Examination of Single Wavelet-Based Features of EHG Signals for Preterm Birth Classification

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***Abstract*—In this study, wavelet-based features of electrohysterogram (EHG) quantifying the electrical activity of uterine muscles are applied for preterm birth classification. EHG has been shown to provide useful information for uterine contraction that leads to the anticipation of delivery. A wavelet-based feature referred to as Δ_l in this study is determined from a difference between the logarithms of variances of detail coefficients of EHG data corresponding to two consecutive levels, i.e., l and $l+1$. Performance on preterm birth classifications using single wavelet-based features of EHG data is examined. A simple thresholding technique is applied for preterm birth classifications. The leave-one-out cross validation is used to validate the performance on preterm birth classifications. From the computational results, it is shown that the wavelet-based features of EHG can provide a reasonable performance on preterm birth classification with the accuracy, the sensitivity and the specificity of 0.7099, 0.6842 and 0.7133, respectively.**

***Index Terms*—electrohysterogram, preterm birth, pregnancy, wavelet analysis, classification**

I. Introduction

The discrete wavelet transform is one of the most significant computational tool that has been applied to various applications including biomedical signal processing. The discrete wavelet transform is a natural tool for characterizing self-similar signals [1], [2]. The derivation of the discrete wavelet transform for the representation of $1/f$ processes [1], [3] makes the discrete wavelet transform can be further applied into the fields of fractals and complex systems analysis. Recently, computational tools and techniques applied for complex systems analysis have been widely applied to applications in biology and medicine [4]. One of those various applications in biology and medicine is cardiology where a number of measures derived from concepts of complex systems analysis applied to characterize heart rate variability (HRV).

In Ref. [4], the wavelet-based approach is applied to extract features of RR interval data for congestive heart failure classification. Such wavelet-based feature of RR interval data is demonstrated to be potentially a good feature for the congestive heart failure classification [4]. The similar wavelet-based approach is also applied for examining the characteristics of epileptic ECoG signals in Ref. [5]. In this study, the wavelet-based approach examined in Ref. [4] is applied to the so-called electrohysterogram (EHG) data for preterm birth classification. The EHG data correspond to the activity of uterine muscles [6] whereas the activitiy of uterine muscles of pregnant women may be used to predict the premature onset of labor [7], [8]. Preterm birth has been one of the most important issues worldwide. Prematurity is the leading cause of newborn deaths [9]. An estimated 15 million babies are born preterm every year [9]. In addition, this number is rising [9]. The preterm prediction and detection are therefore essential as they can help prevent preterm birth. Performance on preterm birth classifications using single wavelet-based features of EHG data extracted using the wavelet-based approach [4] is examined.

The rest of this paper is organized as follows. Section II presents data, wavelet-based feature extraction, and experimental setup. Section III details and discusses the computational results on preterm birth classifications. Finally, Section IV summarizes and concludes the paper.

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II. Methods

A. Data and Subjects

The electrohysterogram (EHG) data examined in this study is obtained from the Term-Preterm EHG Database (TPEHGDB) on PhysioNet (available online at http://www.physionet.org/physiobank/database/tpehgdb/). The TPEHGDB contains 300 recordings of EHG data collected from 1997 until 2006 at the Department of Obstetrics and Gynecology, Medical Centre Ljubljana, Ljubljana [6], [10]. The EHG data were recorded from a general population of pregnant women during regular check-ups either around the 22nd week of gestation or around the 32nd week of gestation [6], [10]. The EHG data were recorded using the sampling frequency of 20 Hz. Each EHG recording is composed of three channels, referred to as s_1, s_2, and s_3, which were recorded from 4 electrodes placed around the navel [6], [10].

All three hundred EHG recordings are classified into four groups according to their corresponding time of delivery (either term or preterm birth) and time of recordings (either early or later period of pregnancy). EHG recordings are classified as *term birth* if the delivery was after the 37th week of gestation; and *preterm birth* otherwise. EHG recordings are classified as *early period* if they were recorded before the 26th week of gestation; and *later period* otherwise. The EHG recordings that were recorded before the 26th week of gestation and on the the 26th week of gestation or after for the pregnancy with term birth are referred to as TE and TL groups, respectively. Likewise, the EHG recordings that

TABLE I
THE NUMBER OF EHG RECORDINGS

	Early period	Later period
Term birth	143	119
Preterm birth	19	19

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were recorded before the 26th week of gestation and on the the 26th week of gestation or after for the pregnancy with preterm birth are referred to as, respectively, PE and PL groups. The numbers of EHG recordings corresponding to each group are summarized in Table I.

B. The Wavelet-Based Features

The discrete wavelet transform (DWT) is applied to decompose an EHG signal into subband components through halfband lowpass and highpass filters. Approximations and details are obtained from the discrete wavelet decomposition using the scaling function and the wavelet function that correspond to, respectively, halfband lowpass filter and halfband highpass filter. For the L-level discrete wavelet decomposition, there are L sets of detail coefficients, i.e., d_l for $l = 1, 2, \ldots, L$, and one set of approximation coefficients, i.e., a_L, obtained. Only the detail coefficients d_l are however used.

The wavelet-based features of EHG signals examined in this study can obtained by the following steps [4]:

1) Apply the discrete wavelet transform to decompose an EHG signal into L levels to obtain the detail coefficients d_l;
2) Compute the variance of detail coefficients d_l corresponding to each level l, $\operatorname{var}(d_l)$;
3) Take the logarithm to base 2 of the corresponding variance of detail coefficients, $\log_2 \operatorname{var}(d_l)$;
4) Subtract the logarithm of variance of detail coefficients corresponding to the level l from that corresponding to the lower level, $\Delta_l = \log_2 \operatorname{var}(d_{l+1}) - \log_2 \operatorname{var}(d_l)$.

C. Experimental Setup

A segment with length of 8192 samples is obtained from the middle section of each channel of EHG recordings, i.e., s_1, s_2, and s_3. The 12th order Daubechies wavelets are applied to decompose EHG segments into 7 levels yielding 7 detail coefficients d_1, d_2, …, d_7 and one approximation coefficient a_7. The coefficients d_1, d_2, d_3, d_4, d_5, d_6, d_7, and a_7 approximately correspond to 5.0–10.0-Hz, 2.50–5.0-Hz, 1.25–2.50-Hz, 0.63–1.25-Hz, 0.31–0.63-Hz, 0.16–0.31-Hz, 0.08–0.16-Hz, 0-0.08-Hz subbands, respectively. Accordingly, there are 6 wavelet-based features, i.e., Δ_1, Δ_2, …, Δ_6, extracted from each EHG segment. Two classifications examined focus on discriminating between pregnancies with term birth and pregnancy with preterm birth. In the first preterm birth classification, single wavelet-based features of EHG segments associated with the TE and PE groups are classified. Single wavelet-based features of EHG segments associated with the TL and PL groups are classified in another preterm birth classification. A thresholding technique is applied for classifying single wavelet-based features into either a term birth pregnancy or a preterm birth pregnancy.

A leave-one-out (LOO) cross-validation is used to validate the performance on the preterm birth classifications as the numbers of EHG recordings associated with the PE and PL groups are small. A threshold τ is obtained from a training set composed of single wavelet-based features of both positive (EHG segments associated with preterm birth pregnancy) and negative (EHG segments associated with term birth pregnancy) classes except a wavelet-based feature of one EHG segment. The left-out wavelet-based feature is used as a testing sample. This process is repeated to include all samples of wavelet-based features as the testing sample. A threshold τ is determined from the training set of wavelet-based features Δ_l as follows [11]:

$$\tau = \begin{cases} \frac{\max M_P + \min M_N}{2} & \text{if } \bar{M}_P < \bar{M}_N \\ \frac{\min M_P + \max M_N}{2} & \text{if } \bar{M}_P > \bar{M}_N \end{cases} \quad (1)$$

where M_P and M_N denote the wavelet-based features Δ_l corresponding to positive and negative classes, and $\bar{M}_P$ and $\bar{M}_N$ denote the means of wavelet-based features Δ_l corresponding to positive and negative classes, respectively. The classification is simply performed using the following rules [11]. In the first case, i.e., $\bar{M}_P < \bar{M}_N$, an EHG segment is classified to belong to a positive class if the corresponding wavelet-based feature Δ_l is less than or equal to the threshold τ; and a negative class, otherwise. On the contrary, in another case, i.e., $\bar{M}_P > \bar{M}_N$, an EHG segment is classified to belong to a positive class if the corresponding wavelet-based feature Δ_l is greather than or equal to the threshold τ; and a negative class, otherwise.

The performance of the preterm birth classifications using single wavelet-based features is evaluted using three conventional measures: accuracy (Ac), sensitivity (Se), and specificity (Sp) given by, respectively,

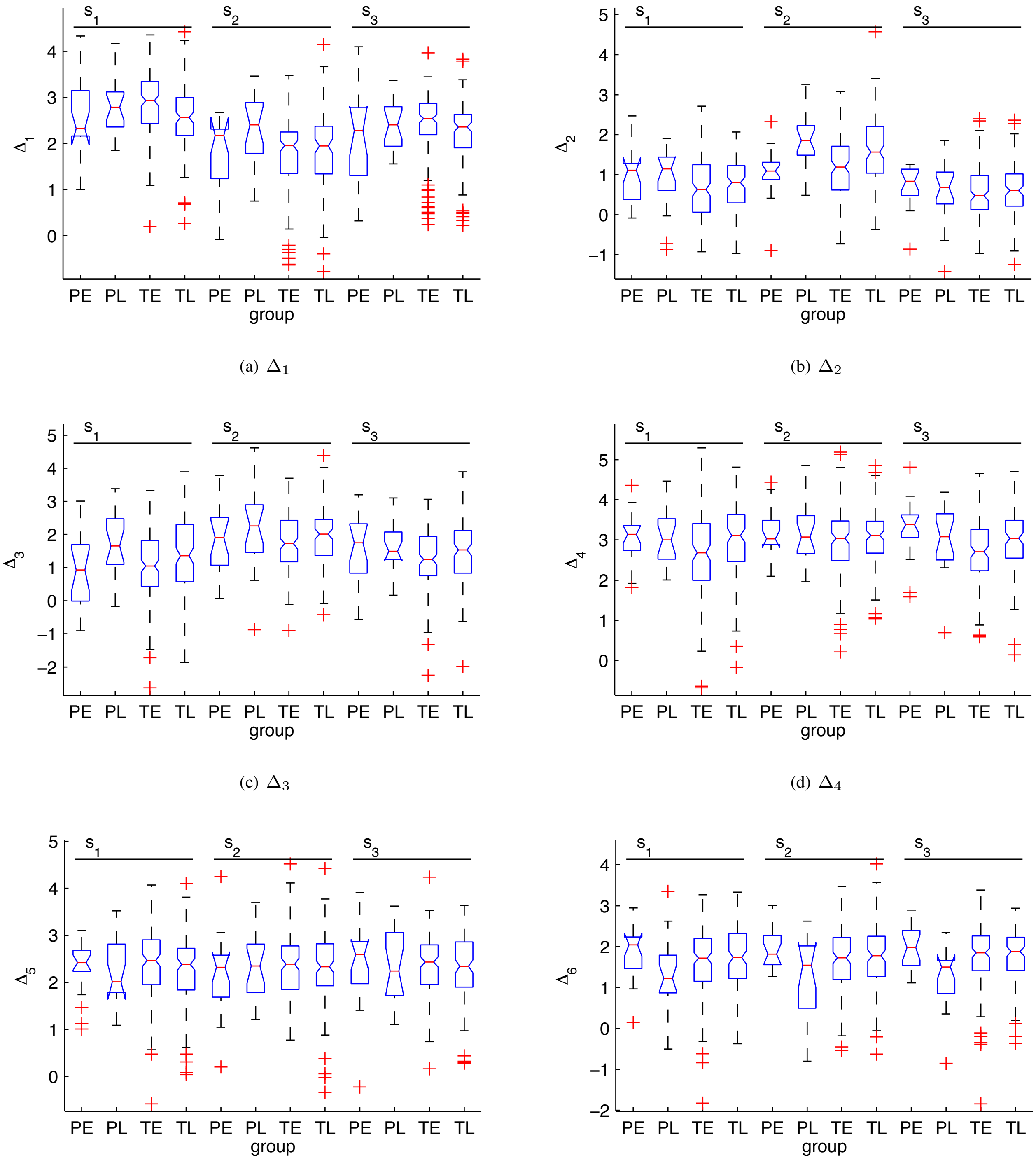
$$Ac = \frac{TP + TN}{TP + TN + FP + FN},$$
$$Se = \frac{TP}{TP + FN}, \text{ and}$$
$$Sp = \frac{TN}{TN + FP},$$

where TP, TN, FP, and FN denote a number of true positives, a number of true negatives, a number of false positives, and a number of false negatives. In addition, the product of sensitivity and specificity, i.e., $Se \times Sp$, is also determined as a performance measure that justifies both the true positive rate and the true negative rate.

The performances on preterm birth classification using other quantitative features including root-mean-square (RMS), median frequency (f_{med}), peak frequency (f_{peak}) and sample entropy (SampEn) provided on the TPEHGDB are also examined and validated using the same procedure. The RMS, median frequency, peak frequency, and sample entropy [6] were determined from filtered EHG signals rather than the original EHG signals. The original EHG signals, i.e., s_1, s_2, and s_3, were filtered using three different 4-pole digital Butterworth bandpass filters with 0.08–4.0-Hz,

TABLE II
THE p-VALUES OF t-TESTS DETERMINING THE SIGNIFICANT DIFFERENCES BETWEEN THE WAVELET-BASED FEATURES OF EHG SEGMENTS.

Feature	PE vs. TE			PL vs. TL		
	s_1	s_2	s_3	s_1	s_2	s_3
Δ_1	0.1692	0.7247	0.0958	0.1144	**0.0334**	0.3756
Δ_2	0.0910	0.4483	0.2411	0.2202	0.3273	0.7419
Δ_3	0.7813	0.8925	0.2714	0.2124	0.3241	0.5735
Δ_4	0.1212	0.5114	**0.0118**	0.8996	0.6346	0.9990
Δ_5	0.5140	0.4565	0.9405	0.9059	0.9413	0.7113
Δ_6	0.2921	0.1829	0.3049	0.0784	**0.0163**	**0.0013**



(a) Δ_1 (b) Δ_2

(c) Δ_3 (d) Δ_4

(e) Δ_5 (f) Δ_6

Fig. 1. Box plots of wavelet-based features Δ_l of EHG segments.

0.3–4.0-Hz and 0.3–3.0-Hz passbands [6] referred to as, respectively, the spectral bands b_1, b_2 and b_3.

III. Results

A. Characteristics of the Wavelet-Based Features

The wavelet-based features Δ_1, Δ_2, ..., Δ_6 of EHG segments associated with all groups, i.e., PE, PL, TE, and TL, are compared in box plots shown in Fig. 1(a)–(f), respectively. The wavelet-based features of EHG segments vary corresponding to level l, channel, and also group. Table II summarizes the p-values obtained from t-tests used to determine whether the wavelet-based features Δ_l of EHG segments associated with the preterm and term births are significantly different from each other. It is shown that there are statistically significant differences between the wavelet-based features Δ_4 of EHG segments of channel s_1 associated with the PE and TE groups, the wavelet-based features Δ_4 of EHG segments of channel s_3 associated with the PE and TE groups, the wavelet-based features Δ_1 of EHG segments of channel s_2 associated with the PL and TL groups, the wavelet-based features Δ_6 of EHG segments of channel s_2

TABLE III
PERFORMANCE ON PRETERM BIRTH CLASSIFICATIONS OF EHG SEGMENTS ASSOCIATED WITH THE PE AND TE GROUPS USING THE WAVELET-BASED FEATURES.

Feature	channel s_1				channel s_2				channel s_3			
	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$
Δ_1	0.7654	0.3684	0.8182	0.3014	0.3889	0.6316	0.3566	0.2252	0.7222	0.4211	0.7622	0.3209
Δ_2	0.7099	0.2105	0.7762	0.1634	0.6049	0.2105	0.6573	0.1384	0.6481	0.5263	0.6643	0.3497
Δ_3	0.7222	0.0	0.8182	0.0	0.5556	0.5263	0.5594	0.2944	0.5247	0.6316	0.5105	0.3224
Δ_4	0.7222	0.1579	0.7972	0.1259	0.7160	0.0	0.8112	0.0	0.7099	0.6842	0.7133	0.4880
Δ_5	0.8519	0.0	0.9650	0.0	0.4198	0.6842	0.3846	0.2632	0.3457	0.7368	0.2937	0.2164
Δ_6	0.5062	0.5789	0.4965	0.2874	0.7654	0.2105	0.8392	0.1767	0.7037	0.3684	0.7483	0.2757

TABLE IV
PERFORMANCE ON PRETERM BIRTH CLASSIFICATIONS OF EHG SEGMENTS ASSOCIATED WITH THE PL AND TL GROUPS USING THE WAVELET-BASED FEATURES.

Feature	channel s_1				channel s_2				channel s_3			
	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$
Δ_1	0.7174	0.2105	0.7983	0.1681	0.7391	0.4737	0.7815	0.3702	0.6522	0.0	0.7563	0.0
Δ_2	0.4420	0.7368	0.3950	0.2910	0.7681	0.1579	0.8655	0.1367	0.4493	0.6316	0.4202	0.2654
Δ_3	0.6449	0.4211	0.6807	0.2866	0.3986	0.7368	0.3445	0.2539	0.7391	0.0	0.8571	0.0
Δ_4	0.7319	0.0526	0.8403	0.0442	0.5362	0.0	0.6218	0.0	0.2609	0.0526	0.2941	0.0155
Δ_5	0.7174	0.2632	0.7899	0.2079	0.5000	0.0	0.5798	0.0	0.6667	0.2632	0.7311	0.1924
Δ_6	0.6304	0.5789	0.6387	0.3697	0.7826	0.4211	0.8403	0.3538	0.7971	0.3684	0.8655	0.3189

associated with the PL and TL groups, and the wavelet-based features Δ_6 of EHG segments of channel s_3 associated with the PL and TL groups with $p < 0.05$ as written in bold in Table II.

B. Performance on Preterm Birth Classifications

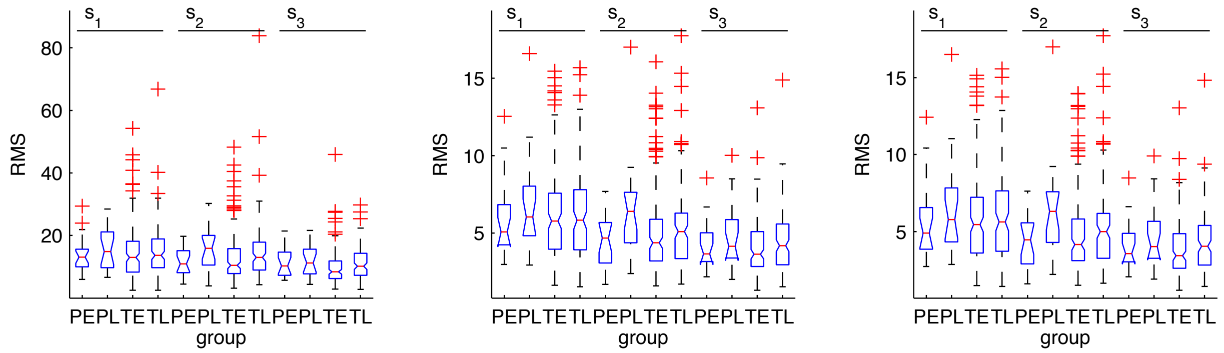
The accuracy (Ac), the sensitivity (Se), the specificity (Sp), and the product of sensitivity and specificity ($Se \times Sp$) of the preterm birth classifications of EHG segments associated with the PE and TE groups using the leave-one-out cross-validation are summarized in Table III. The best accuracy, sensitivity, and specificity obtained for the preterm birth classifications are 0.8519, 0.7368, and 0.9650, respectively, using the wavelet-based feature Δ_5 of channel s_1, the wavelet-based feature Δ_5 of channel s_3, and the wavelet-based feature Δ_5 of channel s_1. The best performance on the preterm birth classification of wavelet-based features of EHG segments associated with the PE and TE groups with respect to the product of sensitivity and specificity is however obtained using the wavelet-based feature Δ_4 of channel s_3 with the product of sensitivity and specificity of 0.4880. The corresponding accuracy, sensitivity, and specificity are 0.7099, 0.6842, and 0.7133, respectively.

Table IV summarizes the accuracy (Ac), the sensitivity (Se), the specificity (Sp), and the product of sensitivity and specificity ($Se \times Sp$) of the preterm birth classifications of EHG segments associated with the PL and TL groups using the leave-one-out cross-validation. The best accuracy, sensitivity, and specificity obtained for the preterm birth classifications are 0.7971, 0.7368, and 0.8655, respectively, using the wavelet-based feature Δ_6 of channel s_3, the wavelet-based features Δ_2 of channel s_1 and Δ_3 of channel s_2, and the wavelet-based features Δ_2 of channel s_2 and Δ_6 of channel s_3. The best performance on the preterm birth classification of wavelet-based features of EHG segments associated with the PL and TL groups with respect to the product of sensitivity and specificity is obtained using the wavelet-based feature Δ_1 of channel s_2 with the product of sensitivity and specificity of 0.3702. The corresponding accuracy, sensitivity, and specificity are 0.7391, 0.4737, and 0.7815, respectively.

The quantitative measures, i.e., RMS, f_{med}, f_{peak}, and SampEn, of spectral bands b_1, b_2 and b_3 of EHG segments are compared in box plots shown in Fig. 2(a)–(c), Fig. 3(a)–(c), Fig. 4(a)–(c), and Fig. 5(a)–(c), respectively. The performances on the preterm birth classifications of various spectral bands, i.e., b_1, b_2 and b_3, of EHG segments associated with the PE and TE groups and those associated with the PL and TL groups using quantitative measures, i.e., root-mean-square (RMS), median frequency (f_{med}), peak frequency (f_{peak}) and sample entropy (SampEn), are summarized in Table V and Table VI, respectively.

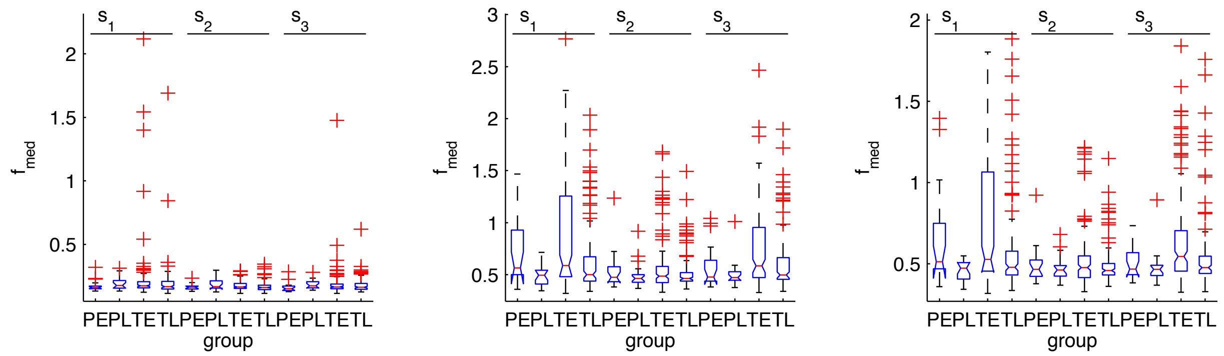
The best performances on preterm birth classification using the RMS, median frequency, peak frequency, and sample entropy of EHG segments associated with the PE and TE groups with respect to the product of sensitivity and specificity are, respectively, obtained at the spectral band b_1 of channel s_1 ($Se \times Sp = 0.2937$), the spectral band b_3 of channel s_3 ($Se \times Sp = 0.3780$), the spectral band b_1 of channel s_1 ($Se \times Sp = 0.4181$), and the spectral band b_1 of channel s_1 ($Se \times Sp = 0.4008$). The accuracy, sensitivity, and specificity obtained for the preterm birth classification using the sample entropy of the spectral band b_1 of channel s_1 are, respectively, 0.8025, 0.4737, and 0.8462.

The best performances on preterm birth classification using the RMS, median frequency, peak frequency, and sample entropy of EHG segments associated with the PL and TL groups with respect to the product of sensitivity and specificity are obtained at the spectral band b_1 of channel s_1 ($Se \times Sp = 0.1457$), the spectral band b_2 of channel s_1 ($Se \times Sp = 0.2967$), the spectral bands b_2 and b_3 of channel s_1 ($Se \times Sp = 0.2834$), and the spectral band b_1 of channel s_1 ($Se \times Sp = 0.3710$), respectively. The accuracy, sensitivity, and specificity obtained for the preterm birth classification



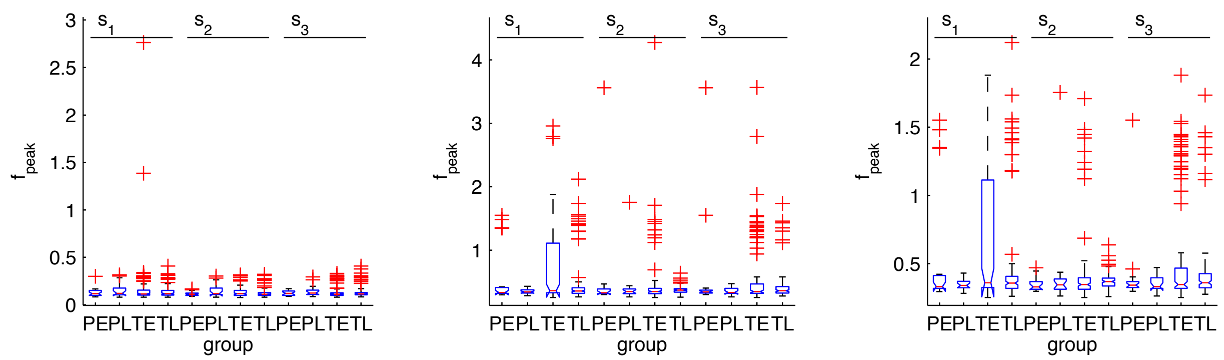
(a) b_1 (b) b_2 (c) b_3

Fig. 2. Box plots of RMS of spectral bands b_1, b_2 and b_3 of EHG segments.



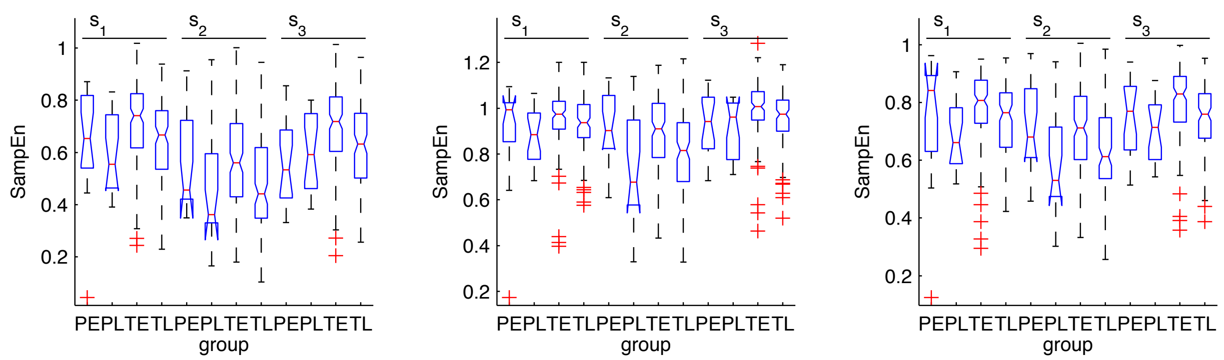
(a) b_1 (b) b_2 (c) b_3

Fig. 3. Box plots of median frequency (f_{med}) of spectral bands b_1, b_2 and b_3 of EHG segments.



(a) b_1 (b) b_2 (c) b_3

Fig. 4. Box plots of peak frequency (f_{peak}) of spectral bands b_1, b_2 and b_3 of EHG segments.



(a) b_1 (b) b_2 (c) b_3

Fig. 5. Box plots of sample entropy (SampEn) of spectral bands b_1, b_2 and b_3 of EHG segments.

TABLE V
PERFORMANCE ON PRETERM BIRTH CLASSIFICATIONS OF EHG SEGMENTS ASSOCIATED WITH THE PE AND TE GROUPS USING THE QUANTITATIVE MEASURES.

Feature	channel s_1				channel s_2				channel s_3			
	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$
0.08–4.0 Hz												
RMS	0.8580	0.3158	0.9301	0.2937	0.8025	0.0	0.9091	0.0	0.8642	0.0	0.9790	0.0
f_{med}	0.2716	0.8421	0.1958	0.1649	0.4259	0.7895	0.3776	0.2981	0.2778	0.8947	0.1958	0.1752
f_{peak}	0.9259	0.4211	0.9930	0.4181	0.4877	0.7368	0.4545	0.3349	0.7963	0.0	0.9021	0.0
SampEn	0.7716	0.3158	0.8322	0.2628	0.5247	0.6316	0.5105	0.3224	0.8025	0.4737	0.8462	0.4008
0.3–4.0 Hz												
RMS	0.3580	0.7895	0.3007	0.2374	0.7840	0.0	0.8881	0.0	0.4259	0.1579	0.4615	0.0729
f_{med}	0.3889	0.7368	0.3427	0.2525	0.2099	0.9474	0.1119	0.1060	0.4383	0.7895	0.3916	0.3092
f_{peak}	0.3333	0.7895	0.2727	0.2153	0.1173	0.9474	0.0070	0.0066	0.1235	0.9474	0.0140	0.0132
SampEn	0.1296	0.8947	0.0280	0.0250	0.6790	0.1579	0.7483	0.1181	0.8457	0.1579	0.9371	0.1480
0.3–3.0 Hz												
RMS	0.3519	0.8421	0.2867	0.2414	0.7654	0.0	0.8671	0.0	0.8519	0.0526	0.9580	0.0504
f_{med}	0.3642	0.8421	0.3007	0.2532	0.2222	0.9474	0.1259	0.1192	0.5679	0.6842	0.5524	0.3780
f_{peak}	0.3333	0.7895	0.2727	0.2153	0.4444	0.6842	0.4126	0.2823	0.2901	0.9474	0.2028	0.1921
SampEn	0.1481	0.8947	0.0490	0.0438	0.6173	0.4211	0.6434	0.2709	0.8580	0.3684	0.9231	0.3401

TABLE VI
PERFORMANCE ON PRETERM BIRTH CLASSIFICATIONS OF EHG SEGMENTS ASSOCIATED WITH THE PL AND TL GROUPS USING THE QUANTITATIVE MEASURES

Feature	channel s_1				channel s_2				channel s_3			
	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$	Ac	Se	Sp	$Se \times Sp$
0.08–4.0 Hz												
RMS	0.8704	0.0	0.9860	0.0	0.8519	0.0	0.9650	0.0	0.8333	0.1579	0.9231	0.1457
f_{med}	0.7593	0.0	0.8601	0.0	0.7469	0.1579	0.8252	0.1303	0.7593	0.0	0.8601	0.0
f_{peak}	0.8272	0.1579	0.9161	0.1446	0.7654	0.2105	0.8392	0.1767	0.8395	0.1053	0.9371	0.0986
SampEn	0.7469	0.4737	0.7832	0.3710	0.4259	0.6842	0.3916	0.2679	0.6914	0.4211	0.7273	0.3062
0.3–4.0 Hz												
RMS	0.7037	0.1053	0.7832	0.0824	0.8210	0.0526	0.9231	0.0486	0.2222	0.2105	0.2238	0.0471
f_{med}	0.4630	0.6842	0.4336	0.2967	0.3642	0.0	0.4126	0.0	0.3827	0.9474	0.3077	0.2915
f_{peak}	0.5370	0.5263	0.5385	0.2834	0.1111	0.9474	0.0	0.0	0.4074	0.6316	0.3776	0.2385
SampEn	0.6728	0.3158	0.7203	0.2275	0.6667	0.5263	0.6853	0.3607	0.8148	0.2632	0.8881	0.2337
0.3–3.0 Hz												
RMS	0.7160	0.1053	0.7972	0.0839	0.8148	0.0526	0.9161	0.0482	0.5123	0.2105	0.5524	0.1163
f_{med}	0.6049	0.4211	0.6294	0.2650	0.7160	0.0	0.8112	0.0	0.3519	0.9474	0.2727	0.2584
f_{peak}	0.5370	0.5263	0.5385	0.2834	0.2037	0.9474	0.1049	0.0994	0.4568	0.6316	0.4336	0.2738
SampEn	0.5926	0.5263	0.6014	0.3165	0.5617	0.6316	0.5524	0.3489	0.7593	0.3158	0.8182	0.2584

using the sample entropy of spectral band b_1 of channel s_1 are 0.7469, 0.4737, and 0.7832, respectively.

IV. DISCUSSION AND CONCLUSIONS

The wavelet-based feature Δ_l defined as the difference between the logarithms of variances of detail coefficients corresponding to consecutive levels, i.e., $l+1$ and l, of EHG signals is applied for preterm birth classification. For the EHG segments obtained during early period, i.e., the EHG segments recorded before the 26th week of gestation, the best performance on the preterm birth classification is obtained using the wavelet-based feature Δ_4 which corresponds to the 1.25–0.63-Hz and 0.63–0.31-Hz subbands of EHG segments. The best performance on the preterm birth classification for the EHG segments obtained during later period, i.e., the EHG segments recorded on or after the 26th week of gestation, is obtained using the wavelet-based feature Δ_1 which corresponds to the 10.0–5.0-Hz and 5.0–2.50-Hz subbands of EHG segments.

The wavelet-based feature of EHG segments provides a substantially better performance on the preterm birth classification using the EHG segments obtained during early period compared to the quantitative measures, i.e., root-mean-square (RMS), median frequency (f_{med}), peak frequency (f_{peak}), and sample entropy (SampEn). On the other hand, the performance on the preterm birth classification using the sample entropy of the 0.08–4.0-Hz subband of EHG segments obtained during later period is slightly superior to that using the wavelet-based features of EHG segments obtained during later period. The computation results suggest that the wavelet-based features of EHG signals can be reasonably used for preterm birth classification.

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