Multi-scale sample entropy and recurrence plots distinguish healthy from suffering foetus

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Currently, the assessment of the state of fetal well-being using ultrasounds is a challenge in the obstetrical world. To assess the fetal well-being, parameters are derived from the fetal heart rate and fetal movements. We estimated the fetal heart rate using a multi-sensor, multi-gate pulsed Doppler system, and we proposed to study the complexity of heart rate by calculating the multi-scale entropy and the parameters deduced from the recurrence plots. The article presents a preliminary study that evaluates the relevance of complexity parameters in assessing the state of fetal well-being. Our results revealed that complexity parameters can distinguish healthy from suffering foetus.

1 Introduction

The assessment of the fetal well-being using ultrasound methods, is a great challenge nowadays. The main problem of the obstetricians is to determine exactly the moment when the foetus confronts itself with lack of oxygen.

The lack of oxygen for a short period can damage neurons and may have major consequences on neurological status and future development of the foetus. For a longer period the lack of oxygen can cause the death of the foetus.

So far it was found that an insufficient supply of oxygen (hypoxia) involves distress of the foetus, which in turn will trigger a change in the values of foetus parameters, such as the cardiac rhythm. A robust mean to evaluate the cardiac rhythm of the foetus is to use a Doppler ultrasound system.

It has been suggested that the variability of cardiac rhythm in adults diminishes during hypoxic conditions [1], and this decrease can be detected before clinical signs appear. This early detection can be achieved using complexity measures of a time series, like sampled entropy [2].

Recent studies [3] have indicated that it is still possible to identify the presence of hypoxic conditions using multi-scale entropy [4, 5] based on sampled entropy.

Since the well-being state of the foetus disappears when hypoxia sets in, we firstly studied the multi-scale entropy based on sampled entropy to verify whether it may indicates the emergence of the hypoxia.

To complete this parameter, we studied the contribution of parameters (mean diagonal length) developed in chaos theory from the recurrences of the time series [6, 7]. We tested this parameters whether it highlights the changes of the cardiac rhythm in the absence of oxygen.

This paper is structured as follows: in section 2 we described our Doppler system while in section 3 we presented the parameters used in our study. In section 4 we illustrated our results. Finally, the section 5 presented our conclusions.

2 Equipment: The Doppler System

Our system was composed from a personal computer (PC) and our Actifoetus unit. The Actifoetus unit contained three groups of four transducers and a Doppler acquisition board. The operating functions of the acquisition board were presented in details in [8].

One group is dedicated to explore the fetal heart. The transducers exploring the fetal heart were non-focused and mono-element. They were circular in shape, with a diameter of 13.5 mm and an acoustic power of 1 mW/cm^2. Geometrically, the transducers were located at the center of gravity and at the tops of an equilateral triangle of sides measuring 40.7 mm.

The transducers were placed on the mother's abdomen. They transmitted a sinusoidal pulse at 2.25 MHz with a pulse repetition frequency (PRF) of 1 kHz. The ultrasound wave propagated through the mother's abdomen towards the foetal heart. The wave interacted with the moving structures of the heart like walls or valves. This interaction had modified the transmitted frequency of the pulse. The frequency content of the backscattered signal contained the heart signature when it was recorded from a volume that included the foetal heart. To discretize the volume, the backscattered signal was recorded from five different depths.

The ultrasound signal received was converted into an electrical signal and amplified to compensate for the attenuation of 1 dB/cm/MHz. The signal was then demodulated in phase (I) and quadrature (Q) [9]. After demodulation, the signals were digitized. The digital outputs of the converters represented the digital Doppler signal.

Once the digital signals were obtained, we processed numerically the Doppler signals to find the foetal heart rhythm [10, 11]. The foetal heart rhythm was computed every 250 ms and corresponded to the interval computed as the average of the consecutive intervals of the heart beats.

The foetal heart rhythm was represented as a time series and was analyzed in order to distinguish the healthy and the suffering foetus. The next section presents the methods used in our preliminary study.

3 Methods

In this section we present the multi-scale entropy (MSE) and recurrence plot methods.

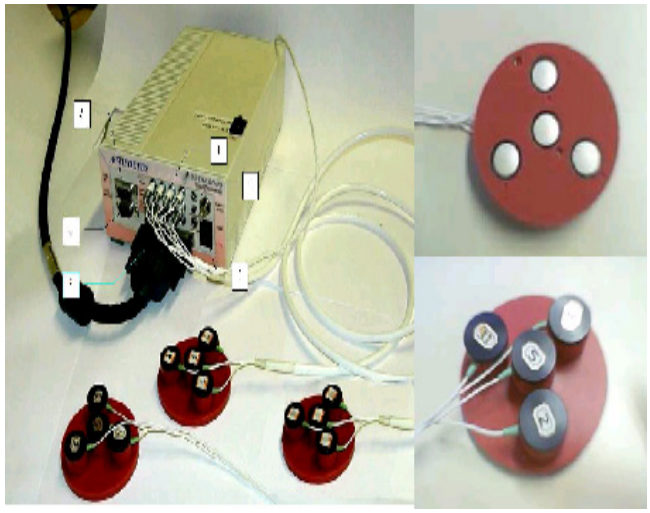


Figure 1: Actifoetus unit composed of three groups with four transducers each. One group was dedicated to detect the foetal heart rhythm.

3.1 Multi-Scale Entropy

Multi-scale entropy analyses the signal at different scales. Starting from the foetal heart rhythm, the scaled versions were obtained averaging a successively number of heart rhythm values in non-overlapping windows of the original time series. The equation (1) computed the scaled versions of the signal

$$x_j^s = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} R_i, \tag{1}$$

were R_i was the heart rate being analyzed, s the scale, while x the scaled version of the R_i.

The previous equation reveals that the number of the samples of the signal within the same temporal window decreased s-times for each scale. The number of samples (at a given scale) contained in temporal window decreases, but they characterized the same time. Because the sampled entropy is much accurate for long signals, we limited our study for the first five scales.

Once the scaled versions of the signal obtained, we computed the sample entropy for each of them. For each scale the sampled entropy was computed in a sliding window manner with a shift time step between two consecutive intervals of two samples. The computation of the sampled entropy for one window of size N was reported below. Because the computation method does not depend on the scale, we ignored the superscript index s. The upcoming steps summarize the computation of the sample entropy:

1. for each $i = 1, \ldots, N - m + 1$ we formed the vectors;

$$\mathbf{V}_i = [x_j(i), x_j(i+1), \ldots, x_j(i+m-1)], \tag{2}$$

2. we computed the maximum value of the m-dimension absolute difference vector;

$$d(\mathbf{V}_i, \mathbf{V}_j) = max(|\mathbf{V}_i - \mathbf{V}_j|) \tag{3}$$

3. for each vector $\mathbf{V}_i$ we computed the number P_i^m of similar vectors ($d(\mathbf{V}_i, \mathbf{V}_j) \leq r$). For the calculus of P_i^m we excluded the self-similarity ($i \neq j$). The probability of such a vector was:

$$C_r^m(i) = P_i^m/(N - m + 1) \tag{4}$$

We computed this probability for each $i = 1, \ldots, N - m + 1$.

4. we computed:

$$\phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} lnC_r^m(i) \tag{5}$$

5. we increased the pattern size m by 1, and we computed:

$$\phi^{m+1}(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} lnC_r^{m+1}(i) \tag{6}$$

6. we computed the sampled entropy:

$$SampEn(m, r, N) = \phi^m(r) - \phi^{m+1}(r) \tag{7}$$

3.2 Recurrence Plot and RQA Parameters

The recurrence plot method was introduced by Eckman [12], and it consists of visualizing the recurrent states of the system using a matrix. Two states are recurrent if they are close within the tolerance r in the phase space of the system. However, in this paper we constructed the recurrence matrix using directly the time series, i.e. 1-D phase-space. We noted the matrix that visualizes the recurrences in the signal with $[\mathbf{RP}]_{i,j=\overline{1,N}}$, N being the length of the signal. As compared with the multi-scale entropy this matrix was computed only for the first scale (original time series of the foetal heart). The elements of the matrix, were given by the relations (8)-(10):

1. for each $i = 1, \ldots, N - m + 1$ we formed the vectors;

$$\mathbf{V}_i = [x_1(i), x_1(i+1), \ldots, x_1(i+m-1)], \tag{8}$$

where we noted with $\mathbf{V}_i$ and $\mathbf{V}_j$ the system state at times i, j. In case of the heart, the states of the system were the values of the cardiac rhythms R_i.

2. we computed the maximum value of the m-dimension absolute difference vector;

$$d(\mathbf{V}_i, \mathbf{V}_j) = max(|\mathbf{V}_i - \mathbf{V}_j|) \tag{9}$$

3. for each pair (i, j) we assigned, using a tolerance r;

$$\mathbf{RP}(i,j) = \begin{cases} 1, & d(\mathbf{V}_i, \mathbf{V}_j) \leq r \quad i,j = 1, \ldots, N \\ 0, & d(\mathbf{V}_i, \mathbf{V}_j) > r \quad i,j = 1, \ldots, N \end{cases} \tag{10}$$

From elements of the matrix **RP**, we computed the parameters that quantify the recurrences of the signal. This quantification is known as the RQA method (Recurrence Quantification Analysis). The RQA parameters are computed using the diagonal segments of the matrix **RP** [7].

The mean diagonal distance was one of the RQA computed parameters. It characterizes the average time when two consecutive segments of the signal are almost identical. Marwan [7] interpreted the parameter as the average time during which the signal can be predicted. The average diagonal length is:

$$Lm = \frac{\sum_{l=l_{min}}^{N} l \cdot P(l)}{\sum_{l=l_{min}}^{N} P(l)}, \tag{11}$$

where we noted with $P(l)$ the diagonal distance histogram, and l_{min} the lowest diagonal distance.

4 Results

4.1 Multi-Scale Entropy

We monitored the foetus over 30 minutes like the Manning test suggests [13]. The figure (2) shows the heart rates of a healthy and suffering foetus, respectively.

As we have already mentioned, the rhythm was evaluated every 250 ms to obtain 7200 values for a period of 30 minutes. We used a window of three minutes (720 samples at

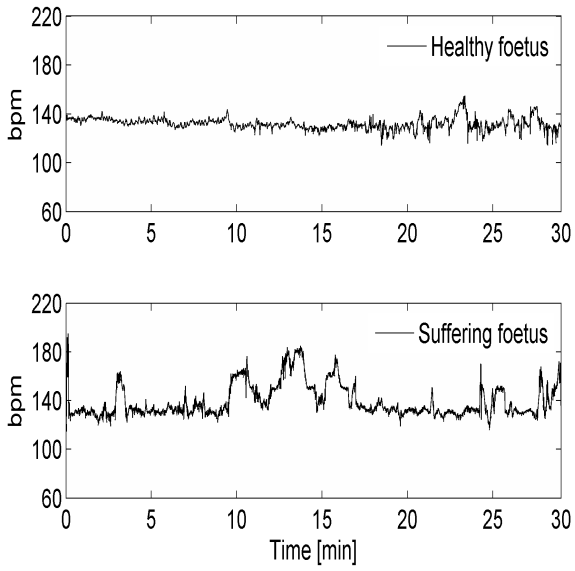


Figure 2: Heart rhythm of a healthy and suffering foetus, respectively.

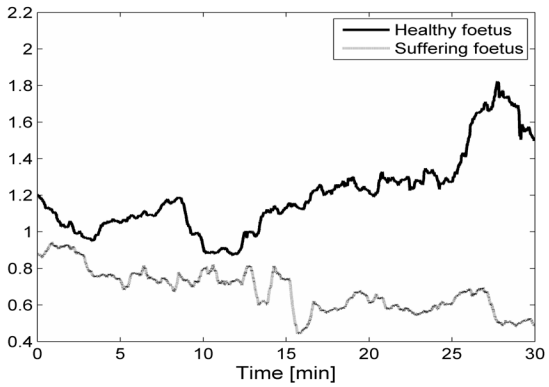


Figure 3: The sample entropy computed for the pattern m=2 at first scale in the case of heart rhythm of the healthy and suffering foetus in figure (2).

first scale), to compute the sampled entropy. Using a sliding window technique we computed at each scale a vector whose elements were the sample entropy values. Finally, we evaluated the mean and the variance associated to this vector. The figure (3) shows the evolution in time of sampled entropy evaluated at first scale for the pattern m=2.

We computed the multi-scale entropy for the pattern with 2 elements (m=2) as described in section 3.1. In our computation we used the recommended value of r=0.15 from standard deviation of the heart rhythm.

The figure (4) shows the multi-scale entropy obtained for five scales. We can observe that the sampled entropy decreased for both rhythms, as the scale increased. We believe that the drop of the value of the multi-scale entropy as the scale increases is normal since the complexity was reduced once we averaged the original heart rhythm series. The variance at each scale sticked around 0.2 for the healthy foetus and 0.16 for the suffering foetus, regardless of the scale. For the computation of the mean and variance 3240 values of sampled entropy were used at first scale, this number being

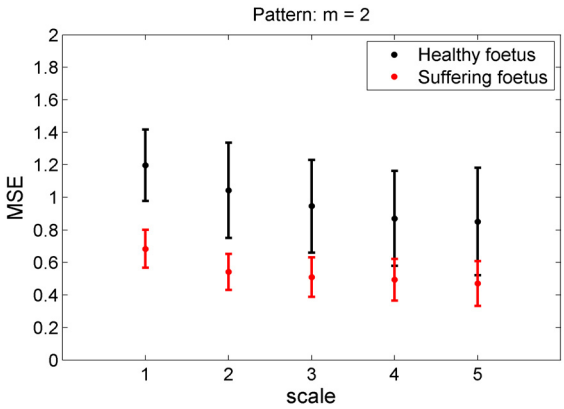


Figure 4: The multi-scale entropy (MSE) for m=2 computed for the healthy and suffering foetus in figure (2).

halved as the scale increased.

Although both values of sample entropy decreased, the multi-scale entropy remained greater for of healthy foetus as compared to a suffering foetus. This is due to the fact that complexity of the heart rate series is higher in case of the healthy foetus. This behaviour of the multi-scale entropy (being higher in case of healthy foetus) is similar with the results reported in [3].

The figure (4) shows that multi-scale entropy measure is able to distinguish completely between the healthy and the suffering foetus for the first three scales. Note that this differentiation was not possible when we used the classical obstetrical parameters, like accelerations[1] which surprisingly are more visible in case of suffering foetus than the healthy foetus.

While the values of the multi-scale entropy in case of a healthy and suffering fetus were completely separated for the first three scales, they were not completely separated for the fourth and the fifth scales, yet, an overlap was observed. This partial separation could be explained by the inaccuracy of the multi-scale entropy, knowing that this parameter converge toward its true value for long signals.

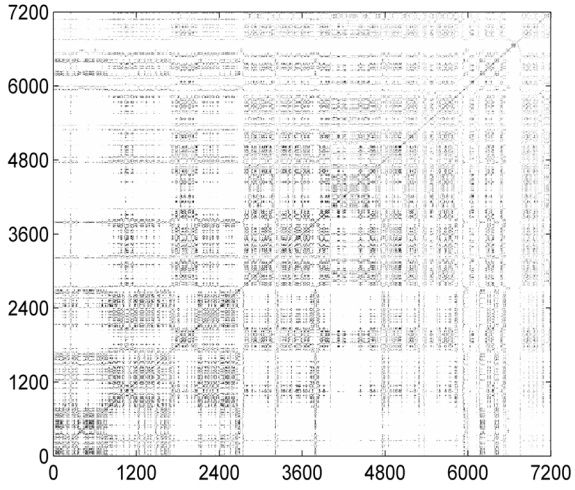
4.2 Recurrence Plot and RQA Parameters

For the same heart rhythms we computed the recurrence plot matrix as indicated in section 3.2. We used the same pattern m=2 and the same r (equal with 0.15 from standard deviation value) as in the case of multi-scale entropy. The two matrices are presented in figures 5(a)-(b), for the entire signals.

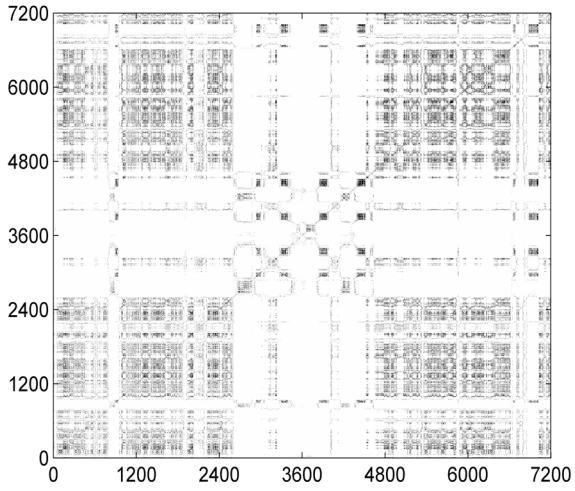
We computed the recurrence plot matrix for windows of three minutes, like in the case of multi-scale entropy. For each window the equation (11) was evaluated. The results were plotted in figure (5(c)) for both healthy and suffering foetus.

We observed that the mean diagonal length is higher in case of the suffering foetus. This meant that the cardiac rhythm of the suffering foetus is more predictable than that of the healthy foetus. A greater predictability is possible when a loss in complexity of the heart system appears. This loss in complexity could be explained by the weak interaction be-

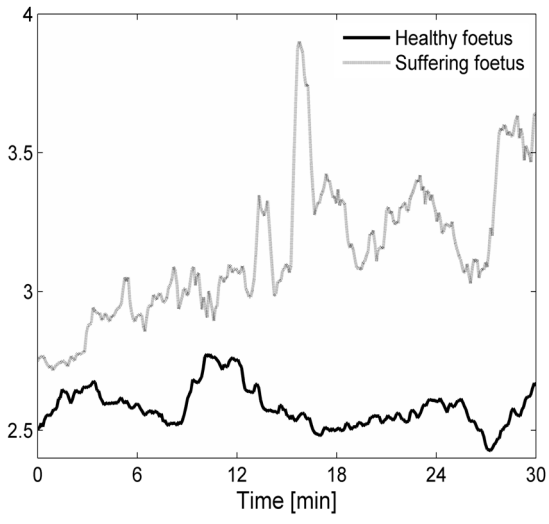
[1] An acceleration is an increase of heart rhythm with at least 15 beats per minute during at least 15 seconds. This is the classical parameter with the smallest false positive rate in detecting hypoxia.



(a)



(b)



(c)

Figure 5: The **RP** matrix computed for: (a) a healthy foetus and (b) a suffering foetus. Figure (c) presents the mean diagonal distance computed in a sliding window manner with a window of three minutes.

tween brain and heart of the foetus, as a consequence of an oxygen concentration drop in blood of the foetus.

5 Conclusions

We developed a pulsed Doppler system capable to monitor the heart rhythm of the foetus. Using the cardiac rhythm, we studied its complexity by computing the multi-scale entropy and the RQA parameter (mean diagonal length) deduced from the recurrence plots. These parameters seemed to be able to discriminate between healthy and suffering foetus, even when the classical parameters are no longer capable to do it. We intend to use these parameters in a system that will be able to asses the fetal well-being.

Acknowledgments

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