Fetal Arrhythmia Classification and Detection using Bayesian Classifier

APSANA S , PG student
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 : Analysis of fetal electrocardiogram has important role during pregnancy, because it provides important information about the condition of the fetus. A continuous monitoring of fECG may increase the early detection of diseases like fetal arrhythmia. But extracting fetal ECG from mother ECG is not an easy one. Because the signal obtained from the abdominal surface of the mother is a collection of noises. It consists of noise generated by fetal brain activity, myographic signals and maternal ECG, etc. Here proposing a novel algorithm for the fetal arrhythmia classification and detection. The extraction of fetal ECG from maternal ECG is done by using independent component analysisi and the detection is done by using bayesian classifier.

Keywords : fetal arrhythmia, fetal ECG, Feature Extraction, Independent component analysis, Naive Bayesian classifier

I. INTRODUCTION

Birth defect is a problem that happens while a baby is developing in the mother's body. Most birth defects happen during the first 3 months of pregnancy. One out of every 33 babies in the United States is born with a birth defect.

Fetal monitoring during pregnancy stage has important role [2, 3], since it allows to the early detection of arrhythmia like diseases. That means if the fetal ECG extraction from the mother ECG is perfectly possible during the early stages of pregnancy, most of the birth defects can be prevent.

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

Fetal electrocardiogram (FECG) extraction has a vital role during pregnancy. Fetal monitoring during pregnancy stage helps the physician to recognize the pathologic condition. Fetal ECG (FECG) signal reflects the electrical activity of the fetal heart and provides valuable information of its physiological state. fECG is acquiring by placing non invasive electrodes on the abdominal surface of mother. However, abdominal ECG (AECG) is always corrupted with power line interference, maternal ECG (MECG) and electromyogram (EMG) where as FECG signal is corrupted by the gestational age, position of the electrodes and the skin impedance, ie the obtained ECG waveform is a mixture of noises [4,5,8].

II. IMPORTANCE OF fECG

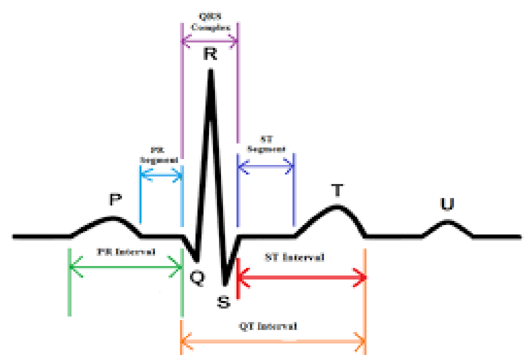

Figure 1: The ECG Waveform

Biomedical signal means a collective electrical signal acquired from any organ that represents a physical variable of interest. FECG is a biomedical signal that gives electrical representation of FHR. Sometimes the FECG is the only information source in early stage diagnostic of fetal health. Because one important factor is that, heart is one of the first organs formed in the very early stages of pregnancy. The fetal ECG consists of mainly three parts:

i) The P-wave: which reflects the contraction of the atriales.ie, The first segment is P-wave which indicates the depolarized wave that distributes from the SA node to the atria

ii) The QRS-complex is associated with the contraction of the ventricles. 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.

iii) The last part of ECG consists of T-wave, which indicates ventricular repolarization and its time is larger than depolarization.

The delay associated to the R-R interval leads to the heartbeats frequency. The R-R interval gives useful information about the heart condition. So by analyzing the fetal ECG it is easy to detect whether there is any problem or not. The abnormalities of ECG can be traced out by a trained physician. However manual detection has its own drawbacks. Here proposing an automatic detection of abnormalities and this is classifying using Bayesian classifier.

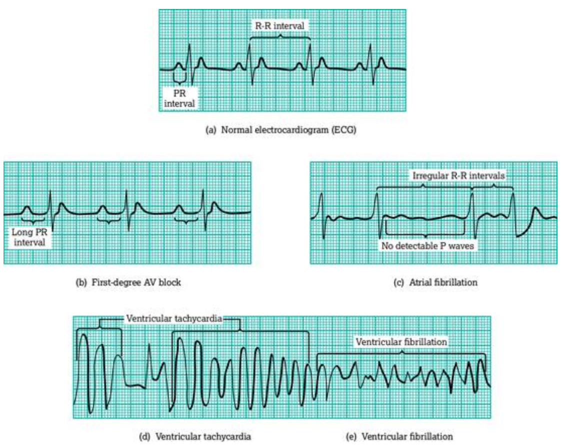

Figure 2: Normal and Abnormal ECGs

III. 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], it is very useful for extraction of fetal ECG. The method is to perform ICA on a set of ECG leads.

The extraction of Fetal Electrocardiogram (FECG) is vital to know the well being of the fetus and useful for doctors to decide the mode of delivery and period. The FECG contains activity of electrical depolarization and repolarization of fetal heart. In this paper, a simple algorithm, Independent Component Analysis (ICA), is used to extract FECG from Abdominal Electrocardiogram (AECG) of mother. ICA is basically a filtering solution which gives the signal from an unknown source. In this problem, the signal from an unknown source is Fetal ECG. It is to be derived from the pure maternal ECG. This algorithm works as a filter for extracting the FECG from multichannel maternal recordings. Noise reduction and subsequent extraction has been attempted by various Independent Component Analysis (ICA) algorithms. ICA comes under the classification of BSS techniques that can be applied to biomedical signal processing by making an additional assumption of independence of original signals.

From the output of ICA, the fECG is obtained [6, 7]. The obtained fECG is then classified using a trained classifier [11, 12, 13, 14]. Here using naïve Bayesian classifier.

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

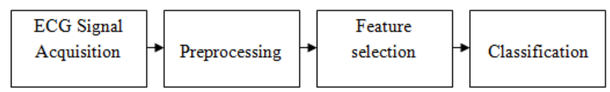

Fig 3: Block diagram

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

The figure 4 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.

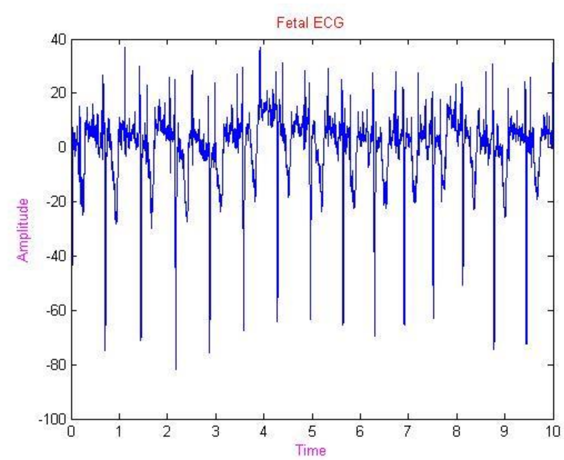

Figure 4: Input raw ECG

When ECG signal obtained from the patient's body surface consists of a mixture of signals including 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.

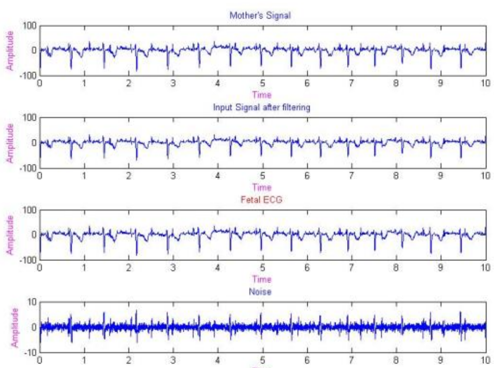

Figure 5: Independent component obtained by fastICA

The result of such preprocessing is shown in figure 5. In figure 5, it shows the mother's signal, signal after preprocessing, fetus's signal and noise signal.

B. FEATURE SELECTION

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 6.

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.

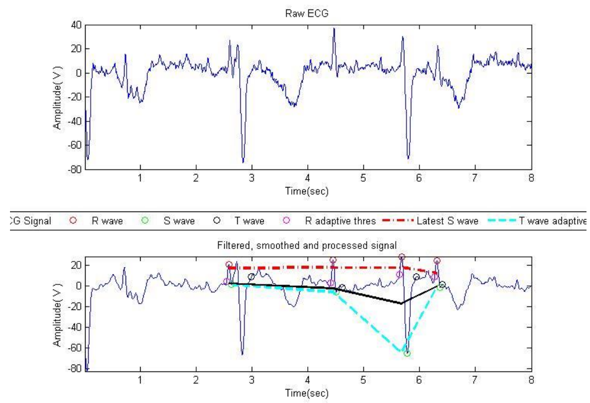

Figure6: Feature Selection

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.

IV. RESULTS

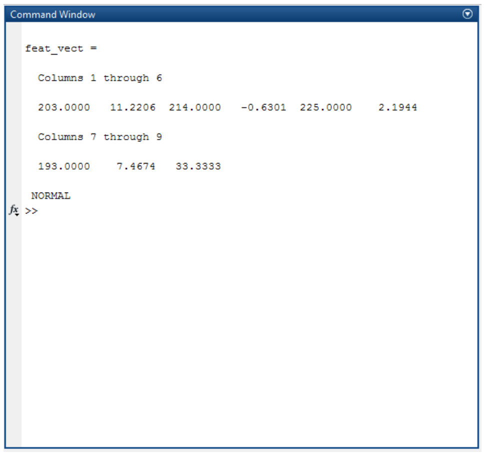

Figure 7: Classification: showing result for normal

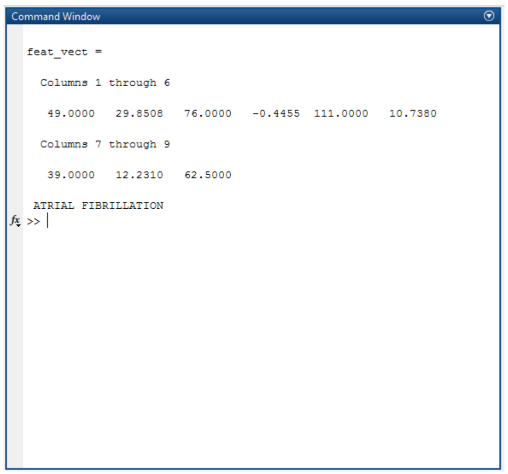

Figure 8: Classification: showing result for atrial fibrillation

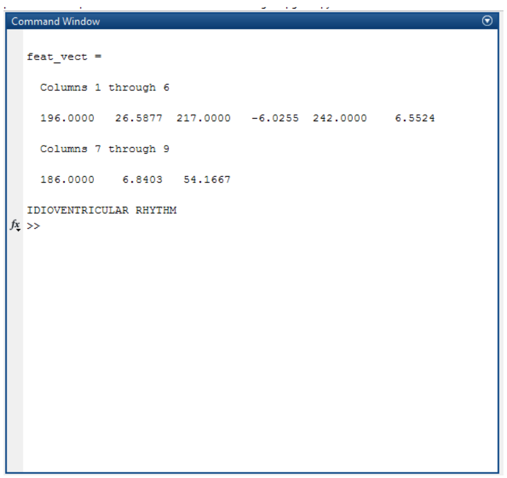

Figure 9: Classification: showing result for Idioventricular Rhythm

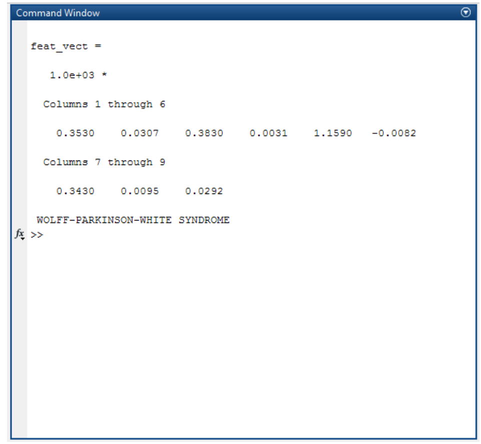

Figure 10: Classification: showing result for Wolff-Parkinson White Syndrome

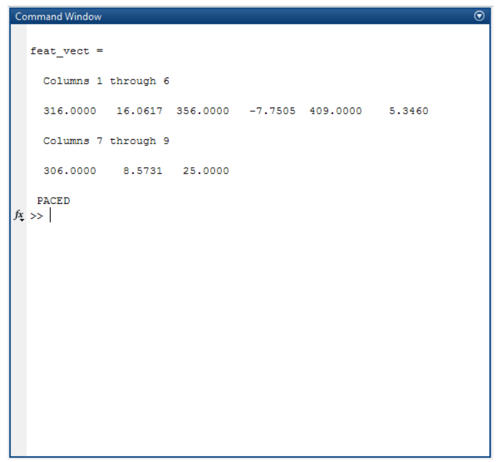

Figure 11: Classification: showing result for Paced

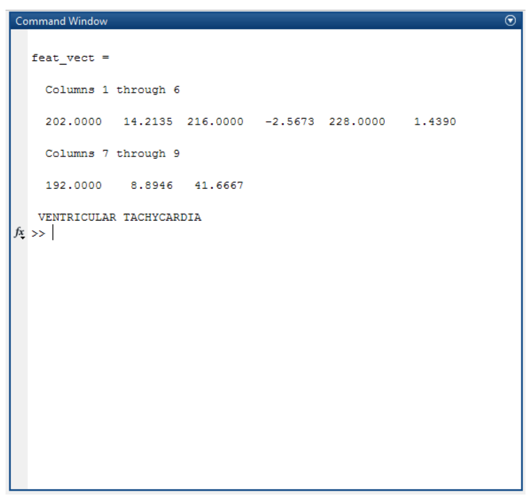

Figure 12: Classification: showing result for ventricular Tachycardia

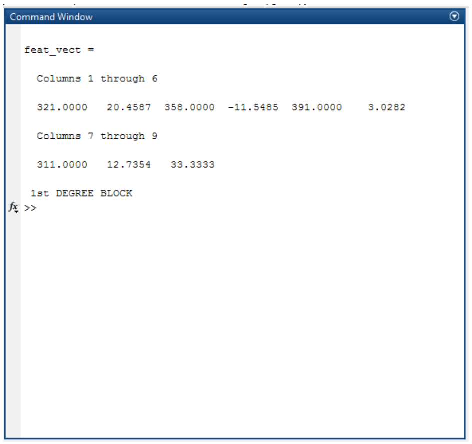

Figure 13: Classification: showing result for 1st degree block

V. 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.

ACKNOWLEDGEMENT

This work is technically supported by Institute of Human Resource Development (IHRD), Kerala, in particular Mr. Aneesh R. P., provided many useful discussions.

REFERENCES

1. Giulia Da Poian,Riccardo Bernardini, Roberto Rinaldo "Separation and analysis of fetal ECG signals from compressed sensed abdominal ECG Recordings" Biomedical Engineering ,IEEETransaction,,2016.
2. Clifford, I. Silva, J. Behar, and G. B. Moody," Non-invasive fetal ECG analysis", Physiological measurement, vol. 35, no. 8, p. 1521, 2014
3. R.Sameni and G. D. Clifford, A review of fetal ECG signal processing; issues and promising directions, The open pacing, electrophysiology & therapy journal, vol. 3, p. 4, 2010.
4. B.Widrow, J. R. Glover Jr, J. M. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, J. Zeidler, E. Dong Jr, and R. C. Goodlin, Adaptive noise cancelling: Principles and applications, Proceedings of the IEEE, vol. 63, no. 12, pp. 16921716, 1975.
5. A. Dess`ı, D. Pani, and L. Raffo, "An advanced algorithm for fetal heart rate estimation from non-invasive low electrode density recordings," Physiological measurement, vol. 35, no. 8, p. 1621, 2014.
6. R. Vullings, C. Peters, R. Sluijter, M. Mischi, S. Oei, and J. Bergmans, "Dynamic segmentation and linear prediction for maternal ECG removal in antenatal abdominal recordings," Physiological measurement, vol. 30, no. 3, p. 291, 2009.
7. B. Azzerboni, F. La Foresta, N. Mammone, F. C. Morabito, L. Feo, and V. Reggio, "A new approach based on wavelet-ica algorithms for fetal electrocardiogram extraction," in in Proc. 13th Eur. Symp. Artif. Neural Netw. Citeseer, 2005.
8. Mohammad Zia Ur Rahman; Rafi Ahamed Shaik Mohammad Zia Ur Rahman; Rafi Ahamed Shaik "Denoising ECG Signals Using Transform Domain Adaptive Filtering Technique" D. V. Rama Koti Reddy 2009 Annual IEEE India Conference
9. K. Sternickel, "Automatic pattern recognition in ECG time series", Comput. Meth. Prog. Biomed., Vol.68, pp.109–115. (pub. 2002)
10. Yun-Chi Yeh, Wen-June Wang, and Che Wun Chiou: "Cardiac arrhythmia diagnosis method using linear discriminant analysis on ECG signals", Elsevier measurement, Vol.42, pp.778-789 (pub. 2009)
11. Elif Derya Ubeyli :" Combine recurrent neural networks with eigenvector methods for classification of ECG beats", Elsevier Digital signal processing, Vol. 19, pp. 320-329, (pub. 2008)
12. Z. Dokur, T. Olmez, ECGbeat classification by a novel hybrid neural network, Compute. Meth. Prog. Biomed. 66 (2001) 167–181.
13. Majid Moavenian, Hamid Khorrami : " A quanlitative comparision of Artificial neuron Networks and Support vector mechines in ECG arrythmias classification", Elsevier Expert system with applications, (pub. 2009)
14. Kim J, Shin H, Lee Y, Lee M: Algorithm for classifying arrhythmia using Extreme Learning Machine and principal component analysis. Conf Proc IEEE Eng Med Biol Soc 2007, 2007:3257-3260.
15. U. Rajendra Acharya, P. Subbanna Bhat, U.C. Niranjan, N. Kannathal, Lim Choo Min and Jasjit S. Suri, "Type-2 fuzzy clustering neuron network", Advances in cardiac signal processing, Springer, pp. 109- 120 (pub. 2007)
16. Jin Zhang; Jia-Lun Lin; Xiao-Ling Li; Wei-Quan Wang "ECG signals denoising method based on improved wavelet threshold algorithm" 2016 IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)
17. S.L. Joshi, R. a Vatti, R. V. Tornekar, A Survey on ECG Signal Denoising Techniques, in: 2013 International Conference on Communication Systems and Network Technologies, IEEE, 2013: pp. 60–64. doi:10.1109/CSNT.2013.22.
18. Francisco Castells, Pablo Laguna, Leif Sornmo, Andreas Bollmann and Jose Millet Roig "Principal Component Analysis in ECG Signal Processing" , Hindawi Publishing Corporation, EURASIP Journal on Advances in Signal Processing, Volume 2007, Article ID 74580
19. D. Sugumar; P. T. Vanathi; Sneha Mohan "A Joint blind source separation algorithms in the separation of non-invasive maternal and fetal ECG" 2014 International

Conference on Electronics and Communication Systems (ICECS), 2014

20. Aapo Hyvarinen "Fast and Robust Fixed-Point Algorithms for Independent Component Analysis", IEEE Transactions on Neural Networks.
21. S. Jokic, V. Delic Faculty of Technical Sciences, University of NoviSad, Jarno M. A. Tanskanen and Jari J. Viik, Tampere University of Technology and Institute of Biosciences and Medical Technology, Finland "Independent Component Analysis in ECG Signal Processing", 2011
22. Yusuf Sevim; Ayten Atasoy "A Fetal ECG separation using non-parametric ICA algorithm" 2008 IEEE 16th Signal Processing, Communication and Applications Conference
23. J. Lee; S. P. Cho "A study of fetal ECG separation from small channel abdominal ECGs using ICA" 30th Annual Conference of IEEE Industrial Electronics Society, 2004. IECON 2004
24. P.Chazal, M. Dwyer, and R. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features", IEEE Trans.Biomed. Eng., vol. 51, no. 7, pp. 11961206, Jul. 2004
25. Hooman Sedghamiz, Linkoping university, "An online algorithm for R,S and T wave detection", December 2013
26. A. K. Mishra, S. Raghav "Local fractal dimension based ECG arrhythmia classification," Biomedical Signal Processing and Control, vol.5,no.2,pp. 114–123, 2010.
27. J. Kim, H. S. Shin, K. Shin, M. Lee,"Robust algorithm for arrhythmia classification in ECG using extreme learning machine, " BioMedical Engineering OnLine, vol8, no. 1, pp. 31-42, 2009.
28. Islam, M.J.; Univ. of Windsor, Windsor; Wu, Q.M.J.; Ahmadi, M.; Sid-Ahmed, M.A "Investigating the Performance of Naive- Bayes Classifiers and K-Nearest Neighbor Classifiers
29. Daniel P. Stormont "An Online Bayesian Classifier for Object Identification"2007 IEEE International Workshop on Safety, Security and Rescue Robotics
30. Aya F. Ahmed; Mohamed I. Owis; Inas A Yassine "Novel Bayesian classifier discriminant function optimization strategies for arrhythmia classification" IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI)