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GMAC: Graph Based Multi-Attribute Closure Based Fetal Heart Rate Detection using Wavelet Analysis

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Abstract : The human electro cardiogram has various information which is used to predict the condition of maternal. The ECG waveform differs with the various conditions of psychological moments and according to that the maternal heart rate also changes. Identifying and predicting the heart rate of the fetal is important in various conditions, also it is difficult to find the conditions of fetal movements. There are various approaches that have been discussed earlier but those approaches still struggle with the accuracy of identifying the fetal heart rate and separate them from mother's rate. We propose a novel graph based multi attribute closure based fetal heart rate detection method. The method performs preprocessing of input ECG signal using wavelet analysis which removes noisy signals from the input pattern. The preprocessed signal is used to extract the features of electrocardiogram signal. The method maintains set of training samples, where each feature of ECG waveform is organized in to number of classes where each feature forms a separate class. The testing samples feature is assigned as a node of graph and for each node of the graph with the training samples we compute the multi attribute similarity measure. There will be an edge created only if there is similarity between the training samples attribute and test set attribute. The multi attribute closure is computed based on the number of edges it has with the training graph. Based on the MAC measure the class of the ECG is identified and the value of the ECG feature is used to form the ECG waveform. The proposed method produces efficient results in FHR separation and reduces the false separation ratio.

Keywords : Wavelet Analysis, Electrocardiogram, Graph-Based Approach, Multi-Attribute Closure.

1. INTRODUCTION

The fetal physiological condition is dependent on the heart rate, which is most related to the mothers cardiogram signal. The Electro Cardiogram represent how the human heart is responding to the electrical signal and it shows the activity of heart that is what we call heart beat. The ECG records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Some ECG stretches two kinds of info, the duration of the power wave journey the heart which in turn chooses whether the power action is standard or slow or uneven and the quantity of electrical work passing through the heart power which enables to find whether the parts of the emotion are too great or overworked.

Wavelets alter a signal processing method used in various requests to decompose, filter, feature withdrawal, etc. Wavelet alter huge impact in biomedical organizations for signal dispensation. For many signals, the low-frequency gratified is the most significant part. It is what stretches the signal its individuality. The high-frequency gratified, on the new hand, imparts taste or nuance. To gain a better gratitude of this process, it does a one-stage discrete wavelet convert of a signal. The rottenness process

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can be repeated, with numerical approximations being disintegrated in turn so that one sign is broken down into numerous lower resolution mechanisms.

In wavelet examination, a signal is driven into an estimate and a detail. The estimate is then himself split into a second-level approximation and detail, and the process is repeated. The transformed signal provides information about the time and the frequency. Using this approximated information low frequency data could be identified, which is more important in cardiac illness calculation.

A characteristic scalar electrocardiographic principal is shown in Fig. 1, anywhere the significant topographies of the waveform are the P, Q, R, S, and T waves, the period of each wave, and convinced time intervals such as the P-R, S-T, and Q-T intermissions.

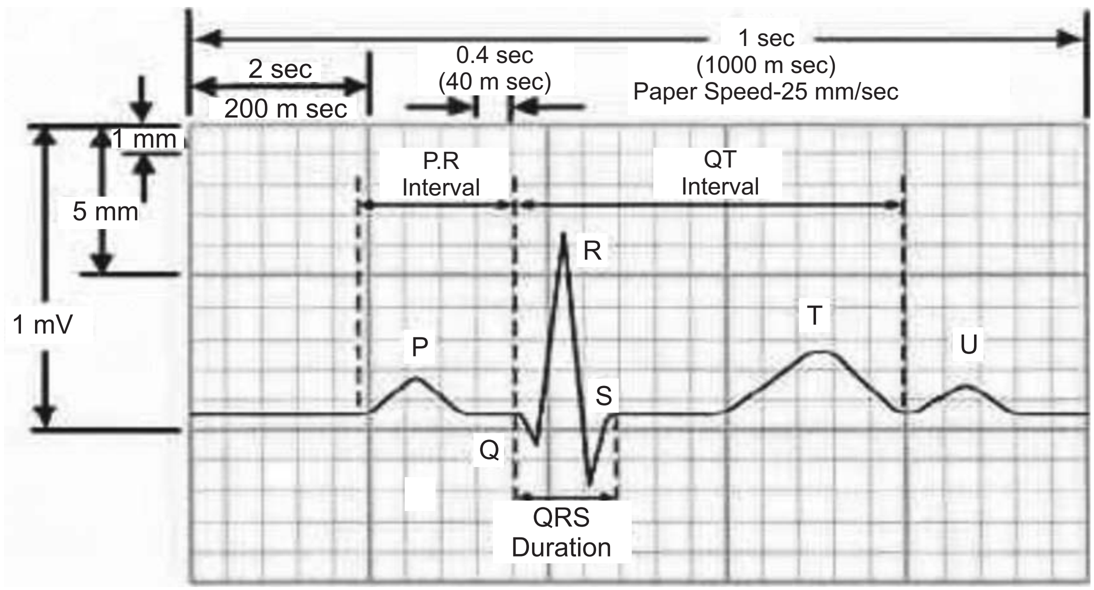

Figure 1: Standard ECG waveform

If we observe figure 1, we may notice that a single period of ECG indicator is a assortment of triangular and sinusoidal waveforms. Each extraordinary nose of ECG signal can be signified by shifted and climbed versions of these waveforms as shown below.

1. QRS, Q and S helpings of ECG signal container be signified by three-sided waveforms
2. P, T and U portions can be meant by triangular waveforms

Once we generate each of these portions, they can be added finally to get the ECG signal.

Let's take QRS waveform as the center one and all unstable takes place with respect to this portion of the indication. From the above discussion any signal from waveform can be identified by the following function.

$$f(x) = (a_o/2) + \Sigma a_n \text{chors}\,(n\pi x / \text{l}) \qquad (1)$$
$$n = 1$$

The above equation shows that the waveforms signal can be represented using the cosine function up to any number of series.

The ECG signals can be represented as a graph where the graph has N number of nodes according to the number of the signal present in the waveform. The similarity between any two graphs can be computed based on the number of similar edges and the number of nodes which are similar in the chart. According to the node similarity, we can identify same class data points.

The multi-attribute closure is the measure which is computed based on the similarity values of nodes of any two graphs; also the node-similarity based closure is calculated based on multiple attribute values which are available in the nodes of graphs. The multi-attribute closure enables the selection and identification of similar class values efficiently.

2. RELATED WORKS

The ultimate aim of FHR detection is to estimate the level of oxygen supply to the organs of fetal where the direct estimation is not possible in the labor. Still, the symptoms of risk have to be identified in some other way by performing heart rate analysis. There are numerous methods has been deliberated earlier in literature, we discuss few of them here around the problem.

In Fetal Electrocardiogram Removal Using Adaptive Neuro-fuzzy Implication Schemes and Undecimated Wavelet Alter [1], FECG is removed from the motherly electrocardiogram using adaptive neuro-fuzzy inference schemes and undecimated wavelet alter is proposed. The presentation of the proposed system is compared with the average discrete wavelet alter. For numerical assessment, the mean four-sided error between de-noised FECG indication and initial FECG indication is used.

A fast method for non-invasive fetal ECG extraction [2], labels a quick and actual simple procedure for approximating the fetal electrocardiogram. It is based on self-governing component analysis, but we supernumerary its computationally challenging runnings for a much more straightforward technique. The resulting process consists of two step ladder: as a dimensionality reduction step and a computationally light post handing out stage used to increase the FECG indication.

A Technique for Subsample Fetal Emotion Rate Approximation under Noisy Circumstances [3], consider a new method for estimating the critical period in fetal ECG waveforms. This method is based on the minimization of a cost meaning that actions the differences amid the discrete Fourier convert of the fetal ECG waveform and the DFTs of its circularly shifted procedures. By the lined phase shift property of the DFT, a we demonstration that the minimization of this cost purpose is equivalent to discovery the cosine waveform that competitions best to the ECG power range. The optimal cosine waveform is formerly used to estimate the critical period. This method is based on the minimization of a cost purpose that measures the alterations between the separate Fourier alter of the fetal ECG waveform and the DFTs of its circularly removed forms. By using the lined phase shift possessions of the DFT, we show that the minimization of this cost purpose is equivalent to discovery the cosine waveform that competitions best to the ECG control range.

A technique of extracting fetal ECG founded on the adaptive linear neural net is proposed in [9]. It can be understood by exercise a small quantity of data. A frivolous procedure, which extracts the fetal ECG through a pre-knowledge about its skewness is obtainable in [10]. By using the skewness, a cost purpose is defined by which Weight course is efficient and through this wanted fetal ECG signal is removed.

A technique founded on the fetal ECG removal procedure OL-JADE [11], which stabs to invert the complete blind extraction process only for the FECG, projected sources in instruction to estimation the FECG power at the conductors. Owing to the recursive sample-by-sample countryside of the blanching stage of OL-JADE, and approached Least Quadrangles solution has been proclaimed in the back forecast arrangement revealing passable exhibition.

Design Practice of a New Wavelet Foundation Purpose for Fetal Phonocardiography Signals [20] presents a new mother wavelet basis purpose for denoising of fPCG indications. The performance of fresh developed wavelet is found to be healthier when likened with the existing wavelets. For this drive, a two-channel filter bank, founded on characteristics of the fPCG sign, is designed. The subsequent denoisedfPCG signals recall the relevant analytic information limited in the original fPCG signal.

A novel method for fetal heart rate organization introducing logical evolution [21] identifies lined and nonlinear associations among the first removed topographies and creates/concepts a set of new ones, which, in short, feed a nonlinear classifier. The classifier, which also uses a mixture method for training, along with the built features was tested using a set of real data attaining an overall presentation.

Outliers Discovery and Processing in CTG Nursing [22], present in part the updated version of a procedure for detection and alteration of outliers. Then, we assess the impact of outliers and dissimilar correction plans on fetal heart rate examination. Obtained consequences demonstrate that the proper outliers' detection is fundamental because they profoundly influence the guesstimate of fetal heart rate capriciousness, intended by the short term variability, a parameter well acknowledged for its logical value.

The impact of a consistent training package on midwives' aptitude to measure fetal heart anatomy by ultrasound [23], propose an original pedagogical perfect for training midwives inconsistent cardiac imaging which is a model using a think-aloud examination throughout a pre- and post-course test and the following group reflection. The self-estimated problems and knowledge holes of two knowledgeable and two novice midwives remained identified. A two-day course through mixed lectures, protests, and hands-on meetings was shadowed by a feedback session three months later consisting of a meeting then check-up.

All the above-discussed plants have the problem of categorizing and separation of fetal heart rate, and we suggest a naval method using data mining here.

3. PROPOSED APPROACH

The proposed method has various stages namely preprocessing, feature extraction, pattern generation, and FHR detection. Each of the stages will be discussed in detail later in this chapter.

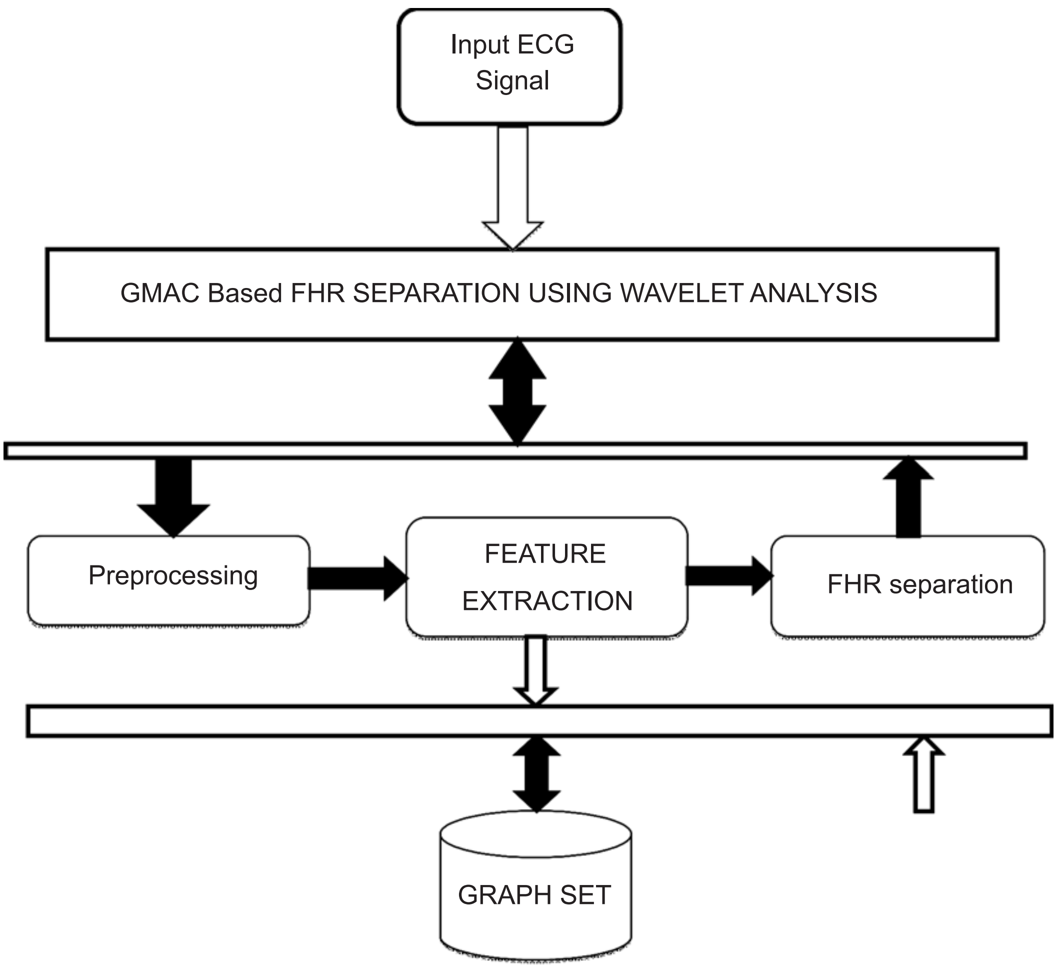

Figure 2: Proposed System Architecture

Figure 2 shows the general architecture of the proposed approach and the functional models of the proposed system.

3.1. Preprocessing Stage:

The wavelet examination is practical on the waveform to decay signals into numerous frequency groups. We select suitable wavelet and a number of rottenness levels for the analysis of signals using DWT. The number of decay levels is chosen based on the leading frequency mechanisms of the signal. The levels are selected such that person parts of the signal that correlate well through the frequencies essential for organization of the signal are booked in the wavelet constants. Since the ECGs consume little useful material above incidence 30 Hz of 173.6 Hz, we have designated five different bands and frequency ranges and one estimate range.

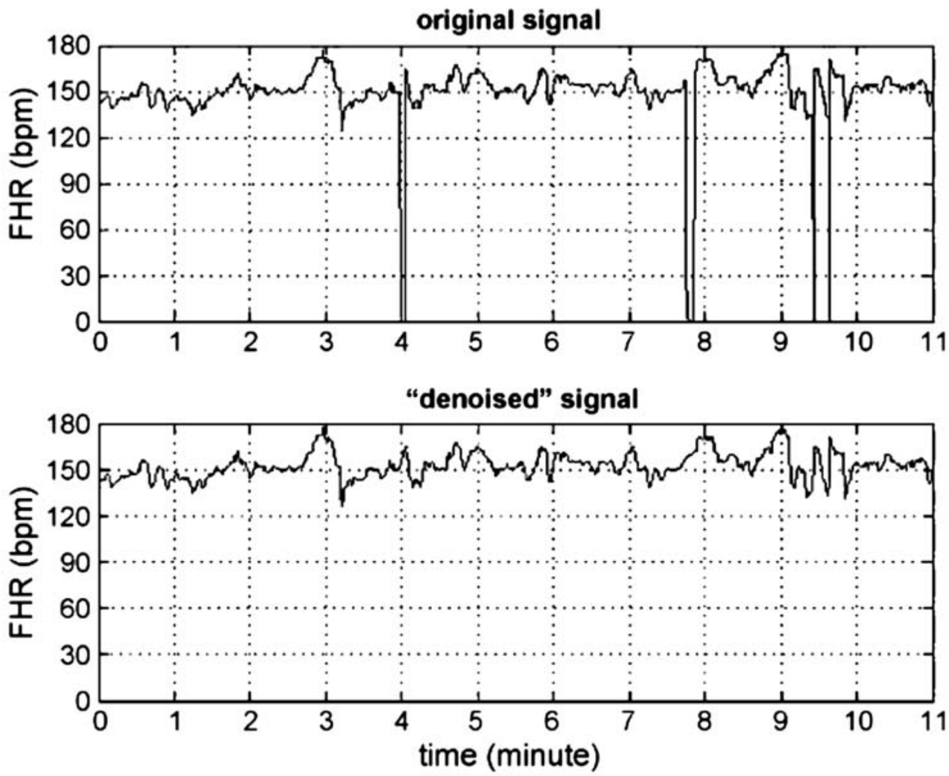

Figure 3: Top graphs show the original FHR signal and the bottom graph depicts the noise removed. We consider the default values for each of the signal and their segment as follows:

Heart beat: 72

Amplitude: P upsurge 25mV, R wave 1.60mV, Q upsurge 0.025mV, T upsurge 0.35mV

Duration: P-R interval 0.16s, S-T intermission 0.18s, P intermission 0.09s, QRS intermission 0.11s

3.2. Feature Extraction:

The preprocessed ECG waveform determination be used for additional processing, in addition, it has many types of machinery namely P, Q, R, S, T waves. Also, the groupings of the mechanisms signify the activity of core at different time surrounds. The electrocardiogram contains various time domain and space domain values; they are amplitudes and intervals of various sectors. We extract P-R interval, R-R interval, Q-T interval, S-T interval, P-wave interval, QRS interval and the amplitude values of P, R, S, Q, T, U waves. We extract Pr-(P-R interval), Rr(R-R interval), Qt (Q-T interval), St(S-T interval), P (P-wave interval), Qrs (QRS interval), PA (P wave amplitude), QA (Q wave amplitude), RA (R-wave amplitude), TA (T-wave amplitude). Each feature extracted is constructed in the form of a pattern in the database for further manipulation.

The procedure of pattern generation is as follows:

Read the preprocessed noise removed signal Ds.

Extract features $$Fi = \int_{i=1}^{N}\int_{j=1}^{N} \forall (j \in Ds)$$

K- Number of features.

Construct pattern $$Ps = \int_{j=1}^{k} Ps \cup Ds(j)$$

Table 1
Example pattern generated in this procedure

Pr sec	*Rr sec*	*Qt sec*	*St sec*	*P mV*	*QRS sec*	*PA mV*	*QA mV*	*RA mV*	*TA mV*
0.17	0.54	0.34	0.19	0.62	0.13	24	0.021	1.54	0.32
0.16	0.53	0.32	0.17	0.59	0.14	26	0.023	1.58	0.34

Table 1, show the snapshot of the pattern made using the proposed approach, and it indicates that the features of the ECG waveform have been extracted and represented in such a way to use it efficiently. Each row of the table is considered as ECG pattern, based on which the separation is performed.

3.3. Graph Generation

The extracted features are used to generate the graphs where each feature set will be considered as a graph. Each distinct graph has N number of nodes and in our case, the number of nodes each graph has 10. The training set has different classes according to the number of emotions we consider and for each emotion we maintain N number of sample charts which has ten features or nodes. Similarly, the input testing set also constructed as a chart using which multi-attribute closure measure is computed.

Algorithm :

Input : Feature Vector FV.

Output : Graph set GS.

Step 1 : Initialize the graph G.

Step 2: for each feature F_i from FV

Create a node $N_{i.}$

Assign value of F_i to N_i

N*i* = Value (F_i).

End.

Step 3: Add graph to figure set GS = $\int \sum Gi(GS) + G$

Step 4: Stop.

3.4. Multi-Attribute Closure

The multi-attribute closure is computed based on the attribute values and their similarity. For each attribute considered, for each input graph with the set of training figures available in the chart set, we compute the graph similarity based on distinct similarity of each node of the chart. Based on computed node similarity of the graph we compute the cumulative similarity of each attribute of the feature set in the training samples. Similarly the same is calculated for each attribute of the feature set of the same class of graphs. Finally, we calculate the multi-attribute closure measure based on the computed attribute similarity measure, which returns a closure value of the input feature vector towards a class of graphs which represent the likeness of the information decoration to the emotion well-thought-out.

Algorithm :

Input : Feature Graph G, Graph Set Gs

Output : MAC Set MS.

Step 1: for each class Cl from C

For each graph G_i of C

For each Node N_i of G_i

Compute Node Similarity NS = $\int_{i=1}^{N} \sum \text{Dist } (\text{Ni} - \text{TG(Ni)}) < \text{DTh}$

End

Add to Cumulative Node Similarity CNS = $\sum$(Nsi(CNS) + NS)

End

Compute Multi Attribute Similarity Measure MASM.

$$\text{MASM} = \int_{i1}^{C} \frac{\text{CNS}}{\varnothing(\text{C}l)}$$

$\varnothing$ – Number of graphs of class Cl

Add MASM to MS.

MS = $\sum$(MASM(MS) + MASM)

end

Step 2 : Stop.

3.5. FHR Separation

The generated graphs are used to perform FHR separation. The generated graphs from the preprocessed signal are used as input and from the data set the pre-computed graph set is retrieved. With the input graph, we compute the multi-attribute similarity measure with the each class of graphs available in the graph set. The graph set which has more graph similarity is identified and based on determined values of each signal values the components of the ECG signal is separated from the input pattern and constructed to form a waveform.

The procedure of FHR separation is as follows:

Read Graph set available Gs from the data set.

In this, each graph represents the pre-identified fetal ECG pattern.

Initialize FHR Similarity Film, distance D, and flag W, Wave setFWS.

For each signal from ECG

Compute Multi Attribute Closure measure MAC.

If MAC is greater than FHR threshold then

Add message to the FWS.

End.

4. RESULTS AND DISCUSSION

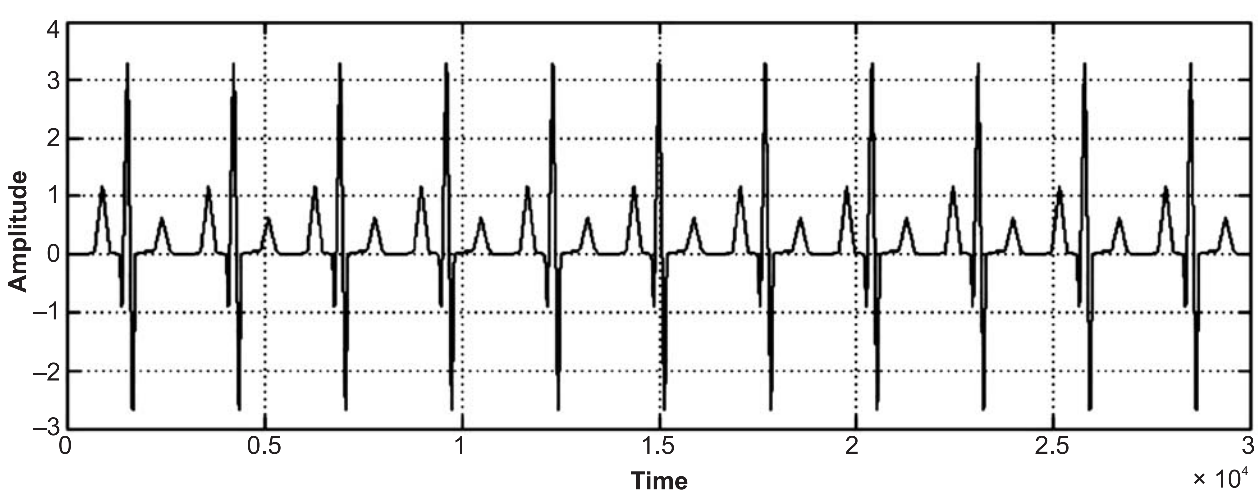

Figure 4: Shows the MECG as input ECG

To inspect the efficacy of the planned system in unraveling the favored FECG signal after the MECG signs, experiments were showed on the replicated signals. The ECG for both the mother and fetus has remained simulated presumptuous sampling degree of 4 000 Hz.

The figure 4shows the electrocardiogram waveforms of the mother.

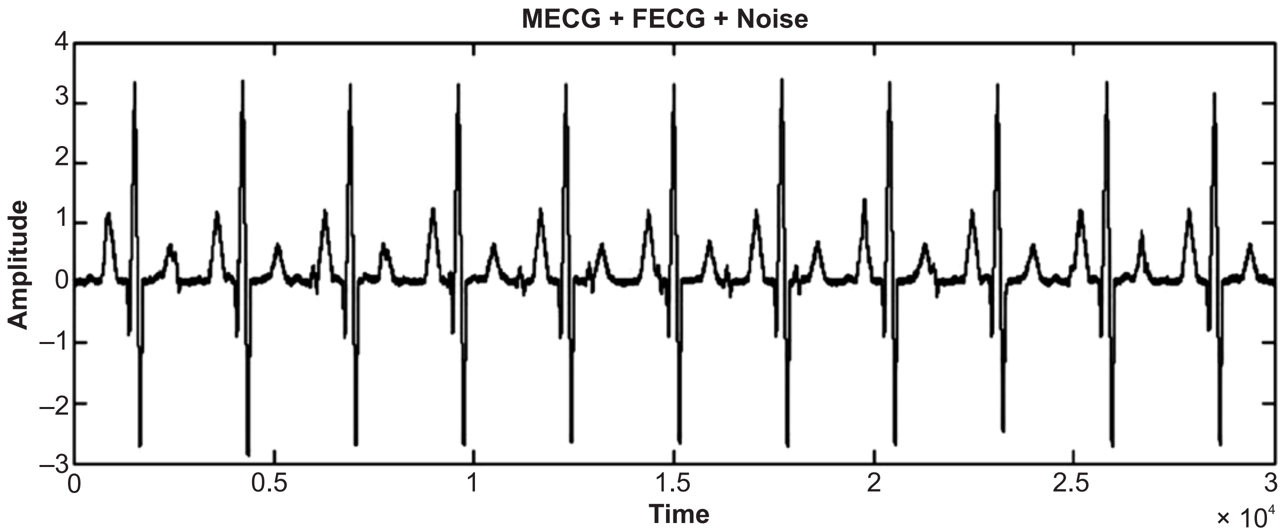

Figure 5: Shows both mother+ fetal+ noise ECG

Figure 5 shows the waveform which contains the electrocardiogram signal of both mothers, fetal with sound signals.

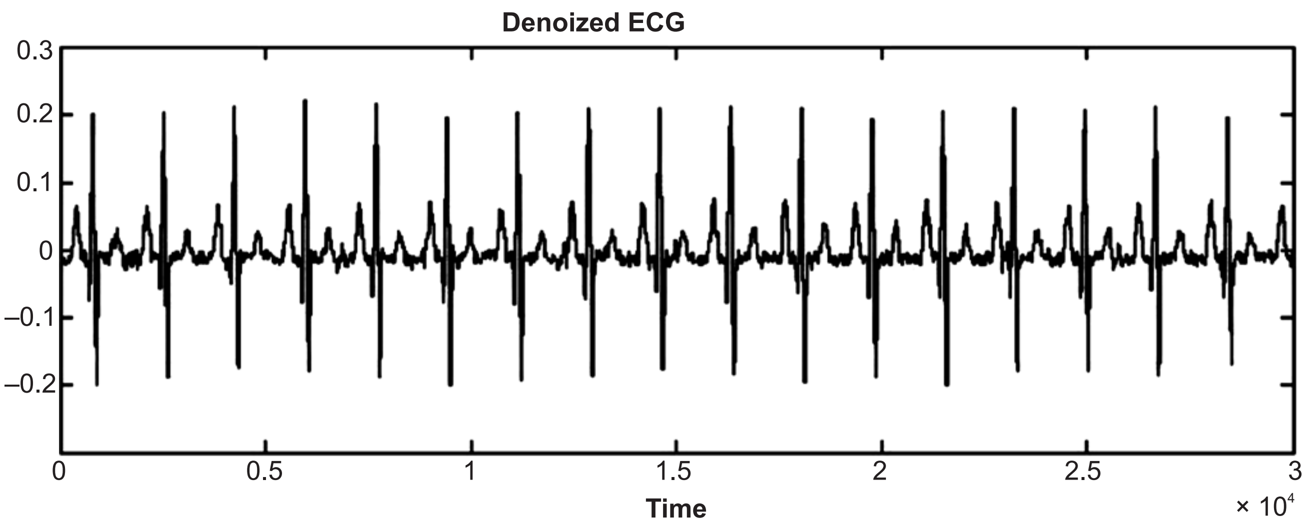

Figure 6: Shows the Noise removed ECG

Figure 6 shows the ECG waveform of both mother and fetal with noise been removed.

Table 2
Comparison of separation accuracy

Method	*Overall Accuracy*	*Average (–)*	*Accuracy (+)*	*Mean Avg*
LDC	68.75	66.92	76.67	71.52
QDC	72.5	73.85	66.67	68.98
1-NN	80.63	83.85	66.67	70.10
Grammatical evaluation	88.13	86.92	93.33	89.73
Proposed	93.36	82.76	98.47	94.615

The picture demonstrations the unglued fetal electrocardiogram after the mothers ECG.

For numerical assessment, the mean square mistake amid the de-noised FECG indication and the original FECG is used. The presentation of the proposed organization is associated with DWT.

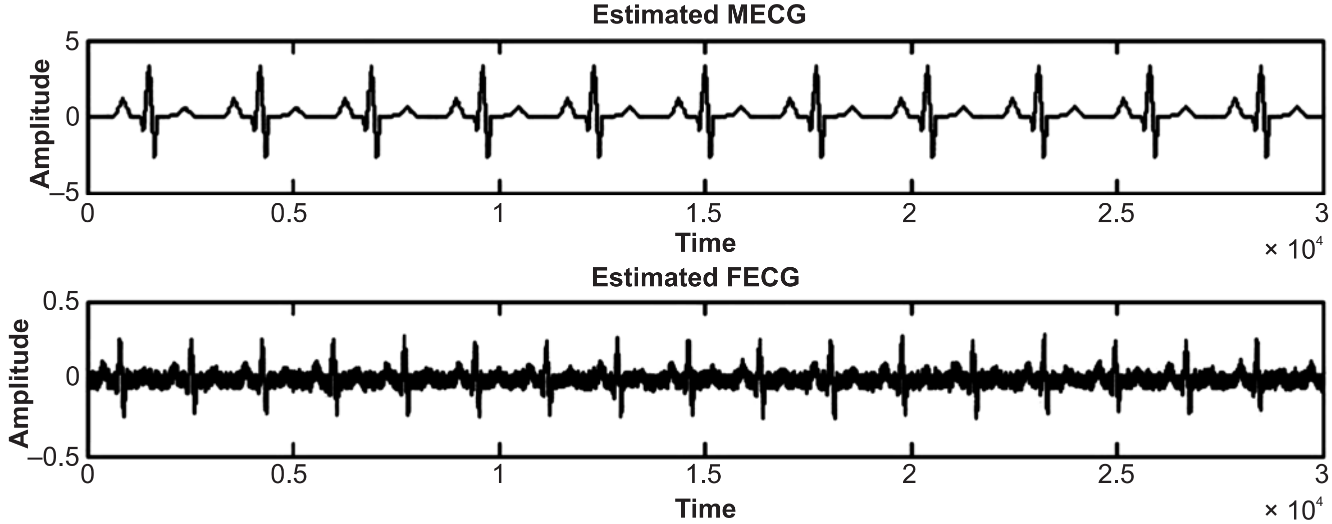

Figure 7: Shows the separated FECG

The table 2 shows the comparison of accuracy produced in FHR separation by various methods. It shows clearly that the proposed approach has produced efficient results compare to earlier standard approaches.

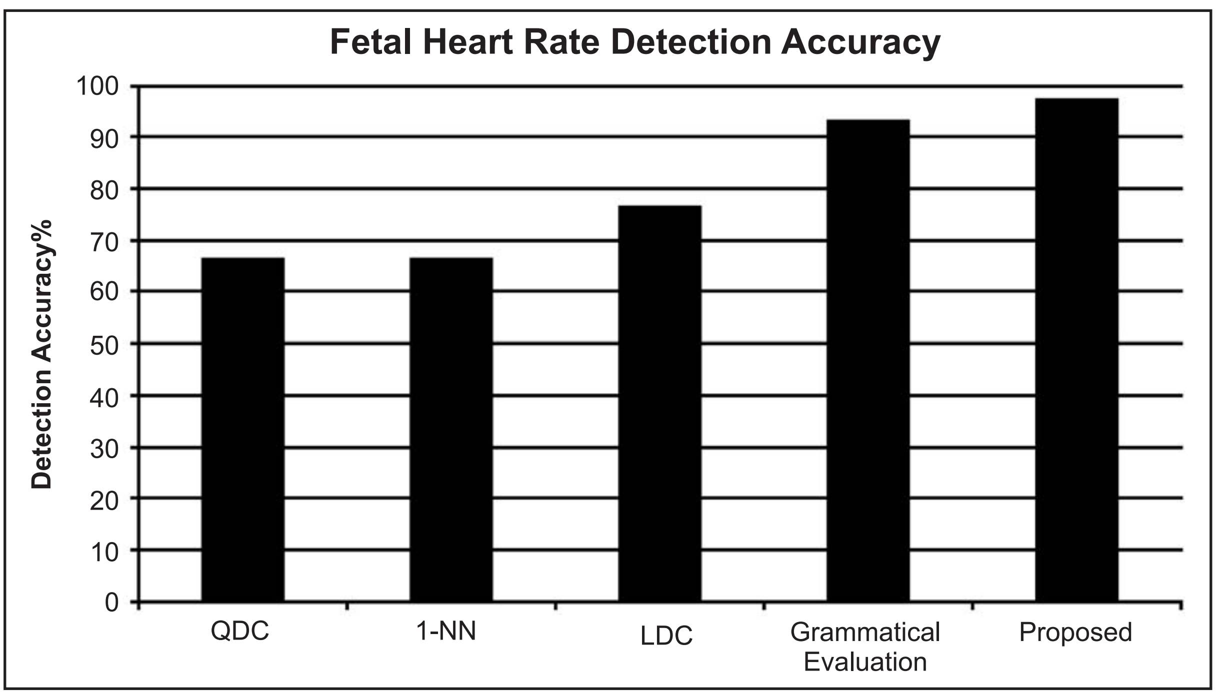

Figure 8: Comparison of heart rate detection accuracy

The figure 8 shows the comparison of heart rate detection of different methods and it shows clearly that the proposed method has produced higher accuracy than others.

The figure 9 shows the comparison of different methods on time complexity where the proposed method has less time complexity than others.

The figure 10 shows the comparison of different methods in false classification produced where the proposed method has less wrong ratio which is negligible.

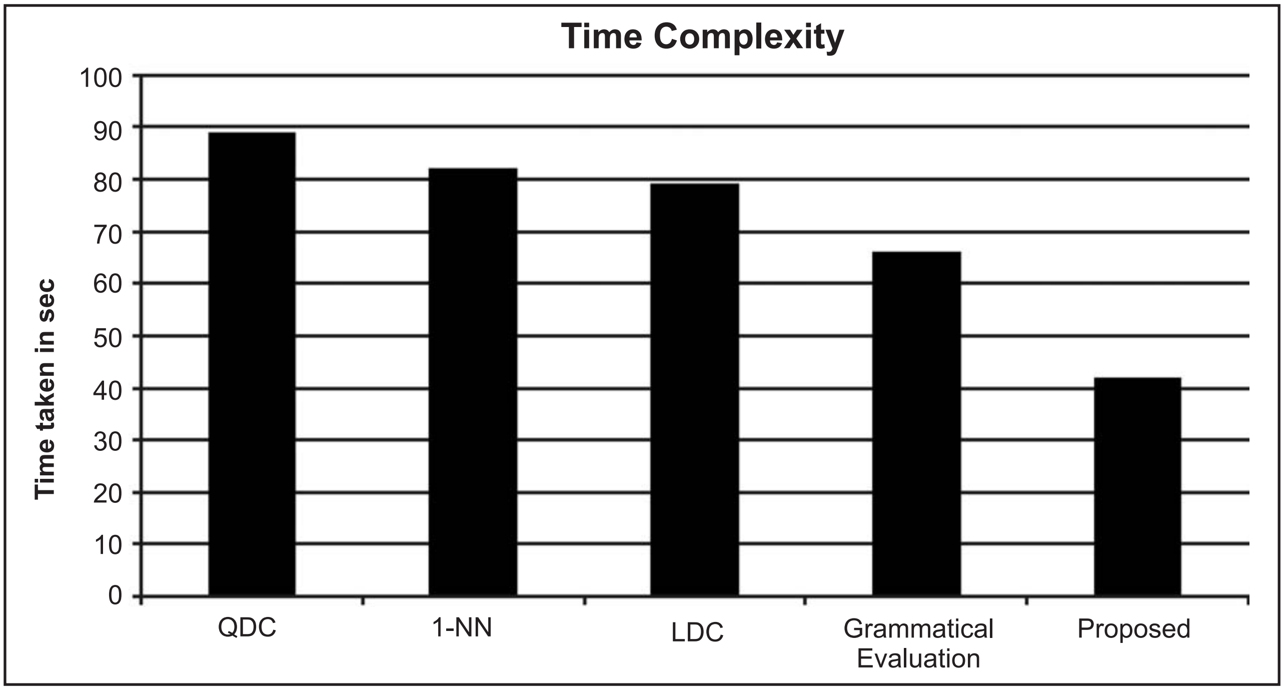

Figure 9: Comparison of time complexity of different methods

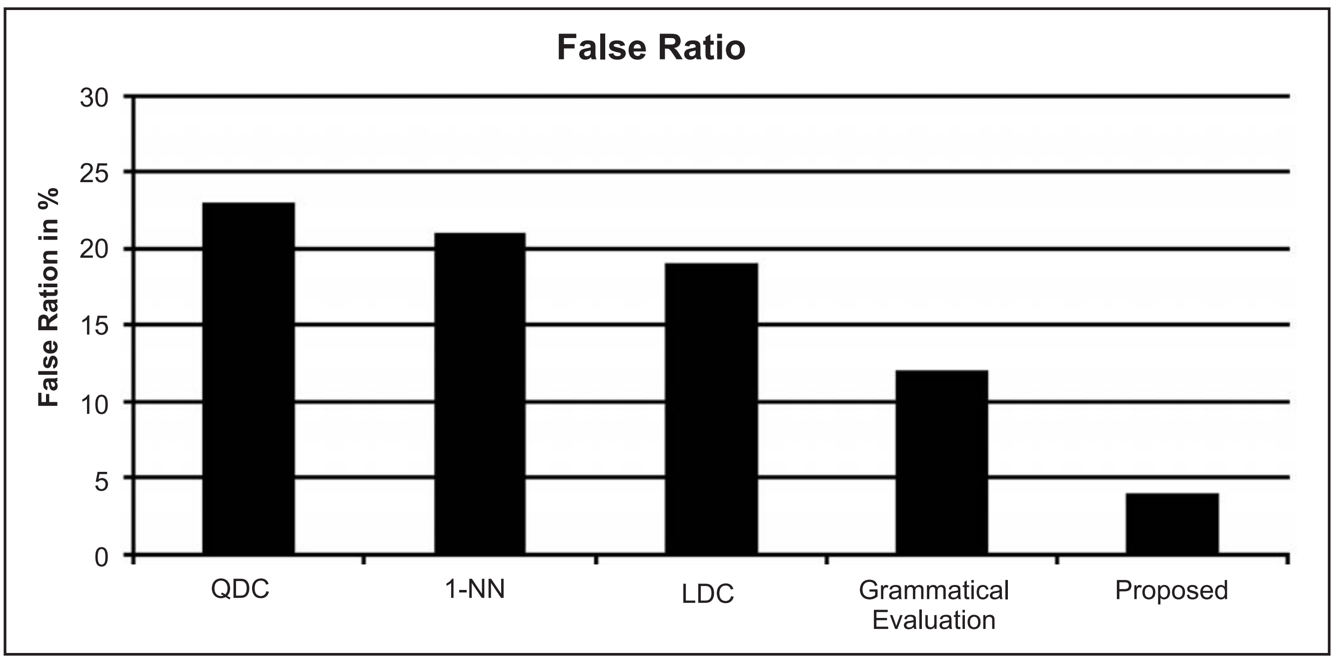

Figure 10: Comparison of different methods in false ratio

The above discussion shows that the proposed fetal heart rate detection approach has produced efficient results in all the factors of FHR detection.

5. CONCLUSION

We proposed a novel graph based multi attribute closure measure to identify the fetal heart rate and perform analysis according to the various psychological conditions. The method preprocesses the input ECG waveform to perform wavelet analysis to boost the signals and separate the low signals and higher signals. The preprocessed signal is used to extract the features of the ECG waveform. The extracted features are converted into graph form and based on the graph available in the graph set the input pattern is compared. The method compute the multi attribute similarity based on the node similarity values and a cumulative similarity measure is computed. With all these measures a multi attribute similarity measure is computed. Based on the MASM the class of the signal is identified and the FHR separation is performed. The proposed method has been used to estimate the fitness of the model towards each grouping of feeling and to deviate the gesture from fetal ECG wave. The planned method has formed well-organized results and the real period recording and parting of long time ECG with contrast to other approaches also shows the competence of the planned method.

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