International Journal of Recent Trends in Engineering & Research

ISSN (ONLINE) : 2455 – 1457 IMPACT FACTOR : 4.101

# A Review of Significant Researches on 4x4 EHG Signal for Classifying Uterine Contraction

**ATHIRA T[1]., SHANIBA ASMI P[2].**

*[1,2]Department of Electronics and Communication Engineering,*
*MES College of Engineering, Kuttippuram, India*

**Abstract-**Pregnancy monitoring is the most important challenge during gestation period. Some early deliveries cause mortality and morbidity of the new born babies. Electrohysterogram is the most promising method for monitoring the uterine contraction thus the physiological wellbeing of the foetal and the mother. As it is a non-invasive method there are no side effects and its accuracy for early diagnosis is more. There are different numbers of electrodes used to collect the signals from the mother's abdomen by placing electrodes on the abdomen. Through this paper we are focusing on different researches used for pregnancy monitoring using 16 electrode database. Based on the studies this paper provides different steps in electrohysterogram data processing such as preprocessing, feature extraction, classifiers for classifying pregnancy and labour contraction.

**Keywords**-Uterine contraction, Electrohysterogram, 16 electrode database, preprocessing, feature extraction, classifiers

## I. INTRODUCTION

Generation and spreading of electrical activity from a given uterine cell to neighboring cell is the main reason for uterine contraction. The progression of contraction is from weak and inefficient to strong and efficient when approaches to labour. During gestation period some may suffer from complications in their pregnancy that may end with a preterm delivery. Preterm delivery or preterm labour means baby being born before 37 weeks of gestation, whereas term delivery implies birth occurring at 37-42 weeks of gestation. Children born before their time have high risk of mortality, as well as health and development problems. Prematurity is now the second-leading cause of death in children under 5 years and the single most important cause of death in the critical first month of life. According to the World Health Organization (WHO), over 1 million children die each year due to complications of preterm birth. Many survivors face a lifetime of disability, including learning disabilities and visual and hearing problems [1]. The primary aim of pregnancy monitoring is check the condition of mother and foetus and to provide necessary medical support for a healthy birth. Monitoring uterine contractility is essential to differentiate the normal contractions of the pregnancy from that leads to cervical dilation of uterus and preterm birth.

There are different methods for monitoring uterine contractions but none of them are effective and precise for early prediction of preterm birth. One of the direct method for accurately measure the uterine contractions is by intrauterine pressure catheter but as it is invasive and chance for rupturing of membrane it can't be used during pregnancy. Another external non-invasive method widely used for monitoring is tocography, but it does not permit to specify the efficiency of contractions. Biological tests, such as fibronectin, have been clinically used for the prediction of premature births, although they have a low predictive value [2]. So a non-invasive and more reliable method is needed for the early detection and prevention of preterm birth threats. This earlier diagnosis would permit an earlier administration of tocolytics agents and therefore a longer maintain of the foetus in uterus, with associated reduction of perinatal mortality and morbidity. One of the most promising and non-invasive method for monitoring uterine activity is Electrohysterogram (EHG) or uterine electromyogram (EMG). In this method the electrical activity of uterus is studied by placing electrodes on the mother's abdomen [3]. The EHG is the signal recorded on the abdominal surface, which represents the electrical activity that triggers mechanical contraction, thus this analysis is a promising method for accurate early recognition of risk in premature labour. There are different numbers of electrodes used for recording the EHG signal and studies have shown that large numbers of electrodes are adequate for EHG analysis. So in this paper we are focusing on multichannel recordings by using 16 channel database.

This paper explains the analysis made by the EHG signal for classifying uterine contraction thus to check the risk in preterm labour. Section 2 discusses data collection, pre-processing of the signal, features extracted from the signal and classifiers used for classification uterine contractions; and section 3 concludes the paper.

## II. DATA COLLECTION AND PRE-PROCESSING

### A. Data collection

In the field of EHG, some studies have recorded their own databases, while some others have used publically available databases [4]. The EHG signals commonly used for research are derived from Icelandic 16-electrode Electrohysterogram Database of PhysioNet. This database comprises 122 EHG recordings (112 pregnancy recordings and 10 labour recordings) made on 45 pregnant women. The measurements were performed using a grid of 16 electrodes, arranged in a 4-by-4 matrix positioned on the abdomen. The signal was sampled at 200Hz and digitized to 16 bits [5].

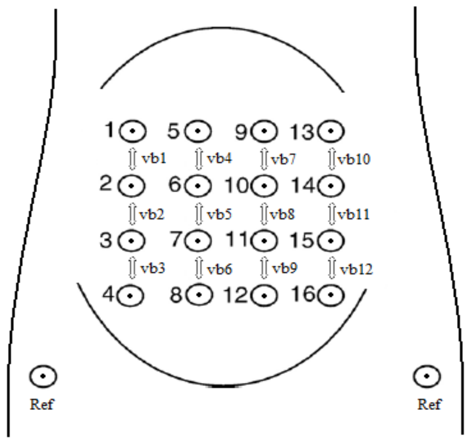


***Figure 2.1. Positioning of electrodes on woman's abdomen***

Some other papers are based on digitized uterine EMG signals recorded on 32 women: twenty two were recorded during pregnancy (33 - 41 week of gestation, WG), seven during labour (37 - 42 WG) and three during both pregnancy and labour (33 – 42 WG). Recordings were made at the University Hospital of Amiens in France and at the Landspitali University hospital in Iceland by using a protocol approved by the relevant ethical committee (VSN 02-0006-V2). Recordings were performed by using a 16 electrode grid, arranged in a 4x4 matrix positioned on the women's abdominal. The third electrode column was always put on the uterine median axis. Reference electrodes were placed on each hip of the woman. Signals were sampled at 200 Hz[6].

### B. Preprocessing

EHG is non-stationary signals which contain not only the useful information but also contain artifacts such as electronic and electromagnetic noise as well as movement artifacts, skeletal EMG, maternal respirations and electrocardiogram from both mother and the foetus. Therefore, the recorded signals cannot be used directly.

So in many papers the 16 unipolar signals distributed over the 4 x 4 matrix were subtracted two by two, according to the vertical axis, is calculated to obtain 12 bipolar signals ($Vb_i$, i = 1 to 12), which is shown in figure (2.1) . Analysis of bipolar electrical signals has the advantage of increasing the signal-to-noise ratio and consequently increasing the signal quality. And also in some other papers before extracting the features, three steps are usually performed such as filtering, normalising and down sampling which are briefly given below:

1) Artifacts or unwanted parts of signals are removed by filtering the signals between 0.1 and 3 Hz.
2) All signals are normalized by dividing each signal by its standard deviation in order to ensure that all features will have equal significance when they are applied to the committee machines.
3) All signals were down sampled in order to reduce the number of the studied packets.

**C. Feature Extraction**

Feature extraction is the important step to extract the relevant information from the signals. In many studies various parameters are calculated from EHG signals and are widely used in studies for pregnancy monitoring and preterm delivery prediction. In literature, different methods are used such as linear and non-linear that includes time, frequency, time frequency analysis, extraction from EHG propagation, graph theory, etc [6]. Various types of linear and non-linear characteristics extracted from the EHG are power spectrum density, mean frequency, median frequency, peak frequency, 95% limit frequency and 10% limit frequency and are calculated as the spectral parameters of contractions. Besides, non-linear approaches, including sample entropy, variance entropy, time reversibility and Lyapunov exponent have been used to describe non-linear characteristics of EHG signals. Velocity, directionality and synchronization of EHG signals provide the propagation information of labour contraction which can be used to monitor the progress of pregnancy. In many studies it was showed that frequency-related parameters are well suited for non-stationary EHG signals. It has been reported for the EHG signal the spectral properties changes from lower frequency contractions during pregnancy to higher frequency at delivery. The power density spectrum (PDS) curve is a function of frequency and represents the relative contribution of each frequency to a signal. The PDS curve of a signal can be used to calculate various parameters of that signal.

In [7] frequency related parameters such as mean frequency, peak frequency, median frequency and 95% limit frequency are extracted and compare their performance using receiver operating characteristics curve. Result had shown that median frequency is the best parameter for distinguishing pregnancy and labour. In [8][9][10][11], the power of the contraction and the median frequency were extracted from the signals corresponding to each channel.

In [12] the non-linear correlation coefficient were used for analyzing the relationships between uterine electrical activity and the result have shown that it is a promising way to improve the clinical usefulness of the EHG signal for monitoring in pregnancy, labour detection, and predicting preterm labour. Based on the fact that the energy distribution of the uterine EMG signals varies throughout pregnancy, in [13] the recorded signals are first decomposed into a 3- level wavelet packet tree then the Normalized Wavelet Packets Energies are calculated. On the other hand, in [14] the use of the multiresolution analysis and the LDB algorithm that selects a basis from a dictionary that illuminates the dissimilarities among the two classes presented an important preprocessing step for increasing the discriminatory powers of the extracted features.

In [15], 20 features (16 linear and 4 nonlinear) are extracted from the EHG: mean frequency (MPF), peak frequency (PF), and deciles (D1...D9) which contain the median frequency, parameters extracted from wavelet decomposition (W1...W5), Lyapunov exponent (LE), time reversibility ($T_r$), sample entropy (SE), and variance entropy (VarEn). In this paper three methods are presented for feature subset selection. The first one is based on the measurement of the Jeffrey divergence (JD) i.e. distance between the parameter histograms computed from the pregnancy and labour EHG classes. The other two methods are sequential forward selection (SFS) and binary particle swarm optimization (BPSO). The goal of these methods is to select, from a given feature set, the features subset that gives the maximum classification accuracy.

In [16] the author investigated the effect of down sampling on the performances of the non-linear parameters for pregnancy or labour classification. Non-linear methods such as Time reversibility, Sample Entropy, Lyapunov Exponents and Delay Vector Variance were used in this work.

In [17] the author explored the possibility of using adaptive filter in order to obtain high SNR in recorded EHG signals. In this paper two adaptive filter algorithms (LMS and RLS) were used and calculated their performance for various filter orders. The SNR for the two filters obtained were then compared with those obtained by bipolar recording and a Laplacian filter.

In [18][19] graph parameters derived from graph theory was used to check whether it is able to discriminate pregnancy and labour. Due to the poor result obtained in paper [18] by using non-linear correlation coefficient ($h^2$) as a preprocessing step Filtered-Windowed-$h^2$ (FW-$h^2$) method was applied for real EHG signals. Based on the statistical tests, it was investigated that FW-$h^2$ is much better.

In [20], the author first selected the best channel using relief method and then extracted 21 linear and non-linear features. The extracted linear features are: mean frequency, Peak Frequency, deciles (D1…D9) which contain the median frequency D5, parameters extracted from wavelet decomposition (W1…W5). The nonlinear features are: Time reversibility, Lyapunov exponent, Sample Entropy, Variance entropy and Detrended fluctuation analysis (DFA). In this paper Binary particle swarm optimization (BPSO) based feature selection method used to select the best features from the selected channels. The result have shown that bipolar channel selection followed by features selection using BPSO is better than monopolar in order to classify pregnancy and labour contractions.

In [21] the analysis focuses on time domain features represented by four parameters and frequency domain features represented by three parameters and identifies the features that can be used as means of classification based on highest difference between pregnancy and labour recordings.

The paper [22] presents a method for feature extraction and classification of EHG between pregnancy and labour group, based on Hilbert-Huang transform (HHT) and extreme learning machine (ELM). For each sample, each channel was decomposed into a set of intrinsic mode functions (IMFs) using empirical mode decomposition (EMD).Then, the Hilbert transform was applied to IMF to obtain analytic function. The maximum amplitude of analytic function was extracted as feature.

In [23] typical linear and nonlinear characteristics of EHG signals, including root mean square (RMS), peak frequency (PF), median frequency (MDF), mean frequency (MNF), parameters from wavelet decomposition (W4, W5) and time reversibility (Tr) are extracted. These characteristics are compared between contraction and non-contraction in term labour group and non-labour group.

 

**D. Classification**

The information extracted from the EMG signals will be then fed into classifier to map different patterns and match them appropriately. Classifiers should be deployed to distinguish different categories of the features extracted. For successful classification, standard classifiers, e.g., support vector machine (SVM), k nearest neighbour (k-NN), linear discriminant analysis (LDA), Quadratic discriminant analysis (QDA) as well as advanced classifiers, such as variety of neural networks were used. The classifiers used in literature are shown in table 2.1

***Table 2.1. Review on significant researches***

| Author & Year | Features | Classifier | Remark |
|---|---|---|---|
| Moslem B., et al (2011) | Mean frequency, Median frequency, Peak frequency , 95% limit frequency | Student's t test | Median frequency showed best result Accuracy: 78.4% |
| Bassam Moslem., et al(2011) | Power of the contraction, Median frequency | Support Vector Classifier (SVM) | 88.4% accuracy is obtained. |
| Moslem B., et al (2011) | Power of the contraction, Median frequency | Artificial Neural Network (ANN) | An overall classification accuracy of 82.65 % was obtained. |
| Bassam Moslem., et al(2011) | Power of the contraction, Median frequency | Support Vector Classifier (SVM) | A decision fusion rule based on the WMV yielded better results than the MV rule. |
| Bassam Moslem., et al(2012) | Power of the contraction, Median frequency | Support Vector Classifier (SVM) | Combination of (VB10+VB2+VB1 +VB4) showed higher discrimination between pregnancy and labour contractions. |
| Malunoud Hassan., et al(2012) | Correlation coefficients, Peak frequency Median frequency | Comparing parameters | Correlation analysis is clearly better than the frequency related parameters to distinguish between non-labour and labour signals. |
| Mohamad O. Diab., et al(2012) | Normalized Wavelet Packet Energy | Artificial Neural Network (ANN) | CCR of 96.3% for pregnancy and 71% labour contractions were obtained. |
| Bassam Moslem., et al(2012) | Features were extracted from LDB (local discriminant bases) algorithm: Power, Median frequency, Relative energy | Support Vector Classifier (SVM) | By using a weighted decision fusion method, an overall classification accuracy of 92.4% was obtained |
| D.Alamedine., et al(2013) | Mean frequency, Peak Frequency, deciles (D1…D9) which contain the median frequency, parameters extracted from wavelet decomposition (W1…W5), Time reversibility, Lyapunov exponent, Sample Entropy, Variance entropy | Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and *K*-nearest neighbors (k-NN) | Variance entropy and D8 are the most discriminating subset and Binary particle swarm optimization (BPSO) with QDA corresponds to the highest percentage of correct classification. |

| | | | |
|---|---|---|---|
| A. Diab., et al(2013) | Time reversibility, Sample Entropy, Lyapunov Exponents, Delay Vector Variance | Comparing parameters | No significant decrease of classification rate by down sampling. |
| Catherine K Marque., et al (2014) | To explore the use of adaptive filters | Sign test | Recurrent Least Square (RLS) filtering algorithm gives higher SNR than Least Mean Square (LMS). |
| N. Nader., et al(2015) | Graph parameters, Assortativity, Clustering coefficient , Local Efficiency, Strength | Graph theory | Graph parameters are promising tools to distinguish between pregnancy and labour signals (AUC= 0.801 for the Strength). |
| S. Al-Omar., et al(2015) | Assortativity, Clustering Coefficient, Efficiency, Modularity, Total Strength | Student's t test | A much better result was obtained after filtered-window-$h^2$ (FW-$h^2$) preprocessing technique than $h^2$. |
| Dima Alamedine., et al(2015) | Mean frequency, Peak Frequency, deciles (D1..D9) which contain the median frequency D5, parameters extracted from wavelet decomposition (W1…W5), Time reversibility, Lyapunov exponent, Sample Entropy, Variance entropy , Detrended fluctuation analysis | *K*-nearest neighbors (k-NN) | Bipolar channel selection followed by features selection using BPSO is better than monopolar in order to classify pregnancy and labour contractions. |
| Alexandru Pasarica., et al(2017) | Normalized relative amplitude, Normalized integrated EHG, Normalized signal variance, Normalized simple square integrate, Normalized root mean square, Normalized frequency ratio, Normalized spectral moments, Variance of central frequency | Student's t test | Time domain parameters Normalized integrated EHG (NIEHG), Normalized signal variance (NVAR) and Normalized simple square integrate (NSSI) and the frequency domain parameter Normalized frequency ratio (NFR) showed promising result. |
| Lili Chen., et al(2017) | EMD method is used to decompose a signal into a finite number of intrinsic mode functions (IMFs) | Extreme Learning Machine classifier (ELM) | Higher classification of labour and pregnancy EHG is obtained by IMF1 with ELM. |
| Zhihui Liu., et al(2017) | Root Mean Square, Peak frequency , Median frequency, Mean frequency, Parameters from wavelet decomposition (W4, W5) and time reversibility(Tr) | Student's t test | Variability of RMS, W4, W5 and Tr of contraction periods were significantly larger than those of non-contraction periods, while others were significantly smaller than those of non-contraction period. |

**E. Classification Performance**

In order to compare the classification performances of various parameters, the receiver operating characteristic (ROC) curve analysis was used in review papers. A ROC graph is a technique for visualizing, organizing and selecting classifiers based on their performances. The ROC curve for binary classification plots the true positive rate (TPR) as a function of the false positive rate (FPR) i.e. sensitivity against 1-specificity [19]. ROC curves are compared by mean of the classic Area under the Curve (AUC), accuracy (ACC), sensitivity (True positive rate) and specificity (1-False positive rate). These measures from the curves are calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (1)$$

$$Sensitivity\ or\ True\ Positive\ Rate(TPR) = \frac{TP}{TP + FN} \times 100 \quad (2)$$

$$Specificity\ or\ False\ Positive\ Rate(FPR) = \frac{FP}{FP + TN} \times 100 \quad (3)$$

Here *TP*, *FN*, *FP*, and *TN*, respectively, represent the numbers of true positives, false negatives, false positives, and true negatives.

## III. CONCLUSION

Uterine EMG or EHG have an important role in monitoring the progress during gestation period thus for early preterm labour prediction. From the survey it is clear that multichannel recording provides better characteristic discrimination between pregnancy and labour contraction than 5 or less number of electrodes. In this paper different step in EHG data analysis such as data collection, preprocessing, feature extraction and classification were reviewed. The parameters extracted from the signal have an important role in contraction monitoring. From this survey it is clear that frequency related parameters are well suited for classification than amplitude related parameters. And also commonly used preprocessing steps are also investigated. It was investigated that bipolar signals is best than monopolar signal as it have high signal to noise ratio. In some of the papers feature selection techniques were used, which is also studied in this review. Proper selection of classifier is also important for discriminating pregnancy and labour contractions.

## REFERENCECS

I. March of Dimes., Howson C. P., Kinney M. V. Lawn J. E., "Save the Children WHO. Born Too Soon: The Global Action Report on Preterm Birth", in PMNCH, World Health Organization: Geneva, 2012.

II. Tanuja Kashyap.,Jaspal Bagga.,Mina Mishra.,Challenges and Techniques available to Predict Preterm Delivery and effectiveness of Eletrohysterogram: A Survey", in IJCRT., Volume 6, Issue 1 February 2018.

III. J Garcia-Casado et al.,"Electrohysterography in the diagnosis of preterm birth: a review", in Institute of Physics and Engineering in Medicine (IPEM).,February 2018.

IV. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG,Mietus JE, Moody GB, Peng C-K, Stanley HE.,"Components of a New Research Resource for Complex Physiologic Signals.", in PhysioBank, PhysioToolkit, and PhysioNet, Jun 13.

V. Alexandersson, A., Steingrimsdottir, T., Terrien, J., Marque, C., Karlsson. B., "The Icelandic 16-electrode electrohysterogram database.", in Sci. Data2:150017, doi:10.1038/sdata.2015.17 (2015).

VI. Shaniba Asmi P., Kamalraj Subramaniam, and Nisheena V. Iqbal.,"A review of significant researches on prediction of preterm birth using uterine electromyogram signal", in Future Generation Computer Systems., https://doi.org/10.1016/j.future.2018.10.033 2018.

VII. Moslem B., Karlsson B., Diab M.O., Khalil M., "Classification Performance of the Frequency-Related Parameters Derived From Uterine EMG Signals", in 33rd Annual International Conference of the IEEE.,Sep 2011.

VIII. Bassam Moslem., Mohamad Diab.,and Mohamad Khalil., "Combining Multiple Support Vector Machines for Boosting the Classification Accuracy of Uterine EMG Signals", in International Conference of the IEEE.,2011.

IX. Bassam Moslem., Mohamad Diab.,and Mohamad Khalil.,"Classification of Multichannel Uterine EMG Signals", in 33rd Annual International Conference of the IEEE.,2011.

X. Bassam Moslem., Mohamad Diab.,and Mohamad Khalil., "A Multisensor Data Fusion Approach for Improving the Classification Accuracy of Uterine EMG Signals", in 18th IEEE International Conference on Electronics, Circuits, and Systems.,2011.

XI. Bassam Moslem., Mohamad Diab., Mohamad Khalil and Catherine Marque.,"Combining data fusion with multiresolution analysis for improving the classification accuracy of uterine EMG signals", in EURASIP Journal on Advances in Signal Processing.,August 2012.

XII. Bassam Moslem., Mohamad Diab.,and Mohamad Khalil.,"Classification of Multichannel Uterine EMG Signals Using a Reduced Number of Channels", in 8th International Symposium on Mechatronics and its Applications.,2012.

XIII. Malunoud Hassan., Jeremy Terrien.,and Charles Muszynski.,"Better Pregnancy Monitoring Using Nonlinear Correlation Analysis of External Uterine Electromyography", in IEEE Transaction on biomedical engineering., 2012.

XIV. Mohamad O. Diab., Bassam Moslem ., Mohamad Khalil ., and Catherine Marque., "Classification of Uterine EMG Signals by Using Normalized Wavelet Packet Energy", in 16th IEEE Mediterranean Electrotechnical Conference., 335 - 338, 2012.

XV. D.Alamedine., M.Khalil.,and C.Marque,"Comparison of Different EHG Feature Selection Methods for the Detection of Preterm Labor.,in Computational and Mathematical Methods in Medicine, Volume 2013, Article ID 485684, 9 pages.

XVI. S.Al-Omar., A.Diab., N.Nader., M.Khalil., B.Karlsson and C.Marque., "Detecting Labor using Graph Theory on Connectivity Matrices of Uterine EMG.", 2015.

XVII. N. Nader., M. Hassan., and W. Falou.,"Classification of pregnancy and labor contractions using a graph theory based analysis", in 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).,2876 - 2879, 2015.

XVIII. Amer Zaylaa.,Ahmad Diab.,Mohamad Khalil.,and Catherine Marque.," Multichannel EHG Segmentation for automatically identifying contractions and motion artifacts", in International Conference on Advances in Biomedical Engineering (ICABME)., 2017.

XIX. Lili Chen.,and Yaru Hao.,"Feature Extraction and Classification of EHG between Pregnancy and Labour Group Using Hilbert-Huang Transform and Extreme Learning Machine.", in Hindawi Computational and Mathematical Methods in Medicine.,Volume 2017, Article ID 7949507, 9 pages.

XX. Zhihui Liu.,Dongmei Hao.,Lei Zhang.,and Juntao Liu., "Comparison of electrohysterogram characteristics during uterine contraction and non-contraction during labor" , 2017.

XXI. Alexandru Pasarica.,Casian Miron.,Hariton Costin.,"Parameter-Based Analysis of Antepartum and Labour Electrohysterogram Signals", in The 10th International symposium on advanced topics in electrical engineering., March 23-25, 2017.