Automated Identification of Abnormal Fetuses Using Fetal ECG and Doppler Ultrasound Signals

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Abstract

In this study, we propose an automated algorithm (support vector machines, SVM) to recognize the abnormal fetus using the timings of fetal cardiac events on the basis of analysis of simultaneously recorded fetal ECG (FECG) and Doppler ultrasound (DUS) signal. FECG and DUS signals from 29 fetuses [21 normal and 8 abnormal] were analyzed. Multiresolution wavelet analysis was used to link the frequency contents of the Doppler signals with the opening(o) and closing(c) of the heart's valves [Aortic (A) and Mitral(M)]. Five types of feature, namely 1) R-R intervals, 2) time intervals from R-wave of QRS complex of FECG to opening and closing of aortic valve, i.e. R-Ao 3) R-Ac 4) for the mitral valve R-Mc and 5) R-Mo were extracted from 60 beats and used as inputs to the SVM. Using leave-one-fetus out cross validation technique, an SVM with polynomial kernel (d=3, C=10) correctly recognized 8 abnormal (heart anomalies) fetuses out of 29 fetuses.

1. Introduction

Good health in the developing human foetus is critical to the future well-being of an adult. At least 8 in 1,000 infants born each year have a heart defect and congenital cardiovascular defects are present in about 1% of live births [1]. Fetal ECG and Doppler ultrasound signals provide clinically significant information about the physiological state of a fetus. The evaluation of fetal cardiac activity has received limited attention. It is known that congenital heart defects (CHD) and fetal distress (e.g. low oxygen levels in fetus) are the most common major causes of congenital abnormalities and fetal mortality [2]. The determination of CHD and fetal distress during fetal life, where the examiner must deal with a patient who cannot be visualized directly and is located within another individual, presents unique challenges. To our knowledge, definitive prenatal diagnosis of this congenital syndrome has not been described. The early identification of a pathological state is fundamental to predict possible complications and to take appropriate decisions

In perinatal medicine, non-invasive cardiotocography (CTG), which is a record of the fetal heart rate (FHR) and uterine contraction activity measured via transducer on the abdomen, is commonly used. As the patterns of CTGs can vary greatly, the ability to make such decisions relies upon intuition and experience. Visual analysis of the CTG has not been shown to improve longterm outcome in low-risk pregnancy, most likely due to inaccurate and inconsistent interpretation [3]. Sometimes abnormal variability in fetal heart rate may not necessarily represent the fetus in distress.

The systolic time intervals (STI) of the fetal cardiac are reported to be sensitive markers of fetal cardiac performance [4]. There is a method that uses systolic time interval (STI) which can be calculated with an invasively measured fetal electrocardiogram (FECG) via scalp electrodes and a Doppler shift of ultrasound beam reflected from moving valves of the fetal heart. Notwithstanding the importance of monitoring fetal cardiac performance with the systolic time intervals, the reasons why it has not been widely applied in clinical practice include the difficulty in obtaining a reliable simultaneous recording of fetal ECG and Doppler ultrasound signals. In our recent study [5], we reported that correlations among the timings in opening and closing of cardiac valves were found to be higher in abnormal fetuses than that in normal ones. Therefore, it was hypothesized that an automated model would be better suitable for constructing relationship among valve's timing intervals extracted from simultaneously recorded Doppler ultrasound (DUS) and fetal ECG signals, and the presence or absence of heart abnormality. Support vector machines (SVM) have recently emerged as a powerful tool for general purpose pattern recognition. It has been applied to classification and regression problems with exceptionally good performance on a range of binary classification tasks [6]. The primary advantage of an SVM is its ability to minimize both structural and empirical risk leading to better generalization for new data classification even with limited training data set. In this study, we propose SVMs

to automatically diagnose abnormal fetus prenatally on the basis of the timings of fetal cardiac.

2. Methods

2.1. Data

Simultaneous recording of the abdominal ECG signals and Doppler ultrasound signals from 21 pregnant women at the gestational age of 28~36 weeks with normal single pregnancies and eight pregnant women who were diagnosed to have fetal abnormalities (heart anomaly(5), LQT syndrome with heart anomaly(2), acute hypoxia for early separation of placenta (1)) were collected from Tohoku University Hospital. A total of 29 recordings (each of 1 minute's length) were sampled at 1000 Hz with 16-bit resolution. The study protocol was approved by Tohoku University Institutional Review Board and written informed consent was obtained from all subjects.

FECG traces were extracted using a method that combines cancellation of the mother's ECG signal and the blind source separation with reference (BSSR) as described in our earlier study [7].

2.2. Wavelet analysis and feature extraction

Interpretation of DUS signals in relation to cardiac valve movements has been performed using time frequency wavelet analysis[8]. One example of DUS signals over a cardiac cycle (from R peak to next R-peak of simulataneously recorded FECG signal) together with and their approximate and details signals at level 2 wavelet decomposition are shown in Fig. 1. The timings of aortic and mitral valve motions (in Fig. 1 panel D) with respect to the ECG, the origin of the events highlighted within the DUS were elucidated and verified by pulsed Doppler ultrasound in our previous study [5,8]. In order to detect the peak timings of aortic valve's motion events, the time durations from R wave within each RR interval chosen for each event were 0.05~0.10 sec for Ao and 0.14~0.26 sec for Ac. On the other hand, for mitral valve's relative timings, 0.00~0.05 sec for Mc and 0.26~0.33 sec for Mo were used in calculation. The correlations of RR with RMc, RAo, RAc and RMo were used as features.

2.3. Automated recognition

Then features were used as input features to the support vector machines (SVM) model, and an output representing the fetus types (+1 = abnormal, -1=normal) for learning the complex relationship of features with the potential of fetal condition (normal or abnormal). All SVM architectures were trained and tested on the MATLAB SVM toolbox [9]. SVM is an approximate implementation of the method of "structural risk minimization" aiming to attain low probability of generalization error and finds the optimal separating hyperplane (OSH) by maximizing the margin between the classes [6]. Regularization parameter ('C') determines the trade off between the maximum margin and minimum classification error. SVM first transforms input data into a higher dimensional space by means of a kernel function and then constructs a linear (OSH) between the two classes in the transformed space.

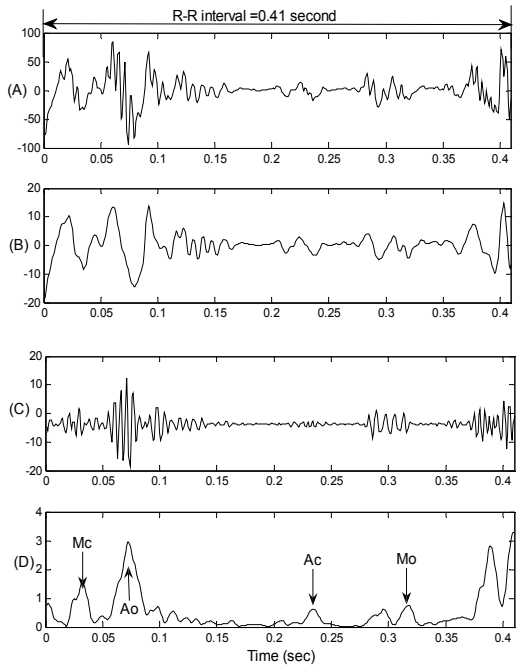

Figure 1. Panel (A) shows an example of Doppler Ultrasound signals from fetal monitor 116 over an RR interval of 0.41 second. Panel (B) shows its approximate signal at level 2. Panel (C) shows the detailed signal after wavelet decomposition of (A) at level 2. Panel (D) shows the cubic splines envelope of maxima of the detailed signal in panel (C). Ao and Ac represent the opening and closing of aortic valve. Mo and Mc represent the opening and closing of mitral valve.

Those data vectors nearest to the constructed line in the transformed space are called the support vectors (SV). An overview of SVM pattern recognition can be found in [9,10]. In this study, we experimented with three kernels as follows.

1) Linear kernel, $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i \cdot \mathbf{x}_j$

2)Polynomial kernel, $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^d$ d is the degree of polynomial

3)Radial basis function (RBF) kernel, $K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right)$ σ is the width of RBF

A leave-one-out cross-validation scheme was adopted to evaluate the generalization ability of the classifier. In this scheme the data set was uniformly divided into 29 subsets with one used for testing and the remaining 28 records used to train and construct the SVM decision surface and tune the parameters for other classifiers. This was repeated for other subsets so that all subsets were used as the testing sample.

The accuracy, sensitivity and specificity were used to assess the performance of the classifiers. Accuracy indicates overall detection accuracy, sensitivity is defined as the ability of the classifier to accurately recognize an abnormal fetus whereas specificity would indicate the classifier's ability not to generate a false negative (normal fetus).

3. Results

Table 1 summarizes the correlations among the valve opening and closing timings. Significant correlations were found among valve timings in abnormal fetuses as compared to that in normal fetuses. R-Ao was found to be strongly correlated (r=0.36, p=0.0013) with R-R intervals in abnormal fetuses. On the other hand, very weak correlation (r=0.08, p=0.459) was found in normal fetuses. Correlation (Corr) between R-R and R-Mc was found to be positive for normal fetuses, however, negative for abnormal fetuses.

Results of leave-one-fetus-out cross-validation tests on classification performance (overall accuracy, sensitivity and specificity) of the SVM as a function of number of Corr (RR,RMc) and Corr (RR, RAo) features were summarized in Table 2. Tests were also conducted to examine performance of the SVMs for different kernel functions and different regularization parameters 'C' values (0.1, 1.0, 10). It is interesting to look at classification performances on test set that 100% accuracy was obtained using polynomial kernel (d=3) with a subset of two features.

4. Discussion and conclusion

This study was designed to test the ability of a SVM model for screening the abnormal fetuses using the correlations among fetal cardiac valve's timing intervals. The results demonstrated that using a combination of Corr (RR,RMc) and Corr (RR, RAo), the polynomial kernel (d=3) gives 100% accuracy with the value of regularization parameter, C=10.

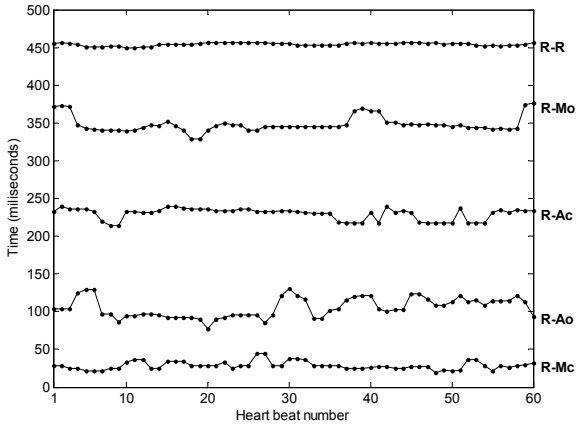

Figure 2. R-R, R-Mc, R-Ao, R-Ac and R-Mo interval series of 60 beats obtained from an abnormal fetus are shown.

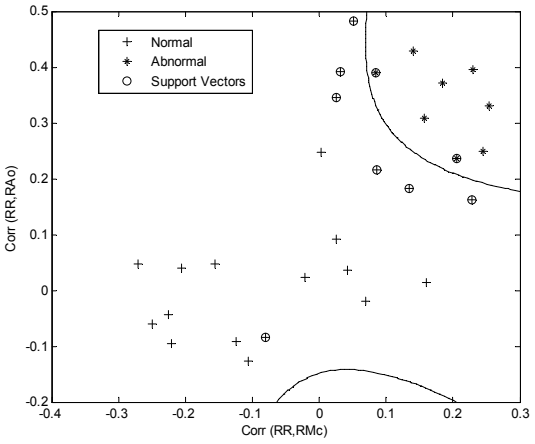

Figure 3. Two-dimensional scatter-plots showing test data and decision boundaries using two features [Corr(RR,RMc) and Corr (RR,RAo)] for the case of a *Polynomial* kernel (d=3).

Our findings show the significant correlation of R-Ao with RR intervals in abnormal fetuses. We speculate that the control mechanism for heart contraction in abnormal fetuses is different from that in healthy fetuses. That could relate to the rigidity of the fetal heart contraction control system in abnormal fetuses. Less flexibility in

cardiac valves' opening and closing in the abnormal fetuses may have contributed to significantly correlated valve movement and timing intervals. In abnormal fetuses, 6 heart anomaly cases had tetralogy of Fallot and double outlet right ventricle, while 2 LQT syndromes with heart anomaly had single ventricle and dilatation of heart. In spite of difference in abnormalities, dysfunction of the control system in heart anomaly or acute emergency state of fetus could be considered a common factor behind the significance in correlation parameters. But the precise explanation requires further research which will be attempted in the future study.

Multiresolution wavelet analysis enabled the frequency contents of the Doppler signals to be linked to the opening and closing of the aortic and mitral valves which was confirmed by M-mode and pulsed Doppler in our previous study [5]. These results suggest potential clinical application for automatic recognition of fetal compromise and distress such as fetal arrhythmia, anoxia and heart failure.

Table 1. Correlations (Corr) (mean) among fetal heart rate and cardiac valve's timing intervals for the normal (first row) and abnormal (second row)fetuses.

	R-R	R-Mc	R-Ao	R-Ac	R-Mo
R-R	1	-0.03	0.08	0.44	0.52
R-R	1	0.18	0.36	0.44	0.64

Table 2. Classification performance of SVM classifier with Linear, Polynomial and RBF kernels for different regularization parameter (C). Acc= Accuracy, Sens=Sensitivity, Spec= Specificity, d= degree of polynomial.

		Cross-validation Set		
Kernel	C	Sens %	Spec %	Accu %
Poly (d=3)	0.1	96.55	100	95.24
	1.0	96.55	87.50	100
	10.0	100	100	100
Linear	0.1	93.10	87.50	95.24
	1.0	93.10	100	90.48
	10.0	96.55	100	95.24
RBF (σ=1.0)	0.1	93.10	100	90.48
	1.0	89.66	87.50	90.48
	10.0	93.10	75.00	100

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