FETAL ECG EXTRACTION AND CLASSIFICATION OF THE HEALTH CONDITION BASED ON BOOSTING CLASSIFIER

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ABSTRACT

The non-invasive method of FECG monitoring is a promising one which can be used in all gestation weeks and also during delivery process, but there are some difficulties in this method. Since in non-invasive method the recording electrodes are placed on the abdomen region of the pregnant woman, they record both maternal electrocardiogram (MECG) and the fetal electrocardiogram (FECG), also in this case it may contain a relatively large amount of noise. The main sources of possible noise in the field of extraction of fetal ECG include the maternal electrocardiogram (MECG). In this work the proposed method includes dynamic ECG model to extract FECG from mixed ECG using adaptive filtering techniques. The extracted FECG signal is undergone for the analysis by decomposing with the help of empirical mode decomposition and the spectral features are extracted from these decomposed signals Finally adaptive boosting classifier is responsible for the FECG health analysis. The parameter analysis for different values of noise level, amplitude and heart rate ratios of fetal ECG's shows its effectiveness and is implemented using MATLAB.

I INTRODUCTION

DSP, or Digital Signal Processing, as the term suggests, is the processing of signals by digital means. A signal in this context can mean a number of different things. Historically the origins of signal processing are in electrical engineering, and a signal here means an electrical signal carried by a wire or telephone line, or perhaps by a radio wave. More generally, however, a signal is a stream of information representing anything from stock prices to data from a remote-sensing satellite.

1.2 FETAL ELECTROCARDIOGRAPHY

Fetal monitoring during pregnancy is important to support medical decision making. FECG is a technique for obtaining important information about the condition of the fetus during pregnancy, by measuring the electrical signals generated by the fetal heart as measured from multichannel electrodes

placed on the mother's body surface. This method of recording the fetal ECG from the mother's body, without direct contact with the fetus is called non-invasive method. The response of fetal heart is an important indicator of fetal health. Fetal heart rate (FHR) variations during pregnancy and labor have commonly been observed as indirect indications of fetal conditions. An abnormal fetal heart rate or pattern may mean that the fetus is not getting enough oxygen or there are other problems. The ultimate reason for the interest in FECG signal analysis is in clinical diagnosis and biomedical applications. The extraction and detection of the FECG signal from composite abdominal signals with powerful and advance methodologies is becoming a very important requirement in fetal monitoring. It helps clinicians in diagnosing the patients during 32-34 weeks of pregnancy.

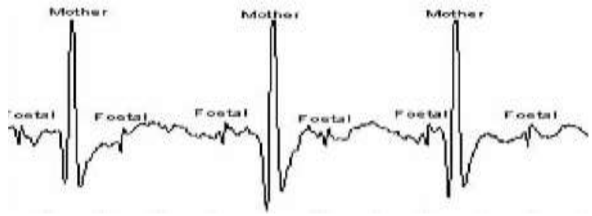


Fig 1.4 Abdominal Signal with maternal & fetal ECG

1.3 Maternal Abdominal Signal

Maternal Abdominal Signal is a signal which is measured from mother's abdomen. The measured signal contains maternal ECG, the small voltage of fetal ECG and severe noise. Maternal Abdominal signal is measured with the help of five electrodes. Each electrode produce unique abdominal signal.

1.4 Maternal Thoracic Signal

Maternal Thoracic Signal is measured from thorax (the part of human body between the neck and the diaphragm, partially encased by the ribs and containing the heart and lungs; the chest).We use three electrodes to measure thoracic signal.

II RELATED WORK

In Z.Zidelmal,a,,*et al.,* introduces a ECG classification based on sum classification. This is work needs large amount of traing dataset

H. Gholam Hosseini *et al.*, The electrocardiograms (ECGs) record the electrical activity of the heart and are used to diagnose many heart disorders. This paper proposes a two-stage feed forward neural network for ECG signal classification.

Sung-Nien Yu *et al.,* In this paper, the authors propose a novel independent components (ICs) arrangement strategy to cooperate with the independent component analysis (ICA) method used for ECG beat classification.

A. De Gaetano *et al.,* A novel supervised neural network-based algorithm is designed to reliably distinguish in electrocardiographic (ECG) records between normal and ischemic beats of the same patient.

Mariano Llamedo *et al.,* In this paper, the authors studied and validated a simple heartbeat classifier based on ECG feature models selected with the focus on an improved generalization capability.

Serkan Kiranyaz *et al.,* This paper presents a personalized long-term electrocardiogram (ECG) classification framework, which addresses the problem within a long-term ECG signal, known as Holter register, recorded from an individual patient.

III PROPOSED SYSTEM

In this project, the fetal ECG is extracted from abdominal signal using adaptive filtering techniques. Here, the thoracic signal is taken as reference signal for fetal ECG extraction. Fetal ECG extraction is done based on Least Mean Square (LMS) adaptive filtering algorithm. After filtering out the fetal signal it is processed by Stationary Wavelet Transform. For each scale, the detail coefficients are processed for the feature extraction. The features are given as the input to the neural network classifier and the trained classifier is responsible for classifying the status of the fetal ECG signal (ie., Normal and Abnormal)

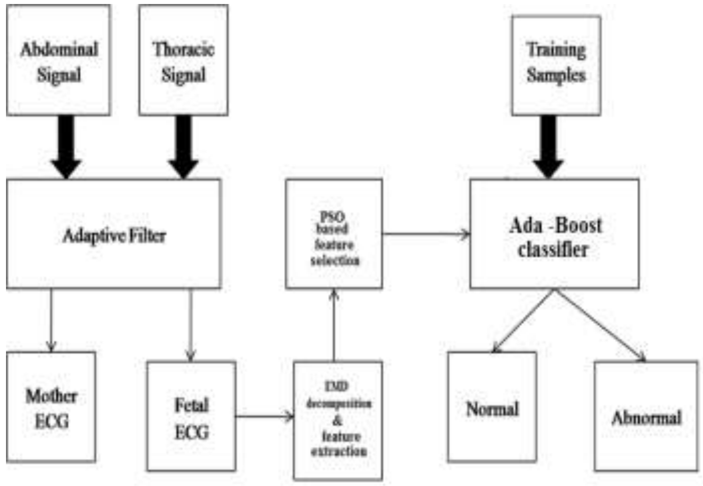


Figure 3.1 Block diagram for the proposed work

A.Least Mean Square Filter

Least Mean Square (LMS) algorithm is a class of adaptive filter used to find the difference between the desired and the actual signal. It can adapt to changes in signal statistics. The LMS algorithm has been widely used in fetal ECG extraction.

Properties of LMS algorithm:

Low computational complexity.

Proof of convergence in stationary environment.

Stable behavior when implemented with finite precision arithmetic.

The LMS algorithm has two inputs: an original input and a reference input.The abdominal signal was used as the original input d(n) and the thoracic signal as the reference input x(n). The coefficients of the adaptive filter were constantly adjusted with the feedback e(n) until the output y(n) was very close to the maternal ECG component

t of the abdominal signal. The algorithm starts by assuming some small weights (zero in most cases), and at each step the weights are updated.

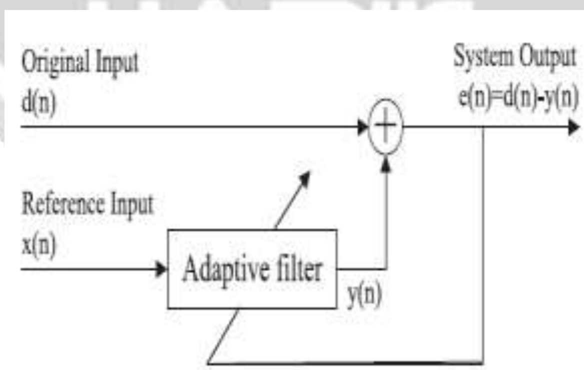


Fig 3.2.1 General block of LMS adaptive filter

The abdominal signal d(n) as the original input at the nth moment is given by,
$d(n)=[d(n),d(n-1),\ldots\ldots,d(n-m+1)]T$

The thoracic signal x(n) as the original input at the nth moment is given by,
$x(n) = [x(n),x(n-1), \ldots\ldots,x(n-m+1)]T$
where m is the length of the adaptive filter.
The LMS update is given by,
$w(n+1)=w(n)+ 2\mu e(n)x(n)$

The filtered output signal y(n) which is close to the maternal ECG will be

y(n)= wT(n) * x(n)

Then fetal ECG can be obtained after adaptive processing as

e(n)= d(n) – y(n) = d(n) - wTx(n)

For decomposition scale as 5 , we get five different fetal ECG in addition with noise at the output of least mean square algorithm.

B. Empirical Mode Decomposition

The EMD is a data dependent method of decomposing a signal into a number of oscillatory components, known as intrinsic mode functions (IMFs). EMD does not make any assumptions about the stationery or linearity of the data. The aim of EMD is to decompose a signal into a number of IMFs, each one of them satisfying the two basic conditions: 1) the number of extrema or zero crossings must be the same or differ by at most one; 2) at any point, the average value of the envelope defined by local maxima and the envelope defined by the local minima is zero. Given that we have a signal, the calculation of its IMFs involves the following steps:

1) Identify all extrema (maxima and minima) in $x(t)$.

2) Interpolate between minima and maxima, generating the envelopes $e_l(t)$ and $e_m(t)$

3) Determine the local mean as $a(t) = e_m(t) + e_l(t)/2$.

4) Extract the detail i.e., $h(t) = x(t) - a(t)$.

5) Decide whether $h_l(t)$ is an IMF or not based on two basic conditions for IMFs mentioned above.

6) Repeat step 1 to 4 until an IMF is obtained.

Once the first IMF is obtained, define $c_l(t) = h_l(t)$, which is the smallest temporal scale in $x(t)$. A residual signal is obtained as $r_l(t) = x(t) - c_l(t)$. The residue is treated as the next signal and the above mentioned process is repeated until the final residue is a constant (having no more IMFs). At the end of the decomposition, the original signal can be represented as follows:

$$x(t) = \sum_{m=1}^{M} c_m(t) + r_M(t)$$

where M is the number of IMFs, $c_m(t)$ is the th IMF and $r_M(t)$ is the final residue.

3.2.3 Analytic Representation of IMFs

After the extraction of IMFs from ECG signals, their analytic representation is obtained. This representation removes the DC offset from the spectral component of the signals, which is an important aspect to compensate for the non-stationarity of the signals [36]. Given that we have an IMF $c_m(t)$, its analytic representation is given as,

$$y(t) = c_m(t) + iH\{c_m(t)\}$$

where $H\{c_m(t)\}$ is the Hilbert transform of $c_m(t)$, which is the mth IMF extracted from the signal $x(t)$. After performing EMD of the signal, the IMFs are used for feature extraction purposes.

C. Feature extraction

The purpose of the feature extraction process is to select and retain relevant information from original signal. The Feature Extraction stage extracts diagnostic information from the ECG signal. In order to detect the peaks, specific details of the signal are selected. The detection of R peak is the first step of feature extraction. The R peak in the signal from the Modified Lead II (MLII) lead has the largest amplitude among all the waves compared to other leads. The QRS complex detection consists of determining the R point of the heartbeat, which is in general the point where the heartbeat has the highest amplitude. A normal QRS complex indicates that the electrical impulse has progressed normally from the bundle of His to the Normally, the onset of the QRS complex contains the high-frequency components, which are detected at finer scales. This work imposes two different feature extraction methodologies for the effective classification of the fECG signals. The features are;

Temporal Statistic

Spectral Statistics

(i)Temporal Statistic features

Researchers have shown that the statistical features of IMFs are useful for discriminating between normal and pathological ECG signals. Their use is motivated by the fact that the distribution of samples in the data are characterized by their asymmetry, dispersion and concentration around the mean. A visual analysis of the IMFs obtained from healthy and epilepsy patients during interictally and ictal periods after Hilbert transform reveals that they are quite different from one another. Interestingly, these differences are appropriately captured using the statistics of the IMFs. For an IMF, these statistics can be obtained by the following quantities:

$$\mu_t = \frac{1}{N}\sum_{i=1}^{N} y_i$$

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \mu_t)^2}$$

$$\beta_t = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \mu_t}{\sigma_t}\right)^3$$

Where N the number of samples in the IMF is μ_t is the mean, σ_t is the variance and β_t is skewness of the corresponding IMF.

(ii) Spectral Statistics features

One important strength of EMD is that it has the ability to perform a spectral analysis of the signals. Its importance in the design of automated systems for ECG is based on the fact that the epileptic seizures give rise to changes in certain frequency bands [37], [38]. A frequency based analysis can therefore be useful for feature extraction from ECG signals. A conceptual interpretation of EMD is that it decomposes a signal into a number of components (IMFs) which are responses to filters having narrow pass bands. The spectral features obtained from IMFs can thus give a rich clue about the physiology of the ECG signals. Traditionally when using EMD, this spectral analysis is done using the calculation of instantaneous frequencies (IF). However, it is well known that the calculation of IF has a physical meaning only for mono-component signals [33]. In practice, when the ECG signals are subjected to EMD, we do not get mono-component signals. As an alternative, we have resorted to the calculation of PSD for feature extraction purposes. The discrimination power of the PSD features can be visually analyzed by their respective plots for three IMFs from the normal and pathological ECG signals. The PSD can be calculated as follows:

$$P(w) = \sum_{-\infty}^{\infty} r_y[n]e^{-jwn}$$

where $r_y[n]$ represents the autocorrelation of $y[n]$, defined as $r_y[n] = E(y[m]y * [m])$. Visual analysis of the PSD of IMFs shows that the statistics of the PSD can be used as relevant features for feature extraction.

1) Spectral Centroid: The researchers have shown that the centroid frequencies of the IMFs extracted from ECG signals form distinct groups when supervised clustering is applied on the ECG signals [7]. These respective groups are indicative of the seizure and non-seizure ECG signals. The centroid frequency is therefore a distinctive feature that can be used for the characterization of ECG signals,

$$C_s = \frac{\sum_w wP(w)}{\sum_w P(w)}$$

where $P(w)$ is the amplitude of wth frequency bin in the spectrum.

2) Variation Coefficient: Since the spectral variation in the IMFs is different for normal and pathological ECG signals, therefore it can be used for their characterization. This variation can be calculated as follows:

$$\sigma_s^2 = \frac{\sum_w (w - C_s)^2 P(w)}{\sum_w P(w)}$$

where C_s is the spectral centroid.

3) Spectral Skew: Skewness is the third order moment and it measures the symmetry/asymmetry of a distribution. Visual inspection of the plot of PSD of IMFs shows that the skewness of the power of IMFs for the normal and pathological ECG signals differs thus potentially yielding a useful feature for the classification of ECG signals. Skewness of the PSD can be calculated as:

$$\beta_s = \frac{\sum_w \left(\frac{w - C_s}{\sigma_s}\right)^3 P(w)}{\sum_w P(w)}$$

After the extraction of temporal and spectral features of each IMF, its feature vector can be obtained by their concatenation as follows:

$$F = [\mu_t\ \sigma_t\ \beta_t\ C_s\ \sigma_s\ \beta_s]$$

The feature vectors obtained from several IMFs can then be used for classification purposes.

D. FEATURE SELECTION

After extraction of features, it has found that, within the extracted features, there are some features, which are irrelevant and noisy. These irrelevant and noisy features lead the misclassification rate. So the objective of feature selection step is to reduce the noisy data and exclude the irrelevant features as much as possible. In other word, find the optimal features from the original features including noisy and irrelevant features, which have higher discriminating power, to improve the recognition rate. Particle swarm optimization (PSO) is one such well-known tool to find the optimum characteristics with the help of local as well as global search in the feature search space in an iterative way. PSO proposed by Dr. Eberhart and Dr. Kennedy in 1995 [11]. In PSO, swarm consists of a group of random particles, which move around the solution space of the problem by updating through iterations for an optimum solution and go until convergence is achieved. A complete description of the PSO algorithm is given in below section.

Particle swarm optimization

In computer science, particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. Also, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods.

Ada-boost classification

AdaBoost, short for "Adaptive Boosting", is a machine learning meta-algorithm formulated by Yoav Freund and Robert Schapire who won the Gödel Prize in 2003 for their work. It can be used in conjunction with many other types of learning algorithms to improve their performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers. AdaBoost is sensitive to noisy data and outliers. In some problems it can be less susceptible to the over fitting problem than other learning algorithms. The individual learners can be weak, but as long as the performance of each one is slightly better than random guessing (e.g., their error rate is smaller than 0.5 for binary classification), the final model can be proven to converge to a strong learner.

While every learning algorithm will tend to suit some problem types better than others, and will typically have many different parameters and configurations to be adjusted before achieving optimal performance on a dataset, AdaBoost (with decision trees as the weak learners) is often referred to as the best out-of-the-box classifier.[1][2] When used with decision tree learning, information gathered at each stage of the AdaBoost algorithm about the relative 'hardness' of each training sample is fed into the tree growing algorithm such that later trees tend to focus on harder-to-classify examples.

$$H(x) = \sum \alpha_t h_t(x)$$

An Adaboost classifier with the form can be trained by minimizing the loss function L, i.e., by optimizing the scalar αt and weak learner ht(x) in each iterations. Before training, every data sample xi is assigned anon-negative weight wi. After each iteration, the weights of misclassified samples will be heavier, which increases these verity of misclassifying them in the following iterations.

A decision tree h TREE(x) is composed of a stump hj(x) at every non-leaf node j. Decision trees are always trained using a greedy procedure, recursively setting one stump at a time, starting from the root and expanding to the lower nodes. Each stump produces a binary decision, given an input x ∈ RK, then the stump can be parameterized with a polarity p ∈ { $\pm 1\}$ 1g, a threshold τ ∈ R, and a feature index k ∈ {1,2,……K}

$$h_j(x) \equiv p_j \operatorname{sign}(x[k_j] - \tau_j),$$

where x[k] is the k-th dimension feature of x. The goal in each stage of stump training is to find the optimal parameters, which will minimize the weighted classification error ε

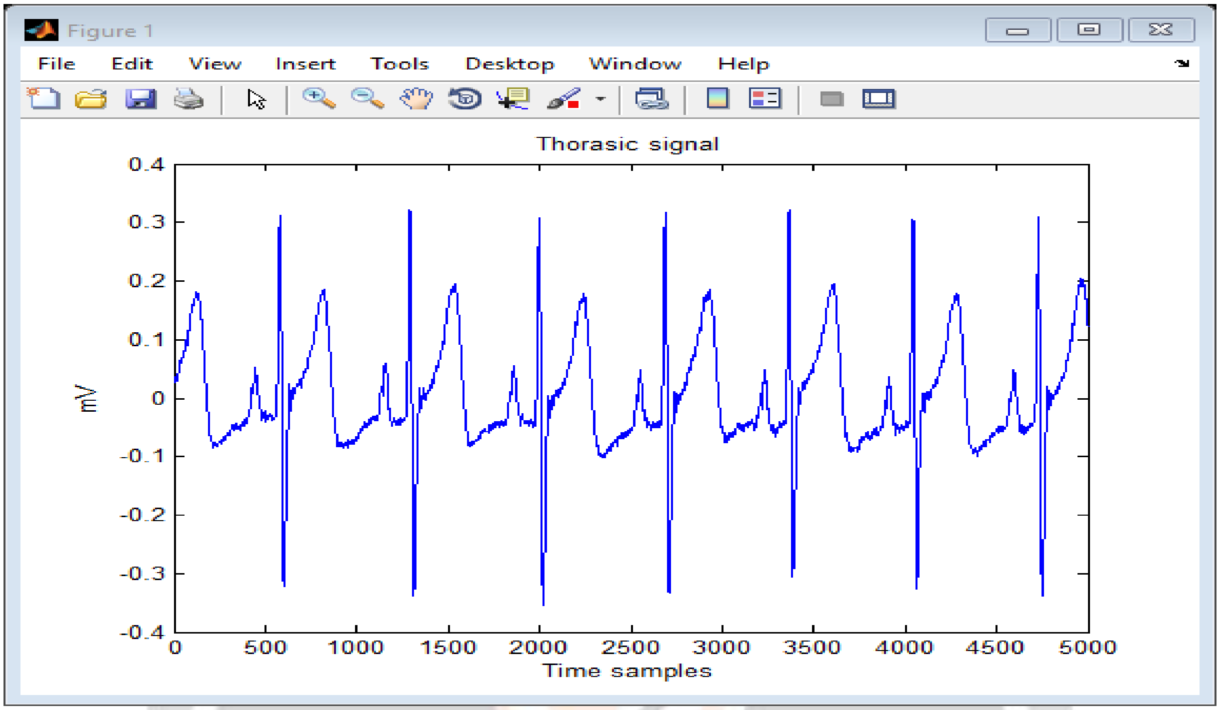
$$\varepsilon \equiv \frac{1}{Z} \sum w_i 1_{\{h(x_i) \neq y_i\}}, \qquad Z \equiv \sum w_i,$$

Given a feature k and an m-subset, the preliminary classification error $\varepsilon_m^{(k)}$ is defined as the smallest achievable training error if only the data samples in this m-subset are considered. That is to say, if all other samples not in this m-subset are trimmed, the preliminary classification error $\varepsilon_m^{(k)}$ is the whole classification error.

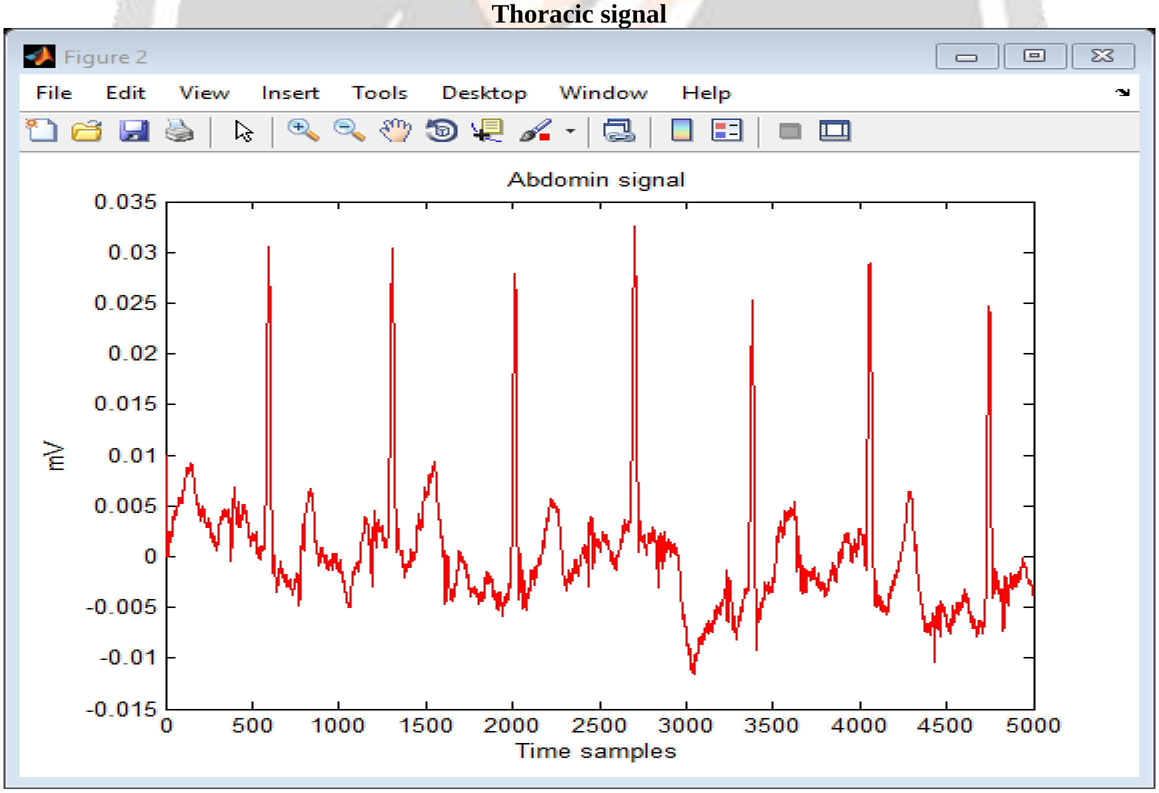
$$\varepsilon_m^{(k)} \equiv \frac{1}{Z_m} \left[\sum_{\substack{i \le m \\ x_i[k] \le \tau_m^{(k)}}} w_i 1_{\{y_i = +p_m^{(k)}\}} + \sum_{\substack{i \le m \\ x_i[k] > \tau_m^{(k)}}} w_i 1_{\{y_i = -p_m^{(k)}\}} \right]$$

where $P_m^{(k)}$ and $\tau_m^{(k)}$ are both optimal preliminary parameters. We can see that using the best features of an m-subset to predict the optimal feature of the entire dataset is reasonable, but if we only use the samples in the m-subset, the training result may perform badly. So we need to find an approach which can reduce the samples of the m-subset as much as possible, while having no effect on the training result. According to the properties of the upper bound of the preliminary error, we propose a new decision trees training method based on comparing the feature performance on subsets of the dataset, and consequently, pruning non-effective features:

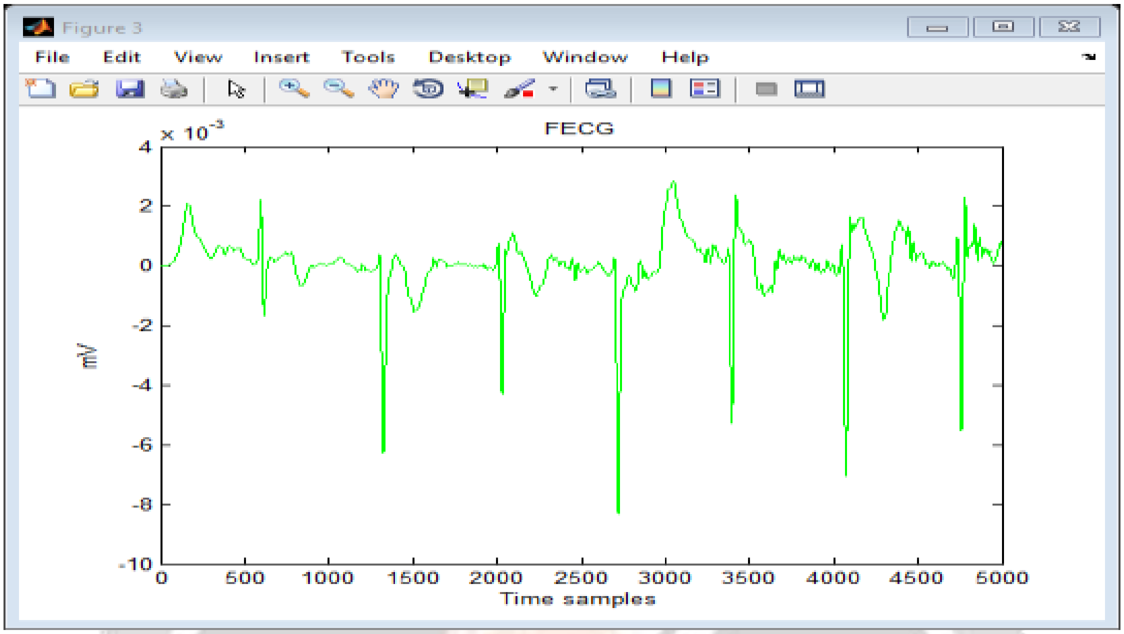
IV - SIMULATION RESULTS



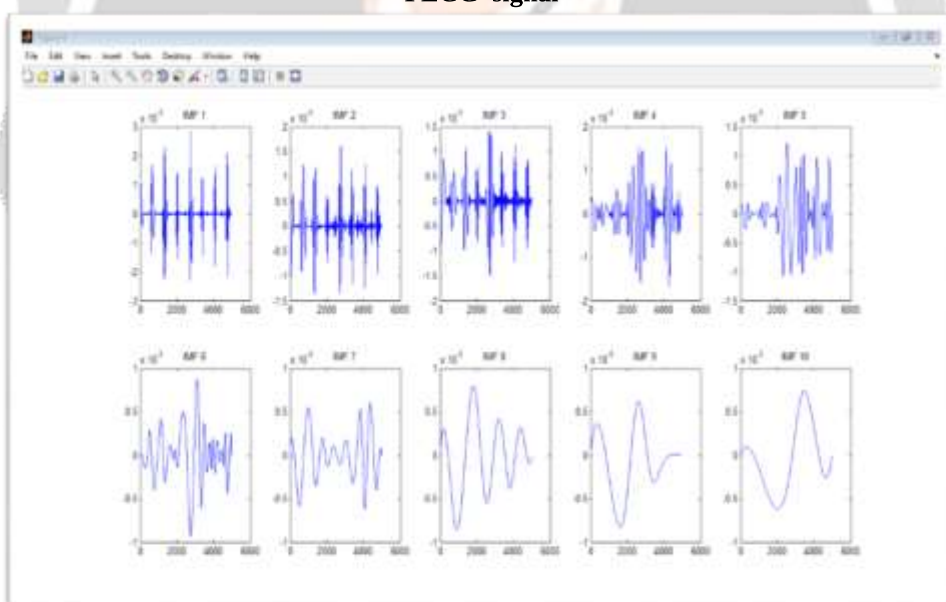
Thoracic signal

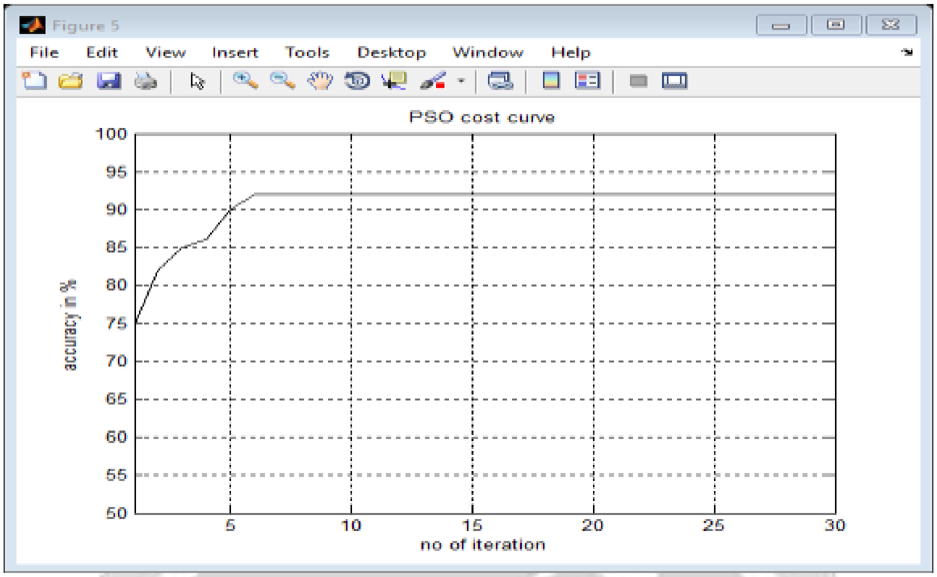


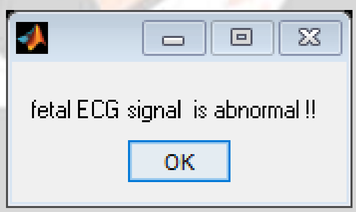
Abdomen signal



FECG signal







V - CONCLUSION

This proposed system is originated with the collection of abdominal waveform and this signal is subjected into LMS filter. The filter is producing the fetal ECG which is an adaptive filter. The EMD based signal decomposition is carried out ans the features extracted and PSO based feature selection makes the system more pricise and finally the system is successfully implementing the Ada-Boost classifier based signal classification system. The results show the effectiveness of the proposed system and the accuracy of the proposed system indicates about the truthfulness of the proposed idea in fetal health monitoring

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