J Inf Process Syst, Vol.15, No.3, pp.478~491, June 2019
https://doi.org/10.3745/JIPS.04.0115

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

Health and Wellness Monitoring Using Intelligent Sensing Technique

Yao Meng*, Sang-Hoon Yi**, and Hee-Cheol Kim***

Abstract

This work develops a monitoring system for the population with health concerns. A belt integrated with an on-body circuit and sensors measures a wearer's selected vital signals. The electrocardiogram sensors monitor heart conditions and an accelerometer assesses the level of physical activity. Sensed signals are transmitted to the circuit module through digital yarns and are forwarded to a mobile device via Bluetooth. An interactive application, installed on the mobile device, is used to process the received signals and provide users with real-time feedback about their status. Persuasive functions are designed and implemented in the interactive application to encourage users' physical activity. Two signal processing algorithms are developed to analyze the data regarding heart and activity. A user study is conducted to evaluate the performance and usability of the developed system.

Keywords

Accelerometer, Electrocardiogram, Healthcare, Persuasive Technology, Real-Time Monitoring

1. Introduction

Wearable technology has been attracting a great deal of attentions in relation to continuous health and wellness monitoring [1-3]. This is not only due to the rapid advances in technologies, e.g., miniaturization, new sensors, seamless integration, computing, and communication, but also motivated by the strong need for better health and wellness both at home and outdoors [4]. Wearable health systems typically collect data using non-invasive sensors integrated on body-worn devices and offer pervasive services for continuous monitoring of health status [2].

When designing wearable systems, both the technological features and the user requirements should be considered to enable the systems to become efficient and applicable healthcare solutions in real-life situations. Therefore, in this study, we describe the development and evaluation of a wearable healthcare system, Wellness Wear, from these two aspects. The wellness wear system implements three main functioning components: a belt for on-body sensing, an interactive application for real-time data analysis and status feedback, and a server for storage and communication.

The electrocardiogram (ECG) and physical activity are automatically inferred by the ECG sensors and the accelerometer integrated in the belt that the user wears. The collected signals are transmitted to a

Manuscript received November 29, 2017; first revision January 18; accepted March 30, 2018.
Corresponding Author: Hee-Cheol Kim (heeki@inje.ac.kr)
* School of Information Engineering, Eastern Liaoning University, Dandong, China (lnddmy@hotmail.com)
** Dept. of Computer Simulation & Institute of Basic Science, Inje University, Gimhae, Korea (yish@inje.ac.kr)
*** Dept. of Computer Engineering & Smart Wellness Lab, Inje University, Gimhae, Korea (heeki@inje.ac.kr)

circuit module via digital yarns. The circuit module installed in the belt also is wirelessly connected to the interactive application, which is installed on a mobile device (e.g., smartphone, tablet, etc.).

The application analyzes the raw sensor data and reports the user's instantaneous heart rate (HR) and gait parameters (i.e., steps count and distance covered). In order to obtain these parameters in real time, we developed two signal processing algorithms to analyze ECG and gait accelerations, respectively. The application also communicates with the server at a remote location via Wi-Fi for uploading sensed physiological data and downloading history information.

Engaging in regular physical activity is known to be challenging, even in cases where people have expressed a desire to increase activity level. In wellness wear, concepts from persuasive technology were used to design the system to support people's desire for behavior change. A set of design principles were identified intended to encourage people to be physically active and used to inform the interface design and implementation of the interactive application.

We designed and conducted a user study to evaluate the wellness wear system. The intent is to investigate user experiences of the system as a means of motivating physical activity and examine the performance of the signal processing algorithms.

This paper is organized as follows. Section 2 provides a description of the wearable healthcare system we developed. Section 3 presents the persuasive principles used to guide the interface design of the system. Section 4 proposes the two algorithms implemented in the interactive application for signal processing and parameter extraction. Section 5 describes the user study and discusses the obtained data. Section 6 concludes the paper.

2. A Wearable Healthcare System

The wellness wear system aims to monitor users' heart conditions and levels of physical activity. We assume that the user wears the smart belt with non-intuitive and comfortable sensors to measure ECG and physical activity. While the user is resting or exercising, signals are recorded and transmitted to the terminal. Mobile devices (e.g., smartphones, tablets, etc.) can be terminals that receive and forward the data as well as platforms that perform the software functionality. The software application analyzes the signals and other body parameters (e.g., height, weight, etc.), and provides the user with real-time signal monitoring, instant parameter feedback, and wellness recommendations. Fig. 1 illustrates this scenario.

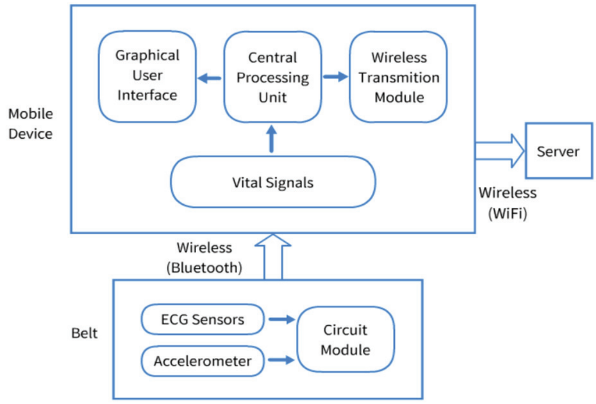


Fig. 1. System architecture of the wellness wear.

2.1 Sensors

In this study, cardiac activity is detected using three ECG sensors, which provide sampling frequency with 240 Hz. As shown in Fig. 2, ECG sensors are integrated in the X-band made from polyester fabric, and the signals acquired from the sensors are sent to a tiny signal-conditioning circuit via digital yarns [5]. We achieve real-time monitoring of heart conditions through a wireless signal transmission from the circuit to the mobile device. Motion artifacts and measurement noise are significantly reduced. Thus stable, continuous ECG is acquired, which not only leads to detection of almost all QRS complexes but also reduces missed beats during high-intensity activities.

A three-axis accelerometer of ADXL335 is embedded into the circuit to measure activity accelerations with a minimum full-scale range of ±3 g and a sampling rate of 240 Hz (Fig. 2). This sensor is able to measure static acceleration of gravity as well as dynamic acceleration resulting from motion, shock, and vibration. The circuit module transmits the sensed accelerations to the mobile device to monitor physical activity in real time.

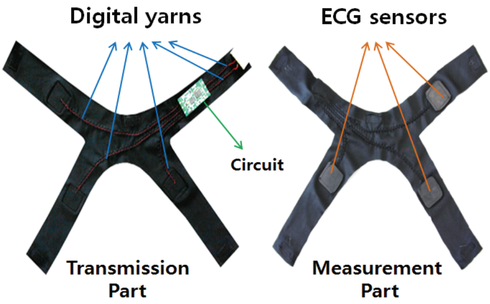


Fig. 2. X-band embedded with accelerometer, ECG sensors, and digital yarns.

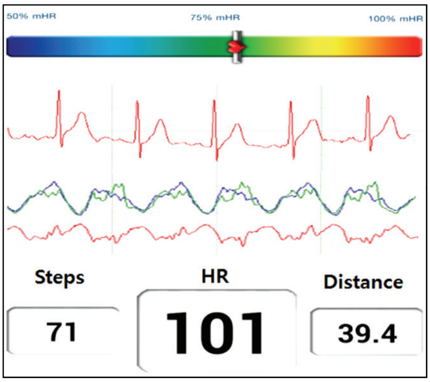


Fig. 3. Signal monitoring and parameter feedback on the interactive application.

2.2 Interactive Application

The two types of sensor signals are transmitted wirelessly to mobile devices via Bluetooth. The interactive application, which runs on an Android-based device, interprets the sensed data and extracts physiological information regarding the user's heart and activity (i.e., HR, steps taken, and distance covered). Fig. 3 depicts signals monitoring on a tablet that shows ECG and three-directional accelerations in the center; step count, distance in meters, and instantaneous HR in beats per minute (BPM) in the bottom; and the ratio of instantaneous HR over maximal HR on the top. The intensity of an activity is rendered by color change from blue to green, and finally red.

Besides receiving and analyzing the sensed data, the interactive application also communicates with a server at the remote location using a wireless connection (Fig. 1). The sensed data and estimated parameters are uploaded to the server, and physiological information can also be downloaded to provide a historical review to the user. The server is responsible for further processing and data mining.

3. Persuasive Design

The wellness wear attempts to persuade users to be more active. It does so by applying six persuasive principles to the interface design of the interactive application. The principles are built on the studies in persuasive technology and prior literature. In the following, we present the implementation of the persuasive features supported by the wellness wear.

- Goal Setting: The concept of setting behavioral goals is identified to be effective to increase physical activity [6,7]. In wellness wear, the number of steps is used as exercise goals and is designed to be set and achieved on a per-week basis. Two goal sources are supported: assigned and self-set. Assigned goal, which is a default value set by the system, derives from users' personal information including gender, weight, and height and represents weekly exercise level as a recommendation to maintain health. Self-set goal is designed to be manually set by users. The minimum and maximum setting of the goals are limited to guarantee a reasonable and healthy workout.
- Personal Awareness: It is important to provide reasonable and accessible information about people's behaviors, especially when this information relates to their goals [8]. Performance feedback and history review have been shown to be effective interventions to promote physical activity [9]. In Wellness Wear, feedback on physical activity is expressed with instantaneous HR and gait parameters during exercise. Users can also see the accumulative results when they complete one exercise session. History review is realized by two approaches. Exercise calendar shows users' exercise achievements and progress toward their goals on a daily basis. Moreover, users can check the trending information of their exercise behavior in the past week or month.
- Social Influence: The desire to project a positive image to other people is often at the root of behavior change. People can generally achieve a greater degree of attitude and behavior change by working together than by working alone [10,11]. In wellness wear, competitions within workout groups are applied to motivate physical activity. The users who belong to the same group can see the exercise ranking among all the participants in the group. The sorting criterion is the number of steps taken by users in a week. Besides the competition position, users can also view the preset goal and goal achievement of every participant.
- Rewards: People enjoy receiving recognition when they meet their goals, and can be persuaded by positive feedback. Studies have demonstrated the positive impact of rewards in computerized settings [10]. In wellness wear, rewards are designed to be earned by making progress toward or meeting the goals. Users can check their rewards in the exercise calendar where different types of trophies represent different milestones of goal achievement. Rewards earned are also shared in the workout group that one individual has joined in.

- Reminders: Delivering specific and timely reminders also have the potential to motivate physical activity. Studies have found that subjects who received concrete reminders about exercise plans increased their physical activity, while general reminders or no reminders had no effect on subjects' exercise level [12]. The wellness wear is designed to provide exercise reminders and recommendations. Users are notified by the reminder to be ready for exercise when the time is near the preset exercise time. Recommended weights (derived from personal information) and suggestions on exercise plan and weight loss are also offered to the users.
- Entertainment: Studies agree that music provides a pacing advantage and a form of distraction from the fatigue of exercising, affects the mood in a positive way, raises confidence and self-esteem, and motivates people to exercise more [13]. Thus, the wellness wear uses music for enjoyment and motivation of physical activity. Once this function is enabled, songs will be played by the interactive application during users' exercise.

4. Data Processing

The processing unit of the wellness wear (i.e., the mobile device) continuously receives raw ECG and acceleration signals provided by the sensors. Two algorithms were implemented in the interactive application to analyze the sensor signals and estimate wellness parameters. The following two sections describe the beat-detection algorithm for HR estimation and the step-detection algorithm for estimation of step count and distance.

4.1 Beat Detection

The data obtained from the three ECG sensors in the X-band have a similar waveform to the standard lead II ECG. Therefore, the QRS detection algorithm developed by Pan and Tompkins [14] was modified to detect heart beats in the wellness wear. Fig. 4 presents a signal sequence of raw ECG and the R waves detected by our algorithm. An overlapped window is applied to slide over the signal so that beat detection can be run in each window to identify R waves. The following steps are performed for the data in every window:

1) Apply a mean filter and a band-pass filter, respectively, to the raw ECG signal (Fig. 4(a)) to reduce noise.
2) Compute the differences between adjacent elements of filtered ECG.
3) Square the differential data to amplify the QRS complex.
4) Compute the moving window integral.
5) Compute a threshold based on the maximum amplitude of integral data.
6) Determine a QRS complex when the integral data are greater than the threshold.
7) Identify the R wave as it is the maximum amplitude in a QRS complex (Fig. 4(b)).

Defining the times of occurrence of two consecutive R waves as $s(t)$ and $s(t+1)$, $t = 1, \cdots, N$, the expression $x(t) = s(t+1) - s(t)$ is obtained for a time period in milliseconds. This $x(t)$ is called *RR interval* time series. A HR time series (min^{-1}) can be obtained by $y(t) = 1000 \cdot \left(60/x(t)\right)$ and the mean HR is simply $HR = N^{-1} \sum_{t=1}^{N} y(t)$.

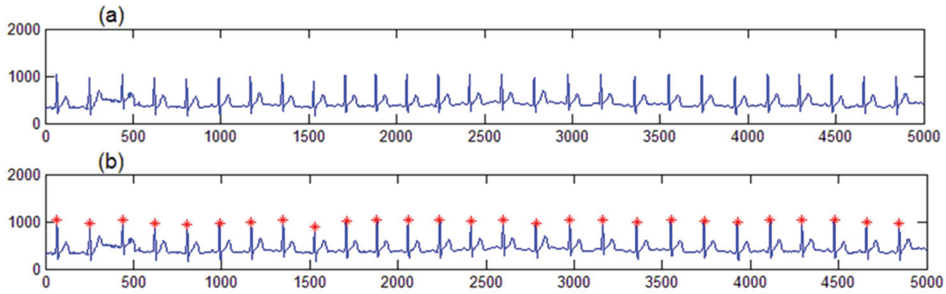


Fig. 4. Beat detection: (a) raw ECG signal and (b) detected R waves (asterisk).

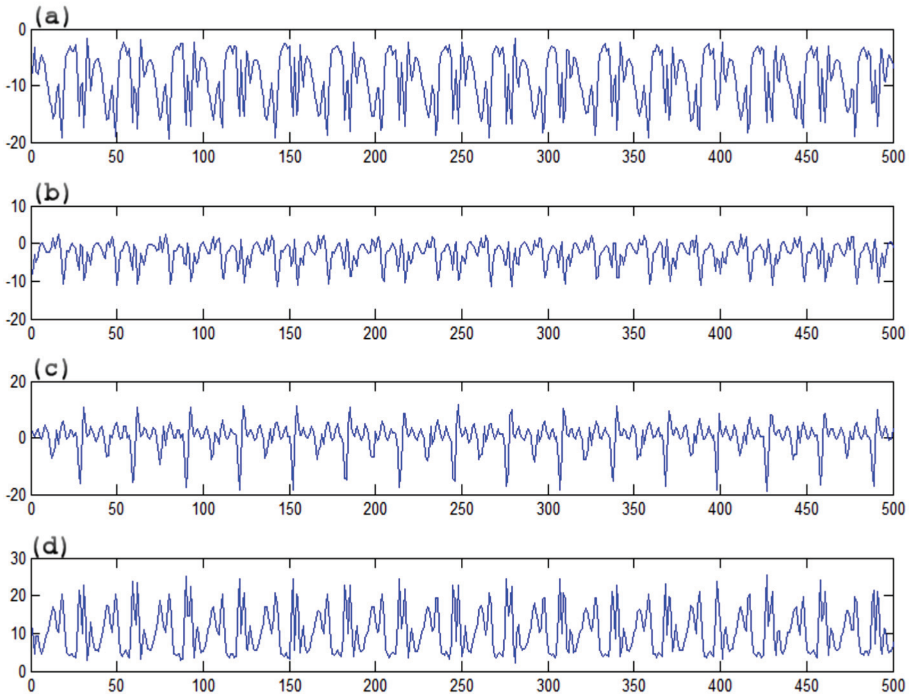


Fig. 5. Raw accelerations in three axes and obtained signal vector magnitude (SVM): (a) raw signal along the vertical axis, (b) raw signal along the anteroposterior axis, (c) raw signal along the mediolateral axis, and (d) SVM merging the three-axis raw signals.

4.2 Step Detection

The data received from the accelerometer in the circuit module are in the form of a three-valued vector that represents the activity accelerations in anteroposterior, mediolateral, and vertical axes, including the effects of gravity. Thus, we combine the three-dimensional input signals into one signal representing acceleration magnitude. The signal vector magnitude (SVM) is obtained using Eq. (1). Fig. 5 presents a signal sequence of raw accelerations and merged SVM.

$$r = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

The positive peak preceding the change (from positive to negative) is taken as the instant of a left- or right-foot contact [15]. Using an overlapped window successively sliding over the accelerations, the following steps are performed to detect footsteps in every window:

1) Calculate SVM.
2) Subtract the mean value to solve baseline wandering.
3) Reduce noise using the Savitzky-Golay smoothing method.
4) Find the zero-crossing points (from positive to negative).
5) Find the peaks preceding the zero-crossing points.
6) Compute a threshold based on the mean magnitude of the previous five detected steps.
7) Determine the first peak, the magnitude of which is greater than the threshold, to be the footstep in the current window (Fig. 6).

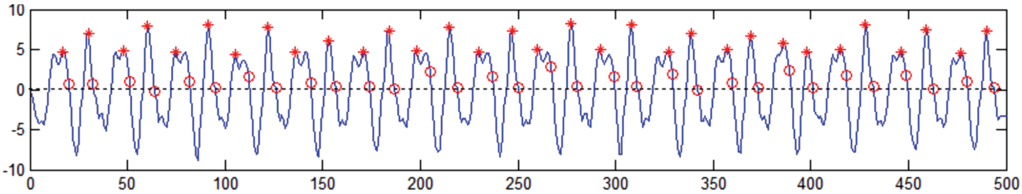


Fig. 6. SVM after mean subtraction and smoothing, detected zero-crossing points (circle), and detected footsteps (asterisk).

Two gait parameters are estimated based on the data processed in the previous procedure. Step count is the accumulative number of detected footsteps. Distance covered is the sum of all step lengths which are obtained using the equation below [16].

$$SL = K \cdot \sqrt[4]{r_{max} - r_{min}} \quad (2)$$

where SL is the length of each step (meter), r_{max} (or r_{min}) is the maximum (or minimum) value of the mean subtracted and smoothed SVM in each step cycle, K was regressed based on the data from the Korean anthropometric survey (Size Korea; the subjects consisted of 1,420 men and 1,421 women ranging in age from 20 to 40 years) [17]. Therefore, Eq. (2) was customized for average Korean people.

5. Evaluation

We carried out a user study to evaluate the user experiences of the wellness wear system and the performance of the proposed algorithms. Data analysis was conducted using IBM SPSS Statistics 20.

5.1 Participants

We recruited 10 individuals in their twenties to participate in this pilot study (see Table 1). Only male subjects were included because the belt positioned around the chest was not fitted for female subjects. We will address this defect when the wearable device is updated from a belt to a T-shirt. Nine participants were classified as normal weight, and 1 was classified as overweight according to body mass index (BMI) calculations performed on their reported height and weight.

Table 1. Participants' information (N = 10)

Participant no.	Gender	Age (yr)	Weight (kg)	Height (m)	BMI (kg/m^2)
B01	M	25	64	1.70	22.145
B02	M	24	60	1.72	20.281
B03	M	25	63	1.79	19.662
B04	M	24	65	1.67	23.307
B05	M	25	75	1.80	23.148
B06	M	23	63	1.70	21.799
B07	M	21	64	1.74	21.139
B08	M	21	70	1.85	20.453
B09	M	21	68	1.79	21.223
B10	M	27	85	1.78	26.827

5.2 Method

The participants were asked to wear the belts and read their performance feedback on the tablets during exercise. They first used the wellness wear freely for 5 minutes and then took part in exercise sessions with different speeds: walk/run on the treadmill for 5 minutes with speed at 2, 4, 6, 8, and 10 kmh. Notably, exercise on a treadmill is different from exercise conducted naturally. In this aspect, the experiment would be affected by setting differences. After completing the exercise sessions, the participants were asked to complete a post-test questionnaire about their experiences with the wellness wear. This questionnaire evaluated the system through the following measurements:

- Effectiveness: capability to help users' exercise and to offer reliable information.
- Efficiency: performance of users' exercise and manipulation.
- Satisfaction: perception of the friendliness of the system.
- Learnability: ease in learning the manipulation for first-time use.

5.3 System Usability

We determined 10 variables (questions) covering four categories (measurements) in the post-test questionnaire to evaluate the wellness wear. Satisfaction scores were assigned to the measurement variables based on participants' feedback. Each response option in the rating scale carries a score from 1 to 5 where 1 being "strongly disagreed" and 5 being "strongly agreed". Then the scores were averaged over all participants for each measurement variable.

Table 2 shows the descriptive statistics of the measurements. The corresponding questions in the post-test questionnaire are linked with the measurements. We found that Measurement #4, easy to familiar, obtained the highest degree of satisfaction, 4.60, followed by Measurement #2c, interface efficient in manipulation with 4.20. Measurement #2b, interaction disturbs exercise, obtained the lowest degree of satisfaction, 3.00. However, the reliability of the reported means is low since the sample size is small and variances are high.

Table 2. Descriptive statistics of the measurements

Measurements	Minimum	Maximum	Mean±SD
Effectiveness			
Helps to exercise	3	5	4.10±0.568
Information trustable	1	5	3.60±1.075
Information suitable	3	5	4.10±0.568
Efficiency			
Exercise performed better	2	5	3.70±0.823
Interaction disturbs exercise	1	5	3.00±1.054
Interface efficient in manipulation	4	5	4.20±0.422
Satisfaction			
Exercise enjoyable	3	5	3.90±0.568
Comfortable to wear	2	5	3.80±1.033
Interface appealing	3	5	4.00±0.707
Learnability			
Easy to familiar	4	5	4.60±0.516

To explore the effects of each measurement variable on the likelihood of further use of the wellness wear, we focused on the correlations between the variable "consider using in the future" and each measurement variable in the questionnaire. The correlation between the target variable and the variable "interaction disturbs exercise" was zero, and all other correlations were positive, which indicated that all of 9 variables were positively influenced upon the further use of the system (see Table 3).

Table 3. Significant correlations between target variable and the measurements

Measurements	Consider using in the future
Effectiveness	
Helps to exercise	0.546
Information trustable	0.419
Information suitable	0.794**
Efficiency	
Exercise performed better	0.240
Interaction disturbs exercise	0.000
Interface efficient in manipulation	0.134
Satisfaction	
Exercise enjoyable	0.695*
Comfortable to wear	0.491
Interface appealing	0.424
Learnability	
Easy to familiar	0.055

Correlation is significant at: *0.05 and **0.01 levels (two-tailed).

Measurement #1c (i.e., information suitable) was strongly correlated (0.794) with the target variable of further usage. Because the information provided by the wellness wear (i.e., HR, steps, and distance) is appropriate for exercise measurement, users are willing to continue to use this system. Moreover, Measurement #3a (i.e., exercise enjoyable) was moderately correlated (0.695) with the target variable of further usage, indicating that users enjoyed exercising with the wellness wear more than they enjoyed exercising without it. Finally, Measurement #1a (i.e., helps to exercise) was correlated (0.546) at a significant level of 0.103 with the target variable of further usage. This correlation may become more significant if the number of participants increases.

We ordered the effects of four measurements on perception of further usage. If we see the decreasing order of correlation coefficients below, the first two measurement variables were identified as significant contributing factors of user acceptance among the 10 measurement variables.

1) Measurement #1c (information suitable, 0.794)
2) Measurement #3a (exercise enjoyable, 0.695)
3) Measurement #1a (helps to exercise, 0.546)
4) Measurement #3b (comfortable to wear, 0.491)
5) Measurement #3c (interface appealing, 0.424)
6) Measurement #1b (information trustable, 0.419)
7) Measurement #2a (exercise performed better, 0.240)
8) Measurement #2c (interface efficient in manipulation, 0.134)
9) Measurement #4 (easy to familiar, 0.055)
10) Measurement #2b (interaction disturbs exercise, 0.000)

Hence, we conclude that 2 out of 10 measurement variables, namely suitable information (effectiveness) and enjoyable exercise (satisfaction), significantly contributed to the user acceptance of the wellness wear. Regarding 8 other measurement variables, more investigations are needed.

5.4 Algorithm Performance

To assess the performance of the beat-detection algorithm, we compared the count of detected R waves with the ground truth. The actual R waves were identified manually using the figures plotted by raw ECG signals. Table 4 shows the detected R wave count, actual R wave count, and error rate for each subject. Using data for the 10 subjects, we obtained the following error rates: errors less than 1% from 2 subjects; errors less than 2% from 2 subjects; errors less than 3% from 4 subjects; and errors more than 3% from 2 subjects. The absolute mean of error rates is around 2.13% and the standard deviation (SD) of the error rates is 1%.

Table 4. Performance of beat-detection algorithm (N = 10)

Participant no.	Actual R waves	Detected R waves	Error rate (%)
B01	606	593	−2.15
B02	579	576	−0.52
B03	592	588	−0.68
B04	601	586	−2.50
B05	608	597	−1.81
B06	609	592	−2.79
B07	622	611	−1.77
B08	629	606	−3.66
B09	605	591	−2.31
B10	617	598	−3.08
			−2.13±1.00[a] (signed) 2.13±1.00[a] (absolute)

[a]Values are presented as mean±standard deviation.

A subject's movements during measurements can generate motion artifacts and measurable noise in the ECG signal. Thus the beat-detection algorithm missed some R waves. The signal in Fig. 7 shows the occurrence of such cases. Several R waves between index 1.905×10³ and 1.903×10³ were missed and were not marked with the asterisks. As a result, the beat-algorithm underestimated the instant HR obtained from this signal sequence. R wave count is probably underestimated when such errors occur frequently. We observed the underestimation for all subjects in our validation.

Thus, we conclude that the beat-detection algorithm can perform well in situations of low- and medium-intensity activities. Motion artifacts and measurement noise, however, greatly contributed to the algorithm's decreased performance. Therefore, lower performance may result during high-intensity activities because of the additional artifacts and noise generated by these activities.

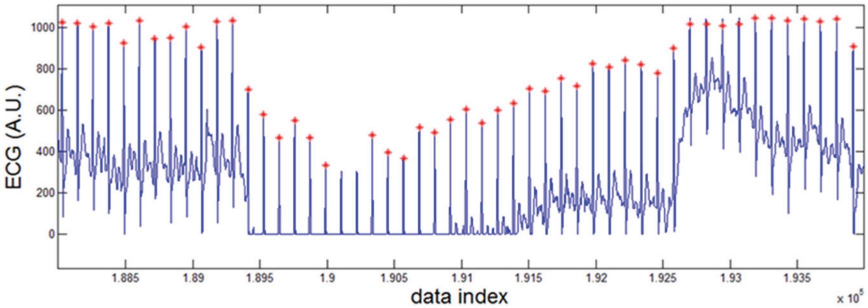


Fig. 7. Missed R waves during running at 8 kmh.

To assess the performance of the step-detection algorithm, we compared the estimated step count and distance with their ground truth. The actual step counts were identified manually using the figures plotted by raw acceleration signals and the actual distances were obtained from the treadmill. Table 5 shows the error rates (mean±SD and range) of estimated step count and distance.

Table 5. Error rate (%) of estimated activity parameters (N = 10)

Activity parameter	Error rate (%)	
	Mean±SD	Range
Step count	−11.02±1.66	4.80
Distance	−7.88±5.32	13.67

Table 5 used the data across five levels of activity (2–10 kmh) of all subjects. The mean errors for step count and distance are -11.02% and -7.88%, respectively. The algorithm underestimated both of these parameters. The sources of error which may affect the underestimation of parameters were also explored. Table 6 shows the error rate of estimated step count for each activity level. The comparison between the estimated step count and the ground truth showed that the algorithm underestimated step count for low-level activity (strolling at 2 kmh) by more than 95% on average, whereas it estimated the step counts for other levels of activity within 2.5% accuracy on average. Using data for all subjects, only the error from low-level activity was significantly correlated with the error from all activities (r=0.739, p<0.05). This finding indicates that lower performance may result during low-intensity activities. Moreover, the step-detection algorithm also missed some steps (Fig. 8) and hence underestimated the step count during high-intensity activities.

Table 6. Error rate of estimated step count for separate activities (N = 10)

Activity	Error rate (%)	
	Mean±SD	Range
Strolling, 2 kmh	-95.51±8.61	25.03
Walking, 4 kmh	2.30±7.01	20.46
Walking, 6 kmh	0.37±1.34	4.36
Running, 8 kmh	-0.66±0.92	2.67
Running, 10 kmh	-0.09±0.18	0.36
All activities, 2–10 kmh	-11.02±1.66	4.80

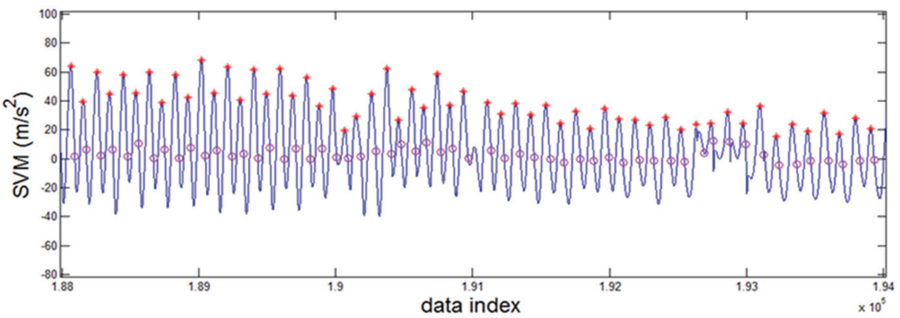


Fig. 8. Missed steps during running at 8 kmh.

6. Conclusion

In this paper, we presented a wellness wear system for real-time heart and activity monitoring. The developed system is composed of a wearable belt to sense vital signals and a mobile application to receive, interpret, and forward the signals (to a remote server). In addition, we implemented a beat-detection algorithm to extract instant HR and realized a step-detection algorithm to record steps taken and distance covered during exercise.

A user study was conducted to evaluate the wellness wear system. We found that suitable information provided (effectiveness) and enjoyable exercise experienced (satisfaction) significantly contributed to the user acceptance of the system for the population in the user study. Regarding the performance of the algorithms, the beat-detection algorithm performed well during low- and medium-intensity activities, whereas its performance decreased during high-intensity activities; the step-detection algorithm worked well during medium- and high-intensity activities, whereas its performance decreased during low-intensity activities.

Acknowledgement

This paper is supported by the Doctoral Scientific Research Foundation of Liaoning Province (No. 201601341) and by Basic Science Research Program through the National Research Foundation of Korea funded by the Ministry of Science, ICT & Future Planning (No. NRF-2017R1D1A3B04032905).

References

[1] S. Park, K. Chung, and S. Jayaraman, "Wearables: fundamentals, advancements, and a roadmap for the future," in *Wearable Sensors*. Amsterdam: Academic Press, 2014, pp. 1-23.

[2] G. Andreoni, C. Standoli, and P. Perego, "Defining requirements and related methods for designing sensorized garments," *Sensors*, vol. 16, no. 6, article no. 769, 2016.

[3] J. Hayward, "Wearable technology 2017–2027: markets, players, forecasts," IDTexEx Report, 2017.

[4] S. Park and S. Jayaraman, "Smart textile-based wearable biomedical systems: a transition plan for research to reality," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 1, pp. 86-92, 2009.

[5] G. S. Chung, J. S. An, D. H. Lee, and C. S. Hwang, "A study on the digital yarn for the high speed data communication," in *Proceedings of the 2nd International Conference on Clothing and Textiles*, 2006, pp. 207-210.

[6] E. L. Bird, G. Baker, N. Mutrie, D. Ogilvie, S. Sahlqvist, and J. Powell, "Behavior change techniques used to promote walking and cycling: a systematic review," *Health Psychology*, vol. 32, no. 8, pp. 829-838, 2013.

[7] S. H. Malik, H. Blake, and L. S. Suggs, "A systematic review of workplace health promotion interventions for increasing physical activity," *British Journal of Health Psychology*, vol. 19, no. 1, pp. 149-180, 2014.

[8] S. Consolvo, D. W. McDonald, and J. A. Landay, "Theory-driven design strategies for technologies that support behavior change in everyday life," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Boston, MA, 2009, pp. 405-414.

[9] S. Procter, N. Mutrie, A. Davis, and S. Audrey, "Views and experiences of behaviour change techniques to encourage walking to work: a qualitative study," *BMC Public Health*, vol. 14, article no. 868, 2014.

[10] B. J. Fogg, "Persuasive technology: using computers to change what we think and do," *Ubiquity*, vol. 2002, article no. 5, 2002.

[11] D. N. Cavallo, J. D. Brown, D. F. Tate, R. F. DeVellis, C. Zimmer, and A. S. Ammerman, "The role of companionship, esteem, and informational support in explaining physical activity among young women in an online social network intervention," *Journal of Behavioral Medicine*, vol. 37, no. 5, pp. 955-966, 2014.

[12] A. Prestwich, M. Perugini, and R. Hurling, "Can the effects of implementation intentions on exercise be enhanced using text messages?," *Psychology and Health*, vol. 24, no. 6, pp. 677-687, 2009.

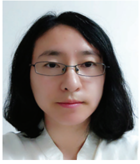
[13] N. Oliver and F. Flores-Mangas, "MPTrain: a mobile, music and physiology-based personal trainer," in *Proceedings of the 8th Conference on Human-Computer Interaction with Mobile Devices and Services*, Helsinki, Finland, 2006, pp. 21-28.

[14] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230-236, 1985.

[15] W. Zijlstra, "Assessment of spatio-temporal parameters during unconstrained walking," *European Journal of Applied Physiology*, vol. 92, no. 1-2, pp. 39-44, 2004.

[16] L. Fang, P. J. Antsaklis, L. A. Montestruque, M. B. McMickell, M. Lemmon, Y. Sun, H. Fang, I. Koutroulis, M. Haenggi, M. Xie, et al., "Design of a wireless assisted pedestrian dead reckoning system: the NavMote experience," *IEEE Transactions on Instrumentation and Measurement*, vol. 54, no. 6, pp. 2342-2358, 2005.

[17] Korean Anthropometric Data of Size Korea, http://sizekorea.kats.go.kr.



Yao Meng https://orcid.org/0000-0003-4092-9650

She received B.S. and M.S. degrees in College of Information from Liaoning University, China in 2003 and 2006, respectively, and Ph.D. in School of Computer Science from Inje University, Korea in 2014. She is currently a lecturer in Eastern Liaoning University, China. Her current research interests include Human computer interaction and biosignal processing.

Sang-Hoon Yi https://orcid.org/0000-0003-2698-3853

He received the B.S. in physics from Seoul National University, Korea in 1981, the Ph.D. degree in physics from Korea Advanced Institute of Science & Technology, Korea in 1988. He is currently a professor in Inje University, Korea. His research interests are in the areas of nonlinear dynamics, biomedical signal processing, brain-heart connection, and u-healthcare.

Hee-Cheol Kim https://orcid.org/0000-0002-5399-7647

He received the M.S. degree in computer science from Sogang University, Korea in 1991 and the Ph.D. in computer science from Stockholm University/Royal Institute of Technology, Sweden in 2001. He is currently a professor in Inje University, Korea. His research interests are in the areas of human computer interaction, software engineering, smart home technology, wellness computing and digital healthcare.