Myocardial Infarction Detection Using Hybrid BSS Method

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***Abstract*— This paper presents a novel technique for detecting myocardial infarction (MI) from ECG. Today, MI is one of the major causes of death worldwide. MI is a minor stage in lifelong cardiac disease, although rarely noticed, but can lead to sudden death. Since it is the first symptom of coronary artery disease, it is very important to detect MI in an early stage. For this purpose, several methods have been employed. But the hurdle is to detect MI efficiently from noisy signal, and also in an early stage. The problem lies in data acquisition system. Several noises get mixed with ECG signal, at the time of data acquisition and this make the extraction difficult. These noises can be due to respiration, EMG etc. The inefficient low pass filters of ECG machine add these noises to ECG signal. So to get a good input data, a perfect denoising technique is required, which is inevitable for the detection of small variations. The existing techniques use filters like notch and adaptive for denoising since they are not considering this raw ECG. It is proved that Independent Component Analysis (ICA) based on blind source seperation (BSS) algorithms, is an effective tool for extracting ECG from a mixed raw signal. Better denoising gives better results for the early detection of MI. Thus the objective of this work is to detect myocardial infarction in an early stage. The classification is based on naïve bayes classifier. The presented algorithm gives 96.77% accuracy on PhysioNet ECG database, which is supported by the National Institute of General Medical Sciences (NIGMS) and the National Institute of Biomedical Imaging and Bioengineering (NIBIB).**

Keywords—Myocardial Infarction, ECG, Polynomial fitting, Bayesian classifier, Naïve bayes classifier, fastICA, EFICA, WASOBI

I. INTRODUCTION

A graphical record of electrical activity of the heart, over a period of time, with electrodes placed on the patient's body is termed as Electrocardiogram (ECG)[1], [2]. From the captured ECG, cardiologists trace the rhythm and functioning of heart. They can also identify the cardiac abnormalities from ECG recordings. Manual classification and detection have its own drawbacks, which necessitates an automated ECG classification and earlier detection techniques. This paper deals with the detection of most crucial cardiac abnormality termed as myocardial infarction, or heart attack.

Today, major cause of increasing cardiac death is myocardial infarction. An important stage of the cardiac disease named coronary atherosclerosis is inflammation in vascular wall. MI is the first symptom of coronary artery disease. The death rate due to MI in the previous years has been accounted as 17.3 million per year, which clearly defines the relevance of MI detection and its need for reducing cardiac death rates.

It is interpreted that ECG consists of P, QRS and T waves resulted by atrial depolarization, ventricular depolarization and ventricular repolarization respectively. It is shown in figure 1. In between the period of ventricular ion change, blood is supplied to the heart muscles, via coronary arteries. When a block occurs on these arteries, it leads to myocardial infarction(MI) [3]. So the key point in early detection of MI is the ST segment. Its duration indicates blood supply to the heart. MI has three stages namely injury, ischemia and infarction. An elevated ST segment occurs at the stage of ischemia.

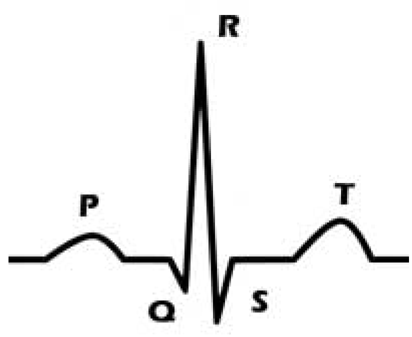

Fig. 1: ECG Waveform

Previous methods [4], [5] of MI detection are supervised learning approaches [6], in which some supervised methods are used. These methods process the ECG recordings, but good beneficial results are not yielded because only the difference between labels of the entire ECG is taken. They does not take the difference between labels of heart beats within the ECG. Semi Supervised Learning (SSL) [7] strategies are introduced to tackle this issue. From the training set, a subset of heartbeats is chosen and classification is done after manual labeling. These processes give good classification results but the problem is in input ECG.

Since this paper aims at extracting ECG from a mixed signal and to detect MI from it, we require accurate detection. The filtering techniques used in earlier methods do not suit for this condition. Inorder to separate the ECG signal as an independent data, from unknown sources of noise, ICA [8] algorithms based on blind source separation methods [9], [10]are used.

In this method, fastICA [11], EFICA[12] and WASOBI[13] algorithms are implemented for extracting ECG from mixed signal input. Then the extracted ECG is fitted with a polynomial fitting algorithm [14],[15] to strengthen the weak parts of signal. This avoids the loss of needed signal content. Peak detection algorithm [16] is implemented to find out the Q, R, S and T peaks. Naïve Bayes classifier[17] based on Bayesian rule[18] is used for classifying the feature to detect those having MI. The accuracy obtained shows that the detection is better than earlier methods.

II. METHODOLOGY

The structure of MI detection in our work consists of three main phases, namely: preprocessing, ECG feature extraction and classification. The proposed method is as shown in figure 2.

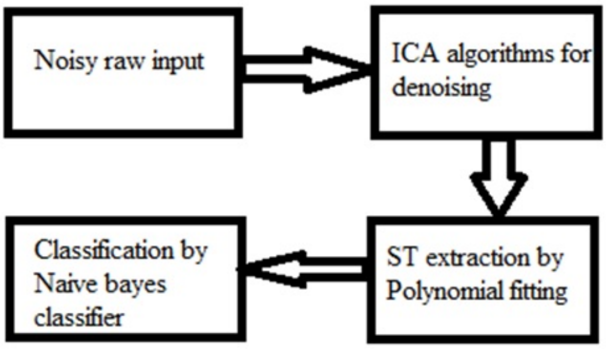

Fig. 2: Block diagram of detection

The noisy raw input is denoised using ICA blind source separation algorithms. The extracted ECG signal is fitted and segmented using polynomial fitting of fifth order and peak detection algorithms. The classification is done using naïve bayes classifier and MI is detected. The detailed block diagram is shown in figure 3.

A. Preprocessing

When skin electrodes capture the ECG signal from the patient's body, it is contaminated with respiratory as well as muscle contraction noises. The denoising methods [19], [20] such as DCT, wavelet transform etc. do not give any noticeable change to raw ECG. But we require exact detection of ECG from the unknown mixed signals.

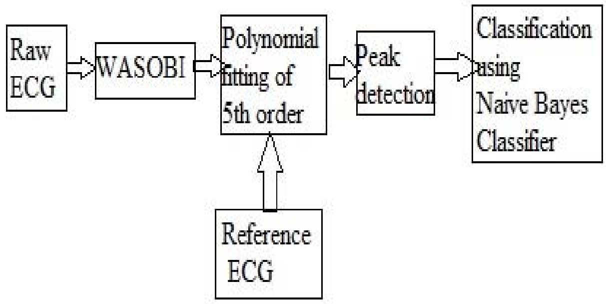

Fig. 3: Detailed block diagram of detection

When PCA [21] algorithms are applied on the raw ECG, uncorrelated components are obtained but not the independent. FastICA is an efficient algorithm for ICA, in which like all ICA algorithms, an initial prewhitening of data is done. In prewhitening, the data is centered and then whitened by performing eigen value decomposition Then an iteration scheme is done, resulting in maximum non-guassanity, that is statistical independence.. The unmixing matrix obtained by the iterative algorithm is used to find out the independent component by inverse matrix operations.

The accuracy of fastICA for finite data samples is improved by the algorithm, which is an improved version of the same, named as efficient fastICA or EFICA. This algorithm models all independent signals since they have a generalized guassian distribution. The algorithm consists of three steps. In the first step, original fastICA is run until convergence, then different nonlinearities are chosen to estimate the score function s of found out sources. Finally, refinement is done for these sources using the above nonlinearities.

In second order blind identification (SOBI) algorithm[22], time coherence of source signals are exploites and stationary second order statistics with joint diagonalization of covariance matrices is done. The whitening of signal is done at first and a unitary factor is found out. Then joint diagolization is implemented to get the unmixing matrix.
Thus the guassian sources with different spectra can be blindly separated using second order statistics.

An improvement on SOBI is obtained when the problem of diagonalization is converted into weighted nonlinear least squares problem termed as weight adjusted second order blind identication(WASOBI).

B. Feature Extraction

MI is strongly reflected in the ST segment of ECG signal. So experiments done in this paper based on ST feature segmentation and analysis. The polynomial fitting algorithm of fifth order is implemented for strengthening

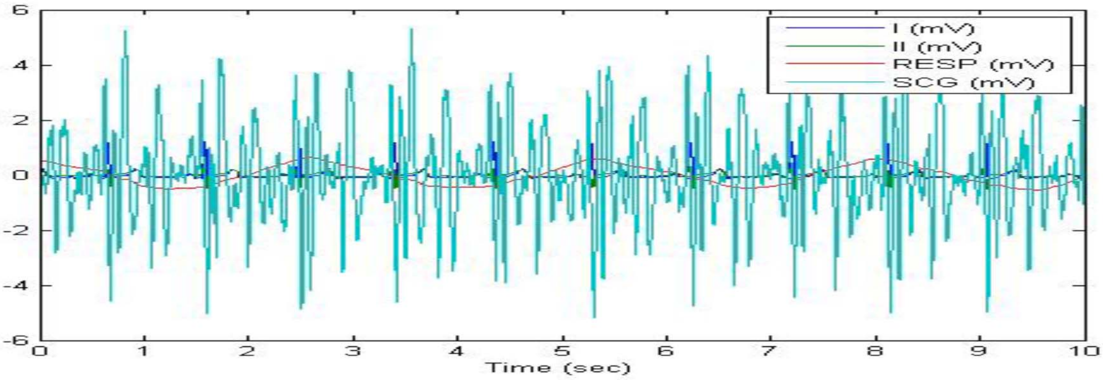

Fig. 4: Input raw ECG

the denoised ECG. When the sampling rate increases, the data points of each ECG cycle reaches 1000. To reduce the dimensionality of data, polynomial function of order smaller in magnitude than 1000 is used. Then the vector of coefficients fitted are obtained by polyfit and polyval functions.

Then the characteristic points Q, R, S and T peaks are detected using peak detection algorithm. The algorithm uses the state-machine logic to determine different peaks in an ECG signal. It has the ability to confront noise by canceling out the noise by high pass filtering and baseline wander by low pass. Besides, it check out criterion to stop detection of spikes From it, the features from ST segments are detected.

By fitting algorithm, large dimensions of each one lead heart beat is compressed to six polynomial coefficients, because order of our polynomial is five. Since 12-lead ECG is used as input, a total of 72 coefficients are obtained for each heartbeat.

C. *MI detection*

If denoising, segmentation and feature extraction is efficiently done, then the final step of MI detection is classifying the obtained data i.e, data with and without MI. Naive Bayes classifier, a modification of Bayesian classifier is used for this purpose. The main advantage is that interactions between features is not considered, classification is based on given features. Also, less feature input is required. The classifier is based on Bayesian theorem.
From the given attributes, an a priori probability is chosen for each classes. Then posterior probabilities are find out using Bayes optimization criterion. Then based on initial hypothesis the class to which each attribute to be given is find out. The naive Bayes classifier combines the probability model with a decision rule. The common rule in this is to find out the hypothesis that is most probable, known as maximum a posteriori or MAP rule of decision. Thus each attribute is labeled with this hypothesis and move to corresponding class.

The classifier is suitable because the dimensionality of the input is high and classifier only requires a small amount of training data to estimate the parameters. For separation and cross validation, our classifier is more accurate than any previous classifiers because of the rigidness of prediction condition. It is proved here that our algorithm with Naïve Bayes classifier is more accurate in early detection of MI than any previous methods.

III. Results and Discussion

A. Database

To illustrate the performance of our algorithm, a series of experiments are done on PhysioNet ECG database.

Large collection of physiological signals can be accessed from physionet termed as physiobank. Physiobank is a collection of digital physiological data which is growing day by day. It includes databases of multi-parameter cardiopulmonary, neural, and other biomedical signals recorded in varying conditions. The database taken for this work is combined ECG, breathing and seismographic signals, shown in figure 4. I and II are the ECG recorded at first and second leads. RESP is the respiratory signal recorded at the leads and SCG is the seismographic signals. All data are recorded in milli volts (mV).

B. Evaluation

First step deals with the extraction of ECG signal. The independent components are obtained as shown in figure 5, 6 and 7. From the independent components obtained, the weak signal can be interpreted as respiratory signal and the signal which is physiologically similar to ECG is interpreted as our needed signal. It can be seen that ECG extracted by efficient fastICA is better than other two BSS algorithms. But for weight adjusted SOBI, when order is increased the signal content also get high.

The preprocessing steps are given more importance because better denoising results in good input data and hence earlier detection of MI. The key feature of MI is ST segment elevation and it can be obtained only if the denoised signal contains all the relevant details of raw ECG.

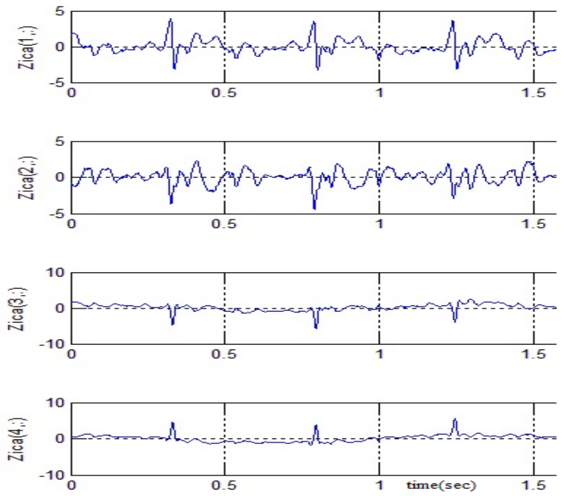

Fig.5: Independent component obtained by fastICA

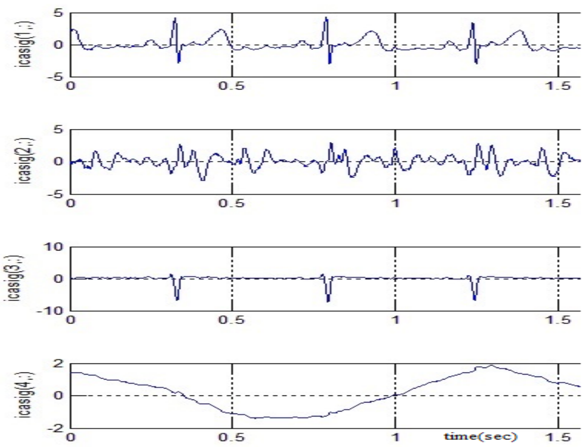

Fig. 6: Independent components obtained by EFICA

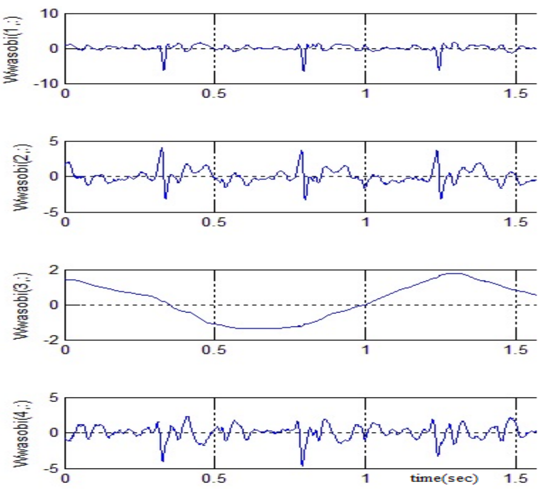

Fig. 7: Independent components obtained by WASOBI

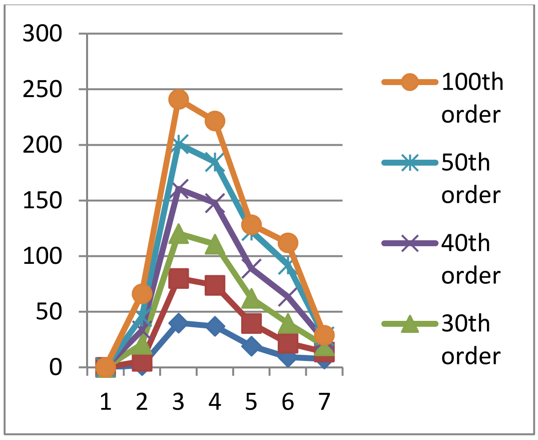

Fig. 8: PSNR values of different order WASOBI for a signal

In WASOBI, the AR order is changed to get more accurate component. Here 100[th] order WASOBI is implemented. The different order WASOBI implementation and the PSNR values are shown in figure 8.

The characteristic points Q, R, S and T are detected by peak detection algorithm after fitting ECG by fifth order polynomial as shown in figure 9.

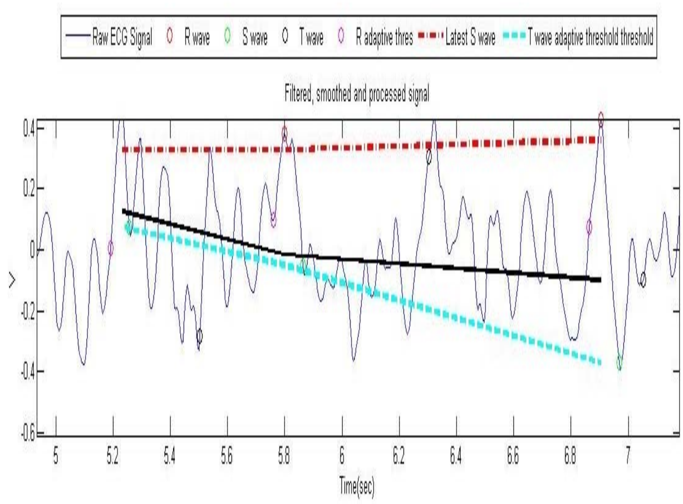

Fig.9: peak detection

The peak detection algorithm used is a state machine logic to detect different peaks in an ECG. Then positive and negative peak detection is done to verify the detected peaks and finally R, S and T peaks are findout. From their amplitudes and idices values obtained features of ST segment is extracted. This feature is used for training and testing in naïve bayes classifier. Then using Naïve Bayes classifier, MI is detected as in figure 10. In the classifier, the prior probabilities are chosen as equiprobable and the posterior probalities are find out by Bayes optimal rule. If the probability of attribute for having MI is greater than that of have not MI, then it is moved to predefined class of MI. In the similar manner the opposite condition is treated.

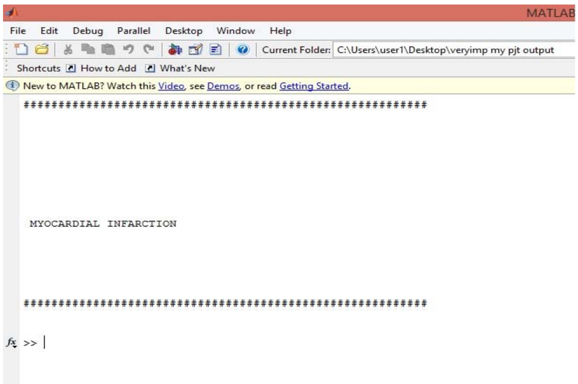

Fig.10:Output of MI detection

The Algorithm is applied for about 100 datas of combined ECG, respiratory and SCG (CEBS) signal taken from PTB diagnostic ECG database and an accuracy of 96.77% is obtained. The accuracy is calculated by the following equation.

$$Accuracy = \frac{TP + TN}{P + N},$$

where TP, TN, P and N denotes the true positive, true negative, positive and negative results.

The comparison of various ICA algorithms are done by finding out peak signal to noise ratio and mean square error and plotted as shown in figure 11 and 12.

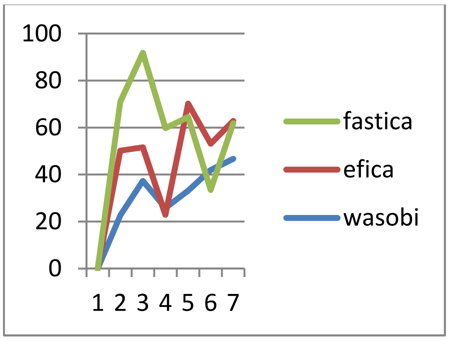

Fig. 11: MSE values for different ICA algorithms on raw data

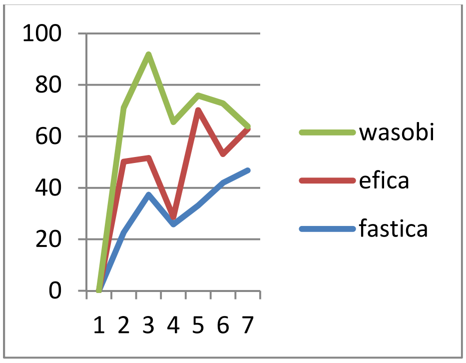

Fig. 12: PSNR values of different ICA algorithms on raw ECG

III. CONCLUSION

The objective of this paper is to detect MI in an early stage from the raw ECG containing respiratory and muscular noises. The challenge is to accurately extract the ECG signal and to classify it. This extraction is effectively implemented by using Independent component Analysis algorithms such as FASTICA, EFICA and WASOBI. The weak part of signal is strengthened by polynomial fitting algorithm and peak detection algorithm is used for feature that is ST segment extraction. It is obtained that MI detection from this noisy signal from PTB diagnostic ECG database resulted in 96.77% accuracy. Our algorithm can be applied in real cases so that earlier detection and diagnosis of cardiac abnormalities can be executed. In future, this algorithm can be used to detect other cardiac abnormalities too. Also, a better classification of abnormal input signals can be done.

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