Classification of Fetal Behavioral States by Using 1D-CNN based on Fetal Electrocardiography

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Abstract

To better understand the development of the fetal Autonomic Nervous System (ANS), estimation of Fetal Behavioral States (FBSes) is an essential parameter. The objective of this work is to use 1D CNN to classify FBSes into two states: quiet and active. Non-invasive electrocardiogram signals were collected from 109 healthy fetuses whose Gestational Age (GA) ranged from 20–40 weeks for a time between 3-10 min. Based on the fetal ECG signal, this study develops a 1D Convolutional Neural Network (CNN) for automatically obtaining features and identifying the behavioral state of the fetus. Our study employs a 1D CNN technique without extracting or selecting features from the fetal ECG signal. These networks can self-learn the distinguishing features of ECG signals. The proposed method for classifying fetal quiet states/active states provided an overall sensitivity, specificity, precision, and F1 score of 72.7/82.6%, 82.6/72.7%, 89.4/60%, and 80.2/69.5%, respectively. According to the results of this study, a deep learning approach combined with fetal ECG signals can be a useful pre-screening tool for fetal neurological assessment throughout gestation which has the advantage of reducing fetal mortality rate.

1. Introduction

Behavioral state was first described by Prechtl in 1974 for infants [1], and subsequently applied to fetuses [2]. Defining fetal states before 32 weeks of gestation is possible, but we can only differentiate between fetal quiet and fetal active states in this scenario [3]. This FBS distribution is stable during the daytime and these states varies depending on the position of the mother as well [4][5]. The frequency of occurrence of these states differs as the gestation progresses [6]. Four FBSes have been identified starting from 32 weeks of gestation, namely quiet sleep (1F), active sleep (2F), quiet awake (3F) and active awake (4F). For these states to be defined, the body/eye movement patterns and heart rate patterns must remain stable for a minimum of 3 min [7].

It is known that Heart Rate Variability (HRV), analyzed using both time domain and spectral domain techniques, is a mirror of the Autonomic Nervous System (ANS) in adults, neonates, and fetuses [7]. In terms of fetal surveillance, it may be beneficial to consider this feature of Fetal Heart Rate Variability (FHRV). It is thus not surprising that impaired FHRV has been associated with conditions, such as fetal acidosis during labor, hypoxic ischemic encephalopathy and fetal growth restriction [8][9]. It is the standard practice in high-risk pregnancies in clinics to monitor the fetal status primarily through fetal Doppler ultrasound, which reflects the fetus' cardiovascular capacity. However, it does not necessarily reflect their neurological status. There is a possibility that FHRV could fill this gap in existing surveillance. Cardiotocography (CTG) cannot accurately detect every single normal heartbeat when determining beat-to-beat HRV. As a result, recent developments in non-invasive fetal electrocardiography (NI-FECG), in which electrodes are placed on the mother's abdomen to obtain the fetal ECG, have led to optimism regarding a clinically feasible monitoring methodology for FHRV. The Gestational Age (GA) and maternal factors greatly influence FHRV, whereas fetal gender and ethnicity have less impact.

One of the most widely used deep learning algorithms in the field of machine learning is convolutional neural networks (CNNs). One of their most notable characteristics is that they learn task-specific features without having any previous domain knowledge [10]. Object recognition, image segmentation, and face recognition are some areas where CNNs have shown to be highly effective. End-to-end learning, i.e., integrating feature extraction and classification into a single algorithm, has been key to the success of CNNs. CNNs are proving to be very effective for computer vision applications based on two-dimensional images, notably in medical imaging. However, this has not been true for biomedical applications that classify one-dimensional biosignals, such as electrocardiography (ECG) and electroencephalography (EEG) [11]. Recently, there has been an increasing interest in using 1DCNNs to solve biosignal-related problems [12][11]. In this article, we describe a 1D CNN architecture that we developed to

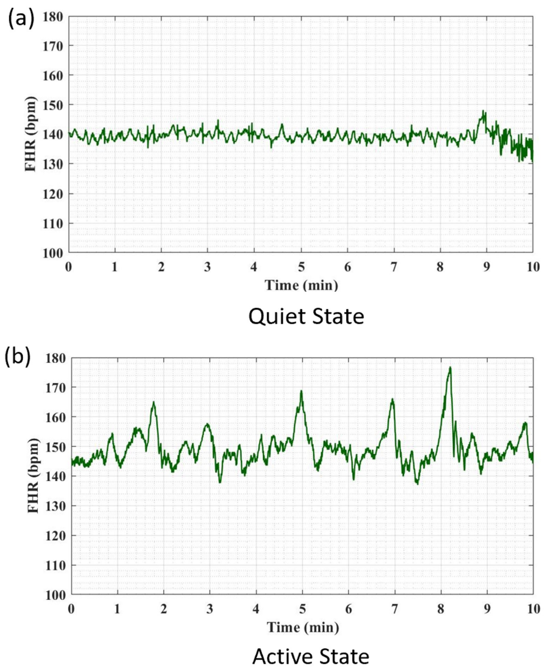

Figure 1. Examples of fetal quiet state and fetal active state obtained from fetal heart rate signal.

classify FBSes into quiet state and active state using NI-fECG information.

2. Methods

2.1. Dataset Information

A total of 105 healthy fetuses with GA ranging from 20–40 weeks were examined using non-invasive electrocardiography (ECG) signals for 3–10 min in a supine position. The datasets were obtained from Kanagawa Children's Medical Center (17 subjects, 16.2%) and Tohoku University Hospital (73 subjects, 69.5%) in Japan, in addition to Children's National Hospital in the United States (15 subjects, 14.3%). On the maternal abdomen, twelve electrodes were placed, and signals were recorded. The fetal ECG was separated from the composite abdominal signal using maternal ECG cancellation and blind source separation with a reference [13]. Fig. 1 illustrates an example of a fetal quiet state and a fetal active state.

2.2. Structure of 1D CNN Technique

Fig. 2 illustrates the structure of 1DCNN where time-series signals are used as inputs. Layer by layer, convolutional layers, and pooling layers are used to extract features and thus form the overall feature map of the input. Afterward, the fully connected layer categorizes the results.

As a result of the convolution operation performed on the local area of the input signals, one-dimensional feature maps are generated, and different convolution kernels produce different output features from the input signal.

In this study, the deep neural network was constructed using three convolutional layers. Accordingly, each layer of the network has a kernel size of [1, 30], [1, 20], and [1, 11], respectively. Additionally, as the network is deepened, the number of filters increases, with 8, 16, and 32, respectively. In order to reduce the dimensionality and complexity of the model, each convolutional layer was followed by a max-pooling layer. Throughout the network, the max-pooling kernel size remained same with kernel sizes of [1, 2]. The max-pooling layers were followed by batch normalization (BN) layers to normalize all filters and rectified linear unit (ReLU) layers to set all feature map values below zero to zero. To prevent overfitting, dropout layers are placed in the model. A final layer, known as softmax, mapped input signals and output signals. As a result, the number of units in this layer equals the number of classes.

2.3. Labeling of Fetal Heart Rate Pattern

Labeling of Fetal Heart Rate Pattern (FHRP) using the criteria outlined in previous studies [14][15] was conducted. All the 3 min window was labeled and used for training purpose.

2.4. Training and Validation

In order to train the proposed model, the stochastic gradient descent with momentum (SGDM) optimizer was used with a mini-batch size of 60 and a maximum of 350 epochs. A learning rate of 0.01 was assigned along with an L2 regularization of 0.0001. The proposed model was validated using a k-fold (k=5) cross-validation procedure.

2.5. Performance Evaluation

A traditional evaluation metric, such as accuracy, sensitivity, specificity, precision, and F1-score, was used to evaluate the performance of the proposed deep learning model.

3. Results

This initial study was conducted to analyze how efficiently the 1D CNN technique could classify FBSes into quiet state and active state. Fig. 3 illustrates the overall performance of the proposed deep learning model. Using the dataset, the model correctly predicted 160 out of 179 quiet states and 90 out of 150 active states. Moreover, only 19 subjects in the quiet state were incorrectly classified as active state, whereas 60 subjects in the active state

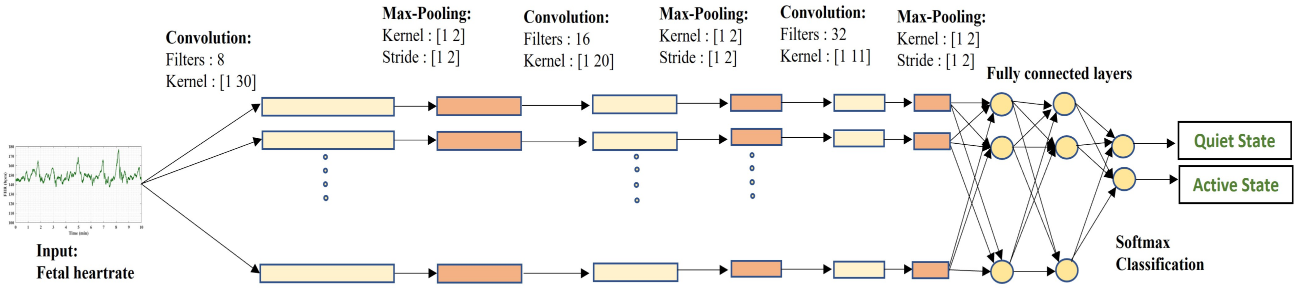

Figure 2. The framework of 1D CNN Technique.

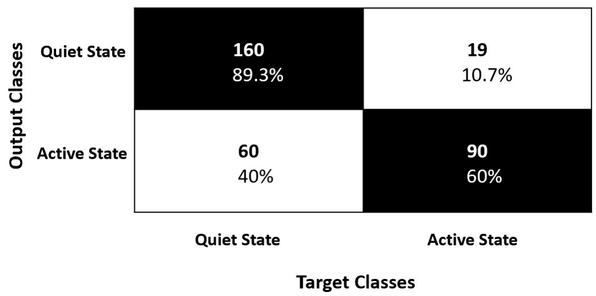

Figure 3. Model performance using confusion matrix.

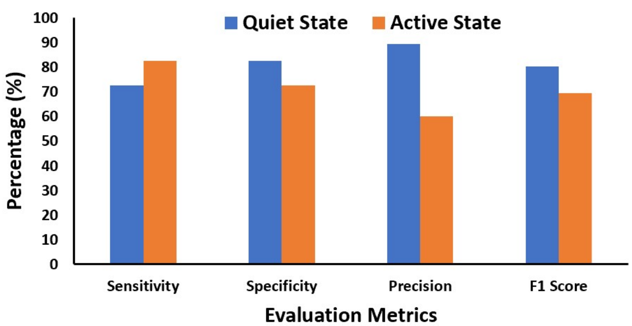

Figure 4. Evaluation metrics.

were misclassified as quiet state. As quiet state prediction was higher compared to active state, the confusion matrices show percentages of proportion of 89.3% and 60% for quiet state and active state datasets, respectively. The overall accuracy of the model is 76%.

According to the evaluation metrics calculated from these confusion matrices (Fig. 4), the sensitivity measures for the quiet and active state datasets are 72.7% and 82.6%, respectively. Additionally, the model showed 82.6% specificity for the quiet state dataset and 72.7% specificity for the active state dataset. The quiet state dataset had the highest precision of 89.4%, while the active state dataset had the lowest precision of 60%.

3.1. Performance related to state of art approaches:

Table 1 shows recent work on fetal behavioral state classification done so far in order to illustrate the performance of the proposed deep learning model compared to the current state-of-the-art studies. Other studies used fetal Magnetocardiography (MCG) signals [14][15]. A difference between the proposed study and the study reported in [15][14] is that the proposed study used recorded ECGs from NI-fECG, as well as a deep learning approach, resulting in slightly higher performance than [15]. Compared with our study, the study reported in [14] showed excellent classification accuracy. There is only one limitation in [14]: the GA range, where they used GA from 36 - 40 weeks. During this late GA period, FBSes become highly consistent and stable, which may have contributed to the high performance.

4. Discussion

The study presented in this article demonstrated the importance of using deep learning to categorize fetal behavioral states. Furthermore, it elaborated on the significance of fECG signals over fMCG signals in classifying fetal behavioral states. The results of this study (accuracy of 76%) suggest that deep learning could be used as a prescreening tool for assessing the development of the ANS in fetuses. Besides providing high levels of performance, deep learning also reduces the need for experts, such as doctors and nurses. Moreover, the sensitivity and specificity measures (72.7% and 82.6%, respectively) obtained in this study demonstrate the efficiency of deep learning in FBS classification. Although it is well known that fMCGs have a higher resolution than fECGs, the study reported in this article, however, indicates that FBS classification performed by fMCG and fECG recordings is almost as accurate with slightly better accuracy. The proposed deep learning approach had a good overall performance and a higher capability to classify fetal quiet state accurately.

Table 1. Comparison study with current state of art.

Study	Year	GA Range	Technique used for recording	Technique used for classification	Overall Accuracy (%)	Quite state Accuracy (%)	Active state Accuracy (%)
Lange[14]	2009	36≤GA<41	fMCG	Quadratic discriminant analysis	91.7	90.9	90.8
Vairavan[15]	2016	30≤GA<38	fMCG	Based on threshold values	70	86.5	53
Our study	**2022**	**20≤GA<40**	**NI-fECG**	**Deep learning (1D CNN)**	**76**	**89.3**	**60**

GA- Gestational Age, fMCG- Fetal magnetocardiography, NI-fECG- Non-invasive fetal Electrocardiography

5. Conclusions

The study presented in this article proposed a deep learning technique used to categorize the Fetal Behavioral States (FBSes), and resulted in an over all accuracy of 76%. Analysis of FBSes is one method of understanding the maturation of the fetal autonomic nervous system (ANS). This deep learning approach needs to be further modified to improve the accuracy of fetal active state classification.

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