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# Foetal heart rate signal spectral analysis by using time-varying autoregressive modelling

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**Abstract:** During labour, foetal monitoring enables clinicians to prevent potential adverse outcomes, whose surveillance procedure is commonly based on analysis of cardiotocographic (CTG) signals. Unfortunately, this procedure is difficult because it involves human interpretation of highly complex signals. In order to improve the CTG assessment, different approaches based on signal processing techniques have been proposed. However, most of them do not consider the progression of the foetal response over time. In this work, we propose to study such progression along the foetal heart rate (FHR) signal by using spectral analysis based on time-varying autoregressive modelling. The main idea is to investigate if a particular FHR signal episode in the time-domain reflects dynamical changes in the frequency-domain that can help to assess the foetal condition. Results show that each FHR deceleration leaves a particular time-varying frequency signature described by the spectral energy components which could help to distinguish between a normal and a pathological foetus.

**Keywords:** Foetal monitoring, cardiotocograph, FHR, autoregressive model, time-varying spectral analysis.

## 1 Introduction

Foetal welfare surveillance during labour is commonly based on the simultaneous recording of foetal heart rate (FHR) and uterine contraction (UC) signals, obtained through an instrument known as cardiotocograph (CTG). Its main aim is the early identification of hypoxic foetuses with risk of deterioration to an acidemia, thereby preventing a potential adverse outcome, and all of this without excessive intervention [1]. However, the CTG analysis is difficult because it involves human interpretation of the highly complex and non-evident relationship between the FHR and UC signals, whose procedure lacks objectivity leading to a poor interpretation reproducibility [1]. In recent years, in order to improve the CTG interpretation, different medical guidelines [2] and computer-based support systems (CS) [3] have been proposed. However, concerning to those methods, guidelines lack consensus in different aspects and it has not been proven that CS improve the results so far.

On the other hand, many approaches have been proposed [1] in order to analyse the CTG recordings using different signal processing methods. These methods are mainly based on time- and frequency-domain features, usually computed from operations performed over spectral components calculated by FFT-based techniques or AR modelling. The main drawback of these kind of time-invariant methods, is that they do not take into account the FHR time-varying characteristics resulting from the direct input/output relationship between the UC and FHR signals. In this context, some approaches [1] consider these characteristics by using Short Time Fourier Transform, quadratic time-frequency distributions or time-varying autoregressive (AR) modelling. Likewise, Continuous and Discrete Wavelets Transform techniques have been proposed in order to consider the transient nature of the UC excitation [1]. However, they are mainly focused on foetal reactivity as a response to a UC event, without taking into account the progression of the frequency dynamical changes occurring over time. The main objective of this work is to analyse such progression along the FHR signal by using spectral analysis based on time-varying AR modelling. The main idea is to investigate if particular FHR episodes in time-domain, triggered by UC events as stimuli, reflect spectral dynamical changes in frequency-domain that can help to assess the foetal condition.

Results show that the FHR signal describes different frequency dynamical changes over time and each time-domain deceleration episode leaves a particular signature described by the spectral energy components which could help to distinguish between a normal and a pathological foetal condition.

## 2 Methodology

The results are presented using real CTG data extracted from the CTU-UHB Intrapartum Cardiotocography database available on the PhysioNet website [4]. It contains 552 CTG recordings sampled at 4 Hz. Codes for the proposed method have been implemented in Matlab® environment version 2015b.

The main idea behind the proposed method is to identify the frequency components present along the FHR signal and analyse their behaviour over time in order to recognize par-

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ticular time-varying characteristics that can help to assess the foetal condition. For this purpose, stationary signal processing techniques no longer can be used to analyse the time-varying frequency changes involved in the FHR signal. In this perspective, we analyse the FHR signal by using time-varying AR modelling. This method offers certain advantages over other standard methods [5], since it allows the extraction of quantitative spectral parameters versus time and requires only a fraction of the samples needed by standard techniques (e.g. Fast Fourier Transform) to obtain the same resolution, even in signals with low signal-noise-ratio.

## 2.1 Time-varying AR model implementation

### 2.1.1 FHR signal pre-processing

**Interpolation**: the FHR signal acquisition usually is subject to different types of artefacts such as loss of data and outliers. Hence, following [6], signal values outside of range between $50bpm$ and $200bpm$ are removed from the signal and then the segments are interpolated by using a Hermite spline method.
**Filtering**: this work focuses on the analysis of frequency components associated with the neural sympathetic foetal reactivity, whose characteristics lie mainly in the frequency range between $0.03$ and $0.15Hz$ [1]. In order to have access to this band of interest, it is necessary to attenuate the very low frequency (VLF) band between $0$ and $0.03Hz$, mainly associated with the morphological characteristics of FHR accelerations and decelerations. For this operation, following [7], we use a non-linear median filter [8], computed over a sliding window, whose size was determined as follows. First, we filtered the FHR signal using different window lengths (6-12$s$). Then, the extracted VLF trends were superimposed on the FHR signal in order to examine which one tracks better the characteristics of accelerations and decelerations. After a visual analysis, we selected a window of $10s$ length. In the sequel, we denote this VLF signal trend as the *trend-line*. Finally, the filtered FHR signal involving the frequencies of interest (in the sequel called as the *filtered FHR signal*), was obtained by the de-trending operation between the raw FHR signal and the trend-line.
**Decimation**: after filtering, the signal is decimated to $1/4^{th}$ of the sample frequency in order to use a reduced AR model order, better suited for a quantitative analysis.

### 2.1.2 Time-varying AR spectrum estimation

As described in [5], an AR model assumes that the current signal sample $y[n]$ at sample number $n$ in a data sequence $y[1], y[2], \ldots, y[N]$, can be modelled as a linearly weighted sum of the $p$ most recent sample values $y[n-1], y[n-2], \ldots, y[n-p]$ and a white zero mean noise $e[n]$ of variance $\sigma^2$. Its time-varying representation can be described by:

$$y[n] = -\sum_{k=1}^{p} a_k(n) y[n-1] + e[n] \tag{1}$$

where $p$ is the model order and $a_k(n)\{k = 1, 2, ..., p\}$ are the AR parameters whose set of values $a_k$ is updated sample-by-sample $n$. The z-transform can be applied to eq. (1) and the time-dependent AR model transfer function can be expressed as:

$$H[z,n] = \frac{Y[z,n]}{E[z,n]} = \frac{1}{1 + \sum_{k=1}^{p} a_k(n) z^{-k}} \tag{2}$$

where $Y[z,n]$ and $E[z,n]$ are the time-dependent z-transforms of $y[n]$ and $e[n]$, respectively. The time-varying AR spectrum can be computed by evaluating $H(z,n)$ around the unit circle in the complex plane, i.e., $z = e^{j2\pi f}$:

$$S_{AR}[f,n] = \frac{1}{\left|1 + \sum_{k=1}^{p} a_k(n) e^{-j2\pi f k}\right|^2} \tag{3}$$

Following [9, 10], the model order $p$ was set to $10^{th}$ and the AR coefficients $a_k(n)$ were computed by using a recursive least squares algorithm with a forgetting factor set to $0.99$.

# 3 Results

The analysis is focused on the progression of the spectral dynamical changes along the FHR signal, whose results will be explained through four real representative cases. Those cases were selected from the CTU-UHB database according to their pH value as a post-delivery gold standard indicator for foetal assessment. The cases shown in Fig. 1 and 2 correspond to foetuses of normal condition (pH$\geq$ 7.25) and the next two cases exhibited in Fig. 3 and 4 are considered as pathological cases (pH$\leq$ 7.05). In each figure, the first graph shows the raw FHR signal (blue) and its trend-line (red). The graph (b) shows the raw UC signal. The graph (c) displays the time-varying AR spectrum estimated from the filtered FHR signal described in Section 2.1.1. The AR spectrum values were normalized between 0 and 1 for each sample $n$ for a better visualization of the frequency components. Finally, the graph (d) shows the average of the spectral energy, calculated in the frequency band of interest ($0.03 - 0.15Hz$) as described in eq. (4), where $F$ is the studied frequency interval length in samples and $E$ is the energy of the frequency components of interest calculated for each sample $n$ (in the sequel denoted as the *spectral energy*).

$$E[n] = \frac{1}{F} \sum_{f=0.03}^{f=0.15} (S_{AR}[f,n]) \tag{4}$$

Results show that each analysed case exhibits different dynamical behaviour in frequency-domain, and that they differ between a normal and a pathological foetal condition. Particularly, an interesting example can be observed in Fig. 1, where a set of UC events triggers deceleration episodes, which reflect important frequency spectral dynamics over time (see Fig. 1c). Apparently, these dynamics present a different behaviour after each deceleration episode, which can be noticed by their spectral energy level plotted in Fig. 1d. It can be observed that each episode leaves a specific trace in the spectral energy that keeps until the next episode. This phenomenon can be also observed in the case displayed in Fig. 2, which shows similar spectral characteristics. Unfortunately, in this case we have incomplete information concerning the UC events (see Fig. 1b), nevertheless, we can clearly observe how every deceleration episode leads to significant spectral energy changes over time, leaving a particular trace after each deceleration (see Fig. 2d).

In contrast to the first two examples, the cases displayed in Fig. 3 and 4 show a completely different spectral behaviour. In particular, if we compare the spectral energy level just before a deceleration with the energy level just after it (see graph d), most of these deceleration episodes do not show a significant variation, i.e. in these cases, the decelerations reflect a less marked response in the spectral energy compared to the first two cases. Likewise, their spectral energy level is gradually decreasing toward the end of the signal, whose behaviour differs with respect to the first two cases. This phenomenon can be explained by the fact that when a foetus is suffering we can assume that the modulation by the autonomous nervous system is minimal and therefore the sympathetic path does not present high activity. Finally, it can be observed that the frequency components of interest of the first two cases (see graph

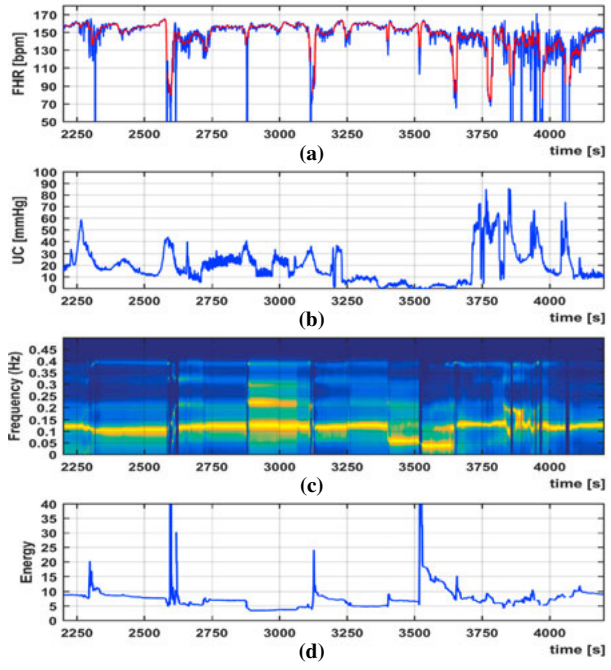


**Fig. 1:** Recording nb. 1020m (last $2000s$), pH=7.37. (a) FHR (blue) and trend-line (red); (b) UC; (c) AR spectrum; (d) spectral energy.

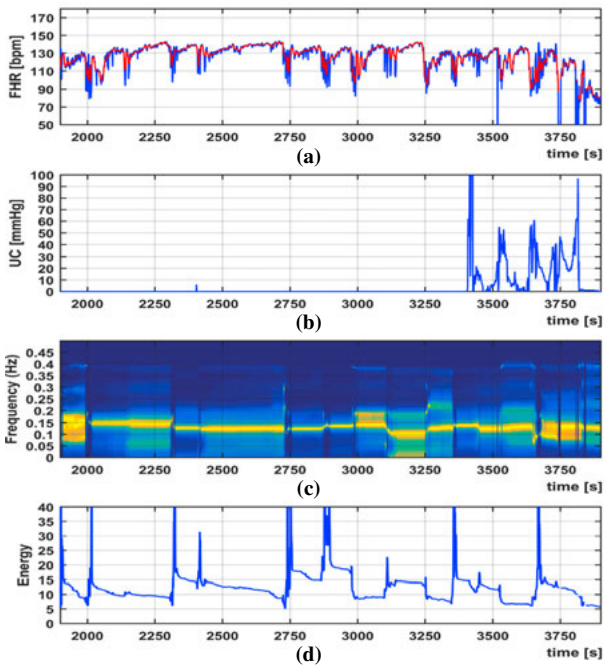


**Fig. 2:** Recording nb. 1322m (last $2000s$), pH=7.37. (a) FHR (blue) and trend-line (red); (b) UC; (c) AR spectrum; (d) spectral energy.

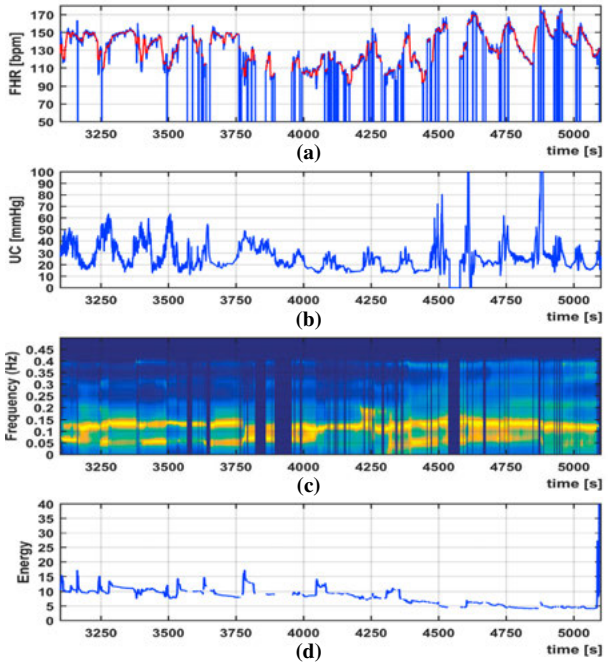


**Fig. 3:** Recording nb. 1490m (last $2000s$), pH=6.93. (a) FHR (blue) and trend-line (red); (b) UC; (c) AR spectrum; (d) spectral energy.

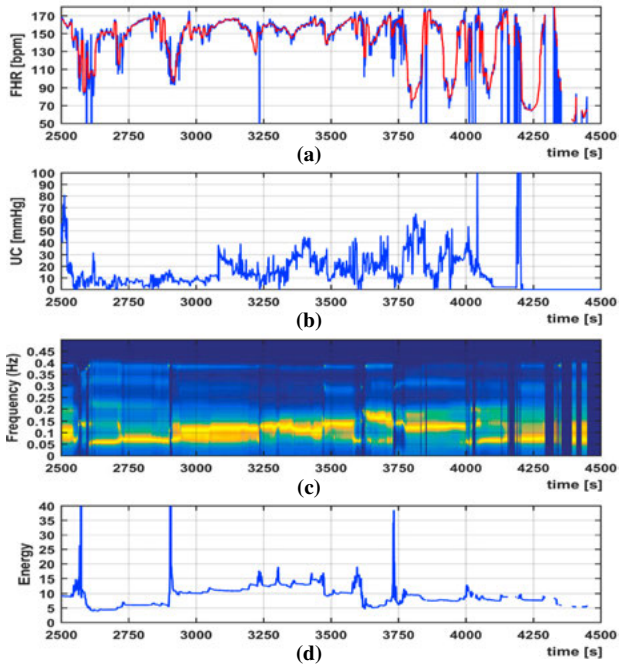


**Fig. 4:** Recording nb. 1070m (last $2000s$), pH=$6.92$. (a) FHR (blue) and trend-line (red); (b) UC; (c) AR spectrum; (d) spectral energy.

c), in general exhibit a finer frequency resolution compared to the components of the last two examples.

As a summary, 1) a case of normal foetal condition shows more significant spectral energy variations through deceleration episodes in comparison with a pathological case; 2) for a pathological case, the spectral energy level presents a decreasing trend over time, whereas a normal case, in general exhibits a more stable or even increasing trend; 3) for a normal case, the frequency components of interest, in general, exhibit a finer frequency resolution compared to a pathological case.

The phenomena described above can be considered as a sign of how the foetal sympathetic nervous system reacts over time in order to estimate the foetal condition during labour.

# 4 Conclusion

The obtained results showed that the time-varying AR modelling is a significant method to analyse the spectral dynamical changes in the FHR signal. In fact, the analysis allowed to recognize that each deceleration episode leaves a particular spectral trace, whose characteristics could help to distinguish between a normal and a pathological foetal condition.

Considering that FHR decelerations are one of the most complex patterns to assess, these results open perspectives for the characterization of decelerations based on time-varying spectral analysis, in order to improve the interpretation and subsequent classification of non-reassuring CTG recordings.

As a future step, we propose to extract time-varying AR spectral-based features in order to classify CTG recordings, applying the current analysis to the entire CTU-UHB database.

### Author Statement

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