

The Relationship between P-Wave Morphology and Atrial Fibrillation

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Abstract:

The objective of this paper is to develop an efficient P-wave detection algorithm based on the morphology characteristics of arrhythmias using time domain analysis.

ECG from normal subjects, and patients with atrial fibrillation were studied. After baseline wander cancellation, power line interference filtration, the step of QRS detection using the pan-Tompkins algorithm is utilized to calculate R peak which represent the reference point to detect P peak.

The algorithm was tested with experiments using MIT-BIH arrhythmia database which included Paroxysmal Atrial Fibrillation PAF prediction challenge, Massachusetts Institute of Technology MIT-BIH normal sinus rhythm, long term Atrial Fibrillation AF and MIT-BIH atrial fibrillation where every P-wave was extracted.

The results reveal that the algorithm is accurate and efficient to detect and classify arrhythmias resulted from atrial fibrillation.

Keywords: Atrial Fibrillation, P-wave, QRS, ECG

1 Introduction:

Cardiovascular diseases (CVDs) remain the biggest cause and one of the leading causes of deaths, worldwide. Cardiovascular disease (CVD) is a general term that includes many different conditions affecting the heart and blood vessels. CVD is caused by narrowed, blocked or stiffened blood vessels that prevent heart, brain or other parts of human body from receiving enough blood. CVD is also a major cause of disability and decreases the quality of life for millions of people [1]. From 58 million deaths globally occurred in 2005, cardiovascular disease (CVD) accounted for 30%. This proportion is equal to that due to nutritional deficiencies, infectious diseases, and maternal and perinatal conditions combined [2].

According to the International Society and Federation of Cardiology Task Force, the duration of normal P-wave is less than or equal to 110 ms.

Other authorities in the field dispute that 120 ms may be a more appropriate cut-off value [2].

In men, the filtered P-wave duration is longer than in women with a slight, but significant, correlation between P-wave duration and age. The maximum P wave duration in the

standard non-filtered 12-lead ECG was 110 ms on average [3].

The normal P-wave duration was 96 to 120 ms. If the LA is enlarged, the P wave is prolonged, but also it can be prolonged in normal size atria [2].

The P-wave become less pronounced with age and so will be more difficult for reading and diagnosing, which can made identification of the P wave, and then diagnosis become extremely difficult [4].

The normal P-wave when present should be shows a morphology (smooth contour) [5], from onset to offset regardless of whether it is mono or biphasic.

The morphology of P-waves can be used to localize several cardiac diseases such as tachycardia, atrial enlargement, stenosis of the cardiac valves (aortic valve disease demonstrated by an increase P-wave duration). P-wave duration usually changing with age (lengthen) so p-wave morphology changes, p-wave dispersion also increases [6].

Because P-wave is close proximity to the QRS complex and have relatively low amplitude, delicate changes in morphology, this wave becomes a challenging problem in terms of extraction, identification, or enhancement [2].

Atrial fibrillation (AF) is the most frequently encountered sustained cardiac arrhythmia in clinical practice and a major cause of morbidity and mortality. Effective treatment of AF still remains an inadequate medical need [7].

During a burst of AF the heart beat is often rapid, irregular and of varying intensity. AF symptoms are: breathlessness, palpitations, chest pain, light headedness, and may lead to a collapse.

AF occurs when the sinus node loses control of the heart rhythm. Other areas of atrium often the four pulmonary veins will produce paroxysmal AF by rapid, uncontrolled electrical impulses which bring blood back to the atria from the lungs. In persistent or permanent AF atrium cells do not conduct the normal impulses from the sinus node in a smooth way which causes them to break up and be discharged quickly across the atrial surface in many different directions.

Atrial fibrillation is recognized in the ECG by the absence of P-waves that normally occurs at

the beginning of each heartbeat. Heart oscillates rapidly, with the waves varying in size, shape and timing, may be visible, termed F (fibrillation) waves. If they are small, they are called fine fibrillatory waves, and if large, coarse fibrillatory waves [8].

These very rapid atrial rhythm (about 400 to 600 beats per minute) which originates from any portion of the atria.

P-wave prolongation has been used as a sign of interatrial conduction disturbance which has been associated with atrial fibrillation (every heartbeat starts by a single electrical impulse from the sinoatrial node, instead of that several impulses with varying origin in the atria spread through it and cause uncoordinated atrial activation and contraction of different parts of the atria) [9].

Also prolongation of P-wave has been used as a sign of prolonged atrial conduction time, which has been associated with a high frequency of atrial fibrillation (AF) [9].

The higher atria rate and uncoordinated atrial electrical conduction leads to ineffective pumping of blood into both ventricles [8].

2 Method

It starts with the preparation of the ECG signal which obtained from MIT-BIH database followed by the details of P-wave morphology method and how P-wave used as a marker for the presence of atrial fibrillation (AF) with a description of the ECG datasets used to validate the methods.

1. Input ECG data:

First ECG signal from MIT-BIH database (fig. 1) was used in this study which consists from P, Q, R, S, T waves and sometimes U-wave. The process involves transforming the original data into a suitable form for the input into specific Data.

For this purpose, the Matlab environment is used which is an interactive system of numeric calculation and graphic visualization.

The loading of the ECG signal under matlab constitutes the first step in our algorithm. It consists in converting the data coded in the initial shape of the MIT-BIH database in a format that is interpretable by matlab program.

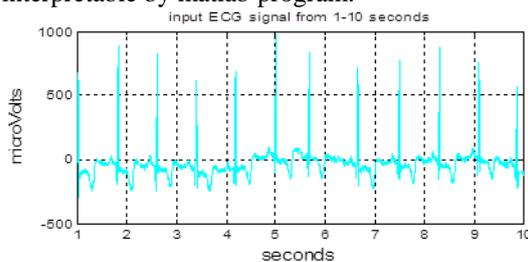


Figure (1): Input ECG signal data

2. ECG signal filtration from power line by using LPF $f_c = 50$ Hz:

ECG signal contaminated by noise with wide range of frequencies such as power line interference, electrode contact noise, motion artifacts, baseline drift, muscle contraction and instrumentation noise generated by electronic devices.

Noise removal step is important to be the first preprocessing step to ensure better result for the next stages such as the detection of R peaks and T peaks as well as the P-wave morphology measurements.

In any step of filtration, it is important to pay attention that the type of filter and the cut off frequency have the lowest effects on ECG waves morphology.

Fourth order Butterworth filter has been considered to be the filter of choice wherever low pass filter needed because it has the lowest distortion on ECG waveform (fig. 2).

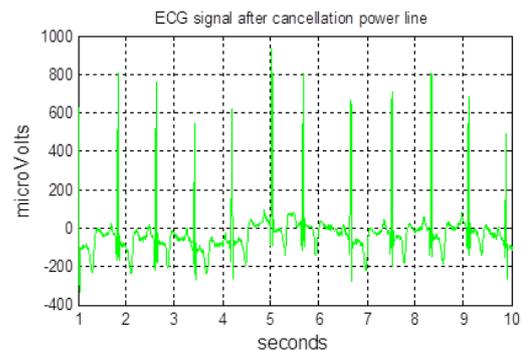


Figure (2): ECG after applying the Butterworth LPF, $f_c=50$ Hz

3. ECG signal after baseline cancellation by using HPF $f_c = 0.5$ Hz:

The baseline wander artifact is an external, high bandwidth components and low frequency activity in the ECG signal (fig, 3) which can mask some important features of the signal. It may be caused by large movements of the chest, or when an arm or leg or the cable is moved during the ECG reading.

Also Poor contact of the electrodes, dirty lead wires and dirty electrodes may affect the electrode impedance which causes low frequency artifacts.

Baseline drift may sometimes be caused by variations in temperature.

Hence it is desirable to remove this noise for proper analysis and display of the ECG signal. The in-band frequency of this type of noise makes its removal difficult without affecting the ECG signal.

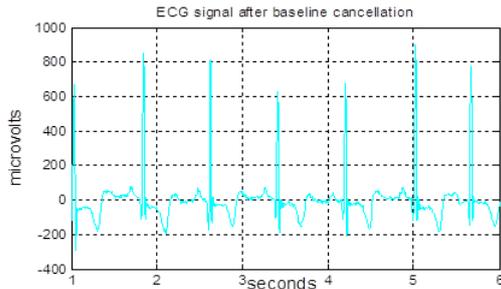


Figure (3): Using Butterworth high pass filter with cutoff frequency=0.5 Hz for baseline wander cancellation

4. QRS detection procedure:

A-Using Band pass Filtration (low pass filter $f_c = 12$ Hz and High pass filter = 5 Hz):

The low pass filter (fig. 4) component presents the difference equation 1 as shown [10]:

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \dots \dots \dots (1)$$

Also the high pass filter (fig. 5) component presents the difference as equation 2[11]:

$$y(nT) = 32x(nT - 16T) - [y(nT - T) + x(nT) - x(nT - 32T)] \dots \dots \dots (2)$$

Where T is sampling period and n is an arbitrary integer.

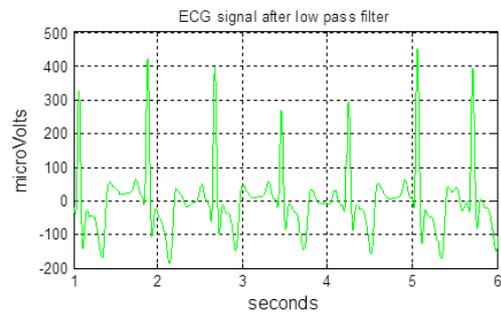


Figure (4) : Filtration using Butterworth LPF, $f_c = 12$ Hz

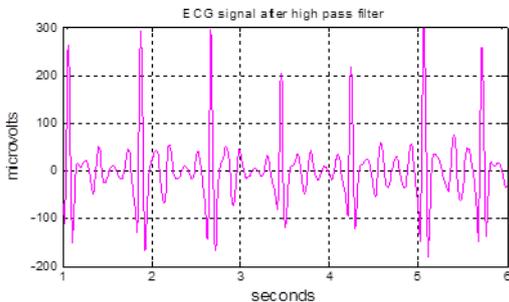


Figure (5): Filtration using FIR Kaiser Window HPF, $f_c = 5$ Hz

B- Using derivative filter:

After the signal has been filtered, it is then differentiated to provide information about the slope of the QRS complex.

Derivative filter is considered to be standard technique for finding the high slopes that normally distinguish the QRS complexes from P and T waves.

It suppresses the low frequency components of P and T waves, and provides a large gain to the high-frequency components arising from the high slopes of the QRS Complex (fig. 6).

The transfer function of five-point derivative filter is implemented with difference equation 3[10]:

$$y(nT) = 2x(nT) + x(nT - T) - x(nT - 3T) - 2x(nT - 4T)/8 \dots \dots \dots (3)$$

Where T is the sampling period and the fraction 1/8 is an approximation of the actual gain of 0.1.

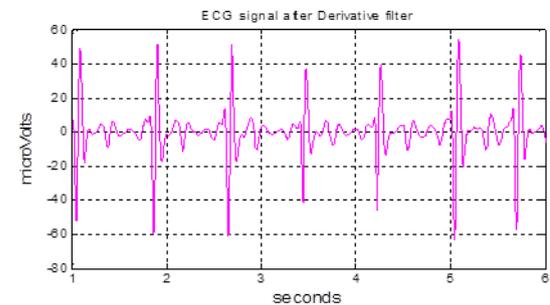


Figure (6): ECG signal by using derivative filter

C - Using squaring method:

Operation makes all the result data positive and emphasizes large differences resulting from QRS complexes; the small differences arising from P and T waves are accentuated.

The high frequency components in the signal related to the QRS complex are further enhanced (fig. 7).

This is a nonlinear transformation that consists of point by point squaring of the signal samples as described in below equation [11]:

$$y(nT) = [x(nT)]^2 \dots \dots \dots (4)$$

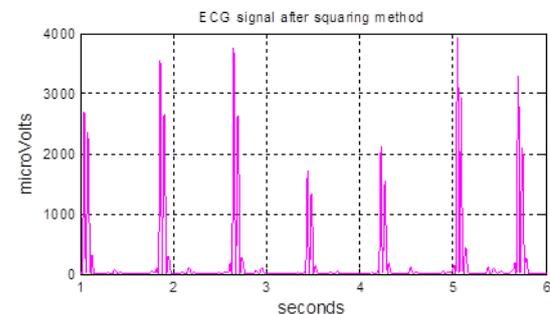


Figure (7): ECG signal output after using squaring function.

D. Moving window integration results:

The squared waveform passes through a moving window integrator (fig. 8). This integrator sums the area under the squared waveform over a

suitable interval, advances one sample interval, and integrates the new predefined interval window.

The features were extracted in a sliding window consisting of 32 beats rather than breaking the heart beats into separately blocks.

Each time the window was shifted in one heart beat (1 R-R interval) forward.

In this program the width of integration window equal to 32 samples and for three times.

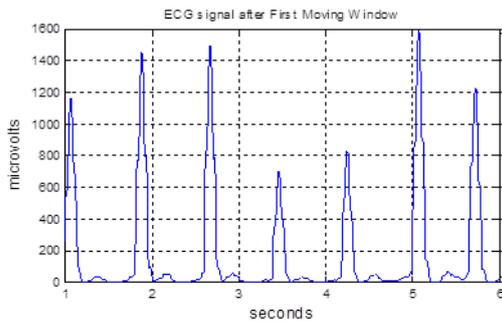


Figure (8): ECG signal output after first moving window integration

It was found that some noisy and abnormal QRS have a ripple wave after applying the first moving window integration filter.

This ripple may lead to great error in case the threshold pass through it thus, the moving integration filter has been applied twice to remove this ripple(fig. 9), and third moving window integration as shown in fig.10.

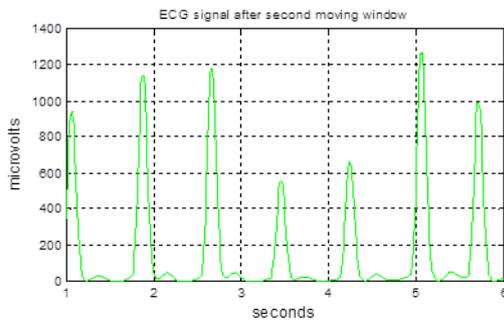


Figure (9): ECG Signal output after second moving window integration

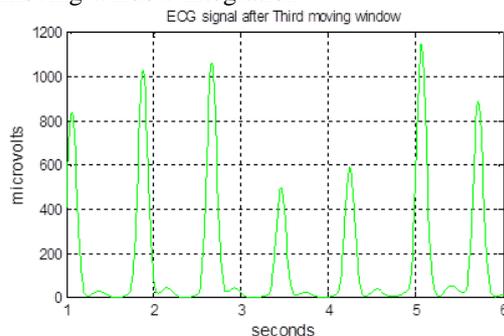


Figure (10): ECG signal output after third moving window integration

E. Thresholding technique:

Two sets of thresholds are used to detect QRS complexes. One set thresholds the filtered ECG, and the other thresholds the signal produced by integration.

Thresholding has been applied to the output of the moving integrating step (fig.11). In preprocessing, R-peak can be detected easily from threshold result because R wave is the most significant wave in ECG signal.

The QRS complex is detected when the slope amplitude is within the threshold.

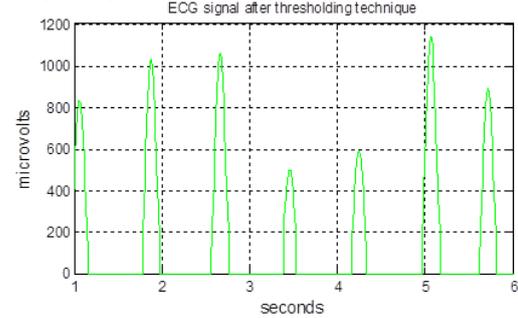


Figure (11): Output ECG signal after thresholding technique

F. Time Correction (False peaks Cancellation) Technique:

The threshold value sometimes becomes less than the noise level which may lead to detect some of P peaks , T peaks, or noise as an R peaks as shown in figure 12, thus timing technique used to delete these false peaks.

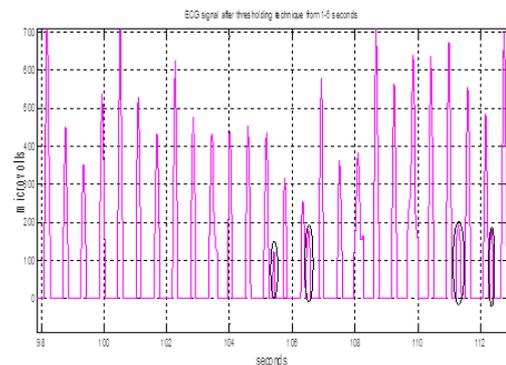


Figure 12: false peaks present after thresholding

To cancel these false peaks, the difference between each successive peaks position of detected peaks has been calculated.

Any value below (0.7) or (0.8) of the mean differences which lies between two peaks with position difference less than (1.0) or (1.2) of the mean value, indicates that one of these peaks is wrong which always the peak with the lowest amplitude peak value.

So figure 12 will become, after time correction, as in figure 13:

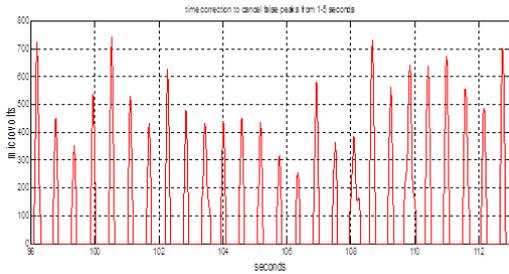


Figure (13): ECG signal after correction method from (98-113) seconds

G. R peak detection results:

A window method is used to detect the real position and value in the original data by seeking for the maximum value for normal R peak, or the minimum value for inverted R peak, within a window of (75) samples before and (75) samples after each detected peak position (fig. 15).

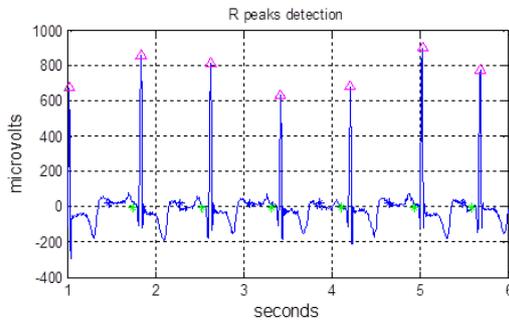


Figure (14): R peaks detection

H. Ectopic R peaks cancellation and R peaks Detection:

Ectopic R peaks like false peaks affecting the choice of site for the correct R peaks like the figure 15.

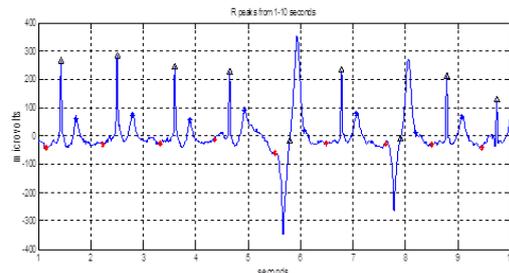


Figure (15): Ectopic R peaks from 1-10 seconds.

Simple way to get rid from these peaks is by removing any amplitude greater the normal mean amplitude for R peaks and in trial and error way.

So, figure 15 will become after time correction, as in the figure 16:

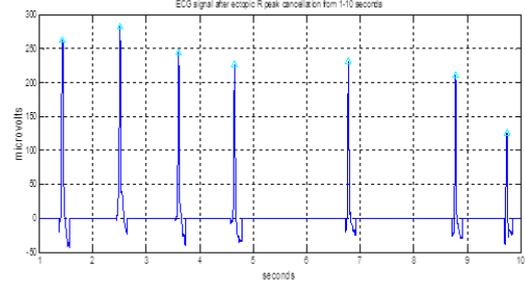


Figure (16): Correct R peaks after cancel ectopic R peaks

5. P wave extraction procedure:

A-Bidirectional Filtration result :

This step has been done using bi-directional filtration method by 4th order Butterworth low pass filter with cut off frequency 12 Hz (fig.17).

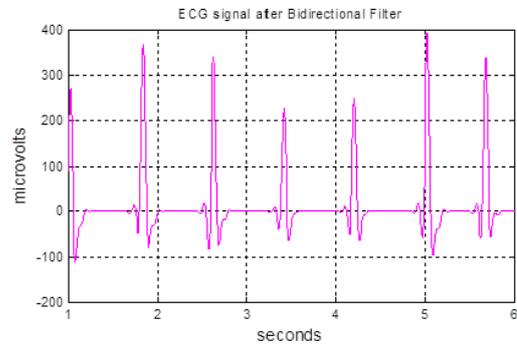


Figure (17): ECG signal after bi-filtration with Butterworth LPF, $f_c = 12$ Hz

B- Correct R Peaks Positions:

Because bidirectional filtration method change R peaks positions; a window with 15 samples after and before the old R peak positions is used to detect the new correct positions of R peaks (fig. 18).

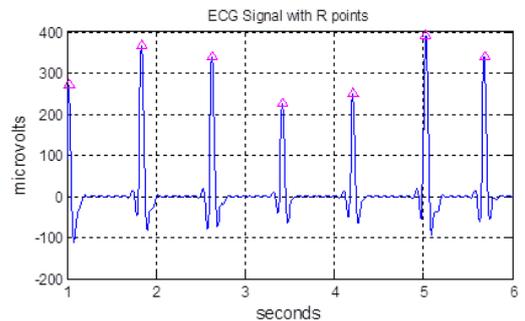


Figure (18): Detection new R peaks positions after bi-directional filter

C- Start and End of ECG signal:

After finding correct R peaks positions, the starting and ending of this signal must be found before finding the P-wave positions (fig. 19).

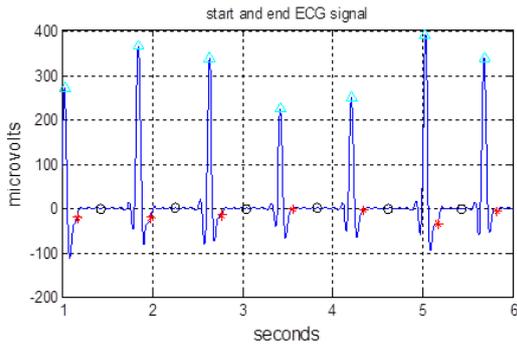


Figure (19): Start, R peak and end output ECG signal waves

D. Detection and extraction of P peaks results:

Detection and extraction of P peak was done by seeking the maximum amplitude value of the signal for normal P-waves, or minimum amplitude value for inverted P-waves, before the R peak of each beat using window method. To get rid of the effect of P-wave of the next beat, the duration between the R peak of the same beat and the R of the previous peak must be calculated and the seeking window ended before the R peak by 60% of the R-R interval, as shown in figure (20).

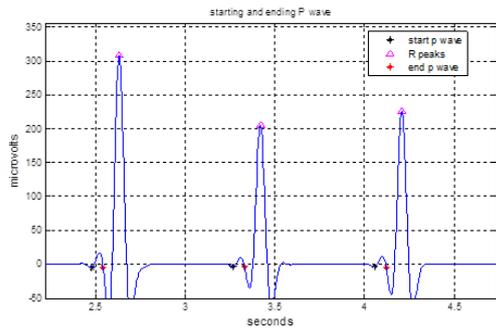


Figure (20): P peak seeking window

After the detection of P peak locations, it becomes easily to extract the P-wave of each beat, using window method followed by correction step conditions (fig. 21).

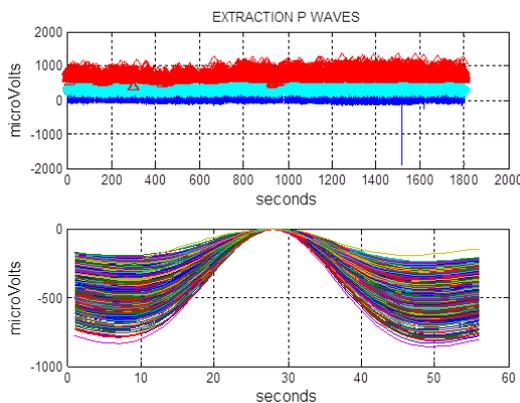


Figure (21): Detection and extraction of P peaks.

E-Extraction of single P waves:

Single P-wave is the aim of this procedure and present the maximum amplitude between these extraction P-waves (fig. 22).

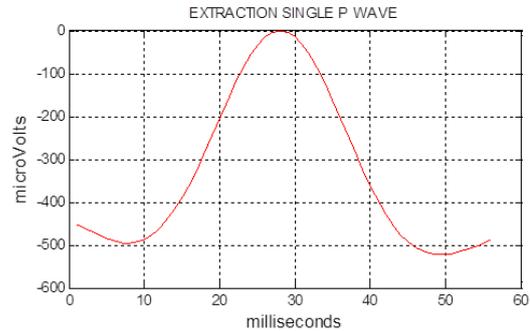


Figure (22): Extracted single P-wave

F. P-Wave Correction Results:

Sometimes, the window of extraction exceed the exact duration of P-wave and need to be reduced. Starting and ending of the P-wave are detected either manually or automatically.

In some cases, they are defined as the points corresponding respectively to the first (onset) and last (offset) deflection from the baseline.

The onset and offset points in other cases are chosen as the points where signal amplitude falls below a fixed level (baseline) or arises above the same level [12].

The starting point is manually considered to be on set point in case the position of minimum value of P wave to the left of P peak lies within the first seven samples. This value is founded experimentally and by manual method.

If not, the sample before the minimum point by seven samples were considered to be the onset point and deleting all points before it.

The ending point is considered to be offset point if the minimum value of P wave to the right of P peak lies within the last seven samples. If not, the sample after the minimum point by seven is considered to be the offset point and deleting all points after it (fig. 23).

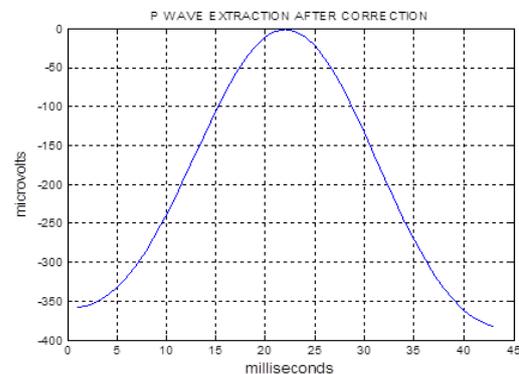


Figure (23): P-wave after correction method

6. Atrial Fibrillation Detection by P-wave duration:

Atrial fibrillation may be caused by abnormalities in atrial conduction. Most studies have shown that a prolonged P-wave duration can increase incidence of AF.

P-wave duration is a marker of atrial conduction derived from standard ECG. Increased P-wave duration has been suggested to be an easily measurable risk factor for detecting heart diseases.

In fact, it has been associated with atrial fibrillation (AF) and also more recently with stroke mortality and cardiovascular disease (CVD) among general people [13].

The summary of the information about Databases used in this study is shown in the table 1.

Table (1): Summary of the information about Databases used in this study

Database	Number of Records	Number of AF arrhythmia	Number of not AF arrhythmia
MIT-BIH normal sinus rhythm database	18	0	18
PAF Prediction Challenge Database (Learning set)	50	2	48
PAF Prediction Challenge Database (testing set)	100	55	45
MIT-BIH atrial fibrillation database	19	18	1
Long term atrial fibrillation	65	5	60
Combined databases	252	80	172

This method has been evaluated on normal and arrhythmic ECG records and demonstrated a good ability to discriminate AF. The method of P-wave extraction is highly depended on the R peak detection so any false in this detection will cause failure in the method.

The onset and the offset points of P-wave duration are detected manually.

More than once filtration step was used but did not affect on the results of R peak and P peak detection and extraction.

The window technique benefits in reducing false R peak so in some data there is no need for adding step to cancel these peaks.

The step for false R peak cancellation is very important in this method. Also this method minimizes the effect of ectopic peaks which can calculates as R peak.

P-wave duration is very important in determining any ECG data is classified as atrial fibrillation so the start and the end of this duration should be chosen in a high accuracy.

The step of P-wave correction is important in remove the increase from the wave beginning and ending. The P waves in the MIT-BIH arrhythmia database are not yet fully annotated; this makes testing and evaluating the developed algorithms quite difficult.

3 Conclusions:

An efficient P-wave extraction algorithm based on the morphology characteristics of arrhythmias is proposed. It is measured from the surface ECG then quantify which signal have atrial fibrillation. The results reveal that the algorithm is accurate and efficient to detect and classify arrhythmias result from atrial fibrillation with sensitivity equal 92.5% specificity of 95% and predictive values of 96;6% and 96.5%

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العلاقة بين شكل الموجة P و الرجفان الأذيني

ناطق الأسدي

عباش الهاشمي

زياد طارق الدهان

قسم هندسة الطب الحيوي – كلية الهندسة – جامعة النهرين

الخلاصة:

الهدف من هذه البحث هو تطوير كفاءة خوارزمية الكشف موجة-P استنادا إلى خصائص مورفولوجية عدم انتظام ضربات القلب باستخدام تحليل نطاق الزمن .

وتضمنت التجارب العادية اشخاص طبيعيين و و تشخيص يعانون من ارتجاج اذيني بعد معالجة الانحراف عن خط الاساس و الغاء او فلترة تأثير مصدر الطاقة . تم استخدام خوارزمية تومكينز المستخدمه للكشف عن موجة QRS لحساب قمة موجة R التي تمثل نقطة المرجع للكشف عن قمة الموجة P . تم اختبار الخوارزمية في التجارب باستخدام قاعدة بيانات عدم انتظام ضربات القلب لمعهد ماساتشوستس للتكنولوجيا والتي شملت نوبات الرجفان الأذيني المؤقت والإيقاع الطبيعي للنبيض و الارتجاج الأذيني المزمن و الارتجاج الأذيني حيث تم استخراج كل موجة P .

بينت النتائج أن خوارزمية دقيقة وفعالة لكشف وتصنيف عدم انتظام ضربات القلب الناتجة عن الرجفان الأذيني