Classification of Fetal ECG Signal using Multi-Class Support Vector Machine

Breesha. S.R[a] and X.Felix Joseph[b]

[a]*Research Scholar, Dept. of EEE Noorul Islam University Kumaracoil*
E-mail: breesha21@gmail.com
[b]*Associate Professor, Dept.of EEE Noorul Islam University Kumaracoil*
E-mail: felixjoseph75@gmail.com

Abstract: Fetal Electrocardiogram (FECG) allows us to detect the causes and symptoms of heart diseases of fetus by the continuous registration of the fetal heart activities. In this work we propose a simple method to investigate the abnormalities of fetus during pregnancy. This is carried out by separating the fetal ECG signal from mother's abdominal Electrocardiogram. FCOMBI BSS method is used for the separation process. Morphological feature extraction method is used for feature extraction and Multi-class SVM is used for the classification of six different classes of fetal ECG signal. The overall system gives the sensitivity as 80.4%, specificity as 83.5% and Accuracy as 85.3%.

Keywords: FCOMBI, Multi-class SVM, BSS.

1. INTRODUCTION

The fetal Electrocardiogram (FECG) is used for the logical diagnosis of heart diseases like Atrial Fibrillation, Wolff-Parkinson white syndrome, First degree block, Ventricular tachycardia, Idioventricular Rhythm and other disorders in the heart activation. Generally the fetal ECG signal has very low power compared to maternal ECG. In addition, the fetal ECG signal disturbed by several sources of interferences, such as intrinsic noise recorder, baseline shift,50/60Hz noises etc… The situation is very critical when the uterine contractions of the mother. The fetal ECG signal was distributed by electrophysiological signals such as EMG (Electromyogram) or EHG (Electrohysterogram) during uterine contractions. The Electrophysiological signals were created due to the uterine muscle rather than due to the heart.

The separation of fetal ECG signal was not easy to solve by simple filtering techniques, because all the three components such as maternal ECG, FECG and noises are similar and overlap. The fetal ECG signal was separated using different new techniques such as BSS (Blind Source Separation)[1], Adaptive noise cancellation[2], Nero fuzzy interference system (ANFIS)[3] for the purpose of cancellation.

The features of fetal ECG signal were more or less similar to that of mother's ECG signal. The waveform is also called PQRST wave. The P-wave was generated by shifting the electrical vector from right atrium to left atrium. The QRS complex was created due to the ventricular contraction. The T-wave occurs when the heart prepares for the next heartbeat. The components, features of fetal ECG signal were illustrated in fig.1.
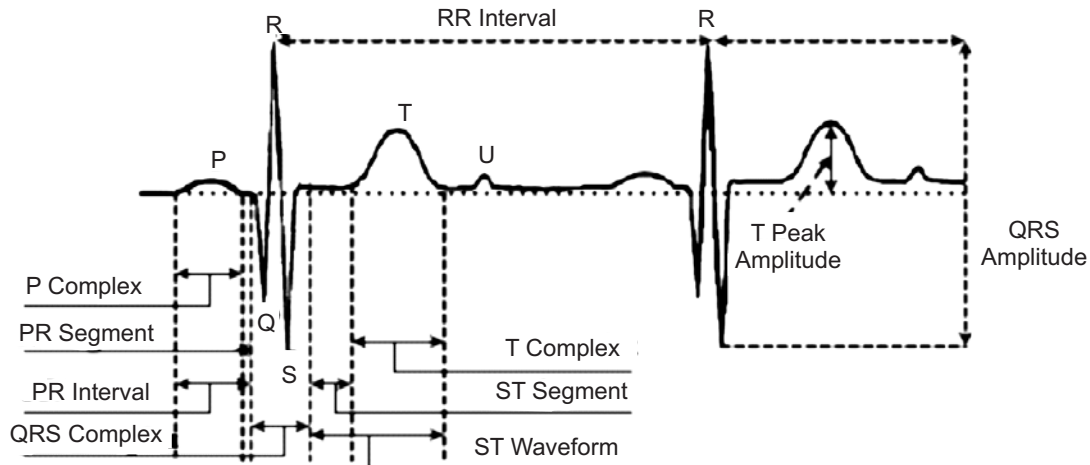
Figure 1: Fetal ECG waveform

The major function of electrical conduction of the fetal heart is to transmit the electrical impulses to atria and ventricles from SA node. Any disturbance in this regular path creates different arrhythmia. Various classifiers are used for the classification of fetal heart diseases.

In this work, the fetal ECG signal was separated from abdominal ECG signal by FCOMBI BSS method. The features of fetal ECG signal were extracted by morphological feature extraction method and the different classes of fetal ECG signal were classified using Multi-class SVM.

2. FECG SEPARATION

The main crucial part of this work is to process the AECG (Abdominal ECG) signal to extract the fetal ECG signal for fetal disease classification. Many researchers carried out this extraction using different developed techniques. For fetal ECG separation, the abdominal signal has to be free from noise. So the preprocessing was carried out before starting the separation process. In the preprocessing stage, the additive noises, DC components were eliminated. The filtered signal was looking smoother. The fetal ECG signal was separated from AECG signal using FCOMBI BSS method.

2.1. FCOMBI Method

FCOMBI method is similar to that of MULTI-COMBI [4] method. The main difference is to apply WASOBI [5] first on the input data instead of EFICA [6]. The reason is that WASOBI is considerably faster in the initial stage than latter for high dimensional mixture of signals. This is the main application of FCOMBI method. Eventually EFICA is applied to the output of WASOBI. The third main step of this algorithm is to again run WASOBI on the cluster of unresolved components in the output of EFICA. The last step is used in rare cases, when the first run of WASOBI, not able to detect the correct clusters.

3. FEATURE EXTRACTION

After the separation of fetal ECG signal, the different features like PR interval, PT interval, peak values of P, Q, R, S, T waves were extracted by using morphological feature extraction method.

Generally there are five deviations in the fetal ECG signal. They are P, Q, R, S and T.

The peak detector is used to recognize the PQRST points in following ways.

1. The first upright (positive) wave labeled as P wave.
2. The first downward (negative) deflection is labeled as Q wave
3. After the Q wave the first upright (positive) wave is labeled as R wave
4. The negative deflection followed by the R wave is labeled as S wave
5. After QRS points, the next first upright (positive) deflection is labeled as T wave.

3.1. Morphological Feature Extraction Method

There are three steps in morphological feature extraction method

1. Find out the standard of PR, PT, ST, TT and QT interval.
2. Obtain the maximum values of P, Q, R, S and T peaks.
3. Take the number of R-peaks count.

PR interval: The PR interval is computing from the first modulation point in the FECG signal (P-wave) to the starting of QRS wave. Mean value and standard deviation are the two features extracted from the PR interval.

Let the PR interval values are denoted by $[P_R]_F$, the mean value is given by

$$[\mu_{PR}]_F \;=\; E[P_R]_F$$

Where $[\mu_{PR}]_F$ is the mean value of fetal PR interval

$E[P_R]_F$ is the expected time value of PR interval.

Then the standard deviation value is calculated by the equation

$$\left[[\sigma_{PR}]_F \;=\; \sqrt{E\left[P_R^2\right]_F - [E[P_R]_F^2}\, \right]$$

Where $[\sigma_{PR}]_F$ is the standard deviation of fetal PR

PT interval: The PT interval of fetal ECG signal is obtained by taking the duration from P wave to the T wave. The extracted features from PT interval are mean and standard deviation.

The equation for mean is given by

$$[\mu_{PT}]_F \;=\; E[P_T]_F$$

Where $[\mu_{PT}]_F$ is the mean value of fetal PT interval

$[P_T]_F$ is the randomly obtained fetal PT interval

$E[P_T]_F$ is the expected period of fetal PT interval

The standard deviation of fetal PT interval is given as

$$\left[[\sigma_{PR}]_F \;=\; \sqrt{E\left[P_T^2\right]_F - [E[P_T]_F^2}\, \right]$$

Where $[\sigma_{PT}]_F$ is the standard deviation of PT interval

ST interval: This interval is obtained in the interval starting from QRS complex wave to the starting of T wave. The mean and standard deviation values are calculated using ST interval.

The mean value of fetal ST interval is given by

$$[\mu_{ST}]_F \;=\; E[S_T]_F$$

Where $[\mu_{ST}]_F$ is the mean value of ST interval

$[S_T]_F$ is randomly obtained from fetal ST interval

$E[S_T]_F$ is the period of fetal ST interval

The standard deviation of fetal ST interval is given by

$$\left[[\sigma_{ST}]_F \;=\; \sqrt{E\left[S_T^2\right]_F - [E[S_T]_F^2} \right]$$

QT interval: The first negative deviation in FECG is called Q-wave. The interval is obtained between starting of Q wave to the offset of T wave. Then mean value of fetal QT interval is calculated for the calculation of standard deviation of fetal QT interval. The mean value can be calculated by using the expected value of interval.

$$[\mu_{QT}]_F \;=\; E[Q_T]_F$$

Where $[\mu_{QT}]_F$ is the mean value of fetal QT interval

$E[Q_T]_F$ is the expected time value of fetal QT interval

The standard deviation is given by

$$\left[[\sigma_{QT}]_F \;=\; \sqrt{E\left[Q_T^2\right]_F - [E[Q_T]_F^2} \right]$$

Where $[\sigma_{QT}]_F$ is the standard deviation of fetal QT interval interval

Maximum peak value: The maximum peak values taken from the change of waves from positive to negative side. After the identification of P, Q, R, S, T waves, the maximum values P_{peak}, Q_{peak}, R_{peak}, S_{peak} and T_{peak} are calculated.

R-peak count: The number of R-peak count $[R_N]_F$ in the FECG signal is calculated after find out the maximum peak values of P, Q, R, S, T wave. It is given by

$$[R_N]_F \;=\; N[R_{peak}]_F$$

Where $N[R_{peak}]_F$ is the number of R-peaks count

4. CLASSIFICATION OF FETAL ECG SIGNAL

The extracted features were used for the classification of fetal ECG signal. In this work six classes such as Atrial Fibrillation, Wolff-Parkinson white syndrome, First degree block, Ventricular tachycardia, Idioventricular Rhythm were classified using Multi-class SVM.

4.1. Multi-class SVM

Support Vector Machines (SVMs) were originally designed for binary classification. Currently there are two types of approaches for multiclass SVM [7].

1. One is by constructing and combining several binary classifiers.
2. The other is by directly considering all data in one optimization formulation.

There are four methods for multiclass classification [8] based on binary classification:

1. One Against One (OAO)
2. One Against All (OAA)
3. Fuzzy Decision Function (FDF) and
4. Decision Directed Acyclic Graph (DDAG)

In this work one against all method is used for the classification purpose.

4.1.1. One Against All

For a '*k*' class problem, the One-Against-All method constructs '*k*' SVM models [9]. The SVM is trained with all of the training examples in the class with positive labels and all other examples with negative labels. The final output of the one-against-all method is the class that corresponds to the SVM with the highest output value. Thus, by solving the optimization problem of SVM using all the training samples in the dataset, the decision function of the SVM is

$$D_i(x) \;=\; w_i^T \varnothing(x) + b_i$$

The input vector '*x*' will be assigned to the class that corresponds to the largest value of the decision functions. Sample '*x*' is classified into the class

$$X \;=\; \arg\max_{i=1,\ldots k} [D_i(x)]$$

5. RESULT AND DISCUSSION

The database signals are taken from MIT physionet ATM bank [10]. The obtained signal consists of both AECG signal and FECG signal. FCOMBI algorithm is applied to the database. The mother's ECG signal, fetal ECG signal and noise signals are separated as shown in the figure 2.
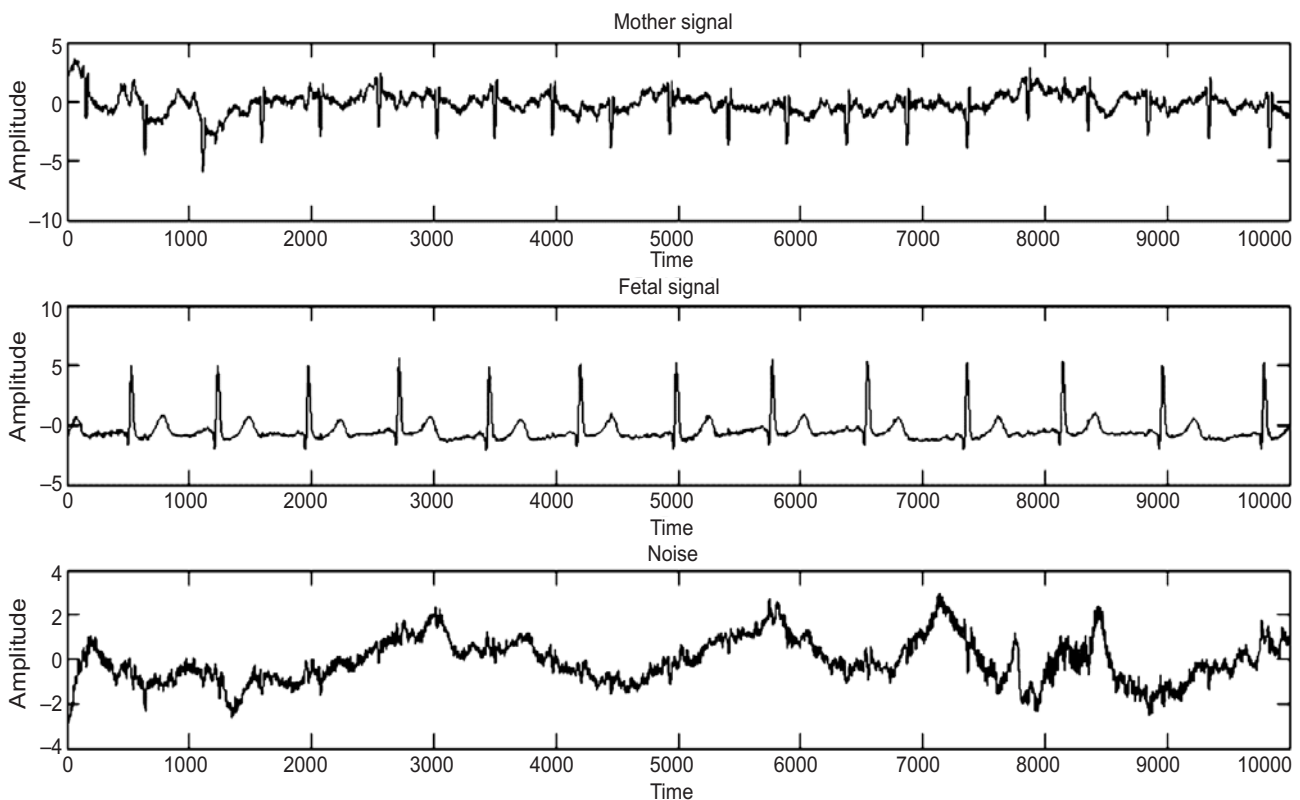

Figure 2: Output Mother, Fetal, Noise signals

The performance parameters like PSNR and SIR values are calculated. These values show the effectiveness of the algorithm. FCOMBI gives the PSNR value as 7.92 and the SIR value as 6.54. These SIR and PSNR values of FCOMBI are better when compared to other extraction techniques like EFICA, WASOBI, MULTI-COMBI, etc…

The proposed Multi-class SVM is implemented in MATLAB. In the developed Multi-class SVM the training and the test vectors was performed by 480 vectors (90 records from each class) of 10 dimensions (dimensions of the extracted feature vectors). The term vector tells the definition of extracted features of the samples of an ECG beat.

Table 1
Confusion matrix for Multi-class SVM classifier

Classifier	Desired Result	Output			
		TP	TN	FP	FN
	Atrial Fibrillation	10	66	4	0
	1st degree block	8	71	1	0
	Wolff-Parkinson-White Syndrome	8	71	0	1
Multi-class SVM	Ventricular Tachycardia	8	70	2	0
	Idioventricular rhythm	13	66	1	0
	Normal	7	72	0	1

The confusion Matrix is mainly used to calculate the performance indices such as Sensitivity, Specificity and Accuracy of the classifier. The true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values are shown in table 1.

5.1. Performance Indices

The test performance of the classifier can be determined by the computation of sensitivity, specificity and total accuracy. The sensitivity, specificity and total accuracy are defined as

5.1.1. Sensitivity

The ratio of number of true positives to the sum of true positive and false negative is called sensitivity.

$$S_t = \frac{T_p}{T_p + F_n}$$

5.1.2. Specificity

The ratio of true negatives to the total value of true negative and false positive is called specificity.

$$S_p = \frac{T_n}{T_n + F_p}$$

5.1.3. Accuracy

The Accuracy of feature extraction and classification is calculated by taking the ratio of sum of total true values which are available in the population.

$$A = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

These statistical Parameter values are shown in table 2.

Table 2
Statistical Parameters of Multiclass-SVM

Classifier	Desired Result	Statistical Parameters		
		Sensitivity (%)	Specificity (%)	Accuracy (%)
Multi-class SVM	Atrial Fibrillation	100	94	85.3
	1st degree block	100	99	
	Wolff-Parkinson-White Syndrome	89	100	
	Ventricular Tachycardia	100	97	
	Idioventricular rhythm	100	99	
	Normal	88	100	

6. CONCLUSION

The purpose of the research was to investigate the accuracy of Multi-class SVM. For that fetal ECG signal is obtained from the abdominal ECG signal using FCOMBI BSS algorithm. It shows better PSNR value as result. The different features were extracted by using morphological feature extraction method. Using the morphological features the fetal ECG was classified for different classes. The Multi-class SVM showed a great performance since it maps the features to a higher dimensional space. The results of the present study demonstrated that the multi-class SVM can be used in classification of the ECG signals by taking into consideration the misclassification rates.

REFERENCES

[1] Burghoff, M., Van Leeuwen, P., "Separation of fetal and maternal magnetocardiographic signals in twin pregnancy using independent component analysis (ICA)," Neurology, Neurophysiology and Neuroscience, 2004.

[2] N.V Thakor and Y.S.Zhu, "Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection", IEEE Transactions and Biomedical engineering, vol.38, no.8, (1991), pp.785-794.

[3] Khaled Assaleh, "Extraction of Fetal Electrocardiogram Using Adaptive Neuro-Fuzzy Inference Systems" IEEE Transactions on Biomedical Engineering, vol. 54, no. 1, January 2007.

[4] Tichavsky, P., Koldovsky, Z., Yeredor, A. Gomez-Herrero, G. Doron, E., A Hybrid Technique for Blind Separation of Non-Gaussian and Time-Correlated Sources Using a Multicomponent Approach

[5] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, and E. Moulines, "A blind source separation technique using second order statistics," *IEEE Trans. Signal Processing,* vol. 45, pp. 434-444, Feb. 1997.

[6] A. Hyv¨arinen, "Fast and robust fixed-point algorithms for independent component analysis*", IEEE Tr. Neural Networks,*vol. 10, no. 3, pp. 626-634, May 1999.

[7] K. K. Chin. Support vector machines applied to speech pattern classification. Master's thesis, University of Cambridge, 1998.

[8] Elif Derya Übeyli, "ECG beats classification using multiclass support vector machines with error correcting output codes" Volume 17, Issue 3, Pages 675-684, May 2007.

[9] Abe, S. (2003) Analysis of Multiclass Support Vector Machines. *International Conference on Computational Intelligence for Modelling Control and Automation (CIMCA 2003),* 385-396.

[10] Https://physionet.org/cgi-bin/atm/ATM.