Volume 8, Issue 4, 082420 (1-12)

Signal Processing and Renewable Energy (SPRE)

https://dx.doi.org/10.57647/j.spre.2024.0804.20

Extraction and noise reduction of the fetal electrocardiogram using Savitzky-Golay and adaptive filters

Ali Ghasemi[1], Farzin Shama[2*]

[1]*Department of Electrical Engineering, National University of Skills (NUS), Tehran, Iran.*
[2]*Electrical Engineering Department, Kermanshah Branch, Islamic Azad University, Kermanshah, Iran.*

[*]**Corresponding author:** f.shama@aut.ac.ir

Original Research

Received:
30 August 2024
Revised:
20 September 2024
Accepted:
2 October 2024
Published online:
30 December 2024

Abstract:

Today, cardiovascular disease is one of the most significant threats to fetuses. The electrocardiogram (ECG) is a common, low-cost way to detect arrhythmias that might cause sudden death. A large number of babies are born with a heart abnormality, which leads to birth defect-related fatalities. Many techniques have been presented for a better ECG signal with low noise. Many resources impair recorded signals because of the tiny amplitude of cardiac impulses, which are only a few millivolts. As a result, they can't help with illness diagnosis. When the patient is physically involved, the negative repercussions are exacerbated. The objective of this research is to find effective ways to remove anomalies in the embryonic cardiac signal. A strategy for minimizing noise is presented in this paper. To enhance the fetal cardiac signal obtained from the mother, an active noise cancellation (ANC) machine was employed in this case (FENC system). Adaptive LMS and normalized LMS are among the algorithms used. Combining the recommended ANC with an (SG) filter improves the FENC system. Findings demonstrate that the suggested FENC is more accurate and suitable than prior approaches.

Keywords: Adaptive filter; Electrocardiogram; Fetal extraction; Noise cancelation; Savitzky-golay (sg) filter; Filter coefficient (fc)

1. Introduction

The most often reported serious illness is now cardiovascular disease, which has surpassed cancer. Cardiovascular infection, especially coronary course malady, is on the increment and, by 2020, will have outperformed cancer as the driving cause of passing around the world [1]. ECG stands for electrocardiogram made out of metal connected to the body parts and the thorax detects electrons, which are subsequently amplified and recorded. The electrocardiogram (ECG) is a low-cost way to detect arrhythmias that might cause sudden death. As a result, the sensitivity and parameters of the ECG are extremely important [1, 2]. One in every 125 babies, according to some estimates, has a heart abnormality, which contributes to birth defect-related fatalities [2]. Although the majority of these heart defects do not create symptoms for several years after birth, they might affect the uncorrected growth pattern. As a result, throughout pregnancy, physicians must consider fetal ECG (FECG) functional evaluations [3]. As a result, the esteem of extraction and the utilization of critical pointers are clear. It is possible to keep both invasive and non-invasive records [4]. The stability electrodes are directly placed on the scalp during invasive recording, which is typically only practicable with intrauterine electrodes during delivery. Despite the great quality of the signals provided by this technique, its application is restricted due to fetal dangers (such as infection and skull damage) and delivery time restrictions. In contrast to the non-invasive recording technique done from the mother's belly, it is gaining popularity daily. As a result, a variety of approaches for assessing cardiac signals have evolved.

In this case, algorithms and implementation complexity are also essential [5]. Utilizing versatile neuro-fuzzy induction,

[3] offers a methodology for upgrading the recuperated fetal ECG. The supplied approach performs an excellent job of capturing the model's nonlinearities. On the other hand, the improved fetal heart signal is just 1.7 dB. In digital signals, the recommended noise reduction technique works beautifully; but, in ECG signals, the corners of the signal cannot be retrieved using this method. For naturally distinguishing cardiac arrhythmias, [5] an adaptive notch filter for noise reduction is suggested. [6] utilizes the doubletree complex wavelet change (DTCWT) as an include extraction approach. The affectability of the framework is assessed. The efficacy of this technique for ECG signal extraction with various morphological types of data has been tested using the suggested method. In [7], two Techniques (SVD and ASWDR) for noise reduction are proposed. Adaptive noise cancelers and some kind of filters for fetal electrocardiogram extraction were proposed by [8–19]. As it were signals with a frequency extend of less than 500 Hz are reasonable for this method [12], proposed an unused approach for extricating the FECG from the maternal signal using v-support vector regression. Despite the reality that the approach laid out works viably, there are still parcels of noises that haven't been explored. Savitzky-Golay filtering [20–25] can also be used in the extraction and noise cancelling of the biological such as applying LMS and NLMS algorithms [26, 27]. Based on these methods and some new algorithms, there are many works on fetal and, maternal ECG noise cancellation [28–40], which it has been tried to be compared with the proposed method in this work.
This paper contains a new method of amalgamation of SG and adaptive filters to reduce noise and extract the heart signal of an embryo from the mother. The reason for using the proposed method is the capability to effectively remove noises in wide frequency bands containing high and low frequencies, which have never been used before together (in the evaluated works of [3–12]) to get these capabilities.

2. Electrocardiography of the fetus

A normal ECG surge is shown in Fig. 1 [1, 4]. Based on this, we can classify this surge into four types: P, QRS, T, and U.

A typical cardiac rhythm consists of four key components: the *P* wave, the *QRS* complex, the T wave, and the *U* wave. The P wave indicates atrial depolarization, followed closely by the contraction of the atria. The QRS complex signifies ventricular depolarization, while the *T* wave reflects ventricular repolarization [15, 16]. The *U* wave is associated with

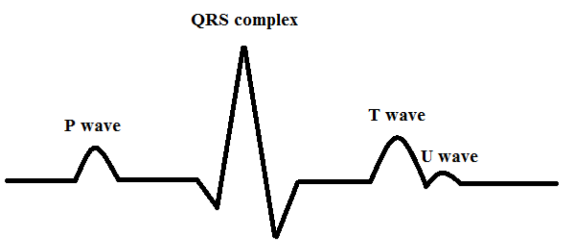


Figure 1. A normal ECG wave. It's broken down inner four parts: *P*, *QRS*, *T*, and *U* [1, 4].

Figure 2. An ECG signal includes both the mother and the fetus [4].

the repolarization of the papillary muscles. Variations in the heart's structure and its environment, including factors like blood composition, can influence the characteristics of these four components [1].
Because the U wave is such an uncommon occurrence, its absence is sometimes overlooked. The far more apparent *QRS* complex usually obscures atrial repolarization, which may only be detected with the insertion of extra, specialized electrodes [1, 2].
One type of problem that occurs during registration is the fetal ECG. This is about reducing accuracy and quality, interference with an ECG signal mother, and also interfering with signals from Midriff muscle compression, which researchers looking to prepare a strategy to overcome this problem. In Fig. 2, test the gastric ECG signal, blend the mother and hatching, appears [4].

For a long time, FECG registration was considered to be a reliable and precise way of monitoring embryo cardiac electrical activity. Despite being a widely used and generally accurate technique for detecting fetal cardiac anomalies, it has several severe drawbacks. Signal interference (muscle artifact) generated by the mother's abdominal contractions is the most significant issue, resulting in impulsive noise. To diagnose sickness and infection, this noise must be minimized [17, 18].

2.1 Creation of a mixture of fetal and maternal ECG

A case study involving forty pregnant women was conducted, and their average characteristics were analyzed to generate standard ECGs using software.
The maternal heartbeat signal was produced using the MATLAB (R2012a) program, as shown in Fig. 3. A sampling rate of 4000 Hz was used to make it. The signal has a 3.4 millivolt amplitude, and the heart rate is about 90 beats per minute (bpm) [1, 2].

As considered, the fetal pulse is altogether speedier than the mother's, with a beat extending from 115 bpm to 155 bpm.

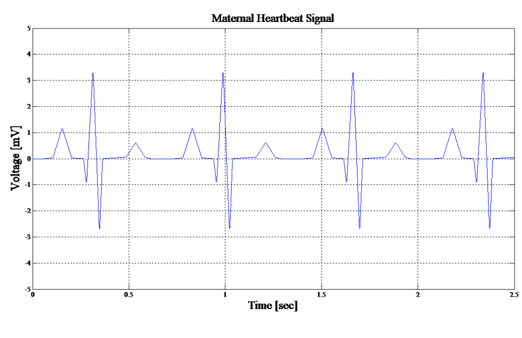


Figure 3. Simulated maternal heartbeat signal.

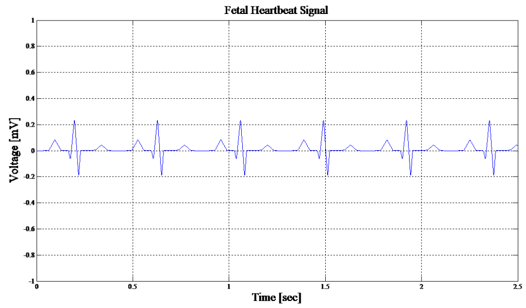


Figure 4. The Simulated fetal heartbeat signal.

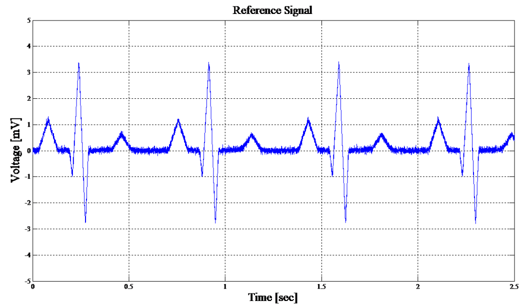


Figure 6. Pre-Savitzky-Golay filtering of the maternal cardiac signal with impulsive noise. (Signal of reference).

Accordingly, the size of the FECG is lower than the ECG of the mother. The distinguishing features of the FECG signal are 138 bpm and 0.24 mV for the voltage ratio, as shown in Fig. 4 [1, 2].

2.2 Noisy ECGs from both the mother and the fetus

The fetal electrocardiogram measured of the mom's belly commonly prevails over the mom's pulse from the thorax divider to the belly. This distribution way must be depicted by a direct FIR filter. Moreover, we must include a little Gaussian noise in Fig. 5 a small Gaussian noise (low-frequency noise) and a big Gaussian noise (high-frequency noise) must also be included in Fig. 5 (b) since they are unmatched in replicating any spectrum of noise sources inside the measurement [19].

2.3 Mom's ECG is measured as a reference signal

From the bosom, the mother's ECG is perfectly visible. Removal of the mom's ECG signal from the embryo ECG signal is the motive of the adaptative noise canceller on this challenge. This noise reduction system needs a reference signal generated by the mother ECG to perform this activity. The maternal ECG signal can contain some additive broad-band noise. The mother's internal sensing reaction is illustrated in Fig. 6, which is a source reaction.

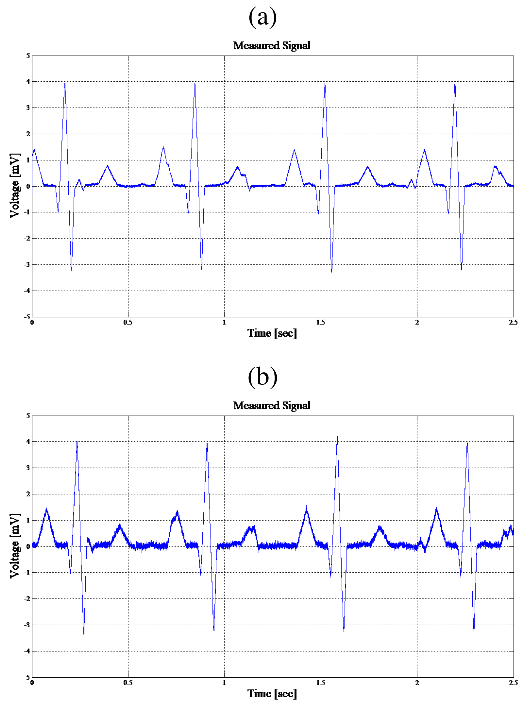


Figure 5. (a) The mother and fetus ECG via low-frequency noise; (b) with excessive-frequency noise.

3. Noise reduction technique

The recommended FECG extraction and noise cancellation (NC) technologies are shown in Fig. 7. The proposed system includes two S-G filters and an adaptive filter. The S-G filter generates Y1 and Y2; an adaptive filter predicts the MECG with noise generates Y3, and the final output is the same error signal that generates the FECG signal. With these values, the algorithm converged, and an acceptable signal error was produced.

3.1 SG filter

S-G filter is practical for a series of digital data points with the target of incrementing the signal-to-noise ratio (SNR) without deforming the signal. The subsets of consecutive data points are fitted utilizing a low-order polynomial with the linear least square method and convolution of all the polynomials is then achieved (Abraham Savitzky and Marcel J. E. Golay, 1964) [20–22]. The information contains a set of focuses x_j, y_j, $j = 1, ..., n$, where x is an autonomous variable and y_j is a watched esteem. They are treated with a set of m convolution coefficients, C_i, concurring with the

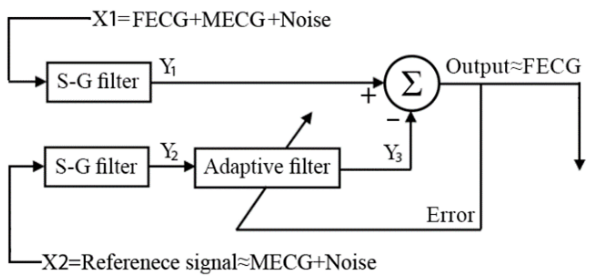


Figure 7. Proposed fetal electrocardiogram extraction and noise reduction framework.

expression [25].

$$Y j = \sum_{i=(1-m)/2}^{(m-1)/2} c_i y_{j+i} (m-1)/2 \leq j \leq n-(m-1)/2 \quad (1)$$

The SG filter typically requires three inputs: the noisy signal (x), the polynomial order (k), and the frame size (f). To determine the optimal values for k and f for a particular signal, the trial-and-error approach is commonly used. Alternatively, these values can also be derived from prior knowledge or previously determined values for a specific signal-to-noise ratio (SNR) [22–25].

3.1.1 Noise cancellation of ECG signals using the SG filter

The S-G filter with differing values of frame size and order is applied to the noisy ECG signal. The produced ECG signal and the detected maternal cardiac signal filtered by the SG filter utilizing various noises are shown in Fig. 8 and . 9.

3.2 Adaptive filter

Adaptive filters are utilized to reduce the noise in fetal ECG as a customary strategy [8, 9, 11, 14]. In adaptive filters, there's no have to know the predetermined data near signal and noise [10]. In Fig. 10, the general structure of the used adaptive filter is illustrated. In this structure, the lead, or another biosensor, that is rather safer for the noise, is used.

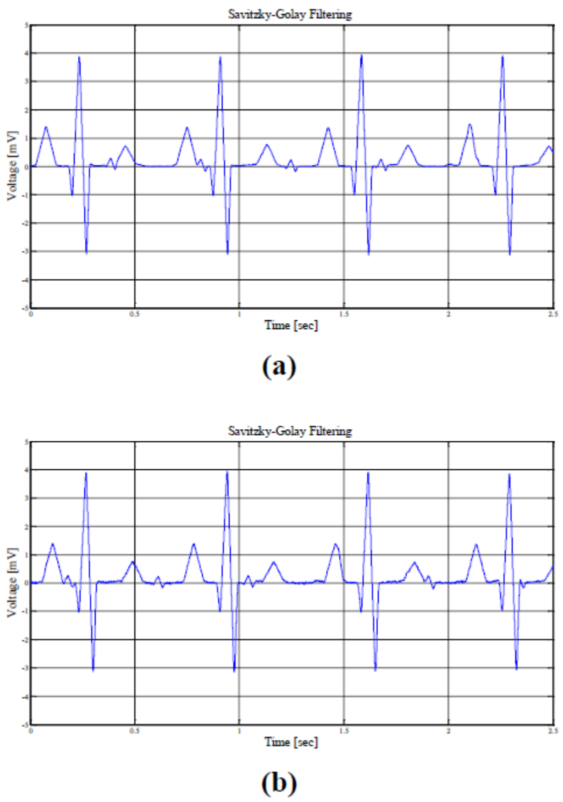


Figure 8. (a) Maternal and fetal ECGs following Savitzky-Golay filtering with low-frequency noise; (b) with high-frequency noise (impulsive noise).

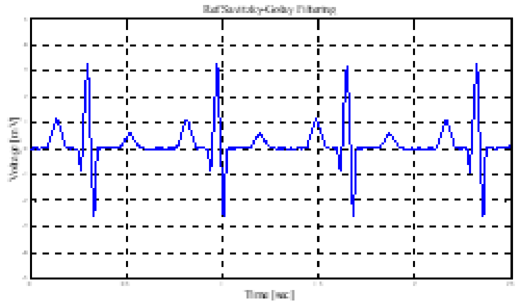


Figure 9. Measured mother heart signal (reference signal) with impulsive noise after Savitzky-Golay filtering.

As a result, the input signals to the filter are a mix of noise and signal, as the reference signal [4, 10, 11].
The following formulae can be utilized to compute the obtained error, or t^{th} sample:

$$y_{[t]} = S_{[t]} + N_{[t]} \quad (2)$$

$$\hat{N}_{[t]} = \sum_{i=0}^{n-1} w_{i[t]} x_{[i-t]} \quad (3)$$

$$e_t = y_{[t]} - \hat{N}_{[t]} = \hat{S}_{[t]} \quad (4)$$

The least-mean-squares (LMS) adaptive filtering algorithm is a fundamental, memory-less iterative approach that utilizes the steepest descent technique, primarily aimed at reducing the mean squared error (MSE) [17]. Least mean square (LMS) is a commonly used error cancellation technique [10, 11, 17].
The least mean squares (LMS) are highly responsive to the characteristics of the input data and the spread of its eigenvalues. As a result, it is advisable to use smaller step sizes to prevent the estimated error from increasing without any limitation. Additionally, LMS is advantageous due to its low computational demands, consistent performance, and unbiased convolution during signal integration [10, 17]. It can be utilized in an adaptive filter as below:

$$w_i + 1_{[t]} = w_{i[t]} + 2\hat{S}\gamma e_t x_{[i-t]} \quad (5)$$

$$w_i + 1_{[t]} = \gamma w_{i[t]} + 2\gamma e_t x_{[i-t]} \quad (6)$$

$y_{[t]}$ is one of the filter inputs that the amalgamation of favorable ($S_{[t]}$) and Undesirable ($N_{[t]}$) signals, another input is $X_{[t]}$ which is intensely subordinate on undesirable signal.$N_{[t]}$ is the yield of the versatile filter that can have an estimation of the commotion signal and et is an error signal

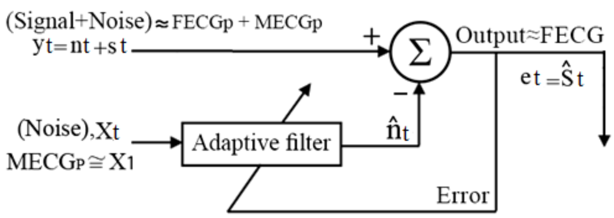


Figure 10. The general structure of the adaptive filter.

that can have a gauge of the signal that's desirable. $W_{i[t]}$, is the filter ratio, and $W_{i+1[t]}$, is the overhaul of the Fc.
The solidness and joining time of the least mean square calculation are decided by the merging coefficient of γ and the signal quality of the reference signal. The greatest esteem of γ for the solidness of the calculation, with the filter length and input signal control of ($x_{[t]}$, has a reversal proportion. A basic strategy for improving the joining rate of the least mean square calculation is the reliance on its solidness on the input signal quality. In the normalized LMS algorithm, the weight adjustments connection is characterized as [26–29]:

$$w(i+1) = w(i) + \gamma_t x_t \varepsilon_t \tag{7}$$

The merging ratio of γ_t may be a time variable parameter and is calculated as follows [25, 26]:

$$\gamma_t = \frac{\alpha}{\hat{L}_x(t)} = \frac{\alpha}{X_t^T X_t}; 0 < \alpha < 2 \tag{8}$$

where $L_{(t)}$ could be a power evaluation of X_t, and alpha could be a consistent number. For a commonsense execution of the NLMS calculation, two taking after focuses are more often than not considered:
A. L_x (0) is the most excellent starting approximation for the input signal control.
B. When the L_x (0) is nil or about nil, γ_t calculated by [25, 30]:

$$\gamma_t = \frac{\alpha}{\mu + \hat{L}_x(t)} \tag{9}$$

where γ may be a positive steady, which anticipates the precariousness within the algorithm making via the nonappearance from an input signal or a little L_x (0).
In this case, the measured signal contains two signals, the desired signal and the interference signal. The purpose of the intercepted signal is to eliminate the signal measured utilizing a reference signal, which is emphatically subordinate to the signal. So, the mother's heartbeat signal is reliably isolated from the heartbeat signal of the baby. As examined already, the electrocardiogram from anodes put on the mother's belly is touchy to foundation commotion contamination, such as the action of the muscles [31, 32].

4. Results and discussion

After modifying the parameters and techniques, the simulation results are shown in Fig. 10. In Figs. 11 . 12 . 13 . 14 . 15 . 16 . 17 . 18, the best performance is attained by the suggested ANC system, which employs an amalgamation of the S-G filter and (LMS) method with an Fc = 16 and $\gamma = 0.009$. It has the values of the parameters of S/N=-24.8 dB, q-S/N=3.96 dB, and S/N increase of 28.66 dB are the characteristics.
The findings are summarized in Table 1. When compared to other techniques, combining the SG filter with the NLMS or LMS algorithm results in a significantly faster rate of error rate reduction and high *S/N* enhancement performance.
The following formula is used to determine the feto-maternal *S/N* (*FM-S/N*) [35]:

$$FM - S/N = 10\log_{10} \frac{\sum_n FEKG}{\sum_n MEKG} \tag{10}$$

The quality of *S/N* (*q-S/N*) is used to quantify the suggested method's performance [35]:

$$q - S/N = 10\log_{10} \frac{\sum_n \widetilde{FEKG}}{\sum_n FEKG - \widetilde{FEKG}} \tag{11}$$

where *FECG* and $\widetilde{FEKG}$ are the desired F-ECG signal and the extracted F-ECG signal, respectively. Table 1 shows the retrieved parameters for *FM-S/N* = -24.8 dB.
The gotten comes about to appear that an amalgamation of SG filter and LMS calculation with an Fc = 16 and γ = 0.009 includes a superior q-S/N and excellent performance in fetal ECG extraction compared to other tasks due to normal FM-S/N in the range of -30 dB to -15 dB. Also, taking into account the amount of FM-S/N = -24.8 dB sometime recently filtered or q-S/N = 3.96 dB after

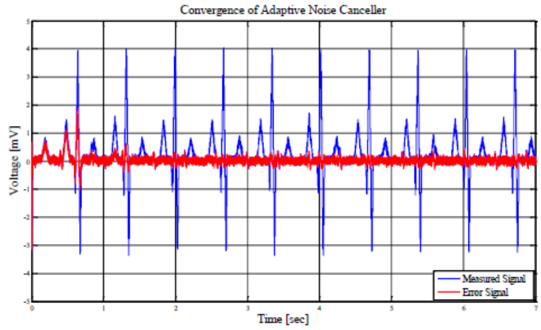
Table 1. Simulated Parameters.

The algorithm used	The amount of time required for convergence and the remaining error in the output of SG filters in (s)		q-S/N (dB)		S/N
(Fc = 16)	Before amalgamation	After amalgamation	Before amalgamation	After amalgamation	improvement(dB)
NLMS $\gamma = 0.\ 00008$	7.415	7.27	-19.90	-19.31	0.59
LMS $\gamma = 0.00008$	1.349	1.267	-10.64	-9.935	0.705
NLMS γ =0.09	0.26	0.0063	-4.894	-1.81	3.084
LMS $\gamma = 0.009$	0.057	0.029	-2.603	3.96	6.563

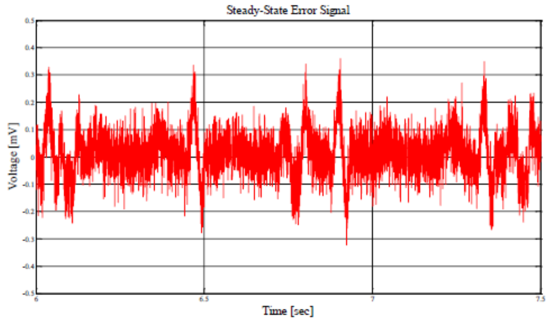
NLMS: normalized MLS

Table 2. A comparison between a few distributed works.

Ref	[3]	[19]	[29]	[33]	Proposed method
Maximum q-S/N (dB)	2.8	2.3801	-9.9347	3.5	**5.2**

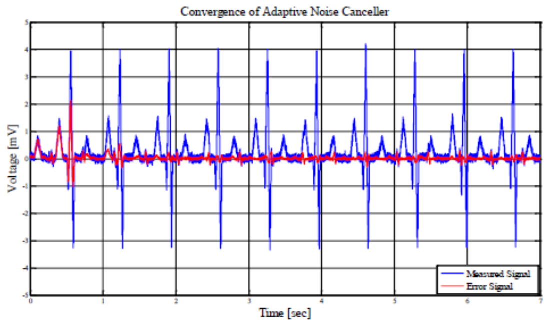


(a)

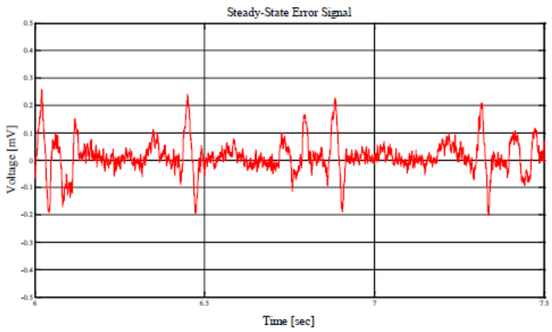


(b)

Figure 11. (a) After 1.349 seconds, the suggested NC system with the LMS method and Fc = 16 and $\gamma = 0.\ 00008$ achieved convergence and error margins in the output; (b) shows the fetal heart recovery using the LMS method with an Fc = 16 and $\gamma = 0.00008$.

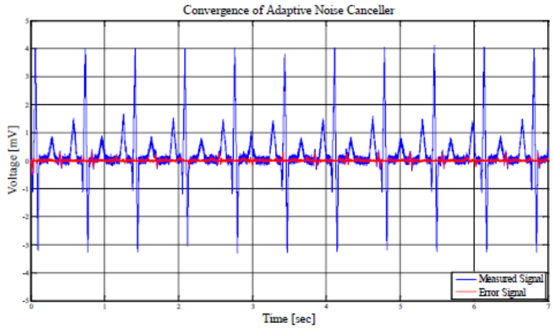


(a)

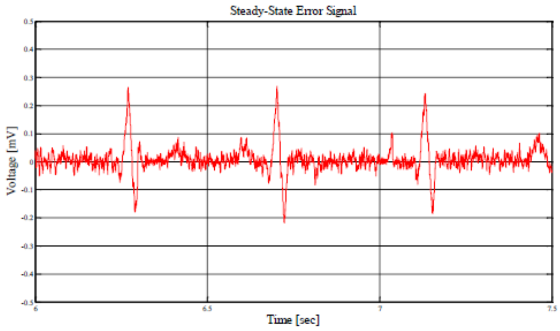


(b)

Figure 12. (a) Output convergence and error margins using the proposed NC system, which uses an amalgamation of SG filter and LMS method with an Fc = 16 and $\gamma = 0.00008$ after 1.267 seconds; (b) Fetal cardiac recovery utilizing the suggested NC system, which combines the SG filter and the LMS method, with an Fc = 16 and $\gamma = 0.00008$.

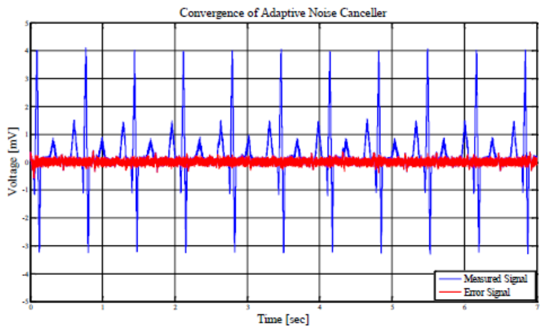


(a)



(b)

Figure 13. (a) Output convergence and error margins utilizing the suggested NC system with an amalgamation of SG filter and LMS method with an Fc = 16 and $\gamma = 0.009$ after 0.029 seconds; (b) Suggested NC system recovers the fetal heart using an amalgamation of SG filter and LMS method with an Fc = 16 and $\gamma = 0.009$.



(a)

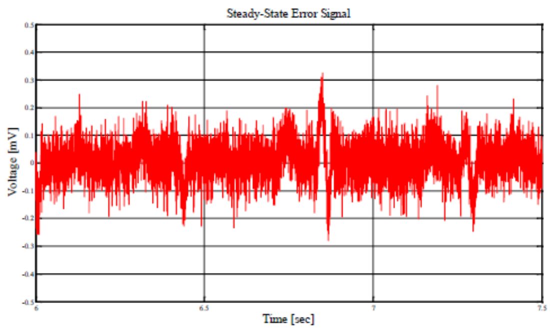


Figure 14. (a) After 0.057 seconds, the suggested NC system with LMS method and Fc = 16 and $\gamma = 0.009$ achieved con-vergence and error margins in the output; (b) Fetal heart recovery with an adaptive filter, employing the LMS method and Fc = 16 and $\gamma = 0.\ 009$.

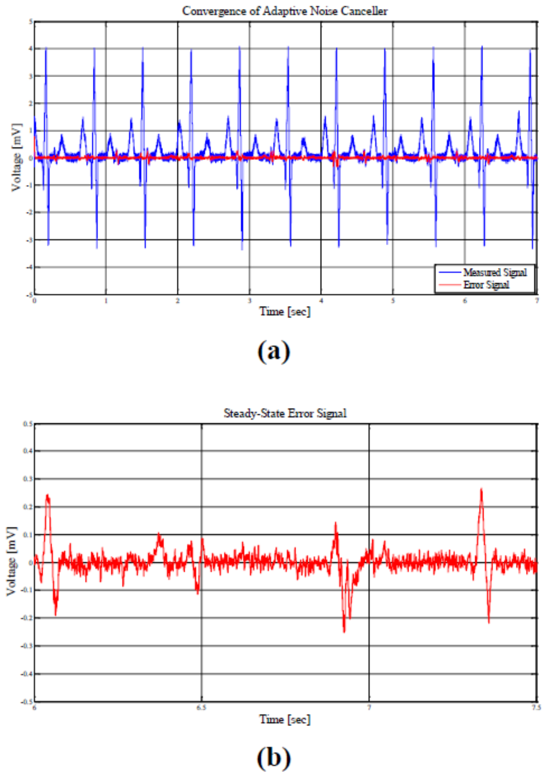


Figure 15. (a) After 0.0063 seconds, the suggested NC system with an amalgamation of SG filter and normalized LMS method with an Fc = 16 and $\gamma = 0.09$ achieved convergence and error margins in the output; (b) Suggested NC system recovers the fetal heart using an amalgamation of SG filter and normalized LMS method with an Fc = 16 and $\gamma = 0.09$.

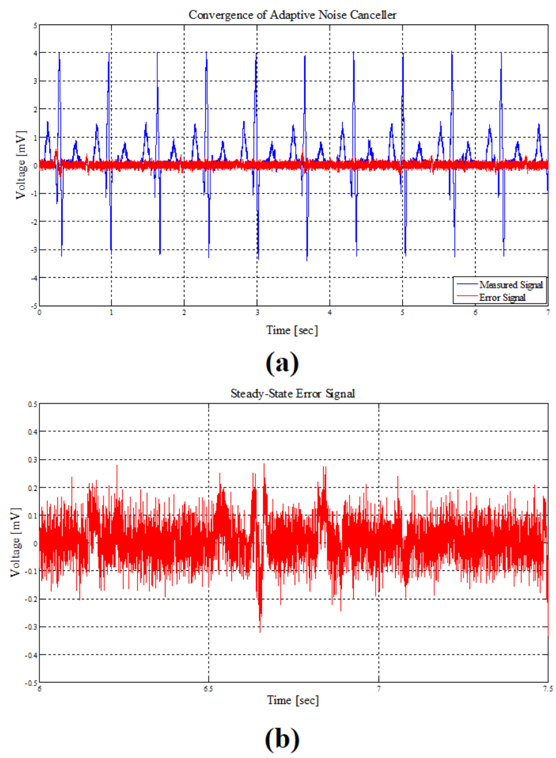
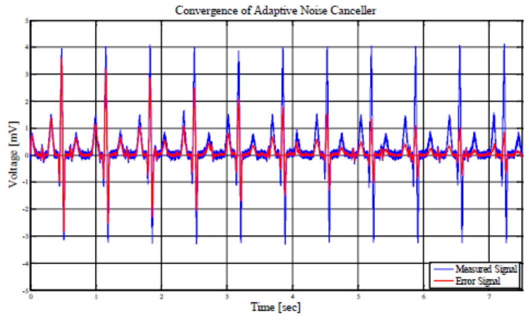
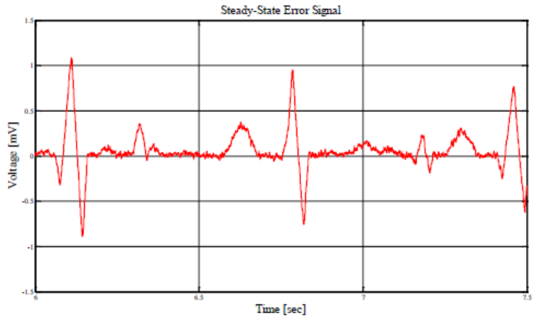


Figure 16. (a) After 0.26 seconds, the suggested NC system with normalized LMS method and Fc = 16 and $\gamma = 0.09$ achieved convergence and error margins in the output; (b) Fetal heart recovery with an adaptive filter, employing the normalized LMS method with an Fc = 16 and $\gamma = 0.09$.

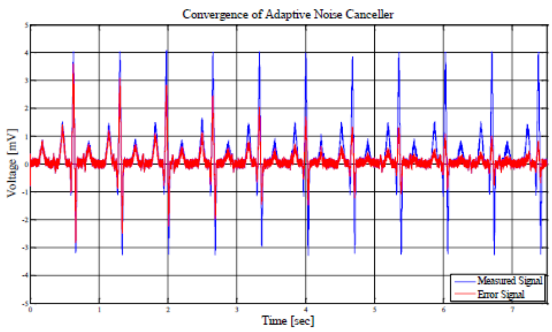


(a)

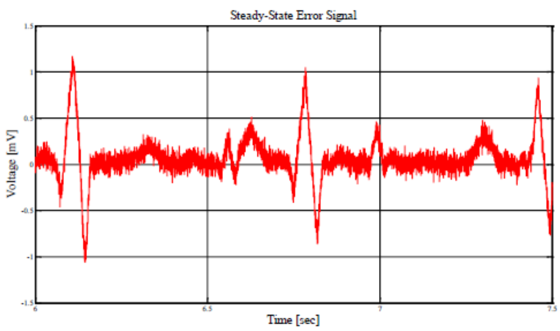


(b)

Figure 17. (a) After 7.27 seconds, the suggested NC system with an amalgamation of SG filter and normalized LMS method with an Fc = 16 and $\gamma = 0.00008$ achieved convergence and error margins in the output; (b) The Proposed NC system, which uses an amalgamation of SG filter and normalized LMS method with an Fc = 16 and $\gamma = 0.00008$, was used to recover the fetal heart.



(a)



(b)

Figure 18. (a) After 7.415 seconds, the suggested NC system with NLMS method and Fc = 16 and $\gamma = 0.\ 00008$ achieved convergence and error margins in the output; (b Fetal heart recovery with an adaptive filter, employing the normalized LMS method with an Fc = 16 and $\gamma = 0.\ 00008$.

filtering, the progress of the 28.66 dB S/N has been obtained. Table 2 shows a comparison of several published studies with the suggested technique. To investigate this table, it can be concluded that:
By using versatile neuro-fuzzy induction, [3] offers a methodology for upgrading the convalesced fetal ECG, while the improved fetal heart signal is down. In digital signals, suggested noise reduction systems work fine; but, in ECG signals, the corners of the signal cannot be recovered by this method. In [19, 29], adaptive noise filters have been introduced for the extraction of fetal electrocardiogram (FECG) signals. The suggested approach performs effectively only for signals with frequencies under 500 Hz. In [33], six algorithms (TVMNF, HHT, DSWPT, WNN, IAC, and FastICA) have been applied for fetal heart extraction. The suggested method has a fine efficiency, but different noises have not been applied to check. Therefore, as shown in Table 2, the proposed method leads to the best Maximum q-S/N (dB) parameter among the discussed works.

5. Conclusions

For evaluating the illness's potential, the capability to attain an exact cardiac signal from a fetus is important. Some noise reduction systems can help improve FECG. This study presents a new approach to reducing FECG noise that combines SG and adaptive filters. The outcomes show that an acceptable S/N may be achieved when compared to conventional algorithms (NLMS or LMS algorithm). This technique may be appropriate for FECG monitoring because of its capability to reduce noise from various sources. The S/N was improved by 28.66 dB using the proposed method.

Authors contributions
All authors contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Open access

References

[1] M. D. Dale Dubin. "Rapid interpretation of ecg.". **6**, 2006.

[2] Andreoli, Carpenter, Griggs, and Benjamin. "Cecil essentials of medicine.". **7**, 2007.

[3] H. Ahmadieh and B. Mohammadzadeh Asl. "Fetal ecg extraction via type-2 adaptive neuro-fuzzy inference systems.". *Elsevier, Computer Methods and Programs in Biomedicine*, **142**, 2017. DOI: https://doi.org/10.1016/j.cmpb.2017.02.009.

[4] B. Widrow, R. C. Goodlin, and the others. "Adaptive noise canceling: principles and applications.". *Proceedings of the IEEE*, **63**:1692–1716, 1975. DOI: https://doi.org/10.1109/PROC.1975.10036.

[5] Q. Wang, X. Gu, and J. Lin. "Adaptive notch filter design under multiple identical bandwidths.". *Elsevier, Int. J. Electron. Commun. (Aeu).*, **82**, 2017. DOI: https://doi.org/10.1016/j.aeue.2017.08.054.

[6] M. Thomas, M. K. Das, and S. Ari. "Automatic ecg arrhythmia classification using dual-tree complex wavelet-based features.". *Elsevier, Int. J. Electron. Commun. (Aeu).*, **69**(**4**), 2015. DOI: https://doi.org/10.1016/j.aeue.2014.12.013.

[7] R. Kumar, A. Kumar, and G. K. Singh. "Electrocardiogram signal compression based on singular value decomposition (svd) and adaptive scanning wavelet difference reduction (aswdr) technique.". *Elsevier, Int. J. Electron. Commun. (Aeu).*, **69**(**12**), 2015. DOI: https://doi.org/10.1016/j.aeue.2015.09.011.

[8] Y. Ma, Y. Xiao, G. Wei, and J. Sun. "Foetal ecg extraction using non-linear adaptive noise canceler with multiple primary channels.". *Iet signal process.*, **12**(**2**), 2018. DOI: https://doi.org/10.1016/j.aeue.2014.12.013.

[9] S. L. Herrera, C. A. Serrano, and P. R. H. Rodriguez. "Fetal ecg extraction based on adaptive filters and wavelet transform: validation and application in fetal heart rate variability analysis.". *IEEE(CCE)*, (), 2016. DOI: https://doi.org/10.1109/ICEEE.2016.7751243.

[10] Y. Gong, P. Gao, L. Wei, C. Dai, L. Zhang, and Y. Li. "An enhanced adaptive filtering method for suppressing cardiopulmonary resuscitation artifact.". *IEEE Transaction On Biomedical Engineering*, **64**(**2**), 2017. DOI: https://doi.org/10.1109/TBME.2016.2564642.

[11] N. Zhang, J. Zhang, H. Li, O. Mumini, O. Samuel, K. Ivanov, and L. Wang. "A novel technique for fetal ecg extraction using single-channel abdominal recording.". *NCBI*, (), 2017. DOI: https://doi.org/10.3390/s17030457.

[12] L. Han, X. j. Pu, and X. j. Chen. "Method of fetal electrocardiogram extraction based on v-support vector regression.". *IEEE, IET Signal Processing*, **9**(**5**), 2015. DOI: https://doi.org/10.1049/iet-spr.2013.0201.

[13] M. Niknazar, B. Rivet, and C. Jutten. "Fetal ecg extraction by extended state kalman filtering based on single-channel recordings.". *IEEE Transactions On Biomedical Engineering*, **60**(**5**), 2013. DOI: https://doi.org/10.1109/TBME.2012.2234456.

[14] R. Singh, A. Singh, and J. Kaur. "Adaptive filter design for extraction of fetus ecg signal.". *Springer*, (), 2015. DOI: https://doi.org/10.1007/978-81-322-2523-2_10.

[15] J. Behar, A. Johnson, G. D. Clifford, and J. Oster. "" A comparison of single-channel fetal ecg extraction methods.". *BMES*, (), 2014. DOI: https://doi.org/10.1007/s10439-014-0993-9.

[16] J. L. Camargo-Olivares, R. Martin-Clemente, S. Hornillo-Mellado, M. M. Elena, and I. Roman. "The maternal abdominal ecg as input to mica in the fetal ecg extraction problem.". *IEEE Signal Processing Letters*, **18**(**3**), 2011. DOI: https://doi.org/10.1109/LSP.2011.2104415.

[17] S. Kadambe and P. Srinivasan. "A pipeline for adaptive filtering and transformation of noisy left-arm ecg to its surrogate chest signal.". *MDPI, Electronics*, (), 2020. DOI: https://doi.org/10.3390/electronics9050866.

[18] A. Khamene and S. H. Negahdaripour. "A new method for the extraction of fetal ecg from the composite abdominal signal.". *IEEE Transactions On Biomedical Engineering*, **47**(**4**), 2000. DOI: https://doi.org/10.1109/10.828150.

[19] R. Sehamby and B. Singh. "Noise cancelation using adaptive filtering in ecg signals: application to biotelemetry.". *International journal of bio-science and bio-technology.*, **8**(**2**), 2016. DOI: https://doi.org/10.14257/ijbsbt.2016.8.2.22.

[20] C. Wang, Z. Wang, J. Wang, and D. Zhao. "Svm-based parameter identification for composite zip and electronic load modeling.". *IEEE Transactions on Power Systems.*, **34**(**1**), 2019. DOI: https://doi.org/10.1109/TPWRS.2018.2865966.

[21] R. W. Schafer. "What is a savitzky-golay filter.". *IEEE Signal processing magazine.*, **28**(**4**), 2011. DOI: https://doi.org/10.1109/MSP.2011.941097.

[22] A. Acharya, A. Rani, and S. H. Agarwal. "Application of adaptive savitzky-golayfilter for eeg signal processing.". *Elsevier.*, ():2213–0209, 2016. DOI: https://doi.org/10.1016/j.pisc.2016.06.056.

[23] H. J. Wayt and T. R. Khan. "Integrated savitzky-golay filter from inverse taylor series approach.". *IEEE, Clemson University.*, (), 2007. DOI: https://doi.org/10.1109/ICDSP.2007.4288597.

[24] J. Luo, K. Ying, P. He, and J. Bai. "Properties of savitzky-golay digital differentiators.". *Elsevier*, (), 2004. DOI: https://doi.org/10.1016/j.dsp.2004.09.008.

[25] A. John, J. Sadasivan, and C. H. S. Seelamantula. "Adaptive savitzky-golay filtering in non-gaussian noise.". *IEEE Transactions on Signal Processing*, **69**(), 2021. DOI: https://doi.org/10.1109/TSP.2021.3106450.

[26] E. Eweda, N. J. Bershad, and J. C. M. Bermudez. "Stochastic analysis of the lms and nlms algorithms for cyclostationary white gaussian and non-gaussian inputs.". *IEEE Transactions on Signal Pro-cessing*, **66**(**18**), 2018. DOI: https://doi.org/10.1109/TSP.2018.2860552.

[27] G. Bakhshi and K. Shahtalebi. "Role of the nlms algorithm in direction of arrival estimation for antenna arrays.". *IEEE Communications Letters*, **22**(**4**), 2018. DOI: https://doi.org/10.1109/LCOMM.2017.2760253.

[28] J. Behar, F. Andreotti, S. Zaunseder, Q. Li, J. Oster, and G. D. Clifford. "An ecg simulator for generating maternal-foetal activity mixtures on abdominal ecg recordings.". *Physiol. Meas.*, **35**():1537–1550, 2014. DOI: https://doi.org/10.1088/0967-3334/35/8/1537.

[29] K. V. L. Narayana and D. A . Bhujanga Rao. "Noise removal using adaptive noise canceling, analysis of ecg using matlab.". *International Journal of Engineering Science and Technology (IJEST)*, **3**(**4**), 2011. DOI: https://doi.org/http://www.ijest.info/docs/IJEST11-03-04-108.pdf.

[30] L. Y Taha and E. Abdel-Raheem. "Fetal ecg extraction using input-mode and output-mode adaptive filters with blind source separation.". *Canadian Journal of Electrical and Computer Engineering*, **43**(**4**), 2020. DOI: https://doi.org/10.1109/CJECE.2020.2984602.

[31] H. Danandeh Hesar and M. Mohebbi. "An adaptive kalman filter bank for ecg denoising.". *IEEE Journal of Biomedical and Health Informatics*, **25**(**1**), 2021. DOI: https://doi.org/10.1109/JBHI.2020.2982935.

[32] P. Bing, W. Liu, Z. Wng, and Z. Zhng. "Noise reduction in ecg signal using an effective hybrid scheme.". *IEEE Access*, **8**(), 2020. DOI: https://doi.org/10.1109/ACCESS.2020.3021068.

[33] D. Taralunga, G. M. Ungureanu, I. Gussi, R. Castrungaru, and W. Wolf. "Fetal ecg extraction from abdominal signals: a review on suppression of fundamental power line interference component and its harmonics.". *Hindawi*, **15**():239060, 2014. DOI: https://doi.org/10.1155/2014/239060.

[34] A. Ghasemi, F. Shama, G. Karimi, and F. Khosravi. "Recovery and noise cancelling of the fetal heart signal using a combination of nlms algorithm and sg filter.". *Circuit World*, **47**(**1**):1–10, 2020.

[35] A. Ghasemi, F. Shama, and F. Khosravi. "A new method for ecg denoising using an amalgamation of adaptive and sg filters.". *Signal Processing and Renewable Energy*, **6**(**2**):1–15, 2022.

[36] R. Jaros, E. Tomicova, and R. Martinek. "Template subtraction-based methods for non-invasive fetal electrocardiography extraction.". *Scientific Reports*, **14**(**1**): 630, 2024.

[37] J. D. K. Abel, S. Dhanalakshmi, and R. Kumar. "A comprehensive survey on signal processing and machine learning techniques for non-invasive fetal ecg extraction.". *Multimedia Tools and Applications*, **82** (**1**):1373–1400, 2023.

[38] O. G. Viunytskyi, V. I. Shulgin, A. A. Roienko, A. V. Totsky, and K. O. Eguiazarian. "Fetal ecg extraction from the abdominal signal using wavelet bispectrum technique.". *Telecommunications and Radio Engineering*, **82**(**9**), 2023.

[39] J. Jebastine. "Fetal ecg extraction and qrs detection using advanced adaptive filtering-based signal decomposition and peak threshold technique from abdominal ecg signals.". *Circuits, Systems, and Signal Processing*, **42**(**10**):6058–6088, 2023.

[40] W. T. Zhang, Z. Z. Huang, Y. Y. Ma, and D. J. Zhang. "A fast adaptive lpca method for fetal ecg extraction based on multi-channel signals.". *IEEE Transactions on Instrumentation and Measurement.*, (), 2023.