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Advance QRS Detection Technique Incorporating Time and Amplitude Thresholds with Statistical False Peak Elimination

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ABSTRACT

In order to improve peak detection effectiveness, this work offers a brand-new peak identification technique that can reduce noise and adjust to variations in ECG signal shape. Segmentation, time and amplitude thresholds, statistical false peak elimination, median and moving average (MA) filtering, and statistical false peak elimination are the pillars upon which the suggested technique rests. An extended median filter is also used to minimize noise at an even deeper level during preprocessing, where the filters are initially employed to reduce undesired noise and interference. Using a time axis (x-axis) and an amplitude (y-axis) threshold, each segment of the data is analyzed after it has been separated into smaller sections. Next, the erroneous peaks caused by any leftover noise are removed using the average peak-to-peak interval. Any peak that is identified twice is removed, and a post- processing stage is added to check for low-amplitude peaks that were missed. The suggested methodology outperforms a number of state-of-the-art approaches in the field when tested utilizing the MIT-BIH arrhythmia and Fantasia data bases.

Keywords: ECG, Moving average, threshold, amplitude thresholds, Time

I. INTRODUCTION

Heart is the one organ that is responsible for almost all of the processes in the Human Body. Major work of a Human Heart is pumping of Blood; Blood is the one thing that is responsible for every process in the entire Human Body. Blood contains Hemoglobin which is oxygen carrying protein; oxygen is the single most important thing that is required by the Human Body. So, the oxygen is supplied to various parts of the body through Blood. Without the Blood many organs that may be from the Brain to Hair everything will not work. We can't put it in words, of "How much our Body depended on the Heart", so, a healthy and hygienic lifestyle to be followed for a better working of the Heart. Health and many diseases are depended on functioning of the Heart, so, it became very essential task to record the functioning of Heart, for that, scientists came up with the idea of Electro-Cardiogram (ECG) Signals which records the activity of the Human Heart.

The human heart's own electrical impulses allow for the recording of the heart's electrical activity in a procedure called an electrocardiogram (ECG). Despite the fact that the ECG generates cardiac electrical activity, signal extraction from the resulting data has become a difficult and complicated undertaking, with important cardiac information being lost in the process. So, there exists a number of techniques and methods for extracting the important information from the ECG signal. Among the PQRST waves in a standard ECG signal, the QRS waves are the most critical; hence, it is crucial to isolate at least these three peaks.

Even though there exists many techniques and methods to extract the QRS peaks from an ECG signal, the signal extraction is not an easy task, because it is susceptible to various noises. There exist a number of noises that degrade these QRS peaks. They are, Baseline Wander (BW) noise,

Baseline Wander (BW) is caused because of a not proper electrode used while fetching the ECG signal. BW is a common type of noise that has to be taken care of every time fetching an ECG signal. As any other noise BW also affects the signal measurements which will be leading to a not accurate ECG signal measurement. The BW affects the Iso-Electric line that is the reference for measuring the ECG signal.
Common sources of unwanted background noise in an ECG signal include power line interference. This is caused because of the effect of voltage interferences. The AC currents will results in loops because of the cables of patient. There exists many reasons why a power line interference will occur that includes perfectly contacting cables and not using the better electrodes while capturing the ECG signal.

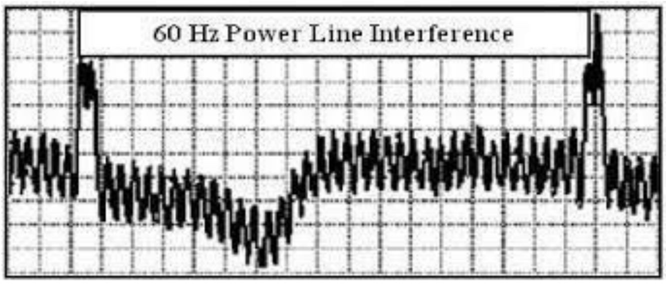

Fig 1. ECG with Power Line Interface Noise

We can observe that the distance between two R peaks of an ECG signal is 60 Hz, but in reality the distance between two R peaks is between 48-52 Hz or mostly 50 Hz. But, here, it is showing 60 Hz for distance between two R peaks. So, it became a quite challenging task to correctly capture the ECG signal without any disturbances for minimizing PLI noise.

II. Literature Review

[1] T. Sharma and K. K. Sharma: Since the QRS complex is the electrocardiogram's (ECG) most noticeable feature, its identification is necessary for distinguishing the ECG's other waves and segments and for extrapolating clinically relevant data QRS detection is challenging because of a number of factors, including variation in QRS morphology, clamor, ancient rarities, and impedance from tall, pointed P and T waves. In this examination, we propose another way to deal with QRS recognizable proof by preprocessing the ECG utilizing weighted all out variety (WTV) de- noising. The amount of smoothing is determined by the regularization parameter in the WTV minimization, which is based on a neighborhood assessment of clamor in the sign block viable. The de-noising is hence locally adaptive.
[2] K X. Lu, M. Pan, Y. Yu: Heart disease is the number one killer throughout the world. Rapid and precise diagnosis relies on the automated electrocardiogram (ECG) analysis method, the first step of which is QRS recognition. One method for detecting QRS complexes that is both fast to calculate and light on memory is the threshold method. In today's mobile world, threshold algorithms may be simply adapted to wireless, wearable, and portable ECG equipment. However, there is still room for improvement in the threshold algorithm's detection rate. Adaptive threshold methods for QRS detection were claimed to be enhanced in this research. Preprocessing, peak-finding, and adaptive threshold QRS detection are the main components of this approach. The sensitivity of the MIT-BIH is 99.72%,

while its specificity is 99.69%, and its detection rate is 99.41%.

[3] R. M. Rangayyan, John Wiley & sons: Inputs and outputs in the form of chemicals, neurotransmitters, or information, as well as mechanical, electrical, or biochemical acts, all contribute to the complexity of physiological processes. Signals representing the type and activity of most physiological processes are present during these processes or are produced as a result of these processes. These signals may be biological, such as hormones and neurotransmitters, electrical, such as potential or current, or physical, such as pressure or temperature.

[4] J. Pan, W.J. Tompkins: We developed a system to identify QRS complexes in electrocardiogram signals in real time. The digital analysis of slope, amplitude, and breadth allows for precise differentiation of QRS complexes. A customized digital band pass filter is used to attenuate the several forms of noise that might be present in an electrocardiogram. This filtering has allowed for the use of lower detection thresholds, improving sensitivity. In order to adapt to changes in heart rate and QRS form in the ECG, the system periodically adjusts thresholds and parameters automatically. The average QRS complexes in a given 24 hour period may be correctly identified using this method 99.3

[5] J.D. Drake, J.P. Callaghan: While recording electromyography (EMG) from the storage compartment, cardiovascular electrical action (ECG) could bewilder the outcomes due to the closeness of the social event objections to the heart and the volume conduction qualities of the ECG through the center.ECG removal approaches have seldom been directly compared to one another or tested against a clean EMG signal (gold standard or criterion measure), and so little research has been conducted in this area. In light of EMG's widespread use, it's crucial to understand how different methods of ECG removal affect the signal's amplitude and frequency. The goal of this research was to evaluate four families of newly discovered and widely used techniques for decontaminating EMG signals from ECG noise. A dual-intensity ECG is recorded.

III.Existing Method

Probabilistic False Peak Elimination (PFPE) using Amplitude and Timing Criteria. The SFPE consists of three stages: the pre-handling stage, the pinnacle identification stage, and the post-handling stage. In the initial step, known as pre- handling, undesirable commotion in the sign is wiped out. In the resulting step, named "Pinnacle Location Stage," we'll really find those peaks that were extracted. Subsequently, the Search-back step is appended to the post-processing phase, where the missed peaks are once again looked for and discovered to improve the quality of the approach.

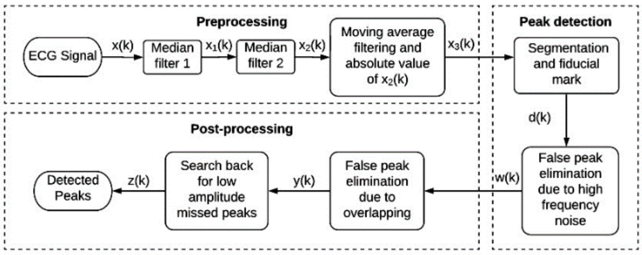

Fig 2: Block Diagram of Existing Method

3.1 Pre-Processing Stage

In the first stage of processing, an electrocardiogram (ECG) signal is recorded from a person who may or may not be a patient. The captured ECG signal will then be transmitted to the filtering step, where the unwanted noise will be removed. In the filtering phase, we use a Moving Average Filter in conjunction with two cascaded Median Filters. To further improve the noise cancellation process. The Median Filters in combination with a Moving Average Filter results in a better Noise reduction than the existing techniques.

3.2 Peak Detection Stage

After the ECG signal has been noise-filtered, it will enter the Peak identification stage, where Amplitude and Time Thresholds will be applied to identify the peaks. The thresholds for estimating the QRS peaks. The thresholds are done based on the statistical analysis of the ECG signal. The thresholds are the values that result in the typical QRS peaks or waves. The particular Q peak or R peak or S peak will have a regular time instants or lengths or heights. These can be used to threshold to extract the near exact Q or R or S peaks. The peak detection will be more better whenever there is better thresholds. For that we have to remove the noise at a greater value. The R peaks are the most and easily detectable among all of the ECG peaks. The typical tallest peak or that which peak that has highest amplitude in an ECG signal is always an R peak. So, the R peaks are easily be extracted and can be used for reference in estimating the other peaks. Like the difference between the two R peaks and the threshold difference between the QR peaks as well as RS peaks. So, the threshold will result in better way, if the R peaks are detected perfectly.

3.3 Post Processing Stage

Post processing stage involves the search back stage which once again searches for any of the missed out peaks in the previous stages. The thresholds may not always result in a better extraction or estimation of the true peaks or all peaks. Therefore, a search-back stage is used to look for the undiscovered genuine peaks.. Search back stage is a new revolution in the ECG QRS peak detection which makes the Peak detection even more better when considering a QRS peak detection. The typical QRS peaks are almost recovered from the signal through this way. Thresholding through amplitude and time instants result in a better way for recovering the true QRS peaks as many as possible. The statistical false peak elimination with two stage filtering with a cascaded median filtering and moving average filter, peak detection through statistical thresholds of time instants and amplitude values and search back stage for searching the truly missed out peaks is a whole new method for recovering the QRS peaks from a typical ECG signal.

Statistical False Peak Elimination (SFPE) examines the collected ECG segments statistically to eliminate false peaks. This method employs statistical thresholds and selection to filter out segments with erroneous peaks. Following the extraction of the segmented ECG signals, the SFPE analyses them using the pseudo genuine pinnacles, working out the contrast between adjoining tops and a mean top to-top distinction, as well as the loads assigned to each of the peaks. Any false peaks in the ECG signal are found using a search-back step after the statistical analysis of the segments has been completed. At this point, the thresholding method produces many real positive peaks. Later, a search-back stage is used to find the peaks that were first overlooked. Search-back acts as a kind of system feedback, rechecking for any lingering false peaks that may have been overlooked.

IV. Proposed Method

Amplitude and Time Thresholds for Statistical False Peak Elimination (SFPE). Three phases are included in the SFPE: pre-processing, peak detection, and post-processing. Noise in the signal is initially reduced in the pre-processing phase. The second step, dubbed "Peak Detection," involves finding the peaks that were retrieved in the first step. The missed peaks are afterwards sought for and found once more during the post-processing stage to improve the approach even further.

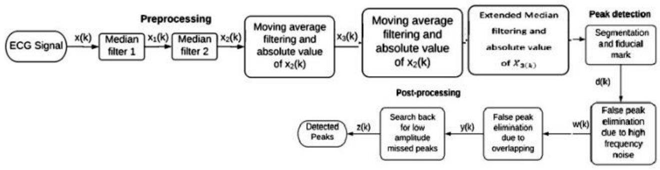

Fig 3 Block Diagram of Proposed Method

4.1 Pre-Processing Stage

Capturing an ECG signal from a potential patient initiates the pre-processing stage. The captured ECG signal will be passed on to the filtering stage in order to remove any noise. Convolution of two cascaded median filters, a moving average filter and an extended median filter makes up the filtering step for improving noise cancellation. The Extended Median Filters and Median Filters work better than the current strategies at reducing noise when combined with a Moving Average Filter.

4.2 Median and Extended Median Filter

A sort of filter called a median filter is used to remove noise from signals that could be 1D, 2D, or 3D. The median filter picks a region where there is noise. The area can be identified so that the signal value at that moment deviates significantly from the other instants that are its neighbours. The value or instant that has a bigger deviation will be supplanted by the middle worth once the middle channel calculates the median of the specific area. The procedure is applied to each instant of the signal, and any value that deviates significantly will be routinely replaced with the median of the selected area. The median filter removes the noise from the signal in this manner. However, we have used cascaded median filters in this instance, which improves noise reduction. The noise is much reduced because to the two-stage median filtering. In a simple median filter implementation, the value of each pixel in the noisy picture is typically replaced by the median of its neighbours. The suggested de-noising approach in this study, on the other hand, compares the value of damaged pixel by the median to decide whether or not it will be replaced, so improving the efficiency of the conventional median filter and the quality of the de-noising operation..

4.3 Moving Average Filter

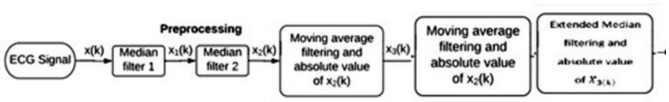

Fig 4: Filtering Stage

Moving average filters are another common type of filter that are used to remove noise from signals, including 1D,
2D, and 3D signals. Additionally, the moving average filter chooses a region that deviates significantly from its surrounding areas. Their neighbours will also be taken into account when calculating the average. Later, the average value for that specific area will replace the moment of the signal in the chosen area that deviates significantly from its neighbours. All of the regions where there is a deviation are subject to the process. Because the average value will be moved throughout the entire signal until the noise is greatly or at least to the acceptable extent, the moving average filter is known as a moving average. The moving average filter and cascaded median filters were combined during the filtering stage to further reduce noise. In comparison to existing approaches or procedures, the combination of filtering decreases noise to a greater extent and considerably better.

4.4 Peak Detection Stage

The R peaks are the most and easily detectable among all of the ECG peaks. The typical tallest peak or that which peak that has highest amplitude in an ECG signal is always an R peak. So, the R peaks are easily be extracted and can be used for reference in estimating the other peaks. Like the difference between the two R peaks and the threshold difference between the QR peaks as well as RS peaks. So, the threshold will result in better way, if the R peaks are detected perfectly. The R peaks are the most frequent and prominent on an electrocardiogram. In any given electrocardiogram (ECG), the peak with the greatest amplitude will always be a R peak. As a result, it is possible to quickly extract the R peaks and use them as a reference point for making estimates of the other peaks, such as the threshold difference between the QR top and the RS top or the contrast between the two Rpeaks. Therefore, if the R peaks are accurately detected, the threshold will produce superior results.

4.5 Post Processing Stage

The search back step, which is a part of the post-processing stage, entails looking again for any missing peaks from the earlier stages. The genuine peaks or all peaks may not always be better extracted or estimated using the thresholds.

So, a new search is conducted behind the scenes to find the genuine peaks that were missed. When thinking about ECG QRS peak detection, search backstage is a recent innovation that improves peak detection even further. This method almost completely recovers the normal QRS peaks from the signal. A better method for retrieving the real QRS peaks as many times as possible is achieved by thresholding via amplitude and time instants. A brand-new technique for recovering the QRS peaks from a typical ECG signal uses statistical false peak elimination, two-stage filtering with a cascaded median filter and moving average filter, peak detection through statistical thresholds of time instants and amplitude values, and search backstage for searching the truly missed out peaks.

The collected ECG segments were statistically analyses using the Statistical False Peak Elimination (SFPE). To get rid of any misleading peaks that might be present in the segments, the technique employs statistical criteria and selection. The SFPE examines the pseudo real peaks and calculates the difference between the nearby peaks after the extraction of the segmented ECG signals. The peak weights and average difference between peaks are calculated as well. After the data has been statistically analysed, a further search is performed to uncover any false peaks in the ECG signal that may have been overlooked. Several genuine positive peaks are now generated by the thresholding procedure. After then, a backstage search is conducted to locate the unnoticed peaks. The algorithm receives input in the form of a search, which allows it to double-check for any missing true peaks.

This method, unlike the vast majority of algorithms in the literature, is constructed from the ground up utilizing three separate procedures. To begin, it has been shown in that P and T waves are attenuated during the preprocessing step by eliminating background noise and other distortions. The second step is to cut up the ECG record into smaller parts so that peak identification may be performed independently on each section. The peak detection process includes the following steps. Each track is split into a maximum of 25000 samples, and extremely low amplitude peaks are removed by setting an amplitude axis cutoff. Now, a cutoff point in terms of time has been established by averaging the distances between successive peaks.

V. RESULTS AND DISCUSSION

By utilizing physiobank atm site, ECG crude signal is gotten. PhysioBank is a very much portrayed computerized accounts of physiologic signs and information. PhysioBank offers different ECG datasets gathered from various sources. By utilizing MATLAB/Simulink , a simulation model compares FLC and ANFIS controller performance, including harmonic reduction and open/closed-loop analyses. After recognized a dataset, select a particular ECG record from that dataset. When the ECG signal document in a reasonable configuration, import it into matlab From MIT-BIH arrhythmia data set record no. 100m document is brought into matlab and denoised the signal by using filters

TABLE :. Result from the MIT-BIH arrhythmia database.

Rec. No.	TB	DB	TP	FP	FN	Se(%)	P+(%)	DER(%)
100	2455	2455	2455	0	0	100	100.00	0.00

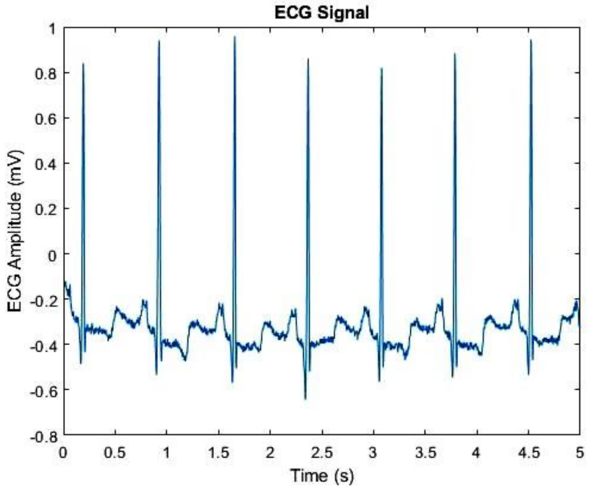

Fig 5: Raw ECG Signal

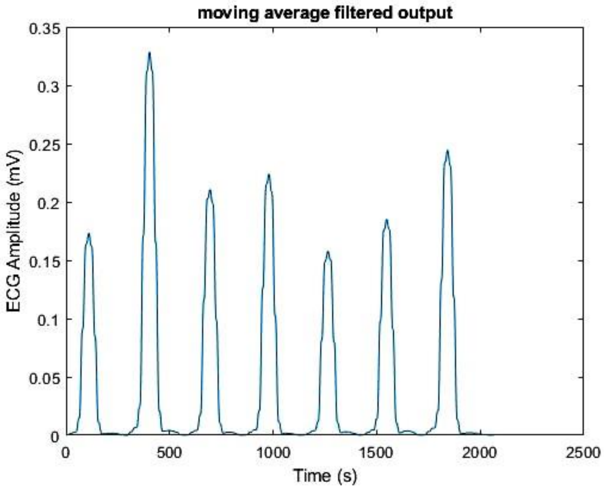

Fig 8: Filtered with Moving Average Filter

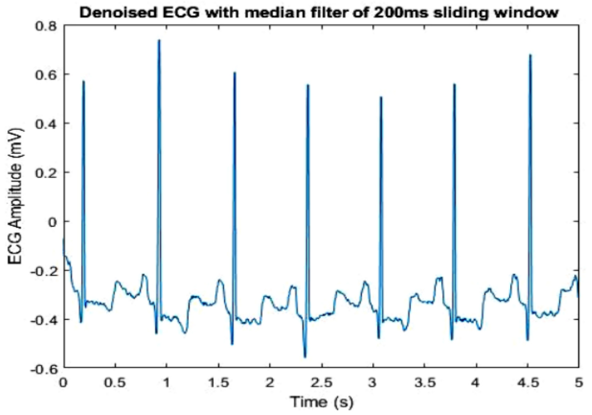

Fig 6: Filtered through Median Filter of 200ms sliding window

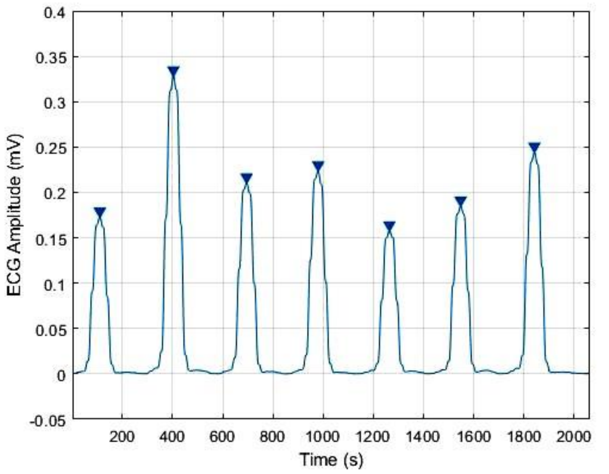

Fig 9: Detecting of Peaks from an ECG Signal

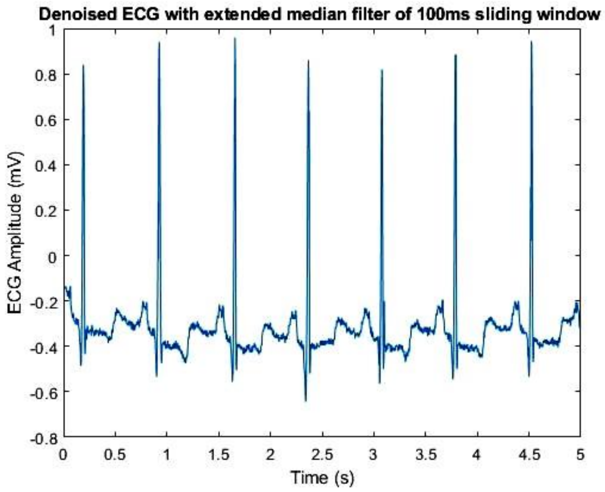

Fig 7: Filtered through Extended Median Filter of 100ms sliding window

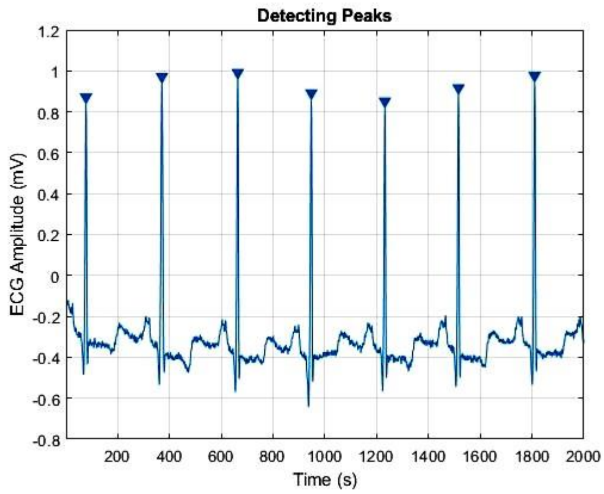

Fig 10: QRS peaks of an ECG signal

Sen- Sensitivity

Pred - Predictivity

DER - Detection error rate FN - False negative peak

FP - False positive peak TB - Total bits

TP - True positive peaks

noilev1 – noise level output using median filter and moving average filter

noilev2 – noise level output using extended median filter and moving average filter

Workspace

Name	Value
delay	17
DER	0
ECG	'100m'
FN	0
FP	0
noilev1	1.0039
noilev2	0.8612
pred	100
sen	100
TB	2455
TP	2455

Fig 11: Result analysis for different parameters

VI. CONCLUSION

Statistical False Peak Elimination (SFPE), which employs a median filtering, a moving average filter, and an extended median filter to reduce noise and interference, can be said to have processed the original ECG signal. The true peaks that are left behind are then delivered to Selective. The SFPE thresholds the QRS peaks that might have been overlooked in the previous step using statistical analysis. The SFPE identifies the true peaks in the QRS, and to further improve the detection, a search process is used to look for any remaining true peaks. The current statistical false peak elimination (SFPE) method, when paired with a search backstage, yields better detection results than the current techniques.

VII. REFERENCES

[1]. Sudipta modak,Luay yassain Taha, Esam Abdel-Raheem, " A Noval method of QRS Detectionusing Time and Amplitude Thresholds with Statistical False Peak Elimination" Received Feb 24, 2021,vol 9, accepted June 13, 2021,

[2]. T. Sharma and K. K. Sharma, "QRS complex detection in ECG signals using locally adaptive weighted total variation denoising," Comput. Biol. Med., vol. 87, pp. 187–199, Aug. 2017.

[3]. B.-U. Kohler, C. Hennig, and R. Orglmeister, "The principles of software QRS detection," IEEE Eng. Med. Biol. Mag., vol. 21, no. 1, pp. 42–57, Aug. 2002R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[4]. R. M. Rangayyan, Biomedical Signal Analysis, 33, John Wiley & sons, 2015.

[5]. J. Pan, W.J. Tompkins, A real-time QRS detection algorithm, IEEE Trans. Biomed. Eng. (3) (1985) 230-236.

[6]. J.D. Drake, J.P. Callaghan, Elimination of electrocardiogram contamination from electromyogram signals: an evaluation of currently used removal techniques, J. Electromyogr. Kinesiol. 16 (2) (2006) 175-187.

[7]. T. Sharma and K. K. Sharma, "QRS complex detection in ECG signals using locally adaptive weighted total variation denoising," Comput. Biol. Med., vol. 87, pp. 187–199, Aug. 2017.

[8]. B.-U. Kohler, C. Hennig, and R. Orglmeister, "The principles of software QRS detection," IEEE Eng. Med. Biol. Mag., vol. 21, no. 1, pp. 42–57, Aug. 2002.

[9]. R. M. Rangayyan, Biomedical Signal Analysis. Hoboken, NJ, USA: Wiley, 2015.

[10]. X. Lu, M. Pan, and Y. Yu, "QRS detection based on improved adaptive threshold," J. Healthcare Eng., vol. 2018, pp. 1 –8, Mar. 2018.

[11]. J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[12]. S. Kadambe, R. Murray, and G. F. Boudreaux-Bartels, "Wavelet transformbased QRS complex

detector," IEEE Trans. Biomed. Eng., vol. 46, no. 7, pp. 838–848, Jul. 1999.

[13]. P. S. Gokhale, "ECG Signal de-noising using discrete wavelet transform for removal of 50 Hz PLI noise," Int. J. Adv. Res. Technol., vol. 2, no. 5, pp. 81–85, May 2012.

[14]. P. Sasikala and R. Wahidabanu, "Robust R peak and QRS detection in electrocardiogram using wavelet transform," Int. J. Adv. Comput. Sci. Appl., vol. 1, no. 6, pp. 48–53, 2010.

[15]. S. Pal and M. Mitra, "Detection of ECG characteristic points using multiresolution wavelet analysis based selective coe fficient method," Measurement, vol. 43, no. 2, pp. 255–261, Feb. 2010.

[16]. Z. Zidelmal, A. Amirou, M. Adnane, and A. Belouchrani, "QRS detection based on wavelet coefficients," Comput. Methods Programs Biomed., vol. 107, no. 3, pp. 490–496, Sep. 2012.

[17]. H. A. N. Dinh, D. K. Kumar, N. D. Pah, and P. Burton, "Wavelets for QRS detection," Australas. Phys. Eng. Sci. Med., vol. 24, no. 4, pp. 207–211, Dec. 2001.

[18]. A. Sharma, S. Patidar, A. Upadhyay, and U. R. Acharya, "Accurate tunable-Q wavelet transform based method for QRS complex detection," Comput. Electr. Eng., vol. 75, pp. 101–111, May 2019.

[19]. S. Sahoo, P. Biswal, T. Das, and S. Sabut, "De-noising of ECG signal and QRS detection using Hilbert transform and adaptive thresholding," Procedia Technol., vol. 25, pp. 68–75, Jan. 2016.

[20]. D. Benitez, P. A. Gaydecki, A. Zaidi, and A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis", Comput. Biol. Med., vol. 31, no. 5, pp. 399–406, Sep. 2001.

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