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An Adaptive Filtering Technique for Enhancing Extraction of Foetal Electrocardiographic Signal from Abdominal Electrocardiogram

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Abstract- non-invasive foetal electrocardiogram (FECG) monitoring provides vital clinical information for assessing foetal well-being during pregnancy. However, abdominally recorded ECG signals are heavily contaminated by maternal ECG (MECG) and noise, making accurate FECG extraction challenging. This study proposes a Blackman-windowed finite impulse response (FIR) adaptive filtering approach for improved separation of FECG from composite abdominal ECG (AECG) signals. Unlike conventional adaptive FIR filters, the proposed method applies final coefficient windowing to enhance stability, reduce distortion, and improve signal-to-noise ratio (SNR). The system is implemented and evaluated through MATLAB simulations. Performance is assessed using SNR and mean square error (MSE) and compared with conventional LMS-based adaptive filters. Results demonstrate that the proposed Blackman-windowed adaptive filter provides superior FECG extraction quality, validating its suitability for non-invasive foetal monitoring applications.

Index Terms- Foetal ECG, Adaptive Filtering, Blackman Window, LMS Algorithm, Biomedical Signal Processing

I. INTRODUCTION

Foetal electrocardiography is an important diagnostic tool for monitoring foetal cardiac activity and detecting abnormalities during pregnancy. The foetal ECG waveform contains valuable information about heart rate, rhythm, and beat-to-beat variability, all of which are critical indicators of foetal health.

For the information in foetal ECG signal to be extracted, it has to be detected and then analyzed. This analysis can only be reliable if the ECG being analyzed is not mixed with any other signals. Incidentally, foetal ECG is naturally mixed with maternal ECG (MECG) and some high frequency random noise in its natural form. This is because it is captured from the abdomen of the pregnant mother through electrode transducers. It therefore becomes necessary that the foetal ECG which is signal of interest must be extracted from these other signals. In this work the target is to extract this signal of interest from abdominal ECG. Many researchers have used different techniques to effect this extraction. The techniques include a wavelet adaptive filtering (that is a combination of wavelet transform and adaptive filter) (Lima-Herrera eta l, 2016, Darsana and Kumar, 2022, Wu etal, 2013), artificial neural network (Ziani eta l, 2023, Barnova eta l, 2024, Kaleem and Kokate, 2019, Ma eta l, 2014) and Adaptive Filtering (Sulas eta l, 2019, Singh and Dewan, 2013, Prasant etal, 2013, Rajesh etal, 2014, Cherian etal, 2014, Mbachu and Nwosu, 2014). Other techniques are wavelet transform (Para and Wadhawani, 2018a, Fuadina eta l, 2019), adaptive volterra filters (Ma etal, 2015), fast independent component analysis (Ionescu, 2016), blind source separation (Islam and Tarique, 2020), template-based cancellation (Vasudev and Dessai, 2016) and projective filtering of time aligned ECG beats (Cherian etal, 2014).

This study introduces a Blackman-windowed adaptive FIR filter to enhance the effectiveness of conventional LMS-based adaptive filtering. By applying coefficient windowing, the proposed method improves convergence behavior and reduces residual maternal components in the extracted FECG.

II. METHODOLOGY

2.1 System Overview

The proposed system employs an adaptive noise cancellation framework in which:

- The AECG serves as the primary input.
- The thoracic MECG acts as the reference input.

An adaptive FIR filter estimates the maternal component, which is subtracted from the AECG to recover the FECG

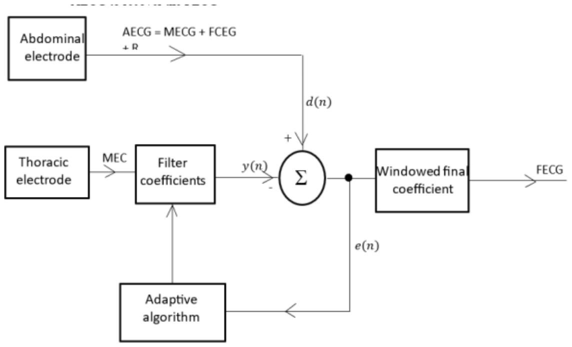

Figure 3.1: Block Diagram of the Developed System

A Blackman window is applied to the final adaptive filter coefficients to enhance spectral characteristics and suppress sidelobe effects.

2.2 Blackman-Windowed Adaptive LMS Algorithm

The conventional LMS coefficient update rule is given by:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}(n)$$

where μ is the step size, $e(n)$ is the error signal, and $\mathbf{x}(n)$ is the reference input vector.

After convergence, the filter coefficients are multiplied element-wise by a Blackman window:

$$\mathbf{w}_B(n) = \mathbf{w}(n) \odot \mathbf{w}_{Blackman}$$

This windowing reduces spectral leakage, improves stability, and enhances extraction quality without significantly increasing computational complexity.

2.3 Simulation Setup

The system is implemented in MATLAB using synthetically generated MECG and FECG signals with physiological characteristics consistent with clinical data. Key parameters investigated include:

- Filter order
- Step size
- Sampling frequency

Optimal values are determined based on convergence speed, SNR, and waveform fidelity.

III. RESULTS AND DISCUSSION

3.1 Performance Metrics

Performance is evaluated using:

- Signal-to-Noise Ratio (SNR)
- Mean Square Error (MSE)

The trial parameters obtained from section 3 are:

L = 100
mu = 0.00085
Sampling frequency = 1000Hz

With these trial parameters the impulse and magnitude responses of the filter are depicted as figure 3.1 and figure 3.2 respectively while the phase and z-domain responses are depicted as figure 3.3 and 3.4 respectively.

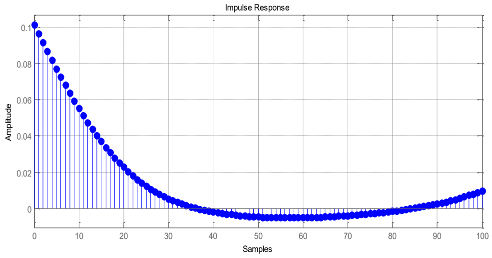

Figure 3.1: Impulse Response of the Adaptive Filter When the Order is 100

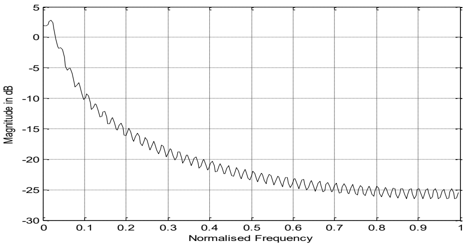

Figure 3.2: Magnitude Response of the Adaptive Filter When the Order is 100

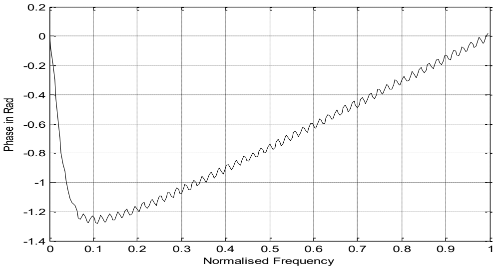

Figure 3.3: Phase Response of the Adaptive Filter When the Order is 100

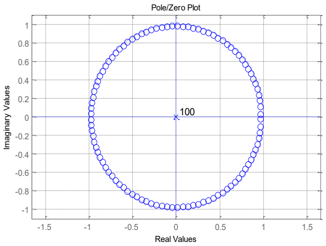

Figure 3.4: Pole/Zero Response in z-domain of the Adaptive Filter When the Order is 100

From the instantaneous impulse response of fig. 3.1 the amplitude of the response tends to collapse to zero as the number of samples approaches maximum value, though does not completely collapse to zero and this implies that the filter is stable but still requires some adjustments of parameters. The magnitude response of fig. 3.2 has a high magnitude of +2.804dB at a normalised frequency of 0.01953. This implies that there is a major contaminant component of maternal ECG at the normalised frequency of 0.01953 which the filter has to remove in addition to removal of other minor contaminant components. The phase response of fig. 3.3 indicates good level of linearity in phase of the filter within the required frequency range and this is desirable. The pole-zero response in z-domain of fig. 3.4 shows that the filter is stable because all the poles and zeroes are confined within a unit circle. All the poles are at the centre as shown.

Table 3.1: Effects of Filter Order Variation on Instantaneous Responses

Order	88	90	92	94	100
Impulse Response	Stable	Stable	Stable	Stable	Stable
Magnitude Response	Stable	Stable	Stable	Stable	Stable
Phase Response	Linear	Linear	Linear	Linear	Linear
z-domain Response	Stable	Very Stable	Very Stable	Very Stable	Very Stable

3.2 Signal Generation and Extraction with the Developed Adaptive Filter

The signal generation and extraction flow block diagram is shown in figure 3.5. A corrupt free maternal ECG is generated using MATLAB and this is depicted as figure 3.6. A corrupt free foetal ECG is also generated as depicted in fig. 3.7. A high frequency random is also generated as such is also contained in AECG and this is depicted as figure 3.8.

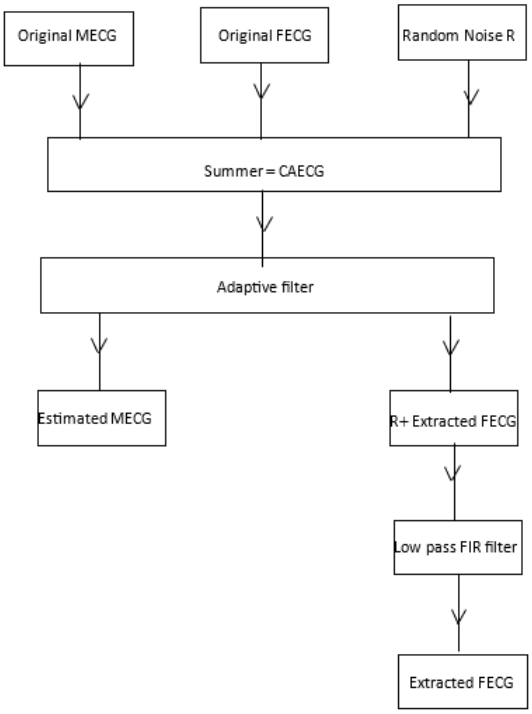

Figure 3.5: Extraction Flow Diagram

The high frequency random noise represents noise generated due to motion of the foetus in the maternal womb. The composite abdominal ECG signal is applied to the developed adaptive filter and the filter output is shown in figure 3.10 while the filtered signal is presented in figure 3.11. The filter output is the noise estimated by the filter which is similar to the corrupting noise and which the filter will subtract from the contaminated signal. The filtered signal is the system output and represents the wanted signal remaining after the noise has been removed. The power spectral densities of the original FECG signal, composite AECG signal and the extracted FECG signal are depicted in figures 3.12, 3.13 and 3.14 respectively. The essence of the power spectral density is to determine the signal power in dB at any frequency within the applicable frequency range.

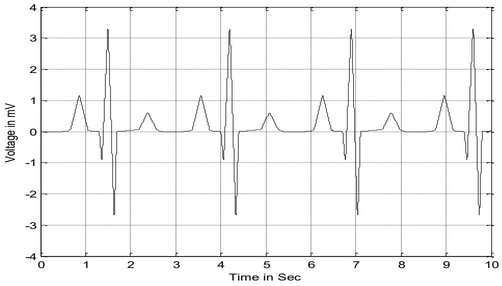

Figure 3.6: Uncontaminated Maternal ECG Signal

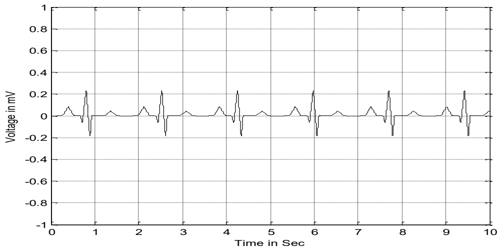

Figure 3.7: Uncontaminated Foetal ECG Signal

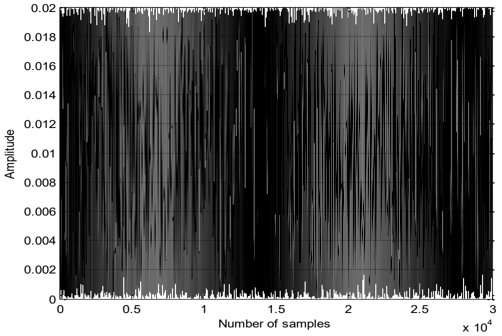

Figure 3.8: Random Noise above 100Hz

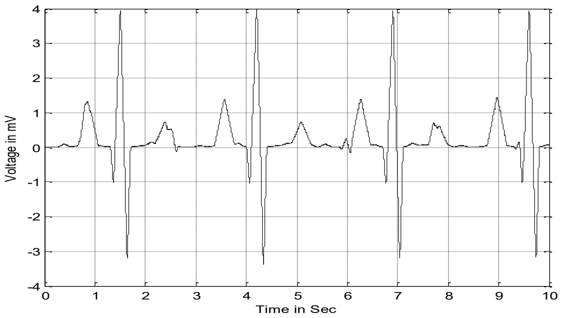

Figure 3.9: Abdominal ECG

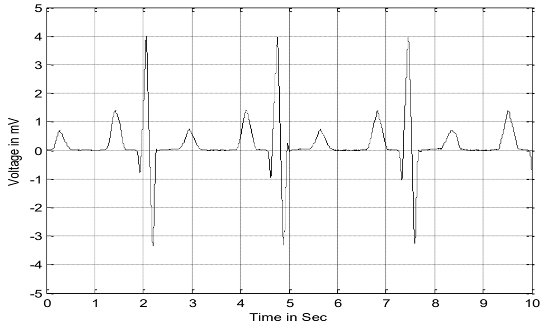

Figure 3.10: Estimated or Filter output

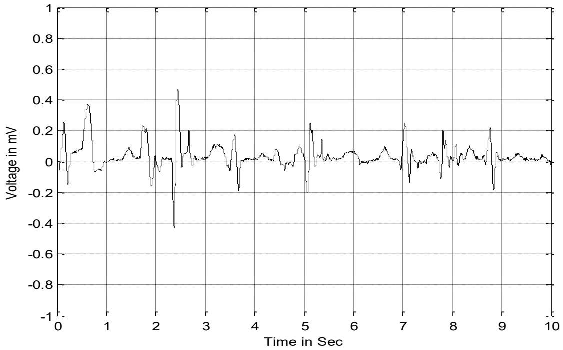

Figure 3.11: Extracted Foetal ECG Signal

Analysing the clean maternal ECG of figure 3.6, clean foetal ECG of figure 3.7 and abdominal ECG of figure 3.8 it can be seen that the maternal ECG of figure 3.6 overwhelmed the foetal ECG of figure 3.7 because the abdominal ECG which is a combination of maternal and foetal ECGs resembles maternal ECG more closely. Therefore, if the maternal ECG is not removed the integrity of the foetal ECG will be highly compromised and cannot reflect the medical condition of the foetus under such circumstance. Also comparing the abdominal ECG of figure 3.8 and extracted foetal ECG of figure 3.11 reveals that the filter substantially removed the maternal ECG and the high frequency random noise from the foetal ECG signal. The estimated noise signal of figure 3.10, that is, the filter output is substantially very close to the main noise signal of figure 3.6

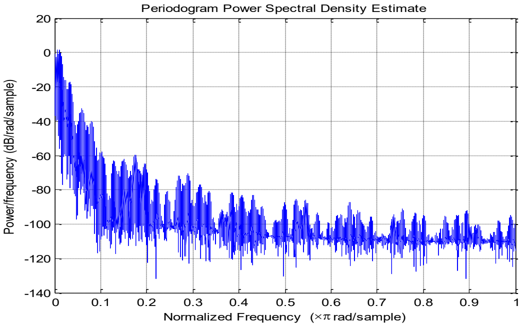

Figure 3.12: Power Spectral Density of the Original Foetal ECG Signal

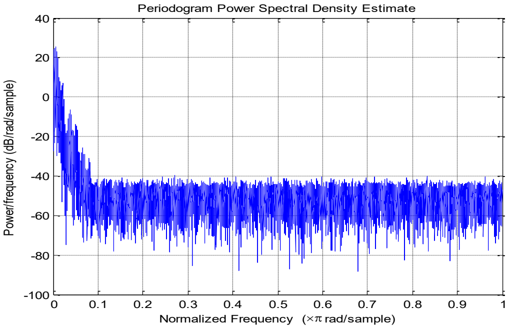

Figure 3.13: Power Spectral Density of the Abdominal ECG Signal

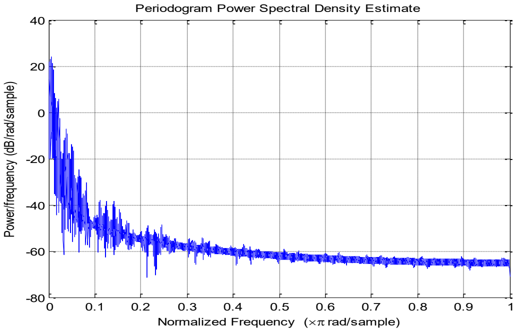

Figure 3.14: Power Spectral Density of Foetal ECG Extracted with Windowed Coefficients

The power spectral density (PSD) is a measure of either the signal power present at a particular frequency instants or degree of noise attenuation at such particular frequency instants. One of the parameters used to evaluate the effectiveness of the developed new adaptive filter is the power spectral density (PSD). Table 3.2 depicts the PSDs of the original foetal ECG, contaminated foetal ECG and the foetal ECG extracted with the new developed model of adaptive filter at nine different normalized frequencies from their power spectral density responses of figures 3.12, 3.13 and 3.14 respectively.

Table 3.2: PSDs of Original, Contaminated and Extracted FECG Signals

Normalised Frequency in Rad	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
PSD of Original FECG	-58.97	-64.95	-85.85	-87.35	-87.19	-102.5	-107.9	-96.7	-101.5
PSD of Contaminated FECG	-38.52	-40.00	-40.00	-42.14	-40.00	-39.76	-43.52	-44.43	-43.53
PSD of FECG Extracted with the Developed Filter in dB	-44.63	-49.69	-53.61	-56.72	-59.73	-61.53	-62.13	-62.36	

The second-row result of table 3.2 is the PSD of the original FECG signal. It can be seen that the PSDs at all the frequency instants are high because there is no noise component present in the signal. If the PSD value of any other signal here at any corresponding frequency instant is less than the PSD value in this second row means that there is noise component in that signal at the considered frequency instant or instants. If the PSD value of any other signal here at any corresponding frequency instant is equal to the PSD value in this second row means that the noise component is completely removed in that signal at the considered frequency instant or instants without removing any component of the useful signal. But if the PSD value of any other signal here at any corresponding frequency instant is higher than the PSD value in this second row means that the noise component is completely removed in that signal at the considered frequency instant or instants with some useful signal components also removed and that can cause signal degradation depending on the degree of removal. In the third row which showcases the PSDs of the contaminated foetal ECG indicates that the PSD at any frequency instant is higher than those of the original foetal ECG at the corresponding frequency instants. This is because of the noise components created by the maternal ECG and random noise presnt in the contaminated FECG. The last row which showcases the PSDs of the FECG extracted with the developed adaptive filter can be seen to possess PSDs that are higher than the PSDs of the contaminated FECG at every frequency instant, but less than the PSDs of the original FECG. This implies that at every frequency instant the filter removed some substantial proportion of noise component at those frequency instants but did not the noise completely. High values of PSDs of the extracted FECG implies higher degree of noise attenuation.

Other parameters used in evaluating the performance of the developed model is mean square error (MSE), signal to noise ratio (SNR) and maximum absolute error (MAE). The mathematical expressions for the three parameters are presented in equations (3.1), (3.2) and (3.3) respectively as stated by Kumar et al (2015)

$$\mathrm{SNR} = 10\ \log_{10} \frac{\sum_{k=1}^{N} X^2(k)}{\sum_{k=1}^{N} [X(k) - Xd(k)]^2} \qquad (3.1)$$

$$\mathrm{MSE} = \frac{\sum_{k=1}^{N} [X(k) - Xd(k)]^2}{N} \qquad (3.2)$$

Where X(k) is original FECG signal and Xd, extracted FECG signal and N the signal length. The equation for the maximum absolute error (MAE) is given (Mehtre and Sundram, 2019) as

$$\mathrm{MAE} = \max(\mathrm{abs}(X(k) - Xd(k))) \qquad (3.3)$$

Applying the equations, the MSE, SNR and MAE were found to be 0.0028, 20.65dB and 0.4821 respectively. These parameters are good enough to qualify the developed filter as being very effective in extracting foetal ECG signal from composite abdominal ECG signal.

3.3: Comparing the Windowed and Unwindowed Adaptive Filter Performance

The new algorithm is validated by comparing the performance of the developed model with that of un-windowed LMS algorithm in separating maternal ECG and foetal ECG from abdominal ECG when used in implementing adaptive filters. In realising this, the abdominal ECG is applied to the un-windowed LMS based adaptive filter. The extracted foetal ECG signal is shown in figure 3.15. The spectral density response of the extracted signal is depicted as figure 3.16.

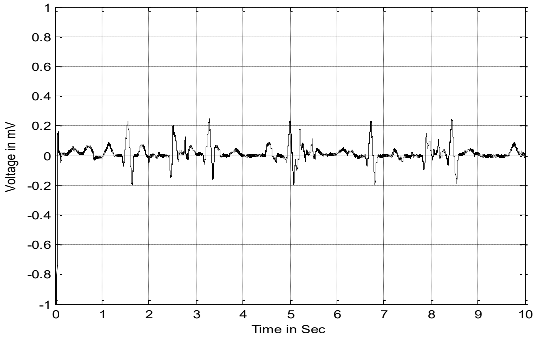

Figure 3.15: Foetal ECG Extracted with Un-windowed Adaptive Filter

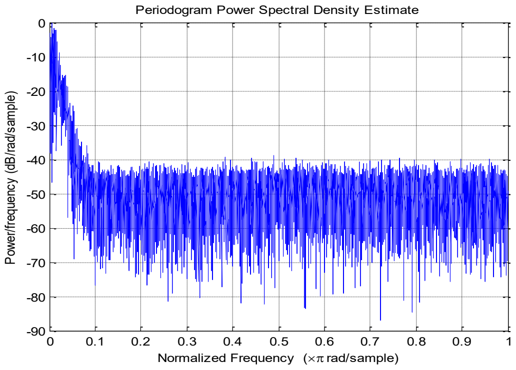

Figure 3.16: Power Spectral Density of Foetal ECG Extracted with Un-windowed Filter

One of the parameters used for the comparison are the power spectral densities arising from the two adaptive filters at corresponding frequency instants and table 3.3 depicts these PSDs.

Table 3.3: Comparison of PSDs of the Developed Model and the Existing Model

Normalised Frequency in Rad	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
PSD of Original FECG	-58.97	-64.95	-85.85	-87.35	-87.19	-102.5	-107.9	-96.7	-101.5
PSD of Contaminated FECG	-38.52	-40.00	-40.00	-42.14	-40.00	-39.76	-43.52	-44.43	-43.53
PSD of FECG Extracted with the Developed Filter in dB	-44.63	-49.69	-53.61	-56.72	-59.25	-59.73	-61.53	-62.13	62.36
PSD of FECG Extracted with Existing Filter in dB	-43.02	-44.72	-42.07	-42.88	-42.30	-43.35	-43.56	-43.39	-42.57

From table 3.3 it can be observed that the PSD at every frequency instant of the developed model is higher than that of the existing model at every corresponding frequency instant and that implies that the developed model provided better attenuation of the noise.

Other parameters used for the comparison are MSE, SNR and MAE. The results of the computations for the two models are presented in table 3.4.

Table 3.4: Comparison of MSE, SNR and MAE of the Developed Model and the Existing Model

Signal	FECG Extracted with the Developed Model	FECG Extracted with the Existing Model
MSE	0.0028	0.0049
SNR in dB	20.65	17.78
MAE	0.4821	0.4990

Examination of table 3.4 shows that the developed model outperformed the existing model in the three evaluation parameters. The results confirm that coefficient windowing significantly enhances maternal ECG suppression while preserving foetal signal morphology.

IV. CONCLUSION

This study presents a Blackman-windowed adaptive FIR filtering approach for non-invasive extraction of foetal ECG signals. By combining the stability and linear phase properties of FIR filters with coefficient windowing, the proposed method improves extraction quality beyond conventional LMS adaptive filters. Simulation results demonstrate superior SNR and reduced error, confirming the effectiveness of the approach.

The proposed technique is computationally efficient and suitable for real-time biomedical signal processing applications. Future work will focus on validation using real clinical datasets and hardware implementation.

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