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Evaluation of Fetal Heart Rate Baseline Estimation Method Using Testing Signals Based on a Statistical Model

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Abstract — **Computer–aided fetal monitoring is based on automated analysis of the fetal heart rate (FHR) variability. The first and the main step in the automated signal interpretation is the estimation of the so called FHR baseline. There are various algorithms for baseline estimation, of different efficiency. For its evaluation, the method of modeling of FHR signal based on the preset baseline component has been developed. The best algorithm is expected to provide the same baseline as the component baseline used to model the FHR signal. Generated signals were used to compare the baselines that have been estimated by two algorithm: the first one relying on artificial neural networks and the classical one using nonlinear filtering of FHR signal.**

I. Introduction

Interpretation of fetal heart rate (FHR) variability is the basic diagnostic tool in present–day perinatal medicine. Reactive patterns provide indirect evidence that the fetus has adequate oxygen supply and the central nervous functions are maintained. Three main types of fetal heart rate variability can be distinguished: fetal heart rate baseline, acceleration and deceleration patterns as well as short- and longterm variability.

Regarding the large complexity and complex shape of FHR waveforms, their reliable visual interpretation is very difficult and often leads to erroneous diagnosis. Clinician extracts only a small piece of information, the main part remains hidden in the trace. In addition, the interpretation can change under the influence of tiredness or level of clinical experience of a person analyzing the trace. Hence, the computer–aided monitoring systems have been widely applied to improve objectivity and repeatability of signal interpretation [1].

The first and the main step in FHR trace analysis is an estimation of the FHR baseline [2]. Basing on the baseline, there are recognized other characteristic patterns like accelerations and decelerations remaining in strict correlation to the fetal state [3]. The FIGO committee [4] has defined the baseline as a mean level of the fetal heart rate when it is stable, acceleration and deceleration being absent. It is determined over a time period of 5 or 10 minutes and expressed in beats per minute (bpm). In the same report the acceleration and deceleration are defined as deflections from the baseline. The baseline within these episodes is an imaginary line presenting a basal fetal heart rate in case there are no accelerations and decelerations. Such definition of baseline is completely useless for automated analysis. Despite the variety of baseline algorithms, none of them is optimal and none can guarantee the baseline being estimated is correct. In order to validate baseline algorithms, it is necessary to develop some test procedures. They rely on the reference baseline obtained from clinical expert, which after the conversion to the digital form, can be compared with baseline estimated using particular algorithm [5]. However, the better approach seems to be the use of artificial FHR signals. Modeling of such signals which is based on three components of FHR signal is presented in this work. Each component is modeled separately with a use of real FHR signals. A given baseline estimation algorithm being tested determines the baseline for a particular artificial FHR signal. The obtained baseline is compared with the baseline which was used to build the artificial FHR signal. Consistency of both baselines gives the prove that the baseline estimation algorithm is good. The best algorithm is expect to provide the same baseline as was used for modeling of the FHR signal. Quantitative evaluation of differences is ensured by relevant set of consistency indices.

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II. Methodology

The shape of fetal heart rate trace as well as a low level of signal loss were the main criteria for selection of FHR signals from the database of real signals. Signals were divided as regards the type of the modeled variability. One-hour records, without accelerations and decelerations patterns were used for modeling the baseline component. Five–minute fragments with classical types of variability were used for modeling short- and longterm FHR variability. Accelerations and decelerations were manually modeled on a basis of visual interpretation of traces comprising such patterns. The obtained signal components were summed to produce the final artificial FHR signal (Fig. 1). In order to ensure the same measurement accuracy as provided by fetal monitors, the samples of modeled signal were rounded to 0.25 bpm. The signal length was established at 1 hour. This corresponds to 14.400 samples of 4 Hz rate, which is a digital form of FHR signal in computer-aided systems.

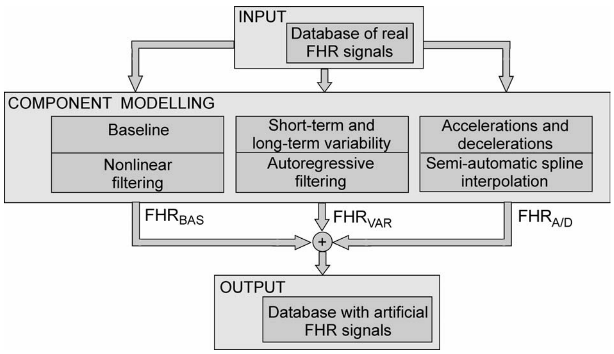

Fig. 1. Diagram of the fetal heart rate signal modeling procedure.

The baseline component was modeled by means of an algorithm based on nonlinear bidirectional low–pass filtering in order to ensure linear phase characteristic [1], [6]. The filter is given by the following equation:

$$H(z) = \frac{(1-a)^2}{(1-a\cdot z^{-1})\cdot(1-a\cdot z)} \tag{1}$$

Considering the sampling frequency 4 Hz, the factor a is set at 0.996 to ensure the cutoff frequency of the filter equal to 0.0021 Hz. The shape of the obtained baseline could be additionally modified. It was based on subtraction of constant component and multiplication of consecutive baseline values by a scaling factor. In that way several various baselines FHR_{BAS} can be obtained for one input FHR signal.

Under physiological conditions the beat–to–beat heart intervals are constantly subject to small changes. This is called shortterm variability. Due to a certain periodicity in the direction and size of these changes they result in oscillations of the fetal heart rate around its mean level. These oscillations are called longterm variability [4]. Essential element used to generate short- and longterm variability is the autoregressive filter [7], [8]. The idea of the autoregressive method is based on assumption that signal can be represented as a white noise signal passed through the filter of the following transfer function:

$$H(z) = \frac{1}{1+\sum_{k=1}^{N} a_k \cdot z^{-k}} \tag{2}$$

The a_k factors, define a filter which amplitude characteristic corresponds to the power density spectrum of a teaching signal (five-minutes fragments of FHR selected earlier). White noise is transformed during filtering into a signal whose spectrum matches the teaching signal spectrum. Since in each new generating process the white noise signal is different, therefore even for one teaching signal the modeled variability components FHR_{VAR} are never identical as to their shape (Fig. 2). They only have the same spectrum. Several methods are known to calculate a_k factors, however, the most common is the one based on Yule–Walker equations:

$$a_k = R^{-1} \cdot P \tag{3}$$

where: R – autocorrelation matrix of teaching signal of size N, P – autocorrelation vector of teaching signal of size N.

Vector and matrix of autocorrelation are defined as follows:

$$P = \begin{bmatrix} r_{xx}(1) \\ r_{xx}(2) \\ \vdots \\ r_{xx}(N) \end{bmatrix} \tag{4}$$

$$R = \begin{bmatrix} r_{xx}(0) & r_{xx}(1) & \cdots & r_{xx}(N-1) \\ r_{xx}(1) & r_{xx}(0) & & \\ \vdots & & \ddots & \\ r_{xx}(N-1) & & & \end{bmatrix} \tag{5}$$

Although, in practice the autocorrelation function $r_{xx}(m)$ is unknown, its value can be estimated basing on teaching signal samples $X(1), X(2) \ldots X(M)$:

$$\hat{r}_{xx}(m) = \frac{1}{M} \cdot \sum_{n=m+1}^{M} X(n) \cdot X(n-m) \tag{6}$$

where: $m = 0, 1, \ldots N$

For a given teaching signal, the once determined factors a_k of the filter are stored in a table ready to use in the consecutive modeling processes. Both the vector and the matrix of autocorrelation have the size N relating to the order of a model. Selecting the optimal N value is very crucial.

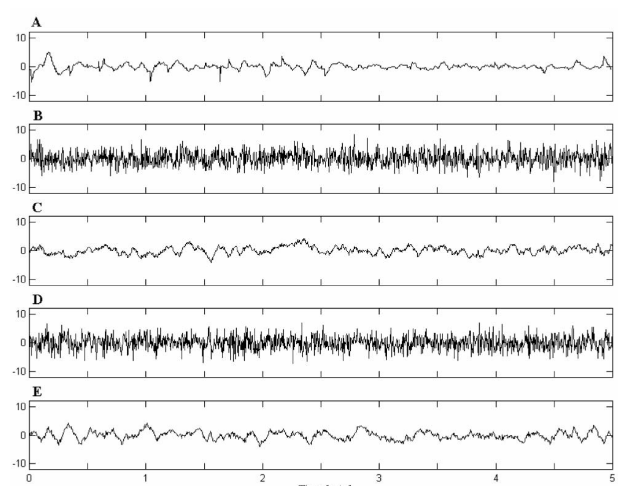

Fig. 2. Components of autoregressive modeling process: A – input learning FHR signal; B,D – white noise; C,E – output signals with short- and longterm variability imposed (corresponding to B and D respectively).

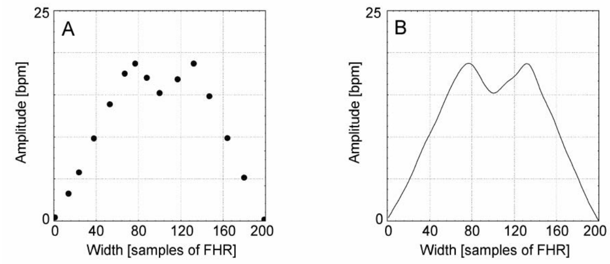

Fig. 3. Characteristic points of the acceleration being modeled – A, final form of the modeled acceleration – B.

Too low order causes the amplitude suppression and the substantial signal loss. On the other hand, too high value causes appearance of components that do not have real equivalents in teaching signal as well as considerable increase of computational time. The order of the model was set at N=12 [9].

Regarding the remarkable irregularity of shapes, it is very difficult to describe mathematically the accelerations and decelerations patterns. Acceleration of FHR signal is defined as a transient increase in heart rate of 15 bpm or more and lasting 15 seconds or more. Decelerations are transient episodes of slowing of fetal heart rate below the baseline level of more than 15 bpm and lasting 10 seconds or more [4]. Their simple approximation is the second order function [10]. But more variety of shapes and better representation of real phenomena can be provided by cubic splines. In the first step of this approach, the user sets the parameters (amplitude and duration) of modeled acceleration/deceleration $FHR_{A/D}$ episode. Afterwards, the characteristic points of the pattern are manually put in the window (Fig. 3A). The pattern is represented by certain number of interpolated 4 Hz samples. Finally, created acceleration (Fig. 3B) is added to the modeled FHR signal.

Using the presented modeling process, there was created a database of FHR signals. Ten characteristic traces were used to test the baseline estimation algorithms. For each of them, there were created three various baselines FHR_{BAS} with different degree of irregularity: having stable level, with constant shift and with fluctuations. Then, each of the baselines was disturbed by adding the short- and longterm variability FHR_{VAR} as well as the acceleration and deceleration $FHR_{A/D}$.

This procedure ensures that the shape of baseline is known for any given output FHR signal because the signal was modeled on its basis. The parameters of acceleration and deceleration were changed ten times for each line and finally the database of 300 test signals was obtained. One of them is shown in Fig. 4. It can be seen that the generated signal approximates the real one not only in the time domain but also in the frequency domain.

III. Results

Generated signals were used to compare the baselines that have been estimated by two algorithm: the first one relying on artificial neural networks and the classical one using nonlinear filtering of FHR signal [1], [6]. The neural network of multilayer perceptron type with sigmoidal function was chosen, that had 120-10-1 structure [11]. Mean absolute difference (MAD) and mean-square error (MSE) coefficients allowed quantitative evaluation of inconsistency of baseline estimated by the algorithms with the preset reference baseline.

In Tab. I the ranges of MAD and MSE value are presented that have been obtained for particular groups of records. For the class I and III the better results were achieved applying nonlinear filtering algorithm, whereas for the class II more accurate estimation was ensured by the algorithm based on neural network. It results from the fact that signals from the class I and III have unimodal histogram of FHR values and

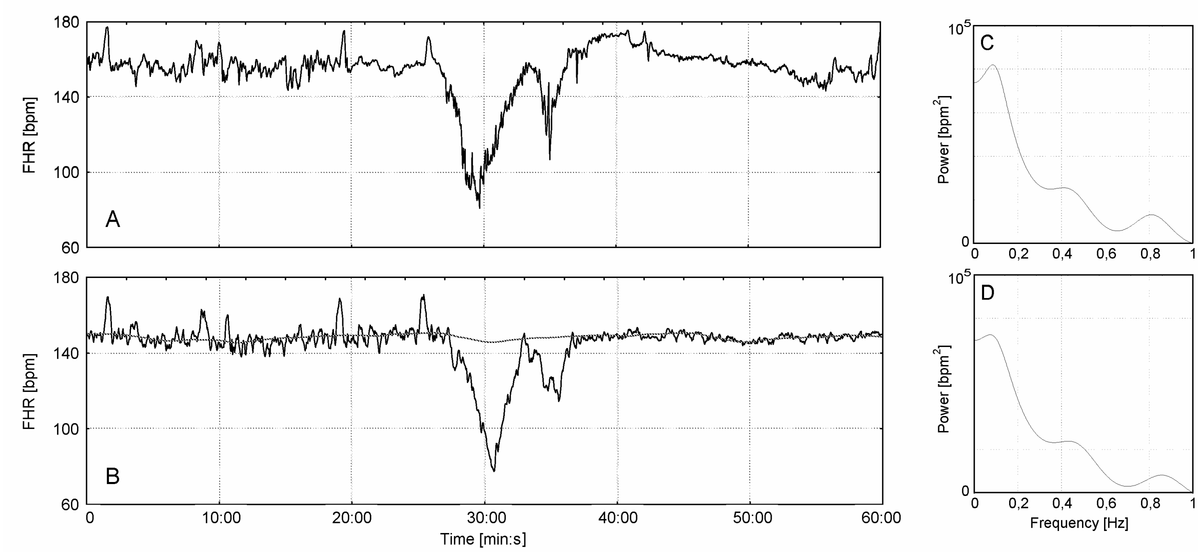

Fig. 4. Real FHR signal – A, artificial FHR trace – B, spectrogram of the real signal – C, and spectrogram of the modeled signal – D.

TABLE I
RESULTS OF COMPARISON OF TWO ALGORITHMS FOR BASELINE ESTIMATION

Baseline class		Nonlinear filtering		Neural network	
No	Description	*MAD*	*MSE*	*MAD*	*MSE*
I	Stable level	0.6÷1.3	0.5÷2.0	1.3÷2.2	1.4÷2.6
II	Constant shift	3.1÷11.1	3.8÷15.2	1.6÷2.6	1.8÷2.9
III	Fluctuation	0.9÷1.6	1.0÷2.1	1.2÷2.4	1.1÷2.9

the prominent frequency controlling the filtering process can be determined explicitly. In case of signals belonging to the class II, histogram of FHR values is bimodal, thus the prominent frequency well matches one part of signal but does not match the other part.

IV. Conclusions

The development of computer technology caused that the new systems for quantitative analysis of FHR signals have become common. Regarding large diagnostic importance of this analysis, it seems necessary to establish the procedure for validating the results of trace analysis. Presented algorithm for modeling the testing fetal heart rate signals, together with indices determining inconsistency between the reference baseline and the baseline estimated by a given algorithm, may be helpful to perform such procedure.

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