ABSTRACT

Fetal Heart Rate (FHR) signals exhibit a random-like variability dependent on the fetus health. Previous studies explain this variability with the presence of power law correlations among neighbor samples, suggesting a fractal structure in the FHR. In this paper we use an efficient algorithm presented in [1], called Chang’s method, to analyze the fractal behavior of FHR sequences. In our study, FHR signals with different levels of the clinically defined Short Term Variability (STV) are analyzed. Using a dataset of 46 FHR signals we show that it is possible to discriminate FHR signals according to their variability using two parameters estimated with Chang’s method. These results are interesting both for FHR diagnostic and simulation purposes.

1. INTRODUCTION

The continuous monitoring of Fetal Heart Rate tracings (FHR) is one of the most important methods used to diagnosis pregnancy complications. In spite of its common use, visual analysis of FHR tracings is prone to misinterpretations. In 1978, Trimbos and Keirse [2] have showed inter and intra-user discrepancies in the interpretation of the fetus physiological state based on FHR signals. Also visual inspection of the signals is a bad means of assessing their random-like variability, which clinicians know to be a good indicator of fetus health. In 1993 Gough [3] identified the fractal behavior of the foetus heart rate variability. In a further analysis, Felgueiras et al. [4] studied in detail the fractal behavior of three classes of FHR patterns and the application of fractal features to FHR pattern recognition.

The purpose of this paper is to present further developments towards reliable means of FHR fractal characterization.

1.1. Fetal Heart Rate Sequence

The instantaneous FHR is obtained as the inverse of the time interval between successive ECG peaks and is expressed in beats per minute (bpm). These sequences are characterized by the presence of a certain amount of variability, which is an indicator of the fetus well being. In clinical practice this variability is measured according to its presence or absence. Short-term variability, STV, is an index defined as the difference between FHR successive beatings. A signal is said to have an abnormal short-term variability if more than 60.5% of the time the signal has an STV value lower than 1bpm.

In collaboration with the Obstetrics department of the main Porto Hospital we collected 46 FHR signals with the computed variability distribution presented in Table 1-1.

<table>
<thead>
<tr>
<th>% Abnormal STV</th>
<th>Sequence Classification</th>
<th># Sequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>≤ 55</td>
<td>Normal</td>
<td>19</td>
</tr>
<tr>
<td>55.65</td>
<td>Suspect</td>
<td>20</td>
</tr>
<tr>
<td>≥ 65</td>
<td>Pathological</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 1-1. Distribution of the FHR sequences according to their STV index.

Figure 1-1 shows the mean value of the “percentage of abnormal STV”. It can be seen that this value varies between 34% and 74%. The lowest value is 29% and the highest value is 78%. The computed standard deviation is not higher than 4%, which occurs for the cases with normal variability.

The study began by pre-processing the FHR tracings in order to remove artifacts induced by the fetal monitors, such as missing data or zero values. The processing was based on an adaptive filtering procedure described by Wessel et al. in [5]. Figure 1-2 illustrates this procedure for a contaminated normal antepartum tracing.
2. METHODS

2.1. Fractional Brownian Motion

Mandelbrot and Van Ness’ fractional Brownian motion (fBm) [6] has been considered a suitable model to describe the long-range correlations exhibited by a wide variety of physiological signals, like for example (see [4]), the Fetal Heart Rate (FHR).

Based in fractional integration and differentiation, using Hurst’s law and Brownian motion, \( B(t, \omega) \), Mandelbrot defined the fractional Brownian motion, \( B_H(t, \omega) \), as the following family of gaussian random variables

\[
B_H(t, \omega) = \frac{1}{\Gamma(H + \frac{1}{2})} \left\{ \int_{-\infty}^{t} (t-s)^{H-\frac{1}{2}} - (-s)^{H-\frac{1}{2}} dB(s, \omega) \right\}
\]

Eq. (1) can be interpreted as a moving average of \( dB(t, \omega) \), in which \( B(t, \omega) \) past increments are weighted by the kernel \( (t - s)^{H-\frac{1}{2}} \).

The fBm is a model for stochastic temporal fractals whose properties of self-affinity and infinite interdependency of its increments are characterized by the parameter \( H \), referred to as the Hurst exponent, comprised between 0 and 1. The Hurst exponent governs the sequence’s scaling property, which is expressed by a power law between fBm’s increments, \( \Delta B \), and the time interval, \( \Delta t \):

\[
\Delta B \propto \Delta t^H
\]

The sequence’s increments are independent only when \( H = \frac{1}{2} \), corresponding to the known Brownian motion. If \( H < \frac{1}{2} \) the increments are negatively correlated and they are positively correlated when \( H > \frac{1}{2} \).

The discretized fBm and the process of its increments, fGn, are respectively defined as

\[
B_H[n] = \frac{1}{T_s} \left( B_H[nT_s] - B_H[(n-1)T_s] \right)
\]

being \( T_s \) the sampling frequency, and \( x_H[n] = B_H[n] - B_H[n-1] \).

The fGn is a Gaussian, stationary process with zero mean whose autocorrelation function is defined as

\[
r_H(k) = E\{x_H(n+k)x_H(n)\} = \frac{V_H}{2} \left( |k|^{2H} - 2|k|^{2H} + |k|^{-2H} \right)
\]

with \( V_H = \Gamma(1-2H)\cos(H\pi)/H\pi \).

The Fourier Power Spectrum, \( S(f) \), of a signal with fractal characteristics exhibits a power law

\[
S(f) = f^{-\beta} \Leftrightarrow \log(S(f)) = C - \beta \log(f)
\]

with \( C = \log(a) \) controlling the variance of the process and \( \beta > 0 \) related to the Hurst exponent, \( H \):

\[
\beta = 2H + 1.
\]

2.2. Chang’s method for fBm sequence’s analysis

Over the last decades several estimators for the Hurst exponent have been reported, both in time and frequency domain. Chang et al [1] proposed an approximate maximum likelihood estimator.

In this article we shall only present a brief introduction of this method. For a more detailed description, the reader should refer to the indicated article. The method is mainly based on the regular properties of the so-called fractional Gaussian noise (fGn). Using this property, the authors established a standard curve between \( H \) and the slope of the log-log plot of the frequencies vs. the power spectrum density (PSD) of an autoregressive (AR) model used to model the fGn process. The relation between the slope and the \( H \) is obtained by means of a quadratic function (Figure 2-1).

The fGn is a Gaussian, stationary process with zero mean whose autocorrelation function is defined as

\[
r_H(k) = E\{x_H(n+k)x_H(n)\}
\]

\[
= \frac{V_H}{2} \left( |k|^{2H} - 2|k|^{2H} + |k|^{-2H} \right)
\]

with \( V_H = \Gamma(1-2H)\cos(H\pi)/H\pi \).

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\[
\beta = 2H + 1.
\]
The method begins by calculating the autocorrelation function of the fGn and estimating its AR parameters. Subsequently, the PSD of the AR parameter is obtained. The Hurst parameter is estimated via the previously established relation between it and the slope. One can also estimate the variance parameter, $C$. This method was chosen because, as it was previously shown by Vieira et al. [7], it achieves better accuracy than others in the analysis of fBm signals due to the use of fGn regular properties in the regression process.

3. RESULTS

Our study began by applying Chang’s method to simulated FHR-like signals with known fBm behavior. For this purpose we started by generating fBm signals using the efficient algorithm proposed by Norros et al. [8]. This method’s originality lies on the conditioning to a fixed number of neighboring intervals of the fBm’s sample being generated in each level. This is achieved by means of a Gaussian Multivariate distribution.

As the FHR signals are characterized by the presence of low frequency events, such as rhythm accelerations and decelerations, we added sine waves with the adequate phase and amplitude, simulating those low frequency events. The resulting signals were then highpass filtered in order to remove very slow trends (using a Butterworth filter), and the accuracy of Chang’s method in estimating $H$ and $C$ was then tested. The mean and standard deviation of the estimated $H$ values for 100 fBm sequences with $H$ ranging form 0.05 to 0.95, with a 0.05 step, are shown in Figure 3-1. The excellent quality of the $H$ estimates is evident.

Figure 3-1. $H$ values estimated using Chang’s method on fBm simulated sequences.

The study proceeded with the application of Chang’s method to the real FHR signals. For the analyzed data, both the Hurst exponent and the variance parameter $C$ (which is the log(S) intercept of the linear fit between log($f$) and log(S)) were computed. Figure 3-2 shows the estimated $H$ and $C$ values for the three variability classes. It can be seen that, in the three cases, $H$ doesn’t change significantly, yet $C$ does. As a matter of fact, the Mann-Whitney test on the $C$ values for the normal and pathological classes yielded a very significant $p$ ($p < 0.05$).

4. DISCUSSION

We successfully applied the method introduced by Chang et al. to the fractal characterization of FHR signals. Our goal was to distinguish between signals with normal, suspect or pathological variability. Our results indicate that, although the Hurst parameter doesn’t seem to give any contribution to this distinction, the variance parameter, $C$, has a definite influence on the discrimination of FHR short-term variability. Thus, in what concerns short-term variability, we come to the conclusion that what matters is not the type of dynamics but its intensity.

Further analysis, namely with larger datasets, must be made regarding the physiological interpretation of these parameters and their use for classification and simulation purposes.

5. ACKNOWLEDGMENTS

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6. REFERENCES


