A Fetal Heart Rate Signal Source Recognition Model Based on Fast Fourier Transform and Ensemble Learning

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Abstract. Fetal heart rate monitoring is a necessary routine examination item in obstetric clinic, which has important significance in the health examination of the perinatal fetus. Accurate extraction of fetal heart rate is a key technology in electronic fetal monitoring technology. There are still some difficulties and challenges in extracting the fetal heart rate from the ultrasound Doppler signals. The ultrasound Doppler fetal monitoring probe is difficult to maintain in the correct position, therefore, the Doppler ultrasound signals obtained may be the abdominal aorta signals which will cause fetal heart rate extraction error. In this paper, a signal source recognition model based on fast Fourier transform (FFT) and ensemble learning for ultrasound Doppler signals source recognition is proposed. The spectral features of the signals are extracted by FFT, and the spectral features are used as the input of ensemble learning model to decide whether the mother’s abdominal aorta signals are detected. The experimental results show that the proposed model can achieve the best recognition effect with the rule that the signals are regarded as from abdominal aorta if more than 93% of the signals get the negative output by the model within the time window of more than 13 seconds.

1. Introduction

Electronic fetal heart rate monitoring is a routine check-up program for obstetrics, which is of great significance for reducing fetal birth mortality and ensuring healthy delivery of the fetus[1]. Electronic fetal heart rate monitoring uses ultrasonic and pressure sensors to obtain fetal heart rate, uterus shrink pressure and fetal movement tags, which are the important basis for obstetricians’ clinical diagnosis of intrauterine fetal distress. A commonly used non-invasive acquisition method of detecting fetal heart rate is Doppler ultrasound (US)[2]. Because the ultrasound Doppler fetal monitoring probe is difficult to maintain in the correct position, the received Doppler signals may be reflected from other parts of the pregnant woman’s body, which may contain a lot of noise signals[3]. Generally, the noise or error signals can be distinguished by its characteristics. For example, for the continuous signals which can not be searched for the fetal heart rate cycle point, it can generally be judged that the probe position is unstable or faulty. However, there is a special situation in the clinic that the error signals are detected by fetal monitor probe from the abdominal aorta of the pregnant woman, which can also be calculated to obtain heart rate clearly[4]. The heart rate obtained above is the maternal heart rate instead of the fetal heart rate. As shown in figure 1, the heart rate values labeled are estimated by the autocorrelation method[5] from the Doppler ultrasound signals with high signal quality, but the clinical expert has confirmed that the heart rate signals are from the abdominal aorta of the pregnant woman. It’s difficult for fetal monitors and caregivers to notice and recognize the situation above.

Aimed at the problem that the abnormal position of probe in the clinical fetal monitoring process will obtain abdominal aorta signals from pregnant woman and leads to error estimation of fetal heart rate,
this paper proposes a signal source recognition model based on fast Fourier transform (FFT) and ensemble learning. The spectral characteristics of the signals are extracted by FFT, and a well-trained ensemble learning model is used to identify the signal characteristics to discriminate the signal source, which can avoid the fetal heart rate acquisition error caused by the abdominal aorta signals. The general flow of the recognition model is depicted in figure 2.

In the thesis, the work of spectral characteristic analysis is shown in section 2, the feature extraction module is described in section 3, the model selection and training process of ensemble learning is shown in section 4 and the experiment results is shown in section 5.

2. Spectral characteristic analysis
Fast Fourier transform (FFT) [6] is a fast algorithm of discrete Fourier transform, which is a general term for efficient and fast calculation methods of the calculation for discrete Fourier transform (DFT). Through adopting this algorithm, the number of multiplications required for the computer to calculate the discrete Fourier transform is greatly reduced. The more of the number of sample points K, the reduction of calculation of FFT algorithm is more obvious. The fast Fourier transform can be used to convert time domain digital signals into frequency domain signals, and the frequency component and the frequency characteristics of signals can be easily analysed by the frequency domain signals.

In this paper, through the artificial identification of obstetric experts and fetal monitor hardware experts, the abdominal aortic signals and fetal heart signals appearing in the clinic were studied, and the distinction between the spectral characteristics of abdominal aorta signals and fetal heart signals were found. The human ear can also distinguish the difference between two kinds of signals above by playing them with the audio player. Therefore, this paper used fast Fourier transform to convert the signals into the frequency domain signals and extract the traditional spectrum features of these signals which can be used as the input of machine learning model to identification and classification.

3. Feature extraction module
In this paper, the number of sampling points was set as 600 when performing fast Fourier transform on the US signals because the signals frequency component is up to 250 Hz. According to the sampling theorem, the sampling frequency should be greater than 2 times of the signal frequency, so the sampling frequency was set as 600 Hz here. The maternal abdominal aortic signal spectrum and the fetal heart rate signal spectrum are shown in figure 3 and figure 4. By comparing the maternal abdominal aortic signal spectrum (figure 3b) and the fetal heart rate signal spectrum (figure 4b) obtained by FFT, it can be found that the difference in spectral characteristics between the two is mainly concentrated in the range of 1-200HHz (especially in the range of 1-100HHz). The maternal abdominal aortic signal composition is more concentrated in the range of 0-50HHz, while the fetal heart rate signal spectrum distribution is relatively more dispersed. Therefore, the spectrum range of 0-200HHz was selected for feature extraction, and the features $F_1, F_2, F_3, F_4, F_5$ and $F_6$ were defined to represent the spectrum features in the interval of 0-25HHz, 25-50HHz, 50-75HHz, 75-100HHz, 0-50HHz and 0-100HHz, which were shown in figure 5. Subsequently, it calculated the sums of signal spectral amplitudes of each interval.
above and the percentage of each sum to the sum of total spectral amplitude, and multiplied the percentage by 100 to convert to an integer value. These values were used as the feature values of the features defined above.

Figure 3. The spectrum image of US signals from abdominal aorta.

Figure 4. The spectrum image of US signals from fetal heart.

According to the above feature extraction method, 2808 characteristic data items were obtained from clinical data from the First Affiliated Hospital of Jinan University which included pregnant abdominal aortic signals, and the category labels of pregnant abdominal aorta signals and fetal heart signals were established for model training.

Figure 5. Defined features of the spectrum image of US signals.

4. Classification based on ensemble learning

In statistics and machine learning, the ensemble learning method uses multiple learning algorithms to achieve better predictive performance than using any one of the learning algorithms alone[7-9]. The main idea of ensemble learning is to first generate a series of learners through certain rules, then combine them with some kinds of integration rules, and finally comprehensively judge and output the final result, so as to obtain better learning effect than a single learner. Ensemble learning usually uses the homogenous weak learners, and it generally generates multiple learners by disturbing the sample set,
features, output representations and algorithm parameters. Finally, a strong learner with higher precision can be obtained after integration.

This paper uses the stacking algorithm[10] in ensemble learning, which is divided into two layers of learning algorithms. The basic level consists of classifiers random forest[11], KNN[12], SVM[13] and Adaboost[14], and will be trained by a complete training set. The second layer uses the XGBoost[15] classifier that excels in the Kaggle and KDD big data algorithm competition. After the basic layer training, the output obtained by each classifier is used as the new input, and the second layer XGBoost classifier is trained to obtain the final classification result. The training process is carried out by the 5-fold cross validation. The 5-fold cross validation randomly divides the training data into 5 portions and each time randomly selects 4 portions as the training set and selects the remaining portion as the test set which can be used to evaluate the performance of model. The process of stacking model training can be seen in figure 6.

![Figure 6. The process of stacking model training.](image)

5. Experiment result

The cross-validation results of the proposed model obtained through training data are shown in figure 7, which includes the evaluation indicators of each individual classifier after model training. It can be seen that each classifier has good performance on the training data, which proves the validity of feature extraction and model application. Although the performance of each classifier is relatively close, the ensemble learning(stacking) classifier achieves the best performance, and the precision and F1 value are the highest. As shown in table 1, the average accuracy of the ensemble learning classifier is 94.72%, the precision is 96.80%, the recall is 92.55%, and the F1-score is 94.62%.

![Figure 7. The cross-validation results of the proposed model obtained through training sample.](image)
Table 1. The results of 5-fold cross validation for the proposed model.

| Item     | Seq 1       | Seq 2       | Seq 3       | Seq 4       | Seq 5       | Avg         |
|----------|-------------|-------------|-------------|-------------|-------------|-------------|
| Accuracy | 94.31%      | 95.37%      | 94.66%      | 92.51%      | 96.79%      | 94.72%      |
| Precision| 97.19%      | 97.22%      | 96.15%      | 94.91%      | 98.52%      | 96.80%      |
| Recall   | 92.03%      | 92.80%      | 92.59%      | 90.31%      | 95.00%      | 92.55%      |
| F1-score | 92.49%      | 94.96%      | 94.34%      | 92.55%      | 96.73%      | 94.62%      |

Figure 8. Statistical result of false positive numbers of US signals at different ω values.

Figure 9. Statistical result of the length of the monitoring window that achieves zero false positives at different ω values.

In order to test the generalization ability and actual use effect of the proposed model, 7 pairs of new US signals were selected for testing. Since the appearance of the general abdominal aortic signal will continue for a period of time in clinical practice, it is of little value to test the data at a short time. Therefore, a certain length of monitoring window was set for auxiliary recognition and judgment of the model in clinical application. The length of the monitoring window is defined as $l$. Here the warning rule for the appearance of abdominal aortic signals is that the ratio of signals recognized as from abdominal aorta by the proposed model (the output is negative) in the monitoring window exceeds $ω$. As shown in figure 8, it can achieve zero misinforming rate when $ω \geq 0.71$. Here we conducted the statistics of the monitoring window length which can achieve zero misinforming rate of all experimental US signal items in the case of $ω \geq 0.71$, and the statistical results are shown in figure 9. It can be seen in figure 9 that with the increase of $ω$, the length of the monitoring window that achieves zero misinforming rate is gradually shortened. The length of the monitoring window achieves zero misinforming rate meets the minimum value of 13 seconds when $ω=0.93$, where the recognition effect of the signal source recognition model is optimal.

6. Summary
According to the problem that the fetal monitor may detect the abdominal aorta of the pregnant woman which will cause the fetal heart rate calculation error in the clinical process, a signal source recognition
model based on FFT and ensemble learning method is proposed, which uses the spectral features as the input to decide whether the gravida abdominal aorta signals are detected. The experimental results show that the signal source recognition model achieves the lowest misinforming rate and get the optimal recognition effect with the rule of recognition that more than 93% of the signals in the monitoring window are judged as the abdominal aortic signals by the proposed model when the monitoring time window is not less than 13 seconds, which proves the feasibility and effectiveness of the proposed model.

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