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Classification of Labour Contractions Using KNN Classifier

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***Abstract*—Uterine contractions of desired strength and frequency are one of the important requirements for the smooth progress of cervical dilation and delivery of baby. Presently, Tocograph is used to monitor the strength, duration and frequency of uterine contractions. One of the major drawbacks of Tocography is subjectivity in interpretation. Therefore, there is a need for an objective method for classification of uterine contractions. In this paper, a K Nearest Neighbor based classification method is presented for automated classification of different types of uterine contractions during labour.**

For the study, CTG signals from Physionet database were used. The signals were annotated by an expert Doctor in three categories: mild (n=33), moderate (n=64) and strong (n=96). After processing of signals, eight features were extracted, followed by implementation of an appropriate classifier. K Nearest Neighbor and Rule based K Nearest Neighbor classifiers were used to classify the uterine contractions into mild, moderate and strong. We achieved an accuracy of 90.91%, 85% and 85.71% for classification using Rule based K Nearest Neighbor classification method.

Keywords—Tocography, Uterine Contractions, Frequency, Rule based K Nearest Neighbor.

I. INTRODUCTION

From very early weeks of pregnancy, the uterus undergoes spontaneous irregular, contractions; these contractions become progressively more intense and regular towards the end of pregnancy and then they become strong enough to expel the fetus during labour. Hence, the uterine contractions during labour are categorized in three groups: Mild, Moderate and Strong. Also, as the labour progresses, the cervix dilates progressively from 0cm (closed) to 10cm (opened completely) to facilitate delivery of baby. Uterine contractions of desired frequency and strength are one of the major contributors towards opening the cervix progressively during labour [1]. Therefore, for smooth transition of labour from one stage to another, uterine contractions are one of the important prerequisites. Although, the exact mechanism responsible for increased uterine activity is not known, two major factors namely hormonal changes and mechanical effect in abdominal and uterine muscles could be the cause for the same. Uterine contractions are initiated by the hormone Oxytocin, which is produced in the hypothalamus and is secreted by the pituitary gland. Sometimes, women fail to produce Oxytocin in quantity desired for labour. This may lead to failure to progress or *prolonged labour* due to insufficient strength of uterine contractions. It is recommended by the World Health Organization (WHO) and the Federation of Gynecology and Obstetrics (FIGO) to use synthetic Oxytocin when there are insufficient contractions. However, over dosage of this has the potential to cause high frequency of uterine contractions termed as *uterine hyperstimulation*. This may lead to fetal distress and also increases the risk of uterine rupture. Hence, 'augmentation' of labour using Oxytocin is critical and great care must be taken to avoid the undesirable effects.

Currently, Tocograph as a part of Cardiotocography (CTG) is used to monitor the strength, duration and frequency of uterine contractions. It is a pressure sensor which picks up the contraction of the uterus and displays it on a graph with the X-axis as time (seconds) and the Y-axis as pressure (mmHg). The sensor is placed at the fundus of the abdomen and is kept in place with the help of a belt. A sample Tocography is shown in Figure 1.

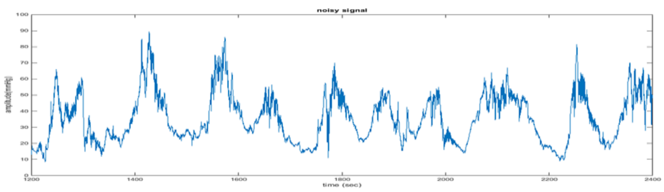

Fig 1: Uterine contractions in Tocography signal

There are several disadvantages of Tocography. Important among them are:
a) Inter and intra-personal variation in interpretation of CTG trace [2].
b) Sometimes there is shift (either up or down) in baseline of signal which makes interpretation difficult. This is known as baseline wandering [3].

To overcome the above disadvantages of Tocography, an automated approach is presented in this paper, wherein the contractions are classified into three types: mild, moderate and strong. Once classified objectively, the frequency of each type of contraction can be obtained. This can be used as a guide by the Doctors to monitor uterine activity during labour especially when Oxytocin is used. The rest of the paper is divided as follows: Section 2 details about data collection, annotation process and an outline of the methodology used in this paper. Preprocessing is discussed in section 3.This is followed by feature extraction and classification in section 4 and 5 respectively. Finally, we conclude in section 6.

II. DATACOLLECTION, ANNOTATION AND METHODOLOGY

Cardiotocography data was obtained from the CTU-UHB Intrapartum Cardiotocography Database of Physionet [4]. All the signals had a sampling frequency of *4* Hz. From the signals, segments of *20* minutes length were taken as input. A Doctor was asked to label the contractions in the signal as mild, moderate or strong, based on clinical expertise. The methodology followed in this paper is as follows.

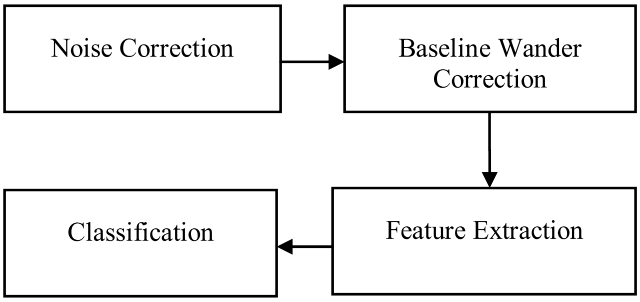

Fig 2: Methodology

III. PREPROCESSING

Tocography signal usually have high frequency noise due to sudden movements during recording. A moving average filter of order 50 was used to compensate for this noise. Moving average is a linear filter, which reduces random noise and at the same time retains the sharp step response. It replaces each value with the average of the neighbors. It can be mathematically represented using the formula:

$$y(i) = \frac{1}{M} \sum_{j=0}^{M-1} x(i-j) \tag{1}$$

Where M is the order of the filter, x is the input signal and y is the output signal.

The output of a moving average filter is shown in Figure 4.

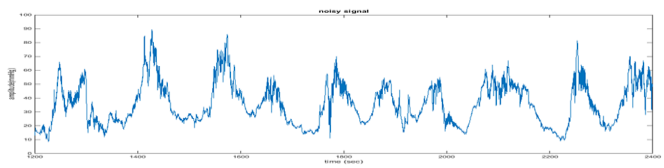

Fig 3: Noisy input signal

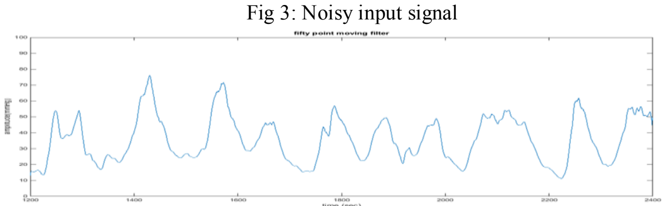

Fig 4: After processing

Baseline wander, as the name suggests is the shift (either up or down) along the X-axis. It is a low frequency noise which affects the apparent intensity of the contractions and makes their interpretation difficult. Therefore, the detection of baseline and its correction is very important for analysis. Significant work has been done to remove baseline wander from the Fetal Heart Rate of Cardiotocography; notable examples includes work done by Spence et.al [5], Taylor et.al [6], Andersson et.al [7] and Das et.al [8]. But, a very little work has been done on the correction of uterine contraction baseline; two examples of this are, work done by Cazares et.al [9], Joao A.L. et.al [2]. Cazares et.al used morphological filter to correct baseline wander. We implemented the following algorithm to correct baseline wander:

(a) Identification of local minima points (LMP). Local minima points are those points which are lesser than their adjacent points. A sample *y(i)* is classified as a LMP if the following condition is satisfied:

$$(y(i-1)>y(i)) \ \& \ (y(i) < y(i+1)).$$

(b) In the next step, a threshold was obtained by dividing the mean of the signal by a correction factor of *1.14* (empirically found value). The minima points which were below this threshold were taken as the candidate minima points.
(c) The candidate minima points were interpolated to obtain a baseline.
(d) The baseline was subtracted from the original signal to obtain a corrected baseline.
The estimated baseline is shown in Figure 5.

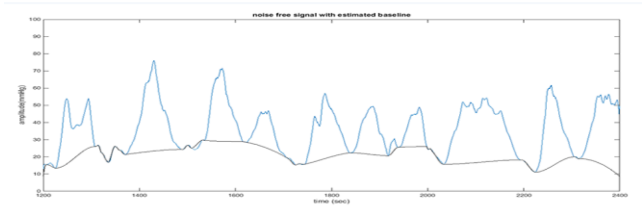

Fig 5: Estimation of baseline

The above method was similar to one of the baseline correction technique used in ECG[10].

IV. FEATURE EXTRACTION

First, end points of the contraction were detected. End points are the points where the signal deviates from zero and returns back to zero with reference to the corrected baseline. Once the end points were found, local peaks were detected by finding local maxima points in-between the end points. Only if local maxima peaks are found in-between the end points, features were obtained. This is to ensure that features were derived only if a contraction was present. However, sometimes due to improper baseline fit some contractions would get completely distorted. These types of contractions were not included further for feature extraction and classification.

We extracted eight features from the signal, which were clubbed into two categories: Morphological and Signal Based.

A. Morphological Features: This includes

- **Intensity**-The maximum amplitude of each contraction peak with reference to baseline.
- **Duration**-The time a contraction takes to rise and return to the baseline.

B. Signal Based Features: This includes

- **Area of each contraction**-Approximate area was calculated using Trapezoidal rule:

$$\int_a^b ydx = \frac{b-a}{2N} * [y(1) + 2 * y(2) + ... + y(N+1)] \quad (2)$$

Where N is the length of the contraction, y (1), y (2) etc….. are pressure values of the contraction, and b & a are the starting and ending points of the same contraction.

- **Average power of each contraction**- It was calculated using the formula:

$$AveragePower = \frac{1}{N}\sum_{n=0}^{N-1} y(n)^2 \quad (3)$$

- **Time to rise:** The time taken by a contraction to reach its peak value from its baseline.
- **Time to fall:** The time taken by a contraction to reach its baseline form peak.
- **Mean Duration Time (MDT)**: Average time spent in each contraction was found by using the formula:

$$MeanDuration = \frac{1}{N}\sum_{n=0}^{N} x(n) \quad (4)$$

Where, x (n) is the time spent in a contraction, N is the length of the contraction.

- **Standard Deviation of MDT:** It was calculated using the formula:

$$StandardDeviation = \sqrt{\frac{\sum_{n=0}^{N}(x(n) - MeanDuration)^2}{N}} \quad (5)$$

Where x (n) is the time spent in a contraction, N is the length of the contraction.

V. CLASSIFICATION

Features were normalized using the formula:

$$f' = \frac{f - \mu}{\sigma} \quad (6)$$

Where, f is the original feature vector, μ is the mean of that feature vector, σ is the standard deviation, f' is the normalized feature vector. The normalized feature vectors were given as input to the classifier. One-vs.-all classification technique was implemented. Since the features did not have normal distribution, a non-parametric classifier was chosen. K Nearest Neighbor (KNN) classifier was used to classify the contractions. It is a supervised nonparametric method of classification [11]. It memorizes the whole training data set along with the label. Given the test point, it calculates the K nearest neighbor from the test point to every training vector and makes a voting. The label with the maximum vote is taken and the test point is given the same label.

For the purpose of classification, feature vectors were split into 70% training and 30% testing, in a non-random manner. On the training data, the total numbers of nearest neighbors were found by the K-fold technique. In the K-fold technique, the training data is split into K-folds, for our study we used 10-fold cross validation technique. The model was trained on K-1 folds and tested on the K^{th} fold. It was repeated K times. Then the average error for all the K-folds was computed. The model with the least error was chosen. The number of neighbors (N) was varied for odd numbers from one to ten and the average error for each fold was calculated. The value of N for which the minimum error was obtained, was chosen. The number of neighbors obtained for Mild, Moderate and Strong were *3, 5* and *3* respectively.

VI. RESULTS AND DISCUSSION

After annotation by an experienced Doctor *33*, *64* and *96* samples of mild, moderate and strong contractions were obtained respectively (Ground Truth). The same contractions and its corresponding features were extracted from the signal using the algorithm mentioned in Section IV.

The classifier was evaluated using accuracy, sensitivity and specificity. Table 1 shows the performance of the KNN classifier.

Table1: Performance of KNN classifier

TYPE	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
Mild	90.91	90.91	90.91
Moderate	77.5	75	80
Strong	82.14	89.29	75

To improve the sensitivity further and thereby the accuracy, Rule based KNN classifier was implemented i.e. certain rules were given to the output of KNN classifier. The rules are listed as follows:

1. If the intensity of the contraction was between *0.9390* and *7.5454* and if the output of KNN classifier was previously classified as non-mild type contraction, then the contraction was assigned to mild type class.
2. If the intensity of the contraction was between *15.0441* and *34.0395* and if the output of KNN classifier was previously classified as non-moderate type contraction, then the contraction was assigned to moderate type class.
3. If the intensity of the contraction was greater than *34.0395* and if the output of KNN classifier was previously classified as non-strong type contraction, then the contraction was assigned to strong type class.

The above threshold values were obtained by the following steps:

1. The distribution of intensity of each contraction type was found by Liliefors test. It was found to have Gaussian distribution except for strong type.
2. Lower limit was found by taking the mean (training

intensity vector) – 1 standard deviation (training intensity vector) and upper limit was found by taking the mean (training intensity vector) + 1 standard deviation (training intensity vector). Table 2 illustrates the performance of Rule Based KNN classifier. The confusion matrix for mild, moderate and strong type class using Rule Based KNN classifier is shown in Table 3, 4 and 5 respectively.

Table 2: Performance of a Rule Based KNN Classifier

TYPE	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
Mild	90.91	90.91	90.91
Moderate	85	90	80
Strong	85.71	100	71

Table 3: Confusion Matrix of Mild Type contraction using Rule Based KNN Classifier.

Uterine contraction	Classified as Mild contraction	Classified as Non-Mild contraction
Mild contraction	10	1
Non-Mild contraction	1	10

Table 4: Confusion Matrix of Moderate Type contraction using Rule Based KNN Classifier

Uterine contraction	Classified as Moderate contraction	Classified as Non-Moderate contraction
Moderate contraction	18	2
Non-Moderate contraction	4	16

Table 5: Confusion Matrix of Strong Type contraction using Rule Based KNN classifier

Uterine contraction	Classified as Strong contraction	Classified as Non-Strong contraction
Strong contraction	28	0
Non-Strong contraction	8	20

By this method we could objectively classify the uterine contractions with good sensitivity, thereby decreasing false alarms. Also, baseline wandering was corrected in an adaptive manner .i.e. the method used is data-driven and does not require pre-defined cut-off frequency. Further, Moving Average filter was used, which requires only $N*(M-1)$ additions and N divisions when compared to FIR based filters which requires $Nlog_2N$ complex additions, it is computationally efficient. Also, there is no phase distortion when compared to Infinite Impulse response filters (IIR).

VII. CONCLUSION

To conclude, significant work is going on in the Cardiotocography based Fetal Heart Rate's signal processing and computerized analysis [12] [13]. But so far, very little research is carried on uterine contraction signal. One such example is classification of uterine contractions into true and false labour using Tocography by Hiwale et.al [14]. We believe that our paper presents one such early attempt for objective classification of labour contractions. The method presented here can be used for frequency calculation, which can be used to guide the Doctors to monitor labour progress especially when Oxytocin is used, to avoid *hyperstimulation*. One of the limitations of this study is that we had only one Doctor who was involved for annotation of signal type. This makes our study susceptible to inter-observation variability in Tocography analysis; this will be tested in subsequent studies.

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REFERENCES

[1]. N. Hatfield, "Introductory maternity and paediatric nursing," Wolters Kluwer Health, China, 3rd Edition, pp. 180-181, 2013.

[2]. J. Bernardes, A. Costa-Pereira, D. Ayres-de-Campos, H. Van Geijn, and L. Pereira-Leite, "Evaluation of interobserver agreement of Cardiotocograms," International Journal of Gynaecology & Obstetrics, vol. 57, pp. 33-37, 1997

[3]. J. A. Marques, P. C. Cortez, J. P. Madeiro, and F. S. Schlindwein, "Computerized Cardiotocography analysis system based on Hilbert Transform," Expert System with Applications, vol. 40, pp. 7159-7658, 2013.

[4]. V. Chudáček, J. Spilka, M. Burša, P. Janků, and L. Hruban, "Open access intrapartum CTG database," BMC Pregnancy and Childbirth, vol. 14, pp. 14-16, 2014.

[5]. M. Mongelli, R. Dawkins, T. Chung, D. Sahota, J. A. Spencer, and A. M. Chang, "Computerized estimation of the baseline fetal heart rate in labour: the low frequency line," BJOG: An International Journal of Obstetrics & Gynecology", vol. 104, pp. 1128-1133, 1997

[6]. G. M. Taylor, G. J. Mires, E. W. Abel, S. Tsantis, T. Farrell, P. F. Chien, et al., "The development and validation of an algorithm for real-time computerized fetal heart rate monitoring in labour," BJOG: An International Journal of Obstetrics & Gynecology, vol. 107, pp. 1130-1137, 2000.

[7]. S. Andersson, "Acceleration and deceleration detection and baseline estimation," Master of Science Thesis, Chalmers University of Technology, Sweden, 2011.

[8]. S. Das, K. Roy, and C. Saha, "A novel approach for extraction and analysis of variability of Baseline," 2011 International Conference on Recent Trends in Information Systems, pp. 336-339, 2011.

[9]. S. Cazares, L. Tarassenko, L. Impe, M. Moulden, and C. Redman, "Automated identification of abnormal Cardiotocograms using Neural Network Visualization Techniques," Engineering in Medicine and Biology Society, 2001, Proceedings of the 23rd Annual International Conference of the IEEE, vol. 2, pp. 1629-1632, 2001.

[10]. A. Jayant, T. Singh, and M. Kaur, "Different Techniques to Remove Baseline Wander from ECG Signal", International Journal of Emerging Research in Management &Technology, vol. 2, pp. 16-19, 2013.

[11]. E. Alpaydin, "Introduction to Machine Learning", MIT Press, USA, 2nd Edition, pp.163-209, 2014.

[12]. B. Guijarro-Berdiñas, A. Alonso-Betanzos, and O. Fontenla-Romero, "Intelligent analysis and pattern recognition in Cardiotocography signals using a tightly coupled hybrid system," Artificial Intelligence, vol. 136, pp. 1-27, 2002.

[13]. N. Krupa, A. M. Mohd, E. Zahedi, S. Ahmed, and F. M. Hassan, "Antepartum fetal heart rate feature extraction and classification using empirical mode decomposition and support vector machine," Biomedical engineering online, vol. 10, pp. 6-10, 2011.

[14]. S. Hiwale, V. Pallavi, F. Celine, and R. S. Singh, "Automated Uterine Contraction Analysis for Detecting False Labour Contractions," First Ama IEEE Medical Technology Conference on Individualized Healthcare, vol. 1, 2010.