Fetal Cardiac Arrhythmia Detection using enhanced Blind Source Separation Technique

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Abstract*— The welfare of fetus in the womb of mother during pregnancy can be monitor by inspecting the fetal electrocardiogram waveform. In signal processing field, there are various techniques for analysing this purpose. Tracking fetal ECG (fECG) can provide important details for detecting fetal cardiac arrhythmia, thus treatment can be done as early as possible and hence we can diminish the mortality rate of babies. In this paper, a novel method for detecting cardiac arrhythmia in fetus in early stages of pregnancy and to classify the cardiac arrhythmia into five classes using enhanced blind source separation technique (BSS) is proposed. The scheme is based on WASOBI based BSS for pre-processing and extraction of fetal ECG. Feature selection is manipulated using the Peak detection algorithm and Multi-class Support Vector Machine (SVM), is employed for the classification of fetal cardiac arrhythmia.

Index Terms*— Abdominal ECG Recordings, Fetal Cardiac Arrhythmia, Fetal ECG, WASOBI based BSS, EFICA, Multi-class SVM.

I. INTRODUCTION

Death can happen if there is severe conditions of abnormalities occur in heart, especially in case of cardiac arrhythmia in fetus. By verifying the ECG signal of adults, different types of cardiac arrhythmia can be detected According to [1] in every 2% of unselected pregnancies, fetal arrhythmias are recognized during the routine obstetrical ultrasound. The target of ECG signal handling is complex and comprises the improvement of estimation precision and reproducibility (between contrasted and manual measurements) and the extraction of data not promptly accessible from the sign through visual appraisal.

Pre-processing stage is the major phase for detecting arrhythmia, because the detection accuracy depends on the accurate fetal ECG characteristics like peaks, intervals and amplitudes. The abdominal ECG recordings contains club of fetal ECG, mother ECG, noises caused by muscle activities, uterine movements, respiration and interferences. So the hectic task to filter these unwanted components and extract required feature that is the fetal ECG, fECG. In [2], current distinguishing modalities of fetal arrhythmia are explained. An electrocardiogram can be defined as, it is an advanced tool that records the electrical sign from your heart to check for different heart conditions like abnormalities and diseases. Cathodes are determined to your chest to record your heart's electrical signs, which cause your heart to throbformatter will need to create these components, incorporating the applicable criteria that follow. The signs are showed up as waves on an associated PC screen or printer. Human heart comprise of 4 chambers. The upper portion chambers are called Atrium (Auricles) and bottom portion chambers are called Ventricles. Each chamber has a valve, which can keeps blood from streaming in reverse. Diastole Phase and Systole Phase are the two stages in heart cycle. In the Diastole Phase, the heart is loose and the heart is loaded up with blood. In the systole Phase, the ventricles agreements and siphon blood into supply routes. Any deformities in these valves can likewise prompt cardiovascular sicknesses.

In [3], prenatal diagnosis and perinatal management have been published by implementing M-mode and Doppler echocardiography which helps in detailed analysis of fetal arrhythmia. Catheter-based intervention strategies [4], are discussed to halt the cardiac diseases.

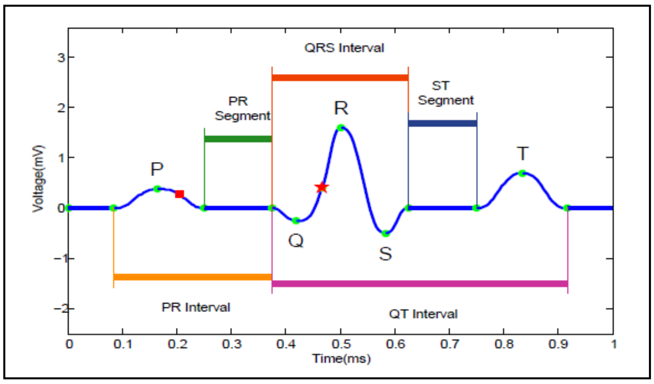

Figure.1: Schematic representation of an ECG curve

An ECG signal can be segregated into heart beats. Each heartbeat includes five standard waves named with the letters P, Q, R, S and T. These waves exhibit the depolarization and the re-polarization times of heart muscles [5]. These details are shown on Fig.1.

In this paper, two BSS based algorithms were used to extract the fetal ECG. One is WASOBI based BSS algorithm and the other one is EFICA based BSS technique. The better performance is showed by WASOBI algorithm. The highlight of this algorithm is, it performs two functions, pre-processing and extraction process. The extracted fetal ECG is analysed for feature selection .The feature selection process is done by executing peak detection algorithm at which state machine logic is used. The cardiac arrhythmia classification process performed by using multi-class SVM classifier, in which five classification is done.

II. Literature survey

By filtering process the noises gets removed out. Numerous advanced procedures existed in biomedical world for preprocessing, like FIR and notch filters [6], Band pass filters [7], ICA algorithms [8], and combination of FIR and Principal Component Analysis method [9], Bayesian nonlinear filtering [10]. The next process is to extract the main element that is fetal ECG. Extraction process has many implementation. In [11], using Adaptive Noise Cancellation (ANC) technique, they implemented non-invasive fetal ECG extraction by applying combination of singular value decomposition (SVD) and smooth window (SW) methods.

In [12], traditional ICA (Independent Component Analysis) is explained and from that Blind source subspace separation technique is derived to extract the fECG. In [13],fetal ECG extraction is done by using improvised least-square algorithm and the original shape of ECG signals were conserved in the regenerated signal .In [14],from abdominal ECG recordings, fetal ECG are separated using combination of fetal beat detection and compressive sensing theory based on sparse representation method. ICA based fECG extraction explained on [15], [16]. Using non-invasive fetal electrocardiogram (NI-fECG), which is a hybrid method, the fetal ECG can be extracted [17].

In [18], different methods of multi-class SVM is differentiated and gives glorious executions. According to [19], a new model is presented for classifying arrhythmia patients into sixteen classes by utilising all three methods of Multi-class SVM like one-against-one, one-against-all and error-correction code, based on the ECG dataset taken from UCI machine learning repository. In [20], cardiac arrhythmia is pre-processed using wavelet transform and classified using LDA (Linear Discriminant Analysis) by reducing the dimension of features selected. In [21], authors proposed classification of ECG signals using multi model decision learning techniques and their results are compared with Neuro-fuzzy algorithm.

Based on sensor networks, continuous monitoring of cardiac arrhythmia is possible [22], which shows advanced growth in wireless technology. The systems of fetal arrhythmias rely upon the age what's more, spread of electrical driving forces or we can say as electrical impulses. A strange drive can be created by the Sino-atrial node itself with an irregular heartbeats or on the other hand by a predominant inert pacemaker cell. According to [23], there exist variety of fetal arrhythmias like Premature Contractions, Tachyarrhythmia's, Brady arrhythmias, Fetal Sinus and Low Atrial Bradycardias, Fetal AV Block, Sinus Bradycardia and Sinus Node Dysfunction, Low Atrial and Junctional Rhythm, Blocked Atrial Bigeminy, Congenital Long QT Syndrome, Ion Channelopathies, Familial Congenital AV Block. Based on [24], the fetal ventricles (right and left ventricles) were investigated in 12 fetal lambs (127-140 days gestation), which vary altogether in their outcome, when the reaction to changes in blood vessel pressure, and to the beginning of in utero ventilation. Using Color tissue Doppler imaging (CTDI) [25], assessment of fetal cardiovascular capacity is explained during the second phase of pregnancy and created reference ranges by utilizing a robotized strategy to examine CTDI readings from cardiac view.

In [26], implementing Dual-gate Doppler (DD) technique in total of 133 pregnancies to measure fetal heart beat and determine reference ranges for normal fetuses. In [27], Doppler imaging is another method that can give estimations of myocardial development and timing of myocardial occasions and may conquer a portion of the inadequacies of ordinary procedures. The high time goal and its capacity to survey left and right cardiovascular capacity make tissue Doppler a great procedure for evaluating heart work in youngsters. The point of this audit is to give an exceptional outline of tissue Doppler strategies for the evaluation of cardiovascular capacity in the neonatal setting, with center around estimations from the atrio-ventricular (AV) plane. Novel quantitative proportions of function incorporate the appraisal of the speed of muscle tissue development during systole and diastole utilizing tissue Doppler speed imaging, and assessment of twisting and rotational qualities of the myocardium using dot following echocardiography or tissue Doppler-inferred strain imaging. A far reaching comprehension of these novel utilitarian modalities, their prescient worth, and impediments can significantly help with overseeing both the typical and maladaptive reactions in the infant time-period. The article [28], examines the novel and developing techniques for appraisal of left and right heart work in the neonatal population.

III. Methodology

The proposed system consist of following steps:

1. ECG signal acquisition
2. Pre-processing
3. Extraction of fetal ECG (fECG)
4. Classification using multi-class SVM

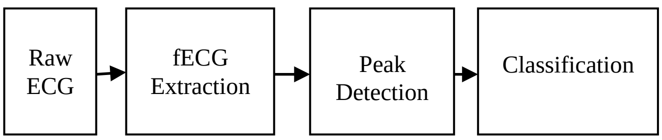

Figure. 2: Main Block Diagram of the proposed model

Fig.2 shows the main block diagram, which comprises of the raw ECG taken from Physionet cardiac arrhythmia database [9] is pre-processed and vital component (fECG) is extracted from the mixture of noises, interferences and mother ECG. From the extracted fetal ECG (fECG), required features are selected and based upon those details disease classification is done.Fig.3 shows the flowchart of proposed method. Using WASOBI (Weight Adjusted Second Order Blind Identification) based BSS algorithm, the raw ECG is pre-processed and fetal ECG is extracted. Using peak detection algorithm, feature selection process is done, at which state logic machine is used for this purpose. After feature selection, fetal cardiac arrhythmia is classified into five different groups using mutli-class SVM. Here we classify Atrial Fibrillation, First Degree Block, WPW (Wolf Parkinson White) syndrome, Idioventricular Rhythm and Normal classes.

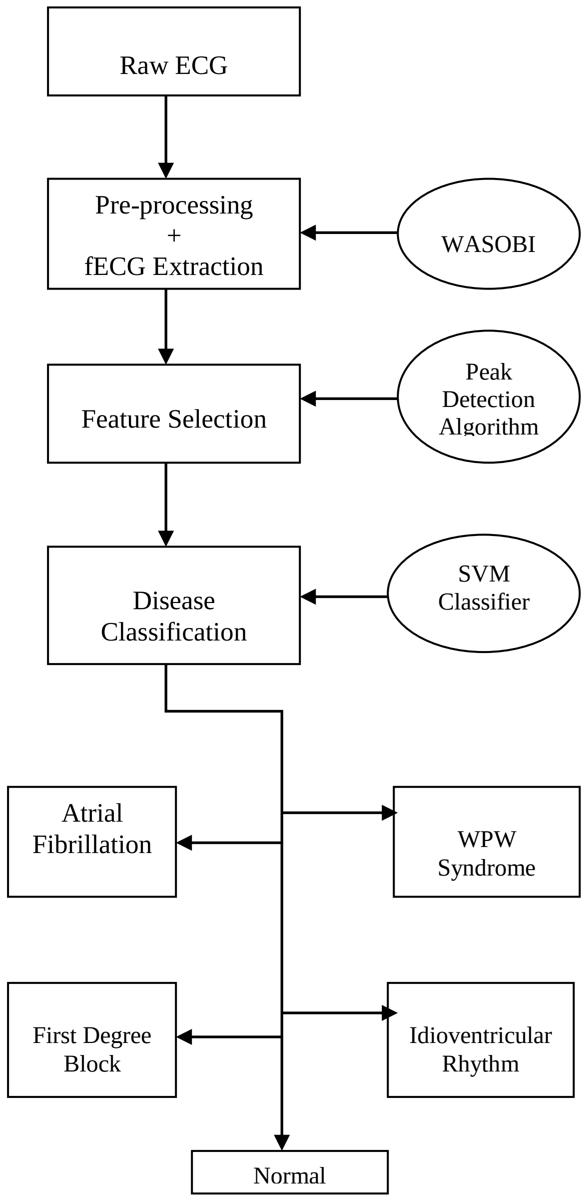

Figure.3: Flowchart of proposed system

A. Pre-processing

For this process, different filters like FIR, Butterworth filter and PCA were used, but accurate result was not obtained. Then we move forward to BSS (Blind source separation) algorithms like ICA, WASOBI, EFICA, and COMBI. The better performance was showed by WASOBI based BSS algorithm. The highlight of using this technique is not only extraction process, it also perform accurate pre-processing task.

B. Fetal ECG (fECG) Extraction

For Filtering and extraction of fetal ECG from mixture of components, WASOBI is implemented. WASOBI is an improved version of SOBI (Second Order Blind Identification) Algorithm. This algorithm reckon on second order data [29]. For that, it requires evaluating the following steps:

1. Whitening process
2. Estimation of Unitary Factor
3. Joint Diagonalization (JD)

Consider the linear and instantaneous Blind Source Separation (BSS) model as follows:

$$x=As \qquad (1)$$

Where, x is the received signal, A is the mixing matrix and s is the original signal. The goal of using WASOBI method is to find the unmixing matrix (W).By using SOS (Second Order Statistics), a large number of cross co-relation matrices can be concurrently diagonalizable. Sources can be separated, at which a set of signals can be retrieved where only immediate linear mixtures are observed. Partition of sources comprises of recuperating a lot of signs of which just momentary straight blends are watched. The straight blend ought to be "aimlessly" prepared. This ordinarily happens in narrow band cluster preparing applications when the exhibit complex is obscure or misshaped. Time soundness of source signals are verified and fixed second order measurements with joint Diagonalization of co-variance frameworks is done. From the start, whitening of fetal signal is done and a unitary factor is discovered. The preprocessing of signal can be done by whitening process, which is achieved by Principal component analysis (PCA).According to [30], after the whitening process, computation of lagged correlation matrix is done at lag τ, given as:

$$Rx[\tau] = ARs[\tau]\, A^H \qquad (2)$$

Where, Rx is lagged correlation matrix, Rs is correlation matrix. From the lagged connection matrix, weighted matrix (W) is discovered by putting together the outcome with respect to connection among second and fourth order of Gaussian sources. At that point, joint diagolization is executed to get the unmixing matrix. If the computed correlation matrices are diagonal, which means the non-diagonal components are zero, the separated signals can be said to be independent from each other. Therefore the Gaussian sources with various spectra can be impulsively isolated by utilizing second order insights. Thus the fetal component can be extracted. An enhancement for SOBI (Second Order Blind Identification) is gotten when the issue of diagonalization is changed over into weighted nonlinear least squares issue named as Weight Adjusted Second Order Blind Identication (WASOBI).Use of Daubechies wavelet of order 8, for the feature extraction has been justified in [31].Utilizing combination of Wavelet Transformation and FASTICA algorithm [32], the abdominal ECG recordings can be separated into maternal and fetal component.

C. Feature Selection

In the wake of removing fetal ECG (fECG) from mother ECG (mECG), now it required to distinguish the features. For recognizing the peaks and the component location, Peak Detection algorithm is used [33].

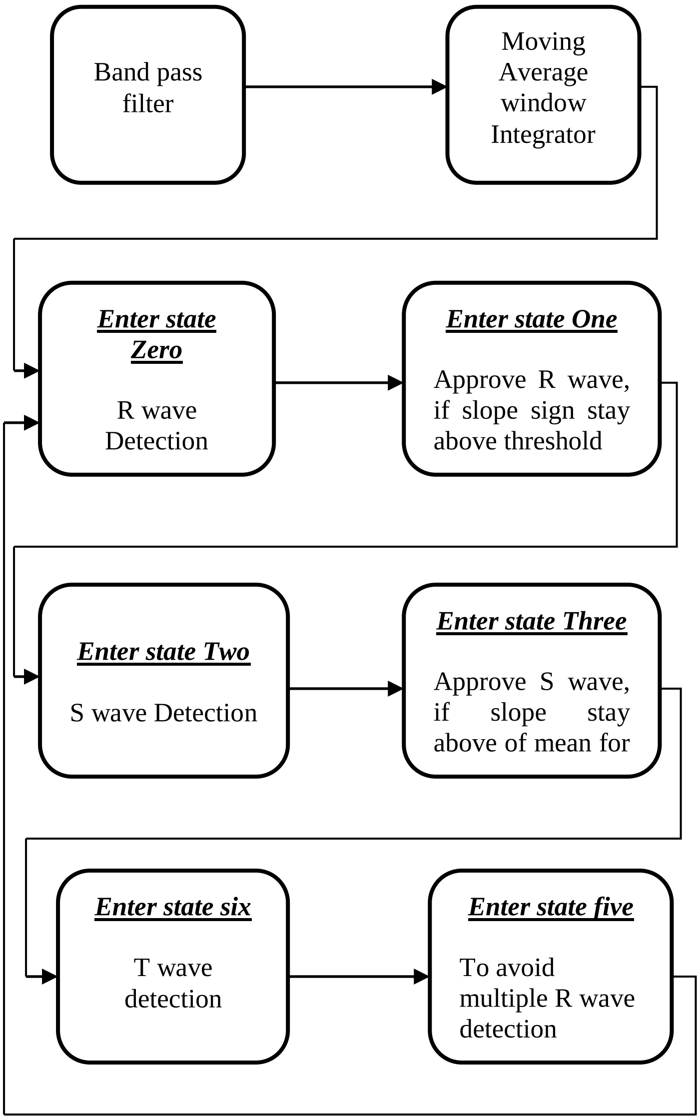

Figure.4: Flowchart of state machine logic algorithm

This algorithm finds the areas and amplitudes signal. And peak discovery is finished by utilizing state machine logic; it set diverse edge values for various fragments of ECG. The highlight of peak detection algorithm is that, it makes weakest part of ECG to be strongest, then only selection part begins. If the watched signal example fulfilled the condition then that bit is put away as relating portion. ECG waveform contains P, Q, R, S, T waves based on working of heart activity. After distinguishing the fragments of ECG, the calculation quantifies the intervals like QR interval, RS interval, ST interval, Width of QRS complex and amplitudes of P, Q, R, S, T waves. Normal ECG has standard qualities for all of this, if it is anomalous then the previously mentioned highlights have various qualities relying on the variation from the normal.Figure.4 shows the detailed flowchart of state machine algorithm[33].

At zero state, the product result of ‘m’ and an underlying weight (w=1.8) is determined. On the off chance that this item is not exactly the mean worth determined in a 15 example span (m1) from the one second interval, and furthermore if the amplitude of the examined test is bigger than the remainder of the examples, the amplitude and the area of the primary example from the one second window is put away as R peak; at that point, we change to condition of one, which reports the unmistakable presence of R peaks.

In condition of one (state one), the put away amplitude from zero state is contrasted and the following four examples, to guarantee that is the most extreme one. Each example in this window must be not as much as it’s past example. In the event that such a condition is forced, the file from zero state is put away as the R peak amplitude and its location. A span containing 0.04 s before this area until the area of this example is thought of, and least amplitude is accepted as Q top. Additionally, weight is refreshed in this state, which implies that if the quantity of recognized R peak is more than eight, 0.3 of mean of these eight R peaks is accomplished and it is partitioned to m. at that point, the state will be equivalent to two.

In the condition of two (state two), if m1 is not as much as m, we change to condition of three for discovering S peak. The time of examination for condition of three is 0.2 s. In the event that, among the eight examples, the considered example is not exactly the remainder of the examples and if each example is not as much as its past example, we guarantee that the examined test is S. At that point, the state is equivalent to four. In the condition of four, if m1 is not as much as m, we change to condition of six for discovering T peaks.

In condition of six (state six), the examined timespan s is expected. The threshold is viewed as dependent on the ongoing estimations of S and m. In the event that m1 is more than this threshold, this condition is adequate for three back to back examples, and the pinnacle (peak) of the examined test is more than its consecutive eight examples (each example in this eight-example window ought to be littler than the past example), this example is put away as T peak and state is refreshed to six. State of six is for counteraction of finding a few R peak in a 0.4 s window. After this delay, the algorithm changes to zero state and this algorithm is repeated for each 1second window.

D. Classification

Before classification, filtered dataset is partitioned into training and testing set. According to [18], Multi-Class SVM (Support Vector Machine) has three well-known methods, they are:

1. One-against-one (OAO)
2. One-against-all (OAA)
3. Error-correction code (ECC)

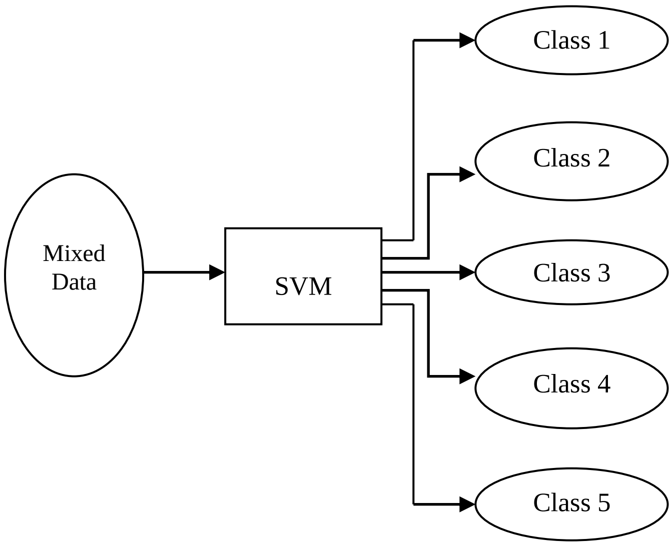

Figure.5: Support Vector Machine

In this stage, a SVM-based classifier is used to train and predict with the feature vectors extracted from training and testing datasets. The algorithm uses two different datasets, which are the training dataset and testing dataset.
Here, we use OAA-SVM for classification. It builds *k* SVM models where *k* is the quantity of classes. The *mth* SVM is prepared with the entirety of the models in the *mth* class with positive marks, and every other model with negative names. The fundamental idea driving SVM is to scan for a harmony between the regularization term and the preparation errors. Based on [34], the input preparing set *x* is relegated to the class that gives higher choice capacity esteem, such as:

(Class of x) = (max ((W^k) ^T× ϕ_(x) + b^k)) (3)

Where,
1 Vector in the feature space of training set is (W^k) ^T
2 Kernel function is ϕ_(x)
3 Training data set is (x)
4 Scalar value is (b)

At the point when an input is acquired it analyse the component estimations of ECG information, which include estimations of both dataset having arrhythmia and not having arrhythmia and take the probabilities of having arrhythmia and not .If it appears abnormal, then the classifier orders the classification into various sorts of arrhythmia, dependent on the feature value obtained after feature selection process.

IV. RESULTS & DISCUSSIONS

In this section, experimental results are described.Table.I shows the mathematical validation of our proposed method and compared with [35] and [36] methods. In [35], ICA algorithm were used for fetal ECG extraction and classification were exploited by Naïve Bayes classifier. In [36], fetal cardiac arrhythmia was detected by exploiting Kernel Support Vector Machine (SVM) classifier with Gaussian Kernel method. For extraction of fetal ECG, we compare two BSS based algorithms like WASOBI and EFICA(Efficient Fast Independant Component Analysis).The better performance is shown by the WASOBI based BSS technique having accuracy 95% ,sensitivity 87% and specificity 98% .

EFICA (Efficient Fast Independant Component Analysis) is a modified version of Fast ICA (FICA).This algorithm joins rapidly as it looks for a part individually. But while implantation, this algorithm shows less accuracy on extraction of fetal ECG. Using WASOBI based BSS technique, accurately fetal components gets extracted and final classification process makes more easy and less time consumed.

The right order or misclassification is evaluated by utilizing four metrics such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).Accuracy can be defined as it characterized as the proportion of the quantity of effectively ordered examples (TP and TN) to the complete number of examples classified. Sensitivity is the pace of being test positive when infection present. Specificity is the pace of being test negative when disorder missing.

The performance of Detection is evaluated by Accuracy, Sensitivity and Specificity.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

TABLE I. Performance Measures

Methods	Quality Evaluation		
	Accuracy	**Sensitivity**	**Specificity**
[35]	93.71%	74.82%	96.29%
[36]	83.33%	75%	91.67%
Proposed System with EFICA	92%	71%	94%
Proposed System with WASOBI	95%	87%	97%

By comparing all performance parameters, Accuracy, Sensitivity, Specificity, highest accuracy and specificity is shown by WASOBI. Specificity is inversely proportional to sensitivity. High specificity means, the method creates less false negatives. Based on all these criteria, the WASOBI based BSS method is better than EFICA version.

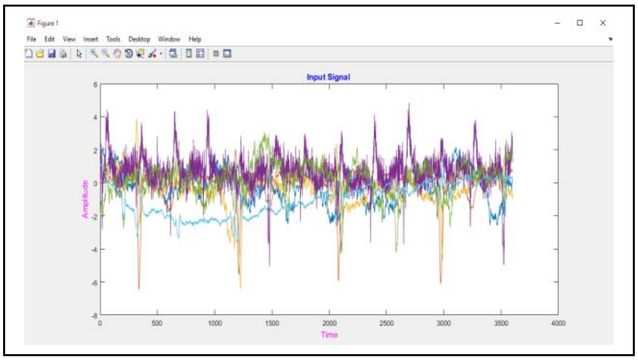

Figure.6: Input raw ECG signal

Figure.6 describes the input raw ECG signal which is given to the Pre-processing and extraction step. The raw input signal contains club of fetal ECG, mother ECG and different noises. From this mixture, first noises are removed and maternal, fetal ECG are separated, which is shown in figure.7

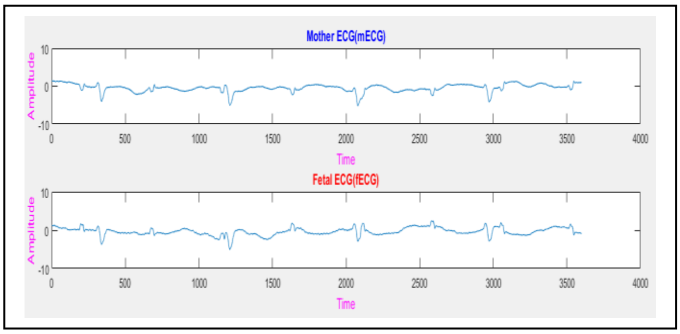

Figure. 7: Separated fECG and mECG

After separating the maternal and fetal component, the main element is fetal ECG, so we extract the fetal ECG only accurately by using the enhanced BSS technique. It is shown in figure.8.

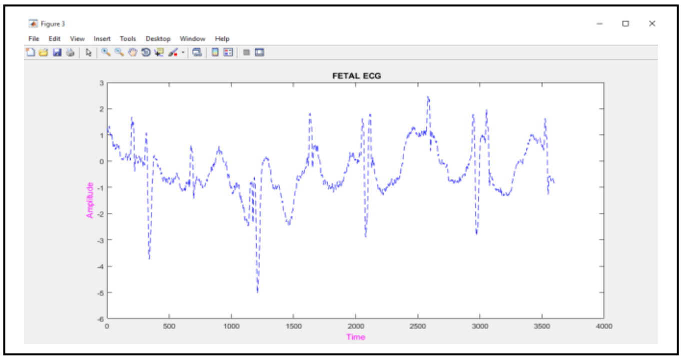

Figure. 8: Extracted fetal ECG (fECG)

After extraction process, the feature selection process is implemented using peak detection algorithm at which state logic machine technique is used. Here the required features are extracted for classification. It is shown in figure.9.

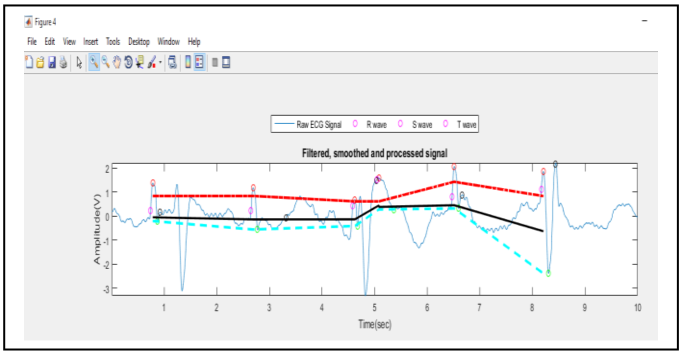

Figure.9: Feature Selection

The Feature vectors of five classifications obtained during feature selection process are QR interval, RS interval, ST interval, width of QRS complex and Heart rate variability. Heart rate variability is the physiological phenomenon of variation in the time interval between heartbeats. It is measured by the variation in the beat-to-beat interval. The obtained datas are recorded in milli seconds (ms). In this paper, total nine feature vectors are selected for classification purpose. The obtained datas are recorded in milli volts (mv).

V. CONCLUSION

The target of this paper is to identify cardiovascular arrhythmia in fetus in the womb of mother during beginning phases of pregnancy. And classify the disease into five classes. The challenge is to precisely extricate fetal segment from the blend of signals and noises. Our proposed strategy viably overwhelm this, by executing WASOBI based BSS procedure and peak discovery calculation in extracted fECG. The outcome is classified by utilizing multi-class SVM. Our proposed method shows accuracy of 95%.

VI. FUTURE SCOPE

Practically, the source that has to be extracted can be 1D, 2D or 3D. 1D refers to acoustic signals, 2D ate images, and 3D can be volumetric data. The detection can also be extended, by using three dimensional signals. Cardiac Arrhythmia is detected based on the ECG analysis. Similarly, we can extend this work by analysing combination of ECG and EEG signals and maybe "Autism" a developmental disorder can be detected.

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