Automatic Cardiotocography Diagnostic System based on Hilbert Transform and Adaptive Threshold Technique

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Automatic Cardiotocography Diagnostic System based on Hilbert Transform and Adaptive Threshold Technique.

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Abstract - **The visual analysis of Cardiotocographic (CTG) examinations is a very subjective process. The accurate detection and segmentation of the fetal heart rate (FHR) features and their time correlation with the uterine contractions (UC) allow a better diagnostic and the possibility of anticipation of many problems related to fetal distress. This paper presents a diagnostic aid system based on digital signal processing techniques to detect and segment changes in the FHR and the uterine tone signals automatically. The FHR baseline detection is proposed after pre-processing filtering. The detection line is an auxiliary signal based on the Baseline and a moving average. The Hilbert Transform is then used with adaptive threshold techniques for identifying fiducial points on the signals. For an antepartum validation database, i.e., exams collected before labor, the positive predictivity value (PPV) found is 96.80% for the FHR decelerations, and 96.18% for the FHR accelerations. For an intrapartum validation database, the PPV found was 91.31% for the uterine contractions, 94.01% for the FHR decelerations, and 100% for the FHR accelerations. For the whole set of exams, PPV and SE were both 100% for the identification of FHR DIP II and prolonged decelerations.**

Index Terms- **Hilbert Transform, Fetal Heart Rate (FHR), Uterine Contractions (UC), Cardiotocography (CTG).**

1. INTRODUCTION

Fetal Medicine aims to monitor and determine actions to provide fetus wellbeing. Cardiotocography (CTG) is an exam applied before or during labor to monitor simultaneously FHR and UC based on Doppler ultrasound and toco sensors, making it possible to identify fetal cardiovascular or neurological risky situations or pathologies [1].

The heart rate is a relevant signal for the analysis of not only the cardiovascular system but also the influence of the autonomous nervous system for the body circadian rhythms. Because of that, the development of different approaches for computerized diagnostic systems are constantly present in the literature [2-4].

According to the American Congress of Obstetricians and Gynecologists (ACOG), common problems found during the analysis of Electronic Fetal Monitoring (EFM) are the poor inter observer and intra observer diagnostics reliability and the high rates of false-positives in visual interpretation [5].

In this scenario, different digital signal processing techniques have been used to extract information from these signals: wavelets [6]; fuzzy inference systems [7]; artificial neural networks (ANN) [8], [9], and also the application of combined techniques of ANN with other signal processing tools, such as multi resolution Principal Component Analysis (PCA) [10]. Nonlinear analysis with entropies and other metrics has also been proposed as possible new metrics for the fetal heart rate analysis [11].

The FHR can be monitored in many different ways, each one with advantages and drawbacks [12]. For example, the fetal scalp ECG is precise and consistent but an invasive technique (and it is available only after ‘crowning’). More recently, the Phonocardiography (PCG) has been used as a

simple and reliable FHR detector based on the recording of the heart beat sounds and the Hilbert Transform (HT) can be used for instantaneous frequency detection and effective noise reduction [13]. ECG instantaneous energy using HT has also been considered for heart sound segmentation [14].

Nevertheless, the CTG can be considered a gold standard examination for the FHR detection [15]. Doppler sensors have similar accuracy to that of fetal abdominal ECG and can also be used in many different clinical situations [16].

Dawes [17] developed an algorithm for the FHR analysis based on low-pass frequency filters to obtain the baseline and identify accelerations and decelerations. This algorithm was used in the System 8000, a commercial software which is now discontinued. Mantel [18] improved some aspects of Dawes' algorithm, for example in the beginning of the recording and the detection of changes of the baseline.

Daumer and Neiss presented the Delayed Moving Window (DMW) [19], a patented algorithm commercially used in CTGOnline system [20]. It intends to be a general tool to detect drifts, jumps and outliers in time series, and it can be used as an online alarm system.

This work presents a complete computerized CTG analysis system based on a group of techniques, which includes pre-processing filtering, and the use of the Hilbert Transform with adaptive threshold as a detector of changes of the time series. The FHR and UC's most important characteristics, such as the FHR baseline, detection and segmentation of FHR accelerations and decelerations, detection and segmentation of UC and the relationship in time between UC and FHR decelerations are all obtained automatically. In case of the detection of abnormal or suspicious CTG traces a set of alarms and warnings is proposed.

2. Materials and Methods

2.1. Development Environment and Data Acquisition

The system was developed using Matlab scripting language. Data were acquired using a GE Corometrics 250CX Series Cardiotocographer, based on pulsed Doppler with a pulse repetition frequency of 4 kHz in single ultrasound mode and uses autocorrelation technique. The equipment pre-processes and sends two 4 Hz time series (FHR and UC) to the diagnostic aid system. The equipment itself has a set of threshold alarms to indicate loss of detection and persistent bradycardia (that could be the detection of maternal heart rate) and can optionally monitor 3-lead maternal ECG and maternal pulse oximetry [21].

2.1.1. Database

Two databases from Trium Analysis Online GmBH were evaluated. The characteristics are presented in Table I.

TABLE I
CTG-I and CTG-A Database Characteristics.

Characteristic	CTG-I	CTG-A
Type of CTG	Intrapartum	Antepartum
Number of exams	32	100
Training dataset (exams)	16	50
Validation dataset (exams)	16	50
Average Duration (minutes)	220	200
Stand. Dev Duration (minutes)	134	140
Maximum Duration (minutes)	38	39
Minimum Duration (minutes)	906	466

The pre-classification procedure was performed by 3 experienced Obstetricians from MEAC-UFC and divided in two steps. First, they marked each CTG trace individually. After that, they compared their results and defined by consensus the presence of each UC occurrence and FHR change and classification.

Fetal outcome information, such as umbilical cord blood acid-base analysis and Apgar score were not available for both databases. Therefore, the system was validated only according to the medical staff pre-classification.

2.2. CTG Features Extraction

The diagram presented in Fig. 1 shows the sequence of steps necessary to obtain the full computerized CTG analysis system. In this example, the CTG trace contains 1000 seconds (4.000 samples) and was extracted from the 0227251 exam. In Fig. 1-a is presented the CTG trace (FHR and UC signals). The first task is to evaluate the signal basal behavior for both monitored signals. The baseline determination is then presented in Fig. 1-b. The baseline must keep the same level even in the presence of FHR accelerations and decelerations and must change only after a long term change. After that, in Fig. 1-c the detection line is calculated, which is an auxiliary signal following the FHR behavior used for detection and segmentation of significant changes in time. The Hilbert Transform output is shown in Fig 1-d, where the minimum and maximum peaks correspond to the beginning and ending of FHR accelerations. The same approach is used for the detection and segmentation of FHR deceleration and uterine contractions (UC signal). Finally, in Fig. 1-e the complete analysis of FHR and UC is presented and the existence of simultaneous occurrences can be evaluated.

For a better representation, let us consider *X(t)* as the FHR time series containing *N* samples *{X(1),X(2),...,X(N)}*. The baseline is named as *Y(t)* and the detection line is *Z(t)*. For the uterine contractions, let us consider *X'(t)* as the original time series, the baseline as *Y'(t)* and the detection line *Z'(t)*.

2.2.1. Pre-processing Module

Because of the external sensors, both FHR and UC signals can present noise and may contain zeroes when there is a loss of detection. In normal exams, zeroes are sporadic and can be discarded from the original signals during a pre-processing phase.

In case of ectopic values, such as abrupt changes in the signal, must be treated as noise and corrected. This is implemented comparing each sample *X(i)* with the next one *X(i+1)*. If the difference between them is higher than a threshold *α=20 bpm*, then the *X(i+1)* sample is replaced with an average from *X(i)* and *X(i+2)*.

If the loss of signal is more than 5 seconds (20 samples), the trace analysis is suspended and the software displays this information to the medical staff as a warning.

For uterine contractions signal *X'(t)*, a similar approach is

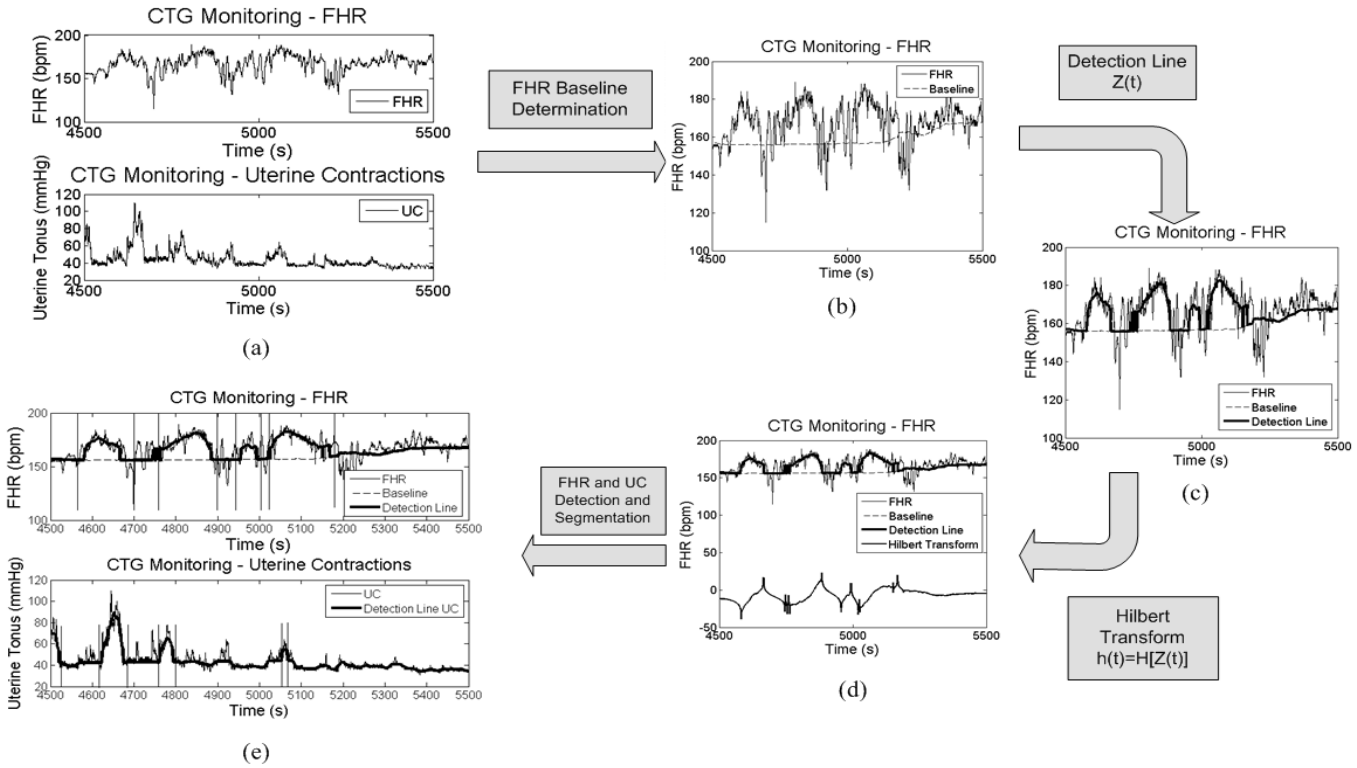

Fig. 1. Computerized CTG System step-by-step block diagram . The CTG trace interval was extracted from the 0227251 exam: (a) the original FHR and UC signals after the preprocessing phase; (b) Baseline signal determination; (c) Detection line signal following the original signal behavior; (d) Hilbert Transform. The same approach is used to detect FHR deceleration and uterine contractions (UC signal). In (e) is presented the system output for FHR and UC.

performed, considering that CTG equipment has two different external sensors, zeroes or ectopic samples detection are not related to the ones found for FHR monitoring.

After this first phase, we must calculate two new signals: the baseline and the detection line.

2.2.2. *Baseline Determination*

FHR baseline level is an important parameter for clinical analysis and its determination is a field of study in itself. It is considered in order to detect fetal bradycardia or tachycardia.

This work presents a new automatic method to determine the FHR baseline based on guidelines definitions and medical staff orientation. The FHR baseline is defined in the literature as the average of the FHR trace considering a 5 to 10 minutes intervals. This process must exclude decelerations, accelerations and periods of high long term variability [5].

The proposed technique to determine the baseline signal *Y(t)* is presented:

I. Firstly, the average μ is calculated for each *k*-samples windows of the original signal X(t) (*k* is equivalent to $\Delta t_s=10$ *minutes* [2]). The windowed signal *W(t)* is generated, as presented in Eq. (1) and (2):

$$\mu = \frac{\sum_{i=p}^{p+k-1} X(i)}{k} \qquad (1)$$

$$W(i)_{i=p}^{p+k-1} = \mu \qquad (2)$$

where p is the loop reference index, starting on $p=0.5*k$ (considering a tolerance interval of 5 minutes in the beginning of the original signal) with increments of *k* samples ($p=p+k$) for each loop.

II. A first baseline reference is then determined as the first sample of *W(t)*. This reference will be considered in the next steps to detect baseline changes.

III. After determining *W(t)* for the whole FHR trace, a new loop is executed with a *k*-samples window comparing the baseline reference with each of the *W(t)* samples. The variable *p'* is considered as the loop reference index starting on $p'=0.5*k$ with unitary increments ($p'=p'+1$).

IV. Two conditions must be satisfied to consider a baseline change:

- Condition 1: the system checks if the absolute difference between the baseline reference value and each of *W(t)* sample is greater than $\beta_1=5$ *bpm* [5].
- Condition 2: if condition 1 is satisfied, then the system must analyze if this difference remains greater than β_1 for more than $\Delta t_c=6$ *minutes* (1440 samples).

V. If condition 2 is satisfied, then a new baseline reference value is determined equals to the last sample of the *W(t)* window.

VI. Finally, for each *p'*, a baseline sample *Y(p')* is determined as the average of the *k*-samples window of the original signal *X(t)* as presented in Eq. 3:

$$Y(p') = \frac{\sum_{i=p'}^{p'+k-1} X(i)}{k} \qquad (3)$$

The parameter Δt_c was determined during the training phase and a discussion about its value is presented in the Discussion Section.

In each baseline reference determination, the system records the new value in the database and monitors it in case of occurrence of tachycardia or bradycardia [5]. In this second case, the system warns the medical staff about the possibility of the maternal heart rate is being detected instead of the FHR.

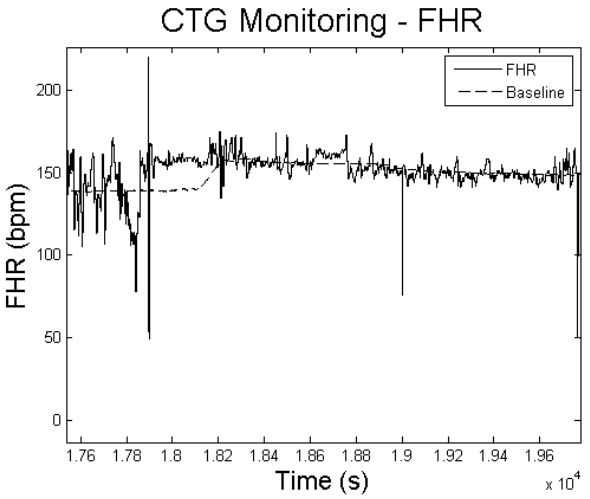

Fig. 2. Change of baseline level through *0208432* exam. The duration of the change lasts more than the defined threshold.

In Fig. 2, a baseline change is presented during the exam *0208432*. The time axis visual analysis shows that the duration of the FHR change was longer than 600 seconds (10 minutes).

It is also important to determine the uterine tonus baseline because this signal has no absolute basal value and may change with maternal position adjustments. This is the main cause of false positives and false negatives of the UC detection.

A particular reference must be established for every single examination. The proposed technique is based on the amplitude threshold β_2=*10mmHg* and it is not necessary to verify the duration of the change.

2.2.3. *Detection Line Determination*

The second signal to be determined is the Detection Line, *Z(t)*, which can be considered as a low pass filter of the original signal based on the previously calculated baseline.

In the beginning, *Z(t)* is equal to the baseline *Y(t)* until there is a significant change in the original signal *X(t)* higher than the trigger γ_1. When this happens, the *Z(t)* is calculated as the moving average of *X(t)* with window length Δt_{mm1}. For the proposed system these parameter values are γ_1 = 10 bpm and Δt_{mm1} = 60 seconds. For the UC signal, the considered values are γ_2 = 10 mmHg and Δt_{mm2} = 60 seconds.

The proposed values were determined according to the medical staff evaluation and the results obtained for the training datasets.

When the difference between the averaged value and the baseline is lower than the trigger levels, *Z(t)* is equal to *Y(t)* again. This process is performed for the complete CTG traces.

Fig. 1-c presents an example of detection line for the FHR signal, calculated after the baseline determination and Fig. 3 presents the UC detection line trace.

2.2.4. *Filter and Detection*

After determining the detection line, its Hilbert Transform is calculated. The application of this filter on the signal *f(t)* results in one analytic signal, which is, by definition, a signal without negative frequency components in its spectrum. Because of this, the complex to real convergence process can be done only considering the real part of this signal [22]. This signal processing technique has been successfully used because of its mathematical properties for different applications, such as signal and image processing [23].

Other important properties that must be considered to analyze its performance as a good detector of the fiducial points in the original time series are the orthogonality property and the energy analysis [24].

The Hilbert Transform $\hat{f}(t)$ of one function $f(t)$ can be expressed as

$$\hat{f}(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \left(\frac{f(\tau)}{t-\tau} \right) d\tau \qquad (4)$$

when the integral exists. Because of the pole in $\tau = t$, it may not be possible to calculate the integral equation. The *P* term in front of the integral represents the use of the Cauchy principal value technique, which increases the number of functions for which the integral in the equation exists [17].

2.2.5. *CTG Signals Segmentation*

The signal is segmented to determine the begin and the end of the changes and also their maximum and minimum values.

In Fig. 3 an example of uterine contraction detection and segmentation is presented. Each contraction is associated with a pair of fiducial points. Firstly, a negative amplitude peak followed by a positive amplitude peak are found. These peaks correspond to the beginning and ending of the contraction, while the zero cross on the Hilbert transform signal represents the maximum value in the original signal. For the FHR signal, a similar analysis can be performed.

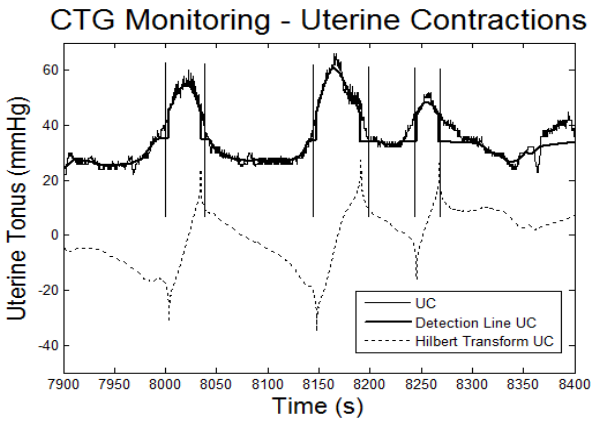

Fig. 3. Uterine contractions segmentation during *2232241* exam. The Hilbert transform helps detect the beginning, ending and maximum points. The segmentation bars are traced slightly before and after the detection.

Negative changes, FHR decelerations, for example, will result in a positive peak followed by a negative peak on the Hilbert transform signal and the minimum is the zero cross.

To minimize the probability of false positives, the proposed system uses also an adaptive threshold technique originally designed to detect QRS complexes in ECG exams described in [25] and [26]. Three different thresholds are proposed: ξ_{ac} and ξ_{dec} for the FHR accelerations and decelerations, respectively, and ξ_{cont} for the uterine contractions, which initial values are presented in Table II. These parameters are adjusted using the general expression

$$\xi[k] = \frac{\tau_1 Re[k] + \tau_2 R[k-1]}{\tau_1 + \tau_2} \psi \ , \qquad (5)$$

where τ_1 and τ_2 are relative weights, $Re[k]$ is an amplitude (absolute value) estimation based on the k^{th} occurrence of the change, which also depends on the value of $\xi[k - 1]$; $R[k - 1]$ is the magnitude (absolute value) of the $(k-1)^{th}$ change, and ψ, $0 < \psi < 1$, is a percentage factor chosen empirically [25].

The detection of the change in the time series is only considered if the filtered signal's peaks are greater than the respective adaptive threshold value.

TABLE II
SET OF ADAPTIVE PARAMETERS AND RESPECTIVE INITIAL VALUES

Parameter	Value
ξ_{ac}	10 bpm
ξ_{dec}	10 bpm
ξ_{cont}	5 mmHg

A FHR trace with two decelerations, two accelerations and their respective detection and segmentation based on the Hilbert Transform can be seen in Fig. 4.

2.2.6. Deceleration Classification

Uterine contractions can affect fetal blood oxygenation, causing a heart rate deceleration. Therefore, as mentioned before, it is necessary to establish a temporal relationship between the FHR and the uterine contractions, especially during FHR decelerations.

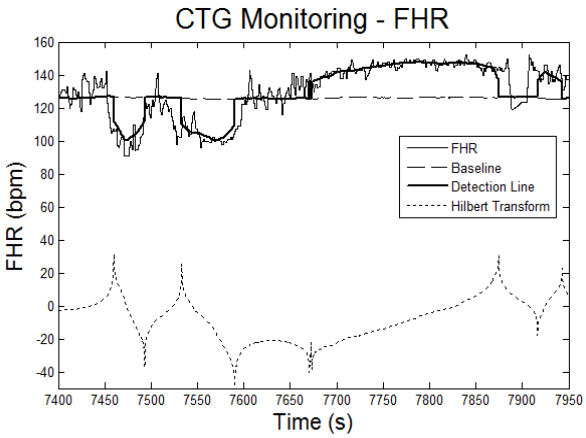

Fig. 4. Example of a detection and segmentation of FHR signal during a CTG exam (*0643162*).

The automatic classification of decelerations is a necessary task for a computerized CTG system, since their visual classification by the medical staff is subjective, hence not very robust and, at times inaccurate.

The method is directly obtained from the previous phase. When the system detects a FHR deceleration, it saves the beginning and ending points in time and the minimum value.

After that, the system checks if there are any uterine contractions already detected during this interval with a tolerance window of ε (ε=*10 seconds*) and it was determined according to the medical staff definition.

If there are no uterine contractions, the deceleration duration is calculated and is classified as variable or prolonged. If there is a contraction, its fiducial points are compared with the deceleration fiducial points, allowing the classification as DIP I or DIP II.

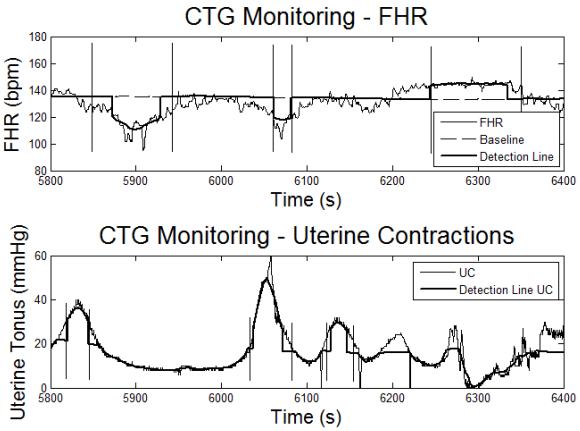

Fig. 5. Detection of a FHR DIP-II deceleration during *2232241* exam. Deceleration nadir occurs after uterine contraction peak.

Fig. 5 presents an example of simultaneous occurrence of changes in both monitored signals during the *1105411* exam. The system detects a late deceleration (fetal distress).

An early deceleration was detected during the *0827261* exam and is presented in Fig. 6. This kind of deceleration is physiological and does not indicate fetal health problems.

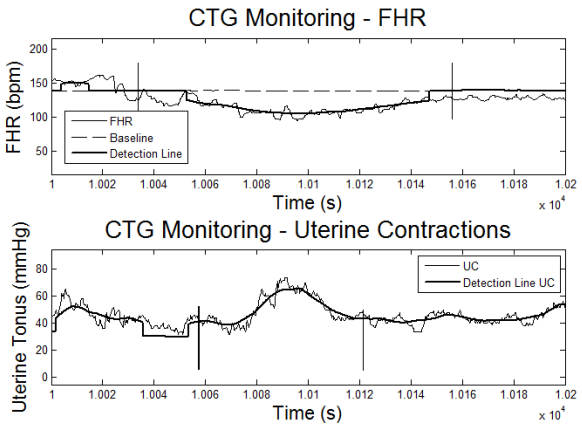

Fig. 6. Detection of a FHR DIP-I deceleration during *0827261* exam Deceleration occurs mirrored with uterine contraction.

TABLE II

CTG SYSTEM SET OF ALARMS AND WARNINGS

Abnormality	Criteria	Alarm/Warning
Fetal Tachycardia	*Y(t) > 160bpm*	User message (optional sound alarm)
Fetal Bradycardia	*Y(t) < 110bpm*	User message (optional sound alarm)
FHR Loss of Detection	*X(t)=0 Interval > 5s*	User message (optional sound alarm)
UC Loss of Detection	*X'(t)=0 Interval > 10s*	User message (optional sound alarm)
Early Deceleration	Deceleration mirrored with uterine contraction	User message
Late Deceleration	Deceleration minimum after UC peak	User message (optional sound alarm)
Prolonged Deceleration	2 min. < Dec. Duration < 10 min.	User message
Absence of FHR Acceleration	No FHR acceleration detection	User message

A prolonged deceleration detected during the *1105411* exam is presented in Fig. 7. This can be related to different maternal or fetal abnormal condition and the exam must be considered as indeterminate or abnormal [5].

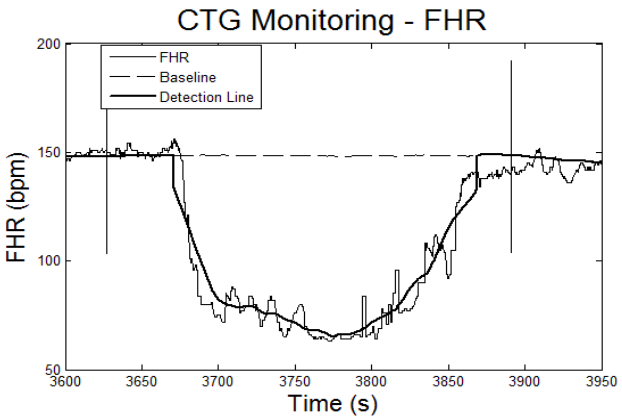

Fig. 7. Detection of a FHR prolonged deceleration during *1105411* exam, which is not related to the uterine contractions and is non-reassuring.

2.1.1. Alarms and Warnings

Based on the extracted CTG parameters for each exam, a set of alarms and warnings based on [5] is proposed in Table II.

3. RESULTS

In this section, the results obtained for the validation datasets are presented and the DMW technique [19] (a patented commercial and CE approved computerized CTG) was considered a reference method for comparison purposes.

Baseline Determination Results

The baseline level can vary several times during a CTG recording. Therefore, all the levels found by the reference and the proposed methods were compared for each exam.

The comparison showed no significant difference ($p<0.05$) between the compared baseline levels for 75% and 83% in CTG-A and CTG-I validation databases, respectively.

Detection and Classification Results

The detection and classification results for the proposed and the reference methods are presented for both the CTG-I and CTG-A validation databases, considering the previously marked values identified by the medical staff.

The considered indices were the sensitivity (SE), for the evaluation of false negatives, and the positive predictivity value (PPV), evaluating the occurrence of false positives.

The results obtained are presented in Table III, which is divided in four groups of results.

In the first group (CTG-I General Results), the proposed system achieved 93.05% of PPV and 91.31% of SE for the uterine contractions, during labor, while the reference method achieved SE 76.18% and PPV 81.63%. No FHR accelerations false positives were found by the proposed method, resulting in 100% (PPV) and 95.45% (SE). The reference method achieved 77.27% (SE) and 94.45% (PPV).

The second group of results presents the FHR decelerations classification for the CTG-I validation database. For the prolonged deceleration, both methods achieved 100% for SE and PPV indices. On the other hand, the lowest SE value, 40%, was found for the reference method when classifying DIP-I decelerations, with the occurrence of false negatives.

The third group presents the CTG-A validation dataset results. Considering the FHR acceleration classification, for the proposed method SE was 94.70% and PPV was 97.16%, while for the reference method SE was 88.22% and PPV was 96.84%.

Finally, the last group in Table III is the deceleration classification for the CTG-A validation database. For the variable deceleration, the proposed system SE was 92.78% and PPV was 96.90%, while for the reference system SE was 92.51% and PPV was 95.57%. The reference method missed one prolonged deceleration while the proposed system detected all of them.

4. DISCUSSION

The presented results show robustness of the system when submitted to artifact noises in rather severe conditions, producing low levels of false positives and false negatives for both *antepartum* and *intrapartum* databases.

The baseline determination is a critical task since the following steps are based on it. As the parameters β_1 and Δt_s follow the medical guidelines, the Δt_c is the main tuning parameter that may influence the system SE and PPV results. If it is chosen a value smaller than Δt_c, the signal baseline may follow any transient changes and it will increase the false negative rates. If it the value is greater than Δt_c, it can miss a real baseline change and increase false positive rates.

When compared the proposed FHR baseline with the reference method, both signals presented a similar overall behavior in all CTG traces, even during the intervals when the statistical significance could not be determined.

During $Z(t)$ determination phase, if the trigger γ_1 is smaller than the selected value, the system may consider normal oscillations as acceleration or deceleration and this will increase false positive rates. On the other hand, if γ_1 is greater than the selected value, the false negative rates may increase and real FHR changes are not going to be detected. A similar discussion applies for the UC signal parameters. If γ_2 is smaller than the selected value, the system may found UC false positives and if it is greater than the selected value, the system can miss a real uterine contraction.

Following the same discussion, for the deceleration classification task, if the parameter ε is smaller than the proposed value, the system may classify an early deceleration as a late one. On the contrary, if it is greater than the selected value, late deceleration may be classified as an early one.

For the acceleration and uterine contraction detection, the proposed method achieved better results than the reference system. Both methods achieved similar results when analyzing variable decelerations.

An important contribution of the proposed technique is the classification of DIP-II and Prolonged FHR deceleration, which are indicative of fetal distress. The proposed system achieves 100% for both SE and PPV indices. Besides, when compared to the reference method, the proposed system improved the classification rates. This indicates not only a good performance in FHR decelerations, but for the system classification capability as a whole.

TABLE III
DETECTION AND CLASSIFICATION RESULTS FOR THE CTG-I AND CTG-A VALIDATION DATASETS FOR THE PROPOSED AND REFERENCE METHODS - SE AND PPV INDICES

Description	Marked	Detected Proposed Method	SE Proposed Method	PPV Proposed Method	Detected Reference Method	SE Reference Method	PPV Reference Method
CTG-I – General Results							
UC	403	410	93.05%	91.31%	373	76.18%	81.63%
FHR Acel	22	21	95.45%	100%	18	77.27%	95.45%
FHR Dec (total)	117	111	88.89%	94.01%	116	75.21%	93.16%
CTG-I – Deceleration Classification							
Variable	78	75	89.74%	93.58%	93	87.17%	93.58%
DIP I	25	22	80.00%	92.00%	12	40.00%	92.00%
DIP II	12	12	100%	100%	9	66.67%	91.66%
Prolonged	2	2	100%	100%	2	100%	100%
CTG-A – General Results							
UC	0	0	--	--	--	--	--
FHR Acel	603	596	95.02%	96.18%	551	88.22%	96.84%
FHR Dec (total)	294	282	92.85%	96.80%	301	92.51%	95.57%
CTG-A – Deceleration Classification							
Variable	291	279	92.78%	96.90%	299	92.78%	95.53%
DIP I	0	0	--	--	--	--	--
DIP II	0	0	--	--	--	--	--
Prolonged	3	3	100%	100%	2	66%	100%

Finally, the system achieves low levels of false positives and false negatives rates not only for FHR accelerations and variable decelerations detection but also for the deceleration classification task.

5. CONCLUSIONS

Fetal monitoring using CTG is being widely used by Obstetricians and Gynecologists because it is a non-invasive,

easy to implement, low cost examination.

This paper presents a new method to automatically detect and segment changes in FHR and UC signals, based on a set of pre-processing techniques, with fixed and adaptive thresholds and the time domain analysis provided by the Hilbert transform. It detects and classifies the existence of simultaneous FHR decelerations and uterine contractions, resulting in high levels of sensitivity (SE) and positive predictivity value (PPV) indices for the considered databases, both before and during labor.

The clinical impact of the proposed system is to allow the possibility of reduction on the level of subjectivity of the CTG analysis and help improve the diagnostic accuracy.

Future works may consider the use of other approaches to detect transient changes in the original signals, such as Wavelets, to compare with the proposed technique.

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