Automatic Detection of Abnormalities in ECG Signals : A MATLAB Study

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Abstract— The Electrocardiogram (ECG) is a diagnostic tool that measures and records the electrical activity of the heart. Interpretation of the ECG signal allows diagnosis of a wide range of heart conditions. These conditions can vary from minor to life threatening. In this paper real ECG records provided by the MIT-BIH Arrhythmia Database are used to build an efficient mechanism for detecting abnormalities in the ECG records. Prior to the detection, selected filters are used to eliminate any interference while maintaining the useful information within the signal. Detection of Heartbeat-related abnormalities of other heart diseases such as AV blockage and Ventricular Fibrillation is implemented. Results of ECG signal pre-processing and abnormality detection demonstrate the suitability of the selected filtering techniques and the efficiency of the detection mechanisms.

Keywords—ECG signal processing, heart-abnormality detection, ECG signal filtering, heartbeat abnormalities, MATLAB, Butterworth and FIR Filters

I. INTRODUCTION

The Electrocardiogram (ECG) is a diagnostic tool that measures and records the heart's electrical activity in detail. Interpretation of the resulting ECG signal allows diagnosis of a wide range of heart conditions. These conditions can vary from minor to life threatening.

An ECG is generated by a nerve impulse stimulus to a heart. The current is diffused around the surface of the body. The current at the body surface builds on the voltage drop, which varies from a few microVolts(μV) up to a few milliVolts(mV) with an impulse variation. Usually, the impulse is of very small amplitude, which requires a couple of thousand times of amplification [1] ECG signals are measured by electrodes placed over different areas of the body and connected to the galvanometer, which picks up the electrical currents resulting from the potential difference between them [2],[3]

The objective of this work is to create a diagnostic tool, on which medical professionals can rely on in their treatment decisions. Mathematical algorithms are used to help in detecting abnormalities that may exist in the measured cardiac electrical wave. These abnormalities include but are not limited to tachycardia, bradycardia, arrhythmias etc. Moreover, the real ECG signal is affected by the surrounding noises, such as muscle noise and power line interference, causing a deformity of the original signal. These unwanted signals need to be removed or filtered for the proper indentification of ECG abnormality. The task is therefore twofold: (i) removal and rejection of the background noises, and (ii) detection of the abnormalities [4]

ECG signals used in this work were selected from MIT-BIH Arrhythmia Database [5] which is a web-based database that contains the widest possible range of ECG records including those of rare cases to challenge the automated arrhythmia analyzers developers.

II. THE ELECTROCARDIOGRAM (ECG)

The electrocardiogram is the recording of the electrical activity of the heart by a device external to the body in a non-invasive way. The electrical signals propagate rapidly through the body knowing that the body is a great conductor due to the large amounts of fluids it contains.

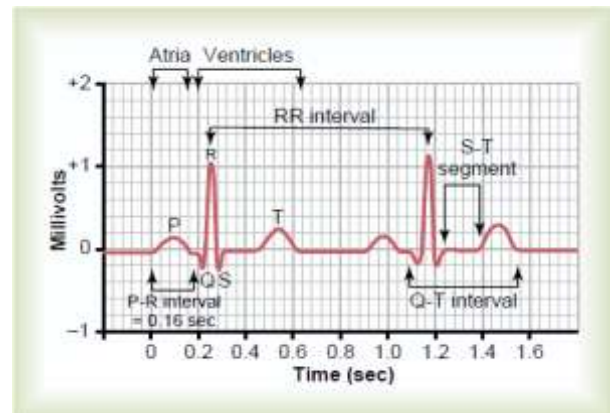A normal ECG signal is shown in Fig. 1. The signal can be divided in three sections:

Fig. 1: Typical ECG waveform

• P wave: is a small increase in the voltage (.1 mv) which represents the depolarization of the atria during atrial systole.

• QRS complex: is a small drop in voltage (Q) followed by voltage peak (R) and another small drop in voltage (S). The QRS complex represents the depolarization of the ventricles during ventricular systole. The atria repolarize on the same period of the QRS complex, however it does not show any effect on the ECG plot due to the size of the atria compared to the ventricles.

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- T wave: is a small peak (slightly bigger than P wave, .3 mv) which follows the QRS complex which represent the repolarization of the ventricles during the relaxation of the cardiac cycle.

The amplitude of the waves, the waves' width and the distance between waves can all be used clinically to diagnose the heart's condition [6][7].

In this work, ECG conditions ranging from normal rhythm to sudden cardiac death are studied and techniques for detecting them are presented.

These ECG conditions can be summarized as follows[8]:

a. Normal Sinus Rhythm (NSR): Normal rhythm of the heart leads to normal heart beat. An ECG is classified as an NSR mainly if the heart rate ranges from 60 to 100 beats per second, and the signal has a regular trend with a P wave for every QRS complex.

b. Tachycardia "Tachyarrhythmia" is a regular rhythm of the heart with a beating rate exceeding 100 beats per minute at rest .

c. Bradycardia is a regular rhythm of the heart with a beating rate below 60 beats per minute. This condition might be considered normal in athletes.

d. Ventricular fibrillation (VF) is a complete absence of rhythm in the electrical activity of the ventricles. It produces no effective muscular contraction and no cardiac output. It is the most serious of all cardiac arrhythmias.

e. Third Degree AV Block (3rd AVB) : this abnormal condition is described by the complete blockage of the impulses from the atria by the Atrioventricular node preventing the conduction to the heart. An ectopic pacemaker in the ventricles will activate them.

f. Sudden Cardiac Death (SCD) is a sudden absence of the electrical activity of the heart and cardiac contraction, resulting in a stop of the blood flow to the vital organs.

II. ECG SIGNAL FILTERING

The ECG signals consist of low and high amplitude voltages in the presence of noise. The ECG machine picks up different types of noises during the recording session making the mission of autodetection of ECG abnormalities nearly impossible without a filtering mechanism. Signal filtering is a challenging task because the value of the actual signal is .5 mV embedded in 300 mV environment.

The sources of noise are as follow:

- Power line interference: AC power line will generate 50 Hz or 60 Hz frequency, the amplitude of the power line noise could be very high.
- Muscle noise: this kind of interference is generated from the natural movements of the body muscles like the expansion of the lungs during air inhalation. This kind of noise is very hard to remove since it is in a close proximity with the actual signal.
- Low frequency interference causing wandering in the baseline of the wave.
- RF interference: like the radio frequencies generated by the surgical or monitoring equipement.

In order to detect abnormalities embedded in the ECG signals, filtering should be applied to remove the noise present in the signal. Four different types of filters were investigated and compared in order to assess their effectiveness. Table I lists four different filters and their main features [9][10][11][12][13].

Table I: Comparison between the filters and their capabilities

Filter	Capabilities
Butterworth	General low-pass filter to remove high frequency noises
Empirical Mode Decomposition (EMD)	Removing power line interference and baseline wander
Median Filter	Smoothing signals and removing baseline wander
FIR band-stop	Used to remove the 50 Hz interference caused by power lines
FIR high-pass	Used to remove the baseline wander

As some of the filters in Table I share the same filtering capabilities, the two types of FIR filters along with the butterworth filter were selected over the Median and EMD filters. The main problem with the median filter is that it calculates the median of the adjacent points, which changes the value of those points (the voltage value of that sample). This is impractical when it comes to biomedical data such as the ECG signal because the magnitude of the point/sample has its physiological interpretation, and it might lead to mis-interpretation of the heart's condition. EMD was eliminated from the filters' list because of its complex nature with no significant added value when compared to the two versions of the FIR filter . The high-pass FIR filter was used to remove the baseline wander and the band-stop FIR filter was used to remove the 50 Hz interference caused by power lines. Finally, the Butterworth filter was selected for its low-pass filtering capabilities.

III. SIGNAL PROCESSING AND ABNORMALITIES DETECTION

First, in the signal processing stage single and double filters were applied to the selected ECG samples to select the most efficient filter in removing the undesired noise. The SNR criterion was used as an evaluation tool. Second, in the abnormalities detection phase, the abnormalities were devided into heart rate related abnormalities and general heart abnormalities and hence two different detection criteria were applied.

A. Signal Pre-processing

The above filtering mechanisms were implemented in MATLAB to observe the effect of each filter on the ECG signals. Double or successive filtering with two different filters has also been considered.

B. Single Filtering

The Butterworth filter depends on two parameters, the order of the filter and the cut-off frequency [10] [11]. The cut-off frequency ω_c is calculated by normalizing the desired frequency, 10 Hz in this case, and the sampling rate, which is chosen as `length(y)/60`, y being the ECG data array. A first order low-pass filter is designed in MATLAB using its built-in function , filter `(B,A,y)` that filters the data in array y with the filter described by vectors A and B which are the Butterworth filter coefficients obtained by the function `[B,A]=butter(1,wc,'low')`. A filtered ECG signal of NSR is illustrated in Fig. 2.
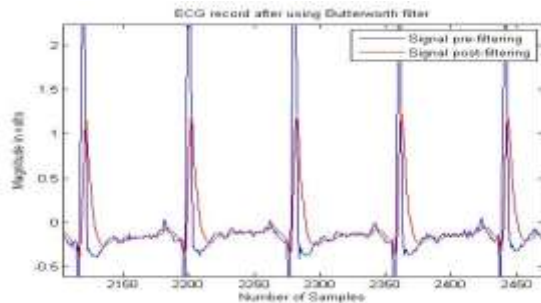

Fig. 2. ECG signal of NSR filtered with Butterworth filter

Unlike the Butterworth filter, the FIR band-stop filter has three parameters [10] [14], in MATLAB `(1000, [w1 w2],'stop')`, namely, the order of the filter, the cut-off frequency and the type of the filter. The cut-off frequency is calculated by normalizing the desired frequency, 50 Hz in this case to remove the power line interference, and the sampling rate, which is `length(y)/60`.

It is important to mention that the higher the order the better the performance of the band-stop filter, however caution must be taken not to over filter the signal. The cut-off frequency wc1 is indirectly involved as a parameter, because the parameter `[w1 w2]` returns the band-stop frequency range specified by the interval w1 to w2. The edges of the interval are calculated by adding and subtracting 9% of the cut-off frequency value. MATLAB has a built-in function filter `(a, 1, y)` that filters the data in y according to the desired parameter a= `fir1 (1000, [w1 w2],'stop')`. A filtered ECG signal of Tachycardia is illustrated in Fig. 3.
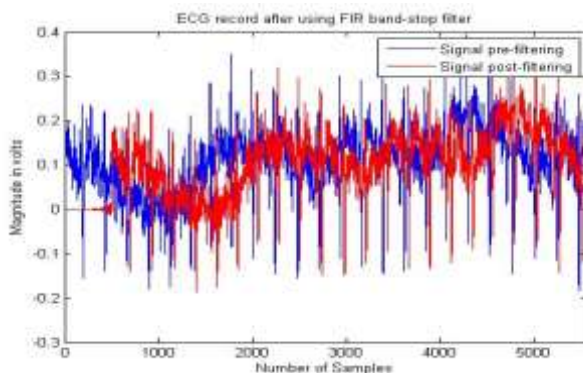

Fig. 3. ECG signal of Tachycardia filtered with FIR band-stop filter

The third filter used in this work is the FIR high-pass filter [10] [12]. It has three parameters, the order of the filter (number of taps) '1000', the cut-off frequency and the type of the filter. The cut-off frequency 'wc2' is calculated by normalizing the desired frequency, 1 Hz in this case to remove the baseline wander, and the sampling rate, which is `length(y)/60`. It is important to mention that the higher the order the better the performance of the filter, however caution must be taken not to over filtrate the signal. MATLAB has a built-in function `filter (h, 1, y)` that filters the data in y according to the desired parameters h=fir1 `(1000, wc2,'high'`. A filtered ECG signal of VF is illustrated in Fig. 4.
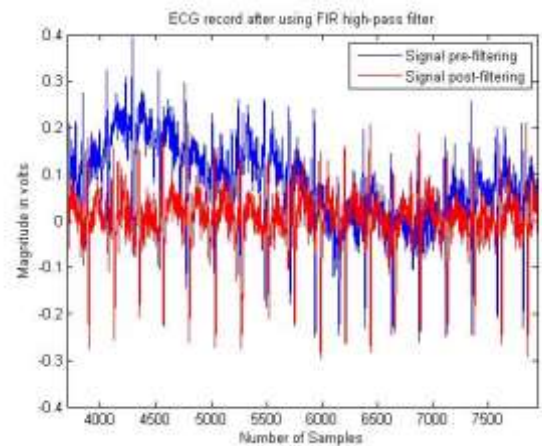

Fig. 4. ECG signal of VF Ventricular Fibrillation filtered with FIR high-pass filter

C. Double Filtering

In order to assess the effectiveness of double or successive filtering, the signal filtered by the Butterworth filter was re-filtered by the FIR band-stop filter with the same parameters used previously in the single filter. A plot of the resulting filtered ECG signal of Tachycardia is shown in Fig. 5 .
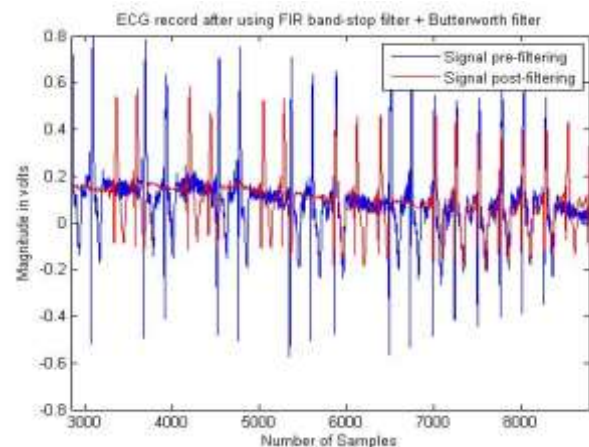

Fig. 5. ECG signal of Bradycardia filtered with Butterworth + FIR band-stop filters

Similarly, the data filtered by the Butterworth filter is re-filtered by the FIR high-pass filter with the same parameters used previously in the single filter in order to observe the

effect of the double filtering. A plot of the resulting filtered ECG signal of 3rd degree AV block is shown in Fig. 6.
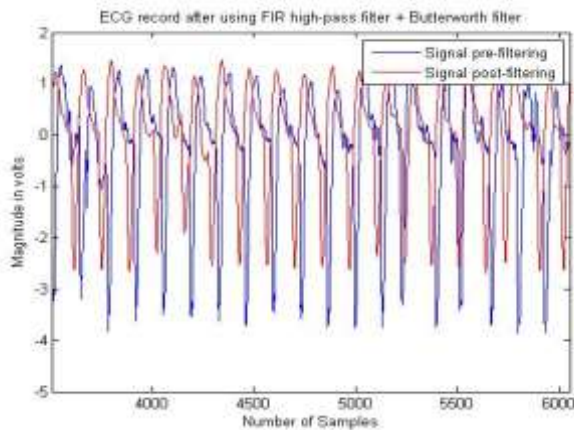

Fig. 6. ECG signal of Third degree AV block filtered with Butterworth + FIR high-pass filters

Finally, the data filtered by the FIR high-pass filter is re-filtered by the FIR band-stop filter with the same parameters used previously in the single filter. A plot of the resulting filtered ECG signal of SCD is shown in Fig. 7.
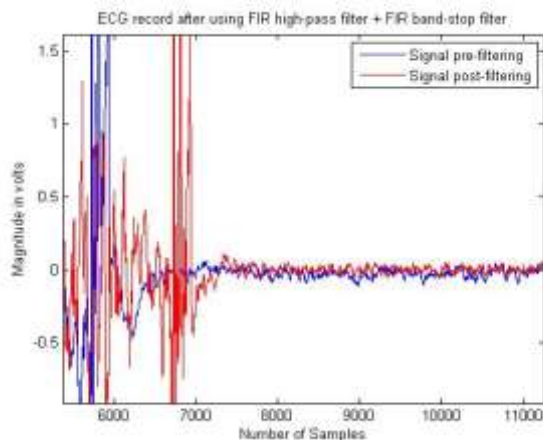

Fig. 7. ECG signal of sudden cardiac death filtered with FIR band-stop filter + FIR high-pass filters

D. Filter Selection

In order to determine the most efficient filter, the Signal-to-Noise Ratio (SNR) is used as evaluation tool assuming that the noise is additive. Every filter (single or double) was tested through this evaluation tool. The filter with the most satisfying results was retained for use in filtering the signals used as input in the abnormalities detection algorithm.

The SNR_v is calculated using the following formula (1):

$$SNR_V = \frac{RMS \ of \ Original \ Signal}{RMS \ of \ Noise \ Signal} \qquad (1)$$

Where the RMS is defined as in (2) [8]:

$$RMS = \sqrt{mean(signal)^2} \qquad (2)$$

Table II below shows the values of the SNR_{dB} for the different filters for all the ECG conditions:

Table II. SNRdB Values For The Different Filters For All The ECG Conditions

Filters / ECG	Butter worth	FIR band-stop	FIR high-pass	Butter woth + FIR band-stop	Butter woth + FIR high-pass	FIR (band-stop+ high-pass)
NSR	1.547	-2.768	-2.847	-0.976	-1.008	-2.588
Tachy-cardia	7.883	-2.922	-3.243	-2.132	-2.511	-3.654
Brady-cardia	3.927	-1.271	-1.788	0.262	-0.399	-2.428
SCD	7.468	-2.349	-1.477	-1.715	-0.738	-2.055
Third degree AV block	5.739	-3.170	-3.300	-1.532	-1.716	-3.869
Ventri-cular Fibri-llation	5.908	-0.008	-1.280	1.151	-0.391	-1.321

The negative SNR_{Db} in TableII is an indication of inefficient filtering since the RMS of the noise is greater than the RMS of the original signal while a positive SNR_{dB} indicates an efficient filter since the RMS of the noise is less than the RMS of the original signal. Inspection of Table II indicates that the Butterworth filter is the most efficient filter among all the filters for all ECG abnormalities.

Clearly the double filtering process did not have better SNR_{dB} values, even when conjugating with Butterworth filter. However FIR high-pass filter is found to be the best filter to remove the baseline wander and was used in ECG signals that presented evidence of this type of noise.

E. Abnormalities Detection Algorithms

Two detection algorithms were built. The first is for detecting the abnormalities related to the heart rate and the other is related to detecting diseases related to the heart. All the ECG records are of one minute duration.

- *Heart rate - related abnormalities detection algorithm*

The algorithm tests three consecutive ECG samples and compares a given sample to its adjacent counterparts and to a threshold value of 0.25 volts. The fixed threshold of 0.25 volts was chosen based on the following:
1. The selected ECG waveforms have a common range of amplitudes (0 to 3 volts) of the samples making the idea of a fixed threshold practical as shown in Fig. 8.
2. The detection mechanism does not rely on the amplitude; however it depends on the number of the "R" peaks of the QRS complexes in the whole waveform.
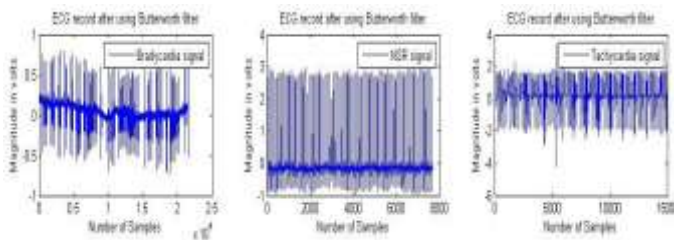
Fig. 8 common range of samples' amplitudes (0 to 3 volts) for different ECG waveforms

The final value of the peaks count, which represents the estimated heart rate is then tested to identify the type of disease according to the ranges given in Table II.

Table III:　Different ranges of heart rates and their physiological interpretation

Heart Rate	Related Condition
Below 60 BPM	Bradycardia
Between 60 and 100 BPM	Normal Heart Rate
Above 100 BPM	Tachycardia

- *General heart diseases detection algorithm*

For the detection general heart diseases , a mechanism was developed to identify any unusual drop in the voltage between the P wave and the QRS complex in addition to the peak detection .

a. *AV Block Detection*

The AV block is mainly characterized by a drop in the voltage between the P wave and the QRS complex due to the latency in the signal propagation between the atria and the ventricles through the AV bundle. The algorithm tests three consecutive ECG samples and compares a given sample to its adjacent counterparts and to a threshold value of -2.5 volts. The threshold of -2.5 volts was chosen to detect the third degree AV block, because the drop in voltage is the main characteristic of such conditions as clearly shown in Fig. 9. A voltage–drop count that exceeds 60 is an indication of a third degree AV Block.
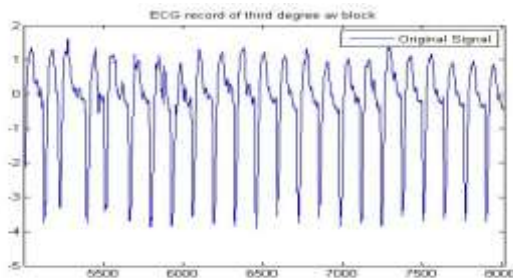

Fig. 9. voltage drop in third degree AV block ECG waveform

b. *Ventricular Fibrillation Condition*

The VF is mainly characterized by the absence of peaks and drops with large magnitudes, the samples magnitude ranges from .3 volts to -.15 volts only. The algorithm tests if any given sample lies outside the interval [-0.5, 0.5]. The samples of the VF ECG waveform have narrow range of magnitudes as shown in Fig. 10, therefore the threshold of $\pm$ .5 volts was chosen.   If the number of peaks counted is equal to

0, it is concluded that the patient suffers from Ventricular Fibrillation.
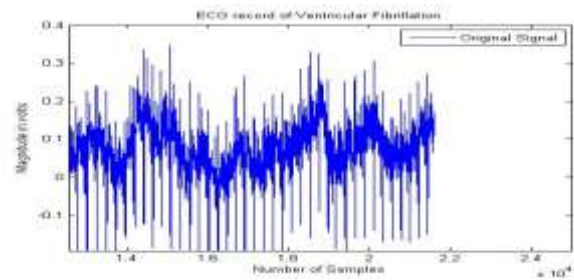

Fig. 10. VF Ventricular Fibrillation ECG waveform with a narrow range of amplitudes

c. *Sudden Cardiac Death Detection*

The SCD is mainly characterized by the absence of peaks and drops along with a semi-linear behavior of the signal. The algorithm tests if any given sample lies outside the range [-0.15,0.15]. The threshold of $\pm$ .15 is very adequate to the SCD condition, as the absence of the electrical activity of the heart on the second half of the ECG waveform has dramatically narrowed the range of the amplitudes of the samples as shown in Fig. 11.
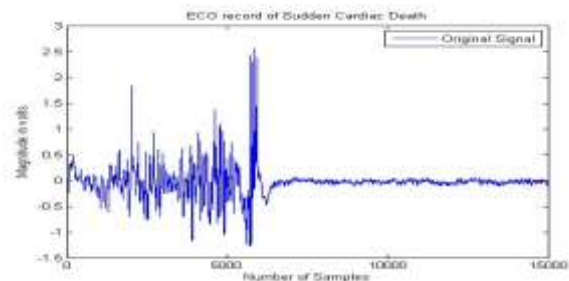

Fig. 11. Absence of the electrical activity of the heart on the second half of the ECG waveform in the SCD Condition

The Results of a sample implementation of the developed techniques for SDC detection are illustrated in Fig. 12.

Fig. 12. Filter selection and abnormality detection for SCD

IV. CONCLUSION

Simple abnormality detection mechanisms were developed and tested using real ECG signals. The raw ECG signals were filtered through Butterworth filter and were used as inputs to the detection algorithms. Two types of detection algorithms were presented, one was built to detect abnormalities related to heart rate and the other was built to detect general heart diseases. Results of MATLAB implementations have shown that the proposed ECG signal filtering and abnormalities detection mechanisms can give a good indication of the underlying physiological disorder. Although computer-based analyses of ECG signals cannot be used as a source of conclusive diagnosis since errors are not tolerated at all whether by misdiagnosing the condition or identifying conditions that do not exist, they can nevertheless give a primary diagnosis to the general physician and be of great help to non-medical professionals as first aid in emergency cases. They may also provide assistance for real-time monitoring of critically ill patients.

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