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Cross-Correlation Analysis of Multichannel Uterine EMG Signals

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Abstract — **The prevention of preterm labor remains one of the primary goals of obstetric research. One way to achieve this goal effectively is to understand the mechanisms regulating the uterine contractility. Herein, we evaluate the correlation between uterine electrical activities recorded from spatially-distributed regions by calculating the nonlinear regression coefficient. Results have shown that, during pregnancy, the degree of interdependence between signals is very high whereas, at labor, the correlation between the signals decreases remarkably. We conclude that pregnancy is characterized by the presence of few local potential sources dominating the other sources while at the onset of labor, the number of these sources increases remarkably which affects therefore the correlation between the signals.**

I. Introduction

As many other biological systems, the human uterus is a complex dynamic system whose state evolves with time: throughout most of pregnancy, there is little uterine activity consisting of infrequent and weak contractions. As labor approaches, the contractions become stronger and more frequent [1, 2]. A large number of studies have proven that this contractile activity depends on the excitability of uterine cells and also on the propagation of the electrical activity to the whole uterus. The excitability is mainly controlled at a cellular level by a modification of ion exchange mechanisms. Propagation is mainly influenced by the cell-to-cell electrical coupling. These two aspects of the uterine myoelectric activity, excitability and propagation, both vary with time and influence the characteristics of the electrical activity [1, 2, 3].

By monitoring the uterine contractile activity during pregnancy, clinicians are able to obtain important prognostic information that can be used for early detection of any sign of preterm labor [4]. However, current techniques used in obstetrical practice for monitoring the contractions impose a compromise between accuracy and invasiveness [5]. Recently, it was shown that, by using electromyographic measurements, the uterine electrical activity can provide valuable information about contractions in obstetric monitoring [2, 4, 6, 7]. The uterine electromyogram (EMG) recorded from the abdominal surface has been found to mirror actual activity in the uterus. As a result, uterine electromyography was extensively studied as a potential noninvasive alternative technique for the conventional methods used in obstetrical practice. Uterine EMG signals were analyzed in time and frequency domains by using different time series analysis techniques. Different features were extracted from signals recorded on different animal species [8], as well as pregnant women [9, 10]. These features were used to characterize the uterine electrical activity during pregnancy and to detect the onset of labor. However, most of the previous studies were based on univariate analysis of localized measurements. One of the most common ways of obtaining a deeper understanding of an electrophysiological system is by recording the electrical activity simultaneously from spatially-distributed regions. The assessment of the interdependence between signals recorded from different regions can give new insights into the functioning of the systems that produce them. Therefore, univariate analysis alone cannot accomplish such a task, as it is necessary to make use of the multivariate analysis.

The aim of this paper is to evaluate the interdependence between uterine EMG signals recorded by 16 transabdominal surface electrodes placed at spatially distributed regions in order to improve our understanding of the mechanisms regulating the uterine contractility during pregnancy and at labor. Due to the intrinsic nonstationarity and nonlinearity properties found in the uterine EMG recordings, linear correlation cannot be used to evaluate this dependency. As a result, we use in this paper the nonlinear regression coefficient (h^2) which describes the dependency of two signals in a most general way without any direct specification of the type of relationship between them [11]. The correlation values of the signals are then compared between the 2 classes of contractions (pregnancy and labor) and a conclusion is finally drawn.

II. Materials and Methods

A. Database description

Uterine EMG signals used in this research were recorded from 10 women. Our database consists of 30 pregnancy contraction signals and 30 labor signals. Recordings were made in the University Hospital of Amiens in France by using a protocol approved by the ethical committee (ID-RCB 2011-A00500-41). Recordings were performed by using a 16 electrode grid, arranged in a 4x4 matrix positioned on the women's abdomen with interelectrode spacing of 2 cm (fig.1). The ground electrodes were placed on each hip. Signals were sampled at 200 Hz. In all the patients, uterine activity was also recorded by a

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TOCO in order to correlate it with the uterine EMG signals. The bursts of uterine electrical activity corresponding to contractions were then manually segmented. In this study, in order to increase the signal to noise ratio, we considered vertical bipolar signals instead of monopolar ones. Our signals form thus a rectangular 3x4 matrix. The recording device has an anti-aliasing filter with a cut-off frequency of 100 Hz. Interfering artifacts were minimized by using a bandpass filter set at 0.1 - 3 Hz.

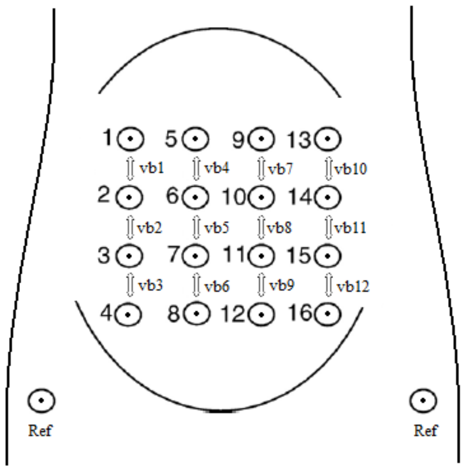


Figure 1- Electrodes configuration on the woman's abdominal wall. Vb_i represent the derived bipolar signals.

B. *Nonlinear cross correlation coefficient:*

The nonlinear correlation coefficient (h^2) is a non parametric measure of the nonlinear relationship between two time series x and y [11] introduced by Lopes da Silva *et al.* [12] in the field of EEG analysis. The nonlinear correlation coefficient technique was applied on uterine EMG signals [13]. The underlying idea is that if the value of signal y is considered as a function of the value of signal x, the value of y given x can therefore be predicted according to a nonlinear regression curve [11]. Then, the nonlinear correlation coefficient h^2 between signals x and y can be calculated as follows:

$$h^2_{y/x} = \frac{\sum_{k=1}^{N} y(k)^2 - \sum_{k=1}^{N}(y(k) - f(x(k)))^2}{\sum_{k=1}^{N} y(k)^2} \qquad (1)$$

where *f(x)* is called the fitting curve. It is important to note that the value of h^2 lies between 0 (x and y are independent) and 1 (y is determined by x). Usually, a scatter plot of y versus x is studied. Then, the values of x are subdivided into bins and the curve of regression is approximated by segments of straight lines. However, in this work, we go further and we search for the best curve that can describe the relation between the signals based on the Root Mean Square Error (RMSE) criterion in order to better estimate more accurately the degree of interdependence between the 12 bipolar signals.

C. *Estimating the fitting curve:*

First, pair-wise scatter plotting was performed. The relationship between each pair of signals was therefore mapped in a two dimensional space. Then, different types of functions (piecewise linear, cubic, quadratic….) were tested as fitting curves. Herein, the cubic polynomial function led to the lowest value of the RMSE between the fitted and the actual data. However, since the recorded signals depend on the position of the recording electrode [14], the same function clearly cannot be used to fit all the different relations between the signals. Therefore, to match the variations of the relations encountered between the signals, the coefficients of the cubic polynomial fitting functions between the 12 bipolar signals were constantly varied maintaining thus the lowest RMSE value. Once the fitting curve leading the lowest RMSE value was found, the (h^2) coefficient was calculated using (1).

III. RESULTS

Our approach was tested on 30 pregnancy and labor contractions. Each contraction has a 12 bipolar signals resolution. The nonlinear regression coefficient (h^2) was calculated pair wise for 12 signals corresponding to each contraction of the two classes by using (1). A matrix of 144 values representing the degrees of dependency between the 12 bipolar signals was obtained for each contraction. Then, the mean values of the (h^2) matrices corresponding to pregnancy and labor were generated and compared to each other. The matrix of the mean values of (h^2) obtained on all the pregnancy contractions is shown in Table 1 while the mean values of (h^2) obtained on all the labor contractions matrices are illustrated in table 2. All the correlation values are presented by decreasing order. From tables 1 and 2, we can notice that the dependence between the signals varies between the signals according to the position of the electrodes. Overall, we can notice that pregnancy is characterized by high correlation values between the signals (table 1) while labor is characterized by considerably lower correlation values (table 2). These observations can be confirmed by comparing the mean values of the pregnancy matrix (mean value ± standard deviation= 0.75±0.053) with the labor matrix (mean value ± standard deviation= 0.093±0.0058). In addition, it is important to note that that signals in each row are highly correlated (fig. 3.a) while the correlation values in each column are relatively lower (fig. 3.b).

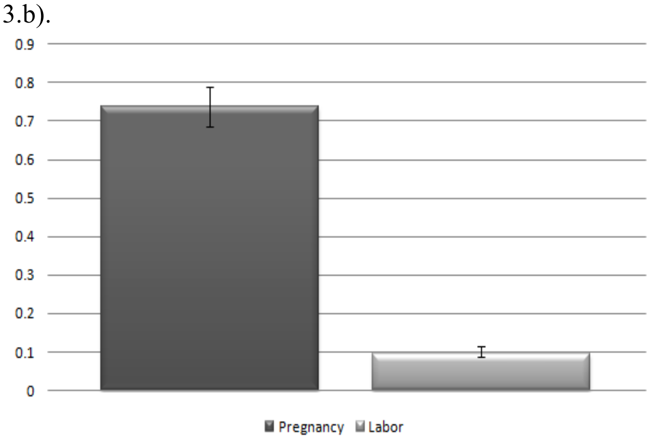


Figure 2 - Average of the values of the nonlinear correlation coefficient (h^2) obtained from the two studied classes: pregnancy and labor.

TABLE I -

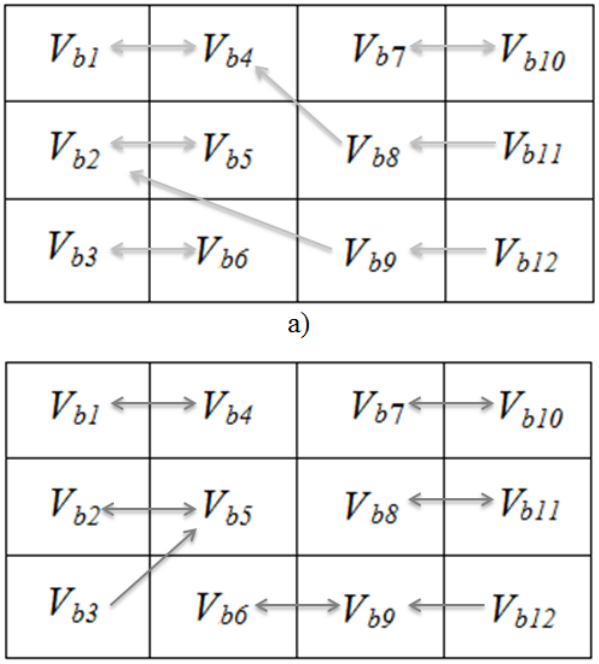
NONLINEAR CORRELATION COEFFICIENT H^2 MATRIX FOR PREGNANCY CONTRACTIONS. THE CORRELATION VALUES MEAN VALUE ± STANDARD DEVIATION ARE EXPRESSED IN PERCENT AND PRESENTED IN DECREASING ORDER STARTING WITH THE MOST CORRELATED CHANNELS

Channel	Channel Correlation mean value ± standard deviation										
1	**4**	**5**	**2**	**8**	**7**	**11**	**6**	**10**	**9**	**3**	**12**
	92±1	89±2	86±2	84±1.5	81±2	72±5	71±4	70±4.5	64±6	60±5	56±10
2	**5**	**1**	**8**	**4**	**6**	**9**	**11**	**7**	**2**	**3**	**12**
	90±1	89±2	88±1	86±1.5	84±1.5	81±2	80±5	77±5	74±7.5	74±4.5	63±15
3	**6**	**2**	**5**	**9**	**8**	**11**	**1**	**4**	**7**	**12**	**10**
	84±1.5	76±4.5	74±5	74±4.5	73±4	69±5	62±5	59±10	52±1.5	51±18	50±10
4	**1**	**5**	**8**	**7**	**2**	**10**	**11**	**6**	**9**	**3**	**12**
	92±1	89±2	88±2	87±1.5	86±1.5	79±4	75±4.5	69±4.5	66±1.7	62±10	53±4
5	**2**	**4**	**1**	**11**	**8**	**6**	**7**	**10**	**9**	**3**	**12**
	90±1	89±2	89±2	84±1.3	82±1.75	82±2	82±2	78±3	76±5	76±5	56±10
6	**3**	**2**	**5**	**9**	**8**	**11**	**1**	**4**	**7**	**12**	10
	87±1.5	86±1.5	84±2	82±2	81±5	77±5	73±4	71±4.5	65±1.6	64±15	60±1
7	**10**	**4**	**5**	**8**	**1**	**2**	**11**	**6**	**9**	**3**	**12**
	90±1	90±1	84±2	83±2	81±2	79±5	79±7.5	68±16	59±15	54±15	47±13
8	**4**	**11**	**2**	**1**	**7**	**6**	**5**	**10**	**9**	**3**	**12**
	89±2	88±2	88±1	85±1.5	84±5.2	84±5.4	82±1.75	82±2.5	76±5	75±4	60±18
9	**2**	**6**	**8**	**5**	**11**	**3**	**12**	**4**	**1**	**7**	**10**
	84±2	82±2	78±5	78±5	76±4	74±4.5	69±3	68±17	66±6	61±15	59±1
10	**7**	**8**	**5**	**4**	**2**	11	**1**	**9**	**6**	**3**	**12**
	90±1	83±2.5	80±3	80±4	79±7.5	79±2	75±4.5	64±1	62±1	55±10	49±12
11	**8**	**5**	**2**	**10**	**7**	**9**	**6**	**4**	**1**	**3**	**12**
	88±2	85±1.3	83±5	81±2	81±7.5	79±4	79±5	77±4.5	75±5	72±5	55±15
12	**9**	**6**	**2**	**8**	**5**	**1**	**11**	**4**	**10**	**3**	**8**
	70±3	67±15	65±15	63±18	58±10	58±12	57±15	55±4	53±12	53±18	50±13

TABLE II –

NONLINEAR CORRELATION COEFFICIENT H^2 MATRIX FOR LABOR CONTRACTIONS. THE CORRELATION VALUES MEAN VALUE ± STANDARD DEVIATION ARE EXPRESSED IN PERCENT AND PRESENTED IN DECREASING ORDER STARTING WITH THE MOST CORRELATED CHANNELS

Channel	Channel Correlation mean value ± standard deviation										
1	**4**	**7**	**2**	**10**	**5**	**9**	**4**	**12**	**3**	**6**	**11**
	45.2±0.4	9.1±0.25	9±0.3	7.1±0.45	6.7±2	5.5±0.02	4.52±0.4	4±0.23	3±0.1	9±0.3	2.5±0.02
2	**5**	**3**	**4**	**10**	**1**	**6**	**7**	**8**	**12**	**11**	**9**
	35±0.46	13.9±0.3	11.4±0.3	9.6±1.8	9.3±0.3	7.4±0.1	6.2±0.1	4.5±0.06	4.1±0.15	3.3±0.04	1.7±0.01
3	**5**	**6**	**2**	**12**	**9**	**11**	**10**	**8**	**1**	**4**	**7**
	21.4±1.9	12.8±1.8	11.9±0.3	10.2±0.6	7.5±0.36	5.3±0.2	4.3±0.1	3.9±0.06	3.3±0.1	1.7±0.01	1.5±0.01
4	**1**	**7**	**10**	**6**	**2**	**12**	**9**	**5**	**11**	**8**	**3**
	47.2±0.4	21.1±1.32	18.9±0.4	14.4±2	10.4±0.4	8.3±1.32	7.2±0.2	7.1±0.3	4.6±0.11	4.2±0.05	0.9±0.01
5	**2**	**3**	**8**	**7**	**10**	**11**	**4**	**1**	**9**	**6**	**12**
	35.3±0.4	23.4±1.9	17.4±1.11	13.1±0.6	12±0.1	11.9±0.9	8.2±0.32	7.7±0.2	2.1±0.12	1.8±0.01	1.5±0.01
6	**9**	**12**	**3**	**4**	**2**	**7**	**8**	**11**	**1**	**10**	**5**
	22±3.6	21.1±1.37	12.9±1.8	11.4±2	7.63±0.1	7.4±0.26	6.6±0.36	6.4±0.3	1.9±0.03	1.2±0.01	1.1±0.01
7	**10**	**8**	**4**	**5**	**9**	**1**	**2**	**6**	**11**	**5**	**12**
	24.9±1.9	22.6±4.2	21.5±1.3	14±0.63	11±0.5	10±0.25	8±0.08	5±0.2	3±0.06	1.4±0.63	1±0.01
8	**11**	**7**	**5**	**6**	**2**	**4**	**3**	**10**	**12**	**9**	**1**
	28.4±2.83	20.6±4.2	17.8±1.1	5.6±0.36	5.5±0.06	5±0.05	4.9±0.06	4.2±0.07	3.7±0.26	2.6±0.01	1±0.01
9	**6**	**12**	**7**	**3**	**4**	**1**	**11**	**5**	**10**	**8**	**2**
	23±3.6	21.1±1.8	13.1±0.5	7.9±0.4	5.2±0.23	5±0.02	3.6±0.25	3.3±0.12	2.3±0.05	1.9±0.01	0.8±0.01
10	**7**	**4**	**5**	**2**	**1**	**8**	**11**	**12**	**3**	**9**	**6**
	26±1.92	19.2±0.4	15±0.01	7.6±1.79	6.1±0.4	5.5±0.07	5.2±0.2	4.4±0.35	3.3±0.13	2.8±0.05	0.8±0.01
11	**8**	**5**	**3**	**10**	**6**	**9**	**4**	**7**	**2**	**1**	**12**
	28.7±2.8	12.3±0.9	6.3±0.2	6.2±0.2	5.2±0.3	4.8±0.25	3.7±0.1	3.6±0.1	2.3±0.04	1.5±0.02	1.2±0.4
12	**9**	**6**	**3**	**4**	**10**	**2**	**1**	**11**	**8**	**7**	**5**
	21.6±1.8	20.8±1.37	10.8±0.6	9.4±1.3	5.5±0.35	3.1±0.15	3±0.23	2.5±0.4	1.9±0.26	1.7±0.01	0.5±0.01



b)

Figure 3 – Representation of the most correlated channels: a) during pregnancy; b) at the onset of labor

IV. Discussion

The results of this study showed first that the correlation values between the signals vary from pregnancy to labor: overall, signals recorded during pregnancy are highly correlated while the correlation values decrease remarkably at the onset of labor. This observation is may be due to the high uterine electrical activity noticed on the median axis (channels Vb_7 and Vb_8) throughout pregnancy and reported in the literature [15]. In fact, it was reported that, during pregnancy, the distance between the recording position on the skin and the signal source in the myometrium is reduced at the median axis compared to other electrode positions [15]. Also, signals generated by the potential sources at the extremities of the recording matrix are filtered by the visceral tissues found between the skin and the sources. Therefore, they might be dominated by the propagated signals generated by the potential sources under the median axis, which explains the high correlation between the signals at each row of the matrix (table 2).

On the other hand, at the onset of labor, higher activities over the whole uterine muscle can be noticed. More potential sources may appear due to the reduction of the distances between the recording electrodes and the potential sources, which explains the drop of the values of the correlation between the signals at this phase (table 2).

These findings may be very useful for monitoring pregnancy and classifying t signals. Indeed, the use of the correlation values may solve classification problems due to the remarkable variation of these values between pregnancy and labor. Finally, although still to be tested, we believe that this approach may be very useful for detecting any signs of preterm labor.

V. Conclusion

The cross correlation analysis of uterine EMG signals recorded by a matrix of 16 electrodes during pregnancy and at the onset of labor was addressed. From this study, we can conclude first pregnancy is characterized by highly correlated signals while labor is characterized by lower correlations between the signals. Also, we can conclude that pregnancy is characterized by the presence of few local potential sources. The number of these sources increases remarkably at the onset of labor which affects therefore the correlation between the signals.

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