Heart rate Estimation of III-Lead ECG Measurement

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Abstract— **The aim of this study is to implement the algorithm proposal able to estimate the heart rate waveform directly from the raw ECG signal based on the modification of previously proposed algorithm by Willis J. Tompkins [1]. Two groups of ECG records comprising of 10 normal ECG signals collected with III-lead measurement and abnormal ECG signals of Congestive Heart Failure ECG subject obtained from MIT-BIH online database were estimated for their heart rate waveforms and compared for the significant different change in waveform. As result shown from the heart rate waveform comparison between normal and abnormal ECG signals, the significant difference can be notified in term variation and heart rate waveform of fluctuation, amplitude level and frequency-domain characteristics.**

Index Terms*— *Electrocardiogram, Heart rate, III - Lead

I. Introduction

ECG signal is a typical bio-electric signal that represents the heart electrical conduction and activities. This electrical pulse is first generated on Sinoatrial node which results in heart contraction. Consequently, the blood is pumped throughout a whole body [1]. The shape of ECG waveform can feature a heart condition in terms of functionality, structural components, healthiness or even illness affection. This kind of signal can represent any changes in cardiac condition that mediate in its waveform.

ECG signal has been previously conducted in some research aiming to extract some distinct features and then classify those features related to the heart disease based on signal processing method through a time-domain analysis and estimation [2, 7]. Signal is directly processed without any transformation made in prior state of processing work flow. The Principal Component Analysis (PCA) [3] and AR modeling [2, 6] are very popularly applied to analyze signal for its mainly dominant components of features estimated before proceeding further in next step of classification. These mentioned pre-processing techniques have been modified and applied in multiclass ECG heart-beat classification.

Some research groups had transformed the ECG signal into frequency-domain representation. Then, the interesting features were investigated or to be recognized [4]. Time-frequency domain is also the most used method in observing the ECG signal on the occurrence of energy in time-frequency domain possibly attaining more important information [8, 10]. More flexible analysis can be reached and carried out more different expectation on result.

This paper addressed on how to record the ECG signal with III-lead ECG measurement and how to implement Matlab scripts for the time-domain analysis modified from previous work on QRS detection rules using the MITBH arrhythmia database [5]. In this work the estimation of heart rate has been further carried out from the previous work. The workflow of how to detect the heart-rate from raw ECG recording is depicted into steps regarding simplicity to implement the algorithm. This algorithm could be expected to reduce computational complexity to be more applicable in clinical level use.

II. Methodology

The measurement of ECG records used in this study is the single polarity lead which records the electrical change in frontal plane .One electrode has a zero potential difference compared with another one to complete a circuit connection .All three leads were connected as depicted in Fig. 1. Lead I, II and III are aVL, aVR and aVF, respectively .How to measure and record ECG signal with III-lead measurement shows as follows:

- First put the Gel on electrodes and then attach them on each limb of subject
- Connect BIOPAC MP150 to computer via Ethernet connection
- After hardware connected successfully, open AcqKnowledge 4.2 program, then select BIOPAC MP150.

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- Setting BIOPAC MP150 to have Gain at 1,000 Hz,NORM, ON and cutoff frequency at 0.5 Hz .
- Connecting lead100S-W)White (Red to VIN +Black Shield, lead100S-R)Red (White toVIN-Black Shield, and lead100S)Black (to GND .
- Setting program AcqKnowledge4.2 by Choosing Menu MP150, setting up Channels to Analog, View by modules, then checking a box in Acquire, Plot, Value, Rename Label and choose Channel Sampling Rate 250 Hz .
- Set up the calculation values :CAL1 to 10 and CAL2 to -10
- Choose Menu MP150, Set up Acquisition, Check box on Record, Save Once, Memory, Sampling rate at 1000 samples/second, Acquisition Length :1800 seconds.
- Attach lead100S-W to electrode on a right arm, lead100S-R to a left arm and lead100S to a left leg .
- Press START in AcqKnowledge 4.2 program and then record signal for 10 minutes .
- Press stop after 10 minutes finished and save file type in.*** mat for further step in analysis.

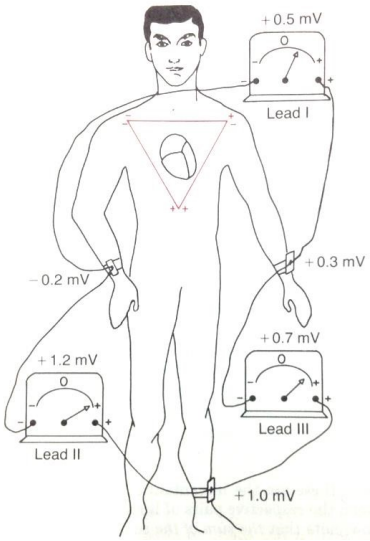

Fig. 1. Measurement of ECG)3-lead] (9[

Each ECG signal was recorded for 3 minutes long from 10 normal subjects with frequency sampling at 1,000 Hz . Each subject was carefully supervised to be at rest with calmness and relax during all time of measurement . Another group of ECG database collected from CHF subjects, which suffered from Congestive Heart Failure, was obtained from MIT-BIH database available online at http//:physionet.org./ This database was analyzed and compared its estimated heart rate to the normal ECG case for evaluating the performance of our algorithm.

The procedure of study mainly consists of data acquisition, preprocessing, signal segmentation, filtering, signal shape transformation, R-peak detection and heart rate estimation .All ECG signal files in both databases were offline processed by following the same procedure shown in Fig. 2 .The work flow of algorithm is straightforward to implement orderly and very simplified to have less complexity in calculation.

The preprocessing section starts with signal segmentation and down sampling of frequency from 1 KHz to 0.2 KHz .The linear and nonlinear filtering were applied to ECG signal to produce a set of periodic vectors with frequency response not higher than 100Hz .Next the filtered ECG signal was differential, squared, and time averaged .The window of analysis was set to meet the consecutive QRS complexes and then the minimum amplitude of QRS complex was estimated as one of thresholds for a lower bound of amplitude and then segmenting the ECG signal after the minimum QRS found .The maximum value)expecting R-peak (was detected for the height of peak and its time occurrence location .The time index was then updated to be a next beginning point of next following segment .The index of time location detected for all R-peaks was converted to RR interval and then the heart rate thereafter estimated. Fig. 3 presented the Pseudo code of heart rate estimation algorithm which was designed, modified and implemented in form of a Matlab script.

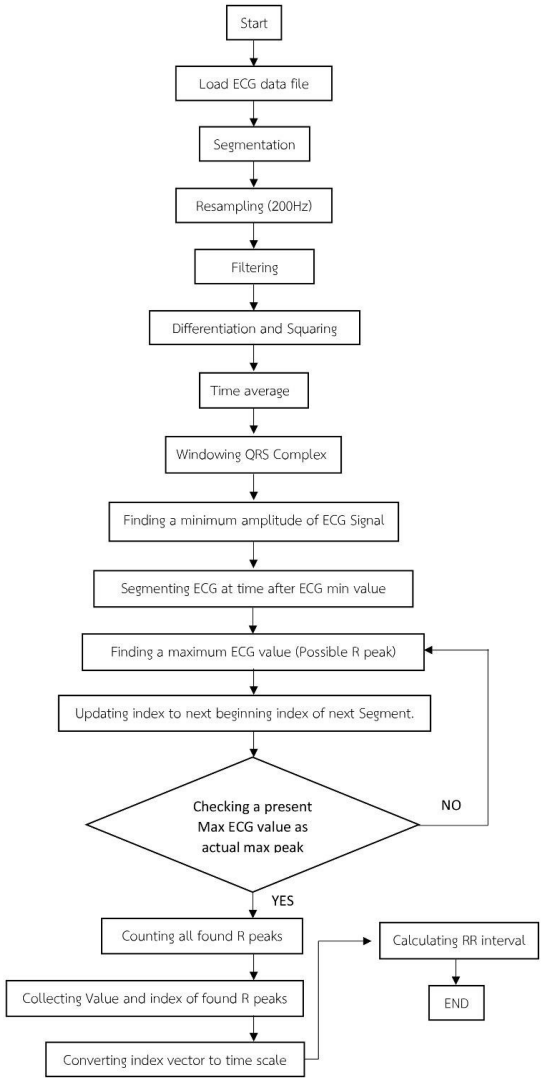

Fig. 2. Flowchart of heart-rate estimation algorithm

Pseudo code:

%Estimating RR interval from ECG signal
Load ecg signal;
ecgsg = ecg (1:N);
fs_2 = 200 Hz;
recg = resample (ecgsg, fs_2, fs_1); %, fs_1 = old frequency, fs_2 =new frequency
recgf = filter (b1, a1, recg);
recgfd = sum (z)/8; % z is difference equation
ecgsg = recgfd^2;
ecgmaw = sum(ecgsg)/32;
%windowing each QRS complex;
minecg = min(ecgmaw);
%Segmenting each ecg after min ecg found;
%Finding max (ecgmaw) for R peak;
%Updating index to next beginning index of segment;
While actual max R peak not found;
R peak found;
End;
%Counting all found R peaks;
%Converting location of R peaks to seconds;
%Calculating RR interval;
End;

Fig. 3. Pseudo code of RR-interval estimation algorithm

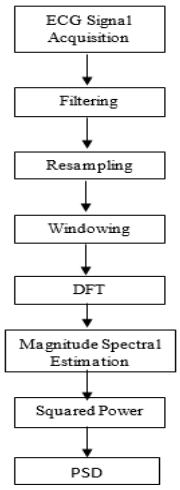

Fig. 4. Flowchart of PSD estimation in ECG signal

In further analysis made in study, the estimation of Power Spectral Density (PSD) was also applied to observe the frequency characteristics of both normal and abnormal ECG signals. The PSD estimation procedure follows the workflow depicted in Fig. 4, which are involved with first the filtered ECG resampled and segmented to meet the window range of analysis. Then, the segment of ECG was transformed to frequency domain with DFT operation and the magnitude spectrum of ECG was estimated within an interested frequency range of 0-125 Hz which adequately covers a whole frequency response of the normally functional heart in human. The different sampling frequency has been used in this estimation at 250Hz which was slightly different in heat rate estimation. These estimated frequency characteristics could be alternatively utilized when making a comparison between cases of ECG signals in terms of significant difference in frequency bandwidth of signal response, average and maximum power, maximum peak location (in Hz), and sub-band energy per subdivided bandwidth.

III. Experiments

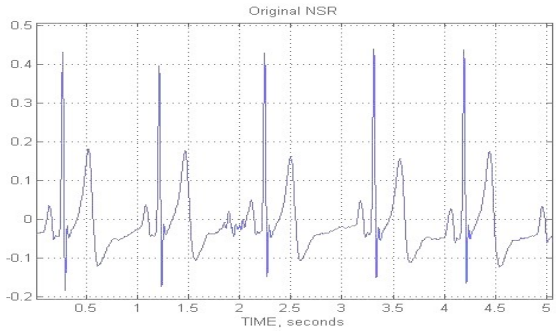

Fig. 5. Normal ECG waveform

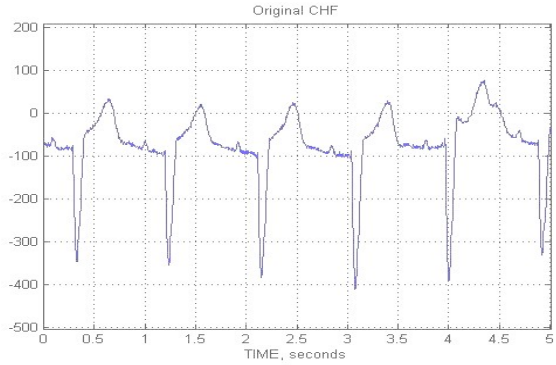

Fig. 6. Abnormal ECG waveform collected from CHF subject

In processing state each normal ECG signal as shown in Fig. 5 and ECG signal of CHF subject shown in Fig. 6 were observed visually first, then analyzed via our designed program. As one can notify, in case of abnormal ECG the T wave in a current complex and P wave of a following complex are messy mixed to each other between current complex to another following complex and look very noisy alike with the dropped amplitude level as compared to the normal ECG .The S wave obviously diminishes and there is no resetting back interval to the signal baseline. Fig. 8 shows the original ECG signal from Normal cases being down resampled to have a new sampling frequency at 200 Hz, filtered by derivative filter, squared in its amplitude to have an absolute value to be very evenly smoothed peaks . Results from processing two different groups of the categorized ECG signals revealed the significant difference in term of quantitation of peaks found in state of time averaged. In case of CHF case, it has a very less number of time averaged peaks as compared to normal one. In Fig. 9 the middle points of positive and negative slopes in individual time averaged peaks were detected automatically as indicated in red and blue markers located at up-slope and down-slop of each time average. The location of red marks represented the exact time occurrence of R waves in QRS complexes of processed ECG waveforms see Fig. 10.

The heart rate waveforms estimated from normal ECG and abnormal ECG are obviously different in fluctuation of waveform baseline and waveform amplitude level. In

Fig. 12, heart rate of normal subject shown on the Left plot has more dynamic response than CHF subject on the Right plot.

Furthermore, the result of PSD estimates plotted in Fig. 13 suggests that some visually observable difference can be recognized between normal ECG and CHF ECG signals. More averaged power over a whole frequency range of 0-125Hz was distributed from normal ECG signal and at higher frequencies some harmonics related to the fundamental frequency of normal ECG normally occur. Theses disappeared in CHF case. In PSD of CHF ECG signal, its spectral power was dramatically decreased started at very low frequency of approximately 10 Hz and eventually fading out at higher frequencies. CHF ECG signal has a very narrow frequency bandwidth about 30 Hz or less as compared to normal ECG which is larger.

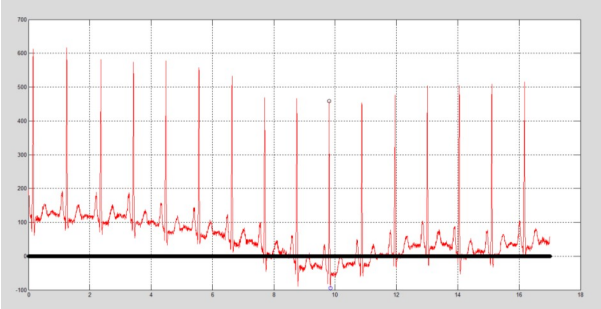

Fig. 7. Plot showing the lowest R-peak and S-peak detected in normal ECG

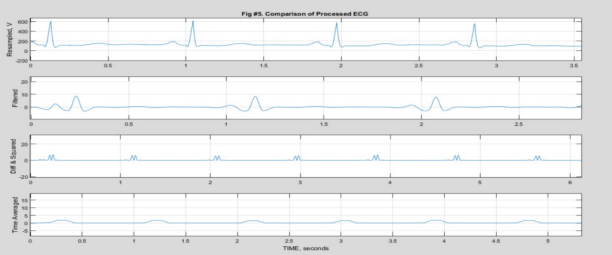

Fig. 8. Plots of each processed ECG signal

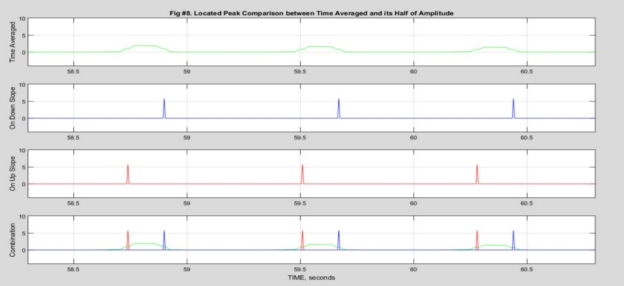

Fig. 9. Plot of Up-slope and Down-slope locations

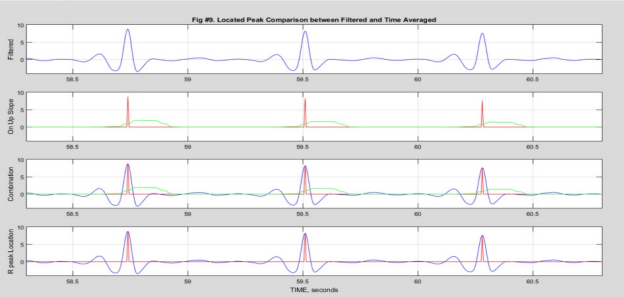

Fig. 10. Plot of comparison among Time Average, Up-Slope and ECG signal

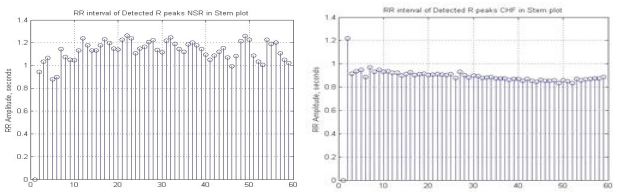

Fig. 11. Plots of RR interval detected from : Left (normal ECG and) Right (abnormal ECG)

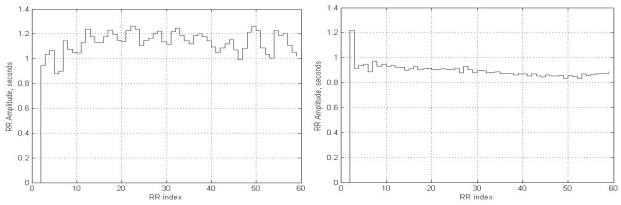

Fig. 12. Heart rate waveforms estimated from : Left (normal ECG and) Right (abnormal ECG)

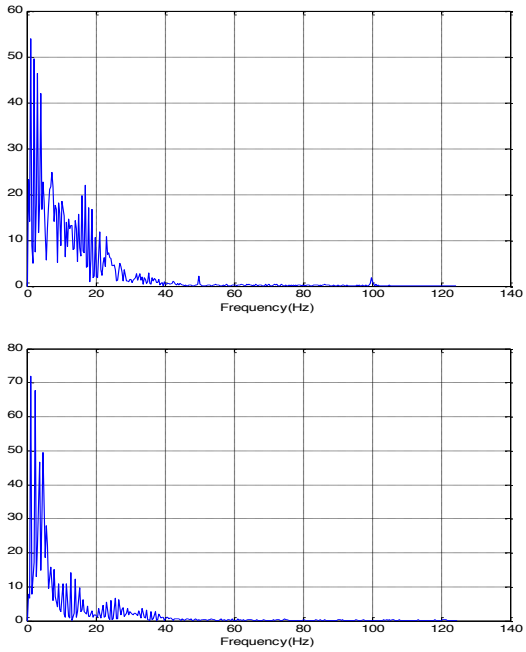

Fig. 13. PSD estimated from : Upper (normal and) Lower (abnormal ECG signals)

IV. Conclusion

This study can be beneficial and contribution to the knowledge on how to estimate the heart rate from raw ECG record with simplicity and modification of previously proposed algorithm with less computational cost. The obtained heart rate is considered to be adequately effective and similar to those resulted from other medical healthcare measurement. As result shown from comparison of heart rate waveform comparison between normal and abnormal ECG signals, the significant difference can be readily notified in terms of fluctuation, amplitude level and frequency-domain characteristics as well.

Further direction of this study will include improvement of performance and reliability of algorithm that are mandatory for acquiring the standard medical instrument calibration for clinical use.

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