



A Novel Algorithm for Fetal arrhythmia classification using Independent Component Analysis

APSANA S

PG Student (Applied Electronics And Instrumentation)
Electronics and Communication Department
Mohandas College of Engineering and Technology, MCET
Kerala, India
apsanasulfath@gmail.com

MANJU G SURESH

Assistant Professor
Electronics and Communication Department Mohandas
College of Engineering and Technology, MCET
Kerala, India
manjusuresh27@gmail.com

Abstract : This paper introduces a new technique for detecting and classifying arrhythmia in fetal ECGs obtained from maternal ECG. The analysis of the fECG can provide important information about the condition of fetus during pregnancy. If the extraction of the fetal ECG from maternal one is possible, then which allows the discovering of diseases or natural heart defects in early stages of pregnancy. That has a very important role in fetal life because which makes it possible to treat them with drug administration or to pre-schedule the delivery. However the fetal ECG obtained from the abdominal surface of mother is a mixture noises. In this work, propose a novel algorithm for fetal arrhythmia classification using independent component analysis for the detection and classification of mother and fetal heart beats. The noise removal and detection of fetal ECG is based on Independent component analysis and classification is done by using Bayesian classifier.

Keywords: Arrhythmia classification, Bayesian classifier, Feature Extraction, Fetal ECG, Independent Component Analysis

stages of pregnancy and they can affect any of the parts or functions of the heart.

Analysis and study of fetal ECG (fECG) and fetal heart rate (fHR) evaluation, provides important information about the condition of the fetus during pregnancy. So if we can acquire the fetal ECG from maternal ECG during early stages of pregnancy, it may increase early detection of fetal arrhythmias. But acquiring the fECG signal from the mother's abdomen is not very easy, since it is typically characterized by a very low SNR. Because the signals recorded is a mixture of noises caused by the fetal brain activity, respiratory signals, EMG signals and maternal ECG. Also the time duration, amplitude and structure of the fetal QRS complex is similar to the maternal one, but difference in amplitude and QRS width. Fetal and maternal beats may overlap in time, making even harder to detect the fetal QRS complexes. So we need advanced techniques for abdominal fetal ECG signals analysis due to the complexity and variability of recorded signals.

I. INTRODUCTION

Heart defects in infants are one of the major problems because it is the main for birth defects. More than 32,000 infants are born each year with some form of heart defect ie, 1 out of every 125 to 150. The heart is one of the first organs formed in the very early stages of pregnancy. The most critical period of this heart development is between 3 and 7 weeks after fertilization. It is clear that chances of heart defects also originate in early

This paper work, propose a novel algorithm for fetal arrhythmia detection and classification using independent component analysis. Here it describes about the detection of fetal heart beats from mother ECG and classification based on features obtained from the fetus ECG. The noise removal and detection of fetal ECG is based on Independent component analysis and classification is done by using Bayesian classifier.



II. RELATED WORKS

Recently, there are a lot of signal processing techniques have been proposed for the fetal ECG extraction from the recordings obtained from abdominal surface of mother [2],[3]. Different types of methods have been proposed for maternal ECG subtraction which consisting of template subtraction [5], [6], Adaptive filtering techniques, in which it use one or more maternal ECG reference signals [4]. Bruno Azzerboni, Fabio La foresta (2005) in the paper 'New Approach Based On Wavelet-ICA Algorithms For Fetal Electrocardiogram Extraction' [7] proposed to fit the recently developed Wavelet-ICA method, based on the joint use of Wavelet Analysis and ICA, to fECG extraction, in order to improve the extraction performance.

There are so many denoising methods are available including denoising signals using Transform Domain Adaptive Filtering Technique [8], wavelet function and thresholding ruling etc. There are numerous research works are concentrated to find a better method for arrhythmia classification by improving the feature extraction methods, such as the pattern recognition in ECG by using DWT [9], linear discriminant analysis and the Eigenvector method [11]. The other work like [12] hybrid neuron network, support vector machine (SVM) [13], extreme learning machine (ELM) [14], and Type-2 fuzzy clustering neuron network [15] are also concentrated to find a better classifier methods.

III. THEORY OF ECG

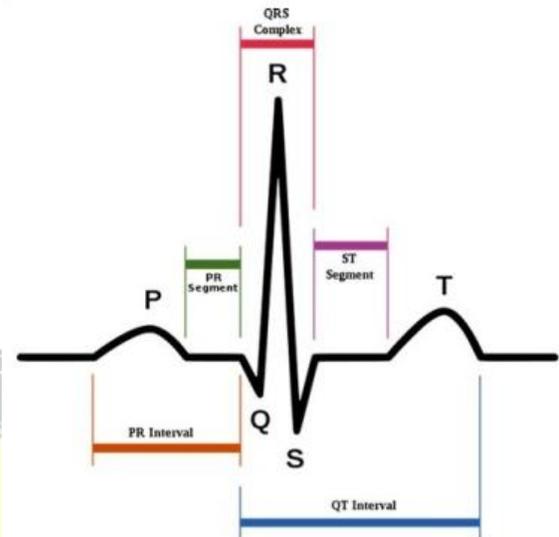


Figure 1: The ECG Waveform

A standard ECG waveform consists of a P wave, a QRS complex, and a T wave. The first segment is P-wave which indicates the depolarized wave that distributes from the SA node to the atria, and its duration is between 80 to 100 milliseconds. One of the important intervals in ECG waveform is the P-R interval which indicates the amount of time that the electrical impulse passing from the sinus node to the AV node and entering the ventricles and is between 120 to 200 milliseconds. The next segment is P-R segment which corresponds to the time between the ends of atrial depolarization to the onset of ventricular depolarization, which last about 100ms.

The QRS complex is the combination of three of the graphical deflections in the ECG waveforms. It is one of the most important segments of ECG waveforms, which represents ventricular depolarization. In adults the duration of QRS complex lasts 0.06–0.10 s. where in children and adult during physical activity, it may be shorter. The first portion of QRS complex is Q waves, it represent depolarization of the interventricular septum.

Next section is R-wave; this represents early depolarization of the ventricles. After R wave the S-wave occurs, which represents late depolarization of



the ventricles. The S-T segment appears after QRS and indicates that the entire ventricle is depolarized. Q-T interval is the last interval which indicates the total time that need for both repolarization and ventricular depolarization to happen, so it is the estimation for the average ventricular action duration. This time can vary from 0.2 to 0.4 seconds corresponding to heart rate. The last part of ECG consists of T-wave, which indicates ventricular repolarization and its time is larger than depolarization.

IV. METHODOLOGY

ECG signals obtaining from the abdominal surface of the mother and the fetus are clearly independent of each other and they can be efficiently separated using ICA [1], so it is very useful for extraction of fetal ECG.

The method is to perform ICA on a set of ECG leads, which includes leads measured on the abdominal region of the mother and possibly also other leads, such as chest ECG leads. The abdominal lead signals are consistsof both fetal and maternal ECGs.

Upon successful ICA, recognizing the ICs containing fetal ECG is generally straight forward based on the different heart rates. Thereafter, fetal ECG can be reconstructed from the recognized ICs carrying fetal ECG information.

A simple method to determine which ICs carry fetal or maternal ECG, is to perform beat detection, e.g., by highpass filtering followed by peak detection by thresholding, and subsequently calculating the heart rates for every IC, which carrying ECG information. If the ICA source separation is successful, ICs with two distinct heart rates can be recognized, with the ICs with the faster heart rate belonging to the fetal ECG

The structure of fetal arrhythmia detection and classification in my work consists of threemain phases: Preprocessing, ECG feature extraction andclassification. The proposed block diagram is shown in figure

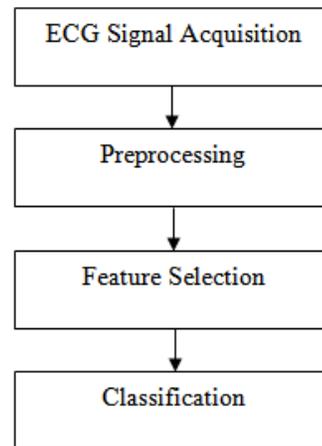


Fig 2: Block diagram

The noisy raw input collected from mother is mixed with respiratory as well as muscular signals are denoised using ICA blind source separation algorithms. The features of extracted ECG signal are detected using state machine logic algorithm. The classification of arrhythmia is done using bayesian classifier.

A. PREPROCESSING

When ECG signal obtained from the patient's body surface consists of a mixture of signalsincluding respiratory as well as muscle contraction noises. There are so many denoising methods are present including DCT, wavelet transforms etc [16, 17]. But they do not give any noticeable change to raw ECG, since it is a mixed signal. My aim is to extract ECG from mixed signals without any knowledge of them. Another one options are PCA [18, 19], ICA [20, 21, 22, 23] etc. but when PCA algorithms are applied on the raw ECG, uncorrelated components are obtained but not independent. So an efficient tool for this type of signal input is ICA algorithms based on blind source separation (BSS).

Preprocessing is done by using FastICA- FICA is an efficient algorithm for ICA, in which preprocessing of data consists of centering and whitening and it is done 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.



B. FEATURE SELECTION

The feature selection of the ECG is done by analyzing certain parameters; these are the RR interval, the PR interval and the QRS duration etc.

The characteristic points P, Q, R, S and T peaks are detected using peak detection algorithm. There are so many ways to detect the peak of the ECG signal [24, 25]. Here the peak detection is done by using the state-machine logic. The state machine logic helps to determine different peaks in an ECG signal. It is very accurate because it has the ability to remove the by high pass filtering and baseline wander by low pass. Also, it checks out criterion to stop detection of spikes. After applying state machine logic, the output shows the exact positions of peaks. The distance between the nearest RR, QQ, SS and TT distances of a normal ECG has standard values. So by analyzing the output we can find out the whether it has any abnormalities or not. [10] discussed about an eye blinking sensor. Nowadays heart attack patients are increasing day by day. "Though it is tough to save the heart attack patients, we can increase the statistics of saving the life of patients & the life of others whom they are responsible for.

C. CLASSIFICATION

If denoising, feature extraction and feature selection is efficiently done, and then the final step is classifying the obtained data. There so many ways to classifying the data [26, 27]. Here I am using Naïve Bayes classifier [28, 29] for Arrhythmia detection and classification. The classifier is based on Bayesian theorem [30]. The main advantage of this classifier is that interactions between features is not considered, only classify based on given features. Also Less feature input is required. It 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, bayesian classifier is more accurate than any previous classifiers.

In this paper the classifier compare the features of output with reference features and detect whether it has any arrhythmia and classify according to the type of arrhythmia. Here analyzing mainly 6 types of arrhythmia. They are Atrial Fibrillation, 1st degree block, Paced, Wolff-Parkinson-White Syndrome, Ventricular Tachycardia, Idioventricular rhythm.

V. RESULTS AND DISCUSSIONS

The figure 3 shows the input raw ECG signal obtained from the abdominal surface of the mother. Since it consists of so many noises like respiratory as well as muscle contraction noises, it needs filtering for accurately analyzing fetal ECG to find arrhythmia.

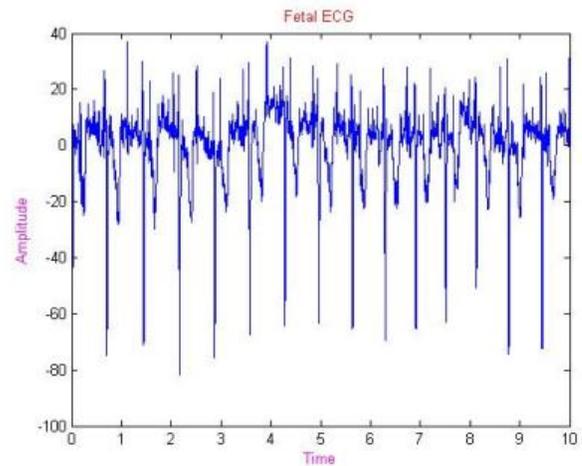


Figure 3: Input raw ECG

The result of such preprocessing is shown in figure 4. In figure 4, it shows the mother's signal, signal after preprocessing, fetus's signal and noise signal.

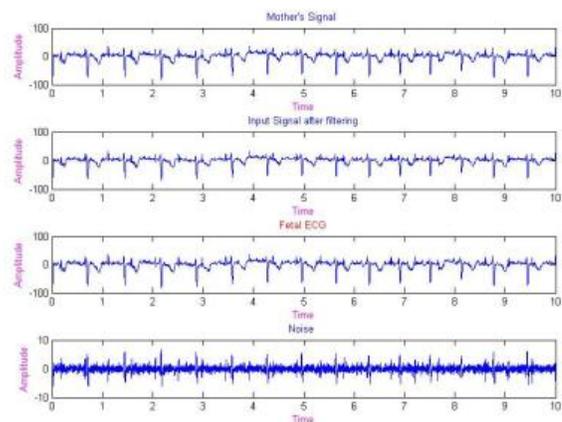


Figure 4: Independent component obtained by fastICA

After the preprocessing the output obtained is the exact fetal ECG. So next step is identifying the



features then only it is possible to predict whether it consists of any type of arrhythmia or not. For that here, using the state machine logic and the result is shown in figure 5.

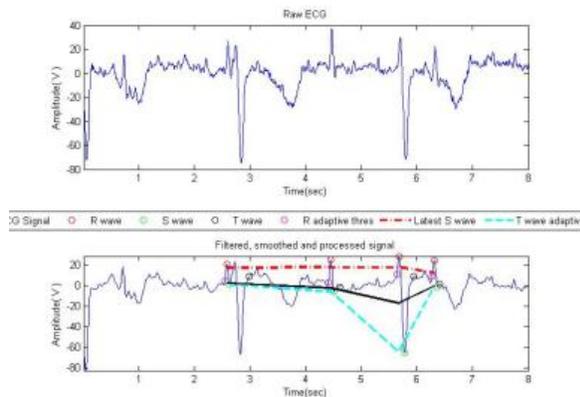


Figure5: Feature Selection

VI. CONCLUSION

The goal of this paper is to detect fetal arrhythmia in an earlier stage of pregnancy from the raw ECG obtained from the abdominal surface of mother which is equipped by respiratory and muscular noises. The challenge is to extract ECG accurately from this mixed signal and to classify exactly. This preprocessing is effectively implemented by using Independent component Analysis algorithms such as FASTICA and applied peak detection algorithm using state-machine logic to determine different peaks in an ECG signal. The result is classified using Bayesian classifier.

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