INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 16 No. 1 (2024) 251-261
https://publisher.uthm.edu.my/ojs/index.php/ijie

Non-Invasive Fetal Well-Being Monitoring Approaches: A Mini Review on Fetal Signal Separation Techniques

Li Mun Ng[1], Nur Anida Jumadi[2]*

[1] *Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA*

[2] *Principle Researcher in Advanced Medical Imaging and Optics (AdMedic), Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA*

*Corresponding Author: anida@uthm.edu.my
DOI: https://doi.org/10.30880/ijie.2024.16.01.020

Article Info

Received: 11 October 2023
Accepted: 9 February 2024
Available online: 22 May 2024

Keywords

Electrocardiography, fetal, phonocardiogram, photoplethysmography, review, signal separation, signal processing

Abstract

Fetal signal separation is vital in producing an accurate interpretation of the health condition of a fetal. In the context of a non-invasive fetal monitoring approach, the signals are acquired from the abdomen of pregnant women. As a result, a mix of maternal and fetal signals is obtained. These maternal and fetal signals are vague, as both signals are interchanged during the signal acquisition stage. Since the signals are overlapped, a signal separation technique must be employed to process the fetal signal for further analysis. This paper presents published studies on applying signal processing techniques involving fetal signal separation. These papers are obtained through a strategy known as the PRISMA technique. The online databases include ACM, Emerald Publishing, IEEE Explore Digital Library, Science Direct, Scopus, and Springer, with published years spanning from 2018 until 2022. Numerous separation techniques were found, such as adaptive filtering, blind source separation (BSS), and alternative approaches. Issues on the existing methods for fetal signal separation are discussed. In addition, the limitations and drawbacks of the research work involving existing fetal signal separation are reviewed in the paper. The potential direction of future research in this field is addressed as well. Based on this mini-review, it can be concluded that noise and ambiguity can still occur in the extracted fetal signals, even when signal processing techniques are applied. In the future, deep learning would be accommodating in improving the efficiency of extracting fetal signals obtained from the non-invasive fetal well-being monitoring technique. Meanwhile, apart from fetal heart rate (fHR) detection, fetal hypoxia can also be another important focus of study for improving fetal well-being monitoring.

1. Introduction

Fetal signals, such as fetal heart rate (fHR), play a crucial role in providing valuable information about the patterns and rhythms of the baby's heart. Monitoring the fHR allows obstetricians to evaluate the fetal's well-being and detect any potential irregularities or distress. Generally, the fetal signal can be acquired invasively or non-invasively [1]. Invasive fetal monitoring techniques include internal fetal monitoring (IFM) that detects fHR, fetal scalp sampling that measures the pH value of the fetal blood scalp, and transvaginal fetal pulse oximetry that determines the oxygen saturation of fetal ($fSpO_2$). Meanwhile, cardiography (CTG) and intermittent auscultation (IA) to detect the fHR patterns are part of the devices used in non-invasive fetal monitoring. Recently, the development of non-invasive fetal monitoring approaches has been active and encouraging, with continual advances being made. Non-invasive electrocardiogram (NI-fECG), phonocardiogram (PCG), and transabdominal fetal pulse oximetry (TfPO) have been introduced as alternatives to support safer and much more reliable fetal well-being monitoring. These non-invasive techniques utilise the same site of sensors or electrode placement on the maternal abdomen.

For example, NI-fECG can acquire the abdominal electrocardiogram (aECG) by placing the electrodes on the maternal abdomen. As for TfPO, the optical sensors are placed on the same site to acquire the photoplethysmography (PPG). These ECG and PPG signals can provide the fHR reading, and any reading discrepancies can indicate the fetal's well-being. Nevertheless, obstetricians and researchers face challenges in exploiting the usefulness of the signals obtained from the non-invasive method since the signals of fetal and mother overlap and, therefore, require a further signal processing technique to separate the fetal signal from this mixed signal. Hence, it is vital to perform signal separation from the mixed signals as it allows the extraction of useful information for monitoring the well-being and development of the fetal during pregnancy and labour phases.

Signal processing refers to signal modification and analysis to obtain information or enhance signal quality. The signal analysis involves using signal separation, extracting one or more signals from a mixture of signals. Both are considered essential techniques in many fields, including audio processing, biomedical engineering, and telecommunications, as these areas often deal with various signal sources such as audio, biological, and communication signals.

Separation of the fetal signal is one of the biomedical applications as the properties of fetal signal always pose challenges to medical doctors and researchers for signal interpretation. These properties include the fetal signal, which is always dominated by the mother signal and is contaminated by noises such as powerline interference, baseline wandering, and low amplitude, thus making it hard to observe and isolate from the mixed signal [2]. Hence, this mini-review highlights recent research in signal processing techniques involving fetal signal separation utilising non-invasive fetal monitoring approaches.

However, the review was limited to the databases accessible within the university's subscription. These databases included journals, conferences, and technical papers. Moreover, only three main signals were considered in this paper: ECG, PPG and PCG. The overall structure of the study takes the form of five sections that begin with a brief introduction in section 1. Section 2 outlines the methodology used to perform the search strategy in collecting the articles relevant to the focus topic. Then, the techniques of signal processing in tackling fetal signal extraction tasks will be reviewed in Section 3, and the limitations of these techniques will be discussed. The direction for future research will be elaborated in Section 4, and this paper will be closed with a conclusion in section 5.

2. Methodology

2.1 Search Strategy

A search strategy was executed to conduct the review process of this study. It was completed by accessing the electronic resources subscribed by Universiti Tun Hussein Onn Malaysia Tunku Tun Aminah Library (UTHM PTTA) to acquire the relevant academic research works from the online databases available. An advanced search feature was considered to narrow the scope by utilising important keywords and Boolean operators. The important keywords include "fetal monitoring", "signal separation", and "non-invasive", along with the use of the AND Boolean operator to refine the search results.

2.2 Review Protocol

In this section, a review protocol was designed to assist the review process, focusing on the fetal signal separation works. This ensured that the relevant and most related results would be included in the review session by employing Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as the search methodology. Thus, the inclusion criteria for the journal paper were: (i) they must be published between 2018 and 2022; (ii) the journal papers must be peer-reviewed articles; and (iii) the journal papers must be composed in the English language. Fig. 1 shows the overall process of applying the PRISMA methodology in the search strategy [3].

Based on Fig. 1, 234 publications were discovered from six online databases in the initial identification phase, including ACM, Emerald Publishing, IEEE Explore Digital Library, Science Direct, Scopus, and Springer. These identified publications then went through a screening process by skimming the titles and abstracts of the articles and the duplicate entries, resulting in the exclusion of 155 articles. Of the remaining 79 studies, 19 were fully assessed for eligibility and included in this mini-review. Mendeley Desktop was used to prepare for all the bibliography insertion and reference management.

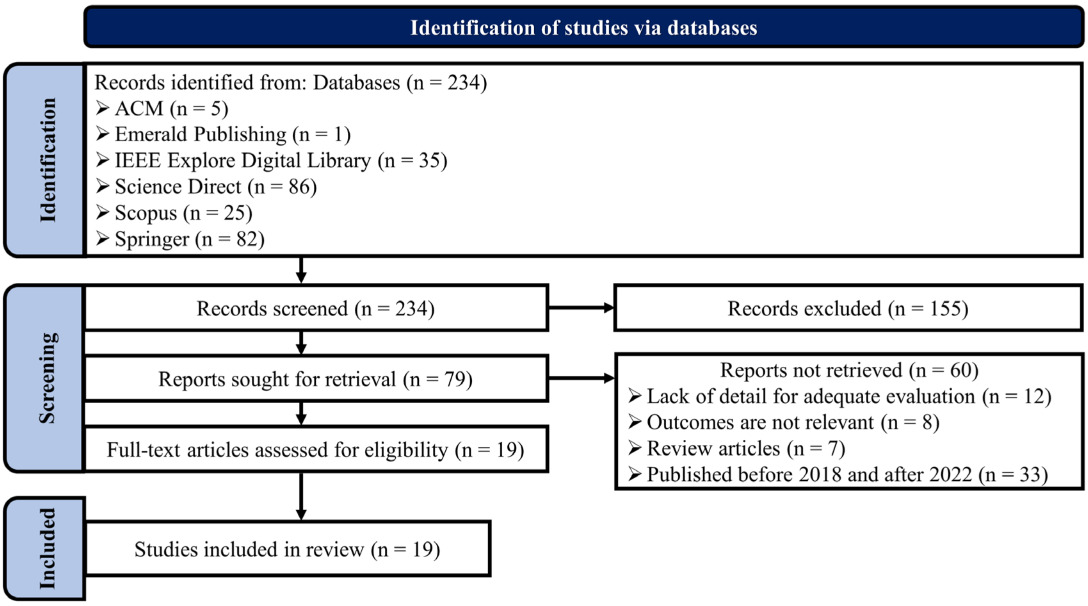

Fig. 1 *PRISMA methodology used in the search papers strategy*

3. Review of Existing Fetal Signal Separation Methods

In this section, the selected 19 articles from Section 2 were reviewed based on the signal processing techniques used for separating the fetal signal acquired from the abdominal of the pregnant mother. These methods include adaptive filtering, blind source separation (BSS), and alternative approaches. At the end of this section, the strengths and limitations of these reviewed studies based on the signal processing techniques used were summarised and discussed.

3.1 Adaptive Filtering

Adaptive noise cancellation (ANC) is a self-adjusting filter that cancels noise [4]. The primary input is the noisy signal to be processed, and the secondary input is a reference signal correlated with the noise in the primary input. The adaptive filter uses the reference signal to estimate the noise in the primary input and then subtracts the estimated noise from the primary input. ANC's most common adaptive filters are recursive least squares (RLS) and least mean squares (LMS).

In a study conducted by Fong *et al.*, the signal separation of fetal photoplethysmogram (fPPG) and maternal photoplethysmogram (mPPG) in TfPO was accomplished by using the ANC method [5][6]. The authors stated that using ANC was advantageous due to its principle, which does not require prior knowledge for filtering the fetal signal. LMS and RLS methods performed well in the fPPG signal extraction task. However, RLS outperformed LMS.

Similarly, Bottrich and Husar make a similar point in their study of ANC applications to filter out the fPPG signal. Initially, they separated fPPG and mPPG signals using two comb filters [7]. Despite the success of fPPG signal separation, the comb filter design would require known fHR, and it should be constant during the measurement, which could be an issue during clinical practice. Then, they further explored the application of ANC to estimate fHR [8] using the same design in this paper [7]. The fHR was constructed based on the frequency spectrum analysis to select the desired peak in the frequency domain. However, the mPPG overlapped with the fundamental frequency of the fPPG, resulting in the fPPG being invisible. The ANC was applied, which took up mPPG reference and mixed PPG signals as inputs to reduce the power of mPPG before the comb-filtering process. The fetal pulse rate was finally computed as 1.44 Hz (86.4 bpm), which was detectable, and the comb filter was applied to generate a better signal quality. The authors suggested evaluating the developed algorithm in real-world applications.

An attempt was made by Dia *et al.* where the researchers replaced the adaptive filter with a non-linear kernel adaptive filter to denoise the maternal electrocardiogram (mECG) and estimate the fetal electrocardiogram (fECG) signals from the aECG signal [9]. The purpose of filter replacement was that this approach did not require perfect cleaning on the mECG signal nor the need for R-peak detection for fHR. The estimated fECG signal would go through a post-processing stage where a non-negative matrix factorisation (NMF) was applied to extract the fECG signal based on the specific features from the spectrogram of physiological signals. This study made the fetal signal extraction from the single-channel NI-fECG estimation possible.

3.2 Blind Source Separation (BSS)

Blind source separation (BSS) is another technique to separate individual signal sources from a mixture of signals [10]. The BSS technique frequently uses principal component analysis (PCA), independent component analysis (ICA), and NMF. This technique was used by Taha *et al.*, Ramli *et al.*, and Xavier [11]–[14] to separate the fetal signal from the combined signal. Taha *et al.* presented a study of BSS by adopting a null space idempotent transformation matrix (NSITM) to perform fetal signal extraction from the mixed ECG signals [11]. The fundamental idea of this methodology was this mixture matrix composed of two components: null space and idempotent transformation matrix (ITM). The ITM of this matrix would be calculated first, and then both fECG and mECG signals would be extracted from the null space of the computed ITM. The components of fECG and mECG signals were successfully extracted from the algorithm and evaluated using various datasets. Besides, as noted by Ramli *et al.*, the evaluation of different BSS techniques to separate the fetal signal, namely Fast Fixed-Point for ICA (FastICA), Joint Approximate Diagonalisation of Eigenmatrix (JADE), and PCA, was conducted [12]. The findings showed that JADE could produce better accuracy (ACC), while FastICA performed better in computational time for signal extraction. Moreover, Xavier selected another BSS technique, MULTI-COMBI, to separate the fetal and abdominal signals [13]. In a later study by the same author, the same technique was studied again but with a different classifier to detect the fetal signal [14]. The results revealed that better performance was achieved when all the parameters (ACC, sensitivity (SE), and specificity (SP)) of evaluation produced improved values compared to the previous study in [13].

Furthermore, a mixed methods approach was employed in this research where Taha and Abdel-Raheem investigated two modes of operation using ANC to separate the fetal signals by adding the BSS technique as enhancement [15]. Mode A was an Input-Mode Adaptive Filter (IMAF) only, and Mode B was an Output-Mode Adaptive Filter (OMAF) combined with BSS. In Mode A, the aECG signals were fed into both the primary input and secondary input of the ANC, and an additional mECG peak detection was added to produce a better reference signal in the secondary input. Meanwhile, in Mode B, NSITM from BSS (BSS-type NSITM) variations were chosen to extract the raw fECG signals and mECG signals from the aECG signals and feed them into the ANC structure in IMAF. This time, the adaptive filter uses the raw fECG signal as its primary input and the extracted mECG signal as its reference signal to estimate the mECG component in the raw fECG signal. A comparative study was performed to evaluate the extraction of these two modes for three different scenarios when the ECG signals were fully overlapped, partially overlapped, and not overlapped. The comparative study outcomes demonstrated that OMAF successfully extracted the fECG signals for all the scenarios. However, IMAF could only separate the fECG signals for partially overlapped and not overlapped scenarios.

A combination of independent component analysis (ICA), RLS, and ensemble empirical mode decomposition (EEMD) was explored by Barnova *et al.* to extract the fECG from aECG recordings [16]. The proposed method, when tested using the Fetal Electrocardiograms, Direct and Abdominal with Reference Heartbeat Annotations (FECGDARHA) database, achieved accuracy values higher than 80 % for 11 out of 12 recordings with an average ACC of 92.75 %, average SE of 95.09 %, average positive predictive value (PPV) of 96.36 %, and average F1-score of 95.69 %. When tested using the PhysioNet Challenge 2013 database, accuracy values higher than 80 % were achieved for 17 out of 25 recordings with an average ACC of 78.24 %, average SE of 81.79 %, average PPV of 87.16 %, and average F1-score of 84.08 %. Moreover, a non-invasive ST-segment analysis was conducted using the records from the FECGDARHA database, and the method achieved high ACC in 7 out of 12 records. However, RLS often has high computation time and complexity. To overcome this issue, Sulas *et al.* [17] used QR-decomposition with a back-substitution technique with RLS (QRD-RLS) adaptive filters in their study to remove the unwanted noise and interference from the mECG signal and extract the fECG signal. The signal-to-interference ratio (SIR) was evaluated, and it was found that multi-reference performed better than single-reference since the accuracy of fetal QRS detection was also higher in multi-reference.

3.3 Alternative Approaches

In contrast to previous research, which used complex signal processing methods, Sheng *et al.* adopted a more straightforward approach with two filters, Savitzky-Golay and Butterworth, to generate desired window sizes and filter the ECG signals at various stages of this study [18]. While eliminating mECG signals, a third-order low-pass Butterworth filter was utilised to filter the thoracic ECG (tECG) signals. Then, the filtered aECG signals again went through the filtering process using the sixth-order Savitzky-Golay filter. This two-stage filtering would omit and clean the mECG signals using various windows to smoothen the signals further, leading to better fECG signal extraction with higher frequency but lower amplitude.

Bottrich and Husar initially started fPPG and mPPG signal separation in TfPO using a two-stage comb filter design [7]. The combined PPG signal was constructed using finite element (FEM) simulations with a tissuemimicking phantom to emulate the signals for mPPG and fPPG signals, respectively. This simple approach enabled the extraction of the fPPG signal; however, the drawback was that the two-stage comb filter design was unable to solve the measurement noise from the PPG signals, thus affecting the extracted fPPG signals, which encouraged a further improvement study, as mentioned in Section 3.1 with the additional use of adaptive filtering method.

On the other hand, alternative approaches were considered by the researchers, too, instead of using adaptive filtering, BSS, and filters as signal processing methods to get the fetal signal isolated. Although Bottrich *et al.* succeeded in fPPG signal extraction using ANC and comb filter design, the researchers produced an enhancement work to improve the fPPG signal quality by processing the fPPG signal using the synchronous averaging method [19]. The aim was to enhance the previous results by generating fetal pulse waves. It was accomplished by using synchronous averaging to reduce the noise in the signal to achieve more robust and reliable information, such as oxygen saturation.

In addition, Schubert *et al.* studied using QRS-triggered averaging to gain the fPPG signal [20]. The authors constructed a PPG device with two LEDs to acquire the desired PPG signals. The team used the R peaks found in the QRS complexes to average the combined PPG signal, aiming to get a blurred gradient. The fPPG signal can be filtered out using 103 averaging windows.

Template subtraction is another popular technique for acquiring fetal signals by subtracting the mean period of mECG from all periods. However, the misalignment between the mECG and the calculated mean period will affect the accuracy of signal extraction. Therefore, Souriau *et al.* investigated dynamic time warping (DTW) to extract fECG signals to solve misalignment by modifying the template subtraction algorithm [21]. Time deformation was considered in DTW as the diffeomorphism of each period of the ECG signals can be expressed as an alignment matrix. To ensure the correct alignment of the ECG signals, the mean of the alignment matrices of the ECG signals was computed with the Fréchet mean and Euclidean mean, respectively. This would ensure that the start and end of a period event in the ECG signal are coordinated for all periods. Fetal ECG Synthetic Database (FECGSYNDB) and FECGDARHA were used to evaluate the performance of DTW. The results showed that DTW performed well when detecting the R-peak of mECG signals. P, Q, R, and T waves would instinctively align and even autocorrect the R-peaks if there are misalignments in the mECG signals. The latter was better among the Fréchet and Euclidean mean because it uses less computation time and does not require a parameter tuning process to calculate the mean of the periods in the ECG signals.

A recent study by Jaba Deva Krupa *et al.* showed that joint time-frequency analysis (JTFA), namely Stockwell transform (ST), which is a combination of Wavelet transform (WT) and short-time Fourier transform (STFT), was useful for fECG extraction [22]. The peaks of mECG and fECG can be detected by ST, which allows window size adjustment to influence the temporal or frequency resolution of the ECG signal analysis. Apart from that, ST also enables the interpretation of the time-frequency domain, which is advantageous in eliminating the residue noises. Several databases were involved for verification and validation including the online public databases obtained from Database for the Identification of Systems (DAISY), PhysioNet/Computing in Cardiology Challenge 2013 (PhysioNet/CinC Challenge 2013) Set-A Dataset, Abdominal and Direct Fetal ECG Database (ADFECGDB), and Non-Invasive Fetal ECG Arrhythmia Database (NIFEADB) and the actual ECG recordings generated via PowerLab data acquisition hardware with a five ECG leads setup.

Roshanitabrizi *et al.* used the impulse-response transfer function to separate the fECG in the frequency domain [23]. This is done by estimating the coherent components between the mECG and aECG signals. The result showed that this frequency-based technique improved the clarity of the ECG waveform. However, the clinicians showed poor agreement in their measurements of CTI, which may be attributed to differences in the ECG appearance from the standard paediatric ECG. This highlights the need for further study of normal morphology.

Besides the ECG and PPG signals, PCG signals can also be applied for fetal monitoring. Mhajna *et al.* applied two different techniques to extract the fetal signal using the developed Invu system [24]. The study involved the use of electrical sensors and acoustic sensors. Thus, for the electrical signals, ECG applied the adaptive mECG template whereas, for the acoustic signal, PCG used the slow envelope of the Hilbert transform to detect peak locations, which are then grouped into 2 clusters using Gaussian mixture models to identify the source of the heart sound that would eventually distinguish the fHR and mHR. Table 1 summarises various signal processing techniques used for fetal signal extraction in terms of their performance, strengths, and limitations found in the studies discussed in Section 3.

Table 1 *Summary of various signal processing techniques used for fetal signal extraction*

Ref. / Year	Signal	Signal Processing (SP) Technique	Dataset	Result	Advantages	Limitations
[9] / 2022	ECG	ANC with non-linear kernel adaptive filter NMF	• Actual ECG recordings PowerLab setup • ABDFECGDB	The method shows high reliability and similarity to reference CTG by having less than 25 % of the mean ratio of outliers	R-peak detection is not required in this method for fHR estimation.	fHR inference was challenging due to the high noise level.
[22] / 2022		Joint time-frequency analysis and non-linear estimation	• DAISY database • PhysioNet/ CinC Challenge 2013 – Set A • ABDFECGDB • NIFEADB • Actual ECG recordings via PowerLab data	(i) PCDB: • ACC: 97.37 % • SE: 98.61 % • PPV: 98.72 % • F1 measure: 98.67 % (ii) ABDFECGDB: • ACC: 98.55 % • SE: 99.16 % • PPV: 99.38 % • F1 measure: 99.27 %	• Window size is scalable • Time-frequency domain is interpretable	The exact position of the T wave is challenging
[21] / 2022		DTW template subtraction	• FECGSYNDB • FECGDARHA	The developed algorithm aligned the mECG signal, which enhanced the fECG extraction	Diffeomorphic alignment of mean mECG waveform to each mECG's period.	Investigation of parameter tuning for α and block size under different conditions
[18] / 2022		Savitzky-Golay and Butterworth filters	DAISY database	mHR and fHR can be determined, which were about 85.5 bpm and 132.5 bpm	ECG waveform peaks can be preserved	May use optimisation methods for filter design
[16] / 2021		ICA, RLS, and EEMD	• FECGDARHA: 12 recordings • PhysioNet Challenge 2013 database: 25 recordings	The proposed ICA-RLS-EEMD obtained an overall accuracy above 80 % for the FECGDARHA and PhysioNet Challenge 2013 databases	Good results were obtained with non-invasive ST segment analysis	High computational complexity and the need for individual parameter tuning
[11] / 2020		BSS-NSITM	• DAISY database • PhysioNet/ CinC 2013 Challenge • FECGSYNDB	The proposed algorithm has shown the highest statistical values of SE, ACC, and PPV using the PhysioNet/CinC 2013 Challenge dataset	NSITM is computationally simpler than alternatives	Using ACF to remove mECG from fECG in NSITM may lead to a loss of information if R peaks overlap

Table 1(continued) *Summary of various signal processing techniques used for fetal signal extraction*

Ref./ Year	Signal	SP Technique	Dataset	Result	Advantages	Limitations
[12] / 2020	ECG	BSS- FastICA, JADE, and PCA	• Physionet Database • Non-Invasive Fetal ECG • Database with five datasets	JADE gave higher accuracy in fECG separation, while FastICA is comparable to JADE after fine-tuning and computationally more efficient for many components	JADE has better performance in reducing the interference of fECG signal separation	JADE's computational load grows faster than FastICA's with more components, but it does not require fine-tuning
[15] / 2020		• Adaptive filtering: IMAF and OMAF • BSS: NSITM	• DAISY database • ADFECGDB • FECGSYNDB	OMAFRLS produced the best fetal signal extraction performance.	BSS-OMAF improves fECG with peak enhancement and mECG separation.	IMAF showed its drawback as it would require post-processing for better fetal signal extraction, affecting its efficiency.
[13], [14] / 2019		MULTI-COMBI-based BSS technique	Physionet ATM bank	The BSS method gave simulated results with low PSNR and SIR values.	The paper provided a simple approach to extracting the fetal signal.	The article did not include a comparison with other fetal signal separation methods.
[23] / 2022		Impulse-response transfer function	• Set A of the 2013 PhysioNet/ Computing in Cardiology challenge database • Clinical Dataset • Simulated Dataset	• Public Dataset: High correlation with fHR based on annotations. • Clinical Dataset: Average standard deviation is 3.49 ± 1.22 with a p-value less than 0.01. • Simulated Dataset: 98.97 % in correlation coefficient	The frequency-based approach enhanced fECG and CTI clarity using an averaging technique.	ECG waveform morphology was not standardised in this study.
[17] / 2019		RLS adaptive filter based on QR decomposition	Ten pregnant women	The values of SIR and accuracy were higher in multi-reference than in single-reference.	The fetal QRS complex can be enhanced with the developed signal processing technique.	The output suffered from residual noise even after using the adaptive filter.
[24] / 2020	ECG and PCG	Adaptive Template, Hilbert transform, and Gaussian mixture	147 pregnant women	The mHR and fHR obtained were highly correlated to CTG	Reliable fHR measurements with beat-to-beat calculation for fetal signal	Only included women from 32 weeks to term, which is insufficient to compare with the CTG standard performed from 24 weeks onward

Table 1(continued) *Summary of various signal processing techniques used for fetal signal extraction*

Ref./ Year	Signal	SP Technique	Dataset	Result	Advantages	Limitations
[5] / 2021	PPG	ANC	TFO system design consists of a multi-detector optode, an embedded optode control system, and custom user-interface software	The non-invasive TFO system was able to accurately measure these fetal SpO2 values, supported by a root-mean-squared error of 6.37 %	Measuring a wide range of fetal SpO2 values and identifying critical levels of fetal hypoxia are possible	Pregnant women are needed to bridge the gap between pregnant sheep and pregnant humans towards eventual clinical use
[20]/ 2020		QRS triggered averaging approach	• BioPac OXYSSH as reference PPG • Developed PPG with two LEDs as synthetic PPG data	• In study 1: mHR was 75.1 ± 4.0 bpm and fHR was 87.4 ± 4.4 bpm. • In study 2: mHR was 64.5 ± 3.3 bpm and fHR was 90.2 ± 3.1 bpm	fHR and fetal oxygen saturation can be analysed with a simple setup	The minimum number of PPG averages required under realistic conditions is absent, and the sample size is small
[6] / 2018		ANC	Developed multi-heart rate model from fPPG and mPPG signals of two subjects.	TFO retrieves high-attenuated fetal signal through 5 cm tissue thickness	Requires no prior knowledge of the mPPG signal	Only involved simulated data and lack of real PPG dataset
[19] / 2020		Synchronous averaging with ANC and comb filter	Synthetic signals	Reconstruction of the fetal pulse wave shape using ANC and comb filter combined with synchronous averaging	The fetal pulse curve can be estimated with greater precision as the number of averages increases	Improper peak detection can skew the curve and degrade signal quality during averaging
[8] / 2019		ANC and comb filter	Synthetic signals	fPPG detection was successfully performed using ANC, peak detection, and comb filtering	The comb filter was able to obtain a fetal signal in time and frequency domains	The fPPG signal is corrupted by noise at its peak frequencies and cannot be removed by comb filters

3.4 Limitations of Signal Separation Techniques in Non-Invasive Approaches

Based on the review of signal separation, the common issue in fetal signal extraction is the struggle to suppress the maternal signal, as it is always dominant over the fetal signal during signal acquisition. Despite various signal processing techniques, as reviewed in the previous section, there is no absolute approach to tackle fetal signal extraction. The two significant challenges of fetal signal extraction are signal noises and ambiguity. The former refers to the need for signal denoising due to white noise and artifacts. The latter indicates the effort in differentiating between fetal and maternal signals to generate an accurate fetal condition based on the filtered signal. General filter design approaches such as comb filter and the Savitzky-Golay and Butterworth combined filters, as reported in [18], can be easy to implement. However, these studies show the need to compress the measurement noises.

Adaptive filtering has great adaptability that can automatically adapt to changes in the input signal, but the output suffers from residual noise, as described by [9][17]. The residual noise still occurred even after applying RLS adaptive filtering [17], which could potentially lead to misinterpretation or misdiagnosis of fetal health conditions. Moreover, the need for parameter fine-tuning for the signal processing technique was mentioned by Barnova *et al.* to optimise the fetal signal extraction performance [15][16]. Although the optimal parameter settings of signal processing techniques can be adjusted for specific applications, they may still be influenced by factors such as the number of electrodes used by the device setting, pregnancy stage, and fetal position, which can affect the quality of the filtered signal. Information loss can occur when R peaks of the maternal and fetal signals of ECG overlap, as stated in [11]. Not only R-peak detection of ECG signal is crucial, but the T wave is essential too, as according to the study by Jeba *et al.* , they face the challenge of locating the T wave position after fetal signal extraction [22]. The T wave could provide helpful information when the heart beats irregularly or in an abnormal rhythm [25].

Only now, there is a general agreement about the fECG waveform morphology as it is not unified universally, causing various interpretations of the signal data. This issue occurred in the study by Roshanitabrizi et al., as the ECG waveform morphology was inconsistent in this study [23]. Fetal physiology is a complex and dynamic system, and hence, poses the most significant challenge to researchers as the understanding of fetal physiology still needs to be completed [26]. This has resulted in insufficient knowledge even though professionals and researchers already understand fetal physiology. In comparison, more resources are available for ECG analysis than PPG analysis, as ECG is more widely used than PPG.

The critical issue is the reliable resources on the PPG data. The inadequate publicly available real PPG dataset becomes an obstacle to improving the existing PPG technology despite the growing body of research on PPG, especially when the researchers look for accurate PPG data to validate their research results. Fetal physiology from studies of animals, such as lamb, as used in D.Fong *et a,l.* [5], was the only choice for them to help understand the basic principles of fetal physiology, which can be applied to humans. Normal subjects were used to simulate data that mimicked both the mother and fetal, as conducted by Schubert et al. in their TfPO studies [20]. In the signal extraction wise, despite the success of the implementation of synchronous averaging to the PPG signal, its drawback was the detection of inaccurate peaks, which would cause distortions on the averaged curve, affecting the signal's quality as informed by [19]. Schubert *et al.* [20] also mentioned that the minimum number of PPG averages required under realistic conditions was unknown, and the sample size is too small to draw any firm conclusions, which requires further investigation on synchronous averaging.

4. Direction for Future Research

Even though various methods of signal processing were developed to separate the fetal signal from the overlapped signals, a reliable and desirable approach still needs to be developed that can serve as an ultimate solution. The fetal signal separation can be inferred that there is no one-size-fits-all solution in fetal signal extraction using signal processing methods, as various approaches yield different extraction results. The best approach must be tailored to the situation's specific needs. Optimisation of the parameters for signal processing and filter approaches can be complicated and challenging, as it involves tuning parameters. This is because the parameters of the algorithm can have a significant impact on the performance of the algorithm.

Henceforth, for future research direction prospects, deep learning has the potential to enhance fetal signal extraction by learning abstract representations from raw fECG signal data and discovering relevant patterns and features for accurate extraction from noisy maternal signals. Deep learning could improve the interpretation of fECG signals in terms of its fHR and morphology analysis, as these two parameters are essential information in determining the conditions of fetal abnormalities and hypoxia. Nevertheless, the research to date has tended to focus on fHR variability rather than fetal hypoxia. Among the 19 reviewed study works, it was found that most of the ECG signal focused on the interpretation of fHR, while the PPG signal mainly focused on oxygen saturation, which is helpful for fetal hypoxia detection. Much research focuses on detecting heart rate variability, but fetal hypoxia can be further investigated as a sign of fetal health conditions.

5. Conclusion

This study reviewed the existing fetal signal separation approaches in fetal well-being surveillance. This study has found that signal processing techniques such as ANC, BSS, and filters are among the popular methods used for fetal extraction tools. However, the extracted fetal signal is still greatly affected by noise, even with the use of various signal-processing techniques. To improve the performance of fetal signal extraction, deep learning is suggested as an assistive technology tool to investigate its effectiveness in eliminating noise, which is the major challenge in improving fetal signal quality, thus providing better assessment in clinical applications. The significance of fetal signal separation in fetal monitoring is explained such that its signal interpretations could provide usefulness in enhancing neonatal outcomes.

Acknowledgement

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).

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Nur Anida Jumadi, Li Mun Ng;* ***data collection:*** *Li Mun Ng;* ***analysis and interpretation of results:*** *Li Mun Ng;* ***draft manuscript preparation:*** *Li Mun Ng, Nur Anida Jumadi. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Cypher R. L. (2019). *When Signals Become Crossed: Maternal-Fetal Signal Ambiguity*. The Journal of perinatal & neonatal nursing, 33(2), 105–107. https://doi.org/10.1097/JPN.0000000000000404

[2] Matonia, A., Jezewski, J., Kupka, T., Jezewski, M., Horoba, K., Wrobel, J., Czabanski, R., & Kahankowa, R. (2020). *Fetal electrocardiograms, direct and abdominal with reference heartbeat annotations*. Scientific data, 7(1), 200. https://doi.org/10.1038/s41597-020-0538-z

[3] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., … Moher, D. (2021). *The PRISMA 2020 statement: an updated guideline for reporting systematic reviews.* BMJ (Clinical research ed.), 372, n71. https://doi.org/10.1136/bmj.n71

[4] Tan, L. and Jiang, J. (2019). *Digital Signal Processing: Fundamentals and Applications, Third Edition*. Academic Press, pp. 421-462. https://doi.org/10.5860/choice.42-6523

[5] Fong, D. D., Yamashiro, K. J., Vali, K., Galganski, L. A., Thies, J., Moeinzadeh, R., Pivetti, C., Knoesen, A., Srinivasan, V. J., Hedriana, H. L., Farmer, D. L., Johnson, M. A., & Ghiasi, S. (2021). *Design and In Vivo Evaluation of a Non-Invasive Transabdominal Fetal Pulse Oximeter*. IEEE transactions on bio-medical engineering, 68(1), 256–266. https://doi.org/10.1109/TBME.2020.3000977

[6] Fong, D. D., Knoesen, A., Motamedi, M., O'Neill, T., & Ghiasi, S. (2018). *Recovering The Fetal Signal In Transabdominal Fetal Pulse Oximetry*. Smart Health, 9–10, 23–36. https://doi.org/10.1016/j.smhl.2018.07.011

[7] Bottrich, M. & Husar, P. (2018). *Signal Separation for Transabdominal Non-invasive Fetal Pulse Oximetry using Comb Filters*. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 5870–5873. https://doi.org/10.1109/EMBC.2018.8513614

[8] Bottrich, M. & Husar, P. (2019). *Extraction of the Fetal Pulse Curve for Transabdominal Pulse Oximetry using Adaptive and Comb Filters*∗. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 15–18. https://doi.org/10.1109/EMBC.2019.8856292

[9] Dia, N., Fontecave-Jallon, J., Resendiz, M., Faisant, M.-C., Equy, V., Riethmuller, D., Gumery, P.-Y., & Rivet, B. (2022). *Fetal heart rate estimation by non-invasive single abdominal electrocardiography in real clinical conditions*. Biomedical Signal Processing and Control, 71, 103187. https://doi.org/10.1016/j.bspc.2021.103187

[10] Senay, S. (2018). *Time-frequency BSS of Biosignals*. Healthcare Technology Letters, 5(6), 242–246. https://doi.org/10.1049/htl.2018.5029

[11] Taha, L., Abdel-Raheem, E. (2020). *A Null Space-Based Blind Source Separation for Fetal Electrocardiogram Signals*. Sensors, 20(12), 3536. https://doi.org/10.3390/s20123536

[12] Ramli, D. A., Shiong, Y. H., & Hassan, N. (2020). *Blind Source Separation (BSS) of Mixed Maternal and Fetal Electrocardiogram (ECG) Signal: A Comparative Study*. Procedia Computer Science, 176, 582–591. https://doi.org/10.1016/j.procs.2020.08.060

[13] Xavier, F. J. (2019). *Separation and Classification of Fetal ECG Signal by Enhanced Blind Source Separation Technique and Neural Network*. International Journal of Advances in Signal and Image Sciences, 5(2), 7. https://doi.org/10.29284/ijasis.5.2.2019.7-14

[14] Joseph, X. F., Waktola, A. T., Senay, D., & Breesha, S. R. (2019). *An enhanced classification technique for fetal ECG signal separation to diagnose fetal heart diseases*. 2019 IEEE International Conference on

Intelligent Techniques in Control, Optimization and Signal Processing (INCOS). https://doi.org/10.1109/incos45849.2019.8951317

[15] Taha, L. Y., & Abdel-Raheem, E. (2020). *Fetal ECG Extraction using Input-Mode and Output-Mode Adaptive Filters with Blind Source Separation*. Canadian Journal of Electrical and Computer Engineering, 43(4), 295–304. https://doi.org/10.1109/cjece.2020.2984602

[16] Barnova, K., Martinek, R., Jaros, R., Kahankova, R., Matonia, A., Jezewski, M., Czabanski, R., Horoba, K., & Jezewski, J. (2021). *A novel algorithm based on ensemble empirical mode decomposition for non-invasive fetal ECG extraction*. PLOS ONE, 16(8). https://doi.org/10.1371/journal.pone.0256154

[17] Sulas, E. Urru, M. Tumbarello, R. Raffo, L. & Pani, D. (2019). *Comparison of Single-and Multi-Reference QRD-RLS Adaptive Filter for Non-Invasive Fetal Electrocardiography*. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2019, 1–5. https://doi.org/10.1109/EMBC.2019.8856824

[18] Sheng, H. S. H. Alshebly, Y. S. & Nafea, M. (2022). *Fetal ECG Extraction using Savitzky-Golay and Butterworth Filters*. 2022 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), Shah Alam, Malaysia, 2022, 215-220. https://doi.org/10.1109/I2CACIS54679.2022.9815469

[19] Bottrich, M. Laqua, D. & Husar, P. (2020). *Estimating the Shape of the Fetal Pulse Curve for Transabdominal Pulse Oximetry using Synchronous Averaging*. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2020, 1–4. https://doi.org/10.1109/EMBC44109.2020.9176692

[20] Schubert, M. Samann, F. & Schanze, T. (2020). *QRS Triggered Averaging for Superimposed PPG Separation*. Proceedings on Automation in Medical Engineering, 1(1), 1-2. https://doi.org/10.18416/AUTOMED.2020

[21] Souriau, R., Fontecave-Jallon, J., & Rivet, B. (2022). *Fetal ECG denoising using dynamic time warping template subtraction*. 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). https://doi.org/10.1109/embc48229.2022.9871318

[22] Jaba Deva Krupa, A., Dhanalakshmi, S., & Kumar, R. (2022). *Joint Time-frequency analysis and non-linear estimation for fetal ECG extraction*. Biomedical Signal Processing and Control, 75, 103569. https://doi.org/10.1016/j.bspc.2022.103569

[23] Roshanitabrizi, P., Krishnan, A., Ingbar, C., Salvador, T., Zhang, A., Donofrio, M. T., & Govindan, R. (2022). *Frequency-Based Maternal Electrocardiogram Attenuation for Fetal Electrocardiogram Analysis*. Annals of biomedical engineering, 50(7), 836–846. https://doi.org/10.1007/s10439-022-02959-4

[24] Mhajna, M., Schwartz, N., Levit-Rosen, L., Warsof, S., Lipschuetz, M., Jakobs, M., Rychik, J., Sohn, C., & Yagel, S. (2020). *Wireless, remote solution for home fetal and maternal heart rate monitoring*. American journal of obstetrics & gynecology MFM, 2(2), 100101. https://doi.org/10.1016/j.ajogmf.2020.100101

[25] Gacek, A. (2012). *An Introduction to ECG Signal Processing and Analysis. In: Gacek, A., Pedrycz, W. (eds) ECG Signal Processing, Classification and Interpretation*. Springer, London. https://doi.org/10.1007/978-0-85729-868-3_2

[26] Garabedian, C., De Jonckheere, J., Butruille, L., Deruelle, P., Storme, L., & Houfflin-Debarge, V. (2017). *Understanding fetal physiology and second line monitoring during labor*. Journal of gynecology obstetrics and human reproduction, 46(2), 113–117. https://doi.org/10.1016/j.jogoh.2016.11.005