A Multi-Dimensional Hidden Markov Model Approach to Automated Identification of Fetal Cardiac Valve Motion

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Abstract— **Fetal cardiac assessment techniques are aimed to identify fetuses at risk of intrauterine compromise or death. Evaluation of the electromechanical coupling as a fundamental part of the fetal heart physiology, provides valuable information about the fetal wellbeing during pregnancy. It is based on the opening and closing time of the cardiac valves and the onset of the QRS complex of the fetal electrocardiogram (fECG). The focus of this paper is on the automated identification of the fetal cardiac valve opening and closing from Doppler Ultrasound signal and fECG as a reference. To this aim a novel combination of Emprical Mode Decomposition (EMD) and multi-dimensional Hidden Markov Models (MD-HMM) was employed which provided beat-to-beat estimation of cardiac valve event timings with improved precision (82.9%) compared to the one dimensional HMM (77.4%) and hybrid HMM-Suppeort Vector Machine (SVM) (79.8%) approaches.**

I. INTRODUCTION

Fetal cardiac assessment techniques are used during pregnancy to identify fetuses at risk of intrauterine compromise or death. Fetal heart rate monitoring is usually performed as Non-Stress Test (NST), which is useful but not enough for a conclusive fetal cardiac assessment [1].

Electromechanical coupling is one of the most significant part of the heart physiology [2] and can be evaluated using sensitive indices based on the opening and closing time of the cardiac valves and the onset of the fetal electrocardiogram (fECG) QRS complex. For example Pre-ejection Period (PEP) is the interval from Q wave of the fECG to the Aorta opening time and is reported as a sensitive indicator of the function state of the fetal myocardium. It also becomes prolonged early in development of hypoxemia and acidosis [3]. Other indices are found from the opening or closing of the valves and have other clinical applications [4].

Fetal cardiac valve motion timings can be obtained from fetal echocardiography. However it is an expensive and highly specialized technique which is performed for high risk pregnancies [5]. A simpler and less specialized method is to use Doppler Ultrasound (DUS) signal. Signal processing is required to obtain a component of the signal that is linked to the valve motions [6], [7]. fECG is also used as a reference to find the valve motion events and calculate the electromechanical coupling indices.

Although several studies proposed to use filtering to find the component representing the valve motions [6], [8], an analysis by Short Time Fourier Transform (STFT) uncovered the variability of the content of the DUS signal on a beat-to-beat basis and the wide changes in the signal content and spectral characteristics [7]. Therefore it was proposed to use Wavelet analysis [9] or Empirical Mode Decomposition (EMD) [10], [11] for decomposing the DUS signal to the component corresponding to valve motions.

Another challenge in identification of the fetal cardiac valve motions is to automate this task. In earlier studies [6]–[9], [12], [13], an expert identified the opening and closing of the valves manually from the peaks of the DUS component. Manual identification process requires special skills and is time consuming and subject to inter and intra observer errors. Therefore an automated technique was proposed in our previous paper, using Hidden Markov Models (HMM) to find the cardiac valve opening and closing as hidden states, from the peak timings of the DUS signal component as observation [10]. HMM only takes one observation symbol at each time, which was the peak timings in [10], while other features such as the amplitude of the peaks can also be used for identification. To incorporate additional features, the hybrid Support Vector Machines (SVM)-HMM was proposed to recognize the events [11]. However combining SVM with HMM made it more complicated, by additional processes such as: nonlinear transformation with Kernel, solving an optimization (dual) problem, repetition of procedure for multiclass SVM and estimating the probabilistic output.

The focus of this paper is to improve the precision of the automated identification of fetal cardiac valve movement by incorporating additional features using Multi-Dimensional HMM (MD-HMM) which is less complex than hybrid SVM-HMM.

II. METHODS

A. Data

The Doppler ultrasound and abdominal ECG signals were recorded simultaneously from 61 pregnant women with normal single pregnancy and the gestational age of 16 to 41 (33±6) weeks, at the Tohoku University Hospital. All recorded signals were 1 minute in length and sampled at

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1 kHz with 16-bit resolution. The study protocol was approved by Tohoku University Institutional Review Board and written informed consent was obtained from all participants. Ultrasonic Transducer 5700 (fetal monitor 116, Corometrics Medical Systems Inc.) with 1.15 MHz signal was used to collect the continuous DUS.

Data were divided into training and testing sets. Training set was obtained from 345 cardiac cycles of DUS components and fECG from 21 fetuses. The cardiac valve motion events of the training set were identified manually based on expertise. Data from the remaining subjects were used for test set. M-mode and pulsed wave Doppler fetal echocardiography were performed simultaneous with DUS and fECG for two test subjects to verify the mitral and aortic valve timings. Convex 3.5 Hz of HITACHI ultrasound scanner (Ultrasonic diagnostic instrument Model EUB-525; HITACHI health medical corporation) was used for this purpose.

B. fECG extraction

Abdominal recordings were bipolarly recorded from the electrodes placed on the maternal abdomen in 12 channels, sampled at 1 kHz with 16-bit resolution and filtered by bandpass filter (1-100 Hz).

fECG was separated from the abdominal mixture, by canceling the maternal ECG and separating by the Blind Source Separation with Reference (BSSR) as described in our earlier study [14]. The R-peaks of the fECG were automatically detected by applying a lower threshold (e.g. $5\times$ mean of the fECG over 10 second intervals) and the derivative of the signal.

C. DUS signal decomposition by Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is a single channel method for decomposing a complicated signal into a set of different oscillatory modes [15]. The decomposed components are called Intrinsic-Mode Functions (IMF) and are zero mean, orthogonal and spectrally independent. For each mode, the highest frequency component is locally extracted out of the input signal. It was proposed in our previous studies to apply EMD to the DUS signal to acquire the component linked to the cardiac valve motions [10], [11].

By applying EMD to the DUS signal, as shown in [10], [11], the first IMF corresponding to valve motions was obtained. The envelope of its absolute value was taken by interpolating its maxima and smoothing by low pass filter. The peaks of the envelope provided the features for identification of the opening and closing of the valves. The envelope was segmented into cardiac cycles using R-R intervals of the simultaneous fECG and then normalized.

D. Identification of valve timing events by multi-dimensional HMM

Considering the synchronous operation of both sides of the fetal heart, the semilunar and atrioventricular valve motions are expressed as the aorta and mitral valve movements respectively throughout the paper.

The valve timings can be automatically identified from the peaks of the envelope of the first IMF using HMM, as described in our previous paper [10]. The timings of the observed peaks of the first IMF envelope were used as observations to find the hidden states: Mitral closing (Mc), transition 1 (TR1), Aorta opening (Ao), transition 2 (TR2), Aorta closing (Ac), transition 3 (TR3), Mitral opening (Mo), transition 4 (TR4).

The identification process was performed in training and decoding phases. In the training phase, the probability of emissions and transition between states were estimated. Each element ij of the transition matrix was found by dividing the number of times the event s_j followed s_i in the training set by the total number of s_i in that set. Each element $b_i(t)$ of the emission matrix was calculated from the number of times an observation was linked with the state s_i in the training set, divided by the total number of s_i. Viterbi algorithm was used for decoding the observation set and finding the most probable sequence of states linked to the peaks of the IMF envelope.

Using one dimensional HMM, the valve motion events are identified using the transition of the states and peak timings only. In this paper it is proposed to use multi-dimensional HMM which was developed for telerobotic applications [16], [17], in order to add new features to the observation, such as the amplitude of the peaks to improve identification.

To add a new dimension, an additional set of emission probabilities was estimated in the training phase which was the probability of observing a peak amplitude given a hidden state at that peak time. The peak amplitudes were quantized and scaled to be mapped into a range of integers from 1 to 200. The emission probability can be expressed as follows:

$$b_{i,d}(o_d(t)) = P(o_d(t)|s = i) \tag{1}$$

where i is the state number, o indicates the observation sequence in discrete time t, which has two dimensions, the timing ($d = 1$) and amplitude ($d = 2$) of the peaks. Since the training set was not rich enough to estimate the emission probability for every time bin and amplitude value, the estimated emission matrices contained some zeros and isolated spikes. Therefore the estimated emission matrix was filtered by a low pass filter and then normalized.

The amplitude and timing of the peaks given each state were independent as verified by Hilbert-Schmidt Independence Criterion (HSIC) test with a Gamma approximation and the median distance as kernel size (type I error upper bound was < 0.17 for Mc, < 0.03 for Ao and < 0.01 for other states) [18]. Therefore the probability density function of the observation, specific to each state (e.g. state i) was modified as follows and used in Viterbi algorithm.

$$B_i(O(t)) = \prod_{d=1}^{n} b_{i,d}(o_d(t)) \tag{2}$$

where n indicates the dimension of the observation which is 2 in this application. More details about the multi-dimensional viterbi algorithm can be found in [16].

E. Cross-validation

The MD-HMM approach was compared to one dimensional HMM and hybrid SVM-HMM, using 10-fold cross validation. The training set was randomly partitioned into 10 subsets with almost equal size; one subset for validation and 9 subsets for training. The whole process was repeated 10 times while each of the 10 subsets was used once for validation.

The precision of the identification of each valve timing event was calculated as follows and averaged over the 10 folds:

$$Precision_i = \frac{t_i}{t_i + \sum_j f_{ij}} \quad (3)$$

where i and j refer to the valve motion events (Mo, Mc, Ao or Ac), t_i is the number of true estimation of the event i and f_{ij} indicates the number of times event j was mistakenly identified as event i.

III. Results

The precision of identifying valve motion events was obtained from 10-fold cross-validation of the training set including 345 cardiac cycles of DUS signal and fECG from 21 fetuses. The new MD-HMM method, one dimensional HMM approach [10] and hybrid SVM-HMM [11] were compared in table I which shows the improved precision of the new method.

The new method was applied to two test data (not involved in training) for one of which, the simultaneous M-mode image of the aortic valve motion and for the other one the pulsed wave Doppler image from mitral was collected. Figure 1 and 2 show the m-mode and pulsed wave Doppler images which verify the identification of the aorta and mitral valve motions respectively. As shown in figure 2, the last Mc event did not appear nor was it identified from the DUS signal. However Mc was identified for 95.1% of all cardiac cycles combined from 61 subjects. The rate of identified events across 61 subjects (8510 cardiac cycles) from training and testing sets, the mean and standard error (SE) of the average interval of fECG R-wave to each valve motion are summarized in table II.

TABLE I

PRECISION (%) OF IDENTIFICATION OF VALVE MOTION EVENTS BY CROSS VALIDATION OF DIFFERENT METHODS APPLIED TO THE TRAINING SET INCLUDING 345 CARDIAC CYCLE RECORDINGS FROM 21 FETUSES.

Methods	Mc	Ao	Ac	Mo	Average
MD-HMM	91.5	89.1	81.5	69.4	82.9
HMM	90.8	88.1	71.2	59.4	77.4
SVM-HMM	90.8	90.6	77.9	60.0	79.8

TABLE II

MEAN $\pm$ SE OF CARDIAC INTERVALS AND THE RATE OF IDENTIFIED EVENTS FOR 61 FETUSES.

Intervals	Mean $\pm$ SE	rate* (%)
R-R	420.9 $\pm$ 34.1	100
R-Mc	26.5 $\pm$ 2.9	95.1
R-Ao	64.1 $\pm$ 3.7	98.8
R-Ac	220.7 $\pm$ 4.7	99.9
R-Mo	297.1 $\pm$ 7.4	99.9

* The rate is calculated from the number of identified cardiac valve events out of 8510 beats from 61 fetuses.

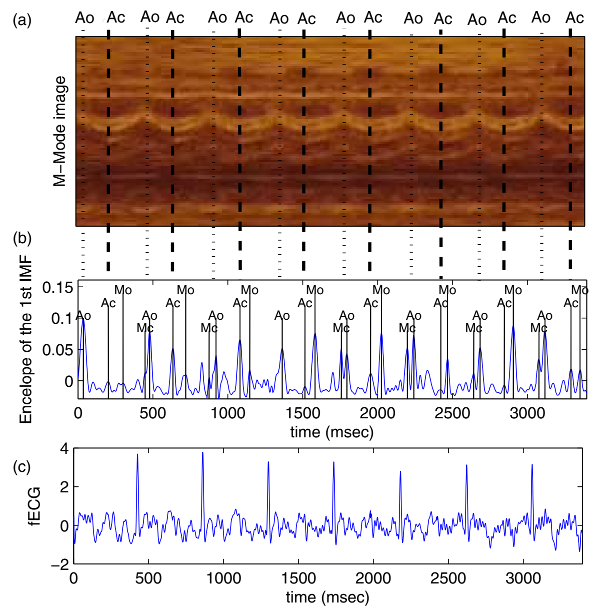

Fig. 1. (a) The M-mode image of the aortic valve operation. The aorta opening (Ao) and closing (Ac) events are depicted by dashed lines. (b) The envelope of the first IMF and the events identified by the MD-HMM method. (c) Simultaneously recorded fECG.

IV. Discussion

In this study a new automated method was proposed to identify the beat-to-beat fetal cardiac valve timings with improved precision. Similar to the previous methods, EMD was used to extract the component linked to the valve motions [10], [11]. The shortcoming of the (one dimensional) HMM is that it only takes one observation symbol at each time [10]. By extending it to the multi-dimensional HMM, multiple features can be used for identification. By adding the peak amplitude feature, the average precision was improved from 77.4% to 82.9%. Other parameters such as the width of the peaks can also be used in future studies.

Another method to incorporate multiple features for this application is the hybrid SVM-HMM which was proposed in our previous study [11]. The precision of the MD-HMM was slightly higher than the hybrid SVM-HMM method. Furthermore, the MD-HMM method is simpler than the hybrid method. The procedures added to HMM for SVM-HMM include: nonlinear transformation with Kernel, solving an optimization problem (dual problem [19]), repetition of procedure in the one-against-all scheme for multiclass SVM and fitting sigmoid (Platt's method) to obtain a probabilistic output. While for MD-HMM training, an extra estimation of the emission matrix is added for each extra dimension which is simply calculated from the number of times an observation is to linked each state, divided by the total number of that

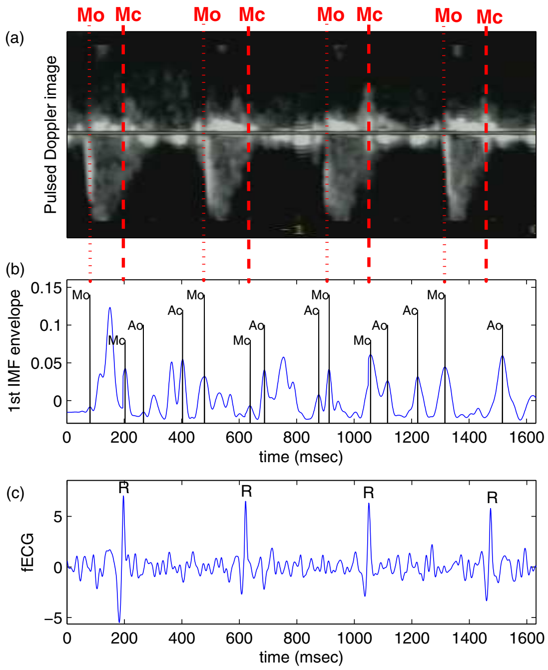

Fig. 2. (a) Pulsed wave Doppler image of fetal mitral valve movements. Dashed lines show mitral opening (Mo) and closing (Mc), (b) The envelope of the first IMF and the valve motion events identified by the proposed method, (c) Simultaneously recorded fECG.

state. For decoding, the emission probabilities are multiplied under the condition of their independence, to obtain the probability density function of the observation for each state required in Viterbi algorithm. Overall, the process of MD-HMM is less complex than the SVM-HMM specially for low dimension, but detailed comparison of their complexity requires further study.

Mitral closing event had the lowest identification rate (table II) and also did not appear in the last beat shown in figure 2. Mitral closes when the pressure of the left ventricle exceeds the left atrial pressure, which is followed by opening of aorta. A reason for lower identification rate of Mc is that time difference between Mc and Ao is very short and in some cases their corresponding peaks of IMF cannot be distinguished.

V. CONCLUSIONS

In this study a new method was proposed for automated identification of fetal cardiac valve motions using a combination of EMD and multi-dimensional HMM. Employing MD-HMM enabled the use of amplitude of the peaks of the first IMF as well as their timings, which improved the precision of the identification of cardiac valve motion. The average precision obtained by the MD-HMM was 82.9%, which was higher than one dimensional HMM (77.4%) and hybrid SVM-HMM (79.8%). More than 95.1% of valve motion timing events were identified using this method and they were also verified by M-mode and pulsed Doppler images for two fetuses.

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