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Detection of preterm labor by partitioning and clustering the EHG signal

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ABSTRACT

This study aims to predict the risk of preterm labor by analyzing electrohysterogram (EHG). To this purpose, the Term-Preterm EHG Database (TPEHG Database) with 300 EHG signals from pregnant women that are categorized into two classes of term (262) and preterm (38) has been taken into account. This research proposes an algorithm based on time-frequency analysis and thresholding methods for quantitative estimation of uterine contractions. This estimation dismantles the EHG signals into small segments where each segment refers to an event. Then, Linear Predictive Coding (LPC) is applied to extract features from these segments. This study also presents a new approach for classification of term and preterm signal records. To this end, the events were clustered using an unsupervised clustering method and then each cluster was categorized independently to detect term and preterm births. As a result, it was possible to omit the unrelated segments of each record using this approach. The results indicate a significant improvement in separability and accuracy in the preterm birth detection index.

1. Introduction

The birth of a baby before 37 weeks of gestational age is known as preterm birth and is the cause of most neonatal deaths [1]. Evaluation of a mother's circumstances can help doctors predict preterm births; even so, preterm deliveries usually occur spontaneously without apparent reasons. Because the causes of spontaneous preterm labor are not clear, there are no treatments for this condition. Some studies,however, have indicated that uterine activity may be employed to distinguish preterm and term labor before the delivery time [2,3]. Electrohysterogram (EHG) is a more accurate and reliable method for monitoring the electrical activity of a uterus than other procedures like tocography and intrauterine pressure monitoring [4–6]. EHG also provides the required information on uterine activity to model contractions [7,8].

Extracting proper features from the EHG signal is the first step to predict a preterm birth. Most studies have considered each record of the EHG signal as one event and all signal samples were used in feature extraction. Median frequency is said to be one of the most useful features to determine whether delivery will be term or preterm [9]. Peak frequency is known as the most useful parameter to predict true labor [10]. Features such as nonlinear correlation [11], sample entropy [12], and the Adaptive Autoregressive (AAR) model for estimating EHG signal spectrograms [13] are also popular for analyzing the EHG.

However, there are also various methods available that can extract features from the wide variety of signals that have been used in different fields of engineering and natural sciences. One of these tools is Linear Predictive Coding (LPC) which is widely used in audio signal processing. LPC uses a linear predictive model to represent the spectral envelope of a signal [14]. The LPC coefficients are calculated from a number of poles that describe the behavior of a signal. On the one hand, since the EHG is a non-stationary signal, extracting one feature vector for the entire time of the record is not precise and may lead to inaccurate results. Hence, a few studies dismantle the signal into segments that are stationary and refer to a distinctive clinical event [15–17]. Dismantling the signal into segments can be done using detection theory [18]. Hysteresis thresholding with two basal tones and detection levels is proposed by Jezewski et al. [19,20]. Thus far, events of uterine activity during pregnancy have been categorized as contractions, Alvarez waves, fetal movements and Long Duration Low Frequency (LDBF) waves [21].

Since the classical way of solving detection problems, in which every event is well identified and indexed clinically, is not available in EHG databases, an unsupervised method can be useful to cluster the events. Studies [16,17,21] have utilized the assessment of experts to label uterine activity during pregnancy.

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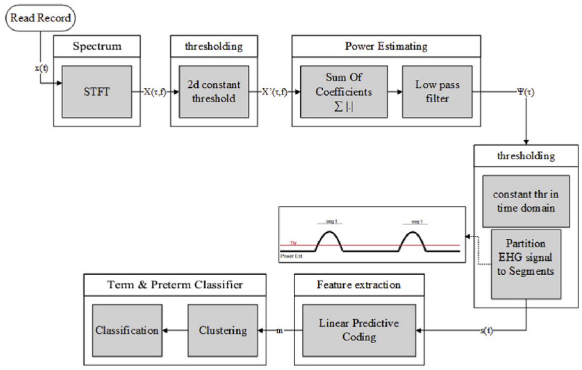

Fig. 1. Block diagram of the proposed algorithm.

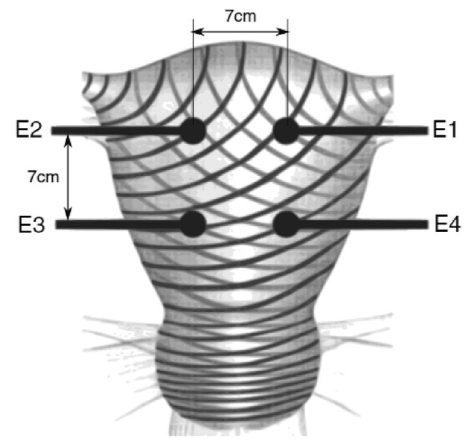

Fig. 2. The placement of the electrodes on the abdomen, above the uterine surface. Channel 1: E2–E1, Channel 2: E2–E3, Channel 3: E4–E3 [9].

Some studies have focused on detecting preterm risk by classifying term and preterm [22,23,17]. Classification based on Artificial Neural Networks (ANNs) is often applied in medical articles [24]. In [22] seven different artificial neural networks were used to detect preterm births. In another classification method for the EHG, a dynamic self-organized network immune algorithm, which classifies term and preterm records, was presented in [23]. Other classifiers, such as Support Vector Machines (SVMs) with the wavelet decomposition for feature extraction, have been examined to classify non-stationary signals of uterine Electromyography (EMG) [17].

In this study, an algorithm based on time-frequency and thresholding methods was proposed for quantitative estimation of uterine contractions based on EHG signal energy. This estimation was used to dismantle signals into a number of smaller segments, each of which referred to an event. Then, Linear Predictive Coding (LPC) was applied for the first time to extract features of the EHG. A new classification method was also utilized to differentiate between term and preterm signal records.

This paper is organized as follows. In Section 2, the utilized database and the method of segmentation are presented in the first subsection and feature extraction and the proposed classifier are specified. The results are set forth in Section 3. Discussion and conclusion are presented in Sections 4 and 5, respectively.

2. Method

A block diagram of the proposed method is shown in Fig. 1. In this block diagram, according to the energy of the EHG signal, each record is first separated into a number of segments. Then, term and preterm are categorized using a new approach to classification and feature extraction. The description of each block is elaborated below.

2.1. Signal description

In the field of EHG, some studies have recorded their own databases [25,3], while some others have used available free databases. Just two free access EHG databases have been published through the Physionet.org platform: the Icelandic 16- Electrode EHG database [26] and the Term-Preterm EHG Database (TPEHG database) [9]. Since the Icelandic database had only one preterm EHG signal record, it was not suitable for this study; therefore the TPEHG database was used. The EHG signals in the TPEHG database were recorded from 300 pregnant women utilizing four electrodes with 20Hz sampling frequency at the University Medical Centre of Ljubljana. The electrodes were noninvasively placed; in a 2×2 grid on the abdomen of the women, spaced 7 cm apart (Fig. 2). In order to obtain a better Signal to Noise Ratio (SNR) for this database, the EHG bipolar signal was measured between electrodes (E2–E1), (E2–E3) and (E4–E3).

The 300 EHG records were grouped as follows:

- Term: 262 electrohysterogram from the period of pregnancy of women who delivered during or after the 37th week of gestation. This group has two subgroups:
  - 143 early recordings: before the 26th week of gestation
  - 119 late recordings: during or after the 26th week
- Preterm: 38 electrohysterogram from the period of pregnancy of women who delivered before the 37th week. This group also has two subgroups:
  - 19 early recordings
  - 19 late recordings

Some studies employed all the channels and compared the results between channels [15,23,27]. Other studies found more accurate results from Channel 3: E4–E3 [22,23,27,9]. Therefore, this research made use of this channel as well.

The TPEHG database also includes clinical information consisting of record number, pregnancy duration, gestational age at the time of recording (rectime), maternal age, number of previous deliveries (parity), previous abortions, weight at the time of recording, hypertension, diabetes, placental position, bleeding during the first trimester, bleeding during the second trimester, funneling and smoking.

2.2. Signal segmentation

As discussed, we expected the EHG signal to consists of uterine contractive activity, Alvarez waves, fetal movements and LDBF waves along with noise from numerous different sources [21,16]. All these events, however, might not be related to preterm labor and might not be observed during each record. Therefore, if these events are grouped based on their similarities, the term and preterm categories can be classified accurately by eliminating unrelated groups. Regarding these hypotheses, the EHG signal was separated into segments each of which was expected to become stationary in its duration and refer to an event.

Uterine pressure is a good candidate for segmentation of the EHG signal. Intrauterine pressure is directly related to uterine contractions and can be utilized to segment the EHG signal. Several methods have been developed to detect intrauterine pressure from the EHG signal. The algorithm based on calculating the root mean square (RMS) envelope had shown a high correlation between the patterns of estimated contractions and contractions in tocograms