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Research paper



Comparison of different feature extraction methods for the analysis of uterine magnetomyography signals to predict term labor

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Abstract

The prediction of term labor by analyzing the uterine magnetomyographic signals attempted in this research. The existing works did not focus on the classification of the signals. Publicly available MIT-BIH database records were divided into term-labor and term-nonlabor groups. This research presents two methods for feature extraction, discrete wavelet transform and wavelet packet transform. Energy, standard deviation, variance, entropy and waveform length of transform coefficients used in the first method. The normalized logarithmic energy of wavelet coefficients from each packet of the total wavelet packet tree used as the feature space for the second method. The labor assessment done through the classification of the features by using five different classifiers for different mother wavelet families. Discrete wavelet transform features extracted using coif5 wavelet with random subspace classification gives the accuracy, precision and FPrates of 93.9286%, 94.2014% and 5.7986% respectively. Using sym8 wavelet for wavelet packet transform features classified with SVM classifier performed well with 95.8763% accuracy, 95.9719% precision and 4.0281% FPrate. The results obtained from the research will be helpful in term labor assessment and understanding the parturition process.

Keywords: *Discrete Wavelet Transform; Labor Prediction; Uterine Magnetomyography; Wavelet Packet Transform.*

1. Introduction

Prediction of labor is an important factor as one-third of complications that leads to maternal death arose at the onset of labor [1]. According to the World Health Organization (WHO) report [2], India accounts for 15% (45,000 Approx.) of all maternal deaths around the world in 2015. The maternal mortality in India depends on many factors like obstetric care, reproductive factors, socioeconomic factors and health care delivery system. However, providing essential care at the right moment reduces the risk of these complications.

Characterization of uterine magnetomyography (MMG) signals helps in labor prediction. The propagation of uterine electrical contractions over the pregnant abdomen can be
observed with 151 channel SARA (SQUID Array for Reproductive Assessment) system [3]. Peak amplitude of MMG signal, gestational age and cervical dilation of patient were used as features for this purpose [4]. Synchronization analysis applied on the MMG signals in order to find uterine magnetic activity in [5]. Frequency and peak power of the signals are good indicators for the prediction of labor [6]. The uterine MMG signals were segmented (multiple change point estimator) and classified (k means clustering algorithm) to detect the uterine contractions [7]. Time-frequency analysis deployed in [8] for quantification of MMG signals. Wavelet transform followed with Hilbert transform used for the identification of uterine contractions [9].

The same technique adopted by authors of [10] for a conclusion that burst duration decreased when the subject approaches labor. The uterine contraction conduction velocity also increases at the onset of labor [11]. Escalona-Vargas et al [12] reported the uterine MMG signals of term pregnancies where the signals were quantified using the quadrant approach. As the electrical activity of the uterus increases at the onset of labor, the frequency and synchronization indices are helpful to understand the parturition process [13].

The studies related to uterine MMG signals to assess labor were limited to either the features extraction that were changed at the labor or the detection of uterine contractions. The classification of uterine physiological signals for labor prediction was attempted by analyzing uterine EMG signals [14]. ANN classifier fed with frequency domain features to classify the term/pre-term labor and non-labor groups in that work. For labor prediction, features extracted by using empirical mode decomposition analysis were employed with six different classifiers in [15]. Wavelet coefficients derived from uterine MMG signals were used to extract the Hilbert phase and amplitude in [8-10]. These features were not employed for the classification purpose. Wavelet packet coefficients are efficient in biomedical signal classification. Khushaba et al [16] used wavelet packet features for classification of driver drowsiness using sym5 as mother wavelet. Normalized wavelet packet energy extracted from uterine EMG signals used as feature to the ANN classifier [17]. The dimension space reduced using principal component analysis on three level wavelet packets by the authors. Electroencephalogram (EEG) signals classified using wavelet packet features along with different classifiers [18]. The classification of ECG signals of MIT-BIH database improved by using wavelet packet transform and random forest classifier [19].

However, the studies limited to only uterine EMG signals classification for labor prediction. The uterine MMG signals were analysed by different teams for the detection of uterine contractions only. In

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our previous work [20], different linear and nonlinear features employed to classify the uterine MMG signals with 87.5% accuracy. Though the same MIT-BIH database used in this study, the classifiers were trained with limited feature space. Conclusions based on the accuracy solely may lead to errors in medical diagnosis. To deal with these problem wavelet analysis attempted in the present research. Twenty four signals from the database were divided into two groups, term-labor and term-nonlabor. For the feature extraction, two methods are presented in this work. In the first method, the signals were decomposed to six levels using discrete wavelet transform (DWT). The wavelet coefficient features like variance, standard deviation, waveform length, energy per waveform length and entropy, were extracted from each level. Wavelet packet transform (WPT) applied, in the second method, to extract the features from all the packets at each level. Multi signal one dimensional wavelet decomposition with an overlapping sliding window technique employed for this purpose. Different mother wavelets that have a proven record for physiological signals were used to decompose the signal up to six levels. The extracted features were applied to five different classifiers in order to assess the labor. Five different mother wavelet families (sym5, sym8, db4, db8 and coif5) used in this work.

2. Materials and methods

a) Data Acquisition and Preprocessing

MIT-BIH (mmgdb) database comprised of twenty five magnetomyography signals out of which recordings from twenty four subjects used in this work [21]. The signals were recorded with 151 channel SARA (SQUID Array for Reproductive Assessment) system at University of Arkansas for Medical Sciences, Little Rock, USA [12]. The records have subject id and channel labels along with maternal information like cervical dilation, Days to delivery, BMI and Gestation Period. First the MMG signals were digitized (250Hz) and then down sampled to 32 Hz. The maternal and fetal cardiac signals attenuated with band pass filter (0.1-1 Hz) and maternal breathing is suppressed with notch filter (0.25-0.35 Hz). Each record in the database have 147 to 148 channels that lasts between 10-20 minutes. In this study we used first 1 min record of multichannel signal as shown in figure1. The twenty four term records were divided based on the patient's time remaining for the delivery after recording (before 48 hours- term labor and after 48 hours-term nonlabor). The feasibility of the division tested by using student's t-test [22]. Table 1 represents the division of dataset into two groups: term-labor and term-nonlabor.

Table 1: Division of MIT-BIH Database into Term-Labor and Term-Nonlabor Groups

Group	Patient ID
Term-labor	202 205 210 212 218 222 224 227 229 230 232 234
Term-nonlabor	203 204 207 209 211 213 214 221 225 226 233 237

The upper trace in the figure 1 is the multichannel signal (148 sensors) and the lower trace is the single channel signal. The subject name is 230_38w5d, that represents the subject ID (230), and the gestation period in weeks and days (38w5d). The magnitude on y axis represents in raw units. To get the physical units (pT), subtract the gain of each channel from the magnitude and divide the result with its base.

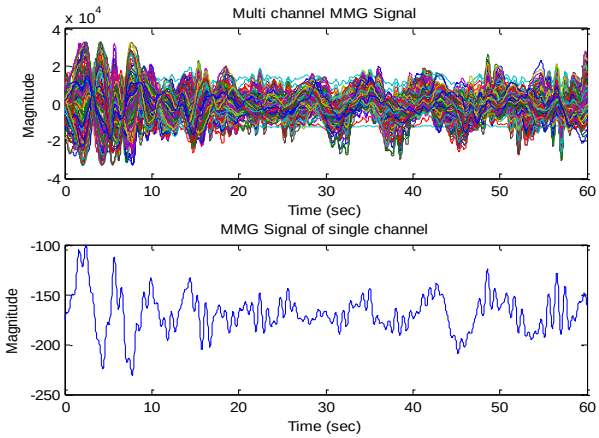


Fig. 1: MMG Signals of A Patient (230_38w5d) with All Channels (Upper Trace) and A Single Channel (Lower Trace).

b) Feature Extraction

The main aim of the feature extraction is to extract informative non-redundant parameters from the raw signals. It is one of the decisive steps in machine learning and pattern recognition. The features can facilitate better human interpretations in medical diagnosis. The features contain the relevant information and can be used for the classification purpose instead of the original input data [23].

1) Discrete Wavelet Transform

Wavelet transforms, the signal-processing algorithms allowed to transform data into time-frequency domain. Discrete Wavelets Transform (DWT) is described in terms of filter banks for bio-medical signal processing applications [24]. The MMG signal passed through filters (first low-pass next high-pass) to get approximate and detailed coefficients. This method is known as the multi-resolution decomposition of the MMG signal. The coefficients represent the energy distribution of the signal in both time and frequency domain. Only the approximate coefficients further divided into detailed and approximation coefficients. By choosing the correct mother wavelet, the coefficients of these filter banks are regulated. Figure 2 illustrates the general DWT tree with six decomposition levels used in this research. cAn and cDn in fig. 2 represents the nth level approximate and detailed coefficients respectively.

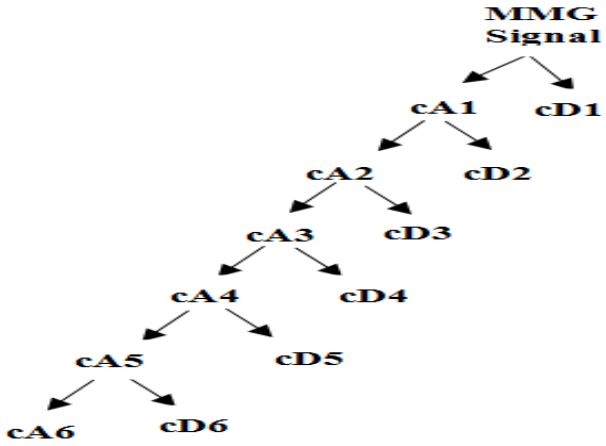


Fig. 2: Discrete Wavelet Transform Tree with Six Decomposition Levels.

DWT used in [8-10] for uterine MMG signal processing to detect uterine contractions. The features extracted from the wavelet coefficients are contractions duration, peak values and their locations etc. For a given set of MMG signals, the decomposition starts along the channels to six levels since it is a multichannel signal. The feature space was constructed, consider the each level as a feature vector, after computing the coefficients variance, waveform length, standard deviation, entropy and energy per waveform length. The feature space has [7] vectors, as the [six] level decomposition makes seven coefficient vectors (cA6, cD1-cD6). Therefore, for

each channel, the feature matrix contains 35 [5] features x [7] feature vectors) different sample values.

2) Wavelet Packet Transform

Wavelet packet transform is an extension of discrete wavelet transform. Discrete wavelet transform decomposes the signal into two frequency bands: high frequency band with detail coefficients and low frequency band with approximate coefficients. The approximate coefficients decomposed further up to required level as new approximate and detail coefficients while the detail coefficients remain unchanged. Wavelet packet transform decomposes both approximate and detail coefficients at each level as shown in figure 3 and the same technique adopted here for uterine MMG signal feature extraction.

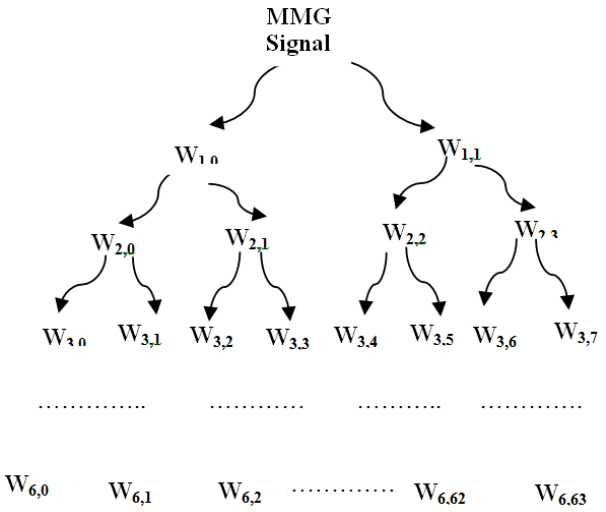


Fig. 3: Wavelet Packet Transform Tree with Six Decomposition Levels.

Figure 3 illustrates the general Wavelet packet decomposition tree with six decomposition levels used in this research. Wj,n in fig. 3 represents the jth level wavelet packet where n is the number of the packet at that level. The uterine MMG signals from MIT-BIH database are multichannel (148) signals. Information from each channel chopped into segments by using sliding window approach. The wavelet packet transform applied on each segment to generate a complete decomposition tree up to level six. Feature space constructed from each node of the wavelet packet tree. The squared values of transform coefficients from each subspace were computed. The logarithm of mean of the results were taken as the features [25]. Features are generated by taking the energy of the wavelet coefficients in the sub band according to the normalized filter bank energy S (l) given in the eq(1).

$$S(l) = \log\left(\frac{\sum_{m=1}^{\infty} W_x(l,m)^2}{N_l}\right) \quad (1)$$

Wx = Wavelet packet transform of signal

l= sub band frequency index

Nl= number of wavelet coefficients in the l^{th} sub band

Since the MMG signal decomposed to 6 levels and the features computed from all packets, the feature matrix contains 127 feature values. The selection of the mother wavelet and decomposition levels are vital issues. The trouble lies in the decision of selecting a wavelet and the scale that will bring the best result for a particular application. Five different mother wavelet families sym5, sym8, db4, db8 and coif5 were used in this work. These wavelets were chosen based on their efficiency for biomedical signal classification [16-19].

c) Classification

The Naïve-Bayes is a simple classifier with applications like spam mail filtering, weather prediction and medical diagnosis [26]. It deploys the Bayes theorem for class probability computation. It depends on the assumption of class independence, but conditional independence is not possible for some applications. The advantage of Naïve-Bayes is that a small amount of information is sufficient for classification. K nearest neighbor (KNN) can be used for many tasks related to the physiological signal classification [27]. Nearest neighbor class will be the class of test data. In our research, KNN classifier with Euclidean distance metric with one nearest neighbor used. Support vector machine (SVM) has a successful record in classification of uterine EMG/EHG signals [28]. The kernel functions i.e. linear kernel, sigmoid kernel, polynomial kernel, and RBF kernel are commonly used. Polynomial kernel function employed in our work. Artificial neural networks (ANNs) are ideal for the classification of patient's uterine contractions to predict the preterm labor [14], [17]. ANNs consists of three different layers input layers, hidden layers and output layers. The hidden layers have artificial neurons (analogous to brain neurons) which are used to process the data. Scaled conjugate gradient backpropagation function used in our network to update the weight and bias values.

One of the ensemble classification techniques, Random Subspace method can be used for bio medical applications like fMRI classification [29]. This classifier is suitable for large set of future space. It uses the conventional KNN, SVM and other classifiers as base classifiers. The ensemble decision of a class label depends on either majority voting or probabilities of base classifiers. First the classifier creates a data subset by taking pre-determined number of features from the feature vector. These subsets are used for training the base classifiers to create an ensemble model. When the test data applied on this model, majority voting employed to decide the test vector class. Since the class of the data is known, supervised algorithms used for all the classifiers. Our classifiers were trained with 2/3 of feature space while the remaining is the test dataset. Inter-patient scheme [19] was adopted to divide the recordings into the train set (16 recordings) and the test set (8 recordings). The suitability of the classifiers for the classification of term labor and nonlabor groups investigated in order to predict the term labor. We investigate the performance of discrete wavelet transform and wavelet packet transform for differentiating term-labor and term-nonlabor groups by using different mother wavelets.

3. Results and discussion

Three metrics were used to evaluate the performance of classification: accuracy, precision and False positive rate derived from true positive, true negative, false positive and false negative. True positive stands for the number of term labor signals that are correctly classified while true negative stands for the number of term nonlabor signals that are also correctly classified. False negative gives the number of labor signals that are predicted as nonlabor signals. False positive is the number of nonlabor signals misclassified as belongs to labor class

Accuracy measures the proportion of both term labor and term nonlabor signals that are correctly identified as labor and non-labor.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} * 100\% \quad (2)$$

Precision or positive predictive value measures the proportion of labor signals that are identified from both labor and non-labor signals.

$$\text{Precision} = \frac{TP}{TP+FP} * 100\% \quad (3)$$

False positive rate (FPrate) is the ratio of misclassified labor signals to the total number of signals that are not predicted as labor class.

$$\text{FPrate} = \frac{FP}{TN+FP} * 100\% \quad (4)$$

Table 2 depicts the classifiers performance metric values for different classifiers Naïve-Bayes, ANN, KNN, SVM and Random Subspace classifiers with different mother wavelets using different mother wavelets db4, db8, sym5, sym8 and coif5.

Table 2: The Classification Results (in %) for the Discrete Wavelet Transform Method

Mother Wavelet	Classifier	Accuracy	Precision	Fprate
Sym8	Naïve-Bayes	55.7143	56.2794	43.7206
	Ann	54.2857	54.2857	45.7143
	Knn	80.0000	81.8803	18.1197
	Svm	84.2857	85.5105	03.9474
	Random Subspace	92.8571	92.8922	07.1078
Sym5	Naïve-Bayes	48.5714	48.5282	51.4718
	Ann	42.1429	41.7097	57.8571
	Knn	72.5000	75.0925	24.9075
	Svm	85.0000	88.1111	02.5690
	Random Subspace	91.0714	91.3266	08.8256
Db4	Naïve-Bayes	53.5714	53.8243	46.1757
	Ann	46.0714	45.5724	53.9286
	Knn	71.4286	72.9458	27.0542
	Svm	77.1429	77.5021	11.7435
	Random Subspace	89.2857	89.3178	10.6822
Db8	Naïve-Bayes	51.4286	51.5297	48.4703
	Ann	46.4286	46.0754	53.5714
	Knn	74.6429	76.0926	23.9074
	Svm	78.5714	83.5651	08.6624
	Random Subspace	90.7143	90.7226	09.2774
Coif5	Naïve-Bayes	52.8571	53.2749	46.7251
	Ann	52.8571	53.1397	47.1429
	Knn	76.7857	77.0968	22.9032
	Svm	82.1429	83.1161	06.3786
	Random Subspace	93.9286	94.2014	05.7986

From the table2 for the sym8 wavelet, Naïve-Bayes and ANN classifiers performed poorly in predicting non-labor signals to give accuracies 55.7143% and 54.2857% respectively. The KNN classifier classify the labor signals with an accuracy of 80% though one-third of non-labor signals misclassified. The SVM classifier performed better with an accuracy 84.2857% than the former classifiers. The Random Subspace ensemble classifier has less misclassification with an accuracy of 92.8571%. The precision values for Naïve-Bayes, ANN, KNN, SVM and Random Subspace classifiers are 56.2794%, 54.2857%, 81.8803%, 85.5105% and 92.8922% respectively. The FPrates of the Naïve-Bayes and ANN classifiers are 43.7206% and 45.7143% respectively while that of KNN classifier is 18.1197%. The SVM classifier FPrate is 3.9474% is smaller than the Random Subspace classifiers FPrate 7.1078. The results confirms the Random Subspace classifier is better in labor prediction among the other classifiers for sym8 wavelet.

The above results were prove again in case of sym5 wavelet for Naïve-Bayes and ANN classifier with accuracies 48.5714% and 42.1429%, precision 48.5282% and 41.7097% and FPrate 51.4718% and 57.8571% respectively. The KNN classifier has the poor performance with 72.5%, 75.0925% and 24.9075% of accuracy, precision and FPrate respectively than that of sym8 wavelet. This is also true in case of Random subspace classifier with accuracy 91.0714%, precision 91.3266% and FPrate 8.8256%. Only SVM classifier did well with accuracy, precision and FPrate of 85%, 88.1111% and 2.569% respectively. In case of db4 and db8 wavelets all the classifiers shows poor results compared with the both sym5 and sym8 wavelets as shown in table2. For the coif5 wavelet KNN and SVM classifier have moderate accuracies of 76.7857% and 82.1429% while the Random subspace classifier has the best classification accuracy (93.9286%) and precision (94.2014%) compared with all classifiers for all mother wavelets. However the FP rate (5.7986%) is more than SVM classifier in case of sym8 (3.9474%) and sym5 (2.569%).

The accuracy, precision and FPrate values presented in table3 for the Naïve-Bayes, KNN, SVM, ANN and Random Subspace classifiers using different mother wavelets db4, db8, sym5, sym8 and coif5.

Table 3: The Classification Results (in %) for the Wavelet Packet Method

Mother Wavelet	Classifier	Accuracy	Precision	FPrate
Sym8	Naïve-Bayes	55.6701	55.7274	44.2726
	ANN	55.6701	56.0660	43.9340
	KNN	81.4433	81.5004	18.4996
	SVM	95.8763	95.9719	04.0281
	Random Subspace	57.7320	58.0702	41.0637
Sym5	Naïve-Bayes	50.5155	50.4237	49.5763
	ANN	59.7938	59.8622	40.1378
	KNN	79.3814	79.4255	20.5745
	SVM	91.7526	92.9825	07.0175
	Random Subspace	63.9175	63.9812	36.0188
Db4	Naïve-Bayes	48.4536	48.3919	51.6081
	ANN	53.6082	55.9740	44.0260
	KNN	76.2887	76.2968	23.7032
	SVM	94.8454	94.8723	05.1277
	Random Subspace	58.7629	58.7872	41.2128
Db8	Naïve-Bayes	49.4845	49.3902	50.6098
	ANN	52.5773	52.5723	47.4277
	KNN	85.5670	85.6351	14.3649
	SVM	91.7526	92.0669	07.9331
	Random Subspace	55.6701	56.0660	43.9340
Coif5	Naïve-Bayes	52.5773	52.5515	47.4485
	ANN	52.5773	75.7895	24.2105
	KNN	86.5979	86.7221	13.2779
	SVM	93.8144	93.9045	06.0955
	Random Subspace	58.7629	59.2175	40.5856

It can be observed from the table 3 that the classification accuracy of SVM classifier for the sym8 wavelet show high accuracy (95.8763%), more precision (95.9719%) and less false positive rate (4.0281%). Wavelet packet decomposition method using different mother wavelets have good discrimination power when the features fed to SVM classifier. Note that the use of mother wavelets db4 and coif5 with SVM achieve similar accuracies (94.8454% and 93.8144% respectively) but slightly lesser than sym8 wavelet. However, lesser accuracies achieved by using db8 & sym5 (91.7526%) with SVM, these values are clinically acceptable when compared with the KNN. Higher accuracies are possible when precision values are higher as evident from table 3. The misclassification rate represented by the false positive rate and it is obvious that FPrate for sym8 with SVM is very less (0.04) compared to other wavelets. It means that only four percentage of the labor signals were misclassified. It is worth noting that the classification results using the coif5 wavelet with KNN achieve good classification results of 86.5979% accuracy, 86.7221% precision and 13.2779% misclassification rate. Db4 wavelet with KNN has very poor performance compared with other wavelets. As expected, the Naïve-Bayes and ANN classifiers have very poor performance compared with KNN and SVM classifiers for all tested mother wavelets in terms of accuracy, FP rate and precision. Unfortunately the Random subspace classifier joins the party with lesser accuracies and higher FPrates. It is worth noting that high accuracy (63.9175%), less FPrate (36.0188%) and high precision (63.9812%) values observed for the sym5 wavelet. The Random subspace classifier shows better performance for the features that were extracted using discrete wavelet transform. Figure 4 depicts the classifier performance using line charts for accuracy, precision and FPrate using different mother wavelets for DWT method. From the line chart for the classifier accuracy, coif5 wavelet gives highest accuracy (93.9286%) follwed by the sym8 wavelet (92.8571%). The precision reflets the coif5 and sym8 wavelets performance among others mother wavelets with the values 94.2014% and 92.8922% respectively. The false positive rate for using coif5 wavelet is 5.7986% while sym8 wavelet has 7.1078%. However, using sym5 and db8 wavelets produced encouraging results of accuracy and precision above 90% and FP rate below 10%. Moreover, db4 wavelet gives the dissappointed yet resonable classification results with 89.2857%, 89.3178% and 10.6822% of accuracy, precision and FPrate respectively. It is worth noting that the FPrates for SVM classifier are smaller when compared with Random subspace classifier. We can observe the same from the figure 5. When using sym5 wavelet the SVM classifier has the lowest FPrate of 2.569% compared with the Random

subspace classifier FPrate of 8.8256%. Using db4 and coif5 wavelets SVM produces higher FPrates as evident from the figure4.

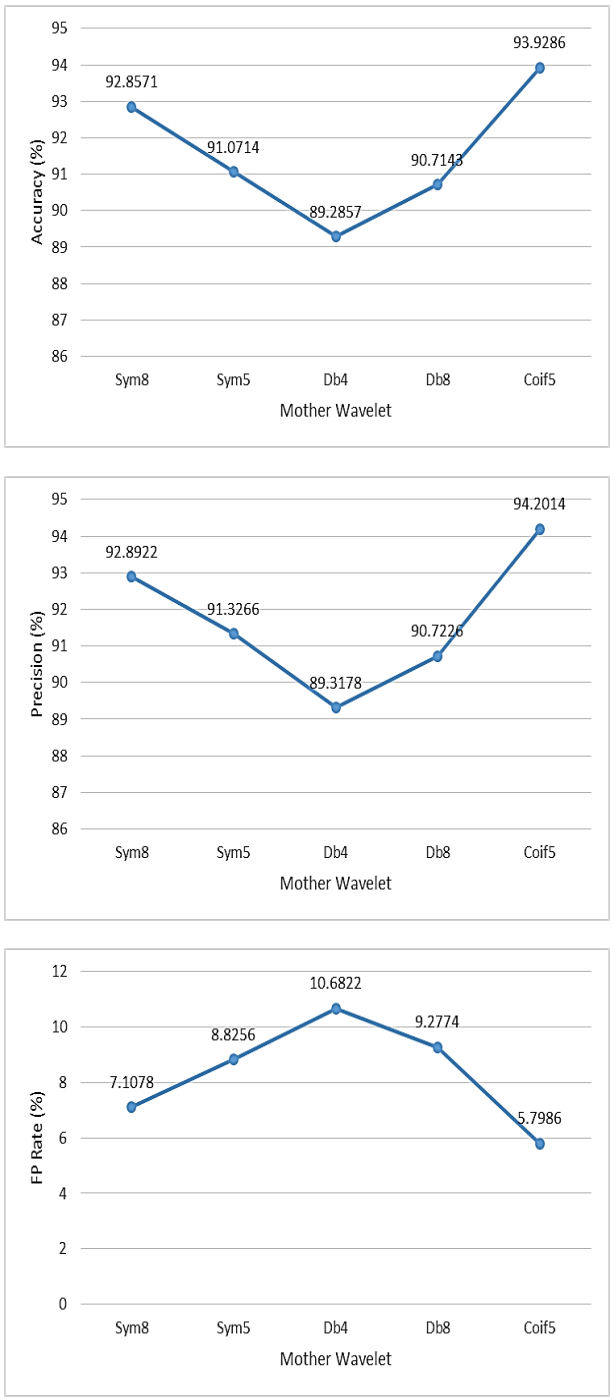


Fig. 4: Accuracy (Left), Precision (Middle) and Fprate (Right) of Random Subspace Classifier for the DWT Method Using Different Mother Wavelets.

For the wavelet packet transform employed for feature extraction in the second method, SVM classifier performed better over remaining classifiers. Line charts that shows the classification results using different mother wavelets represented in the figure 6 for WPT method. It is evident from the figure 6, use of sym8 wavelet produced highest accuracy (95.8763%) and precision (95.9719%) and lowest FPrate (4.0281%) among the other wavelets. Db4 wavelet and coif5 wavelets were able to produce better results. Moreover, all mother wavelets produced most encouraging results more than 90% discrimination accuracies and prcisions and less than 10% FP rates.

The two feature extraction methods, implemented in this work, are compared in terms accuracy, precision and FPrate against different mother wavelets are displayed in figure 7.

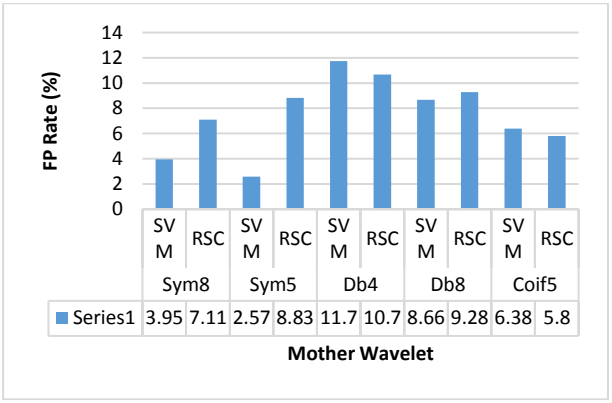


Fig. 5: FP Rate Values for SVM and RSC Classifier Using Different Mother Wavelets.

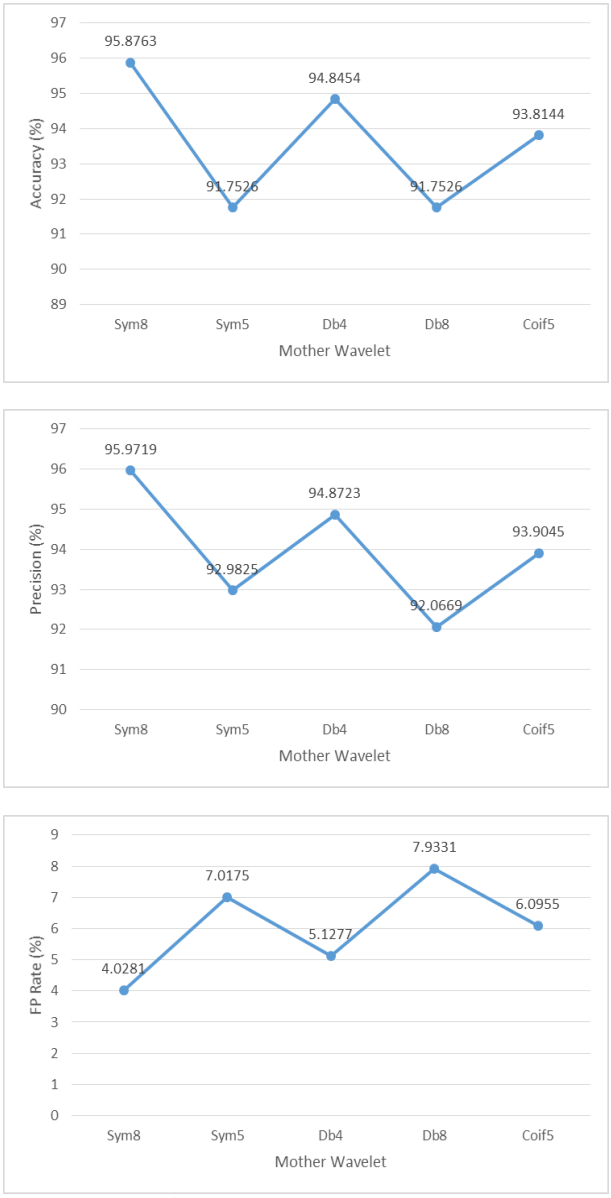


Fig. 6: Accuracy (Left), Precision (Middle) and Fprate (Right) Values for the SVM Classifier Combined with Wavelet Packet Transform Using Different Mother Wavelets.

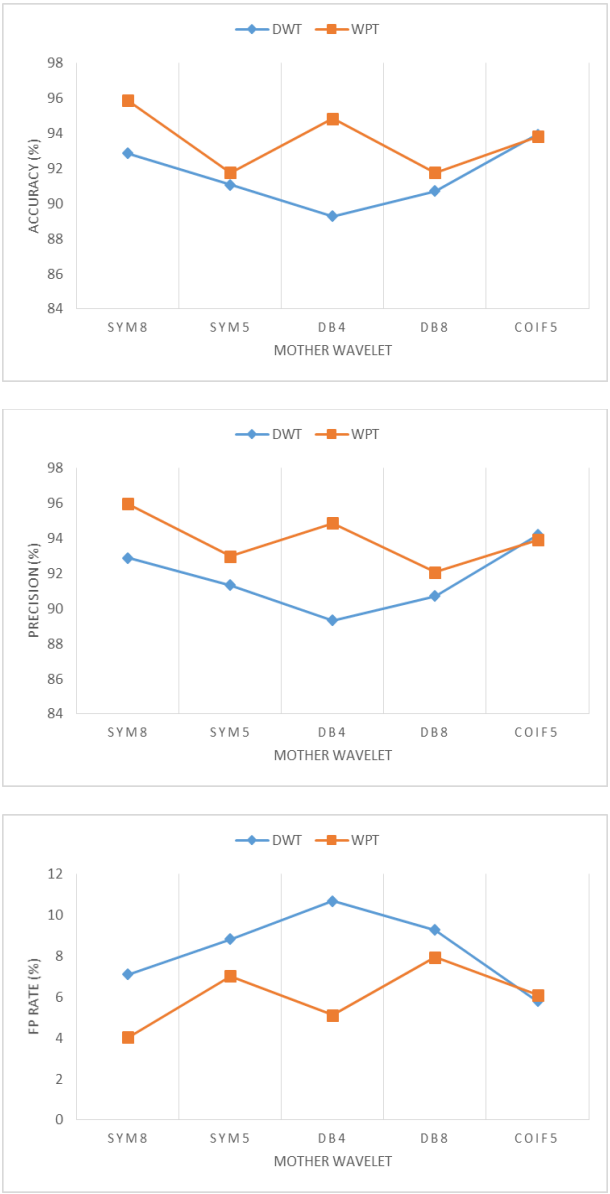


Fig. 7: Comparison of DWT and WPT Methods Using Accuracy (Left), Precision (Middle) and Fprate (Right) Values for Different Mother Wavelets.

For the DWT method the classification results obtained using Random subspace classifier are used while the WPT method employed the SVM classifier results. From all the line charts of the figure 7, we can observe the superiority of WPT method over DWT method in all aspects (accuracy, precision and FPrate). The classification results using coif5 wavelet has the similar results for the two methods. The usage of sym5 and db8 wavelets also produced the approximately equal values. It is worth noting that db4 wavelet have contrasting performance for two methods.

The limitation of the work is that the patients delivered within [2] and 3 days were in two different groups who may have similar signal characteristics and maternal factors. Class independence condition and large set of feature space might affected the Naïve-Bayes and ANN classifiers performance. The KNN classifier employed the Euclidean distance for the DWT features and Chebyshev distance for the WPT features. The SVM classifier has the lower FP rates than the RSC classifier though the accuracies are smaller using the DWT features. The RSC randomly selects the feature subspace, its performance varies for different learners. Selecting the optimal number of predictors and base learners is a difficult task while implementing the RSC classifiers. To conclude, DWT features extracted using coif5 mother wavelet performed better using RSC classifier with

The accuracy, precision and FPrates 93.9286%, 94.2014% and 5.7986% respectively. Sym8 wavelet used for extracting WPT features classified with SVM classifier produced 95.8763% accuracy, 95.9719% precision and 4.0281% FPrate. However, the authors personally prefer WPT+SVM combination over the other things as evident from the above figures and tables.

In the previous research [20], we achieved 87.5% accuracy for SVM classifier by extracting different linear and non-linear features. As the MMG signals have different and unique characteristics compared with uterine EMG/EHG signals, it is uncommon to compare with the results of Maner et al. [14], Ren et al. [15] and Diab et al. [17] though they achieved reasonable accuracies when classifying the term and preterm labor signals. The feature extraction using wavelet packet transform of EMG [17], EEG [18] and ECG [19] signals and classification with different classifiers gave high discrimination accuracies. So the WPT technique adopted here for uterine MMG signals for the first time and DWT method employed in our recent work. We achieved clinically acceptable discrimination accuracies in all cases by extracting the features from all subbands of DWT and from all the packets of complete wavelet packet tree. The maternal factors that affect the onset of labor were ignored while separating the term records as term-labor and term-nonlabor groups.

4. Conclusion

The uterine MMG signals were analyzed using discrete wavelet transform and wavelet packet transform techniques for the prediction of term labor. The term records taken from MIT-BIH database were separated in to two different groups, term-labor and term-nonlabor. Then the discrete wavelet transform and wavelet packet transforms were applied to decompose the multichannel signal to six levels using different mother wavelets. Variance, standard deviation, waveform length, energy and entropy of transform coefficients from the DWT and the normalized wavelet packet energy from the wavelet packet transform were used as features in the present work. The combination of DWT features and RSC classifier gives the accuracy, precision and FPrates 93.9286%, 94.2014% and 5.7986% respectively. WPT features classified with SVM classifier performed well with 95.8763% accuracy, 95.9719% precision and 4.0281% FPrate. So the combination of DWT+RSC and WPT+SVM showed clinically acceptable performance for assessing the term labor. The authors wanted to extend the proposed techniques on large set of patients and pre-term records as well. In future the authors may think about the dimension reduction and optimization techniques to test the viability of the present techniques in labor assessment. The physicians can use the results for better term & preterm labor assessment to reduce the morbidity and mortality of new born babies and unwanted hospital visits and treatments in case of false labor.

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