An Approach to Identify " R Peak" of an Ecg Signal Using Shannon Energy to Improve Clinical Diagnosis

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Abstract:- A novel method for processing Electrocardiogram (ECG) signals, with a focus on interpreting the QRS complex and extracting its characteristics. The algorithm incorporates a variety of techniques, including median filtering, the Shannon energy transform, segmentation, time and amplitude thresholds, and statistical false peak elimination (SFPE). These filters play a crucial role in the preprocessing phase, reducing undesired background noise and interference. With in the algorithm, the Shannon energy (SE) is computed, and an SE envelope is generated by applying a predefined threshold. This envelope serves the purpose of pinpointing R waves in the time domain. False peaks, stemming from residual noise, are eliminated by averaging peak-to-peak intervals. The algorithm's performance is evaluated using MIT-BIH arrhythmia database, demonstrating significant improvements in signal quality, reduced noise, and closer alignment to the original signal. This underscores the efficiency of the proposed signal processing technique.

Keywords:*Electrocardiogram(ECG),QRS complex, Shannon energy transform, signal quality improvement*

1. Introduction

As far as diagnostic biological signals go, the ECG has the widest public recognition. It's a visual picture of how the heart works, and it's simply captured by sticking electrodes to the skin of your chest and arms. The ECG signal gets contaminated by noise and other artefacts in a clinical setting throughout the acquisition process. Isolating the target signal from background sounds such as power line interference, muscle artifacts, baseline wandering, and motion artefacts is a major challenge when dealing with biological data such as the ECG. It's easy for noise to interfere with biological signals since they have a small amplitude and a slow frequency. Power-line Interference and Baseline Wander are two of the most common artefacts in an electrocardiogram. The act of breathing introduces some baseline drift. For ECG signal denoising we can use many filtered techniques , transforms to reduce the noise and improve the signal quality we can use many techniques different algorithms of artificial neural networks, machine learning techniques to enhance the peaks where peak detection plays a virtual role in the medical care which shows the abnormalities in patients' heart. The methodology it shows the improvement and better accuracy from the signal.

2. Objectives

Develop a method that combines various filtering techniques for pre-processing ECG signals to reduce noise and interference, particularly in the QRS complex region. Implement the Shannon energy (SE) calculation to identify the R waves in the ECG signal's time domain and create an SE envelope using a predefined threshold. Apply statistical false peak elimination (SFPE) methods, such as averaging peak-to-peak intervals, to accurately eliminate false peaks caused by residual noise. Evaluate the algorithm's performance by comparing processed ECG signals to the original signals from the MIT-BIH arrhythmia database, quantifying improvements in signal quality, noise reduction, and alignment with the reference data. Demonstrate the efficiency and effectiveness of the proposed signal processing technique in enhancing the interpretability and reliability of ECG signals, potentially leading to improved clinical diagnosis and monitoring of cardiac conditions.

3. Methods

Beats per minute (BPM) are used to quantify the rate of the heart. P waves, QRS complexes, and T waves are the building blocks. The P wave is used to describe the alterations occurring in the atrial cells. Both the QRS and the T wave are used to interpret changes in ventricular cell activity and ventricular membrane potential, respectively. One of the essential portions, the T wave, is said to be succeeded by the wave form U. In this case, O is the origin. There are two phases to each given QRS detector design. First, the digital ECG data is filtered to get rid of unwanted noise, P waves, and T waves. Non-linear modifications, such as a squaring function, are applied to the result to support the R waves. Tompkins' algorithm, for example, adjusts the threshold, then the average RR-interval, the rate restrictions, and finally it rejects T waves [12]. The second step is to apply decision criteria to confirm the presence of R waves.

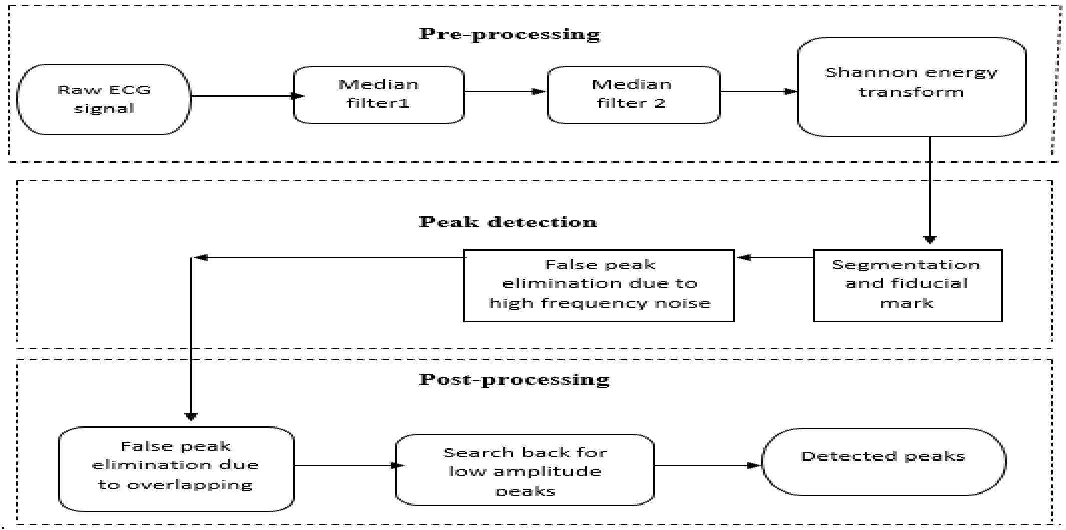

Fig. 1: Block diagram for peak detection of ECG signal

2.1 Dataset Utilized

The proposed technique's effectiveness is evaluated using the MIT-BIH arrhythmia database available on Physio Net, a public repository for physiological signals. This database proves to be an ideal resource for analysis due to its diverse range of morphological changes evident in the records.Within the MIT-BIH arrhythmia database, the ECG recordings, each spanning 30 minutes, present a unique challenge as they are afflicted by both high and low-frequency background noise, along with interferences from P and T waves. The database provides a sampling frequency of 360 Hz and maintains an 11-bit resolution within a 5-mV range. Twenty-five men and twenty-two women, ranging in age from 23 to 89 years old, provided the data.

2.2 Pre-Processing

There are two phases in this process that aim to remove unwanted background activity and artifacts from the ECG reading. Two middle channels and a 20-example moving normal channel make up its construction.

2.2.1 Median Filtering:

One of the first things that happens during the pre-processing step is that the whole record is run through two median filters, the second of which has a window size that is twice as large as the first. The user may choose between two different window sizes: either 50ms or 100ms, or 100ms and 200ms. This is on the grounds that P waves seem 50-100ms before the QRS complex and T waves seem 50-100ms after it. By flowing these two middle channels, we can diminish the P and T waves as well as dispose of the gauge float. Similarly, we will be able to reduce, if not get rid of entirely, any additional low-frequency noise that may have been present while recording.

2.2.2 Shannon Energy Transform

The suggested approach makes advantage of the energy in the signal. The square of the sign is practically equivalent to the energy of the sign. The signal's average energy throughout its spectrum is determined using Shannon energy. In other words, the high components should be discounted into the low ones. Each sample's energy in the local spectrum is determined using Shannon energy (SE). The Shannon energy is computed down below:

$$SE = -|a[n]| \log(|a[n]|)$$

$$s[n] = -a^2[n]\log(a^2[n])$$

Where a[n] is the normalized amplitude obtained after the processing of median filter

When the Shannon energy is calculated, it produces a central peak and a number of smaller spikes. Main peak identification is complicated by these spurts

2.3 Peak Detection

In this phase, the ECG signal is segmented into smaller segments according to the number of samples it consists of, and false peak removal is performed. The peaks are identified by processing each section independently.

2.3.1 Segmentation

Now that the record has been pre-processed, it is split into sections containing M samples each. The ideal amount of samples to ensure high accuracy and quick processing time is less than 25000, however this might vary depending on the length of the record. The idea is to analyse the ECG signal in smaller sub segments in order to better accommodate the signal's evolving shape. It is recommended to initialise the algorithm with R=[2, 6, 20, 26, 40, 60, 72, 74], where R is the total number of segments to be generated, so that the split of samples is handled automatically. If the record length is less than 50000, then two segments will be picked at random from the vector R.

2.3.2 Statistical False Peak Elimination

At this stage, we process each component separately. To begin, a fiducial mark vector, W, is constructed by summing the peaks of the relative multitude of neighbourhood tops in the fragment, with a base top to-top time span Milli seconds. Next, we use the method to get the mean amplitude, A, of these peaks,

$$A = \frac{\sum_{n=1}^{Q} W(n)}{Q}$$

Peaks in vector W are located at coordinates (Q, W(n), n), where Q is the total number of peaks and W(n) is the weight of the vector at coordinate (n). To emphasise vectors, we employ both upper- and lowercase italics.

2.4 Post processing

In the post-processing phase, you'll do two things: get rid of overlapping peaks that are causing false positives, and go back and find the peaks you missed. This is a crucial step since it's possible that a peak may appear twice when the ECG record is segmented, once at the conclusion of one segment and once at the beginning of the next. Additionally, certain recordings exhibit irregularities in amplitude, with sections featuring excessively high amplitudes while others have significantly lower ones. It is imperative to subject these recordings to post-processing procedures to optimize genuine detection and minimize the occurrence of false positives.

4. Results

combination of these two techniques reduces background noise and brings attention to the distinctive aspects of the QRS complex in ECG data, hence increasing the reliability of R-peak recognition.

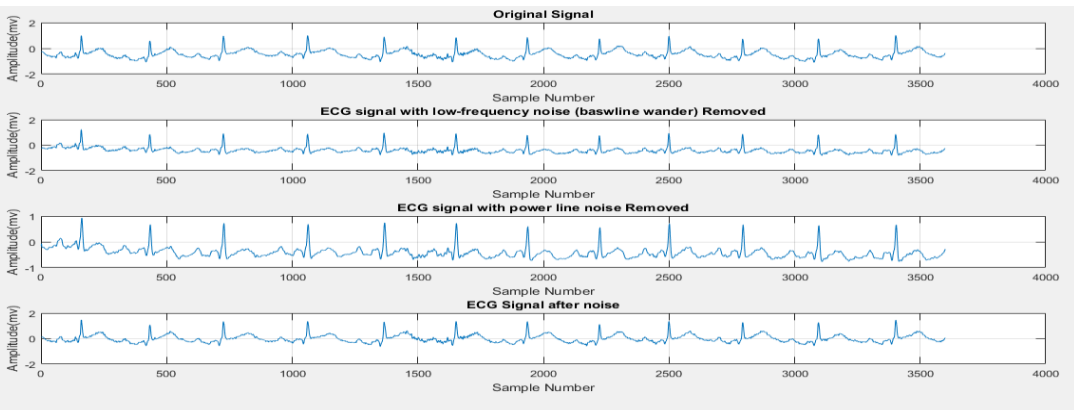

Fig. 2: a) original ECG signal b) baseline wander noise removal c)power line noise removal

d) Signal after noise removal

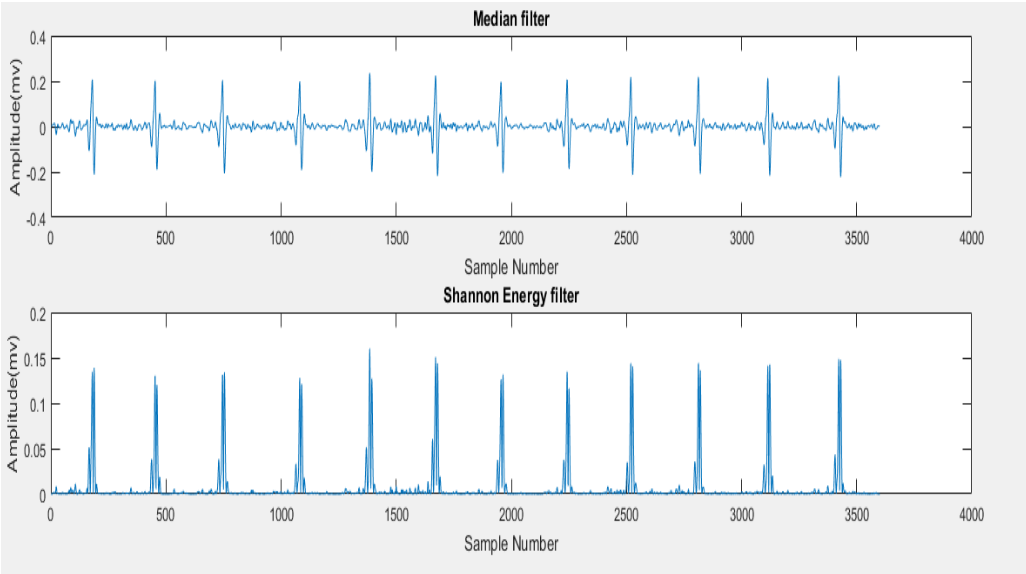

Fig. 3: a) Raw ECG signal b)Median filter c) Shannon energy of 228 record

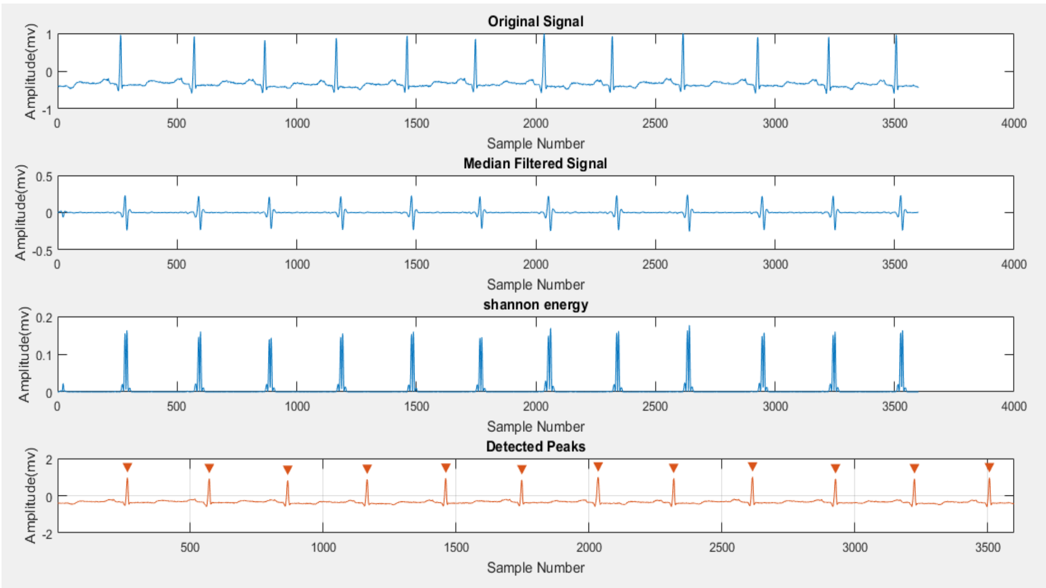

Fig.4: a) raw ECG signal b) median filtered signal c) Shannon energy d)Detected R peaks

Table 1: Results from the MIT-BIH arrhythmia database:

Rec.no	TB	DB	TP	FP	FN	Se(%)	P+(%)	DER(%)
100	2273	2273	2273	0	0	100.00	100.00	0.00
101	1865	1865	1865	0	0	100.00	100.00	0.00
102	2187	2187	2187	0	0	100.00	100.00	0.00
103	2084	2084	2083	1	1	99.95	99.95	0.10
104	2229	2230	2229	1	0	100.0	99.96	0.00

105	2572	2575	2568	7	2	99.88	99.65	0.41
106	2027	2020	2021	1	7	99.63	99.95	0.42
107	2137	2141	2137	4	0	100.00	99.81	0.19
108	1763	1763	1759	4	4	99.77	99.77	0.23
109	2532	2532	2532	0	0	100.00	100.00	0.00
111	2124	2126	2124	2	0	100.0	99.91	0.09
112	2539	2542	2539	3	0	100.0	99.88	0.12
113	1795	1795	1795	0	0	100.00	100.00	0.00
114	1879	1878	1878	0	1	99.95	100.00	0.05
115	1953	1953	1953	0	0	100.00	100.00	0.00
116	2412	2408	2400	8	12	99.51	99.92	0.83
117	1535	1537	1535	2	0	100.00	99.87	0.13
118	2278	2278	2278	0	0	100.00	100.00	0.00
119	1987	1988	1987	1	0	100.00	99.95	0.05
121	1863	1863	1862	1	1	99.95	99.95	0.11
122	2476	2476	2476	0	0	100.00	100.00	0
123	1518	1521	1518	3	0	100.00	99.8	0.2
124	1619	1619	1619	0	0	100.00	100.00	0
200	2601	2599	2599	0	2	99.92	100.00	0.08
201	1963	1960	1959	1	4	99.8	99.89	0.25
202	2136	2137	2134	3	2	99.87	99.84	0.34
203	2980	2957	2948	9	32	99.92	99.31	1.38
205	2656	2650	2652	2	4	99.85	99.9	0.15
207	1860	1865	1860	5	0	100	99.73	0.27
208	2955	2948	2950	2	5	99.83	99.9	0.17
209	3005	3002	3002	0	3	99.9	100	0.1
210	2650	2644	2644	0	6	99.78	100	0.22
212	2748	2751	2748	3	0	100	99.89	0.11
213	3251	3247	3247	0	4	99.88	100	0.12
214	2262	2265	2262	3	0	100	99.87	0.13
215	3363	3366	3363	3	0	100	99.91	0.09
217	2208	2208	2208	0	0	100	100	0
219	2154	2157	2154	3	0	100	99.86	0.14
220	2048	2050	2048	2	0	100	99.9	0.1

221	2427	2426	2426	0	1	99.96	100	0.04
222	2483	2485	2483	2	0	100	99.92	0.08
223	2605	2605	2604	1	1	99.96	99.96	0.08
228	2053	2054	2051	4	2	99.9	99.8	0.3
230	2256	2258	2256	2	0	100	99.91	0.09
231	1571	1571	1571	0	0	100	100	0
232	1780	1782	1780	2	0	100	99.89	0.11
233	3079	3077	3077	0	2	99.94	100	0.06
234	2753	2753	2753	0	0	100	100	0
Total	**109494**	**109428**	**109402**	**26**	**92**	**99.92**	**99.96**	**0.11**

Detection Error Rate, Positive Predictivity, and Sensitivity are some performance measures that will be used to evaluate the suggested QRS detector.

$$Se = \frac{TP}{TP+FN} = 99.92\%$$

$$P+ = \frac{TP}{TP+FP} = 99.96\%$$

$$\text{DER} = \frac{FP+FN}{TB} = 0.11$$

Table 2: comparison of previous method:

Adaptive Parameters and Parameter evaluation	S. Modak et al. method [7]	Proposed method
Signal to noise ratio (SNR) in dB	32.57dB	36.81 dB
Mean square error (MSE)	0.0723	0.0416
Sensitivity(se)	99.82%	99.92%
Positive predictivity(p+)	99.88%	99.96%
Detection error rate (DER)	0.31	0.11

5. Discussion

Results shows SNR Improvementthatthis method has provided an increase in SNR from 32 dB to 36dB. This signifies that the enhancement in signal quality achieved by our new method is better compared to the previous methods. The signal is standing out even more prominently over the noise. MSE Reduction, The MSE has decreased from 0.072 to 0.0416 with our new method. This reduction indicates that the processed signal is now much closer to the original signal, resulting in a smaller overall error between the two. In simpler terms, our new method has done a better job in preserving the true signal characteristics and reducing errors

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