Classification of pregnancy and labor contractions using a graph theory based analysis

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Abstract— In this paper, we propose a new framework to characterize the electrohysterographic (EHG) signals recorded during pregnancy and labor. The approach is based on the analysis of the propagation of the uterine electrical activity. The processing pipeline includes i) the estimation of the statistical dependencies between the different recorded EHG signals, ii) the characterization of the obtained connectivity matrices using network measures and iii) the use of these measures in clinical application: the classification between pregnancy and labor.

Due to its robustness to volume conductor, we used the imaginary part of coherence in order to produce the connectivity matrix which is then transformed into a graph. We evaluate the performance of several graph measures. We also compare the results with the parameter mostly used in the literature: the peak frequency combined with the propagation velocity (PV +PF). Our results show that the use of the network measures is a promising tool to classify labor and pregnancy contractions with a small superiority of the graph strength over PV+PF.

I. Introduction

Preterm Labor (PL) defined as labor before completing the 37th week of gestation is the main cause of newborn morbidity and mortality. A key to treat the PL is its early detection [1]. One of the most promising markers of PL is the electrical activity of the uterus. For this purpose, the most representative method is the electrohysterogram (EHG), electrical uterine activity recorded on the woman's abdomen, that mainly depends on two factors: the excitability of uterine cells and the propagation of the electrical activity in the uterine muscle [1].

Numerous studies have shown that the analysis of the propagation, or synchronization, of the uterine electrical activity is a powerful tool to characterize and to discriminate pregnancy and labor contractions [2]. The nonlinear correlation coefficient was recently used to estimate the correlations between 16 EHG signals recorded by a matrix of 4x4 electrodes [2]. Results showed an increase in the correlation with the weeks of gestation and a significant difference between nonlabor and labor contractions.

Alternatively, the propagation velocity of the electrical activity, referred to as conduction velocity (CV), has been quantified by analyzing either the propagation of whole bursts of uterine electrical activity [3] or single spikes within a burst in [3] [4]. The combination of the propagation velocity (PV) and the peak frequency (PF) showed the highest performance to discriminate labor and nonlabor data [3].

Very recently, a comparative study was performed between several correlation measures applied to EHG signals [5]. Authors showed a high variability among the tested methods. They evidenced also that the correlation spreads to the whole matrix and in all directions [5].

As the methods used to compute the connectivity between EHG signals showed high variability, we believe that one of the potential causes of this variability is the effect of the volume conductor between the uterus and the skin, related to the abdominal wall. For this reason, we used in this paper the imaginary part of the coherence [6] which was shown to be insensitive to the volume conductor effect. In almost all previous studies, the correlation matrices were always reduced by keeping only their mean and standard deviation. Despite the encouraging results obtained, useful information was probably missing due to this averaging. To characterize the correlation matrix and quantify the associated connectivity graph, graph theory based analysis seems to be a good candidate. This field has shown a growing interest in the last years, especially to characterize brain networks [7]. According to this approach, the obtained correlation matrix can be represented as a graph consisting of a set of nodes interconnected by edges.

In this paper, we test for the first time the application of graph theory analysis to characterize uterine contractions. The clinical potential of the extracted network measures will be compared to classical parameters previously used.

II. Methods And Procedure

A. Overview

The ultimate objective of the project is the classification of labor and pregnancy EHG signals. The complete pipeline is shown in Figure 1. The first step consists of recording and denoising the EHG signals (figure 1a). The second step is to compute the connectivity between the denoised signals (figure 1b). The obtained connectivity matrix is then represented by a graph (figure 1c) from which several measures can be extracted (based on graph theory). These

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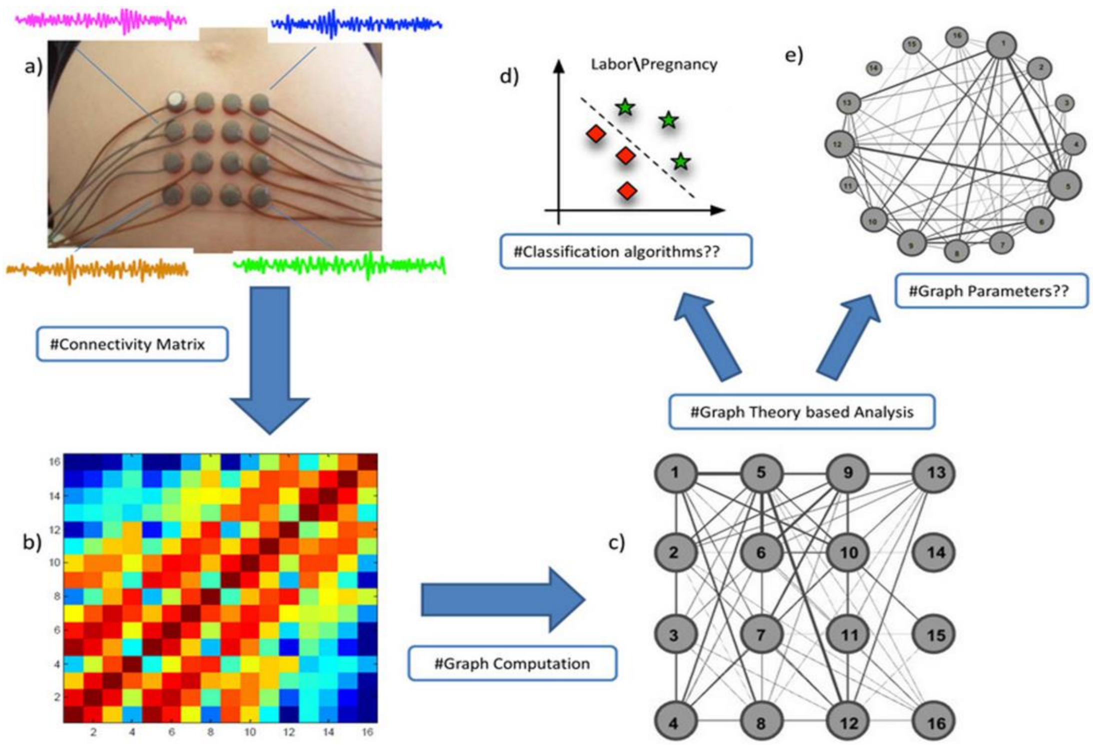

Figure 1. Structure of the investigation. (a) EHG signals recorded using a grid of 4x4 electrodes. (b) Connectivity matrix. (c) Simple graph where each electrode is a node and the edges are the value of correlation between signals. (d) Classification labor\pregnancy using graph algorithms. (e) Extraction of graph parameters.

measures will be used to, first characterize uterine pregnancy and labor contractions at different term (figure 1e), then to evaluate the clinical ability of this approach in the classification of these 2 classes of contractions (figure 1d).

B. The imaginary part of Coherence (Icoh)

The coherence (C) function gives the linear correlation between two signals X and Y as a function of the frequency. It is defined as their cross-spectral density function C_{XY} normalized by their individual auto-spectral density functions C_{XX} and C_{YY}. Nolte et al. [6] have shown that the use of the imaginary part of the coherence function can reduce the effect of the volume conductor. In this paper, we evaluate the imaginary coherence (Icoh) defined as:

$$\text{Icoh} = \frac{|\text{Im}C_{XY}(f)|}{\sqrt{|C_{XX}(f)||C_{YY}(f)|}}. \tag{1}$$

C. Graph Theory

Once the connectivity matrix is calculated, from the Icoh, it is then transformed into a graph. A graph is an abstract representation of a network, consisting of a set of nodes (N) and edges (V), indicating the presence of an interaction between the nodes [8]. An analysis based on graph theory consists of extracting different parameters from the graph:

Assortativity: Networks with positive assortativity values are therefore likely to have high-degree hubs interconnected between them and low-degree hubs interconnected between them. Networks with negative assortativity values are likely to have high-degree hubs connected with low-degree hubs [7] [9].

Clustering Coefficient: Clustering Coefficient is defined as the fraction of triangular connection around a node:

$$C_i = \frac{2t_i}{k_i(k_i-1)}. \tag{2}$$

where t_i denotes the number of triangular connections around the node and k_i denotes the degree of the i^{th} node [7].

Local Efficiency: It is the inverse of the shortest path parameter between a pair of nodes.

$$E = \frac{1}{N(N-1)} \sum_{i,j \in N,\, i \neq j} \frac{1}{d_{ij}}. \tag{3}$$

where i, j denotes respectively the i^{th} , j^{th} nodes, d_{ij} is the value of the shortest path length between nodes i and j [10].

Strength: The strength shows the importance and contribution of each node with respect to the rest of the network.

$$S_i = \sum_{j \in N} w_{ij}. \quad (4)$$

where i, j denotes respectively the i^{th} , j^{th} nodes, w_{ij} is the value (weight)of the relation between nodes i and j [7] [12].

D. Data

The signals were recorded from 16 monopolar channels of a 4x4 matrix located on the woman's abdomen. The third electrode column was always put on the uterine median axis (see [11] for more details). The sampling frequency was 200 Hz. The EHG signals were segmented manually and denoised using a CCA-EMD method, developed in our team [12]. After segmentation and denoising, we obtained 183 labor and 247 pregnancy bursts. The analysis below has been applied to these segmented uterine bursts.

III. RESULTS

The *Icoh* method – as a bivariate method, we used all the combinations between the 16 signals - was applied to each burst in labor and pregnancy databases. The matrices were thresholded to keep the values above the mean of the matrix in order to remove the insignificant coupling. To investigate the possible difference of connectivity between pregnancy and labor, we averaged the matrices of each class. Thus an average matrix (graph) is obtained representing pregnancy contractions and another one for labor contractions. Results are shown in Fig. 2; nodes are labeled by the electrodes numbers. We used the 'GEPHI' software for graph visualization.

Fig. 2 shows the corresponding graphs for each class: pregnancy (a-c) and labor (b-d). In figures 2a and 2b, we present the graphs as a grid of 4x4 nodes where each node represents the corresponding electrode. The edges represent the connectivity values between the two corresponding electrodes. In figures 2c and 2d, we present the same graphs in a circular layout. The thickness of an edge depends on its weight (Icoh value) and the diameter of a node depends on its strength.

It is clear from Fig. 2 (c- d) that the number of significant edges in the averaged labor graph is higher than in the pregnancy graph. In terms of node strength, we can notice that nodes in the labor graph are larger than those in the pregnancy graph. The same remark applies to edges thickness. Nodes 1, 5 and 12 in Fig. 2 (d) have the highest strength since they are the larger nodes in the graph, and their connecting edges are the thickest in the labor graph. We then investigate the clinical potential of the obtained graphs by extracting different network measures.

To compare our results with the classical published ones, we compute the PV +PF parameter [3]. We used the ROC curves to quantify the performances of these parameters. Results are shown in Fig. 3 and Table 1. Fig. 3 shows the ROC curves for the graph parameters used in our work as well for the PV + PF.

Clustering Coefficient, Efficiency and Strength have a good classification rate, with the highest Area Under Curve (AUC) for Strength, unlike the Assortativity that presents the worst classification rate. Table I summarizes the ROC test values for the different parameters; Efficiency presents an (AUC) of 0.797 with 82% sensitivity and 71% specificity, while Assortativity presents a very low AUC (0,478) with 96% sensitivity but 6% specificity. Clustering Coefficient has an AUC of 0.785 with 78 % sensitivity and 73% specificity while PV+PF parameter has an AUC of 0.789 with 72 % sensitivity and 79% specificity. Strength has the higher AUC (0.801) with 81 % sensitivity and 71% specificity.

IV. DISCUSSION

In this paper, we obtained a mean graph for all pregnancy contractions and another one for all labor contractions. As shown in Fig. 2 (c-d) we obtained an increase in the connectivity during labor; which means that more correlation between different parts of uterus exists during labor. This is in agreement with the results of Hassan et al. when he used the nonlinear correlation method [2]. A possible explanation for this correlation increase during labor is the propagation phenomenon, associated with the presence of gap junctions that increase in number just before and during labor [15].

A central finding of this study is that graph parameters are promising tools to distinguish between pregnancy and labor signals (AUC= 0.801 for the Strength) even if the sensitivity of 80% is not clinically sufficient. A possible explanation of this rate is that Icoh decreases the volume conductor effect, but it could not eliminate it effectively. For this reason, estimating the connectivity and the directionality at the source level using an appropriate inverse method will be our next step.

When compared to the literature, the results are slightly higher than those obtained by the well-known PF+PV (AUC = 0.789) [3]. However using the PV+PF could give us information about the local propagation velocity of signals,

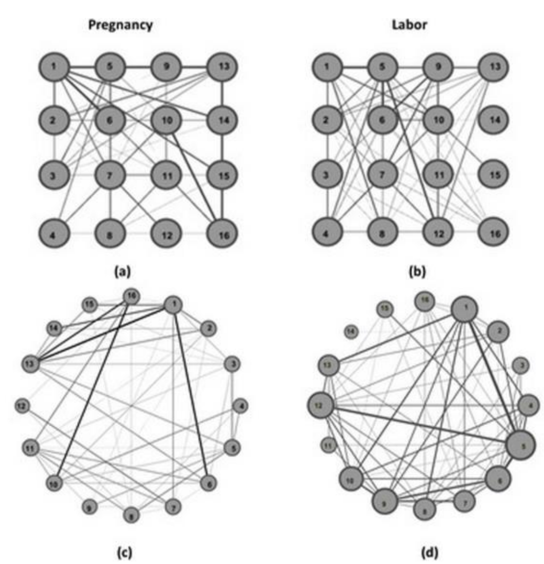

Figure 2. Graph results (a-c) Mean pregnancy graph (b-d)Mean labor graph

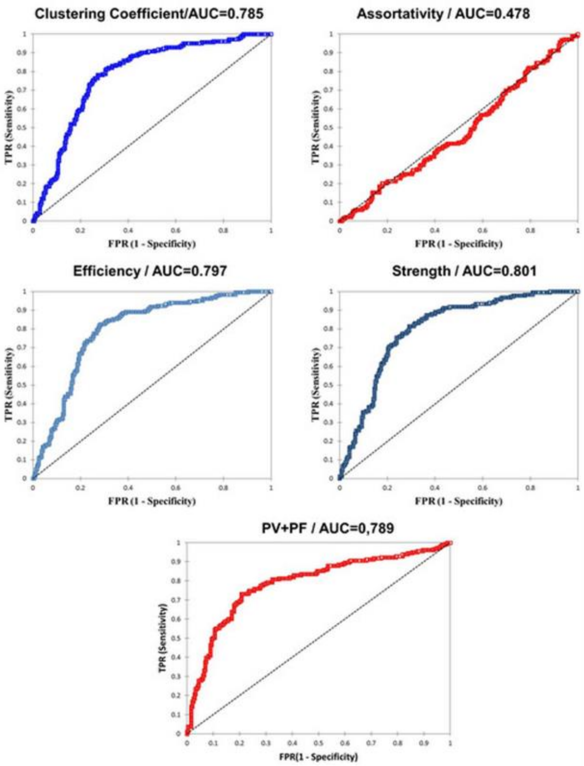

Figure 3. Comparison of ROC curves for different

while our approach takes in consideration all the signal information in the whole matrix. We can estimate also which electrodes are strongly connected.

This can lead us to know which parts of the uterus offers the most important information. However, combining the strength parameter with PV+PF could improve the obtained classification rate. Further work is planned to compare our results with methods developed by our team such as Filtered Windowed h^2 (FW-h^2) and of another team such as the conduction velocity (CV).

V. CONCLUSION

We have presented in this paper the preliminary results of the complete framework aiming at characterizing the propagation of the uterine electrical activity. Multichannel EHG recordings using a 4x4 electrode matrix positioned on the woman's abdomen are done during pregnancy and labor. We used the Imginary part of coherence (Icoh) to obtain the connectivity matrix of these signals. This matrix is then transformed into a graph. We can conclude that the Strength graph parameter extracted from the obtained graphs could be a powerful classification parameter.

The results were interesting and encouraging. We expect this approach to be further useful for a better classification between pregnancy and labor and thus would help for the early prediction of preterm labor. In future work, we aim to improve the classification rate either by combining more graph parameters, or by using classification algorithms based on graph analysis. We will thus be able to classify between labor and pregnancy contractions and later normal labor and preterm labor activity.

TABLE I. COMPARISON OF SIGNIFICATIVITY IN LABOR VERSUS PREGNANCY CLASSIFICATION FOR DIFFERENT PARAMETERS

	Sensitivity (%)	*Specificity (%)*	*AUC*
Efficiency	82	72	0.797
Assortativity	96	6	0.478
Clustering Coefficient	78	73	0.785
Strength	82	71	**0.801**
PV+PF	73	79	0,789

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