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Classification of Multichannel Uterine EMG Signals

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Abstract – Classification of multichannel uterine electromyogram (EMG) signals is addressed. Signals were recorded by a matrix of 16 electrodes. First, signals corresponding to each channel were individually classified using an artificial neural network (ANN) based on radial basis functions (RBF). The results have shown that the classification performance varies from one channel to another. Then, a decision fusion method based on these classification performances was tested. After fusion, the network yielded better classification accuracy than any individual channel could provide. The high percentage of correctly classified labor/non-labor events proves the efficiency of multichannel recordings in detecting labor. These findings can be very useful for the aim of classifying antepartum versus labor patients.

I. INTRODUCTION

The bioelectrical signal recorded noninvasively from the abdominal wall of pregnant women during their gestational period is called the uterine electromyogram (EMG). This signal reflects the electrical properties of the uterine muscle contraction [1, 2] and provides valuable information about function aspects of the uterine contractility [3]. As a result, uterine EMG was extensively studied for many years. Many studies have demonstrated that it is potentially the best predictor of delivery and of great value for the diagnosis of preterm delivery [4, 5, 6]. However, classifying uterine EMG signals into labor/non-labor or term/preterm classes remains a major challenge for the researchers. The aim of this study is to use multichannel analysis in order to distinguish pregnancy signals from labor signals. Multichannel analysis is a recent technique based on simultaneously recording the electrical activity at different locations. Multichannel classification has been already applied to EEG [7, 8] and ECG [9] but rarely to uterine EMG signals. In this study, we use a 4x4 electrode matrix positioned on the woman's abdomen to record the uterine EMG signals. Then, in order to increase the signal to noise ratio, we consider vertical bipolar signals. Our signals form thus a rectangular 3x4 matrix and each contraction had a 12-channel resolution [10]. However, when using multiple biosensors at the same time, classifying the recorded biosignals becomes a complex task due to the large number of features encountered in this situation [11]. A fusion method is therefore required. The fusion method is a way to combine information from several channels, i.e., from different spatial regions. In our work, we use a decision fusion method which is defined as the process of fusing information from individual data sources after each data source has undergone preliminary classification [12]. The decision fusion method minimizes the amount of data to be transmitted between the individual sensors and the central fusion processor by limiting it to just the current decisions derived by the sensors [13]. In this paper, we extract first two classically used features from signals corresponding to each channel. These features are then fed to a classifier in order to classify our contractions into labor or non-labor classes. The binary classification problems are solved by an artificial neural network (ANN) classifier with a Gaussian radial basis function (RBF) kernel. Finally, a decision fusion rule based on the weighted sum of the individual decision of each channel is tested.

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II. METHODOLOGY

A. Database description:

Our analysis in this paper is based on digitized uterine EMG signals recorded on 32 women: twenty two were recorded during pregnancy (33 – 41 week of gestation, WG), seven during labor (37 – 42 WG) and three during both pregnancy and labor (33 – 42 WG).

Recordings were made at the University Hospital of Amiens in France and at the Landspitali University hospital in Iceland by using a protocol approved by the relevant ethical committee (VSN 02-0006-V2). Contractions were monitored for at least one hour. Recordings were performed by using a 16 electrode grid, arranged in a 4x4 matrix positioned on the women's abdomen (fig.1). The third electrode column was always put on the uterine median axis. Reference electrodes were placed on each hip of the woman. Signals were sampled at 200 Hz. 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. An example of the bipolar signals recorded on woman in labor is presented in figure 2. All the bursts presented a good signal to noise ratio on all bipolar channels. The recording device has an anti-aliasing filter with a cut-off frequency of 100 Hz.

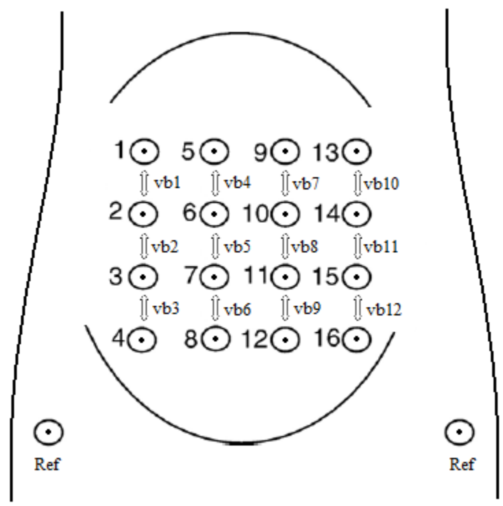

Figure 1- Electrodes configuration on the woman's abdominal wall

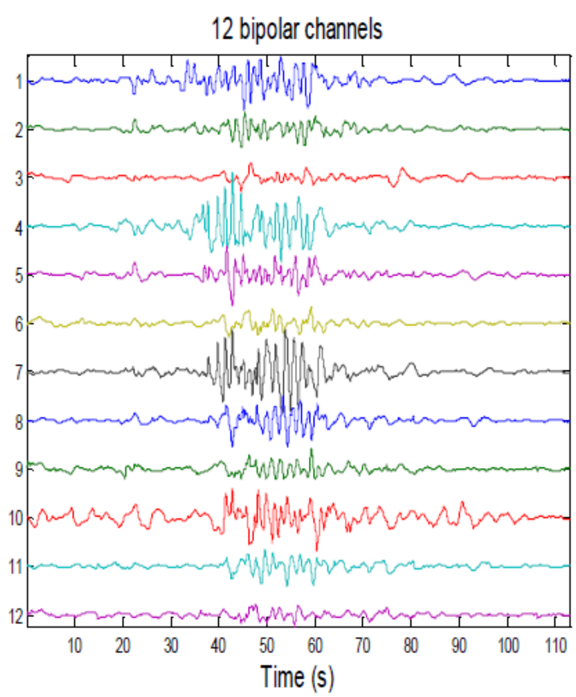

Figure 2 - Example of 12 vertical bipolar signals obtained from the 4x4 matrix on woman in labor.

B. Preprocessing:

Throughout this work, each individual channel was preprocessed before extracting the features. Preprocessing is performed in two stages: (1) unwanted signals were removed by filtering the contraction signals between 0.1 and 3 Hz; (2) all signals were normalized into the same amplitude in order to ensure that all features will have equal significance when training the model [14].

C. Feature extraction:

Feature selection is an important step for solving classification and pattern recognition problems [15]. A good feature selection method will not only improve the performance of the classifier, but also reduce dimensionality of the input data and the computational complexity of the classifier. However, since the focus of this paper is to demonstrate the importance of multichannel recordings for the classification of uterine EMG signals, we wish to favor a small number of features. Therefore, only two features were used. The power of the contraction and the median frequency were extracted from the signals corresponding to each channel. These two classical features were chosen based on previous studies [6, 16, 17] and have shown that they may have either some predictive worth or some physiological significance.

D. Radial basis function network:

Neural networks can be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections [18]. They have been successfully used to solve complicated pattern recognition and classification problems in different domains particularly in biomedical engineering and signal diagnosis.
Radial basis function neural network is one of the most commonly used families of neural networks for pattern classification tasks. This type of network has two layers: a hidden layer and an output layer as shown in figure 3. Each unit in the hidden layer employs a radial basis function as the activation function. Various functions have been tested as activation functions for RBF networks. In pattern classification applications, the Gaussian function is preferred [18]. A Gaussian function is defined as:

$$\varphi_h = exp\left(-\frac{\|(x-\mu_h)^2\|}{2\sigma_h^2}\right) \tag{1}$$

Where μ_h et ${\sigma_h}^2$ are the mean (position) and the variance (width) of the Gaussian kernel function corresponding to the class h. x is the input vector and $\|.\|$ represents the Euclidian distance. Both the positions and the widths of these kernels must be learned from the training patterns. The output unit implements a weighted sum of hidden unit output.

$$y_m = g\left(\sum_{h=1}^{H} \varphi_h \omega_{hm}\right) \tag{2}$$

For m=1,…,*M*, where ω_{hm} are the output weights, each corresponding to the connection between a hidden unit and an output unit, *M* represents the number of output units and *g(.)* is the activation function for nodes in the output layer. A linear or a sigmoid activation function can be considered. The weights ω_{hm} show the contribution of a hidden unit to the respective unit.
For training, there are a variety of learning algorithms for the RBF network. The basic one employs a two-step learning strategy, or hybrid learning. It estimates kernel positions and kernel width using an unsupervised clustering algorithm, followed by a supervised least mean square (LMS) algorithm to determine the connection weights between the hidden layer and the output layer. After this initial solution is obtained, a supervised gradient-based algorithm can be used to refine the network parameters.

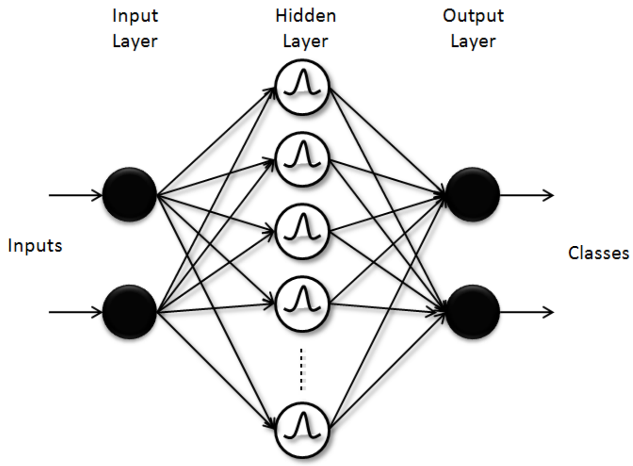

Figure 3 – RBF network in pattern classification

E. Decision fusion:

For each individual channel, a single RBF network was trained using the training data. Each classifier gave its "opinion" about a given input for each of the two classes. Then, a fusion decision rule was applied. Our multichannel fusion method is based on the observation that the channel with a high accuracy should have more influence on the decision making than the channel with a lower accuracy. Weights, noted λ_i *(i=1,..12)*, are therefore associated to each channel to express quantitatively its goodness. The weights are supposed to represent its reliability. Herein, reliability measures which rank the channels according to their goodness are obtained based on the classification success of the trials during an independent training phase [19]. The final decision will be based on the weighted decision of each component classifier combined. However, in order to reduce the error due to the small sample size of training data, we used the leave-one-out cross validation method where a single observation taken from the entire samples is used as the validation data while the remaining observations are used for training the classifier. This is repeated such that each observation in the samples is used once in the validation data [15]. In this phase, the training set consisted of an equal number of trials from the two classes (pregnancy, labor). Otherwise, the classifier will be biased toward the class from which it has seen most feature vectors [11].

40 contractions randomly chosen from each class of contractions (pregnancy, labor) were used in the training phase. Finally, an independent test set was used to evaluate our approach's classification success rate.

III. RESULTS:

First the network was trained using the training set. Features were extracted from each channel, as explained above and fed to the RBF network. Each classifier gave its decision about the given input. In this paper, the results of the classification are given in terms of correct classification rate (*CCR*). The *CCR* of the training data for each channel are indicated in table 1.

Table 1 - Classification table of pregnancy and labor contractions for each channel

CHANNEL	CCR OF PREGNANCY CONTRACTIONS	CCR OF LABOR CONTRACTIONS	OVERALL CLASSIFICATION ACCURACY
VB_1	73.3	37	55
VB_2	66.7	52	59
VB_3	80	43.3	62
VB_4	56.6	86.6	76
VB_5	56.6	73.3	65
VB_6	53.3	73.3	63
VB_7	36.6	46.6	42
VB_8	46.6	33.3	40
VB_9	40	76.6	58
VB_{10}	80	56.6	68
VB_{11}	63.3	63.3	63
VB_{12}	30	60	45

The results show that the classification performance varies from one channel to another. Specifically, channel Vb_4 had the highest overall predictive value (76%) while for channel Vb_8 had the lowest (40%). As a result, the highest weight was assigned to channel Vb_4 while the lowest weight was assigned to channel Vb_8 after training. Here it should also be noted that the correct classification rate of pregnancy contractions was remarkably higher than of labor contractions. These observations are discussed later in the paper. Based on the classification accuracy obtained on the trials in the training set, the weights λ_i were assigned to each channel.

Next, the trained network was used to classify the test signals. Herein, the testing method was also the leave-one-out cross validation method. The final decision is based on the weighted sum of each classifier. 97 pregnancy contractions vs. 37 labor contractions were used in the test phase. The final decisions of the individual channels were fused by using the weighted decision fusion rule. Table 2 shows the classification results of the test set.

First, we notice that the overall classification accuracy was higher than any of the individual channels.

By fusing individual decisions, an overall classification accuracy of 82.65 % was achieved. The *CCR* was as high as 93% for pregnancy contractions and 72.3% for labor contractions as indicated in Table 2.

The high percentage of correctly classified labor/non-labor events indicates explicitly just how efficient multichannel analysis is at detecting labor. Therefore, it can be seen that multichannel recordings can remarkably increase the classification rate of uterine EMG signals for both pregnancy and labor contractions.

Table 2 - Classification table of pregnancy and labor contractions for each channel for the test data by using a weighted decision fusion rule

	WEIGHTED DECISION FUSION METHOD
CCR OF PREGNANCY CONTRACTIONS	93
CCR OF LABOR CONTRACTIONS	72.3
OVERALL CLASSIFICATION ACCURACY	82.65

IV. DISCUSSION:

In this paper, we demonstrate the importance of multichannel recordings for the classification of uterine EMG signals. Herein, we have used a matrix of 16 electrodes positioned on the abdominal wall of the pregnant women. Two classical features (power and median frequency) were extracted from each signal corresponding to each channel and were fed to the classifier. The results showed that the classification performance varied from one channel to another. Channels located on the median axis of the uterus showed lower *CCR* than the others. One possible explanation of this observable fact is that, throughout pregnancy, the channels located over the median axis show more activity than the channels located at the extremities where the activity remains weak. However, at labor, when the synchronization in the uterus becomes stronger, the uterine activity is considered to be fully propagated through the whole uterus and the uterine contractions become more coordinated[3]. Hence, a more homogeneous distribution of the power may be noticed. Electrodes positioned on the extremities are therefore more sensible to these variations than the ones positioned on the median axis; thus they had more influence on the decision making than the channels at the center of the matrix.

On the other hand, when a decision fusion rule was applied, an improved accuracy of the classification decision compared to a decision based on any of the individual data sources alone was obtained.

In addition to the noticeable improvement in the classification performance, multichannel recordings provide a certain number of important advantages. First, the measurements of one electrode are always confirmed by the measurements of the other electrodes; thus, the cooperative arrangement enhances the confidence of the final decision. Also, even though multiple electrodes would provide redundancy, this would enable the classifier to provide information in case of partial failure, data loss from one electrode which may occur when doing recordings that can last for more than an hour. These comparative aspects prove that multichannel recordings can be an efficient method for classifying bioelectrical signals. Although still to be tested, we believe that these results may be generalized by using other features and a large signal database. However, we believe that multichannel classification methods could help in classifying contractions leading to term or preterm labor.

V. CONCLUSION

Uterine EMG signal recorded by using multiple sensors was addressed. From this manuscript, we can conclude first that the classification of uterine EMG signals can be improved by using a multichannel fusion rule. Although simple parameters were used, the classification results were very promising. The high percentage of correctly classified labor/non-labor events indicates explicitly just how efficient this approach method is at detecting labor. Although still to be tested, we believe that the proposed classification method could help in classifying contractions leading to term or preterm labor. As our ultimate goal is to improve the detection of preterm labor, we find these results very promising.

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