A REVIEW OF R PEAK DETECTION TECHNIQUES OF ELECTROCARDIOGRAM (ECG)

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ABSTRACT

Heart disease is one of the trivial issues regarding health problems over the last few decades in India. Numerous methods have been developed with still-ongoing modifications and ideas to observe and evaluate ECG signals based on each heart beat. The majority of research revolves around arrhythmia classification, heart rate monitoring and blood pressure measurements that require highly accurate assessments of rhythm disorders which can be possible by measuring QRS complex of ECG signals, so accurate QRS detection methods are very important to be utilized. There have been proposed many approaches to find out the R peak detection to analyze the ECG signals in the past few years. Most recent and efficient techniques of R peak detection have been reviewed in this paper. Techniques which have been reviewed in this paper are Pan and Tompkins, Wavelet Transform, Empirical Mode Decomposition, Hilbert-Huang Transform, Fuzzy logic systems, Artificial neural networks.

KEYWORDS: *ECG; QRS complex; R peak and ANN; Wavelet Transform; Fuzzy logic systems*

1.0 INTRODUCTION

An electrocardiogram (ECG or EKG) also known as heart waves which measures the heart's electrical activity over the time with respect to different reference planes. To analyze the heart problems a very popular method used is ECG. Every heart contraction produces an electrical impulse which can be registered and recorded efficiently by placing the knobs on the human body (Trivedi P., and Ayub S., 2014). The heartbeat produces a series of waves with a time-variant morphology which can be easily calculated by counting these detectable peaks. The ECG is a part of bioelectric signal, which provides important and relevant information about the heart state (Sahoo SK,et al.,2016),. Based on the difference in position, chest configuration, anatomy of the heart, age, size, relative body weight and various other factors, ECG of every person is different (Rodriguez R, et al.2015). Physicians all over the world are using the ECG to detect or anomalies.

As shown in the Figure 1 each beat consists of three different waves, P wave (atrial depolarization), QRS (ventricular depolarization) and finally T wave (ventricular repolarization). In the ECG signal, these three waves are continuously repeated, representing heartbeats and clinical status of the activity of the heart over the time. R wave has the highest amplitude in heart signal than the other portions (Singh Vikramjit,

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et.al., 2014). The ECG voltage level fall in the range 0.05 to 5mV and the frequency components of the ECG signals lies in the band 0.05 to 100Hz for a normal subject.

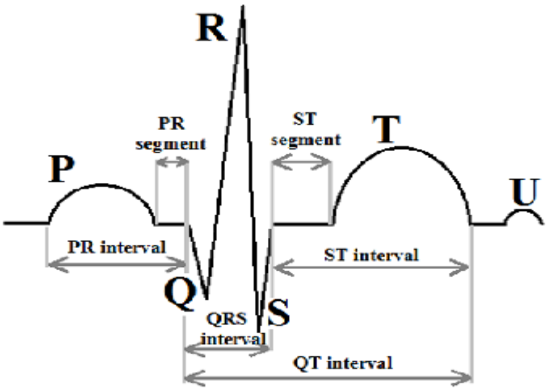

Figure 1. Normal ECG signal, made of P wave, QRS complex and T wave (Mujeeb Rahma and Mohamed Nasor,2012).

1.1 Amplitude

P-wave: represents the contraction of the atria — 0.25 mV
R-wave — 1.60 mV
Q-wave — 25% R wave
T-wave — is the relaxation of ventricles 0.1 to 0.5 mV
QRS complex: the current generated when the ventricles depolarize that results in contraction of the right and left ventricles (Oweis Rami J. and Al-Tabbaa Basim O., 2014).

Table 1. Amplitude and time intervals between different segments of ECG

Sl. no.	Parameter Points	Amplitude (mV)	Time duration(msec)
1	P wave	0.1-0.2	60-80
2	PR-segment	-	50-120
3	P-R	-	120-200
4	QRS	-	80-120
5	ST-segment	-	100-120
6	T –wave	0.1-0.3	120-160
7	S-T	-	320
8	R-R	-	400-1200

The heart rate of a normal person lies in between 60 to 100 beats/minute. Any change in the heart rate is called Arrhythmia which can be broadly classified in two categories based on R-R interval i.e. Bradycardia and Tachycardia. If heart rate is slow or below 60 beats /min and the distance RR> 1.2 s during activity, then Bradycardia occurs and if the heart rate is high or above 100 beats /min and the distance RR <0.6 s, this indicates a disorder called Tachycardia (Mujeeb Rahma and Mohamed Nasor, 2012). The QRS complex is having most of the energy of heartbeats, so, an accurate determination of the QRS complex is essential for ECG analysis, in particular, accurate and efficient R peak detection in the analysis of computer-based ECG.

As R peak has higher amplitude than other portions of the ECG signal, hence R peak detection is easier than others. In most of the R Peak detection algorithms there are three differentiated stages: First stage is carried out the data acquisition process. In this process the MIT-BIH database is considered as a reference for ECG signals (MIT–BIH Arrhythmia Database Directory, 1992). Second is preprocessing stage where different techniques are applied to the signal to remove the noise and any existing artifact and the third stage is the suppression stage which is used to suppress the waves in ECG signal except the R-peaks and labeling them with their time of occurrence.

1.2 Literature Review

During last many years, various methods have been developed for R peak detection. Numerous R peak detection algorithms based on the filtering techniques (Dhir J.S, Panag N.K.,2014), empirical mode decomposition (EMD) (Tyagi Shivi and Patil Mahendra Kumar, 2013), wavelet transform (Jenkal W, et al.,2016), derivatives (Falconi Arteaga, et.al., 2015) genetic algorithms (Das, et al., 2013 and Li Hongqiang, et.al.,2017), Hilbert transform (Prasad S.T. and Dr. Varadarajan S., 2013), artificial neural networks (Izzah T.A. et al. 2013 and Mohamed B, et al., 2015) and hybrid approach (Meyer C., et.al., 2006), Markov models (Andreao R. V., et al., 2006),etc. represented in literature have been developed to detect R peaks. The decision rules and filtering techniques based methods are very adequate so suitable for all ECG analysis (Arzeno N.M., et al.,2008). Many designs constitute of a preprocessing or feature extraction stages and then a decision block (Kohler B. U., 2002). To emphasize the QRS complex several signal processing approaches are applied in preprocessing stage, which also suppresses the noises but these methods have few drawbacks. The Empirical mode decomposition in (Hongyan X. and Minsong H.,2008) can overcome the problem to select the mother wavelet in Wavelet based QRS detection method, but under noisy situations it is very tough to choose the set of intrinsic mode functions (IMF). By offering more useful filtering technique and threshold modification methods performance can be improved (Hongyan X. and Minsong H.,2008). In subsequent years various modifications have been done on the method of Pan Tompkins. The high pass filter and differentiator in Pan Tompkins' algorithm are replaced with a Savitzky-Golay filter in a novel Pan Tompkins algorithm (Pan J. and Tompkins W.J.,1985)

2.0 R PEAK DETECTION METHODS

R peak detection techniques have been investigated for several decades. Many techniques related to this area of research for R peak detection have been proposed for accurate and fast ECG feature extraction. There are various methods for R peak detection. Some recent and efficient techniques are reviewed and discussed in the following sections:

- Pan and Tompkins.
- Wavelet Transform.
- Empirical Mode Decomposition
- Hilbert-Huang Transform
- Fuzzy logic systems.
- Artificial neural networks.

2.1 Pan and Tompkins

Pan and Tompkins (PT) is very popular algorithm for R peak detection and its block diagram is shown in Figure 2. It is also known as the low-pass differentiation algorithm (LPD). In this algorithm QRS complex is detected depending on slope, amplitude and width. The QRS detection technique is divided into three different stages: linear digital filtering, non-linear transformations, and decision rule algorithms. In the first step algorithm passes the signal through a band pass filter cascaded into a low-pass and a high-pass filter configuration. The low-pass filter is used to limit the operating range of an ECG signal and also to reduce higher frequency noise effects while the high-pass filter is used to highlight the onset of each QRS complex (Oweis, R. J., & Abdulhay, E. W., 2011). The band-pass filter reduces undesired interferences such as the influence of the muscle noise, the baseline wander, the power line interference and frequency noise impacts. After filtration by an analog band-pass filter the signal is passed through an A/D converter at a sampling frequency of about 200 Hz. Now to marks all R peaks of the ECG signal the resultant signal of the previous stage is then passed through a set of thresholds. Then the output of the band-pass filter goes to differentiation element providing complex slope information.

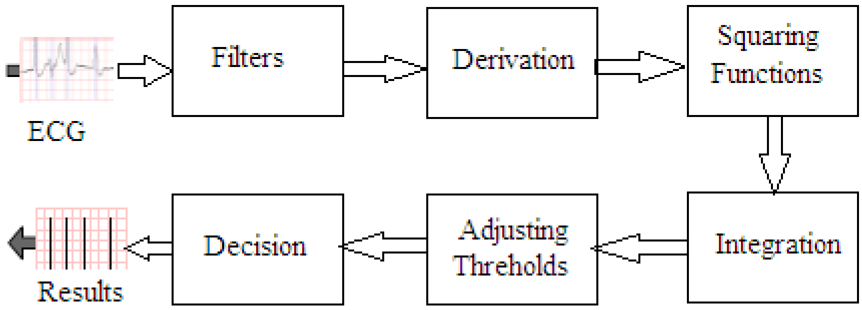

Figure 2. Block Diagram of Pan Tompkin Method

Then to make all data point positive the signal is squared point by point, which intensifies the slope of the frequency response and helps to detect false positives caused by higher than usual T waves. Finally a sliding window integrator is used in order to obtain the information about slope and width of the QRS complex. In the last step two sets of thresholds are adjusted. The highest peak of these two thresholds is considered as an R peak. After identifying the peak, threshold adaptation can be done depending on the amplitude of the peak and this most important task of the decision rule. If we consider a larger intervals that may not detect some signal peaks and if we consider smaller one that would detect too many peaks. In a certain time interval if the high threshold is unable to detect the peak in this case, lower threshold is used and to identify the peak which has been lost, the algorithm has to search back in time. When a new peak is identified and it exceeds the high threshold, then this peak is considered as a signal peak otherwise considered as a noise peak. (Christos P., et al., 2003). The accuracy of the system turned out to be 99.77%.

2.2 Wavelet Transform

Wavelets are mathematical functions having a finite oscillatory nature which makes them useful in real life situations where the signals are not stationary. It is a mathematical tool which decomposes a signal into basic functions which are known as wavelets. The signals decomposed into a set of orthogonal waveforms localized both in time and frequency domains. The wavelet transform is calculated separately for different segments of the time-domain signal at different frequencies, resulting in Multi-Resolution Analysis (MRA) (Oweis, R. J., & Abdulhay, E. W., 2011). The time and frequency resolution product is constant in this analysis. Thus, it provides a feature of a giving good frequency resolution and poor time resolution at low frequency, whereas good time resolution and poor frequency resolution at high frequency which makes it excellent for signals having low frequency components for long durations and high frequency components for short durations. The wavelet transform has recently emerged as one of the most dominant tools for analyzing challenging signals across a variety of areas in engineering and medicine (Addison, P. S., 2010).

Wavelet transforms are mainly of two types: Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transforms (DWT). DWT can be used to extract the features of ECG to complete proper classifications. There are two types of filters, a low pass filter (LPF) and a high pass filter (HPF) which are used in Discrete Wavelet Transform (DWT) to decompose the signal into different scales. The approximation is the output coefficients of the LPF and the detail is output coefficients of the HPF. For second-level decomposition the approximation coefficient can be again sent to the low and high pass filter of the next level. In this way we can estimate the approximation and detail coefficient and breaks down the signal into its different components at the different levels of scales.

The block diagram of the Wavelet Transform is shown in Figure 3. Specific details of signal are selected to detect the R peaks. Generally R peak has the highest amplitude in the ECG signals. Several methods for R Peak detection have been designed to trace non-stationary ECG signals which are based on the Multi Resolution wavelet transform. The wavelet transforms of some ECG signals cannot perform accurately due to serious baseline drift, high frequency noise and artifacts. Baseline drift is of main concern during R peak detection, which gets removed by composing and decomposing the ECG signal in DWT.

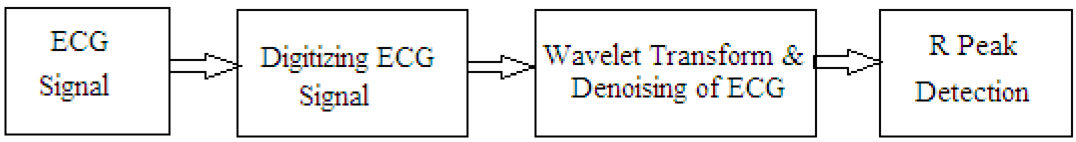

Figure 3. Block Diagram of Wavelet Transform

ECG Records obtain from the MIT-BIH arrhythmia database is a dual channel ECG signal which is filtered by a band pass filter. To make the analysis of ECG signal easier in different frequency ranges, it is decomposed at different levels of scales with the help of the wavelet transform. Then the maxima of the absolute of the DWT, which exceeds the given threshold for each scale can be located. Multi level wavelet decomposition can be performed using DWT. Zero crossings indicate the characteristic waveforms of ECG. Based on the wavelet transform R peak is detected by using filters. Peak that corresponds to an R wave within the search window is found using maximums and minimums in the search window. Then fixed an adaptive threshold value less than the value of Premature Ventricular Contraction (PVC) and greater than that of R waves. Once we find the PVCs they are eliminated. This adjusts the signal quality changes and the need for manual adjustments for different patients is eliminated. The adaptive threshold algorithm uses the first wavelet to search the maximums and minimums and to estimate the wavelet amplitude of the normal R waves. Jenkal W. et al. (2016) implemented the QRS detector and obtained a sensitivity of 99.66% and a positive predictivity of 99.8% for signals taken from the MIT-BIH database.

2.3 Empirical Mode Decomposition

The new nonlinear technique, called Empirical Mode Decomposition (EMD) method has been first designed by N. E. Huang et al. This technique is introduced for the analysis of nonlinear and non-stationary signals. The key part of this method is that it breaks down any complicated data set into a series of Intrinsic Mode Functions (IMFs), through a sifting process (see Figure 4). Since the decomposition is based on the oscillations in signals at a very local level in time scale, so it is applicable to nonlinear and non stationary processes. The major advantage of this approach is that the signal is used itself to derive the basic functions so this decomposition method is an adaptive and highly efficient. It also reduces ECG-ridden noise by filtering all undesired decomposed fragments so this procedure is an adaptive filtering.

The first IMFs can sift out the noise and preserve the QRS content with respect to other signal components (Tang, J. T., et al., 2008). So SNR is improved by first IMFs. The length of the signal cannot determine experimentally though produced IMFs count is directly proportional to the signal length. Trial-and-error methodologies are applied to the selection criteria of IMFs.

An IMF is a function that satisfies two conditions:

(a) Equal number of zero crossings and extrema or at most differed by 1.
(b) At any point, the mean value of the envelope defined by minima and maxima, being symmetric with respect to zero.

The high frequency or fast oscillations are represented by the lower order IMFs and low frequency or slow oscillations are represented by upper order IMFs. QRS region is the high frequency component of ECG signals. Hence lower order IMFs can be combined together to reconstruct the signal which highlights QRS region over the other waves and low frequency noises like baseline drift due to respiration etc. (S. Pal, and M. Mitra, 2010).

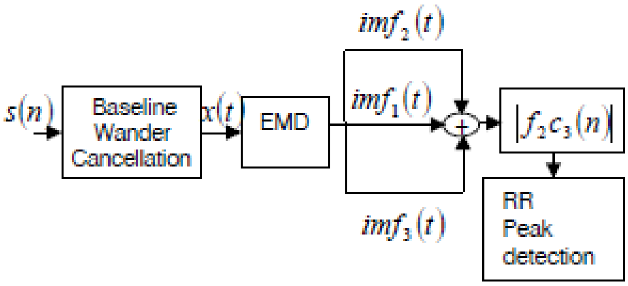

Figure 4. The various IMFs of the ECG signal

The algorithm is simple and consists of three blocks: Band-Pass Filter, Empirical Decomposition signal, sum the first three Intrinsic Functions Mode (IMF). The IMFs take its absolute value *a(t)*, retain the amplitudes larger than threshold, and finally, find the position of the maximum of a segment of time duration *tR* starting from the first non-zero value. Now the first R-peak is detected. Similarly, find all other R-peak positions are collected and find whether the peak is positive or negative until the end of $a(t)$ is reached.

This algorithm consists of at least nine steps with more than a few specific equations for extraction.

2.4 Hilbert Transform

Hilbert transform is a threshold detection scheme which is very important to distinguish and to identify the R-peaks in ECG signals. The threshold value cannot be constant for all ECG signals so it requires special attention. It should be defined with apropos to the ECG signal whose R peaks are to be detected (Kohler B.U., et al., 2002).

The ECG signal must be filtered and represented in such way so that the peak detection process yields efficient results even in the presence of noise within certain tolerable limits (Wilson J.D., et al., 2008). So Hilbert Transform is appropriate for this purpose. The Hilbert transform of a real-time function *f*(*t*) is

$$H\{f(t)\} = -\frac{1}{\pi}\int_{-\infty}^{+\infty} f(\tau)\frac{d\tau}{\tau - t} = -\frac{1}{\pi t} * f(t) \qquad (1)$$

Equation (1) shows that this transformation does not change the independent variable so the output *F(t)* is also a function of t and it is a linear function of *f(t)* also. Convolution between *f(t)* and $1/\pi t$ is applying for a obtained *F(t)* .

$$F(t) = \left(\frac{1}{\pi t}\right) * f(t) \qquad (2)$$

F(t) and *f(t)* together create a strong analytic signal which can be written with amplitude and phase. The analytic signal is expressed as

$$y(t) = f(t) + jF(t) \qquad (3)$$

$$F\{f(t)\} = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t}\, d\omega = F(j\omega) \qquad (4)$$

Applying the Fourier Transform we have:

$$F\{H\{f(t)\}\} = jsgn(\omega)F(j\omega) \qquad (5)$$

where *sgn* represents sign function. As this is an odd transformation so in the output of this transform, dominant peaks are detected at zero-cross points in ECG signal .Hilbert transform of the function *f(t)* represents its harmonic conjugate and both are orthogonal to each other. Figure 5 shows the block diagram of Hilbert Transform.

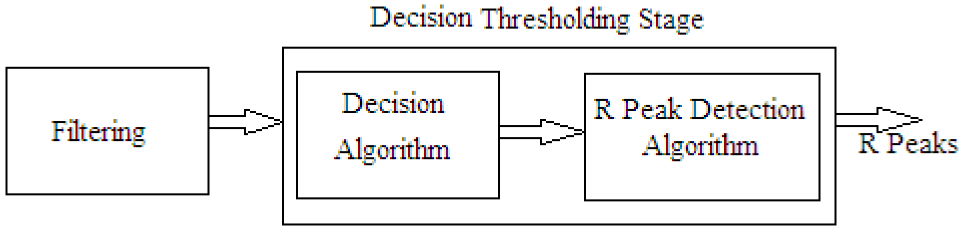

Figure 5. Block Diagram of Hilbert Transform

This algorithm consists of two stages: first is filtering to remove the noise from ECG signals without affecting the data present in the signal and the second stage is decision thresholding followed by the R-peak detection procedure. As the data are primarily located up to 60Hz, hence the data is band-pass filtered up to 60 Hz, then to obtain a complex signal Hilbert Transform is applied and enhanced signal is obtained which is used for efficient peak detection. In the second stage, set the initial value of threshold, then the signal values above threshold determines. Now calculate the number of peaks in the signal and repeat the last step until the new peak count does not exceed or is equal to the earlier counted peaks. Determine the sample with highest amplitude in each group then consider each detected peak and search for a sample around the peak, on either side with some suitable and appropriate leeway, with amplitude greater than that of the detected peak (Simranjit S. K. et al., 2012). By combining all the peaks, construct a signal which represents the R peaks of the given ECG signal. Prasad S.T. and Dr. Varadarajan S., (2013) implemented HHT technique as a tool for ECG QRS detection. The outcome was a sensitivity of 99.84% and specificity of 99.92%

2.5 Fuzzy Logic Systems (FLS)

FLS gives the method of reasoning that resembles human reasoning. FLS has improved decision rules of judgment, since it involves all intermediate possibilities between digital values YES and NO. Fuzziness concepts have enrolled the depiction of possibilities among “yes” and “no” decisions through membership functions and decision rules (Upasani, D. E., and Kharadkar, R. D., 2012).

The fuzzy method is especially useful in a complicated medical situation where variables and diagnostic rules are in large number. For better automated analysis, check, modify, add and delete every fuzzy variable is very easy. The main characteristic of parallel reasoning guarantees about final decision will be dependent on every possible conclusion regarding beat/rhythm labeling. This is a significant advantage over more deterministic algorithms and permits multi conclusions to exist which are common in clinical practice (Zong W, and Jiang D., 1998). If the medical situation is very complicated and input variables are high, then rule frame consist of a very high dimensional support. Fuzzy-based classification system first normalized the raw ECG signals, preprocessed the signals and then disintegrated into smaller number of frequency components. Every frequency component is related to ECG signal features. Therefore the entire decomposed features are classified into a set of pre-defined categories.
Input features of the decision process are first quantified, which is the main part of interception. Generally, membership functions and the definition of rules in the knowledge base are chosen appropriately to undergo iterative adjustment in terms of fuzzy variable. The results have revealed almost 100% correct detection.

2.6 Artificial Neural Networks (ANN)

An ANN is a system in which various neurons are connected to each other (see Figure 6). To classify the we present the inputs and corresponding targets to the Neural Network, a structure compares the emerging output to the desired target and then adjusts the weights inside the network, that store data gained from training sets until a match occurs (Abibullaev B., Seo H.D., 2010).

The stored empirical expertise desired outputs ANN is trained based on particular input (Ramlee R. A., et al., 2016). After in ANN which is based on training sets can be used to make judgment whenever needed. Once the network is trained by using specified input parameters the network can be made capable to do judgment through supervised training and inter neuron connection known as synaptic weights to give the best results.
Single-layer feed-forward network, matrix-vector input, and multi-layer feed-forward network are neuron models and architectures used in ANN and several training algorithms such as back propagation, conjugate gradient algorithm, and Levenberg-Marquardt can be used to train the network structure. The structure of the Back-propagation network has three layers. There are 10 neurons in 1st and 2nd layer and one neuron in 3rd layer. First two layers used Tan-Sigmoid transfer function and 3rd layer used a linear function.
This structure is used to detect the R-peak in ECG Signal. If the r peak is present, then network gives the output 1, otherwise gives 0. The sampling rate of the recorded MIT-BIH arrhythmia database is 360Hz. The samples or some specific features of the beat can be used as the input data of ANN. Features of each sample are firstly extracted to reduce the neural network size by using a function called Features Extractor. The inputs of feature extractor are the number of sample n and the ECG signal. Amplitude, RR interval, duration, differentiation, zero-crossing flag and the first element flag are the 6 input used to design the architecture.

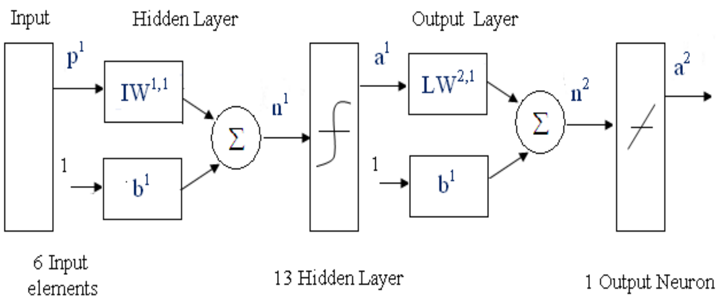

Figure 6. Structure of Artificial Neural Network

Each layer contains a weight matrix, a bias vector and an output vector which are represented by *W*, *b* and *a* respectively. The term *IW* is for the input layer weight and *LW* is the hidden layer weight.

It is a challenging task to choose the number of neurons in the hidden layer. If the number of neurons is too large then the memory is distributed over a large number of weights. But if the number is too small, the network cannot make generalizations when presented with slightly different inputs. When the output is not satisfactory, one more time the network is trained to reduce the difference between the desired output and actual output. The Preprocessing was used before training the network, which normalize the inputs to make training smoother and faster.

Mohamed B, et al., (2015) discussed computerized detection and classification of five cardiac conditions using ANNs. The core enhancement produced a three-layer network with 25 inputs, 5 neurons in the output layer and 5 neurons in its hidden layers that resulted in 91.8% recognition rate of the five cardiac conditions and an average accuracy of 84.93%.

3.0 CONCLUSION

After completion of above mentioned review, it may be concluded that appropriate R Peak detection techniques with sustained accuracy must be used to detect the type of arrhythmia. In this review, we have studied the performance of six R peak detection techniques, so anyone can use this review as a basis for their work and then start their work.

Accurate R peak detection can be achieved using Pan-Tomkins algorithm After comparing with other methodologies, implementation of this algorithm could be simple, but as this method uses the squaring function, so if there is a noise in the signal then that might be increased and could be replaced with a rectification stage. DWT does not follow each physiological temporal variation hence it gives stable features to morphology variations and provides simple implementation, consistency and moderate accuracy but it suffers from high mathematical complexity and low prediction.

Study reviews that Hilbert Transform is a stronger technique for frequency-domain analysis than FFT and DWT techniques. Therefore, to asses low and high frequency contents of an ECG signals Hilbert Transform is highly recommended. Hence it can be concluded that to obtain the desired R Peak detection more than one analysis technique must be combined and implemented.

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