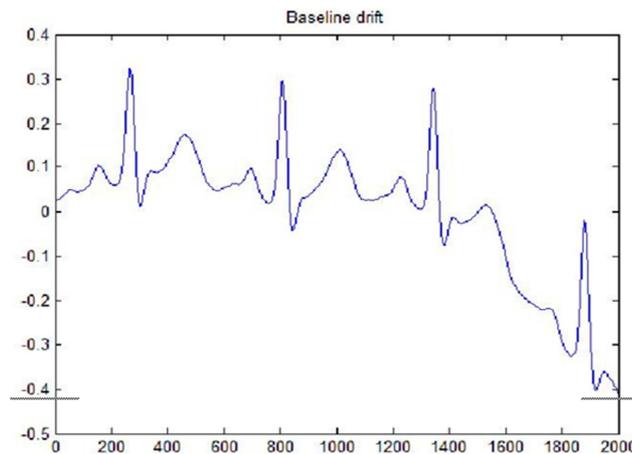


Figure 5: Original ECG

The original ECG signal is shown in figure 5. and the filtered ECG signal is shown in figure 6.

In previous work, all ECG signals are processed by a DCT based band pass filter whose pass band is set to a frequency interval $[f_1 f_2]$ so as to eliminate the influence of both low-and high-frequency artifacts.

In this paper, all the noise and baseline drift is removed by using a discrete wavelet transform based filtering technique which is more reliable and having less mean square error value compared to that of DCT based bandpass filter. The performance comparison of the two filtering approaches is shown in Figure 7. Next step is to detect R, S and T points in the filtered ECG. Figure 8 shows the detection of R and T points in the filtered ECG signal. A peak finding algorithm is used to detect the characteristics points in the filtered ECG signal.

SVM classifier is used for classification. A discriminant function $f: X \rightarrow R$ classifies an observation $x \in X$ into one of two classes, labeled +1 or -1. The equations for Sensitivity, Specificity and Accuracy are shown below.

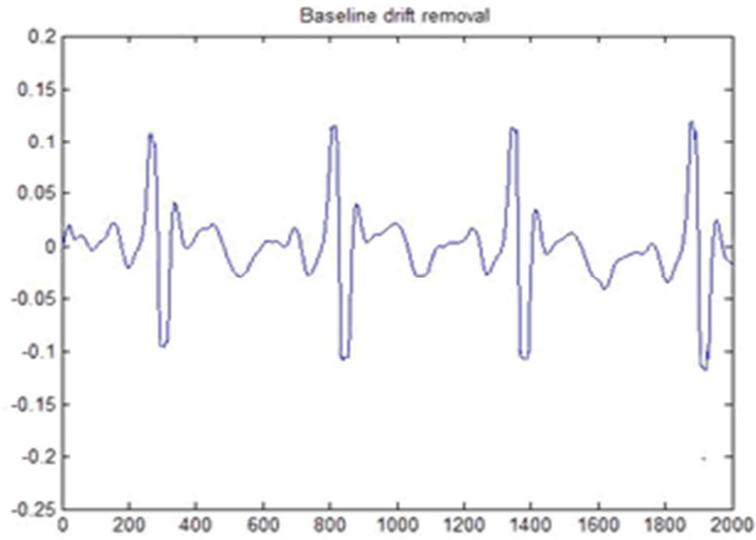


Figure 6: Filtered ECG

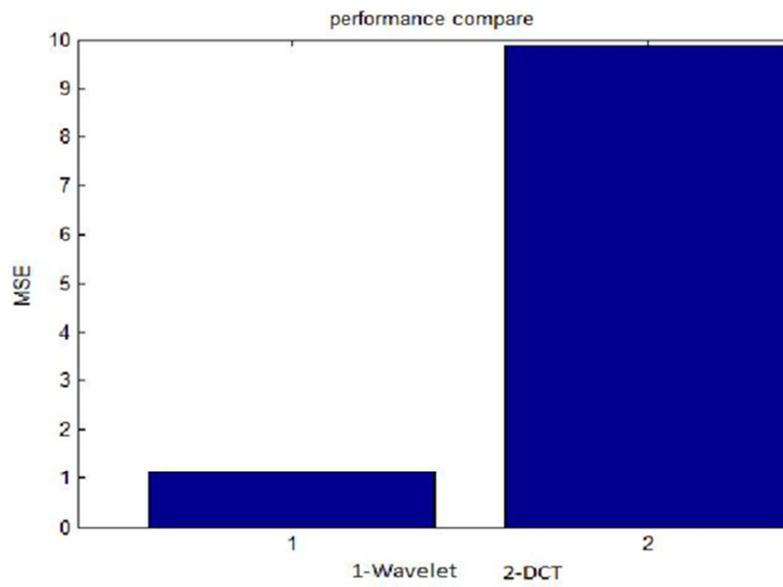


Figure 7: Performance Comparison

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

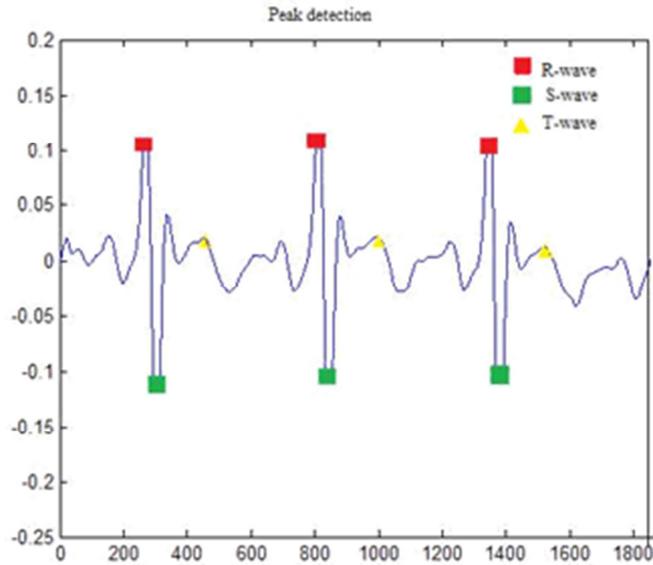


Figure 8: Detection of R, S and T Points

$$\text{Accuracy} = \frac{TP + TN}{P + N} \tag{5}$$

where TP, TN, FP, FN, P and N are true positive, true negative, false positive, false negative, positive and negative respectively. Compared to other classifiers such as knn(k-nearest neighbor) classifier, SVM classifier yields better results in the classification of ECG signals and obtained a classification accuracy of 91 %.

Table 1: Performance Comparison of KNN and SVM Classifier

	Sensitivity	Specificity	Accuracy
KNN	85 %	80 %	84 %
SVM	91 %	88 %	91 %

Figure 9 shows the performance comparison of KNN and SVM classifiers plotted by taking the sensitivity and specificity values for different scale factors (). Sensitivity and specificity are higher for large scale factors.

CONCLUSIONS

In this paper, we proposed an automated classification of ECG beats using SVM classifier. The proposed system accomplishes preprocessing effectively by using discrete wavelet transform, which is an efficient tool for denoising biological signals. A set of features are exploited to characterize each beat. The proposed system solves the problem of automatic detection of MI from patients ECG. This paper consider both intra and inter ECG differences for better classification.

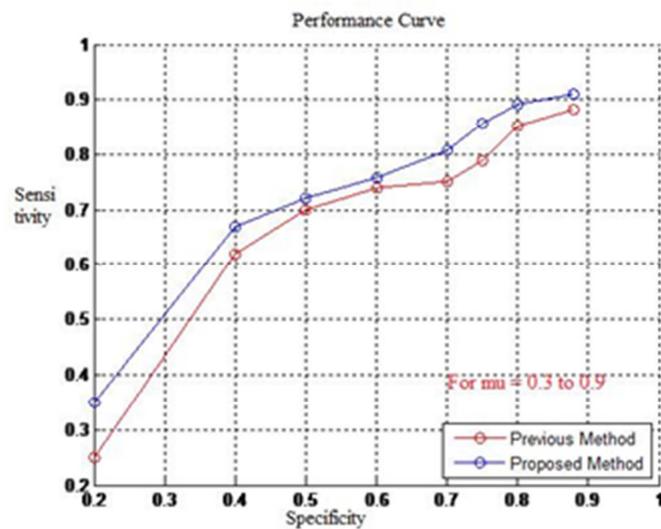


Figure 9: Performance Comparison

When tested on real ECG datasets from the PTB diagnostic database, our method achieves better performance than previous algorithms. The proposed system is very much useful in clinical application for the detection of myocardial infarction. Of course, there is a scope for improvement. That is further tuning of the parameters will yield better results.

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REFERENCES

1. Li Sun, Yanping Lu, Kaitao Yang, and Shaozi Li, ECG Analysis Using Multiple Instance Learning for Myocardial Infarction Detection, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 59, NO. 12, DECEMBER 2012
2. P.Chazal, M. Dwyer, and R. Reilly Automatic classification of heartbeats using ECG morphology and heartbeat interval features,, IEEE Trans. Biomed. Eng., vol. 51, no. 7, pp. 11961206, Jul. 2004
3. M. Mitra, and B. B. Chaudhuri A rough set based inference engine for ECG classification, IEEE Trans. Instrum. Meas., vol. 55, no. 6, pp. 21982206, Dec. 2006.
4. Philip de Chazal, Richard B. Reilly, A Patient-Adapting Heartbeat Classifier Using ECG Morphology and Heartbeat Interval Features, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 53, NO. 12, DECEMBER 2006
5. Farid Melgani and Yakoub Bazi, Classification of Electrocardiogram Signals With Support Vector Machines and Particle Swarm Optimization, IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 12, NO. 5, SEPTEMBER 2008
6. Turker Ince, Serkan Kiranyaz, Moncef Gabbouj. A Generic and Robust System for Automated Patient-Specific Classification of ECG Signals. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 56, NO. 5,

MAY 2009.

7. H. S. Shin, C. Lee, and M. Lee. Ideal filtering approach on DCT domain for biomedical signals: Index blocked DCT filtering method (IBDCTFM). *J. Med. Syst.*, vol. 34, no. 4, pp. 741753, 2010
8. L. Shyu, Y. Wu, and W. Hu. Using Wavelet transform and fuzzy neural network for VPC detection from the hotler ECG. *IEEE Trans. Biomed. Eng.*, vol. 51 Jul 2004.
9. Z. Zidelmal, A. Amirou, and J. Merckle. ECG beat classification using a cost sensitive classifier. *elsevier journal. Biomed. Eng.*, vol. 51 May 2013.
10. M.I. Johnstone, B.W. Silverman, Wavelet threshold estimators for data with correlated noise. Technical report, Dept. of Statistics, stanford univer-sity 1996.
11. J.Pan, and W.J. Tompkins, Areal time QRS detection algorithm. *IEEE Trans. Biomed. Eng.*, vol. 32 March 1985.