Automated Estimation of Fetal Cardiac Timing Events From Doppler Ultrasound Signal Using Hybrid Models

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***Abstract*—In this paper, a new noninvasive method is proposed for automated estimation of fetal cardiac intervals from Doppler Ultrasound (DUS) signal. This method is based on a novel combination of empirical mode decomposition (EMD) and hybrid support vector machines—hidden Markov models (SVM/HMM). EMD was used for feature extraction by decomposing the DUS signal into different components (IMFs), one of which is linked to the cardiac valve motions, i.e. opening (o) and closing (c) of the Aortic (A) and Mitral (M) valves. The noninvasive fetal electrocardiogram (fECG) was used as a reference for the segmentation of the IMF into cardiac cycles. The hybrid SVM/HMM was then applied to identify the cardiac events, based on the amplitude and timing of the IMF peaks as well as the sequence of the events. The estimated timings were verified using pulsed doppler images. Results show that this automated method can continuously evaluate beat-to-beat valve motion timings and identify more than 91% of total events which is higher than previous methods. Moreover, the changes of the cardiac intervals were analyzed for three fetal age groups: 16–29, 30–35, and 36–41 weeks. The time intervals from Q-wave of fECG to Ac (Systolic Time Interval, STI), Ac to Mo (Isovolumic Relaxation Time, IRT), Q-wave to Ao (Preejection Period, PEP) and Ao to Ac (Ventricular Ejection Time, VET) were found to change significantly ($p < 0.05$) across these age groups. In particular, STI, IRT, and PEP of the fetuses with 36–41 week were significantly ($p < 0.05$) different from other age groups. These findings can be used as sensitive markers for evaluating the fetal cardiac performance.**

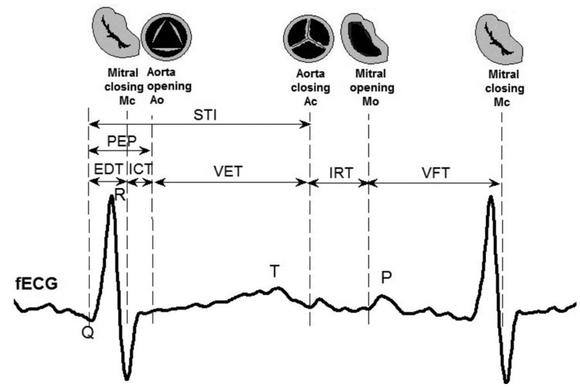

Fig. 1. Illustrative example of fetal cardiac intervals: STI, EDT, ICT, PEP, VET, IRT, VFT.

***Index Terms*—Doppler ultrasound (DUS), empirical mode decomposition (EMD), fetal cardiac intervals, fetal monitoring, hidden Markov models (HMM), hybrid SVM/HMM, support vector machine (SVM).**

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I. Introduction

EACH year 1 out of 125 babies is born with congenital heart disease (CHD) [1]. Prenatal CHD has even around tenfold higher incidence, since a majority of these defects end in intrauterine death [2]. Even with the improved treatment options that are now available, every fifth child with CHD dies during the first year of life. The mortality rate correlates closely with the severity of the heart defect and its early clinical manifestations. By diagnosing these conditions prenatally, it may be possible to reduce perinatal morbidity and mortality [3]. Furthermore, it provides tremendous medical, psychological, and economical benefits [4].

Various antenatal fetal assessment techniques have been advocated to evaluate antepartum fetal risks. Fetal circulation is one of the main concerns in fetal assessment which has a crucial importance, especially the evaluation of the heart action may give more useful information about the fetus in the antenatal period [5]. Fetal heart rate (FHR) monitoring is commonly used for this purpose and usually performed by using Cardiotocography (CTG) which is a combination of Doppler ultrasound (DUS) and measured uterine activity.

However, FHR monitoring is not enough for a thorough assessment of the fetal state. There are more sensitive markers for assessing the cardiac performance which are illustrated in Fig. 1.

By these markers the electromechanical coupling of the heart is evaluated, which is a fundamental and clinically significant part of the heart physiology [6], [7]. The opening and closure timings of the cardiac valves are the main bases for estimating these electromechanical indices [8]. Among these markers the systolic time intervals (STI) have received considerable attention as indicators of myocardial function. From a clinical standpoint, preejection period (PEP), isovolumetric contraction time (ICT), and left ventricular ejection time (VET) are the most useful of STIs [8]. For example, PEP is reported as a sensitive indicator of the function state of the fetal myocardium, and it becomes prolonged early in the development of hypoxemia and acidosis [8]. Another study suggested to use ICT as a reliable index which can be substituted for fetal cardiac contractility [9]. Other cardiac intervals are also valuable for clinical applications [8], [10]. Several methods have been proposed for obtaining these intervals.

Fetal echocardiography is a technique which can visualize different parts of the heart structure as well as the blood flow through the valves. However, it is an expensive method and only particular maternal and fetal conditions indicate the need for it. Furthermore, in most cases, primary care physicians or obstetricians cannot appropriately analyze the heart views and only qualified individuals can perform this highly specialized examination [11]. Due to these problems simpler and more accurate alternative methods have been investigated.

Starting in 1980s, a number of noninvasive methods have been proposed which mainly aimed to analyze the STI by using the abdominal ECG and the DUS signal [12]–[15]. Band-pass filter was used in these methods for filtering the DUS signal, after which the cardiac events were identified manually. The major problem with these methods is the highly variability of the DUS signal over time as well as the poor quality of the abdominal ECG.

In 2001, Koga *et al*. used the digital narrow band-pass filter to divide the DUS signal into different frequency shift ranges. The mitral and aortic valve motions were then identified from the peaks in one of the filtered signals [15].

With the improved signal processing techniques and more powerful processors over the last decade, the information content of the DUS signal has been acquired more easily. In 2001, Shakespeare *et al.* proposed a method in which the DUS signal was analyzed by the short time Fourier transform (STFT) [16]. They have shown that the high-frequency component of the DUS signal is linked to the valve movements, while the low frequency one is associated with the cardiac wall motion. They also demonstrated the variability of the content of the DUS data on a beat-to-beat basis.

A common issue which is noticed in all of these studies is the transient nature of the DUS signal as well as the wide changes in the signal content and spectral characteristics. Therefore, another method was recently proposed which applied the multiresolution wavelet analysis to the DUS signal [17]. Wavelet analysis is a powerful method for decomposing nonstationary signals with variable spectral characteristic over time. Using wavelet analysis, the DUS signal is decomposed into different scales with resolution levels. As shown in [17], valve movements were visualized as peaks in the detailed signal at level 2 wavelet decomposition. Each peak was then manually assigned to be linked to the opening and closure of the cardiac valves. Since the abdominal ECG is noisy and it is difficult to observe the fetal R-wave, the extracted fECG was used, which was separated from the abdominal ECG mixture using blind source separation with reference [18]. Furthermore, the correlation of the cardiac cycle length (R–R interval) with the interval of the R wave to each valve motion was investigated which has potential clinical applications. This correlation was found to be more significant for the abnormal cases and it was introduced as a criterion for diagnosing fetal heart abnormalities. Automatic identification of these abnormalities was investigated in their next studies [19], [20].

Based on the current methods, fetal cardiac valve movements can be recognized manually from a high-frequency component of the DUS signal. However, DUS is usually corrupted by noise and interferences and it is also sensitive to the position of the fetus and the transducer. Therefore, current methods which are based on manual recognition may not be practical and reliable. Thus, an automated approach is proposed in this paper, to identify the occurrence of the cardiac events based on the pattern, timings, and sequence of the valve and wall movements in the DUS signal components.

In this paper, instead of STFT or the wavelet analysis, it is proposed to use empirical mode decomposition (EMD) because it is a data-driven algorithm which is used for decomposing nonlinear and nonstationary time series [21]. It has been used extensively in many different applications, such as: speech processing, image processing, and biomedical signal processing [22]–[26]. EMD has been also used for better estimation of the FHR, using an ultrasound Doppler signal [27], [28].

Three approaches are introduced to be combined with EMD for automated identification: hidden Markov model (HMM), support vector machine (SVM), and hybrid SVM/HMM. The hybrid method has been originally proposed for speech processing applications [29], [30] and to our best knowledge, it has never been used in this application. Furthermore, the changes of the cardiac intervals from the 16th to 41th week of gestation were evaluated in this paper.

II. Methods

A. Subjects

Simultaneous recordings of the abdominal ECG signals and DUS signals from 45 pregnant women at the gestational age of 16 to 41 weeks with normal single pregnancies were collected from Tohoku University Hospital in Japan. A total of 45 recordings (each of 1 min. length) were sampled at 1 kHz with 16-bit resolution. All 45 subjects were divided into three age groups for analysis: 16–29 weeks, 30–35 weeks, and 36–41 weeks, including 15, 12, and 18 fetuses, respectively. The study protocol was approved by Tohoku University Institutional Review Board and written informed consent was obtained from all subjects. The continuous DUS data were obtained using ultrasonic transducer 5700 (fetal monitor 116, Corometrics Medical Systems, Inc.) with 1.15 MHz signals. To compare the actual appearance of the aortic valve's opening and closing pattern with valve timing events appeared in DUS signals, pulsed-wave Doppler signals were obtained from convex 3.5 Hz of HITACHI ultrasound scanner (ultrasonic diagnostic instrument Model EUB-525;

HITACHI health medical corporation). The detailed procedure for experimental setup and transabdominal ECG data collection was described in our previous study [18]. fECG signals were extracted from the composite abdominal signal using a method that combines the cancelation of the mother's ECG signal and the blind source separation with the reference signal (BSSR) as described in our earlier study [18] and summarized as follows.The electrical activities of the heart form a vector in the direction of excitation which is called the heart vector [31]. The cancelation of the maternal ECG component was performed by subtracting the linear combination of mutually orthogonal projections of the heart vector. After removing maternal ECG, BSSR, which is a kind of neural network methods, extracted fetal ECG signals from complex mixed signals using DUS signal as the reference [18].

B. Empirical Mode Decomposition

One of the main methods used in this paper is EMD, which was first introduced by Huang *et al.* [21]. It is a single channel method for decomposing a complicated signal into a set of different oscillatory modes. These components are called intrinsic-mode functions (IMF) and are zero mean, orthogonal, and spectrally independent. The IMFs do not necessarily have constant frequency or amplitude.

EMD is an empirical procedure which is defined only by an algorithm and basically does not focus on any analytical formulation for theoretical analysis. It has been used extensively in image, speech, and audio processing applications as well as biomedical signal processing [22]–[26], where its effectiveness is shown.

In brief, the EMD adaptively decomposes a signal into the IMFs through a specific algorithm which is called "sifting procedure." Therefore for each mode, the highest frequency component is locally extracted out of the input signal.

The sifting process is based on two constraints.

1) The number of zero crossing and extrema in the whole data must be the same or at most differ by one.

2) At each point, the mean value of the upper and lower envelopes which are constructed based on the local maxima and minima is zero.

The sifting algorithm begins with identifying local maxima and minima of the signal to be decomposed. Then, the local maxima and minima are interpolated to find the upper and lower envelopes, respectively. Then, the mean of these two envelopes is subtracted from the signal. The process is repeated for the residue until it meets a stoppage criteria which limits the size of the standard deviation computed for two consecutive residues. The first IMF is then obtained from the residue of the final subtraction. The whole procedure is performed on the residue of this IMF to find the second IMF. This process continues to obtain all IMFs and the final residue has zero or one extrema. More details can be found in [21].

EMD can be used for analyzing nonlinear and nonstationary signals. It is a data driven algorithm which is able to decompose the signal in a natural approach and does not need any prior information about the component of interest. Therefore, in this paper it is proposed to apply EMD to the DUS signal to decompose it to the IMFs which naturally have different frequency bands. An example of applying EMD to the DUS data is shown in Fig. 2. As discussed in the next sections, the peaks of the envelope of the first IMF provide the features for the identification of the cardiac events.

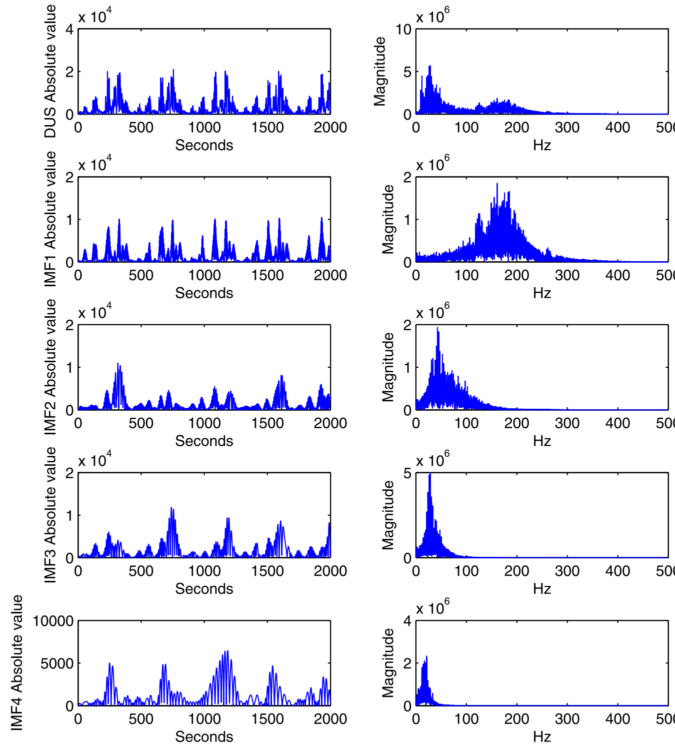

Fig. 2. Decomposition of the DUS signal using EMD.

C. Identification of Cardiac events

After applying EMD to the DUS data, according to the findings in the previous research, the component with the higher frequency band (higher than 100 Hz), i.e., the first IMF, is linked to the valve motions [16]. On the other hand, the low-frequency components generally correspond to the wall motions.

More precisely, the absolute value of the first IMF has a sequence of peaks which is associated with opening and closure of the atrioventricular and semilunar valves. For a better assessment, the envelope of that IMF was obtained using a low-pass filter. The intervals of the cardiac cycles were also found using R-R intervals of the fECG. Then, the filtered IMF was normalized over each cardiac cycle and its peaks were detected.

In previous studies, the cardiac events were manually assigned to the peaks and the intervals were calculated. In this paper, we aim to identify them automatically. To this end, each peak should be classified as an indicator of one of the cardiac valve timing events or none of them.

The first approach is based on HMM. It can find the events based on the probabilistic model of their occurrence sequence and timings. However, it was also noted that the amplitude as well as the timing of the peaks can also be used to classify them. Therefore, in the next approach, SVM was used as a powerful classifier to identify the events. Because the temporal dependence of the occurrence of events is not considered in SVM, some extra peaks might be classified as the same event in

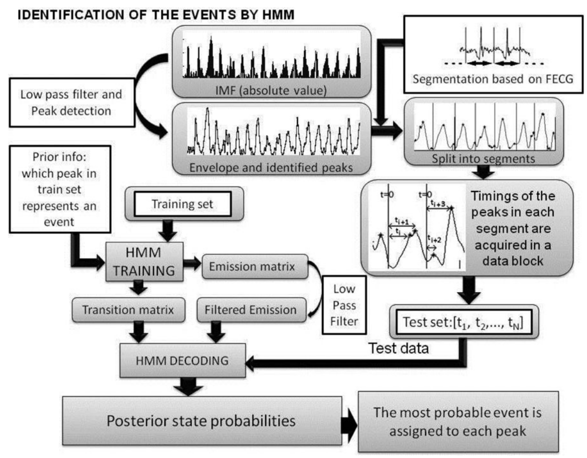

Fig. 3. HMM approach block diagram.

some cardiac cycles, or a wrong order of events might be noted. Thus, as the last approach Hybrid HMM-SVM is proposed to be used in order to overcome the defects of SVM and HMM. The time segment of each cardiac cycle was set by using fECG as a reference.

1) Hidden Markov Model: HMM was developed in the 1960s [32] and has been widely used in many signal processing applications. In contrast to the Markov model, in HMM the observed symbols are emitted from some hidden states. The formal definition of HMM is [33]:

$$\lambda = (A, B, \pi) \tag{1}$$

A is a transition matrix, B is the emission matrix, and π is the initial probability. Given a sequence of observations, the HMM process is aimed to find the sequence of the hidden states that the model went through, based on the transition probability that each state follows another one and the emission probability of the observations from each state. More details can be found in [33]. If there is an available set of examples from a process, the model can be estimated by either supervised or unsupervised training. In this study, the supervised approach was used because both input and output of the process were available as a limited training set, for which we had prior information. In our experiments, HMMs from statistics toolbox of MATLAB was used.

In the first approach, HMM was applied to the filtered version of the first IMF for recognizing valve movements. The sample procedure for detecting a cardiac event is shown in Fig. 3. First the peaks of the first IMF were identified based on the positive first derivative and negative second derivative criteria. In order to find the timing of the peaks of the IMF envelope in each cardiac cycle, the whole sequence had to be split into different segments using the R-R intervals of the fECG. The time difference from the beginning of the segment to the occurrence of each peak in that segment was then calculated, assigned to each peak and denoted by t_i. This dataset made our observation set. The hidden states $S = (s_1, s_2, \ldots, s_N)$ were set as the opening (o) and closure (c) of the Mitral (M) and Aortic (A) valves: Mo, Mc, Ao, Ac, and four transitional states: T1, T2, T3, and T4, which may occur between each pair of valve motion states.

A training set for which we had prior information about the timings of cardiac events was then used for the HMM training process. First, HMM was trained based on the prior information about the training set (if each peak represented one of the valve motion or transitional events) to provide an estimation of the transition and emission matrices. Each element ij of the transition matrix was estimated as the number of times the event s_j followed s_i in the training set, divided by the total number of s_i in that set. Each element $b_j(k)$ of the emission matrix was estimated by the number of times an observation (peak timing) was linked with the state s_j in the training set, divided by the total number of s_j. Since the training set may not be rich enough to estimate the emission probability for every time bin, the estimated emission matrix may contain many zeros and isolated spikes. Therefore, the estimated emission matrix was filtered by a low-pass filter and then normalized. This filtered matrix and the transition matrix were then used for HMM to decode the new data. After decoding, a matrix containing the probability of the occurrence of each event was obtained for each peak. Then, the event with the highest estimated probability of occurrence among all events was assigned to each peak.

2) Support Vector Machine: In this approach, SVM was used to classify the peaks of the IMF envelope as a sign of each event (or no event). SVMs developed by Vapnik [34] are a powerful technique for classification. Two class SVM is designed to find a separating hyperplane with the maximum margin with the classes. In the case of nonlinear classification, the data are first transformed by a Kernel function into the higher dimensional space in which it becomes linearly separable. SVM is based on the "structural risk minimization" criteria in order to attain low probability of generalization error [35]. More details on SVM can be found in [36].

To construct SVMs, a kernel function $K(\mathbf{x}_i, \mathbf{x})$ must be first selected. The choice of the kernel may affect the performance of SVM. The radial basis function (RBF) is one of the kernels which is used in many applications. It is defined as follows:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right) \tag{2}$$

where σ is the width of the RBF function. In this study, the RBF kernel was used and σ was experimentally chosen to be 1.

SVMs are usually formulated for binary (two-class)problems. However, they may be extended to multiclass problems. In this study, the one-against-all approach was used for multiclass SVM [36]. The classes were the same as the states in the HMM approach.

SVM was used as the second approach for classifying the peaks corresponding to one of the valve motion or other transitional events. For example, the procedure for recognizing an event from the first IMF is shown in Fig. 4. In order to obtain the features, first EMD was applied to the DUS data, the envelope of the IMF was taken and all peaks were determined based on the positive first derivative and negative second derivative criteria. Then, the signal was broken into the segments using R-R intervals of FECG as the reference. The time interval from the beginning of each segment to the occurring time of each peak in that segment and the amplitude of the peak were acquired as the features in a matrix $\mathbf{Y}$. SVM uses a training set with the prior knowledge which assumes the events associated with the

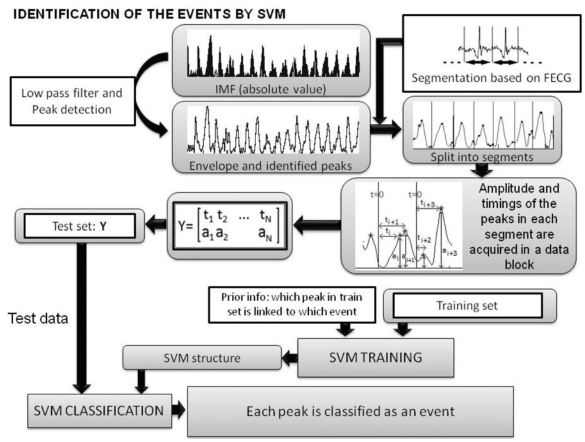

Fig. 4. SVM approach block diagram.

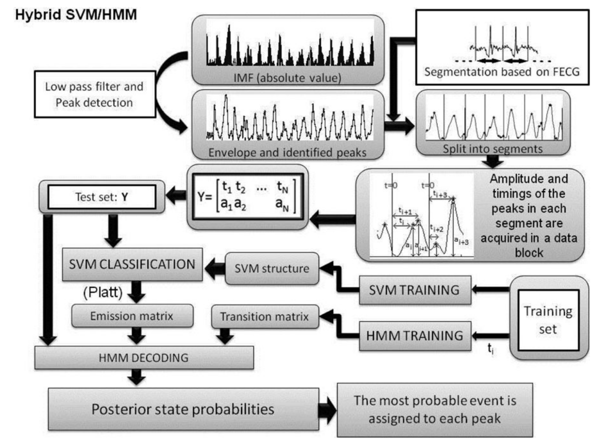

Fig. 5. Hybrid SVM-HMM approach block diagram.

peaks. The SVM structure was developed based on the training set. The new data were classified by SVM to find the event represented by each peak, based on the amplitude and timing of the peaks. The SVM functions from the bioinformatics toolbox of MATLAB were used for this study.

3) Hybrid SVM/HMM: The hybrid SVM/HMM method has been developed for the speech recognition [29], [30]. In this paper, we propose to use it for recognizing the cardiac events. It is a combination of HMM and SVM. In order to combine SVM and HMM, a probabilistic output of SVM must be obtained, because HMM is based on probability models. Platt's SVM method [37] can provide such an output. In this method the distance of each sample from the separating hyperplane is transformed to the posterior probability of classifying the sample. The posterior probability output of the SVM, $P(\text{class}|\text{input})$, is obtained by calculating: $P(y = +1|f(x))$, where

$$f(x) = \sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b \tag{3}$$

and parametric sigmoid is fitted to the output of the SVM classifier:

$$P(y = +1|f(x)) = \frac{1}{1 + \exp(Af(\mathbf{x}) + B)}. \tag{4}$$

The parameters A and B are determined by minimizing the negative log likelihood of the training data which has the form of a cross-entropy error function. In the hybrid SVM/HMM process, the transition matrix and the initial probability are first determined based on the HMM training process. The SVM is also trained using the training set. The SVM classification process is then performed on the new data, and the emission probability distribution is obtained by using the output of platt's SVM through the Bayes' rule. Therefore, the HMM model is constructed. Based on this model, the most probable hidden states are recognized through the decoding process.

For example the procedure of identifying the events from first IMF is shown in Fig. 5. First the data were broken into segments. Here again, the fECG was used as a reference for segmentation. Then, the time and the amplitude of the peaks were taken into the matrix $\mathbf{Y}$. A training set for which we had prior information was used for SVM and HMM training. The new data were then classified by the hybrid SVM/HMM method to obtain the probability of the occurrence of the events for each peak. Then, one of the valve motion or transitional events for which the estimated occurrence probability was higher than other events was assigned to each peak.

III. Results

In order to evaluate the results, the timings of opening and closure of the valves were verified by the pulsed-wave Doppler images. It visualizes the direction and the characteristics of the blood flow through the valves. In this technique, the aortic blood flow Doppler waveform is recorded from the long axis of the five-chamber view of the heart. The M-mode cursor is placed perpendicular to the interventricular septum at the level of the mitral valve to examine end-systole and end-diastole (closure of atrioventricular valves).

In this paper, the total number of 45 different datasets of DUS and corresponding fECG were used for testing the algorithm and obtaining the timings. In order to train the hybrid SVM/HMM classifier, the timings of the events for 30 cardiac cycles from three different normal fetuses were determined manually based on expertise. The algorithm was then applied to new data sets from different fetuses to find the timings during 40 cardiac cycles for each dataset. Fig. 6 shows an example of the high-frequency IMF and the identified events, the fECG and the pulsed Doppler image of the mitral valve movement for three cardiac cycles from one of the test sets. Fig. 7 shows the result of using another dataset with the fECG and the pulsed Doppler image of the aortic valve movement. Fig. 8 shows estimated timings of the valve movements from one of the test datasets. Only few event timings were missed using this method. Table I shows the percentage of the estimated events using all datasets from 45 fetuses and the mean and standard error of the average estimated time intervals over all fetuses.

The identification of the events by using the SVM, HMM, and the hybrid SVM/HMM method were compared in Fig. 9. By comparing the results with the pulsed Doppler image, it is shown that the hybrid method performs better than our previous study [17].

The estimated intervals were also analyzed by Kruskal–Wallis test to investigate their changes during pregnancy. Data from all

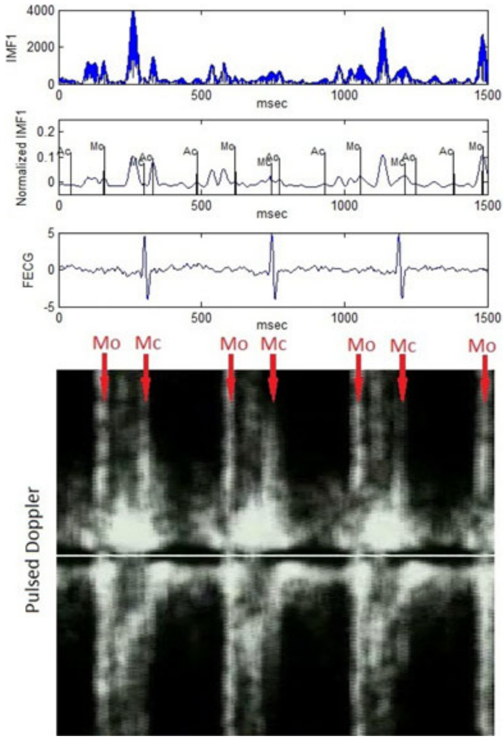

Fig. 6. (a) First IMF of the DUS signal decomposed by EMD. (b) Envelope of the normalized IMF and the identified timings. (c) The simultaneous fECG signal extracted from abdominal ECG signals using BSSR. (d) Pulsed wave Doppler signal of fetal mitral valve movements annotated to show how the specific signals are linked with opening and closing events. Mo and Mc represent the opening and closing of mitral valve.

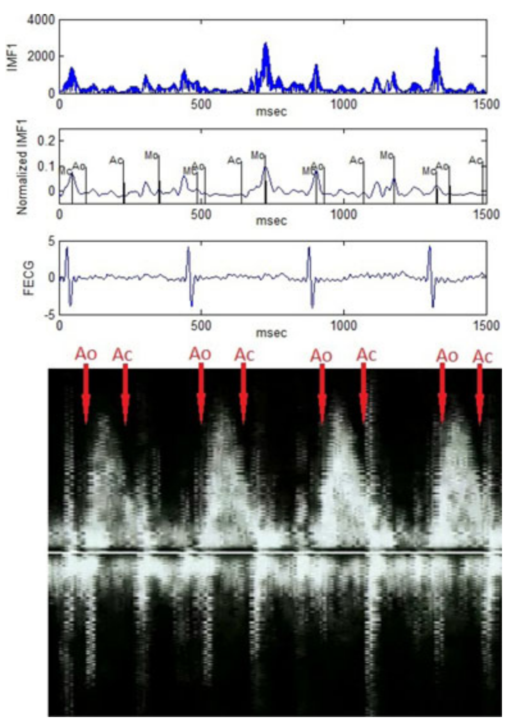

Fig. 7. (a) First IMF of the DUS signal decomposed by EMD. (b) Envelope of the normalized IMF and the identified timings. (c) The simultaneous fECG signal extracted from abdominal ECG signals using BSSR. (d) Pulsed wave Doppler signal of fetal aortic valve movements annotated to show how the specific signals are linked with opening and closing events. Ao and Ac represent the opening and closing of aortic valve.

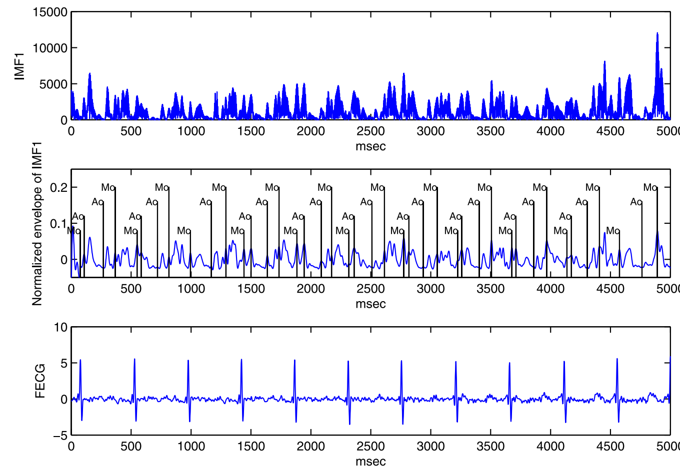

Fig. 8. Example of identified events: mitral opening and closing (Mo and Mc) and aortic valve opening and closing (Ao and Ac).

TABLE I
MEAN ± STANDARD ERROR OF THE AVERAGE TIME INTERVALS (MSEC) OVER 45 NORMAL FETUSES AND THE ACCURACY OF IDENTIFIED EVENTS

intervals	Mean± Standard Error	rate (new method)	rate (previous study [17])
R-R	413.6 ± 26.0	100.0%	100.0%
R-Mc	14.3 ± 2.3	91.1%	84.0%
R-Ao	51.1 ± 3.4	95.3%	87.0%
R-Ac	204.6 ± 5.5	98.8%	97.6%
R-Mo	276.4 ± 5.4	94.5%	89.7%
Ao-Ac	153.5 ± 6.3	94.6%	87%

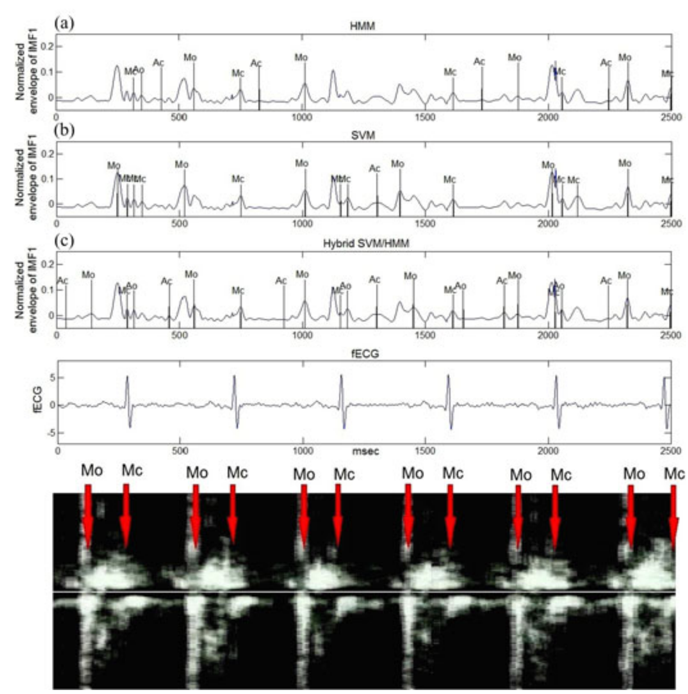

Fig. 9. Comparison of the identification of the valve movements by using (a) HMM, (b) SVM and (c) Hybrid SVM/HMM.

TABLE II
RESULTS OF KRUSKAL–WALLIS TEST (P-VALUES) AND PAIRWISE COMPARISON WITH MANN–WHITNEY—WILCOXON METHOD FOR CHANGES OF THE ESTIMATED INTERVALS VERSUS DIFFERENT AGE GROUPS

Interval	p-value	Mean±SE age group 16-29	Mean±SE age group 30-35	Mean±SE age group 36-41
EDT	0.0967	25.3±4.8	24.2±5.5	26.4±4.0
ICT	0.0558	36.4±2.6	35.6±2.7	37.7±3.4
IRT	0.0218	73.0±4.6 (A)	69.7±4.5 (A,C)	72.2±4.9 (C)
PEP	0.0026	61.7±4.8 (A)	59.9±5.2 (A,C)	64.0±4.0 (C)
STI	1×10^{-8}	213.9±5.2 (B)	214.0±7.1 (C)	218.2±7.1 (B,C)
VET	0.0333	152.2±3.7 (A,B)	154.2±6.9 (A)	154.2±7.7 (B)

The mean ± Standard Error (SE) (ms) of the timings for different age groups are shown. Significant differences between pairs of age groups: 16–29 versus 30–35, 16–29 vs 36–41 and 30–35 vs 36–41 are marked by (*A*), (*B*) and (*C*), respectively.

TABLE III
RESULTS OF MULTIPLE COMPARISON BY MANN–WHITNEY–WILCOXON METHOD (P-VALUES)

intervals	16-29 vs 30-35	16-29 vs 36-41	30-35 vs 36-41
IRT	0.0032	0.1973	0.0222
PEP	0.0095	0.0966	0.0004
STI	0.4588	0.0000	0.0000
VET	0.0192	0.0091	0.4808

45 fetuses were divided into three different age groups: 16–29, 30–35 and 36–41 weeks, including 15, 12, and 18 fetuses, respectively. Table. II and III show the results of Kruskal–Wallis test (p-values), mean and standard error of the timings for each age group, as well as their pair-wise comparison with the Mann–Whitney–Wilcoxon method.

Fig. 10 shows the result of comparison of the changes in PEP with the findings of an earlier study [38].

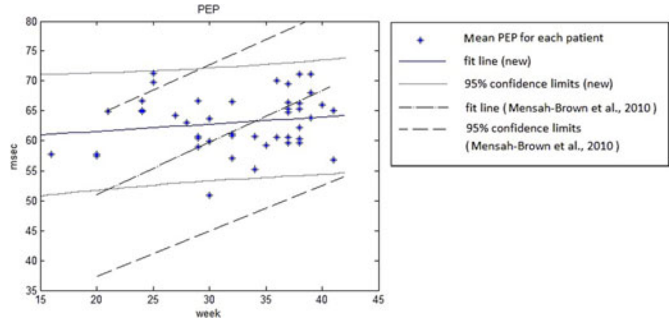

Fig. 10. Changes of the mean and 95% confidence interval of PEP compared to the results of the previous study [38].

IV. DISCUSSION

In previous studies, intervals of cardiac events have been estimated from the DUS signal by using digital filtering, STFT, or wavelet [8], [16], [17], [20], [39]. The DUS signal is nonlinear and nonstationary and wide changes in the signal content and spectral characteristics are noted on a beat-to-beat basis. The transient nature of the DUS signal and its variability is also shown in previous papers [16]. Therefore, it is not convincing to use fixed parameters such as cut-off frequency for filtering methods or wavelet parameters for the whole signal and different subjects. Thus, EMD which is a data-driven method is more suitable for this application. EMD has been extensively used for decomposing nonlinear and nonstationary signals, including the DUS signal but for estimating the FHR [27], [28], and it has not been used for this specific application before. The results show that by applying EMD, the component which is linked to valve movements is practically separated, and its peaks which correspond to the events can be discriminated.

All previous studies were based on manual identification of the cardiac event timings. However, it is sometimes difficult to recognize the peaks manually, especially for nonexperts. Moreover, the appearance of the particular types of events in DUS signal strongly depends on the location of the ultrasound transducer and the fetus. Some peaks which are linked to the cardiac events may not be visible in some situations or some extra peaks may appear which may be confusing for manual recognition. It also takes time to carefully investigate the DUS signal component in order to recognize the events. There are some visual errors as well as inter- and intra-observer errors when events are recognized based on human observation. Therefore, in this paper an automated method is proposed to recognize the events. For this purpose, the hybrid SVM/HMM method is proposed to be used, which has been previously employed only in speech processing applications. Furthermore, to our best knowledge, the combination of EMD and the hybrid SVM/HMM has never been used before. The hybrid method classifies the peaks of the decomposed component of the DUS signal to be linked to each cardiac event, based on the pattern of the peaks, the timings and the sequence of the events. The better training of the classifier with the DUS signals with different patterns, the more powerful automated recognition of the cardiac events. As shown in Table I, by using this method, a higher percentage of the valve movement events was identified, compared to the previous manual method. The results were also compared with the pulsed Doppler images which verified the successful identification of the events.

The estimation of the timing of cardiac events would have been very difficult without using FECG as a reference for segmentation. In this study, the position of the R-waves was used for segmentation of the signal into different cardiac cycles.

Results of this method provide the continuous and beat-to-beat identification of cardiac intervals, which can be used for clinical purposes.

The relationship between the cardiac intervals and the gestational age was also investigated in this study. According to the Kruskal–Wallis test and pairwise comparison with Mann–Whitney–Wilcoxon, STI was found to be the most changeable with the age. On the other hand, ICT was more stable during pregnancy as also reported by Koga [15]. According to a recent study by Mensah–Brown *et al.*, PEP increases with the gestational age (r = 0.57, $p < 0.0001$) [38]. In this study, based on the pairwise comparison, it is found that PEP slightly decreases ($p < 0.0095$) from the age group of 16–29 to 30–35, and then significantly increases to the age of 36–41 ($p = 0.0004$, Table III). As shown in Fig. 10, the estimated timings are mostly in the same range of 95% confidence interval of the previous study [38], especially after 30 weeks. The results of pairwise comparison indicate that except for EDT (electromechanical time delay) and ICT, all intervals of the age group 36–41 are significantly different from previous ages. For example STI does not change significantly from the age of 16–29 to 30–35 ($p = 0.4588$), but after that sharply increases toward the final weeks of pregnancy ($p < 0.0001$). The trend of changes in PEP is also different in the final stage. Therefore, the final weeks of pregnancy are the most critical.

IRT intervals were found to be longer in this study than the timings reported in [40]. The reason may be that the age of the fetuses analyzed in [40] was from 6 to 10 weeks of gestation, but the average age of the fetuses we analyzed was 31 weeks. The cardiac function changes with the development of the fetal heart. A part of the difference may be related to this developmental change.

A limitation of this study is that the quantitative comparison with the pulsed wave Doppler image-based valve motion timings was not provided. More accurate methods such as trans-vaginal pulsed Doppler imaging can be used in the first trimester fetuses [40]. However, our system is compatible with this wide-continuous monitoring of fetal heart during second to third trimesters. More accurate quantitative comparison of the results of the proposed method with pulsed Doppler images requires image processing and recognition process which is beyond the scope of this study. The quantitative comparison can be done in future studies.

V. Conclusion

DUS signal is nonlinear, nonstationary, noisy and it is variable on a beat to beat basis. Therefore, using a combination of EMD as a data-driven method for decomposing nonlinear and nonstationary signal and hybrid SVM/HMM for automated identification of the events improves the estimation of cardiac intervals. Results show that 94.5% of mitral opening, 91.1% of mitral closing, 95.3% of aortic valve opening, and 98.8% of aortic valve closing were identified by this method, which were higher than the manual approaches. The identified timings were verified by pulsed doppler images.

Furthermore, the trend of changes of the cardiac intervals for growing gestational age groups was analyzed. Results show that STI, IRT, VET, and PEP change significantly from early to late gestational fetuses. In particular, the intervals which correspond to the last weeks before delivery are significantly different from their values during the earlier weeks.

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