IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

IDENTIFICATION OF TRUE AND FALSE LABOR THROUGH UTERINE CONTRACTION SIGNALS

[1] Tirupati M. Goskula, [2] Dr. V. S. Chaorasia, [3] Dr. A. K. Mitra

[1] Research Scholar, [2] Professor, [3] Professor

[1] MIET, Gondia, India

Abstract: Woman health care during pregnancy period is utmost important job and with-it safe delivery of child by identifying the true labor is another skill and challenging task for experts. Early assessment of first stage of true labor is significant task so that expert can take care and can provide the necessary aid to the laboring mother to avoid the risk of mothers and child life. Maternal mortality is unacceptably high in under developed countries like India, which contributes one-fifth of total maternal deaths globally. The motivational factors and the necessity to develop a system for differentiating True and False Labor based on Uterine Contraction are discussed in this paper. The objective of the research is to develop the diagnostic system for the analysis of uterine contraction for differentiation of true and false labor with advantage of early detection of true labor. The system is experimented under the supervision of expert clinician and the results of these experiments are discussed. The results of the experiments are promising and suggest that the presented system is accurate, robust, simple to implement and is very useful for diagnosis of true and false labor.

Index Terms **- Electromyography (EMG), Short-time Fourier transform (STFT), continuous wavelet transform (CWT), Tocodynamometry (TOCO)**

I. INTRODUCTION

The birth rate throughout the world is decreasing noticeably, but still nearly 385,000 babies born each day around the world. In underdeveloped country like India this rate are 67,385 babies per day [1]. Thus, the Maternal and Child health-care is an important task every moment. The safe delivery of child and manage complications during delivery are well-known approach worldwide. Still the most common cause of death of infant and laboring mother between the ages of 15 and 49 is complication occur during the labor [2]. Maternal mortality is unacceptably high. In 2017, about 295 000 death occurs during pregnancy and delivery out of which 94% deaths were in low-resource areas [3]. The death of a Child and Maternal woman during childbirth is distressing and can be reduced by managing potential complications during childbirth. One of the complications during childbirth is usually weak contractions. The uterine contractions are a result of complex electrophysiological phenomena. The uterine myometrial activity is low throughout pregnancy and increases significantly. If labor is not progressing, a health care provider may give the woman medications to increase contractions and speed up labor [4]. The identification of labor is very important task and mostly it is identified by experience of skilled medical expert. The palpation is the classic method of detection the labor and with the advancement of technology during the last decade, techniques like external Tocodynamometry (TOCO) [5,6] Intrauterine pressure catheter (IUPC) [7, 8] and Electromyography (EMG) [9,10, 11, 12] are commonly used for diagnosis of true labor.

In classic palpation technique the patient is positioned supine with head and knees supported. The expert fingers and hands with the body of the woman or child and apply pressure to sense the auscultation [13]. It helps to collect the data about uterine contractions, the size of the pregnant uterus, any uterine masses, with position of fetus. This technique is very old, non-invasive, inexpensive and harmless but requires the constant bedside presence of a trained observer. In another study [14] this technique in 236 patients was studied and concluded that this technique is an inaccurate means of determining contraction strength.

In Modern techniques the analysis is carried out on basis of the frequency, duration, and strength of uterine contractions. Contractions must be last long enough, frequent, and intensive enough to make the cervix dilate and the fetus descend through the birth canal. For women in spontaneous labor, contractions are usually two to five minutes apart, last from 30 to 60 seconds, and have moderate strength [15].

II. DEVELOPMENT OF EMG SIGNAL DE-NOISING MODULE

The EMG signals are normally corrupted with different types of noises like noise while traveling through tissue, inherent noise in electronics equipment, ambient noise, and so forth. The frequency band of these unwanted signals is lies beyond and within the frequency spectrum of EMG signals [Kale et al., 2009]. These noises contaminate the uterine contraction signal to such an extent that the signal can become unsuitable for further analysis or diagnosis. This chapter discusses wavelet based effective noise suppression procedure for signal enhancement [Hussain et al., 2006].

The de-noised EMG signals are also analyzed in frequency and time-frequency domain. The signal analysis framework helps to detect any significant local changes in uterine contraction and hence reveals the important information at its early stage. However, the analysis of EMG signal is very complex because of its non-stationary and non-deterministic nature. After making series of experimentation and comprehensive literature survey, it is realized that, a single signal analysis technique is not capable to know all the features of the EMG signal.

2.1 Signal De-noising using Wavelet Transform

The wavelet transform is successfully applied to non-stationary signals for analysis and processing and provides an alternative to the Short-time Fourier transform (STFT). In contrast to STFT, which uses a single analysis window, the wavelet transform uses short windows at high frequencies and long windows at low frequencies. Moreover, Fourier transform used for decomposition of a signal only concentrated in frequency while the wavelet well concentrated in time and frequency both. The analysis of a non-stationary signal using the FT or the STFT does not give satisfactory results while the main advantage of wavelet analysis is its ability to perform local analysis.

The continuous wavelet transform (CWT) correlates the signal with families of waveforms that are well concentrated in time and frequency, which are obtained by the dilations and translations of an analysing wavelet ψ(t), so-called mother wavelet [Daubechies I., 1990]. A mother wavelet is a small wave which oscillates with an amplitude that starts out at zero, increases, and then decreases back to zero. The CWT is defined as the convolution between the original signal s (t) and a wavelet ψ(t) which can be calculated by:

$$\mathrm{CWT}_{\psi}(a,b) = \int_{-\infty}^{+\infty} s(t)\,\psi^{*}_{a,b}(t)dt \qquad (1)$$

$$= \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \qquad (2)$$

Here 'b' is the translation parameter and 'a' is the scaling parameter.

The disadvantages of the CWT are that it adds excess redundancy and is computationally intensive, so usually use in offline analysis applications. It does not provide the phase information of the analysed signal, thus not convenient where phase information is useful. Additionally, the original signal cannot be reconstructed from the CWT coefficients; so Discrete Wavelet Transform (DWT) is used in application where the signal reconstruction is important. The general block diagram of de-noising the signal using discrete wavelet transform is shown in fig. 1.

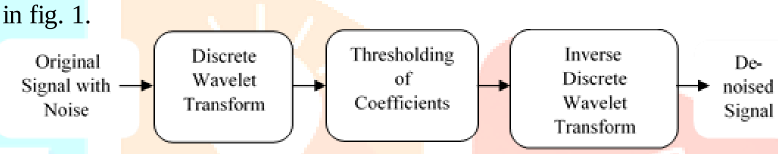

Figure 1. Signal De-noising using Wavelet Transform

III. DESIGN AND IMPLIMENTATION OF UTERINE CONTRACTION DIFFERENTIATION ALGORITHM

3.1 Analysis of EMG Signals for Feature Extraction

The EMG signals are analyzed in time-frequency domain using Discrete Wavelet Transform (DWT). This analysis provides few important diagnostic features for accurate differentiation of true and false labor. The DWT of the original signal is then obtained by concatenating all the coefficients, A and Ds, starting from the last level of decomposition.

3.2 Implementation of Wavelet Transform for Extraction of Statistical Parameters

The de-noised Uterine Contraction signals are used for extraction of features for its classification as true and false labor. The features are extracted through time-frequency domain analysis of these signals. A very useful implementation of DWT, called multi-resolution analysis, is the procedure of decomposition of an input signal x (n).

Each stage consists of two digital filters and two down samplers by 2 to produce the digitized signal. The original sampled signal x (n) is passed through a high pass filter h (n) and a low pass filter l (n). The down sampled outputs of first high pass filters and low pass filters provide the detail, D and the approximation, A. The first approximation A1 is decomposed again and this process is continued. By such means, we can easily extract useful information from the original signal into different frequency bands and at the same time the information is matched to the related time period.

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. The computed detail and approximation wavelet coefficients of the Uterine Contractions were used as the feature vectors for representation of signals. Each Uterine Contraction signal is transformed into time-frequency domain using fourth order Coiflets wavelet. The signals were decomposed to three levels. The decomposition process gives D1, D2 and D3 detail coefficients along with an A3 approximation coefficient [Qian S et al., 1996; Davy M. et al., 2001; Addison P., 2002; Debbal S. et al., 2004] The waveforms of true labor signals along with their approximation and decomposed coefficients are shown in figure 2a, 2b, 2c, 2d respectively and waveforms of false labor signals along with their approximation and decomposed coefficients are shown in figure 3a, 3b, 3c, 3d respectively.

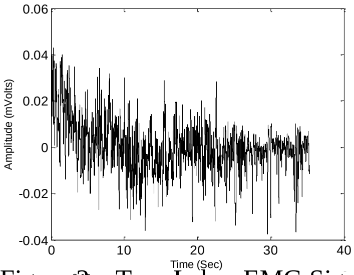

Figure 2a: True Labor EMG Signal

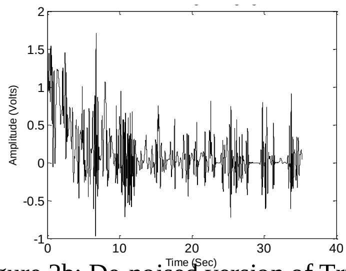

Figure 2b: De-noised version of True Labor EMG Signal

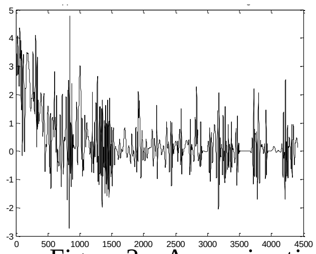

Figure 2c: Approximation Coefficient of True Labor EMG

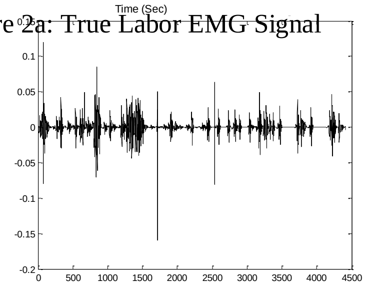

Figure 2d: Level 1 Detail Coefficients of True Labor EMG

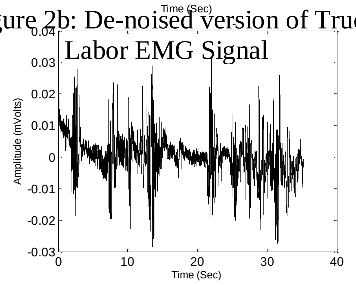

Figure 3a. False Labor EMG Signal

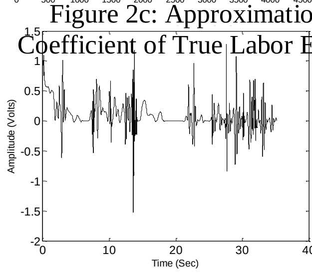

Figure 3b. De-noised version of False Labor EMG Signal

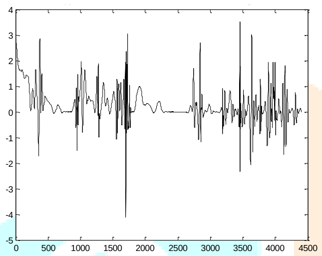

Figure 3c. Approximation Coefficients of False Labor

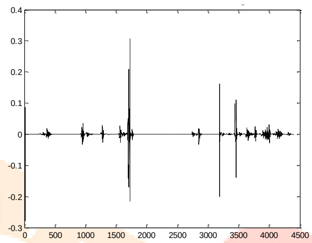

Figure 3d. Level 1 Detail Coefficients of False Labor EMG Signal

3.3 Determination of Statistical Features

The following statistics features of these wavelet coefficients were calculated from the decomposed coefficients to represent the time-frequency distribution of the Uterine Contraction signals.

- Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. Some distributions of data, such as the bell curve are symmetric. This means that the right and the left are perfect mirror images of one another. But not every distribution of data is symmetric. Sets of data that are not symmetric are said to be asymmetric. The measure of how asymmetric a distribution can be is called skewness. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution. In a normal distribution, the graph appears as a classical, symmetrical "bell-shaped curve." The mean, or average, and the mode, or maximum point on the curve, are equal. When a distribution is skewed to the left, the tail on the curves, left-hand side is longer than the tail on the right-hand side, and the mean is less than the mode. This situation is also called negative skewness. When a distribution is skewed to the right, the tail on the curve's right-hand side is longer than the tail on the left-hand side, and the mean is greater than the mode. This situation is also called positive skewness [16].

$$Skewness = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left[\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}\right]^3} \qquad (3)$$

- Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal. Distributions of data and probability distributions are not all the same shape. Some are asymmetric and skewed to the left or to the right. Other distributions are bimodal and have two peaks. In other words there are two values that dominate the distribution of values. Another feature to consider when talking about a distribution is not just the number of peaks but the shape of them. Kurtosis is the measure of the peak of a distribution, and indicates how high the distribution is around the mean. The kurtosis of distributions is in one of three categories of classification: Mesokurtic, Leptokurtic and Platykurtic
- Mesokurtic- Kurtosis is typically measured with respect to the normal distribution. A distribution that is peaked in the same way as any normal distribution, not just the standard normal distribution, is said to be mesokurtic. The peak of a mesokurtic distribution is neither high nor low, rather it is considered to be a baseline for the two other classifications.
- Leptokurtic -A leptokurtic distribution is one that has kurtosis greater than a mesokurtic distribution. Leptokurtic distributions are identified by peaks that are thin and tall. The tails of these distributions, to both the right and the left, are thick and heavy.
- Platykurtic - The third classification for kurtosis is platykurtic. Platykurtic distributions are those that have a peak lower than a mesokurtic distribution. Platykurtic distributions are characterized by certain flatness to the peak, and have slender tails.

$$Kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^2} \qquad (4)$$

- Crest Factor: The crest factor is the ratio of peak value to RMS value of waveform. This ratio is also called to peak-to-RMS ratio.

$$Crest\ Factor = \frac{peak\ value}{RMS\ value} \qquad (5)$$

- Shape Factor: The shape factor is the ratio of RMS value to Mean value of waveform. This ratio is also called to RMS-to-Mean ratio.

$$Shape\ Factor = \frac{RMS\ value}{Mean\ value} \qquad (6)$$

Table 1: The Extracted Features of two exemplary records from two classes

Data Set	Extracted features	Sub-bands			
		D1	D2	D3	D4
True Labor	Skewness	-0.019176085	0.004494556	-0.003552346	-0.62018758
	Kurtosis	9.306854978	8.665623559	6.529043699	3.33891299
	Crest Factor	329.63370598	2.4441658224	0.64672175	0.97008452
	Shape Factor	3316.205853	92.52890779	-20.03841567	-0.31376817
False Labor	Skewness	0.038564984	0.101382764	0.028136902	-0.39968424
	Kurtosis	43.86027312	32.27884709	25.9132601	1.90636876
	Crest Factor	283.041118	84.409323682	59.4389861	7.77833856
	Shape Factor	-2693.516316	89.42261404	-19.97229468	-0.17802709

These extracted features will be employed for classification of true and false labor.

3.4 Adaptive Neuro-Fuzzy Interference System

A Neuro-fuzzy (ANFIS) system is a class of adaptive networks, which are functionally equivalent to fuzzy inference system (FIS). It is a combination of neural network and fuzzy systems in such a way that neural network is used to determine the parameters of fuzzy system. ANFIS largely removes the requirement for manual optimization of the fuzzy system parameters. A neural network is used to automatically tune the system parameters, for example the membership functions bounds, leading to improved performance without operator invention. The Neuro-fuzzy system with the learning capability of neural network and with the advantages of the rule-base fuzzy system can improve the performance significantly and can provide a mechanism to incorporate past observations into the classification process. In neural network the training essentially builds the system. However, using a neuro-fuzzy scheme, the system is built by fuzzy logic definitions and is then refined using neural network training algorithms.

3.5 Adaptive Neuro-Fuzzy Interference System

Every Uterine Contraction signals are first decomposed to three levels using wavelet transform. For all these four decomposed coefficients Skewness, Kurtosis, Crest Factor and Shape Factor are calculated and used as input to the ANFIS based expert system. These features can serve as useful parameters in classifying the Uterine Contraction signals. Figure 4 shows the developed ANFIS.

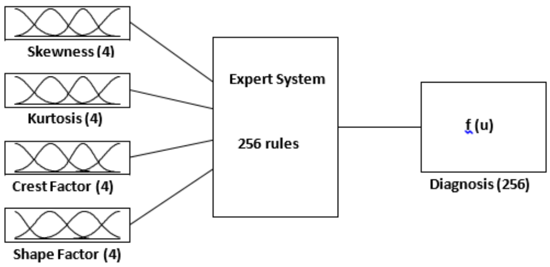

Figure 4. Fuzzy Inference System

The ANFIS system based on Expert knowledge contains 256 rules and 4 inputs and one output. The structure of expert ANFIS is shown below.

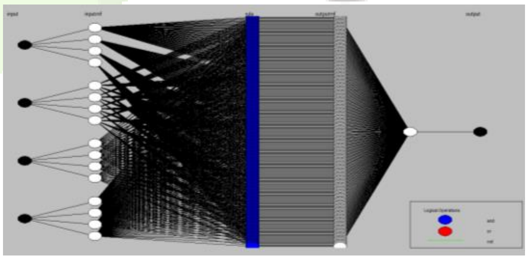

Figure 5. Topology of ANFIS

The four ANFIS classifiers were trained with the back-propagation gradient descent method in combination with the least squares method when four features for each decomposition coefficient representing the Uterine Contraction signals were used as inputs. To improve classification accuracy, the fifth ANFIS classifier was trained with the outputs of the four ANFIS classifiers. The fuzzy rule architecture of the ANFIS classifiers was designed by using Gaussian membership function. Each ANFIS classifier was implemented by using the MATLAB software package. The data sets were divided into two separate sets – the training data set and the testing data set.

The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the two classes of Uterine Contraction signals. For training the ANFIS in each run the relevant training data sets (of 30 true and 30 false) were used. The training data set were classified as 1 if the labor is normal and 2 if it was abnormal.

The examination of initial and final membership functions indicates that there are considerable changes in the final membership functions of the wavelet coefficients. The final membership function of all the four inputs (skewness, kurtosis, crest factor and shape factor) are depicted in figure 6, 7, 8 and 9 respectively.

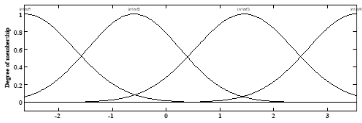

Figure 6. Final Membership Function of Coefficient A3 of skewness

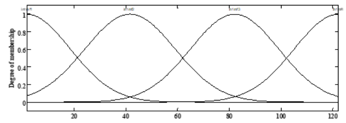

Figure 7. Final Membership Function of Coefficient A3 of Kurtosis

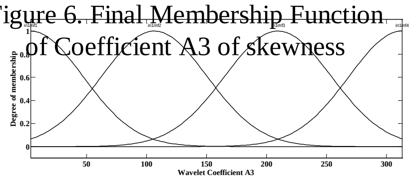

Figure 8. Final Membership Function of Coefficient A3 of Crest Factor

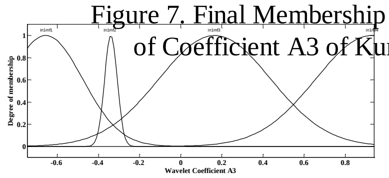

Figure 9. Final Membership Function of Coefficient A3 of Shape Factor

IV. EXPERIMENTAL TESTING AND RESULTS OF DEVELOPED ALGORITHM

The experimental testing were carried out by using signals, apart from the 60 signals used for training the ANFIS, are presented below for correct detection of true and false labor and the result of four different cases presented here for correct and wrong detection of true and false labor EMG signals.

Case I: A known normal EMG signal is taken from the available data base. Figure 10 shows the waveform of a True Labor EMG signal.

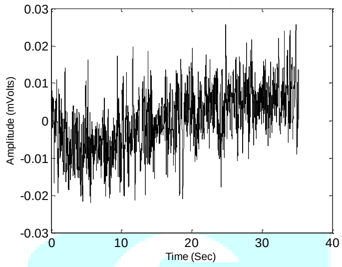

Figure 10. True labor EMG Signal with Noise (Case I)

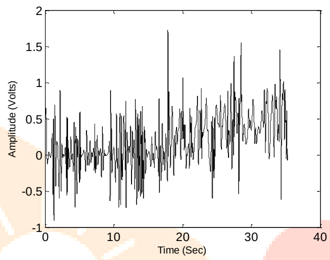

Figure 11. De-noised True Labor Signal using Wavelet 'coiflet 4' (Case I)

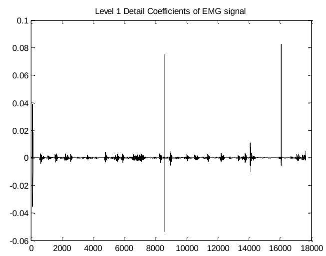

Figure 12. Coefficients of True Labor EMG Signal (Case I)

This signal is then passed through the developed wavelet based de-noising algorithm. The result of de-noising of this signal is shown in figure 11.

The de-noised version of true labor EMG signal is then used for extraction of important diagnostic features. For this purpose, the signal is considered in time-frequency domain. The representation of signal in time-frequency domain, in which, the signal is decomposed into three levels as shown in figure 12.

The selected features viz. skewness, kurtosis, crest factor and shape factor are determined from the time-frequency domain signals. Table 2 gives the values of all the determined features.

These features are fed as input to the ANFIS model for diagnostic decision. The result obtained from this model is compared with the opinion of the medical expert available during the testing. Following are the results obtained from the model and opinion of the medical expert.

Opinion of the medical expert: **True Labor**

Result from the developed system: **True Labor**

Table 2: The Extracted Features of True Labor EMG Signal (Case I)

Data Set	Extracted features	Sub-bands			
		D1	D2	D3	D4
True Labor	Skewness	0.1911	0.4257	0.0618	-1.1461
	Kurtosis	74.5531	75.9453	63.7046	41.7661
	Crest Factor	389.0714	262.2886	729.8745	40.0718
	Shape Factor	2.2288e+03	159.5201	35.4383	-0.2887

These features are fed as input to the ANFIS model for diagnostic decision. The result obtained from this model is compared with the opinion of the medical expert available during the testing. Following are the results obtained from the model and opinion of the medical expert.

Opinion of the medical expert: **True Labor**

Result from the developed system: **True Labor**

Case II: A known False Labor EMG signal is taken from the available data base. Figure 4.4 shows the waveform of a False Labor EMG signal, its result of de-noising, decomposed coefficients and extracted features are shown in figure 13, 14 and table 15 respectively.

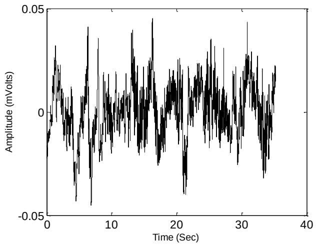

Figure 13. False labor EMG Signal with Noise

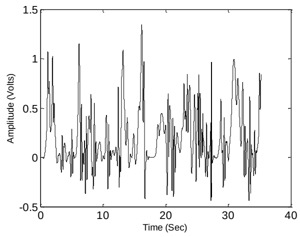

Figure 14. De-noised Signal using Wavelet 'coiflet 4'

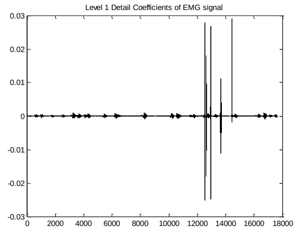

Figure 15. Coefficients of False Labor EMG Signal (Case II)

Table 3: The Extracted Features of False Labor EMG Signal (Case II)

Data Set	Extracted features	Sub-bands			
		D1	D2	D3	D4
False Labor	Skewness	0.0981	0.2501	0.0517	-0.4521
	Kurtosis	95.3569	97.9233	70.6139	5.1775
	Crest Factor	359.1997	198.4014	583.2623	14.9403
	Shape Factor	2.9227e+03	180.2549	38.3718	-0.3514

Opinion of the medical expert: **False Labor**

Result from the developed system: **False Labor**

Case III: Another case of known False Labor EMG signal is taken from the available data base. Figure 16 shows the waveform of a False Labor EMG signal, its result of de-noising, decomposed coefficients and extracted features are shown in figure 17, 18 and table 3 respectively.

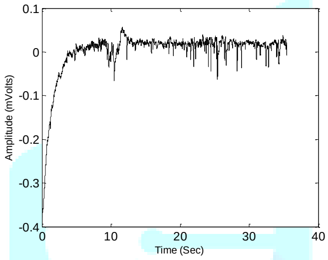

Figure 16. False labor EMG Signal with Noise

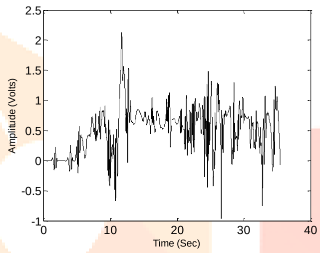

Figure 17. De-noised False Signal using Wavelet 'coiflet 4'

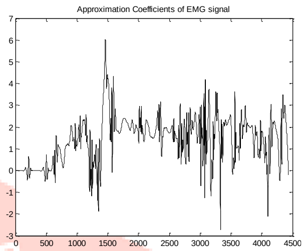

Figure 18. Coefficients of False Labor EMG Signal (Case III)

Table 4: The Extracted Features of False Labor EMG Signal (Case III)

Data Set	Extracted features	Sub-bands			
		D1	D2	D3	D4
False Labor	Skewness	0.0054	-0.1514	-0.0599	-0.9097
	Kurtosis	7.5102	9.8569	6.3456	12.5365
	Crest Factor	107.8554	50.7578	173.7152	17.4356
	Shape Factor	-5.209e+03	263.9374	65.4461	-0.2754

Opinion of the medical expert: **False Labor**

Result from the developed system: **True Labor**

Similarly, the remaining signals from the available data sets are used for quantitative evaluation of the developed system and the results of 29 signals are depicted in table 5, as Correct and Wrong detection. Also these results are used for determination of the performance efficiency of the developed system.

The test performance of the classifiers can be determined by computation of sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined and calculated as:

$$Sensitivity = \frac{Number\ of\ true\ positive\ assessment}{Number\ of\ all\ positive\ assessment} = \frac{TP}{(TP + FN)} \quad (7)$$

$$Specificity = \frac{Number\ of\ true\ negative\ assessment}{Number\ of\ all\ positive\ assessment} = \frac{TP}{(TP + FN)} \quad (8)$$

$$Specificity = \frac{07}{(07 + 01)} = 87.5\% \quad (9)$$

$$Total\ Classification\ Accuracy = \frac{Number\ of\ correct\ assessment}{Number\ of\ all\ assessment} = \frac{TP + TN}{(TP + TN + FN + FP)} \quad (10)$$

$$Total\ Classification\ Accuracy = \frac{20 + 07}{(20 + 07 + 01 + 01)} = 93.1\% \quad (11)$$

The values of the statistical parameters (sensitivity, specificity and total classification accuracy) are given in Table 6. The developed model has overall classification accuracy of about 93%. It can also be seen from Table 6 that the system has sensitivity of 95.23% and 87.50% for normal and abnormal signals respectively. Similarly the system achieved 100% and 100% specificity for normal and abnormal signals respectively.

Table 5: Evaluation of the developed system

Sr. No.	EMG Signal	Opinion of the Medical Expert	Result from developed system
1	emg31	True	True
2	emg32	True	True
3	emg33	True	True
4	emg34	True	True
5	emg35	True	True
6	emg36	True	True
7	emg37	True	True
8	emg38	True	True
9	emg39	True	True
10	emg40	True	True
11	emg41	True	True
12	emg42	True	True
13	emg43	True	True
14	emg44	True	True
15	emg45	True	True
16	emg46	True	True
17	emg47	True	True
18	emg48	True	True
19	**emg49**	**True**	**False**
20	emg50	True	True
21	emg51	True	True
22	emg52	False	False
23	emg53	False	False
24	emg54	False	False
25	emg55	False	False
26	emg56	False	False
27	**emg57**	**False**	**True**
28	emg58	False	False
29	emg59	False	False

Table 6 The values of Statistical Parameters

EMG Data Sets	Statistical Parameters		
	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
True Labor	95.23	100	93.1
False Labor	87.50	100	

V. CONCLUSION

This research work proposed a method for differentiating between the true and false labor through uterine contraction signals. The specific objective of the research was to arm the sensitive group, say pregnant women residing in the rural areas having lack of basic hospital facilities which would help them by providing or forecasting accurate estimation of the labor, so that they can take preventive measures to consult nearby doctor or get hospitalized for further treatment.

The results of this study suggest that, the EMG is the best methodology for the targeted application. To a large extent, this body of work achieves the targeted objective in comprehensiveness of its reporting and suitability of classification; which serves the interest of scholars, engineers, product designers and developers.

Qualitative and quantitative testing of the developed system is done to validate the performance of the system. In qualitative testing the results obtained from the developed system are compared with the opinion of the medical expert. However in quantitative testing, numerous number of EMG signals (True and False labor) were used. The results show that the developed methodology has classification accuracy of 93.1%.

The specific advantages of the overall developed system are summaries as under:

- It is highly cost-effective and simple to operate; hence can be used for identification of true labor in remote places also.
- The developed system is based on passive signal acquisition technique; in which no energy is emitted during acquisition hence it eliminates the risk of exposure to harmful radiations to both mother and fetal.
- The system is simple and, which makes it suitable for long-term monitoring and offers easy portability.
- Due to its simple operation, it can also be used by ordinary woman for diagnosis, but it is not at all suggested to do this. It should be diagnosed and interpret by the expert.
- Last but not the least, it is efficient.

The limitations of the developed system are listed as follows.

- This noise and artifacts in the signal are a serious issue to be considered, as this adversely affects the quality of the signal.
- Though, the efficiency of the developed system is enough good to consider it as one of the method for identification of true labor, it is always suggested to confirm the result by other ways.

VI. CONCLUSION

Although the developed system for detection of True and False labor provides encouraging results, there are number of future directions which may be proposed in this domain. Some of the areas for future work are as given below.

- Further area of research can be to include few more number of parameters from EMG signal analysis in the classification process, which may further reduce the error of the developed system.
- It is proposed to implement the more advanced technique for effective de-noising of EMG signals.

A more comprehensive clinical validation of the presented system can also be considered as a future avenue for research.

VII. REFERENCES

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