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QRS Detection in Electrocardiogram Based on Smart Algorithm

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Abstract: The accurate detection of QRS complexes in electrocardiograms (ECGs) is crucial for diagnosing various cardiac conditions. The QRS complex is the combination of three of the graphical deflections seen on a typical electrocardiogram (ECG or EKG). This project divided two parts, the first part was done by the simulation which presents the detection process of QRS using classical method named Pan and Tompkins algorithm (PTA). The data for this study was obtained from the PhysioNet heart database, which is a well-known resource for analyzing cardiovascular signals. The proposed method leverages advanced signal processing techniques to identify QRS complexes with high precision. The algorithm's performance is evaluated using standard ECG datasets, demonstrating significant improvements in detection accuracy compared to traditional methods. The technique that was deployed demonstrated a remarkable level of precision, attaining a 99.3% accuracy rate through the utilization of neural network for classification. Additionally, the smart algorithm's adaptability to different ECG signal variations and noise levels underscores its potential for real-world applications in smart devices and remote cardiac monitoring systems. This advancement in QRS detection technology represents a significant step forward in the development of intelligent healthcare solutions, enabling more effective and timely cardiac care.

Introduction

1. Background

From World Health Organization (WHO) reports, the world's leading cause of death is cardiovascular disease . Those diseases caused the death of nearly 17.3 million people in 2008, where this number represent 30% of all deaths in the world . The result of the interest of medical researchers in the study of heart diseases and its treatments is that a distinctive development of preventive methods, medical and technological. The techniques of diagnosis of cardiovascular diseases used in health facilities are improved as a result of the success of one of these researches. The researchers develop these methods according to the results of this research. Electrocardiogram (ECG) analysis used in the heart test is the most important and common among cardiologists [1]. Because of the simplicity and low cost of this scan, it was a wonderful screening tool for various heart abnormalities. Several attempts have been made to find a comprehensive, satisfactory global solution to determine the QRS complex. Over the last two decades, heartbeat records had been studied and analyzed extremely, as well as Pan-Tompkins algorithm , which has been used extensively in cardiac detection literature. These technologies have become an inseparable part of our lives. Developments in smart phones and computers have made it easy to use these tools even in high-growth countries . As a result of these developments in the smart devices has increased the possibility of the application of more sophisticated algorithms such as wavelet algorithm and the Pan- Tomkins method . However, there are always limitations in the use of such applications in smart devices as a result of energy consumption in signal processing processes. Another factor that causes constraints in the analysis of ECG signals in real time, capacity of the device memory as well as its processor capability. A QRS detector were designed based on a smart algorithm and median filter, this detector is characterized by strength and speed and this is the main objective of this study. The selected factors have been tested across the MIT-BIH data base, which is an appropriate justification for their chosen. The developed technique has been compared on standard databases with the various detection methods for QRS complex[2].

2. Problem Statement

Despite the advancements in QRS detection algorithms, significant challenges persist. Noise artifacts, baseline wander, signal interference, and morphological differences in ECG signals among individuals pose obstacles to accurate QRS complex identification. Additionally, conventional algorithms often lack the adaptability required to handle the complexities inherent in diverse patient populations, leading to suboptimal performance in real-world scenarios.

3. Objective(s)

The primary goal of this research is to design, develop, and validate a novel smart algorithm for QRS complex detection in ECG signals. Specific objectives include:

- Simulate an active algorithm capable of robustly identifying QRS complexes in noisy and diverse ECG recordings.
- Implementing Neural Network and signal processing techniques to enhance the algorithm's adaptability to varying patient demographics and ECG signal characteristics.
- Evaluating the performance of the proposed algorithm against existing methods through comprehensive comparative analyses involving accuracy, sensitivity, specificity, and computational efficiency metrics.

4. Scope of Work

This study will primarily focus on the development and validation of the smart algorithm for QRS detection. The algorithm will be designed to handle various challenges encountered in clinical

ECG recordings, including noise, artifacts, and morphological variations. The research will utilize a diverse dataset encompassing ECG recordings from different patient demographics and clinical conditions. Practical implementation of QRS detection for classify three types of heart disease . Performance evaluation will involve rigorous testing and comparison with state-of-the-art QRS detection algorithms.

5. Project structure

This project on "QRS Detection in Electrocardiogram based on Smart Algorithm" aims to develop a robust algorithm for identifying the QRS complex in ECG signals. It includes an introduction to the problem, a literature review of existing methods, and a methodology detailing data collection and algorithm design. The project concludes with an evaluation of the algorithm's performance using standard datasets to demonstrate its effectiveness.

LITERATURE REVIEW

1 Introduction

To achieve an accurate and quick diagnosis, automatic ECG analysis algorithms play a crucial role, beginning with QRS detection. QRS complex detection is reviewed as the first step in ECG analysis. In this case, the QRS complex is one of the most significant waveforms in ECG investigation. The QRS complex is represented by a combination of three graphical deflections witnessed in a typical ECG analysis. Moreover, it the central and most compelling section of the illustration. It is viewed as the main spike as considered in an ECG line. It displays the electric movement of the heart during a ventricular contraction; its occurrence and shape provide details about the heart's status. It serves as a framework for automating cardiovascular identification based on its form. The ECG analytical algorithms consider this to be the basis for the cardiac cycle classification[3].

In this case, QRS detection offers the basis for automating the ECG analysis algorithms . For decades, the QRS complete detection algorithm has been analyzed, resulting in various hardware and software techniques for completing the same. There are currently numerous QRS detection algorithms – motivation for this variation is the need to enhance the process as each algorithm seeks to be better and faster than others [4].

QRS length is among the critical features of the QRS complex, which is applied in the assessment and organization of ECG signals. The QRS field is the length over and beyond S and Q nodes above the isoelectric (ISO) axis. The R-R interval is the spectrum of the two Heartbeat rate (HBR) and QRS complexes subsequent to it. The PR interval subsequently demonstrated the duration between the initiation of atrial depolarization and the start of ventricular growth while allowing for the manifestation of systole [5]. In this relation, the R- wave is the R-wave amplifier, the largest R-wave node. The R-T interval is between crests, describing the T-wave and QRS complex successive crests. It can be considered as the time interval between the ventricular depolarization peak and consecutive ventricular polarization peak.

ECG compression techniques have sought to minimize ECG the created dataset size and maintain all scientifically relevant characteristics like the P-wave, QRS complex and T-wave, as previously adopted. The compressed signal allows for better efficiency by programmers for the real-time processing of rhythmic classification networks. Many ECG compression techniques were suggested in the literature. These methods were divided into processes of direct extraction, transformation, and parameters [6]. The latest extraction function algorithm presents morphologic and statistical features derived from regular and irregular ECG signals to finish this paragraph. Added to the extraction capabilities, the compressed shape of the signal enables us to verify the classification efficiency improvements during a classification stage.

2. Recent Studies of QRS Detection

The process of detecting heart signals is complex and requires a lot of accuracy because of its relationship to diagnosing diseases |. According to Chazal , 178 structures were generated from a QRS Complex – representing ECG beats. Subsequently, transformation, the features were in a summation of 229 transformed features. Techniques for evaluating feature in this context were achieved by reviewing various ECG based literature. In a comparable simulation, 30 features for a neural network were obtained employing the backpropagation training algorithm[7] . Subsequently, the two models discussed in this section demonstrate that the more inputs, the more challenging the classification network structure. As mentioned at the beginning of this research, it was stated that there might be challenges in computing the QRS Complex. For example, the classification speed reduces significantly in a normal personal computer that is cannot complete the research. Managing this challenge involves essential and crucial features from ECG waveforms that must be familiarized from the new study.

Hamdi et al. suggested a novel method for medical assessment and clinical evaluation assistance of the ECG signals based on the deterministic finite automata (DFA) and some requirements. This research confirms that regular grammar is helpful in the extraction of QRS complex and clarification of ECG signals. The DFA applied to represent a normalized QRS complex as a sequence of negative and positive peaks. A QRS is deemed a set of adjacent peaks that fulfill specific standard deviation criteria and duration. The suggested approach in this study is employed to numerous sorts of ECG signals gathered from the standard MIT- BIH arrhythmia database. Numerous metrics are evaluated, including QRS intervals, RR distances and peak amplitudes. Regular grammar and DFA demonstrated functional for ECG signal diagnosis. The proposed method offered a sensitivity rate of 99.74% and the positive predictivity rate of 99.86% [7].

Adam et al. utilized a new discrete wavelet transform (DWT) approach fused with nonlinear features for automated characterization of cardiovascular diseases (CVDs). ECG signals of normal, and dilated cardiomyopathy (DCM), hypertrophic cardiomyopathy (HCM), and myocardial infarction (MI) are exposed to five levels of DWT. The relative wavelet of four nonlinear features such as fuzzy entropy, sample entropy, fractal dimension, and signal energy is obtained from the DWT coefficients. These features are supplied to the sequential forward selection (SFS) method and then ranked utilizing the ReliefF process. The suggested protocol in this study reached maximum classification accuracy of 99.27%, sensitivity of 99.74%, and specificity of 98.08% with K-nearest neighbour (kNN) classifier using 15 features ranked by the ReliefF method [8].

Zhang et al. introduced an adaptive threshold algorithm in ECG signal feature extraction using Kalman filtering theory. Low computational cost, low storage requirement, and fast response feature are attained using two sets of adaptive threshold systems in various requirements. As evidence of the hypothesis, the suggested algorithm in this study is validated in Matlab and implemented on field-programmable gate arrays (FPGA) utilizing the MIT-BIH database. The results showed the proposed algorithm uses a low resource of FPGA and displays 99.30 % detection sensitivity and 99.31 % positive prediction on average, respectively. The suggested algorithm can quickly adjust various individuals with the self- adjusting system in satisfying detection accuracy [9].

Yakut et al. enhanced extraction of QRS complex method having low complexity is suggested. This approach comprises two steps as preprocessing and decision making. To assess the proposed method's implementation, it was examined utilizing the ECG recordings (about 1.3 million beats) taken from the five standard databases as MITBIH Arrhythmia, Fantasia, MIT-BIH Noise Stress Test QT and European ST-T. In this study, 1296137 beats of 272 cases were studied for QRS detection, and the average sensitivity was achieved as 99,60%, while the average positive predictivity, +P was presented as 99,77%. The impact of the suggested method is that the training, selection, setting, and prediction processes are not necessary while determining the essential parameters [10].

Shaik et al. suggested using an adaptive threshold method on spectrogram computed using Short Time Fourier Transform (STFT) for QRS complex detection in ECG signal. The proposed algorithm comprises preprocessing the raw ECG signal to wipe out the power-line interference, computing the STFT, using adaptive thresholding technique, and identifying QRS peaks. The proposed algorithm provides good outcomes in terms of sensitivity of 99.56%, specificity of 99.52% and QRS detection error rate of 0.93% achieved against the MIT-BIH Arrhythmia database [11].

Berwal et al. proposed a high-performance QRS complex detector appropriate for medical devices. In this study, a Biorthogonal wavelet filter bank with fourth-level decomposition is first employed to get the denoised ECG signals. The soft threshold method is employed to obtain the QRS complex peaks by the QRS complex peak detector block. The proposed model has been tested for its robustness on multiple datasets. Sensitivity of 99.31%, positive predictivity of 99.19%, and the Detection Error Rate (DER) of 1.49% shown by the suggested design make it appropriate for QRS complex detectors utilized in wearable healthcare devices [12]. **Table 1.1** explains the most QRS complex detection proposed in the previous studies

Table 2.1 QRS complex detection proposed in the previous studies.

Study	Methodology	Key Findings
Chazal [5]	Transformation and feature evaluation	Increased features challenge classification networks
Hamdi et al. [7]	DFA for QRS extraction, metrics evaluation	Sensitivity: 99.74%, Positive Predictivity: 99.86%
Adam et al. [8]	DWT + nonlinear features, classification	Accuracy: 99.27%, Sensitivity: 99.74%, Specificity: 98.08%
Zhang et al. [9]	Adaptive thresholding using Kalman filtering	Sensitivity: 99.30%, Positive Prediction: 99.31%
Yakut et al. [10]	Enhanced QRS extraction method	Sensitivity: 99.60%, Positive Predictivity: 99.77%
Shaik et al. [11]	Adaptive thresholding on STFT for QRS detection	Sensitivity: 99.56%, Specificity: 99.52%, QRS Error: 0.93%
Berwal et al. [12]	Biorthogonal wavelet + QRS peak detection	Sensitivity: 99.31%, Positive Predictivity: 99.19%, DER: 1.49%

3. ECG and Noise

A cardiac signal is an effective medical signal that gives important information about the condition of the heart, the frequency of the heart peats in ranges from 0.05 to 100 Hz and has a voltage value of 0 to 10 mV, this signal is distorted by noise of high and low frequencies, leading to failure diagnosis of the heart status or no diagnosis at all [13].

Noise types in ECG Signal

1. Power Line Interference:

This noise is caused by electromagnetic interference from power transmission lines, nearby medical equipment, improper grounding to the patient and ECG device, the frequency of this noise is 50/60 Hz as in Fig 2.1. [14]

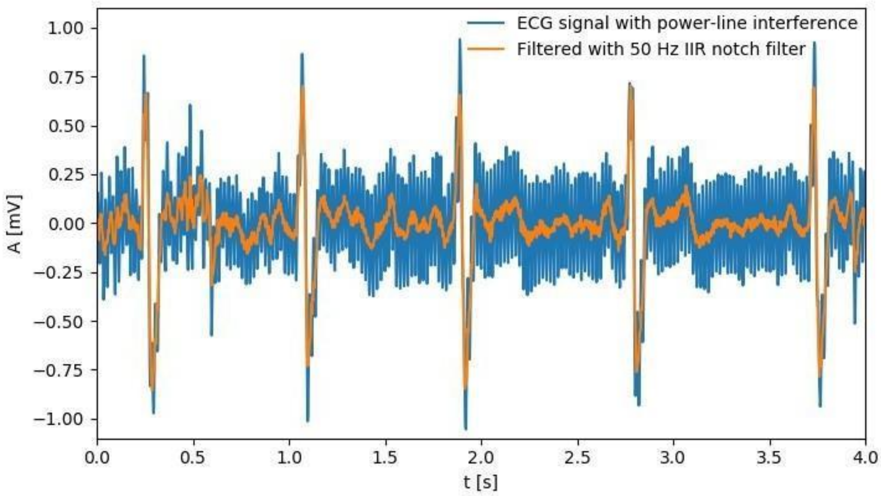

Figure 2.1 Power line interference

2. Electromyogram (EMG) Noise:

This noise arises from the electrical activity of the muscles of the patient body and consists of a maximum frequency 10 Hz, due to the combined of this frequency with a heart signal the analyzing and processing of data will be difficult as in Fig 2.2 [14]

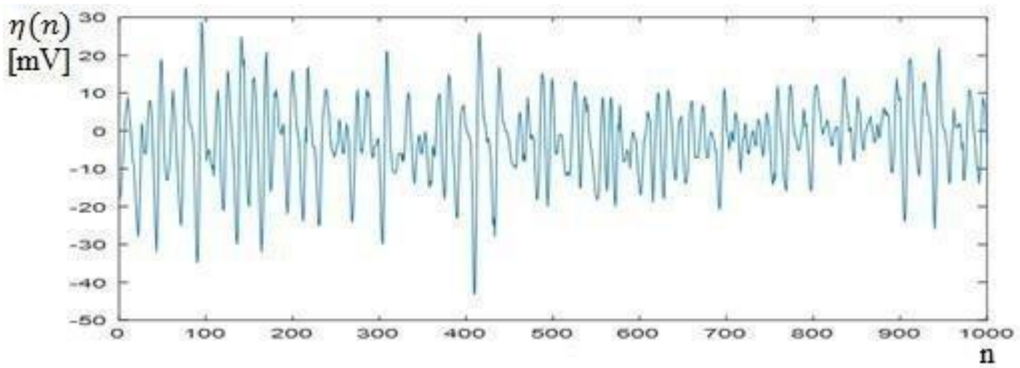

Figure 2.2 EMG noise

3. Baseline Wander:

It is low frequency that occurs as a result of the movement of the body during the signal detection process and also called the baseline deviation, it's frequency from 1 to 10 Hz and cause a defect in the detection of the signal as in Fig 2.3 [14]

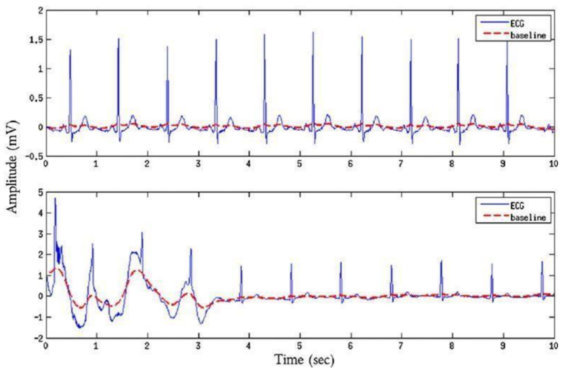

Figure 2.3 baseline wonder

4. Baseline shift:

Base line shifts occur abruptly due to sudden movement of the patient. These can be lessened by reducing movement of the patient. They are visible in the signal as a sudden increase or decrease (step change) in the DC offset.

A simple example is shown in Fig 2.4 [14]

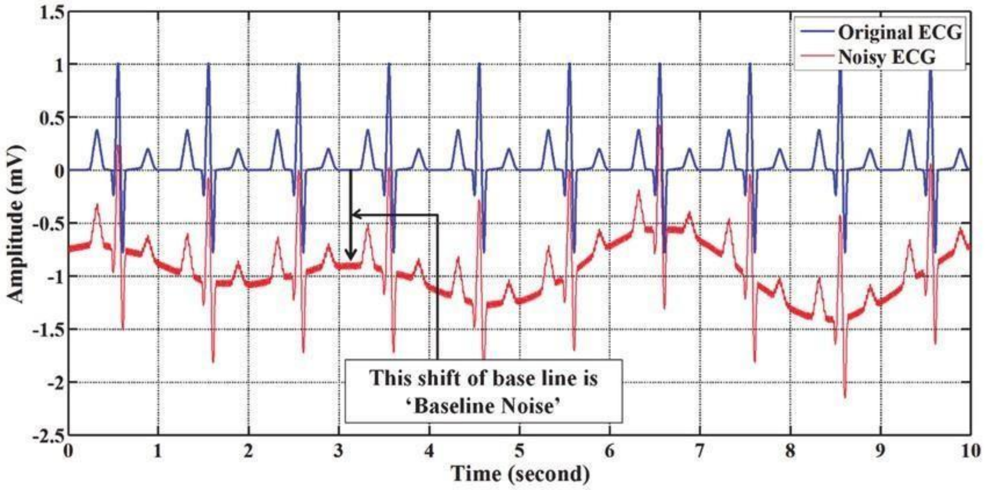

Figure 2.4 Baseline drift

5. Electrode Contact Noise:

This type of noise results from the loss of contact between the body's skin and Electrode, this leads to the separation of the sensing process, which separates the system from the subject. Duration of this type of noise is 1 per second [14].

4. Noise Reduction Methods of ECG Signal

The ECG signal contains many high and low frequencies interfering with its original frequency. Because of these interference, there have been many ways of filtering and analyzing the noise of signal over the years. In signal processing techniques, the device or process used to remove some unwanted components or features is the filter. This process is part of the signal processing, that the complete or partial cancellation of some of the characteristics of the signal is the specific feature of the filters, filters are not limited to the field of signal processing only,which is involved in the image processing, telecommunications and others[14]. Depending on the method used in signal processing, filters are divided into two main types:

- Analog Filter.
- Digital Filter.

The filters are divided into two other main types depending on the components that are included in the construction of filters and they are:

- Active Filter.
- Passive Filter.

Each type of filter above is divided into four types of filters depending on the type of component to be nominated and these types are:

- Low Pass Filter (LPF).
- High Pass Filter (HPF).
- Band Pass Filter (BPF).
- Band Reject Filter (BRF).

Fig 2.5 below shows main types of filters:

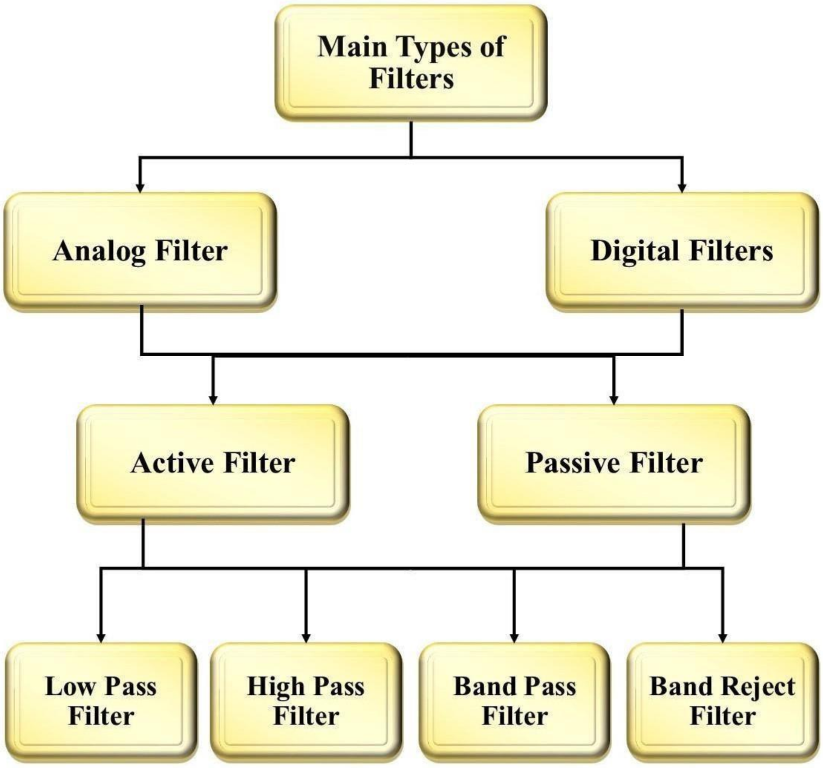

Figure 2.5 Main Filter Types

The choosing of filter type is based on the researcher himself because of its conviction that this type of filter produces better results than the others, As well as compatibility with the method of signal analysis and calculation of heart rate, There are many types of filters classified according to their use and design methods and we will mention the types used in the filtering of ECG signal [15].

5. Filter Types of ECG Signal

Figure 2.6 below shows most common filters used to analyze ECG signal:

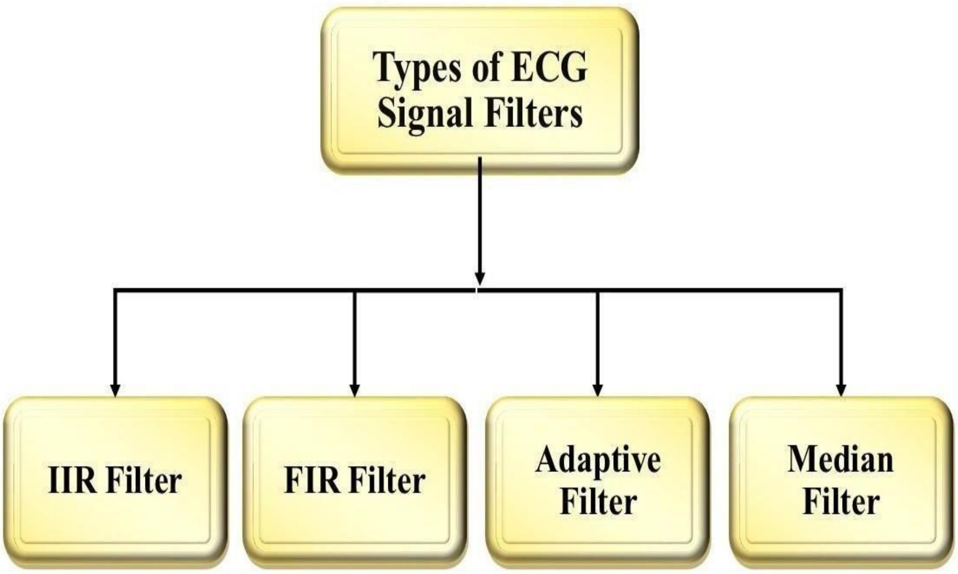

Figure 2.6 Common filters of ECG

1. IIR Notch filter:

It is not complicated filter, can be using the notch filter (IIR) to remove the stationary power line interference, if the attenuation of notch filter is higher than noise effect in ECG signal thin it will have the power to remove interference noise of power line (PLI). In practice, however, at 50 Hz it can eliminates PLI noise [15].

2. FIR Filter:

Finite Impulse Response (FIR) filters are simple and stable filters. Window method is the simplest FIR filter design method. And all frequencies below the cut off frequency are passed with unity amplitude and others are blocked. The different windows used are Rectangular Window, Hanning window, Hamming window, and Blackman window. Using these windows High pass filter and Low pass filters are designed with cut off frequency 3Hz and 100Hz respectively. Then the noisy ECG signal is passed through these filters to remove noises [15].

3. Adaptive Filter:

The adaptive filter reduces the mean squared error between primary input (ECG signal) and the reference input (noise with ECG signal). An adaptive noise canceller is an efficient method to denoise noisy ECG signal [14] .The algorithm used is Recursive least squares (RLS) .Advantages of adaptive filter method are:

- Filtering response is fast
- Residual errors are small
- When working in time varying environment it has excellent performance Drawback of adaptive filter method is:
- This method requires reference signal (either signal or noise characteristics) information for the effective filtering process.
- When RLS algorithm is used it has high computational complexity and stability problems.

4. Median Filter:

Median filter is a digital filtering technique used to remove distortions from the image or signal. This type of filter is used as a pre-analysis step to enhance the results after analysis. Median filter has extensive uses in the field of image processing as well as has applications in the field of signal processing because at the same time it works on filtering the signal from distortions as well as improving its edges.

a) Algorithm description:

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median [16].

b) Edge preservation properties:

Median filtering is one kind of smoothing technique, as is linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but adversely affect edges. Often though, at the same time as reducing the noise in a signal, it is important to preserve the edges. Edges are of critical importance to the visual appearance of images, for example. For small to moderate levels of Gaussian noise, the median filter is demonstrably better than Gaussian blur at removing noise whilst preserving edges for a given, fixed window size. However, its performance is not that much better than Gaussian blur for high levels of noise, whereas, for speckle noise and salt-and-pepper noise (impulsive noise), it is particularly effective.

c) Median Filter types:

1. Standard median filter (SMF):

The standard median filter is a simple rank selection filter also called as median smoother, introduced by Tukey in 1971 that attempts to remove impulse noise by changing the luminance value of the center pixel of the filtering window with the median of the luminance values of the pixels contained within the window. Although the median filter is simple and provides a reasonable noise removal performance, it removes thin lines and blurs image details even at low noise densities. The filtered image S = {S(i,j)} from SMF can be defined by the following equation[17]:

$$\mathbf{S(i,j) = Median\ (k,l) \in Wm,n\ \{D\ (i+k,j+l)\}} \quad \text{(2,1)[18]}$$

Where Wm,n is a sliding window of size m x n pixels centered at coordinates (i, j). The median value is calculated by using equations with ns= m x n although SMF can significantly reduce the level of corruption by impulse noise, uncorrupted pixel intensity values are also altered by SMF. This undesired situation happens because SMF does not differentiate between uncorrupted from corrupted pixels. Furthermore, SMF requires a large filter size if the corruption level is high. Yet, large filter of SMF will introduce a significant distortion into the image.

It is worth noting that equations is normally using sorting algorithm such as quicksort or bubble-sort to arrange the samples in increasing or decreasing order. Even though sorting algorithm can be easily implemented, sorting procedure requires long computational time when Wm,n is a large filter because the number of samples (i.e. ns= m is big. Thus, in order to avoid from using any direct sorting algorithm, the use of local histograms has been proposed for median value calculation. The time required to form local histogram can be reduced by using a method proposed by Huang et al, where instead of updating m n samples, only 2m samples need to be updated in each slidingiteration.

2. Weighted Median Filter (WMF)

Weighted median filter is one of the branch of median filter (WMF). It was first introduced by Justusson in 1981, and further elaborated by Brownrigg. The operations involved in WMF are similar to SMF, except that WMF has weight associated with each of its filter element. These weights correspond to the number of sample duplications for the calculation of median value. The filtered image $S = \{S(i, j)\}$ from WMF can be defined by the following equation:[19]

$$S(i,j) = Median(k,l) \epsilon Wm,n\ \{Wm,n\ (k,l) \otimes D(i+k,j+l)\} \qquad (2, 2)\ [20]$$

Where operator $\otimes$ indicates repetition operation. The median value is calculated using equation (2, 2) with n_s is equal to the total of $Wm,n(k,l)$. Normally, the filter weight $W_{m,n}$is set such that it will decrease when it is located away from the center of the filtering window. By doing so, it is expected that the filter will give more emphasis to the central, and thus improve the noise suppression ability while maintaining image details . However, the successfulness of weighted median filter in preserving image details is highly dependent on the weighting coefficients, and the nature of the input image itself. Unfortunately, in practical situations, it is difficult to find the suitable weighting coefficients for this filter, and this filter requires high computational time when the weights are large. [21]

3. Directional Median Filter:

Directional median filter, or also known as stick median filter, works by separating its 2-D filter into several 1-D filter components [22]. Each filter component or stick, presented as a straight line, corresponds to a certain direction or angle θ. For a window of size m×n pixels, there are m+n-2 sticks that will be used. The computed median values from these 1-D filters are then combined to obtain the final result. In, the output intensity is defined as:

$$S(i,j) = max\{Median(k,l) \in W_{\theta} \{D(i+k, j+l)\}\} \qquad (2,3)[20]$$

Where W_{θ} is the stick. Here, the output intensity is defined as the largest median value determined at each location.

4. Iterative Median Filter:

Iterative method requires the same procedure to be repeated several times. In general, iterative median filter with n_i iterations, requires n_i -1 temporary images. Iteration procedure enables median filtering process to use smaller filter size and reduce the computational time, while maintaining local features or edges of the image. The number of iterations n_i can be set by the user, or the iteration process stops when the output image converged (i.e. the current output image is equal to the previous output image). In practical, the number of iterations needed is dependent to the level of corruption and also the nature of the input image itself. [21]

5. ECG Recording

To record the electrical activity of the heart, ten electrodes installed on the chest area of the human body. The electrical activity of the heart is recorded in the form of waves drawn on a graph. The patterns of these different waves express the electrical activity of the heart. The doctor diagnoses the patient’s condition based on the results of this test. It should be noted that some types of heart disorders may not appear during this type of procedure, so the doctor may use other types of planning devices that help plan the electrical activity of the heart during different times of the day.

The ECG is measured at 25 mm/sec (5 large squares/sec), and the electrical energy is adjusted so that 1 mV = 10 mm (2 large squares) in the vertical direction. Hence, each small 1-mm square is 0.04 sec in time and 0.10 mV in voltage. Five fundamental waves exist on the screen of the ECG device (as shown in Figure 2.7), each symbolizing a particular point inside the heart, and these waves are [22]:

- P wave (atrial depolarization) (The first wave appeared on the device's screen, as it reveals depolarization due to the passage of electric current in the left and right atria).
- Q wave (depolarization due to the passage of current through the septum between the two ventricles).
- R wave (This wave is the greatest in terms of current strength, and it suggests depolarization of the left and right ventricles).
- S wave (It shows depolarization of the walls of the left and right ventricles).
- T wave (Represents ventricular repolarization. Generally, the T wave shows a positive deflection. This occurs because the last cells to depolarize are sited in the subepicardial region of the ventricles and these cells have shorter action abilities than observed in the subendocardial areas of the ventricular wall).

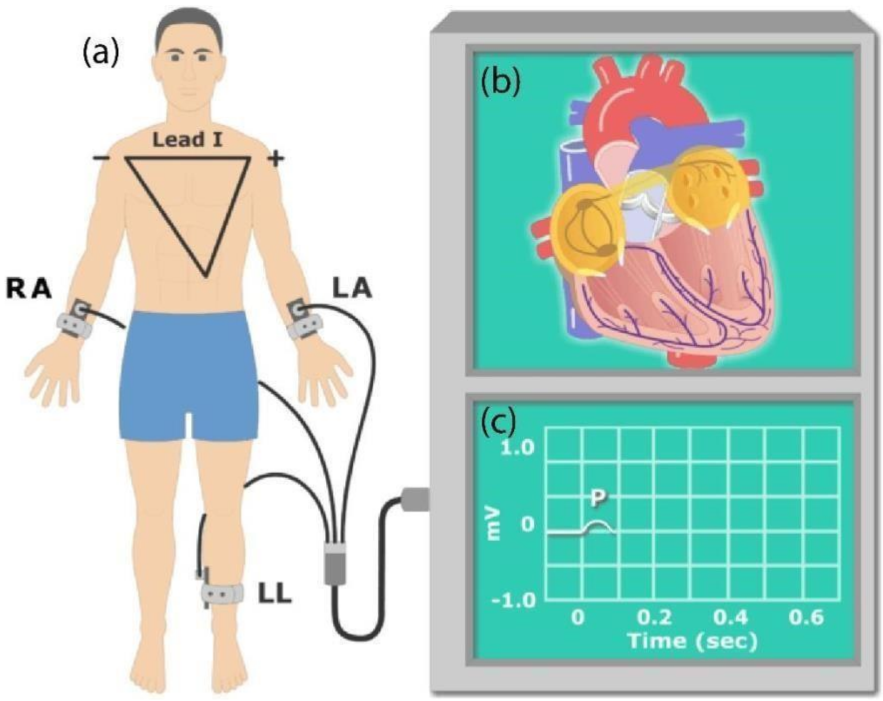

Figure2. 7 a) the human body, (b) heart anatomy, and (c) ECG graph.

7. Artificial Neural Network

Artificial Neural Networks (ANNs), frequently referred to as neural networks, are innovative systems and computing methodologies for machine learning, understanding demonstration [23], and, lastly, using gained information to improve the final outcomes of complex systems [24]. An Artificial Neural Network (ANN) is a statistical paradigm that depends on how nervous systems that are biological, such as the brain, analyze data. Several artificial intelligence specialists believe that artificial neural networks are the greatest, if not the only, way to develop intelligent machines [21]. The structure of ANN is identical to that of the human brain, with neuron nodes connected in a web-like arrangement. There are billions of neurons in the human brain. Each neuron thus has a cell body that processes data by sending inputs and outputs to and from the brain. The fundamental concept behind such networks is (in part) inspired by how the biological neural system processes data and information to acquire knowledge. Creating new frameworks for the information processing system is the main idea behind this notion. Figure 2.8 shows the basic structure of an artificial neural network. A neuron is the basic processing unit of a neural network. A biological neuron, in essence, receives input from many other sources, integrates it in some way, needs to perform a generally nonlinear operation on the outcome, and then outputs the final result.

Artificial Neural Networks (ANNs) are advanced computational models inspired by the human brain's structure and functioning. They consist of interconnected processing units called neurons, which are organized in layers. Each neuron processes input data and passes the result to other neurons in the subsequent layer, mimicking the way biological neurons transmit signals.

ANNs can learn from data through a process called training, where they adjust the weights of the connections between neurons to minimize the difference between the predicted and actual outputs. This learning process is typically achieved using algorithms such as backpropagation, which iteratively updates the weights based on the error gradient.

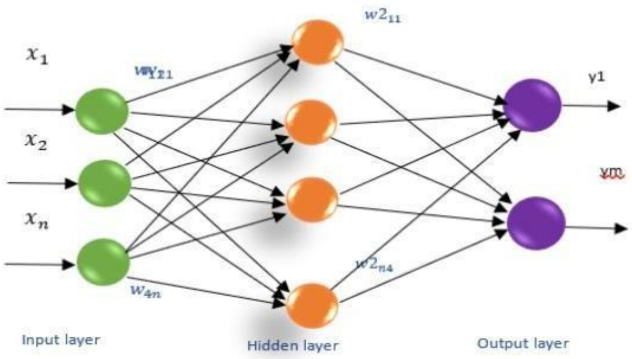

Figure 2.8 Neural Network Scheme

Proposed System Simulation and Experimental work

1. Introduction

The main objective of this work is to find an accurate methods for extraction of the QRS complex. The correct extraction of QRS leads to correct diagnosis of the persons whether he has a heart disease or not and designing of several practical applications such as mobile application to monitor the patient's situation and then send information to the doctor and Biometrics registration by means of a cardiac signal imprint due to the difficulty of rigging and other applications.

This chapter consists of two parts, theoretical and practical part. The theoretical part includes two algorithms for the analysis of the ECG signal which are modified Pan- Tompkins Algorithm and biorthogonal wavelet transform. The practical part is that one of these algorithms will apply which is modified Pan-Tompkins by loading it into a processor and then the processor analyzes newly recorded heart signals from several people.

Finally, the results of both algorithms are compared and the differences between them are determined, as is the comparison between the results of the analysis by simulations and by the practical part.

2. Theoretical Part

Different methods were used to analyze the ECG signal in order to reach the best results that determine the diagnosis of the condition of the person being tested. The researchers had the greatest credit for the current medical technologies that deals with heart disease. The researches varied between development of methods that used in the analysis of ECG signal and the use of the modern method and testing their results. Our proposed work analyzes the ECG signal by two algorithms, first are developed called Modified Pan- Tompkins method and second is biorthogonal wavelet transform.

Matlab environment was used to develop and test algorithms. The advanced stages of this chapter will demonstrate the role of MATLAB in this work in detail as well as its relation to the practical part.

3. Pan-Tompkins Algorithm

In chapter two, the standard Pan-Tompkins method of signal analysis and extraction of required features by applying an appropriate threshold technique was explained.

Pan-Tompkins algorithm is one of the most widely used algorithms in which ECG signals have been analyzed. Many experiments have been done on it and developed for ease of implementation, besides their steps are divided which lead to that the process of updating a particular part is clear and easy.

In this chapter we will present our proposed method of modifying this algorithm as well as showing the difference between it and its standard method of analysis and their results, in addition to explaining all subsequent algorithm steps that have been programmed and tested in Matlab environment.

4. Standard Pan-Tompkins Algorithm

In this section we implement the standard algorithm in order to know weakness points in it and how to improve it so that we can design a strategy for develop the algorithm, Also to calculate results so we can compare with the proposed work, this algorithm implemented and tested in Matlab, Fig. (3. 1) shows steps of algorithm working.

We have developed this algorithm and get different results, but better result we get when change preprocessing part and this related to types of filters because it is hard to estimate the correct cut off frequency, As a result information will lost and therefore accuracy decrease because of wrong analysis, Also there is another part is critical and play a huge role in results which is the appropriate threshold, most results depend on this part because it is identify number of peaks found in whole ECG record.

5. Modified Pan-Tompkins Algorithm

Our proposed development in this part is Concentrate in two sections of the standard method as shown in block diagram below (fig.3.2)

a) Change Type of Filters:

we replace low and high pass filters by two dimensions median filter, this filter work entry by entry and enhance signal according to neighbor coordinates which denoted by equation below:

$$Y(\, m_o, n_o \,) = Median[\, X(m_i, n_i),\ (2m_i, n_i)] \quad \text{………………… (3, 1)}$$

Where (S) represents output signal, $(\, m_o, n_o \,)$ represent dimension of output signal matrix, X represents input signal while (m_i, n_i) represent dimension of its matrix and $(2m_i, n_i)$ represent dimension of the window that slide on signal.

Median filter will work to eliminate the distractions caused by the movement of the patient's body and breathing movement, which is called baseline deviation, it also works to remove high frequencies of the interference of power line resulting from the flow of electricity in the neighboring apparatus. This is not only what this filter does, but also Because of its other edge-cleaning properties, subsequent analyzes will improve due to the quality of the signal resulting from the filtering process.

b) Threshold Optimization:

Besides to the changes we had made in preprocessing part, we also enhance threshold equation and these enhancements have been conducted experimentally until we get best result, Equation below shows threshold equation:

$$Threshold = mean\,(ECG\ Signal) * 0.31 \quad \text{……………………… (3, 2)}$$

According to that enhancement accuracy, predictively have been raised and error rate reduced to very low value.

3. Description and Scheme of Proposed Algorithm

The main parts of this system are:

- Input parts which is distorted heart signal.
- Analysis and processing unit, which is developed Pan-Tomkins algorithm.
- The results-extraction unit, developed Threshold technology.
- The decision-making unit.
- Output unit which is present noise free signal

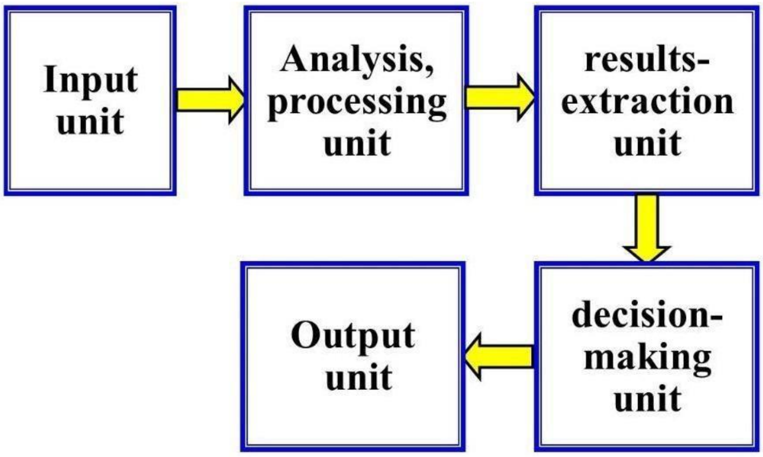

Figure 3.3 proposed system schematic of Pan-Tompkins algorithm

By looking to scheme we can describe each section:

1. Input unit include choosing one of 48 ECG record, each record contain 650000 samples which is read by algorithm input unit, ECG signal processed by sampling frequency 360 Hz.
2. Analysis and processing unit, first apply filtering technique to remove all noise types and smoothing the signal by using two dimension median filter, then smoothed signal applied to three process which are derivative, squaring and averaging respectively in order to find slope of the curve, enhance peaks and reduce very low values that's considered very low frequencies and figure out signal information as width of peaks, minimum and maximum points in signal.
3. Results-extraction unit, in this section, algorithm applies optimized threshold to get R peaks from processed signal, there are several steps to find the threshold value which is updated in each new record.
4. Decision-making unit, this unit defines the extraction of R peaks correct or not from position and number.
5. Output unit, present results which is got from ecg record and display noise free signal.

3. Practical Part

Accurate and efficient classification of ECG signals is crucial for diagnosing heart-related conditions. This work investigated an approach for ECG signal classification and disease prediction. The proposed system leverages Wavelet scattering (WS) for feature extraction and Neural Network (NN) or Support Vector Machine (SVM) classifiers. This conclusion section summarizes the key findings and highlights potential areas for future exploration. This part includes implementation our work practically, there are limitation and obstacles when applying the theoretical part in practice due to several reasons, including the difficulty in obtaining good electronic materials, which gives quality in the results and speed in the analysis and thus save time to researcher, lack of time as the segment needs long time in processing and correcting errors, these errors may be due to faulty electrical and electronic connection between parts or due to incorrect programming of the processor that is the focus of the whole circuit, as well as the difficulty of obtaining records of heart signal from the databases located in local hospitals, All these factors cause obstacles when analyzing ECG signal in practice.

4. Schematic of Practical System

Figure below (fig 3.10) shows practical system schematic, there are four main stages that sensed signal pass through it.

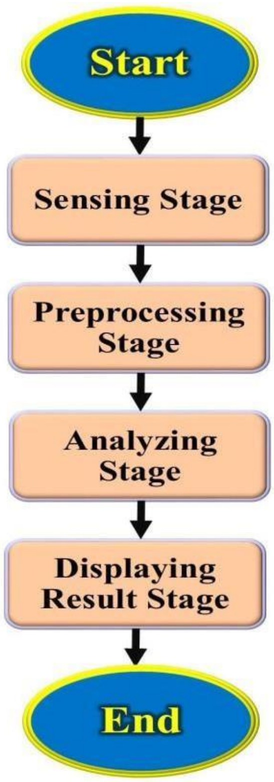

Figure 3.4 Practical Work Scheme

3.3.3 Description of Practical System

Heartbeat signal that will be sensed from a human body will pass through several steps until results are got, these steps are:

1. Sensing Stage:

This stage represents the beginning of the system's work, where the three probes of ad8232 are connect to a human body, two of them are connected to the right of the heart and the other one to the left of the heart as shown in the following figure below (fig 3.11) :

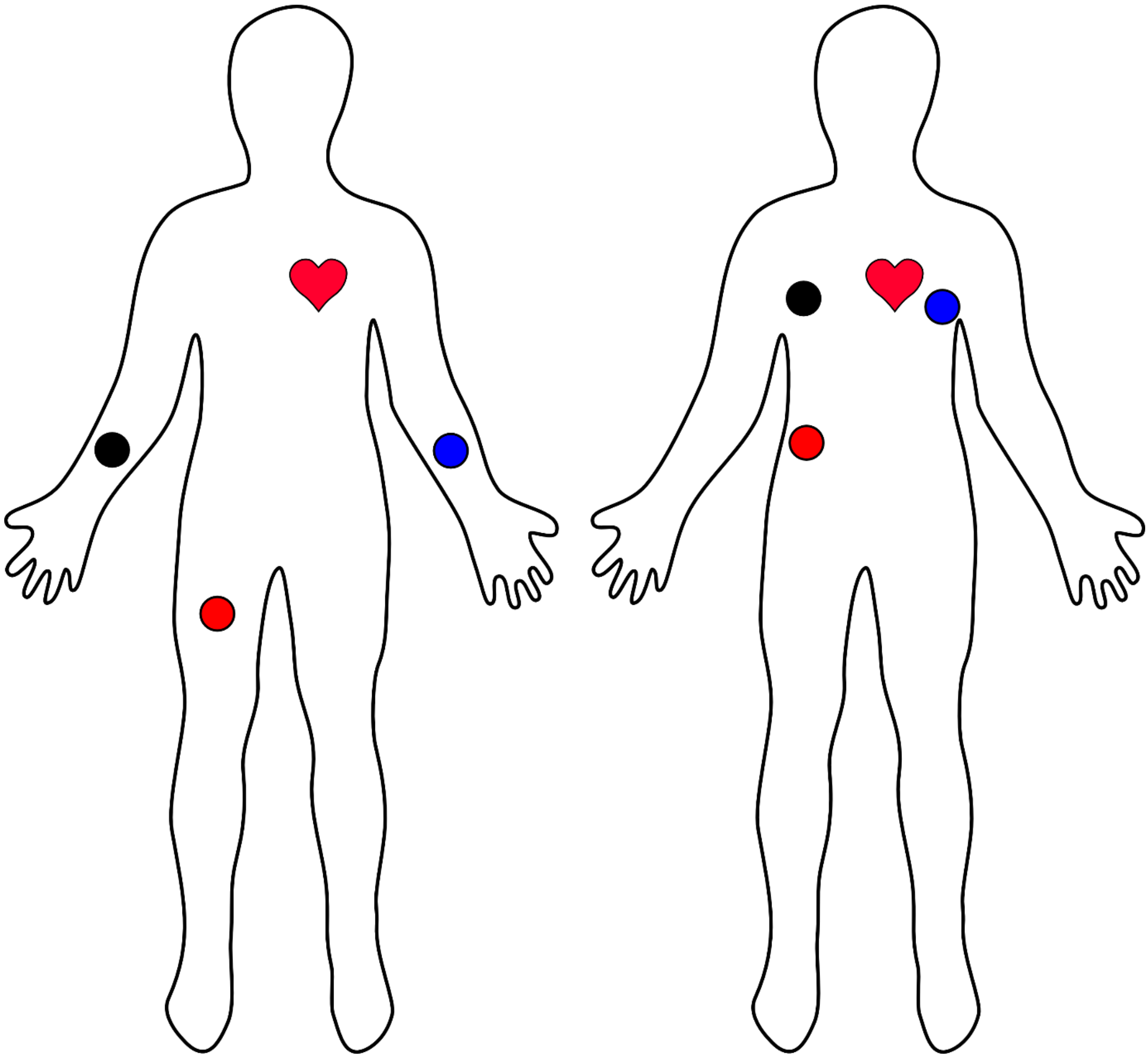

Figure 3.5 Connection of Three Probes on Human Body

Sends an instruction from the Arduino to the sensor to start the process of sensing. After the sensing process comes the initial processing of the signal.

2. Pre-processing Stage:

At this stage signal passes from the sensor to the amplifier circuit to strengthen the signal before being sent to a storage location by the Arduino, after the signal is enlarged and received by Arduino processor, it will verifies the correctness of the data entering it, if it is accepted it will be sent to the storage location otherwise it will be deleted and Arduino then delays receiving data for milliseconds to get good data from the sensor.

3. Analyzing Stage:

This phase represents the heart of the system, the stored signal is sent to the Pan Tompkins algorithm and processed and extracted the desired information. Pan Tompkins algorithm will work within Matlab program installed inside lattepanda to work on the analysis of the sensing heart signal from the human body. The processing steps of the algorithm does not differ between the practical and theoretical part where it goes through the same steps of filtering and reconfiguration and then update the value of a suitable threshold to extract peaks of R waves.

Results and Discussion

1. Introduction

This chapter presents the results and discussions for the thesis objectives. The outcomes for each objective are presented in the same order as in the previous chapter. As a result, the subsection presents findings and discussions for a specific goal. The results are linked to achieve high accuracy for the system in real-time to use to provide an initial diagnosis of the patient's condition.

The heartbeat monitoring system was put to the test. The test results will be presented in this chapter, along with a discussion of these results from various perspectives to demonstrate the system's accomplishments. As previously stated, the system is divided into two parts: theoretical (which includes simulation using MatLab2019b to simulate PAT) and practical to diagnose specific cases that have been identified (ARR, CHF, NSR) which illustrated in figure (4.1).

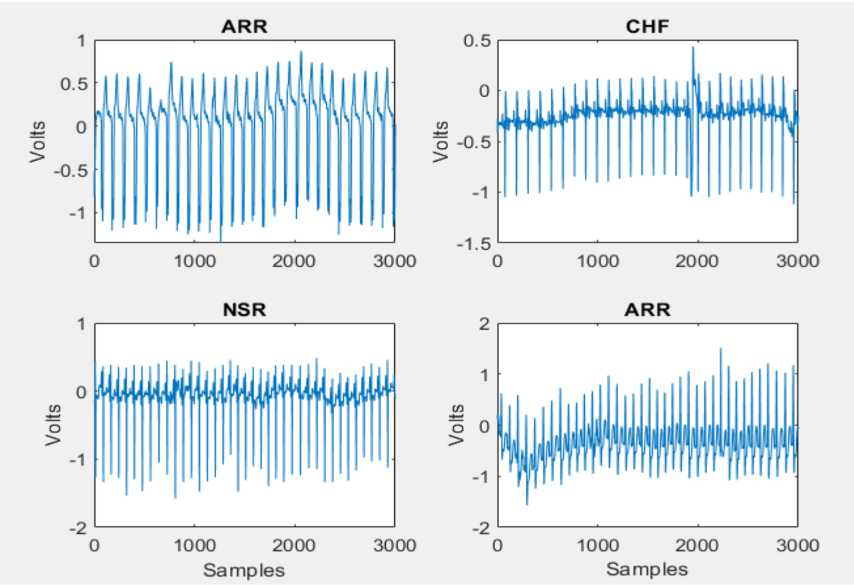

Figure 4.1 Three classes of ECG signal

All ECG signal classification simulation results have been explored. This chapter is a record of the results obtained from the theoretical section. The obtained and recorded results are divided into three sections. The first section discusses the results of the remove noise technique, the second section discusses the results of the developed feature extraction technique using one of two methods (BSS and WS), and the final section illustrates the results of classification.

Results of classification. The effectiveness of the proposed methods was determined by comparing the results. The suggested technique uses an ECG signal from the database of MIT-BIH to classify the output as normal or abnormal. To pre-process the signal of input, filter techniques such as DWT, Notch filter, and others are utilized.

2. The results of ECG diagnostic system

The system is excuited on mini- computer which called LattePanda with some supported components to get on. A variety of methods has been established for pre- processing ECG signals in terms of frequency content and signal morphology. The various methods for forecasting the signals all produced favorable outcomes. High accuracy and low computational algorithm to classify the normal and abnormal heartbeats are designed and evaluated. The wavelet scattering algorithm and the developed SVM classification method are used in three cases (NSR, ARR, CHF) classification method. The overall algorithm features for heartbeat and classification to the three categories are highly efficient and low computational. As an outcome, the ECG monitoring and diagnostic system employs a three-class heartbeat classification method that employs the wavelet scattering algorithm to extract features using the SVM method.

The algorithm was programmed into the microcontroller that is inside the mini- computer (Lattepanda), Lenardo Arduino is the processing inside device and is based on C and C++ programming to create the programming codes and provide these codes to any compatible boards after they have been verified and compiled.

Two procedures have been implemented to assess the performance of the system for monitoring and diagnosing ECG signals. First, the system was tested and assessed using the same data records that were utilized in the previous section to assess the diseases classification approach.

Second, the ECG sensors read the actual ECG signal from a human body. The system is analyzed the ECG samples by executing the feature extraction and classification programming algorithm. Windows are typically used as the main way of exhibiting information and handling applications in GUIs. Each window indicates a distinct task or application and can be resized, relocated, reduced, or closed. The Lattepanda device connected to the LCD screen through the HD connection which displayed the running progress and the algorithm outputs The interface of system utilize many menus, these menus are frequently used in GUIs to provide a hierarchical list of options and commands. Menus can be accessed via the top-of-the-window menu bar or a right-click context menu. They enable users to perform various actions and access various application functions as shown in Figure 4.2. The outputs can appear the following:

- Information of the patient(name, gender, age)
- Filter type
- Recorder name
- Recorder length
- Load (load the recorder of patient)
- Save (save the information and state of patient)
- ECG recording(No of samples, ECG shape of patient)
- Processing (pre-processing of ECG)
- Classification
- Record time
- Test ECG
- Three cases (ARR, CHF, NSR)
- Diagnostic decision
- DAQ port (chose com3)
- Connect
- Exit

The system saves the ECG samples and the patient report in the memory of device for recall the data when needed. The folder contant the information and report of the patient, it will save the folder in name of patient to upload from device memory in any time.

Actual ECG signal reads from a human body were used to test the system. At the same sampling frequency, the sensors read the ECG signal from the body. The system then analyzes the ECG samples by running the feature extraction and classification programming algorithm. The system's results are promising for high accuracy and Arrthymia detection to disease diagnostics.

After the data processing process to eliminate noise and the data extraction process, it is classified into normal, abnormal, and normal conditions, and then the abnormal condition is diagnosed in the two cases (arrhythmia, congestive heart failure). The diagnosis is made for the pathological condition for each case according to the percentage of the threshold value of accuracy 85%. The case that forms a percentage more than this value indicates the concerned condition of the patient.

As shown in figure (4.2), this section provides an analysis of the results with specific examples from some patients. Manual inspection revealed that feature selection was utilizing all of the required features for each case.The classification of all cases appears to have a high degree of accuracy.

The amount of beat type and number in the patient is undoubtedly the main reason for differences in diagnostic results of patients' conditions.

For example, if the patient has 465 premature ventricular contractions and 1522 regular beats, the network will see both possible combinations for a sufficient number of times. Despite its widespread use, ECG analysis is an intricate process that necessitates the expertise of a specialist with broad specific knowledge.

Not only the patient's health, but also his or her life, is frequently dependent on the timely decoding of all data. This is complicated further by the complexity of manual ECG analysis, which increases the possibility of errors or incomplete diagnosis in.interpretation.

As a result, many studies aim to detect abnormalities using automated methods, such as DNNs in ECG analysis. The system effectiveness has been tested on 17 patients in different cases as explain in table 4.1 and figures (4.3-4.16)

Figure 4.2 GUI of identification of heart disease

Table 4.1 recorders of Patients

No. of case	Details of case	No. of samples	Ratio of diagnostic	Diagnostic
Case 1-	Ali-42- male	7680	99.832	ARR
Case 2-	Assad-51-male	61440	100	NSR
Case-3-	Adyan-19- famale	61440	99.8	NSR
Case4	Ahlam-60- famale	30720	99.9996%	ARR
Case-5-	Haider-46- male	30720	99.97	ARR
Case-6	Mena-46- famale	61440	99.9	CHF
Case-7	Marwa-37- famale		99.8322	ARR
Case-8	Obaid- 73- male	30720	99.83	ARR
Case-9	Mohmmed-44- male	30720	99.97	ARR
Case-10	Rabab-33- famal	61440	100	ARR
Case-11	Qussy-42-male	7680	100	NSR
Case-12	Huda-35-famal	61440	99.99	CHF
Case-13	Bushra-62- famale	30720	99.88	CHF

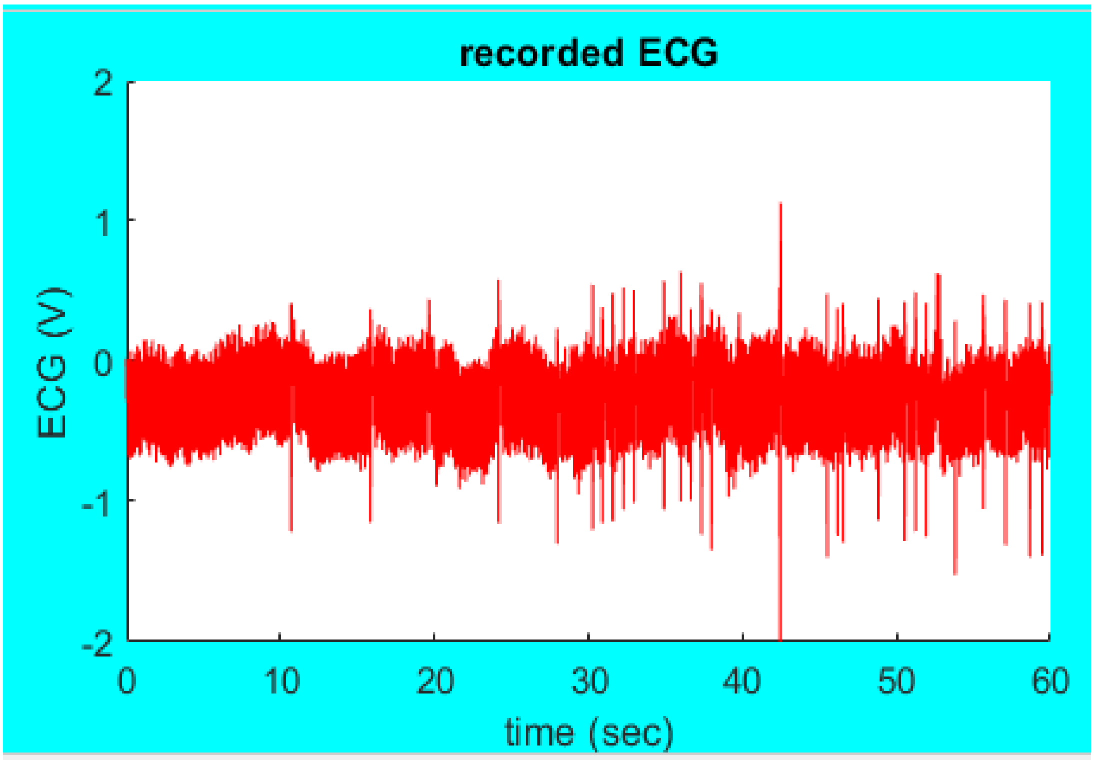

Figure 4.3 ARR-before Pre-processing: This figure likely shows an ECG signal representing a case of Arrhythmia (ARR) before any pre-processing techniques are applied. It demonstrates the raw signal characteristics associated with this particular heart condition.

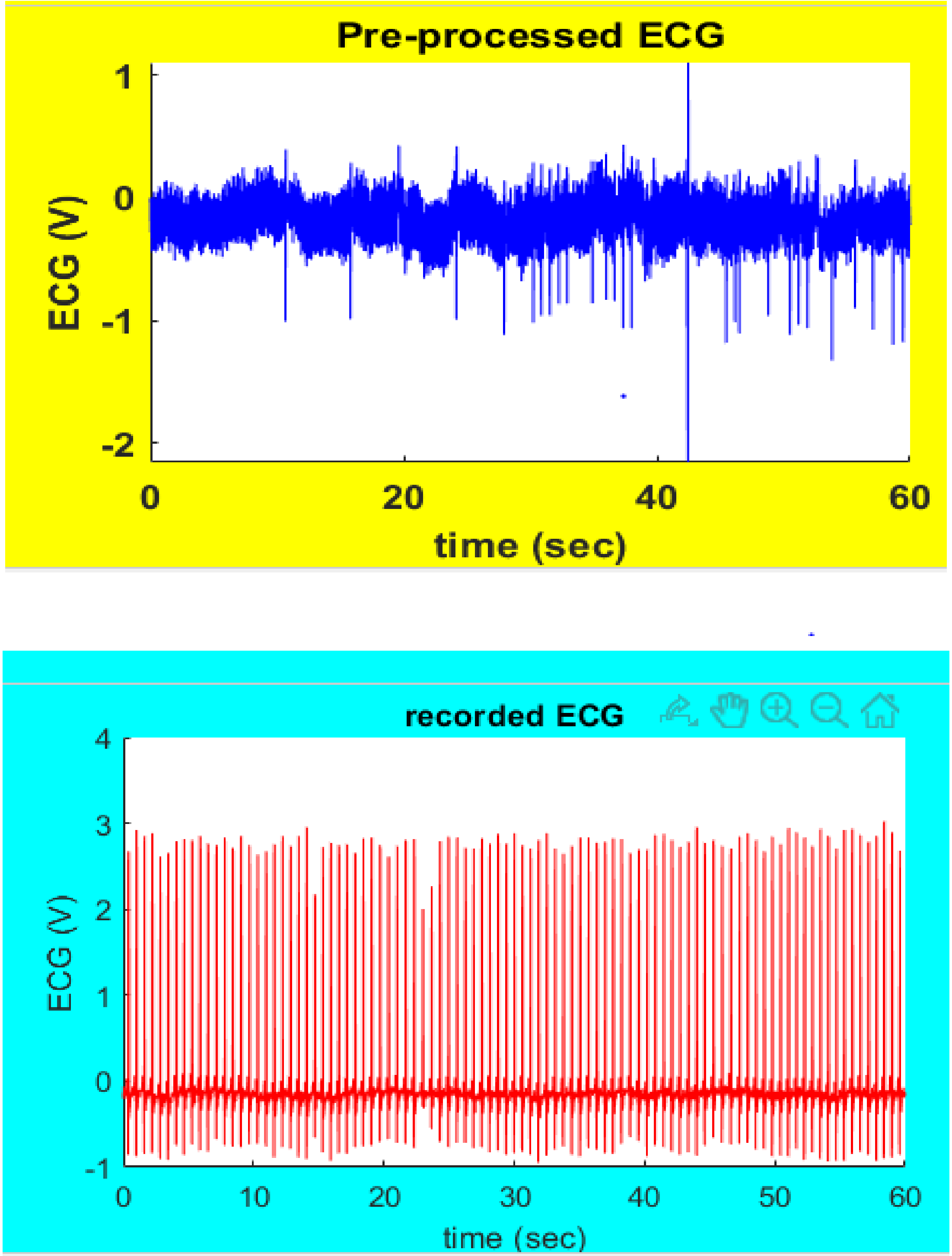

Figure 4.5 NSR-before Pre-processing: Similarly, this figure shows an ECG signal representing Normal Sinus Rhythm (NSR) before pre-processing. NSR is the normal rhythm of the heart, and this figure likely illustrates what a typical ECG signal looks like in this state.

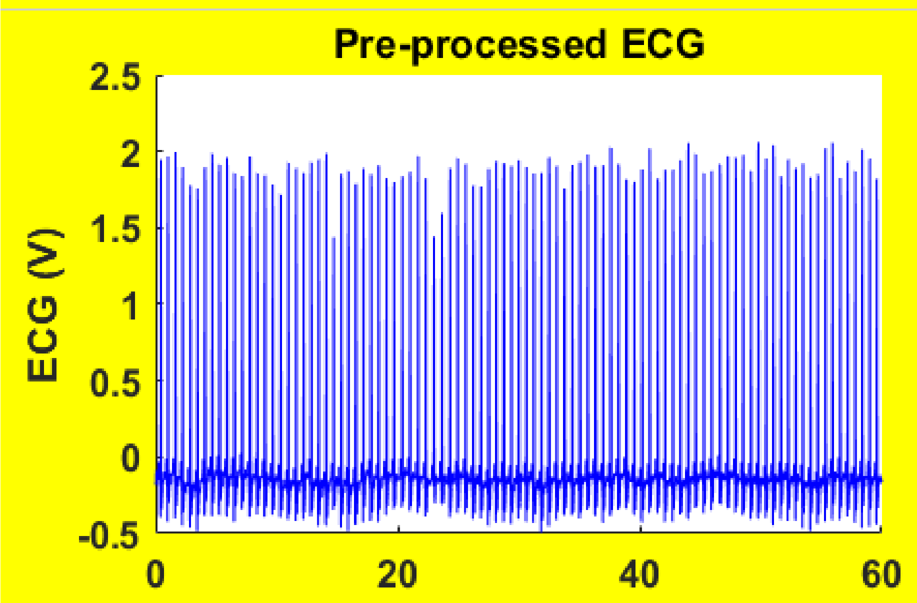

Figure 4.6 Case-2- NSR-after Pre-processing

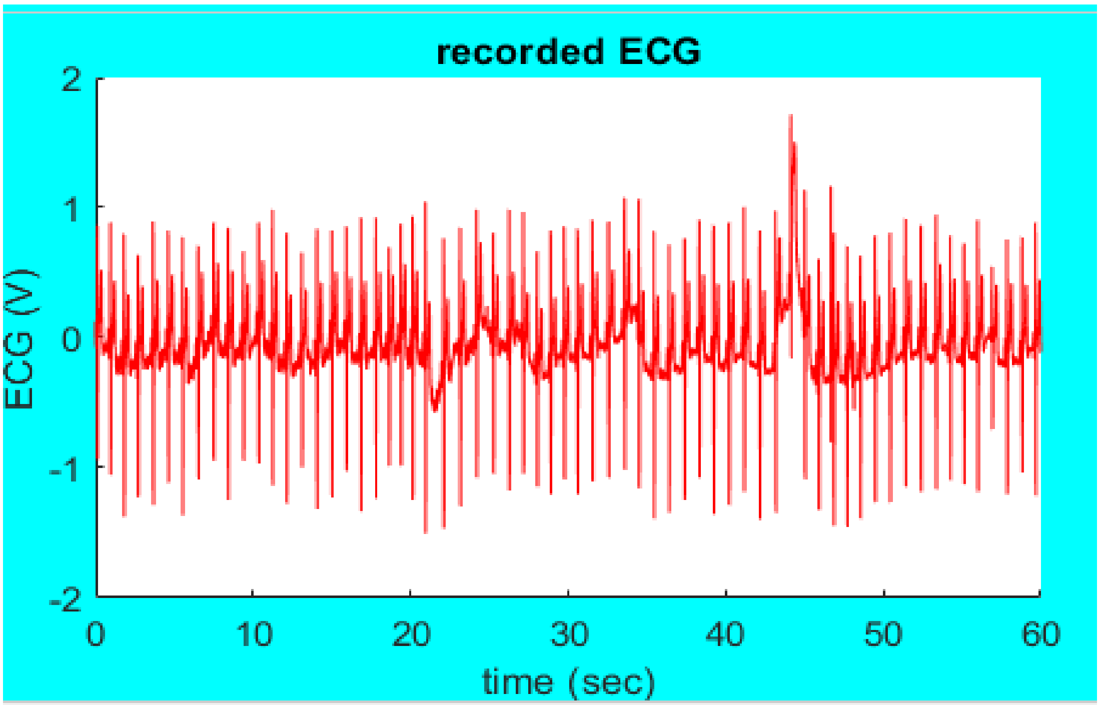

Figure 4.7Case-3-NSR-before Pre-processing: This figure specifically represents a case (Case 3) of NSR before any pre-processing is done. It may show variations in the NSR pattern compared to the generic NSR signal shown in Figure 4.5.

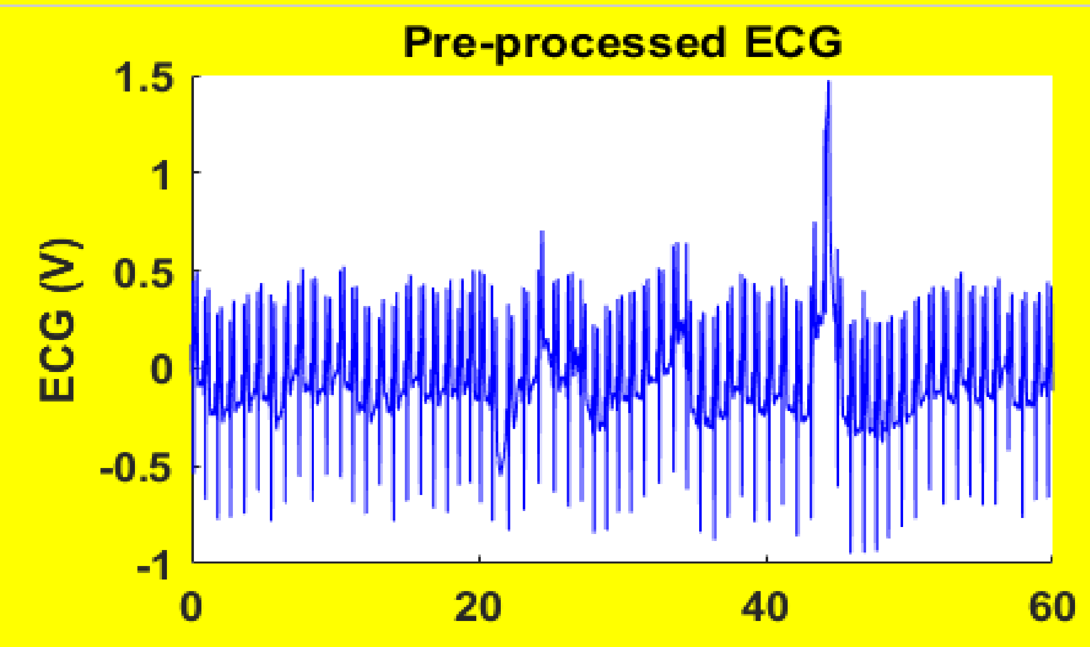

Figure 4.8 Case-3- NSR-after Pre-processing

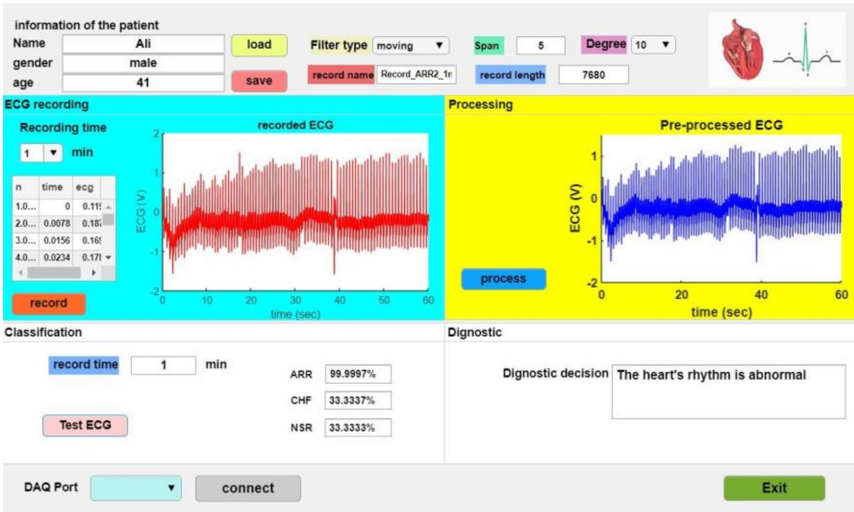

Figure 4.9 Case-6- ARR-after test

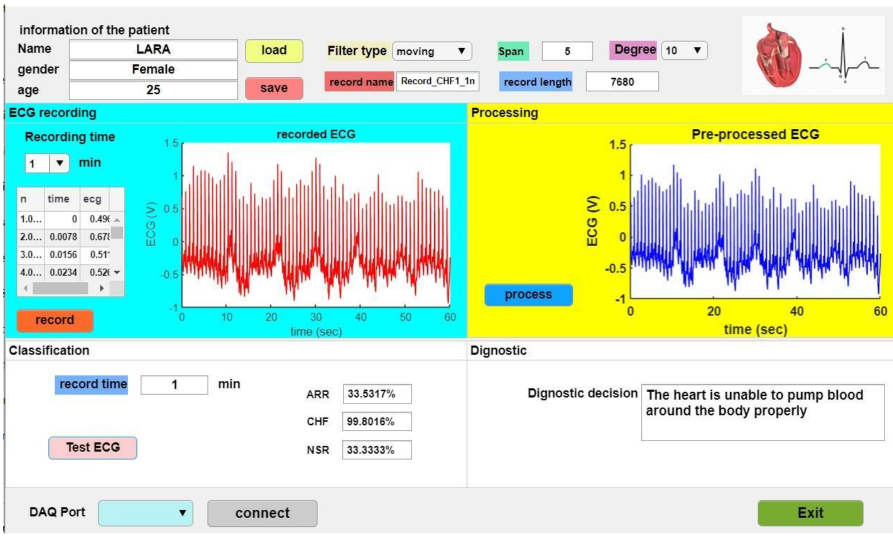

Figure 4.10 Case-6- CHF-after test

3. Noise Treated In This Project

1. Baseline Wander

Baseline wander refers to low-frequency noise caused by body movement or electrode placement issues. To address this, we will implement high-pass filtering techniques such as the Butterworth filter to remove baseline drift while preserving the ECG signal's integrity.

2. Powerline Interference (PLI)

PLI, originating from electrical mains at 50 or 60 Hz, can corrupt ECG signals. We will employ notch filters to selectively eliminate PLI frequencies while retaining vital cardiac information, ensuring accurate QRS detection.

3. Muscle Artifacts

Muscle artifacts, caused by muscle contractions or electrode movement, introduce high- frequency noise. Our project will explore techniques like wavelet denoising to effectively suppress muscle artifacts without distorting the underlying ECG morphology.

4. Electrode Motion Artifacts

Electrode motion artifacts occur due to electrode displacement or poor skin-electrode contact. We will implement signal processing algorithms, such as template matching or adaptive filtering, to detect and mitigate these artifacts, enhancing the reliability of QRS detection.

5. Other Environmental Noise

Additional environmental noise, such as electromagnetic interference or external vibrations, can interfere with ECG signals. Our project will investigate adaptive filtering methods and signal averaging techniques to mitigate these sources of noise and improve the accuracy of QRS detection in challenging conditions.

Conclusion and Future Work

1. Conclusion

In this research, several techniques were used to analyze the signal and purify it from the types of noise that the ECG signal is exposed to. After obtaining a pure signal, different algorithms are used to extract the featuresthat are then used to classify the signal by one of the machine learning methods**.** These algorithms' performance was evaluated by running them through the MIT/BIH Arrhythmia dataset. The conclusions are divided intothe following categories:

- The noise removal of ECG signal is based on multi-techniques:\
- Discrete Wavelet Transform(DWT) to remove baseline wander.
- Powerline Interference removal using Notch filter
- Noise Removal of Electromyographic (EMG) by Adaptive filter
- The feature extraction algorithms is based on multi- techniques:
- The wavelet scattering algorithm is a mathematical framework that is utilized to analyze signals and extract features. Thealgorithm begins by transforming the input signal using a wavelet transform.
- The algorithms are utilized in classification using machine learning as SVM and NN, the dataset divide to 70% for learning and 30% for testing which recording different percentage for each algorithm, SVM with wavelet scattering is recording high rate of accuracy with 99.7%.
- Design and implement device by LattePand to classify ECG signal for normal or abnormal then diagnostic abnormal for ARR or CHF. SVM with wavelet scattering is selected among algorithms which used because high accuracy ratio

2. Product Implementation

A device for measuring the ECG signal and classified can be developed as follows

1. Adding a small printer that prints the signal on a graphic sheet to be attached with the report to the doctor
2. The device can be linked to the central computer used in the hospital or clinic to save data in the patient record so that the doctor and patient can retrieve it when needed.

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