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Fetal Heart Rate Analysis using a Non-linear Baseline and Variability Estimation Method

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*Abstract-***Automated analysis of the fetal heart rate (FHR) curve plays a significant role in computer-aided fetal monitoring. Our study proposed a novel analyzing system of FHR signals which is constituted of FHR baseline estimation module, FHR acceleration/deceleration detection module, and FHR variability estimation module. In baseline estimation module, a novel non-linear FHR baseline estimation method using empirical mode decomposition and computational intelligence method of Kohonen neural network (KNN). We also designed a time-domain detection method of accelerations and decelerations according to international standards. Then the FHR variability estimation module was also designed using a combination method of empirical mode decomposition and moving-average filtering methods. We designed quantitative methods to test the performances of baseline and variability estimation. The results show that the new analysis system reaches a mean subjective satisfaction rate of 96.5% above medium, in terms of FHR baselines. The basal FHR values are close to the estimations from the experts, with a mean absolute error of 2.19 bpm. The acceleration/deceleration detection rate rises with the new baseline estimation method adopted. Besides, the long-term variability estimations are also close to those of the experts' with an MAE of amplitudes of 1.77 bpm and an MAE of cycles of 0.51 cpm.**

Keywords-fetal heart rate (FHR); baseline; empirical mode decomposition (EMD); Kohonen neural network (KNN); FHR variability;

Ⅰ. INTRODUCTION

Electronic fetal monitoring (EFM) is an effective approach to evaluate the status of fetal intrauterine growth and safety. Cardiotocography (CTG), which incorporates the information of fetal heart rate (FHR) and uterine pressure (UP), is one of the most widely used methods in EFM [1]. Currently, CTG analysis is dominantly based on visual inspection, with interpretation largely dependent on the training and experience of the clinician(s) involved，which may lead to insufficient accuracy and uniformity of the interpretation. Hence, the methods and systems for automatic judgment of CTG, using artificial-intelligence and signal processing technologies, have become a research hot-spot in recent years.

Generally, the analysis of CTG signals mainly includes two levels: parameter extraction and classification (i.e., FHR pattern recognition) and subsequent interpretation of patterns. In the last forty years (but especially from the late 80s to the mid-90s [2-7]) there have been several attempts to develop computerized systems for a quantitative/qualitative analysis of the FHR. Berdiñas et al. [8] designed CAFÉ system that integrated algorithms (implemented via conventional programming techniques) with artificial intelligence (AI) paradigms (rule-based systems and artificial neural networks), in order to automate and perform all the phases involved in real time antenatal monitoring, from the analysis and interpretation of CTG signals to diagnosis.

Georgieva et al. [9] have been developing OxSys system for intelligent FHR analysis and risk assessment in labor. They designed novel methods for the parameter extraction from the CTG signals including uterine contractions, or intervals with unassigned baselines, and they also used artificial neural networks (ANN) for FHR diagnostic analysis.

Although previous systems have gone so far as to incorporate different levels of computerized-CTG signal analysis, we have found there are still problems existing at each level and should be studied with combinations of varied signal processing and AI methods. For instance, a number of studies [10,11,12] have pointed out the inaccuracy of extraction of basic FHR parameters such as FHR baselines and accelerations/decelerations, especially when the labor activities become increasingly complex.

Our system, focusing on the analysis of FHR signals, includes novel methods for the parameter extraction of FHR tracings. By modeling an FHR signal as combinations of baseline variability parts and acceleration/deceleration parts, we designed different modules to obtain the information of FHR baselines, accelerations/decelerations and long-term variability.

Ⅱ. METHODS AND MATERIALS

A. The acquisition of FHR signals

All the experimental FHR signals are clinical records from Guangzhou Baiyun District People's Hospital by SFR618 fetal monitors made in Sunray Medical Apparatus Co, Ltd. 40 FHR tracings were randomly selected from the database, all measured in beats per minute (bpm) over a period of 20 minutes.

B. System structure

The designed FHR analyzing system is mainly constituted by three major modules: FHR baseline estimation module, FHR acceleration/deceleration detection module, and FHR variability estimation module, all providing the indispensable parameters for the scoring analysis of the FHR tracings. The three modules are not independent from each other, since FHR acceleration/deceleration module relies on the FHR baseline module, and FHR variability module relies on the FHR acceleration/deceleration module.

C. Preprocessing of the FHR tracings

Due to the data acquisition problem, there are a number of missing points or artifacts in the original FHR tracings. In order to recover the disturbed FHR signals, we eliminated these artifacts and used linear interpolation to fill the gap between two adjacent values.

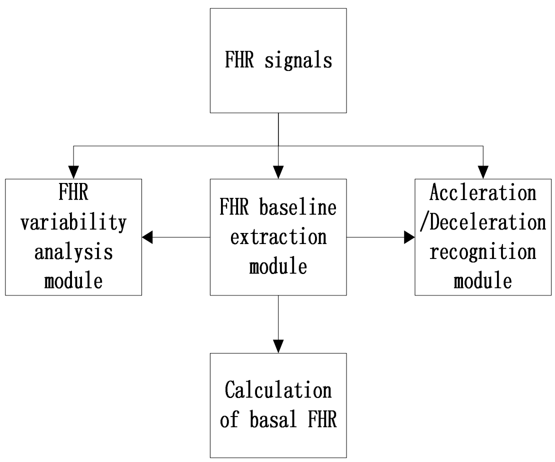

Fig.1. Block diagram of proposed FHR analyzing system

D. FHR baseline extraction module

Baseline, expressed in beats per minute (bpm), is defined as the approximate mean fetal heart rate during at least ten minutes of stable segments, excluding accelerations and decelerations [13]. Precise FHR baseline estimation plays a critical and essential role in the proper analysis for fetal Cardiotocography (CTG). Dawes et al. [14], Mantel et al. [6], Jimenez et al. [15], Krupa et al. [16] have studied and proposed different FHR baseline estimation algorithms and the Toitu system [16], the Nottingham/Hong Kong system [17], the Montreal system [18], the Sonicaid 8000/8002 [16] and 2CTG system [19] have also adopted a variety of baseline estimation algorithms. The above baseline estimation algorithms have dominantly adopted linear methods like low-pass filters or time-domain average method, which necessitate the preset of a number of parameters according to the statistical analysis of the FHR tracings, or a priori from the signal characteristics [12]. As a possible solution to the above issue of FHR baseline estimation, the proposed system adopted a non-linear FHR signal baseline estimation algorithm based on empirical mode decomposition and post-processing clustering method of Kohonen neural network.

In our study, an FHR tracing was assumed as combination of peaks or valleys with varied amplitudes and intervals, including FHR variability like long-term variability, accelerations and decelerations, while beat-to-beat variability that disturbs the overall trend of such peaks or valleys could be modeled as interference.

First, we used empirical mode decomposition (EMD) to make a decomposition of the FHR signals. The information of original signal is clearly represented at each frequency band. The original signal can be reconstructed by adding up those wavelet signals at the same sample point. We summed up the IMFs and the residue from the third level to reconstruct the FHR signal, as follows:

$$y(t) = \sum_{i=3}^{N} IMF_i(t) + r_N(t) \qquad (1)$$

y(t) is the reconstructed signal, and N is the number of IMFs.

The rest IMFs were modeled as interference which contained the major components of beat-to-beat variability.

The reconstructed FHR signal resembles the original FHR signal in the oscillations from FHR variability, accelerations and decelerations while eliminating high-frequency beat to beat variations that may not affect the overall trend of the FHR patterns. The next step is to sort out the characteristic points that closely demonstrate the trend of FHR oscillations. We extracted extreme points of the reconstructed signal as such characteristic points.

By appropriately extracting the characteristics from the extreme points, a training set was hence determined which was input to the Kohonen neural network.

The Kohonen method was chosen because some studies [21] have proved the Kohonen method gave superior results over the more traditional back-propagation neural networks. Besides, the Kohonen network is unsupervised that is ease of use.

The Kohonen network does not use an activation function, the output does not consist of the output of several neurons, and it is trained in an unsupervised fashion, which means that the Kohonen network is presented with data, but that the correct output corresponding to the data is not specified a priori. When data are presented to a Kohonen network, one of the output neurons is selected as a “winner”. The winning neuron becomes the output from the Kohonen network. These winning neurons represent groups, or clusters, in the data set. In our study, the sorted groups were designated as characteristic points from baseline part and from non-baseline part. A cubic spline interpolation was employed to obtain the anticipated FHR baseline as the first step. Since the interpolated curve was not as smooth as an FHR baseline should be, a moving average filtering was adopted

E. Acceleration/deceleration recognition module

Acceleration and deceleration are important clinical indexes for fetal growth. In the same report [13], acceleration is defined as an increase in heart rate from the baseline, lasting for at least 15 seconds, with a peak of at least 15 bpm above the baseline. Equivalently, a deceleration is defined as a decrease in heart rate from the baseline for at least 15 seconds, during which at least one sample is 15 bpm below baseline. It is clear that correct recognition of accelerations or decelerations rely directly on the performance of estimated FHR baselines. In our system, a time -domain searching method was designed for acceleration/deceleration detection (Fig.2.).

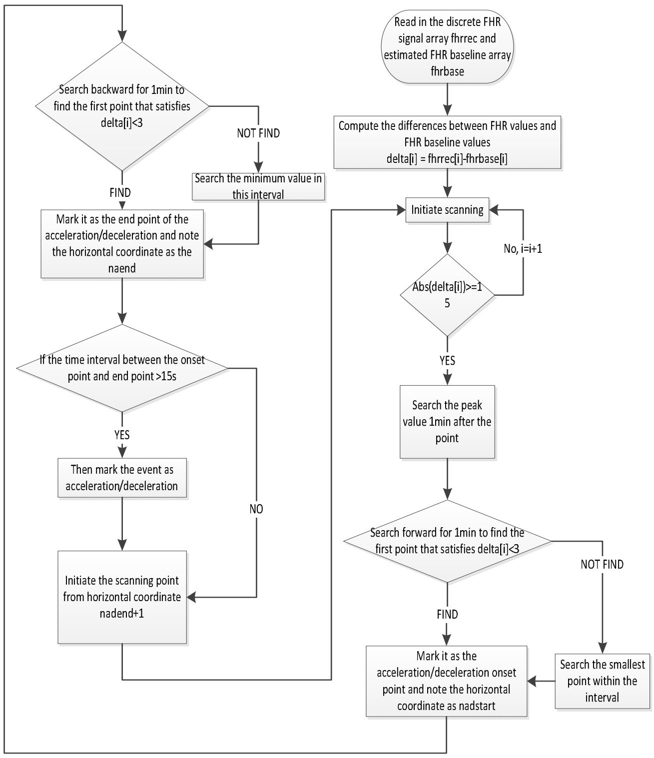

Fig.2. Flow chart of algorithm for acceleration/deceleration module

F. FHR variability analyzing module

The repeat and frequent oscillations in the baseline part of FHR signals are defined as FHR-baseline variability that can be classified into long-term variability (LTV) and short-term variability (STV). Long term variability parts are the oscillations on the FHR baseline that our eyes can identify, and they are evaluated by the amplitudes and cycles. The FHR variability analyzing module mainly deals with the estimation of the amplitudes and cycles of the long term variability parts.

First, we calculated the FHR accelerations and decelerations using the above detection method. By eliminating these acceleration or deceleration parts from the FHR tracing, the rest of such FHR signal was the baseline part.

Then we integrated every independent baseline part of long term variability. By using a 10-span moving average smooth filter respectively, we obtained a imaging line that runs through the middle of the oscillations of long-term variability. It is necessary to point out that we still used the EMD-reconstructed FHR signal in the estimations in order to reject the interferences from beat-to-beat variability.

The mean deflections from the imaging lines and the zero-crossings of such oscillations were calculated to obtain the mean amplitudes and cycles of the long-term variability. Suppose the oscillations be modeled as sinusoids of different frequencies, whose amplitudes can be calculated using the following equation (2),

$$Amp = \frac{2\sqrt{2}}{M}\sum_{i=1}^{M}\left|LTV(i) - IMLINE(i)\right| \tag{2}$$

in which M is the length of the baseline part, LTV(i) denotes the EMD reconstructed FHR value at a given time point i, and IMLINE(i) denotes the value of the calculated 10-span-filter-smoothed imaging line at time point i. However, the oscillations may not be approximated to be sinusoids, thus we would rewrite the equation (3) as

$$Amp = \frac{K}{M}\sum_{i=1}^{M}\left|LTV(i) - IMLINE(i)\right| \tag{3}$$

where K is a coefficient that needs to be determined in a training process.

The cycles of LTV can be estimated from zero-crossings, as in equation (4):

$$Cycle = 60 \times zerocross \times \frac{fs}{M} \tag{4}$$

in which fs is the sampling frequency of the FHR signal, which is 1.25Hz, M is also the length of the baseline part, and zerocross is the number of crossings of the reconstructed FHR baseline part with the 10-span-filter-smoothed imaging lines.

III. RESULTS

First, we evaluated the performance of the proposed EMD-KNN FHR baseline estimation algorithm in our system. It was compared with an existing baseline estimation algorithm of a fetal monitor's platform and a cited linear baseline estimation algorithm [12], which were all implemented with MATLAB 7.x platform.

In order to provide the possible uncertainty, two clinical experts were invited as the control groups to support the validation of the computer-aided results. They evaluated the baselines computed by the fetal monitor platform's algorithm (Alg1), the cited algorithm (Alg2) and the EMD-KNN algorithm (Alg3). They scored the baselines estimated by the three algorithms as ideal, medium or poor for each sample. The clinical assessment of different methods is shown in Table 1.

We can see clearly that the subjective satisfaction of either expert increases from Alg1 to Alg3 evidently. More than 95% samples were scored above the medium level by the two experts for the baseline estimation of Alg3.

The absolute differences between the expert-estimated basal FHR values and computer-aided basal FHR values were also calculated as another indicator for the algorithms' performance (Table.2.).

TABLE 1. ASSESSMENT LEVEL BY 2 OBSERVER FOR DIFFERENT BASELINE ESTIMATION ALGORITHM PERFORMANCE

Assessment Level	Alg1	Alg2	Alg3
Ideal baseline by Expert 1	3%	53%	70%
Medium baseline by Expert 1	33%	33%	28%
Ideal baseline by Expert 2	3%	53%	65%
Medium baseline by Expert 2	35%	38%	30%

TABLE 2. MEAN ABSOLUTE DIFFERENCES BETWEEN COMPUTER-AIDED BASAL FHR VALUES AND THE BASAL FHR VALUES ESTIMATED BY THE EXPERTS

Mean absolute difference	Alg1	Alg2	Alg3
Expert 1	4.675	4.375	2.075
Expert 2	4.95	4.65	2.35

It is evident that the mean absolute differences of the basal FHR values from Alg3 are smaller than those from the rest, indicating that the baseline generated by Alg3 follows the baseline part of the FHR tracings more accurately and closely, while reducing the interference from the non-baseline part.

The generated baselines were also used to aid the computerized acceleration/deceleration detection. In this part, we combined the three different baseline estimation algorithms together with the acceleration/deceleration detection algorithm in our system. With the indicators of Correct (automatic detections accord with the experts' evaluations), Over-detect (automatic detections detect more accelerations/decelerations than experts do) and Fail-to-detect (automatic detections fail to detect the accelerations/decelerations experts detect), the statistical results are shown in Fig.3.

Despite the inter-observer disagreement, the Alg3 outperformed the others in the correct recognition percentage with less false detection (over-detect and fail to detect) percentage, in both acceleration and deceleration detection.

To evaluate the performance of the FHR variability module, we first randomly selected 10 of the 40 FHR tracings to set the optimal coefficient K. The optimal K value was estimated 3.5 in our system. The mean absolute errors of amplitudes and cycles are listed in Table 3.

IV. DISCUSSION AND CONCLUSION

From the above results and analysis, the new FHR analysis system, which adopts EMD-KNN algorithm as its baseline estimation method, evidently ameliorates the estimation results of basal FHR values and the detection rates of FHR accelerations/decelerations. Besides, with improved acceleration/deceleration detection, it is more reliable to estimate the FHR long-term variability. Each module of the FHR analysis system is interconnected and each step of estimation is based on previous ones. Therefore, the baseline estimation module is the most critical part and is the most significant innovative point of our study. We combined the filtering method of EMD and clustering method of KNN, which focused on the overall characteristics of the FHR data, rather than the discrete numerical points on which previous methods focused. Though problems still exist when such method deals with some irregular FHR patterns, it successfully estimates the baselines of those FHR tracings with continuous accelerations/decelerations, which are not rare during both antepartum and intrapartum labor monitoring (Fig.4.).

Our next step is to extract the characteristics of FHR tracings in numerical methods and use different baseline estimation algorithms according to such numerical characteristics, since the EMD-KNN method is time and hardware consuming. The ultimate goal is to develop an artificial-intelligence based CTG analyzing system, which can reliably helps the obstetricians in their clinical practice.

TABLE 3. MEAN ABSOLUTE DIFFERENCES BETWEEN COMPUTER-AIDED LONG-TERM VARIABILITY AMPLITUDES AND CYCLES AND THOSE ESTIMATED BY THE EXPERTS

Mean absolute difference	Amplitudes (bpm)	Cycles （cpm）
Expert 1	1.67	0.48
Expert 2	1.87	0.53

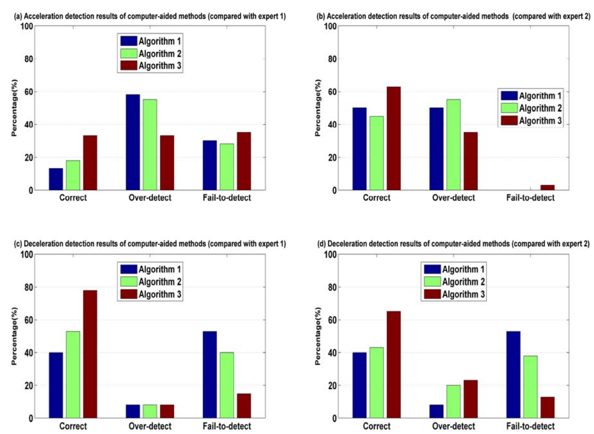

Fig.3. (a) Acceleration detection results of computer-aided methods (compared with expert 1) (b) Acceleration detection results of computer-aided methods (compared with expert 2) (c) Deceleration detection results of computer-aided methods (compared with expert 1) (d) Deceleration detection results of computer-aided methods (compared with expert 2)

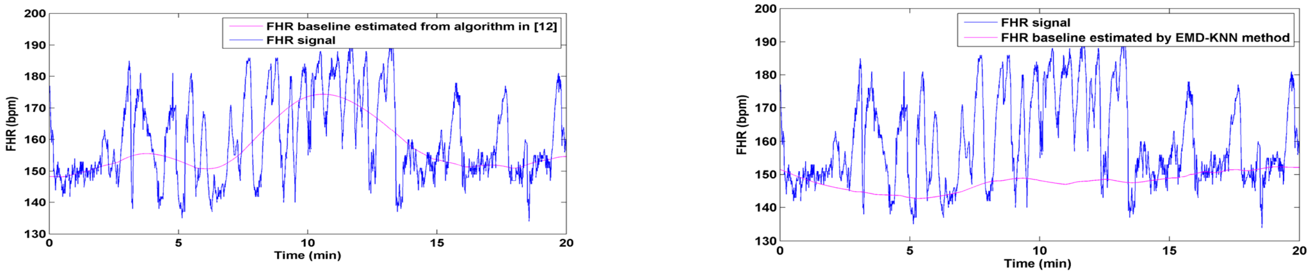

Fig.4. (a) A complex FHR tracing of consecutive accelerations with baseline estimated using the modified algorithm from Mantel's method [12]. The baseline is inaccurate due to distribution from the continuous accelerations. (b) The same complex FHR tracing with baseline estimated by the proposed EMD-KNN method. The baseline is not affected by the contribution from continuous and long-time accelerations

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