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ORIGINAL

Extraction of fetal electrocardiogram signal based on K-means Clustering

Extracción de la señal del electrocardiograma fetal basada en el agrupamiento K-means

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ABSTRACT

Fetal electrocardiograms (ECG) provide crucial information for the interventions and diagnoses of pregnant women at the clinical level. Maternal signals are robust, making retrieval and detection of Fetal ECGs difficult. In this article, we propose a solution based on Machine Learning by adapting the k-means clustering to detect the fetal ECG by recording the ECGs. In our first preprocessing part, we tried normalized and segmented ECG waveform. Next, we used the Euclidean distance to measure similarity. To identify a certain number of centroids in our data, the results classified into two classes are represented in the last part through graphs and compared with other algorithms, such as the CNN classifier, to demonstrate the effectiveness of this innovative approach, which can be deployed in real-time.

Keywords: ECG; Machine Learning; K-means; Fetal electrocardiograms.

RESUMEN

Los electrocardiogramas (ECG) fetales proporcionan información crucial para las intervenciones y diagnósticos de las embarazadas a nivel clínico. Las señales maternas son robustas, lo que dificulta la recuperación y detección de ECGs fetales. En este artículo, proponemos una solución basada en Machine Learning adaptando el clustering de k-means para detectar el ECG fetal mediante la grabación de los ECGs. En nuestra primera parte de preprocesamiento, intentamos normalizar y segmentar la forma de onda del ECG. A continuación, utilizamos la distancia euclídea para medir la similitud. Para identificar un cierto número de centroides en nuestros datos, los resultados clasificados en dos clases se representan en la última parte mediante gráficos y se comparan con otros algoritmos, como el clasificador CNN, para demostrar la eficacia de este enfoque innovador, que puede aplicarse en tiempo real.

Palabras clave: ECG; Machine Learning; K-means; Electrocardiogramas Fetales.

INTRODUCCIÓN

In today's world, machine learning models are increasingly implemented worldwide for people segmentation and anomaly detection. In the field of health, the diagnostic phase is essential for the orientation of the patient and his follow-up.(1) Machine learning brings new solutions to healthcare professionals to save time and optimize the correct diagnosis. It opens new perspectives in the identification of diseases. For example, it can help doctors more easily detect abnormalities in patients' organs or predict future diseases in the human body. Monitoring the fetus's condition should be constant during a woman's pregnancy to ensure good health. Continuous monitoring allows physicians to increase their presence and make better decisions faster in an emergency.

The objective is not to replace the doctor with the machine but to support him in analyzing and interpreting the enormous amount of data collection.[2,3] Machine Learning also makes it possible to promote good diagnoses and fight against medical errors by generating differential diagnoses and suggesting complementary examinations. They seem capable of solving many health problems doctors encounter, particularly interpreting ECG, EMG, and EEG biological signals.[4] Congenital heart defects are the leading cause of death from congenital disabilities. For this, one of the best techniques is monitoring the cardiac signal, which gives us essential information about the state of the fetus.[5]

The fetal electrocardiogram (ECG_Fetal) can be monitored by placing electrodes on the mother's abdomen. However, it is weak and confused with multiple noise sources, including the mother's ECG, which is unusually high in amplitude. Several approaches to extract ECG_F from signals picked up by electrodes implanted on the surface of the mother's body have been proposed in previous research.[6,7,8,9] However, these approaches have been treated with 2 methods, and the first requires many dangerous sensors for the fetus's health.[10] The second is to use another deep learning approach, such as CNN.[11]

The identification of arrhythmias has the potential to be simplified into a straightforward and practical categorization of heartbeats. As a result, numerous techniques have been proposed in this field, as referenced in several studies.[12,13] With the advancements in artificial intelligence (AI), AI has emerged as a robust solution to various challenges that previously lacked effective solutions. These challenges include classifying intricate models, predictive tasks, and computer vision.

One approach involves employing deep learning architectures within the realm of AI methods. In these architectures, the initial layers composed of convolutional neurons serve as feature extractors, while the fully connected layers at the end play a pivotal role in arriving at the final decision.[14,15]

This article focuses on one of the most powerful algorithms, K-means. It is one of the most popular clustering algorithms. It makes it possible to analyze a data set characterized by descriptors to group similar data into groups or clusters.[6,17] He proposes a new approach using a classifier based on this kind of deep architecture to classify ECG beats. The second section of this article provides our approach's methodology with a description of our database. The third section gives our proposed algorithm and the data extraction method. The last part is devoted to the result and comparing our approach with other methods to demonstrate our proposed approach's effectiveness.

SYSTEM DESCRIPTION AND METHODOLOGY

Dataset visualization

It is impractical to ask doctors to review the voluminous data collected from the human body or scans. However, the results of the processing performed on the data should be presented to the physicians in a clear and classified format where they can easily understand the interrelationships between the collected information. Visualization is considered an independent tool and an important area of research, with many applications in science and everyday life.

In this part, we are interested in visualizing the data collected on the bodies of pregnant women and the analyses. However, our application repels several problems that hinder the application in the real case, such as the cost of the material, the lack of experience in the medical field. These cited problems related to data collection guided us toward the use of authentic databases that help us visualize accurate patient data.[18]

Our research selected the direct abdominal and fetal ECG database (ADFECGDB), which can be accessed at https://physionet.org/physiobank/database/ADFECGDB, as our primary data source. These data were gathered from the Department of Obstetrics at the Medical University of Silesia using the KOMPOREL system. This system utilizes ECG (electrocardiography) sensors to capture the electrical signals generated by the heart, enabling the assessment of cardiac activity, including heart rate and the time intervals between heartbeats. Electrocardiography (ECG) represents the electrical potential that regulates heart muscle activity.[19,20] The potential is collected by electrodes placed on the skin's surface, allowing for the detection of various cardiac irregularities. ECG plays a vital role in diagnostic examinations in the field of cardiology.

Recordings were obtained from five pregnant women aged between 38 and 41 weeks. Each recording contains four differential signals (Figure 1) acquired from the maternal abdomen and a baseline direct fetal ECG obtained from the fetal head.

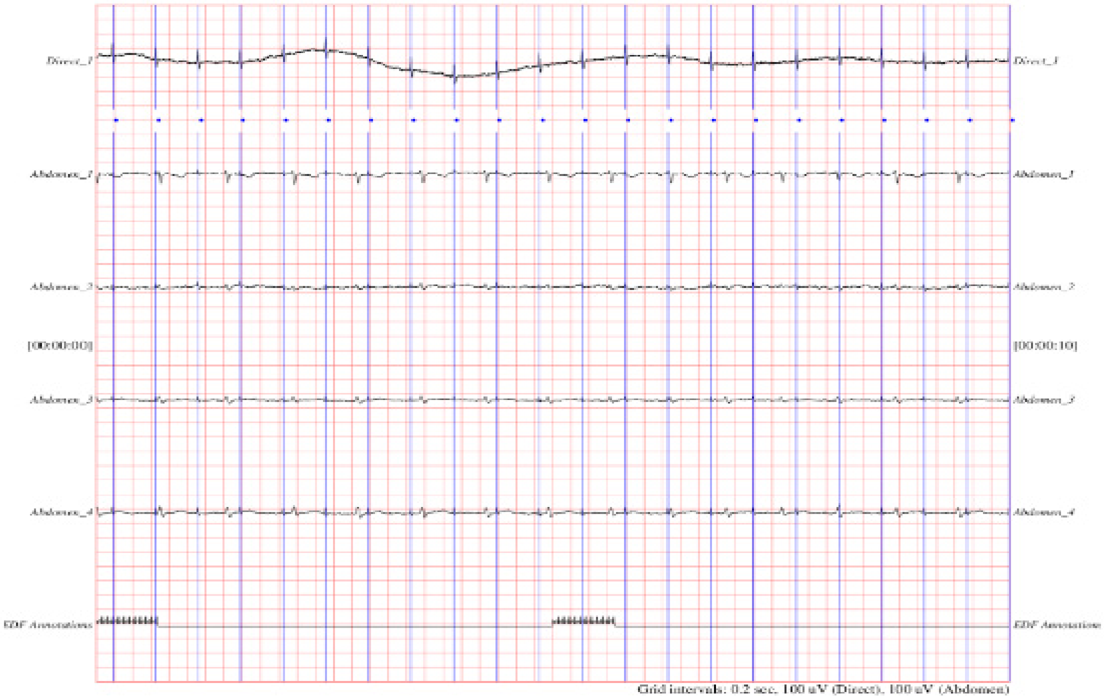

Figure 1. Representation of collected data ECG

FETAL ECG signal extraction based on the K MEANS algorithm

Our innovative approach is based on a carefully designed two-phase methodology to efficiently process and analyze data figure 2. The first phase, pre-processing, is of crucial importance as an essential prerequisite. During this stage, the raw data undergoes a process of cleaning, normalization and transformation. The goal of preprocessing is to eliminate noise and inconsistencies, ensure data consistency, and prepare it for the next phase. The clustering phase, the second step of our approach, revolves around the exploitation of preprocessed data. This step aims to group the data into homogeneous sets, thereby identifying underlying structures or patterns. Using advanced clustering techniques, our method can discover relationships, trends, and similar groups of data within the initial set. Clustering makes it much easier to interpret data by organizing it logically, which can be essential for informed decision-making and in-depth analysis.

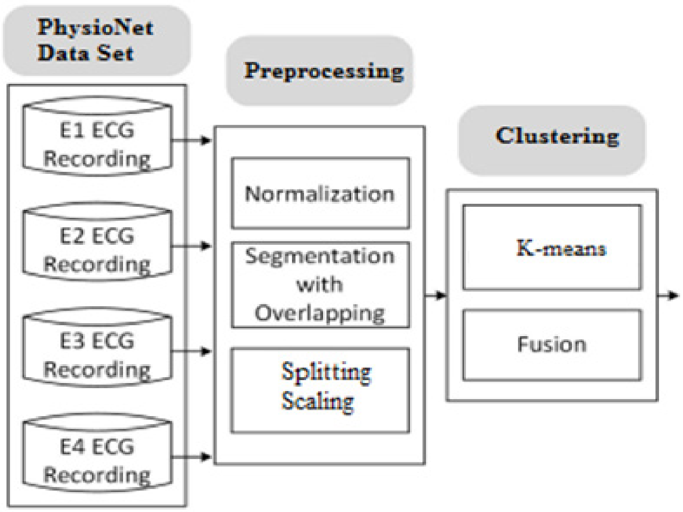

Figure 2. Data Processing Workflow

By skillfully combining preprocessing for data preparation and clustering for exploring their internal structures, our approach offers a comprehensive solution for data management and analysis. It can be successfully applied in a variety of areas, from geospatial data mining to customer segmentation, providing valuable insights for strategic decision-making and meaningful discoveries. As shown in figure 2, this is demonstrated by seeking

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to group the data into K distinct clusters in the observations of the data set. However, based on the data's similarity, similar data end up in the same cluster. Moreover, an observation can only be found in one cluster at a time. The same observation cannot, therefore, belong to two different clusters. An ECG sensor deployed in the mother's abdomen measures a combination of the information. In mathematical terms, our equation is interpreted as follows:

$$X=aFE+bMe+B \qquad (1)$$

knowing that Fe= ECG Fetal, Me=ECG Maternal, B =Noise.

Kmeans ECG Clustering

In order to organize our data into separate clusters, the K-Means algorithm requires a method for assessing the level of similarity between various data points. Consequently, data that closely resemble each other exhibit a smaller dissimilarity distance, whereas dissimilar objects have a greater separation distance. In our case, we chose to use the Euclidean distance, which is the geometric distance that is calculated as follows:

$$d(x_1, x_2) = \sqrt{\sum_{j=1}^{n} (x_{1n} - x_{2n})^2} \qquad (2)$$

After loading the data to separate the F and M ECGs, we must separate our data into two categories figure 3: training and test. The first category helps us train our model, and the second is used to test the model's success rate. It is the essential step of the preprocessing.

```
# Splitting the dataset into the Training set and Test set
"""from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)""
# Feature Scaling
"""from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
sc_y = StandardScaler()
y_train = sc_y.fit_transform(y_train)"""
```

Figure 3. Data separation and Splitting

According to our algorithm, we must first define the number K of clusters. The problem is finding an optimal K. One of the most popular methods for doing this is the elbow method. The idea is to perform k-means clustering for a range of k clusters, and for each figure 4 value, we compute intraclass. When plotting the figure 5 distortions and the plot looks like an arm, the curve's inflection point is the best value of k.

```
# Using the elbow method to find the optimal number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

Figure 4. The optimal number of cluster

We notice in figure 5 that the curve is shaped like an arm. According to Elbow's method, the optimal value of K is either two or three. This agrees with the dataset used divided into two or three classes.In our case and according to EQ 1, if we neglect noise B, we fall into two classes: the first is that of the Fetal, and the second is that of the Maternal. Our equation, therefore, is reformulated as follows:

X=aFE+bMe (3)

In figure 6, we successfully deploy the K-Means algorithm, an unsupervised learning method, to classify our data into two distinct classes: fetal and maternal. This implementation is designed to solve the problem of segmenting our data based on two well-defined categories. The K-Means process begins with the initialization of two cluster centers, which serve as starting points for classification. Then, each data point is assigned to the closest cluster, based on Euclidean distance. This step is repeated iteratively until convergence, when the cluster centers no longer change significantly. The result of this implementation is the division of our data into two clusters figure 7 shows us two classes of observations in red and blue, respectively, which describe the excellent separation of fetal and maternal data, each grouping together data points sharing similar characteristics.

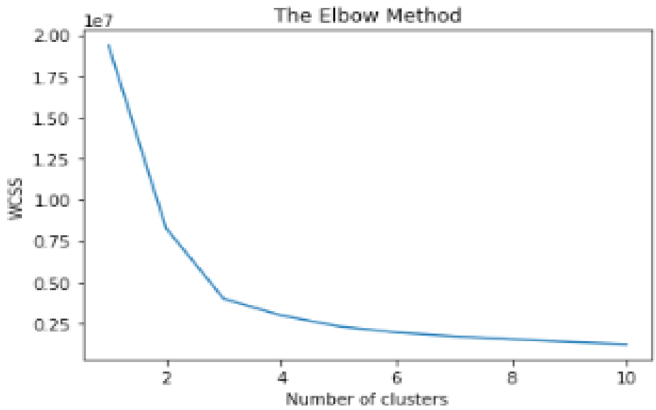

Figure 5. The Elbow Method

We are now going to implement the K-Means algorithm with two classes in figure 6:

```
# Fitting K-Means to the dataset
kmeans = KMeans(n_clusters = 2, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)
```

Figure 6. Initialize the number of clusters

The result of this application is:

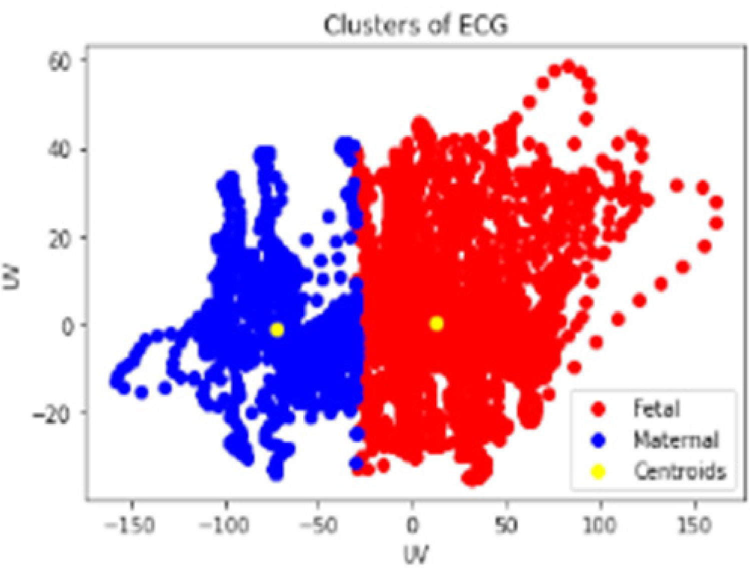

Figure 7. Results of clusters

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RESULTS AND DISCUSSION

To verify the performance of our proposed K-means algorithm, we performed simulations in the following 5-axis ECG recording. In figure 8, we present the results of the simulation based on the approach described in this work to determine the MECG and FECG signals. According to the global algorithm, we start by building the images of our data separated from axis 1, which demonstrates the variance of the Maternal ECG, and the same for axis 2, which presents the ECG of the Fetal. In Axis 3, we presented the 2 ECGs to compare their changes. Due to its low amplitude, the contribution of the fetus in terms of energy is meager. However, the powerful fetal heartbeat allows it to be easily illustrated in the time-frequency and time-scale domains, which is the main focus of this article. In axes 4 and 5, the Fetal and Maternal ECGs in summer are present with their RR interval.

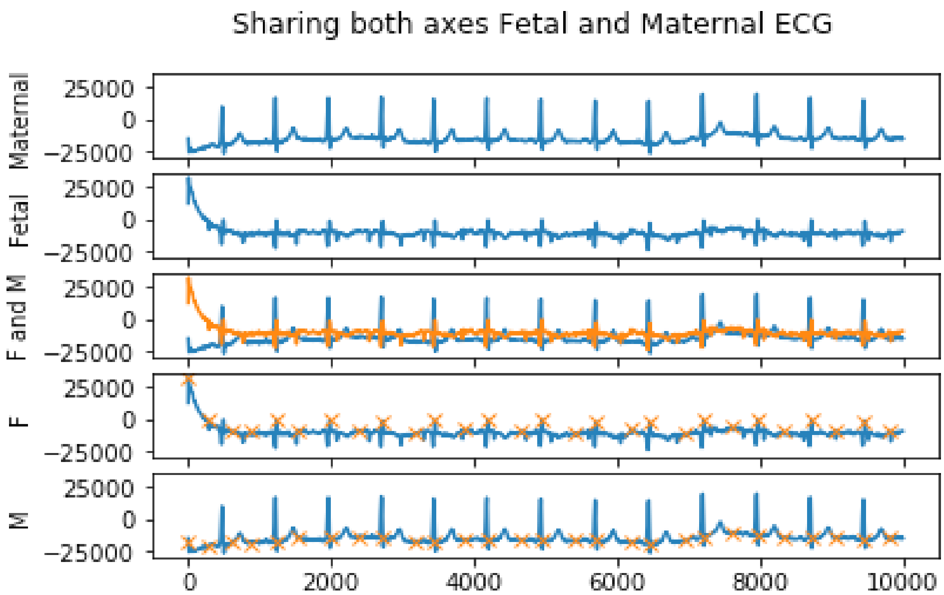

Figure 8. Sharing both axes, Fetal and Maternal ECG

Comparison with Related Work

So far, several methods of extracting MECG and FECG signals have been carried out. Among these methods,[21] have proposed an empirical mode decomposition method[22,23] and have proposed a least error algorithm mean squares. A solution that combines 3 algorithms, ICA, TS, and EKF, has been proposed.[24] They used the TS subtraction algorithm and the ICA algorithm to extract the Fetal and Maternal signals and then EKF to filter the Fetal and Maternal ECG components. One of the main requirements of[25] is to improve the 'FastICA' algorithm by adding an element to deal with the initial weight in the iterative Newton algorithm, which reduces the iteration time. Compared to previous work,[26] sought to improve the number of cross-relations under the same number of iterations. Figure 1 compares a set of proposed algorithms on works with their performance.

Similarly, proposed a method to estimate Fetal and Maternal ECG signals using the EKS approach with an adaptive system to estimate the actual ECG component. The results showed that our proposed Kmeans algorithm had higher accuracy.[27] The K-Means algorithm identifies several centroids in a data set, a centroid being the arithmetic mean of all data points belonging to a particular cluster. In recent years, several types of research have been conducted applying deep learning algorithms, such as several studies,[28,29,30,31,32,33] which have sought to process the signals. Studies have identified the characteristics of FECG signals using neural networks.[34,35,36,37,38,39] Figure 9 indicates that when extracting R waves, the efficiency and performance of the algorithms are similar to our proposed algorithm. However, deep learning algorithms demonstrate efficiency and performance in extracting the characteristics of low-amplitude signals because they can select a specific signal automatically. Studies have an approach based on convolutional CNNs as a solution that automatically extracts the signal and determines the fetal ECG.[40,41,42,43,44] Compared to our proposed algorithm, the disadvantage of these approaches is that the generalizability and accuracy of the model could not simply be increased only if adding more samples would impact the model's accuracy. On the other hand, our algorithm is deployed to discover groups that have not been explicitly defined and classify a dataset into several groups according to our approach, regardless of the size of our database.[45,46,47]

Authors	Methods	Year	Database	Sensibilité	Score	Avg
Gurve et al. [26]	ICA	2020	ADFECGD and PhysioNet2013	93.30	94.00	93.60
Gurve et al. [26]	NNMF + ICA	2020	ADFECGD and PhysioNet2013	95.30	94.60	94.80
Taha et al. [9]	FastICA	2020	PhysioNet2013	97.30	93.30	95.70
Barnova et al. [10]	EEMD	2021	ADFECGD and PhysioNet2013	81.79	87.16	84.08
Barnova et al. [10]	EEMD + RLS + ICA	2021	ADFECGD and PhysioNet2013	95.09	96.36	95.69
Sarafan et al. [16]	FastICA + TS + EKF	2020	PhysioNet2013	-	-	92.61
Zhang et al. [27]	K-means + PCA	2019	PhysioNet2013	96.23	95.35	95.78
Panigrahy et al. [20]	EKS + DE + ANFIS	2017	PhysioNet2013	91.47	92.18	-
Jaba et al. [28]	PSF + ANC	2021	DaISy and PhysioNet2013	97.92	94.66	96.12
Liu et al. [29]	SQA + FTM	2014	PhysioNet2013	94.13	93.74	93.90
Mollakazemi et al. [30]	PCA + WT	2021	PhysioNet2013	-	-	98.77
Jallouli et al. [31]	Clifford Wavelet Entropy	2021	PhysioNet2013	99.76	99.2	99.47
Rasti-Meymandi et al. [32]	AECG-DecompNet	2021	PhysioNet2013	97.40	93.52	95.42
Fotiadou et al. [6]	DNN+ LSTM	2020	PhysioNet2013	98.10	-	-
Vo et al. [23]	1-D Octave convolution	2020	PhysioNet2013	-	-	90.70
Ting et al. [24]	2-D-CNN	2021	PhysioNet2013	95.20	-	-
Mohebian et al. [25]	Conv1D + CycleGAN	2021	ADFECGDand NI-FECG	-	-	99.70
Our method	FastICA + SVD + WT	2022	ADFECGD and PhysioNet2013	96.90	98.23	95.24

Figure 9. Comparison of methods used in related works for the extraction of FECG and MECG signals
* Score: is the positive predictive value, and Avg is the harmonic mean of precision and recall

CONCLUSION

Fetal electrocardiograms have become a way to recognize fetal heart disease and change. However, extracting this signal is very important and challenging in medical practice. In this article, we have proposed a K-means Clustering algorithm to obtain Fetal and Maternal signal separates. This algorithm has been integrated into a graphical interface. The proposed method can be used as a new Fetal signal extraction and detection method. In future work, deep learning methods and multi-channel signals can be considered.

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