

A NOVEL ALGORITHM FOR THE ARRHYTHMIA DIAGNOSIS IN FETAL MONITORING SYSTEM

Radha Abburi¹, A.S.Chandrasekhara Sastry²

¹ Department of ECE, BVRIT Hyderabad College of Engineering for Women, Bachupally, INDIA

² Department Of ECE, KL University, Vaddeswaram, Vijayawada, Andhra Pradesh-522502, INDIA

ABSTRACT

The fetal ECG signal is analyzed using wavelet transform for extraction of Fetal Electrocardiogram (ECG) signals to diagnose. The paper presents the various wavelet transform methods available for denoising and delineating the abdominal electrocardiogram(AECG).The AECG signal has been denoised and delineated using a proposed methods which combines the features of adaptive thresholding with wavelet transform and SVM classifier. Both the simulated version and real-time version of the abdominal electrocardiogram signal was used for performing extraction and classification operation. Extraction of fetal electrocardiogram signal was done using various wavelet transforms such as Daubechies, Biorthogonal and Symlet wavelets. While experimenting with various wavelets it was evident that the Daubechies wavelet proved more efficient in the removal of noise for extraction. The extracted signal was slope threshold to find the maximum point (R peak) in the fetal electrocardiogram signal. Hence the abdominal electrocardiogram was delineated to get the individual parameters which can then be utilized for analysis. The performance of the hybrid method is been compared with other methods. The performance of the classifier was evaluated in terms of training performance and classification accuracies. The results are to be compared to find a better method for ECG classification.

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KEY WORDS

Fetal ECG, FECCG extraction, Wavelet Transform, SVM classifier

*Corresponding author: Email: radhasundi@gmail.com

INTRODUCTION

The objective of the work is to formulate and implement a new method for the extraction of Fetal ECG features from the abdominal ECG signal using Hybrid signal processing technique. Extraction of fetal ECG features and classification during first trimester of pregnancy will help the physician to know the well being of the fetal. Unwanted Noise signals significantly distort fetal ECG recordings, and consequently the presence of noises is troublesome in extracting the features in ECG signal. Hence, devising efficient methods for successful removal of noises and extraction of fetal ECG from ECG recordings have been still a major challenge. The performance of the algorithms employed previously for extraction of adult ECG signal and classification will not be efficient enough to do the same for the Fetal ECG. Therefore, an efficient algorithm to extract and classify fetal ECG is the objective of this work. In the method of recording, the fetal ECG signals have a very low power relative to that of the maternal ECG. In addition, there will be several sources of interference, which include intrinsic noise from a recorder, noise from electrode-skin contact, baseline drift (DC shift), 50/60 Hz noise etc.

The situation is far worse during the uterine contractions of the mother. During these contractions, the ECG recordings will be corrupted by other electrophysiological signals called uterine electromyogram (EMG) or electrohysterogram (EHG), which are due to the uterine muscle rather than due to the heart. The response of the fetal heart to the uterine contractions is an important indicator of the fetal health. As such a need arises to effectively monitoring the fetal ECG during the uterine contractions. But monitoring the fetal ECG during these contractions is a difficult task because of very poor SNR. The three main characteristics that need to be obtained from the fetal ECG extraction for useful diagnosis includes the Fetal heart rate (FHR), Amplitude(P, Q, R, S, T, QRS) of the different waves and Duration of the waves (S-to-T, R-R Interval,). In literature several methods are been proposed for the extraction of fetal ECG signal. Ruben Martin Clemente et al [1] proposed a simple algorithm based on independent component analysis with simple procedure. The method reduces the dimension and has computational simplicity for extraction. The modification is done based on reduction in dimension and simple post processing stage. But the convergence behavior is always a problem when the algorithm is implemented using reconfigurable architectures. An autonomous algorithm to locate the QRS complex in the fetal ECG signal based on subspace decomposition is presented in [2]. The method is iterative so computational time increases. A novel merging

technique is used to detect the fetal ECG R-peaks which requires proper phase alignment which is difficult in long time data. J. L. Camargo et al [3] in their paper presented a multidimensional ICA method to detect the fetal ECG signal. The paper also presents the difficulty in analyzing the delay in the transit time of the signal from maternal heart to mother's abdomen for which the method fails its applicability. To support in clinical implementation for classification of fetal heart rate Shishir Das et al [4] proposed generative models instead of scalar features for the process. The method depends on feature sequences of local patterns. The patterns along with umbilical cord pH values classifies known category with good performance. Liang Han et al [5] proposed a V-support vector regression method to extract the fetal electrocardiogram from the multichannel abdominal ECG.

The nonlinear dependency of maternal ECG on abdominal ECG is utilized for the estimation of V-SVR. The estimated maternal component is subtracted from the abdominal ECG to get the fetal ECG. The disadvantage is phase difference will lead to complete erroneous extraction. The requirement of new methods for classification of fetal ECG signal is getting increased day by day. One such work is proposed earlier in literature where the authors [6] present a neural network based extraction algorithm. Different learning constants were utilized in the project. Few works [7] are done towards giving solutions to the age old problem of electrode numbers. When most of the works are based on multiple channel electrodes the work is based on extraction of fetal ECG from single lead channel. Heart rate variability analysis is been done based on spectral analysis technique. A similar single lead extraction method using extended nonlinear Bayesian filtering framework is proposed in [8]. The extended state Kalman filtering based proposed work uses the dynamic model to discriminate the information in the simulated data. An hybrid method using wavelet transform and adaptive filtering is used in the paper [9] for the fetal ECG extraction. The obtained scale coefficients in wavelet transform were processed using LMS and spatial selective filter. Proper value for threshold determines the efficiency of the system. In [10] George Georgoulas et al have proposed a support vector machine methodology to classify and predict the metabolic acidosis on newborns. The paper presents feature extraction methods through time and frequency domains and classification is done using support vector machines (SVMs). Krupa et al [11] proposed a new method to feature extract and classify the fetal ECG using empirical mode decomposition and support vector machine. The classification is done using the standard deviations of the EMD components. The accuracy of the findings is 86% and the geometric mean of sensitivity and specificity was 94.8%. An adaptive neuro-fuzzy inference system (ANFIS) based fetal diagnosis algorithm is proposed in [12]. Fetal heart rate and uterine contraction data are used for the classification of the normal and the pathologic state. The accuracy of the method is reported as 97.2. Hasan Ocak proposed a SVM – genetic algorithm based fetal ECG arrhythmia diagnosis algorithm [13]. The SVM is constructed using the features extracted from normal and pathological fetal heart rate and uterine contraction. The accuracy reported in the paper is 99.3% and is shown as a better method when compared to the existing neural network based algorithm like ANFIS and ANN. Many methods proposed and executed in the literature classify only few classes [14]. For multiclass training and classification Ben Fei and Jinbai Liu proposed a Binary tree of SVM (BTS) algorithm. The reported BTS training speed is higher due to Log complexity. Similarly a multi-class classification algorithm based on support vector machines for decision tree architecture is proposed in [15]. The hierarchy of binary decision subtasks was determined using clustering algorithm. The method is reported to be faster due to its Log complexity than the widely used multi-class SVM methods like “one-against-one” and “one-against-all”. In this paper the ECG signal recorded by the standard twelve lead system and those obtained by simulating it in MATLAB software is used.

LITERATURE SURVEY

a) ECG waves and their intervals

The ECG signal consists of five waves each with definite time period and amplitude. The ECG signal features are similar for the fetal and maternal but the duration and amplitude differs. The P wave representing the spread of electrical impulse through the atrial musculature (activation or depolarization). But in the fetal ECG it's difficult to extract the P wave since the wave is been contaminated by the noises. Its duration is not more than 0.11 seconds and amplitude of not more than 10% that of R-Wave for maternal and for the fetal it will be half and one-tenth in the maternal duration and amplitude respectively. The QRS complex duration is from 0.08s to 0.12s. The S-T segment follows the QRS complex. The T wave is slightly rounded and slightly asymmetrical. The heart rate is calculated based on the Interval between R wave and the next R wave. RR intervals are irregular for sinus node disease and ventricular arrhythmias.

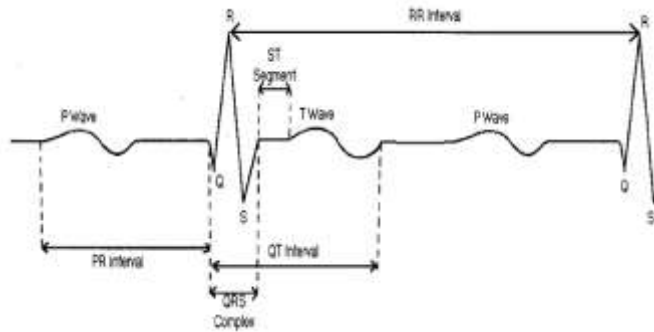


Fig. 1: Basic ECG waveform with the characteristics waves

ECG signal characteristics can be studied using several techniques such as Pan and Tompkins algorithm, Kalman filter, Extended Kalman filter, Wavelet transforms. The basic principles used here for denoising is Wavelet transform. This method has the advantage of preserving both time and frequency information in the signal

b) Wavelet transform

The mother wavelet similar to the feature of the fetal ECG signal wave is allowed for simultaneous time and frequency analysis by the way of a time-frequency localization of the signal. Like conventional Wavelet systems dilating and translating the ECG mother wavelet $\psi(t)$ is given by

$$\Psi_{a,b}(t) = |a|^{-1/2} \Psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where the scaling factor and translation factor are real ($a \neq 0$). To analyze the low frequency components the mother wavelet is stretched by a large value of 'a'. Since the high frequency components is less important or not required for clinical investigation too high value of "a" is avoided.

Thresholding and Denoising Scheme: The wavelet transform decorrelates the fetal ECG signal information into a small number of coefficients which are compared with a threshold. The decomposition level and largest transform co-efficient determines the threshold value (th). In this work the threshold is set adaptively.

Thresholding Method: The selected detail coefficient is used to perform the detection of fetal R-wave. For this purpose a threshold limit is set to remove the noises or unwanted peaks in the signal. There are several thresholding methods known. Here we apply both soft and hard thresholding in which the samples below a predetermined threshold are set to zero. The threshold is selected as 12% of maximum value In some researches the detail coefficient has been chosen to detect R wave based on Energy, frequency and correlation Analysis

c) The feature extraction using wavelet transform

In the preprocessing algorithm, the wavelet transform is used to remove the unwanted noises in the signal. The wavelet decomposes the components, on thresholding the noise components and taking inverse wavelet transform the information of the fetal ECG signal will be retrieved. The noise components are occurring in the finest scales which can be removed. Further, by employing the thresholding mechanism the slope of the R wave is identified to detect its onset. The following equation of slope thresholding is

$$Z = (2 * c) / 16$$

Where , c is maximum value of the slope

Z is slope thresholding value.

Then, the QRS complex is extracted by employing the method of forward searching and reverses searching ten samples with respect to the identified peak point in the denoised signal. Then by employing same mechanism, other waves such as the P wave and T wave were also extracted separately from the denoised signal. The individual delineated signals (P wave, QRS complex, T wave) are then separately correlated with each of the various diseased ECG signals to obtain the maximum correlation value. Based on the correlation values the arrhythmia present in the test signal can be identified. Then the results can be compared with the physician's annotations for accuracy.

d) SVM classifier

In pattern recognition problem selection of most suitable subset of the extracted features is very important. Using fewer features better generalization can be done. Various dimensionality reduction technique like principal component analysis use linear combination of original features by which the relevant information are preserved, The computed Eigen values has uncorrelated features which improves the classification operation. Once the dimensionality is reduced the feature vectors are allotted suitable labels. Based on the feature vectors and the kernel functions choice the SVM decision surfaces are constructed. The most important kernels used are polynomial learning machines, the radial basis function (RBF) networks and the two-layer perceptrons. For the classification of our work RBF kernels whose width is specified depending on the data in priori and is common for all the kernels and Polynomial kernels of degree is used. Using same penalty parameters for different classes will reduce the specificity. The two penalty parameters ratio is set to inverse of the corresponding cardinalities of the classes. In this research work, we experimented with various configurations of the learning machines varying the width for the RBF kernels and the degree for the polynomial kernels. For each configuration of the kernel we tested different values for the parameters.

The New Tree based SVM classifier depending on recursive operation is performed with less classifier iteration / groups. In tree based classifier binary classifiers are used in every nodes of the tree and the branch contains the decision output. Recursively each node finalizes with one class samples by employing the probabilistic outputs to measure the similarity between samples are classes used for training.

PROPOSED METHOD

A SVM-Wavelet based Extractor-classifier is presented as a diagnostic tool to aid physicians in the classification of fetal heart diseases. The proposed methodology using a strategy of hybrid approach of Wavelet transform and Support Vector Classifier system. In this work two intelligent approaches are composed, it will achieve good reasoning in quality and quantity. In other words we have Wavelet based extraction and Machine learning calculation. The feature vectors extracted using wavelet transform were applied as the input to an SVM classifier. The experimental procedure involved in the methodology is as follows:

Data Collection:

The source of the ECG is obtained from MIT-BIH and EDF Arrhythmia Database (MITDB). From this database variety of data including normal and abnormal cases extracted.

Preprocessing:

The obtained ECG signal is preprocessed by wavelet transform for the removal of noise components to enhance the quality of ECG signals and help us to detect significant signal events.

Feature extraction and selection:

Extraction of salient features from the ECG to allow detailed waveform analysis. The features, which represent the classification information contained in the signal are used as inputs to the classifier.

Classifier design:

Designing an intelligent system to automatically classify the shape of the ECG waveform and interpret shape changes by using an appropriate classifier model. Then the training algorithm is used to train and test the input signal and classify them into different categories.

Optimization/Diagnostic decision:

To validate the findings and show agreement between the system and human experts. The performance of the classifier is evaluated in terms of training performance and classification accuracies. All the necessary algorithms are implemented in MATLAB.

Database:

The proposed algorithm is tested with various databases and simulated database. The database used throughout the work was from MIT-BIH Physionet database , EDF database and DaISy (Database for the Identification of Systems).The database contains cutaneous potential recordings of pregnant woman (8 channels),Sampling of 10s, The channels 1-5 is abdominal and 6,7,8 thoracic. The simulated ECG signals using dynamic model are used in this work. The simulated database is generated using dynamic models with Gaussian equation and simple MATLAB functions. The synthetic ECG signals for maternal and fetal is generated for various noise levels.

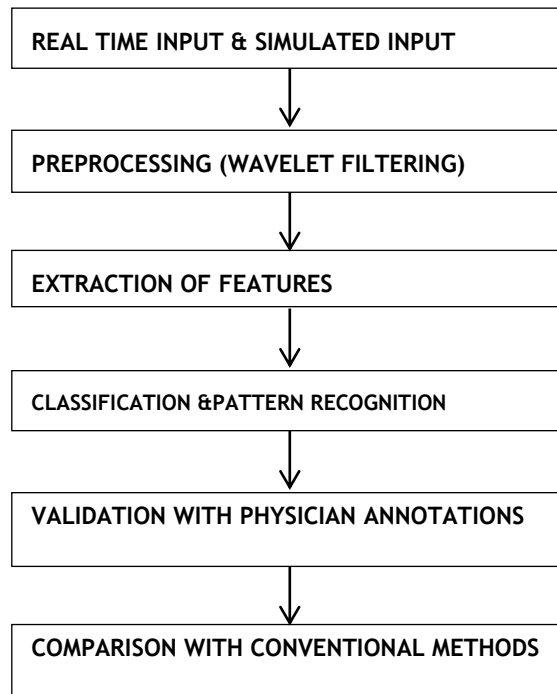


Fig. 2: Block diagram of proposed method

RESULTS AND INFERENCE

The wavelet transform methods were implemented for preprocessing stage with adaptive thresholding using different wavelets like biorthogonal wavelets, daubechies, coiflets [Figure 3-7] and symlets and tested with simulated and real time signals. For Example Considering bi-orthogonal [Figure- 4] and compactly supported wavelet families (bior1.3, bior2.6, bior3.5, bior5.5, bior3.7) for the 3-level and 5-level decompositions with discrete wavelet transform, the performances are very close to each other and they generally give better results for soft thresholding than hard thresholding denoising rule. Other orthogonal wavelets like Daubachies Db1, Db2, Db3, Db8 [Figure- 6] are applied. Uniformly distributed white noise is added to the ECG signal. From the Table-1 it is seen that 5-level decomposition gives better denoising. The visual inspection of the denoised signal for the bior2.6 and bior5.5 is better than the rest of the biorthogonal set of wavelets and wavelet packet analysis. The computed signal-to-noise ratios are approximately 10.5 dB for the used biorthogonal wavelets family. 1 thoracic and 3 abdominal signal are used with different noise levels imitating the placement of electrodes at different location of the maternal's abdomen. From the application of wavelet denoising techniques all wavelets removes the noise at lower energy levels while failing to remove at higher amplitudes. The shape of the signal/frequency components are altered when high noise components present.

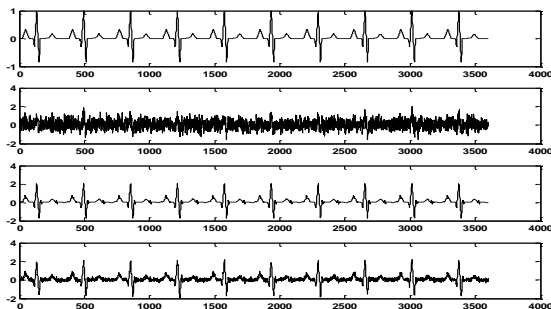


Fig. 3: Multichannel input channel 1, 2,3 and 4 given to the algorithm, thorax containing maternal signal abdominal signal containing maternal+fetal+noise of various levels

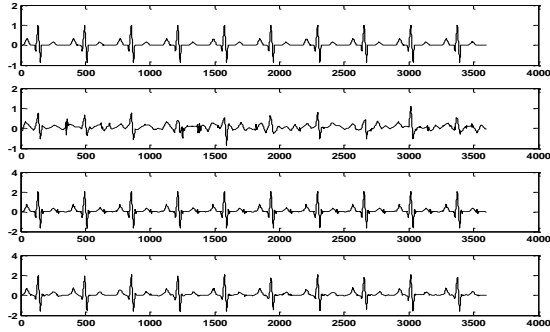


Fig.4: Multichannel output denoised by Biorthogonal wavelet BIOR 2,6 decomposition level 5

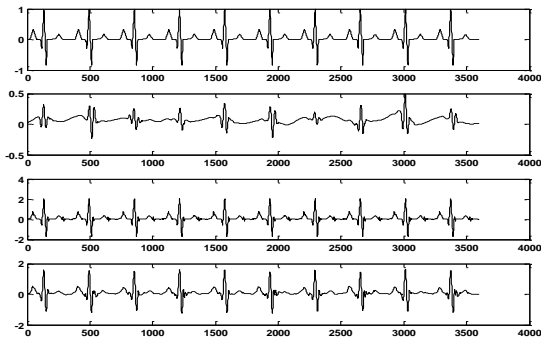


Fig.5: Multichannel output denoised by coiflet 5 decomposition level 7

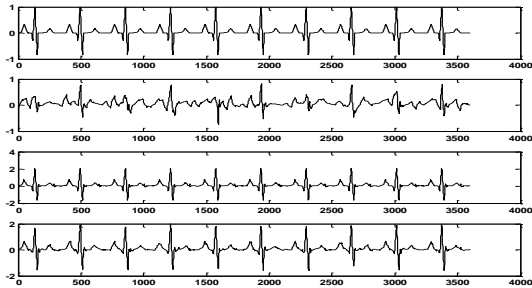


Fig. 6: Multichannel output denoised by Daubechies 5 decomposition level 7

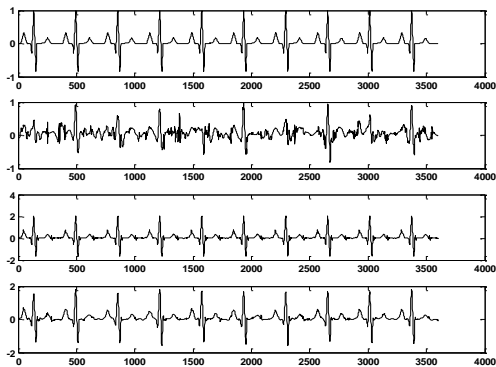


Fig.7: Multichannel output denoised by rbio 3,5 decomposition level 7

Table 1. PSNR and MSE comparison of few wavelets which is used in the extraction and denoising of ECG signals

Wavelet	Coif1	Sym2	Db1	Db2	Bior 5,5	Rbio 3,5
PSNR	68.8789	68.6466	68.9327	68.6466	68.8974	69.0033
MSME	0.0084	0.0089	0.0083	0.0089	0.0084	0.0082

The extraction of fetal ECG is done and the patterns are classified using SVM classifier. The performance of the classifier is obtained and our classifier gives better performance and accuracy. The SVM model for classification of fetal Electrocardiogram (ECG) signals into one of the few known categories is done and diagnostic decision is to be arrived at a regarding the condition of the fetus.

Table 2. Performance of the classifier

Classifier	Positive Predictive Value	Negative Predictive Value
Neural Network	100	100
SVM	100	100
KNN	100	100
Naive Bayes	89.21	93.7
Daubechies	94	93
Symlet	95	94
PSO-based	96	95

Features like Heart Beat and amplitude is extracted. Using derivative method the features are extracted. m=maternal f =fetal.

Classification of basic features using different classifiers like Neural Networks, K-Nearest Neighbor and Naïve bayes algorithm are investigated and compared with the SVM classifier. The extracted QRS amplitude and Heart rate is given to the different classifier and trained .For testing different data set is given and checked .The performance is given in **Table- 2**.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

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None.

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