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Signal Processing Techniques for Classification of Fetal Electrocardiogram: A survey

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Abstract: *Fetal heart features are different from those of adult heart in many aspects. This paper presents the detailed survey on different features of fetal heart, which are P-wave, QRS wave and T-wave amplitude and width, segment intervals like PQ interval, RR interval, Heart rate, Heart rate variability, fetal heart axis, these are the standard and most required features. This paper reviews the different techniques used to analyze fetal ECG such as preprocessing, feature extraction, classifying the fetal ECG into normal and abnormal class. Several studies have been published based on these techniques. Out of these few significant studies have been compared in this paper. According to the literature, classification accuracy claimed is in the range of 92 to 99.68%. Although there has been significant variation in the range of accuracy it is at the cost of various other factors such as computational complexity.*

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I. Introduction

Fetus examination is critical and crucial area. Cardiac deformities are manifested with an average of one in every hundred infants conceived in a year. Fetus health also refers to the health of women during pregnancy, childbirth and the postpartum period. Pregnancy can provide an opportunity to identify existing health risk and fetus and to prevent future health problems for mother and fetus. In developing nations like India particularly in rural and downtrodden areas, pregnant women are not conscious about the balanced nutrition diet and their health care during earliest stage of pregnancy which causes maternal mortality, fetus morbidity, early infant death or handicapped child. To address this issue several researchers have published their work.

For diagnosing fetus health, it is important to analyze fetal ECG, which gives us adequate information about fetus status. There are many researchers who studied fetus electrocardiogram, and defined its properties. Obtaining fetus electrocardiogram is also difficult. There are various methods and techniques of recording and extracting fetus electrocardiogram, like Invasive and Non-invasive, direct and indirect method, linear and nonlinear decomposition and more. Fetal heart rate monitoring is helpful to know about fetus well-being and to detect the threat in pregnancy or in the time of labor. Fetal heart rate monitoring is especially helpful in pregnancy conditions such as high blood pressure, diabetes and problems with fetal growth [1].

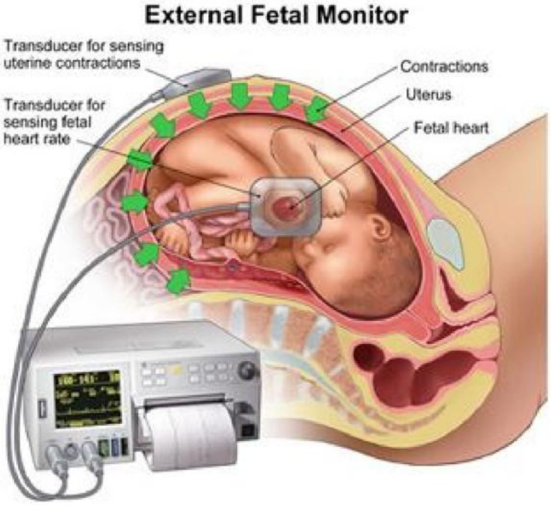

Figure 1: Measurement of fetal ECG[3]

According to [3][4] Fetal monitoring test includes:

- Non-stress test (it measures the fetal heart rate respect to fetal movements)
- Stress test (it is a procedure which provides diagnosis of possibility of coronary artery disease and probability of prognostic parameters like need for urgent surgery, risk of myocardial infarction, and sudden death)
- A contraction stress test (is a procedure which observes fetal heart rate with uterine contractions which are stimulated with methods of medication)
- A biophysical profile-BPP (it is a test which combines a non-stress test with ultrasound)

Methods of obtaining fetus ECG:

1. **Invasive** (Internal fetal heart monitoring): Invasive diagnostic test is the type of medical test in which physicians use instrumentation to physically enter to the body. Electrocardiography (ECG) acquisition system uses contact method which makes electrode contact with human skin. A clinic ECG system uses an electronic transducer directly connected to fetal skin. Electrode with wire connected to the monitor and is joined to the fetal scalp through the cervical opening. Internal monitoring gives more consistent and accurate reading of the fetal heart rate compare to external monitoring because movement factors do not affect it. Invasive monitoring can be used when non-invasive monitoring of the fetal heart is in-adequate or closer and accurate readings are needed. With invasive monitoring, some slight discomfort during the insertion of the electrode may experience. Risks of invasive monitoring may include infection and bruising of the fetal scalp or other body part of fetus.

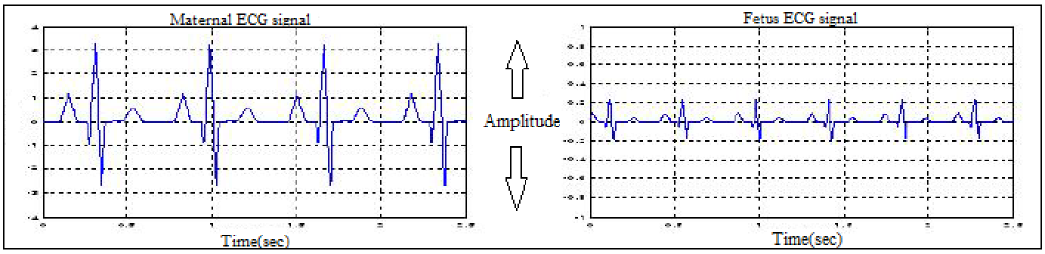

Figure 2: Maternal and fetal ECG[32]

2. **Non-invasive** (External fetal heart monitoring): It uses an instrument to listen and record fetal heartbeat through the mother's abdomen. A fetoscope (type of stethoscope) the most basic external monitor. Another type of monitor is Electronic Doppler ultra-sound device. As scalp electrodes fetoscope or Doppler ultra-sound device can also be used to monitor the fetal heart rate at regular intervals during period of labor. An ultrasound transducer situated on mother's abdomen, conducts the sound of fetal heart to a computer. Pattern and rate of the fetal heart are display on the computer screen and printed on graph paper. Here no radiation used and no comfort affected by the application of the transducer on the abdominal or fetus skin but the elastic belts that hold the transducer in place around abdomen may give slight discomfort which can be readjusted to feel comfortable.

Alternative measurement techniques for fetus monitoring:

1. Echocardiography
2. Phonocardiography
3. Pulse oximetry
4. Cardiotocography
5. Magnetography

II. Adult Heart Properties

Though adult heart and fetal heart are of same biological structure and same features but differs in terms feature values. Morphologically, adult and fetus ECGs have similar patterns, but the relative amplitudes and intervals of the fetal complexes go through considerable changes throughout pregnancy and even after birth. The most significant change concerns the T-wave, which is rather weak for fetus and newborn. An adult heart beats about 60 to 80 times per minute.

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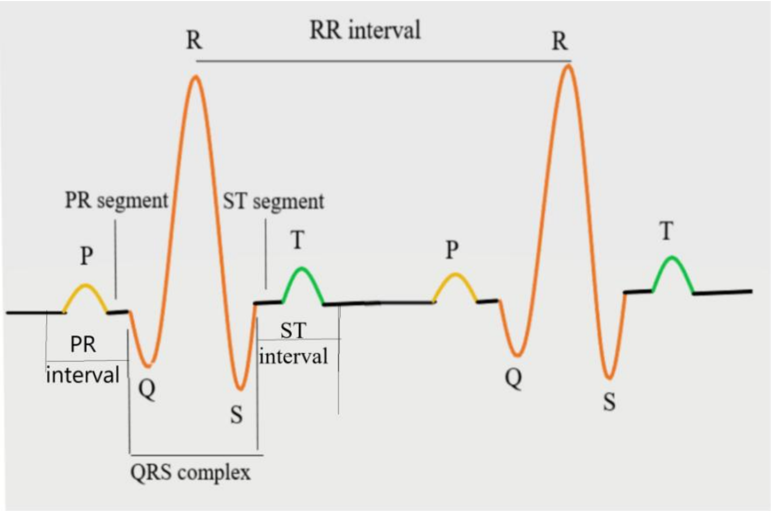

Figure 3: ECG P-QRS-T wave

In reference to above figure..
QRS normal amplitude is 2.5 - 3.0 mV.
Segment intervals:

- RR-interval: 0.6-1.2 secs.
- P-wave: 80 ms.
- PR-interval: 120-200 ms.
- PR-segment: 50-120 ms.
- QRS complex: 80-100 ms.
- ST-segment: 80-120 ms.
- T-wave: 160 ms.

III. Fetus Heart Properties

There is some functional difference between fetal and the adult heart. It is known that left ventricle is responsible to pump blood to body and right ventricle does pumping of blood to lungs to get oxygen. For the fetus, placenta supplies oxygen, therefore pumping of blood to the lungs is no longer made for this purpose. Instead, both the ventricles pump blood throughout body including lungs [1][9]. For this, there used two shunts, the foramen ovale and the ductus arteriosus, that performs linking outgoing vessels of both the ventricles. This allows entering blood to the right atrium and bypasses pulmonary circulation. Similarly the ductus venosus avessel that bypasses blood through liver. It carries oxygen with nutrients and blood from the umbilical cord to right side of fetal heart [10]. This change slightly after birth, with the first breath the foramen oval closes and ductus arteriosus closes partially in just 10-15 hours post birth and closes completely up to three weeks. After cutting the umbilical cord when the blood flow between the mother and the fetus stops, theductus venosus also closes shortly [10].

Fetus ECG features values (standard):
P-wave: Single ECG beat starts with P-wave, which is produced due to depolarization (contraction) of right and left atria. P-wave has normal amplitude of**0.05mv** [2].

QRS complex: This is the highest peak of ECG beat, consisting of Q-R-S waves combine and produces due to re-polarization (relaxation) of ventricles. Where, Q and S waves are having negative amplitude and R peak has highest amplitude of **0.25mV** [2].To obtain R-peak by Gaussian, Gaussian gives R wave, first derivative of Gaussian gives Q and S wave, and second derivativeof Gaussian gives Q-R-S wave, combination of these is used to describe the QRS complex.

T-wave: T-wave produces due to re-polarization of atria**.** Amplitude in adults is less than 5mm in limb leads, less than 15mm in precordial leads. Elevation in T-wave and ST-segment can cause fetal-Hypoxia, adultcoronary artery disease. Shape of ST- segment discriminates between fetus coping with normal stress of labour and in distress, which also includes persistent rising of T-wave amplitude, negative T-wave and depressed ST-segment**.** T wave abnormalities are peaked T-waves, hyperacute T-waves, inverted T-waves, biphasic T-waves, camel hump T-waves, flattened T-waves [11].

Heart rate and Heart rate variability: Normal fetus heart rate is in between 120-160 beats per minute. However, FHR variations are different to fetus, children and adults, the FHR is known to possess periodic variations over the pregnancy [12]. Although, the HRV of fetus is less dynamic than HRV of an adult. As the fetal autonomic nervous system involves, the HRV pattern becomes more complex [13][14].It is also found that a number of heart rate accelerations and decelerations that a fetus undergoes per hour is related to its health, and is dependent on gestational age [16]. HRV features are useful to investigate effects of short term and long term stress using rodent model. It determines optimal HRV feature set by using algorithm called support vector machine-recursive feature elimination (SVM-RFE). According to [28][31] HRV features have their variants in time and frequency domain.

HRV time domain features:
- Mean of RR interval (mRR)
- Standard deviation of RR interval (SDRR)
- HR mean (bpm)
- HR standard (bpm)
- Coefficients of variants of RR intervals (CVRR)
- RMSSD
- pNN5 (it defines the proportion of consecutive NN-intervals that differ by 5ms)
- RR triangular index

HRV frequency domain features:
- VLF power
- LF power
- FH power
- nLF (normalized low frequency)
- nFH (normalized high frequency)
- $\ln(\frac{LF}{HF})$, (the ratio of LF and HF calculated in terms of natural logarithms)

Segment Intervals:-
- P-wave:- 43.9ms
- QRS duration:- 47.2ms or 0.12seconds in adults
- T-wave:- 123.8ms
- RR interval:- 102.1ms

Fetal Heart Axis: Fetus facing the frontal plane is having heart axis $+135^0$, fetus in vertex position rotates to face the sagital plane is having heart axis $+90^0$, while fetus opposing the frontal plane has heart axis of $+45^0$.

IV. Fetus Electrocardiogram Analysis Evolves

In analyzing electrocardiogram there involves three step procedure. ECG signal goes through these steps and gives output in the form of feature set and a class of normality/abnormality. Raw ECG signal passes through the analyzing steps like preprocessing, feature extraction and classification.

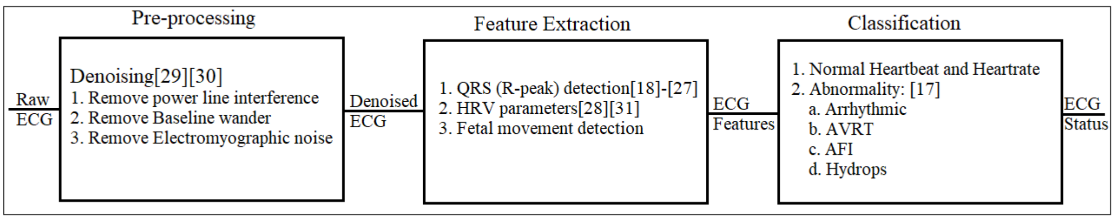

Figure 4: Block diagram of ECG signal processing

1. **Preprocessing:** Preprocessing is applied to remove noise from ECG signal which can include baseline wander, electromyographic signal, power line interference etc. [29] compares noise removal techniques and found low pass filter using Butterworth approximation is best suited filter to filter the ECG signal. Preprocessing is the first step in analyzing any signal as it removes noise and interference from the signal. Noises present in fetus ECG signal are baseline wander, power line interference, Myographic signal (muscle noise), maternal ECG signal etc. for obtaining fetus features it is recommended to have noiseless

fetal ECG. The techniques to de-noise ECG are RC low pass filter, Low pass filter using Butterworth filter, Low pass filer using Chebyshev approximation, RLC notch filter, Butterworth band reject filter[29], A fix lag Kalman smoother to remove powerline interference, non-linear Bayesian filter, Savitzky-Golay filter, adaptive least mean square (LMS) cancellation technique, FIR(finite impulse response) to remove baseline wander, IIR(infinite impulse response) to remove power line interference etc.. In [29] they have compared various filters, for testing they have taken the signal having different amplitude and frequency ranges and pass the signal through filters and found out Butterworth low pass filter more reliable among all, whereas Butterworth high pass filter creates more distortion and Chebyshev filter has poor response.

Butterworth low pass filter can e design using
[B, A]= butter (n, w_n) [29]
Where, n is the order of filter and w_n is the cutoff frequency
B is numerator and A is denominator, the filter coefficients of length n+1

De-noising with wavelet transform:
In [23] they proposed discrete wavelet transform to address the problem of non-stationary nature of ECG signal, by this DWT characterization delivers stable feature to the variations of non-stationary ECG signal. It is derived from mother wavelet by translation and dilation operations Wavelet de-noising involves three processes which are Discrete wavelet transform (DWT), Inverse discrete wavelet transform (IDWT) and Thresholding.

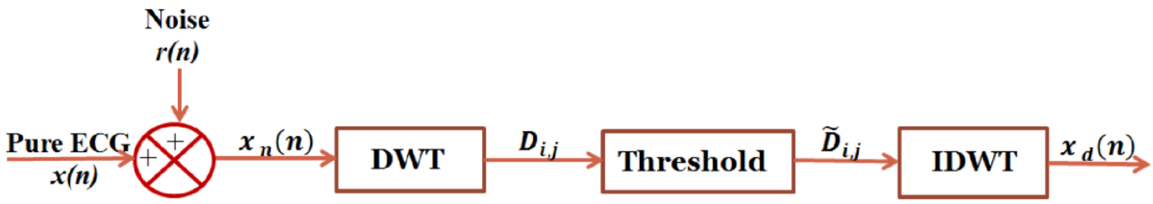

Figure 5: wavelet transform de-noising evaluation diagram [30]

Wavelet transform is used to remove noises present in ECG signal which are baseline drift, myographic noises and power line interference. It takes ECG signal from standard database, mix it with these noises and obtain noised ECG signal (ECG x_nn). This process is evaluated with the help of parameters like input and output SNR and mean square error:

Input SNR_{IN}= $10\log_{10}(\frac{\sum_n x2(n)}{\sum_n r2(n)})$

Output SNR_{OUT} = $10\log_{10} (\frac{\sum_n X_d^2(n)}{\sum_n (X_d(n)-X(n))^2})$

Mean square error MSE = $\frac{1}{N}\sum_n (x_d(n)-x(n))^2$

So, according to [30], there involves three steps in the working of wavelet transform de-noising which is as follows:

1. **Removal of Baseline wander:** for removing base line wander, use DWT to decompose the noisy ECG signal. The noise present is simulated with the sinusoidal signal having frequency range between 0-0.5Hz. The noisy ECG X_d(n) goes through 8 levels of approximation for removing noise under following formula:

$X_d(n) = \sum_{k=1}^{k=8} D_k$

Where D_k has different frequency ranges between 0-0.5Hz at 8 different levels from k= 1 to 8

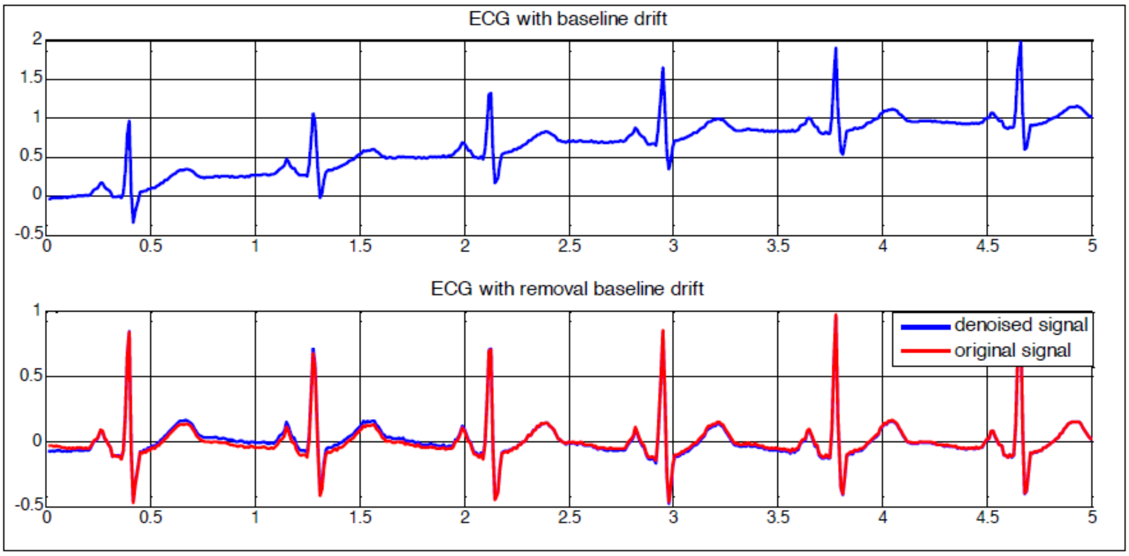

Figure 6: Removal of Baseline wander[30]

2. **Removal of EMG:** the EMG noise (electromyographic noise) contains additive Gaussian noise, to eliminate this DWT coefficients are used which are computed by different wavelets and to select best suited wavelet among all suggested, best thresholding method is used.

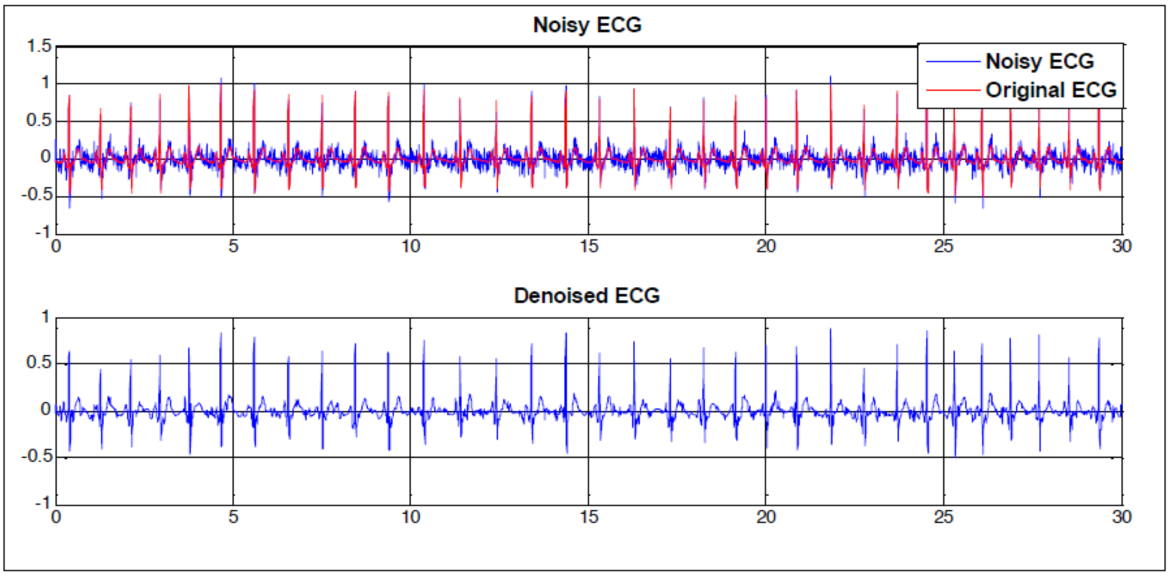

Figure 7: Removal of EMG noise simulation[30]

3. **Removal of power line interference:** To synthesize this noise, sinusoidal signal is superimposed on the ECG signal. Appropriate level of decomposition is selected on the basis of matching of frequency between superimposed signals. Here also thresholding is used to estimate the impact of noise on details coefficients which then used to reconstruct the de-noised ECG signal.

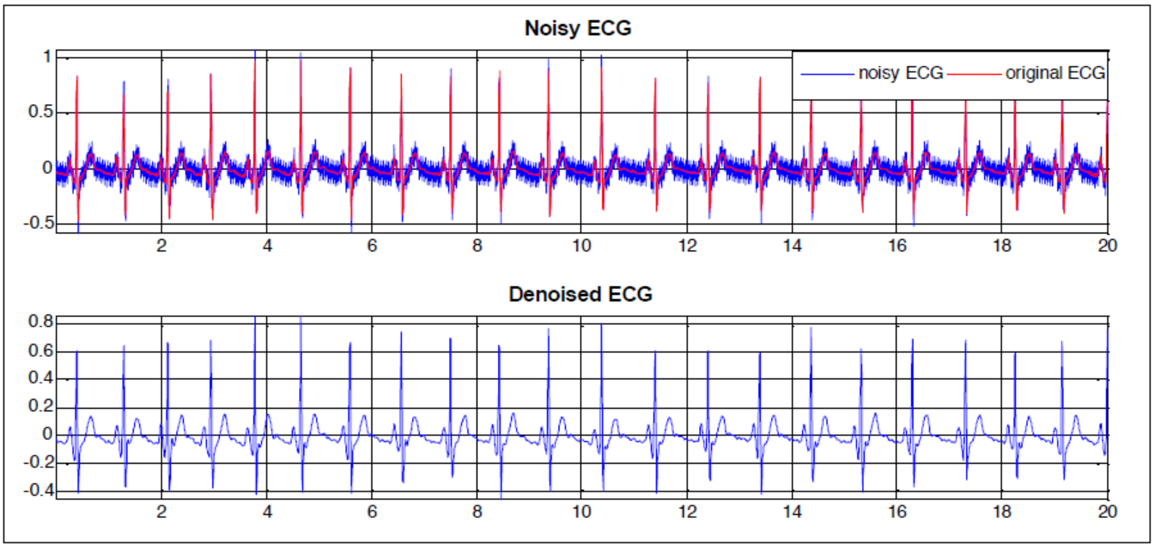

Figure 8: Removal of Power line interference

2. **Feature extraction:** For feature extraction some proposed techniques are PCA/ICA based feature extraction techniques, Wavelet transforms techniques, FPGA based separation techniques, techniques using compressed sensing, linear and non-linear decomposition techniques, feature extraction algorithms like MICA algorithm, pan-Tompkins algorithm, PTE algorithm. Among these many techniques of feature extraction, it is seen that wavelet transform used in [19][21][24][25] earned significant predictivity and accuracy around 92-99.68% when used with SVM and ANN classifiers. Whereas, variations of wavelet transform proposed in [22][23] uses mathematical approach and DWT thus found more complex and gives less predictivity. Once the signal is de-noised, feature extraction algorithm is applied on signal to get various essential features. There are various feature extraction techniques stated by researchers which on application on ECG signal give features like P-wave amplitude, QRS complex, T-wave amplitude, segment intervals like RR interval, fetal heart axis. These features can also be used to diagnose diseases.These techniques differ in feature selection techniques like PCA/ICA, wavelet transform based techniques, compressed sensing based techniques, method of adaptive noise canceller, high frequency removal using digital filter etc.

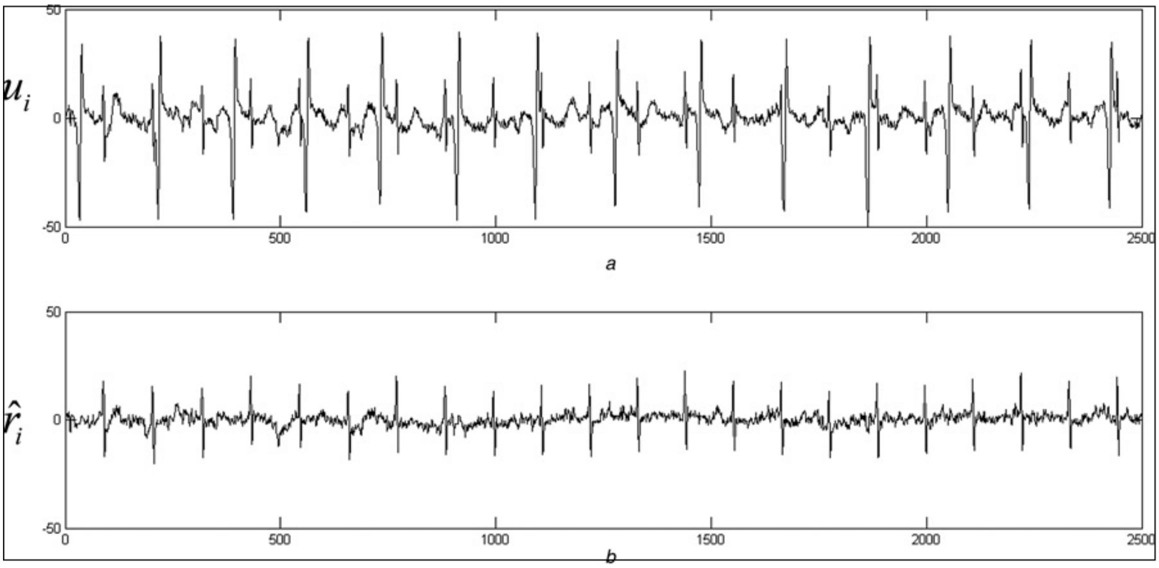

Figure 9: FECG extraction on real ECG signal[33]

2.1 PCA/ICA based feature extraction technique: PCA/ICA based feature extraction technique uses the famous Pan Tompkins QRS detection algorithm to attenuate maternal peaks from abdominal ECG which then leaves only significant fetal peaks in the signal.

Pan Tompkins algorithm:

1. Band pass filtering: The band pass filter reduces the muscle noise, power line interference, base line wader and T-wave interference. Here passband of 5-15Hz is used.
2. Low pass filter: Here the cutoff frequency of 11 Hz and the gain of 36are taken. Filter processing delay is of 6 samples.
3. High pass filter: High pass filter design is done by subtracting output of first order low pass filter from output of all pass filter (the samples in original signal).
4. Derivative filter: signal derivative is used to provide the QRS complex slop information. The signal gets differentiated after filtering.
5. Squaring function: step after derivative is squaring function, which does nonlinear amplification of output of the derivative and makes all data points positive.
6. Moving window integration: from moving average integration, feature information of waveform is obtained in addition to slop of the R-wave.
7. Fiducial mark: it gives the temporal location of QRS complex and is obtained by rising edge of the waveform feature which can be mark as maximal slope or R-peak.
8. Adjusting the threshold: The highest among two thresholds in each of two sets is considered for the first analysis of a signal. Low threshold are results of the improvement of signal to noise ratio when de-noised by Band-pass filter. The lower threshold is considered if QRS complex is not detected during certain time period, so that a search back technique can be applied for detection of QRS complex.
9. T-wave identification: When an RR-interval is less than 360ms (it required being greater than 200 ms latency), a judgment is made to determine whether the identified wave is QRS complex or a T-wave. If the maximum slope occurred during this waveform is less than half of a QRS waveform preceding it, then it is identified to be a T-wave, otherwise it is noted as a QRS complex.

2.2 Wavelet based feature extraction techniques:

Wavelet decomposition can be used for noise removal as well as feature extraction. Combining with machine learning algorithm, wavelet can also be used for classification. In [18]-[27] they have discussed about wavelet and its decompositions used with various classifiers and compare the results they produced. In [20][21][22][26] they used wavelet transform for abnormal heart beat detection, QRS complex detection, P-wave detection and T-wave detection. Work performed in [19] they used two different feature extraction algorithms to obtain feature vector, which are wavelet transform and AR(auto regressive model). Support vector machine (SVM) with Gaussian kernel is implemented for further classification of heart rhythm. This gives efficiency of 99.68%.

Figure 10 shows comparison of various feature extraction techniques used in fetal ECG analysis along-with their accuracy reported.

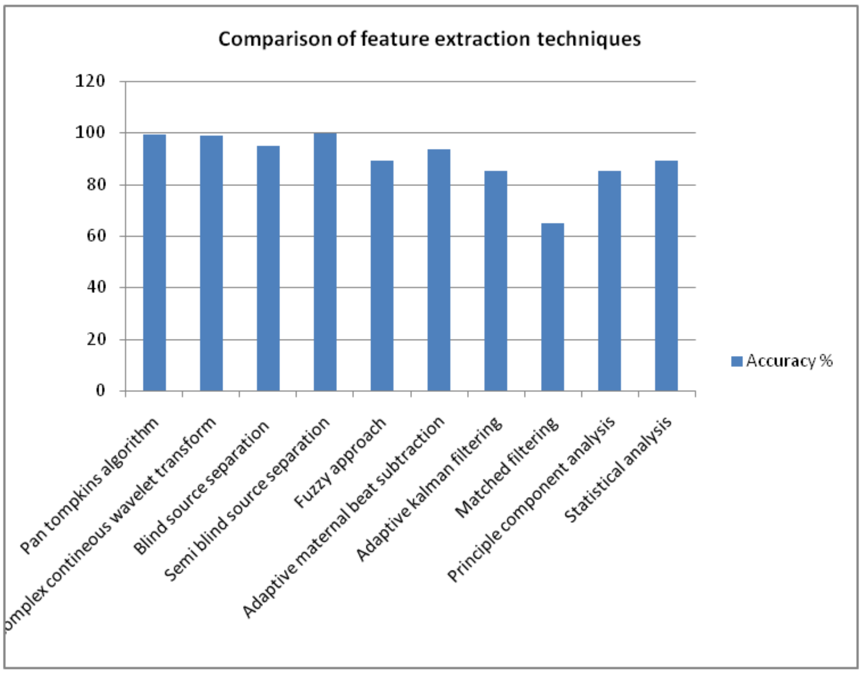

Figure 10: Comparison of feature extraction techniques

3. **Classification:** After extracting features, to classify them in normal and abnormal class various classification techniques are proposed and studied by researchers which are SVM(support vector machine) classifier, LDA(linear descriminant analysis), Quadratic analysis, ANN/KNN classifier, Fuzzy decision classifier, Fuzzy KNN, Neuro Fuzzy etc. In [28] they have proposed SVM classifier and obtained accuracy of 96%. In classification step extracted fetal features are classified as normal and abnormal (arrhythmic) class. Mostly HRV (heart rate variability) features are considered as they are the most significant feature to take into account. SVM recursive feature elimination uses sequential backward elimination based on SVM. It develops individual multiclass SVM. SVM classifier has highest accuracy (93.11%) with an optimal HRV feature set consisting mRR, CVRR and SDRR as time domain features, whereas nLF and nHF are frequency domain features[31].Though there are many more machine learning tools for classification, SVM is proved to be most reliable and efficient classifier. SVM is a popular machine learning algorithm used for pattern recognition, object identification, image segmentation, character recognition and classification. SVM classifier utilizes complex features to classify ECG into normal/abnormal class by the process of clustering, classification and ranking. The process of separating values and grouping performed by decision function between these two classes. Weight and bias values is applied in classification process to minimize the cost function [28].

Consequences of abnormal feature values:

Whenever classifier classifies abnormal beats that means it is threat to human health. Abnormal feature values are the indications of cardiac diseases which are necessary to cure. Some cardiac diseases are mentioned below [17]:

1. AVRT (Atrioventricular Reciprocating Tachycardia): If Heart rate>200bpm, which can cause Rapid heart rates, Abnormal electric connection in heart(creates extra connection between one of atria and one of ventricles)
2. AVRT creates extra connection between upper atria and lower ventricle, called “accessory gateway” which is abnormal connection. Normal electric connection between atria and ventricle which consist of AV node and its bundle, is the normal cardiac conducting system
3. AFI (Atrial Flutter): If Atrial rate>300bpm, this causes premature delivery, hydrops, fetal death, If heart rate goes 300-600bpm, cause fetal tachyarrhythmia.
4. Hydrops: Hydrops fetalis is a life threatening problem of severe edema (swelling) in fetus and newborn [17].
5.

V. Conclusion

As summary of this review paper, we observe difference between maternal and a fetus heart properties with different feature sets. Alongside, we discuss and compare various techniques and algorithms to process fetus Electrocardiogram and obtained its feature values. This processing includes preprocessing, feature extraction and classification. Also we discuss the cardiac diseases that can occur as result of abnormal feature values. From this study it is seen that existing fetus ECG processing techniques are having accuracy in the range of 92 to 99%, among which Pan Tompkins algorithm is having highest accuracy of 99.3%. Also, among all studied classifiers SVM classifier is the most reliable classifier proven up to date having accuracy 96%.

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