On Development of Fuzzy Filter for De-noising ECG Signal

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Summary
Electrocardiogram (ECG) is a quasi-periodic rhythmic signal harmonized with the activity of the heart. Investigation of the electrocardiogram (ECG) signals has turned into an emergent procedure for diagnosing cardiac arrhythmias. Since ECGs are low level signals and frequently contaminated by noise which inclines to change the morphology of the signal, the accurate diagnosis is drastically hampered. This research proposes a fuzzy filtering method based on the adaptable window to eliminate the noise. The efficacy of the proposed approach has been validated over experiments to compare with the commonly employed signal error calculation measures like Signal to noise ratio (SNR), Root Mean Square (RMS) error, and Maximum Amplitude (MAX) error.
Key words:
ECG signal, Fuzzy filter, membership function, QRS complex.

1. Introduction

Over the last few decades innumerable researches have been exploring on automating the examination of Electrocardiogram (ECG) signals and analyzing the heart activity. Biomedical function of the heart is being documented by superficial electrodes on chest and limbs. The examination of the ECG signal is a traditionally employed technique for identifying cardiac diseases [1].
With electrocardiograms containing arrhythmias, ECGs appear to be involved with distortions in the perceived waveform. These distortions, as accompanied by a patient carrying arrhythmia, happen in a regularity and morphological resemblance that they might be observed as a graphical arrangement in the temporal area.
The ECG waveform can be distorted by cardiovascular diseases like atrial fibrillation, ventricular fibrillation and conduction problems [2]. The quality of ECG signals also become degraded owing to several sorts of matters like electrode displacement on the QRS-complex, instrumental noise, electromechanical interference, power line interference, temperature, pressure and humidity. Existence of noise is one of the primary stimulating complications in Biomedical Signal Processing [1]. Since noise influences to wrong interpretation, ECG signal denoising is obligatory.
Numerous research works have been cited in literature on mathematical approaches and computational procedures to suppress noise in ECG signals [3–8].
Golden *et al.* developed a Fourier transform-based method [9] to outline ECG signal characteristics. This approach ignores the time computation, which distresses the estimation accuracy. Yochum *et al.* [10] recommended a wavelet transform-based approach to detect the P, QRS and T patterns in ECG signal. Although they made trade-off between frequency and time resolutions it provides low productivity in flattening ECG signals. Azbari *et al.* [11] employed principal component analysis (PCA) for ECG signal analysis. Rezgui and Lachiri [12] applied support vector machine for ECG biometric recognition. Sansone *et al.* [13] developed a neural networks based method for ECG pattern recognition. Lastre-Domínguez *et al.* [14] developed a shift unbiased finite impulse response (UFIR) filter for denoising ECG signal. This method is capable of detecting durations and amplitudes of the P-wave in the standard ECG signal with normal heartbeats.
This research focuses on suppressing noise from the ECG signal employing a fuzzy filter. The filter is designed on the basis of the s- shaped membership function where the fuzzy membership value is assigned for each neighborhood interval of the ECG signal. The objective of the proposed research is to find an effective solution to detect P wave depending on the morphological characteristics of arrhythmia*s* employing fuzzy similarity computation in the ECG signal. The subjects for investigation includes normal persons, patients with alteration of artefactual amplitude, atrial fibrillation and patients with ventricular tachycardia. The method is justified employing MIT-BIH Arrhythmia Database as a benchmark.
The remaining part of the paper is organized as follows. Section 2 outlines the ECG signal. Section 3 describes Noise Reduction and Filter Design techniques. The experimental results are presented in Section 4. Finally, Section 5 draws the overall conclusions of this research.

2. ECG Signal

An ECG is a biological signal keep tracking of the functionality of the heart. Owing to its quasi-periodic behavior, a typical ECG signal is formed of a sequence of cardiac cycles. The standard waveform is consisting of three

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significant morphological features, in their order: P wave, QRS complex and T wave, as illustrated in **Fig. 1**.
Each segment described in the ECG waveform has significant impact on the condition of the heart. The P wave is produced by atrial depolarization and its duration is usually less than 120 ms. The standard shape of the P wave does not contain any peaks or notches. It may be positive, negative, or biphasic in the residual leads. An absent P wave in the ECG wave pattern may indicate sinoatrial block [7]. The QRS complex wave outline is affected by conduction syndromes. Ventricular development might cause a broader than normal QRS complex. The ST fragment can be depressed due to myocardial infarction. The standard time interval of the QRS segment is from 0.04 to 0.09 seconds and if it is more than 0.1 seconds indicates the ventricular depolarization and will cause to beating of the heart. The P wave of the ECG wave pattern usually deals with very weak signals ranging from 0.5 mV to 5 mV.

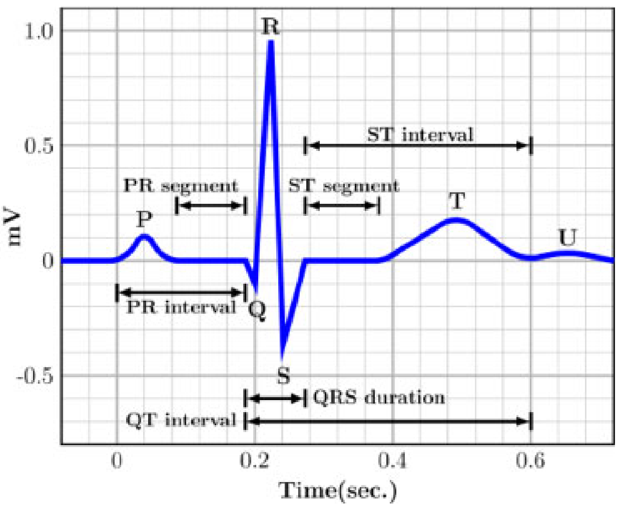

Fig. 1 The normal electrocardiogram.

3. Noise Reduction and Filter Design

Noise reduction is the process of eliminating noise from the signal. All ECG signal processing devices have traits that make them vulnerable to noise. Usually, window functions are used in the spectral analysis and finite impulse response filters to truncate the infinite data series to some finite limits. A window function is a mathematical tool that produces zero value outside some selected interval, that is, the data that are beyond the truncation points are ignored. This windowed series may be processed more efficiently for filter design. The practical window functions generally have a trade-off between the width of its main-lobe and attenuation of its side-lobes [8]. **Table 1** gives the equations for different window types. Where M denotes the order of the filter, which is equal to the filter length.

Table 1: Different window types

Window Type	***Weight Equations***
Rectangular	$w(n)=1 \quad (1)$
Bartlett	$w(n)=1-\dfrac{2\left\lvert n-\left[\frac{M}{2}\right]\right\rvert}{M} \quad (2)$
Hanning	$w(n)=0.5-0.5\cos\left(\dfrac{2\pi n}{M}\right) \quad (3)$
Hamming	$w(n)=0.54-0.46\cos\left(\dfrac{2\pi n}{M}\right) \quad (4)$
Blackman	$w(n)=0.42-0.5\cos\left(\dfrac{2\pi n}{M}\right)+0.08\cos\left(\dfrac{4\pi n}{M}\right) \quad (5)$

The graphs in **Fig. 2** illustrates the impact of various window functions in the frequency response of low pass filters, with a cut-off frequency of 5 KHz and sampling frequency of 4.41 KHz.

In order to remove the noise, a fuzzy filter is proposed using adjustable windows. This adaptive window based fuzzy filter decreases the intervention existing in the ECG signal. The ECG signal from MIT-BIH Arrhythmia Database is employed and degraded with Gaussian noise, Brownian noise, and power-law noise. The degraded signal is then filtered using the proposed fuzzy filter. The acquired outcomes are compared on the basis of commonly used signal error calculation methods like SNR, MSE and MAX.

The traditional filters employed for signal processing applications usually use fixed length window to process the signal contents. ECG signals differ in characteristics from common digital signals since they carry special information about P wave, QRS complex and T wave. Here, Fuzzy rules are applied for deciding the amplitude level of a given sample interval in the ECG signal from the neighborhood of that sample. This is a variation of the Median filter and Neighborhood Averaging filter. The decision process includes the following steps:

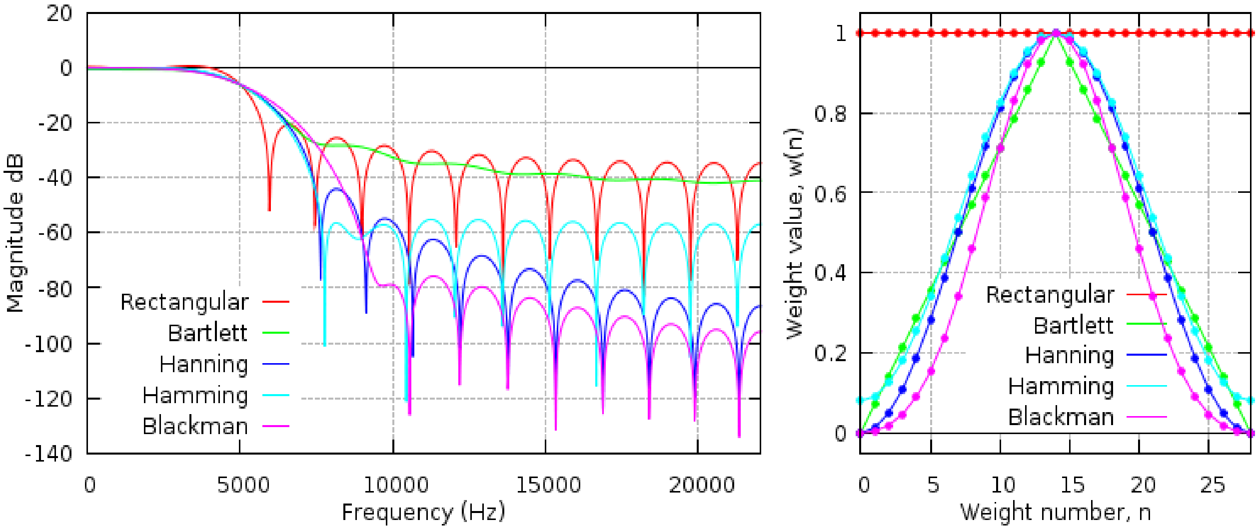

Fig. 2 Frequency response of various window filters.

1. The ECG signal is sampled at regular intervals.
2. The sampling amplitudes of the neighborhood intervals (*p* neighborhoods) are stored and organized in ascending or descending order.
3. Fuzzy membership value is assigned for each neighborhood interval with the following concepts:

i. A Gaussian membership function, as shown in **Fig. 3**, is used. The membership function is given by the expression:

$$\mu_A(x,c,w,f) = \exp\left[-\frac{1}{2}\left|\frac{x-c}{w}\right|^f\right], \qquad (6)$$

where *c* is the center, *w* width and *f* the fuzzification factor. The parameters for this research are chosen empirically as: (c=5, w2=2, f=2).

ii. The maximum and minimum amplitudes obtain the membership value 0.

iii. Membership value 1 is assigned to the mean value of the amplitudes of the neighborhood.

iv. Consider only $2\times p+1$ sample intervals ($p/2<=n$) and they are the median sample value and *p* preceding and onward sample values in the sorted list.

v. The sample value that has the maximum membership value is chosen and considered as output.

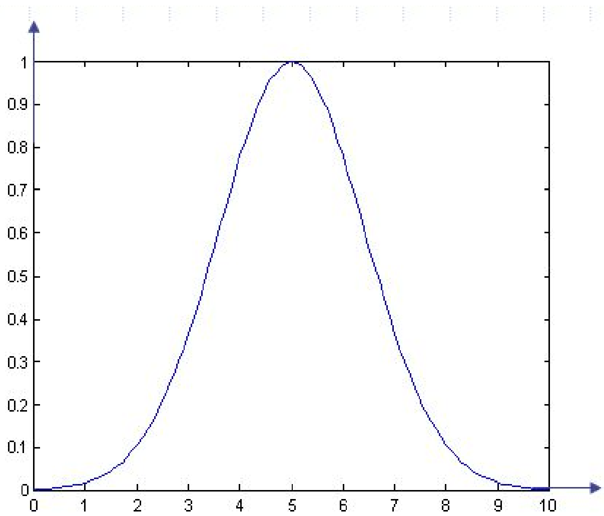

Fig. 3 Gaussian membership function.

This method combines the benefits of both the median filter and averaging filter. For p=0, it performs like a median filter and for $p/2<=n$, it turns as averaging filter. This approach can effectively reduce the noise that concerns to sharp transitions. Moreover, it does not produce any zig-zag amplitude like averaging filter.

4. Experimental Results

The evaluation of the quality of the ECG signal has been performed under various subjective methods, consulting with the cardiologists and other medical experts. The three common noise sources are associated with biomedical signals. These are (i) baseline wander, the low frequency high-bandwidth components caused by perspiration or body movements, (ii) power line interference due to electromagnetic fields and can cause low-amplitude 60 Hz sinusoidal waveforms and (iii) muscle noise, especially in recording during exercise and overlaps with the PQRST complex. When filtering the ECG signal, care must be taken not to change the desired signal information and the possible distortion caused by the filter should be carefully quantified. The response of the proposed filter is shown in **Fig. 4**.

The MIT-BIH arrhythmia database was used to validate the proposed fuzzy filter design. The signal to noise ratio (SNR) is a parameter to assess the quality of the filtering techniques. The SNR is defined as the ratio of the amplitude of the signal to the amplitude of the noise [15-17] and is expressed in dB by the equation:

$$SNR\,(dB) = 10\log_{10}\left\{ \frac{\sum_{j=0}^{J-1}\left[y(j)^2\right]}{\sum_{j=0}^{J-1}\left[y(j)-\tilde{y}(j)\right]^2} \right\}, \qquad (7)$$

where $y(j)$ is the amplitude of the original signal and $\tilde{y}(j)$ is the amplitude of the reconstructed signal, and j is the index of each sample of the signal of length J.

The performance of the proposed filter has been compared to the traditional Wavelet Transform (WT) and Discrete Time Wavelet Transform (DT-WT) based ECG de-noising techniques and the results are furnished in **Table 2**. In this investigation, we calculated the SNR prior and afterward applying the fuzzy filter to compare their values for the same signals at the decisive situation.

The root mean square error RMSE) is usually expressed by the following equation [18-22]:

$$RMSE\,(mV) = \sqrt{\frac{\sum_{j=1}^{J}\left[y(j)-\tilde{y}(j)\right]^2}{J}}\,. \qquad (8)$$

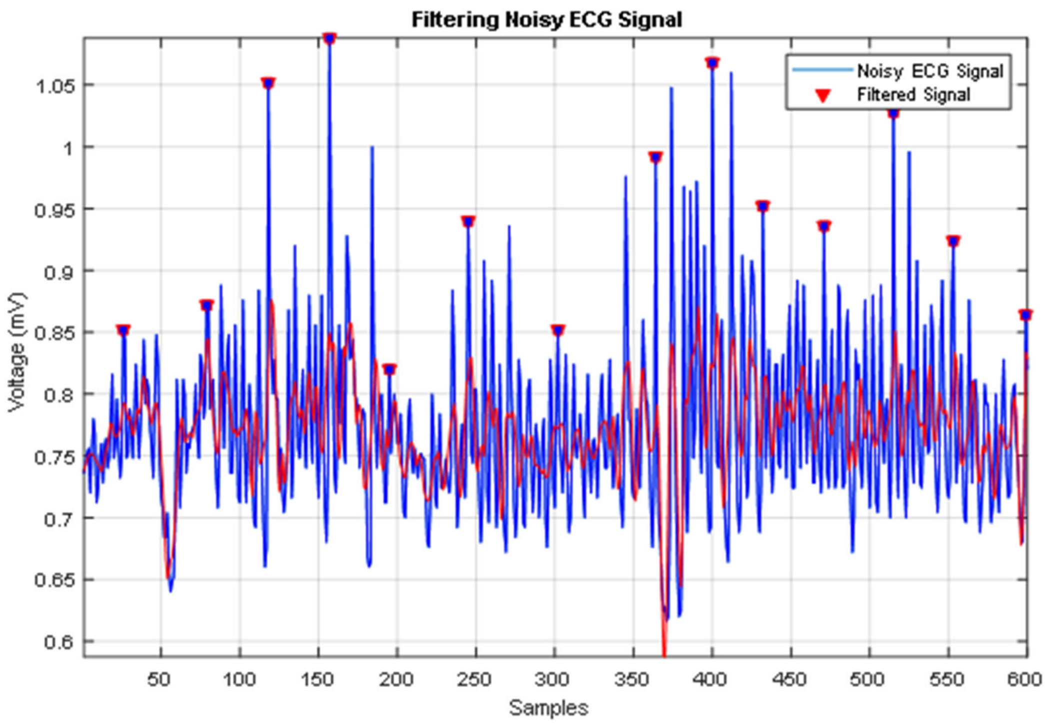

Fig. 4 Response of the filter in noisy environment.

Table 2: Comparison of the traditional WT and DT-WT based approach with the proposed fuzzy filter for MIT-BIH arrhythmia records.

ECG Recording	*DWT Filter*	*DT-WT Filter*	*Fuzzy Filter*
MIT 100	42.65	45.83	102.35
MIT 101	48.42	49.40	108.45
MIT 102	45.49	49.87	107.26
MIT 103	52.20	55.42	109.39
MIT 104	54.14	57.52	108.67
MIT 105	62.82	66.19	102.43
MIT 106	47.46	51.89	97.36
MIT 107	54.58	55.52	108.72
MIT 108	43.32	48.16	96.48
MIT 109	51.26	53.77	116.87
MIT 111	33.98	37.23	103.73

The Maximum Amplitude Error (MAX), representing the local distortion of the signal, is defined as [23-25]:

$$MAX\,(mV) = \max_{n}\left\{\left|y(j) - \tilde{y}(j)\right|\right\} \tag{9}$$

The variance of *RMSE* intervals for this filter was considerably smaller than traditional measurements and the *MAX* was 0.75 mV.

To justify the performance of noise suppression, we added baseline wander noise of -5 dB to the ECG signal by simulation and the proposed filter was able to suppress it, as shown in **Fig. 5**.

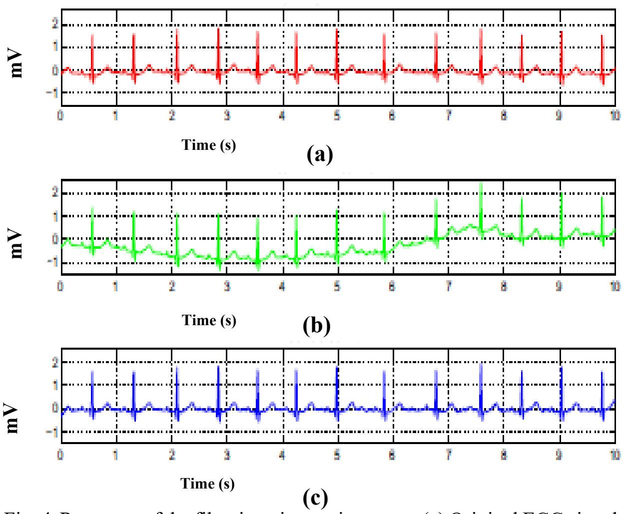

Fig. 4 Response of the filter in noisy environment. (a) Original ECG signal (b) ECG signal corrupted by baseline wander (c) Output after noise suppression.

5. Conclusion

This research addressed on fuzzy filtering technique for ECG signal. Different standard windowing methods like Kaiser, rectangular, Bartlett, Hanning, Hamming and Blackmann window are compared with the proposed fuzzy filter to justify the efficacy of the method, Since the ECG signals are very weak periodic signals, they are vulnerable to peripheral electro-magnetic noise interferences which distress the clinical diagnosis adversely. Our proposed filter is able to recover the ECG signal from noisy environments caused by baseline wander and power line interference, thereby motivating the cardiac experts for trustworthy and responsible clinical diagnosis.

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Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] G. Ranganathan, R. Rangarajan, and V. Bindhu, "Evaluation of ECG Signals for Mental stress assessment using Fuzzy Technique", International journal of Soft computing and Engineering, Vol. 1, No. 4, 2011, pp. 195-201.

[2] M.B. Messaoud, B. Khelil, and A. Kachouri, " Analysis and Parameter Extraction of P wave using correlation Method", The International Arab Journal of Information Technology, Vol. 6, No. 1, 2009, pp. 40-46.

[3] R. Sameni, M. B. Shamsollahi, C. Jutten, and G. D. Clifford, "A nonlinear Bayesian filtering framework for ECG denoising," IEEE Transactions on Biomedical Engineering, vol. 54, no. 12, pp. 2172–2185, 2007.

[4] L. Smital, M. Vitek, J. Kozumplik, and I. Provaznik, "Adaptive wavelet wiener filtering of ECG signals," IEEE Transactions on Biomedical Engineering, vol. 60, no. 2, pp. 437–445, 2013.

[5] W. Lu, H. Hou, and J. Chu, "Feature fusion for imbalanced ECG data analysis," Biomedical Signal Processing and Control, vol. 41, pp. 152–160, 2018.

[6] T. Yousefi Rezaii, S. Beheshti, M. Shamsi, and S. Eftekharifar, "ECG signal compression and denoising via optimum sparsity order selection in compressed sensing framework," Biomedical Signal Processing and Control, vol. 41, pp. 1–27, 2018.

[7] M. Akhbari, M. B. Shamsollahi, O. Sayadi, A. A. Armoundas, and C. Jutten, "ECG segmentation and fiducial point extraction using multi hidden Markov

model," Computers in Biology and Medicine, vol. 79, pp. 21–29, 2016.

[8] J. Rodrigues, D. Belo, and H. Gamboa, "Noise detection on ECG based on agglomerative clustering of morphological features," Computers in Biology and Medicine, vol. 87, pp. 322–334, 2017.

[9] D. P. Golden, R. A. Wolthuis, and G. W. Hoffler, "A spectral analysis of the normal resting electrocardiogram," IEEE Transactions on Biomedical Engineering, vol. 20, no. 5, pp. 366–372, 1973.

[10] M. Yochum, C. Renaud, and S. Jacquir, "Automatic detection of P, QRS and T patterns in 12 leads ECG signal based on CWT," Biomedical Signal Processing and Control, vol. 25, pp. 46–53, 2016.

[11]] P. Ghobadi Azbari, S. Mohaqeqi, N. Ghanbarzadeh Gashti, and M. Mikaili, "Introducing a combined approach of empirical mode decomposition and PCA methods for maternal and fetal ECG signal processing," The Journal of Maternal-Fetal and Neonatal Medicine, vol. 29, no. 19, pp. 3104–3109, 2016.

[12] D. Rezgui and Z. Lachiri, "ECG biometric recognition using SVM-based approach," IEEJ Transactions on Electrical and Electronic Engineering, vol. 11, pp. S94–S100, 2016.

[13] M. Sansone, R. Fusco, A. Pepino, and C. Sansone, "Electrocardiogram pattern recognition and analysis based on artificial neural networks and support vector machines: a review," Journal of Healthcare Engineering, vol. 4, no. 4, pp. 465–504, 2013.

[14] C. Lastre-Domínguez, Y.Shmaliy, O. Ibarra-Manzano, J. Munoz-Minjares, and L. Morales-Mendoza, "ECG Signal Denoising and Features Extraction Using Unbiased FIR Smoothing", BioMed Research International, 2019(2):1-16.

[15] N.Q. Al-Naggar and M.H. Al-Udyni, "Performance of Adaptive Noise Cancellation with Normalized Last-Mean-Square Based on the Signal-to-Noise Ratio of Lung and Heart Sound Separation", Journal of Healthcare Engineering, Volume 2018, pp.1-10.

[16] S. Sebastian and S. Rathnakara, "Separation of heart sound artifact from respiratory signals using singular spectrum based advanced line enhancer," International Journal on Advanced Computer ;eory and Engineering, vol. 2, pp. 106–111, 2013.

[17] B. Y. Lu, "Unidirectional microphone based wireless recorder for the respiration sound," Journal of Bioengineering and Biomedical Science, vol. 6, no. 3, p. 195, 2016.

[18] A. Njmcová , R. Smíšek, L. Maršánová, L. Smital, and M. Vítek, "A Comparative Analysis of Methods for Evaluation of ECG Signal Quality after Compression", BioMed Research International, Volume 2018, pp. 1-26.

[19] A. S. Al-Fahoum, "Quality assessment of ECG compression techniques using a wavelet-based diagnostic measure," IEEE Transactions on Information Technology in Biomedicine, vol. 10, no. 1, pp. 182–191, 2006.

[20] M. Elgendi, A. Al-Ali, A. Mohamed, and R. Ward, "Improving remote health monitoring: a low-complexity ECG compression approach," Diagnostics (Basel), vol. 8, no. 1, article no. 10, pp. 1–17, 2018.

[21] M. S. Manikandan and S. Dandapat, "Wavelet energy based diagnostic distortion measure for ECG," Biomedical Signal Processing and Control, vol. 2, no. 2, pp. 80–96, 2007.

[22] A. Adamo, G. Grossi, R. Lanzarotti, and J. Lin, "ECG compression retaining the best natural basis k-coefficients via sparse decomposition," Biomedical Signal Processing and Control, vol. 15, pp. 11–17, 2015.

[23] S. Dandapat, L. N. Sharma, and R. K. Tripathy, "Quantification of diagnostic information from electrocardiogram signal: A review," Advances in Communication and Computing, vol. 347, pp. 17–39, 2015.

[24] Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion (WDD) measure for ECG signal compression," IEEE Transactions on Biomedical Engineering, vol. 47, no. 11, pp. 1422–1430, 2000.

[25] Andrea Němcová, Radovan Smíšek, Lucie Maršánová, Lukáš Smital, and Martin Vítek, "A Comparative Analysis of Methods for Evaluation of ECG Signal Quality after Compression", BioMed Research International, Volume 2018, pp. 1-26.

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