fetal heart rate variability,
time event series,
missing samples

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THE INFLUENCE OF SIGNAL LOSS EPISODES ON FETAL HEART RATE VARIABILITY MEASURES

The most important features indicating appropriate fetal development are the measures of instantaneous variability of a fetal heart rate (FHR), describing fluctuations of the beat-to-beat heart intervals. The most popular method for the FHR acquisition is the Doppler ultrasound technique. However, it is very sensitive to various motion artifacts distorting the signal being acquired. The aim of our work was to evaluate the influence of signal loss episodes on the parameters quantitatively describing the instantaneous variability of the FHR. For this purpose we artificially inserted signal loss episodes to the recordings, in different patterns and percentage, in accordance with the real characteristics of the signal loss segments. We particularly would like to answer the question if the signals with significant amount of signal loss can be reliably evaluated by means of instantaneous variability measures, and which of these measures (numerical indices) are more robust to the missing values.

1. INTRODUCTION

The main task of fetal monitoring is to ensure that all vital fetal organs are properly supplied with oxygenated blood. As a direct measurement of fetal oxygen saturation is impossible, the risk symptoms are being identified through the fetal heart rate (FHR) signal analysis. The most important features indicating appropriate fetal development are the measures of instantaneous variability of the fetal heart rate, describing fluctuations of beat-to-beat intervals [12]. The indices describing this variability have been originated from the fetal ECG signal recorded during labour via a direct contact electrode [2], [6]. Along with development of the ultrasound monitoring methods the same indices have been applied to the FHR signal for evaluation of the fetal state during pregnancy [19]. Nowadays the Doppler ultrasound technique, based on acquisition of mechanical activity of the fetal heart, is the most popular method for the FHR monitoring [13], [20]. However, it is particularly sensitive to motion artifacts coming from fetal movements or uterine contractions. These disturbances together with transducer displacement are the main reasons of signal loss episodes [14], [21].

In fetal monitoring the sampling rate of 4 Hz is an established standard, which means that every 250 ms a new FHR value is provided by the monitor [7]. If a signal loss episode is

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recognized by a monitor the zero value is provided on the monitor output as a measurement value (the so called ”missing data” or ”missing measurement”). However, for the purpose of automated analysis of the FHR signal (i.e. determination of FHR baseline, detection of acceleration or deceleration events, and quantification of other important clinical features describing FHR signals) the missing values have to be replaced by the valid ones [8]. Most often they are replaced by the mean value of the fetal heart rate estimated from the neighboring measurements or using a linear interpolation of them.

The aim of our work was to evaluate the influence of signal loss episodes on the parameters describing quantitatively the instantaneous variability of the FHR. We particularly would like to answer the question if the signals with significant amount of signal loss can be reliably evaluated by means of instantaneous variability measures, and which of these measures (numerical indices) are more robust to the missing data. For this purpose we artificially infused signal loss episodes to the signals, in different patterns and percentage (up to 50%), and the FHR variability indices estimated for distorted signals were related to the ones calculated for the original signals without signal loss episodes.

2. METHODOLOGY

In this paper we used the CTU-UHB Intrapartum Cardiotocography Database [3] provided open access on physionet.org [4]. The database contained 552 recordings collected in the University Hospital in Brno, Czech Republic. All the cardiotocographic (CTG) recordings were acquired within 90 minutes before delivery and contain the FHR signal as time series evenly sampled at 4 Hz. Basing on the additional parameters describing each recording we used only the signal acquired during the first stage of labour. In the next step we removed from the recordings all the deceleration patterns, commonly occurring during labour, as they would incorrectly increase the FHR variability indices [2]. The decelerations were defined using FIGO Guidelines [16]. Finally, as a research material we selected 2567 segments of five-minute duration, for which the original percentage of signal loss episodes was lower than 5%

2.1. SIGNAL LOSS EPISODES

In order to evaluate the influence of signal loss on the FHR variability indices we had to artificially distort the selected signal segments. In [17] the authors used random permutation algorithm to insert signal loss. However, in this way the signals were distorted by a very large number of very short sequences of missing data. We noticed that the distortions obtained in this way are not consistent with the characteristics of the real signal loss episodes occuring. What is more, those very short sequences are easier to interpolate without a significant change in the signal variability characteristics. In consequence the evaluation of their impact on the FHR variability features is too optimistic.

Knowing that, we decided to find out what is the real distribution of the length of signal loss episodes and to insert missing values according to this distribution. As a basis we used the original recordings from the CTU-UHB database. All the signal loss episodes were detected in the signals acquired during the first stage of labour. The number of sequences of a given length was summed up and used to create the probability distribution (Fig.1a). It can be noticed that the most frequent sequences are composed of 4 or 5 values, which corresponds to about two heart cycles in normocardia range ($110 \div 150$ bpm). In all the following stages of analysis the signal loss episodes selected according to that characteristic were artificially inserted to the recordings instead of the original valid measurements. For this purpose a Matlab (The MathWorks Inc.) function was written for a random generation of signal loss patterns according to the obtained

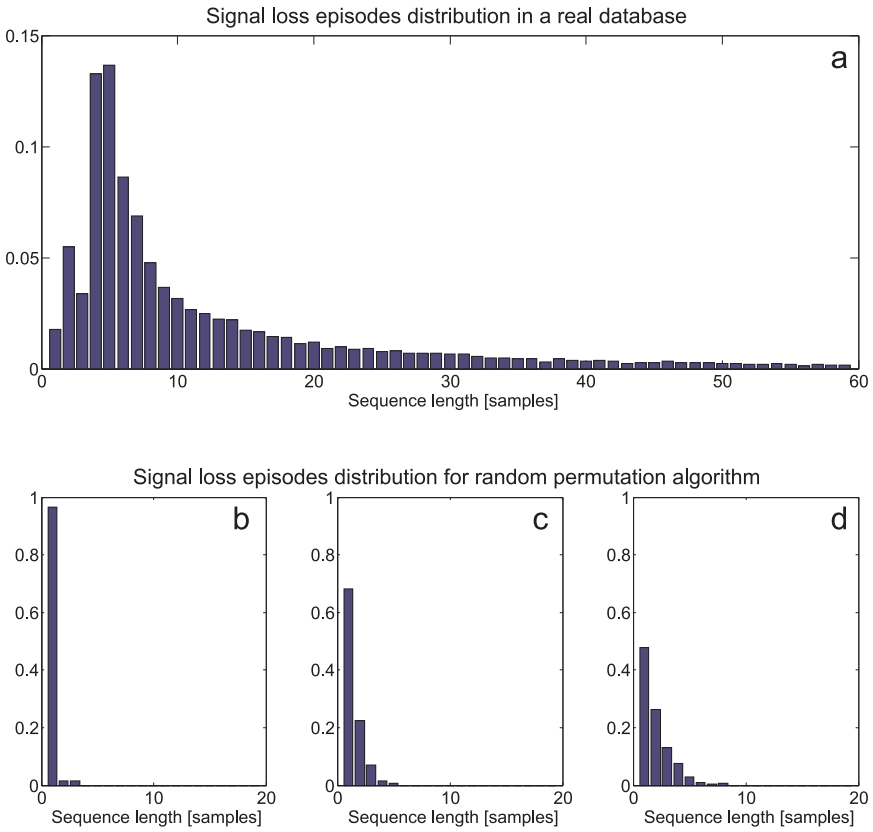

Fig. 1. Probability distribution of the signal loss episodes understood as the lengths of sequences of neighboring missing values observed in the CTU-UHB database recordings (a), together with the probability distribution plots for the random patterns of signal loss episodes generated using the permutation algorithm with different percentage of missing data: 10% (b), 30% (c) and 50% (d).

distribution. Each five-minute segment of the FHR signal was artificially distorted by inserting of different patterns of signal loss episodes. Using the algorithm a set of 100 patterns was generated for each signal segment and five percentage levels: 10, 20, 30, 40 and 50%.

The inserted signal loss episodes need to be reconstructed before the FHR variability indices are calculated. Although some advanced methods of time series reconstruction were proposed in the literature [15], in this paper we decided to apply a simple linear interpolation as the worst case scenario.

2.2. FHR VARIABILITY INDICES

The instantaneous variability of the fetal heart rhythm is considered to be a valuable predictor of the fetal state. In automated analysis of the fetal heart rate signal two main components of instantaneous variability (short- and long-term) are evaluated quantitatively using various measures (numerical indices). As the indices have been originated from the fetal ECG signal, the most crucial for a reliable FHR variability assessment is that the indices should be calculated on basis of events – individual heart beats, which is a standard in fetal ECG signal processing [9], [10]. Therefore, to calculate the FHR variability indices consistent with those derived from fetal electrocardiogram, it is necessary to provide the FHR signal in a form of time event series. Various methods for conversion of evenly sampled time series into the time event series have been proposed by Cesarelli [1] and Jezewski [11], and in this paper we used the latter approach.

Table 1. Formulas for calculating the short- and long-term indices describing the FHR variability. N stands for the number of intervals in the one-minute signal window. The heart interval $T(i)$ is calculated according to the formula: T(i) [ms] = 60000 / FHR(i) [bpm].

STV – beat-to-beat STV $= \frac{1}{N}\sum_{i=1}^{N-1}\lvert T(i+1)-T(i)\rvert$	$[ms]$	
LTV – beat-to-beat LTV $= \max\limits_{1\le i\le N} T(i) - \min\limits_{1\le i\le N} T(i)$	$[ms]$	
STI – by De Haan STI $= 1000 \cdot IQR\left(\arctan\left(\frac{T(i)}{T(i-1)}\right)\right)$	$[a.u.]$	$i = 2,3,4...N$
LTI – by De Haan LTI $= IQR\left(\sqrt{T(i-1)^2+T(i)^2}\right)$	$[a.u.]$	$i = 2,3,4...N$
STV – by Yeh STV_Yeh $= \sqrt{\sum_{i=1}^{N-1}\frac{\left(D(i)-\bar{D}\right)^2}{N-2}}$ where: $D(i) = 100 \cdot \frac{T(i)-T(i+1)}{T(i)+T(i+1)}$	$[ms]$	$i = 1,2,3...N-1$
STV – standard deviation STV_SD $= \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(T(i+1)-T(i)\right)^2}$	$[ms]$	
LTV – standard deviation LTV_SD $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(T(i)-\bar{T}\right)^2}$	$[ms]$	

Only the most popular short- and long-term indices were evaluated, and the formulas for their calculation are presented in Table 1. All indices were calculated in successive one-minute windows and the values obtained for five-minute long signals were averaged. Along with the standard indices we used two additional features describing the fractal dimension of a signal. They were obtained using Higuchi method for calculating the fractal dimension [5], provided that in the last step of this algorithm the values were calculated separately in two scaling regions. In this way the short-term and long-term changes were distinguished. The separation (critical) time was the same as established in [17] and was equal to 3 s. Unlike the classical variability parameters, defined on a basis of time event series representation, fractal dimension is always calculated for evenly sampled signal.

3. RESULTS

The stability of different variability indices was evaluated in presence of artificially inserted signal loss patterns. First, the indices were calculated for the whole set of the undistorted signals. The results in form of the median value together with 25^{th} and 75^{th} percentile are presented in Table 2. Then the signal loss patterns with a given percentage of missing values were inserted into the analyzed signals. The obtained variability indices were related to the ones calculated on basis of undistorted signals, and thus the relative (normalized) values of indices were determined. The same operation was repeated for all the five percentage levels and the analysis was performed using the relative index values. The numerical values of the mean relative difference between the indices calculated for the original FHR recordings and for those with signal loss at the level of 50% are presented in Table 2.

Table 2. The overview of results obtained for the different FHR variability indices together with their relative change in presence of 50% of missing values. The I_{REF} represents the index value for signal with zero signal loss, whereas $I_{50\%}$ - for signal with 50% of missing values. The I_{REF} is expressed as median value with 25^{th} and 75^{th} percentile. The relative change of indices is presented as a mean value and standard deviation.

		γ_0		$(\gamma_{50} - \gamma_0)/\gamma_0$ [%]		
short-term	STV [ms]	2.65	(1.89; 4.00)	−34.66	±	4.15
	STI [a.u.]	4.47	(3.31; 6.15)	−57.07	±	11.66
	STV_Yeh [ms]	4.76	(3.51; 6.87)	−28.13	±	4.44
	STV_SD [ms]	4.22	(2.94; 6.45)	−28.04	±	4.64
	STV_FD [a.u.]	1.35	(1.27; 1.44)	−7.07	±	1.51
long-term	LTV [ms]	64.41	(43.37; 97.81)	−9.07	±	4.35
	LTI [a.u.]	25.09	(16.83; 36.98)	−3.14	±	6.19
	LTV_SD [ms]	14.28	(9.70; 21.94)	−6.63	±	4.11
	LTV_FD [a.u.]	1.76	(1.66; 1.84)	−4.20	±	1.76

The difference between short-term and long-term indices is clearly visible. While the long-term indices were decreased (maximum by 9.07% for the LTV), the short-term indices (except the STV_FD) were reduced by at least 28.04%. The highest difference was noted for the STI index and it was equal to –57.07% (11.66%). The STV_FD proved to be the most resistant to signal loss as it was only decreased by 7.07%. The plots of changes of particular indices with the increasing percentage of signal loss are presented in Figure 2.

4. DISCUSSION

The distribution of lengths of signal loss episodes obtained in the first stage of the analysis was significantly different from the situation where the missing values are generated using the random permutation algorithm, as proposed in [17]. In case of the random permutations the most frequent signal loss sequences are one-sample long, and what is more, the distribution depends on the assumed percentage of signal loss (Fig.1 b, c, d). The impact of such short sequences is meager as they can be easily interpolated without significantly distorting the short-term variability of FHR. These slight distortions are further reduced when the signal is converted to the time event series representation. In consequence, the impact of randomly inserted missing values on the FHR variability is lower than in case of the same number of missing values but generated according to the real characteristics of the signal loss episodes.

When compared to the results from [17], where the missing values were generated using the random permutations, we observed much higher decrease of the FHR variability estimates. However, the results cannot be directly compared, as the indices in [17] were calculated using the evenly sampled FHR series or values averaged over periods of 2.5s. In this paper the variability indices were calculated on a basis of the time event series, according to their classical definitions originating from the direct fetal ECG. It can be easily proven that applying formulas of the short-term indices to the FHR signals evenly sampled at 4 Hz, instantly decreases the estimates. It is caused by the fact that most heart cycles between 110 and 150 bpm are represented in the sampled signal by two identical values. As all the formulas focus on differences between successive values, their repeating leads to a decrease of the FHR variability indices. On the other hand, averaging the samples over periods of 2.5s also distorts the information. It usually leads to averaging the measurements from 4 to 6 heart beats. As a result the most important information on the beat-to-beat changes is lost whereas the long-term component turns out to be the dominating one.

Only the STV_FD and LTV_FD indices can be directly compared with [17], as the fractal dimension parameter has to be calculated on a basis of evenly sampled time series. In case

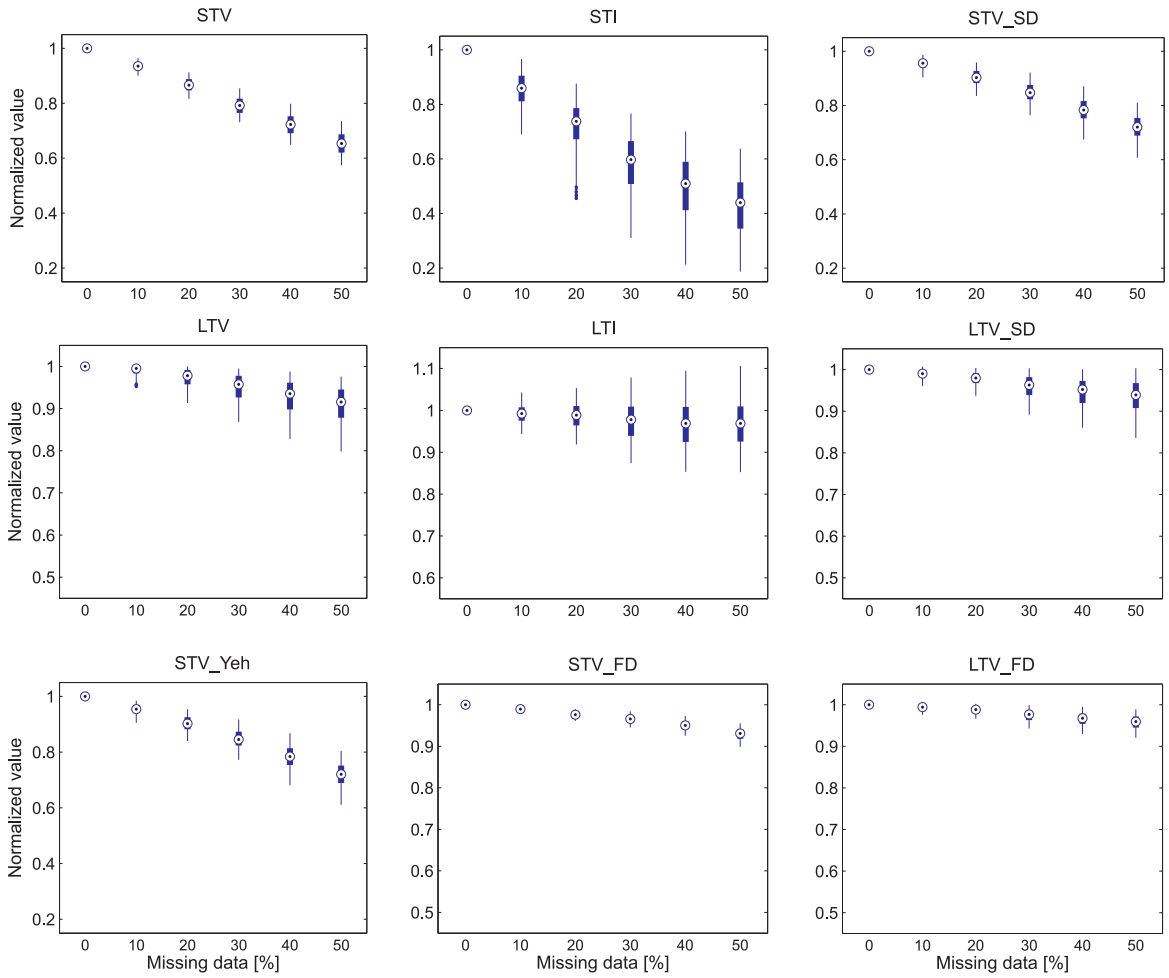

Fig. 2. The normalized values of the calculated FHR variability indices against the increasing percentage of signal loss. The results are presented as a median value, 25^{th} to 75^{th} percentile range, and minimum/maximum value range.

of 50% missing values inserted randomly (using the permutation algorithm) these two indices were decreased by 4.8% and 0.9% respectively [17]. In turn, when the same level of signal loss was generated in accordance with the distribution plot presented on Figure 1a, the indices were decreased by 7.07% and 4.20% respectively. This comparison reveals that the random permutation algorithm gives too optimistic results.

Generally, the influence of signal loss episodes on the long-term indices was found negligible. For the highest percentage of signal loss the LTV index was decreased by 9%, whereas the LTI index only by 3%. What is interesting, values of all the long-term indices except of LTI were always decreased after inserting the signal loss episodes. However, some LTI values were also increased compared to those calculated for original undistorted signal. The short-term indices, in turn, are highly sensitive to the signal loss. For 50% signal loss the most indices were decreased (by 28% $\div$ 35% on average). At the same time the STI index was decreased by 57%. It turns out that the STI and LTI indices, in their concept being insensitive to occasional erroneous values, are more vulnerable to large number of missing values than any other indices.

5. CONCLUSIONS

The results proved that reconstruction of real characteristics of signal loss episodes is crucial for the evaluation of their impact on the FHR variability indices, as the random permutation algorithm leads to too optimistic conclusions. Among all evaluated indices the ones based on fractal dimension are considerably less distorted by signal loss. However, the clinical usefulness of these indices has not yet been proven [18]. An additional study has to be conducted to find out if the fractal dimension parameters reflect the real changes of the FHR signal variability, and what is more important, to determine the physiological ranges for those indices.

The knowledge of how the numerical indices are distorted by the signal loss episodes can be used to improve the interpretation of results of signal analysis. As most numerical algorithms for FHR signal analysis provide only one value of variability index for the whole recording, being some kind of mean or median value, it should be calculated taking into consideration the amount of missing samples. A straightforward solution is to ignore those values, calculated for one-minute segments, for which the signal loss amount is higher than an established threshold.

6. ACKNOWLEDGEMENTS

This work was financed in part by the Polish National Science Centre.

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