Pattern Recognition Letters 136 (2020) 286–292

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Deep learning strategies for foetal electrocardiogram signal synthesis

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ARTICLE INFO

Article history:
Received 21 September 2019
Revised 12 June 2020
Accepted 19 June 2020
Available online 21 June 2020

Keywords:
Deep learning
Foetal electrocardiogram
Convolutional neural network
Deep belief neural network
Back propagation neural network

ABSTRACT

One of the most difficult tasks for the physicians is to acquire a quality foetal electrocardiogram (fECG) to analyze, manage and plan according to the condition of the foetus in the womb. Hence the foetal electrocardiogram signal is not preferred to execute the analysis to monitor the Foetal condition. Other traditional methods are being used to access the foetal condition. The foetal electrocardiogram signal can be acquired either by using invasive or non- invasive techniques. Since the invasive technique is harmful for the foetus, non-invasive technique is mostly adopted. The foetal electrocardiogram signal can be acquired only after twenty five weeks the foetus is developed in the womb, which is referred as the Antepartum period. This article portrays the use of Deep learning techniques for non-invasive foetal electrocardiogram signal synthesis using artificial intelligent techniques. Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back propagation Neural Network (BPNN) have been utilized and tested for the proposal. The outcomes and performance are compared with reference to the synthesized high quality foetal electrocardiogram signal.

1. Introduction

The graphical replica of foetal heart's electrical activity, the foetal electrocardiogram (fECG) is depicted in Fig. 1 Cardiac complications are amongst the most common birth defects. Hence, diagnosis is very important in the foetal stage to plan and manage the baby during Antepartum stage - 26th week of pregnancy until the birth of a child, as well as the Intrapartum stage - during child birth when the baby is born. It is from the Antepartum stage where the foetal electrocardiogram signal can actually be detected. A descriptive detail of pregnancy stages and Foetal growth is shown in Table 1. Though the first observations of foetal electrocardiogram was made by Cremer et al. in 1906 [1], foetal electrocardiogram (fECG) signal acquisition has always been a challenging assignment for Physicians and Engineers. In the clinical perspective, foetal signals recorded by electrocardiogram (ECG) convey more information compared to conventional sonography, auscultation and other techniques. The foetal electrocardiogram signal can be acquired either by using invasive or non- invasive techniques. Since the invasive technique is harmful for the foetus, non-invasive technique is mostly adopted. Non-invasive foetal electrocardiogram signal can be acquired from electrodes placed over the maternal abdomen. This signal is a composite of three different signals. First, the non-linearly transformed maternal electrocardiogram (mECG). Second, the weak foetal electrocardiogram (fECG). Third, various Internal/external - high/ low frequency noisy signals. The unwanted signals must be eliminated to synthesize high quality foetal electrocardiogram. Bayesian procedures for filtering are adapted in this work. This article portrays the deep learning strategies using Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back propagation Neural Network (BPNN) to synthesize high quality foetal electrocardiogram.

2. Literature survey

The field of artificial intelligence is the major contributor to the problem discussed in this article. Convolutional Neural Network is among the top of the list of machine learning techniques. To list a few, Chen et al. 2015 [2] have shown Ultrasound modality using Convolutional Neural Network to locate abdominal plane from foetal ultrasound videos. Chen et al. 2015 [3] have adapted the Ultrasound modality using Recurrent Neural Network to Locate abdominal plane from fetal ultrasound videos. Baumgartner et al. 2016 [4] have used the Ultrasound modality using CNN for the purpose of labeling 12 standard frames in 1003 mid-pregnancy foetal US videos. Yu et al. 2016 [5] adapts the Ultrasound modality using CNN for the purpose of labeling frame-by-frame segmentation by dynamically fine-tuning CNN to the latest frame. Ravishankar et al. 2016 [6] adapts the Ultrasound modality using CNN for the purpose of l Hybrid system using CNN and texture features

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https://doi.org/10.1016/j.patrec.2020.06.016
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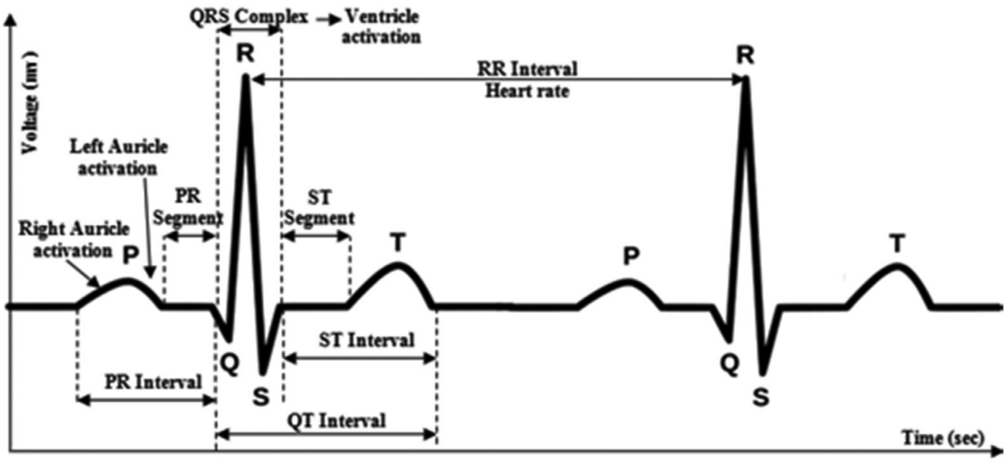
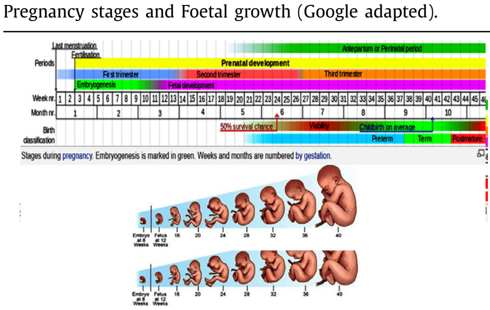


Fig. 1. Foetal electrocardiogram signal replica.

to find abdominal circumference. Rajchl et al. 2016 [7] adapts the MRI using CNN and CRF for segmentation of structures. Rajchl et al. 2016 [8] adapts the MRI using CNN for Crowd-sourcing annotation efforts to segment brain structures. Kumar et al. 2016 [9] adapts the Ultrasound modality using CNN for the purpose of labeling 12 standard anatomical planes, CNN extracts features for support vector machine. Deep learning artificial intelligent neural networks are referred to as Deep Neural Network (DNN) which includes Deep Auto encoder (DA), convolutional neural networks (CNN), deep belief networks (DBN), Recurrent Neural Network (RNN), Deep Convolutional Inverse Graphics Network, stacked auto encoder (SAE), Deep Boltzmann Machine (DBM), Deep Residual Network, etc. [10]. Deep learning is one among the major explored area with remarkable applications in the field of time series signal evaluation, object recognition, facial recognition, medical image examination and image classification. Mirowski et al. 2008 [11] used convolutional neural networks for epileptic seizure prediction from EEG signals. M. Huanhuan et al. 2014 [12] utilized a combination of deep belief network (DBN) with support vector machine (SVM) for classification of ECG signals. DBN was used for feature learning and SVM was utilized for learning and classification. Acharya et al. 2017 [13] portrayed a deep learning algorithm for traditional diagnosis support systems. The technique showed the advantage of not having to execute feature extraction and de-noising processes. Priya Ranjan Muduli et al. 2016 [14] proposed deep learning approach for fECG signals. The methodology improved the computation speed imposed in the telemonitoring system. E. Fotiadou et al. 2019 [15] proposed a convolutional encoder-decoder framework was proposed to eliminate the residual noise from single-channel fECG. Shenda Hong et al. 2020 [16] reported an in-depth review on Deep learning methods have been portrayed with promising results on predicting health-care tasks specially for ECG signals.

Table 1
Pregnancy stages and Foetal growth (Google adapted).



Bayesian procedures for filtering have been utilized by several researchers in the perspective of the problem. Y. Yin et al. 2010 [17] used Bayesian methodology in combination with Artificial Neural Networks (ANN) for fECG signal extraction. Generalized Gaussian distribution was used for modeling the ECG signal. Back propagation neural network (BPN) was imposed for estimating the nonlinearity. Real-time ECG signal recordings were used to test the Bayesian neural networks technique. Simulated ECG signal recording was experimented with polynomial neural networks. The methodology was effective but the quality of signal mining was not reported. R. Sameni et al. 2007 [18] published that Bayesian filtering technique can be employed for denoising ECG signals. Oikonomou et al. 2005 [19] presented good performance for foetal ECG signal extraction by using Bayesian technique for fECG signal extraction using PCA (principle component analysis) methodology.

3. Proposed methodology

The proposed Deep Learning strategy is depicted in Fig. 2. The proposed system uses two input channels, one from the chest and the other from the abdomen of the maternal subject. The maternal electrocardiogram (mECG) signal recorded from the chest consists of the mECG and other noises. The abdominal electrocardiogram (aECG) recorded from the abdomen constitutes the weak foetal electrocardiogram (fECG), transformed version of mECG and other noises. High and low frequency noises are eliminated by traditional filtering. The Bayes filter is used to predict a faultless approximation of the nonlinearly transformed mECG ingredient in the aECG. Extended Kalman filter and extended Kalman smoother were employed for this purpose. The deep learning neural network system is employed to adaptively estimate the nonlinear relationship of the nonlinear transformed signal of mECG and faultlessly ally into line the estimated mECG signal with the maternal signal component in the aECG signal for removal. The removal of mECG signals and noise signals leads an outcome with the desired high quality fECG signal. This article portrays the deep learning strategies using three different architectures, Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back propagation Neural Network (BPNN) to synthesize high quality foetal electrocardiogram.

3.1. The back propagation neural network

One of the most widely used multilayer, feed forward neural network is the Back propagation neural network - BPNN. Liszka-Hackzell J et al. [20] implemented BPNN several decades ago

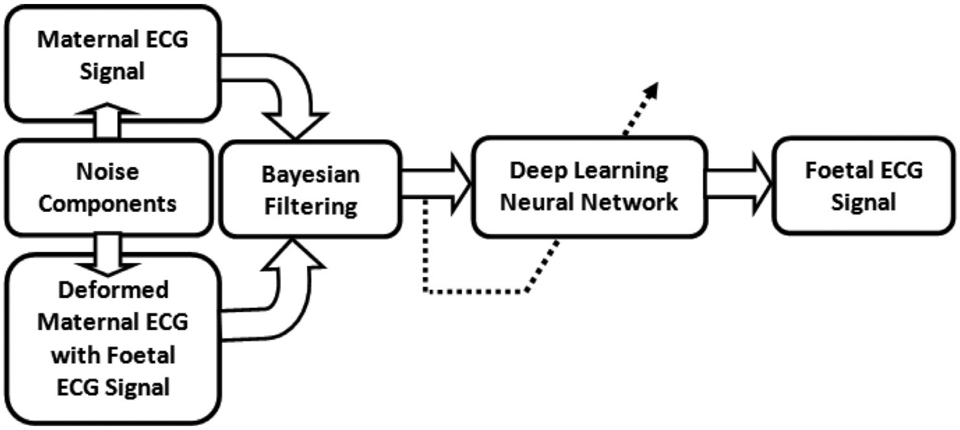


Fig. 2. Proposed deep learning strategy.

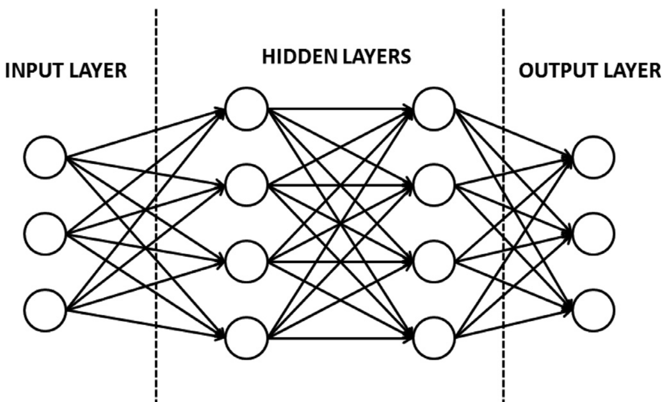


Fig. 3. Back propagation neural network - BPNN.

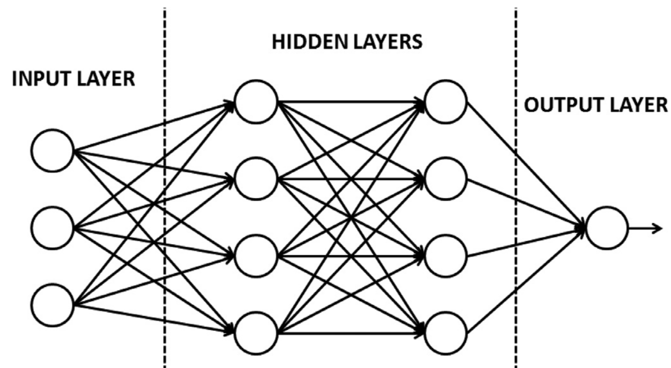


Fig. 4. Convolutional neural network - CNN.

in 1994. Typical back propagation neural network architecture is shown in Fig. 3. It consists of an input layer, hidden layer and output layer. The hidden layer may have more than one layer depending upon the requirements. The well known Back propagation technique works by estimating the non-linear relationship between the input signal and the output signal by adjusting the network connection weights. Back propagation network works in two phases, the training phase and the testing phase. In other words, feed forward and Back propagation phases. During the feed forward phase, an input signal pattern is applied to the input layer and this is disseminated to the entire layers one after the other through the network until the output layer produces an output. This output is then compared to the expected output, which results with an error signal for each of the output nodes. These output error signals are propagated in reverse direction from the output layer to the hidden layer. This process is repeated until each node in the network has received an error signal. The errors are then utilized by the nodes to update the weight for each connection weights until the network converges to a state which permits all the learning signal patterns to be encoded. The network architecture was implemented with 72 neurons in the input layer. The hidden layer constitutes for 2 layers of 84 neurons each. The learning rate for initial signal patterns was 0.06 which is referred as the unsupervised learning rate. This initial learning was established for 800 epochs. The supervised learning rate was about 0.07 with 970 epochs.

3.2. The convolutional neural network

CNN is a multilayer artificial neural network design which is made up of single or multiple convolutional layers followed by a single or multiple fully connected layers as shown in Fig. 4. The CNN topology can be implemented with alternating convolution and pooling layers. In this research work, a three layer CNN was employed. The Convolution layer constitutes the first layer of the CNN. The vital job of the convolution layer is to extract features from the input ECG signals. These features are compressed by the Max – pooling function. The softmax layer implemented with a uni-dimensional output is the fully connected network layer. The CNN is initially convolved with a definite kernel size with the input layer which yields the first layer of CNN. To reduce the number of neurons in the hidden layer, max-pooling is employed. The mapping features from the second layer are convolved with the kernel to yield the third layer. The process was repeated awaiting the structure to result with six layers. Finally the fully connected seventh and eighth layers were devised to be fully linked to the last layer with a single output neuron. The CNN topological detail are provided in Table 2, where the Kernel size refers to the filter size

Table 2
CNN Architectural details.

CNN Layers	Neurons	Function	Kernel	Tread
0–1	475×3	Convolution	92	1
1–2	210×3	Max-pooling	2	2
2–3	192×10	Convolution	22	1
3–4	86×10	Max-pooling	2	2
4–5	42×10	Convolution	9	1
5–6	34×10	Max-pooling	2	2
6–7	26	Fully connected	–	–
7–8	8	Fully connected	–	–
8–9	1	Fully connected	–	–

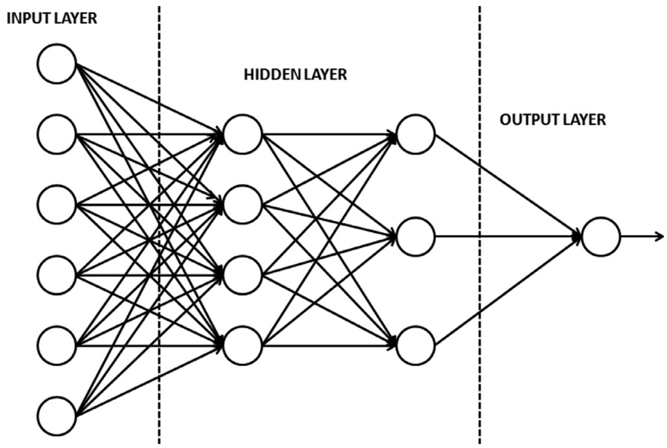


Fig. 5. Deep belief neural network - BNN.

which convolves just about the mapping features and the tread feature controls the tactic of filter convolution about the mapping features. The tread is set with a value to be 1in this work, therefore the filter and the layers of mapping features are convolved by sliding one unit every time.

3.3. The deep belief neural network

The BNN topological structure is shown in Fig. 5. The BNN is triggered one layer after another by a proficient greedy learning method using unsupervised learning algorithm and it is then fine tuned with respect to the output targets using supervised learning. BNN is a composition of restricted Boltzmann machine (RBM) which is comprised of a two-layer neural network, a visible layer and a hidden layer. The neurons in the first layer are linked to every other neuron in the second layer. Every neuron in a layer is trained to learn one feature from the input data by constructing random decisions on whether to convey the input or not. The received inputs by the RBM are encoded into numbers. To reconstruct the inputs, reverse translation is done. The network is learned to rebuild in both forward and backward phases. This process is repeated until all layers in the structure are trained. The network architecture was implemented with 98 neurons in the input layer. The hidden layer constitutes for 2 layers with a total of 84 neurons. The learning rate for initial signal patterns was 0.05. This initial learning was established for 700 epochs. The supervised learning rate was about 0.07 with 760 epochs.

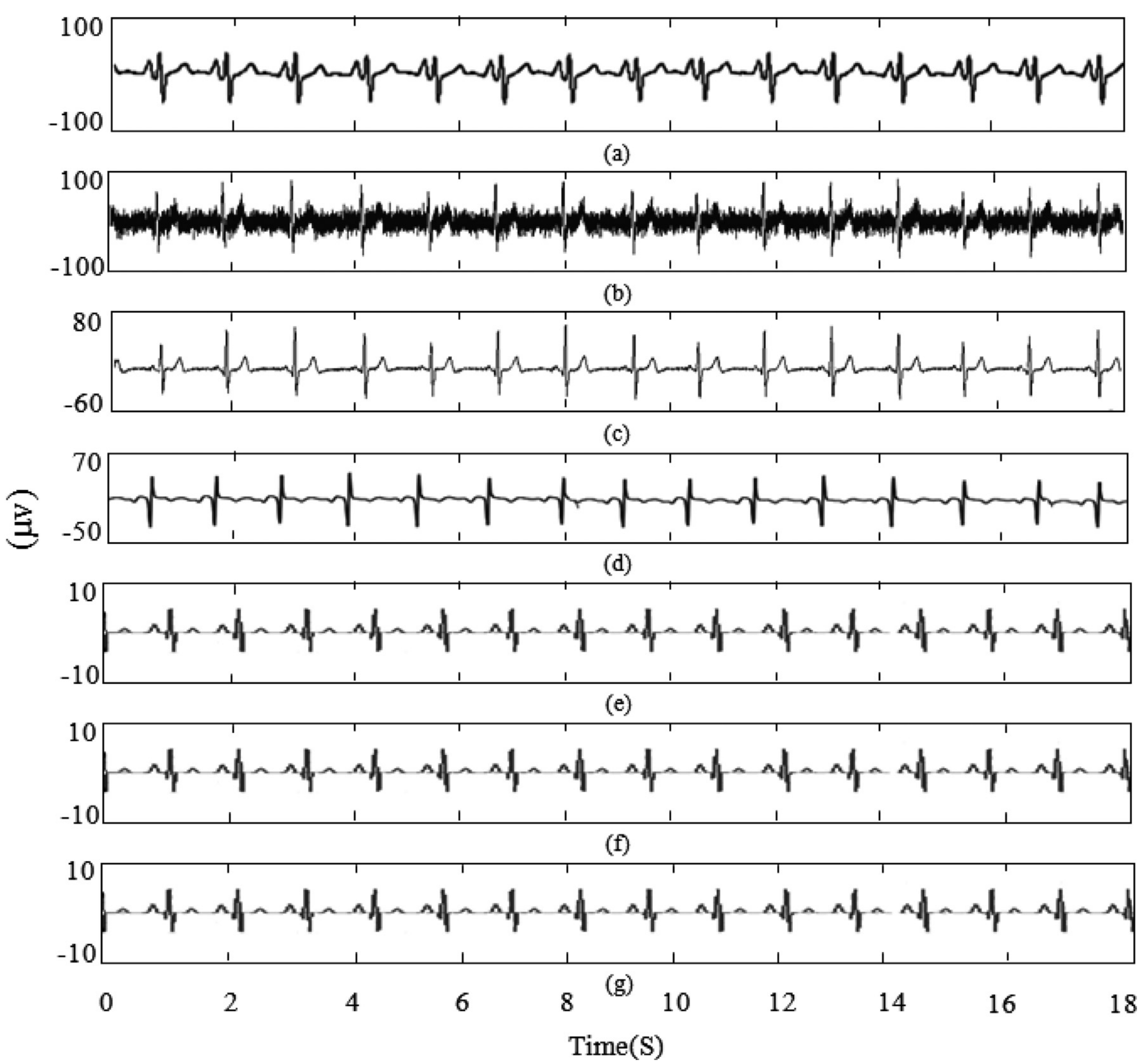


Fig. 6. Synthesized fECG signals. (a) Thoracic Signal Recording, (b) Abdominal Signal Recording, (c) Filtered Abdominal Signal, (d) Maternal signal estimation, (e) Synthesized fECG – BPNN, (f) Synthesized fECG – CNN, (g) Synthesized fECG – BNN.

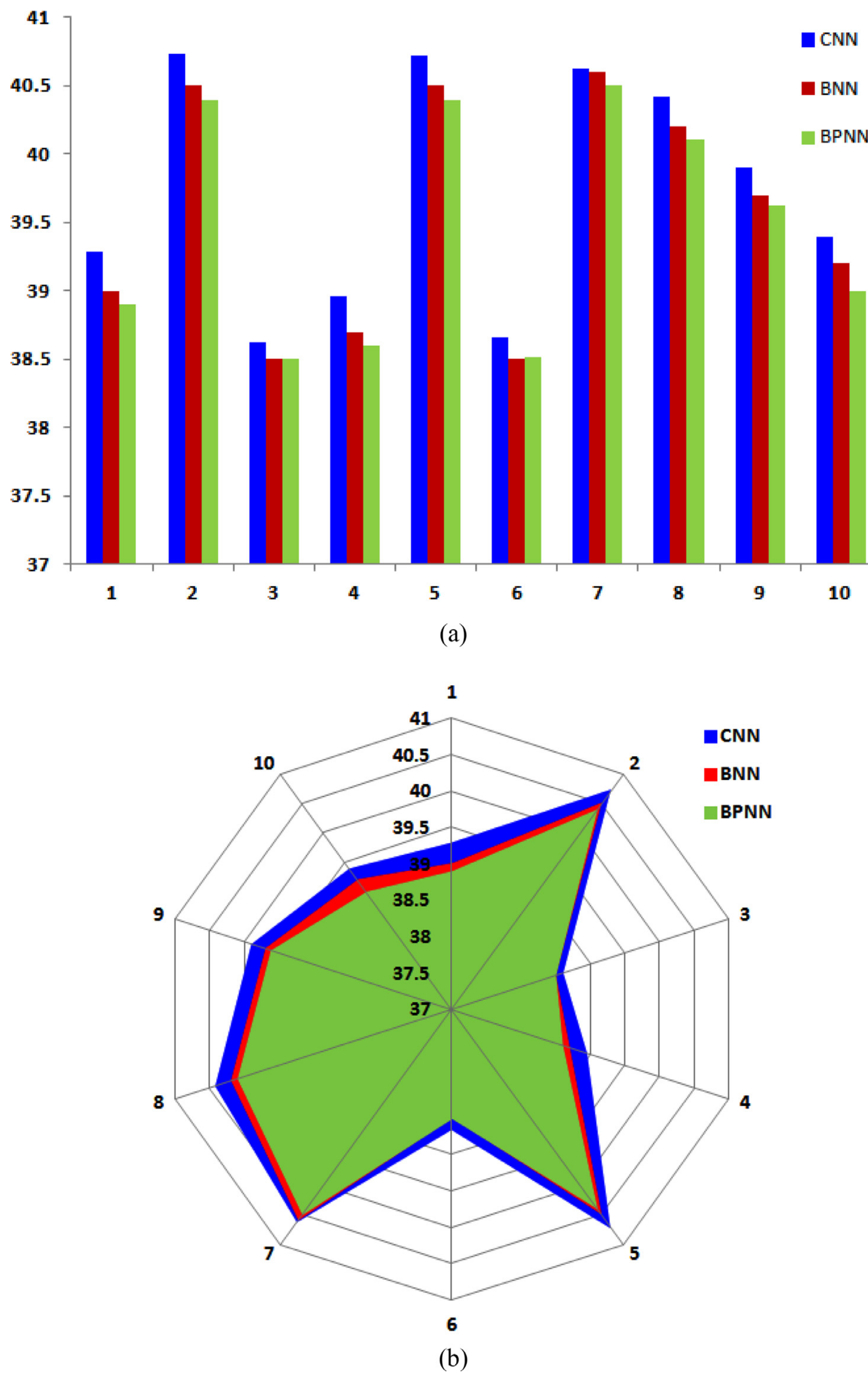
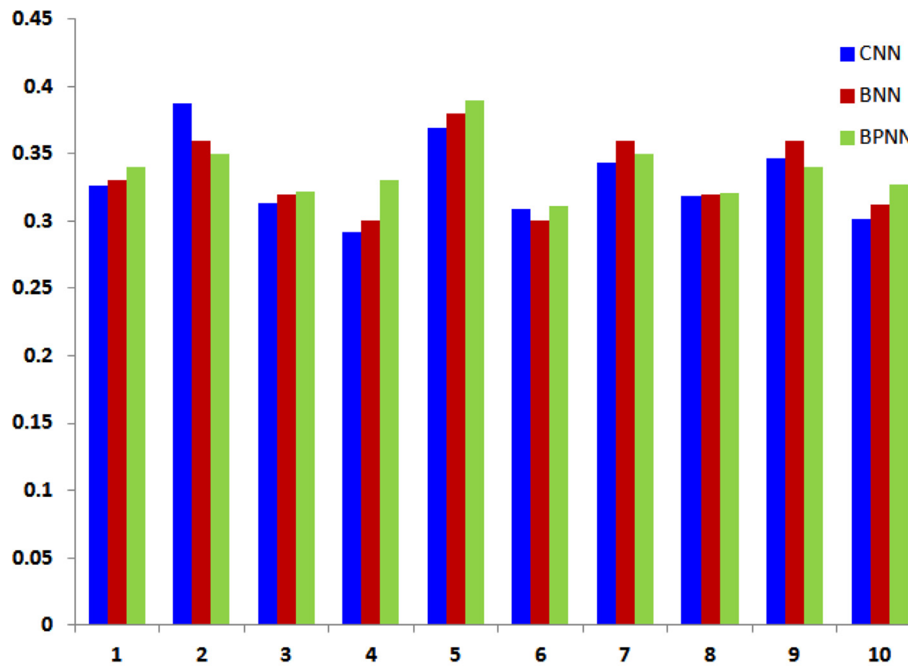


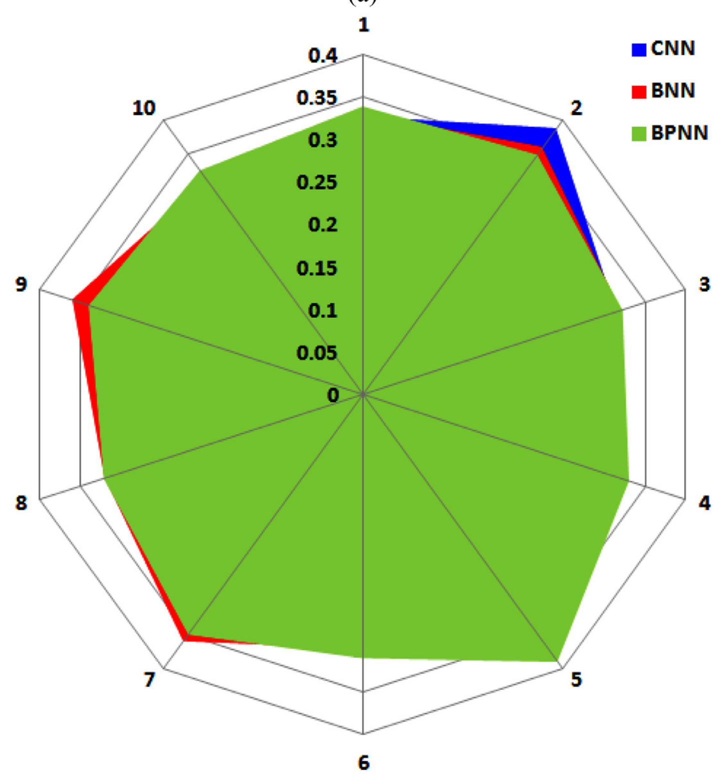
Fig. 7. (a) SNR improvement accomplished (b) Radar plot of SNR improvement.

3.4. Deep learning approach

Conventional Back propagation learning algorithm has been engaged for all the network topologies. Back propagation algorithm was enforced with a definite size of ten in a batch. The activation function that was imposed in this work is the linear activation function. In CNN, it was imposed for all the convolutional and the first 2 fully connected layers. The softmax function was used to establish the last fully connected layer. In BPNN the learning rate for initial signal patterns was 0.06 which is referred as the unsupervised learning rate. This initial learning was established for 800 epochs. The supervised learning rate was about 0.07 with 970 epochs. In CNN for data convergence the learning rate was set to 0.7 with regularization 0.2 to prevent over-fitting of data and momentum 3×10^{-4} to control the learning speed during training phase. The learning rate in BNN for initial signal patterns was 0.05. This initial learning was established for 700 epochs. The supervised learning rate was about 0.07 with 760 epochs.



(a)



(a)

Fig. 8. (a) PRD accomplished (b) Radar plot of PRD.

4. Results and discussion

All possible signals were investigated in this work. Different variety of data sets including data from Physionet and DalSy Database, real time maternal signals and simulated signals were employed. Deep learning strategies using three different architectures, Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back propagation Neural Network (BPNN) were tested and their performance is validated to synthesize quality foetal electrocardiogram. The explorations were evaluated with the preferred performance parameters, signal to noise ratio (SNR), improved signal to noise ratio (SNR_{enh}) and percentage root mean square difference (PRD) defined by Eqs. (1) to (3).

$$SNR = 10\log_{10} \frac{\sum_{n=1}^{N} \hat{S}_f^2(n)}{\sum_{n=1}^{N} \left[\hat{S}_f(n) - S_f(n)\right]^2} dB \tag{1}$$

$$SNR_{enh} = SNR_{out} - SNR_{in} \tag{2}$$

$$PRD = \frac{\sum_{k=1}^{n} \{x(k) - y(k)\}^2}{\sum_{k=1}^{n} \{x(k)\}^2} \times 100 \tag{3}$$

To depict an end result of the research work, the result of one of the explored examination with recordings obtained from a maternal subject is portrayed in Fig. 6. (a) Thoracic Signal Recording, (b) Abdominal Signal Recording, (c) Filtered Abdominal Signal Recording, (d)Maternal signal estimation, (e) Synthesized fECG – BPNN, (f) Synthesized fECG – CNN, (g) Synthesized fECG – BNN. The abdominal signal is embedded with other noise signals due to several factors. These noisy signals were eliminated with conventional filters. The resulted noise free abdominal signal is shown in Fig. 6(c). The Bayes filter is used to predict a faultless approximation of the nonlinearly transformed mECG ingredient in the aECG, the outcome of this filter is shown in Fig. 6(d). The deep learning strategies using three different architectures, Back propagation Neural Network (BPNN), Convolutional neural network (CNN) and Deep belief neural networks (BNN) to synthesize high quality foetal electrocardiogram are depicted in Fig. 6(e), (f) and (g).

The imposed input SNR in this work ranges from −30 dB to 15 dB which was estimated using Eq. (1). The SNR of the synthesized signal was also evaluated using Eq. (1). SNR improvement was calculated using Eq. (2). The SNR improvement attained for the synthesized fECG signal from 10 sets of data is ploted in Fig. 7(a). To analyze the SNR improvement accomplished a radar plot is depicted in Fig. 7(b). The plot clearly shows that CNN offered better SNR improvement compared to BPNN and BNN. However, all the three deep learning strategies showed good improvement in SNR, their SNR improvement is arround 39. On an average the SNR improved by Back propagation Neural Network (BPNN), Convolutional neural network (CNN) and Deep belief neural networks (BNN) were 39.454, 39.732 and 39.54. Similar analysis to check the quality of the synthesized fECG signal was carried out and depicted in Fig. 8(a) and (b). There is not much of a difference seen between the three techniques. The PRD for all the three methodologies was arround 0.3, which proves that the synthesized fECG is of high quality.

Conclusion

This article portrays the use of Deep learning techniques for non-invasive foetal electrocardiogram signal synthesis using artificial intelligent techniques. Convolutional neural network (CNN), Deep belief neural networks (BNN) and Back propagation Neural Network (BPNN) have been utilized and tested for the proposal. The outcomes and performance are compared with reference to the synthesized high quality foetal electrocardiogram signal. All possible signals were investigated in this work. Different variety of data sets including data from Physionet and DaISy Database, real time maternal signals and simulated signals were employed. CNN offered better SNR improvement compared to BPNN and BNN. However, all the three deep learning strategies showed good improvement in SNR, their SNR improvement is arround 39. The PRD for all the three methodologies was arround 0.3, which proves that the synthesized fECG is of high quality. The methodology was investigated by running the algorithm in PyTorch using a single GTX 1080 Ti X GPU with the training data sizes from 64 to 1024. The projected time was about 1000 to 9000 s for training 450 epochs. This research work would definitely trigger a wider research vision to extend further analysis with deep learning strategies and the available diverse artificial intelligent networks. This research work can be extended further to extort twin fECG signals. The proposed methodology can be implied on IURG (Intrauterine growth restriction) affected signals for extraction of good quality fECG signals which can be very near to high quality.

Declaration of Competing Interest

None.

Reference

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