Fetal electrocardiogram extraction and signal quality assessment using statistical method

Li Mun Ng[1], Nur Anida Jumadi[1,2], Farah Najidah Noorizan[1]
[1]Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia
[2]Principal Researcher in Advanced Medical Imaging and Optics (AdMedic), Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia

Article Info

Article history:

Received Jan 22, 2025
Revised Oct 29, 2025
Accepted Nov 5, 2025

Keywords:

Adaptive filtering
Electrocardiogram
Fetal
Independent component analysis
Signal extraction

ABSTRACT

Abdominal electrocardiogram (aECG) can be used to monitor fetal heart rate (fHR), providing critical insights into fetal health during pregnancy. However, separating the mixed signals of fetal ECG (fECG) and maternal ECG (mECG) within the aECG remains a critical challenge. This paper investigates the integration of statistical metrics, including signal-to-noise ratio (SNR), skewness, kurtosis, standard deviation, and variance to assess fECG signal quality during extraction using three adaptive filtering metods ((Least mean square (LMS), normalized LMS (NLMS), and recursive least square (RLS)) and independent component analysis (ICA). The findings reveal that RLS achieves the best performance among the three AF methods, with the highest SNR of 5.6 dB at the step size, μ of 0.9. For ICA with a bandpass Chebyshev filter (low-cut frequency = 1 Hz, high-cut frequency = 50 Hz) produces an SNR of 0.86 dB. Additionally, both RLS and ICA yield similar fHR values of 133 bpm with a PE measurement of 0.9%. In conclusion, integrating statistical metrics with ICA and RLS effectively extracts fECG with good signal quality. Future research could explore other ECG datasets and incorporate machine learning to further improve fECG extraction and signal quality assessment.

Corresponding Author:

Nur Anida Jumadi
Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia
Batu Pahat, Malaysia
Email: anida@uthm.edu.my

1. INTRODUCTION

An electrocardiogram (ECG) is best known for its applicability in recording the electrical activity of cardiac [1]. It traces the entire cycle of electrical impulses as they travel through the cardiac muscle during contraction and relaxation. The illustration in Figure 1 displays the ECG signal waveform generated by a single heartbeat, highlighting its distinct components: the P wave, QRS complex, T wave, and ST segment. Each of these elements represents a specific phase of cardiac activity, and a detailed analysis of their variations provides crucial insights into the heart's health [2]. By examining the alterations in these waveforms, healthcare professionals can uncover potential cardiovascular issues and better understand the functioning of the heart during different stages of its rhythm.

The ECG is a crucial tool in monitoring the health status of a developing fetus. Recent research has focused on the challenging task of isolating the fetal ECG (fECG) signal from the abdominal ECG (aECG) signal, which includes contributions from both the maternal ECG (mECG) and the fetus. This procedure holds significant importance as the extracted fECG signal can be processed and analyzed to assess the well-being of the fetus during pregnancy. The challenge lies in the fact that the fECG signal often resembles the mECG signal due to its overlapping characteristics in both frequency and temporal domains. This overlap leads to the production of strikingly similar waveforms, making it difficult to distinguish between the two signals. As a result, accurately recognizing and isolating the fECG from the mECG becomes a complex task, complicating analysis and interpretation in clinical settings [3]. During pregnancy, the fetal's heart beats significantly faster than the mother's heart. Typically, the fetal heart rate (fHR) ranges from 110 to 160 beat-per-minute (bpm) [4], whereas maternal heart rate (mHR) generally falls between 70 and 90 bpm [5]. Therefore, suitable techniques and strategies must be employed to successfully isolate and separate the fetal signal from maternal interference.

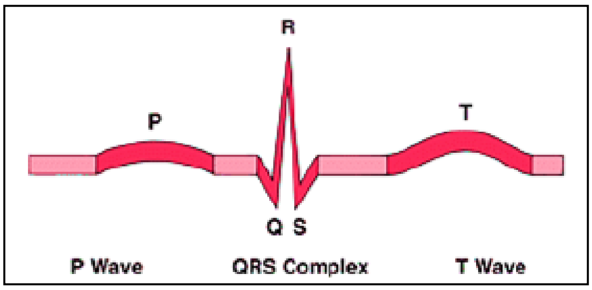


Figure 1. An ECG signal waveform of one heartbeat [1]

The study by Siew *et al*. [7] demonstrated that the ensemble Kalman filter (EnKF) effectively extracts fECG from single-channel ECG, outperforming the extended Kalman filter (EKF) in accuracy [6]. In another study, a combination of Butterworth and Savitzky-Golay filters was used for mECG extraction, with the Savitzky-Golay filter also applied for fECG extraction. A comparative study by Gan *et al*. [8] comparative study on the use of Chebyshev Type 1 and Butterworth filters showed that Chebyshev Type 1 proved more effective in extracting the fECG signal. Recent findings of Jeba *et al*. [9] introduced a time-frequency analysis algorithm that employed the Stockwell transform and Shannon Energy Entropy to identify maternal peaks. This approach allows for fECG signal extraction even in cases of overlapping beats without extensive preprocessing. The algorithm applied the Stockwell transform as a time-frequency tool along with Shannon Energy Entropy to identify maternal peaks, while the S-transform was used to identify fetal peaks. This method enhanced performance in the time-frequency domain, effectively identifying both maternal and fetal peaks, and eliminated the need for explicit preprocessing.

Blind source separation (BSS) is a computational technique that isolates the mixed signals without having to acquire prior knowledge of the original signals [10]. Independent component analysis (ICA) and principal component analysis (PCA) are the two most popular methods of BSS in extracting mixed signals. In a major study by Taha and Raheem [11], a novel algorithm known as the null space idempotent transformation matrix (NSITM) was developed to extract fetal electrocardiogram (fECG) signals from maternal abdominal recordings using the BSS approach. This algorithm calculated an intrinsic temporal matrix (W) from the initial ECG input and estimated the raw fECG and mECG signals from the null space of W. The clean fECG signal was obtained by eliminating the interfering mECG component from the raw fECG signal. Similarly, Ramli *et al*. [12] conducted a comparative study to assess the effectiveness of various BSS algorithms, including fast fixed-point for ICA (FastICA), joint approximate diagonalization eigenmatrix (JADE), and PCA, for extracting fECG signals from maternal abdominal recordings. Despite requiring fine-tuning, FastICA achieved comparable accuracy to JADE and exhibited greater flexibility in handling low-quality input signals.

In another approach, ICA was combined with singular value decomposition (SVD) for fECG signal extraction [13]. Initially, SVD provided approximations of fECG estimates, but these contained noise and missing waveforms. FastICA then utilized mECG signals to separate noise from the fECG, effectively reducing residual noise in the fECG signals and addressing the issue of missing waveforms. Several researchers have explored adaptive filter-based (AF) approaches for extracting the fECG signal [14]. Ranjanikar *et al*. [15] proposed a comprehensive model that used adaptive noise cancellation to remove background artefacts and noise from fECG signals, enabling the extraction of fECG and the computation of fHR. Kahankova *et al.* [16] focused on optimizing AF control parameters to achieve more efficient and accurate non-invasive extraction of the fECG signal.

On the other hand, Al-Sheikh *et al*. [17] proposed a new AF algorithm named the discrete wavelet transform recursive inverse (DWT-RI) for fECG signal extraction from the aECG signal. The proposed algorithm effectively suppressed mECG projections and extracted fECG components from the aECG signal. The performance of the proposed algorithm was evaluated against other traditional AF algorithms, including least mean square (LMS), recursive least square (RLS), and RI, using both synthetic and actual clinical data. The results demonstrate that the DWT-RI AF algorithm outperforms other algorithms' accuracy and positive predictivity, making it a promising tool for fECG extraction. Using this approach, researchers have been able to perform the fECG signal extraction efficiently, demonstrating its versatility and robustness across different research contexts [18]–[20].

While these techniques have demonstrated potential, they often rely on specific algorithmic assumptions and do not fully utilize statistical measures like signal-to-noise ratio (SNR), kurtosis, and variance, which could offer deeper insights into signal quality and stability. This gap highlights the need for methodologies that systematically integrate statistical metrics with advanced signal processing to optimize the separation of fECG from mECG, particularly in noisy or low-quality datasets. This study aims to bridge this gap by comparing two prominent methodologies, namely adaptive filtering (AF) and ICA, through a statistical analysis framework. AF is valued for its computational simplicity, and its performance will be assessed using three algorithms: LMS, Normalized LMS (NLMS), and RLS. On the other hand, ICA excels at separating independent components from mixed signals. By incorporating statistical measures such as SNR, kurtosis, and variance, this study seeks to evaluate and enhance the effectiveness of these methods for fECG extraction. The fECG signals analyzed in this study are sourced from the database for the identification of systems (DAISY) and processed using Python and MATLAB software.

Briefly, Section 1 provides an overview of the topic and reviews recent advances in fECG signal extraction methodologies. Section 2 details the materials and methodology, section 3 presents the results and discussion of the signal quality analysis, and section 4 concludes the study with key findings and recommendations for future research. By combining statistical insights with proven signal processing methods, this research aims to improve the reliability, accuracy, and clinical applicability of fECG extraction techniques.

2. RESEARCH METHOD

The methodology adopted in this study follows a sequential and structured order. First, the DAISY ECG dataset used for the experiments is described in section 2.1. Section 2.2 outlines the simulation tools and preprocessing techniques applied to prepare the ECG data for analysis. Following this, section 2.3 details the application of AF and ICA to separate the fECG and mECG signals from the aECG recordings. Finally, section 2.4 presents the statistical methods used to assess the quality of the extracted fECG signals.

2.1. Database selection

DAISY database was chosen for this study [21]. It is an online dataset comprising various data categories such as biomedical systems, electrical and electronic systems, biochemical systems, and mechanical systems that are available to be used by researchers. This study obtained a set of ECG recordings for the fECG signal separation. It is a 10-second cutaneous potential recording of a pregnant woman consisting of eight channels, where channels A1 to A5 are aECG signals and channels T6 to T8 are thoracic ECG (tECG) signals. The number of samples for this ECG dataset is 2500, which gives the sampling frequency at 250 Hz. Figure 2 displays the plotted ECG channels from the DAISY dataset. For the AF method, only channels A1 (representing aECG) and T8 (representing tECG) were used for analysis, as this combination yielded the most significant results. On the other hand, all channels were employed in the ICA analysis.

2.2. Simulation tools and data pre-processing

This study employed Python and MATLAB as simulation tools to run the experiments. The purpose of utilizing two different tools is to explore their capabilities for simulating biomedical engineering applications. PyCharm 2022.3.1 (Community edition) [22] and MATLAB 2024b [23] were used to conduct the statistical analysis for the fECG signal extraction. The AF method was performed using Python, whereas the ICA approach was carried out using MATLAB 2024b.

Prior to extracting the fECG signal, the aECG data were preprocessed with the use of various filters and frequencies for data cleaning. Five bandpass filters, namely Butterworth, Chebyshev Type I and Type II, Elliptic, and Bessel, were tried out using two low-cut frequencies (f_{Low}), 0.5 Hz and 1 Hz, and two high-cut frequencies (f_{High}), 45 Hz and 50 Hz. To identify the best filter, the SNR analysis was implemented. From the combination of filter testings (the complete results are not shown here), the final chosen filter was the bandpass Chebyshev Type II with f_{Low}=1 Hz and f_{High} = 50 Hz. This is because it shows the most optimal SNR results compared to other filters.

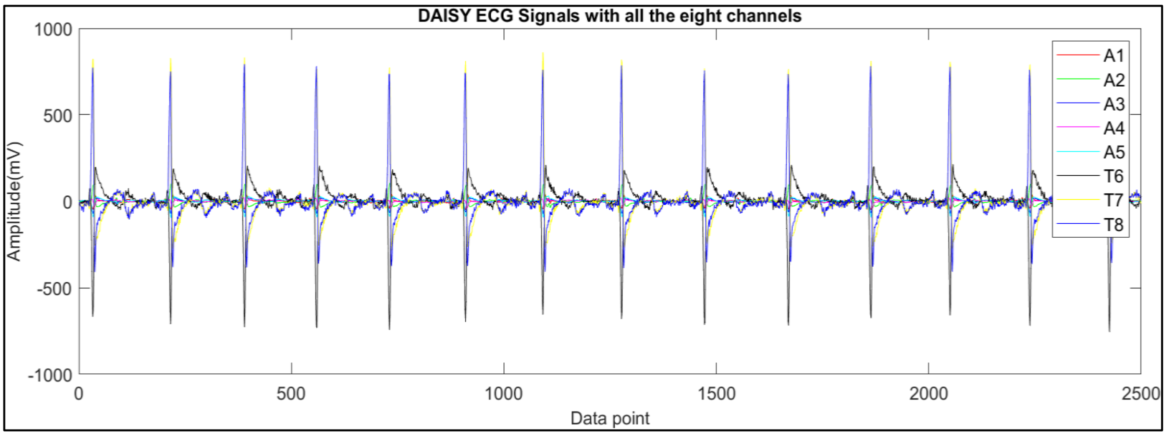


Figure 2. The plotting of all the ECG channels from the DAISY database with f =250 Hz

2.3. AF and ICA implementation

AF is a digital filter with self-adjusting properties [24]. Figure 3 illustrates the general block diagram of an AF containing a primary signal (aECG signal), *d*, and a reference signal (tECG signal), *u*, as an input to be processed by the AF, which yields an estimate of output (mECG signal), *y*. An estimation error (fECG signal), *e*, will be obtained after the subtraction of *d* and *y*, giving the system output. The general equation of the AF is expressed in (1). Three AF algorithms will be compared, namely LMS, normalized LMS (NLMS), and RLS, to improve the performance of signal extraction.

Step size, μ, is a crucial parameter that controls the rate at which the filter coefficients are updated [25]. It determines how much of the new information is incorporated into the filter's response and how quickly the filter adapts to changes in the input signal. A more significant step size leads to faster adaptation, meaning the filter responds more rapidly to changes in the input signal. However, a more significant step size can also lead to instability and oscillations in the filter's output. Conversely, a smaller step size leads to slower adaptation, providing more excellent stability and reducing the risk of oscillations. Different step sizes were investigated in this study when applying AF for fECG signal extraction.

$$e(i) = d(i) - y(i) \tag{1}$$

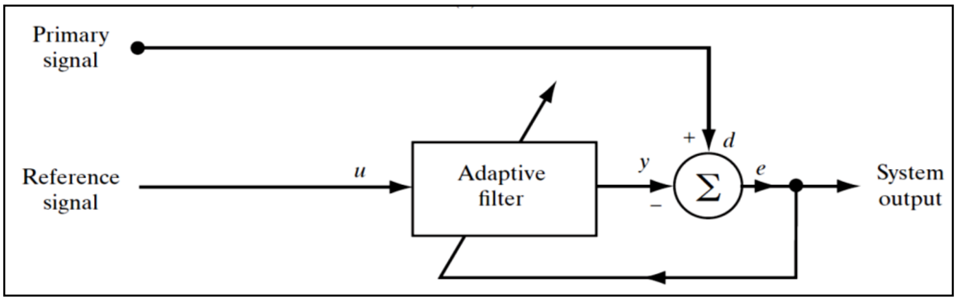


Figure 3. Adaptive filter block diagram [26]

LMS, NLMS, and RLS are the conventional AFs commonly used in signal separation procedures to minimize the error between the desired output and the actual output [26]. The LMS algorithm is one of the most widely used and studied AFs, primarily due to its simplicity, low memory requirements, and computational efficiency. Its update rule follows a gradient-descent approach, adjusting filter coefficients based on the error between the desired signal and the actual output as formulated in (2). i represents the number of iterations. $w(i+1)$ is the estimate of tap-weight vector (at time n+1) whereas $w(i)$ is the tap-weight vector. The estimation error signal with complex conjugation is denoted as $e*$, and lastly, $d(i)$ is the input signal.

$$w(i+1) = w(i) + \mu e^*(i)d(i) \tag{2}$$

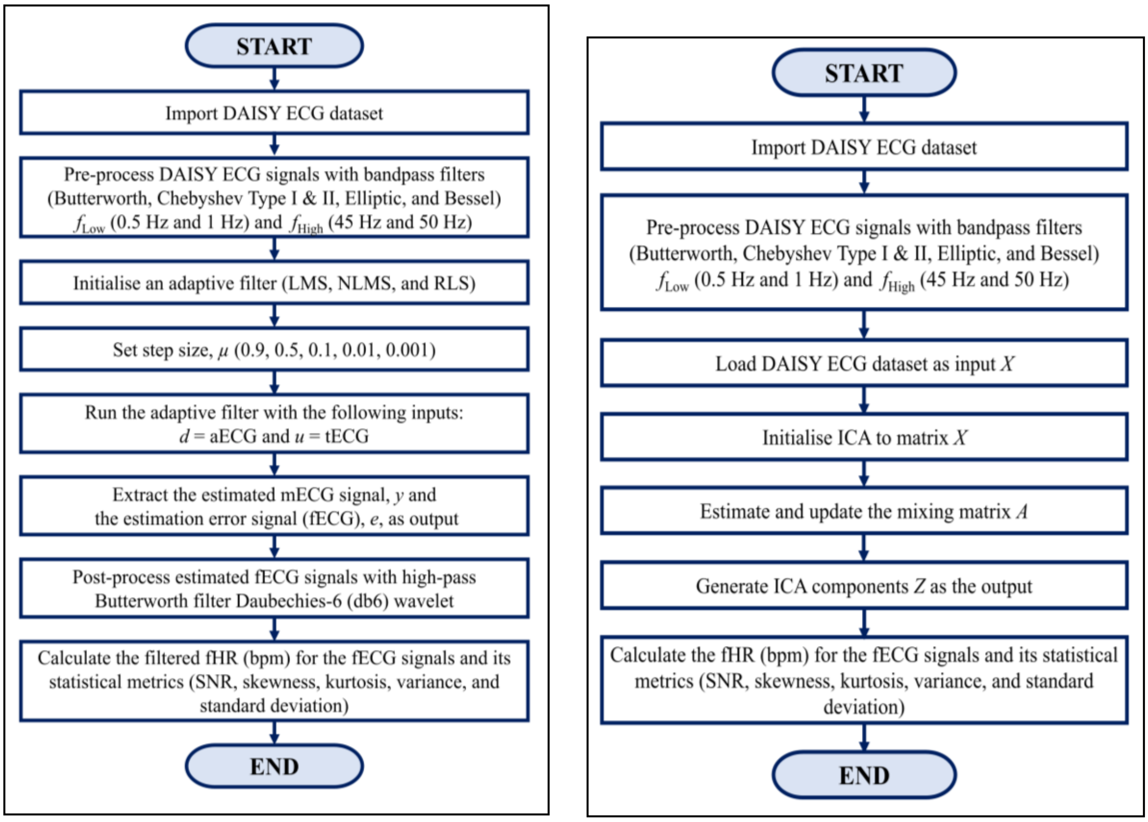
NLMS is an extension of LMS that normalizes the step size to improve convergence stability faced by LMS [27]. By normalizing, the algorithm adapts to variations in the power of the input signal, which improves performance in cases of non-stationary signals as presented in (3), where $\tilde{\mu}$ means the positive real scaling factor and $\|d(i)\|$ is the Euclidean norm of the adaptive tap-input vector, $d(i)$.

$$w(i+1) = w(i) + \frac{\tilde{\mu}}{\|d(i)\|^2} e^*(i)d(i) \tag{3}$$

Meanwhile, RLS is a more advanced AF algorithm that recursively minimizes the least squares error. Unlike LMS and NLMS, RLS takes into account all previous error values (not just the current one), which allows for faster convergence and better performance with non-stationary signals. The update rule involves an inverse correlation matrix as provided in (4), where $k(i)$ is the gain vector and $\xi^*(i)$ is the estimation error of RLS.

$$w(i) = w(i-1) + k(i)\xi^*(i) \tag{4}$$

Figure 4 shows the overall framework of fECG signal extraction with statistical analysis using AF (Figure 4(a)) and ICA (Figure 4(b)). First, the operation of AF is initiated by loading the DAISY ECG dataset, consisting of both aECG and tECG signals as inputs. These ECG signals had been pre-processed as mentioned in section 2.2. Next, the LMS AF was initialized, and μ was set to 0.1. The AF would run with the aECG signal as the primary signal, d, and the tECG signal (reference signal) as u. The estimated mECG signal, y, would be generated after going through the AF mechanism. Then, a deduction occurred between d and y that would produce the e signal, the desired fECG signal extracted as the system output at the end of the process. To enhance the estimated e signal, a post-processing step was performed, which involved the use of a high-pass Butterworth filter followed by wavelet denoising using a Daubechies-6 (db6) wavelet. The final step would be the calculation of the filtered fHR and its statistical metrics. This process was then repeated for various step sizes, ranging from μ = 0.001 to 0.9. Additionally, the same procedure was applied to two other AF algorithms, NLMS and RLS, respectively.



(a) (b)

Figure 4. Process of fECG signal extraction (a) using AF in PyCharm and (b) using ICA in MATLAB 2024

In contrast to AF, ICA is a statistical technique that seeks to uncover the underlying structure of complex data by decomposing it into a set of statistically independent components [28]. The formula for ICA is expressed in (5), where Z is the matrix of ICA components, *A* is the ICA mixing matrix, and *X* is the matrix of ECG signals (aECG signal). This equation represents the core operation of ICA; the input aECG signals, *X*, are first transformed into independent components, *Z*, using the ICA mixing matrix, *A*. The independent components are then separated, generating the final output, the extracted fECG signal, *Z*.

$$Z = A * X \tag{5}$$

The process of the ICA application in MATLAB is shown in Figure 4(b). The process of fECG signal extraction began with the use of the DAISY ECG dataset that had been preprocessed as input *X*. The ICA was then initialized to input *X*. Mixing matrix *A* would be estimated and updated, leading to Z as the overall output, representing the fECG signal extracted. The next step was calculating the fHR and its statistical measurements. HR is calculated by using the formula presented in (6). The final step was to obtain the statistical analysis after each iteration performed by ICA.

$$Heart\ rate, HR\ (bpm) = \frac{60}{RR-intervals\ (in\ seconds)} \tag{6}$$

2.4. Statistical methods for signal quality

In signal processing, SNR measures the level of the desired signal relative to the background noise. A higher SNR indicates a clearer and more distinct signal, while a lower SNR suggests that the signal is more obscured by noise. Standard deviation, σ quantifies the spread of data around the mean, $\bar{x}$. A lower σ, means the data points are closer to the $\bar{x}$, while a higher value indicates greater dispersion. When squaring the standard deviation and it becomes variance, σ^2. Meanwhile, σ^2 plays a crucial role in assessing the spread or dispersion of a signal's amplitude around its μ value. It is a statistical measure that quantifies the signal's energy distribution and provides insights into the signal's characteristics. Skewness, γ_1 measures the asymmetrical data. A positive skewness indicates that the ECG signal's tail is longer on the right side than the left, while a skewness of zero represents a symmetric signal. Kurtosis, γ_2 describes how peaked or flat the data distribution is compared to a normal distribution. High kurtosis signals have a sharp peak near the mean with heavy tails, while low kurtosis signals are flatter and less peaked. Let ECG signals be denoted by *x* with *N* as sample points, and these statistical measurements were expressed in (7) to (11), respectively.

$$Signal - to - Noise\ Ratio, SNR = 10.\log_{10}\left(\frac{Signal^2}{Noise^2}\right) \tag{7}$$

$$Standard\ Deviation, \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|x_i - \bar{x}|^2} \tag{8}$$

$$Variance, \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{9}$$

$$Skewness, \gamma_1 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\bar{x}}{\sigma}\right)^3 \tag{10}$$

$$Kurtosis, \gamma_2 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\bar{x}}{\sigma}\right)^4 \tag{11}$$

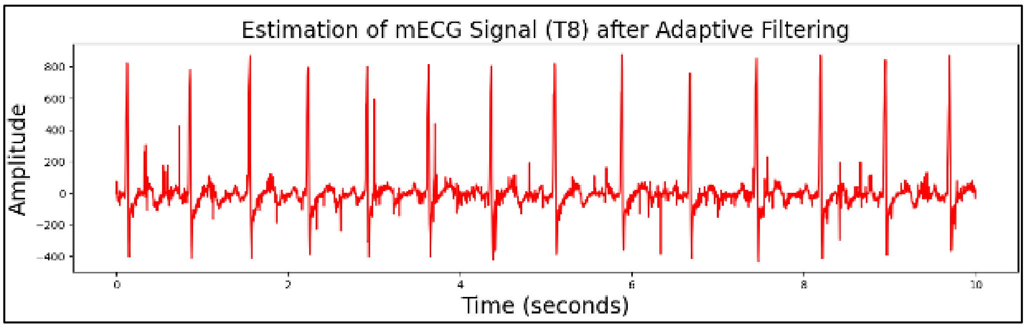
Since the DAISY database did not provide the real values of fHR and mHR, the results from this study were compared with the estimated fHR (135 bpm) retrieved from [29] using percentage error (PE) analysis. The corresponding formula is expressed in (12), where calculated HR represents the extracted fECG heart rate obtained from this study, whereas reference HR is obtained from [10].

$$PE = \left|\frac{Calculated\ HR - Reference\ HR}{Reference\ HR} \times 100\ \%\right| \tag{12}$$

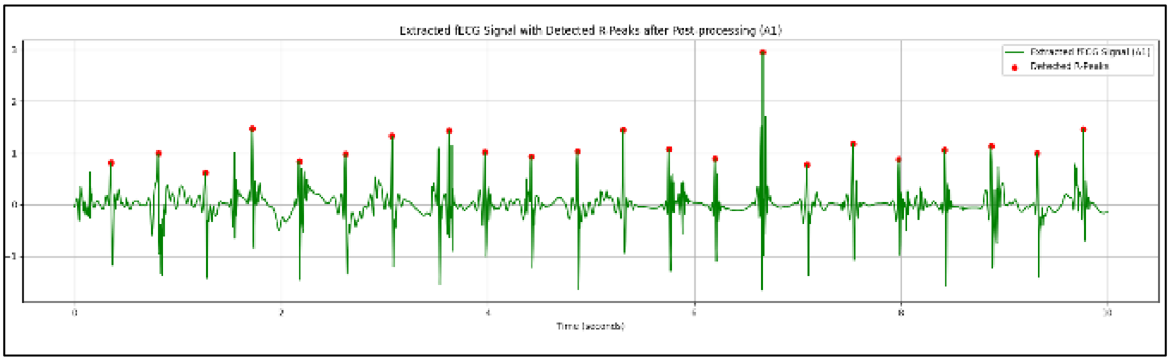
3. RESULTS AND DISCUSSION

This study investigated the effects of comparing two methodologies, namely AF and ICA, within a statistical analysis framework to extract the fECG signals. While earlier studies have explored the application of various signal separation algorithms, they often rely on specific algorithmic assumptions. However, they have not explicitly addressed the influence of statistical measures such as SNR, kurtosis, and variance, which can provide more objective and quantitative insights into signal quality and stability.

To begin with, the signal extraction results are displayed in Figure 5 for the first (A1) and eighth (T8) channels of the DAISY ECG dataset after employing the AF. The A1 and T8 channels represent the primary signal, *d*, and reference signal, *u*. After evaluating other channels' combinations, only this pair of channels could output a satisfactory result (in terms of fetal bpm). Figure 5(a) displays the estimation of the mECG signal after passing the RLS, whereas Figure 5(b) depicts the extracted fECG signal, which has been post-processed using a high-pass filter and wavelet denoise to remove the residual noise to enhance the fECG signal waveform. Furthermore, incorporating a post-processing stage for signal enhancement would further refine the extracted fECG signal quality, enable more accurate interpretations, and enhance fetal well-being monitoring.



(a)



(b)

Figure 5. Signal extraction results for (a) the estimated mECG (T8) signal, y, after going through AF and (b) the post-processing of the extracted fECG signal, e (A1)

The AF results are summarized in Table 1, showcasing the extraction of fECG signals using various step sizes (μ = 0.001 to 0.9). The table also presents statistical measurements, estimated fHR readings, and the analysis of heart rate discrepancies using the *PE* formula. The signal quality assessment for LMS, NLMS, and RLS filters was evaluated using SNR, skewness, kurtosis, variance, standard deviation, R-peak detection, and fHR. The SNR of the LMS filter improved to 4.61 dB at a step size of 0.01, while the RLS filter achieved the highest SNR of 5.6 dB at 0.9, showing its superior noise reduction. Skewness and kurtosis varied across filters, with the RLS filter providing stable results and minimal waveform distortion at larger step sizes. Although the LMS filter consistently detected all R-peaks with minimal PE (1.64%), it could not compute any heartbeat when using a bigger step size (μ = 0.9), thus resulting in a null result. Meanwhile, the RLS filter at step size 0.9 achieved the lowest PE (0.92%), showcasing a robust R-peak detection. On the contrary, the NLMS filter showed reduced accuracy and increasing signal distortion at higher step sizes. Overall, from the signal quality assessment, the RLS filter demonstrated the best balance between noise reduction and fECG signal preservation, especially when the step size is large.

On the other hand, Figure 6 shows the extraction results of ICA from the DAISY ECG dataset. Signal quality assessment-based statistical measurements and the fHR computation results were tabulated in Table 2. The table highlights the effects of varying f_{Low} and f_{High} filter settings on ECG Channel A2 before and after applying ICA. The HR before ICA was consistent at 81.73 bpm, with 22 R-peaks detected across all settings, resulting in a stable mean fHR of 133.77 bpm and minimal PE (0.91%). The SNR improved slightly after ICA, reaching a maximum of 0.86 dB with filters set to 0.5 to 50 Hz or 1 to 50 Hz. Skewness and kurtosis values showed moderate deviations, with skewness peaking at 1.35 (1 to 45 Hz) and kurtosis ranging from 9.42 to 10.36. Variance and standard deviation remained stable, suggesting minimal impact on signal amplitude. Overall, filters with higher f_{High} (50 Hz) provided optimal noise reduction and signal preservation, confirming the effectiveness of ICA in fECG signal extraction.

Table 1. Signal quality assessment using AF. Note: Primary signal, d=A1, reference signal, y=T8

AF filter	LMS			NLMS			RLS		
Step size (μ)	0.001	0.01	0.9	0.1	0.5	0.9	0.1	0.5	0.9
HR before AF (bpm)					84				
SNR before AF (dB)					-5.74				
SNR after AF (dB)	2.93	4.61	N/A	-1.15	-3.62	-5.27	-4.13	1.41	5.6
γ_1	-2.01	2.35	N/A	3.89	2.74	3.17	-4.17	0.36	0.25
γ_2	38.70	48.25	N/A	61.64	70.35	78.11	177.43	47.76	12.06
σ^2	0.29	0.18	N/A	0.98	1.70	2.42	1.23	0.27	0.08
σ	0.54	0.42	N/A	0.99	1.30	1.56	1.11	0.52	0.29
Fetal R-peak	23	23	0	20	14	9	19	22	22
fHR after AF (bpm)	137.21	137.27	N/A	119.55	81.59	60.30	115.78	131.14	133.76
PE (%)	1.64	1.68	N/A	11.44	39.56	55.33	14.24	2.86	0.92

It was observed that the signal quality assessment results correlated well with the accuracy of the extracted fECG signals when compared to the reference fHR. Both methods demonstrated the capability to extract fECG signals, yielding similar percentages of error in fHR values. However, the AF method produced slightly higher SNR values, indicating marginally better signal clarity under the evaluated conditions. The importance of assessing signal quality is worth noting to avoid meaningless interpretation of the results involving AF techniques. This was proven when only one combination of channels (A1 and T8) was possible when extracting the fECG signal using the AF approach. Likewise, even though the ICA method could perform signal extraction for all channels, only channel A2 exhibited the best result for fHR, which is close to the reference HR.

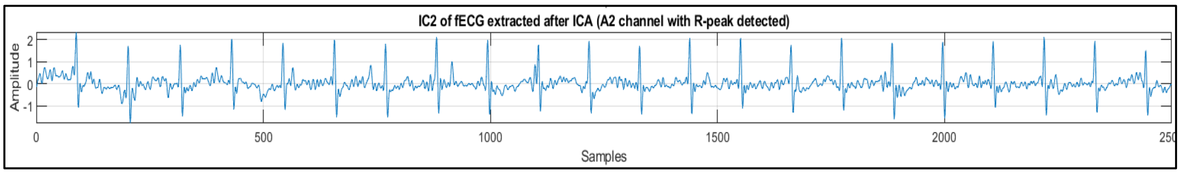


Figure 6. The extracted fECG signal after applying ICA from the A2 channel, with r-peaks detected

Table 2. Signal quality assessment-based statistical measurements using ICA

ECG Channel	Low-Cut Off (f_{Low}) and High Cutoff Frequency (f_{High}) (Hz)	Before ICA	HR (bpm)	SNR (dB)	After ICA	SNR (dB)	γ_1	γ_2	σ	σ^2	Fetal R-Peak	Mean fHR (bpm)
A2	0.5 and 45		81.73	0.71		0.79	1.24	9.42	1.31	0.16	22	133.77
	1 and 45		81.73	0.71		0.85	1.35	10.36	1.31	0.15	22	133.77
	0.5 and 50		81.73	0.71		0.86	1.27	10.29	1.32	0.18	22	133.77
	1 and 50		81.73	0.70		0.86	1.27	10.3	1.31	0.18	22	133.77
											PE (%)	0.91

A detailed examination of the results from both AF and ICA suggests significant differences in their effectiveness for fECG extraction, particularly when supported by integrated statistical analysis. AF relies on the reference channel, T8, which is utilized in an iterative noise-reduction process. This approach is notably effective for extracting fECG when the reference channel strongly correlates with the target fetal signal. In contrast, ICA adopts a different strategy by implementing BSS, which operates on the principle of statistical independence rather than utilizing a reference channel.

This study explored a comprehensive method of integrating statistical measures such as SNR, kurtosis, and variance further enhances the selection of the optimal method and channel for fECG extraction. For example, the SNR helps identify channels with higher signal clarity and lower noise interference, while kurtosis and variance provide insights into signal distribution and stability, enabling the identification of channels with unique and distinguishable signal characteristics. By applying these statistical assessments, the suitability of channels like T8 and A1 for AF or A2 for ICA can be systematically validated. However, further and in-depth studies may be needed to ensure a more accurate and reliable fECG extraction process tailored to the specific characteristics of the data.

This study demonstrates the applicability of both AF and ICA for fECG signal extraction. However, the dataset used involved only a single subject and lacked a reference fHR, limiting its use for clinical validation. These factors suggest that the dataset is more suitable for simulation purposes rather than a robust comparison analysis. Another limitation found is the contribution of fetal signals in the thoracic channel. Although not directly visible, the fetal signals can still be detected in tECGs due to their proximity to the abdominal region, despite being weaker. Future studies may explore the performance of these methods using larger, multi-subject datasets with annotated reference signals, as well as investigate feasible ways of improving simulation-based evaluation frameworks when real clinical references are unavailable.

4. CONCLUSION

In conclusion, the integration of statistical analysis with AF and ICA enabled the successful extraction of the fECG signal with optimal quality, showcasing the effectiveness of this approach in enhancing signal clarity. This study has demonstrated that the RLS algorithm outperformed the LMS and NLMS algorithms in fECG extraction, achieving the optimal results for AF. Given the importance of accurate HR measurement in medical settings, the lower error rate of ICA and RLS of AF makes it an appropriate choice for clinical applications, thus making the fECG signal achievable. It is essential to understand that there are no one-size-fits-all solutions, as not all the ECG channels from the DAISY dataset can use the same filter specifications for fECG signal separation. This is evident in the AF approach, where an additional step was necessary to post-process the estimated fECG signal after extraction to enhance the signal quality. Expanding the current study by comparing the obtained results with a broader range of ECG datasets is highly recommended for future research. Additionally, investigating the performance of AF and ICA in fECG signal separation using single-channel and multi-channel approaches would provide valuable insights. Future research could also explore emerging signal separation techniques with a combination of machine-learning approaches for robust fetal extraction and signal quality assessment.

ACKNOWLEDGEMENTS

This research was supported by Ministry of Higher Education (MOHE) through Fundamental Research Grant Scheme (FRGS) (FRGS/1/2023/TK07/UTHM/02/13) and Universiti Tun Hussein Onn Malaysia (UTHM) through TIER 1 (vot Q545).

FUNDING INFORMATION

The funding information can be referred to in the acknowledgment section.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Li Mun Ng	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Nur Anida Jumadi	✓			✓		✓				✓		✓	✓	✓
Farah Najidah Noorizan							✓						✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that there is no conflict of interest related to the manuscript.

DATA AVAILABILITY

The data that support the findings of this study are openly available in DAISY at https://ftp.esat.kuleuven.be/pub/SISTA/data/biomedical/foetal_ecg.txt, reference number [6].

REFERENCES

[1] J. Hampton and J. Hampton, *The ECG Made Easy*, 9th ed. 2019.

[2] K. Amini, A. Mirzaei, M. Hosseini, H. Zandian, I. Azizpour, and Y. Haghi, “Assessment of electrocardiogram interpretation competency among healthcare professionals and students of Ardabil University of Medical Sciences: a multidisciplinary study,” *BMC Medical Education*, vol. 22, no. 1, 2022, doi: 10.1186/s12909-022-03518-0.

[3] G. D. Clifford, I. Silva, J. Behar, and G. B. Moody, “Non-invasive fetal ECG analysis,” *Physiological Measurement*, vol. 35, no. 8, pp. 1521–1536, 2014, doi: 10.1088/0967-3334/35/8/1521.

[4] T. Ghi *et al.*, “Intrapartum fetal heart rate between 150 and 160 bpm at or after 40 weeks and labor outcome,” *Acta Obstetricia et Gynecologica Scandinavica*, vol. 100, no. 3, pp. 548–554, 2021, doi: 10.1111/aogs.14024.

[5] J. L. Muñoz, “Physical changes during pregnancy,” *MSD Manual Consumer Version*, 2024. https://www.msdmanuals.com/home/women-s-health-issues/normal-pregnancy/physical-changes-during-pregnancy (accessed Jan. 18, 2025).

[6] S. Sarafan, T. Le, M. P. H. Lau, A. Hameed, T. Ghirmai, and H. Cao, “Fetal electrocardiogram extraction from the mother’s abdominal signal using the ensemble kalman filter,” *Sensors*, vol. 22, no. 7, 2022, doi: 10.3390/s22072788.

[7] H. S. H. Siew, Y. S. Alshebly, and M. Nafea, “Fetal ECG extraction using Savitzky-Golay and Butterworth filters,” in *2022 IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2022 - Proceedings*, 2022, pp. 215–220, doi: 10.1109/I2CACIS54679.2022.9815469.

[8] S. E. S. Gan, S. K. Debnath, Y. S. Alshebly, H. Nugroho, S. Bagchi, and M. Nafea, “Fetal ECG extraction from abdominal ECG using Chebyshev and Butterworth filters,” *ISCI 2021 - 2021 IEEE Symposium on Computers and Informatics*, pp. 25–30, 2021, doi: 10.1109/ISCI51925.2021.9633595.

[9] A. Jaba Deva Krupa, S. Dhanalakshmi, and R. Kumar, “Joint time-frequency analysis and non-linear estimation for fetal ECG extraction,” *Biomedical Signal Processing and Control*, vol. 75, 2022, doi: 10.1016/j.bspc.2022.103569.

[10] S. Senay, “Time-frequency BSS of biosignals,” *Healthcare Technology Letters*, vol. 5, no. 6, pp. 242–246, 2018, doi: 10.1049/htl.2018.5029.

[11] L. Taha and E. Abdel-Raheem, “A null space-based blind source separation for fetal electrocardiogram signals,” *Sensors (Switzerland)*, vol. 20, no. 12, pp. 1–28, 2020, doi: 10.3390/s20123536.

[12] D. A. Ramli, Y. H. Shiong, and N. Hassan, “Blind source separation (BSS) of mixed maternal and fetal electrocardiogram (ECG) signal: A comparative Study,” *Procedia Computer Science*, vol. 176, pp. 582–591, 2020, doi: 10.1016/j.procs.2020.08.060.

[13] J. Hao, Y. Yang, Z. Zhou, and S. Wu, “Fetal electrocardiogram signal extraction based on fast independent component analysis and singular value decomposition,” *Sensors*, vol. 22, no. 10, 2022, doi: 10.3390/s22103705.

[14] A. Al-Safi, “ECG signal denoising using a novel approach of adaptive filters for real-time processing,” *International Journal of Electrical and Computer Engineering*, vol. 11, no. 2, pp. 1243–1249, 2021, doi: 10.11591/ijece.v11i2.pp1243-1249.

[15] M. A. Ranjanikar, S. V. Joshi, J. M. Waghmare, S. V. Shinde, and R. Y. Patil, “Fetal electrocardiogram extraction using adaptive filters approach,” *Disruptive Developments in Biomedical Applications*, pp. 203–228, 2022, doi: 10.1201/9781003272694-17.

[16] R. Kahankova, M. Mikolasova, and R. Martinek, “Optimization of adaptive filter control parameters for non-invasive fetal electrocardiogram extraction,” *PLoS ONE*, vol. 17, no. 4 April, 2022, doi: 10.1371/journal.pone.0266807.

[17] B. Al-Sheikh, M. S. Salman, A. Eleyan, and S. Alboon, “Non-invasive fetal ECG extraction using discrete wavelet transform recursive inverse adaptive algorithm,” *Technology and Health Care*, vol. 28, no. 5, pp. 507–520, 2020, doi: 10.3233/THC-191948.

[18] M. Aqil and A. Jbari, “Electrocardiogram features detection using stationary wavelet transform,” *International Journal of Electrical and Computer Engineering*, vol. 15, no. 1, pp. 374–385, 2025, doi: 10.11591/ijece.v15i1.pp374-385.

[19] I. Kaoula, A. Guessoum, and B. Kazed, “Generalized recursive algorithm for fetal electrocardiogram isolation from non-invasive maternal electrocardiogram,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6312–6323, 2023, doi: 10.11591/ijece.v13i6.pp6312-6323.

[20] A. Phuphanin, M. Tasakorn, and J. Srivichai, “Electrocardiogram signal processing algorithm on microcontroller using wavelet transform method,” *International Journal of Electrical and Computer Engineering*, vol. 14, no. 2, pp. 1530–1543, 2024, doi: 10.11591/ijece.v14i2.pp1530-1543.

[21] B. De Moor, “DaISy: Database for the identification of systems,” *Dept. EE and K.U.Leuven*, [Online]. Available: http://homes.esat.kuleuven.be/~smc/daisy/%5Cnwww.esat.kuleuven.be/sista/daisy/.

[22] JetBrains, “PyCharm: The Python IDE for professional developers by JetBrains,” *JetBrains*, 2023, [Online]. Available: https://www.jetbrains.com/pycharm/.

[23] T. M. Inc., “MATLAB version: 24.2.0.2773142 (R2024b),” *The MathWorks Inc.*, 2024, [Online]. Available: https://www.mathworks.com.

[24] L. Tan and J. Jiang, *Digital signal processing: Fundamentals and applications*, 3rd ed. Academic Press, 2013.

[25] N. J. Bershad and J. C. M. Bermudez, “A switched variable step size NLMS adaptive filter,” *Digital Signal Processing: A Review Journal*, vol. 101, 2020, doi: 10.1016/j.dsp.2020.102730.

[26] S. S. Haykin, *Adaptive filter theory*, 5th ed. 2014.

[27] D. Nilay, P. Utpal, and D. Chintan, “Active noise control using LMS & NLMS algorithm,” *Journal of Engineering and Technology (JET)*, vol. 1, no. 1, pp. 1–8.

[28] A. Tharwat, “Independent component analysis: An introduction,” *Applied computing and informatics*, vol. 17, no. 2, pp. 222–249, 2018, doi: 10.1016/j.aci.2018.08.006.

[29] Y. S. Alshebly and M. Nafea, “Isolation of fetal ECG signals from abdominal ECG using wavelet analysis,” *Irbm*, vol. 41, no. 5, pp. 252–260, 2020, doi: 10.1016/j.irbm.2019.12.002.

BIOGRAPHIES OF AUTHORS

Li Mun Ng received her first degree from Universiti Tun Hussein Onn Malaysia (UTHM), Bachelor of Electronic Engineering with Honours, Malaysia, in 2018. She has also a Master's degree in Electrical Engineering from UTHM, Malaysia, in 2021. She is pursuing her Ph.D in Electrical Engineering in the Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, UTHM. Her main research interests focus on biomedical engineering, signal processing, artificial intelligence, and the application of fuzzy logic. She can be contacted at email: limun.ng@gmail.com.

Nur Anida Jumadi is an Associate Professor in the Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM). Born in 1983, she obtained her bachelor's degree in Electrical Engineering from Kolej Universiti Tun Hussein Onn (KUiTTHO) in 2006, followed by a master's degree in Medical Electronics and Physics from Queen Mary, University of London, in 2008. She earned her PhD in Electrical, Electronic, and System Engineering from Universiti Kebangsaan Malaysia (UKM) in 2015. She specializes in medical diagnosis and prognosis using artificial intelligence, with a focus on developing non-invasive medical devices based on optical sensors. She is actively engaged in advancing healthcare technology through innovative research. She can be contacted at email: anida@uthm.edu.my.

Farah Najidah Noorizan was born on 25 September 1999 in Kedah, Malaysia. She pursued her diploma at Politeknik Sultan Salahuddin Abdul Aziz Shah and graduated with a Diploma in Medical Electronic Engineering in 2020. She then pursued her degree at Universiti Tun Hussein Onn Malaysia (UTHM) by pursuing a Bachelor of Electronic Engineering with Honours and graduated in 2024. She is now continuing her studies at UTHM for her Master of Electrical Engineering. Her main research interests are in biomedical engineering and artificial intelligence. She can be contacted at email: farahnajidah259@gmail.com.