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Denoising of ECG Signal using UFIR Smoothing with Notch Filter

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Abstract: ***The electrical activity of the heart is test with an electrocardiogram (ECG). The fundamental information for the taking decision about various types of heart diseases identified by electrocardiogram. There have been numerous attempts over decades to extract the characteristics of the heartbeat through ECG records with high accuracy and efficiency using a variety of strategies and techniques. In this paper a novel scheme is acquainted, the problem is solved by isolated time space using q-lag unbiased finite impulse response (UFIR), then the received time changing of optimal average horizon for the shape of the ECG signal. A complete statistical analysis is furnished by normalized histogram and statistical classifiers, P wave features extraction based on the detected fiducial points is deliberated. In this concept by utilizing QRS detection, morphological top-bottom hat transformation and notch filters is ameliorated PSNR and latency constraints, furnishes high accuracy and reduced elapsed time.***

Keywords: Electrocardiogram (ECG) denoising, unbiased finite impulse response (UFIR) filtering, P wave feature extraction, normalized histogram, QRS complex detection.

I. INTRODUCTION

The electrocardiogram acquainted to analysis the rhythmical throbbing of the arteries as blood is propelled through them. An electrocardiogram records the electrical signal in your heart. It is a simple and painless test employed to quick diagnose heart problems and monitor your heart health. The electrical signals from the heart to check various heart conditions, but it is susceptible to noises. ECG denoising is a major pre-processing step which attenuates the noises and emphasize the normal waves in ECG signals. In particular several algorithms have been developed to analyze and capture the reliability properties and rhythm variables in ECG signals, based on the clustering of syntactic features to detect noise and extract information about atrial behavior. Learned by P through ECG signals, QRS, and T waves, appropriate methods of ECG signals denominating and feature extraction are utilized. However, reaching accurate results is still challenging due to the data collection equipment.

Here we introduced an ameliorated unbiased finite impulse response(UFIR),impartial sensitivity only for odd degree polynomials correct lag q should be taken from other points for even degree polynomials. P shift theory, q=-p>0, unbiased finite impulse response (UFIR) filtering, Savitsky-Golay is considered sensitive in particular to odd order polynomials, to provide the best denoting effect, this approach must be set individually for each polynomial indicating the correct lag q and not necessarily at the midpoint.

Furthermore, it provides smoothing filtering by p<0, filtering by p=0 and predictive filtering by p>0.The Savitsky-Golay filter was recently modified to be optimal in the minimum mean square error (MSE) sense, the modification is equivalent to a proper UFIR filter, which produces the maximum probability estimate because these two solutions require information about the noise that is not well studied in the ECG signals. An optimal q lag state space UFIR smoothing algorithm is proposed for the ECG signals denoising, artifact removal and stable features evaluation using different classifiers under unknown noises of the ECG signals. It provides high accuracy pattern classification for ECG signals and ameliorated PSNR and better RMSE values, furnishes feature extraction and reduces time elapsing.

For the rest of the paper is organized as follows, ECG Signal Data Base and Model are described in section II, followed by the Features Extraction in State Space using an UFIR Smoother in section III, in section IV discusses Simulation Results and finally the conclusion of the work is discussed in section V.

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II. ECG SIGNAL DATABASE AND MODEL

MIT-BIH arrhythmia database is publicly available dataset which provides standard investigation material for the detection of heart arrhythmia. It is used for purpose of fundamental research and medical device development on cardiac rhythm and related diseases. This work employs the MIT-BIH Arrhythmia Benchmark, which contains many records taken from different databases, such as the MIT-BIH Arrhythmia (MITDB). MITDB holds 48 records with simple and extraordinary rhythms taken from 47 subjects. Records were sampled up to 360 Hz per lead with 11-bit resolution in the 10mV range. This database provides records in two leads, the most common being MLII (Modified Lead II). Other leads, such as V1, V5, etc. are also used. An important issue is choosing a bottle that most clearly reflects the ECG signal morphology.

A. ECG Signal Model in Discrete-Time State-Space

To provide effective denoting and extraction of features, in this subsection we will model the ECG signal in isolated-time state-space. We refer to the ECG signal on the horizon [m, n] at n points from m = n - N + 1to n, where n is the discrete time indicator. Inherent ECG noise is not yet well understood and its misinterpretation can cause assessment errors. Therefore, we assume that the underlying process in each ECG pulse is time-constant and decisive. We assume that the scalar dimensions of the ECG signal are provided in the presence of an unknown distribution (not necessarily Gaussian) and zero mean noise with a coverage. According to such estimates, we represent the ECG signal at discrete-time status-space with the following status and observation equations, respectively.

$$x_n = Fx_{n-1} \quad (1)$$

$$y_n = Hx_{n+vn} \quad (2)$$

where $x_n \epsilon \mathbb{R}^K$ is the ECG process state vector, y_n is the scalar observation, v_n is the scalar measurement noise, $F\epsilon \mathbb{R}^{K\times K}$ is the system matrix projecting the initial state x_{n-1} to x_n and given by

$$F = \begin{bmatrix} 1 & \tau & \frac{\tau^2}{2} & \cdots & \frac{\tau^{K-1}}{(k-1)!} \\ 0 & 1 & \tau & \cdots & \frac{\tau^{K-2}}{(k-2)!} \\ 0 & 0 & 1 & \cdots & \frac{\tau^{K-3}}{(k-3)!} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \quad (3)$$

For scalar measurement, we assign the observation matrix as H= [1 0 . . . 0] $\epsilon \mathbb{R}^{1\times K}$ and suppose that noise v_n is zero mean with unknown distribution. The batch UFIR is applied to (1) and (2) to provide state estimate.

B. Adaptive Optimal Horizon N_{opt} :

The UFIR filter can minimize the mean square error (MSE) on [m,n] if N is set horizontally to N_{opt}. To enable it in the absence of a reference signal (ground truth), we follow and find the N_{opt} for ECG signals by reducing the trace of the derivative of the measurement residual matrix V(N) to the mean square value (MSE) as

$$\widehat{N}_{opt} = arg_N \, min \frac{\partial \, tr \, V(N)}{\partial \, N} + 1 \quad (4)$$

The solution for the optimization equation (12) along with an algorithm is provided with use further process, the optimal horizon was found to be N_{opt}=21 working. K=21 and a 2-degree polynomial for the three states database is used, N_{opt} varies over different parts of the ECG signals. So we do N_{opt} adaptive (N_{apt}) from N_{min} = K = 3 to N_{opt}.

$$N_{min} \leq N_{apt} \leq N_{opt} \quad (5)$$

Where N_{min} is the minimum horizon applied for a rapid excursion between Q_p and S_p. For this, we separate the five parts of the ECG signal with the following points: Q_{int}, Q_p, S_p and S_{int}. upto Q_{int}, the soft part of the ECG signal N_{opt}. Between Q_{int} and Q_p, the horizon N_{apt} simply decreases from N_{opt} to N_{min}.

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The QRS complex between Q_p and S_p is processed with N_{min} to follow a rapid excursion around R_p from S_p to Sint, Horizon N_{apt} simply increases from N_{min} to N_{opt}, the horizon eventually becomes N_{opt} above Sint. Accordingly, custom UFIR smoothing is provided as

$$\hat{X}_{n-q/n} = \begin{cases} \hat{X}_{n-q/n}(N_{opt}), & 1 \le n \le Q_{int} \\ \hat{X}_{n-q/n}(N_{apt}), & Q_{int} \le n \le Q_p - 1 \\ \hat{X}_{n-q/n}(N_{min}), & Q_p \le n \le S_p \\ \hat{X}_{n-q/n}(N_{apt}), & S_p + 1 \le n \le S_{int} \\ \hat{X}_{n-q/n}(N_{opt}), & S_{int} + 1 \le n \le T \end{cases} \quad (6)$$

Here T represents the heartbeat length. If N_{apt} is provided, we can design a UFIR smoothing algorithm using subsequent iterations, which will reduce the computational load.

III. FEATURES EXTRACTION OF STATE SPACE USING UFIR SMOOTHER

The ECG signal in state space using an unbiased finite impulse response (UFIR) smoothing features extraction are provided in five stages as shown in the figure 1, which consists of different stages 1) Detrend, 2) QRS complex detection, 3) Segmentation, 4) UFIR smoothing, 5) Windowing of ECG signals, 6) Fiducial Detection, 7) Notch filter, 8) Interference removal by top-bottom hat transformation and 9) Interference removal.

1) *Detrending:* ECG demonstrated a detrending method to eliminate the level of RR interval fluctuations in data b and tested its properties. The detrending approach sensitivity predicts the trend of a given signal based on pre-formulation. The process of removing the baseline wandering in the ECG signal by the detrending method begins with setting the cutoff frequency by determining the regulation parameter, unlike the FIR and IIR digital filters, the total segment of the input signal is considered during the detrending operation and no time is obtained to get processing signal.
2) *QRS Complex Detection:* QRS detection is a basic step in determining the heart rate for subsequent rhythm classification, so the high QRS detection rate method is the most important component of the ECG analysis algorithm. The QRS-complex was discovered using citations from the arrhythmia MIT-BIH database following the procedure proposed by Pan Tompkins. Note that the highest number of citations identified the QRS complex with a probability of 93.4%.
3) *Segmentation:* The QRS-complex is localized, the point closest to the R-peak in each heart rate. Next, by taking 100 samples to the left and 200 samples to the right, a window is created to describe the heart rate as shown in Figure 1. Does not cover all points of interest (P-wave, QRS-complex and T-wave), its width increased. The segmentation process is performed heuristically with the aim of analyzing the morphological waves.

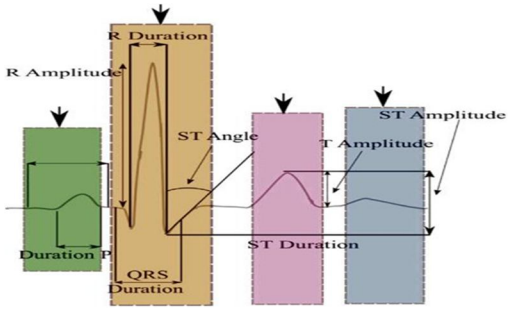


Fig.1 The heart rate pulse representation of P-wave, QRS-complex and T-wave

4) *UFIR Smoothing:* We will progress an effective computational algorithm for the extraction of ECG signal features. For this, we first localize specific points on the ECG heart rate pulse and then calculate the corresponding amplitude, duration, and angle. Unlike the developed methods, this algorithm is based on the UFIR Smoothing flutter used with p-shift and l = 2 and p <0. N_{opt} = 21 suites were found for the softer parts of the isolated ECG signal and the data used as N_{min} = 3 feet QRS complex. Note that N_{opt} and N_{min} must be specified for the measured ECG signals. The N_{opt} and N_{apt} described for the database used apply beyond the Horizon N_{opt} = 21 QRS complex. To avoid large bias errors, N_{apt} is specified and applied to all EGC signals. The UFIR filtering provided is performed using smoothing with a lag q.

5) *Windowing of ECG Signals:* The UFIR smoother delivers denoting and evaluation of the three states of the ECG signal as shown in Figure 2, for the first state consists of denoised ECG signals, the second state is time derivative of the denoised signal and the third state is the second derivative of the denoised signal. Using information about ECG signal status, the R-peak, QRS_{max} and QRS_{min} are determined and a window is applied to cover the QRS complex. P-Wave Detection is provided starting at Q and ending with the heart rate. Here, in the second case a window is applied to cover the P_{on}, P_{peak}, P_{off} points determined by P_{max} and P_{min}. Similarly, the T-wave is detected, in which case the T_{on} and T_{of} are covered by a window created for T_{max} and T_{min}.

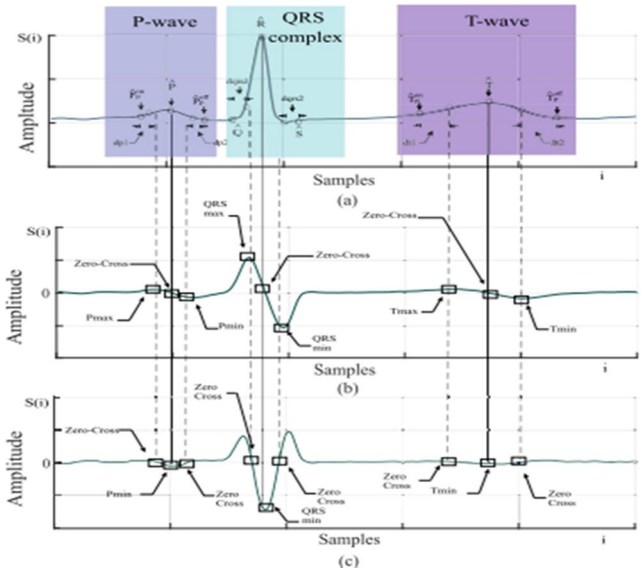


Fig.2 UFIR Denoising and Extraction of three states of ECG signals

6) *Fiducial Detection:* In this division, we utilize the above results to deliver identification and extraction of reliable points such as duration and amplitude of various identified fiduciary points. By providing the windows of P-wave, QRS- complex and T-wave, we utilize P_{on} as the starting point of P-wave, P as P-peak, P_{off} as the ending point of P-wave, Q is starting point of the QRS complex as a final point, R as R-peak ,S is the ending point of QRS complex, Ton as the starting point of the T-wave, T as the T-peak, and T_{of} as the starting point of the T-wave. The fiducial points are summarized as follows.

a) QRS – Complex: The Fiducial points for the QRS-complex are decisive by searching the maximum QRS_{max} and the minimum QRS_{min} in the second position, which are proven by the third position at zero cross points. Two variables " dqrs1 " and " dqrs2 " were introduced to calculate the starting and ending points of the QRS-complex. The R-peak is marked as $\hat{R}$ at the zerocross point of the second state and verified by QRS_{min} of the third state.

b) P and T Waves: The confidence points for the P and T waves are decisive by searching P_{max}, T_{max}, P_{min} and T_{min} in the second position, which are verified by the third position at zero cross points. Two variables ‘‘dp1’’ and ‘‘dp2’’ were introduced to calculate the starting and end points of the P-wave. identically, two variables "dt1" and "dt2" were introduced for the T-wave. P-peak and T-peak assigned as P and ˆ T are found at the zeros cross of the second position, respectively. These points are confirmed by Pmin and Tmin in Figure 2. The $\hat{P}_p^{on}, \hat{P}, \hat{P}_p^{off}, \hat{Q}, \hat{R}, \hat{T}_p^{on}, \hat{T}, \hat{T}_p^{off}$ provided fiduciary points are calculated for the ECG wavelengths and amplitude to indicate the corresponding points, P wave as

$$P_{dur} = P_p^{off} - P_p^{on} \cong P_p^{off} - S\hat{P}_p^{on}, \quad (7)$$

$$P_{amp} = S(P_p) - S(P_p^{on}) \cong \hat{P} - S\hat{P}_p^{on}, \quad (8)$$

For QRS Complex as

$$QRS_{due} = S_p - Q_p \cong \hat{S}_p - \hat{Q}_p, \quad (9)$$

$$QRS_{apm} = R - S(Q_p) \cong \hat{R} - S(\hat{Q}_p), \quad (10)$$

7) *Notch Filter:* Notch filter is also called as band stop filter or band reject filter. These filters attenuate signals within a specific frequency band called the stop band frequency range, and pass signals upper and lower this band. For example, if a notch filter has a stop band frequency of 1000mhz to 1050mhz, it sends signals from DC to 1000mhz and more than 1050mhz. It only blocks signals from 1000 MHz to 1050mhz. The optimal response to any notch filter is a completely flat response within the usable range except for the notch frequency. Here it drops very fast by providing a high level of attenuation that can remove the unwanted signal.

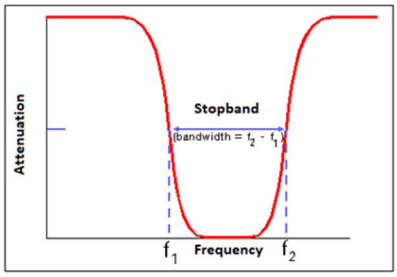


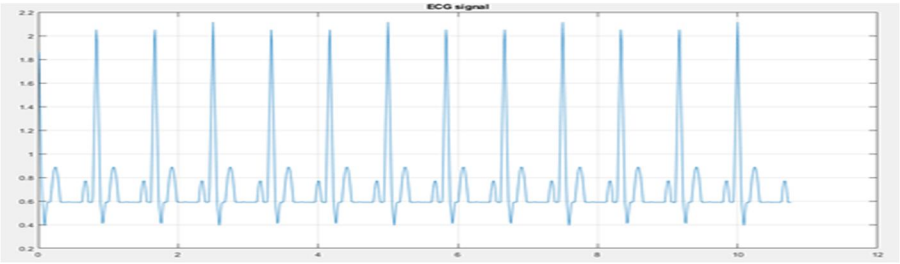
Fig.3 Notch filter Frequency Responce

8) *Interference Removal by top-bottom hat Transformation:* Morphological signal processing involves a wide collection of theoretical concepts and mathematical tools for signal analysis, non-linear signal operators, design techniques and application systems related to mathematical operations. The morphological operators of opening and closing are very easy, and the morphological top-hot transformation that arises from these operators has confirmed to be powerful tools and has been utilize in a variety of applications, giving accomplished results in terms of noise reduction, edge detection and object identity. Top-hat transformation (S_{TH}) is acquired by subtracting the signal opening from the original signal, while the bottom-hat transition (S_{BH}) is acquired by removing the original image from the signal closed signal.

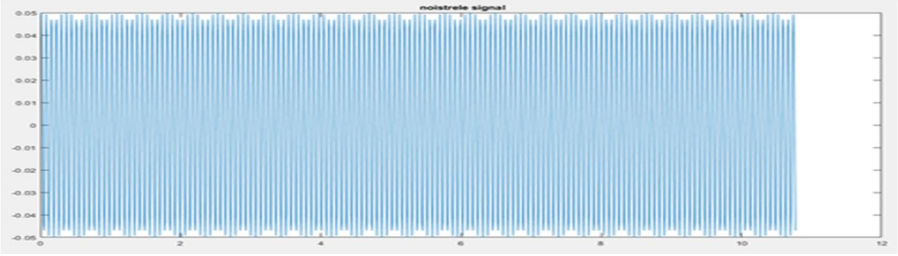
$$S_0 = S + S_{TH} - S_{BH} \quad (11)$$

IV. SIMULATION RESULTS

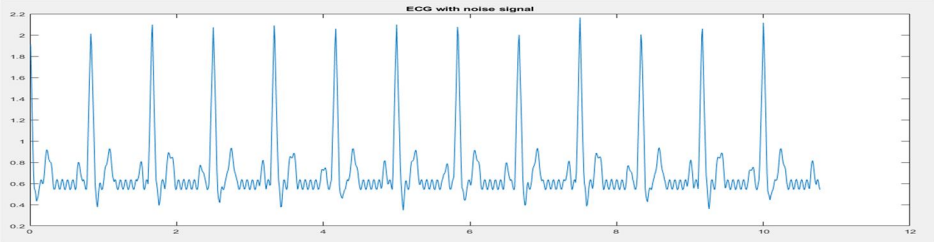
As reported by simulation results are extracted by the given input signal is evolved by using MAT Lab software. Here an input ECG signal is taken in fig.4(a) a noise signal added to the ECG signal fig.4(b) then the resultant of ECG with noise signal fig.4(c) is evolved. After filtering and removal of artifact Measurement residuals produced by the UFIR smoother (q-lag1 and q-lag2). The first-time derivative signal is produced by using windowing of the ECG signal. By conducting the accurate features extraction of the signals, the P wave features is extracted and produces normalized histogram. The interference is removed by using top-bottom hat transformation and notch filter attenuate the noise signal and finally gets the denoised ECG signal.



(a)



(b)



(c)

Fig.4 (a) Original ECG signal, (b) Noise signal, (c) ECG signal with noise

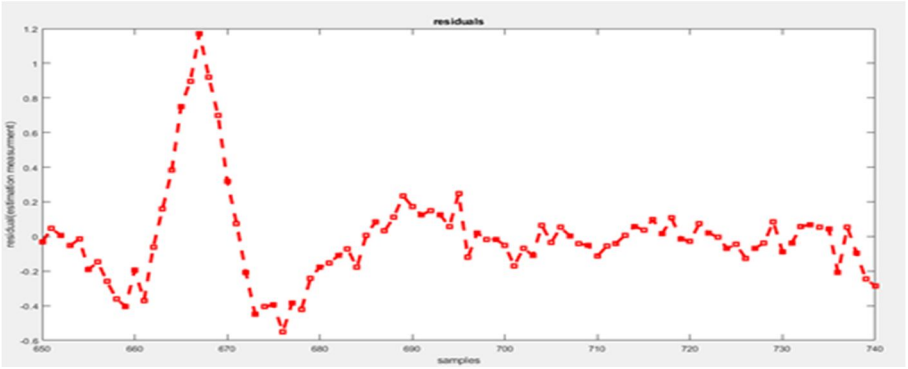


Fig.5 Measurement residuals produced by the UFIR smoother

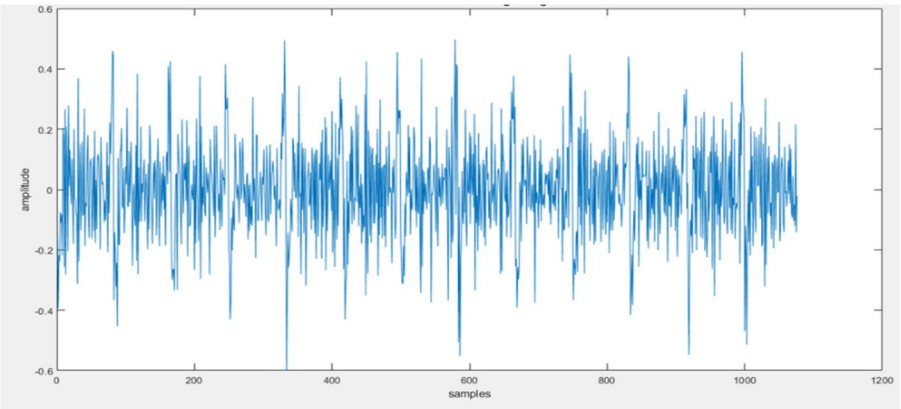


Fig.6 First-time derivative signal

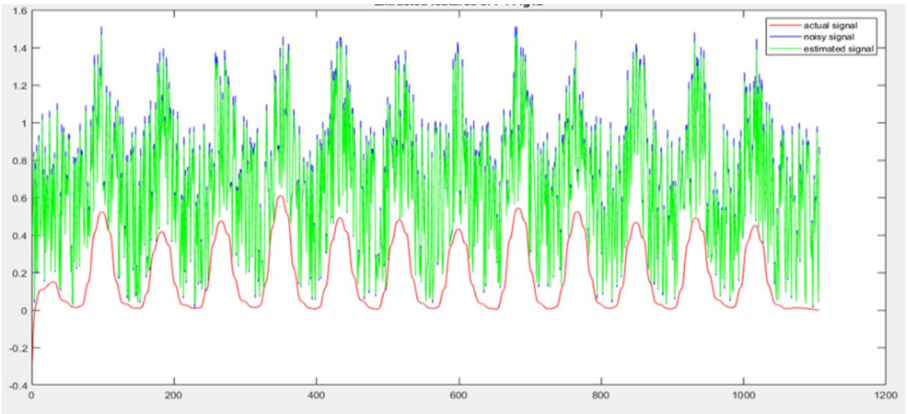


Fig.7 Extracted features of P-wave

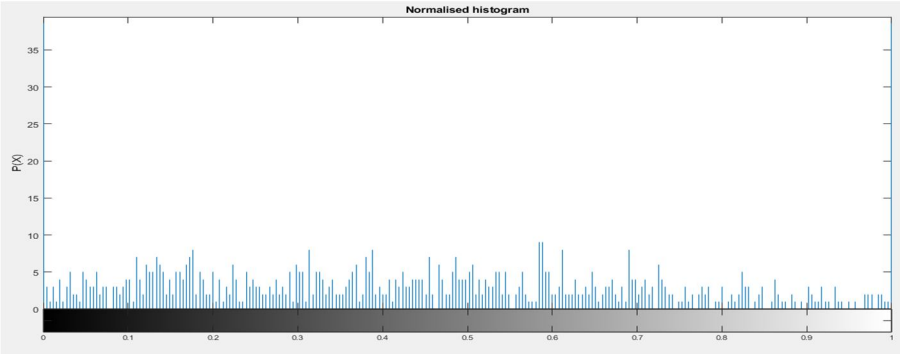


Fig.8 Normalized histogram

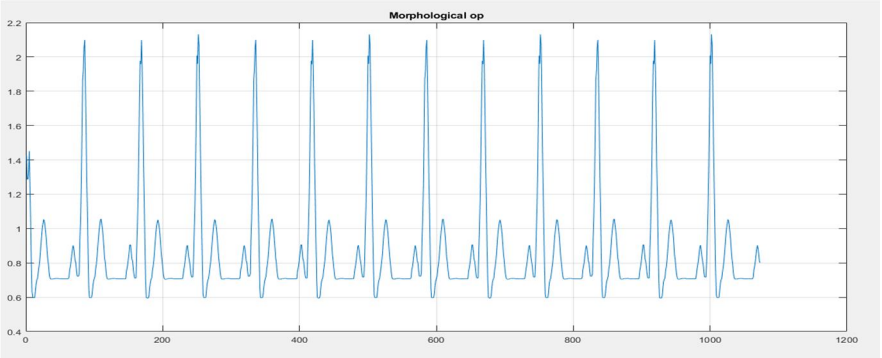


Fig.9 Morphological output

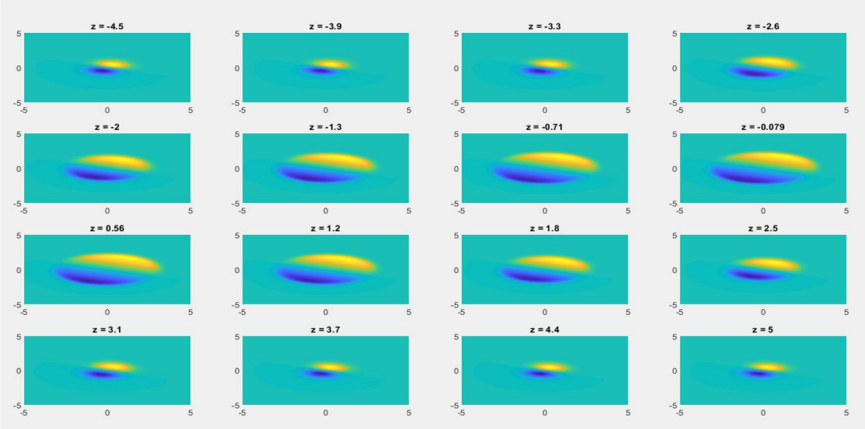


Fig.10 Notch filter output

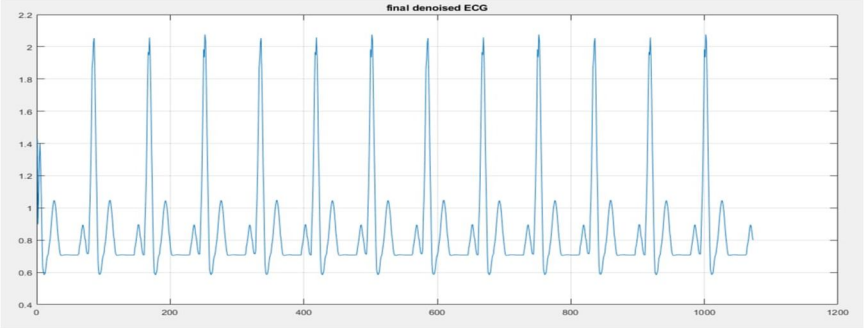


Fig.11 Final Denoised ECG signal

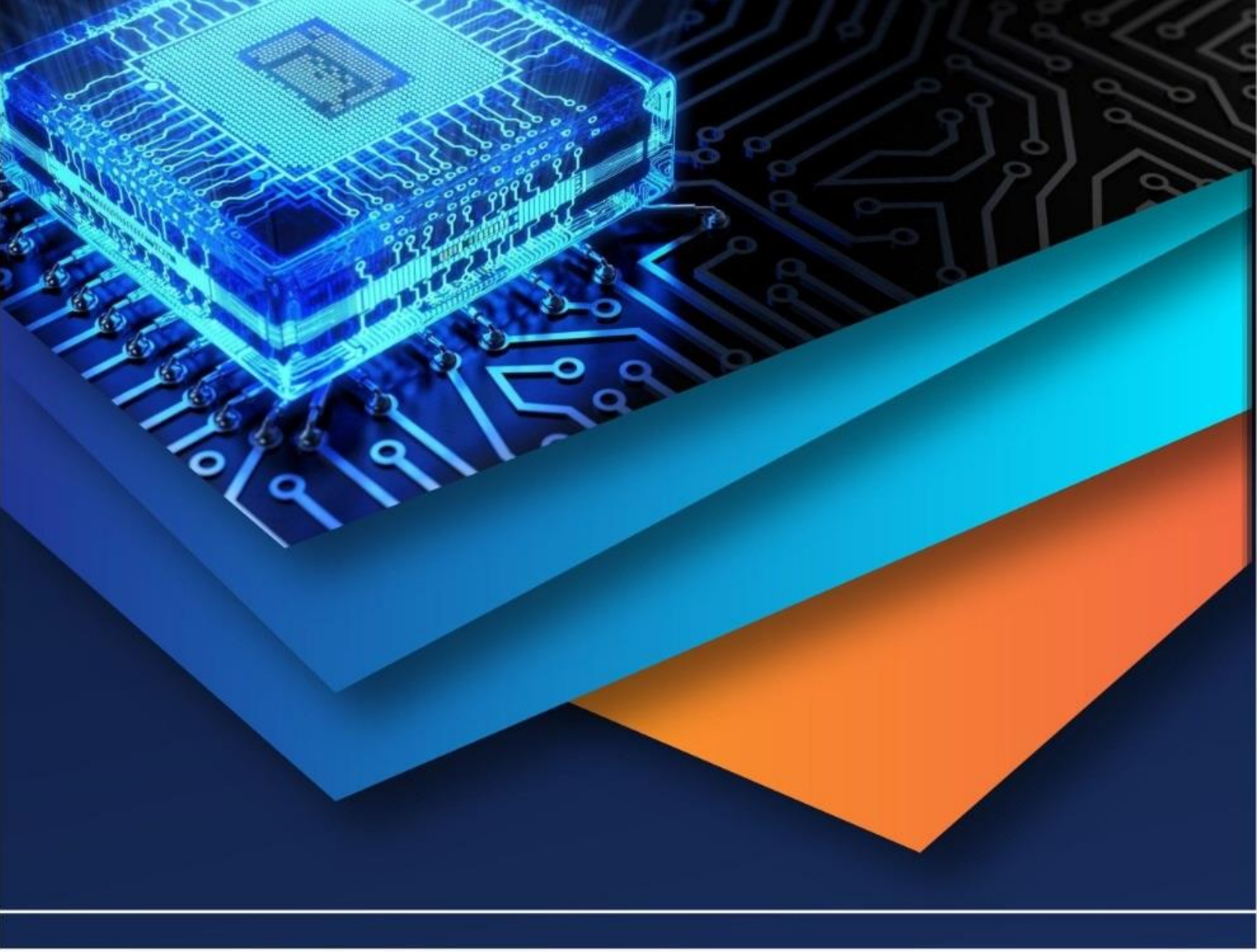
V. CONCLUSION

This method proposed a novel technique which remove the measurement of noise and extract concurrently features of ECG signal in state space using unbiased finite impulse response (UFIR). This smoother does not require the noise statistics and initial values and is thus more suitable for ECG signals, whose noise is still not well understood. This approach involves power line interference and baseline navigation of ECG signals, such as notch filtering and morphological filtering. Simulation results show that the proposed paper provides better performance of baseline wandering elimination for ECG signals and reduces the root mean square error (RMSE). The Specific advantages due to its suitability to non-stationary and non-linear time series. May be even the most complex problem that has not yet been solved is that the biomedical timeline is often recorded over long periods of time that extend over days and weeks. The state-space UFIR smoothing approach enhanced in this process for ECG signal denoising and feature extraction has demonstrated better results than existing methods.

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