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Automated Detection of Premature Delivery Using Empirical Mode and Wavelet Packet Decomposition Techniques with Uterine Electromyogram Signals

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ABSTRACT

An accurate detection of preterm labor and the risk of preterm delivery before 37 weeks of gestational age is crucial to increase the chance of survival rate for both mother and the infant. Thus, the uterine contractions measured using uterine electromyogram (EMG) or electro hysterogram (EHG) need to have high sensitivity in the detection of true preterm labor signs. However, visual observation and manual interpretation of EHG signals at the time of emergency situation may lead to errors. Therefore, the employment of computer-based approaches can assist in fast and accurate detection during the emergency situation. This work proposes a novel algorithm using empirical mode decomposition (EMD) combined with wavelet packet decomposition (WPD), for automated prediction of pregnant women going to have premature delivery by using uterine EMG signals. The EMD is performed up to 11 levels on the normal and preterm EHG signals to obtain the different intrinsic mode functions (IMFs). These IMFs are further subjected to 6 levels of WPD and from the obtained coefficients, eight different features are extracted. From these extracted features, only the significant features are selected using particle swarm optimization (PSO) method and selected features are ranked by Bhattacharyya technique. All the ranked features are fed to support vector machine (SVM) classifier for automated differentiation and achieved an accuracy of 96.25%, sensitivity of 95.08%, and specificity of 97.33% using only *ten* EHG signal features. Our proposed algorithm can be used, in gynecology department of hospitals to predict the preterm or normal delivery of pregnant women.

Keywords: *preterm delivery; premature baby; empirical mode decomposition; wavelet packet decomposition; uterine electromyogram; electrohysterogram.*

INTRODUCTION

Delivery of an infant before 37 weeks of gestation is commonly categorized as preterm birth and is still a major cause of infant mortality worldwide [28, 37]. The world health organization (WHO) claims that the prevalence of preterm birth, 1 in 10 babies or 15 million babies per year, constitutes a public health problem worldwide and this rate is increasing [11,12, 69, 70]. The birth of a preterm infant can even cause considerable emotional and economic costs to families [9]. In 2005, the United States reported $26.2 billion annual societal economic burden related to preterm birth [9]. Global progress in infant survival and health to 2015 and beyond cannot be achieved without addressing preterm birth. Even though developments in perinatal and neonatal care have improved the survival for preterm newborns, the survived ones have a higher risk of health problems and developmental disabilities than infants born at full term [12, 37]. Thus, monitoring of uterine function during term (normal) and preterm delivery is important for developing methods and to solve clinical problems related to labor.

The repeated depolarization and repolarization of uterine smooth muscle cells results in series of myometrium contractility [51]. The spontaneous electrical discharges from the myometrium consist of discontinuous bursts of spike-like action potentials (AP) [51, 67]. These APs causes the contractility of the uterus [51, 52]. To quantitatively assess the activity of uterus, a noninvasive method uterine electromyogram (EMG) is developed; which records the electrical signals of uterus from the abdominal surface for the assessment of uterine contractility [20, 53, 64]. This EMG tool has been used successfully for obtaining uterine activity details during pregnancy and labor [13, 48, 66].

Clinically uterine EMG records are analyzed only during the presence of intermittent burst of APs that characterize the mechanical contractions of uterus [51]. The EMG records obtained during bursts of uterine activity are generally studied by examining the signal amplitude distribution [21, 29, 42] or by computing the power density spectrum and median frequency [21, 42]. Studies show that the characterization of fast wave low (FWL) and fast wave high (FWH) frequencies are used to diagnose the preterm delivery risk [42, 48, 63]. However, the amplitude and other characteristics of the uterine EMG signal is influenced by different situations such as the location of electrodes placement, the gap between the electrodes, and the skin impedance of the patient [68]. Poor conductivity because of high impedance reduces the uterine signal quality and increases the noise in the recordings [68]. Thus, the amplitude and other related characteristics of EMG signals cannot be utilized to compare term and preterm pregnancies [42]. Computer-aided approaches using signal processing methods have been explored and developed by various researchers for analyzing the EHG signals [6, 19, 33, 34, 35, 57, 64]. Findings of studies on prediction of preterm delivery from EHG signals are summarized in Table 1.

Table 1: Summary of research work on prediction of term and preterm pregnancies using EHG signals.

Author (Year)	Data	Methods/Features	Classification	Findings
Diab et al., (2007)[18]	-64 contractions are available From 16 women	Autoregressive (AR) and Wavelet Decomposition Features: -Variance vectors computed	Statistical Analysis	Accuracy 91.7%
Maner et al., (2007)[56]	Term = 134 and Preterm = 51 women	Features (Statistical values): burst duration, number of bursts per unit time, power spectrum, total burst activity	Artificial Neural Network (ANN)	Accuracy 92%
Marque et al., (2007)[53]	396 Contractions (257 for training and 139 for testing)	Redundant Wavelet Packet transform	Gradient back-propagation with momentum Neural Network Classifier (BPMNNC) and Levenberg-Marquardt Neural Network Classifier (LMNNC)	BPM: Posterior: -Sensitivity: 85% -Specificity: 93% Anterior: -Sensitivity: 90% -Specificity: 91%
Hassan et al., (2009)[32]	-11 women; 5 recorded during pregnancy and 6 during labor	Features: Non-linear correlation coefficient	Non-linear regression analysis	Not mentioned
Fergus et al., (2013)[23]	300 EHG signals (262 term and 38 preterm)	-Wavelet Transform -Fourier Transform Data Balancing: SMOTE Features Used: -Power Spectral Density -Peak frequency	Linear Discriminant Classifier (LDC) Polynomial Classifier (POLYC) Logistic Classifier (LOGLC) Decision Tree (DT)	LDC: -Sensitivity: 96.67% -Specificity: 90.00% -AUC: 0.70 POLYC: -Sensitivity: 96.67% -Specificity: 90.00% -AUC: 0.95 LOGLC: -Sensitivity: 96.67% -Specificity: 90.00% -AUC: 0.94 DT: -Sensitivity: 96.67% -Specificity: 90.00% -AUC: 0.93
Naeem et al.,	300 EHG signals (262	Discrete Cosine Transform	Kohonen Self-Organising Network	Trainable Cascade-Forward

(2014)[58]	term and 38 preterm)	Features: autocorrelation zero-crossing, approximate entropy, mean power frequency, median frequency, peak frequency, root mean square, sample entropy	Trainable cascade-forward backpropagation network.	Network: -Accuracy: 85.3%
Ren et al., (2015)[60]	300 EHG signals (262 term and 38 preterm)	Empirical Mode Decomposition Data Balancing: SMOTE Features: Shannon Entropy	Support Vector Machine (SVM) Random Forests (RF) Multilayer Perception (MLP) Adaboost (AB) Bayesian Network (BN) Simple Logistic Regression (SLR)	AB: Area Under Curve (AUC): 0.986
Fergus et al., 2016[24]	300 EHG signals (262 term and 38 preterm)	Data Balancing: SMOTE Features: Integrated EMG, mean absolute value, simple square integral, wavelet length, log detector, root mean square, variance, difference absolute standard deviation, maximum fractal length, average amplitude change, median frequency, peak frequency	Levenberg-Marquardt trained feed-forward neural network classifier (LMNC), radial basis function neural network classifier (RBNC), and random neural network classifier (RNNC)	Sensitivity = 91%, Specificity = 84%, AUC = 0.94
Current Study	**300 EHG signals (262 term and 38 preterm)**	**EMD and Wavelet Packet Decomposition** **Data Balancing:** **Adaptive Synthetic Sampling Approach (ADASYN)** **Features:** **Fractal Dimension (F_D^x)** **Fuzzy Entropy (E_F^x)** **Interquartile Range (I_{QR}^x)** **Mean Absolute Deviation (AD_M^x)** **Mean Energy (Ω_M^x)** **Mean Teager-Kaiser Energy (Ω_{MTK}^x)** **Sample Entropy (E_S^x)** **Standard Deviation (D_S^x)**	**SVM using Radial Basis Function (RBF)**	**SVM RBF Classifier using only 10 Ranked features (10-fold):** **-Accuracy: 96.25%** **-Sensitivity: 95.08%** **-Specificity: 97.33%** **AUC: 0.962**

It is evident from Table 1 that few studies have reported success in their efforts to accurately distinguish preterm and normal delivery using EHG signals. Compared to linear methods [49, 62, 64], non-linear methods [19, 25, 41] have shown superiority in differentiating the term and preterm pregnancies due to the non-stationary uterine EMG signals [63]. Among large number of features such as mean frequency [64], power spectrum [50] peak frequency [49], median frequency [25], parameters from wavelet transform [7, 18], largest lyapunov exponent [19, 41], fractal dimension, sample entropy [25], and variance entropy [38], features namely fractal dimension and sample entropy of the burst electrical activity have yielded promising results [25]. Despite this, there is still room to improve the accuracy of preterm delivery prediction which can significantly improve the survival rates of preterm infants. Moreover, accurate detection of preterm labor and subsequent preterm delivery is necessary for improving the outcome of premature neonates; avoid needless expenses and side-effects of treatments in women who do not deliver preterm irrespective of intervention.

This study proposes a new algorithm for the prediction of women at risk of preterm delivery after a true preterm labor signs using nonlinear analysis of EHG signal. The workflow of the proposed technique is shown in Figure 1. EHG signals of term and preterm pregnancies are subjected to eleven levels of empirical mode decomposition (EMD) to obtain the intrinsic mode functions (IMFs). On these IMFs, six levels of wavelet packet decomposition (WPD) are performed to obtain different coefficients, from which 8 features such as fractal dimension (F_D^x), fuzzy entropy (E_F^x), interquartile range (I_{QR}^x), mean absolute deviation (AD_M^x), mean energy (Ω_M^x), mean Teager-Kaiser energy (Ω_{MTK}^x), sample entropy (E_S^x), and standard deviation (D_S^x) are evaluated. Data balancing using adaptive synthetic sampling approach (ADASYN) is employed in order to maintain the balance of features evaluated between two classes and lessen the bias presented by the imbalanced data. After the data balancing, pool of features is subjected to particle swarm optimization (PSO) and ranked using Bhattacharyya method. These ranked features are fed to support vector machine (SVM) classifier with RBF kernel for automated identification of term and preterm delivery using their uterine EMG signals. The combination of EMD, and WPD increased the amount of information that can be extracted from the signal. We have clearly showed that, by combining the two methods the performance of our system has improved as compared to individual (EMD or WPD) system. The nonlinear methods used are able to capture the subtle information present in the EHG signals. Furthermore, the usage of ADASYN has also improved the performance as compared to SMOTE algorithm.

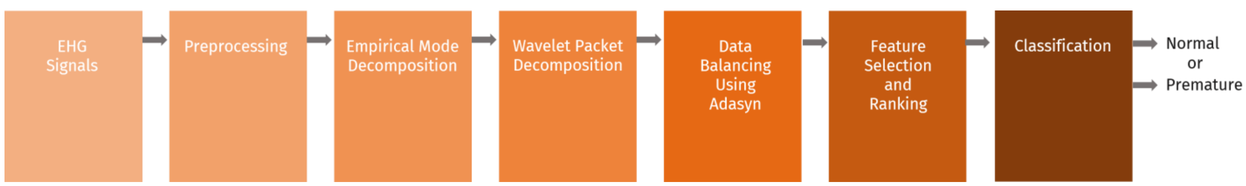

Figure 1: Proposed system algorithm.

DATA USED

The normal and preterm EHG (uterine EMG) signals necessary for this experiment were downloaded from an open access The Term-Preterm EHG Database (TPEHGBD) [25, 30]. The TPEHG DB was developed at the Faculty of Computer and Information Science, University of Ljubljana, while the records were collected at the University Medical Centre Ljubljana, Department of Obstetrics and Gynecology [30]. The records available in the database were collected during regular check-ups on 22nd or 32nd week of gestation. A total of 300 uterine EMG records (most of which are 30 minutes in duration) from 300 pregnancies having 262 records of normal delivery and 38 preterm deliveries were downloaded. Figure 2 displays the typical term and preterm

EHG signals obtained. The 262 records were acquired during pregnancies where delivery was on term (> 37 weeks) and 38 records obtained during pregnancies ended prematurely (≤ 37 weeks) [25, 30]. Table 2 summarizes the details of the data used in this work.

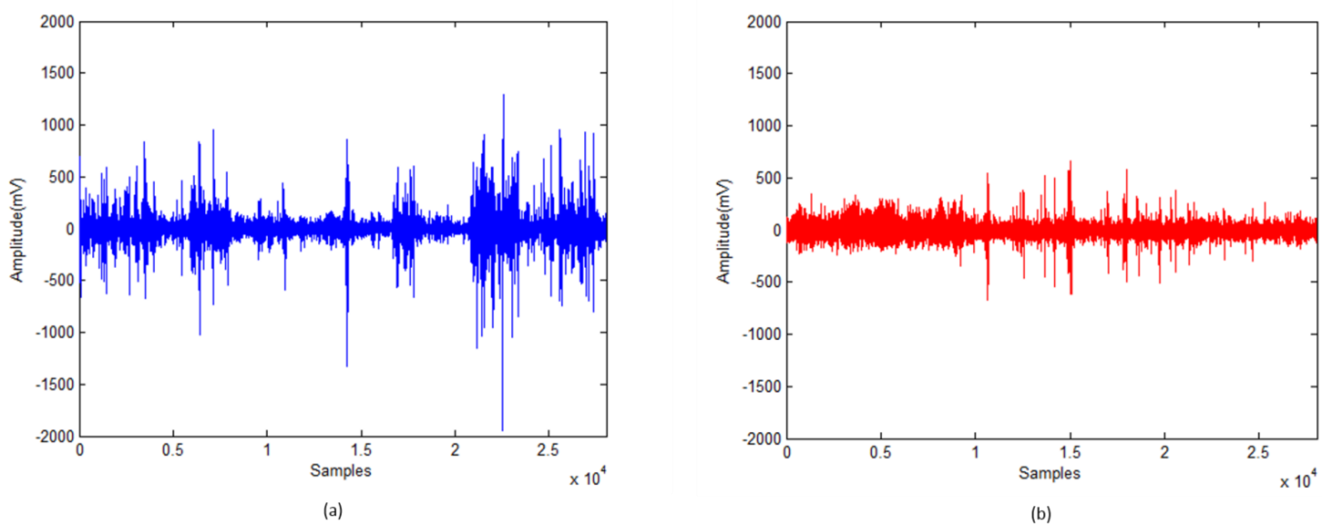

Figure 2: Typical term and preterm EHG records.

Table 2: Summary of the data used.

Database	Status of signal	Quantity	Subjects
The Term-Preterm EHG Database	Normal Delivery	262	143 records taken before start of 3rd trimester (26 weeks of gestation) 119 records taken during or after the 3rd trimester (26 weeks of gestation)
The Term-Preterm EHG Database	Premature Delivery	38	19 records taken before start of 3rd trimester (26 weeks of gestation) 19 records taken during or after the 3rd trimester (26 weeks of gestation)

METHODS

Pre-Processing

The EHG signal records obtained from the database were subjected to filtering using 4-pole band-pass Butterworth filter [25, 30] with cutoff frequency of 0.3-3Hz before being downloaded. From the filtered EHG signal of 30 minutes duration, first and the last 180 seconds length of signals were removed in order to avoid transient effects due to filtering process. The remaining 24 minutes (1440 seconds) length of EHG signals are subjected to EMD and WPD for extraction of features. The brief explanation on these methods is discussed in the next section.

Empirical Mode Decomposition (EMD)

Huang et al., 1998 proposed EMD a nonlinear signal decomposition method which decomposes the signal into mono-component functions known as intrinsic mode functions (IMFs)[8,39].

In this work, EMD is implemented up to 11 levels and total of 11 IMFs are obtained from each EHG signal of term and preterm pregnancies. On these 11 IMFs of each EHG signal, WPD is performed up to 6 levels. The signals are decomposed only up to 11 IMFs as it cannot decomposed further and the stop criteria is of resulting signal resembles a cycle of sine wave with only one maximum and one minimum point.

Figure 3 illustrates the EMD process. But in this figure, we have shown only IMF1, IMF6 and IMF11 in Figure 3(b), 3(c) and 3(d) respectively.

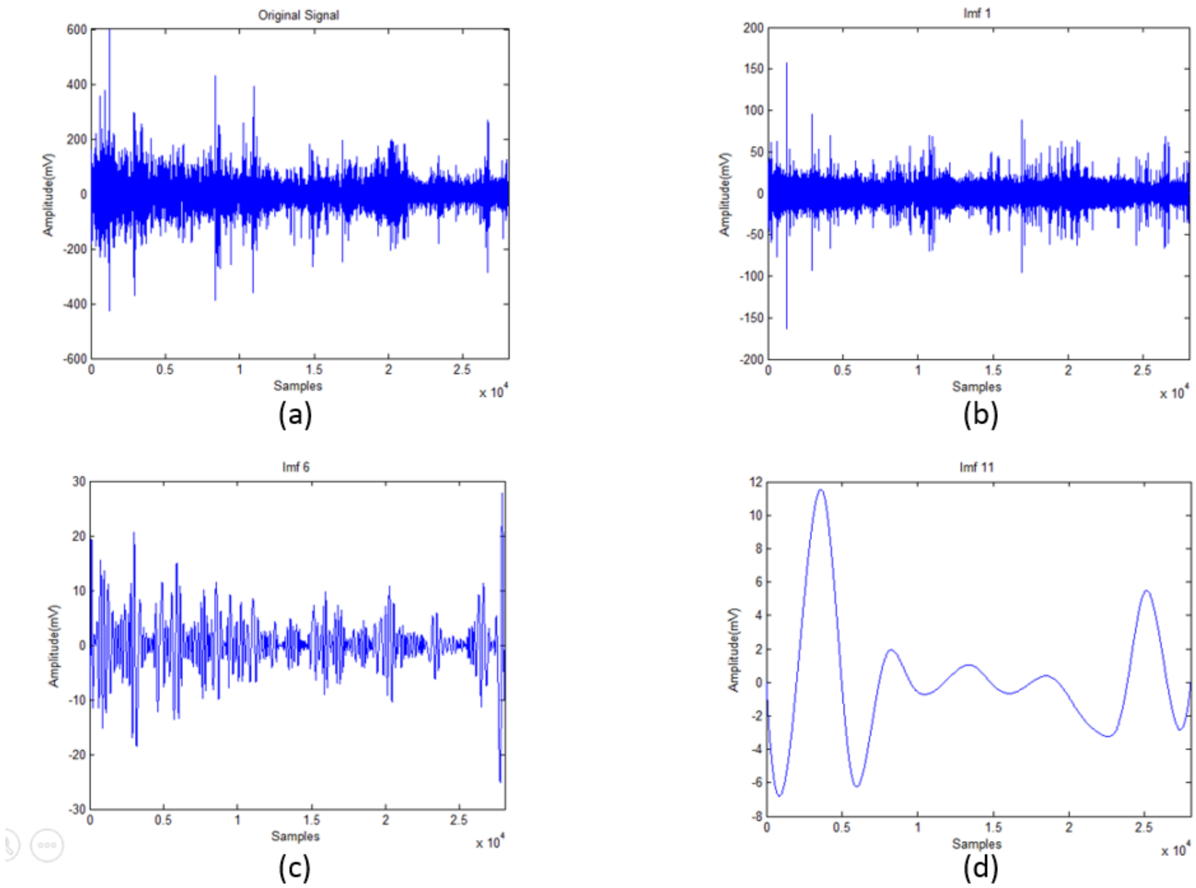

Figure 3: Illustration of EMD process: (a) original EHG signal, (b) IMF1 signal, (c) IMF6 signal, and IMF11 signal.

Wavelet Packet Decomposition (WPD)

This is a generalized form of wavelet decomposition technique that provides the level by level transformation of a signal from the time domain into the frequency domain [31]. Wavelets are the result of translated and scaled shapes of the basic mother wavelet [5, 10]. Moreover, mother wavelets are localized in the time-frequency domain, and have fluctuating amplitudes within a finite time. Hence, the wavelet coefficients yielded during wavelet transform are signals in the time-frequency domains [5, 10]. As compared to DWT method, WPD decomposes the signal into both the low frequency components (approximations) and the high frequency components (details) at every level using more filters [55]. Further, WPD decomposes both the detail and approximation coefficients to form a full binary tree structure [17]. In this work, 6 level WPD is implemented on each IMFs of 300 EHG signals using Daubechies 8 (db 8) and obtained a total of 12 coefficients. Only 6 levels of the WPD is performed as applying the decomposition further to the 7th level would reduce accuracy to 95.45% due to reduction in the number of prominent features within the decomposed waveforms. Figure 3 shows the IMF1, IMF6 and IMF11 waveforms obtained using EMD process on original ENG signal. Figure 4 shows the typical waveform of WPD level 1 obtained using db8 applied on IMF1 as original signal. Detail and approximate coefficients of WPD obtained at level 6 are shown in Figure 5.

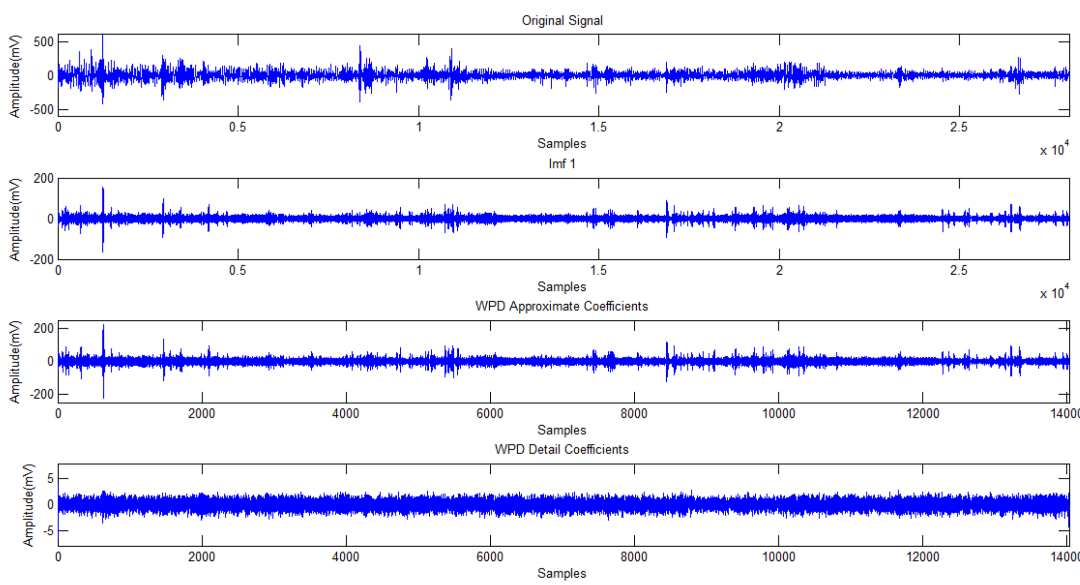

Figure 4: Typical waveform of WPD level 1 using db8 applied on IMF1 as original signal.

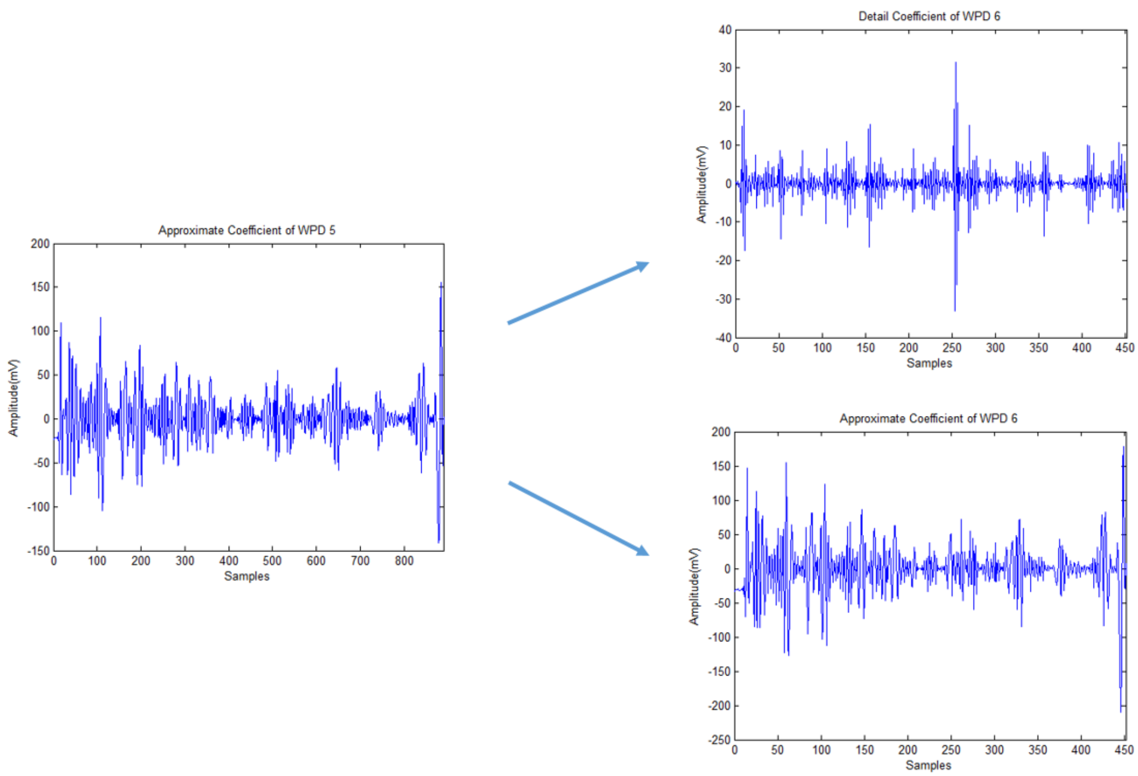

Figure 5: Detail and approximate coefficients of WPD obtained at level 6.

Thus, a total of 12 x 11 coefficients are obtained from each term and preterm EHG signal. We have performed the experiment with all mother wavelets and obtained the highest performance using db8. Hence, we have chosen this mother wavelet function.

After EMD and WPD, a total of 300 EHG signal x 12 WPD coefficients x 11 IMFs are obtained. From these 39,600 coefficients, eight different features such as fractal dimension (F_D^x), fuzzy entropy (E_F^x), interquartile range (I_{QR}^x), mean absolute deviation (AD_M^x), mean energy (Ω_M^x), mean Teager-Kaiser energy (Ω_{MTK}^x), sample entropy (E_S^x), and standard deviation (D_S^x) (3) are extracted [3].

Data Balancing

Among the huge number of features extracted (39,600 x 8) from 300 EHG signals, majority are from EHG recordings of normal pregnancies (term EHG signal). This is due to the imbalance in the term and preterm EHG data available from the database as the database included 262 term birth signals and only 38 preterm birth signals. To avoid this bias introduced by the data imbalance and to maintain the balance of features contributed by both the term and preterm EHG signals, we have employed data balancing using adaptive synthetic sampling approach (ADASYN) [36]. The algorithm initially calculates the degree of class imbalance and for each data example belonging to minority class; it finds the K nearest neighbors and calculates the density distribution ratio. Finally using the density distribution ratio, algorithm automatically computes the number of synthetic data examples that required to be generated for each minority class. Thus, ADASYN method is used to up sample or increase the features of minority class EHG signal and to provide a balanced representation of the data distribution in the resulting dataset. We have applied this ADASYN method to increase the number of signals of the minority class from 38 to 244.

Feature Selection and Ranking

The aforementioned features are extracted using algorithms written in MATLAB. In this work, the particle swarm optimization (PSO) technique developed by Kennedy and Eberhart in 1995 is used for feature selection. The algorithm initially creates particles subset and assigns initial velocity values to them. The best function value and location are obtained by computing the objective function at each particle location. Then, new velocity values are determined using the particle's and their neighbor's best location and the particle's current velocity. Therefore, values of particles' and neighbor's velocities and locations are repeatedly updated and this process is repeated till a stopping criterion is met [45]. The significant features selected are then ranked using Bhattacharyya distance [22].

Classification

It is performed on all the ranked features using classifier for obtaining the best result. In this paper, SVM classifier with RBF kernel function is used for automated classification of preterm and normal delivery using uterine EMG signal records [22]. ***SVM*** classifier separates the training data into two groups by constructing a hyperplane in the higher-dimensional space [22]. We have also performed the classification using linear discriminant analysis, quadratic discriminant analysis, decision tree, k-nearest neighbor, and radial basis classifiers. However, we have obtained the highest classification accuracy using SVM classifier. So, we have presented the performance only using this classifier.

In this work, we have validated the performance of the proposed system with five-fold and ten-fold cross-validation. However, we have obtained better performance using ten-fold cross-validation.

RESULTS

A total of 39,600 x 8 features are extracted from WPD coefficients of IMFs obtained from 300 (262 term and 38 preterm) EHG signals. Significant features are selected from the pool of features extracted using PSO and are later ranked by Bhattacharyya method. Results (mean and standard deviation (SD) values) for first top 10 highly ranked features obtained for EHG signals of term and preterm pregnancies are presented in Figures 6, 7 and Table 3.

Table 3: Results of features obtained and ranked by Bhattacharyya for term and preterm pregnancies EHG signals.

Features	Term (Normal)		Preterm		Criterion
	Mean	SD	Mean	SD	
$AD_M^{2\_A_5}$	1.77E+01	1.51E+01	2.00E+01	1.07E+01	0.0573
$E_s^{11\_D_4}$	5.81E-03	1.30E-03	5.85E-03	6.44E-04	0.0300
$E_s^{2\_A_4}$	5.53E-01	2.53E-01	4.70E-01	1.35E-01	0.0288
$\Omega_M^{5\_D_4}$	-8.48E-01	7.99E-01	-6.81E-01	4.93E-01	0.0198
$\Omega_M^{4\_D_2}$	-2.78E+00	6.56E-01	-2.76E+00	4.38E-01	0.0102
$D_S^{8\_D_1}$	3.22E-04	3.79E-04	3.18E-04	2.86E-04	0.0049
$E_S^{4\_A_6}$	1.23E+00	2.04E-01	1.15E+00	1.89E-01	0.0048
$I_{QR}^{3\_A_2}$	7.85E+01	4.16E+01	7.75E+01	3.89E+01	0.0035
$\Omega_{MTK}^{8\_D_5}$	2.81E+00	9.08E-01	2.71E+00	7.67E-01	0.0033
$F_D^{4\_A_6}$	2.00E+00	2.12E-02	2.00E+00	2.04E-02	0.0003

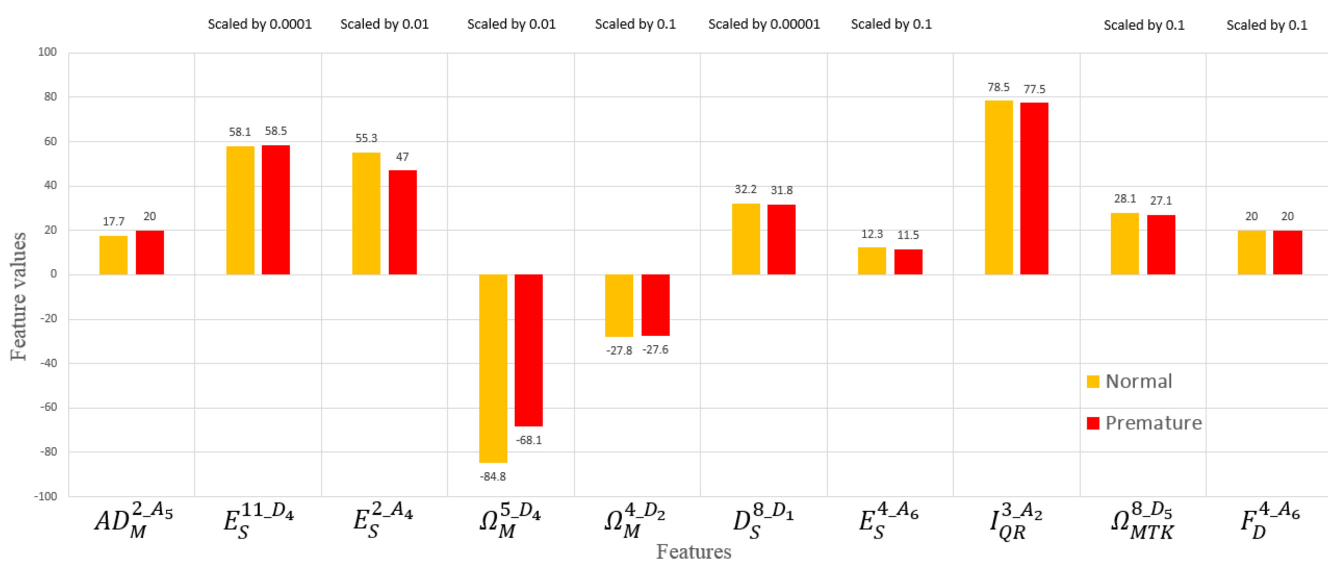

Figure 6: Bar charts displaying the mean values of the features obtained for term and preterm pregnancies EHG signals.

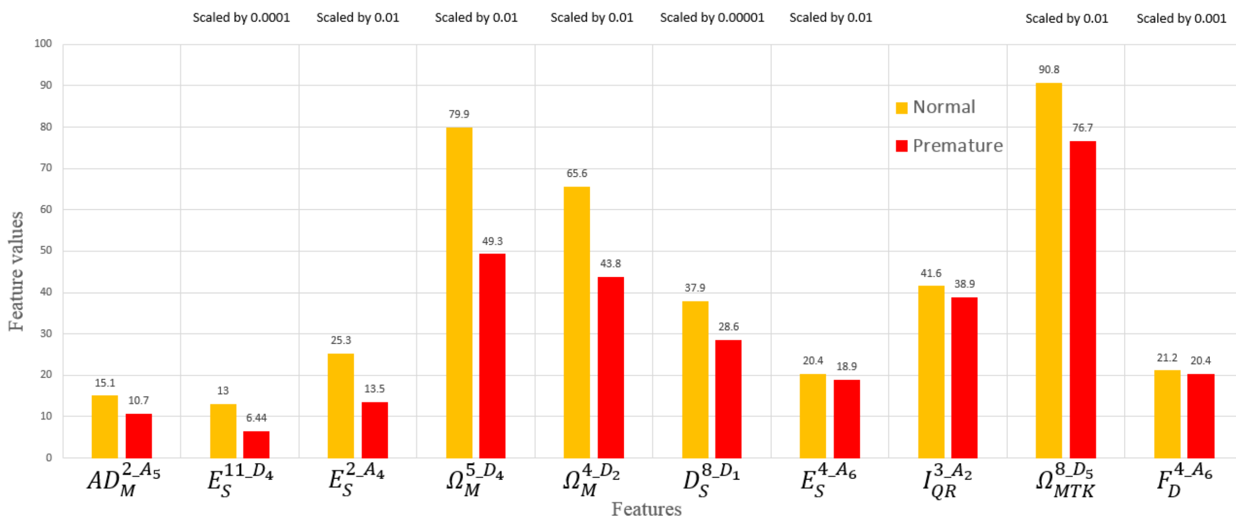

Figure 7: Bar charts displaying the SD values of the features obtained for term and preterm pregnancies EHG signals.

It is evident from the Table 3 and Figures 6, 7 that, the values of term pregnancy EHG signals are slightly higher than the preterm delivery. This is due to the frequent and higher uterine activity during term, thus showing large amplitude in EMG signal [13].

Furthermore, it can be seen in Table 3 and Figures 6, 7 that the mean and standard deviation values of normal and pre-term EHG signals are not distinctive. It is due to the PSO technique employed in this work. PSO is an optimized feature selection approach, hence it does not necessary select statistically significant features but selects a set of features that will complement each other when fed into the classifier for classification process. The selected feature might be statistically insignificant on its own, however, this insignificant features are correlated to other features therefore boosting the performance of the classifier [65]. Thus, we can achieve high performance rate in this work.

The ranked features are fed to SVM classifier with radial basis function (RBF) kernel one by one to attain a maximum classification performance using least number of features. Classification results obtained are tabulated in Table 4.

Table 4: Classification results obtained for term and preterm EHG signal features using SVM classifier.

Method		Number of Features	Accuracy (%)	Sensitivity (%)	Specificity (%)
EMD	10-fold	10	92.29	88.93	95.41
WPD	10-fold	10	93.08	93.85	92.37
EMD and WPD	10-fold	10	96.25	95.08	97.33
	5-fold	10	94.47	91.39	97.33

We have obtained the highest accuracy, sensitivity and specificity of 92.29%, 88.93% and 95.41% with only EMD method using ten features. Highest accuracy of 93.08%, sensitivity of 93.85% and specificity of 92.37% is achieved only with WPD method using ten features. It can be seen from the Table 4 that, combination of EMD and WPD method performed better than individual methods. Hence, in this work, we have used combined the two methods to obtained the highest performance. Both 10-fold and 5-fold cross validation methods are employed to validate the performance of SVM classifier (for EMD+WPD method). Plot of accuracies achieved for ten-fold and five-fold cross-validation for different numbers of features are shown in Figure 8 and Figure 9 respectively with SVM classifier.

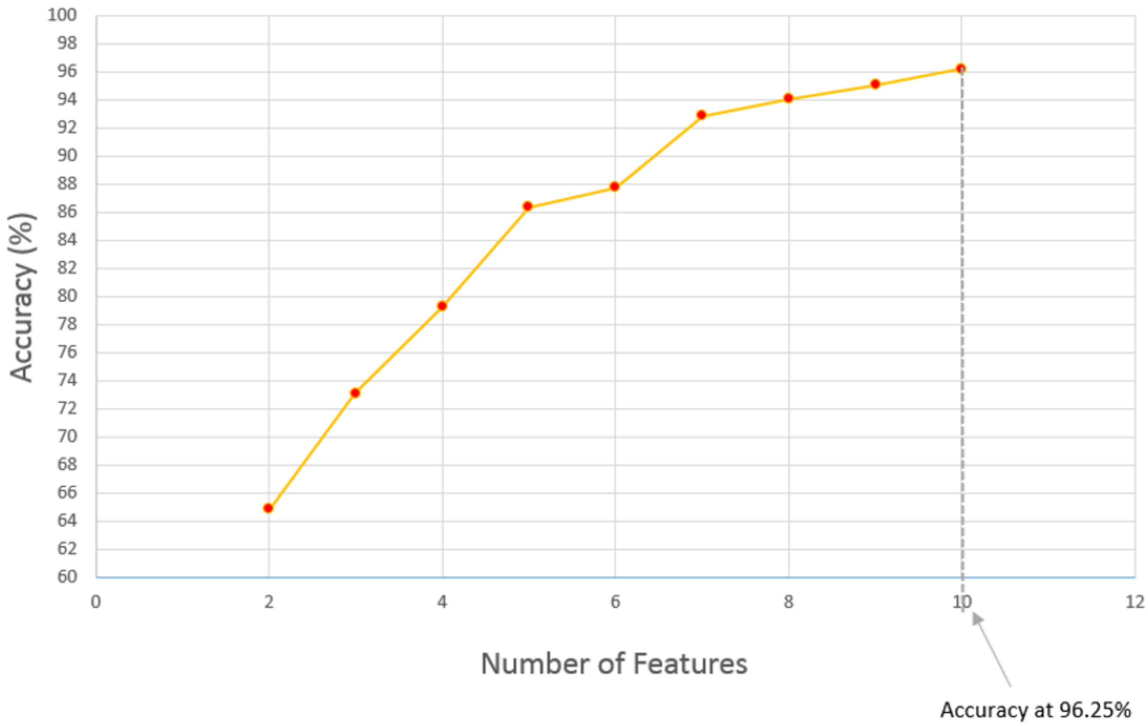

Figure 8: Plot displaying the accuracies achieved for different number of features using 10-fold validation with SVM classifier.

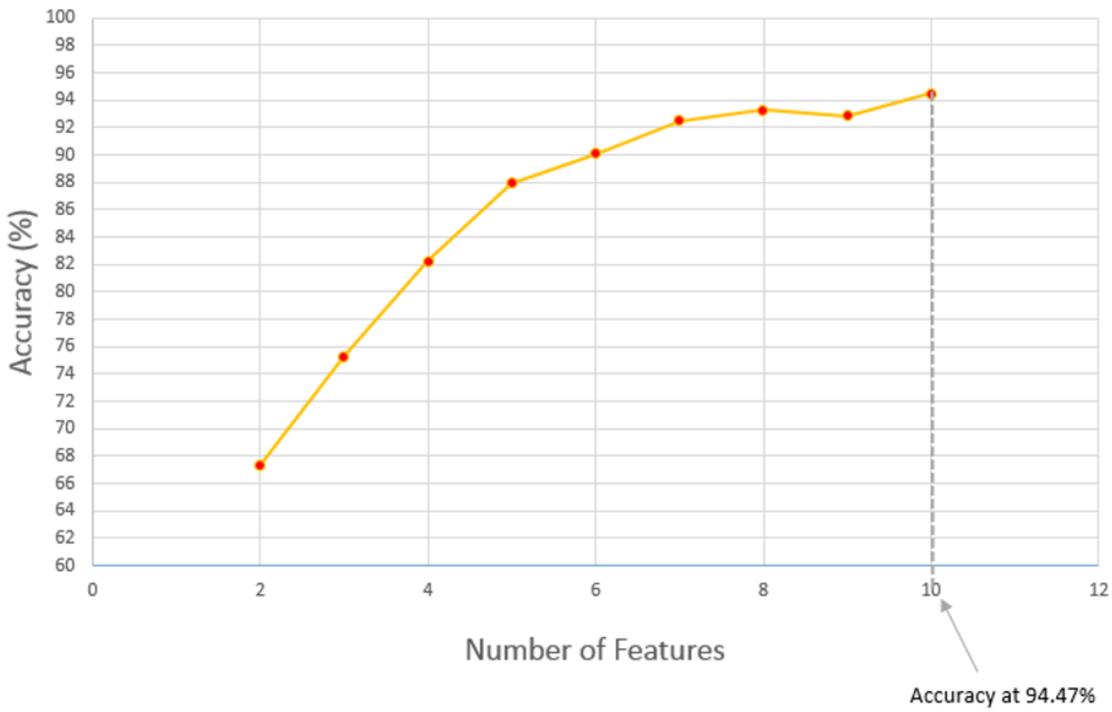

Figure 9: Plot displaying the accuracies achieved for different number of features using 5-fold validation with SVM classifier.

DISCUSSION

A multiresolution analysis of nonlinear uterine EMG signal using EMD combined with WPD methods is proposed in this work for the prediction of women at risk of preterm delivery. The EMD method is able to analyze the nonlinear EHG signal by dividing the signal into IMFs and a residue [4, 54]. The EMD technique is able to capture both the temporal and frequency resolutions of the signal [40, 59]. On these IMFs, WPD another decomposition method is applied to obtain the different frequency level information of the signal. The key uniqueness of this technique is that, it captures the hidden signs present within the non-linear signal [15]. WPD decomposes both the detail and approximation coefficients of the signals simultaneously [47]. Thus, using WPD, time-frequency information is captured. In addition, WPD retains the orthogonality, smoothness, and localization properties and thus, provides a great deal of freedom in handling with different types of transient signals [31].

Therefore, combination of both time-frequency decomposition methods used in this work (EMD and WPD) provides multiresolution information of the EHG signals and is better choice compared to using EMD alone [60, 61] and other nonlinear methods reported in the literature [19, 25, 41] for the analysis of uterine EMG signals. The novelty of our work is that, the proposed method outperformed the other methods (Table 1) by achieving an accuracy of 96.25%, sensitivity of 95.08% and specificity of 97.33% in the classification of term and preterm pregnancies using EHG signals with 10-fold cross-validation.

Other highlight of our work is the usage of ***entire database consisting of 300 uterine EMG records*** and the extraction of entropy features. Entropy feature describes the information available in dynamical systems and is the most commonly utilized parameter for evaluating complexity of bio-signal analysis [27]. This parameter measured quantifies the amount of regularity by examining the time series signal and its pattern [2, 16]. The E_s^x parameter is suitable for complex and irregular time series signal [43]. It evaluates patterns of signal and distinguishes the patterns, which is otherwise difficult and challenging. It is highly sensitive to noise and robust in obtaining significant evidence from the signal [44].

Moreover, we have performed ***data balancing using ADASYN method***, which is more efficient than the other synthetic approach such as synthetic minority oversampling technique (SMOTE) experimented by few studies [14]. In addition, a ***10-fold and 5-fold cross-validation*** *approaches* are employed to validate the performance of classifier in the proposed algorithm and attained high sensitivity and specificity using only ten features from EHG signals. Furthermore, the proposed algorithm is completely automated, reproducible and no inter-observer variability involved. The possible profits from the implement of proposed algorithm includes the decline in preterm delivery rate, better perinatal outcome, developments of efficient treatment procedures, and decline in cesarean-section rate.

Development of an integrated index [1, 2, 26] to predict the preterm pregnancies using EHG signals is in progress as our future work. Furthermore, prediction of early signs of true preterm labor using uterine EMG signals will be explored.

CONCLUSION

Prediction of true preterm labor signs and the risk of having preterm delivery is an urgent challenge in obstetrics. This paper proposes a new computer-aided approach for improved prediction and characterization of women at risk of having preterm delivery or normal delivery using their uterine EMG signals. The EMD combined with WPD can categorize the two classes with an accuracy of 96.25%, sensitivity of 95.08% and specificity of 97.33% using 10 uterine EMG signal features with 10-fold cross-validation. The proposed system does not require any extensive computational machinery. Thus, it is easy to operate and cost effective. Therefore, clinicians can use this algorithm in their clinics to screen the pregnant women who experience preterm labor and subsequently predict the possibility of women going to have preterm delivery. Due to high specificity of the proposed system, it can be used to predict the women who may not deliver preterm, thus, unnecessary costs and side-effects of treatments can be avoided.

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