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Time-Frequency Analysis of Electrohysterogram for Classification of Term and Preterm Birth

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** Short Paper*

***Abstract*:** In this paper, a novel method for the classification of term and preterm birth is proposed based on time-frequency analysis of electrohysterogram (EHG) using multivariate empirical mode decomposition (MEMD). EHG is a promising study for preterm birth prediction, because it is low-cost and accurate compared to other preterm birth prediction methods, such as tocodynamometry (TOCO). Previous studies on preterm birth prediction applied prefilterings based on Fourier analysis of an EHG, followed by feature extraction and classification, even though Fourier analysis is suboptimal to biomedical signals, such as EHG, because of its nonlinearity and nonstationarity. Therefore, the proposed method applies prefiltering based on MEMD instead of Fourier-based prefilters before extracting the sample entropy feature and classifying the term and preterm birth groups. For the evaluation, the Physionet term-preterm EHG database was used where the proposed method and Fourier prefiltering-based method were adopted for comparative study. The result showed that the area under curve (AUC) of the receiver operating characteristic (ROC) was increased by 0.0351 when MEMD was used instead of the Fourier-based prefilter.

***Keywords*:** Preterm birth, Time-frequency analysis, MEMD

1. Introduction

Preterm birth is one of the major threats on an infant's life and health. Approximately 1% of all births on the globe are preterm, and more than 70% of infant mortality and morbidity are due to preterm birth [1]. If a patient is predicted to have preterm labor in advance, extensive medical care can be provided to prevent the preterm birth or related illnesses. On the other hand, a reliable method for predicting preterm birth is as yet unavailable [2].

Currently, tocodynamometry (TOCO) is used widely for the prediction of preterm birth. Using TOCO, preterm birth is diagnosed by monitoring the uterine contractions [2]. On the other hand, a preterm birth prediction using TOCO is inaccurate due to the low sensitivity of the tocodynamometry, and huge variations of the diagnosis from practitioners [2].

A prediction of preterm birth using non-invasive Electrohysterogram (EHG) is a highly efficient and accurate method compared to the conventional prediction methods including TOCO [2]. EHG is an electrical activity on uterine myometrium with a 0.04−0.5mV amplitude and 0−1Hz frequency [3]. Owing to the advancement of signal processing techniques and computing power, the preterm birth prediction by an analysis of the EHG becomes the most reliable and cost-effective method.

Conventional methods on preterm birth prediction using EHG typically utilize Fourier-based prefilters, which are suboptimal to nonlinear and nonstationary signals, such as EHG. Therefore, this paper proposes a novel preterm birth prediction method that applies multivariate empirical mode decomposition (MEMD) to prefilter EHG. MEMD is a time-frequency analysis technique that has been proven to be optimal for analyzing nonlinear and nonstationary signals [4]. The proposed method extracts sample entropy (SampEn) feature from the prefiltered data and classifies the term and preterm group with SampEn features.

An experiment on the proposed method was performed using the Physionet EHG database (TPEHG database). For a comparative study, an infinite impulse response (IIR) prefilter with a similar frequency response to that of MEMD was used. The experimental result showed that the

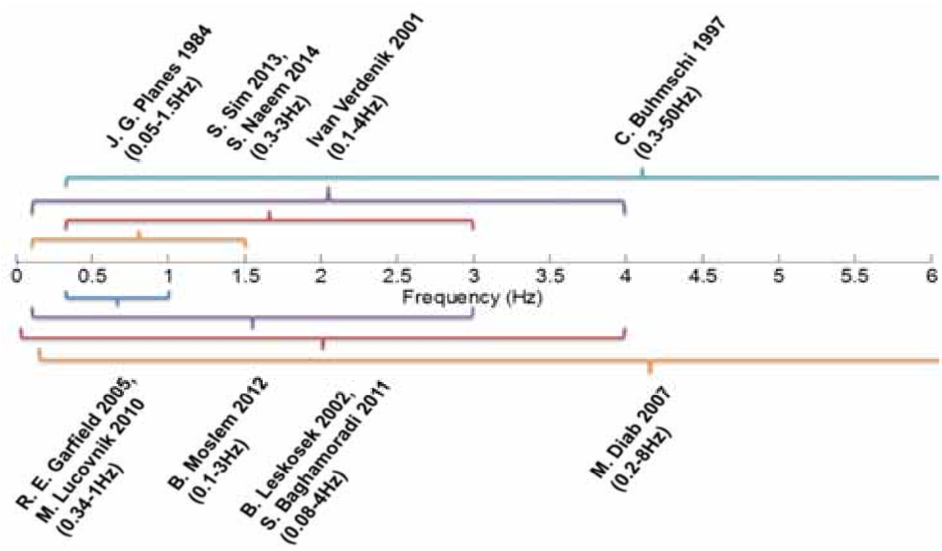

Fig. 1. Prefilter passbands of previous studies on EHG.

area under curve (AUC) of the receiver operator characteristic (ROC) curve of the proposed method was 0.0351 higher than that using the IIR filter.

This paper is organized as follows. Chapter 2 reviews previous studies on the preterm birth predictions using EHG, chapter 3 describes the proposed preterm birth prediction method with MEMD, chapter 4 presents the experiment process with the Physionet EHG database, chapter 5 provides the experiment results and chapter 6 concludes the paper.

2. Preterm Birth Prediction via Electrohysterogram

Conventional preterm birth prediction methods using EHG adopt Fourier-based lowpass or bandpass filters for preprocessing. The features extracted after the prefiltering are root mean square, variance, log detector, mean frequency, median frequency, peak frequency, spectral moment, frequency ratio, approximate entropy, sample entropy, maximal Lyapnov exponent, etc. [3, 6-24]. The classification methods used in conventional methods include the artificial neural network, K-nearest, decision tree, Parzan classifier, etc. [6, 11, 13, 20, 24, 25].

Fig. 1 illustrates the passbands of prefilters used in conventional preterm birth prediction methods using EHG. The passbands of these filters vary widely; Garfield et al. used 0.34–1Hz [6], Planes et al. used 0.05–1.5Hz [7], Moslem et al. used 0.1–3Hz [9], Baghamoradi et al. and Leskosek et al. used 0.304–3Hz [11, 18], Sim et al. and Naeem et al. used 0.08−4Hz [12, 14], Verdenik et al. uses 0.1 − 4Hz [16], and Diab et al. uses 0.2 − 8Hz [19]. Considering that these studies investigated numerous features and classification methods, the wide variety of prefilter bands suggest that Fourier-based prefilters are unable to properly decompose the EHG signals, due to their nonlinearity and nonstationarity.

3. The Proposed Preterm Birth Prediction Method

This section proposes a preterm birth prediction method using MEMD as the prefilter. MEMD is a time-frequency analysis technique that analyzes the signal without an assumption of sinusoidal basis functions, which enables MEMD to decompose the EHG signals and other nonlinear and nonstationary signals more accurately. After prefiltering, the sample entropy feature is extracted from the prefiltered signal and the binary classifier is applied.

The Physionet EHG database is used to evaluate the proposed method. The Physionet database provides 300 term and preterm subjects, each of which includes a single trial with a three-channel signal. The database provides three variations of these signals with different prefilterings with a passband frequency of 0.08–4Hz, 0.3–4Hz and 0.3–3Hz. In this paper, the 0.08–4Hz prefiltered signals were used to preserve low frequency components. Fig. 2 shows

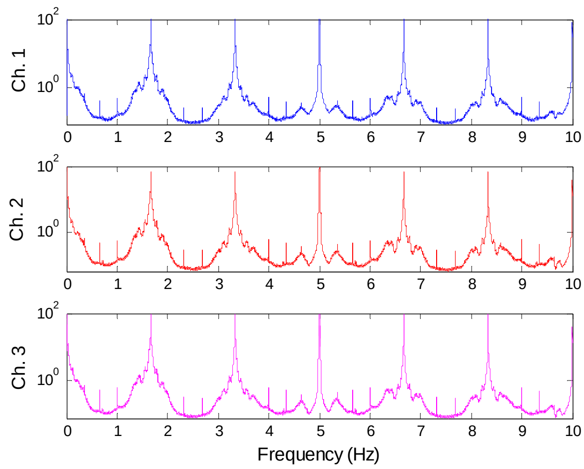

Fig. 2. Average power spectra of the Physionet database.

the averaged power spectra of 0.08–4Hz prefiltered, three-channel signal. The power spectra were averaged over all subjects. In all three channels, strong cardiac signals were evident over 1Hz, which indicates that the signal requires further prefiltering.

3.1 Multivariate Empirical Mode Decomposition

To remove the cardiac signals and other noise from EHG, the proposed method adopted prefiltering using MEMD. MEMD is a time-frequency analysis technique that is optimal for nonlinear and nonstationary signals. MEMD is fully data-driven without sinusoidal basis functions, whose algorithm is described in Table 1 and [4].

In this study, n = 3 because the data is three-channel signal. MEMD decomposes EHG data into several intrinsic mode functions; MEMD of the Physionet database gave 15 to 18 IMFs. To avoid the mode mixing problem, noise-assisted MEMD is used, where a Gaussian noise channel is added to the signal before MEMD is applied and discarded after the decomposition is complete. The amplitude of noise is 0.1 times the standard deviation of the EHG signal, which is averaged over three channels.

Fig. 3 shows the noise-assisted MEMD of a Physionet data (TPEHG546), the first channel and only a portion of 50 seconds from the start. Figs. 3(a) and (b) show the raw signal and its 16 IMFs generated by MEMD, respectively. Since MEMD is fully data-driven, the frequency bands of each IMF can be changed by input signals. On the other hand, as shown in Fig. 3(b), IMFs with higher numbers always represent lower frequency components. Fig. 4 shows the power spectra of each IMF of the MEMDs of the Physionet database. The proposed method uses the sum of the 5th to 8th IMFs, because its power spectrum resides within the expected frequency band (0–1Hz) of EHG and it

Table 1. The MEMD algorithm.

1. Choose a suitable point set for sampling on an $(n-1)$ sphere.
2. Calculate a projection, denoted by $\{p^{\theta_k}(t)\}_{t=1}^{T}$, of the input signal $\{\mathbf{v}(t)\}_{t=1}^{T}$ along the direction vector $\mathbf{x}^{\theta_k}$, for all k (the whole set of direction vectors), giving $\{p^{\theta_k}(t)\}_{t=1}^{K}$ as the set of projections.
3. Find the time instants $t_j^{\theta_k}$ corresponding to the maxima of the set of projected signals $\{p^{\theta_k}(t)\}_{t=1}^{K}$.
4. Interpolate $[t_j^{\theta_k}, \mathbf{v}(t_j^{\theta_k})]$ to obtain multivariate envelop curves $\{e^{\theta_k}(t)\}_{t=1}^{K}$
5. For a set of K direction vectors, calculate the mean $\mathbf{m}(t)$ of the envelop curves as $\mathbf{m}(t) = 1/K\ \sum_{k=1}^{K} e^{\theta_k}(t)$.
6. Extract the "detail" $\mathbf{c}_i(t)$ using $\mathbf{c}_i(t) = \mathbf{v}(t) - \boldsymbol{m}(t)$ (i is an order of IMF). If the "detail" $\mathbf{c}_i(t)$ fulfills the stoppage criterion for a multivariate IMF, apply the above procedure to $\mathbf{v}(t) - \mathbf{c}_i(t)$, otherwise apply it to $\mathbf{c}_i(t)$

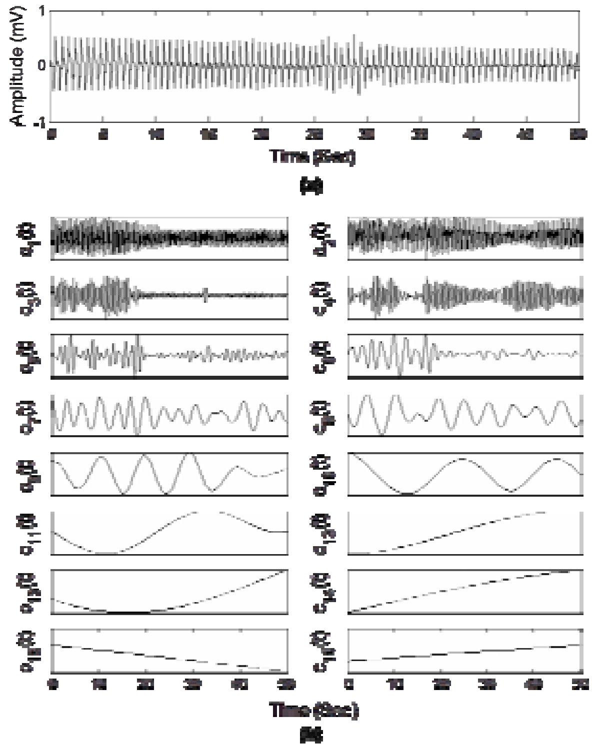

Fig. 3. Physionet EHG signal and its MEMD (a) EHG signal, (b) 16 IMFs generated by MEMD of signal in (a).

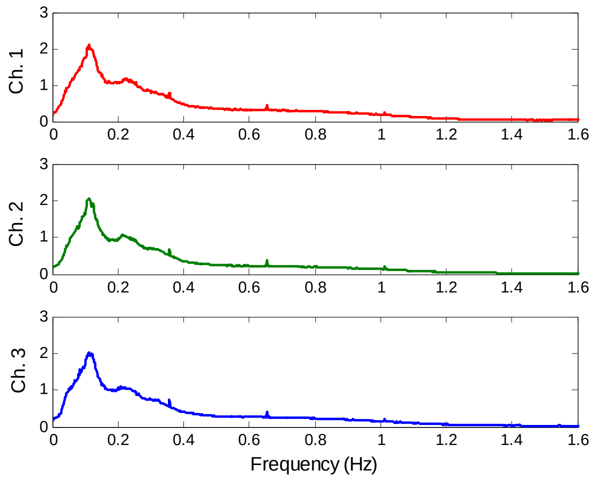

Fig. 4. Power spectra of the sum of IMFs from the 5th to 8th.

yields the optimal classification performance. Fig. 5 shows the averaged power spectra of each IMF from the Physionet database. As the figure shows, the peaks of the power spectrum of IMF 5, 6, 7, and 8 reside within the 0–1Hz band.

3.2 Feature Extraction

The proposed method extracts sample entropy feature from the prefiltered signals. SampEn is one of the most widely used and reliable features in the previous studies [8, 11-15, 17]. Before feature extraction, a portion of 1.5

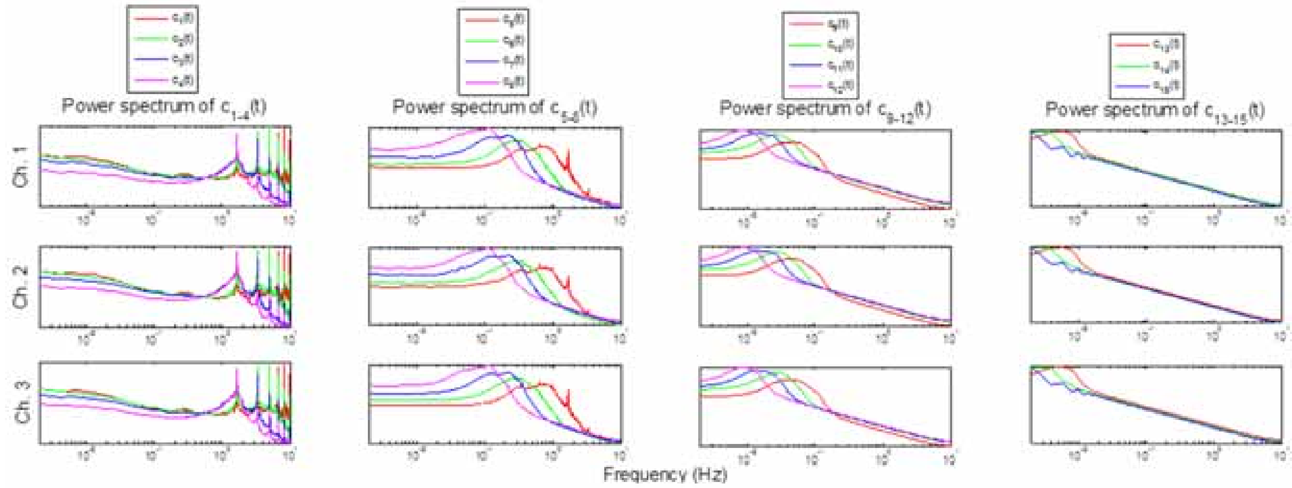

Fig. 5. Power spectra of the MEMD IMFs generated from the Physionet EHG database

minutes of both ends of a signal is removed to remove the bidirectional filtering effects. Principle component analysis (PCA) is applied to remove the multi-channel redundancy and only one principle component is used for feature extraction.

The sample entropy is a measurement to indicate how predictable the signal is, whose definition is as follows.

$$SampEn(m,r,t) = -log\left(\frac{C_m + 1}{C_m}\right) \quad (1)$$

m, r and t represent the dimension, tolerance and down-sampling ratio, respectively. Downsampling is performed before calculating C_m, which reduces an input signal with N samples to a downsampled signal with N/t samples. C_m is a number of m-sampled segment pairs in a downsampled signal, whose Chebyshev distance between two segments are less than the tolerance, r. As the signal becomes increasingly unpredictable, SampEn tends to be higher.

3.3 Classification

The linear classifier is used to classify the term and preterm group. Since the feature is a scalar value, classification can be achieved simply by thresholding these features.

Fig. 6 shows the distribution of the sample entropy features from both term and preterm groups. Figs. 6(a) and (b) shows the term/preterm group feature distributions extracted from MEMD and IIR prefiltered data, respectively. The SampEn parameters for feature extraction were $m = 2$, $r = 2\sigma$, $t = 20$ where σ is a standard deviation of the EHG signal. As shown in the figure, the sample entropy features from the MEMD prefiltered signal follow the Gaussian distribution, and the features from the FIR filtered signal follow the exponential distribution. In both MEMD and FIR cases, the SampEn features from preterm birth have lower expectation compared to term birth. Therefore, the classifier in the proposed method labels the SampEn features with a value lower than the threshold as preterm.

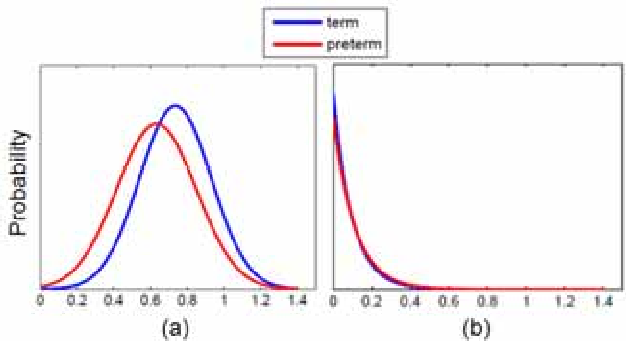

Fig. 6. Sample entropy feature distributions (m = 2, r = 2σ, t = 20) prefiltered by (a) MEMD, (b) FIR.

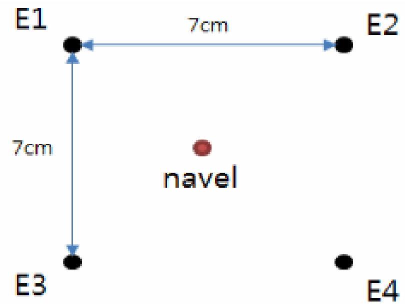

Fig. 7. Placement of the electrodes in a Physionet EHG recording.

4. Experiment

This study used Physionet EHG database, which includes 262 term and 38 preterm patients. Fig. 7 shows the electrodes placement used in the Physionet EHG database recording, which used four electrodes around the navel to obtain a three-channel signal. To eliminate the effect of the biased data, 100 trials were conducted, where each trial randomly selects 38 term patients among 262 patients and conducts the experiment on the balanced dataset. The experiment procedure is described in Table 2.

Table 2. Experimental procedure.

1.	Randomly select 38 term patients among 262 term patients
2.	Extract SampEn from the EHG signals of the 38 term patients and 38 preterm patients
3.	Calculate an ROC curve from 76 features using linear classifier
4.	Repeat **Step 1** to **Step 3** 100 times
5.	Calculate the averaged ROC curve from 100 trials

Table 3. Performance of the linear classifiers.

	MEMD	IIR
Area under ROC	0.6049	0.5698

For a comparative study, an additional experiment is conducted where the IIR filter (5th order Butterworth) replaces MEMD. The Passband of IIR filter is 0.4–1Hz, which is similar to the power spectra of the 5-8th IMFs in Fig. 5. As a result, the experiment procedure in Table 2 is performed twice (using MEMD and IIR filter).

The performance of the proposed method using MEMD and the conventional method with the IIR filter were evaluated by analyzing their ROC curve. As there were 100 random trials for each method, the true positive rate (TPR) and false positive rate (FPR) were averaged over 100 trials to obtain the averaged ROC curve for each method. The AUC of the averaged ROC was used as a performance measure.

5. Results

The performance of the proposed method was measured by the ROC curve. The ROC curve portrays the performance of the classifier by plotting the true positive rate (TPR) against false positive rate (FPR). TPR is the ratio of the correctly labeled preterm data (true positive) among all the preterm data. Similarly, FPR is the ratio of correctly labeled term data (false positive) among all the term data. The formal definition of the TPR and FPR are as follows.

$$\text{True positive rate}\left(\text{TPR}\right)=\frac{\text{True positive}\left(\text{TP}\right)}{\text{Positive}\left(\text{P}\right)} \quad (2)$$

$$\text{False positive rate}\left(\text{FPR}\right)=\frac{\text{False positive}\left(\text{FP}\right)}{\text{Negative}\left(\text{N}\right)} \quad (3)$$

TP (FP) is the number of preterm datasets (term) that are correctly labeled as preterm (term), and P (N) is the number of preterm (term) datasets. P and N are both fixed to 38 in Table 2. TP and FP change according to the threshold set in the linear classifier.

Fig. 8 shows the ROC curves drawn by the proposed method using MEMD and he IIR filter. The performance of the classifiers in the ROC curve is typically determined by the AUC of ROC. Table 3 lists AUCs of the classifiers

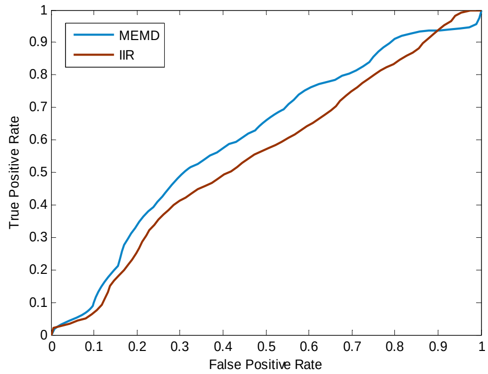

Fig. 8. ROC curves of the linear classifiers using the features extracted from the MEMD and IIR prefiltered signals.

with MEMD and IIR, which shows that the AUC of the proposed method is 0.0351 higher than the other. .

6. Conclusion

In this paper, a novel method of preterm birth prediction by time-frequency analysis of an EHG using MEMD was proposed. The proposed method analyzed the EHG signals using MEMD, which is the optimum for nonlinear and nonstationary biomedical signal processing compared to the conventional Fourier-based prefilters. The proposed preterm birth prediction method extracted the sample entropy features from the MEMD prefiltered signals and classified the term and preterm groups using the linear classifier. The experiment using a randomly chosen dataset from the Physionet EHG database showed that the AUC of the ROC curve of the proposed method using MEMD was 0.0351 higher than that using the conventional method with an IIR filter.

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