Investigating and Importance of Fetal Monitoring Methods and Presenting a New Method According to Convolutional Deep Learning Based on Image Processing to Separate Fetal Heart Signal from Mother

Morteza Zilaie, Zohreh Mohammadkhani, Keyvan Azimi Asrari, Sadaf Noghabi and Seyed Reza Talebiyan

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Morteza Zilaie[1] Zohreh Mohammadkhani[2] Keyvan Azimi Asrari[3] Sadaf Noghabi[4] Seyed Reza Talebiyan[5]

[1] Islamic Azad University Science and Research Branch, Khorasan Razavi, Mashhad 9187153886, Iran
[2] Islamic Azad University Science & Research Branch, Khorasan Razavi, Mashhad, 9187153886, Iran
[3] The University of Pavia, Italy
[4] The University of Pavia, Italy
[4] Imam Reza International University, Khorasan Razavi, Mashhad, Iran
mortezazilaie@gmail.com

Abstract. This Fetal electrocardiogram is a standard method to identify and diagnose fetal diseases. Therefore, effective techniques are needed to monitor fetal conditions during pregnancy and delivery. Meanwhile, obtaining the fetal electrocardiogram (FECG) signal, which contains the electrical activity of the fetal heart, has great importance, Of course, this signal is contaminated with many noises and disturbances and the most important of them is the mother's electrocardiogram signal. Inherently, the NI-ECG signal contains the maternal ECG signal, which has a larger amplitude than the fetal ECG signal. Therefore, it is not easy to detect the fetal QRS complex in order to control the condition of the fetus and prevent congenital defects. According to the above explanations, in this article, a deep learning approach based on a convolutional neural network is proposed to separate the electrocardiogram signals of the mother from the fetus without separating the mother's ECG signal. The proposed algorithm is able to reliably detect the fetal QRS complex. Also, in addition to not needing feature extraction steps, it has been able to show more suitable performance than the best methods proposed in previous research in terms of detection accuracy.
Keywords: Fetal heart signal, Deep learning, Electrocardiogram, convolutional neural network, QRS complex.

1 Introduction

Today, one of the prominent and challenging issues in the field of medicine is to check the condition of the heart of the fetus, so that according to the available statistics, one out of every 125 babies is born with heart failure. It may look healthy or it can be so severe that the child will have problems at birth [1]. There are also some possible complications such as Hypoxia caused by the closure of the umbilical cord around the neck of the fetus, which causes heart failure, or congenital heart disorders that may affect the growth of the fetus after years.

Ways and methods of monitoring the fetal heart and checking its performance can prevent damage to the fetus and increase the hope of the fetus' survival [2]. The fetal heart rate (FHR)1 provides valuable information regarding the physiological conditions of the fetus, therefore, many studies have been conducted to determine the fetal heart rate and monitor and check the function of the fetal heart automatically [3]. Doppler ultrasound methods, fetal phonocardiography (PCG), fetal magnetocardiography (MCG), cardiotocography (CTG), cranial ECG (SECG), invasive electrocardiogram, non-invasive electrocardiogram, are among the suggested methods [4].

Doppler ultrasonography and phonocardiography are only able to determine the fetal heart rate (FHR) and do not provide the doctor with information about the morphology of the electrical signal of the fetal heart, so it is considered ineffective in many cases. The method of fetal magnetocardiography, which uses sensors located near the mother's abdomen to identify the magnetic field and the heart of the fetus, in addition to high costs and patient complaints about the signal collection process, is not recommended for long-term use due to the need to not move during recording. At the same time, this method shows the waveform of the fetal electrocardiogram signal with high accuracy and has a relatively good signal-to-noise ratio.

Cardiotocography (CTG) uses an ultrasound transducer and a pressure-sensitive transducer of uterine contractions to determine the fetal heart rate. Cardiotocography requires extensive training and high costs, as well as the safety and safety of the fetus in this method is doubtful. The SECG method is considered an invasive method and is very risky because it causes infection, so it is not suitable for long-term fetal monitoring. Doppler ultrasound and phonocardiography methods are not capable of showing the morphology of the electrical signal of the fetal heart.

Among all the methods, the non-invasive electrocardiogram method, in addition to providing an accurate estimate of the FHR, has complete monitoring of the morphology of the fetal heart rate waveform, etc.

According to the explanations given, the fetal electrocardiogram method (non-invasive) has priority over other methods, but there are limitations such as; Noises that have both biological and non-biological origin and make it difficult to record the signal limit of this method [5]. In order to increase the efficiency of this method, various types of research have been proposed to extract and separate the maternal electrocardiogram (MECG) from the fetal (FECG) signals more efficiently with this method, which will be briefly mentioned below and their disadvantages will be stated.

In research by Ping Gao et al., the blind source separation (BSS)2 method was used to extract fetal signals from a single-channel signal [6]. The results showed that the use of SVD alone is inefficient and the combination of ICA + SVD is more efficient in separation. The research was done by Fanelli et al., which used the combination of principal components extraction method, decision rules, and Matched Filter to extract the ORS complex of the mother signal [7]. In this method, researchers have used the Kalman method as well as pattern matching to estimate the mother signal. The research was done by Kwang Jin Lee and Boreom Lee in 2016 using the full filter of successive changes, which first reduces the noise components of the abdominal ECG to effectively remove the maternal ECG through TSPCA and then separates the fetal ECG [8]. Xuwilson and colleagues have used principal component analysis and vertical imaging to reduce the effects of the maternal signal on the fetal signal [9].

They used the PCA clustering method to identify the fetal QRS complex. Research was done by Karimi Rahmati and colleagues in 2016 using PCA, and ICA techniques to extract FECG and detect R peak [10]. In another study, Feng tried to reduce the non-linear effects of maternal heart rate in fetal heart extraction by filtering [11]. Another research was conducted by Nannan Zhang et al. in 2017, which used ANC to remove MECG signals from recorded abdominal signals and combined SVD + SW techniques for estimation.

This method requires a reference signal that is morphologically similar to the maternal abdominal signal waveform [12]. Two other significant investigations are [5, 13]. In the work [13] on the compression and then recovery of the fetal signal with deep learning, no direct signal recovery has been done. In fact, the focus of [13] is based on the assumption that the fetal ECG signal is available, and we need a proper compression and recovery algorithm to send and receive it and recover the original signal from the signal received from the channel and remove its noise, which is the same as deep learning. In [5], which is closer to the proposed method of the article, the main features of the fetal ECG signal have been directly extracted using the convolutional neural network. The accuracy of this work in the best case has reached 77%.

The database cited in this study was Physionet. [14-16] have all used signal-based deep learning, which has the limitations of one-dimensional and noisy deep learning systems in all three. None of these three references have a separate step for noise and artifact removal. In the methods based on adaptive filters, due to the need for reference MECG signal (mother's electrocardiogram signal), the absence of a pure signal, and its contamination with noise, efficiency decreases. There are many problems in non-linear methods of signal separation due to the complexity of calculations. Linear decomposition is stationary and therefore not a good estimator for non-stationary FECG signals. The proposed method of this research uses fetal and maternal heart rate signal images and deep learning to detect the fetal QRS complex, which is expected to be more effective than conventional methods due to the innovative combination of deep learning and image approach in signal separation.

2 Deep Learning

Below is an implicit classification of the set of deep learning methods available [14].

Table 1. Implicit classification of the set of existing deep learning methods

Deep Learning Methods	**CNN-based Methods**	Alex Net
		Clarifai
		VGG
		Google Net
		SPP
	RBM-based Methods	Deep Belief Networks
		Deep Boltzmann Machines
		Deep Energy Models
	Autoencoder-based Methods	Sparse Autoencoder
		Denoising Autoencoder
		Contractive Autoencoder
	Sparse Coding-based Methods	Sparse Coding SPM
		Laplacian Sparse Coding
		Local Coordinate Coding
		Super-Vector Coding

An overview of a convolutional neural network architecture is shown in Figure 1. In general, a CNN network consists of three main layers, which are: the convolution layer, pooling layer, and fully connected layer.

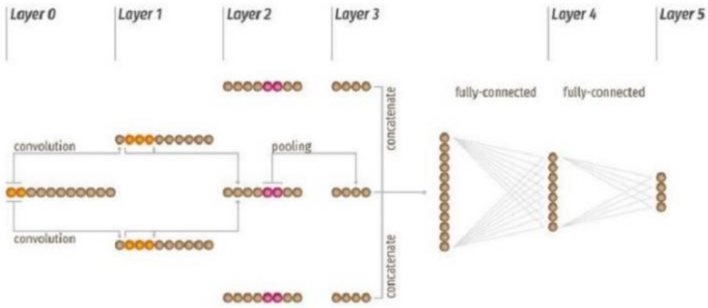

Fig. 1. A convolutional neural network

2.1 Convolution Layer

In these layers, the CNN network uses different kernels to convolution the input image and also create a map of intermediate features, and this map creates different features. Convolution operation has several benefits:

The weight-sharing mechanism in each feature map reduces the number of parameters. Local connectivity learns the relationship between signal samples. It causes immutability and stability against noise and shift.

2.2 Pooling Layer

A pooling layer is usually placed after a convolution layer and it can be used to reduce the size of the feature map and network parameters. Like convolutional layers, pooling layers are stable to noise and limited spatial variations due to considering the relationships between signal samples in their calculations.

2.3 Fully Connected Layer

After the last pooling layer, there are fully connected layers that transform the feature map into a unified vector to continue the recognition process. Fully connected layers work like their counterparts in traditional artificial neural networks and include almost 90% of the parameters of a CNN network.

3 Suggested Method

Considering that in the past works, based on the review, all the articles have taken help from the deep neural network with the input of fetal and maternal heart rate signals, and with this approach, they have tried to determine the QRS complex of the fetus and separate it from the mother. The designed approach in this research, instead of examining the signal in the form considered in previous works, uses the image recognition approach. In the proposed approach, which is completely designed based on the behavioral pattern of the doctor and specialist, by drawing the heart signal of the fetus and the mother in terms of time, the deep neural network is trained, which separates the mother's heart rate as a long peak from the fetal heart rate as a peak. In short, label the right place of the QRS complex of the fetus.

This idea, that is, dealing with an image with a complex medical time-varying signal, can be more efficient than conventional methods, because there are some deep neural networks with very comprehensive initial training on servers such as Google or Amazon, which are used to separate specific areas of the image from other areas have been trained and this issue will greatly help to increase the accuracy of the work. After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll-down window on the left of the MS Word Formatting toolbar.

3.1 Database

Considering that the research is related to FECG and the database [17] is used, according to the given explanations, the database is simulated in 10 situations related to pregnancy based on real data and simulated for each pregnancy. 7 different physiological parameters have been measured. Taken tests, which are specified by Base Line definitions and numbers 0 to 5, include tissue, abdominal, baseline with noise, fetal movement with noise, and uterine contraction with noise. These parameters are measured and measured along with different levels of noise for each situation in 5 repetitions. Therefore, according to 10 pregnancy conditions, 7 measured gauges, 5 different noises, and 5 repetitions, a total of 1750 signals will be produced, which can be seen in 145.8 hours of time efficiency and 1.1 million information peaks related to the fetus. Each sub-branch shows the pregnancy status in the form of a name, and the next two digits show the noise level. The noise levels are assumed to be 0, 3, 6, 9, and 12 dB respectively in the simulation, and the pregnancy status includes the numbers 0 to 20. In addition, the test repetition number is the third number that is placed in the file. This database can be added to the current MATLAB path, and it should be noted that in the default state, the data cannot be read by Windows software and has a Linux extension. Figure 2 shows an example of database images. The horizontal axis is the sample number based on the sampling frequency of 1000 Hz and the vertical axis is the amplitude of the sampled signal in millivolts after amplification.

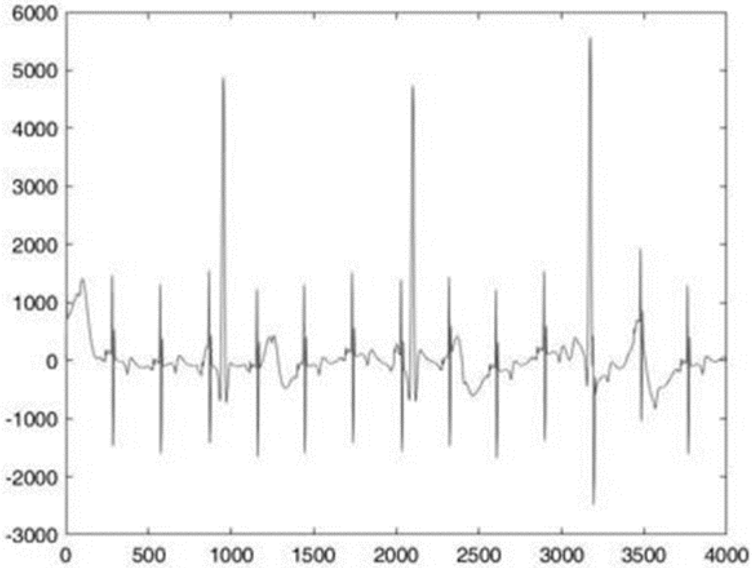

Fig. 2. Sample database image

3.2 Labeling images according to the input pattern of deep neural network

In the first step of the proposed method, fetal and maternal heart rate signal images should be drawn and labeled according to the input pattern of the trained deep neural network available in MATLAB software. Considering that the collected database had a different labeling than what we intended, this was done by using the information of that database and manual labeling, and finally, for each signal, a large number of separated signal images with labels on the heart rate of the fetus was determined. The input labels in the previously trained deep neural network were in the form of rectangular windows from the beginning to the end of the desired signal in the image, which were stored separately in a text file, and this file was later read by the software and converted into information related to the network as the appropriate label was added. This stage took a lot of time due to the high number of images and the need for high accuracy, but in the end, one hundred and forty-one images, each of which included seven to eight fetal heartbeats on average, were labeled. For this part of the work, a separate code was designed which, after drawing each image, allowed the user to specify the left and bottom right corners of the rectangle with a mouse click, after this step, the labeled coordinates were automatically displayed and in the user's confirmation form was added to the database

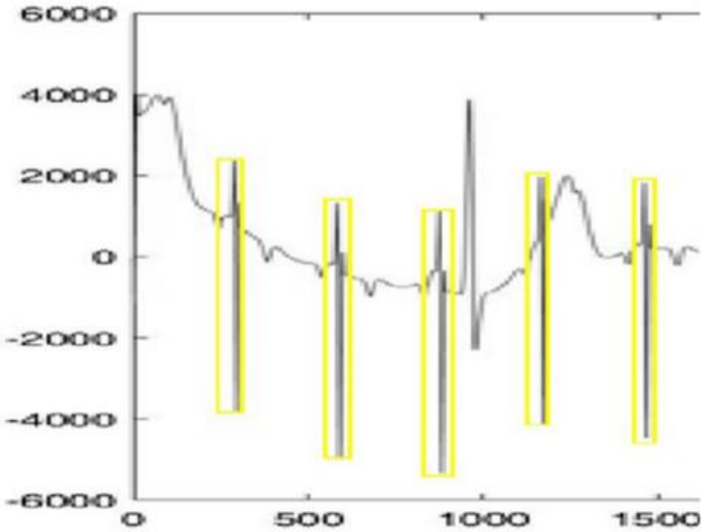

Fig. 3. Sample labeled image

In this way, about 140 images were obtained for deep neural network training. With the identification of the manual labeling of the database, the second step in the proposed method was to find a deep neural network that could properly separate and show the specified parts in the image. Image segmentation is determined and after implementation, the neural network with the best correct percentage was selected as the selected network.

3.3 Deep neural network

The pre-trained network of MATLAB software, which was used with some minor changes in the parameters in the proposed method, to isolate and recognize the selected part of the image, includes the following 15 layers.

Table 2. Details of deep neural network used

Layer number	Layer name	layer type
1	image input	Image Input
2	Conv	Convolution
3	max pool	Max Pooling
4	Relu	ReLU
5	Conv_1	Convolution
6	Conv_2	RelU
7	Avgpool	Average Pooling
8	Conv_2	Convolution
9	Relu_2	ReLU
10	Avgpool_1	Average Pooling
11	Fc	Fully Connected
12	Relu_3	ReLU
13	fc_rcnn	Fully Connected
14	Softmax	Softmax
15	Classoutput	Classification Output

Table 3. Description of each layer

1	32x32xl images with zero center normalization
2	32 5x5x3 convolutions with stride [1 1] and padding [2 2 2 2]
3	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
4	ReLU
5	32 5x5x32 convolutions with stride [1 1] and padding [2 2 2 2]
6	ReLU
7	3x3 average pooling with stride [2 2] and padding [0 0 0 0]
8	64 5x5x32convolutions with stride [1 1] and padding [2 2 2 2]
9	ReLU
10	3x3 average pooling with stride [2 2] and padding [0 0 0 0]
11	64fully connected layer
12	ReLU
13	2 fully connected layer
14	Softmax
15	Cross entropy ex with classes stopSign and Background

As can be seen from the structure of the network in Tables 1 and 2, the first and last layers are considered input and output, respectively, and the rest of the layers are a combination of five different types of layers. The input of this network is the black and white image of the signal. Layers No. 2, 5, and 8 are considered convolutional layers that perform two-dimensional input convolution. The number of rows and columns padded around the base matrix is assumed to be 2 to maintain the dimensions of the output. The next layer is the Pooling layer, in this layer the inputs are down sampled and divided into square areas based on the settings given in the software, and finally the average of each square and five images for each area is calculated. In the proposed neural network, layers 3, 7, and 10 are pooling layers, respectively, and in these layers, the amount of pad performed was equal to zero. The next layer is the ReLU layer, which includes layers 4, 6, 9, and 12. In these layers, the data is threshold, and values less than the threshold level are equal to zero. The 13th and 11th layers are all connections, the details of which were mentioned in the theory related to neural networks, and finally, the penultimate layer is the 14th SoftMax layer, which is the final division based on values for the output layer. In this way, the deep neural network used to detect the image area is a neural network with fifteen layers, in which different layers including convolutions, pooling, ReLU, Fully Connected, and Softmax are used.

This network has been the foundation of deep learning in this work. After this step, the pre-trained deep neural network is re-trained based on the existing database data, and its correct percentage is estimated in the labeled images of fetal and maternal heart signals.

4 Results

According to the structure of the deep neural network, the data was divided into two categories, training and testing, First, it was retrained with 70% of the data, which means a total of 100 images of the network. After this stage, the deep neural network was evaluated using the test data, which included a total of 41 fetal and maternal heartbeat signals (287 fetal heartbeats). For analysis similar to previous works, in addition to the fetal heart rate in these signals, about 821 peaks (including noise and mother's heart rate) were detected with MATLAB software, which could be wrongly detected as fetal heart rate.) and not specifying the false peaks as the location of the beat, correct negative diagnosis (TN), the following results were obtained. The result of the implementation is given in Table 3.

Tp	Fp	Fn	Tn
276	21	11	800

Table 4. Test results of the trained neural network

Se	PPV	Acc
0.96	0.93	0.97

where in

$$Se = \frac{TP}{TP + FN} \qquad\qquad PPV = \frac{TP}{TP + FP}$$

Due to the lack of a similar approach to this work, the results were compared with signal-based deep neural network [14-16]. These results, which took place in the years 2018 to 2020, are very similar to the current research in terms of the database. For example, the deep neural network used in [14] including input and output has 12 layers and is trained directly. According to the results given in [14-16], the best average results obtained in these methods with the same conditions as the present research were Se=89.06, and PPV=92.77 in terms of percentage, which is clearly weaker than the results obtained in the proposed method.

5 Conclusion

In this article, a method for detecting fetal heart rate signals and separating them from maternal heart rate signals based on a deep neural network is proposed. Considering the importance of automatically separating the heart rate of the fetus from the mother in diagnosing the deficiencies in the fetus and their appropriate treatment, providing an accurate estimate of the state of the heart rate of the fetus and analyzing its morphology can be very useful.
Despite the limitations such as the mother's strong heartbeat and other noises in the environment, the proposed method based on a deep neural network was able to combine the fetal signal with the mother based on the drawn image without the need for feature extraction or pre-processing steps. Acceptability compared to the previous methods to determine the fetus's heart rate in different areas of the image.

In addition to not needing feature extraction steps, the proposed method has shown a very good performance in terms of correct percentage. Finally, the work that was done compared with relatively new articles in this field and its proper efficiency was confirmed. It is hoped that due to the increasing progress of medical engineering sciences and wireless networks, systems can be produced that can be easily carried and used by pregnant mothers, and the information of the fetus and the mother, including heart rate and all items her vitals should be taken at the right time and sent to the medical condition control centers and provided to specialist doctors, to minimize possible risks for the fetus and the mother.

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