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Virtual Instrument Based Real Time ECG Monitoring Device

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Virtual Instrument Based Real Time ECG Monitoring Device

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Abstract. This study presents a real-time ECG monitoring system based on a virtual instrument. The device was designed using surface electrode, lead wire, instrumentation amplifier (IN114), and passive low pass filter with cut-off frequency (fc, 180 Hz). Thereafter, the ECG signal was transferred via DAQ card by initializing the analog input and sampling rate to the Labview for further analysis. Further, digital notch filter (fc, 47 to 53 Hz), bandpass filter (fc, 0.05 to 20 Hz), and FIR high pass filter using Kaiser window (order-56, and fc – 3.5 Hz) was employed in order to remove the power line interference, detect fiducial point from ECG, and eliminate the baseline wondering. In addition, we examined the various wavelet to choose the best to use wavelet denoise based on signal-to-noise ratio (SNR). Finding suggests the SNR (58.75 dB) of sym8 wavelet was higher comparing with another wavelet. Hence, the wavelet denoising was implemented into the developed device to remove the distortion and to detect the better peak in real time. Further, multiresolution analysis with Haar wavelet with the decomposing level of 1 was incorporated into the developed ECG monitoring device to detect the R-R peak, followed by automatic heart rate detection. Thus, this finding suggests the promising result that has the potential to assess the cardiovascular conditions. In future, the developed device will be tested with healthy subjects in order to standardize the functionality and significant features will be extracted from the morphology of ECG waveform for the analysis of cardiovascular diseases.

1. Introduction

Cardiovascular diseases (CVDs) is one of the leading intimidations to the human being and its parameter of pathology contributes to the essentiality of day-to-day monitoring [1]. CVDs accounted for 37% of untimely (under the age of 70) noncommunicable disease mortality in 2012 [2–4]. At present, ECG and its physiognomies are usually employed in order to test the CVDs abnormalities, however, the hiked price and complication structure of regular ECG monitoring device lead the problem that ECG examination can only be performed in the presence of skilled professionals.

An electrocardiogram (ECG) records the electrical activity of the heart and displays in terms of a graph by placing adhesive or metal electrode on the skin [5-8]. The recent use of computers allows the visualization and analysis of the morphology of the ECG signal, which is composed of multiple cycles that include numerous sample points [9]. These samples points are fiducial, namely, the P wave, QRS complex, and T wave as presented in Fig. 1 [8]. Analyzing the ECG signal by identifying these points is a crucial step and has become possible by analyzing its characteristics wave patterns [10]. The fiducial R peak detection and implementation into a real-time ECG monitoring system seem to be

challenging. In addition, detection of R peak is extensively utilized to estimate heart-rate variability (HRV) and analyze heart rhythm irregularities [11, 12].
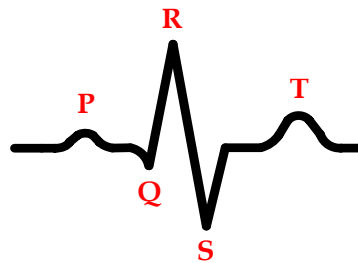

Figure 1. Segmented ECG signal.

Significant research efforts have been devoted to the development of computer-based real-time ECG monitoring system. A study conducted by us reported a real-time ECG monitoring device, however, the device seems to be complex due to the incorporation of multiple pre-processing stages [13]. In addition, a curve-fitting based method was employed to detect the R-peak in order to compute the heart rate. Similarly, a study conducted by Deb and his team presented a low-cost ECG monitoring device for smart product user [14] and employed threshold method to detect the R-peak, which co-indices with the finding of Srivastav and others [15]. In general, most of the studies employed slope-based threshold methods [16, 17], mathematical-morphology-based methods [10], digital filtering methods [16], and The Pan and Tompkins methods [18]. However, these methods have the adverse effect on performance [16] due to the variation in frequency of the morphology of the ECG signal. Therefore, this study presents a simple, and effective PC based real-time ECG monitoring device based on virtual instrument technology that aims at strengthening routine ECG heart monitoring by incorporating a non-stationary approach to detect the R-peak and R-R interval as the extension of the previous study.

The use of both PC and virtual instrumentation techniques enables the realization of a new generation of superior devices [4]. Even, the performance of the device becoming ever higher and with the raising different software efficiency applications, which are considered as a significant tool on the desk of an engineer [5,6].

The paper is organized as section II illustrates the method for designing of an ECG monitoring device, which includes the description of analog front-end ECG signal acquisition system, post-signal processing, and for the automatic detection of R-peak. Section III describes the contribution of this research paper in terms of the result. Finally, a conclusion is made in Section IV.

2. Methodology
Figure 2 shows an overview of the ECG monitoring device. The designing of the device comprises four major steps, namely, analog front-end ECG acquisition, post-signal conditioning, R-peak detection method, and heart rate detection algorithm. The ECG signal was acquired using an adhesive surface electrode integrated with lead and employed lead-II configuration, as it is known as a monitoring lead based on the principle of Einthoven's triangle. Thereafter, the ECG signal was transmitted to the computer via data acquisition (DAQ) card for post-processing, R-peak and heart rate detection.
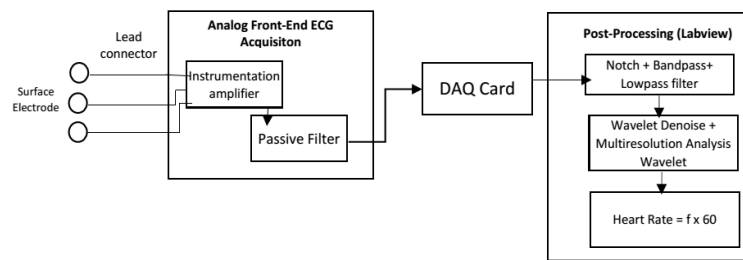
Figure 2. Overview of ECG monitoring Device using virtual instrument.

2.1 Construction of Analog Front-End ECG Acquisition system
This study utilized a few components in order to acquire and pre-process the ECG signal from the subjects, which outperform our previous finding. The analog front-end acquisition system consists of an instrumentation amplifier (IN114) instead of AD620 due to higher common mode rejection ratio, lower power consumption, followed by a low-pass filter designed using passive component (Resistor and capacitor) with the cut-off frequency of 180 Hz in agreement with the earlier study [19], which limits the bandwidth of the ECG signal.

2.2 Automatic CO_2 waveform segmentation
The post-processing steps involved the designing notch filter, band-pass filter, wavelet noise, which removed the power line interferences, baseline movement and limit the bandwidth of the signal. A second order band-stop Butterworth infinite impulse response (IIR) filter was designed with a cut-off frequency of 47 to 53 Hz as advocated by [20] in order to remove the power line interferences. Further, an IIR bandpass filter with cut-off frequency of 0.05 to 20 Hz was employed to extract the ECG fiducial points, namely, P-wave, QRS-wave, and T-wave in agreement with an earlier study [21]. In addition, a FIR high pass filter using Kaiser window with an order of 56 and a cut-off frequency of 3.5 Hz was designed in order to remove the baseline noise based on respiration frequency in agreement with an earlier study [22].

Furthermore, wavelet denoising was performed prior to apply peak detection algorithm in order to remove the distortions from the ECG signal, which remains after filtering. Firstly, we studied the effect of various wavelet techniques such as Daubechies, Haar, BiorSplines, and Symlet in order to choose the most appropriate one based on the signal-to-noise ratio (SNR) value using

$$\text{SNR} = 20 \times \log \frac{\text{mean} \times (\text{raw ECG signal})^2}{(\text{processed ECG signal})^2} \tag{1}$$

The db8, db2, haar, bior3.9, bior1.3, bior6.8, sym6, and sym8 wavelet transform were applied on filtered ECG signal. Further, the decomposition of the ECG signal was performed into 7 levels using the wavelet transform. The obtained coefficients were different in length for seven decomposed level (CA7, CD7, CD6, CD5, CD4, CD3, CD2, and CD1). The soft threshold method was applied CD1, CD2, CD3, CD4, CD5, CD6 while coefficients CA7 and CD7 were made zeroes. Thereafter, a signal was reconstructed based on new coefficients.

2.3 R-peak and heart rate (HR) detection using multiresolution analysis

Multiresolution analysis (MRA) is used to detect the R-peak compared to the curve-fitting-based peak detection method because MRA is capable of detecting in noisy ECG signal. Firstly, the MRA theory was described in 1986 by Mallat [23] and Meyer [24]. It seems to be easy to interpret than Fourier transform. Additionally, MRA can be expressed with several sub-band coding forms by employing multi-rate filter banks. MRA is based on the multiresolution theory and can be described mathematically in order to provide an accurate explanation of expansion on the bases of orthogonal in the Hilbert space $L^2(R)$. According to Daubechies [25], a multiresolution contains close subspaces in a sequence as follows

$$C_2 \subset C_1 \subset C_0 \subset C_{-1} \subset C_{-2} \tag{2}$$

like that they contain the flowing properties:

i) Upward completeness:

$$\bigcup_{n \varepsilon Z} C_n = L^2(R) \tag{3}$$

ii) Downward completeness:

$$\bigcap_{n \varepsilon Z} C_n = \{0\} \tag{4}$$

iii) Scale invariance:

$$f(t) \varepsilon C_n \leftrightarrow f\left(2^n t\right) \varepsilon C_0 \tag{5}$$

iv) Shift invariance:

$$f(t) \varepsilon C_0 \leftrightarrow f(t-n) \varepsilon C_0, \text{for all } n \varepsilon Z, \text{ and} \tag{6}$$

v) Orthonormal basis:

$$\{\varphi(t-m) | m \varepsilon Z\}, \tag{7}$$

For C_0, $\varphi \varepsilon C_0$, $\varphi(t)$ is known as scaling function. The scaling function includes an orthogonal basis for C_0. The orthonormal basis $\{\varphi_{n,m}\}$ can be expressed using shift and scale variance for the space C_n [25].

$$\varphi_{n,m} = 2^{\frac{-n}{2}} \varphi\left(2^{-n} t - m\right), \text{for } n, m \varepsilon Z \tag{8}$$

orthonormal basis function can be written as follows

$$\psi_{n,m} = 2^{\frac{-n}{2}} \varphi\left(2^{-n} t - m\right), \text{for } n, m \varepsilon Z \tag{9}$$

like that $\{\psi_{n,m}\}$, $m \varepsilon Z$, is considered an orthonormal basis for a space W_n, W_n is the complement of the space C_n in C_{n-1}.

$$C_i = \left(C_{i+1} \oplus W_{i+1} \right)$$ (10)

$\psi(t)$ is known as wavelet function.

Multiresolution analysis analyzed the ECG signal by computing wavelet coefficients, which comprises a hierarchical and fast scheme. The scheme includes the calculation of sequentially coarser approximation of x(t) and the difference between the subsequent levels. Besides, subdivision filtering approach comprises analysis and synthesis steps, which means reconstruction and decomposition level in wavelet analysis [26]. Further, it employs quadrature mirror filters (QMF) by the wavelet (high pass a(m)) and scaling (lowpass b(m)) in the discrete wavelet transform [25]. The convolving between an approximate signal at level *i-1* with the coefficients *b(m)* will allow estimating the detail signal at level *i*,

$$a(m) = \frac{1}{\sqrt{2}} \langle \varphi(t), \varphi(2t-m) \rangle \text{ and } b(m) = \frac{1}{\sqrt{2}} \langle \varphi(t), \varphi(2t-m) \rangle = -1^n \times h(1-m)$$ (11)

In this research, undecimated wavelet transform (UWT) was employed because the discrete wavelet transform does not translation invariant. The UWT with Haar wavelet transform was applied to the denoised ECG signal in order to detect the R- peak with decomposition level of one. Further, the heart rate from the ECG signal was computed by estimating the time taken by successive R-R peak.

$$\text{Heart rate (HR)} = f \text{ x } 60$$ (12)

Where f represents the frequency, calculated by taking the inverse of the R-R peak interval.

3. Results and Discussions

3.1 Result of pre-processed signal

Initially, the amplification and low pass filtered were designed in order to acquire and displays the ECG signal. The experiment was performed using a digital oscilloscope to observe the characteristics of the signal as pre- presented in the Fig. 3. It should be noticed that displayed signal is contaminated with noise, which makes difficult to identify the peaks. Therefore, the post-processing was essential to remove the unwanted noise from the signal.

Figure 3. Illustration of pre-processed ECG signal contains the distortion.

3.2 Result of post-processed signal

The post-processing steps involved the digital filter design and denoised of the signal. Figure 4 (Refer subfigure - b, c, and d) elucidate that the filtered signals are noise free. Further, It is observed that reconstructed signals are quite clean after denoising (Refer Fig. 4-e). In addition, computation of SNR reveals that remaining noises were also removed from the signal. The calculated SNR for the different wavelet transform is presented in Table I. It can be noticed that sym8 has slightly higher SNR compared to the wavelet transform. Therefore, the sym8 with the decomposition level of 7 via a soft threshold was employed in this study.

Table 1. Signal-to-noise ratio to select the wavelet transform method for the denoising

[a]Segmented ECG signal (Recording time in second)	Wavelet transform	SNR
30	db8	46.5687
30	db2	52.37
30	haar,	56.67
30	bior3.9	44.56
30	bior1.3	46.32
30	bior6.8	42.65
30	sym6	55.63
30	sym8	58.75

[a]Segmented ECG signal utilized the length of the 30-second epoch to compute the SNR.

The virtual instrument based real-time ECG monitoring device is developed successfully, which is capable of detecting the R-peak and heart rate of the healthy subjects by employing the multivariate transform as presented in Fig. 4. The lead II configuration is utilized to acquire the ECG signal by placing the surface electrode on the chest of the subjects as presented in Fig. 5. Figure 5 exhibits the preliminary set-up of the developed ECG monitoring device.

Figure 4. (a) Raw ECG signal acquired by one of the healthy subjects; (b) After applying the notch filter (47 to 53 Hz); (c) IIR Band Pass filtered (0.05 to 20 Hz); (d) FIR high pass filter using Kaiser window (order of 56 and cut-off frequency of 3.5 Hz); (e) Denoised signal; (f) R-peak detected by the multiresolution wavelet transform.

Figure 5 (a). ECG acquisition and heart rate monitoring device

Figure 5 (b). Illustrates the heart rate and R-R interval of the proposed ECG monitoring system.

4. Conclusion

This paper presents a real-time ECG monitoring system using a virtual instrument. The wavelet denoising was incorporated in order to remove the power line interferences and baseline wondering in real time. The various wavelet such as db8, db2, haar, bior3.9, bior1.3, bior6.8, sym6, and sym8 was examined and signal-to-noise ratio value was estimated in order to find out the best. Finding suggests that sym8 contains higher SNR, followed by haar wavelet. Hence, sym8 was integrated to denoise the signal. Further, the multiresolution wavelet transform was applied in order to detect the R-peak in contrast to the traditional method because it allows identifying the long-term trend and short-term variations of the signal. In addition, the heart rate was calculated based on successive RR-interval. In the future, the developed device will be tested with healthy subjects in order to standardize the functionality. In addition, significant features will be extracted from the morphology of the ECG signal and incorporated into the developed device for the assessment of cardiovascular diseases.

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