2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

An Autoencoder-Based Fetal Heart Rate Detector for Noninvasive Recordings

Abuzar Ahmad Qureshi[1], Lu Wang[1], Tomoaki Ohtsuki[1], Kazunari Owada[2], Naoki Honma[2], and Hayato Hayashi[2]

***Abstract*— Antenatal fetal health monitoring primarily depends on the signal analysis of abdominal or transabdominal electrocardiogram (ECG) recordings. The noninvasive approach for obtaining fetal heart rate (HR) reduces risks of potential infections and is convenient for the expectant mother. However, in addition to strong maternal ECG presence, undesirable signals due to body motion activity, muscle contractions, and certain bio-electric potentials degrade the diagnostic quality of obtained fetal ECG from abdominal ECG recordings. In this paper, we address this problem by proposing an improved framework for estimating fetal HR from non-invasively acquired abdominal ECG recordings. Since the most significant contamination is due to maternal ECG, in the proposed framework, we rely on neural network autoencoder for reconstructing maternal ECG. The autoencoder endeavors to establish the non-linear mapping between abdominal ECG and maternal ECG thus preserving inherent fetal ECG artifacts. The framework is supplemented with an existing blind-source separation (BSS) algorithm for post-treatment of residual signals obtained after subtracting reconstructed maternal ECG from abdominal ECG. Furthermore, experimental assessments on clinically-acquired subjects' recordings advocate the effectiveness of the proposed framework in comparison with conventional techniques for maternal ECG removal.**

I. Introduction

The fetal electrocardiogram (ECG) reveals useful information about the physiological condition of a fetus during pregnancy and labor [1]. The abdominal ECG, which is acquired non-invasively, contains strong contamination of maternal ECG signal and other undesirable signals due to body motion and muscle activity, thus yielding a low signal-to-noise ratio (SNR) for fetal ECG [2]. In this sense, the complete elimination of maternal ECG is of utmost significance and remains a daunting signal processing task. Since the abdominal ECG is most significantly corrupted by the strong presence of maternal ECG [3], a reliable cancellation of the maternal ECG morphology is necessary for determining fetal HR.

In the literature, several different techniques and frameworks have been proposed for maternal ECG removal. These methods can mainly be categorized as adaptive filtering, blind source separation (BSS), and template subtraction (TS).

[1]A.A. Qureshi, L. Wang and T. Ohtsuki are with the Graduate School of Science and Technology, Keio University, Kanagawa 223-8522, Japan. Email: abuzar@ohtsuki.ics.keio.ac.jp, lucia.wang@keio.jp, ohtsuki@keio.jp

[2]K. Owada, N. Honma and H. Hayashi are with Atom Medical Corporation, Tokyo 113-0033, Japan. Email:{kazunari-utc, n-honma-utc, hayato.hayashi}@atomed.co.jp

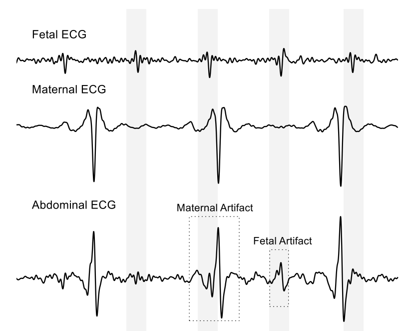


Fig. 1. The abdominal, maternal and fetal ECG signals. Owing to their stochastic nature, the fetal peaks may coincide with the maternal peaks which can influence the correct identification of fetal heartbeat in abdominal ECG recordings.

[4]-[11]. The BSS methods have been discussed extensively in [7]. The objective of BSS techniques is to decompose the composite signal into its constituents: fetal ECG, maternal ECG, and interference [8]. However, these methods are limited by the assumption that the mixture system is linearly contaminated [9]. The adaptive filtering methods aim to minimize the error between noisy ECG and a reference ECG recording. Although these methods have proven to be effective in eliminating maternal ECG contamination, they depend on structurally similar reference ECG that imposes computational burden [10]. The TS methods are superior in the sense that they rely solely on a single-channel abdominal recording [11]. It is worth noting that, during artifact reduction, the TS methods may also deteriorate the fetal ECG artifacts if the fetal and maternal heartbeats coincide as seen in Fig. 1. This can significantly affect the extraction of fetal HR.

Previously, we studied the reconstruction of maternal ECG from abdominal ECG using autoencoder in [12]. Building upon that, in this paper, we propose an improved framework for fetal HR detection. Our framework comprises three main modules: preprocessing raw abdominal signals, reconstructing and canceling the estimated maternal ECG, and estimating fetal HR. Specifically, we focus on maternal ECG cancellation by leveraging neural-network autoencoder, aiming to learn the compressed encoding of abdominal ECG and using appropriate features for decoding, thus reconstructing maternal ECG morphology. The autoencoder endeavors to establish the non-linear mapping between abdominal

ECG and maternal ECG thus preserving inherent fetal ECG artifacts. The framework is supplemented with an existing BSS algorithm for post-treatment of residual signals. It is shown that autoencoder-based maternal ECG cancellation significantly improves fetal HR detection.

The rest of the paper is organized as follows. The suggested framework is presented in section II, experiments and results are discussed in section III and finally, section IV concludes this paper.

II. The Proposed Framework for Fetal Heart Rate Detection

A. Preprocessing

The first module of the proposed framework is preprocessing of abdominal ECG data. This is mainly done to subdue saturated and invalid information in the signals, primarily due to the noisy outputs of the analog-to-digital converters in sensors. Centering and amplitude normalization is performed. The mean of the signal is subtracted to eliminate the sharp voltage jumps. A bandpass filter (BPF) with a passband of [2.0, 46] Hz is then employed to minimize the fundamental noise components. The filter is designed by cascading a low-pass and a high-pass filter between 2 and 46 Hz, using a linear-phase Kaiser window. The preprocessing treatment denoises the recordings to a considerable extent while also preserving the fetal ECG artifacts.

B. Canceling Maternal ECG

The maternal R-peak locations are first determined by the well-known Pan-Tompkins algorithm [13] which estimates the R-peak through a series of filters and adaptive thresholds. We denote the preprocessed abdominal ECG of a subject as $\boldsymbol{x}^A = [x_1^A(t), x_2^A(t), \ldots, x_N^A(t)]$ for $t = 1, 2, \ldots, T$, where N corresponds to the number of electrode channels. Similarly, the preprocessed maternal ECG is denoted as $\boldsymbol{x}^M = [x_1^M(t), x_2^M(t), \ldots, x_N^M(t)]$ for $t = 1, 2, \ldots, T$. Both the recordings are then segmented by a time window that is centered around the estimated maternal R-peak,

$$C_i^A(t) = x_i^A(t) \cdot rect\left(\frac{t - \tau_i}{D}\right), \tag{1}$$

where $C_i^A(t)$ is the i^{th} extracted abdominal cycle, $x_i^A(t)$ is the i^{th} preprocessed abdominal ECG recording, τ_i is the location of the estimated maternal R-peak, and D is the set duration which ensures that the fetal ECG artifacts are preserved and that the extracted segments are non-overlapping cycles. After performing the same procedure on $\boldsymbol{x}^M$, we obtain $\boldsymbol{C}^A = [\boldsymbol{c}_1^A, \boldsymbol{c}_2^A, \ldots, \boldsymbol{c}_n^A]$ and $\boldsymbol{C}^M = [\boldsymbol{c}_1^M, \boldsymbol{c}_2^M, \ldots, \boldsymbol{c}_n^M]$ where $\boldsymbol{c}_i \in \mathbb{R}^D$ and $\boldsymbol{C}^A, \boldsymbol{C}^M$ correspond to the segmented cycles of $\boldsymbol{x}^A$ and $\boldsymbol{x}^M$, respectively.

We design an encoder-decoder network that establishes the non-linear mapping between the abdominal ECG artifacts and the maternal ECG artifacts. Specifically, the encoder takes the input $\boldsymbol{C}^A$ and maps it to a hidden representation $\boldsymbol{C}'$ through a deterministic mapping function $\boldsymbol{C}' = f_\theta(\boldsymbol{C}^A) = \phi(\boldsymbol{W}\boldsymbol{C}^A + \boldsymbol{b})$ which is parameterized by $\theta = \{\boldsymbol{W}, \boldsymbol{b}\}$. Here, ϕ is an activation function, $\boldsymbol{W}$ is a weight matrix, and $\boldsymbol{b}$ is a bias vector. The extracted feature set by the autoencoder is given by $\boldsymbol{C}'$. The latent representation $\boldsymbol{C}'$ is then mapped back to a reconstructed vector $\boldsymbol{C}^M$ through the decoder. The deterministic mapping of the decoder can be formulated as $\boldsymbol{C}^M = g_{\theta'}(\boldsymbol{C}') = \phi(\boldsymbol{W}'\boldsymbol{C}' + \boldsymbol{b}')$ which is parameterized by $\theta' = \{\boldsymbol{W}', \boldsymbol{b}'\}$. By optimizing the parameters of the autoencoder, the reconstruction loss $L(\boldsymbol{c}_i^A, \boldsymbol{c}_i^M)$ can be minimized,

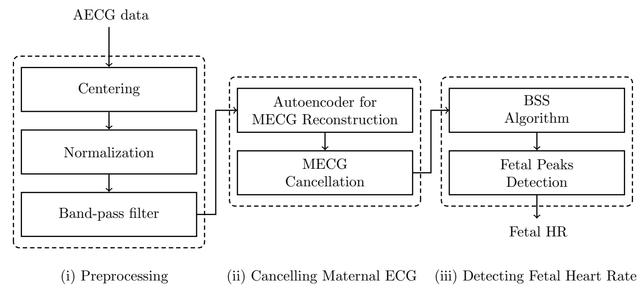


Fig. 2. The flowchart of the proposed framework: (i) Preprocessing, (ii) Canceling Maternal ECG, and (iii) Extracting Fetal Heart Rate.

$$\theta^*, \theta'^* = \arg\min_{\theta, \theta'} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{c}_i^A, \boldsymbol{c}_i^M), \tag{2}$$

where n is the number of training samples, $\boldsymbol{c}_i^A$ is the i^{th} input data from the training samples and L is a loss function (e.g. mean-squared error). The autoencoder reconstructs the maternal ECG segmented cycles corresponding to the abdominal ECG segmented cycles. The reconstructed maternal ECG cycles are denoted as $\hat{\boldsymbol{c}}^M = [\hat{\boldsymbol{c}}_1^M, \hat{\boldsymbol{c}}_2^M, \ldots, \hat{\boldsymbol{c}}_n^M]$ which are rejoined to obtain $\hat{\boldsymbol{x}}^M$, the maternal ECG morphology. The residual signal $\boldsymbol{x}^R$ can thus be extracted as follows,

$$\boldsymbol{x}^R = \boldsymbol{x}^A - \hat{\boldsymbol{x}}^M. \tag{3}$$

The reconstructed maternal ECG is directly subtracted from the test subjects' composite recordings.

C. Extracting Fetal Heart Rate

In the third module, the joint approximation diagonalization of eigen-matrices (JADE) algorithm [14] is employed to extract the fetal ECG signal. The basic premise of the BSS method is to separate a mixed observed signal into its components. In this case, the mixture signal are the remnants obtained after subtracting reconstructed maternal ECG in previous step. So the observed data can be represented by $\boldsymbol{x}^R = [x_1^R(t), x_2^R(t), \ldots, x_N^R(t)]$ for $t = 1, 2, \ldots, T$, assumed to be linearly contaminated with the source $\boldsymbol{x}^S$ due to the mixing matrix $\boldsymbol{A}$. The mixing activity can be depicted by,

$$\boldsymbol{x}^R = \boldsymbol{A}\boldsymbol{x}^S, \tag{4}$$

where $\boldsymbol{x}^R$ is the residual signal obtained after subtraction, $\boldsymbol{x}^S$ is the source signal, and $\boldsymbol{A}$ is the unknown mixing matrix of interest. With the output of the BSS algorithm, the peak-detection process can be easily carried out using the algorithm in [9].

III. Experiments and Results

The implementation steps for autoencoder-based maternal ECG removal and fetal HR estimation are detailed here along with the performance evaluation.

A. Data Description and Measurement

The experiments are conducted on clinically-acquired 12-lead ECG data that are recordings of duration 60 s each. This data was obtained from Atom Medical Corporation, Japan as a result of laboratory collaboration.

The abdominal ECG data were recorded by a non-invasive sensor at a sampling frequency of 1000 Hz. Here, the 11 electrodes correspond to various spatially oriented abdominal ECG recordings which were placed on the expectant mothers' abdomen and 1 electrode corresponds to maternal ECG. Two abdominal channels were selected for maternal ECG reconstruction. Furthermore, reference annotations were also acquired from Atom Medical Corporation and associated medical experts, in terms of the fetal HR and the fetal RR interval. These annotations are used for numerically assessing the performance of the proposed framework for fetal HR estimation. To evaluate the performance of the proposed framework for fetal HR estimation, we consider the root-mean-squared error (RMSE) between the estimated fetal RR interval, $\widehat{\text{FRRI}}$, and the reference FRRI given by

$$\text{RMSE}(\text{FRRI}, \widehat{\text{FRRI}}) = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left\|\widehat{\text{FRRI}}_i - \text{FRRI}_i\right\|_2^2}. \quad (5)$$

In addition, the averaged absolute error (AAE) compares the estimated fetal heart rate, $\widehat{\text{FHR}}$, with the reference FHR, given by

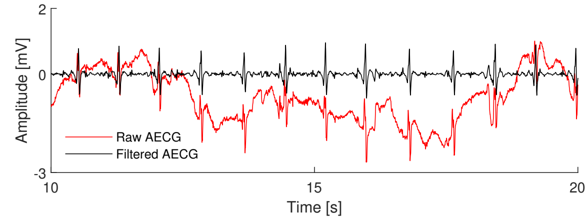
$$\text{AAE}(\text{FHR}, \widehat{\text{FHR}}) = \frac{1}{K}\sum_{i=1}^{K}\left\|\frac{60 \cdot f_s}{\widehat{\text{FRRI}}_i} - \frac{60 \cdot f_s}{\text{FRRI}_i}\right\|, \quad (6)$$

where f_s is the sampling frequency and K corresponds to the total number of fetal RR intervals.

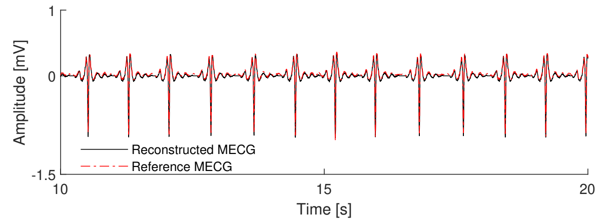
B. Experimental Results and Discussion

After preprocessing raw abdominal ECG recordings of the subjects, the location of the R peaks is determined using the Pan-Tompkins algorithm [13]. An example of preprocessing is shown in Fig. 3 (a). For each estimated maternal R peak, a vector of size 700 is obtained. This corresponds to a segmented cycle centered around the R peak with a duration of 0.25 s to the left and 0.45 s to the right. The set of vectors corresponding to all the R peaks forms the input to the autoencoder trained to reconstruct the maternal ECG morphology using the abdominal ECG cycles as input. Consecutive extracted cycles of the subjects' abdominal ECG are fed to the trained autoencoder. The network outputs the corresponding reconstructed maternal ECG cycles. The reconstructed cycles are rejoined to form the reconstructed maternal ECG morphology. This is subtracted directly from the abdominal ECG to obtain the residual signals.

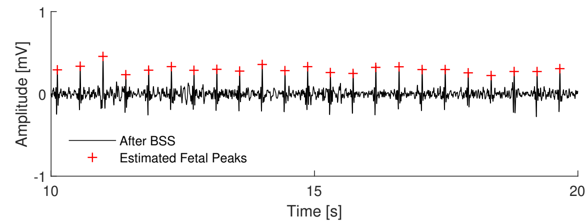
The residual signals are still expected to contain remnants of high-frequency noise components, which can potentially affect the estimation and correct identification of fetal ECG. This necessitates the use of a BSS algorithm on the residual signals. In this paper, we employ the JADE algorithm [14] for processing the residual signals. Due to the BSS algorithm, the constituent signals exhibit enhanced and more pronounced peaks thus aiding our peak detection process for fetal HR estimation.



(a) The raw and preprocessed abdominal ECG.



(b) The reconstructed maternal ECG along with the reference.



(c) The output of BSS module indicating correctly detected fetal peaks.

Fig. 3. Examples of the proposed method's stages for subject A.

TABLE I

THE RMSE FOR AMPLITUDE BETWEEN REFERENCE AND RECONSTRUCTED MATERNAL ECG. RESULTS ARE AVERAGED OVER ALL ABDOMINAL ECG CHANNELS.

RMSE [mV]				
Subject A	Subject B	Subject C	Subject D	Subject E
0.0036	0.0039	0.0038	0.0041	0.0046

1) Experiment 1: In the first experiment, we intend to assess the maternal ECG reconstructed from abdominal ECG using the trained autoencoder. The idea is to reconstruct the maternal ECG in lieu of performing artifact reduction on AECG itself so that fetal HR artifacts can be fully preserved. An autoencoder is designed which consists of 7 fully-connected layers. In the encoder, the input layer is succeeded by 3 hidden layers of node size 128, 64, and 32. Here, 32 is the encoding dimension, defined as the feature number [15]. The decoder is designed to be inversely symmetric to the encoder. Furthermore, we have employed exponential linear units (ELU) and *tanh*[1] as activation functions for hidden layers and the output layer, respectively [16], [17].

We compare the reconstructed maternal ECG with the reference maternal ECG for each subject. A visual evaluation of reconstructed maternal ECG along with the reference is

[1]The hyperbolic tangent activation function is represented by $\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x})$.

TABLE II

THE PERFORMANCE OF THE PROPOSED FRAMEWORK (SHOWN IN BOLD) WITH REGARDS TO THE ESTIMATED FETAL RR INTERVAL AND FETAL HR IN TERMS OF RMSE [MS] AND AAE [BPM] RESPECTIVELY.

	RMSE [ms]				AAE [bpm]			
	TS [4]	TS_M [5]	TS_{PCA} [6]	Proposed	TS	TS_M	TS_{PCA}	Proposed
Subject A	16.273	12.661	5.1962	**4.2470**	1.3563	0.9527	0.4444	**0.4168**
Subject B	22.990	22.946	23.289	**13.631**	2.8626	2.9997	3.1327	**1.8863**
Subject C	7.2042	7.4583	7.6265	**0.9451**	0.5950	0.6090	0.5859	**0.1861**
Subject D	14.173	14.125	14.349	**14.094**	1.0495	0.9948	0.9675	**0.8683**
Subject E	5.6465	5.8810	5.9194	**0.9722**	0.5560	0.5786	0.5606	**0.1969**

shown in Fig. 3 (b) for subject A. Furthermore, the RMSE to measure amplitude variation between reconstructed and reference maternal ECG is also calculated for all the subjects, given in TABLE I. It is evident that the autoencoder is able to reconstruct the maternal ECG from the abdominal ECG thus allowing for maternal ECG elimination.

2) Experiment 2: In the second experiment, the fetal HR is calculated to evaluate the performance of the entire framework. We also assess the fetal RR interval. Since the proposed method focuses on autoencoder-based maternal ECG removal, we validate the results by comparison to the TS methods. Specifically, the proposed method is compared to the following: TS [4] whereby a maternal ECG template cycle is built and updated while canceling previous cycles, TS_M [5] whereby the maternal ECG template is scaled with a constant to reduce mismatch between the template and individual maternal ECG cycles, and TS_{PCA} [6] whereby singular value decomposition (SVD) is used to obtain principal components (PCs) and the components constituting for maternal ECG can be subtracted. For an equitable comparison, the second module in the proposed framework is replaced with the TS algorithms while all the other system parameters are kept constant.

The RMSE results for the fetal RR interval and the AAE results for the fetal HR are given in TABLE II. From the table, it is evident that the proposed method yields better results than the conventional methods. The performance can be attributed to the fact that the autoencoder reconstructs the maternal ECG quite accurately, as shown in TABLE I. Consequently, the reconstructed maternal ECG subtraction preserves the fetal HR artifacts in the abdominal recordings. Furthermore, the use of the BSS algorithm further enhances fetal HR detection in the proposed framework.

IV. CONCLUSION

In this paper, we introduced an improved framework for fetal HR detection. Our framework incorporates the use of neural-network autoencoder for maternal ECG reconstruction supplemented with an existing BSS algorithm for enhanced fetal HR detection. Furthermore, it is seen that autoencoder-based maternal ECG reconstruction and subsequent cancellation benefits the extraction of fetal HR which is evident from better performance achieved during numerical assessments on the subjects' recordings. With the improved fetal HR accuracy, the suggested framework is expected to enhance clinical applications of fetal ECG and assist clinicians in timely diagnosing fetal heart diseases.

REFERENCES

[1] R. Martinek *et al.,* "Nonlinear Adaptive Signal Processing Improves the Diagnostic Quality of Transabdominal Fetal Electrocardiography." in *Advanced Biosignal Processing and Diagnostic Methods.* Intech, 2016, ch. 3, pp. 55-84.

[2] J. Behar *et al.,* "Combining and Benchmarking Methods of Foetal ECG Extraction without Maternal or Scalp Electrode Data," in *Physiol. Meas.*, vol. 35, no. 8, pp. 1569–1589, Aug. 2014.

[3] R. Sameni and G. Clifford, "A review of fetal ECG signal processing: Issues and promising directions," in *The Open Pacing, Electrophysiology & Therapy Journal*, vol. 3, pp. 4–20, Jan. 2010.

[4] S. Cerutti *et al.,* "Variability analysis of fetal heart rate signals as obtained from abdominal electrocardiographic recordings." in *JPM - Official Journal of the WAPM*, vol. 14, no. 6, pp. 445–452, 2009.

[5] S. M. M. Martens, C. Rabotti, M. Mischi and R. J. Sluijter, "A Robust Fetal ECG Detection Method for Abdominal Recordings", in *Physiol. Meas.*, vol. 28, pp. 373-388, 2007.

[6] J. Behar *et al.,* "A Comparison of Single Channel Fetal ECG Extraction Methods," in *Annals of Biomedical Engineering*, vol. 42, no. 6, pp. 1340–1353, Jun. 2014.

[7] R. Jaros, R. Martinek, and R. Kahankova, "Non-adaptive Methods for Fetal ECG Signal Processing: A Review and Appraisal," in *Sensors*, vol. 18, no. 11, pp. 1-24, 2018.

[8] F. S. Najafabadi, A. Zahedi, and M. A. M. Ali, "Fetal Heart Rate Monitoring based on Independent Component Analysis," in *Computers in Biology and Medicine*, vol. 36, pp. 241–252, 2006.

[9] L. Wang, T. Ohtsuki, K. Owada, N. Honma and H. Hayashi, "Joint Multiple Subspace-based BSS Method for Fetal Heart Rate Extraction from Non-invasive Recordings," in *IEEE Eng. in Med. & Biol. Soc. (EMBC)*, Montreal, QC, Canada, 2020, pp. 616-620.

[10] W. Zhong, Z. Cao, X. Guo and G. Wang, "A Novel Framework for Maternal ECG Removal from Single-Channel Abdominal Recording," in *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, San Diego, CA, USA, 2019, pp. 616-621.

[11] J. Behar *et al.,* "A practical guide to non-invasive foetal electrocardiogram extraction and analysis," in *Physiol. Meas.*, vol. 37, no. 5, pp. R1–R35, 2016.

[12] A. A. Qureshi, L. Wang, T. Ohtsuki, K. Owada, N.Honma, and H. Hayashi, "Reconstructing Maternal ECG from Abdominal ECG Using Autoencoder," in *International Conference on Emerging Technologies for Communications (ICETC)*, Tokyo, Japan, Dec. 2020.

[13] J. Pan and W. J. Tompkins, "A Real-time QRS Detection Algorithm," in *IEEE Trans. Biomed. Eng.*, vol. 32, pp. 230–236, Mar. 1985.

[14] J. Zhang and A. C. Sanderson, "JADE: Self-adaptive differential evolution with fast and reliable convergence performance," in *Proc. IEEE Congr. Evol. Comput.*, Singapore, Sep. 2007, pp. 2251–2258.

[15] Hou, Borui *et al.,* "LSTM-based Auto-encoder Model for ECG Arrhythmias Classification." in *IEEE Trans. on Instrum. Meas.*, vol. 69, pp. 1232-1240, 2019.

[16] W. Zhong, L. Liao, X. Guo, and G. Wang, "A deep learning approach for fetal QRS complex detection," in *Physiol. Meas.*, vol. 39, no. 4, pp. 1-10, 2018.

[17] D. Clevert, T. Unterthiner, and S. Hochreiter, "Fast and accurate deep network learning by exponential linear units (ELUs)," in *Proc. Int. Conf. Learn. Represent.*, 2016, pp. 1–14.