Combination of XGBoost Analysis and Rule-Based Method for Intrapartum Cardiotocograph Classification

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Abstract:

Cardiotocograph (CTG) contains uterine contraction (UC) and fetal heart rate (FHR) signals, which is an important information of clinical pregnant woman care. National Institute of Child Health and Human Development (NICHD) is one of the reference guides for clinical care and it classified pregnant woman into three categories including I, II, and III to evaluate the status of fetus. However, when it comes to manual interpretation was time-consuming and not easy to observe the slight differences. In this study, we combined rule-based method and eXtreme Gradient Boosting (XGBoost) analysis for intrapartum cardiotocograph classification. Because the category II of NICHD is defined unknown status, XGBoost analysis was used to classify the category II into IIa and IIb, and analyze their probability of fetal distress (FD). From the clinical trial of 68 pregnant women, the results of three categories (I, II and III) were consistent and no statistical difference with the clinicians' interpretation and the average Kappa was about 0.72. The results also indicated that the probability of FD was 28.8% and 71.2% in category IIa and IIb, respectively. It shows the proposed method has potential to provide a clinical assistant tool for pregnant women care.

Keywords: Cardiotocograph (CTG), National Institute of Child Health and Human Development (NICHD), eXtreme Gradient Boosting (XGBoost), Fetal Distress (FD)

1. Introduction

Advanced maternal age (AMA) is defined as a phenomenon that women become pregnant at the age above 35, and it has increased in high-income economy countries recently [1]. In 2018, a research from Pew Research Center in America revealed that 86% of American women had ever given birth at ages 40 to 44 [2]. A study by EU researchers indicates that 20% of birth in England and Wales were given by women ages above 35 years, while 4% were given by women ages ≥ 40 years, compared with that of 6% and 1% birth respectively in 1980 [1]. The most general reason of this trend is attributed to the advancements in assisted reproductive technologies (ART). However, this trend potentially causes clinic risks [1]. According to previous studies [3], advanced maternal age is associated with the incidence of complications of pregnancy, such as abortion, gestational toxemia, gestational diabetes, and fetal growth retardation. These complications not only trouble pregnant women but also affect the health of the fetuses. Among all these complications, fetal distress (FD) may lead to hypoxia of the fetus, thereby reducing fetal movements, reducing fetal heart rate, and provoking acidemia. In addition, Hypoxic Ischemic Encephalopathy (HIE) caused by FD may also lead to chronic, long-term injury or even death to the fetus [4]. The placenta is the main source of nutrition for the fetus, while the function of the uterus gradually declines with the age of women [5]. In 2014, scholar Dr. Parker, S. pointed out that advanced maternal age would cause an increasing chance of early placental exfoliation, which would reduce the oxygen circulation rate of fetus and thus provoke FD [6] and may lead to growth retardation. According to statistics, the incidence of FD during delivery is three out of a thousand [7], therefore, in 2013, Dr. Austin Ugwumadu et al. looked for the relevant fetal compensation strategies through observation of the changes in fetal heart rate during pregnancy, hoping to lower the incidence of FD [8].

Other studies have shown that there is a correlation between prenatal and fetal physiological signals and FD [9-15], for example, cardiotocograph (CTG) signals can assist obstetricians and nurses in clinical interpretation. CTG is mainly used as a clinical reference for fetal health and FD [9] by monitoring the changes of Uterine Contraction (UC) and Fetal Heart Rate (FHR) of pregnant women. However, in recent years many experts and scholars or organizations, for example, National Institute of Child Health and Human Development (NICHD) [10] and Royal College of Obstetricians and Gynecologists (RCOG) [11], have established different classification rules based on different clinical experiences in using CTG signals, so as to make clinical results more objective. In order to improve the speed of interpretation and decrease human error, various methods of intelligent CTG interpretation

have been proposed in recent years. According to the definition of NICHD, the research team from National Taiwan University carried out the development of automated NICHD 3-tier classification system in 2014. In this study, researchers collected 62 CTG data before delivery and compared the CTG data with the visual interpretations from 8 obstetricians, and the results showed the average statistics kappa value of category I, II, III, and overall were respectively 0.89, 0.78, 0.50 and 0.79. Compared with the traditional classification method, the kappa value here was higher (0.15-0.38), but the value of category III was lower [12]. In 2016, according to RCOG, a Malaysian research team classified a group of pregnant women into normal, suspicious and pathological categories, and analyzed the baseline, variability, deceleration, acceleration based on FHR to construct an instant classification system [11]. The proposed methods were employed to confirm the accuracy of classification based on the visual interpretation of three obstetricians, kappa values of 0.668, 0.587 and 0.630 for the 80 clinical CTG signals.

As it can be seen from the above, the automatic interpretation system of NICHD or RCOG has its advantages and feasibility; however, some classification results are clinically vague, such as the category II of NICHD and the suspicious category of RCOG. In 2016, Penfield, CA et al. proposed a classification system for NICHD category II signals, called "ABC system," which divided category II tracings into IIA, IIB, and IIC subcategories. The system mainly classified the changes in the new Fetal heart rate tracing characteristics in category II. They demonstrated that the ABC system could improve the team communication and increase on-site management of category II FHR tracings by private physicians [13]. In 2017, Sabina Martı Gamboa et al. started to estimate the association between atypical variable decelerations and neonatal academia and compare the CTG signals of 102 cases of fetal acidemia (umbilical arterial cord gas pH $\leq$ 7.10) and of 100 normal fetuses (umbilical arterial cord gas pH > 7.10), so as to estimate the correlation among typical variable decelerations of CTG, neonatal acidemia, and the morbidity of FD [14]. The results show that certain atypical features, as slow return and loss of moderate variability within decelerations are associated with neonatal acidemia. The slow return could help in the gradation of acidemia risk levels, as an indicator of gravity.

In view of this, this study used the classification rules of NICHD with rule-based method to classify our results into category I, II, and III, and by literature results [14], the atypical variable decelerations directly into category III, e.g. slow-return, to improve its consistency with the interpretation by clinicians. In addition, every UC during pregnancy is a kind of stimulation to the fetus; for normal fetuses, such stimulation can be recovered in a short time, however, if the fetus has FD, the fetus may not be able to maintain internal regulation through

compensation strategies [15].

Extreme Gradient Boosting (XGBoost) is an open-source library that provides an efficient and effective implementation of the gradient boosting analysis. XGBoost is a class of ensemble machine learning algorithms that can be used for classification predictive modeling problems. In this study, we utilized XGBoost analysis as the classifier based on sequence analysis to classify category II data into IIa and IIb by further examining UC and FHR. It could improve the understanding of category II signals in clinical application, increase on-site management of category II by private physicians, and provide a more accurate clinical basis for FD.

2. Materials and Methods

The proposed system for intrapartum CTG classification was developed by rule-based method and XGBoost analysis in this study. Data sources were mainly obtained from a clinical database and then analyzed accordingly. The clinical CTG signals were divided into category I, II & III by the rule-based method on the features such as baseline, variability, acceleration, and deceleration following NICHD and Chen, C. Y. [12] definition. In order to reduce the processing time, we modified and simplices the rule as Table 1.

2.1. Clinical Data Collection

The clinical CTG records were taken from the fetal monitor (Avalon FM20, Royal Philips, Eindhoven, Netherlands) in the delivery room of the National Cheng Kung University Hospital. The medical records were documented between January 2017 and April 2018. The excluding rules of clinical CTG records were Sinusoidal pattern of FHR (SP), multiple births, the mother has heart and lung diseases, and the fetus has congenital anomalies. The flowchart of clinical CTG selection is shown in Figure 1. The data, which included numerical data in the database and converted images, comprised of the age of the pregnant woman, gestational age, FHR, UC, birthing methods, and anesthesia methods, as shown in Table 2. The sixty-eight records of UC and FHR were selected in this study and the data included30 & 30 records were with FD & Non-FD, respectively, that were verified by professional medical staffs. The information was obtained under the specification of the Institutional Review Board (IRB) program (A-ER-105-477). Each record was continuous measurement at least 40 minutes with 1 Hz sampling rate.

2.2. The Preprocessing of CTG Signals

During prenatal checkups, CTG records were affected easily by the noise and missing data. It may cause by the movement of pregnant woman or sensors which greatly affects the

identification results made by the medical staff or computerized analysis [11]. Therefore, before performing feature extraction, we referred the research [16-17] for CTG preprocessing that included linear interpolation, trend removes and data smoothing to remove the noise and motional artifact.

2.3. Features Extraction of FHR and UC

Features extraction from clinical CTG data was import in this study following Table 1. At first, various types of features were extracted from the FHR signal like baseline, variability, acceleration, and deceleration for instance, the time difference between FHR & UC as a feature. Five parameters were defined from the extraction of the time and frequency domains, as well as the morphological features. In this section, FHR features were extracted based on the NICHD criteria [12]. The algorithm used for feature extraction and classification in this study was developed and program implemented by MATLAB (version 9.9.0.1495850, R2020b, Natick, Massachusetts, The MathWorks Inc.).

A. Baseline (BL) of FHR detection:

According to the definition of NICHD, the BL of FHR is determined by approximating the mean FHR rounded to increments of 5 beats per minute (bpm) during a 10-minute window. Moreover, it excluding the state of accelerations and decelerations. There must be at least 2 minutes of identifiable baseline segments (not necessarily contiguous) in any 10-minute window, normal (BLN), tachycardia (BLT) and bradycardia (BLB) were also determined, as shown in Equation (1). Where the BV in the above formula represents the difference between the maximum and minimum values of the FHR within one minute; *i* represents the FHR reference line in the *i-th* minute; and *n* is the total number of times the difference before and after the FHR is less than 5 bpm.

$$if\ \ BV \leq 5, BL_{(i)} = \frac{1}{n}\sum_{1}^{n} FHR_{(n)}$$

$$if\ \ BV > 5, BL_{(i)} = BL_{(i-1)}$$

$$BV = FHR_{max}^{(n)} - FHR_{min}^{(n)} \quad (1)$$

B. Baseline variability (BV) of FHR detection:

The FHR BV is a response that shows FHR changes within a short period of time when the fetal central nervous system is stimulated. It also reflects the normal development of fetal nerves and the adequacy of oxygen in the body [15]. Through the BV, we could observe whether the abnormal heart rate of the fetus was due to metabolic acidosis or neurological damage that maybe caused by hypoxia. FHR variability with 0 beats per minute (bpm) does not exist in the living fetus, and we used the definition of Chen et al., with an amplitude of 2 bpm as BVA, an amplitude between 2-5 bpm as BVMI, it means that the fetus may have been

neurologically harmed due to hypoxia [15]. An amplitude between 6-25 bpm as BVMO, an amplitude more than 25 bpm as BVMA [12]. The BV is calculated by the equation (2) of the difference between the FHR maximum and minimum values in every minute. *n* represents one minute. Moreover, the BV would exclude the AC and DE condition.

$$BV = FHR_{max}^{(n)} - FHR_{min}^{(n)} \quad (2)$$

C. Acceleration (AC) of FHR detection:

The manifestation of the FHR acceleration is closely related to fetal health and is usually generated when there is fetus activity. We compare the lowest point of acceleration with the peak position of UC and calculate the continuous acceleration time of FHR. The duration and magnitude of the acceleration during measurement are used as evaluation criteria. Generally, the duration is more than 15 seconds and the amplitude are greater than 15 bpm, as shown in Equation (3). FHR onset & FHR recovery means the start and the end of continuous acceleration time, respectively. The FHR acceleration represents the normal oxygen concentration in the blood of the fetus with no metabolic academia; therefore, the fetus is currently in a normal state. However, during the monitoring process, when no acceleration is observed, it does not mean that the fetus is abnormal. The determination must be done through FHR variability and deceleration.

$$FHR_{max} - BL \geq 15 \ \ bpm$$
$$and \quad FHR_{recovery} - FHR_{onset} \geq 15 \ \ sec \quad (3)$$

D. Deceleration (DE) of FHR detection:

UC is the state in which the uterus practices childbirth during pregnancy. When the uterus contracts, it is squeezed inwardly, and the blood flow in the placenta changes. We used the valley detection method is based on an algorithm that fits a quadruple polynomial to sequential groups of data points, to determine the nadirs of FHR decelerations [13]. At this moment, the DE is the degree of FHR decline that is consistent with the UC. The DE standard is longer than 15 seconds and the deceleration size is more than 15 bpm, as shown in Equation (4). The nadir location of FHR deceleration was compared with the UC peak location to classify early and late decelerations.

$$BL - FHR_{min} \geq 15 \ \ bpm,$$
$$and \ \ FHR_{recovery} - FHR_{onset} \geq 15 \ \ sec \quad (4)$$

E. Early DE (EDE) & Late DE (LDE) of FHR detection:

When the uterus contracts under normal conditions, the fetus initiates a compensatory mechanism to balance the oxygen in the body. Generally, the time difference between the

lowest point of FHR and the last max value before the lowest point of FHR lasts at least 30 seconds, and there is no time difference between the position of FHR_{nadir}, which is the lowest position of FHR deceleration, and the position of UC_{max}. After the end of the contraction, the FHR returns to normal. Such stimulation does not affect the fetus and belongs to the state of EDE, as shown in Equation (5).

The state of late deceleration reflects the condition where the fetus may face hypoxia. Therefore, the FHR is delayed and decelerated after UC. LDE is defined as that FHR starts to decelerate to the bottom at least 30 seconds, and its time difference from UC starts is more than or equal to 18 seconds, as shown in Equation (6).

$$EDE = FHR_{onset}(n) - FHR_{nadir}(n) \geq 30 \ sec \quad and \ FHR_{nadir}(n) = UC_{max}(n) \tag{5}$$

$$LDE = FHR_{onset}(n) - FHR_{nadir}(n) \geq 30 \ sec \quad and \ UC_{onser}(n) - FHR_{onset}(n) \ \geq 18 \ sec \tag{6}$$

F. UC Duration:

UC feature samples are firstly obtained by setting the threshold value (Thr). When the threshold of the UC data is extracted, and the UC is greater than the threshold value, an intersection point is generated. The time interval between the two intersection points (a, b) is used as the basis for judging the UC, as shown in Equation (7). The difference between the time point at which the maximum occurs and the time when the FHR decelerates can be used to determine whether the FHR deceleration state is early deceleration or late deceleration.

$$UC_{var} = UC_{max}(n) - UC_{min}(n)$$
$$if \ UC_{var} \leq 5, \ UCThr(i) = \frac{1}{n}\sum_{i=1}^{n} UC_{(i)}$$
$$else \ UC_{var} > 5, UCThr(i) = UCThr(i-1)$$
$$and \ t_{a\rightarrow b} \geq 30, UC = UC_{max}(t_{a\rightarrow b}) \tag{7}$$

2.4. Signal Truncation for Sequence Analysis and XGBoost Analysis

In this study, we design a CTG category II advanced analysis method based on UC to further classify the signals into IIa and IIb. Since the traditional method requires a long-term evaluation such as EDE & LDE in the interpretation of CTG, it is not applicable in the interval of a UC, and therefore only the parameters of BL, BV, AC, and DE in each interval are taken in this study. In the sequence analysis, based on UC, the CTG signal is evaluated as normal and abnormal FHR through truncation and the above parameters, and the ratio of the 2 CTG signals is used to further classify the category II signal, shown in Figure 2. In this study, we applied a machine learning classifier, the XGBoost [18], to classify the category II CTG signals following NICHD rules and further classify into IIa and IIb. The input features

included 4 characteristics of FHR and UC obtained by the rule-based method (BL, BV, AC, DE), and the abnormal ratio in the sequence analysis. In addition, we take the results from clinicians as the ground truth of the classifier training model. This method was chosen due to its significant advantages, including dealing with missing values, requiring data scaling and implying a computationally efficient variant of gradient boosting analysis [18]. It provided satisfactory results in ML competitions and was successfully used in other studies and domains [19, 20]. We can efficiently select features parameters, reduce overfitting and the computational complexity with supervised learning of XGBoost. Through supervised learning and additive training to execute iteration and update the objective function, then build a model after training to predict the results. Objective function of XGBoost as shown in Equation (8) and (9)

$$\text{Obj}(\emptyset) = \sum_i l(\hat{y}i, yi) + \sum_k \Omega(fk) \quad (8)$$

$$\text{where } \Omega(f) = \gamma\text{T} + \frac{1}{2}\lambda\|\omega\|^2 \quad (9)$$

where l is loss function, to estimate the difference between $\hat{y}i$ and yi, which is the training error. Ω is regularization term, including T and γ denote decision node and hyperparameters, respectively. By adjusting ω, the weight of decision node, to avoid overfitting.

3. Results

The data collected in this study was mainly CTG records provided by the clinical database under IRB program. There were two kinds of CTG data, FD and Non-FD, that were accordance with the clinical medical records. After backtracking the CTG information, the data was given to three clinicians, their average obstetric experience more than 10 years, to interpret the relevant CTG records and classify into category I, II and III that followed NICHD. Then, we utilized the rule-based method to classify the data and calculated the ratio of FD in each category. The results made by the clinicians and rule-based method were compared to evaluate the accuracy. The comparison results of Kappa in each category were shown in Table 3, and the average Kappa was about 0.72. There was no statistical difference between the results from the clinicians and rule-based method.

In order to improve the clinical evaluation of categories II of NICHD, we tried to classify the category II into IIa and IIb and to analyze their correlation of the probability of FD. Category IIa means that the fetus has a higher probability of returning to the category I state, and IIb means that the fetus has a higher probability of developing FD, thus, surgery must be performed immediately. This processing method not only utilized the results of the sequence analysis but also included the features of the rule-based extraction, which was used as an input in the XGBoost analysis. The sequence analysis mainly used the UC time as the

standard when extracting the FHR segment. The FD ratio was calculated through Equation (10). The results from the XGBoost analysis and classification were shown in Table 4. It can be found that the FD ratio of IIa is significantly lower than IIb, and there is a statistical difference (p<0.05). Although I and IIa, IIb and III are not statistically consistent, clinicians still can take IIa and IIb as the basis for clinical care.

$$\text{FD ratio} = \frac{\text{Number of FD}}{\text{Quantity in the Category}} \quad (10)$$

4. Discussion

Based on clinical experience, clinicians diagnose the fetal status such as FD by CTG changes with visual analysis, usually dominated near the end of CTG signal period. It is not a very objective method if without consideration of all the long-term CTG signal (more than 40 minutes) [4]. The results of CTG interpreted by clinicians were compared with the proposed system, we found that there were statistically consistent with the clinicians' visual analysis through the Kappa value. However, we further analyze the different signals that compared between clinicians and proposed system. We found out the difference usually caused by the local and global view of CTG signal. For example, there was a result put under category I by clinicians' visual analysis; nevertheless, in global view, once its variability met LDE, the proposed system did not classify it as category I but category II. Since the long-term CTG signal consideration that more than 40 mins by visual analysis, it is time-consuming and difficult to execute in the clinical environment. A relative objective comment based on long-term CTG analysis by the proposed system was necessary for clinical evaluation. The categories of IIa and IIb was carried out by the XGBoost analysis improved the information of fetus in original category II. The FD ratio from original category II by rule-based method was about 65.2%, and after further classify by XGBoost analysis into categories IIa and IIb, the FD ratio was changed to 28.8% and 71.2%, respectively. It could provide much reliable information for clinical evaluation. The sequence analysis in this study not only contained the original part of the feature analysis in rule-based method, but also gained a new feature by the abnormal ratio of all the CTG records. However, the definition of variable DE is not clear at present, it is also difficult to define a good feature extraction method in our system. Therefore, more clinical trials and big-data set for further analysis and verification are required.

5. Conclusions

Combine the rule-based method and XGBoost analysis, it could improve clinical evaluation of the CTG signal. According to the literature [21], in some cases of variable DE such as slow return that was highly correlated with FD, it was also correlated with the

magnitude and the shape of the *p*H value of the fetal cord blood. This was significantly correlated with fetal acidemia statistically. In future studies, the proposed method can be combined with other physiological parameters of the fetus for further clinical evaluation to improve the interpretation. Overall, the proposed method has highly potential to be an assistive and warning system for pregnant women care to improve the care quality and reduce the burden of medical staff.

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Compliance with Ethical Standards

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval: The experimental protocol was established, according to the ethical guidelines of the Helsinki Declaration and was approved by the Human Ethics Committee of National Cheng Kung University Hospital (IRB Number: A-ER-105-477).

Informed Consent: Written informed consent was obtained from individual or guardian participants.

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403 **Table 1. The rules definition of categories I, II & III based on NICHD**

CTG	FHR & UC
Signal preprocces	Zero Deletion
	Denoising
	Signal segmentation
Features extration	Baseline of FHR (BL): Normal (BLN), 110 ≥ BL ≥ 160 bpm & ≥ 10 min Tachycardia (BLT), BL >160 bpm & ≥ 10 min Bradycardia (BLB), BL <110 bpm & ≥ 10 min
	Baseline variability of FHR (BV): unit = bpm Absent (BVA), BV < 2 Minimal (BVMI), 5 ≥ BV ≥ 2 Moderate (BVMO), 25 ≥ BV > 6 Marked (BVMA), BV > 25
	Acceleration of FHR (AC): Onset to nadir ≥ 15 sec & AC increase ≥ 15 bpm
	Deceleration of FHR (DE): Onset from UC peak to FHR nadir ≥ 30 sec EDE, No lag time (DE < 1 sec) LDE, Lag time (DE ≥ 18 sec) Variable (DE): Onset from UC peak to FHR nadir < 30 sec and VDE decrease ≥ 15 bpm (15-120 sec)
The Rules	**Categary III**
	BLB and BVA ≥10 min
	BVA and LDE
	BVA and VDE
	Categary I
	BLN and BVMO and EDE
	Categary II
	Exception of I & III

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407 **Table 2. Parameters of pregnant women and newborns**

	FD, N=30	Non-FD, N=30
Maternal age, years	33±9	32±7
Gestational age, weeks	30±9	32±8
Delivery		
Cesarean section	27	8
Non cesarean section	3	22
APGAR 1′		
<7	14	6
≥7	16	24
APGAR 5′		
<7	3	0
≥7	27	30
Anesthesia		
General anesthesia	2	3
Non general anesthesia	28	27
Fetus weight, g	2055±1371	2367±1771
Male fetus	12	20

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Table 3. Comparison results of clinicians and our rule-based method

factor / categories	Kappa (Selection number from clinicians' analysis and our rule-based method)
I	**0.82 (36/30)**
II	**0.61 (12/23)**
III	**0.74 (12/7)**
average	**0.72**

*there was no statistic difference between clinicians analysis and our rule-based method groups

Table 4. The results of FD ratio in each category between clinicians and the proposed method

Categories \ Method		Clinicians' analysis	The proposed method
I		30.0%	**22.8%**
II	**IIa**	64.3%	**28.8%**
	IIb		**71.2%**
III		92.8%	**88.8%**

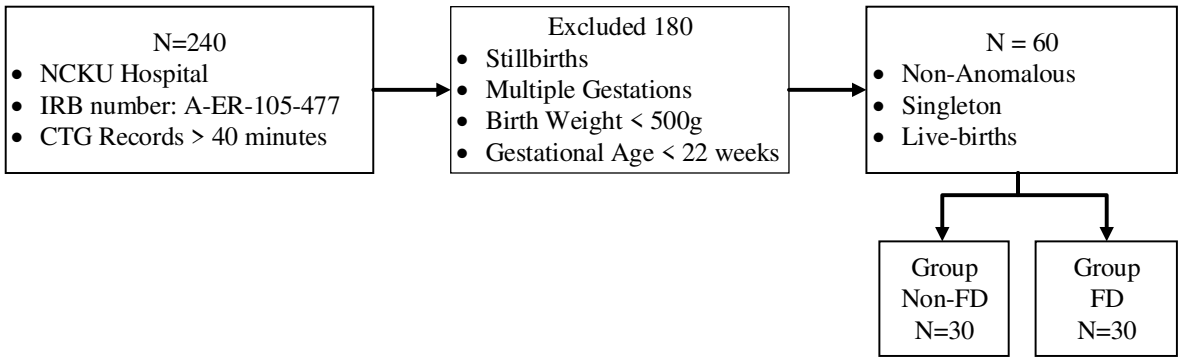
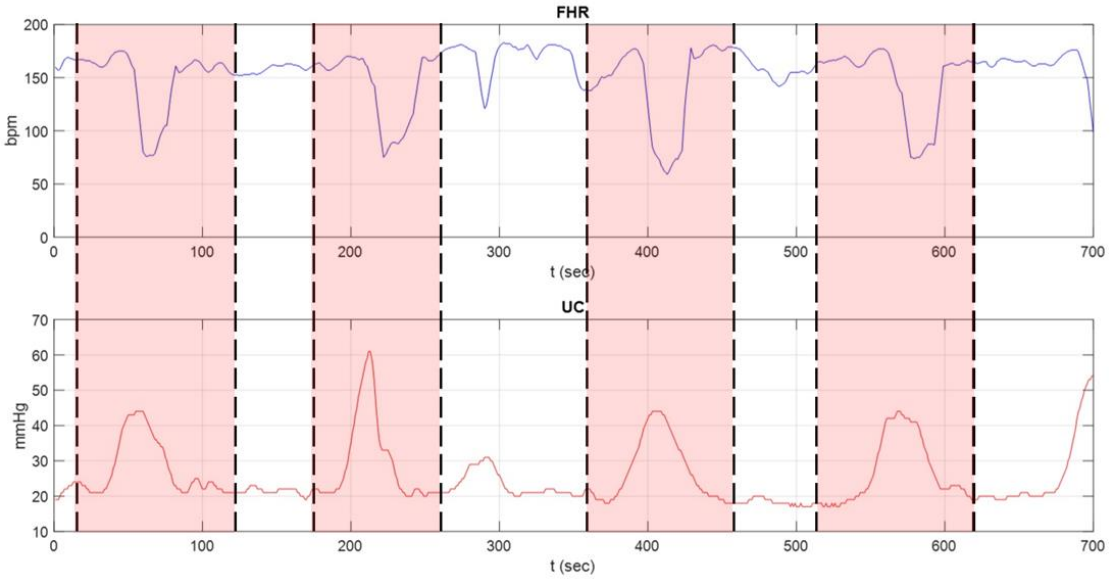


Figure 1. The flowchart of clinical CTG selection.



423

424 **Figure 2. CTG segmentation based on UC analysis**

Figures

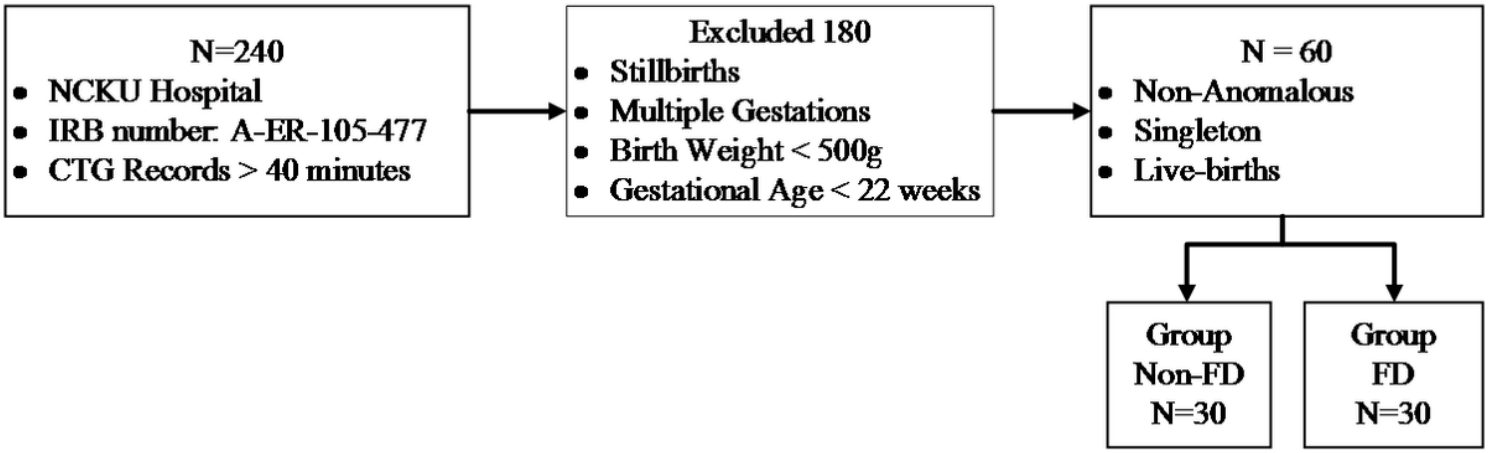


Figure 1

The flowchart of clinical CTG selection.

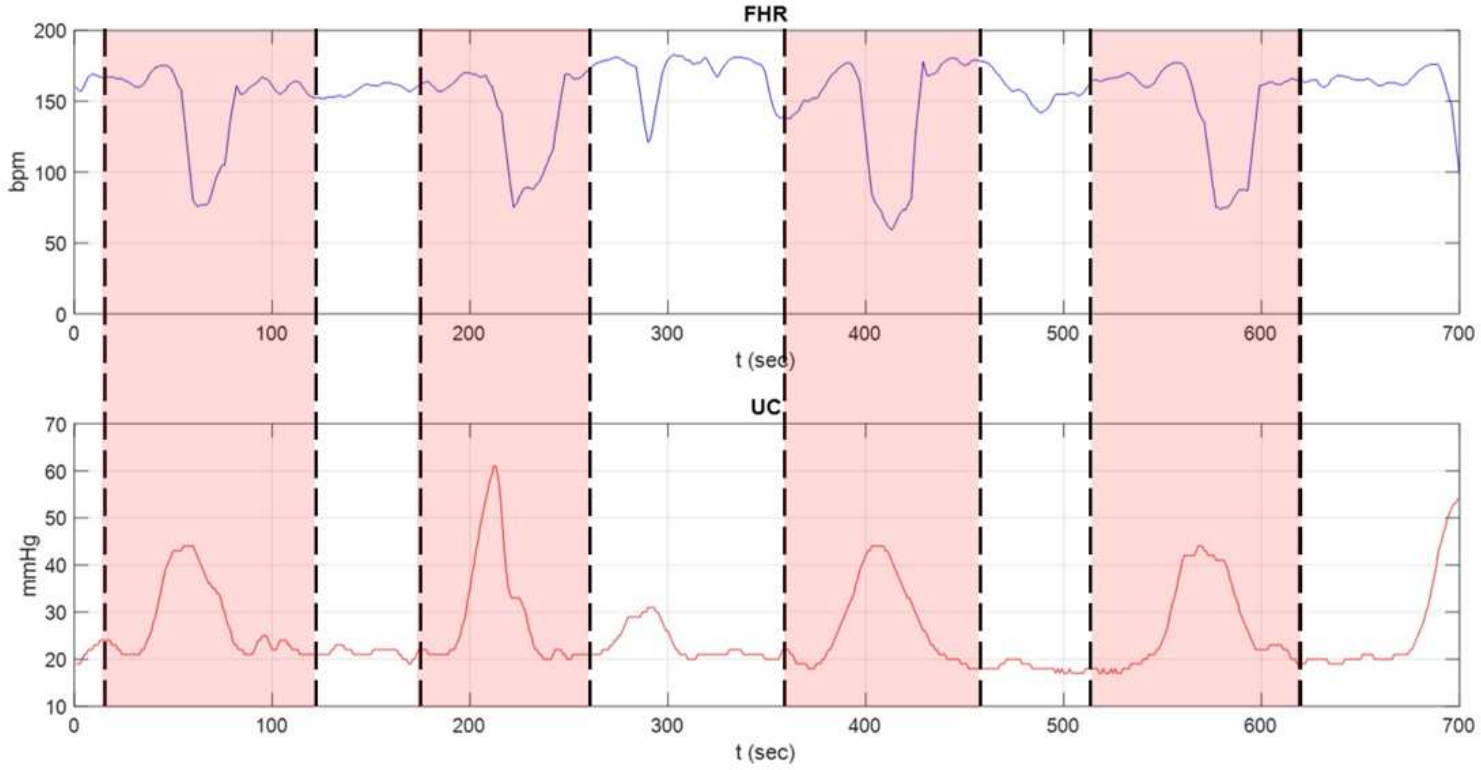


Figure 2

CTG segmentation based on UC analysis