Unsupervised Fetal Behavioral State Classification Using Non-Invasive Electrocardiographic Recordings

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Abstract

Understanding the Fetal Behavioral States (FBSes) is one of the ways to understand the fetal Autonomic Nervous System (ANS) maturation. This preliminary work aims to automatically classify FBSes using the unsupervised k-means clustering technique. Non-invasive electrocardiogram signals were recorded from 67 healthy fetuses with Gestational Age (GA) range of 20–40 weeks for a duration of 10 min. Features extracted from the original fetal Heart Rate (HR) and detrended HR are used to classify the FBSes. Results showed that during the early gestational period, the prominent state was 1F compared to other states and the least common state was 4F. The decrease in 1F frequency and the increase in 2F frequency in late gestation represent the coordination and overall maturation of the fetal ANS. Results showed that the k-means clustering algorithm had good overall performance and stronger classification ability with good Cohen's κ score. Unsupervised classification of FBSes based on electrocardiography data is possible. It is achievable to incorporate this algorithm into future devices for in depth understanding of fetal brain maturation and well-being.

1. Introduction

Fetal Behavioral State (FBS) estimation is one of the ways to understand fetal Autonomic Nervous System (ANS) development [1]. Fetus exhibits four different behavioral states: 1F (quiet sleep), 2F (active sleep), 3F (quiet awake-this state seldom occurs), and 4F (Active awake). The FBSes are usually defined by combining fetal Heart Rate Variability (HRV) and fetal movements [2]. These states are repetitive over time and exhibit distinct changes when moving from one state to another. As the gestation progresses, FBSes become more consistent and stable [3].

In clinics, fetal well-being is assessed using cardiotocography (CTG), which provides rudimentary information on fetal Heart Rate (HR) baseline and its variations. But it does not provide the complete electrophysiological analysis of the heart, which can only be obtained using non-invasive fetal electrocardiography (NI-fECG) or fetal magnetocardiography (fMCG). Compared to fMCG, NI-fECG is easier and cheaper[4]. NI-fECG allows detection of the morphology of signal (P, R, and T waves), and from this R-R series, HRV can be determined. NI-fECG obtained by placing electrodes on the mother's abdomen has many advantages: continuous long-term monitoring, ease of use, and safety. However, NI-fECG is highly sensitive to background noise, maternal ECG, respiration, and motion interference [5].

Supervised learning is a process in which the model itself is trained with the input data set, and a mapping function is generated from the input data to the target data. While in the case of unsupervised learning, there is no training procedure, and thus structures in data sets have not been discovered [6].

The clustering technique is the most widely used method in unsupervised learning techniques. This technique separates the data set into groups based on the similarity within the cluster and dissimilarity between other clusters (e.g., distance) [7]. Clustering aims to group heterogeneous data into different homogeneous groups. The k-means algorithm is a widely used clustering technique in many fields. This algorithm divides n number of data into k number of clusters, where k needs to be defined initially. This will affect the k-means algorithm efficiency and outcome [7].Previous studies on FBSes classification used threshold-based classification [8] [9] and here, using clustering technique, we used robust non-linear classification technique.

This preliminary work aims to classify the FBSes into the four states (1F, 2F, 3F and 4F) using unsupervised k-means clustering technique and analyze how efficiently the k-means algorithm could classify it.

2. Methods

2.1. Subjects and ECG Signal Processing

Non-invasive Electrocardiogram (ECG) signals were recorded from 67 healthy fetuses with a Gestation Age

(GA) range of 20–40 weeks for a duration of 10 min with participants in the supine position. These data set were obtained from Kanagawa Children's Medical Center (11 samples, 16%), Children's National Hospital in the US (15 samples, 23%), and Tohoku University Hospital (41 samples, 61%). Twelve electrodes were placed on the maternal abdomen, and signals were recorded. We used maternal ECG cancellation and blind source separation with a reference to separate fetal ECG from the composite abdominal signal [10].

2.2. Heart Rate Variability Feature Extraction

Each 3 min window of the HR segment produces a Fetal Heart Rate Pattern (FHRP). The fetus exhibits four different HR patterns based on the difference in oscillation bandwidth, baseline, and accelerations on HR signal. HRV features including the standard deviation of fetal HR, the percentage ratio of acceleration and deceleration greater than or equal to 10 bpm from detrended HR (DHR), and the percentage ratio of fetal HR greater than or equal to 160 bpm were extracted from the same. DHR is calculated by subtracting the floating baseline from fetal HR [8].

2.3. k-means Clustering Algorithm

The FBS classification framework is shown in Fig. 1. Several pre-processing steps followed by feature extraction were done, as explained in the previous section. After feature extraction, the k-means clustering algorithm was performed with an Euclidian distance where centroid, inter, and intra-cluster distance were used to select the clusters as follows

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| x_i^{(j)} - c_j \|^2 \tag{1}$$

where J is the objective function, k is the number of clusters, n is the number of cases, $x_i^{(j)}$ is the i^{th} case, and c_j is the centroid for cluster j.

2.4. Visual Analysis of Fetal Heart Rate Pattern

Visual analysis of FHRP was done based on the criteria mentioned in previous studies [11][8][9]. All the 3 min window was scored and then compared with clusters produced by the natural k-means clustering algorithm.

2.5. Statistical Analysis

Sensitivity, specificity, and F-score were generated for all gestational periods. In each epoch, the similarity between the output of the k-means clustering algorithm and the visual inspection method was calculated to evaluate the classifier's efficiency. Cohen's kappa (κ) was also calculated, which measures the agreement between k-means clustering and visual inspection method.

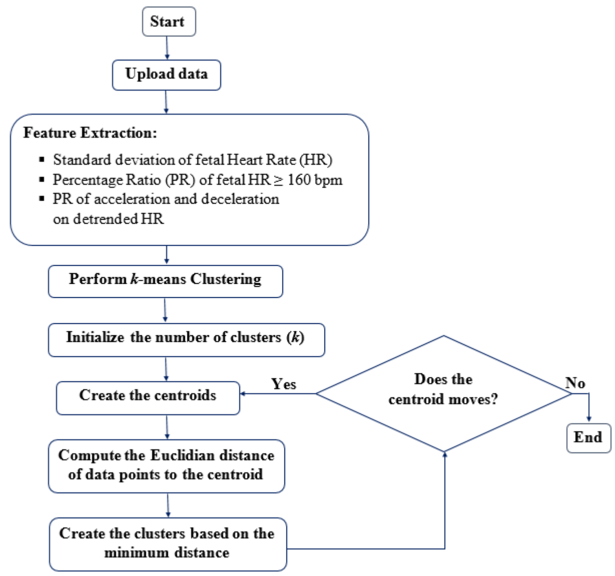

Figure 1. Framework for fetal behavioral state classification using the natural unsupervised k-means clustering algorithm.

3. Results

This preliminary study was conducted to classify FBSes into quiet sleep (1F), active sleep (2F), quiet awake (3F), and active awake (4F) using unsupervised k-means clustering technique, and analyze how efficiently the k-means algorithm could classify it. Fig. 2 shows clusters formed by the k-means clustering algorithm in four different gestational age periods, which are (a) 20–25 weeks, (b) 25–31 weeks, (c) 31–36 weeks, and (d) 36—40 weeks.

Table 1 shows how efficiently k-means clustering has classified the FBSes in four different gestational periods. This had led to 91.67%, 71.67%, 91.15%, and 92.96% correctly classified cases for 20–25 weeks, 25–31 weeks, 31–36 weeks, and 36–40 weeks, respectively. It is also observed that 1F is a more prominent and frequently occurring behavioral state, and 4F is the least common behavioral state in all considered gestational periods. A decrease in 1F frequency and an increase in 2F frequency could be observed as the gestation progresses.

Table 2 shows the detailed performance of the k-means cluster for FBS classification. It is observed that classification sensitivity, specificity, F-score, and Cohen's κ is above 80% for all the GA ranges except 25–31 weeks. But still,

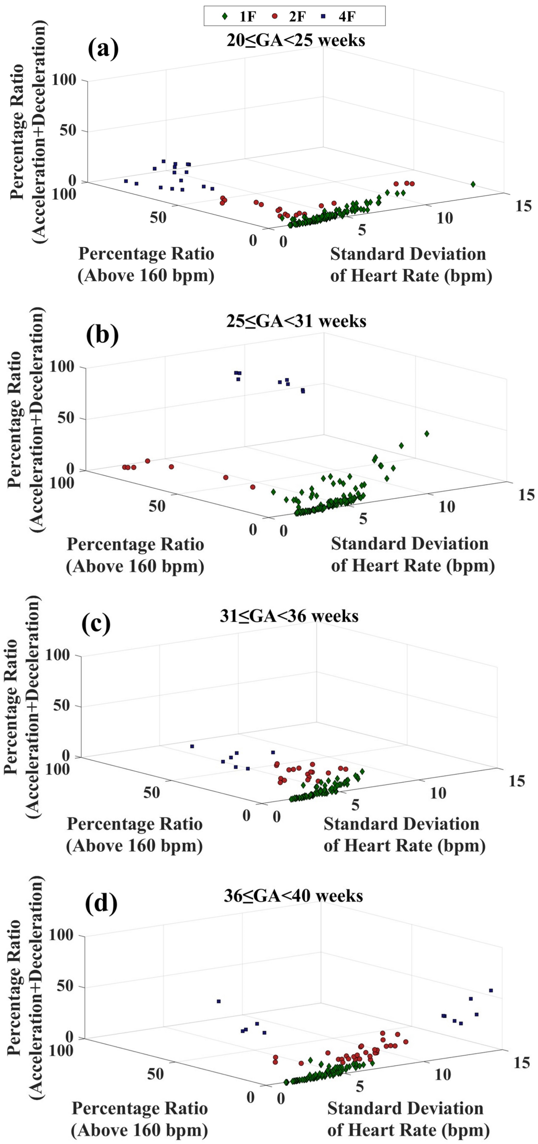

Figure 2. Clustering analysis performed by the k-means clustering algorithm in four different gestational periods: (a) 20–25 weeks, (b) 25–31 weeks, (c) 31–36 weeks, and (d) 36–40 weeks.

a moderate agreement could be observed for 25–31 weeks with Cohen's κ value of 57.25%.

4. Discussion

This paper presented a preliminary work to classify FBSes into quiet sleep (1F), active sleep (2F), quiet awake (3F), and active awake (4F) using the unsupervised k-means clustering technique. Fig. 1 showed the clusters formed by the k-means clustering algorithm. The study reported in [8] classified the FBS using HRV parameters like standard deviation of fetal HR, percentage ratio of acceleration and deceleration greater than or equal to 10 bpm from detrended HR (DHR), and percentage ratio of fetal HR greater than or equal to 160 bpm. Similar classification trend could be observed in our results where 1F showed lower percentage ratio of acceleration and deceleration greater than or equal to 10 bpm from DHR compared to other two states. In addition, 2F showed lower percentage ratio of fetal HR greater than or equal to 160 bpm compared to 4F.

In this study, we observed that 1F is the commonly occurring FBS and 4F is the least commonly occurring state. These results are consistent with the study reported in [1], where they observed the same when mothers were in supine position. The decrease in 1F frequency and the increase in 2F frequency in late gestation represent the coordination and overall maturation of the fetal ANS. Results showed that the unsupervised k-means clustering algorithm had good overall performance and stronger classification ability with good Cohen's κ score.

5. Conclusions

The unsupervised k-means clustering technique was used to classify Fetal Behavioral States (FBSes) in the preliminary study presented in this paper. The FBSes analysis is one of the ways to understand the fetal Autonomic Nervous System (ANS) maturation. It is feasible to identify FBSes using unsupervised k-means clustering of fetal HR using these HRV features.

The decrease in 1F frequency and the increase in 2F frequency in late gestation represent the coordination and overall maturation of the fetal ANS. Automated, unsupervised, and robust classification of FBSes based on Electrocardiography (ECG) data is possible. Moreover, it is advantageous to incorporate these algorithms into future implantable devices to improve fetal well-being. The major limitation of this study is that the 3F state could not be included as this state rarely occurs. Further studies with different maternal positions need to be done to understand the influence of maternal sleep positions on FBSes. Further investigation using the fetal distress group should be incorporated to understand the difference in the FBS from healthy fetuses.

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Table 1. Performance evaluation of the proposed Fetal Heart Rate Pattern (FHRP) detection approach for all data sets.

20–25 weeks	**Predicted State**									**% Correctly Classified**
		1F N	2F	4F	Total	1F %	2F	4F	Total	
Original State	1F	120	0	0	120	100	0	0	100	
	2F	6	18	0	24	25	75	0	100	91.67
	4F	0	0	16	16	0	0	100	100	
25–31 weeks	**Predicted State**									**% Correctly Classified**
		1F N	2F	4F	Total	1F %	2F	4F	Total	
Original State	1F	100	0	0	100	100	0	0	100	
	2F	13	7	0	20	65	35	0	100	71.67
	4F	0	2	8	10	0	20	80	100	
31–36 weeks	**Predicted State**									**% Correctly Classified**
		1F N	2F	4F	Total	1F %	2F	4F	Total	
Original State	1F	64	1	0	65	98.46	1.54	0	100	
	2F	6	18	0	24	25	75	0	100	91.15
	4F	0	0	7	7	0	0	100	100	
36–40 weeks	**Predicted State**									**% Correctly Classified**
		1F N	2F	4F	Total	1F %	2F	4F	Total	
Original State	1F	86	4	0	90	95.56	4.44	0	100	
	2F	4	25	1	30	13.33	83.33	3.34	100	92.96
	4F	0	0	11	11	0	0	100	100	

Table 2. Overall statistics for the unsupervised k-means clustering algorithm.

GA Range (weeks)	**Sen. (%)**	**Spec. (%)**	**F-Score (%)**	**Cohen's κ**
20≤GA<25	91.67	95.00	94.43	90.20
25≤GA<31	66.67	82.73	72.74	57.25
31≤GA<36	91.15	93.09	92.85	83.85
36≤GA<40	92.96	95.07	91.98	85.37

GA, Gestational Age; Sen., Sensitivity; Spec., Specificity.

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