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RESEARCH ARTICLE

DETECTION OF FETAL ELECTROCARDIOGRAM SIGNALS FROM MATERNAL ABDOMINAL ECG RECORDINGS

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ABSTRACT

Fetal electrocardiogram (fECG) is a signal that contains vital information about the health of the fetus throughout pregnancy. During pregnancy, it is important to monitor and analyse this signal because it represents the electrical activity of the developing fetal heart. Early detection of fetal ECG problems during the fetus' development is crucial because it allows early treatment and provides knowledge about diseases that may emerge at a later time. Extraction of fetal ECG from the abdomen ECG signal is valuable in these aspects. In order to extract the fetal ECG from the recorded abdomen ECG signals correctly, it must be handled appropriately. It could be challenging to separate the fetal ECG signal from other physiological artifacts and noises in the mother abdominal signal. In this study, signal processing techniques were used to separate the fetus ECG signal from real abdominal ECG recordings. These methods include Ensemble Empirical Based Denoising, Finite Impulse Response Filter, Independent Component Analysis, and Pan & Tompkins approach. The results show that utilizing only the ICA technique to extract fECG signals is insufficient and that additional algorithms, such as those indicated above, should be used together. The mECG and fECG signals can be successfully extracted using the suggested approach.

Keywords: fECG extraction, mECG and fECG separation, Wearable fECG monitoring.

1. INTRODUCTION

ECG monitoring of the mother and baby is very important for the health of the mother and baby, especially in the last weeks of pregnancy, as it allows the detection of cardiac anomalies and early intervention before the baby is born[1]. Pregnant women must frequently attend the hospital for ECG tests, which are performed with ultrasound-based equipment. Non-invasive ECG measuring techniques have been developed to address these issues. Especially with the widespread use of wearable sensor systems, it will be possible to monitor mother and baby ECG for 24 hours[2, 3]. In non-invasive systems, measurements are made from certain points in the mother's navel[4]. In these measurements, the ECG signals of the mother and the baby are mixed with each other. The detection of fECG has been studied using a variety of signal processing techniques in the literature[5]. The fundamental approaches to fECG signal processing can be mainly categorised as adaptive and non-adaptive processes [6]. Each technique has benefits and drawbacks of its own. Adaptive methods are based on learning systems and need a clear mECG signal recorded from mother's chest as well as an abdominal ECG signal includes both mECG and fECG signals. Examples of adaptive techniques include least squares algorithm[7], recursive least squares algorithm, adaptive linear neuron-based methods[8] adaptive neuro-fuzzy extraction system, Kalman filter-based methods, nonlinear adaptive techniques, and hybrid neural networks, artificial neural networks, and adaptive neuro-fuzzy extraction systems.

The non-adaptive methods do not need a clear mECG signal recorded from the mother's chest so the signals are measured directly from the abdomen of the pregnant woman. Independent Component Analysis (ICA)[9], Wavelet Transform (WT)[10], Empirical Mode Decomposition (EMD)[11], Singular Value Decomposition (SVD), filtering techniques[6], correlation technique[12], average techniques are among the non-adaptive methods[6]. Despite numerous studies on the subject, there is still a need for practical methods to separate the maternal and fetal ECG signals from each other.

Some of the studies on fECG extraction in the literature are as follows: Liu et al. performed fECG extraction with Independent Component Analysis (ICA), Ensemble Empirical Mode Decomposition (EEMD), Wavelet Shrinkage (WS) based noninvasive fECG separation and an adaptive integrated algorithm for noise reduction. First, they separated the noisy fECG signals from the mixed abdominal ECG data using the ICA technique. Second, the noisy fECG was cleared that was found with partial reconstruction of IMFs. Finally, they used EEMD to decompose the noisy fECG. In the study, four-channel abdominal recordings from Abdominal and Direct Fetal ECG Database[13] were used as test data. Although all WS, EMD-WS and EEMD-WS algorithms were able to effectively reduce noise, they concluded that EEMD-WS outperformed the other three algorithms.
Taralunga et al.[14] proposed a method for fetal ECG extraction from abdominal signals based on ICA and EMD. The performance of the proposed algorithm, called ICA_EMD, was evaluated on both simulated and real data and compared with the results obtained by ICA. They performed the ICA_EMD method in two steps. Firstly, they obtained the ICs with the JADE algorithm, then the EMD was applied to the ICs containing the fECG, and the fetal ECG extraction process was completed. They observed that the proposed ICA_EMD method has a higher performance than the JADE algorithm in both simulated and real data.

In this study, separation of fECG from a mother's abdominal ECG recordings was realized. The steps of the method used in the separation of the fECG from the abdominal ECG(aECG) recordings are given in Figure 1.

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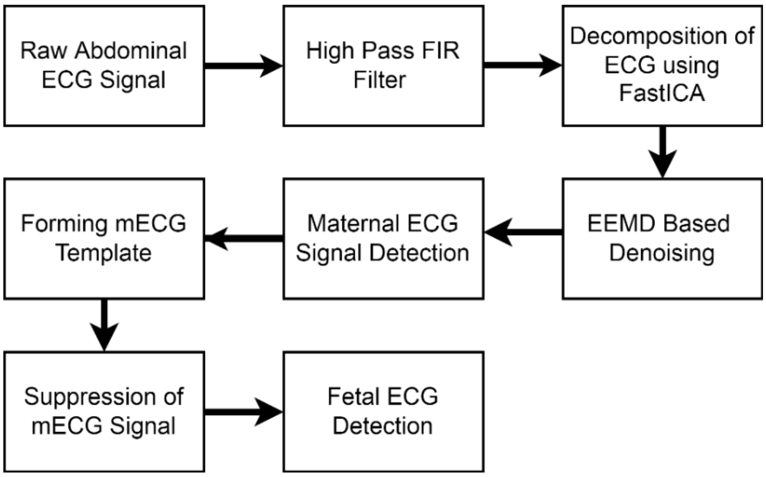

Figure 1. The steps of fECG extraction method from abdominal ECG recordings.

The algorithm has four basic steps. The first step of the algorithm is eliminating DC components in the ECG recordings by using a high pass FIR filter. In the FAST ICA block, the mixed ECG recordings are separated into their independent components. As a third step the EEMD denoising technique is applied to separated components to obtain a more clean maternal ECG. In the last step, the denoised mECG signal is used as a template to suppress of mECG signal from the mixed abdominal ECG signals.

In the article, methods are presented in section II, experimental results and discussions are given at the sections following it.

2. METHODS

2.1. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a mathematical technique for finding hidden signals in the observed mixtures of signals and it is primarily used to separate the mixed signals in multi-sensor/source applications[15]. ICA is also one of the popular methods that separate the fECG signal from aECG and it uses the statistical independence of the predicted components and aims to find independent components by maximizing this independence. The definition of independence for ICA can be done in two ways; mutual information is minimized and non-Gaussianity is maximized[15]. The mathematical model of the ICA is given as in Eq. 1, where x is a linear mixture of two or more independent source signals, s is the independent components and A is considered to be the mixing matrix.

$$x = A.s \tag{1}$$

The aim of the model is to find the A and s using x. The matrix A is calculated as a square matrix and the independent components can be found by calculating the inverse of this matrix[15]. When we

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multiply both sides of equality in Eq. 1 by the inverse of the mixing matrix, we obtain Eq. 2, where W, is the inverse of the mixing matrix.

$$s = W.x \tag{2}$$

2.1.1. FastICA algorithm
FastICA is a popular and effective algorithm of independent component analysis[16]. It is very useful to separate signal components when the number of observations is less. In order to increase the success of the algorithm, the preprocessing stages such as centering and whitening are applied to the observed mixtures[15].The aim of the centering is to find the general average of the data and subtract it from each element of the data vector[17]. In whitening, data correlation is maximized and the variance of the data vectors acquired using by Eigen Value Decomposition (EVD)[9].

2.2. Ensemble Empirical Mode Decomposition
The Empirical Mode Decomposition (EMD) technique has a data-driven working mechanism[18, 19]. It is a method that works on the analysis of single channel signals and very useful technique for the separation of nonlinear and non-stationary time series[18, 20].

The EMD technique enables the data to be analysed according to the time scale feature of itself without any previous operation and staying in the time domain. It is therefore adaptable and applicable for all types of ECG signals[20]. It divides the signal into components called Intrinsic Mode Functions (IMF) at different time scales [18]. IMFs are non-stationary components in finite and few oscillations resulting from the separation of complex data[19]. In EMD method, the signal is divided into IMFs by a repeated shifting process. Each IMF must comply with the following two conditions:

- First, the number of extremes and the number of zero crossings must be equal in the entire signal recording.
- Secondly, the average value of the envelope defined by the local maxima and the envelope defined by the local minima must be equal to zero in all records[21].

The steps of the EMD algorithm for the raw signal are as follows:
a) Peak points of the raw signal are determined.
b) The lower envelope and the upper envelope of the signal are obtained separately.
c) The average envelope is determined and subtracted from the original signal and the first Intrinsic Mode Function candidate (IMF1) is created. This step is shown in the Eq. 3. Here $s(t)$ represents the raw signal, $m_1(t)$ represents the mean envelope, and $h_1(t)$ represents the first found IMF candidate.

$$h_1(t) = s(t) - m_1(t) \tag{3}$$

If $h_1(t)$ provides the conditions of being IMF, it is accepted as the first IMF obtained in the elimination process. If it does not provide the conditions of being an IMF, steps a) and b) for $h_1(t)$ are repeated until the condition of being IMF fulfilled(Eq. 4).

$$h_{1,1}(t) = h_1(t) - m_{1,1}(t) \tag{4}$$

After the steps are provided iteratively, the IMF after n cycles is shown as in Eq. 5.

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$$h_{1,n}(t) = h_{1,n-1}(t) - m_{1.n}(t) \quad (5)$$

d) The first IMF ($c_1(t)$) is removed from the original signal and $r_1(t)$ is now obtained (Eq. 6):

$$r_1(t) = s(t) - c_1(t) \quad (6)$$

e) $r_1(t)$ accepted as the new signal for the second IMF; It is expressed as $c_2(t)$. The above steps are repeated again to get the second residual $r_2(t)$. Now the signal can be expressed as in the following Eq. 7.

$$r_p(t) = r_{p-1}(t) - c_p(t) \quad (7)$$

The original data can be obtained by summing all the IMFs and the last residual signal:

$$s(t) = \sum_{i=1}^{K} c_i(t) + r_L(t) \quad (8)$$

Here K is the number of IMFs obtained after separation[22].

Although EMD has a large application area, it also has weaknesses. It can cause mode mixing when reconfiguring many of the Intrinsic Mode Functions of the signal[22]. Ensemble Empirical Mode Decomposition(EEMD) is obtained by adding a finite amount of Gaussian white noise to the signal processed with EMD and it is very effective eliminating the mode mixing problem[23].

In EEMD, firstly white noise is added to the original signals to obtain grouped data sets. EMD is then applied to each ensemble dataset until it reaches the final ensemble count. The final value is obtained by averaging the successive components resulting from the batch operation.

The steps of EEMD can be summarized as follow[22]:

1. Add a set of white noise $n(t)$ into the original signal $s(t)$ (Eq. 9) and get the new signal:

$$Y(t) = s(t) + n(t) \quad (9)$$

2. Decompose $Y(t)$ into n IMFs by EMD method(Eq. 10).

$$Y(t) = \sum_{i=1}^{n} imf_i(t) + r_n(t) \quad (10)$$

3. Add j different white noise sequences to the original signal (Eq. 11) and repeat the steps 1 and 2:

$$Y_j(t) = \sum_{i=1}^{n} imf_{ij}(t) + r_{nj}(t) \quad (11)$$

4. Calculate the average amount parsed by EEMD with the same IMF value (Eq. 12):

$$Y_j(t) = 1/\mathrm{n}\left(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{imf}_{\mathrm{ij}}(\mathrm{t}) + \mathrm{r}_{\mathrm{nj}}(\mathrm{t}) \right) \quad (12)$$

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5. Add $imf_j(t)$ and the last remainder to obtain the denoised signal (Eq. 13):

$$Y(t) = \sum_{i=1}^{n} imf_i(t) + r_n(t) \tag{13}$$

2.2.1. EEMD based denoising technique

EEMD based denoising technique steps are as follows:

- Firstly, a region that does not contain information is determined in the signal. Noise thresholds are calculated with this selected region.
- The raw signal is separated into IMFs by the EEMD method.
- Each of the obtained IMF is filtered according to thresholding technique.

In this study, soft thresholding technique was used with universal threshold determination. med_i in Eq. 14 is the median absolute deviation of the IMF_i , σ_i indicates the noise level of the IMF_i and t_i in Eq. 15 indicates the threshold value. L is the size of the IMF.

$$\sigma_i = med_i/0.6745 \tag{14}$$

$$t_i = \sigma_i(2\log(L))^{1/2} \tag{15}$$

2.3. Pan & Tompkins Method

The Pan and Tompkins method is used to detect the QRS complex in the ECG signal and it provides good QRS detection performance when high quality ECG signal data is available[24, 25]. The algorithm has following stages: bandpass filter, derivative, a squaring function, a moving window integration (MWI), thresholding and decision. In bandpass filter stage, the algorithm passes the signal through a low pass and a high pass filter to reduce the artefacts such as muscle noise, power line interference, and lead cable movements[24]. While band-pass filter reduces the effect of noise, it maximizes the QRS energy to a suitable frequency[25]. The derivative process is used to detect the largest sloping QRS complex that suppresses P and T waves of the ECG signal[26]. After differentiation, the signal is squared[27]. The squaring function reduce higher amplitudes of T waves to prevent misdetection[25]. The aim of moving window integration is to get information about the waveform and slope of the R wave[27]. The integrated window is important in this process. The widest integrated window should be used to match a possible QRS complex [26]. After the signal has been preprocessed, the next step is the decision phase. In this step, the decision is given whether the MWI result is a QRS complex or not by using thresholds[25].

3. RESULTS

The steps of the study can be summarized in 5 steps: The first step is applying a high-pass filter, the second step is applying FastICA to the high-pass filtered signals. The third step is applying EEMD based denoising to prepare the signal to the Pan-Tompkins method which is used to obtain the QRS points template of the mother ECG signal. Finally, the template is used to suppress mother ECG signals in mixed ECG signals.

The database, that is used in the study, contains multichannel fetal electrocardiogram recordings measured from 5 pregnant women between 38 and 41 weeks of pregnancy [28]. The recordings include four signals measured from the navel and a direct electrocardiogram signal recorded

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simultaneously from the head of the fetal. In the study, Abdomen_1, Abdomen_2, Abdomen_3, Abdomen_4 signals in the r01.edf signal records of a pregnant woman were used. The records are shown in Figure 2. All records have 16-bit resolution, 1 kHz sampling frequency and 10 seconds signal length.

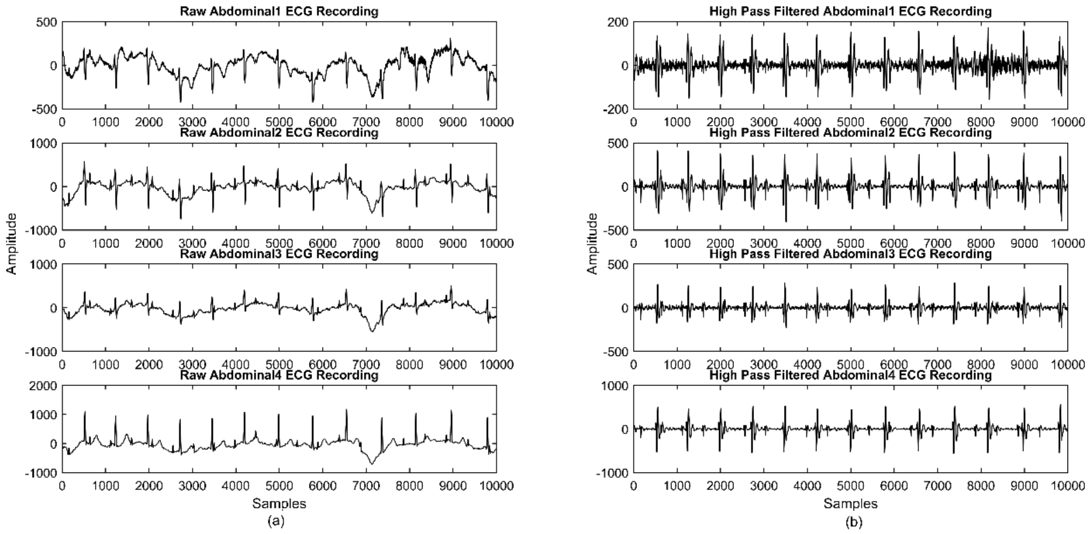

Figure 2. (a) Abdominal recordings used in the study. (b)Recordings of ab-1, ab-2, ab-3, ab-4, filtered through FIR filter.

The raw signals in Figure 2(a) were subjected to a high pass filter with a 5 Hz cut-off frequency as a pre-processing step before to FastICA to remove DC levels. The results of high-pass filtered signals are shown in Figure 2(b).

The abdominal signals that passed through a high-pass FIR filter, were separated into independent components using the FastICA technique. Four abdominal signals without DC components were used as the FastICA input, and the algorithm was directed to find four independent components at the output. Negentropy was employed in FastICA as a non-Gaussianity metric. The output of the FastICA algorithm is given in Figure 3.

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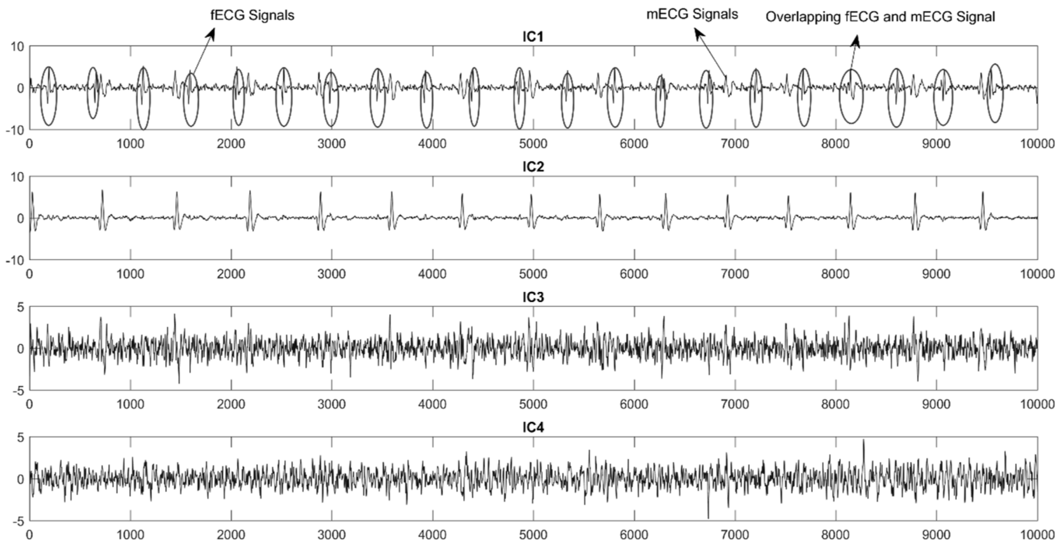

Figure 3. The result of FastICA algorithm: The Independent Components of the ab-1, ab-2, ab-3, ab-4 abdominal signals.

The mECG, fECG, and locations where these two signals overlapped in the IC1 signal can be seen in Figure 3. The IC2 signal is the maternal ECG signal. The majority of the noisy components, as well as the fECG and mECG signals, are present in the IC3 and IC4 signals.

We require the mECG QRS points in order to remove the maternal ECG signal from the mixed ECG data. In the study, the Pan-Tompkins method was used but it needs a high SNR ratio so EEMD based denoising technique was applied to the IC1 and IC2 components to get a cleaner signal. Figure 4 shows the results of the EEMD-based denoising technique on the Independent components.

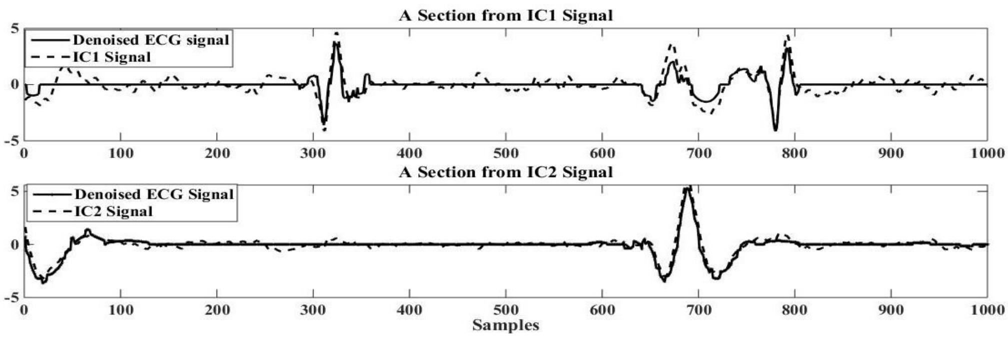

Figure 4. A section from independent components and the results of EEMD based denoising technique.

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The denoised IC2 signal was subjected to the Pan & Thompkins algorithm, and the QRS points of the mECG signal were located (Figure 5). Based on the acquired QRS points, a maternal ECG template was generated.

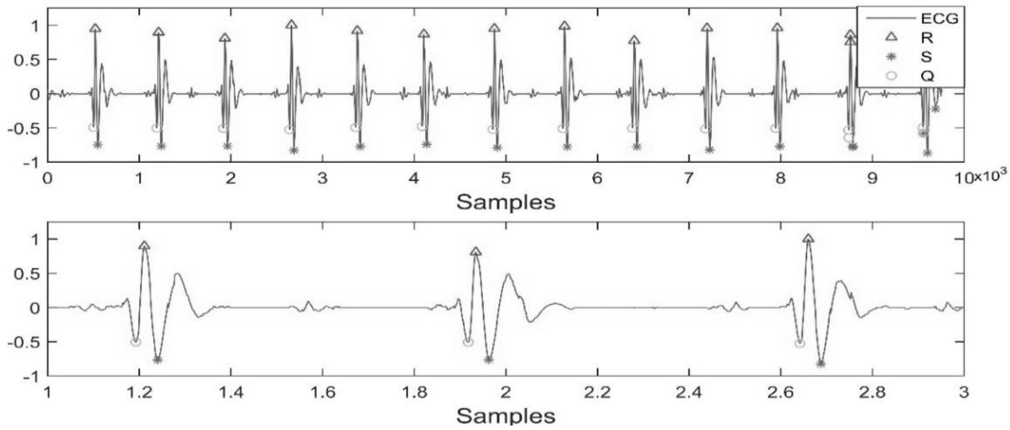

Figure 5. The detected QRS points of denoised IC2 signal using by Pan & Thompkins algorithm.

In Figure 6(a), direct fetal ECG signal, mECG signal and the peak points of fetal ECG detected by our algorithm are plotted on top of each other. As can be seen in Figure 6(a), the algorithm is unable to detect one R point and misdetected one R point in the fECG records. To obtain the fetal ECG signal, the created template was applied to the denoised IC1 data. The result of the masking and detected R points are given in Figure 6(b).

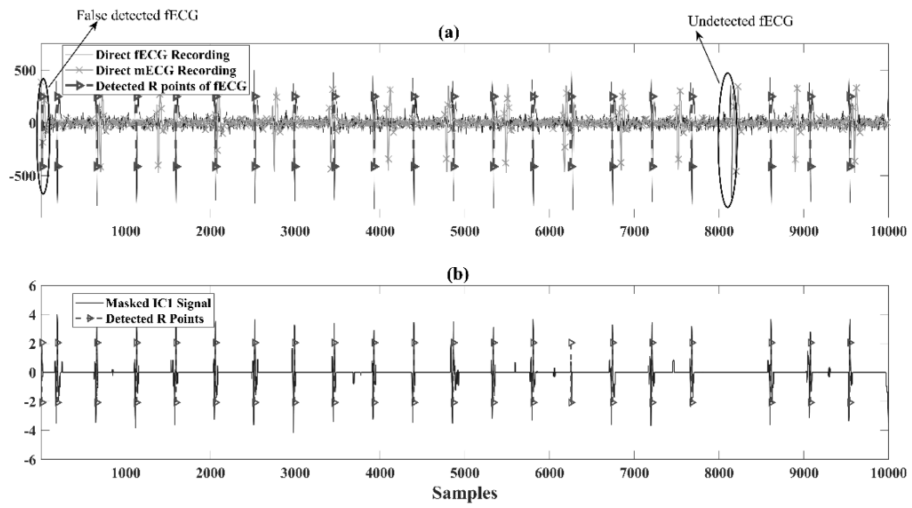

Figure 6. (a) Direct fECG Recording, Direct mECG Recording and Detected R points of fECG detected by our algorithm. **(b)** Masked IC1 signal and detected R points of fECG.

To evaluate the results of the study, we used sensitivity *(Se)*, positive predictive value *(PPV)* and accuracy *(F_1)* values of the classification rates. *TP*, *FP* and *FN* values in the formula indicate true positives, false positives, and false negatives, respectively. *TP*; true fECG R-peaks, *FP*; false fECG R-peaks, *FN*; shows undetectable R-peaks. *PPV* refers to the probability of detecting true fetal ECG R-peaks, while the *Se* value indicates the ability to detect the R-peak. F_1 indicates the possibility of accurate detection of fetal ECG R-peaks [28].

In Eq. 18, 19 and 20, formulas for *Se*, *PPV* and F_1 are given respectively.

$$Se = \frac{TP}{TP+FN} * 100 \tag{18}$$

$$PPV = \frac{TP}{TP+FP} * 100 \tag{19}$$

$$F_1 = 2\frac{PPV.Se}{PPV+Se} = \frac{2.TP}{2.TP+FN+FP} * 100 \tag{20}$$

The studies given in previous sections were made on the R04 records in the database. In Table 1, the detected R peaks of the all records in the database by the proposed method are given.

Table 1. The Results of ECG Signal Extraction Method from aECG Recording.

ECG Data Record No.	ECG Type	Number of R-peaks in ECG Records	Number of detected R-peaks in ECG Records	Percentage of Success (%)
R04	fECG	21	20	95.23
	mECG	15	15	100
R07	fECG	21	19	90.47
	mECG	12	12	100
R08	fECG	21	16	76
	mECG	15	15	100
R10	fECG	20	18	90
	mECG	18	18	100

Performance measures of the proposed method for the Fetal R peak detection are given in Table 2.

Table 2. Performance Measures for Fetal R-peak detection.

ECG Data Record No.	Se(%)	PPV(%)	F_1(%)
R04	95.23	95.23	95.23
R07	95	100	97.43
R08	94.11	94.11	94.11
R10	100	94.7	97.29

According to Table 2, the proposed algorithm shows 91.9% average success in the extraction of fECG in recordings R04, R07 and R10. The success rate is low at recording R08 due to much overlapping of mECG and fECG signals. When we compare the results with the study[15] that is used the same data, the proposed method shows a slight increase in separation fECG. In R04 data, fetal R peak detection success is 95.4% while in the other study it is 90.4%. The success rate of R07 and R10 are the same in both studies.

4. CONCLUSION

In this study, it was aimed to separate the fECG signals from the abdominal ECG recordings in order to early detection of anomaly and illness from the Fetal ECG signals. In the study, the abdominal ECG recordings of a pregnant mother was used to test separation techniques. The results show that the FastICA method can recover mECG signals from aECG recordings but it is insufficient to separate fECG signals. Additional techniques such as EEMD and Pan-Tompkins algorithms were used together with FastICA to extract fECG signal from the aECG recordings.

The study proves that aECG recordings are include linear mixtures of fECG and mECG signals as well as nonlinear components of them so the FastICA algorithm is insufficient separating aECG signals. The other conclusion about the study is that the techniques used in this study are unable to detect overlapping mECG and fECG signals. In the future, it is planned to study on the techniques to separate overlapping ECG signals and embedded system solutions for wearable fetal ECG monitoring systems.

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REFERENCES

[1] Verdurmen, K.M., Eijsvoogel, N.B., Lempersz, C., Vullings, R., Schroer, C., van Laar, J.O., Oei, S.G. (2016). A systematic review of prenatal screening for congenital heart disease by fetal electrocardiography, International Journal of Gynecology & Obstetrics, 135 129-134.

[2] Yang, Z., Zhou, Q., Lei, L., Zheng, K., Xiang, W. (2016). An IoT-cloud based wearable ECG monitoring system for smart healthcare, Journal of medical systems, 40 1-11.

[3] Spanò, E., Di Pascoli, S., Iannaccone, G. (2016). Low-power wearable ECG monitoring system for multiple-patient remote monitoring, IEEE Sensors Journal, 16 5452-5462.

[4] Martinek, R., Kahankova, R., Nazeran, H., Konecny, J., Jezewski, J., Janku, P., Bilik, P., Zidek, J., Nedoma, J., Fajkus, M. (2017). Non-invasive fetal monitoring: A maternal surface ECG electrode placement-based novel approach for optimization of adaptive filter control parameters using the LMS and RLS algorithms, Sensors, 17 1154.

[5] Sameni, R., Clifford, G.D. (2010). A review of fetal ECG signal processing; issues and promising directions, The open pacing, electrophysiology & therapy journal, 3 4.

[6] Preethi, D., Valarmathi, R. (2018). An Analysis of FIR Filter Algorithms in Fetal Heart Rate Monitoring, 2018 International Conference On Advances in Communication and Computing Technology (ICACCT), IEEE, 265-268.

[7] Widrow, B., Glover, J.R., McCool, J.M., Kaunitz, J., Williams, C.S., Hearn, R.H., Zeidler, J.R., Dong, J.E., Goodlin, R.C. (1975). Adaptive noise cancelling: Principles and applications, Proceedings of the IEEE, 63 1692-1716.

[8] Kahankova, R., Martinek, R., Mikolášová, M., Jaroš, R. (2018). Adaptive linear neuron for fetal electrocardiogram extraction, IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom), IEEE, 2018, pp. 1-5.

[9] Alkhodari, M., Rashed, A., Alex, M., Yeh, N.-S. (2018) Fetal ECG Extraction Using Independent Components and Characteristics Matching, International Conference on Signal Processing and Information Security (ICSPIS), IEEE, 1-4.

[10] Cardenas-Lattus, J., Kaschel, H. (2017). Fetal ECG multi-level analysis using daubechies wavelet transform for non-invasive maternal abdominal ECG recordings, 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), IEEE, 1-6.

[11] Gupta, P., Sharma, K.K., Joshi, S.D. (2016). Fetal heart rate extraction from abdominal electrocardiograms through multivariate empirical mode decomposition, Computers in biology and medicine, 68 121-136.

[12] Hasan, M.A., Reaz, M.B.I., Ibrahimy, M.I. (2011). Fetal electrocardiogram extraction and R-peak detection for fetal heart rate monitoring using artificial neural network and Correlation, The 2011 International Joint Conference on Neural Networks, IEEE, 15-20.

[13] Goldberger, A.L., Amaral, L.A., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.-K., Stanley, H.E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals, circulation, 101 e215-e220.

[14] Taralunga, D.D., Gussi, I., Strungaru, R. (2016). A new method for fetal electrocardiogram denoising using blind source separation and empirical mode decomposition, Revue Roumaine des Sci Techn, serie Électrotechnique et Énergetique, 61 94-98.

[15] Nikam, S., Deosarkar, S. (2016) Fast ICA based technique for non-invasive fetal ECG extraction, 2016 Conference on Advances in Signal Processing (CASP), IEEE, 60-65.

[16] Hyvärinen, A., Oja, E. (2000). Independent component analysis: algorithms and applications, Neural networks, 13 411-430.

JSR A
Journal of Scientific Reports

[17] Hassan, N., Ramli, D.A. (2018). A comparative study of blind source separation for bioacoustics sounds based on FastICA, PCA and NMF, Procedia Computer Science, 126 363-372.

[18] Roshini, M., Thanaraj, K.P. (2016). Extraction of Fetal QRS Complex from Abdominal ECG Signals, International Journal of Computer Trends and Technology (IJCTT), 34-1 29-34

[19] Taralunga, D.D., Gussi, I., Strungaru, R. (2016). A new method for fetal electrocardiogram denoising using blind source separation and empirical mode decomposition, Revue Roumaine des Sci. Techn., serie Électrotechnique et Énergetique, 61 94-98.

[20] Wei, Z., Xiaolong, L., Jin, Z., Xueyun, W., Hongxing, L. (2018). Foetal heart rate estimation by empirical mode decomposition and MUSIC spectrum, Biomedical Signal Processing and Control, 42 287-296.

[21] Jaros, R., Martinek, R., Kahankova, R. (2018). Non-adaptive methods for fetal ECG signal processing: a review and appraisal, Sensors, 18 3648.

[22] Yin, J., Chen, X., Zhang, P., Shao, L., Li, J., Liu, H. (2020). Research on ECG signal denoising by combination of EEMD and NLM, 2020 Chinese Control And Decision Conference (CCDC), IEEE, 5033-5038.

[23] Gong, Y., Wang, Z., Xu, G., Zhang, Z. (2018). A comparative study of groundwater level forecasting using data-driven models based on ensemble empirical mode decomposition, Water, 10 730.

[24] Pavlatos, C., Dimopoulos, A., Manis, G. (2005). Papakonstantinou, G., Hardware implementation of Pan & Tompkins QRS detection algorithm, IFMBE Proc, 1727-1983.

[25] Fariha, M., Ikeura, R., Hayakawa, S., Tsutsumi, S. (2020). Analysis of Pan-Tompkins algorithm performance with noisy ECG signals, Journal of Physics: Conference Series, IOP Publishing, 012022.

[26] Bali, J., Nandi, A., Hiremath, P., Patil, P.G. (2018). Detection of sleep apnea in ECG signal using Pan-Tompkins algorithm and ANN classifiers, Compusoft, 7 2852-2861.

[27] Patel, A.M., Gakare, P.K., Cheeran, A. (2012). Real time ECG feature extraction and arrhythmia detection on a mobile platform, Int. J. Comput. Appl, 44 40-45.

[28] Gini, J.R., Ramachandran, K., Nair, R.H., Anand, P. (2016). Portable fetal ECG extractor from abdECG, 2016 International Conference on Communication and Signal Processing (ICCSP), IEEE, 0845-0848.