Design of a Wireless Non-Contact Wearable System for Infants Using Adaptive Filter

Md Shaad Mahmud
University of Massachusetts Dartmouth
North Dartmouth, MA
Email: mmahmud@umassd.edu

Honggang Wang, Hua Fang
University of Massachusetts Dartmouth
North Dartmouth, MA
Email: hwang1,hfang2@umassd.edu

***Abstract*—Cardiovascular signal is a fundamental physiological sign to assess health condition. Continuous and long term health monitoring of infants would be helpful to prevent and predict illness. However, there is no noninvasive method to monitor their health. The developed system consists of a non-contact electrocardiogram (ECG) sensor with fully integrated analog front end (AFE), an accelerometer, and a Bluetooth low energy (BLE) module with USB charging module. The accelerometer output is the reference signal for Least Mean Square (LMS) adaptive filter. The LMS filter is a noise canceler that will adaptively remove the motion artifacts and interferences.**

***Index Terms*—Wearable, BLE, Simblee, ECG, Accelerometer, Health monitoring, infants**

1. Introduction

For infants, continuous and real-time monitoring plays a crucial factor for urgent medical treatment. Cardiovascular monitoring of Neonatal Intensive Care Unit (NICU) is demonstrated by its wide range of use in the medical arena. The neonates are monitored 24 hours a day, and extracted vital signs can be a predetermined factor for early detection and accurate diagnosis. Currently, in the hospitals, it utilizes patches, adhesive gels, and wired sensors to monitor the infants. Besides, premature infants have undeveloped skin, which is uncomfortable, even painful when the sticky sensors must be removed. The study shows that interruption of natural movement, disturbance and less communication with parents has effects on infant's growth and physical development [1]. The most popular issues.

Recently, with the advancement of sensor technologies, wireless communication, and longer battery life has created a new generation of constant health monitoring for infants. In case of monitoring health, ECG signals are most popular for observing heart and cardiovascular diseases. Several proposals have presented for ECG measurement using non-contact capacitive-based electrodes [5]. However, the quality of the ECG signal strongly correlated to noises. ECG signal can be corrupted by power line interference, muscle contraction, baseline drifting, electrode contact noise, and environmental noise. These noises are random in both amplitude and phase, hence designing fixed-point filters won't help to improve the signal. A dynamic system could be the answer for this kind of problem. An adaptive filter, which self-adjusts its output function per an algorithm driven by an error signal. This digital filter can reconstruct the distorted ECG signal, and converges to the optimal solution. Most of the general filters have fixed coefficients, the coefficient of an adaptive filter is dynamic and changes based on the magnitude of the error signal. Figure 1 is a clear depiction of effectiveness of the adaptive filter. The output signal is more accurate and peaks are easily detectable. That is, by means combining the ECG signals with an adaptive filter, the motion artifacts can be reduced [3].

This study presents an improved version of the work previously done in [4] and [5]. We developed a wireless sensor node for long term health monitoring. Two capacitive electrodes were attached to the diaper with the sensor node itself. From our previous studies, we realized, larger electrodes provide high gain and signal-to-noise ratio (SNR), however the trade-off is with higher motion artifacts. The improvement of the developed system is:
(1) Extraction of ECG signal in a non-contact manner with reduced motion artifacts using adaptive filters. The whole sensor node, including the electrodes was mounted on baby diaper around the abdomen.
(2) The rule of thumb while designing wearable sensor, user comfort should be considered. Therefore, our system is very compact in size only 51mm X 16mm X 6mm.

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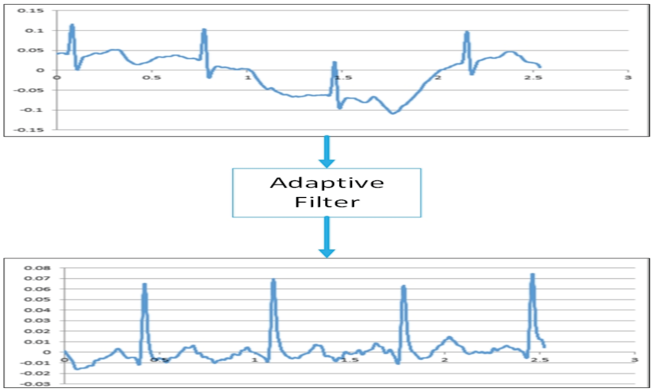

Figure 1. Effectiveness of the LMS adaptive filter.

(3) This system can run for months with a single charge. We used low power components, like, a single-chip instrumentation amplifier with low power and noise. The AD8232 runs on very low supply current of 180 uA. Also, the wireless communication is achieved with Bluetooth low energy (BLE).
(4) A wireless microprocessor is used to process the data, which includes IoT features. All the components are surface mounted to save space and power. The distance between electrodes and the preamplifier were shortened to reduce external noise.
(5) The system provides a real time solution which can later be used for prediction of different syndromes. Our system can detect arrhythmia or syncope from the ECG signal. In addition, to improve the SNR, adaptive filter is implemented. Finally, to validate the work we compared the results with a commercial non-contact health monitoring device.

2. MOTIVATION AND BACKGROUND

When developing the wearable sensor for health monitoring, it is important to realize that these devices will be used by medical professionals, the quality and the accuracy should be as high as possible. Most of the wearable devices suffer from a common problem, motion artifact. Using adaptive filter can improve the accuracy of the measurement while body movement or any other external noises.

With the conventional ECG measurement system, sophisticated equipment and wired wet adhesive gel based electrodes are required, and it is not feasible for long term monitoring specially with premature infants. It can be the cause of skin irritation, disturbance of natural movements, interrupted sleep, and occurrence of external noise. Many studies have been in recent years to overcome with these drawbacks [6]. Hence, researchers have proposed dry electrodes, which was initially introduced to reduce skin irritation. However, it requires a high input impedance to electrodes. To overcome this high input impedance amplifier can be used to lower the skin-to-electrode resistance [7]. But, this system requires direct contact with the body, and it is also not feasible for long term monitoring as it leaves marks and creates discomfort. Additionally, the ECG signal was influenced by noise due to hair on the skin.

Yudong et al. placed the electrodes on a chair and a mattress to calculate the ECG, but it still doesn't eliminate the motion artifacts [8]. Peltokangas et al. developed a multi-channel method to acquire high quality ECG signal. Eight electrodes were stitched to a bed sheet and ECG signals were recorded from different channel. Also, Wu et al. tried the similar method and added an individual pre-amplifier to each electrode to improve SNR [9]. But this was limited due to the size of the electrodes, this system was unable measure ECG when lying on the edge of the bed. Yousefi et al. and Maryam et al. developed a bio wearable sensor with adaptive filter, but it was exposed and had a high risk of corrupting the signal [10]- [11]. Chi et al. proposed a capacitive bio-potential electrodes with the features of body sensor network [12]. It consists of a conductive plane as a reference to eliminate the grounding effect. Electrodes were made as the size of coin and it could operate with 3.3 V supply voltage. The system was tested at varying separation between the skin and electrodes. Later, the same author implemented a dry active electrode made of FR4 PCB. Which can measure ECG through insulation fabric. A direct comparison of different studies based on their performance could be difficult to accomplish, as they use different scenario, datasets and measurement technology.

3. METHODS AND MATERIALS

3.1. Method

We developed a wearable system, consisting of sensors for non-contact ECG measurement and accelerometer based adaptive filter to remove noise. The size of the complete system is very compact and can be installed quickly. Currently, measuring ECG of infants requires tedious preparation, sophisticate and bulky equipment's, let alone discomfort. The conventional electrode surface is made of silver/silver Chloride (Ag/AgCl), copper or gold coated and the size of both the dry and wet electrodes are not small. For this study, small-scale capacitive electrodes were attached to the diapers. In previous studies, the researchers placed the flexible electrodes on top of the chest to reduce the air gap between electrode and the body [8]. However, due to the rib motion, the surface was always unbalanced. This eventually cost the effectiveness of the wearable system. Since in this case, the electrode was placed around the abdomen the advantages are quite significant, such as constant pressure and reduced air gap, as shown in figure 2. It also shows the acceleration axes, which indicates the longitudinal element (Y), lateral element (X), and sagittal element (Z). The subjects were asked to lay down and placed in a sleeping position with the sensor node attached to the abdomen.

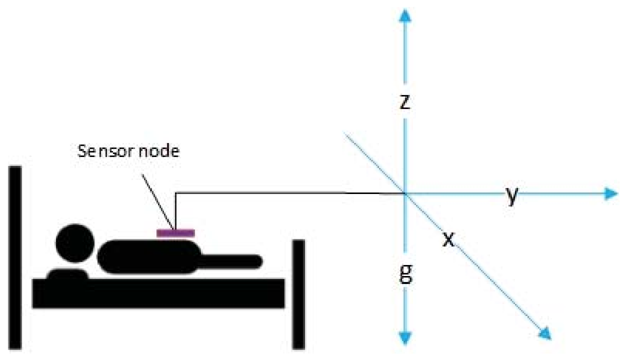

Figure 2. Generated coordinates and vector direction of gravity while sleeping horizontally.

3.2. System Design

The integrated system comprised of electrodes with shielding, an analog front end, a wireless microprocessor, charging circuit and Lithium-ion battery. The wireless unit is used as a local processor which sends the data to the host system through Bluetooth 4.0. The front side has two capacitive electrodes for ECG measurement. Figure 3 shows a block diagram of the measurement system. To get the best result, two buffer circuit was attached to the sensing electrodes. Signal pre-amplification and filtration is done in the analog front. The AFE is custom designed, fully capable of extracting and smoothing small bio-potential signal in the presence of different noise sources. The Simblee, a single chip microprocessor with BLE capability is chosen to process that in sensor node. It is ultra-low power wireless module introduced by RF Digital Co [13]. The signal is converted to analog to digital converter (ADC), the microprocessor has 12-bit ADC. Also, it supports serial communication as SPI and USART. An accelerometer, ADXL 345 is a three-axis motion sensor. It is connected to the microprocessor to fetch motion activities in different directions. With the help of Inter-Integrated Circuit (I2C) bus communication the accelerometer can talk to the microprocessor. All the components require low power to operate, the overall power consumption is quite small. Simblee has a USB interface to program the processor. It is also used for charging 3.7 V Li-on battery with a power circuit. The output signal can be displayed on a mobile phone or computer. We have developed an app and graphical interface to show the ECG graph. The software can also detect arrhythmia.

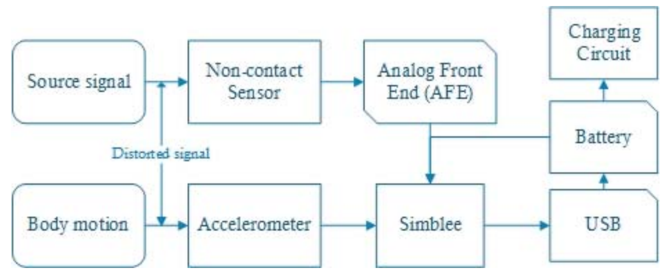

Figure 3. Proposed block diagram of the wearable system.

3.3. Hardware Specification

A prototype was developed and designed to measure the ECG and verify the adaptive algorithm. We developed wearable sensor node with capacitive coupled ECG monitoring system as shown in figure 4, including an accelerometer, battery and electrodes. The hardware module can be divided into three major parts. The first one is the sensing part which is the electrode and an accelerometer. As a non-contact, ECG electrode, EPIC (Electric Potential Integrated Circuit) sensor is used. It can measure ECG, EEG and movement of the eye through cloths or insulators. The PS25255 (Plessy's Semiconductor) is most suitable for our project due to its small size and low power consumption. The actual size of the PS25255 is 10 mm x 7 mm x 2 mm and only consume 40 mA once it is active. For the accelerometer, we selected ADXL 345, which has 400uA of maximum current consumption. The sensitivity of the accelerometer can be adjusted from 1.5g to 16g. For this project, we selected 1.5g so that even a tiny movement can be detected. In the second part, we have a pre-amplifier, which combines multistage amplifier and filtration. As we are trying to measure small changes in electric field, the input impedance of the sensor is important. High input impedance achieved by using single chip instrumental amplifier AD8232, although, PS25255 has a built-in pre-amplifier. The AD8232 provides a CMRR (common-mode rejection ratio) of 80db and only takes 180 uA to operate. The module also has three Butterworth filters, 8th order low pass and 8th order high pass filter with cutoff frequency of 40 Hz and 0.5 Hz respectively. There is an additional noise due to the 60Hz AC power supply, to eliminate this a notch filter was implemented. Multistage amplifier is used to boost the gain up to 1000 V/V. Last part of the hardware belongs to wireless microprocessor and power unit. The AFE is connected to ADC of Simblee RFD77101, which converts the analog signal with a sampling rate of 120 Hz. Simblee is also known as IoT4EE (IoT for Everyone and Everything). Unlike other IoT devices, Simblee can directly upload GUI description code to the cell phone. The USB charging circuit is tested with Lion battery of 3.7 V.

3.4. Adaptive Filter

The idea of canceling or reducing the unwanted signals without distorting the actual signal is very complex, as the noise and relevant signal share the same frequency

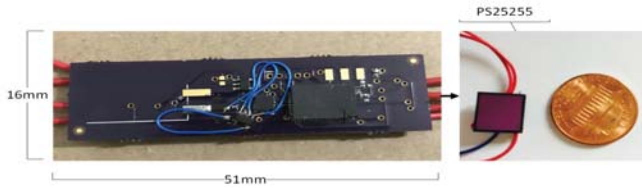

Figure 4. Actual prototype of the wearable system with non-contact ECG electrode.

spectrum. In fact, if the unwanted signal and relevant shares the frequency spectrum, then using a classical filter should be discarded [10]. Overall, for long term monitoring an adaptive filter is essential. This type of filter is used for certain application in which the frequency of the noise is unknown. The coefficient changes continuously with system input. The proposed system utilizes body acceleration movement as a reference to the motion artifacts combined with the noisy ECG signal. The acceleration is obtained from 3-axis accelerometer which is fabricated with a microcontroller. This approach is promising since the body acceleration can also provide level of activity and body orientation of the patient. This information could be a determinant factor for overall status of the health [8].

TABLE 1. DESCRIPTION OF THE VARIABLES

Symbol	Defination
y[n]	Filtered output
x[n]	Noise reference input
M	Filter order
μ	Step size
w[n]	Filter coefficient
e[n]	Error signal
d[n]	Desired output

The LMS error reduction algorithm is one of the popular methods to update the weight of an adaptive filter. The LMS filter requires a tuning set of FIR filter coefficients to model the difference between the input and the reference signal. The computation complexity in LMS adaptive filter is relatively low compared to other adaptive filters. However, it is correlated with the filter order (M), which is the number of coefficients to be used in weight vector. This algorithm updates the weights on a sample-by-sample basis shown in (3) [14]. This is a practical way to calculate the weights of an adaptive filter in real-time as it takes less computation. The scalar operator,μ, known as step-size is relative to stability, learning rate and bandwidth. It is chosen based on characteristics of the input signal. The developed algorithm doesn't require prior information of the incoming signal and instead uses an instantaneous estimate.

The LMS adaptive filter follows the steps given below-
1. Initiate the weights of the coefficients to zero.
2. Set the order and the step size of the LMS adaptive filter.
3. The predictive output is calculated with the equation given below.

$$y[n] = \sum_{i=0}^{M-1} (w_i[n] * x[n-1]) \tag{1}$$

4. Compute the estimated error using this equation-

$$e[n] = d[n] - y[n] \tag{2}$$

5. The new dynamic weights change as shown in equation (3).

$$w_i[n+1] = w_i[n] + \mu * x[n-1] * e[n] \tag{3}$$

X[n-1] is the present input signal, and i is the number iteration. It varies from 0 to M-1. The total number of multiplication in LMS can be defined as 2M+1.
6. These will be circulated in a loop until the output is completely filtered.

The LMS adaptive filter requires less resources such as power, memory, and time to operate compared to other adaptive filters. The length of the filter M is normally set depending on the amount memory require for the filter. The step-size is correlated to the updating process of the filter coefficient. For example, with high value of step-size shows higher rate of convergence. However, it also provides higher chances of getting error compare to small-valued step-size [14].

Before actually implementing the adaptive filter, a simulation was set up using Matlab to roughly represent the actual event. This helps simple testing of characteristics of an LMS adaptive filter. The filtered measured signal if the heart rate signal of the patient, which is derived with Pan-Tomkins algorithm [11].

4. RESULTS

Several measurements were conducted with the developed prototype to demonstrate the ECG and heart rate signal with an adaptive filter. However, special permission needed for an infant's participation in clinical research. Unfortunately, due to this limitation, the experiment was performed by two adults and their physiological data were taken in our department's laboratory. Although a non-contact sensor is the most convenient sensor to measure ECG, when compared to wet contact electrodes, it is much more complex and vulnerable to noise. Therefore, the effectiveness of the electrodes is crucial in this kind of system. Generally, the raw signal generated from our body is in the range of millivolts (mV), hence difficult to extract in a non-contact manner. With the proposed system, the overall quality of the signal was good. In this research, the separation between the sensor and skin was almost constantly which helped to improve the results.

Figure 5 shows the comparison between the proposed ECG system with commercially available EPIC evaluation kit and standard gel-based electrodes. This depicts that our proposed non-contact sensor is competitive against the medical grade ECG sensor.

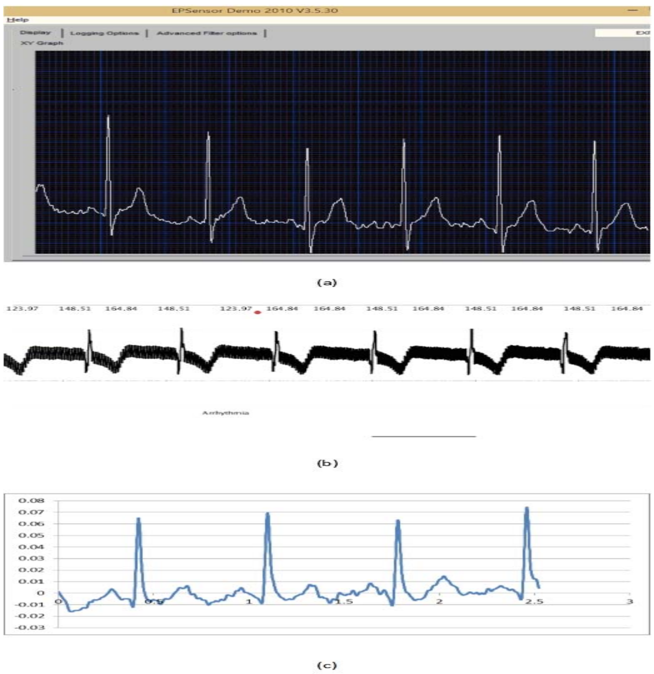

Figure 5. Output signal of the ECG sensor from different system. a)ECG output of the EPIC system b)Filtered output of the proposed system, electrodes placed on the waist with 1V peak voltage c) output of the commercial device with AgCl electrodes.

The optimal solution of the LMS adaptive filter parameter is collected from over 72 independent trials of the experiment. Data is obtained from the abdomen of the subjects. The information was mainly corrupted from one axis: that is parallel to the z axis shown in figure 3.

Since we focus on real-time solution, the LMS adaptive filter was implemented within the microcontroller. The algorithm is tested on Simblee and the output is shown in laptop/PC with the help Processing software. It was found that LMS adaptive filters to show significant improvement in heart rate accuracy. The clock time is selected at 8 MHz, which speed up the execution time to process the data.

From the literature review, it is known that a small step-size is suitable since it provides low error. Larger μ increases the learning rate, but at the cost of higher adjustment error. For real-time health monitoring system low adjustment error is desirable [15]. Experimental results show that the size of the mu should be $0.01 < \mu < 0.028$ which provides lowest Root Mean Square Error (RMSE). Therefore, $\mu = 0.016$ is used to implement the adaptive filter. The different filter order was chosen to show the execution time. The filter order was varied using a constant step-size ($\mu = 0.016$). The accuracy of the heart rate is correlated with filter order. We found that with high order filter decreases the adjustment error. Also, it was expected from previous studies, authors in [12] and [13] used M=10 and M = 20 which significantly reduced the motion artifacts. In this experiment, improvement of RMSE and accuracy were noticed for M = 16. To enhance the accuracy of the measurement, filter order of M = 24 was also tested.

The output ECG signal is processed by an adaptive filet using body acceleration. Instead of using single axis, the experiment was done with sums combination of three axis (X+Y+Z). For example, in case of misalignment, a single axis accelerometer could be misleading. It could provide an ineffective reference signal to the system. Hence, utilizing this method shows improvement in ECG signal. The accelerometer is sampled at 80 Hz, it requires 1 ms to turn on and 0.2 ms to sample the data [15]. The results summarized in figure 6 and 7 show that ECG measurement between adaptive and non-adaptive LMS filter. Figure 6 (a) is the output due to motion artifacts and 6 (b) is the output after applying an LMS adaptive filter. The same results were found in figure 7 where the signal is corrupted by muscle contraction. From these figures, it can be clearly realized that LMS filter has removed all types of noises.

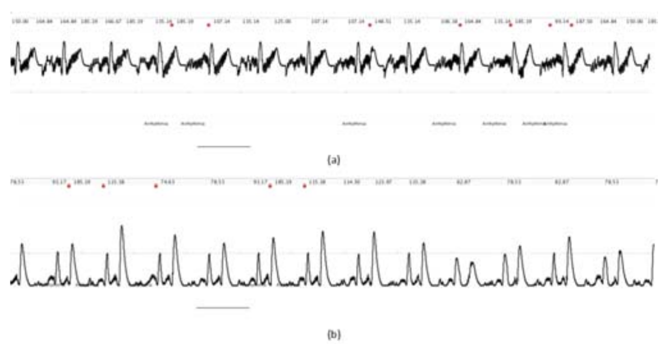

Figure 6. Output of Adaptive Filter under motion artifact

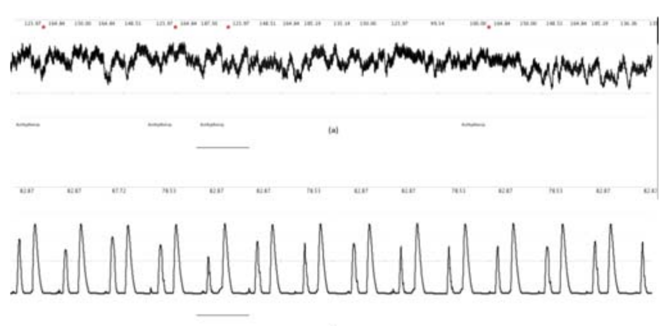

Figure 7. Output of Adaptive Filter under muscle contraction.

To observe the effects of body acceleration, the power spectral density (PSD) was processed using an LMS filter in Matlab. The FFT signals in figure 8 correspond to the experimental results shown in figure 6 and 7. The spectral central frequency of 2Hz resembles to the cardiac frequency during movement. 2.45Hz is the center frequency band of body acceleration. Figure 8 shows that the signal can be attenuated using LMS adaptive filter even if the frequency overlap. Also, the PSD for each axis was calculated, which indicates the movement occur primarily in the Z-direction, although motion in all other direction was also measured.

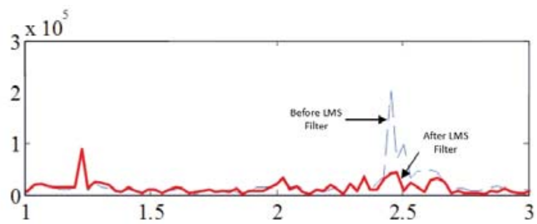

Figure 8. Frequency Spectrum of Standard ECG Signal before and after LMS adaptive filter.

5. CONCLUSION

The studies conducted for this thesis consist of adults laying down in a bed. However, future experiment should consist of infant subjects to determine more effectiveness of the developed prototype with an adaptive filter.

The results show that despite the signal being corrupted by noise and interferences, the use of high precision hardware design and digital signal processing can bring desirable signal output. As the working frequency of medical devices is in the range of 0.01 Hz to 3 Hz (maximum), the signal gets corrupted by interference easily; therefore, filtering, amplifying and separating analog signals needs to be carefully dealt with. The components to design the system were low cost, low power and easy to implement. This can be used for home or remote health monitoring and it does not hamper the daily activity of the patient. Moreover, the system requires no physical connection to the body, which is a very important factor to be taken into consideration when it comes to measure physiological for premature infants. The undeveloped skin of premature infants makes it quite difficult to wire up all the sensors. In the second phase of the research, the plan is to convert the FR4 PCB circuit into a sticker, like flexible PCB, and attach it to a diaper. Finally, the proposed method can be used as an example of smart combination of signal processing and sensor design for a wide range of application.

6. Acknowledgement

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References

[1] M. Choi, J. Jeong, and S. Kim, "Reduction of motion artifacts and improvement of R peak detecting accuracy using adjacent non-intrusive ECG sensors," *Sensors*, vol. 16, no. 5, p. 715, May 2016.

[2] H. J. Lee, S. H. Hwang, H. N. Yoon, W. K. Lee, and K. S. Park, "Heart rate variability monitoring during sleep based on Capacitively coupled textile electrodes on a bed," *Sensors*, vol. 15, no. 5, pp. 11295-11311, May 2015.

[3] M. Magno, L. Benini, C. Spagnol and E. Popovici, "Wearable low power dry surface wireless sensor node for health-care monitoring application", *Wireless and Mobile Computing, Networking and Communications (WiMob)*, Lyon, France, 2013.

[4] S. Mahmud, H.Wang, Y. Kim, D.Li, "An Inexpensive and Ultra - Low Power Sensor Node for Wireless Health Monitoring System," Presented at the *IEEE HealthCom*, Boston, MA, 2015.

[5] S. Mahmud, H.Wang, Y. Kim, "Real time non-contact remote cardiac monitoring," Presented at the *2016 IEEE International Conference on Communications (ICC),* Kuala Lumpur, Malaysia, 2016.

[6] K. K. Kim, Y. K. Lim, and K. S. Park, "The electrically noncontacting ECG measurement on the toilet seat using the capacitively-coupled insulated electrodes," *The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society.*

[7] V. P. Rachim, S.-C. Kang, W.-Y. Chung, and T.-H. Kwon, "Implementation of extended Kalman filter for real-time Noncontact ECG signal acquisition in Android-Based mobile monitoring system," *Journal of Sensor Science and Technology*, vol. 23, no. 1, pp. 7-14, Jan. 2014.

[8] L. Yudong, S. Niu, J. Cordero, S. Yantao, "Development of a biomimetic non-invasive radial pulse sensor: Design, calibration, and applications", *in Robotics and Biomimetics (ROBIO)*, Bali, Thailand, 2014

[9] M. Peltokangas, J. Verho, A. Vehkaoja, "Night-time EKG and HRV monitoring with bed sheet integrated textile electrodes," IEEE Trans. *Inf. Technol. Biomed.*, 2012, 16, 935-942.

[10] R. Yousefi, M. Nourani, S. Ostadabbas, and I. Panahi, "A motion-tolerant Adaptive algorithm for Wearable Photoplethysmographic Biosensors," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 2, pp. 670-681, Mar. 2014.

[11] M. Nasiri, K. Faez, and A. M. Nasrabadi, "A new method for extraction of fetal electrocardiogram signal based on Adaptive Nero-Fuzzy inference system," *2011 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, Nov. 2011.

[12] Yu.M. Chi, S.R. Deiss, G. Cauwenberghs. "Non-contact low power EEG/ECG electrode for high density wearable biopotential sensor networks," Presented at the *Wearable and Implantable Body Sensor Networks,*. BSN, pages 246-250, 3-5 2009.

[13] RF Digital Co. *https://www.simblee.com/* , Accessed on: Dec. 10, 2015.

[14] B. Eilebrecht, T. Wartzek, J. Willkomm, A. Schommartz, M. Walter, and S. Leonhardt, "Motion artifact removal from Capacitive ECG measurements by means of Adaptive filtering," in *5th European Conference of the International Federation for Medical and Biological Engineering*. Springer Science + Business Media, 2011, pp. 902-905.

[15] B. Ko et al., "Motion artifact reduction in electrocardiogram using adaptive filtering based on half cell potential monitoring," *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2012.