Fetal Monitoring: Multi-Channel Fetal ECG Denoising Based on Artificial Intelligence Approach

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***Abstract* - Continuous electronic fetal monitoring using cardiotocography (CTG) represents the standard of evaluating the health status of the fetus and the risk of the pregnancy, in developed countries. However, the CTG has many limitations: high false positive rates, cannot be used for long term monitoring, poor sensitivity, it offers just the fetal heart rate and its variability etc. In this context, the fetal electrocardiogram (fECG) signal is used to obtain additional diagnostic information. On the other hand, the standard in clinical practice for obtaining the fECG is invasive, can pose a risk for both mother and fetus, can only be used during birth (very limited time window). An alternative is the abdominal fECG, that is recorded using a matrix of electrodes placed on the maternal abdomen. This approach is noninvasive and can be used for long term monitoring. The main drawback is the small signal to noise ratio for the abdominal fECG. Thus, the challenge is to isolate the fECG signal from other types of noise that are recorded by the abdominal electrodes: the maternal electrocardiogram (mECG), the electromyogram (EMG), the electrohysterogram (EHG), power line interference (PLI) etc. In this paper the author proposes an algorithm based on artificial neural network approach to extract the fECG signal waveform from abdominal recorded signals (ADS). The performance evaluation of proposed approach is realized on a database with simulated abdominal signals. A comparison is introduced, with other approaches described in literature for fECG denoising from abdominal signals.**

Keywords–fetal monitoring; artificial intelligence, fetal electrocardiogram, abdominal recorded signals

I. INTRODUCTION

Electronic fetal monitoring (EFM) is a technique used to track the fetal heart rate (FHR) and uterine contractions during labor and delivery. The goal of EFM is to ensure the well-being of the fetus and identify any signs of distress that may require intervention to prevent harm to either the fetus or the mother. EFM has been widely used in obstetrics for several decades and is considered the standard of care for many high-risk pregnancies.

There are two main types of EFM: external and internal. External EFM uses ultrasound and a tocodynamometer placed on the mother's abdomen to monitor the fetus heart rhythm and the contractions of the uterus. This is the most commonly used method and is non-invasive, making it a popular choice for low-risk pregnancies. Internal EFM, on the other hand, uses an electrode attached to the fetal scalp to measure the direct fetal electrocardiogram (fECG) signal that offers a more accurate FHR. This method is more invasive, as it requires the insertion of a fetal scalp electrode into the uterus, but it provides more accurate readings of the FHR and is usually reserved for high-risk pregnancies.

The main drawback of external EFM technique are: it offers an average determined FHR, it cannot be used for long term monitoring, there is a high intra- and inter-observer variability that sometimes leads to unnecessary C-section interventions. On the other hand, the internal EFM is invasive, can pose a risk for both mother and fetus and it is restricted to be used only in the short window of delivering (after the rupture of the membrane).

An alternative technique that can tackle all the drawbacks of the current EFM approaches is to record the fECG signal via electrodes placed on the maternal abdomen. Hence, it is non-invasive, it offers not only the FHR but also the beat-to-beat morphological variations of the fECG signal, *i.e.*, more diagnostic information, and it allows for continuous monitoring of the fetal health status during labor, which is important for detecting any changes in fetal well-being.

However, the main drawback is the small signal to noise ratio (SNR) for the abdominal fECG. Thus, the challenge is to isolate the fECG signal from other types of noise that are recorded by the abdominal electrodes: the maternal electrocardiogram (mECG), the electromyogram (EMG), the electrohysterogram (EHG), power line interference (PLI) etc.

There are many different approaches described in literature that try to extract the abdominal fECG: adaptive filtering [1], [2], wavelet analysis [3]–[5], blind source separation [6]–[8], empirical mode decomposition [9], [10], etc.

With the development of artificial intelligence techniques, there are few researchers that considered machine and deep learning approaches for denoising the abdominal fECG. In [11] the authors propose a encoder – decoder framework based on deep convolutional network for removing different types of noise from abdominal recorded signals (ADS). Fotiadou *et al* introduce a multi-channel deep convolutional encoder – decoder network that is able to learn how to obtain the best combination of input channels in order to offer at the output, a clean multi-channel fECG signal [12].

In this paper, a multi-channel blind source separation method for extracting the fECG signal from abdominal recordings is introduced, which is based on deep-learning stacked-long short-term memory (LSTM) network. The model is evaluated on simulated abdominal signals.

II. Materials and Methods

A. Problem Definition

Each channel from a multi-channel abdominal recorded signals represents a mixture of different types of signals: fECG, mECG, EHG, EMG, PLI etc. Let $\mathbf{x}(t)$ be the set of multi-channel abdominal signals, then $\mathbf{x}(t) = \{\mathbf{x}_1(t), \mathbf{x}_2(t), \ldots \mathbf{x}_m(t)\}^T$, where m is the number of abdominal recorded channels (the number of electrodes placed on the maternal abdomen). Let $\mathbf{s}(t)$ be the independent signal sources, then $\mathbf{s}(t) = \{\mathbf{s}_1(t), \mathbf{s}_2(t), \ldots \mathbf{s}_p(t)\}^T$, where p is the number of independent source signals (e.g. fECG, mECG, PLI, EMG etc). The recorded mixture of signal sources on different locations on the maternal abdomen can be expressed as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{1}$$

where $\mathbf{A}$ is the mixing matrix, $\mathbf{A} = [a_{i,j}] \in \mathbb{R}^{m \times p}$. Hence, an abdominal channel recorded by the i^{th} electrode is $\mathbf{x}_1(t) = a_{i,1}\mathbf{s}_1(t) + a_{i,2}\mathbf{s}_2(t) + \ldots a_{i,p}\mathbf{s}_p(t)$.The aim is to obtain the estimated sources, $\mathbf{s}^*(t) = \{\mathbf{s}^*_1(t), \mathbf{s}^*_2(t), \ldots \mathbf{s}^*_p(t)\}^T$,by separating the set of abdominal signals, through the determination of an, so called, unmixing matrix, $\mathbf{B} = [\mathbf{b}_{i,j}]^{p \times m}$:

$$\mathbf{s}^*(t) = \mathbf{B}\mathbf{x}(t) \tag{2}$$

If $m>p$ then the system of equations is overdetermined and a linear approach can be used for determining the unmixing matrix. Usually, other types of noise can be easily removed from the abdominal signals in the preprocessing step, thus one can assume that the abdominal signal is a mixture of mECG and fECG. In this case, at least two abdominal channels are required.

In this paper an artificial intelligence approach, based on stacked – LSTM network, is used to estimate the source signals. Hence, the multi-dimensional mapping of the mixing matrix in the neural network is obtained by training the weight coefficients, as opposed to the classic blind source separation method, which generates the mixing matrix by iterative calculation.

B. Proposed Method

Figure 1 depicts the components that compose the proposed Stacked-LSTM network structure: an encoding component, a separation component, and a decoding component. The mixed signal's features are represented in the encoding phase. To determine the source signal mask, the separation component is trained using a stacked LSTM block, and the source signal waveform is restored using the decoding component.

The encoding feature representation of the abdominal signals as input is extracted using 1-D convolution layer.

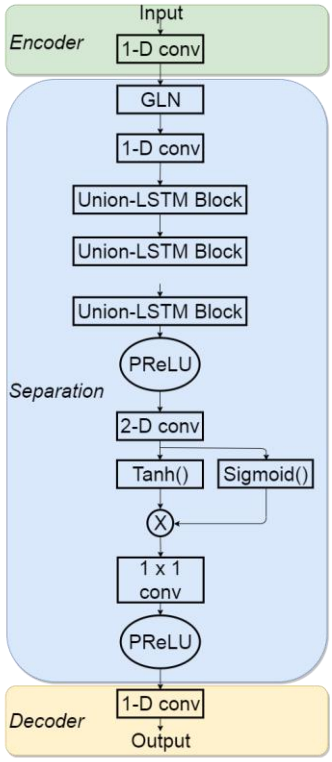

Figure 1. The proposed separation structure based on the Stacked-LSTM network

Linear encoding is used to encode mixed signals for further processing. The abdominal signal is processed using 512 convolution kernels to create a multi-dimensional coding feature that serves as input for the separation network.

Next, the source signal mask is generated using the separation component of the proposed Stacked-LSTM network. The separation phase involves determining the mask for each source signal, which is achieved through training the network. The mask obtained for each source signal corresponds to the mixing matrix A in (1). The separation component has the following steps:

- Group normalization is performed, i.e. the channels are grouped and the variance and mean are computed for each group. The 1-D convolution layer is used to extract the features.
- The extracted feature sequence is used as input for the stack Union-LSTM that consists of six LSTM blocks.
- Next, the parametric rectified linear unit (PReLU) activation function is used in order to prevent the he vanishing gradient problem. The Tanh() and Sigmoid() activation function are used for obtaining the multi-dimensional characteristics of the mixed source signal and, respectively the mask information of the two source signals.
- The time domain mask obtained in the previous step is multiplied with the encoding feature representation of the mixed signal in order to obtain the feature encoding of the source signals.

The final 1-D deconvolutional layer is used to decode the source signals and obtain a time-domain waveform.

The performance index used to evaluate the separation process is the scale-invariant source-to-noise ratio (SI-SNR) (a higher SI-SNR determines a lower separation error). Normalization is used prior to the calculation of the SI-SNR, to maintain the same scale.

$$SI\text{-}SNR = -10\log\frac{\|s_{target}\|^2}{\|s^{*}-s_{target}\|^2} \quad (3)$$

$$s_{target} = \frac{\langle s^{*}, s\rangle s}{\|s\|^2} \quad (4)$$

Equation (3) represents the loss function used during the training of the network with the gradient descent method.

C. Dataset

The mECG and fECG are generated using an electrocardiogram generator described in [13], ECGSYN. It creates a synthetic ECG signal with customizable parameters such as, number of beats, sampling frequency, mean heart rate, waveform morphology, low frequency (LF) / high frequency (HF) ratio, standard deviation of the RR interval. By utilizing a model that involves three linked ordinary differential equations, ECGSYN can generate an ECG signal that mimics many features of a human ECG, such as respiratory sinus arrhythmia, beat-to-beat variations in morphology and timing, R-peak amplitude modulation, and QT dependence on heart rate [13].

The model creates a path in a 3D state-space with coordinates (*x, y, z*). The ECG's quasi-periodic nature is represented by the trajectory's motion around a limit cycle with a radius of one in the (*x, y*) plane. Each complete revolution of this circle represents one heartbeat or one RR interval. The trajectory's movement in the *z* direction mimics the interbeat variability in the ECG signal. The P, Q, R, S, and T waves of the ECG, are determined by events linked to negative and positive attractors / repellers in the *z* direction [13].

Three differential equations are used to describe the dynamical motion:

$$\dot{x} = \alpha x - \omega y$$
$$\dot{y} = \alpha y - \omega x$$
$$\dot{z} = -\sum_{i\in\{P,Q,R,ST\}} a_i \Delta\theta_i exp\left(-\frac{\Delta\theta_i^2}{2b_i^2}\right) - (z - z_0) \quad (5)$$

where $\alpha = 1 - \sqrt{x^2+y^2}$, $\Delta\theta_i = (\theta - \theta_i)\ mod\ 2\pi$, $\theta = atan2(y, x)$ and ω is the angular velocity of the trajectory around the limit cycle.

With the help of the signal generator described, the mECG and fECG signals are obtained with specific characteristics for adult and fetal heart, respectively. Thus, the RR intervals in the fECG signal are chosen to be as least double of the ones in the mECG signals, since usually, the normal FHR is much higher (almost double) than the maternal HR. The two signals are sampled at 1kHz, with a length of 20000 samples and are mixed together with different SNRs (5 - 20 dB with the step of 2.5 dB). The mixed dataset has 140.000 samples.

III. Results

The flowchart that describes the approach used in the paper is depicted in Figure 1

An example of a fECG and mECG signals generated with the ECGSYN generator are presented in Figure 3 and Figure 4, respectively. The mixture between the two signals, that form the synthetic abdominal signal, can be observed in Figure 5. The parameter configuration of the proposed method is as following: encoder filter number - 512, frame length – 16, kernel size – 3, 1D block channel number – 512, 1D block number - 8, repeat number – 3. Five-fold cross-validation was used in all experiments.

The performance of the model introduced in this paper is compared with the performance of the Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NFM) as blind source separation (BSS) reference methods. The TABLE 1 presents the results obtained with the stacked-LSTM model and the ICA and NFM methods.

The experimental results show that the Stacked-LSTM method has the best performance, with a loss value of – 20.03 dB in average and it is significantly better than the traditional BSS methods.

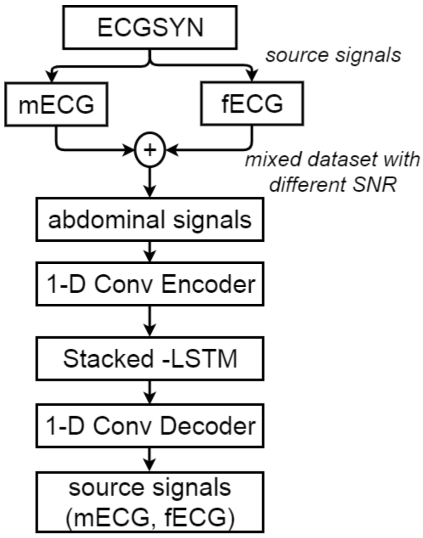

Figure 2 The flowchart of the proposed approach

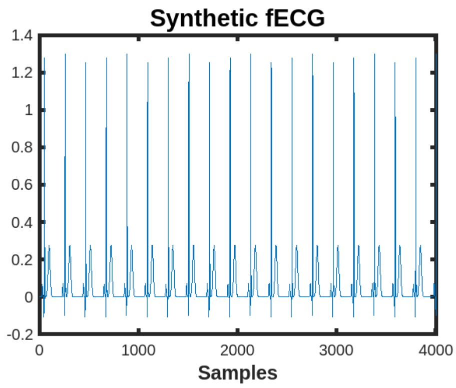

Figure 3. Synthetic fECG generated with ECGSYN

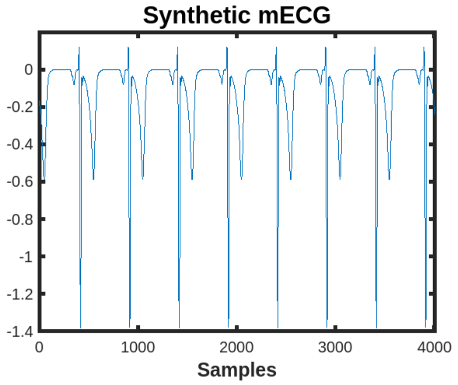

Figure 4. Synthetic mECG generated with ECGSYN

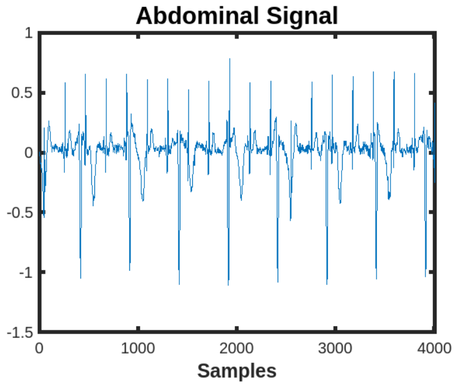

Figure 5. The synthetic abdominal signal as a mixture of the synthetic fECG and mECG signals

TABLE 1 LOSS OF THE COMPARED METHODS (dB)

Mixture	Stacked-LSTM	ICA	NFM
ADS 5 dB	-29.4	1.07	4.22
ADS 7.5 dB	-25.61	1.56	4.68
ADS 10 dB	-22.92	2.92	5.14
ADS 12.5 dB	-20.37	3.21	5.72
ADS 15 dB	-18.21	3.83	6.23
ADS 17.5 dB	-13.53	4.60	7.67
ADS 20 dB	−10.19	5.07	9.95

The proposed method is a BSS approach and in consequences is compared with classical BSS methods. However, when compared at a glance with approaches that use CNN for ADS denoising, the results obtained are comparable and, in some cases, exceed the ones obtained in [11], [12]. Nevertheless, one should interpret this comparison with extreme care because it is not a fair comparison due to the different databases that were used in the studies.

IV. CONCLUSIONS

The paper introduces a novel Stacked-LSTM-based deep learning model that can address the issue of multi-channel blind source separation in the case of abdominal recorded signals. The proposed model can effectively separate and restore the mixed signals, the mECG and the fECG, into their respective source signals by learning relevant information. The experiments demonstrate that the proposed model has excellent performance. One of the limitation of the introduced approach is that the model needs to be validated also on real abdominal signals.

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