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QRS Detection Algorithm for Electrocardiogram Signal

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Abstract— *For analysing ECG recordings QRS detection algorithms are necessary. There are many QRS detection techniques published in literature. Most of the techniques published are focus on clean clinical data. In this paper an algorithm is proposed which is suitable for both clinical ECG data and telehealth ECG data. The proposed algorithm is compared with two recently published algorithms i.e., Gutierrez-Rivas (GR) algorithm, UNSW algorithm and one standard unofficial benchmark algorithm i.e., Pan-Tompkins (PT) algorithm. This algorithms are implemented in 4 databasesMIT-BIH ARR (Arrhythmia) Data base, MIT-BIH NST (Noise Stress Test) Data Base, Telehealth Data Base, NSR Database. Sensitivity and Positive Predictivity are two parameters which are used to analyse the algorithms. Compared to previous algorithms proposed algorithm performs better sensitivity and positive predictivity.*

Keywords-*Electrocardiogram (ECG), QRS, Telemedicine, Databases. Sensitivity, Positive Predictivity.*

I. INTRODUCTION

American Heart Association produce a list by assembling more than 190 countries, show that heart disease remains the number 1 global cause of death. With 17.3 million deaths every year they reported that the number is anticipated to rise by 6.3 million solely making it 23.6 million by 2030 [1]. According to World Health Organisation, one person dies due to heart attack for every 33 seconds in India. India is presently witnessing nearly 2 million heart attacks a year and greater number of victims are youngsters. The main source of deaths in India is Cardio Vascular Disease (CVD). India had spent 1.3 % of G.D.P on healthcare in the year 2016.In the year 2017, India has increased the investment on healthcare to 2.5% of G.D.P [2]. Now it is the time for India to adopt e-Health and e-Health is a key pillar of Digital India.

Early diagnosis presents an opportunity for preventative treatment. One of the standard tools to monitor heart function is ECG (Electrocardiogram). An ECG shows the electrical activity of the heart as line tracing on paper. Generally ECG is a laboratorytest that checks the electrical activity of the heart for problems. The key step for identification of fatal cardiovascular signs is regular and continuous monitoring of ECG, intervention and reliable treatment time-to-time.The main feature of the E.C.G is P, Q, R, S, T points. These points give us crucial information about the cardiac health of a particular person.The most significant characteristic waveform of E.C.G is the Q.R.S complex and the QRS complex is the important reference for the cardiac cycle [3].

Telehealth uses electronic information and telecommunication technologies to support and develop long distance clinical health care, patient and professional health-related information, public health and Health information. Technologies include video conferencing, the internet, store-and-forward imaging streaming media and terrestrial and wireless communication [4].Now a days, usage of telehealth system has been increased significantly, due to its advantages. The advantages include that, the patient can monitor his/her with in the home itself, so that, there is for the patient for the patient to go to laboratories. The cost that patient spend will also get significantly reduced [5], [6].

One of the fundamental problems that the patient experiences in telehealth environment is the non-expert nature of the patient due to this the signal quality may also get reduced.Additionally, the traditional ECG devises uses adhesive electrons, where as in telehealth ECG monitoring devises are commonly based on dry metal plate single-led measurements, which results in much low signal amplitude and nosier waveforms, this is due to poor transduction between electrodes and skin.Moreover, in telehealth recordings, the artifacts from physiological and non-physiological sources are more often [7].There are various methods for reducing the artifacts that degrading the telehealth ECG signal. One of the methods is to apply a conductive get to the patient so that the gel can prevent the dead skin cells and allow good conduction between the skin cells and electrodes [8].

In literature, there are many techniques for suppression of artifacts and for filtering the ECG signals [9]-[11].But, this techniques terminate many benefits in using a single-led-dry-electrode system in telehealth ECG systems [12]. This system is very simple, ease and expedient to use.Extra problem present in telehealth environment is that, it involve an investigation of a huge amount of data i.e., because of the advantage of the telehealth environment, patient regularly monitor their health and medically expert should investigate this larger amount of data, which require a lot of effort.

Algorithmic investigation can reduce the effort from workload. Most of the ECG algorithms inevitably pinpoint QRS complexes and also compute heart rates. For more than 40 years, ECG data analysis has been an important area of research by using various methodologies. Algorithm design is one of the renowned methodologies for automated analysis of ECG data. In recent years, the algorithm design has become more wide spread with increase in people performing regular cardiac health check-up.

A wide variety of methodologies are presented in the literature for specifically QRS detection [13]. One of the renowned algorithm in QRS detection is Pan-Tompkins (PT) algorithm [14], which is referred to as unratified benchmark in QRS detection of ECG data [15]-[17].Clinically data is usually collected using gelled adhesive electrodes applied in error-free locations, whereas telehealth data is collected using dry electrodes. Most of the ECG algorithms are emphasis on clean-clinical data. Telehealth data is used for first time to determine the effect of artifact masking on trend detection in heart-rate records [18].

This paper produces a new QRS detection algorithm especially designed for poor quality telehealth signals. The proposed algorithm is applied to both clinical ECG database [15] and telehealth ECG database and performance of proposed algorithm is compared with the performance of the well-known PT algorithm [14] and recently published GR and UNSW algorithm.

II. DATA BASES

Every algorithm is needed to test on ECG data bases for which the exact locations of QRS are known. This is done to determine with how much accurately the ECG algorithms are being able to detect QRS complex. The ECG data bases used here are:

1) MIT-BIH ARR (Arrhythmia) Data base [19].
2) MIT-BIH NST (Noise Stress Test) Data Base [19].
3) Telehealth (TELE) Data Base [21].
4) MIT-BIH Normal Sinus Rhythm (NSR) Data Base [19].

All the algorithms conferred in this paper i.e., UNSW, GR, PT, Proposed algorithms are tested on each of the data bases. The databases are described in following sections.

ARR Data Base:

In research, for QRS detection algorithm, one of the frequently used database is ARR database [19]. The recordings in this database are recorded in a supervised clinical environment. For this recording, adhesive electrodes are used and gel is applied in precise locations. The ARR databases contain 48 recordings recorded from 47 subjects. Each recording is of half an hour in duration. All 48 recordings were annotated by two or more cardiologists. Previously these cardiologists marked the locations of each QRS complex [21].

NST Database:

NST database [19] is also one of the widely used database which contain around 12 ECG recordings. By using 2 clean recordings (118,119) these 12 ECG recordings were created. These 2 clean recording were taken from ARR database. To these 2 clean recordings a particular measured amounts of artifact noise were added. [22] These artifact noise was collected from electrode motion. Once the recording (118,119) of ARR database was started; after the first 5 minutes noise was added. The noise was added in a 2 minutes segment fashion i.e., 2 minutes noise added segments followed by 2 minutes clean segments and so on. To 2 clean recordings (118,119) 6 different levels of noise were added which results in 12 recordings. There SNR (Signal-to-Noise Ratio) of each noisy section in each file are 24, 18, 12, 6, 0, -6db.

TELE Database:

In a telehealth environment 300 ECG signals are recorded and are described in [21].These signals were recorded using single lead –I. This ECG database is sampled at a rate of 500Hz. This is done by using dry metal Ag/Agcl plate electrodes. The patients will hold these electrodes in each hand and also 1 reference electrode plate is also placed below the pad of the right hand. Out of 300 telehealth recordings 250 recordings are taken from 120 patients randomly whereas the remaining 50 recordings were taken from 168 patients which are manually selected. This is done to acquire a larger portrayal of poor quality data. Three independent professionals interpret the data by observing the signals of artifacts and QRS complexes. All the independent professionals then interpret the signals as a group to reunite those individual interpretations. Out of the 300 telehealth ECG recordings [23] 50 recordings were rejected. Those 50 rejected recordings include 29 recordings from 250 randomly selected recordings and 21 recordings from 50 manually selected poor quality recordings. These 50 recordings were rejected because the interpreted RR intervals in the specified record overlap with the interpreted artifact mask. Due to this, calculation of heart rate cannot be performed. Out of 300 telehealth recordings; after rejecting 50 recordings; remaining 250 recordings are available in open database as the Tele Database [20].

NSR Database:

MIT-BIH Normal Sinus Rhythm Data-Base [19] contain 18-long term ECG signals. These ECG signals are collected from 5 men of 26 to 45 years of age and 13 women of 20 to 50 years of age. The ECG signals in this database was found to have no significant arrhythmias.

III. ALGORITHMS

The algorithms used in this paper are discussed here. The algorithms include a well-known PT algorithm and two newly published GR Algorithm and UNSW Algorithm and one newly published proposed algorithm.
The three published algorithms are used here to compare its results to the proposed algorithm.

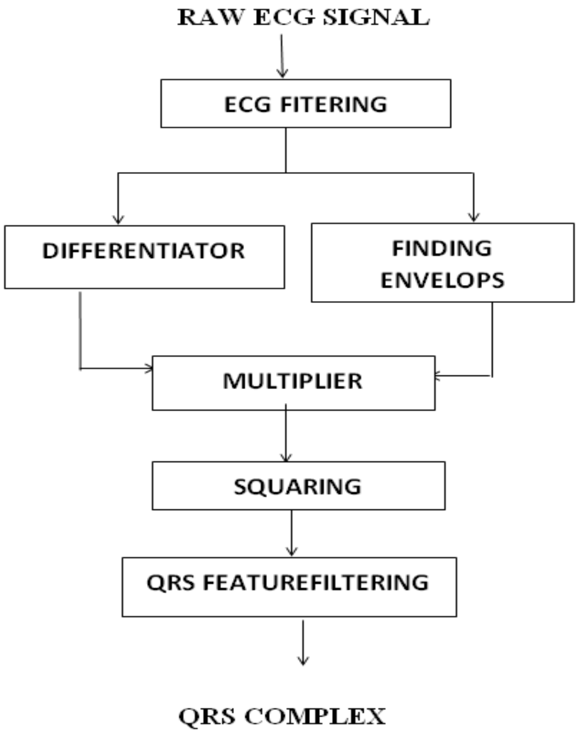
PT Algorithm:
The PT Algorithm [14] is one of the very famous algorithms in QRS detection [25] and has become a unofficial benchmark algorithm for the QRS detection. In the PT algorithm; the Raw ECG signal is passed through the B.P.F and the output of differentiation is squared and then a moving window integration is performed. At last a threshold is set for both the filtered signal and the integrated signal.

GR Algorithm:
The GR algorithm is also one of the recently published algorithms for QRS detection of ECG signal. They used the concept of finite state machine to update the threshold. This threshold is set to pre-processing ECG stage which contain a series of operations like derivative operation then a moving average operation followed by the squaring operation. The performance results of the GR algorithm as it appears in [15] is used here and is used to compare them with the performance of the proposed algorithm.

UNSW Algorithm:
The UNSW algorithm is recently published QRS detection algorithm and this is useful for Telehealth signals also. As mentioned in [24]; in the UNSW algorithm; the raw E.C.G data is first filtered and the filtered output is used to take out the features of the QRS complex. These extracted features are the combination of derivative of filtered ECG signal and amplitude characteristics of ECG signal. Then the QRS features are filtered and a threshold is determined. The results of the UNSW algorithm as it appear in [24] is used here to compare the performance of the proposed algorithm.

Proposed Algorithm:
The block diagram of the proposed algorithm is as shown in the below figure. The block diagram consists of stages as follows.

1) ECG Filtering:
The raw ECG signal, which is obtained from any o he database. To that raw ECG signal first detrending operation is performed. This is done to minimise then transient start up effects. Then it is passed through the median filter. It is done to reduce the baseline drift of the ECG signal. Then it is passed through the BPF. This is done to acquire only QRS complex from the raw ECG signal. The band pass filter is also used to reduce the muscle noise, influence of 60 Hz interference, baseline wander, and T-wave interference. Let the filtered ECG signal be $x(n)$.



2) Differentiator:
The filtered ECG is signal given to the differentiator. The differentiator used here is the FIR derivative filter. A traditional derivative filter is not used because it is not robust to noise. The derivative of the filtered ECG signal $x(n)$ is $d(n)$

3) Amplitude Envelope:
To calculate amplitude envelope it is required to calculate upper envelope of $x(n)$ and lower envelope of $x(n)$. Let the upper envelope of $x(n)$ is $u(n)$ and the lower envelope of $x(n)$ is $l(n)$. Now amplitude envelope is calculated as
$a(n)= u(n) – l(n)$

4) Multiplier:
At multiplying stage; the derivative of the filtered ECG signal $x(n)$ and amplitude envelope of the filtered ECG signal $x(n)$ is multiplied. This is done to satisfy the detection of QRS feature i.e., the desired feature of the QRS detection should be able to identify, if there is any sudden increase in derivative and the larger local amplitude. Let the output of multiplier is m (n).

5) Squaring:
After multiplying derivative of the filtered ECG signal $x(n)$ and amplitude envelope of the filtered ECG signal $x(n)$, the resultant signal is multiplied point by point. This is done to make all the data points positive and it also perform nonlinear amplification to emphasize higher frequencies. The output of the squaring operation contain only QRS complex with some possible artifacts. Let the output of the squaring operation is s (n).

6) QRS Feature Filtering:
The output of the squaring operation may contain artifacts so, after squaring operation it is given to moving average filter. It will eliminate the high frequency artifacts from the signal s (n). Here moving average filter is simply used as a low pass filter. Finally the output of moving average filter should be clean QRS complex. Let the signal be y (n).

IV. PERFORMANCE MEASUREMENTS

The two parameters that are used as performance metrics for analysing the algorithms, and to find the advantages of the proposed algorithm over the existing algorithms are, sensitivity and positivity predictivity. Sensitivity is the ability of the algorithm to detect correct beats. Positive Predictivity is the ability of the algorithm to discriminate between true and false beats. In other words, in total collected detected beats, how much percentage of true beats were present is given by sensitivity and in total beat detections, how much percentage were really true beats. By using the following equations the sensitivity and positive predictivity are calculated.

$$Se = \frac{T_P}{T_P + F_N}$$

$$+p = \frac{T_P}{T_P + F_P}$$

Where T_P is Number of true positives which refers to beats that are correctly detected. F_N is number of false negatives which refer to beats that are not detected. F_P is number of false positives which refers to falsely detected beats.

V. RESULTS

Illustration of QRS feature of an ECG from 100 record ARR database is as shown in below figure.

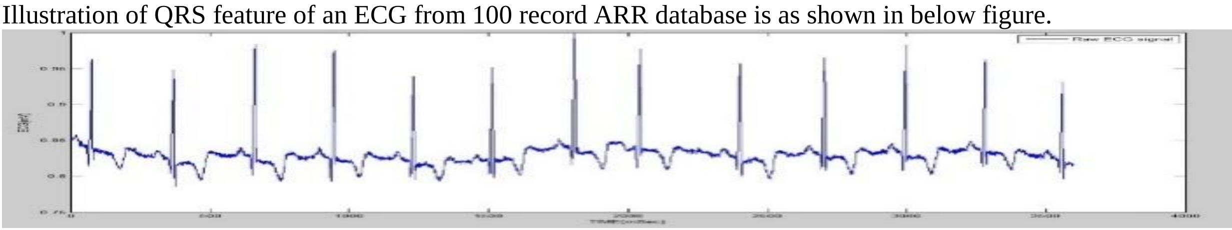


Fig (1): Raw ECG signal

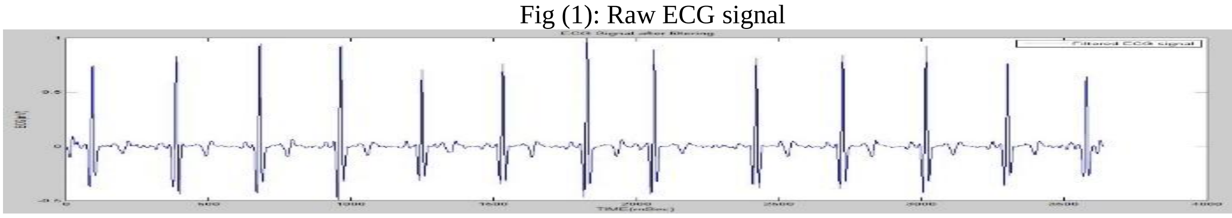


Fig (2): Filtered ECG Signal

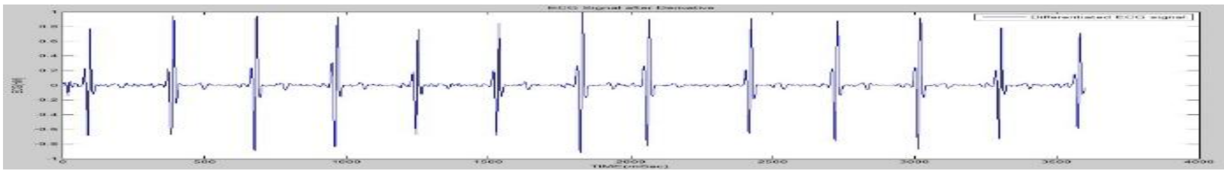


Fig (3): Differentiated ECG Signal

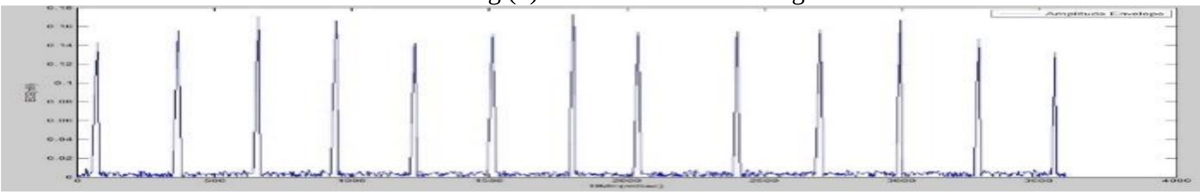


Fig (4): Amplitude Envelop

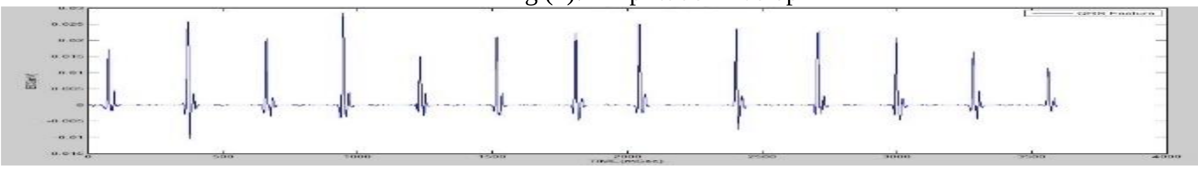


Fig (5): QRS Feature

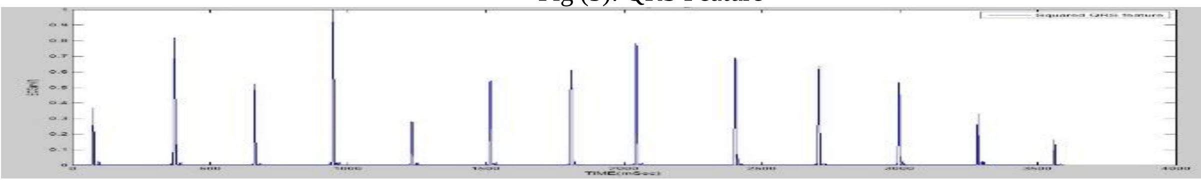


Fig (6): Squared QRS Feature

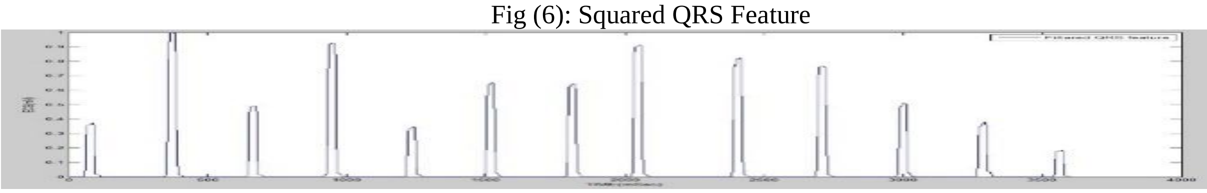


Fig (7): Filtered QRS Feature (QRS Complex)

The sensitivity and positive predictivity is calculated for all records of the above databases and they are as shown in the below tables.

Data Base	**PT**	**GR**	**UNSW**	**PROPOSED**
MIT-ARR	99.75	99.54	99.75	99.77
MIT-NST	99.08	91.65	93.12	94.07
TELE	43.26	49.91	97.88	96.54
MIT-NSR	99.96	99.96	-------	99.96

Table 1: Sensitivity (Se) of algorithms

Data Base	**PT**	**GR**	**UNSW**	**PROPOSED**
MIT-ARR	99.54	99.73	99.80	99.81
MIT-NST	81.83	86.36	86.23	87.13
TELE	59.46	65.16	71.67	74.27
MIT-NSR	99.98	99.99	-------	99.95

Table 2: Positive Predictivity (+P) of algorithms

This percentages of PT, GR, and UNSW for various databases in this paper are taken from []. The sensitivity and positive predictivity for the proposed algorithm is higher than all algorithms for MIT-ARR database. For MIT-NST database the sensitivity for proposed algorithm is less than PT algorithm but the positive predictivity is more for proposed algorithm compared to remaining algorithms. For TELE database the sensitivity of proposed algorithm is less than UNSW but the positive predictivity is more for proposed algorithm compared to remaining algorithms. UNSW algorithm is not performed for MIT-NSR database. The sensitivity of proposed algorithm is obtained same as other algorithms for MIT-NSR database whereas the positive predictivity for the proposed algorithm is obtained less compared to other algorithms.

VI. CONCLUSION

A new QRS detection algorithm is published in this paper and is performed with four different types of databases. The performance metrics i.e., sensitivity and positive predictivity is calculated and is compared with four previously published algorithms. The proposed algorithm performs better than the previous algorithms for both clinical and telehealth ECG data.

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