

Implementation of Fuzzy-rule based Activity Classification and Optimized Adaptive Filter-set for Wearable ECG Recording

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Abstract

An enhanced and optimized adaptive filter with optimal filter coefficients selection is proposed and implemented to resolve motion artifact issue in wearable ECG Recording. A two-electrode small size chest belt ECG system mounted with 3-axis accelerometer is implemented for ECG and activity ubiquitous recording in daily life. In ubiquitous ECG recording, ECG signal is often distorted due to different state of activity. Body movement incurs activity noise in ubiquitous ECG recording, and causing low accuracy in R-peak (heart beat) detection. Thus, a new adaptive filter methodology is proposed in this paper to look for an optimized filter coefficients base on different state of activity. A simple fuzzy rule-based algorithm is suggested for activity state classification and a set of high pass filter coefficient is applied base on different state of activity. In the case of low activity state, low high pass filter coefficient is used, whereas, in the case of high activity state, a high pass filter coefficient is used. The experiment result shows significant improvement of R-peak detection accuracy during fast movement activity state.

Keywords: ECG, Adaptive Filter-set, Real-time Monitoring

1. Introduction

In medical research field, heart diseases are one of the major causes of death around the world. Another major emerging concern is world population of older people over age 65 is steadily increasing nowadays. Population ageing is a major issue nowadays where the process of older individuals becomes a proportionally larger share of the total population. The older population is growing at the rate faster than the total world's population. It is expected that the number of older persons will be triple over the next 50 years. According to the number of world population by this age group, the number of people in this group is expected will be tripled from 605 million in year 2000 to 1,963 million in year 2050. Thus, ubiquitous healthcare monitoring on ECG signal and activity data has drawn a big interest for various researchers. Simultaneous monitoring of ECG signal and activity data could potentially screen some abnormalities in real time monitoring. Early alarm can cause a pre-alert sign of a personal health status.

Therefore, there are numbers of researches available in the field of ubiquitous monitoring. Ishijima studied on how to measure ECG using conductive fiber [1]. Tamura developed an under bathing ECG measurement system to measure ECG signal at unconstrained condition

[2]. Motion artifact is an undeniable problem that cause serious signal distortion in ubiquitous ECG recording. A general method to eliminate low-frequency component (motion artifact) is to use high-pass filter for filtering the low-frequency component. A higher high pass filter coefficient is required if there is a high distortion in ECG due to motion artifact.

Adaptive filters for motion artifact removal in ECG recording have become a common study [6]. Baseline removal by using impedance cardiograph (ICG) during breathing [7] and power line noise removal and other respiratory interference in the electrocardiogram are heavily studied in literature. However, the ECG signal processing techniques using adaptive filter is not practically implementable in daily life. This is because the existing adaptive filter has its great difficulty in selecting the reference signal when a person is in motion. When outputting an incorrect signal and feeding back the incorrect error, it turns the further computation output even worse. Due to the frequent changes in physical activity, a lot of issues have been raised for discussion in ubiquitous ECG recording.

In this study, a chest-belt type ECG measurement system mounted with three-axis accelerometer is developed and implemented for ubiquitous ECG recording in daily life. Three-axis accelerometer is used to measure the activity data (x, y and z). We propose an adaptive filter using an optimal selected filter coefficient to remove motion artifact. With the obtained three-axis data, activity status can be classified into different states. Optimal filter coefficients are selected to minimize the distortion of ECG signal due to the frequent change of physical activity. The proposed method has significantly improved the heartbeat detection rate during high movement activity state.

2. Implementation and Processing

2.1. Wearable Wireless ECG Measurement System

Figure 1 shows of the system architecture for wireless ECG measurement. It consists of three stages: ECG and Three-axis accelerometer measurement system, wireless transmission, and PC monitoring program. The ECG and Three-axis accelerometer measurement system is to measure ECG data and three axis accelerometer data. Measured data are sent to remote monitoring PC via 2.4GHz Zigbee transmission or sent to Smart phone via Bluetooth transmission. ECG data and three-axis accelerometer data are recorded and monitored wirelessly at remote monitoring PC or Smart phone.

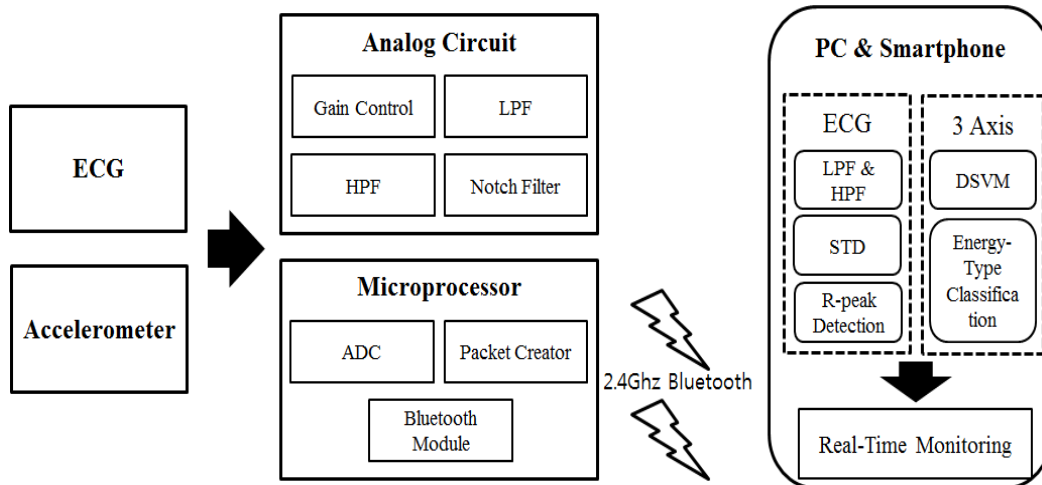


Figure 1. System Architecture for Wireless ECG Measurement

ECG measurement system is integrated with 3-axis accelerometer and mounted on a chest-belt, making a chest-belt type motion tolerance ECG measurement system. Figure 2 shows the block diagram of the chest-belt type ECG measurement system. The ECG measurement system consist of a low pass filter, high pass filter and an instrument amplifier (INA118) Low pass filter is designed with 35 Hz cutoff frequency. High pass filter with 0.05 Hz cut-off is implemented to filter low frequency noise. Twin-T notch filter is implemented to reject 60 Hz power line noise. High frequency component is further rejected at 35 Hz using a second order Butterworth filter. Lastly, the noise filtered signal is further amplified with a gain factor of 20. Output of the analog signal is converted with an ADC and data is sent to PC using Zigbee or sent to Smart phone using Bluetooth transmission. The wireless technology used is depending on the wireless transceiver used. The wireless transceiver used is subject to the receiver wireless technology.

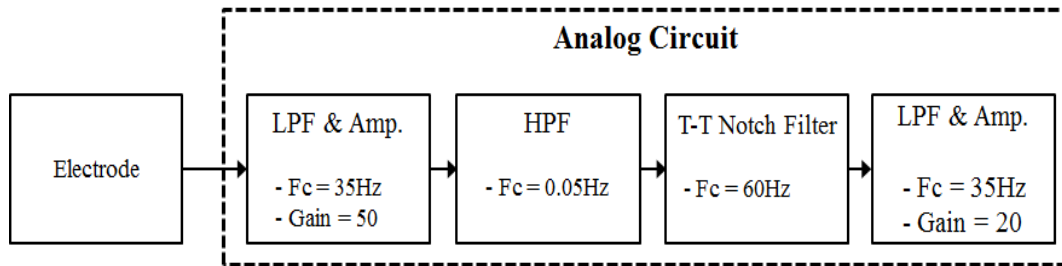


Figure 2. Block Diagram for Chest-belt type ECG Measurement System

Figure 3 show the snap shot of a in-house designed two electrode wearable wireless ECG measurement system. The two electrode chest-belt is easy to be worn around user chest and promote better user flexibility and convenience in real-time ECG measurement.

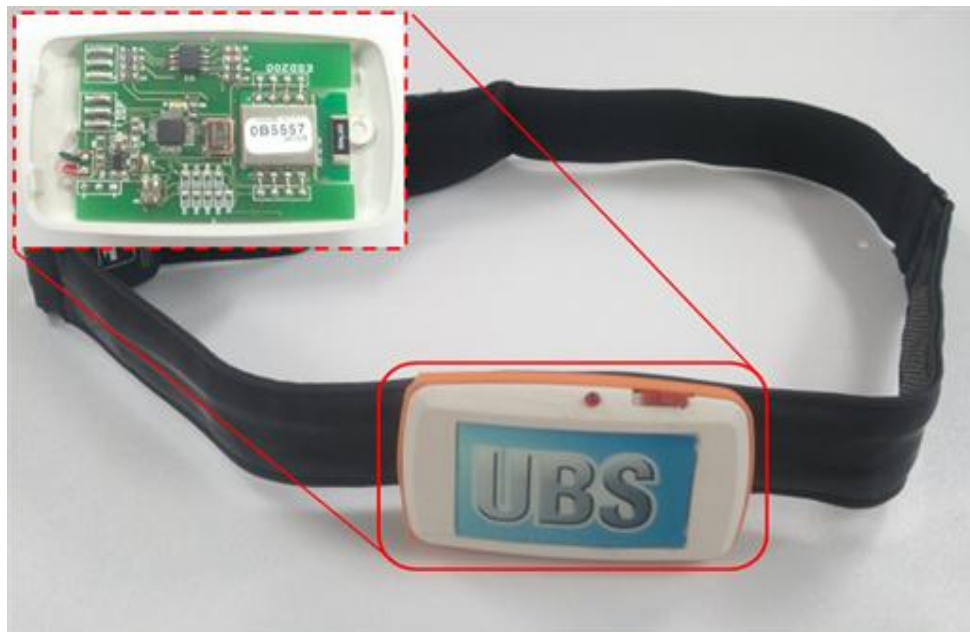


Figure 3. Wearable Wireless ECG Measurement System

2.2. Pre-Processing R-peak Detection Algorithm

In this study, the dedicated R-peak detection algorithm is described in Figure 4 Raw ECG data is first process through a 35Hz LPF using formula $H(z)$. Then the signal is further smoothen using a moving average filter $y(n)$. The final smoothen ECG signal is then being differentiated using equation $y'(n)$. The differentiation process is to enhance the QRS component so that the respective QRS peak can be detected using variable threshold method. Variable threshold is calculated based on equation V_{th} . Every five successive peak detected, the highest peak is excluded to ensure optimum mean result. The average of 4 peak value*0.55 is defined as the threshold for QRS peak identification. The threshold will be recalculated for every five successive peak detect, thus, making a varying threshold value as shown in Figure 5

The enhanced QRS component is originate from differential ECG. Thus the QRS peak detected is not exactly the R-peak in original ECG signal. Therefore, from the QRS peak, we relocate the R-peak in the original ECG signal by finding the maximum point within the window using equation (1). Figure 6 shows the actual R-peak detection in original ECG signal.

$$\text{Actual R-peak}(j) = (\text{QRS_peak}(i)-20:\text{QRS_peak}(i)+20) \quad (1)$$

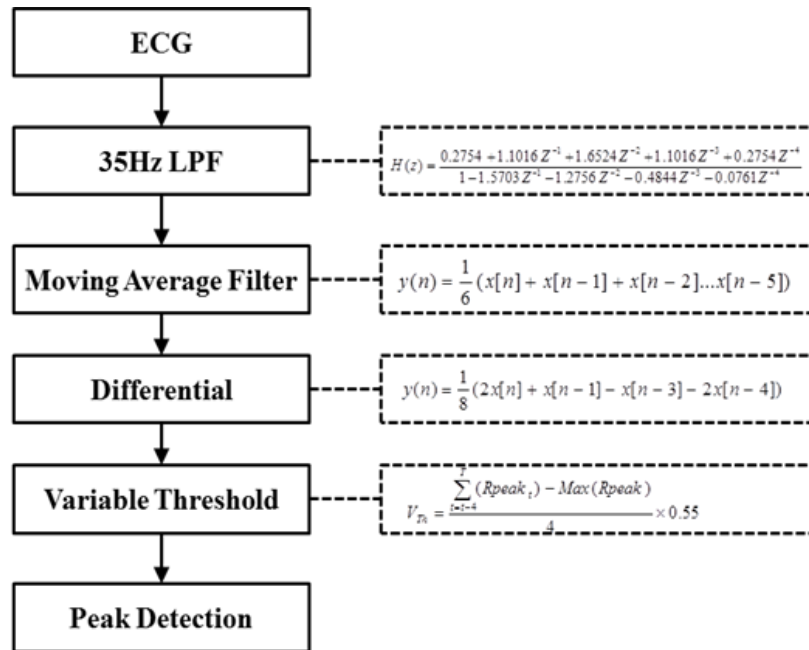


Figure 4. Block Diagram of Pre-processing

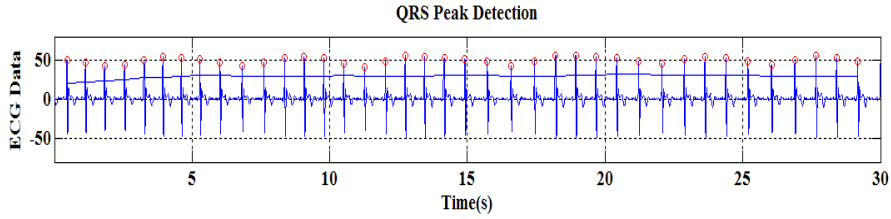


Figure 5. QRS Peak Detection using Variable Threshold

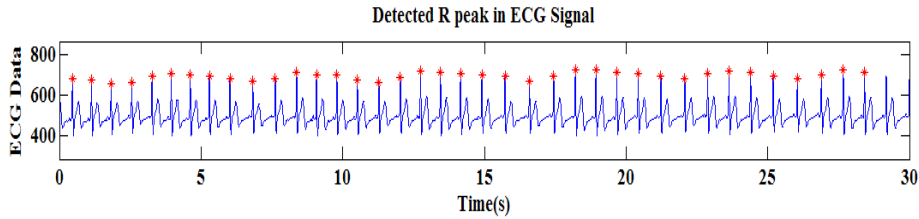


Figure 6. Actual R-peak Detection in ECG Signal

2.3. Adaptive Filter-set

Motion artifact is the key challenge for ubiquitous ECG recording in daily life. The conventional adaptive filter used to filter motion artifact appear to be non-practical due to the frequent changes of physical activity in daily life will cause the frequent changes in filter coefficient, and finally the overload re-calculation data [8, 9].

By adapting the existing studies, we propose a filter set to improve the performance of the R-peak detection. The filter set configuration is shown in Figure 7. A set of high pass filter coefficient for 0, 2, 4, 6, 8 km range from 0.1 to 1 Hz. An optimized filter coefficient is selected based on different activity state. Real time ECG and three-axis accelerometer measurement are recorded. The recorded 3-axis data is used to calculate the integral signal vector magnitude (ISVM) method to classify each of the activity status in daily life [10].

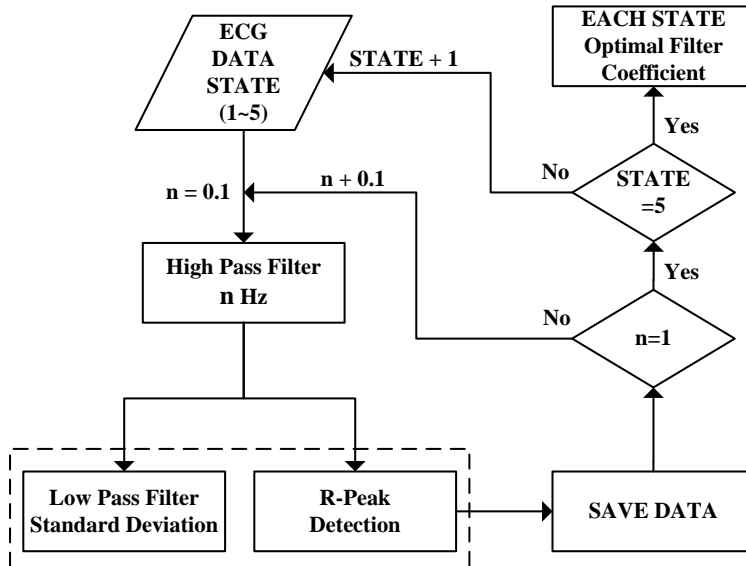


Figure 7. Filter-set Configuration

The sum of squared three-axis accelerometer data (x, y, z) is first performing a root operation, then the result is put into a modules to have only positive integer outcome. Then, we did a summing operation throughout a defined period of time. This mathematical operation is to calculate ISVM and the equation as shown in (2):

$$ISVM = \int_{t=0}^T (SVM) dt \quad (2)$$

While classifying each of the activity status, we apply an optimized filter coefficient to minimize the distortion of the ECG signal and thus improving the accuracy in R-peak detection.

2.4. Activity Classification using Fuzzy Systems

A fuzzy classification algorithm is designed to determine each of the activity state. SVM and ISVM are calculated by using 3-axis data. The mean and variance of ISVM are also calculated. Fuzzy classification system makes use with ambiguous information effectively to perform accurate probability plotting. Knowledge based fuzzy rule set contain a list of expert control rules and the content is represented by language rule. Decision making is performed base on the fuzzy rule set in the knowledge base.

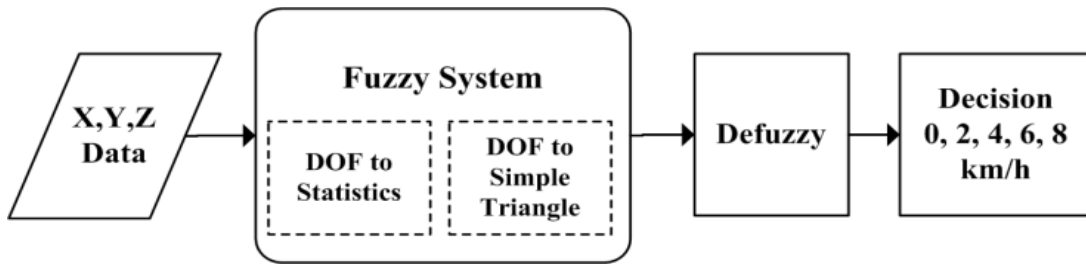


Figure 8. Structure of Fuzzy Classifier

The final outcome of defuzzification is to determine five activity states: 0, 2, 4, 6, 8km/h. The proposed structure of fuzzy system is shown in Figure 8.

Statistic ISVM data are first transformed into simple triangle membership function to represent each the activity state. Then, the average value and standard deviation of each of the membership function is calculated. The membership functions are overlapped with each other by extrapolating the absolute true value (y-axis) of a membership function to average ISVM value (x-axis) of another membership function. The goodness of fit of the membership function is calculated as per equation (3) and (4)

$$w_i = u_{Ai}(ISVM(DOF \text{ to } statistics)) \wedge \quad (3)$$

$$u_{Bi}(ISVM(DOF \text{ to } simple \ triangle))$$

$$S = \sum_{i=1}^n w_i C_i / \sum_{i=1}^n w_i \quad (4)$$

3. Experiment and Results

3.1. A Set of High-pass Filter Coefficients

A set of high pass filter coefficients from 0.1 to 1.0Hz is implemented on each of the activity status: 0, 2, 4, 6, 8 km. The performance evaluation on the active filter set has been carried out.

Total of 10 healthy experimenters are asked to record their ECG data and Three-axis accelerometer data under different activity state: 0, 2, 4, 6, 8 km. For each of the experimenter, a three minutes ECG data and 3-axis accelerometer are recorded for each of the activity status: 0, 2, 4, 6, 8 km. Finally, standard deviation and DSVM for each of the activity is calculated based on the collected data.

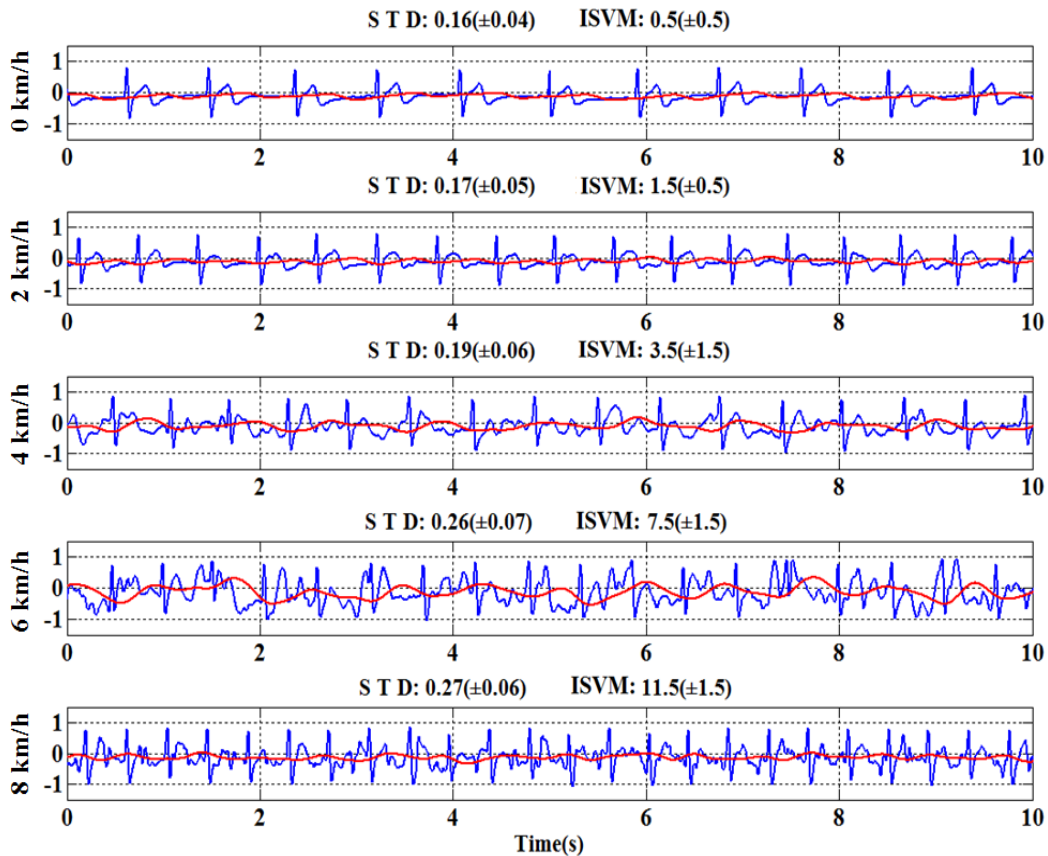


Figure 9. STD and ISVM of each State

Figure 9 shows a plotting of STD versus waking speed and ISVM versus walking speed. The results show variable filter coefficient is used due to the STD and ISVM.

Table 1. Changes According to the Filter Coefficients

HPF (Hz)	6 km/h			8 km/h		
	SE (%)	+P (%)	FDR (%)	SE (%)	+P (%)	FDR (%)
0.6	96.57	95.77	0.25	94.95	94.41	0.32
0.7	96.94	96.14	0.08	95.21	94.67	0.12
0.8	97.43	96.62	0.00	95.34	94.85	0.08
0.9	97.66	96.85	0.00	95.85	95.35	0.06
1	98.16	97.45	0.00	95.09	95.71	0.06

$$Sensitivity(SE) = \frac{TP}{TP + FN} \quad (5)$$

$$Positive(P) = \frac{TP}{TP + FP} \quad (6)$$

$$Failed\ Detection\ Rate(FDR) = \frac{FD}{Number\ of\ Peak} \quad (7)$$

At the state of no activity, or 2 or 4km/h, a low pass filter coefficient with less than 0.5Hz is applied and there is high success rate in R-peak detection. However there is low heartbeat detection rate in the case of 6 and 8km/h. Therefore, we select a higher high pass filter coefficient (0.6Hz and above) to retain the success rate in R peak detection. Table 1 shows the use of high pass filter coefficient from 0.6Hz to 1.0Hz in activity status: 6and 8km. When we are detecting the normal R peak, it means true positive (TP); when detecting the peak point but is not an R-peak, it means false positive (FP); when there is an additional peak point detection, it means fail negative (FN); when there is no peak point detected, it means fail detection (FD).

In addition, the sensitivity, positive and fail detection rate are calculated by using formula (5), (6), and (7) respectively. In the case of 6km, a high pass filter coefficient of 0.8Hz is selected and in the case of 8km, a high pass filter coefficient of 0.9Hz is selected. With the selection of 0.8and 0.9Hz high pass filter 6and 8km respectively, a high heartbeat detection rate is achieved.

3.2. Determine the Activity Status

ISVM based on the experimental data is calculated to determine each of the activity status. Figure 10 shows the result of ECG filtering for each of the activity status.

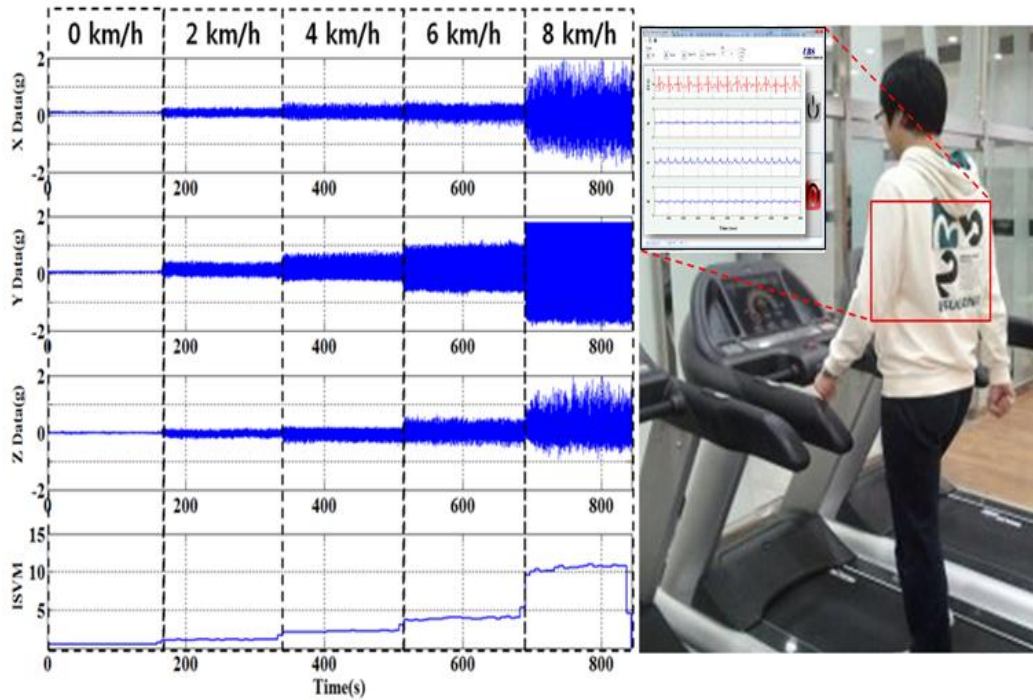


Figure 10. Result of ISVM Calculation Base on Real-time Experiments

We classify the state of movement speed into two categories: slow movement category (0, 2, 4km) and fast movement category (6 and 8km). Under slow movement category, high pass filter coefficient with 0.5 Hz or below is selected for motion artifact filtering. Motion artifact is seen to be removed effectively using the respective filter coefficient and R-peak detection rate is increased. However, the distorted ECG signal can only be partially recovered under fast movement category due to the reason of high motion artifact during fast movement (6 and 8km).

In this paper, we show the capability of selecting filter coefficient base on different speed of movement. From Figure 11, we can observe that a lower filter coefficient is selected when there is slower in movement, whereas, a higher filter coefficient is selected when there is faster in movement.

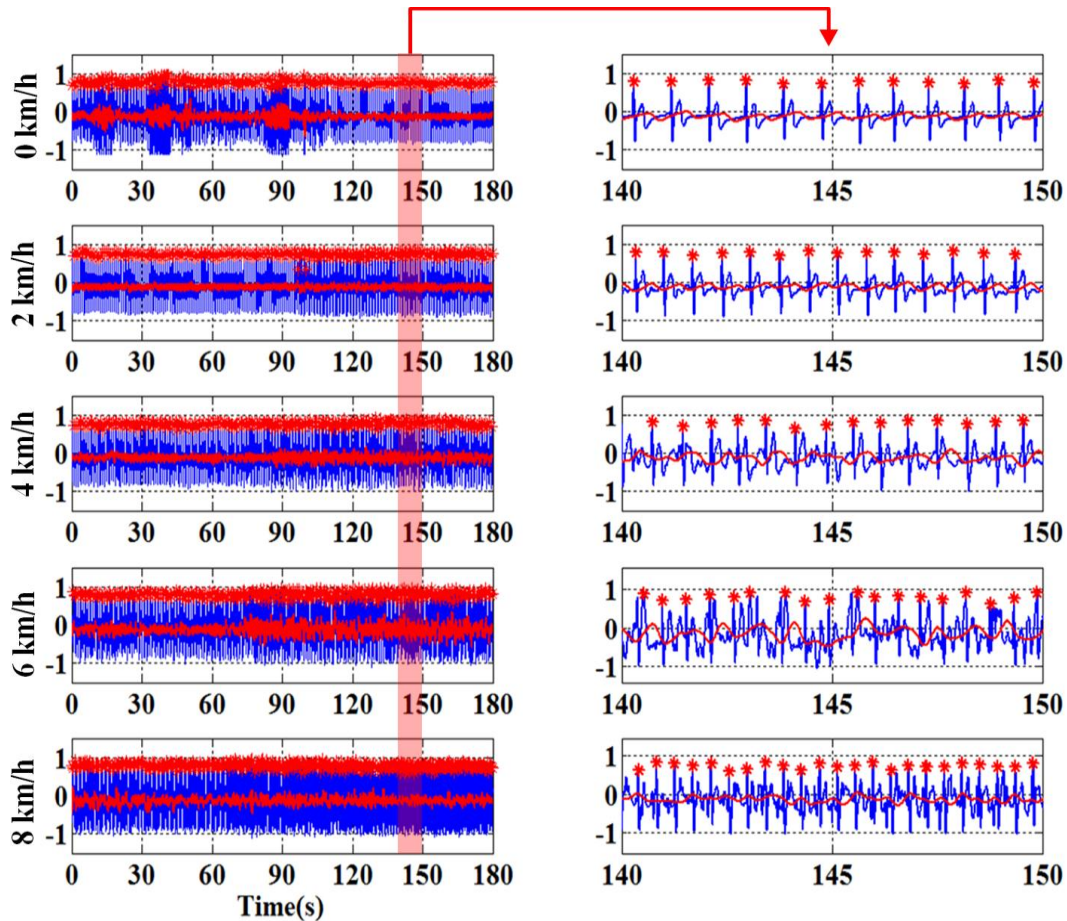


Figure 11. Result of ECG Filtering

3.3. Long Term ECG Measurement in Real-time

A real time experiment has been set up to evaluate the performance of optimal filter-set coefficients on daily life long-term ECG measurement. In the experiment, 3-axis data are recorded for activity state classification.

Throughout the experiment, user is wearing the wearable wireless ECG measurement system and walked around in Dongseo University school compound. The walking distance is approximately to be 2km and the walking route is as shown in Figure 12. ECG signals and 3-axis acceleration data are recorded simultaneously throughout the walking activity and the signal monitoring display is as shown in Figure 13.

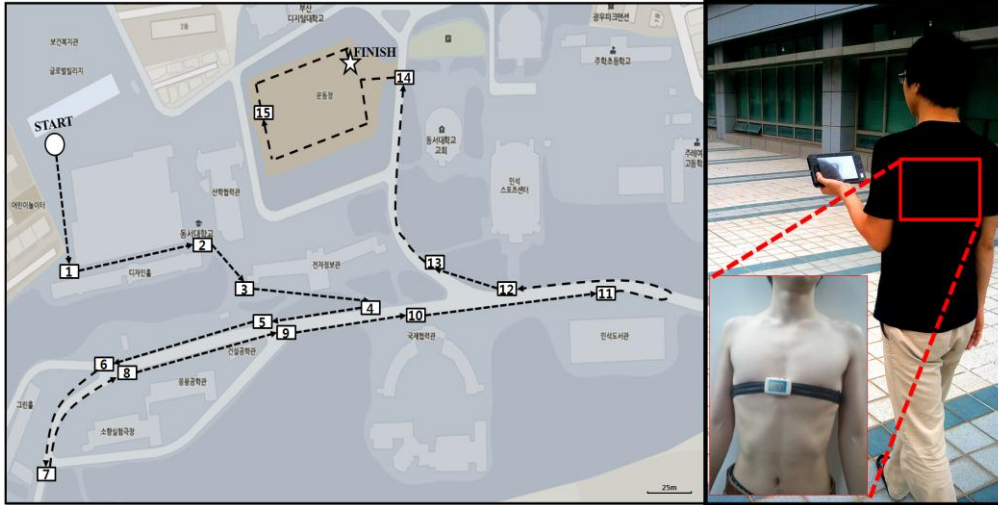


Figure 12. Experiment Route Long-distance

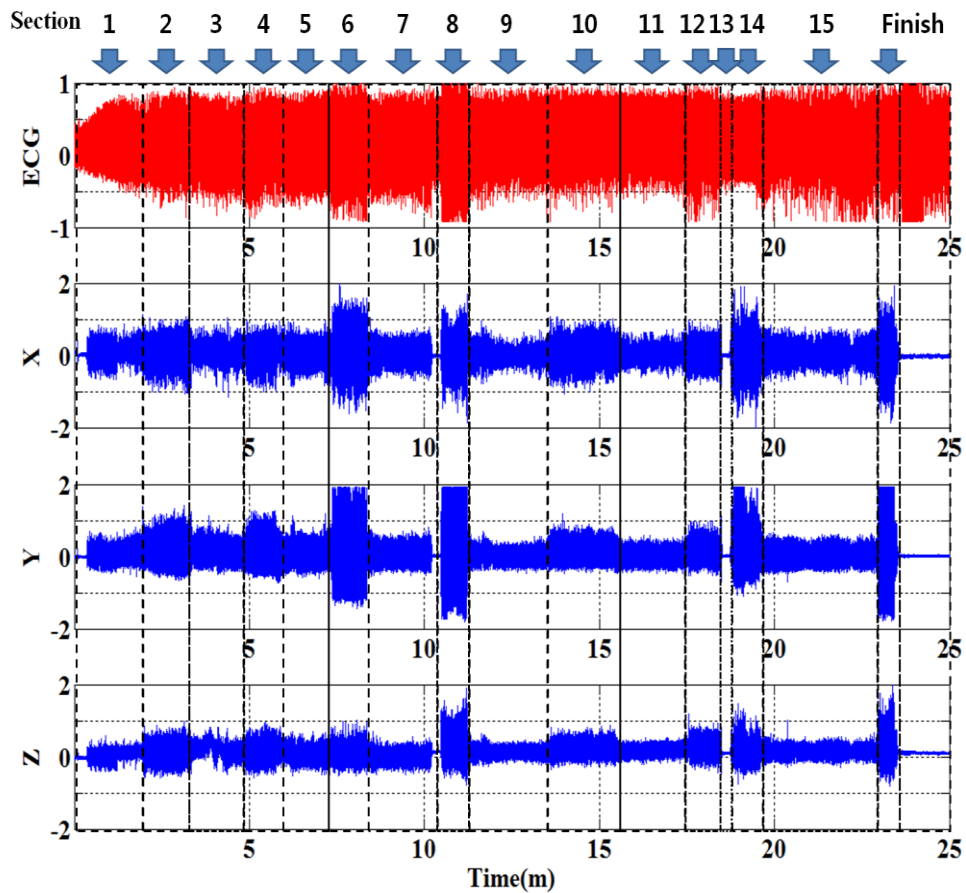


Figure 13. Result of ECG Filtering

Furthermore, by utilizing the measure 3-axis accelerometer data, ISVM for each of the section is calculated. A fuzzy classification algorithm is applied to classify the state of activity based on the calculated ISVM.

Table 2. Result of Fuzzy Classification

Section	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Finish
Speed	2	4	2	4	2	6	2	8	4	4	4	4	0	8	2	8
classification	2	4	2	4	2	6	2	8	4	4	4	4	0	8	2	8

In low activity state (State 1,2,3), the general filter and the proposed adaptive filter-set technique are both capable to achieve 100% R-peak detection success rate.

However, in fast movement activity state (State 4 and 5), in comparison with general filter, the proposed adaptive filter set has seen to have significant improvement in R-peak detection. The result is tabulated and shown in Table 3.

Table 3. Comparison of Heartbeat Detection Success Rate between General Filter and Filter-set

Section	State	Total	R-peak Detection			Compare (%)	
			General Filter (%)	Filter-set (%)			
1	2	159	159	100	159	100	0
2	3	135	135	100	135	100	0
3	2	291	291	100	291	100	0
4	3	161	161	100	161	100	0
5	2	179	179	100	179	100	0
6	4	202	193	95.54	200	99	+3.46
7	2	188	188	100	188	100	0
8	5	101	86	85.14	95	94.05	+8.91
9	3	216	216	100	216	100	0
10	3	232	232	100	232	100	0
11	3	144	144	100	144	100	0
12	3	94	94	100	94	100	0
13	1	66	66	100	66	100	0
14	5	192	166	86.45	185	96.35	+9.9
15	2	207	207	100	207	100	0
16	5	42	31	73.80	34	80.95	+7.15
Average			2548	96.30	2586	98.14	+7.36

4. Conclusion

In this study, an ultra-small size chest-belt wearable ECG measurement system is designed and implemented. Adaptive filter using optimum filter coefficient is proved to be a practical solution to minimize motion artifact in ubiquitous ECG recording.

Fuzzy algorithm which used for activity state classification is applied for the use of optimum filter-set selection. High movement speed like 6 and 8km/h would distort original ECG data, causing low accuracy in heartbeat detection. By implementing a 0.8 Hz high pass filter coefficient at 6 km/h and a 0.9 Hz high pass filter coefficient at 8 km/h, a significant improvement in heartbeat detection is presented. When there is no movement (0 km) or slow movement (2 and 4 km), a lower filter coefficient is selected. The selection of filter coefficient is made variable according to the state of activity. The performance of the proposed method is evaluated. From the evaluation result, real-time ECG monitoring in daily life is confirmed to be practically implementable.

For the upcoming researchers, a continuing effort to remove the time-varying motion artifact is needed. An optimal signal processing technique on various adaptive filters should be developed.

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