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Foetal heart rate assessment by empirical mode decomposition and spectral analysis

<https://doi.org/10.1515/cdbme-2019-0096>

Abstract: This paper focuses on studying the time-variant dynamics involved in the foetal heart rate (FHR) response resulting from the autonomic nervous system modulation. It provides a comprehensive analysis of such dynamics by relating the spectral information involved in the FHR signal with foetal physiological characteristics. This approach is based on two signal processing methods: the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and time-varying autoregressive (TV-AR) modelling. First, the CEEMDAN allows to decompose the signal into intrinsic mode functions (IMFs). Then, the TV-AR modelling allows to analyse their spectral dynamics. Results reveal that the IMFs can involve significant spectral information (p -value < 0.05) that can help to assess the foetal condition.

Keywords: Foetal monitoring, cardiotocograph, empirical mode decomposition, time-varying autoregressive spectrum.

1 Introduction

Cardiotocography (CTG) is a commonly used technique for foetal surveillance, which provides the foetal heart rate (FHR) and uterine contraction (UC) signals. During labour, a good understanding of the foetal health condition allows to prevent potential adverse outcomes. Currently, this procedure involves a visual interpretation of different morphological patterns defined in guidelines [1]. Unfortunately, the foetal assessment by this methodology has demonstrated to lack objectivity and specificity. In order to improve the CTG interpretation, several computer-based support systems have been proposed, however there is no evidence that they can solve the problems so far [2].

Current clinical research emphasizes that the foetal compensatory mechanisms, modulated by the autonomic nervous system (ANS), reflects dynamics in the FHR that can involve significant information about the foetal condition [3]. Therefore, for a correct CTG assessment it is necessary to consider such time-variant characteristics. In this perspective, sev-

eral approaches based on time-varying signal processing techniques have been proposed [2]. However, most of them focus only on foetal reactivity due to UCs, without studying the implicit FHR dynamics as a time-variant modulated response.

This work presents a comprehensive analysis of such dynamics by using two signal processing methods: the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) [4] and time-varying autoregressive (TV-AR) modelling. First, the CEEMDAN allows to decompose the signal into intrinsic mode functions (IMFs). Then, the TV-AR modelling allows to analyse their spectral dynamics over time.

The main hypothesis is that the IMFs involve significant spectral information about the foetal condition, whose dynamics are related to standard FHR frequency bands. In order to prove this hypothesis, we first evaluate the significance of the spectral information involved in the IMFs. Then, we examine the frequencies involved in each IMF and compare them to the FHR frequency bands already studied in the literature.

Results reveal that the IMFs involve significant information about the foetal condition (p -value < 0.05), whose spectral dynamics can involve frequencies that range the standard FHR frequency bands studied in the literature.

2 Methodology

The FHR signal involves different frequency contributions [2]. A very low frequency (VLF) band ($0 - 0.03\text{Hz}$), related to the decelerations trending; a low frequency (LF) band, associated to the sympathetic ANS stimuli ($0.03 - 0.15\text{Hz}$); a medium frequency (MF) band ($0.15 - 0.5\text{Hz}$) related to the foetal movements and maternal breathing; and a high frequency (HF) band ($0.5 - 1.0\text{Hz}$) corresponding to the foetal breathing.

The proposed methodology focuses on studying the FHR dynamics involved in those standard frequency bands. The main idea is to evaluate if the time-varying spectral behaviour of such dynamics involves significant information about the foetal condition, and also compare its frequency contribution with the standard FHR frequency bands. For this purpose, we first decompose the FHR signal by the CEEMDAN, then for each IMF the TV-AR spectrum is computed. On the one hand, the CEEMDAN allows to decompose nonlinear and non-stationary time series into a finite number of IMFs. It is based on the energy associated with the signal oscillations and it

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does not require a priori known basis as other methods such as wavelet or Fast Fourier transform (FFT). On the other hand, TV-AR modelling provides quantitative spectral parameters and requires only a fraction of the samples needed by standard methods (e.g. FFT) to obtain the same resolution [2].

2.1 CTG dataset selection

The proposed analysis is evaluated in real FHR data extracted from the CTU-UHB database [5], which contains 552 recordings sampled at 4Hz. From this database, we selected a dataset according to the outcome information, particularly pH and BDecf values. Values of $\text{pH} < 7.05$ and $\text{BDecf} \geq 12$ indicate a foetal acidosis, whereas values of $\text{pH} > 7.20$ and $\text{BDecf} < 12$ indicate a normal foetus [2, 5]. Considering this criteria, the selected dataset includes 354 normal and 18 acidotic cases.

2.2 FHR signal decomposition

The FHR signal is usually subject to signal outliers and loss of data. Therefore, following [6], as a preprocessing step, outliers values outside of range between 50bpm and 210bpm are removed from the signal. Then, loss of signal data $\leq 75\text{s}$ length is interpolated by using a Hermite spline method. Fig. 1(a) and (b) shows the signal before and after the preprocessing step, respectively.

As described above, the information of interest involves frequencies $\geq 0.03\text{Hz}$. Therefore, following [7], before the signal decomposition we obtain a *detrended FHR signal* by attenuating the VLF band ($0 - 0.03\text{Hz}$). For that, we first compute a *floating-line* (Fig. 1(c)) by a median filter over a sliding window of 10s. Then, the detrended FHR signal (Fig. 1(d)) is computed by the subtraction between the floating-line and the preprocessed FHR signal. Finally, the detrended FHR signal is decomposed into IMFs by the improved CEEMDAN, by using a noise standard deviation $\text{Nstd} = 0.03$ and 50 realizations.

2.3 TV-AR spectrum estimation

In order to analyse the spectral behaviour of the IMFs, we employ TV-AR spectral-based analysis. The TV-AR spectrum can be represented by eq. 1, where p is the model order and $a_k(n)$ corresponds to a set of time-dependent AR coefficients.

$$S_{AR}[f, n] = \frac{1}{|1 + \sum_{k=1}^p a_k(n)e^{-j2\pi f k}|^2} \quad (1)$$

Following [7], the order p is set to 6 and the AR coefficients $a_k(n)$ are computed by using a recursive least squares algorithm with a forgetting factor of 0.99 [8].

Fig. 1: FHR signal nb. 1212. (a) Raw FHR signal; (b) Preprocessed signal; (c) Floating-line (red); (d) Detrended FHR signal.

3 Results

Fig. 2 shows an example of the IMFs and TV-AR spectra computation. The first column plots the IMFs obtained from the signal of Fig. 1(d). The second column shows the corresponding TV-AR spectra and their spectral average (blue line) in order to recognize the frequency range involved in each IMF. The spectral energy values are normalized between 0 and 1 for a better visualization of the frequency components.

For each FHR signal of the dataset we obtained a different number of IMFs between 12 and 17. Nevertheless, for the analysis we consider only the first 7 IMFs because, as we can observe in Fig 2(p), the remaining IMFs do not involve spectral dynamics inside of the frequency band of interest ($\geq 0.03\text{Hz}$).

In order to analyse the information involved in the TV-AR spectra, we calculate the following indicators: total energy (E), energy of the main component (E_{mc}), and frequency of the main component (f_{mc}), which are computed as described in eq. 2 and 3. In these equations, S_{AR} is the TV-AR spectrum described in eq. 1, f_N corresponds to the Nyquist frequency ($f_N = 2\text{Hz}$), and f_{mc} is the frequency value that presents the maximal energy level for each sample n .

$$E[n] = \sum_{f=0}^{f_N} (S_{AR}[f, n]) \quad (2)$$

$$E_{mc}[n] = S_{AR}[f, n], f = f_{mc} \quad (3)$$

Fig. 2: Example of FHR signal decomposition by CEEMDAN, one row for each IMF. (left column) IMFs computed from the detrended FHR signal presented in Fig. 1(d); (right column) TV-AR spectrum computed from each IMF.

After that, for each indicator we compute 7 statistical coefficients: arithmetic mean (mean), median, standard deviation (std), mean absolute deviation (mad), root mean squares (RMS), sample entropy (SampEn) [9] and approximate entropy (ApEn) [10]. In summary, we extract 147 features computed in the last 35 minutes of the recording in order to consider representative data as close as possible to the delivery.

The extracted features were evaluated by a Wilcoxon rank-sum test. It was applied for each feature considering the hypothesis that the median value of the acidotic group significantly differs from the median value of the normal group. As a result, we obtained 18 significant features (p -value < 0.05), which are presented in Table 1. Here, the first 3 columns rep-

resent the category of the features (IMF number, indicator and statistical coefficient). Fourth column depicts the p -value of each feature. Finally, the last column indicates the frequency range (approximately) involved in each IMF, based on the spectral information presented in Fig. 2.

As shown in Table 1, features extracted from the IMF 1, 2, 4 and 6 involve significant information, whose spectral dynamics lie in frequency ranges of (0.8 – 1.8Hz), (0.3 – 0.9Hz), (0.09 – 0.22Hz) and (0.03 – 0.08Hz), respectively. If we examine the frequency bands already studied in the literature (see Section 2), we can recognize that the IMF 6 involves dynamics in the LF band, which are associated to the foetal ANS activity. The IMF 4 involves dynamics in the LF and MF (related

Tab. 1: Significant features ordered according to their frequencies.

Feature			p-value	Frequency band
IMF 6	E	std	0.0079	0.03 – 0.08Hz
IMF 6	E	RMS	0.0096	
IMF 6	E	mean	0.0213	
IMF 6	E	mad	0.0214	
IMF 6	E_{mc}	std	0.0126	
IMF 6	E_{mc}	RMS	0.0141	
IMF 6	E_{mc}	mean	0.0197	
IMF 6	E_{mc}	mad	0.0214	
IMF 4	E_{mc}	SampEn	0.0038	0.09 – 0.22Hz
IMF 4	E_{mc}	ApEn	0.0259	
IMF 2	E_{mc}	SampEn	0.0257	0.3 – 0.9Hz
IMF 2	E_{mc}	ApEn	0.0362	
IMF 1	E	RMS	0.0084	0.8 – 1.8Hz
IMF 1	E	med	0.0306	
IMF 1	E	mean	0.0102	
IMF 1	E_{mc}	med	0.0117	
IMF 1	E_{mc}	mean	0.0227	
IMF 1	E_{mc}	RMS	0.0393	

to the foetal movements and maternal breathing) bands. The IMF 2 involves dynamics in the MF and HF (associated to the foetal breathing) bands. Finally, the dynamics of the IMF 1 involves higher frequencies, which are not common in the literature. Nevertheless, the frequencies between 0.4 and 1.7Hz have been considered as an estimate of the the foetal parasymphetic activity [11].

It is important to note that all of the features based on f_{mc} were identified as non-significant. This indicates that the frequency value of the IMFs does not provide significant information about the foetal condition.

In summary, the IMFs computed from the FHR signal can involve significant spectral information (p -value < 0.05), whose dynamics described by their spectral energy can help to distinguish between a normal and an acidotic foetus.

4 Conclusion

The IMFs dynamics can involve significant spectral information (p -value < 0.05) related with the standard FHR frequency bands, which can help to assess the foetal health condition. As a result, the proposed hypothesis has been proven.

Considering that the IMFs involve spectral information inside of standard bands, they can be helpful to describe important physiological characteristics associated to the foetal behaviour.

As a further step, we propose to evaluate the performance of the extracted spectral-based features by an automatic computer-based classification.

Author Statement

Research funding: The research behind this work has been funded in part by the National Commission for Scientific and Technological Research CONICYT through a Chilean Scholarship Program for Graduate Studies. Conflict of interest: Authors state no conflict of interest.

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