IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 July 2023, accepted 19 August 2023, date of publication 24 August 2023, date of current version 30 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3308409

RESEARCH ARTICLE

Extracting Fetal ECG Signals Through a Hybrid Technique Utilizing Two Wavelet-Based Denoising Algorithms

P. DARSANA AND VAEGAE NAVEEN KUMAR, (Senior Member, IEEE)

School of Electronics Engineering, Vellore Institute of Technology, Vellore, Tamilnadu 632014, India

Corresponding author: Vaegae Naveen Kumar (vegenaveen@vit.ac.in)

This work was supported by the Vellore Institute of Technology, Vellore, India.

ABSTRACT Developing an intelligent technique for fetal heartbeat detection to monitor the cardiac function of the fetus in the initial stages of pregnancy is crucial. In this research work, two hybrid algorithms are proposed that use a combination of recursive least square algorithm (RLS) and stationary wavelet transform (SWT) for fetal ECG extraction. The goal of this research is to enhance the fetal ECG signal, reduce noise and artifact, and accurately detect the R-peaks by employing improved spatially selective noise filtration (ISSNF) method or threshold-based denoising approach in the wavelet domain. Accurate fetal R-peak detection can provide important clinical information and aid in the diagnosis and treatment of fetal heart conditions. The primary aim is to extract a clear fetal ECG signal from the mixed abdominal signal. The abdominal signal is divided into multiscale components using SWT, with different levels of noise determining the scale of wavelet decomposition. The RLS algorithm is then utilized for removing maternal ECG components, and either ISSNF or threshold-based algorithms are employed for denoising in the wavelet domain. We evaluate the effectiveness of our proposed method using both synthetic and clinical data. Our analysis involves qualitative and quantitative measures, including visual inspection, signal-to-noise ratio (SNR) computation, and QRS complex recognition. Our findings reveal that the proposed system exhibits superior performance when compared to conventional adaptive filtering techniques. The experimental results suggest that the proposed system has the potential to extract fetal ECG signals that are clear, with good SNR results and minimal disturbances.

INDEX TERMS ECG extraction, fetal ECG, improved spatially selective noise filtration, recursive least square algorithm, stationary wavelet transforms, threshold-based algorithm.

I. INTRODUCTION

There are two primary approaches to measuring the fetal electrocardiogram (ECG): invasive and non-invasive techniques. When obtaining an abdominal ECG measurement, two types of signals are detected: maternal ECG signals and fetal ECG signals [1]. Invasive fetal ECG extraction is performed during delivery by placing electrodes on the fetal scalp when the cervix is dilated. In contrast, it is possible to conduct a non-invasive measurement of the fetal ECG during the initial phase of pregnancy by attaching electrodes to the mother's abdominal area. One of the main challenges a fetal ECG measurement system has to face is the presence of unwanted interferences such as power line noise, noise due to electrode-skin contact, and muscle noise. Doctors can obtain an accurate diagnosis of the fetal heart's health and closely monitor it by processing the extracted fetal ECG signal. This helps in identifying medical conditions like congenital heart abnormalities, slow heart rate, fast heart rate, and oxygen deprivation. Existing fetal ECG extraction techniques can be categorized as linear or nonlinear and adaptive filtering techniques [2].

In the linear decomposition approach, fixed basis functions or data-driven basis functions are used to decompose the

The associate editor coordinating the review of this manuscript and approving it for publication was Gang Wang.

signal into different components. The time, frequency, and scale characteristics of the fetal ECG waveform determine the selection of basis functions. Singular value decomposition (SVD) can be used as a data-driven decomposition technique [3], [4], [5]. In this method, the basis functions are derived from the data itself using some statistical measures. The composite abdominal ECG signal can be used to measure the electrical impulses of the fetal heart through a popular method called blind source separation (BSS) [6], [7], [8]. Independent component analysis (ICA) is a subsection of BSS with the key assumption that the underlying signals are independent [9]. A novel technique to speed up the traditional ICA is proposed [10]. In another approach, periodic component analysis (πCA) which is a form of semi-blind source separation is proposed [11]. Generally, the fetal ECG waveform contaminated with different types of noises is not always linearly separable. The limited performance of linear decomposition methods can be replaced with nonlinear transforms [12]. The proposed techniques involve utilizing the noisy signal along with its time-shifted duplicates to generate a state space representation of the signal. The trajectory of the state space is then smoothed by employing conventional or principal component analysis (PCA) filters. One of the key advantages of this approach is that it requires only a single maternal abdominal channel reading. Additionally, the selection of time delay required for generating the phase space representation is determined empirically, which may contribute to the smoothing of the state space trajectory. Thus, significant inter-beat variations can be erased in the cardiac signals. Increased computational complexity is another disadvantage when compared with linear methods.

Adaptive filtering is a widely used method for fetal heart rate measurement from the mixed abdominal signal. However, its traditional methods typically need a reference maternal ECG or linearly independent channels to reconstruct the ECG's morphology from the references [13], [14]. But with successive cancellation techniques, direct training for fetal ECG extraction without a reference signal is possible, although the resulting fetal ECG signal may still contain the mother's ECG signal and other artifacts [15]. Wavelet transforms (WT) have been recognized as a promising technique for extracting fetal ECG signals, and various techniques have been developed using this method [16], [17]. An extended Kalman smoother framework has also been proposed for extracting fetal ECG from a single-channel abdominal signal, but it has the limitation of not being able to separate the fetal ECG signal when it overlaps with the maternal ECG signal [18], [19]. Additionally, dynamic adjustment of thresholds on the wavelet coefficients is necessary for effective denoising using this approach [20].

Extracting the fetal ECG from abdominal recordings is a challenging task, as the fetal ECG is often buried in a high level of noise caused by the maternal ECG, movement artifacts, and other sources of interference. To improve the quality of the fetal ECG signal and remove unwanted noise,

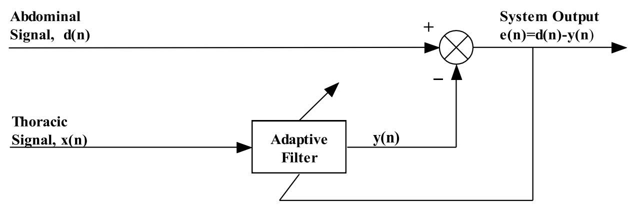


FIGURE 1. Adaptive filtering configuration. The abdominal signal is continuously compared with the maternal thoracic reference signal. Finally, the error signal contains the noisy fetal ECG signal.

various techniques can be used. One promising method in adaptive filtering for noise removal is the Kalman filtering (KF) technique [21]. To extract the fetal ECG from a mixed signal, an extended state KF method is proposed and demonstrates better experimental results than the previously introduced KF algorithm [22]. Additionally, a study compares various single-channel fetal ECG extraction methods and the performance evaluation is done both qualitatively and quantitatively [23]. A new approach of adaptive filtering technique is introduced for detecting fetal QRS complex from the maternal abdominal ECG signal [24]. Recent work proposes an adaptive noise canceller with multiple sub-filters for fetal ECG Extraction [25]. After conducting a detailed study, it has been concluded that using multiple approaches to create hybrid systems to achieve accurate fetal heart rate estimation may offer the most promising approach [26]. However, fetal ECG signals are often noisy and contaminated with various artifacts, which can make R-peak detection challenging. The investigation of the stationary wavelet transform (SWT) in signal processing is of significant importance in various applications, including fetal ECG extraction [27]. SWT offers the capability to analyze non-stationary signals with time-varying frequency content, making it suitable for extracting the fetal ECG signal from complex abdominal recordings. By exploring the potential of SWT in fetal ECG extraction, our research contributes to the understanding and utilization of this valuable signal processing tool in the specific context of prenatal monitoring and diagnosis.

In recent years, there has been extensive utilization of deep learning architectures, specifically convolutional neural networks (CNNs), in fetal ECG extraction methods [28], [29], [30]. Ting et al. [28] obtain the maternal ECG signals from multiple electrodes placed on the mother's abdomen. These signals are transformed into a spectrogram using the short-time Fourier transform and fed into a 2D CNN for fetal heart rate detection. However, this method necessitates the use of at least four channels to extract maternal ECG signals, which complicates the measurement process by requiring multiple electrodes to be attached to the mother's abdomen. Fotiadou et al. [29] successfully employ an encoder-decoder CNN architecture to denoise a single-channel fetal ECG.

However, extracting the fetal ECG directly from only the maternal ECG is challenging. AECG-DecomposeNet utilizes a two U-net architecture in series, where one is dedicated to extracting the maternal ECG and removing it from the abdominal ECG, and the other focuses on effectively extracting the fetal ECG [30]. However, the drawback of this method is its reliance on two separate networks. Building and training artificial intelligence (AI) and machine learning (ML) models for fetal ECG extraction can be complex and time-consuming. Fetal ECG signals can exhibit significant variations in morphology, noise levels, and maternal-fetal coupling. AI and ML models trained on specific datasets may struggle to generalize well to unseen data with different characteristics. Some AI and ML algorithms may have high computational requirements, making real-time processing challenging. The use of AI and ML algorithms in medical applications raises ethical and legal concerns. Issues such as privacy, data security, and the potential impact of algorithmic decisions on patient care need to be carefully addressed to ensure responsible and ethical use of these technologies.

This paper proposes a hybrid approach for fetal ECG extraction that utilizes the recursive least square (RLS) adaptive algorithm and SWT. Improved spatially selective noise filtration (ISSNF) or threshold-based algorithms are utilized to enhance the fetal ECG extraction process and improve the signal-to-noise ratio. Our research focuses on the development of a methodology for fetal ECG extraction using two distinct approaches: the combination of RLS, SWT, and ISSNF algorithm, and the combination of RLS, SWT, and a threshold-based algorithm. The purpose of our study is to address the challenges associated with extracting the fetal ECG signal from abdominal recordings by leveraging the advantages of wavelet transformation and adaptive filtering techniques. WT based adaptive filtering combines the benefits of time-frequency analysis, adaptability, and multiresolution analysis to enhance fetal ECG extraction. It provides a robust and efficient approach for isolating and extracting the fetal ECG components from noisy maternal ECG signals. SWT has gained significant popularity in recent times, especially in the fields of ECG denoising and biomedical signal processing applications [31], [32], [33]. This advanced technique is being widely used due to its effectiveness in extracting fetal ECG signals and its application in various medical signal analysis tasks. In simpler terms, the stationary wavelet transform is a powerful method that allows us to analyze and process biomedical signals, particularly those related to fetal ECGs [34]. It enables us to separate and extract relevant information from complex signals, providing valuable insights for medical professionals and researchers. Overall, the stationary wavelet transform has emerged as a significant tool in the field of biomedical signal processing, offering enhanced capabilities for the extraction of fetal ECGs and facilitating crucial advancements in healthcare and medical research.

Our preliminary findings from research work, utilizing wavelet-based RLS adaptive filtering, are presented and discussed at a conference [35]. We have since modified our proposed algorithm by incorporating a threshold-based denoising algorithm, which has led to improved R-peak detection accuracy. To further validate our approach, we have expanded our database to include more real-world data. The proposed system decomposes both the abdominal and thoracic signals into wavelet coefficients using SWT to obtain finer details. The RLS algorithm is then applied to remove maternal ECG components, followed by denoising using either the ISSNF algorithm or the threshold-based algorithm in the wavelet domain. Finally, the inverse stationary wavelet transform (ISWT) is applied to reconstruct the fetal ECG signal. To assess the effectiveness of our proposed method, we evaluate both synthetic and clinical data using qualitative and quantitative measures. These measures include visual inspection, computation of the signal-to-noise ratio (SNR), and recognition of the QRS complex. Our proposed methodology offers a novel approach to fetal ECG extraction, addressing the limitations of existing techniques and providing potential improvements in prenatal healthcare.

II. MATERIALS AND METHODS

The proposed methodology in this paper utilizes a combination of RLS adaptive filtering and WT techniques for fetal ECG extraction from abdominal signals. Specifically, SWT is applied to both the abdominal ECG signal and maternal thoracic ECG signal. To enhance the signal-to-noise ratio performance, various signal processing techniques can be used, such as ISSNF and threshold-based methods. This approach offers a promising direction for fetal ECG extraction.

A. ADAPTIVE FILTERING ALGORITHM

Adaptive filtering is a widely used technique to denoise and extract fetal ECG from the abdominal signal, as shown in Fig. 1. The structure of the adaptive filter includes two inputs, namely the composite abdominal signal, which functions as the primary input, and the thoracic signal, which serves as the reference input. The abdominal signal comprises a blend of maternal ECG and fetal ECG, which is contaminated by multiple forms of interference. Through the continuous modification of weight vectors using the feedback signal, the adaptive filter can produce an output that is more closely aligned with the maternal aspects of the abdominal signal, leading to the elimination of maternal components and enabling the extraction of fetal ECG components. In this context, the RLS algorithm is utilized for adaptive filtering, with the weight updating equation of the RLS algorithm constituted in the following form [23].

$$w(n) = w(n-1) + e^{*}(n)k(n) \tag{1}$$

where $w(n)$ is the adaptive filter weight vector at iteration n and $k(n)$ is the gain vector given by:

$$k(n) = \frac{P(n-1)x(n)}{\Delta + x^{H}(n)P(n-1)x(n)} \tag{2}$$

where $P(n)$ is the inverse correlation matrix of the input signal and Δ is the forgetting factor. The initial value of the correlation matrix can be defined as $P(0) = \delta^{-1}I$ where δ and I are the regularization parameter and identity matrix respectively. The correlation matrix update is given by:

$$P(n) = \Delta^{-1}P(n-1) - \Delta^{-1}k(n)x^H(n)P(n-1) \tag{3}$$

Hence the output $y(n)$ in RLS adaptive filter and the error signal $e(n)$ are as follows:

$$y(n) = w^H(n-1)x(n) \tag{4}$$

$$e(n) = d(n) - y(n) \tag{5}$$

The adaptive filtering-based approach has a major limitation, which is its reliance on the reference maternal thoracic ECG signal. The accuracy of fetal heartbeat beat estimation is directly impacted by the quality of this reference signal. In the design of an RLS-based adaptive system, the selection of filter parameters is crucial. Parameters such as the forgetting factor (Δ) and filter length must be carefully chosen. The forgetting factor ranges from 0 to 1, with lower values emphasizing recent data and a Δ value of 1 guaranteeing equal contribution from all past data. Increasing the forgetting factor improves the extraction results but also increases computational complexity [23]. The filter length in an adaptive system is determined by the sampling rate of the input signal. This filter length is directly related to the number of coefficients and the computational cost required for the system. RLS adaptive algorithm outperforms other adaptive algorithms in terms of both convergence speed and filtration quality. Adaptive filters can be sensitive to signal artifacts, such as baseline wander, electrode movement, or muscle interference in fetal ECG extraction. These artifacts can affect the adaptation process, leading to inaccurate or distorted fetal ECG measurement. Moreover, the interference from these artifacts can also impact the SNR results. Additional preprocessing techniques or noise reduction methods may be required to enhance the performance of adaptive filters in noisy environments.

B. STATIONARY WAVELET TRANSFORM

The use of wavelet transform (WT) has emerged as a robust computational technique for processing biomedical signals and its various applications. The utilization of WT for ECG denoising is widespread [27], [36]. Wavelet transformation offers several advantages that make it suitable for analyzing non-stationary and transient signals, such as the fetal ECG. Firstly, the wavelet transformation allows for a multiresolution analysis, enabling the identification and extraction of both low-frequency trends and high-frequency components present in the fetal ECG signal. This adaptability to different frequency scales is crucial in fetal ECG analysis, as it permits the identification of fetal cardiac activity amidst the complex and overlapping maternal and noise components. Secondly, the SWT specifically employed in our methodology provides the advantage of offering a precise time-frequency representation. This enables the identification and localization of transient features in the fetal ECG signal, which is valuable for accurate R-peak detection and subsequent analysis. Thirdly, the wavelet domain provides an effective platform for denoising the fetal ECG signal. By applying the RLS algorithm in the wavelet domain, we can exploit the sparsity and energy concentration properties of the fetal ECG to enhance its extraction and denoise the signal effectively.

Careful selection of the following parameters is crucial for the effective implementation of wavelet-based ECG denoising technique: 1) optimal wavelet selection, 2) the suitable decomposition level, and 3) the appropriate noise removal algorithm. In this paper fetal ECG extraction and recognition of fetal heartbeats are done in the wavelet domain using SWT and RLS algorithms. SWT is an undecimated wavelet transform. The characteristic of translational invariance makes SWT superior to discrete wavelet transform (DWT) [37]. Choosing the best wavelet function from a set of orthogonal and bi-orthogonal wavelets belonging to the wavelet family depends on several characteristics including reconstruction ability, energy preservation, and symmetry [36]. The optimal wavelet function is the one which gives highest output signal to noise ratio. Based on experimental experience, the Bior 1.5 wavelet, which is a member of the wavelet family, is specifically chosen due to its superior reconstruction ability.

The SWT based approach is simple, reliable and gives a satisfactory performance. The abdominal and the thoracic signals are decomposed into a collection of approximation coefficients and detail coefficients using the wavelet function $\Phi(n)$ and scaling function $\Psi(n)$ in a similar manner to DWT, within the SWT technique. In DWT, the decomposition at level i gives the approximation coefficients, A^i and the detail coefficients, D^i. A^0 is the original signal where h and l are high pass and low pass filters respectively.

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

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

In SWT decomposition, the approximation coefficients and the detail coefficients are A^i_ε and D^i_ε respectively. The value of ε in DWT is invariably 0, however in SWT, $\varepsilon = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n]$, [33]. l^i and h^i are low pass and high pass filters respectively such that $l^i \uparrow 2 = l^{i+1}$ and $h^i \uparrow 2 = h^{i+1}$.

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

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

In DWT, the original signal length is down sampled at every decomposition level whereas in SWT, the down sampling operation is absent and the signal length is maintained at every stage. The approximation and detail coefficients at a specific level of wavelet decomposition are obtained through a convolution operation. This involves up sampling the coefficients of the low-pass and high-pass filters and convolving them with the approximation coefficients from the previous level. Thus, the translational invariance property is obtained by maintaining the signal length at N. The performance of the hybrid approach we develop between RLS algorithm and SWT can be improved with either ISSNF method or threshold-based noise removal algorithms in the wavelet domain. Thus, the high level of noise caused by the maternal ECG, movement artifacts, and other sources of interference can be removed and fetal ECG signals can be extracted efficiently.

C. IMPROVED SPATIALLY SELECTIVE NOISE FILTRATION TECHNIQUE

To approach the fetal ECG extraction process systematically, we need to establish an efficient denoising algorithm within the domain of wavelet analysis. This algorithm is known as spatially selective noise filtration technique (SSNF). SSNF is particularly useful in biomedical signal processing because it can remove noise while preserving important features of the signal, such as the shape of the waveform, the amplitude, and the frequency content [39]. Moreover, it can be used to remove different types of noise, including baseline wander, powerline interference, and muscle artifacts.

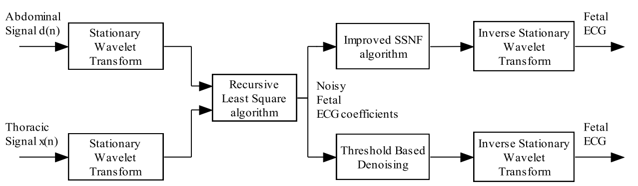


FIGURE 2. Proposed methodology for fetal ECG extraction. Abdominal and thoracic signals are processed in the wavelet domain using RLS algorithm. Then either ISSNF or threshold based denoising techniques are applied. Finally, ISWT is applied to get the noise free fetal ECG signal.

To enhance the signal-to-noise ratio (SNR) results, an enhanced version of conventional SSNF algorithm is utilized [40]. This algorithm is known as improved spatially selective noise filtration technique (ISSNF). The algorithm works by calculating the spatial correlation $Cor_R(g,k)$ between signal components for every wavelet scale, g. The signal components exhibit a high degree of correlation, while the noise components have a low degree of correlation.

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

The following steps constitutes the ISSNF algorithm:

1) For accurate extraction of edges from coarse scale components to fine scale components, it is essential to select $\lambda(g)$ and $th(g)$ parameters in advance with precision. The selection of parameters $\lambda(g)$ and $th(g)$ are explained below.
2) Determine the correlation $Cor_2(g,k)$ among signal components for every level of 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:

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

4) The component values in $NorCor_2(g,k)$ and $W(g,k)$ are compared. If $|NorCor_2(g,k) \geq \lambda(g) * W(g,k)|$, 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 on a continuous basis leading to the power of unextracted pixel values are almost equal to some reference 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 a reference noise power at the g^{th} wavelet decomposition level. After M data points have been extracted, calculate the variance of noise power, σ_g^2. Then iterate this process until

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

Finally, all the signal components are extracted from the original noisy data and saved in the new data vector $W_{new}(g,k)$. Specifically, the choice of thresholding method has a major influence on the SNR performance. How to choose the parameters $\lambda(g)$ and $th(g)$ are discussed as follows. The reference noise power $(N-M)\sigma_g^2$ is multiplied by a factor $th(g)$ at coarse scales where $h(g) \geq 1$. For different signals, $th(g)$ should vary. However, we can choose a common $th(g)$ as general case since the filtering results are not sensitive to $th(g)$. According to [40], we can choose $th(1) = 1.1 - 1.2$, $th(2) = 1.2 - 1.4$, $th(3) = 1.4 - 1.6$, and $th(g) = 1.6 - 1.8$ when $g \geq 4$. This way, any of these combinations satisfies a priori the requirements for denoising in fetal ECG extraction. Thus, the most appropriate parameters are selected based on visual inspection of the extracted signals, which in some cases is even more decisive than quantitative measures. This makes sure that after denoising, the amplitude of the fetal QRS complexes will not be decreased too much. These considerations enable us 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 [40]. Based on several experiments for a wide range of fetal ECG signals, we choose $\lambda(g) = [1.15, 1.06, 1, 1, 1]$. The ISSNF algorithm is followed by ISWT and the fetal ECG signal can be extracted in the time domain.

D. THRESHOLD-BASED ALGORITHM

Donoho proposes hard thresholding and soft thresholding algorithms for noise removal in the wavelet domain [41]. Even though soft thresholding algorithms performs satisfactorily, hard thresholding gives better results in some applications [40], [42]. It is proposed that hard thresholding gives better results with undecimated wavelet transform [43].

A simple and efficient hard thresholding algorithm is proposed [40]. The algorithm is as follows:

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

The threshold is $t(g) = a.\sigma_g$, where a is a constant. A threshold $t = \sigma, 2\sigma, 3\sigma, \ldots$ will suppress 68.26%, 95.44%, and 99.74% of values for i.i.d. Gaussian noise [40]. Based on experimental experience, we select $a = 2.7$ and that gives good results.

E. PROPOSED SYSTEM FOR FETAL ECG EXTRACTION

Our study aims to explore mainly two hybrid approaches for the extraction of the fetal ECG signal, considering the complexity and variability of the data. By proposing two distinct approaches, we aim to provide a comprehensive analysis and comparison of their performance. Thus, the proposed methodology presents two combinations: the first method being RLS, SWT, and ISSNF algorithm, and the second method being RLS, SWT, and threshold-based algorithm. Fig. 2. illustrates the proposed methodology for the two methods to extract the fetal ECG signal, where each method involves four primary steps: multi resolution decomposition, maternal ECG cancellation, denoising technique for artifacts removal (either ISSNF or threshold-based algorithm), and the fetal ECG measurement. The procedure is as follows:

(1) In each method, the multiresolution components of both the abdominal and thoracic signals are extracted by applying the SWT. Different wavelets from the Matlab Wavelet Toolbox are employed to evaluate their efficiency at various parameters, and after careful analysis, the Bior 1.5 wavelet is found to exhibit the best reconstruction capability. In light of the frequency characteristics, a decomposition scale of 5 is selected.

(2) After transforming into the wavelet domain, both the approximation coefficients and detail coefficients are subjected to the RLS adaptive algorithm in each method. The coefficients of the abdominal signal act as the primary input to the adaptive filter, while those of the thoracic signal serve as the reference input. By effectively subtracting the maternal ECG signals from the composite abdominal ECG signal, the adaptive filter allows for the extraction of the fetal ECG signal.

(3) The RLS based adaptive filtering technique in the wavelet domain results in fetal ECG components containing various artifacts and other noises. The level of correlation among signal components is notably high, while the degree of correlation among noise components is considerably low. So, at each wavelet scale, spatial correlations are computed for both the approximation and detail coefficients in each method.

(4) The noise components are eliminated by ISSNF algorithm in method-1 and threshold-based algorithm in method-2.

(5) After processing the wavelet coefficients, they are applied with ISWT in both methods. The resulting signal is a noise-free fetal ECG signal, which can be used to determine R-peaks in the fetal ECG waveform.

III. EXPERIMENTAL RESULTS

The ability to monitor the fetal heartbeats throughout the time of pregnancy is crucial for early detection of potential cardiac issues in the fetus. Our study on fetal ECG measurement technique using RLS based hybrid approach is motivated by the desire to combine the simplicity of adaptive filtering with the benefits of wavelet transforms and noise removal techniques. In this context, we employ a hybrid approach combining RLS, SWT and noise removal algorithms. The first method involves utilizing the RLS, SWT, and ISSNF algorithms, while the second method involves using RLS, SWT, and a threshold-based algorithm.

To evaluate the performance of these methods, experiments are conducted on various databases, including both synthetic and clinical data. Since the proposed methods involve adaptive filtering and wavelet transforms, they are compared with other research works utilizing similar approaches. Experimental evaluation of the proposed methodology is conducted using MATLAB (R2015a). For this purpose, both abdominal and thoracic signals are utilized in the experiments and the R peak detection performance is assessed using different metrics, including accuracy, positive prediction, and sensitivity.

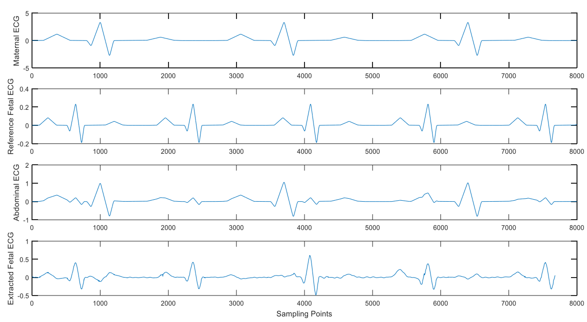


FIGURE 3. The experimental results of synthetic data depicting the extracted fetal ECG signal using the RLS, SWT, and threshold-based algorithm. The figure displays four waveforms arranged from top to bottom, representing 1) the simulated maternal thoracic signal, 2) the simulated fetal electrocardiogram, 3) the simulated abdominal signal, and 4) the extracted fetal ECG signal.

The synthetic data are obtained using a publicly available software tool, which is commonly used for analysing fetal ECG measurement techniques [44]. In our experiments, both the maternal ECG signals and fetal ECG signals are generated with a sampling frequency of 4000Hz. To simulate maternal ECG waveform, five synthetic signals with heart rates ranging from 65 to 94 beats per minute and a maximum voltage of 3.5 millivolts is generated. Fetal heart beats are simulated with heart rates ranging from 120 to 160 beats per minute, and a maximum voltage of 0.25 millivolts, which is faster than the mother's heartbeat. For analysis purposes, 25 simulated abdominal signals are generated by mixing maternal and fetal ECG signals. Fig. 3. displays the simulated waveforms, including the maternal and fetal ECG signals, the simulated abdominal signal, and the extracted fetal ECG signal, all generated using RLS, SWT, and threshold-based algorithms. Both algorithms are effective in extracting fetal ECG signals using the synthetic database.

A. DaISy DATABASE

To experimentally evaluate the algorithm, real data is obtained from the DaISy clinical open access database curated by Lathauwer [45]. This database contains five ECG signals of the abdomen and three ECG signals of the chest, all obtained from a pregnant woman. The DaISY database is illustrated in Fig. 4. The sampling frequency and duration of the signal are 250Hz and 10 seconds respectively. For the proposed methods, both quantitative and qualitative evaluations are performed using simulations and observations. However, we excluded the 4th channel from experimental evaluation due to its high instability. Fig. 5. illustrates the experimental results of the proposed system using method-1 (RLS, SWT, ISSNF algorithm) and method-2 (RLS, SWT, threshold-based algorithm) with DaISy database. The feasibility of the proposed methods is evaluated by analyzing the fetal ECG extraction results with abdominal ECG signal as the original input and maternal thoracic ECG signal as the reference input. The extracted ECG waveforms are plotted for the first 1000 sampling points and the R peaks of QRS complex are highlighted in a rectangle. The performance of the proposed method is evaluated using SNR based on eigenvalue analysis and cross-correlation analysis. In addition, the RLS algorithm is directly applied to the same clinical data for performance comparison.

In order to assess the effectiveness of the proposed approach, the fetal ECG signal waveform that has been extracted is segmented into M sections using the R-peaks as reference points. To extract R-peaks in fetal ECG signal, peak amplitude thresholding can be employed [20]. This method involves setting a threshold on the fetal ECG signal amplitude and detecting peaks that exceed this threshold. R-peaks with amplitudes higher than the threshold are identified as the QRS complex peaks. Let $f\,(n)$ represent the fetal ECG signal, and $S\,(n)$ be the second-order difference of $f\,(n)$.

$$S\,(n) = f\,(n) - 2f\,(n-1) + f(n-2) \tag{14}$$

If the consecutive elements $S\,(i)$ to $S\,(k)$ (where $i < k$) are all positive ones, the threshold, T is defined as:

$$T = \frac{1}{2}\sum\nolimits_{t=i}^{k} S\,(n)\,|_{S(n)>0} \tag{15}$$

All the n elements in $S\,(n)$ are compared with the threshold, T. If any element $n_{\mathrm{i}}(1 \leq n_{\mathrm{i}} \leq n)$ satisfies $S\,(n_i) > T$ or $S\,(n_i) < -T$, the corresponding element $S\,(n_i)$ will be detected as an R-peak.

To determine the signal-to-noise ratio (SNR), both eigenvalue and cross-correlation analysis techniques are employed [20]. Each signal section is of the same duration

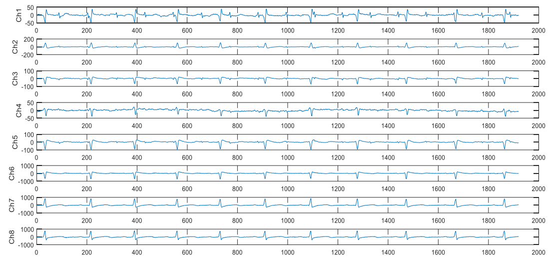
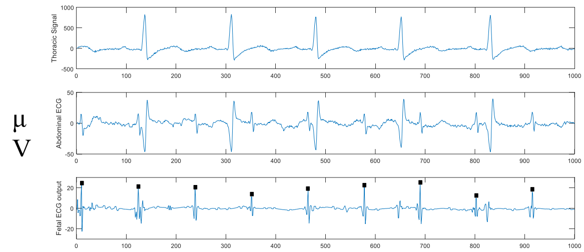
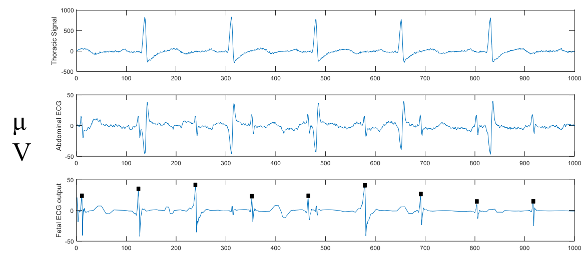


FIGURE 4. DaISy database. Five waveforms (Ch1 to Ch5) from top to bottom are the abdominal signals and the remaining (Ch6 to Ch8) are the thoracic waveforms.



(a)



(b)

FIGURE 5. (a) Fetal ECG extraction using RLS, SWT and ISSNF algorithm. (b) Fetal ECG extraction using RLS, SWT and threshold-based algorithm. The waveforms in each figure from top to bottom are 1) the thoracic signal, 2) the abdominal signal, and 3) the extracted fetal electrocardiogram (FECG). Fetal R-peaks are marked in both cases.

and contains only one R-peak. We determine the SNR based on eigenvalues using the following definition:

$$\mathrm{SNR}(E) = \frac{\lambda_{\max}}{\mathrm{M}-\lambda_{\max}} \tag{16}$$

where $\lambda_{\max}$ is the maximum eigen value of 'M' signal sections. Additionally, the proposed approach is evaluated using the SNR based on cross-correlation coefficients, which is determined using the following formula:

$$\mathrm{SNR}(C) = \frac{\mu}{1-\mu} \tag{17}$$

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 x represents the signal segment. Fig. 6. depict a comparison between the denoising performance of the ISSNF algorithm and the threshold-based algorithm with respect to two metrics, SNR(E) and SNR(C), using 12 sets of clinical data. Fig. 6. also shows the SNR results using RLS algorithm alone.

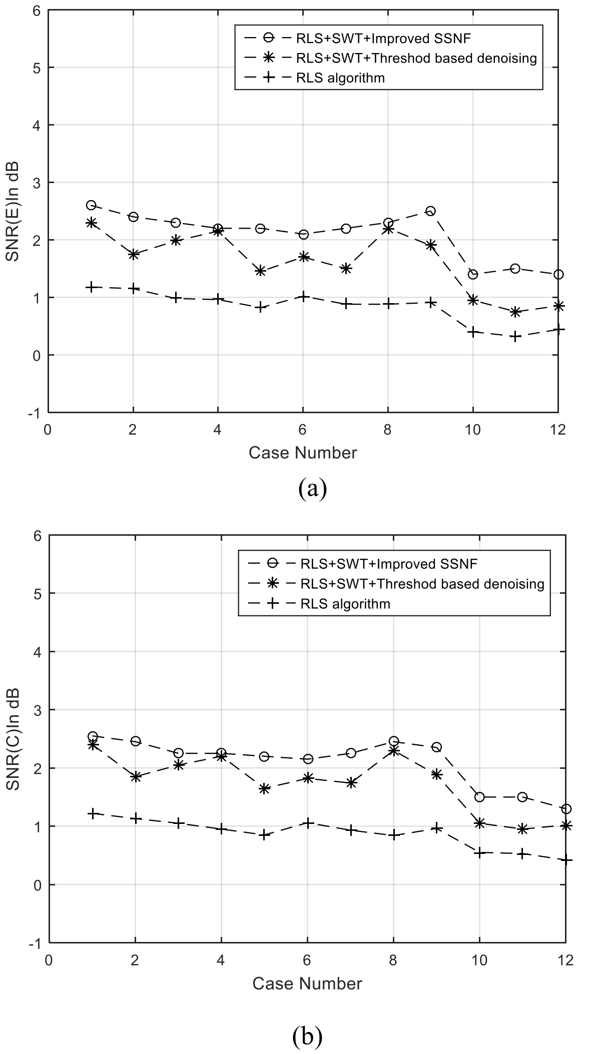


FIGURE 6. **(a) SNR based on eigen value analysis (b) SNR based on cross correlation analysis.**

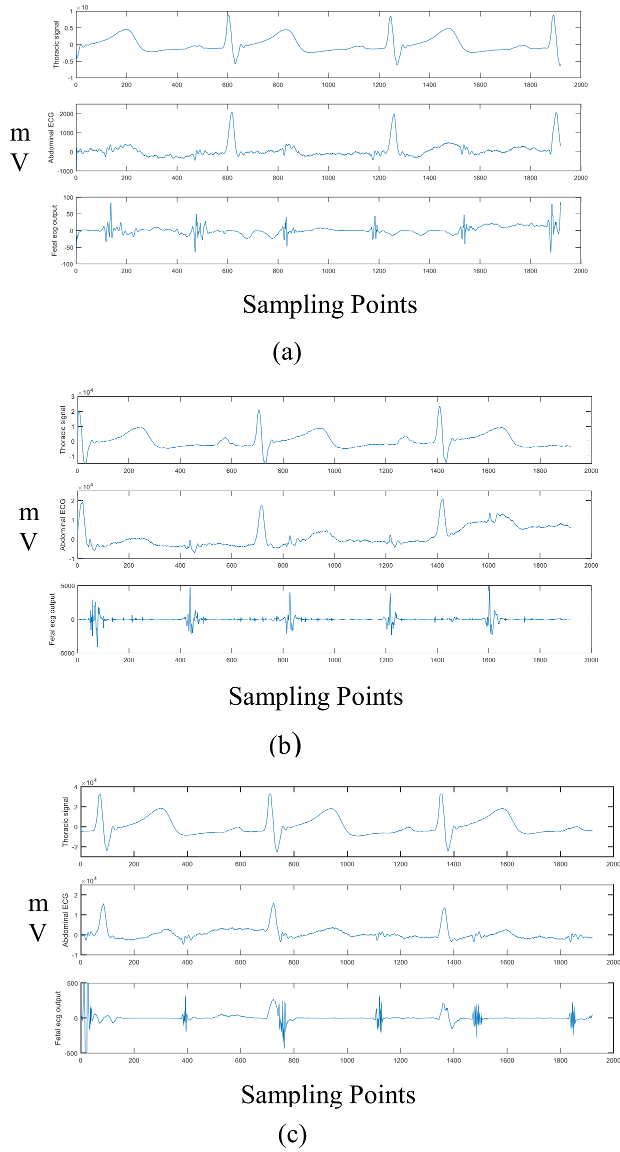


FIGURE 7. **Experimental results of non-invasive fetal ECG database using RLS, SWT, and ISSNF algorithm. (a) Results of the record 'ecgca274' (b) Results of the record 'ecgca771' (c) Results of the record 'ecgca649'. Three waveforms from top to bottom in each case are 1) the maternal thoracic signal, 2) the abdominal ECG, and 3) the extracted fetal ECG.**

B. PHYSIONET NON-INVASIVE FETAL ECG DATABASE

The Physionet non-invasive fetal ECG database (PNIFECGDB) consists of 55 multichannel abdominal ECG signal recordings obtained from a pregnant woman with a fetal gestational age ranging from 21 to 40 weeks [46]. The recordings are non-invasive and each recording consists of 3-4 abdominal channels and two thoracic channels.

All signals are sampled at 1 kHz with 16-bit resolution. To detect R-peaks in fetal ECG signals, the same set of records used in [22], [23], [24], [25], and [38] are used for fetal ECG extraction.

Fig. 7 and Fig. 8 depict the experimental results obtained from applying two different methods, method-1 (which involves RLS, SWT, &ISSNF technique) and method-2 (which involves RLS, SWT, & a threshold-based algorithm) to the PNIFECGDB dataset. Fig. 7 shows the results of method-1, while Fig. 8 shows the results of method-2. Fig. 7(a) depicts the fetal ECG extraction experimental results of method-1 using the record 'ecgca274' with channel 1 abdominal signal as input, and channel 4 thoracic signal as reference input. Fig. 7(b) shows the fetal ECG extraction results using the record 'ecgca771' with channel 1 abdominal signal as input, and channel 4 thoracic signal as reference input. Fig. 7(c) shows the fetal ECG extraction results using the record 'ecgca649' with channel 1 abdominal signal as input, and channel 4 thoracic signal as reference input.

Fig. 8 shows the results of method-2 using the same dataset. To plot the ECG waveforms, the first 1920 sampling points are utilized. When selecting the length of the signal, certain considerations are taken into account for stationary wavelet-based preprocessing.

Specifically, the length of the signal (example, 1920) must be divisible by 2^m where m denotes the wavelet decomposition level (here m is 5 and so $2^5 = 32$, and 1920/32 = 60 is perfectly divisible).

IV. DISCUSSION

Our research introduces a novel approach for fetal ECG extraction by combining the RLS algorithm with the SWT and either the ISSNF algorithm or a threshold-based algorithm. This innovative combination of techniques enhances the accuracy and robustness of fetal ECG extraction, offering a promising advancement in the field of prenatal monitoring and healthcare. It can be observed that both the algorithms using method-1 (RLS, SWT, ISSNF) and method-2 (RLS, SWT, threshold-based algorithm) can effectively eliminate maternal ECG and noise components, resulting in efficient extraction of the fetal ECG signals. Threshold based algorithm need less computation when compared with ISSNF algorithm and performs satisfactorily with SWT. However, the edges can be analyzed easily with ISSNF method. In the simulations, the extracted fetal ECG waveform is not correct for the first part in both methods since the RLS algorithm changes the adaptive filter coefficients before reaching the stable state. The experiments are also conducted using RLS algorithm alone. Although using the RLS algorithm directly without applying WT and denoising techniques is a straightforward approach, the resulting fetal ECG signal may still contain some maternal ECG components and other disturbances. We can observe that the combination of SWT and RLS adaptive filter along with ISSNF or threshold-based algorithm works excellently in fetal ECG extraction.

Different datasets and algorithms are utilized by researchers for fetal ECG extraction, but one significant drawback is the limited availability of extensive public databases that provide expert maternal thoracic signal references. Our proposed approach using adaptive filtering requires a maternal thoracic signal reference for efficient application. However, many databases solely offer abdominal ECG signals with no associated reference ECG signal from the thoracic area. Since there is no established database that can be used as a benchmark for evaluating the effectiveness of other algorithms, we have employed the DaISy clinical data database to assess the performance of our algorithm and tackle this problem. The proposed methods are compared to that of the algorithm proposed by [20], based on eigenvalue analysis and cross correlation analysis. Table 1 and 2 shows the comparison, indicating better $SNR(C)$ performance with our proposed method.

After conducting an SNR analysis utilizing eigenvalues and cross-correlation coefficients with the DaISy database, our findings demonstrate that our proposed threshold-based algorithm performs comparably to the ISSNF algorithm. Furthermore, our proposed method offers the additional benefit of reduced computational complexity. The best performance is obtained for case 1. In the proposed method, combining channel 1 abdominal signal with channel 6 thoracic signal produces case 1. Another effective combination for good SNR performance is case 8, which involves combining channel 5 with channel 7. For cases 10-12, the abdominal signal remains constant and is combined with thoracic signals from channels 6-8. Specifically, channel 5 is used as the abdominal signal for these cases. The fetal ECG components are weak in this abdominal signal. Hence the SNR results are comparatively low. Table 1 and 2 present a comparison of the performance of our proposed algorithms and the algorithm introduced by Ref. [20] in terms of SNR(E) and SNR(C) in dB, as evaluated using the DaISy database. Out of the 12 cases in each table, the SNR(E) result of the seventh case in Table 1, where channel 3 and channel 7 are used, is slightly lower than the existing method. For all other cases, the SNR(E) and SNR(C) of both methods using method-1 (RLS, SWT, ISSNF algorithm) and method-2 (RLS, SWT, threshold-based algorithm) are higher than the SNR results using LMS, SWT and ordinary SSNF algorithm proposed by Ref. [20].

The fetal heart rate is almost double the maternal heart rate, resulting in the chances for overlap between fetal QRS complexes and maternal QRS complexes. Additionally, fetal heartbeats are weaker, making it more difficult to identify overlapped fetal QRS points during adaptive filtering and increasing the risk of misdetection. However, a heuristic algorithm can eliminate misdetected fetal QRS complexes and identify overlapped fetal QRS points by comparing the differences in interval between successive fetal QRS complexes. A difference of greater than 150% between the two intervals suggests the presence of overlapping fetal QRS complexes, while a difference of less than 45% indicates the possibility of misdetection, in which case the related beats can be discarded.

The fetal R peak detection algorithm's effectiveness can be assessed by utilizing the Sensitivity (SE), Positive Prediction (PP), Accuracy (A), and F1 statistics.

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

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

$$A = \frac{TP}{TP + FP + FN} * 100\% \tag{20}$$

$$F1 = 2\frac{PP * SE}{PP + SE} \tag{21}$$

The performance evaluation based on R-peak detection involves calculating the true positives (TP), false positives (FP), and false negatives (FN). We evaluate the performance of two algorithms, the RLS, SWT, ISSNF algorithm, and the RLS, SWT, threshold-based algorithm, for extracting fetal ECG signals in the presence of noise. We compare the results obtained from these algorithms with other existing research works that use the same databases, namely DaISy database and PNIFECGDB database.

The DaISy database comprises multiple channels of abdominal signals, with each channel containing 22 fetal

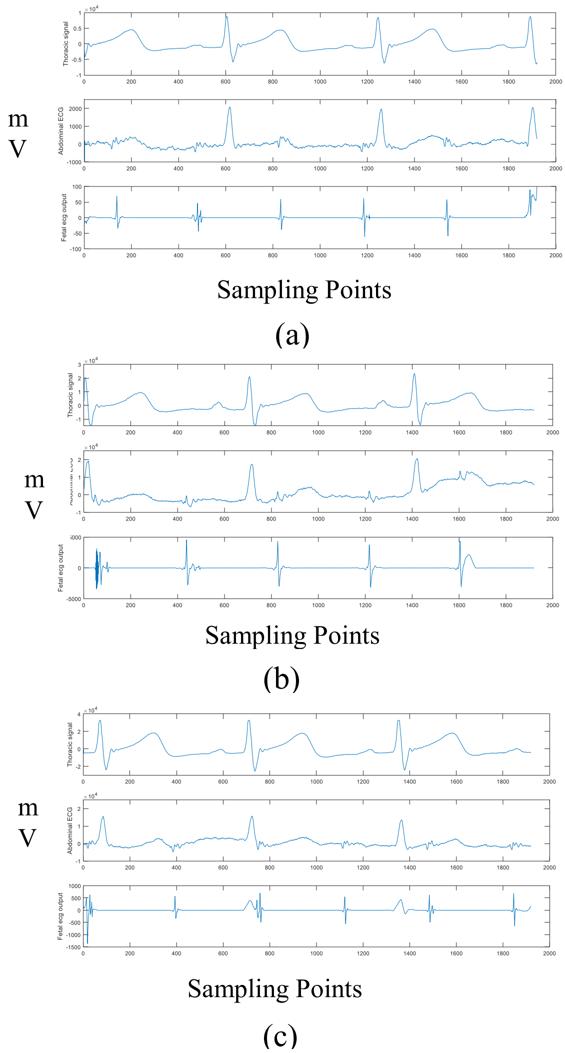


FIGURE 8. **Experimental results of non-invasive fetal ECG database using RLS, SWT, and threshold-based algorithm. (a) Results of the record 'ecgca274' (b) Results of the record 'ecgca771' (c) Results of the record 'ecgca649'. Three waveforms from top to bottom in each case are 1) the maternal thoracic signal, 2) the abdominal ECG, and 3) the extracted fetal ECG.**

TABLE 1. **SNR (E) comparison results in dB using eigen value analysis.**

Input (DaISY)	LMS algorithm [20]	LMS, SWT, SSNF [20]	RLS, SWT, ISSNF (Proposed method-1)	RLS, SWT, Threshold-based algorithm (Proposed method-2)
Ch1,Ch6	0.90	2.20	2.60	2.30
Ch2,Ch6	0.80	1.80	2.40	1.80
Ch3,Ch6	0.60	1.20	2.30	1.98
Ch5,Ch6	0.40	0.80	2.20	2.15
Ch1,Ch7	0.70	1.20	2.20	1.45
Ch2,Ch7	0.20	0.80	2.10	1.70
Ch3,Ch7	0.40	1.60	2.20	1.50
Ch5,Ch7	0.40	1.90	2.30	2.20
Ch1,Ch8	0.20	0.90	2.50	1.90
Ch2,Ch8	0.20	0.40	1.40	0.95
Ch3,Ch8	0.20	0.40	1.50	0.75
Ch5,Ch8	0.20	0.40	1.40	0.85

TABLE 2. **SNR (C) comparison results in dB using cross correlation analysis.**

Input (DaISY)	LMS algorithm [20]	LMS, SWT, SSNF [20]	RLS, SWT, ISSNF (Proposed method-1)	RLS, SWT, Threshold-based algorithm (Proposed method-2)
Ch1,Ch6	0.60	2.20	2.55	2.40
Ch2,Ch6	0.40	1.50	2.45	1.85
Ch3,Ch6	0.30	1.20	2.25	2.05
Ch5,Ch6	0.20	0.70	2.25	2.20
Ch1,Ch7	0.50	1.40	2.20	1.65
Ch2,Ch7	0.20	0.70	2.15	1.82
Ch3,Ch7	0.20	1.40	2.25	1.74
Ch5,Ch7	0.20	2.20	2.45	2.30
Ch1,Ch8	0.10	0.80	2.35	1.88
Ch2,Ch8	0.10	0.20	1.50	1.05
Ch3,Ch8	0.10	0.20	1.50	0.95
Ch5,Ch8	0.10	0.20	1.30	1.02

cardiac beats in total. The study analyzes a total of 264 fetal beats, which are divided into 12 cases. The first approach utilizes RLS, SWT, and ISSNF techniques to detect these fetal heartbeats. The results show that this algorithm is able to correctly detect 258 beats (TP), while missing 6 (FN) and misdetecting 3 (FP). The second method is also employed that use RLS, SWT, and a threshold-based algorithm, and it is found to detect 260 beats (TP) correctly, with 4 missed (FN) and 4 misdetected (FP). Notably, the majority of the missed fetal QRS complexes occur in areas where they overlapped with maternal QRS complexes, and misdetection is more common in areas with low signal-to-noise ratio. The sensitivity, positive prediction, and accuracy values obtained from these methods are presented in Table 3.

The R-peak detection analysis is also performed using PNIFECGDB. The obtained values of SE, PP, A, and F1 are shown in Table 4. The same set of 1-minute recordings used in Ref. [38] from the PNIFECGDB are selected for R-peak detection analysis. A total of 767 FQRS are manually annotated by an expert in the medical field through visual inspection techniques by making use of the channel where the fetal QRS appeared with the highest quality [38]. The proposed method, which utilizes RLS, SWT, and ISSNF, is able to accurately detect 724 heartbeats (TP), with 43 heartbeats missed (FN) and 18 false detections (FP).

The procedure is repeated for the second method using RLS, SWT and threshold-based algorithm. It could detect correctly 735 beats (TP), missed 32 (FN) and mis detected 12 (FP). The statistical result from Table 4 shows the method-2 using threshold-based algorithm is much better than method-1 using ISSNF method for PNIFECGDB with the additional advantage of reduced computational

TABLE 3. Detection of R-peaks in the DaISy database.

Method	SE	PP	A
DWT-RI algorithm [24]	100	91.30	91.30
MSF-ANC algorithm [25]	-	91.66	84.61
Wavelet based detection [38]	98.86	100	98.86
RLS, SWT, ISSNF algorithm (Proposed method-1)	97.72	98.85	96.62
RLS, SWT, Threshold-based algorithm (Proposed method-2)	98.48	98.48	97.01

TABLE 4. R-peak detection using Physionet non invasive fetal ECG database.

Method	SE	PP	A	F1
RLS [23]	96.20	95.60	-	95.90
LMS [23]	95.80	95.00	-	95.40
ESN_a [23]	96.80	97.20	-	97.00
ESN_{na} [23]	96.80	97.20	-	97.20
EKS(Par-EKS) [22]	92.56	93.57	86.95	93.06
Wavelet-based detection [38]	95.57	97.99	93.73	-
EKS+ANFIS [18]	93.81	95.97	90.20	94.87
EKF+ANFIS [18]	92.75	94.85	88.21	93.79
EKS+DE+ANFIS [19]	94.21	96.05	90.66	95.12
EKF+DE+ANFIS [19]	93.03	95.05	88.41	94.03
PCA [11]	92.70	96.79	89.91	94.70
RLS, SWT, ISSNF algorithm (Proposed method-1)	94.39	97.57	92.20	95.95
RLS, SWT, Threshold-based algorithm (Proposed method-2)	95.82	98.39	94.35	97.09

complexity. For the DaISy database, the two algorithms perform almost the same. For the DaISy database, all possible input signal combinations have been tested, and the resulting SNR and R-peak detection outcomes are presented in Tables 1, 2, and 3. In the case of PNIFECGDB, where the reference fetal ECG signal is not provided, an additional set of records has been experimentally evaluated through visual inspection, resulting in a total of 1432 manually annotated fetal QRS complexes. The proposed method, incorporating RLS, SWT, and ISSNF, accurately detects 1357 heartbeats (TP), with 75 heartbeats missed (FN) and 28 false detections (FP). The same procedure is repeated for the second method, utilizing RLS, SWT, and a threshold-based algorithm, which correctly detects 1372 beats (TP), missed 60 (FN), and have 22 misdetected beats (FP). Through visual inspection analysis, the proposed method-1 achieved an accuracy and F1 score of 92.95% and 96.34%, while the proposed method-2 achieved an accuracy and F1 score of 94.36% and 97.08%.

Table 5 presents a comprehensive comparison of R-peak detection performance between the two proposed approaches. The accuracy (A) and F1 score parameters, derived from Table 3 and Table 4, are utilized for this evaluation. This comparison allows for a comprehensive assessment of the

TABLE 5. Comparison between the two proposed methods.

Proposed Methods	Database	A	F1
RLS, SWT, ISSNF (Proposed method-1)	DaISy	96.62	98.28
RLS, SWT, ISSNF (Proposed method-1)	PNIFECGDB	92.20	95.95
RLS, SWT, Threshold-based (Proposed method-2)	DaISy	97.01	98.48
RLS, SWT, Threshold-based (Proposed method-2)	PNIFECGDB	94.35	97.09

effectiveness of the two approaches in accurately detecting R-peaks. With the proposed method-2 using RLS, SWT, and threshold-based algorithm, 97.01% and 94.35% accuracy are achieved using DaISy database and PNIFECGDB respectively.

In the presence of multiple fetal sources, the spatial correlation patterns might become more intricate. ISSNF should be designed to consider both the commonalities and differences in spatial correlations among the fetal signals. In situations involving twins or triplets, consider incorporating domain-specific knowledge about fetal heart rate variability, morphological differences, and expected spatial patterns. This knowledge can guide the algorithm in making more accurate decisions during source separation and filtering.

V. CONCLUSION

The paper proposes a hybrid approach based on RLS adaptive filtering, which utilizes the combination of the SWT with two denoising algorithms, for fetal heart rate estimation. Method-1 utilizes RLS, SWT, and the ISSNF algorithm, while method-2 uses RLS, SWT, and a threshold-based algorithm. The proposed system uses the SWT to process the abdominal and thoracic ECG signals and applies the RLS algorithm in the wavelet domain. Both denoising algorithms are effective in efficiently estimating fetal heartbeats even when maternal and fetal ECG signals overlap. The experimental results are quantitatively analyzed by calculating SNR and detecting R-peaks. While both methods perform well using both denoising algorithms, the threshold-based approach is particularly promising due to its improved R-peak detection and reduced computational complexity. The proposed methods have been validated using both synthetic and clinical data, and their SNR performance in practical situations is a significant advantage. The incorporation of conventional techniques allows for a comprehensive benchmarking of the proposed hybrid approach against existing methods. The proposed system will be further validated through its application to additional clinical data in future research. The ultimate objective is to diagnose abnormal heart rate activity during pregnancy using the proposed methodology.

REFERENCES

[1] G. Camps, M. Martinez, and E. Soria, "Fetal ECG extraction using an FIR neural network," in *Proc. Comput. Cardiol.*, Sep. 2001, pp. 249–252.

[2] Sameni, "A review of fetal ECG signal processing issues and promising directions," *Open Pacing, Electrophysiol. Therapy J.*, vol. 3, pp. 4–20, Jan. 2010.

[3] P. P. Kanjilal, S. Palit, and G. Saha, "Fetal ECG extraction from single-channel maternal ECG using singular value decomposition," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 1, pp. 51–59, Jan. 1997.

[4] A. Al-Zaben and A. Al-Smadi, "Extraction of foetal ECG by combination of singular value decomposition and neuro-fuzzy inference system," *Phys. Med. Biol.*, vol. 51, no. 1, pp. 137–143, Jan. 2006.

[5] P. Bergveld and W. J. H. Meijer, "A new technique for the suppression of the MECG," *IEEE Trans. Biomed. Eng.*, vol. BME-28, no. 4, pp. 348–354, Apr. 1981.

[6] L. de Lathauwer, B. de Moor, and J. Vandewalle, "Fetal electrocardiogram extraction by blind source subspace separation," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 5, pp. 567–572, May 2000.

[7] H. Zhang, Z. Shi, C. Guo, and E. Feng, "Semi-blind source extraction algorithm for fetal electrocardiogram based on generalized autocorrelations and reference signals," *J. Comput. Appl. Math.*, vol. 223, no. 1, pp. 409–420, Jan. 2009.

[8] Y. Ye, P. C.-Y. Sheu, J. Zeng, G. Wang, and K. Lu, "An efficient semi-blind source extraction algorithm and its applications to biomedical signal extraction," *Sci. China Ser. F, Inf. Sci.*, vol. 52, no. 10, pp. 1863–1874, Oct. 2009.

[9] R. Martín-Clemente, J. L. Camargo-Olivares, S. Hornillo-Mellado, M. Elena, and I. Román, "Fast technique for noninvasive fetal ECG extraction," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 2, pp. 227–230, Feb. 2011.

[10] L. Yuan, Z. Zhou, Y. Yuan, and S. Wu, "An improved FastICA method for fetal ECG extraction," *Comput. Math. Methods Med.*, vol. 2018, pp. 1–7, May 2018.

[11] R. Sameni, C. Jutten, and M. B. Shamsollahi, "Multichannel electrocardiogram decomposition using periodic component analysis," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1935–1940, Aug. 2008.

[12] M. Kotas, "Projective filtering of time-aligned ECG beats," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1129–1139, Jul. 2004.

[13] A. M. Kaleem and R. D. Kokate, "An efficient adaptive filter for fetal ECG extraction using neural network," *J. Intell. Syst.*, vol. 28, no. 4, pp. 589–600, Sep. 2019, doi: 10.1515/jisys-2017-0031.

[14] N. J. Outram, S. H. Curnow, E. C. Ifeachor, and P. W. J. Van Eetvelt, "Techniques for optimal enhancement and feature extraction of fetal electrocardiogram," *IEE Proc. Sci., Meas. Technol.*, vol. 142, no. 6, pp. 482–489, Nov. 1995.

[15] K.-C. Lai and J. J. Shynk, "A successive cancellation algorithm for fetal heart-rate estimation using an intrauterine ECG signal," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 9, pp. 943–954, Sep. 2002, doi: 10.1109/TBME.2002.802010.

[16] M. Jallouli, S. Arfaoui, A. Ben Mabrouk, and C. Cattani, "Clifford wavelet entropy for fetal ECG extraction," *Entropy*, vol. 23, no. 7, p. 844, Jun. 2021, doi: 10.3390/e23070844.

[17] R. Jaros, R. Martinek, and R. Kahankova, "Non-adaptive methods for fetal ECG signal processing: A review and appraisal," *Sensors*, vol. 18, no. 11, p. 3648, Oct. 2018.

[18] D. Panigrahy and P. K. Sahu, "Extraction of fetal electrocardiogram (ECG) by extended state Kalman filtering and adaptive neuro-fuzzy inference system (ANFIS) based on single channel abdominal recording," *Sadhana*, vol. 40, no. 4, pp. 1091–1104, Jun. 2015.

[19] D. Panigrahy and P. K. Sahu, "Extraction of fetal ECG signal by an improved method using extended Kalman smoother framework from single channel abdominal ECG signal," *Australas. Phys. Eng. Sci. Med.*, vol. 40, no. 1, pp. 191–207, Mar. 2017, doi: 10.1007/s13246-017-0527-5.

[20] S. Wu, Y. Shen, Z. Zhou, L. Lin, Y. Zeng, and X. Gao, "Research of fetal ECG extraction using wavelet analysis," *Comput. Biol. Med.*, vol. 43, no. 10, pp. 1622–1627, 2013, doi: 10.1016/j.compbiomed.2013.07.028.

[21] O. Sayadi and M. B. Shamsollahi, "ECG denoising and compression using a modified extended Kalman filter structure," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 9, pp. 2240–2248, Sep. 2008, doi: 10.1109/TBME.2008.921150.

[22] M. Niknazar, B. Rivet, and C. Jutten, "Fetal ECG extraction by extended state Kalman filtering based on single-channel recordings," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 5, pp. 1345–1352, May 2013, doi: 10.1109/TBME.2012.2234456.

[23] J. Behar, A. Johnson, G. D. Clifford, and J. Oster, "A comparison of single channel fetal ECG extraction methods," *Ann. Biomed. Eng.*, vol. 42, no. 6, pp. 1340–1353, Jun. 2014.

[24] B. Al-Sheikh, M. S. Salman, A. Eleyan, and S. Alboon, "Non-invasive fetal ECG extraction using discrete wavelet transform recursive inverse adaptive algorithm," *Technol. Health Care*, vol. 28, no. 5, pp. 507–520, Sep. 2020.

[25] J. D. K. Abel, D. Samiappan, R. Kumar, and S. P. Kumar, "Multiple sub-filter adaptive noise canceller for fetal ECG extraction," *Proc. Comput. Sci.*, vol. 165, pp. 182–188, Jan. 2019.

[26] R. Kahankova, R. Martinek, R. Jaros, K. Behbehani, A. Matonia, M. Jezewski, and J. A. Behar, "A review of signal processing techniques for non-invasive fetal electrocardiography," *IEEE Rev. Biomed. Eng.*, vol. 13, pp. 51–73, 2020.

[27] N. H. Beni and N. Jiang, "Heartbeat detection from single-lead ECG contaminated with simulated EMG at different intensity levels: A comparative study," *Biomed. Signal Process. Control*, vol. 83, May 2023, Art. no. 104612.

[28] Y.-C. Ting, F.-W. Lo, and P.-Y. Tsai, "Implementation for fetal ECG detection from multi-channel abdominal recordings with 2D convolutional neural network," *J. Signal Process. Syst.*, vol. 93, no. 9, pp. 1101–1113, Sep. 2021, doi: 10.1007/s11265-021-01676-w.

[29] E. Fotiadou, T. Konopczyński, J. Hesser, and R. Vullings, "End-to-end trained encoder–decoder convolutional neural network for fetal electrocardiogram signal denoising," *Physiolog. Meas.*, vol. 41, no. 1, Feb. 2020, Art. no. 015005, doi: 10.1088/1361-6579/ab69b9.

[30] A. Rasti-Meymandi and A. Ghaffari, "AECG-DecompNet: Abdominal ECG signal decomposition through deep-learning model," *Physiolog. Meas.*, vol. 42, no. 4, Apr. 2021, Art. no. 045002, doi: 10.1088/1361-6579/abedc1.

[31] S. Kumar, A. Rajpal, N. K. Sharma, S. Rajpal, A. Nayyar, and N. Kumar, "ROSEmark: Robust semi-blind ECG watermarking scheme using SWT-DCT framework," *Digit. Signal Process.*, vol. 129, Sep. 2022, Art. no. 103648.

[32] A. Ahmadi, H. Bazregarzadeh, and K. Kazemi, "Automated detection of driver fatigue from electroencephalography through wavelet-based connectivity," *Biocybern. Biomed. Eng.*, vol. 41, no. 1, pp. 316–332, Jan. 2021.

[33] N. H. Beni, R. Foodeh, V. Shalchyan, and M. R. Daliri, "Force decoding using local field potentials in primary motor cortex: PLS or Kalman filter regression?" *Phys. Eng. Sci. Med.*, vol. 43, no. 1, pp. 175–186, Mar. 2020, doi: 10.1007/s13246-019-00833-7.

[34] N. H. Beni and N. Jiang, "Heartbeat detection from the upper arm using an SWT-based zero-phase filter bank incorporated with a voting scheme," in *Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2022, pp. 1314–1318, doi: 10.1109/EMBC48229.2022.9871123.

[35] P. Darsana and V. N. Kumar, "A quantitative and qualitative research on fetal ECG extraction using wavelet based adaptive filtering," in *Proc. Int. Conf. Comput., Commun., Secur. Intell. Syst. (IC3SIS)*, Jun. 2022, pp. 1–5, doi: 10.1109/IC3SIS54991.2022.9885469.

[36] F. Mochimaru, Y. Fujimoto, and Y. Ishikawa, "Detecting the fetal electrocardiogram by wavelet theory-based methods," *Prog. Biomed. Res.*, vol. 7, pp. 185–193, Sep. 2002.

[37] G. P. Nason and B. W. Silverman, "The stationary wavelet transform and some statistical applications," in *Wavelets and Statistics*, vol. 103, A. Antoniadis and G. Oppenheim, Eds. New York, NY, USA: Springer-Verlag, 1995, pp. 281–299.

[38] E. Castillo, D. P. Morales, G. Botella, A. García, L. Parrilla, and A. J. Palma, "Efficient wavelet-based ECG processing for single-lead FHR extraction," *Digit. Signal Process.*, vol. 23, no. 6, pp. 1897–1909, Dec. 2013, doi: 10.1016/j.dsp.2013.07.010.

[39] Y. Xu, J. B. Weaver, D. M. Healy, and J. Lu, "Wavelet transform domain filters: A spatially selective noise filtration technique," *IEEE Trans. Image Process.*, vol. 3, no. 6, pp. 747–758, Nov. 1994.

[40] Q. Pan, L. Zhang, G. Dai, and H. Zhang, "Two denoising methods by wavelet transform," *IEEE Trans. Signal Process.*, vol. 47, no. 12, pp. 3401–3406, Dec. 1999.

[41] D. L. Donoho, "De-noising by soft-thresholding," *IEEE Trans. Inf. Theory*, vol. 41, no. 3, pp. 617–627, May 1995.

[42] N. Saito, "Simultaneous noise suppression and signal compression using a library of orthonormal based and the minimum description length criterion," *SPIE*, vol. 2242, pp. 224–235, Jan. 1994.

[43] A. Cohen, I. Daubedhies, and J. C. Feaurean, "Biorthogonal ses of compactly supported wavelets," *Commun. Pure Appl. Math.*, vol. 45, no. 5, pp. 485–560, 1990.

[44] *Adaptive Noise Canceling (ANC) Applied to Fetal Electrocardiography. Math Works: Products & Services*, DSP System Toolbox, 1994.
[45] B. D. Moor, P. D. Gersem, B. De Schutter, and W. Favoreel, ''DAISY: A database for identification of systems,'' *J. A Spec. Issue Comput. Aided Control Syst. Des.*, vol. 38, no. 3, pp. 4–5, Sep. 1997.
[46] A. L. Goldberger, L. Amaral, L. Glass, J. M. Hausdorff, P. C. H. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, ''PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals,'' *Circulation*, vol. 101, no. 23, pp. e215–e220, 2003.

P. DARSANA received the B.Tech. degree in electronics and communication engineering from the University College of Engineering, Thodupuzha, in 2002, the M.Tech. degree in communication engineering from the Amal Jyothi College of Engineering, Kanjirappally, Kerala, under MG University, Kerala, India, in May 2012. She is currently pursuing the Ph.D. degree in electronics and communication engineering from the Vellore Institute of Technology, Vellore, India. She is an Associate Professor with the Department of Electronics and Communication, Amal Jyothi College of Engineering. She has authored more than six publications in Scopus-indexed journals and conferences. Her current research interests include biomedical signal processing, image processing, and statistical signal processing.

VAEGAE NAVEEN KUMAR (Senior Member, IEEE) received the B.Tech. degree in instrumentation engineering from Nagarjuna University, Guntur, India, in 2001, the M.Tech. degree in electronics engineering from Jawaharlal Nehru Technological University, Kakinada, India, in 2010, and the Ph.D. degree in electrical and electronics engineering from the Vellore Institute of Technology, Vellore, India.

He is currently an Associate Professor with the School of Electronics Engineering, Vellore Institute of Technology. He has authored more than 15 SCI-IF publications and more than 16 Scopus-indexed journals and conferences. His publications are in IEEE Sensors Journal, *Biocybernetics and Biomedical Engineering*, *Biomedical Signal Processing and Control*, *Sensors and Actuators— A: Physical*, *Measurement: Journal of the International Measurement Confedeation*, and *IET Science Measurement and Technology*. His current research interests include sensors and signal conditioning, signal processing, soft computing, intelligent systems, electronic noses, genomic signal processing, and the IoT. He is a Lifetime Member of ISTE and a member of the International Association of Engineering. He has been a Faculty Advisor and a Coordinator for the IEEE Signal Processing Society, VIT Student Chapter, since 2017.