International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I8P211

Volume 71 Issue 8, 131-142, August 2023

Original Article

A Novel Method for Fetal ECG Extraction using ICA based Wavelet Transform

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Received: 26 May 2023 Revised: 01 July 2023 Accepted: 22 July 2023 Published: 15 August 2023

Abstract *- Developing an intelligent technique to monitor fetal heart function at the beginning stages of pregnancy is crucial, and the research aims to achieve that by proposing two hybrid algorithms. The proposed algorithms integrate independent component analysis (ICA) and stationary wavelet transform (SWT) to extract fetal electrocardiogram (FECG) signals. The objective is to improve the clarity of the FECG signal, reduce noise and artifacts, and accurately detect the R-peaks using an improved spatially selective noise filtration (ISSNF) method or a threshold-based algorithm (TBA) in the wavelet domain. Accurate detection of fetal R-peaks can provide valuable clinical information for diagnosing and treating fetal heart conditions. In order to isolate the FECG signal from the mixed abdominal signal, the study utilizes ICA to separate the maternal ECG (MECG) and FECG signals. The signals with high noise levels are subsequently broken down into multiscale components utilizing SWT, with the choice of wavelet decomposition scale determined by the noise level. Either the ISSNF or TBA methods are utilized for denoising in the wavelet domain. The performance of the proposed methodology is assessed by making use of three clinical databases through qualitative and quantitative measures, including visual inspection, computation of signal-to-noise ratio (SNR), and recognition of the QRS complex. The analysis findings suggest that the proposed system, especially when utilizing the TBA, surpasses conventional techniques for FECG extraction in terms of performance. The experimental findings demonstrate that the proposed system has the potential to extract clear FECG signals with good SNR results and minimal disturbances.*

Keywords *- Fetal ecg, Improved spatially selective noise filtration, Independent component analysis, Stationary wavelet transforms, Threshold-based algorithm.*

1. Introduction

The use of an electrocardiogram (ECG) to monitor the fetal heartbeat during pregnancy is a crucial tool for medical professionals. Timely identification of abnormalities in the heartbeat provides valuable information about the baby's development, enabling healthcare professionals to assess its physiological condition. [1] Anomalies in the heartbeat detected by the ECG can be indicative of potentially dangerous conditions. However, the conventional FECG monitoring performed utilizing cardiotocography (CTG) has high inaccuracies, which can lead to various diagnostic problems and unnecessary invasive procedures. [2]

Fetal ECG (FECG) extraction offers better health monitoring, data preservation, and higher accuracy than traditional CTG, and its low data rate allows for wireless applications. In addition, the FECG provides essential information on ECG shape, enabling the diagnosis of specific conditions that standard fetal monitoring services may not detect [3]. Despite these benefits, the FECG signal is weak compared to the maternal electrocardiogram (MECG), and there is high noise, making it challenging to isolate FECG from the abdominal electrocardiogram (AECG) and obtain an accurate assessment. The challenge primarily arises from the overlapping frequency components between MECG, FECG, and noise during the process of isolating the FECG signal.

Several techniques have been proposed for extracting FECG, each with its own limitations. Many of these techniques aim to decrease the influence of MECG signals, with adaptive filtering being one such technique that employs the maternal thoracic signal as a reference to eliminate its presence in the AECG. [4].

However, this method is simple but prone to disturbances caused by noise and MECG variance between the two electrode signals. The wavelet transform is a promising tool widely used in the literature for FECG extraction algorithms [5]. It decomposes the signal at different resolutions, allowing for analysis at different windows and isolating the FECG signal details using recursive inverse adaptive filtering [6].

When thoracic ECG is available, the least mean squares (LMS) algorithm in conjunction with a wavelet is employed. In this approach, the MECG serves as a reference signal to eliminate noise from the AECG components while maintaining the signal's integrity.[7] Our preliminary findings from research work utilizing wavelet-based recursive least squares (RLS) adaptive filtering are presented and discussed at a conference [8]. These algorithms effectively remove unwanted noise from the AECG without disturbing the structure of the FECG waveform. The utilization of wavelet-based noise removal techniques enables the elimination of interfering signals from the AECG captured through a single electrode, facilitating subsequent analysis. The isolation of the FECG from the MECG can be achieved by comparing the power difference after eliminating all remaining interferences. The periodic component analysis is another approach employed to detect and extract repetitive patterns or periodic elements from a given AECG signal.[9] The autocorrelation method is utilized in fetal ECG extraction by computing correlations between a signal and its delayed versions. [10] Linear decomposition methods involve breaking down the complex AECG signal into its individual linear components, aiding in the analysis and extraction of FECG information.[11]

The principal component analysis aims to remove high-power vectors to eliminate MECG but may affect FECG [12]. Blind source separation (BSS) techniques enable the separation of mixed signals into their underlying source components, even in the absence of prior knowledge about the sources. Independent component analysis (ICA) is an example, which means it can separate signals without prior knowledge of the source signals, and ICA has been shown to perform well in the presence of high levels of noise and interference, making it suitable for use in FECG extraction from the AECG [33]. Hybrid systems using ICA in FECG extraction have several advantages over traditional ICA-based approaches [14,15,16]. These include improved accuracy, robustness to artifacts, increased signal-to-noise ratio (SNR), real-time monitoring, and adaptability.

In recent years, neural network methods have emerged as prominent techniques for FECG extraction. [17,19,34] These methods leverage the power of deep learning algorithms to extract fetal ECG signals from noisy recordings automatically. By leveraging the power of these advanced techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the automated extraction process ensures accurate and reliable identification of fetal ECG signals, eliminating the need for manual intervention. By training on large datasets, neural networks can learn complex patterns and relationships within the data, enabling accurate and efficient FECG extraction. These techniques have shown promising results, demonstrating their potential to enhance fetal monitoring and diagnosis in various clinical applications. However, these methods necessitate a time-consuming training process for the model. Another approach employed in this field is the template-matching algorithm [20]. In contrast to neural networks, the template matching method relies on multiple probability functions and is susceptible to high-frequency disturbance. On the other hand, wavelet mode maximum methods provide a more straightforward implementation and find extensive applications in FECG extraction. [21]

However, no preferred methods for FECG monitoring exist, and most require further validation. FECG extraction has not yet become a standard practice in hospitals due to the challenges and limited availability of reliable methods. In performing fetal ECG extraction, the current techniques face three difficulties. One, there will be different types of noises. Two, if MECG and FECG signals are overlapped, extracting the FECG from the overlapped signal would be difficult. Three, it will be fairly difficult to measure SNR. Comparative studies assess algorithms' ability to locate FECG positions and extract signals, but proximity to MECG can affect their performance. The challenging field of non-invasive FECG extraction requires new approaches and algorithms for medical use.

This paper presents a novel composite formulation that combines ICA and Stationary Wavelet Transform (SWT) for achieving an optimal measurement of the FECG signal and SNR computation. Previous studies have demonstrated the robust performance of ICA in FECG extraction systems. In the proposed approach, the ICA algorithm is applied to separate the MECG and FECG signals. The noisy FECG signals are subsequently subjected to wavelet decomposition utilizing SWT, resulting in the generation of multiple resolution components. The proposed methodology involves a sequential application of ICA, SWT, and a noise removal algorithm. Either the Improved Spatially Selective Noise Filter (ISSNF) technique or threshold-based algorithm (TBA) is used for denoising in the wavelet domain. By utilizing ICA, the proposed system could effectively separate the MECG and FECG signals.

Moreover, the ISSNF technique or TBA enables the extraction of the clean FECG signal, which is further refined through inverse SWT. This innovative fusion of different techniques demonstrates enhanced performance when compared to existing research findings in the field. By leveraging the complementary strengths of ICA and SWT, the proposed method achieves more accurate and efficient extraction of FECG signals, contributing to advancements in fetal monitoring and diagnosis.

2. Materials and Methods

Both ICA and WT hold great promise as approaches in the field of biomedical signal processing. This research paper introduces a novel methodology that combines the power of

SWT and ICA algorithms to extract FECG from abdominal signals. The proposed approach aims to enhance the accuracy and effectiveness of FECG extraction by leveraging the complementary strengths of both techniques. Additionally, to further improve the SNR performance, the researchers incorporate the use of the ISSNF technique and TBA. By employing these advanced noise reduction methods, the researchers intend to enhance the quality and fidelity of the extracted FECG signals for more accurate analysis and diagnosis in clinical settings.

2.1. Independent Component Analysis

The extensive application of ICA in the field of FECG processing involves its utilization for the purpose of denoising and extracting clean FECG signals from the complex AECG signal. This technique has proven effective in separating and isolating the desired FECG component from the mixture of signals, resulting in improved signal quality for further analysis and interpretation. The fundamental principle behind ICA is that the observed data (AECG), i.e., the signal x, is a linear mixture of the MECG, FECG, and other disturbances [22,23]. ICA is a BSS technique. BSS involves addressing a scenario where the original sources and the mixing matrix are unknown, with only the observed signals being available for the separation process. The primary goal of BSS is to extract independent and unidentified sources solely based on these observed signals. By employing various algorithms and techniques, BSS aims to uncover the underlying sources and untangle them from the mixed observations, enabling the recovery of the individual source signals without prior knowledge of their characteristics or the mixing process.

The objective of ICA in the proposed study is to separate the target FECG and MECG from the AECG signal, considering their statistical independence. Mathematically the research problem can be considered an under-constrained problem because the count of unknown variables is higher than the count of known variables. The desired FECG signal is linearly mixed with other sources as follows:

$$x = As \tag{1}$$

Where x is the AECG signal, both A and s are unknown variables, where A is the unknown mixing matrix, and s is the FECG signal. The objective of the study is to measure the distinct FECG signal by determining its relationship with the inverse of the unknown mixing matrix, A, through the equation $s = Wx$. i.e.,

$$s = A^{-1}x \tag{2}$$

The composite abdominal signal x contains a mixture of MECG and FECG, both of which are affected by various types of noise interference. Thus, the clean FECG can be extracted by canceling the maternal components from the abdominal signal. The ICA is performed based on a divide-and-conquer strategy. ICA aims to decompose the square matrix A into several small pieces. $A = U\Sigma V^T$ where U and V are rotation matrices, and Σ is a diagonal matrix that is real and non-negative. The unknown matrices are determined using two steps.

1) Examine the covariance matrix, $\langle xx^T \rangle$ of the observed data. This results in a partial solution to the ICA problem.
2) Finding the unknown rotation matrix, V

The covariance of the abdominal signal can be determined by relating it to the underlying sources.

$$\begin{aligned} \langle xx^T \rangle &= \langle (As)(As)^T \rangle \\ &= \langle (U\Sigma V^T s)(U\Sigma V^T s)^T \rangle \\ &= U\Sigma V^T \langle ss^T \rangle V\Sigma U^T \\ &= U\Sigma^2 U^T \end{aligned} \tag{3}$$

In the context of linear algebra, it is known that symmetric matrices, such as covariance matrices, can be orthogonally diagonalized using their eigenvectors. Let's consider a matrix E, where its columns correspond to the eigenvectors of the covariance matrix of variable x . Thus,

$$\langle xx^T \rangle = EDE^T \tag{4}$$

Where D represents the diagonal matrix consisting of the associated eigenvalues, it is worth noting that the eigenvectors of the data's covariance matrix create an orthonormal basis, implying that matrix E is orthogonal. By utilizing the eigenvectors of the data's covariance matrix, we have discovered a partial solution to matrix A . Matrix U is composed the stacked eigenvectors, while matrix Σ consists of the square roots of the corresponding eigenvalues. It takes the form of a diagonal matrix. Furthermore,

$$W = VD^{-\frac{1}{2}}E^T \tag{5}$$

is the solution to ICA and this matrix can be used to estimate the underlying sources. After decomposing the matrix, A and performing data whitening, the problem is successfully simplified to find a rotation matrix V, where the estimated source signal. $\hat{s}$ can be obtained as V times the whitened data, x_W.

2.2. Stationary Wavelet Transform

WT is recognized as a highly potent and effective tool that has been frequently used in biomedical signal processing [35]. This is due to its ability to analyse signals at multiple scales and its efficient representation of non-stationary signals. FECG extraction algorithms commonly employ it as a prevalent technique, frequently referenced in the existing literature. The integration of WT with additional noise-reducing techniques has the potential to yield more noise-reduction benefits. Wavelet-based denoising techniques have shown promise in removing different types of noise from AECG signals, such as power line interference, baseline wander, and muscle artifacts. Removing such noise can make the ECG signal easier to analyse and interpret, leading to potentially more accurate diagnoses and better patient outcomes. However, the effectiveness of wavelet-based denoising techniques depends on several factors, including the wavelet selection, denoising threshold, and the presence of other noise sources or artifacts in the signal. Thus, careful consideration and validation of the denoising method are crucial to ensure its effectiveness in removing interference signals from AECG signals.

Discrete wavelet transforms (DWT) and SWT are two types of wavelet-based analysis methods. They both employ a decomposition approach to split signals into multiple frequency bands. These two wavelet transforms differ in their approach to signal decomposition. One key distinction between the DWT and the SWT lies in their treatment of signal resolution during the decomposition process. In DWT, the resolution is successively reduced by half at each level of decomposition, whereas in SWT, the resolution remains unchanged throughout the decomposition process. [25] In the case of DWT, the signal undergoes a two-step process. Initially, it is divided into low and high-frequency sub-bands, followed by down-sampling each sub-band by a factor of 2 before advancing to the subsequent decomposition level. This process is repeated iteratively to achieve multilevel decomposition. As a result, the resolution of the signal is reduced at each level of decomposition. In contrast, the SWT does not involve down-sampling the signal. Instead, it decomposes the signal into a series of wavelet coefficients while preserving the resolution at each level of decomposition. The SWT addresses the issue of translation invariance inherent in the DWT. By employing a different approach, SWT overcomes this limitation, allowing for improved translation-invariant analysis of signals. Wavelet-based noise reduction algorithms demonstrate a remarkable capability to eliminate a significant portion of interference signals present in the AECG signal, thereby facilitating easier analysis of the underlying FECG signal.

The SWT is a reliable and effective technique in processing signals. In the context of wavelet analysis, the wavelet function, $\Psi(n)$, is often referred to as the mother wavelet or analyzing wavelet. Similarly, the scaling function, $\Phi(n)$, can be referred to as the father wavelet or synthesis wavelet. The wavelet decomposition generates a set of coefficients consisting of both approximation and detail coefficients, providing valuable information about the signal's various frequency components. In DWT, the decomposition process at level i yields two sets of coefficients: the approximation coefficients, denoted as A^i, which capture the coarse-scale information of the signal, and the detail coefficients, denoted as D^i, which represent the fine-scale details or high-frequency components of the signal. The original signal A^0 represents the input signal, while h and l correspond to the high pass and low pass filters, respectively, used in the decomposition process to separate the input signal into its high-frequency and low-frequency components. [25, 26]

$$A^i = l * A^{i-1}, \quad i = 1,2,\ldots,N \tag{6}$$

$$D^i = h * A^{i-1}, \quad i = 1,2,\ldots,N \tag{7}$$

In SWT-based wavelet decomposition, the resulting coefficients are divided into two categories: the approximation coefficients, denoted as A_ε^i and the detail coefficients denoted as D_ε^i. The value of ε in DWT is invariably 0, however in SWT, $\varepsilon = [\varepsilon_1, \varepsilon_2,\ldots,\varepsilon_n]$, [36]. $l^{\,i}$ and $h^{\,i}$ are low-pass and high-pass filters, respectively, such that $l^{\,i} \uparrow 2 = l^{\,i+1}$ and $h^{\,i} \uparrow 2 = h^{\,i+1}$.

$$A^i_{\varepsilon_1,\ldots\ldots\varepsilon_i} = l^{\,i-1} * A^{i-1}_{\varepsilon_1,\ldots\ldots\varepsilon_{i-1}}, i = 1,2,\ldots,N \tag{8}$$

$$D^i_{\varepsilon_1,\ldots\ldots\varepsilon_i} = h^{\,i-1} * A^{i-1}_{\varepsilon_1,\ldots\ldots\varepsilon_{i-1}}, i = 1,2,\ldots,N \tag{9}$$

In order to improve the performance of the hybrid approach that combines ICA and SWT for fetal ECG signal extraction, either the ISSNF or TBA methods are used in the wavelet domain. These methods effectively remove the noise caused by MECG, movement artifacts, and other sources of interference. By reducing the high noise level in the signal, the FECG signals can be extracted more efficiently and accurately. The SWT-based approach, coupled with effective noise reduction techniques, can considerably enhance the precision and dependability of FECG signal extraction from AECG signals.

2.3. Improved Spatially Selective Noise Filtration

A systematic approach for extracting fetal ECG requires the implementation of an efficient denoising algorithm that operates within the domain of wavelet analysis. This algorithm is known as the spatially selective noise filtration technique (SSNF), which is particularly useful in biomedical signal processing [27]. The SSNF algorithm is capable of removing noise from a signal while preserving essential features such as waveform shape, amplitude, and frequency content. Moreover, it demonstrates effectiveness in eliminating diverse forms of noise, including powerline noise, baseline wander, and muscle artifacts. To improve the SNR results, an enhanced version of the conventional SSNF algorithm has been employed [28]. The ISSNF is the modified version of the SSNF technique. ISSNF operates by calculating the spatial correlation $Cor_R(g,k)$ between signal components for each wavelet scale, g. The degree of correlation between the signal components is high, while that of noise components is low.

$$Cor_R(g,k) = \prod_{i=0}^{L-1} W(g+i,k); k = 1,2,\ldots,N \tag{10}$$

The following steps constitute the ISSNF algorithm:

1) To achieve precise edge extraction from coarse-scale to fine-scale components in the ISSNF algorithm, it is crucial

to select the $\lambda(g)$ and $th(g)$ parameters with great accuracy ahead of time. The steps for selecting these parameters are outlined below.

2) Calculate the correlation $Cor_2(g,k)$ among the signal components at each level of the wavelet decomposition, g

3) Get $Nor\ Cor_2(g,k)$ such that the power of $Cor_2(g,k)$ is normalized with respect to $W(g,k)$.

$Nor\ Cor_2(g,k) = Cor_2(g,k)\sqrt{\frac{P_W(g)}{P_{Cor}(g)}}$ Where $P_w(g)$ and $P_{Cor}(g)$ are defined as:

$$P_w(g) = \sum_{k=1}^{N}\left(W(g,k)\right)^2 \quad , \quad P_{Cor}(g) = \sum_{k=1}^{N}\left(Cor_2(g,k)\right)^2 \tag{11}$$

4) The component values in $Nor\ Cor_2(g,k)$ and $W(g,k)$ are compared. If $|Nor\ Cor_2(g,k) \geq \lambda(g) * W(g,k)|$, the corresponding components are selected and stored in $W_{new}(g,k)$. Then reset $W(g,k)$ and $Cor_2(g,k)$.

5) Perform the iterations continuously, leading to the power of unextracted pixel values being almost equivalent to a specific predefined noise power at the g^{th} wavelet decomposition level.

6) Follow the step-by-step procedures repeatedly till the power of data points that have not been extracted approaches the predefined noise power at the g^{th} wavelet decomposition level. Once M data values have been extracted, the noise power variance, σ_g^2 can be computed. Subsequently, repeat this process until

$$P_W(g) - th(g)(N-M)\sigma_g^2 \leq 0.05P_W(g) \tag{12}$$

After extracting the FECG signal components from the primary noisy source, these components are stored in a new data vector denoted by $W_{new}(g,k)$.

The choice of thresholding method is critical in determining the SNR performance of a wavelet-based denoising technique. To ensure optimal SNR performance, it is important to carefully select the thresholding parameters $\lambda(g)$ and $th(g)$. The reference noise power $(N-M)\sigma_g^2$ is multiplied by a factor $th(g)$ at coarse scales where $th(g) \geq 1$. For different signals, $th(g)$ should vary.

However, a common $th(g)$ can be chosen as a general case since the filtering results are not sensitive to $th(g)$. According to [28], the thresholding parameter $th(g)$ can be selected such that $th(1) = 1.1-1.2$, $th(2) = 1.2-1.4$, $th(3) = 1.4-1.6$, and $th(g) = 1.6-1.8$ when $g \geq 4$. By following this approach, any of these combinations inherently fulfill the prerequisites for denoising during FECG extraction. Consequently, the optimal parameters are determined through a visual examination of the extracted signals, which, in certain instances, hold more significance than quantitative metrics.

This ensures that after denoising, the amplitude of fetal QRS complexes remains reasonably preserved without excessive reduction. These considerations are used to select an optimal fit as $th(g) = [1.1, 1.3, 1.5, 1.7, 1.7]$ and the results are satisfying. A weight factor $\lambda(g)$ is introduced at fine scales to avoid noise extracting as edges [28]. Based on several experiments for a wide range of FECG signals, $\lambda(g) = [1.15, 1.06, 1, 1, 1]$ is chosen. ISWT follows the ISSNF algorithm, and the FECG signal can be extracted in the time domain.

2.4. Threshold-Based Denoising

In Donoho's work on noise removal in the wavelet domain, he suggests two algorithms: hard thresholding and soft thresholding [36]. While soft thresholding is generally effective, in certain applications, hard thresholding can produce superior results [28]. In fact, it is believed that hard thresholding is particularly effective when used with an undecimated wavelet transform [36]. One straightforward and efficient hard thresholding algorithm is presented in Donoho's work [28]. The algorithm can be summarized as follows:

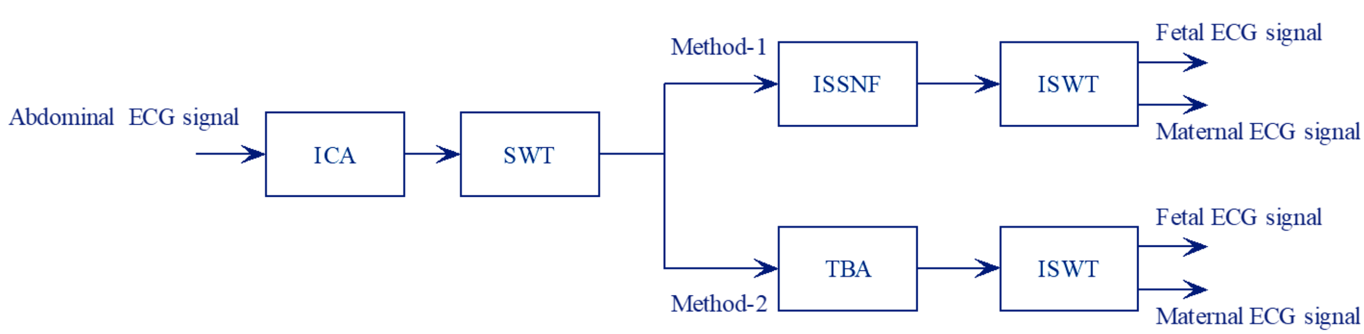

Fig. 1 Proposed system configuration. The abdominal signals are applied with ICA, followed by SWT and the denoising algorithm. Finally, the maternal and fetal ECG signals are extracted

$$\widehat{W}(g,k) = \begin{cases} W(g,k) \text{ when } W(g,k) \geq t(g) \\ 0 \quad \text{when } W(g,k) < t(g) \end{cases} \tag{13}$$

To establish the threshold for the hard thresholding algorithm, Donoho proposes using the equation $t(g) = a.\sigma_g$, where a is a constant [32]. By setting the threshold to be equal to σ, 2σ, 3σ, and so on, the algorithm can effectively suppress 68.26%, 95.44%, and 99.74% of values for i.i.d. Gaussian noise [28]. Through experimental observations, it is determined that setting $a = 2.7$ results in optimal performance for the algorithm.

2.5. Proposed System for Fetal ECG Measurement

The methodology proposed for extracting the fetal ECG signal is depicted in Figure 1. It consists of four main steps: separation of the maternal ECG signal using ICA, wavelet decomposition, artifact removal using denoising techniques, and measurement of the fetal ECG signal.

- The first step in the analysis is to load the abdominal ECG data, which is then subjected to ICA to separate the maternal and fetal ECG signals. Through this process, a noisy estimate of the MECG and FECG signals is obtained.
- Both the noisy MECG and FECG are applied with SWT, and the multiresolution components are extracted. The efficiency of various wavelets from the Matlab Wavelet Toolbox is evaluated to determine which one has the best reconstruction capability. After careful analysis, it is found that the Bior 1.5 wavelet is the most effective. A decomposition scale of 5 is chosen based on frequency characteristics to improve the reconstruction capability further.
- When using the ICA in the first step, the resulting MECG and FECG components often contain artifacts and other types of noise. It is observed that the signal components are highly correlated, while the noise components exhibit a low degree of correlation. To address this issue, spatial correlations are calculated for both the approximation and detail coefficients at each wavelet scale.
- Either the ISSNF algorithm or the TBA is used to eliminate the noise components in both MECG and FECG components.
- Once the wavelet coefficients have been processed, they are subjected to ISWT. The output of this process is MECG and FECG signal that is free from noise, which can be used to identify the R-peaks in the FECG waveform.
- The proposed methods are implemented and evaluated using three publicly available real databases and compared with other related works.

3. Results

The suggested approach employs a hybrid algorithm to measure FECG by integrating the advantages of ICA, SWT, and noise elimination methods. Two methods are employed, one utilizing ICA, SWT, and ISSNF algorithms and the other using ICA, SWT, and a threshold-based algorithm. The performance of these methods is evaluated through experiments on various databases containing clinical data. The performance of the proposed methods is compared with similar research works that use ICA and wavelet transforms. MATLAB (R2015a) is used for conducting experiments, and only abdominal signals are utilized for experimental evaluation. At least two abdominal channels are required for the experimental purpose, and two or more combinations of abdominal channels are used as inputs for performance evaluation.

To evaluate the suggested technique's effectiveness, the FECG signal's extracted waveform is divided into M segments using the R-peaks as a basis for partitioning. The SNR is then computed using Eigen value and Cross-correlation analysis methods [7]. Each signal segment has a uniform duration and encompasses a single QRS complex. The SNR calculation, utilizing Eigenvalues, follows the defined formula:

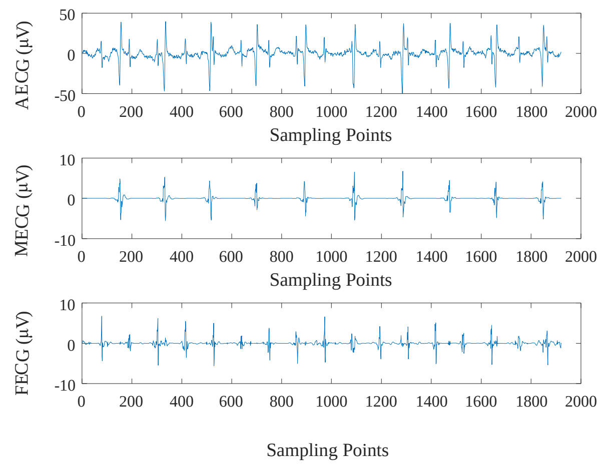

Fig. 2 The FECG extraction using ICA, SWT, and ISSNF on the DaISy database. The figure displays three waveforms arranged from top to bottom, representing 1) the AECG signal, 2) the extracted MECG signal, and 3) the extracted FECG signal

$$\mathrm{SNR}(E) = \frac{\lambda_{\max}}{\mathrm{M} - \lambda_{\max}} \tag{14}$$

The variable $\lambda_{\max}$ represents the largest Eigenvalue among the 'M' segments of signals. The performance is also evaluated using SNR utilizing cross-correlation analysis which is given by:

$$\mathrm{SNR}(C) = \frac{\mu}{1 - \mu} \tag{15}$$

Where $\mu = \frac{2}{M(\mathrm{M}-1)} \sum_{i=0}^{M-2} \sum_{k=i+1}^{M-1} x(i)^T x(k)$ and the notation $x(.)$ represents an individual signal piece.

Due to the significantly higher fetal heart rate compared to the maternal heart rate, fetal QRS complexes may overlap with maternal QRS complexes. Hence there is a potential risk of missing or losing fetal QRS points that overlap during the process of extracting the FECG signal. Furthermore, fetal heartbeats are much weaker than maternal heartbeats, making it challenging to detect fetal QRS complexes accurately. To identify overlapped fetal QRS points and eliminate misdetected fetal QRS complexes, a heuristic algorithm can be used. This algorithm compares the interval differences between successive fetal QRS complexes and identifies any differences greater than 150%, indicating overlapping fetal QRS complexes.

Conversely, if the difference is less than 45%, misdetection is possible, and the related beats can be removed. To evaluate the performance of the fetal R-peak detection algorithm, it is possible to use various statistical measures, including Sensitivity (SE), Positive Predictivity (PP), Accuracy (A), and F1 score. These measures can be used to assess how effective the algorithm is at detecting fetal R-peaks.

$$SE = \frac{TP}{TP+FN} * 100\% \tag{16}$$

$$PP = \frac{TP}{TP+FP} * 100\% \tag{17}$$

$$A = \frac{TP}{TP+FP+FN} * 100\% \tag{18}$$

$$F1 = 2\frac{PP*SE}{PP+SE} \tag{19}$$

The statistical measures require the computation of accurate positive identifications (TP), incorrect positive identifications (FP), and missed positive identifications (FN). The effectiveness of two algorithms, namely the ICA, SWT, ISSNF algorithm, and the ICA, SWT, TBA, are compared with previous research using the same databases (DaISyDB, ADFECGDB, and PNIFECGDB).

3.1. DaISy Database

In order to assess the proposed methodologies, actual data is gathered from DaISyDB, a widely recognized real open-access database organized by Lathauwer [30]. By utilizing this diverse dataset, the proposed methods can be rigorously tested and validated, providing valuable insights into their effectiveness for FECG extraction. This database comprises a total of eight recordings, including five combined AECG recordings and three thoracic ECG recordings, all acquired from a pregnant individual. The signal has a sampling frequency of 250Hz and a duration of 10 seconds. One channel is excluded from the evaluation due to its high instability. The proposed system's performance is evaluated using both quantitative and qualitative methods, including simulations and observations. Experimental results for method-1 (ICA, SWT, ISSNF algorithm) and method-2 (ICA, SWT, TBA) for DaISyDB are illustrated in Figure 2 and Figure 3, respectively.

The feasibility of the proposed methods is analysed by comparing the FECG extraction results obtained using the AECG signal as input. The extracted FECG waveforms for the first 1920 sampling points are plotted, and the R-peaks of the QRS complex are detected. When selecting the length of the signal, certain considerations are considered for stationary wavelet-based preprocessing. Specifically, the length of the signal (example, 1920) must be divisible by 2^m where the variable m denotes the wavelet decomposition level (here, m is 5 and so $2^5 = 32$, and 1920/32 = 60 is perfectly divisible). The effectiveness of the suggested methodologies is assessed by utilizing two evaluation techniques: SNR analysis based on Eigenvalues and Cross-correlation coefficients. Additionally, the performance of the proposed methods is compared with the direct application of the ICA algorithm on the same clinical data.

Upon visually comparing both illustrations, it becomes evident that Figure 3 exhibits superior signal quality compared to Figure 2 due to a noticeable noise reduction. However, when the maternal-fetal signals overlapped, the proposed method-1 produced FECG signals with a low SNR. This issue is effectively addressed by applying the proposed method-2, as highlighted by the black box in Figure 3. Table 1 presents a comparison between the ISSNF technique and TBA for denoising in terms of SNR(E) and SNR(C) for the DaISy database.

3.2. Physionet Non-invasive Fetal ECG Database

The PNIFECGDB dataset consists of 55 recordings of multichannel AECG signals obtained from a single subject during the gestational age period of 21 to 40 weeks. [31] Within the database, there are 3 to 4 abdominal channels and 2 thoracic channels available for analysis. All channels are sampled at a frequency of 1 kHz and have a resolution of 16 bits. The same set of recordings used in previous studies [2,5, 6] are utilized for fetal ECG extraction and R-peak detection analysis in the proposed system. Results of the experimental analysis conducted using method-1 (ICA, SWT, ISSNF algorithm) and method-2 (ICA, SWT, threshold-based algorithm) on PNIFECGDB are presented in Figure 4 and Figure 5, respectively.

Figure 4 shows the fetal ECG extraction results from method-1 (combining ICA, SWT, and ISSNF) using the record ‘ecgca274’ with the channel 1 AECG input signal, extracted MECG signal, and the extracted FECG signal, respectively. The results of FECG extraction using method-2 (combining ICA, SWT, and TBA) for the same record are depicted in Figure 5. The first 9600 sampling points are utilized to plot the ECG waveforms, which satisfies stationary wavelet preprocessing (where m is 5 and so $2^5 = 32$, and 9600/32 = 300 is perfectly divisible). For the proposed methodology using NIFECGDB, the qualitative and quantitative analyses are performed using visual observations and R-peak detection, respectively.

3.3. Abdominal and Direct Fetal ECG Database

In order to validate the proposed approach, the Abdominal and Direct Fetal Electrocardiogram Database (ADFECGDB)

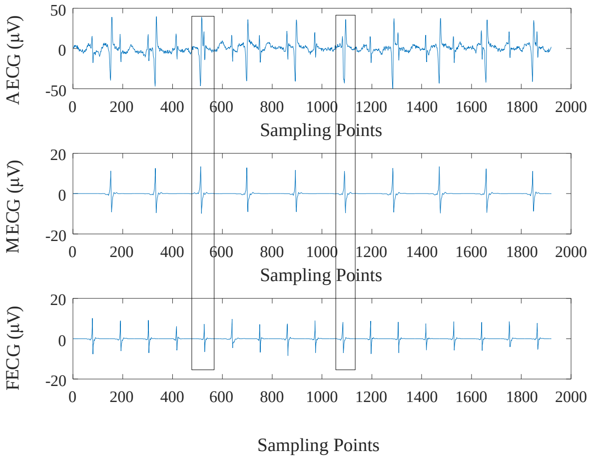

Fig. 3 The FECG extraction using ICA, SWT, and TBA on the DaISy database. The figure displays three waveforms arranged from top to bottom, representing 1) the AECG signal, 2) the extracted MECG signal, and 3) the extracted FECG signal

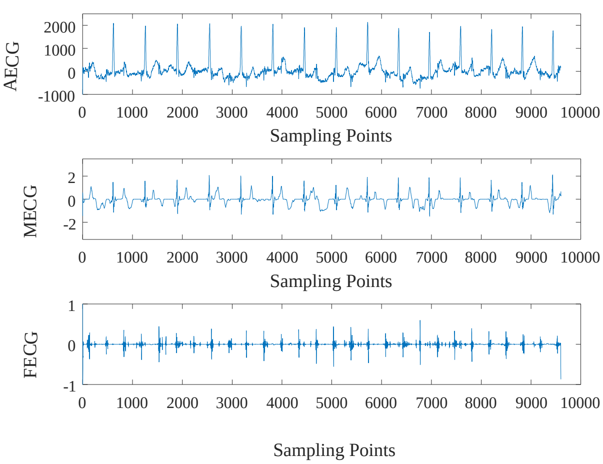

Fig. 4 The FECG extraction using ICA, SWT, and ISSNF on the record 'ecgca274'belonging to the PNIFECG database. The waveforms from top to bottom are 1) the AECG signal, 2) the extracted MECG signal, and 3) the extracted FECG signal

is employed, which is a publicly accessible clinical database [32]. The dataset used in this study comprises recordings from five pregnant women who delivered between 38-41 weeks of gestation. Each record in the database includes four signals captured from the maternal abdomen and one signal obtained from the fetal scalp. The sampling rate for these signals is 1 kHz, and they are recorded for a duration of 5 minutes.

The experimental results of FECG extraction using proposed method-1 (comprising of ICA, SWT, and ISSNF) with the record 'r01' are depicted in Figure 6. The figure displays the channel 5 AECG input signal, the extracted MECG signal, and the extracted FECG signal, respectively.

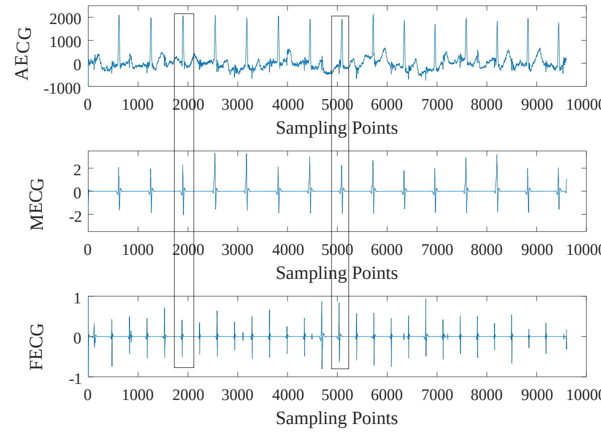

Fig. 5 The FECG extraction using ICA, SWT, and TBA on the record 'ecgca274'belonging to the PNIFECG database. The waveforms from top to bottom are 1) the AECG signal, 2) the extracted MECG signal, and 3) the extracted FECG signal.

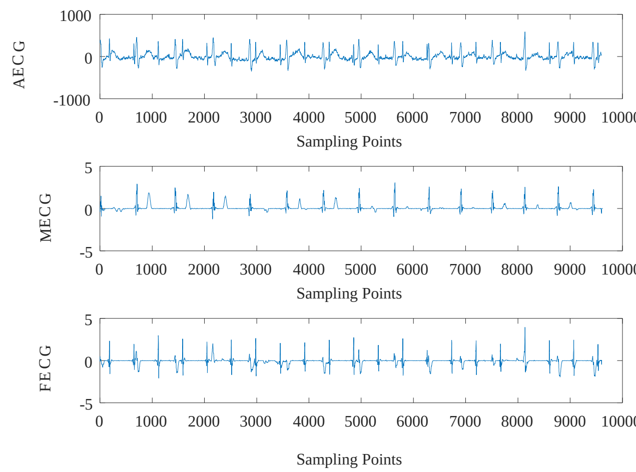

Fig. 6 ECG extraction using ICA, SWT and ISSNF on the record 'r01'belonging to the ADFECG database. The waveforms from top to bottom are 1) the abdominal ECG signal, 2) the extracted maternal ECG signal, and 3) the extracted fetal ECG signal.

Figure 7 illustrates the FECG extraction results obtained using proposed method-2 (comprising of ICA, SWT, and TBA) on the same record as in Figure 6.

The quality of FECG signals obtained through proposed method-2, as compared to method-1, is significantly better, indicating that the former method produces superior results. The effectiveness of the proposed methods is assessed by evaluating the SNR through Eigenvalue analysis and Cross-correlation analysis.

Table 2 presents a comparison of SNR(E) results for each record in the ADFECGDB when compared to a recent study. On the other hand, Table 3 showcases the SNR(E) and SNR(C) performance of the proposed methods on ADFECGDB, along with a comparison to similar research works.

Table 1. SNR performance on DaISy database

Method	SNR(E)	SNR(C)
LMS algorithm [7]	0.90	0.60
LMS+SWT+SSNF [7]	2.20	2.20
RLS+SWT+ISSNF [8]	2.60	2.55
RLS+SWT+TBA [Our work]	2.30	2.40
ICA+SWT+ISSNF [Proposed method-1]	2.75	2.62
ICA+SWT+TBA [Proposed method-2]	3.67	3.42

Table 2. SNR(E) in dB on ADFECGDB

Record	Fast ICA+SVD [21]	ICA+SWT+ISSNF (Proposed method-1)	ICA+SWT+TBA (Proposed method-2)
r01	3.19	1.15	4.78
r04	2.75	0.89	3.92
r07	5.35	2.17	5.67
r08	3.13	1.38	4.24
r10	3.26	2.13	4.09

Table 3. SNR(E) and SNR(C) performance on ADFECGDB

Method	SNR(E)	SNR(C)
Fast ICA [16]	0.99	0.59
Improved fast ICA [16]	1.55	2.02
Fast ICA+SVD [21]	2.60	2.55
ICA+SWT+ISSNF (Proposed method-1)	1.54	1.68
ICA+SWT+TBA (Proposed method-2)	4.54	4.82

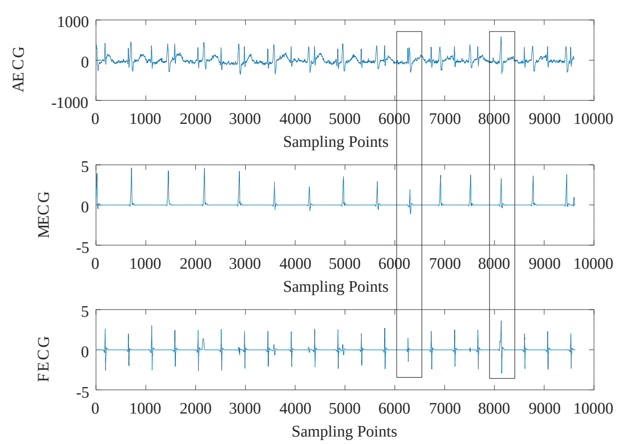

Fig.7 The FECG extraction using ICA, SWT, and TBA on the record 'r01'belonging to the ADFECG database. The waveforms from top to bottom are 1) the AECG signal, 2) the extracted MECG signal, and 3) the extracted FECG signal

4. Discussion

The experimental results using various databases indicate that algorithm-1 (which involves ICA, SWT, and ISSNF) and algorithm-2 (which involves ICA, SWT, and TBA) effectively separate MECG and noise components and extract FECG signal efficiently. The TBA-based approach, especially when combined with SWT, demonstrates superior effectiveness and efficiency compared to ISSNF. When employing only the ICA algorithm without SWT and denoising techniques, the extracted FECG still contains maternal components and disturbances.

However, the combination of ICA and SWT, along with the TBA, achieves excellent results in extracting FECG signals. While various datasets and algorithms have been employed by researchers for FECG extraction, the lack of extensive publicly available databases presents a significant limitation. Three clinical databases are used to assess the proposed methodology using method-1 and method-2. The lack of a benchmark database makes it difficult to directly compare the proposed algorithms with existing methods, as there is no standardized reference for performance evaluation.

By utilizing the DaISy database, the SNR(E) and SNR(C) performance are evaluated. Table 1 presents a comparison of the SNR results between the proposed methods and the algorithm introduced by References [7, 8] for the DaISy database. The results indicate that the proposed approach using the TBA outperforms the ISSNF algorithm, offering the additional advantage of reduced computational complexity. Table 4 presents a comparison between the R-peak detection performance of the proposed method-1 and proposed method-2 on three different databases: DaISyDB, NIFECGDB, and ADFECGDB. The statistical results presented in Table 4 indicate that the second method, using the TBA, outperforms the first method using ISSNF, for all three databases.

The DaISy database contains multiple channels of abdominal signals, with each channel comprising a total of 22 fetal cardiac beats. Different combinations of abdominal channels are used for experiments. The study examines 572 fetal beats derived from 26 abdominal input signal combinations. In the first approach, ICA, SWT, and ISSNF techniques are employed to detect these fetal heartbeats, resulting in the correct detection of 560 beats (TP), while 12 beats are missed (FN), and 4 beats are misdetected (FP). The second method uses ICA, SWT, and TBA, which detects 568 beats (TP) accurately, misses 4 beats (FN) and misdetects 2 beats (FP).

The majority of missed fetal QRS complexes are in areas where they overlap with maternal QRS complexes, and misdetection is more prevalent in areas with low SNR. Table 4 showcases the enhancements in SE, PP, A, and F1 scores achieved by the proposed method-2 when utilizing the DaISyDB.

Table 4. R peak detection analysis on three databases

Method	Database	SE	PP	A	F1
ICA+SWT+ISSNF	DaISyDB	97.90	99.29	97.22	98.59
ICA+SWT+ISSNF	NIFECGDB	97.78	98.68	96.53	98.23
ICA+SWT+ISSNF	ADFECGDB	96.54	98.67	95.30	97.59
ICA+SWT+TBA	DaISyDB	99.30	99.65	98.95	99.47
ICA+SWT+TBA	NIFECGDB	99.09	99.35	98.45	99.22
ICA+SWT+TBA	ADFECGDB	97.84	98.69	96.58	98.26

Table 5. The analysis of R-peak detection utilizing various databases.

Method	Database	SE	PP	A	F1
DWT-RI [6]	DaISy	100	91.3	91.3	-
MSF-ANC [5]	DaISy	-	91.66	84.61	-
Wavelet [2]	DaISy	98.86	100	98.86	-
PSF + ANC [17]	DaISy, PhysioNet2013	97.92	94.66	-	96.12
Fast ICA + SVD + WT [21]	ADFECGDB, PhysioNet2013	96.90	98.23	-	95.24
Conv1D+ CycleGAN [18]	ADFECGDB, NI-FECGDB	-	-	-	99.70
EEMD + RLS + ICA [14]	ADFECGDB, PhysioNet2013	95.09	96.36	-	95.69
Fast ICA [16]	ADFECGDB	99.03	98.53	-	98.78
Improved fast ICA [16]	ADFECGDB	99.37	99.00	-	99.19
RLS+SWT+ISSNF [8]	DaISy, NI-FECGDB	97.72	98.85	96.62	-
RLS+SWT+TBA (Our work)	DaISy, NI-FECGDB	98.48	98.48	97.01	-
ICA+SWT+ISSNF (Proposed method-1)	DaISy, NI-FECGDB, ADFECGDB	97.41	98.88	96.35	98.14
ICA+SWT+TBA (Proposed method-2)	DaISy, NI-FECGDB, ADFECGDB	98.74	99.23	97.99	98.98

The PNIFECGDB is also used for R-peak detection analysis, and the SE, PP, A, and F1 values obtained are presented in Table 4. The same set of 1-minute recordings from PNIFECGDB used in Ref. [2] is selected for the analysis, where 767 FQRS are manually annotated by an expert in the medical field using visual inspection techniques on the channel with the highest-quality fetal QRS appearance. The proposed method, utilizing ICA, SWT, and ISSNF, detects 750 heartbeats (TP) accurately, with 17 heartbeats missed (FN) and 10 false detections (FP). The same process is repeated for the second method using ICA, SWT, and TBA, which accurately detects 760 heartbeats (TP), misses 7 (FN), and misdetects 5 (FP). The statistical result presented in Table 4 indicates that the second method, using the threshold-based algorithm, outperforms the first method using ISSNF for the PNIFECGDB database.

In this research, the effectiveness of the suggested techniques for extracting fetal ECG signals is assessed by examining each record within the ADFECGDB. Additionally, the proposed algorithm's performance is compared to that of the Fast ICA and SVD algorithms utilized in a prior study (referenced as [21]). The SNRs for each record, as determined by Eigenvalue analysis, are presented in Table 2. Furthermore, Table 3 offers a comparative analysis of SNR performance, utilizing both Eigen value coefficients and Cross-correlation coefficients, compared to previous research conducted on the same database. Different combinations of abdominal input signals are used for experiments. The study examines 231 fetal beats derived from 11 abdominal channel combinations.

In the first approach, ICA, SWT, and ISSNF techniques are employed to detect these fetal heartbeats, resulting in the correct detection of 224 beats (TP), while 7 beats are missed (FN), and 3 beats are misdetected (FP). The second method uses ICA, SWT, and TBA, which detects 228 beats (TP) accurately, misses 3 beats (FN) and misdetects 2 beats (FP). To evaluate the detection of fetal ECG signals in the ADFECGDB, the signals from the fetal head are used as a reference standard for calculation purposes. The calculated parameters include SE, PP, A, and the F1 score. The results are shown in Table 4. The second method also demonstrates superior performance compared to the first method for the ADFECGDB.

Table 5 presents a comparison between the R-peak detection performance of the proposed algorithms and state-of-the-art methods on three different databases: DaISyDB, NIFECGDB, and ADFECGDB. The table displays the mean SE, PP, A, and F1 scores, calculated based on the FECG extracted from the MECG for each of the three datasets. The obtained results indicate that the proposed method-2 achieves comparable outcomes to state-of-the-art methods while offering the advantage of reduced computational complexity. This means that it can deliver similar performance to the existing advanced techniques while requiring fewer computational resources. By striking a balance between effectiveness and efficiency, the proposed method-2 provides a promising solution for FECG signal extraction, enabling practical implementation in real-world scenarios.

5. Conclusion

In order to estimate the fetal heart rate, the research introduces a hybrid ICA-based filtering technique that combines SWT with two denoising algorithms. Two methods are proposed: method-1, which uses ICA, SWT, and the ISSNF algorithm, and method-2, which uses ICA, SWT, and the TBA. The fetal and maternal components of the AECG signals are separated using ICA processing. The SWT is then used to apply to the MECG and FECG components that are still impacted by noise.

Even when MECG and FECG signals overlap in the wavelet domain, ISSNF and TBA techniques efficiently estimate fetal heartbeats. Calculating SNR and looking for R-peaks allows for quantitative analysis of the experimental results. While FECG extraction using the ISSNF and TBA approaches both works well, the threshold-based approach exhibits improved R-peak detection and lower computational cost. The suggested approaches' SNR performance in real-time scenarios is a considerable advantage, proven using clinical data. Future studies will confirm the suggested approach through the use of more clinical data, with the ultimate goal of employing the proposed methodology to diagnose aberrant heart rate activity during pregnancy.

References

[1] A.S.A. Huque et al., “HMM-based Supervised Machine Learning Framework for the Detection of fECG R-R Peak Locations,” *IRBM*, vol. 40, no. 3, pp. 157-166, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[2] E. Castillo et al., “Efficient Wavelet-based ECG Processing for Single-lead FHR Extraction,” *Digit Signal Processing*, vol. 23, no. 6, pp. 1897-1909, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[3] Peter Van Leeuwen et al., “Fetal Electrocardiographic Measurements in the Assessment of Fetal Heart Rate Variability in the Antepartum Period,” *Physiological Measurement*, vol. 35, no. 3, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[4] Reza Sameni, and Gari D. Clifford, “A Review of Fetal ECG Signal Processing; Issues and Promising Directions,” *Open Pacing Electrophysiology Journal*, vol. 3, pp. 4-20, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[5] Jaba Deva Krupa Abel et al., “Multiple Sub-filter Adaptive Noise Canceller for Fetal ECG Extraction,” *Procedia Computer Science*, vol. 165, pp. 182-188, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Bahaa Al-Sheikh et al., “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. [CrossRef] [Google Scholar] [Publisher Link]

[7] Shuicai Wu et al., “Research of Fetal ECG Extraction using Wavelet Analysis,” *Computers in Biology and Medicine*, vol. 43, no. 10, pp. 1622-1627, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[8] P. Darsana, and Vaegae Naveen Kumar, “A Quantitative and Qualitative Research on Fetal ECG extraction using Wavelet based Adaptive Filtering,” *2022 International Conference on Computing, Communication, Security and Intelligent Systems*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Fahimeh Jamshidian-Tehrani, and Reza Sameni, “Fetal ECG Extraction from Time-varying and Low-rank Noninvasive Maternal Abdominal Recordings,” *Physiological Measurement*, vol. 39, no. 12, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] Rachel Hall-Clifford et al., “An Open-source Autocorrelation-based Method for Fetal Heart Rate Estimation from One-Dimensional Doppler Ultrasound,” *Physiological Measurement*, vol. 40, no. 2, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ruilin Li, Martin G. Frasch, and Hau-Tieng Wu, “Efficient Fetal-maternal ECG Signal Separation from Two Channel Maternal Abdominal ECG Via Diffusion-based Channel Selection,” *Frontiers in Physiology*, vol. 8, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] Mahesh B. Dembrani, K.B. Khanchandani, and Anita Zurani, “Extraction of FECG Signal based on Blind Source Separation using Principal Component Analysis,” *Progress in Intelligent Computing Techniques: Theory, Practice, and Applications*, pp. 173–180, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] S.V. Vinoth, and S. Kumarganesh, “Fetal ECG Extraction using LMS Filter,” *SSRG International Journal of Electronics and Communication Engineering*, vol. 3, no. 11, pp. 3-5, 2016. [CrossRef] [Publisher Link]

[14] Katerina Barnova et al., “A Novel Algorithm based on Ensemble Empirical Mode Decomposition for Non-invasive Fetal ECG Extraction,” *PLoS ONE*, vol. 16, no. 8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[15] Sadaf Sarafan et al., “Investigation of Methods to Extract Fetal Electrocardiogram from the Mother’s Abdominal Signal in Practical Scenarios,” *Technologies*, vol. 8, no. 2, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Li Yuan et al., “An Improved FastICA Method for Fetal ECG Extraction,” *Computational and Mathematical Methods in Medicine*, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[17] Abel Jaba Deva Krupa, Samiappan Dhanalakshmi, and R. Kumar, “An Improved Parallel Sub-filter Adaptive Noise Canceler for the Extraction of Fetal ECG,” *Biomedical Engineering*, vol. 66, no. 5, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[18] Samson D. Yusuf et al., “Analysis of Butterworth Filter for Electrocardiogram De-Noising using Daubechies Wavelets,” *SSRG International Journal of Electronics and Communication Engineering*, vol. 7, no. 4, pp. 8-13, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[19] Kwang Jin Lee, and Boreom Lee, “End-to-end Deep Learning Architecture for Separating Maternal and Fetal ECGS using W-net,” *IEEE Access*, vol. 10, pp. 39782-39788, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[20] Abdel Salam Malek et al., “Automated Detection of Premature Ventricular Contraction in ECG Signals using Enhanced Template Matching Algorithm,” *Biomedical Physics and Engineering Express*, vol. 6, no. 1, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[21] Jingyu Hao et al., “Fetal Electrocardiogram Signal Extraction Based on Fast Independent Component Analysis and Singular Value Decomposition,” *Sensors*, vol. 22, no. 10, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[22] Jonathon Shlens, “A Tutorial on Independent Component Analysis,” *arXiv preprint*, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[23] A. Hyvärinen, “Fast and Robust Fixed-point Algorithms for Independent Component Analysis,” *IEEE Transactions on Neural Networks*, vol. 10, no. 3, pp. 626-634, 1999. [CrossRef] [Google Scholar] [Publisher Link]
[24] A.D. Sheena, “Seismic Noise Removal and its Applications – A Review of Exploring Wavelet Transform in Civil Engineering,” *SSRG International Journal of Civil Engineering*, vol. 4, no. 12, pp. 1-6, 2017. [CrossRef] [Publisher Link]
[25] G.P. Nason, and B.W. Silverman, “The Stationary Wavelet Transform and Some Statistical Applications,” *Lecture Notes in Statistics*, vol. 103, pp. 281-299, 1995. [CrossRef] [Google Scholar] [Publisher Link]
[26] Ashish Kumar et al., “Stationary Wavelet Transform based ECG Signal denoising Method,” *ISA Transactions*, vol. 114, pp. 251-262, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[27] Yansun Xu et al., “Wavelet Transform Domain Filters: A Spatially Selective Noise Filtration Technique,” *IEEE Transactions on Image Processing*, vol. 3, no. 6, pp. 747–758, 1994. [CrossRef] [Google Scholar] [Publisher Link]
[28] Quan Pan et al., “Two Denoising Methods by Wavelet Transform,” *IEEE Transactions on Image Processing*, vol. 47, no. 12, pp. 3401-3406, 1999. [CrossRef] [Google Scholar] [Publisher Link]
[29] Shubham Srivastava et al., “ECG Pattern Analysis Using Artificial Neural Network,” *SSRG International Journal of Electronics and Communication Engineering*, vol. 7, no. 5, pp. 1-4, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[30] B. De Moor et al., “DAISY: A Database for Identification of Systems,” *Journal A*, vol. 38, no. 4, 1997. [Google Scholar] [Publisher Link]
[31] Ary L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals,” *Circulation*, vol. 101, no. 23, pp. e215-e220, 2000. [CrossRef] [Google Scholar] [Publisher Link]
[32] Abdominal and Direct FECG Database. [Online]. Available: https://physionet.org/physiobank/database/adfecgdb
[33] Radek Martinek et al., “Comparative Effectiveness of ICA and PCA in Extraction of Fetal ECG from Abdominal Signals: Toward Non-Invasivefetalmonitoring,” *Frontiers in Physiology*, vol. 9, 2018. [CrossRef] [Google Scholar] [Publisher Link]
[34] Mohammad Reza Mohebbian et al., “Fetal ECG Extraction from Maternal ECG using Attention-based CycleGAN,” *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 2, pp. 515-526, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[35] 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. [CrossRef] [Google Scholar] [Publisher Link]
[36] D.L. Donoho, “De-noising by Soft-threshoding,” *IEEE Transactions on Information Theory*, vol. 41, no. 3, pp. 617–627, 1995. [CrossRef] [Google Scholar] [Publisher Link]