Biosensor Interface Controller for Chronic Kidney Disease Monitoring Using Internet of Things (IoT)

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Abstract. This paper describes the simulation done on a low-cost biosensor interface controller for Chronic Kidney Disease (CKD) monitoring system using Internet of Things (IoT). Healthcare monitoring systems are devices that keep track of human activities and health conditions using biosensors. The developed monitoring system will aid in chronic disease patients for early detection of prevailing diseases. Early prevention can be done by monitoring the electrocardiogram (ECG). However, ECG signals typically contain contaminants that cause inaccuracy in the ECG signals produced and difficulty in diagnosing the heart’s activity. The objective is to design and simulate a system to perform pre-processing of ECG signals to prevent ECG measurements from signal contamination. Next, to calculate the heart rate using filtered ECG signals and the Pan-Tompkins algorithm. The simulation was done on MATLAB and Simulink by generating pre-recorded ECG signals that will be pre-processed to obtain viable results when compared to a normal ECG cycle wave. The results show that the filtered ECG produced has all the elements of a normal ECG cycle wave with less signal contamination within the range of 0.8 – 1.3mV. The filtered ECG signals were processed for QRS peak detection to obtain the heart rate. Results show that the heart rate displayed was within the range of the pre-recorded heart rate which is 79 – 82 beats per minute (BPM). The QRS peaks detected were also identical to the results from the Pan-Tompkins algorithm.

1. Introduction
Healthcare monitoring systems are widely used to monitor patients with severe or chronic disease [1]- [2]. Healthcare monitoring systems are devices that keep track of human activities and health conditions using wireless sensors network (WSN) [3]-[4]. Chronic disease mortality rates have been reported to increase in 2005 with a total death count of more than 58 million around the world [5]. In Malaysia, a recent report done by the National Renal Registry states that the number of new dialysis patients has increased over the span of 10 years from 4,606 in 2008 to 8,431 in 2018 [6]. Hence, healthcare monitoring systems are playing a vital part in observing the vital signs of patients as well as detecting prevailing diseases earlier. However, one of the downsides of a healthcare monitoring system is the expensive cost of equipment. Countries with low and high income have been spending a huge amount of money on chronic diseases [7]. Diseases that prevail from chronic diseases can be prevented by monitoring specific vital signs of the patients. In this case, Chronic Kidney Disease (CKD) is known to prevail other chronic diseases such as cardiovascular disease (CVD) and...
anemia [8]. Previous studies show that the prevalence of CVD [9] and Anemia [10] is high in CKD patients due to the low erythropoietin hormones in the body. Early prevention can be done by monitoring the electrocardiogram (ECG), heart rate, and blood oxygen level ($SpO_2$). Simulation on the biosensor interface controller was done on MATLAB and Simulink. The AD8232 ECG sensor was used to get the ECG measurements.

ECG signals typically contain contaminants that can be classified into the following categories. Those are power line interference, electrode pop or contact noise, patient–electrode motion artifacts, electromyographic (EMG) noise, and baseline wandering [11]. These contaminants cause inaccuracy in the ECG signals produced and difficulty in diagnosing the heart’s activity. The AD8232 has an integrated Analogue Front End (AFE) of Analog Devices. The AFE performs pre-processing of ECG signals to prevent ECG measurements from contamination. Pre-processing is important to produce accurate signals which will be used to calculate the heart rate as well as diagnosing the heart’s activity. This paper will focus on the simulation of ECG signal processing using MATLAB and Simulink for heart rate detection. The pre-processed ECG signals produced from the AD8232 will be used to produce ECG signals and heart rate.

2. Literature Review

2.1. ECG Signals

A typical ECG machine functions to acquire electric signals of the heart’s activity. The ECG machine will display a graph containing the information on the heart’s activity. The normal heart will display a normal cycle wave. Figure 1 shows the normal cycle wave of the heart. The P wave represents the contraction of the atrium to push blood into the ventricle. The QRS wave complex represents the contraction of the ventricle.

The heart rate of a patient can be calculated using the ECG signals by detecting two similar peaks of the signal. The R peak is the point with the highest amplitude of the ECG signal making it to be detected easily. In previous studies, the QRS complex is filtered out for easy detection of R peaks [12]. The R peaks then can be used to window the R-R interval as it is easily distinguished in the ECG signal. The R-R interval can be used to calculate the heart rate of a person. Figure 1 shows the R-R interval in an ECG signal.

The number of QRS peaks that are detected in one minute is used to calculate the heart rate (HR) in beats per minute (BPM) [13]. The heart rate can be calculated using equation (1).

$$HR = \frac{60,000}{R-R \text{ interval}(ms)}$$  \hspace{1cm} (1)

Millisecond is used to calculate because the R-R peaks will be detected in millisecond. Therefore, the R-R intervals will be divided into one minute. For an example, if the R-R intervals is 500ms, \((60,000/800)\text{ms} = 75\text{BPM}\).

![Figure 1. R-R peak intervals in normal ECG cycle wave[11]](image)

The AD8232 is an integrated signal conditioning block for ECG and other bio-potential measurement applications. The AD8232 is compatible to be interfaced with an Inter-Integrated Circuit ($I^2C$) of the Arduino UNO microcontroller. The AD8232 is integrated with an AFE which is capable to extract, amplify, and filter small bio-potential signals in the presence of noisy conditions. This means noise created by the motion or remote electrode placement and other signal contamination can
be reduced. The AD8232 comes with 3-lead ECG electrodes which will be connected via a 3mm audio jack.

2.2. Design and Simulation

ECG signals can be broken down into a series of sine waves and triangular waves also known as a Fourier series. These series of repeating sine waves are known to be P waves, T wave, U wave, and a triangular form known as a QRS complex. The addition of these signals forms an ECG signal. The Simulation of ECG was done in MATLAB Simulink using the Pan-Tompkins algorithm [14] for QRS detection. Simulink blocks were used to construct the algorithm for ECG signal processing. Figure 4 shows the Simulink model that was constructed to process ECG signals. This Simulink model functions to filter our noise from the signals produced by the AD8232 sensor, detection of QRS peaks, and determine the heart rate of the patient.

The ECG signals from the AD8232 were imitated by using pre-existing ECG signals. The ECG pre-existing signals used has a resting heart rate of 79 – 82 BPM. Thus, if the heart rate display block displays a heart rate within a range of the input heart rate, the Simulink model of this ECG signal processor is validated. The sample rate converter block is used to convert the sample rate from the AD8232 to match the output sampling rate. The sample output rate was set at 200Hz with a tolerance of 0.01. The sample rate converted was also set with a 198Hz two-sided bandwidth of interest. Before the signal goes through the sample rate converter, it will go through a buffer. The buffer block will convert the scalar samples to a lower output rate. The output buffer size was set at 90 per channel.

The ECG signal processor block is a Simulink subsystem block which consists of a Bandpass Filter, Differentiator Filter, Moving Average Window, QRS Peak Detection, and Unbuffer. The ECG signal processor functions to filter the ECG signal to find out the patient’s heart rate. The bandpass filter is a combination of a high-pass filter and a low-pass filter [15]–[17]. The bandpass filter is used to remove noise from muscle motions, respiratory variation, and baseline wander. In this model, the bandpass filter was set to correct any attenuation of the QRS complex and remove artifacts from the motion of the heart. The transfer function of the second-order low-pass filter is shown in equation (2), where the high cutoff frequency is about 11Hz.

\[
H(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2}
\]  

(2)

Equation (3), the transfer function of the high-pass filter where the low cutoff frequency is about 5Hz.

\[
5Hz.H(z) = \frac{z^{-16} + z^{-17} + \frac{1}{32}z^{-32}}{1-z^{-1}}
\]  

(3)

This differentiator filter applies a full-band differentiator filter on the input signal to differentiate all the frequency components [15]–[17]. This block is built using an equiripple Finite Impulse Response (FIR) filter design. The filter order of this block is set at 51 with a maximum passband ripple left at default. The differentiator filter was built using the Pan-Tompkins algorithm is shown in equation (4) where the output signal delay is 2 samples.

\[
H(z) = \frac{1}{10}(-2z^{-2} - z^{-1} + z^1 + 2z^2)
\]  

(4)

The moving average window was developed using a ‘Discrete FIR Filter’. This block is used to shift the data collected one data at a time. The window size was also determined in this block. The Pan-Tompkins algorithm is shown in equation (5), where N is the width of the window and depends on the number of samples.

\[
y(nT) = \frac{1}{N}[x(nT - (N - 1)T) + x(nT - (N - 2)T) + \cdots + x(xnT)]
\]  

(5)
detecting the R peaks and the threshold of the ECG signal. First, the parameters of the R peaks and the threshold are declared. The amplitudes of R peaks are coded to detect a range of $0.05 - 0.07$mV with a width of larger than 10ms. Any signal not in the stated range will not be detected and will be considered noise. The threshold is determined using the mean estimates of average QRS peaks with 8 samples and the average noise peak. With the detected R peaks, the R-R peaks will be used to determine the heart rate. The QRS peak detection is built using the Pan-Tompkins algorithm below.

$$\text{Peak} > \text{ThrSig} \rightarrow \text{SigLev} = \frac{1}{8} \text{Peak} + \frac{7}{8} \text{SigLev}$$

$$\text{ThrNoise} = \frac{1}{2} \text{ThrSig}$$

Where $\text{Peak}$ is the overall peak. $\text{ThrSig}$ is the threshold applied to the signal peak. $\text{SigLev}$ is the running estimate of the signal peak. $\text{ThrNoise}$ is the threshold applied to the noise peak.

### 3. Results and Discussion

The simulation was done using MATLAB and Simulink to process the ECG Signals to obtain filtered ECG Signals, QRS Peaks, and heart rate. Figure 2 shows the filtered ECG signals that were generated using pre-recorded ECG signals. The ECG signal generated has a heart rate range of 79 – 82 BPM. The filtered ECG signal clearly shows the normal sinus of the patient with a resting heart rate of 79 – 82 BPM when compared to a normal ECG theoretical cycle wave. The y-axis shows the amplitude of the signals in mV and the x-axis shows the time in seconds. The peak amplitude of the P, R, and T wave are in the range of 0.8 – 0.9mV, 1.0 – 1.3mV, and 0.9 – 1.0mV respectively. The peak amplitude of the T wave is greater than the P wave as expected.

![Figure 2. Filtered ECG Signal Simulink Scope](image)

Figure 3 shows the ECG signals at various steps in digital signal processing for QRS peak detection. The results are identical in every step when compared to the Pan-Tompkins algorithm results. The y-axis represents the amplitude in mV and the x-axis represents the time in seconds. Figure 3(a) shows the output of the ECG signals after filtered using a bandpass filter algorithm. When comparing it to Figure 2, it is definite that the peak amplitudes of P, T, and U wave are lower compared to the signals in Figure (a). The bandpass filter has filtered out the high and low signals causing the P, T, and U waves to have a lower amplitude by using a low-pass and high-pass filter algorithm. Figure 3(b) shows the output from the next process of ECG signals after filtered through a differentiator filter. The output displays the QRS complex with higher amplitude and the P, T, and U waves in a lower amplitude. The R peak amplitude has decreased from 0.3mV to 0.12mV while the peak amplitude of P, T, and U are in the range of 0.01 – 0.04mV. This filter also has remove the negative values in figure 3(a). Figure 3(c) shows the output of the moving average filter. The moving average window produces a signal that includes information about both the slope and the width of the QRS complex. Figure 3(d) shows the final step in signal processing for QRS peak detection. The processed signals show a stream of pulses marking the locations of the QRS complexes after application of the adaptive thresholds. At the same time, the moving average window completely filters out the P, T, and U. The amplitude of these pulses is in the range of $0.05 - 0.07$mV.
Figure 3. QRS peak detection signal processing steps. (a) Output of Bandpass filter. (b) Output of Differentiator filter. (c) Output of Moving Average Window (d) Output of QRS Peak Detection

Figure 4 shows the Simulink model in operation. The ECG source generated was set at 79 – 82 BPM and the heart rate displayed on the display Simulink block is 80 BPM. The heart rate was calculated using the QRS peaks detected in Figure 3(d). One second is equivalent to 60Hz, which means if more than one QRS peak is detected within a second, the signals have a frequency of more than 60Hz. According to Figure 3(d), it is observed that more than one QRS peak is detected within a minute. This implies the heart rate of this ECG signal to be higher than 60BPM. Thus, alluding the Simulink block can process the ECG signal to obtain the QRS peaks and heart rate. Otherwise, if a heart rate range of 79 – 82 BPM was not displayed, then the Simulink model is imposed to have an error.

Figure 4. Operating Simulink model displaying the heart rate

4. Conclusion
The pre-processing of ECG signals was designed and simulated using MATLAB and Simulink to prevent ECG measurements from signal contamination. The heart rate was calculated using filtered ECG signals and the Pan-Tompkins algorithm. The filtered ECG was within the range of the expected peak amplitudes without noise or artifacts caused by muscle motions, respiratory variation, and baseline wander motion. The detected QRS peaks do not have any noise causing the heart rate to be detected correctly. The R peaks in the QRS complex that was filtered were in the expected threshold range of 0.05 – 0.07mV. The heart rate of the processed signal unveils the expected range of 79 – 82 BPM. Thus, proving the algorithm used to develop Simulink blocks for heart rate detection is valid.

Acknowledgement
This work is funded by Ministry of Education Malaysia under grant (FRGS/1/2018/TK04/UKM/02/1) and AKU254:HICoE (Fasa II) ‘MEMS for Biomedical Devices (artificial kidney)’.

References
[1] F. F. Zulkifli, J. Sampe, M. S. Islam, and M. A. Mohamed, “Architecture of ultra low power micro energy harvester using RF signal for health care monitoring system: A review,” Am. J. Appl. Sci., vol. 12, no. 5, pp. 335–344, 2015.
[2] J. Sampe, N. A. A. Semsudin, F. F. Zulkifli, M. S. Islam, and M. Z. A. Razak, “Hybrid energy harvester based on radio frequency, thermal and vibration inputs for biomedical devices,” *Asian J. Sci. Res.*, vol. 10, no. 2, pp. 79–87, 2017.

[3] T. N. T. Mohamad, J. Sampe, and D. D. Berhanuddin, “Design and performance analysis of interface circuits in hybrid input energy harvesting for semi-active RFID tag,” *ASM Sci. J.*, vol. 12, no. SpecialIssue4, pp. 108–117, 2019.

[4] N. H. Mohd Yunus, J. Sampe, J. Yunas, A. Pawi, and Z. A. Rhazali, “MEMS based antenna of energy harvester for wireless sensor node,” *Microsyst. Technol.*, vol. 26, no. 9, pp. 2785–2792, 2020.

[5] WHO, “Preventing Chronic Diseases: A Vital Investment,” 2015.

[6] G. B. Leong and L. D. Guat, *Dialysis in Malaysia*. 2018.

[7] OECD/WHO, *Health at a Glance: Asia/Pacific 2020*, vol. 6011, no. 24312. 2020.

[8] M. E. Stauffer and T. Fan, “Prevalence of anemia in chronic kidney disease in the United States,” *PLoS One*, vol. 9, no. 1, pp. 2–5, 2014.

[9] M. Volpe et al., “Blood levels of erythropoietin in congestive heart failure and correlation with clinical, hemodynamic, and hormonal profiles,” *Am. J. Cardiol.*, vol. 74, no. 5, pp. 468–473, 1994, doi: 10.1016/0002-9149(94)90905-9.

[10] G. Sunder-Plassmann and W. H. Hörl, “Effect of erythropoietin on cardiovascular diseases,” *Am. J. Kidney Dis.*, vol. 38, no. 4 SUPPL. 1, pp. 20–25, 2001.

[11] N. Djermanova, M. Marinov, B. Ganev, S. Tabakov, and G. Nikolov, “LabVIEW based ECG signal acquisition and analysis,” *2016 25th Int. Sci. Conf. Electron.* 2016, 2016.

[12] T. P. Utomo, N. Nuryani, and Darmanto, “QRS peak detection for heart rate monitoring on Android smartphone,” *J. Phys. Conf. Ser.*, vol. 909, no. 1, 2017.

[13] P. F. Shahina Begum, Mobyen Uddin Ahmed, *Physiological Sensor Signals Analysis to Represent Cases in a Case-Based Diagnostic System*. Springer, 2013.

[14] J. Pan and W. J. Tompkins, “A Real-Time QRS Detection Algorithm,” *IEEE Trans. Biomed. Eng.*, vol. 32, no. 3, pp. 230–236, 1985.

[15] M. Faseehuddin, J. Sampe, and S. Shireen, “Lossy and lossless inductance simulators and universal filters employing a new versatile active block,” *J. Microelectron. Electron. Components Mater.*, vol. 48, no. 2, pp. 97–113, 2018.

[16] M. A. Albrni, M. Faseehuddin, J. Sampe, and S. H. M. Ali, “Novel dual mode multifunction filter employing highly versatile VD-DXCC,” *Inf. MIDEM*, vol. 49, no. 3, pp. 169–176, 2019.

[17] M. Faseehuddin, N. Herencsar, M. A. Albrni, and J. Sampe, “Electronically tunable mixed-mode universal filter employing a single active block and a minimum number of passive components,” *Appl. Sci.*, vol. 11, no. 1, pp. 1–26, 2021.