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Computerized Algorithm for Fetal Heart Rate Baseline and Baseline Variability Estimation based on Distance Between Signal Average and α Value

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Abstract: This study proposed new algorithm for FHR baseline (BL) and baseline Variability (V) calculation. In this study, we present a method for estimating baseline as one of the most important features present in the (FHR) signal. An algorithm based on digital (CTG) using Math Lab programming to estimate FHR baseline and baseline variability, the research in this study rely on detection of baseline value and baseline variability which gives an indication of the fetal status and health condition. The results are compared with the opinion of experts (obstetricians) baseline and baseline variability estimation. The obtained results shows slightly difference with the expert's opinion as a first step for further work to estimate the other parameters of the CTG.

Key words: Cardiotocogram, fetal heart rate, baseline, baseline variability, short term variability, long term variability, uterine contraction

INTRODUCTION

Develop automated systems for medical applications works instead the human become increasingly extensive (Alsubael, 2009; Jose and Mythili, 2009). Recently, image and signal processing systems play a great role on developing new approaches to analyze, extract and retrieve the significant information from the image and the signal (Madhloom *et al*., 2010; Hendel *et al*., 2010; Ahmed *et al*., 2010).

Cardiotocography (CTG) is a widely used non-invasive tool for checking the fetal conditions in the antepartum period (RCOG, 2001; Sahhaf *et al*., 2010; Swarnalatha and Prasad, 2010). CTG signal is compensation of two signals Fetal Heart Rate (FHR) and Uterine Activity (UA) can be monitored simultaneously (Romano *et al*., 2006). Electronic Fetal Monitoring (EFM) has been widely used for antepartum (the period before labour) and intrapartum (the period during labour and delivery) fetal surveillance. The term EFM means the continuous recording and monitoring of Fetal Heart Rate (FHR) and Uterine Contraction (UC). Figure 1 (Susan and Christine, 2005) shows CTG segment with the FHR at the upper part of the figure and UC at the lower part.

More than 60% of fetal deaths occur before the onset of delivery, hence it would be natural to extend the principles of intrapartum Fetal Heart Rate (FHR) monitoring to the antepartum period. A substantial number of antepartum deaths occur in women who have risk factors of uteroplacental insufficiency (UPI). Cardiotocogram (CTG) consists of two distinct signals, its continuous recording of instantaneous Fetal Heart Rate (FHR) and Uterine Activity (UC). During stressful situations for the fetus, such as the uterine contractions at the time of delivery, the sympathetic nerves may act as a compensatory mechanism to improve the fetal heart pumping activity which is reflected in the FHR signal variations (Parer, 1997).

For the last three decades many researchers have employed different methods to help the doctors to interpret the CTG trace pattern from the field of computer programming and signal processing. They have supported and incorporated the doctors and interpretations in order to reach a satisfactory level of reliability so as to act as a decision support system in obstetrics. Optimization problems arise in a wide variety of scientific and engineering applications including signal processing, system identification, filter design, function

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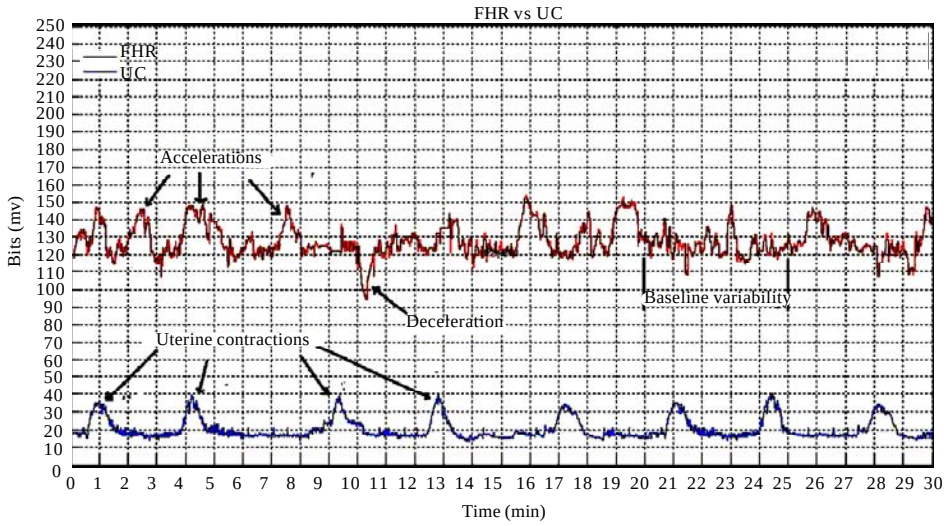

Fig. 1: Examples of CTG trace FHR (top) and uterine activity (bottom)

approximation, regression analysis and so on (Erdogmus, 2010; Vatansever and Ozdemir, 2009). Up to now, none of them has been adopted worldwide for everyday practice (Van Geijn, 1996). Baseline is considered as one of the fundamental features of the FHR pattern recognition, as most of the other features rely on its value. It can also be called as the resting level of the fetal heart rate. Up to present days there is no consensus on the best methodology for baseline estimation in computer analysis of Cardiotocogram. Attitudes towards fetal monitoring have altered as more research findings are published and reviewed highlighting both the beneficial and detrimental effects of continuous electronic fetal heart rate monitoring (EFM) (Van Geijn, 1996). Researcher established a few methodologies for FHR estimation based on mathematical and computerized analysis programs (Mantel *et al*., 1990; Arduini *et al*., 1993; David *et al*., 2007; Ruffo *et al*., 2010).

Most proposed mathematical algorithms for computerized estimation of FHR baseline are satisfactory when the FHR tracings are regular with long and stable FHR segments. These kinds of tracings are found most commonly during the antepartum and the early hours of delivery. Baseline estimation is more complex when the FHR tracings are irregular and any misinterpretation would affect the overall interpretation of the CTGs (RCOG, 2001).

When interpreting a CTG, there are four main parameters to consider relating to the FHR and uterine contractions (UC) as shown in Fig. 1:

- Baseline heart rate (BL)
- Baseline Variability (V)
- Periodic Changes
- Accelerations (Acc)
- Decelerations (Dec)

In this study, we focus only on the estimation of FHR baseline and baseline variability as the most important parameter in CTG signal. Fetal heart rate baseline which is controlled mainly by the autonomic nervous system. Sympathetic activity results in tachycardia, while parasympathetic activity, mainly the vagus nerve, results in bradycardia. In normal circumstances, the vagal activity is dominant, exerting a constant slowing of the heart rate, stabilizing it at 110-160 bpm the baseline fetal heart rate is also controlled by receptors in the aortic arch:

- Chemoreceptors which are stimulated by changes in oxygen levels. An acute fall in oxygen levels leads to an increase in parasympathetic activity, resulting in a slowing of the heart rate
- Baroreceptors which are stimulated by changes in arterial pressure. Hypertension leads to an increase parasympathetic activity, resulting in a slowing of the heart rate. Hypotension leads to an increase in sympathetic activity, resulting in a rise in the heart rate

The baseline heart rate is also related to gestational age and the maturity of vagus nerve. The more mature the fetus, the more evident the slowing effect that the vagus nerve exerts upon the heart rate becomes. The baseline FHR is the heart rate during a 10 min segment rounded to

Table 1: RCOG guidelines for baseline classification

Reassuring	Non-Reassuring	Abnormal
110-160 bpm	100-109 bpm	<100 bpm or
	161-180 bpm	>180 bpm

Table 2: Baseline variability classification

Normal variability	≥ 5 bpm Between contractions
Non-Reassuring Variability	< 5 bpm for >40 min or more but <90 min
Abnormal Variability	< 5 bpm for 90 min or more

the nearest 5 beat per min increment excluding periods of marked FHR variability, periodic or episodic changes and segments of baseline that differ by more than 25 beats per min (bpm). The minimum baseline duration must be at least 2 min. If minimum baseline duration is less than 2 min then the baseline is indeterminate.

According to the Royal College of Obstetricians and Gynecologists (RCOG), the mean level of the FHR when this is stable, excluding accelerations and decelerations. It is determined over a time period of 5 or 10 min and expressed in bpm. Baseline is classified as Reassuring, Non-reassuring and Abnormal based on the values given in Table 1 (RCOG, 2001).

Great interest has been dedicated to the variability of the FHR around its mean value, namely FHR variability (FHRV) which can support more detailed and objective analyses (Sibony *et al*., 1994). Short Term Variability (STV) and Long Term Variability (LTV) are usually distinguished. STV refers to the continuous variation in difference between successive inter-beat intervals and it is difficult to interpret reliably with the naked eye. Due to a certain periodicity in the direction and magnitude of these changes, the values of FHR are distributed around their mean level. These changes are called LTV. LTV refers to fluctuations in the FHR over seconds (Jezewski *et al*., 2006; Divon *et al*., 1985; Signorini *et al*., 2003; FIGO, 1995; Figueras *et al*., 2005; Pardey *et al*., 2002; Van Geijn, 1996). Baseline variability is defined as minor fluctuation in baseline FHR. It is assessed by estimating the difference in bpm between the highest peak and lowest trough of fluctuation in one-minute segments of the trace. Table 2 shows the different types of baseline variability (RCOG, 2001).

Motivation: To improve CTG analysis, more objective methods for CTG interpretation are of crucial importance; therefore, considerable efforts have been spent and several analysis methodologies have been proposed in recent years (Magenes *et al*., 2004). For example, some automatic software provides signal-processing facilities to offer support to clinicians to determine and quantify some of the most employed parameters (average, variability, accelerations and decelerations of FHR, frequency of UC). However, the introduction of these computerised classification systems has led only to a partial reduction of intra- and inter-observer variation. Since 1970 many researchers have employed different methods to help the doctors to interpret the CTG trace pattern from the field of signal processing and computer programming. They have supported doctors and interpretations in order to reach a satisfactory level of reliability so as to act as a decision support system in obstetrics. Up to now, none of them has been adopted worldwide for everyday practice (Van Geijnt, 1996). There is currently no consensus on the best methodology for baseline and baseline variability estimation in computer analysis of cardiotocographs. The algorithm proposed in this study will help and support the doctors and interpretations to make a good interpretation for all pregnancy cases before delivery and its application can be used in all hospitals as first computerized detection software for CTG pattern parameters analyzer. Fetal heart rate Variability (V) is an important parameter that can provide early information about fetal's well being and identify those at risk of diseases such as Sudden Infant Death Syndrome (SIDS) (Camm *et al*., 1996). Previous studies of variability signals obtained using (CTG) have shown that fetal acidosis and fetal hypoxia are directly associated with reduced (FHRv) which is directly related to increasing risk of prenatal mortality (Di Renzo *et al*., 1996; Maulik *et al*., 1983; Leeuwen *et al*., 2007; Freeman *et al*., 2003).

The main objective of this research is to develop effective algorithm for FHR baseline and baseline variability estimation using conventional programming. The major tasks involved are listed below:

- Research on the CTG signals, its feature and analysis. Acquiring normal and abnormal CTG signals
- Design and development of conventional FHR estimation baseline and baseline variability algorithm based on RCOG guidelines and Furthermore, validating the conventional process by comparing the results with visual interpretation of the expert's

There is currently no consensus on the best methodology for baseline and baseline variability estimation in computer analysis of cardiotocographs. For example in the Toitu System, FHR values are divided into 20 categories each comprising 10 bpm intervals ranging from 0 to 200 bpm and the baseline in each 5 min period corresponds to the mean value of the group having the

largest amount of samples. In the Nottingham/Hong Kong system, baseline corresponds to the average FHR value in a sliding window 6 mins wide. In the Montreal System, baseline is defined as the mean FHR in 1 in segments after exclusion of accelerations, decelerations, periods of artifact and signal loss. It is considered inexistent when less than 5% of values coincide with this average value (Ayres-de-Campos and Bernardes, 2004). In system Sonicaid 8000/8002, baseline is determined using a low pass digital filter with forward and backward propagation, excluding values that differ for more than 60 m sec from the preceding ones and starting from the mean of FHR values in the first 2 min. The 2CTG system uses a low-pass digital system that crosses the tracing five times, starting from a value determined by histogram analysis of the FHR distribution (Mantel *et al*., 1990; Arduini *et al*., 1993). Nearly all the proposed mathematical algorithms for computerized estimation of FHR baseline are satisfactory when the FHR tracings are regular with long and stable FHR segments. These kinds of tracings are found most commonly during the antepartum and the initial stages delivery. Baseline estimation is more complex when the FHR tracings are irregular and any misinterpretation would affect the overall interpretation of the carditocographs. In Sisporto 2.0 system 5% of the FHR values are considered along with the abnormal short-term variability to estimate the baseline (Ayres-de-Campos *et al*., 2000). Other method proposed baseline estimation based on number and continuity of occurrences. They have taken = 5% from occurrences number of the FHR values, the percentage of the consecutive occurrence of each one along with the number of occurrences in calculating the baseline (Krupa *et al*., 2008). There is not a unique method to compute short term variability of the FHR but different formulas have been proposed and are employed in clinical and scientific environments: this leads to different evaluations and makes difficult comparative studies. Nine short term variability indexes: Arduini, Dalton, Organ, Sonicaid 8000, Van Geijn, Yeh, Zugaib a modified version of Arduini index and Standard Deviation were considered and compared to test their robustness in CTG applications. A large set of synthetic foetal heart rate series with known features was used to compare indexes performances (Cesarelli *et al*., 2009).

MATERIALS AND METHODS

CTG Classification: CTG is classified as normal, suspicious and pathological and the baseline classified as Reassuring, Non-reassuring and Abnormal based on the values given in Table 3 (RCOG, 2001).

Experimental: In present study, we have assumed a virtual imaginary baseline which is equal to the mean value of the whole FHR signal of 30 min segment. This virtual baseline is our reference to calculate the true baseline. All this work is based on software program analyzing through the limitation of virtual imaginary baseline of the FHR signal and limiting minimum and maximum values of the wanted signal to be taken in the evaluation in certain periods of time according to the definitions of (RCOG). The algorithm is implemented entirely using MATLAB 7.4 functions using CTG data stored in excel files in the windows XP file system. A CTG data samples were used in this research used to test the algorithm is twenty two semi-synthetic CTG signals derived from one researcher work (Krupa *et al*., 2008). The

Table 3: CTG classification

Categories	**Cardiotograph (CTG) classification**			
Normal	A CTG where all four features fall into the reassuring category			
Suspicious	A CTG whose features fall into one of the non-reassuring categories and the remainder of the features are reassuring			
Pathological	A CTG whose features fall into two or more of the non-reassuring categories or two or more abnormal categories			
	Fetal heart-rate feature classification			
Categories	Baseline (bpm)	Variability (bpm)	Decelerations	Acceleration
Reassuring	119-160	≥5	None	Present
Non-Reassuring	100-109	<5 for≥40 butt	Early deceleration	The absence of
	161-180	<90 min	Variable deceleration	accelerations with an
			single prolonged deceleration	otherwise normal
			Up to 3 min	CTG is of uncertain
				significant
Abnormal	<100	< 5 for≥90 min	A typical variable deceleration	
	>180		Late deceleration single	
	Sinusoidal pattern		prolonged deceleration greater	
	for≥10 min		than 3 min	

reason behind using modified signals (semi-synthetic) is to cover all types of baselines (Reassuring, non-reassuring and abnormal). The sample of CTG signals was handed over to three obstetricians. Obstetricians were asked to estimate the CTG samples parameters baseline and baseline variability; the obtained computerized results are compared with the estimated results made by the three experts.

Features measurement in time domain: Since we are dealing with a time series signal, the following set of time domain features are extracted (Magenes *et al*., 2000, 2001). Virtual and true baseline are shown in formula 1 and 2 below:

- Virtual imaginary baseline FHR:

$$R = \frac{1}{N}\sum_{i=1}^{N} y(i) \quad (1)$$

- The true baseline,

$$BL = \frac{1}{N}\left[\int_{L}^{H} y\,dy\right] \quad (2)$$

Where:
N : Total number of samples
Y : FHR signal data
H : Highest limit for the wanted signal
L : Lowest limit for the wanted signal
BL : True baseline for the wanted signal

Baseline estimation algorithm: Baseline is an imaginary line that is drawn across the FHR tracing signal. The algorithm we have implemented calculates the baseline and classified whether it is reassuring, non-reassuring or abnormal. The decision is made according to the RCOG guideline. The details are provided in Table 2. Figure 2 shows the overall procedure employed to calculate the true baseline.

The first part of the measurement is based on finding the value of virtual imaginary baseline (R) and its value is the mean of whole FHR signal. Second part of measurement is done by evaluating the minimum and maximum limits of FHR signal (H and L) to be taken in our measurement according to RCOG baseline definition. As mentioned before the FHR signal is a noisy with spiky artifacts which occur due to fetal movements or displacement of the transducer. In the preprocessing stage the biosignals are conditioned, where the spiky artifacts are removed using a method described in (Ayres-de-Campos *et al*., 2000). Figure 3a and b show the signal before and after pre-processing.

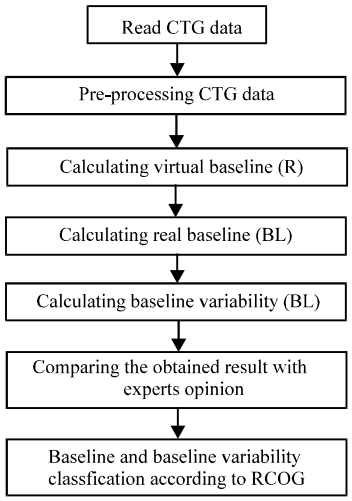

Fig. 2: Full program structure

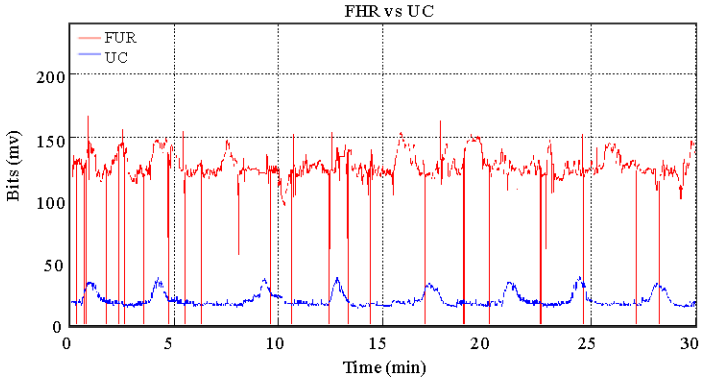

Fig. 3a: CTG signal before pre-processing

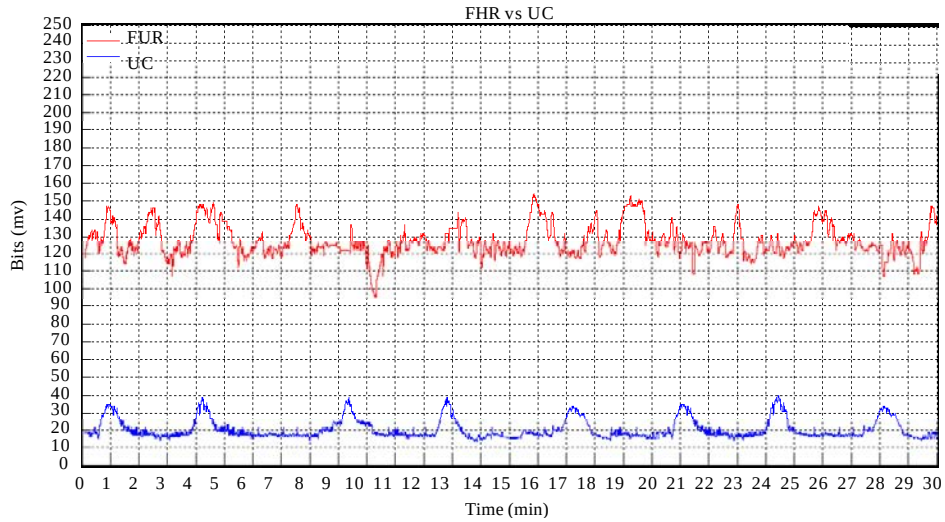

Fig. 3b: CTG signal after processing

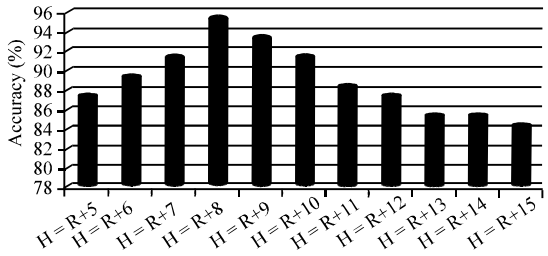

Fig. 4: Accuracy of new signal limitations, where $\alpha = 1, 2..., 15$

The processing of CTG signals is to remove the spiky unwanted signal by using the low-pass filter and compensating the missing data during the process of measuring the data from the pregnent mother using the linear-interpolation method for missing data compensation. Figure 3b shows the FHR signal after the pre-processing.

The maximum and minimum limits (H and L) limits are taken so that any value above H and below L will be omitted, where $H = R + \alpha$ (bpm) and $L = R - \alpha$ (bpm). The remaining FHR signal within the boundaries of H and L will be taken in the calculation of the real baseline (BL). After long experiment to choose the best value of (α) to be added and subtracted from the imaginary virtual baseline (R) to calculate the maximum and minimum limits (H and L) and comparing the obtained results with the experts opinion, we found $\alpha = 8$ bpm gives better results and best accuracy about 95% as shown in Fig. 4.

Figure 5 shows the limited boundaries for calculation of baseline and Fig. 6 shows the remains of the FHR signal after the process used in the algorithm to calculate the true base line (BL).

Figure 6 shows clear signal without acceleration and deceleration changes and it well be used to calculate the best FHR baseline according to RCOG definition.

Baseline variability estimation algorithm: This part of the algorithm is to calculate the value of FHR variability which is calculated according to (RCOG) definition of baseline variability. Figure 7a and b show FHR variability signal in one minute period. After the first occurrence of FHR acceleration and for a period of two minutes, the calculation of estimated baseline variability based on the calculation the maximum and minimum values of the FHR signal in one minute segment and the baseline variability will be calculated according to the formula 3 below:

- Baseline Variability V:

$$V = Y_{Max} - Y_{Min} \quad (3)$$

where, Y is the CTG data signal.

RESULT AND DISCUSSION

Baseline calculation results: The 22 set of data signals (M1-M22) are modified signals (semi-synthetic) signals were used to test the algorithm. The same sample signals were handed over to three deferent obstetricians. Obstetricians were asked to estimate the FHR samples baseline; the computerized results are compared with the

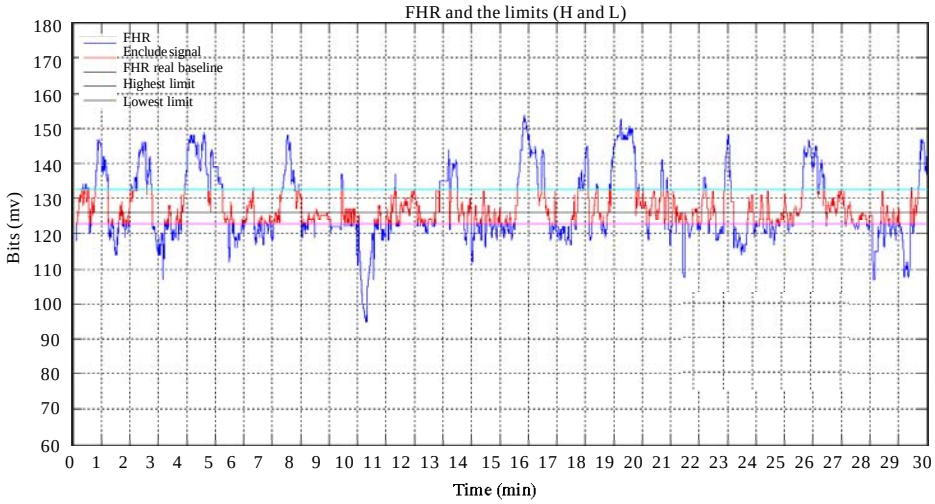

Fig. 5: Algorithm limits

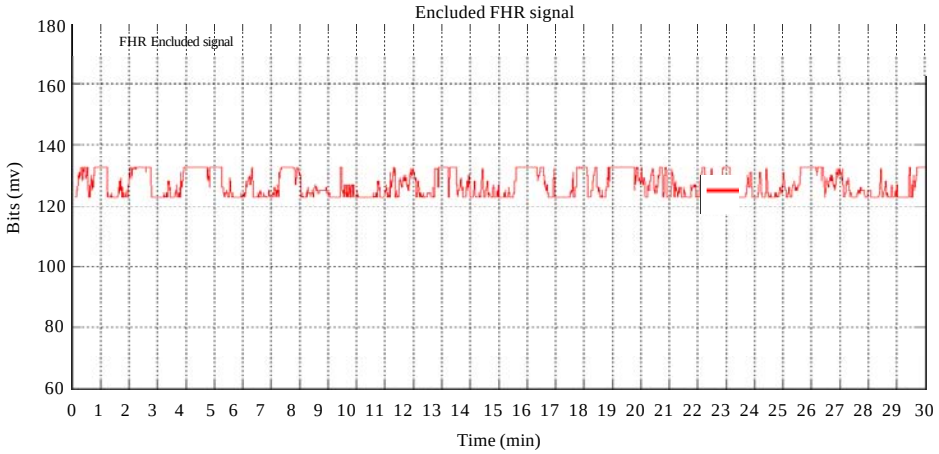

Fig. 6: Signal included in real baseline calculation

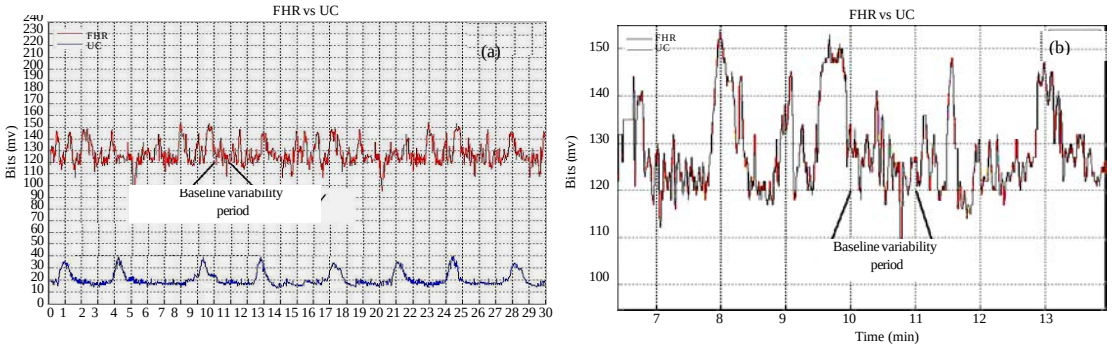

Fig. 7(a, b): Baseline variability included signal

Table 4: Computerized and visual estimation of Baseline FHR results for Semi-synthetic CTG signals

	Interpreted FHR baseline (bpm)			
Signals	Expert 1	Expert 2	Expert 3	This study
M1	120	125	120	127
M2	200	195	195	199
M3	120	125	120	126
M4	80	75	70	77
M5	140	145	145	149
M6	130	130	130	130
M7	200	205	205	211
M8	60	65	60	65
M9	140	135	140	141
M10	130	130	130	133
M11	130	130	135	129
M12	130	135	135	134
M13	120	125	120	126
M14	120	120	120	126
M15	120	135	125	126
M16	70	70	70	76
M17	140	140	140	148
M18	130	135	130	134
M19	140	130	140	142
M20	160	160	170	164
M21	80	85	90	84
M22	80	90	90	82

Table 5: Computerized and visual estimation of FHR Baseline variability results for Semi-synthetic CTG signals

	Interpreted FHR baseline variability (bpm)			
Signals	Expert 1	Expert 2	Expert 3	This study
M1	5	6-25	> 5	7
M2	5	6-25	< 5	5
M3	10	6-25	> 5	8
M4	5	6-15	> 5	7
M5	5	6-20	> 5	5
M6	7-10	6-15	> 5	8
M7	10-15	6-20	> 5	13
M8	5	6-15	> 5	8
M9	7	6-20	> 5	9
M10	10	6-25	> 5	15
M11	2-5	6-10	> 5	5
M12	2-5	6-10	> 5	8
M13	10	6-25	> 5	7
M14	10	6-20	> 5	11
M15	10	6-20	< 5	9
M16	10	6-10	> 5	12
M17	7-10	6-25	> 5	5
M18	2-5	6-10	> 5	8
M19	7	6-25	> 5	12
M20	10	6-25	> 5	13
M21	10	6-20	> 5	7
M22	10	6-20	> 5	10

estimated results made by the three experts as shown in Table 4. The output results are all within (+/-6) bpm difference and almost similar to the experts estimated results, except signal M7 and M17, where the two signals are irregular CTG signal.

The obtained results shows the baseline of the 22 CTG signals were all in reassuring category (RCOG, 2001) except signals (M2, M4, M7, M8, M16S and M22) were considered in the non-reassuring category and M20 where considered in abnormal category.

Baseline variability calculation results: The baseline variability computerized results are compared with the estimated results made by the three experts as shown in Table 5. The output results are all within (+/-5) bpm difference and almost similar to the experts estimated results. There is a difference between the presentation of each expert estimated results due to the different in there hospitals system guidelines.

The obtained results shows the baseline variability of the 22 CTG signals were all in reassuring category (RCOG, 2001) except signals (M2, M5, M11 and M17) were considered in the non-reassuring category.

CONCLUSION

In this study, the difference with other proposed methods, the work based on calculation of imaginary baseline as a reference to find the other FHR parameters and real baseline (BL) is within the signal limits (boundaries H and L) according RCOG baseline definition. The outcome of the baseline estimation using the above discussed algorithm is more convincing when the cardiotocography signals are regular. With an irregular FHR signal it shows noticeable differences when compared with expert's baseline estimation. Same thing goes for baseline variability estimation, in this algorithm the outcome values for variability are different from one expert to another, as a result of different guidelines used in there hospitals, where some experts give range for variability (for example 5-20 bpm) and some give range more or less than certain value (for example<or>5 bpm) and the other experts gives one certain value. In this study the obtained baseline variability results are within the range of compared results and other values are slightly different due to the FHR signal regular or irregular. The major problem in all CTG analysis and classification researches is how to establish full CTG parameters estimation and classification method. Research is still in progress and many significant features in time and frequency domains would be extracted along with the morphological features. Acceleration, deceleration and uterine activity would be considered in the future work to support the feature extraction. Advanced classification techniques and improved features analyses procedures would be employed to enhance the outcome of the project.

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