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Classification of Abdominal Electromyogram Signals for Detecting Pregnancy Contractions Using Support Vector Machine in the Wavelet Packet Domain

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ABSTRACT

One of the early signs of natural labor is the occurrence of contractions in the abdominal region of a pregnant woman. However, the presence of contractions in the uterus alone is not a definitive indicator of the onset of natural labor. One of the recent research topics has been the processing of abdominal electromyogram signals from pregnant women to detect preterm labor. The objective of this paper is to classify abdominal electromyogram signals into two classes: labor contractions and pregnancy contractions, in order to detect preterm labor. Due to the differences in the energy distribution of abdominal electromyogram signals throughout pregnancy, the signals are decomposed by a three-level wavelet packet transform. The energy of the wavelet packets at the final decomposition level is then calculated and used for signal classification. The results show that the support vector machine is capable of distinguishing pregnancy contractions from labor-induced pain with a classification accuracy of 86%, sensitivity of 88%, and specificity of 83%, based on the energy features of the wavelet packet.

1. INTRODUCTION

Abdominal electromyogram (EMG) is a method for monitoring uterine activity by recording the electrical activity of the uterus from the abdominal wall of a pregnant woman. Numerous studies have analyzed abdominal EMG recordings. Abdominal EMG is recorded by placing surface electrodes on the abdominal wall of a pregnant woman to detect the uterine electrical activity [1]. Bassam Moslem and colleagues compared the performance of different frequency parameters. These parameters include peak frequency, mean frequency, frequency threshold, and average frequency, which were used to predict preterm labor. The mentioned parameters were calculated using the power spectral density obtained from the fast Fourier transform. To classify these parameters for each pregnancy condition, receiver operating characteristic curve analysis was employed. It was found that the average frequency showed the

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best classification performance [2]. Lou and others presented a classification method based on wavelet packet decomposition and a multilayer perceptron, which distinguished between early and non-early labor data. Eleven early labor signals and 28 non-early labor signals were tested, achieving a classification accuracy of 64% [3]. Manner and colleagues employed the Kohonen method on abdominal EMG data for classifying labor and pregnancy contractions. Features such as the mean and standard deviation of the power spectrum, peak frequency, burst count per minute, and total burst activity were used. This experiment was conducted on 134 pregnancy contractions and 51 labor contractions, resulting in an accuracy of 80% [4].

The purpose of this paper is to apply a wavelet packet decomposition approach to analyze abdominal EMG signals in a binary tree structure. The energy of the wavelet packets at level three is then calculated. Principal component analysis is applied to reduce the dimensionality of the input data. Finally, a support vector machine (SVM) is used as a classifier to categorize the signals into two classes: labor contractions and pregnancy contractions.

2. DATABASE

The analysis presented in this paper is based on abdominal EMG signals recorded from 32 women: 22 during pregnancy (weeks 33–41 of gestation), 7 during labor (weeks 37–42), and 3 during both pregnancy and labor (weeks 33–42). These recordings were made at two medical universities in France and Iceland [5]. The recordings were carried out using 16 electrodes placed in a 4x4 matrix on the abdominal wall of the pregnant woman. The placement of these electrodes is shown in Figure 1. Each of these electrodes represents a channel, and the signals were sampled at a frequency of 200 Hz. To obtain a good signal-to-noise ratio, the difference between two channels was used. As a result, 16 channels were reduced to 12 channels.

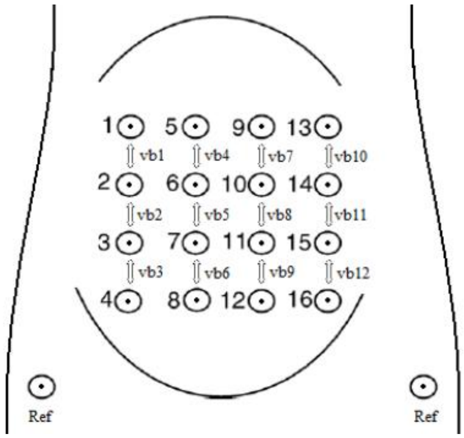

Fig. 1. Electrode Placement on the Abdominal Wall [6]

3. PREPROCESSING OPERATIONS

During this work, all the signals are initially preprocessed. This operation is performed to reduce noise and improve signal quality for subsequent processes. The preprocessing steps include: removing unwanted signals by filtering the signal within the 0.1 to 3 Hz range. All signals are then normalized by dividing each signal by its standard deviation [7].

4. SIGNAL SEGMENTATION OPERATIONS

The second step is signal segmentation. Since the lengths of the obtained signals vary, the issue can be addressed by segmenting the signals into windows. For this purpose, each signal is divided into 120-second windows, each containing 24,000 samples. Feature extraction operations are then performed separately for each window of the signal.

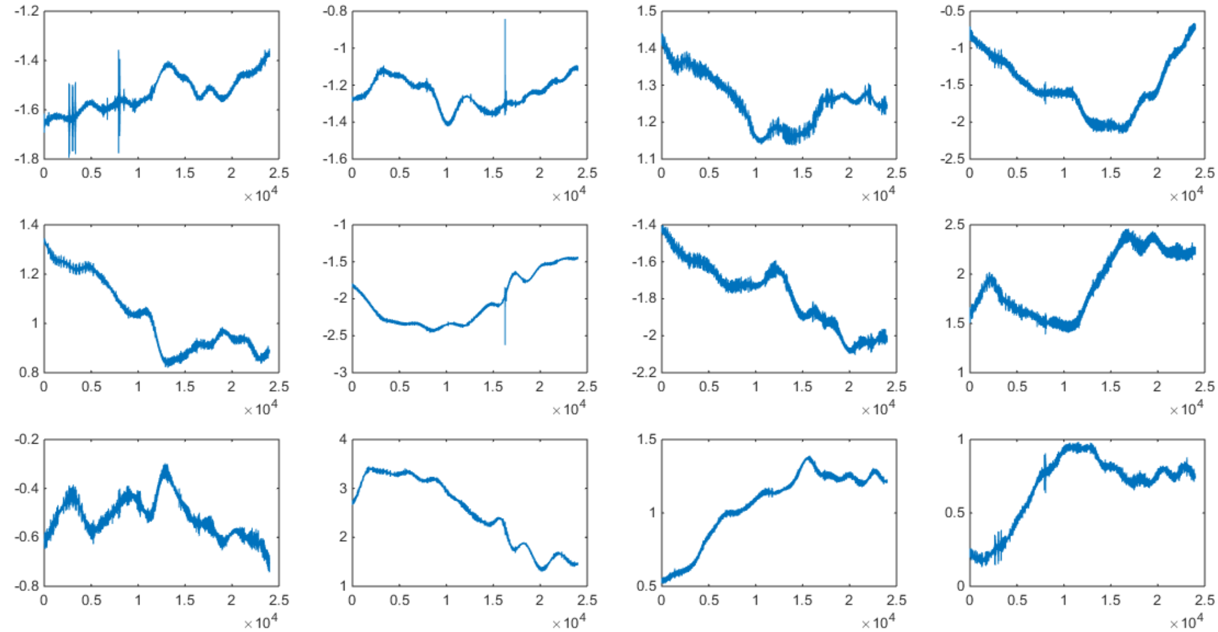

Fig. 2. Segmented Signals of Labor Contractions for Each Channel

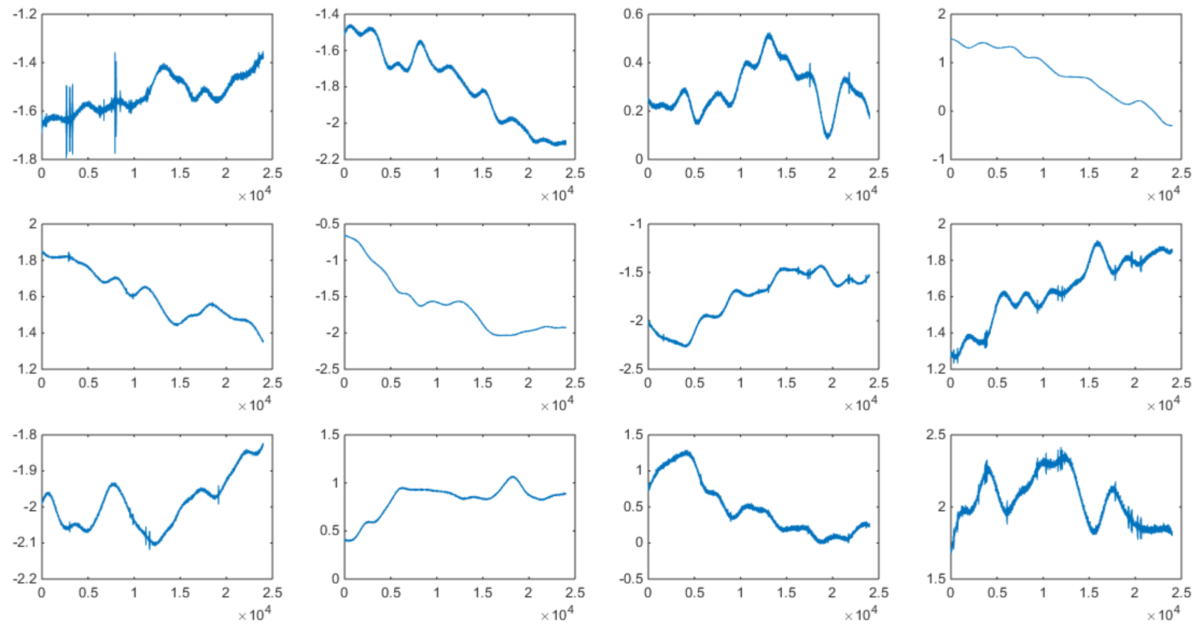

Fig. 3. Segmented Signals of Pregnancy Contractions for Each Channel

5. WAVELET PACKET TRANSFORM

The wavelet packet transform is implemented using a two-channel filter bank. The difference between this and the discrete wavelet transform is that, in the discrete wavelet transform, at each stage, the approximation coefficient passes through low-pass and high-pass filters, whereas in the wavelet packet transform, both the approximation and detail coefficients pass through the filters. The wavelet packet transform allows for the analysis of information in both high and low-frequency bands effectively. In this method, h(n) represents the impulse response of the low-pass filter, and g(n) represents the impulse response of the high-pass filter, corresponding to the scaling function and the wavelet function, respectively. The sequence of wavelet functions is defined as follows:

$$\boldsymbol{W_{2n}(x) = \sqrt{2}\sum_{k=0}^{2N-1} h(k)W_n(2x-k)} \tag{1}$$

$$\boldsymbol{W_{2n+1}(x) = \sqrt{2}\sum_{k=0}^{2N-1} g(k)W_n(2x-k)} \tag{2}$$

where n is the local time parameter and j is the scale parameter. The wavelet packet coefficients at each node (j , n) are expressed as follows:

$$\boldsymbol{(C_{j,n}(k)) = (f(t), 2^{-j/2}w_n(2^{-j}t-k)} \tag{3}$$

Where j represents the level, and n denotes the number of nodes per level, given by $n = 1,2,\ldots,2^j - 1$. A vector of wavelet packet coefficients corresponding to the node (j,n) is represented by $C_{j,n}$. The energy of the node (j,n), based on the wavelet packet coefficients $W_{j,n}$ is computed as follows:

$$\boldsymbol{E_n = \sum_k |C_{j,n}(k)|^2} \tag{4}$$

Support Vector Machine (SVM) is a classification method based on machine learning theory. This classifier is commonly used for binary classification problems and has been extensively utilized in numerous studies [8-14]. In this approach, two hyperplanes are positioned at the boundary of the two data classes, and the objective is to find the maximum-margin boundary between them. That is, the two hyperplanes are pushed apart until they reach the closest data points of each class. The goal is to determine two hyperplanes that are maximally separated, making the region between them the optimal decision boundary. The separating hyperplane between the two classes is defined as follows [15]:

$$\boldsymbol{w^T.x + b = 0} \tag{5}$$

In the above equation, the parameters w and b refer to the weight vector and bias, respectively. For the input vector x, the discriminant function of the support vector machine is determined by the following equation (6) [15]:

$$\mathbf{f(x) = sgn(\sum_{i=1}^{N} a_i y_i K(x_i\, x) + b)} \tag{6}$$

In the above equation, the parameter N represents the number of training samples. Additionally, x_i is the input vector with the label $y_i \in \{-1, +1\}$, where -1 and +1 correspond to the two classes, respectively. The term $K(x_i, x)$ is the main mapping function that transforms the input vectors into an extended feature space, known as the kernel function [15]. The coefficients a_i are obtained by solving the following quadratic optimization problem:

$$\boldsymbol{L(a) = \sum_{i=1}^{N} a_i - (\tfrac{1}{2})\sum_{i=1}^{N}\sum_{j=1}^{N} a_i a_j y_i y_j K(x_{i,} x_j)} \tag{7}$$

$$\boldsymbol{\sum_{i=1}^{N} a_i y_i = 0} \tag{8}$$

The kernel function $K(x_i, x_j)$ can be expressed as $K(x_i, x) = \varphi(x).\varphi(x_i)$, where $\varphi(x)$ represents the feature vector in the expanded feature space, which may have infinite dimensions. Commonly used kernel functions include linear, Gaussian, sigmoid, polynomial, and radial basis function (RBF) kernels. In this study, the following Gaussian kernel function is employed:

$$\boldsymbol{K}(\boldsymbol{x_i}, \boldsymbol{x}) = \boldsymbol{exp}\left(\sum_i \frac{(x_i - x_j)^2}{2\sigma_i^2}\right) \tag{9}$$

6. EVALUATION METRICS

In this study, the performance of the proposed method is evaluated using quantitative parameters such as Accuracy, Sensitivity (TPR), and Specificity (FPR). These evaluation metrics are calculated as follows [16]:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \times \mathbf{100} \tag{10}$$

$$\boldsymbol{TPR} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \times \mathbf{100} \tag{11}$$

$$\boldsymbol{FPR} = \frac{\boldsymbol{FP}}{\boldsymbol{FP+TN}} \times \mathbf{100} \tag{12}$$

In equations (11), (12), and (13), the parameters TP represent the number of true positives, FN represents the number of false negatives, FP represents the number of false positives, and TN represents the number of true negatives.

7. CONCLUSION

A total of 137 pregnancy contractions and 137 labor contractions were used to test this method. Initially, each signal was decomposed at three levels of the wavelet packet tree using Symlet5 as the mother wavelet. Then, 8 components related to energy values from the third level of the wavelet packet decomposition were calculated for each signal. To reduce the input dimensions, PCA was applied to the 8 components, and the data was transferred to a 2-dimensional space. These data were then used as input for training the classifier. In this study, the classification results based on the evaluation metrics mentioned earlier are provided in Table 1. This table shows that 86% of the contractions were correctly classified. This high percentage of correct classification demonstrates the effectiveness of the proposed method in detecting preterm labor as a suitable approach.

Detecting both preterm and non-preterm labor is a complex task. Our study highlights the significance of analyzing uterine electromyogram signals in monitoring pregnancy and detecting labor. The results of our study indicate that energy distribution analysis is a good method for classifying abdominal electromyogram signals. Wavelet packet energy is suitable for classifying these signals when energy distribution between the two classes changes. The proposed method significantly aids in identifying patients suspected of preterm labor. The ultimate goal is to improve the accuracy of classifying uterine electromyogram signals to assist in the detection of preterm labor.

Table 1. Labor and pregnancy contraction classification parameters

Certainty	Sensitivity	Classification accuracy	Data
% 82.9	% 87.8	% 86	**Total contractions**

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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