# Unobtrusive Monitoring of ECG-derived Features During Daily Smartphone Use

Sungjun Kwon, Seungwoo Kang, Youngki Lee, Chungkuk Yoo and Kwangsuk Park, *Senior Member, IEEE*

*Abstract*— **Heart rate variability (HRV) is known to be one of the representative ECG-derived features that are useful for diverse pervasive healthcare applications. The advancement in daily physiological monitoring technology is enabling monitoring of HRV in people's everyday lives. In this study, we evaluate the feasibility of measuring ECG-derived features such as HRV, only using the smartphone-integrated ECG sensors system named *Sinabro*. We conducted the evaluation with 13 subjects in five predetermined smartphone use cases. The result shows the potential that the smartphone-based sensing system can support daily monitoring of ECG-derived features; The average errors of HRV over all participants ranged from 1.65% to 5.83% (SD: 2.54~10.87) for five use cases. Also, all of individual HRV parameters showed less than 5% of average errors for the three reliable cases.**

## I. Introduction

The advancement in daily physiological monitoring technology unfolds unprecedented opportunities for diverse pervasive healthcare applications. Electrocardiogram (ECG) is especially sensitive indicator that shows the status of the heart and the activation of the autonomic nervous system (ANS). The daily ECG monitoring enables not only the detection of the heart disease but also diverse healthcare applications based on ECG-derived features.

Heart rate variability (HRV) is one of the representative ECG-derived features that are useful for diverse pervasive healthcare applications. Because of its sensitiveness for indicating the change of ANS, numerous previous works have studied the technology based on HRV for daily healthcare services including stress analysis, emotion detection, and even sleep quality estimation [1-4].

In our previous study, we proposed an unobtrusive mobile ECG monitoring system, Sinabro[1], which monitors a user's ECG opportunistically during daily smartphone use [5]. To sense ECG signals unobtrusively, we designed an ECG sensor which is embedded in a smartphone case. The Sinabro system also includes the middleware for supporting smartphone healthcare applications based on ECG-derived features. In addition, we conducted the preliminary feasibility study of the proposed system for daily ECG monitoring.

In this study, we further evaluate the performance of the Sinabro sensor system in terms of the accuracy for extracting ECG-derived features such as HRV. We performed the evaluation with 13 subjects for five representative smartphone use cases that have the opportunity for ECG sensing using the Sinabro system. To estimate the accuracy of the extracted features, we calculated the error rate of the features by comparing them with that obtained from the reference signal.

## II. System prototype

In our recent study, we presented a novel approach for unobtrusive daily ECG sensing and the mobile ECG monitoring system, Sinabro, integrated with a smartphone platform [5]. Obtrusiveness is a major obstacle to ECG monitoring in daily situation. For ECG sensing, two parts of the body that show a certain level of bio-electric potential difference should be stably contacted with the electrodes for a certain time duration. Thus, the users' conscious cooperation is required for the stable contact, which makes ECG monitoring obtrusive. To address such obtrusiveness, we proposed an approach that overlays ECG sensing onto daily smartphone usage. e.g., phone calls, texting, and gaming; ECG is sensed opportunistically while users use a smartphone for such activities. To realize the approach for unobtrusive ECG monitoring, we developed the sensor system that includes the phone-case sensor and the smartphone middleware. Here we briefly describe the prototype system.

### A. Sensor design

We designed unobtrusive ECG sensor embedded in a smartphone-case. Figure 1 shows the prototype. The multiple metal-based dry electrodes are placed on the rounded edge of the case to measure ECG naturally when two body parts of the users are contacted with the smartphone, i.e., the right and left hands, one hand and one ear.

This work supported by the R&D program of MKE/KEIT (Grant No. 10041854).

S. J. Kwon is with the Interdisciplinary Program of Bioengineering, Seoul National University, Seoul 110 799, Korea. (Phone: +82 2 7408593; fax: +82 2 32762821; E-mail: sjkwon@bmsil.snu.ac.kr).

S. W. Kang is a research professor and C. K. Yoo is a Ph.D candidate in the Department of Computer Science, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Republic of Korea. (Phone: +82-70-8635-3586; E-mail: sngwoo@kaist.ac.kr, ckyoo@nclab.kaist.ac.kr).

Y. K. Lee is an assistant professor of Department of Information Systems at Singapore Management University, Singapore. (Phone: +65-6808-5421; E-mail: youngkilee@smu.edu.sg).

K. S. Park is a professor in the Department of Biomedical Engineering, College of Medicine, Seoul National University, Seoul 110 799, Korea. (Phone: +82 2 20723135, E-mail: pks@bmsil.snu.ac.kr).

[1] *Sinabro*: Korean word that means "little by little without any conscious effort"

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

Figure 1. The design of the smartphone-case sensor. (a)-(c) is the metal-based dry electrodes placed in a smartphone case. (1) The multi-channel ECG sensor module with microcontroller and Bluetooth. (2) Li-Polymer battery

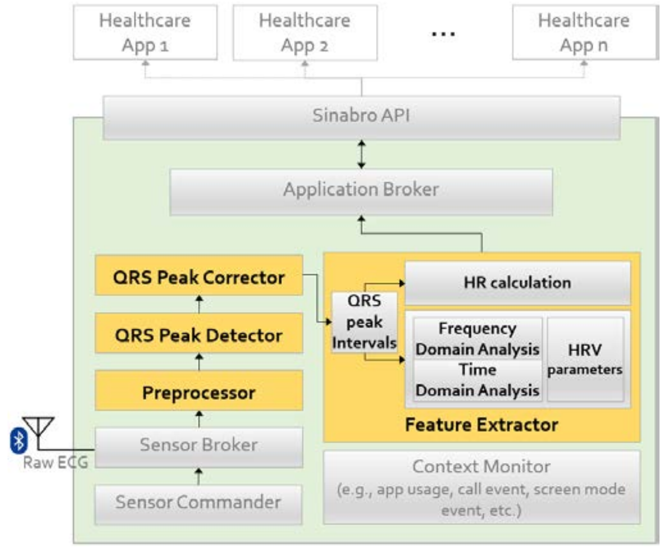

Figure 3. The middleware architecture of Sinabro system. In this study, we quantitatively estimated the accuracy of ECG-derived features that were extracted by the proposed system to evaluate the feasibility of the Sinabro sensor system for supporting healthcare applications.

Our system targets three main cases of daily smartphone use (see Figure 2); phone call, holding in landscape mode with two hands (e.g., gaming, taking picture, and watching a video), holding in portrait mode with two hands (e.g., typing and gaming). We placed three electrodes in the back and one in the front to sense ECG naturally at such moments. During phone calls, the electrode (a)-front and (b) will be touched with the ear and the hand, respectively. When the users hold the smartphone in portrait or landscaped mode with two hands, the user's hands will be contacted with electrode (a)-rear, (b), or (C). Thus, the system can sense ECG from the combination of those electrodes; (b) and (c), (a)-rear and (b), and (a)-rear and (c).

The sensor module captures three channels of ECG from the combinations of the multiple electrodes, and delivered the data to the smartphone middleware through a Bluetooth interface.

### *B. Smartphone middleware with feature extraction*

Figure 3 shows the middleware architecture of the Sinabro system. The smartphone middleware monitors users' smartphone usage information such as the screen mode change and the application type they used, and detects opportunities to sense ECG signal. The middleware sends a trigger message to the sensor module to start ECG sensing when an opportunity is detected. During the moment, the middleware extracts useful features and contexts from the received raw ECG data. The extracted information is delivered in real-time to multiple applications that request them using Sinabro APIs.

The middleware calculates HRV parameters from raw ECGs through a series of processing modules. First, the raw ECGs are filtered with the band-pass filter (5Hz–35Hz) by the preprocessor to stand out QRS peaks and to remove power noise and EMG. Second, the QRS peak detector module finds reliable QRS peaks from the filtered signals. Third, the QRS peak corrector removes false-positive peaks from the output of the peak detector and interpolated the missing peaks using a Piecewire-cubic Hermite interpolation method; false positives are filtered out when their power value is less than or over than a certain threshold and their interval to the previous/next peak is abnormal. Finally, HR and HRV are calculated from the interpolated peaks by the feature extractor.

## III. Evaluation and Result

To evaluate the feasibility of the Sinabro sensor system for supporting healthcare applications, we quantitatively estimated the accuracy of ECG-derived features that were extracted by the proposed system.

### *A. Evaluation setting*

13 subjects recruited from Seoul National University participated in the evaluation (male/female: 9/4, avg. age: 25.1, SD: 3.1). The participants were asked to use the smartphone with the prototype of the sensor system under the five predetermined smartphone use activities, i.e., texting in portrait and landscape mode, playing high and low interactive game, calling. The raw ECG data and the HRV parameters calculated by the system were acquired during the smartphone


Figure 2. The target use cases of the Sinabro sensor

use. The reference ECG data were also acquired by the bio-signal acquisition system, the BIOPAC MP150 ECG module [6], with Ag/AgCl electrodes.

Each smartphone use activity was performed for 5 minutes. For texting, the participants were asked to hold the phone naturally in portrait and landscape mode with their two hands and have a conversation with the experimenter using a mobile messenger. During the conversation, both hands of the participants were contacted with the electrodes placed on the smartphone case. For gaming, the participants were asked to play two games that require different level of interaction. One game was the action game which incurs frequent and strong inputs (at least 1–2 inputs per second, up to 5). The other was the low interactive baseball game which involves relatively less frequent, softer inputs (avg. 0.5 per second). The games were played only in landscape mode and two hands were also contacted with the electrodes during the play. The participants were asked to keep holding the phone with two hands, but we did not ask them to maintain the contact between the electrodes and their hands stably. For calling, they had a conversation with the experimenter through phone call. They were asked to hold the phone with their left hand and touch it to their left ear.

### *B. Evaluation metric*

To estimate the accuracy of HRV parameters extracted by the Sinabro sensor system, we calculated the error rate of each parameter by comparing them with that from the reference signal. The HRV parameters from the reference signal were calculated using the QRS peak duration manually detected by the experienced experts. The HRV parameters that we used include high frequency (HF: 0.15-0.40 Hz), low frequency (LF: 0.04-0.15 Hz), LF/HF, normalized HF, normalized LF, very low frequency (VLF: 0.0033-0.04 Hz), total frequency (TF: 0.01-1.00 Hz), mean HR, RMSSD, and SDNN.

### *C. Results*

We observed that different use cases showed different accuracy of calculating HRV parameters. The average errors over all participants ranged from 1.65% to 5.83% (SD: 2.54~10.87) for five use cases (see Figure 4). There were

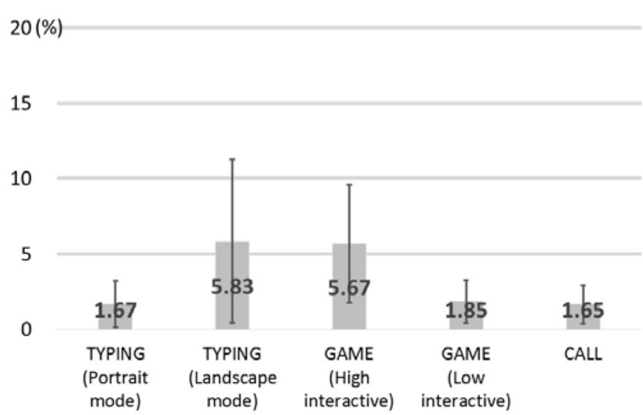


Figure 4. The average error rate and standard deviation (SD) of HRV parameters for each smartphone use case

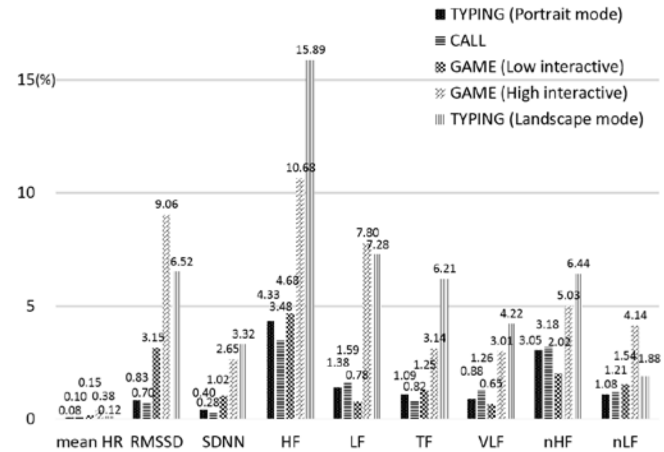


Figure 5. The average error rates for HRV parameters in each use case

three relatively reliable use cases among the five, i.e., type in portrait mode, call, and low interactive game. They showed less than 2% of average error rate. In addition, their SDs were 2.54-3.04; there were not large differences among participants. However, the average error rates for the other two cases, i.e., type in landscape mode and high interactive game, were relatively larger than those of the previous three cases, about 6% of average error rate. These two cases showed relatively large variations among individual participants. Participants 2, 12, 13 had large errors for the cases. Participants 2 and 12 showed 34.57% and 23.88% of average errors for the case of typing in landscape mode, respectively. For the high interactive game case, participants 12 and 13 showed 22.57% and 20.79%, respectively. However, except those three participants, the average error rates decreased, from 0.82 % to 2.23 %. We believe that these initial results were encouraging in developing our opportunistic ECG sensing system to provide HRV parameters without user's explicit intervention.

Figure 5 shows the detailed average error rates of individual HRV parameters for the five different use cases. All of parameters showed less than 5% of average errors for the three reliable cases, i.e., typing in portrait mode, call, low interactive gaming in landscape mode. Mean HR, SDNN, VLF and nLF had less than 5% for all five cases. The mean HR was almost correctly obtained; it had the smallest error, 0.17%. This shows that the Sinabro system can provide highly accurate HR monitoring results. TF, VLF, nLF, SDNN showed relatively low errors, about 1-2.5% on average. Other three parameters, LF, RMSSD, nHF, showed about 4% on average. HF had the largest error, 7.81%. Similar to the previous results, typing in landscape mode and high interactive gaming resulted in relatively high error rates. The errors of HF were greater than 10% for landscape-mode typing and high interactive gaming. Those of LF and RMSSD were about 7-9%. We observed that such high error rates mainly resulted from the incorrect interpolation of multiple consecutive QRS peaks that could not be detected, especially for HF and LF.

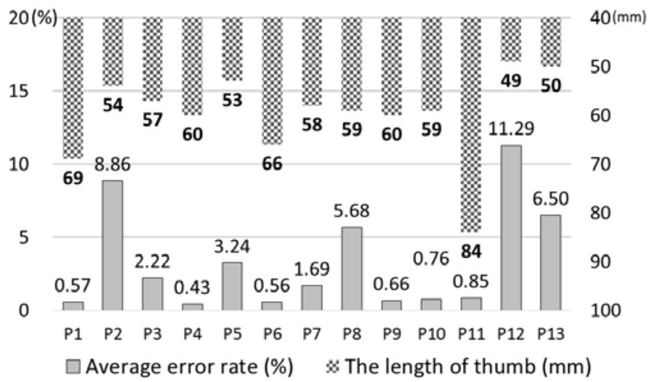


Figure 6. The average error rate of HRV and the length of thumb for the participants

## IV. DISCUSSION

The current feasibility study shows the potential of the Sinabro system for unobtrusive daily monitoring of ECG-derived HRV parameters. However, there are also limitations and further challenges to address. It is necessary to conduct future study to investigate the effect of individual differences that affect the sensing reliability. Different users may have different behaviors such as holding posture, typing habits, and touch intensity. In addition, they might have different ECG signal powers. It is an important issue to develop a solution to handle such effect.

We examined one of major aspects that might affect the evaluation results. Our current investigation focused on the effect of the thumb length on the error rates. In the evaluation, all participants used only their thumbs when they were typing on soft keyboard. Also, it was natural to use two hands to hold the phone and thumbs to press buttons in order to manipulate the interface of mobile games used for the study. The size of the phone integrated with the prototype sensor was 76mm * 142mm. In portrait mode, it might be possible for most of users to touch the middle of the screen's bottom half area without changing the posture of hands holding the phone if the thumb length is greater than about 40 mm. Thus, typing on keyboard and pressing buttons with thumbs in portrait mode were unlikely to incur unstable contact between electrodes and hands in many cases. However, in landscape mode, it was not easy for the participants with short thumb length to touch the middle of the screen without the change of holding posture. Accordingly, the contact between the hands and the electrodes became unreliable, thereby incurring the distortion of ECG signals.

We found that the thumb length actually affected the result. Figure 6 shows the average HRV error rates of the participants and their thumb length. The average thumb length over all participants was 59.85 mm. The thumb lengths of three participants, 2, 12, and 13 who showed relatively large error rates were 54, 49, and 50 mm, respectively. They have short thumb compared to others. From these results, we observed that there was the correlation between the average error rates and thumb lengths. According to the Pearson correlation, the correlation coefficient was -0.616 and p value was 0.025 ($< 0.05$).

There were other interesting observations. Participant 5 had relatively short thumb length, i.e., 53 mm, but showed low error rate, 3.24 %, compared to the three. In addition, participant 8 whose thumb length is 59 mm showed relatively large error rate, 5.68 %, compared to those with similar thumb length (P4, P7, P9, and P10). Unlike other participants, P8 showed greater than 10 % of error especially for the low interactive gaming case. The error was mainly caused during the operation of interpolating consecutive missing QRS peaks. There might be different aspects that caused such results in addition to thumb length. It is necessary to conduct further study to analyze these results in more detail.

## V. CONCLUSION

In this study, we investigate the feasibility of the Sinabro sensor system for supporting mobile healthcare applications by estimating the accuracy of ECG-derived feature extraction. We conducted the evaluation with 13 subjects in five predetermined smartphone use cases which have the opportunity for ECG sensing using the Sinabro system. The initial results are encouraging in developing our opportunistic ECG sensing system to provide HRV parameters without user's explicit intervention. In future work, we will study diverse aspects which are important for applying the proposed system to real life. We will enhance the sensing reliability by detecting the sensing opportunities more correctly. For example, the middleware should make a distinction between the both-handed texting and single-handed texting. In addition, an accurate ECG detection technique should be included in the middleware to improve the sensing reliability. The effect of the case-sensor on the quality of the phone signal also will be investigated in the next step.

## REFERENCES

[1] E. Ertin, N. Stohs, S. Kumar, A. Raij, M. al'Absi, and S. Shah, "AutoSense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field," in Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems, 2011, pp. 274-287.

[2] M. Malik, J. T. Bigger, A. J. Camm, R. E. Kleiger, A. Malliani, A. J. Moss, et al., "Heart rate variability standards of measurement, physiological interpretation, and clinical use," European heart journal, vol. 17, pp. 354-381, 1996.

[3] A. Riener, A. Ferscha, and M. Aly, "Heart on the road: HRV analysis for monitoring a driver's affective state," in Proceedings of the 1st International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2009, pp. 99-106.

[4] L. Salahuddin, J. Cho, M. G. Jeong, and D. Kim, "Ultra short term analysis of heart rate variability for monitoring mental stress in mobile settings," in Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE, 2007, pp. 4656-4659.

[5] S. Kang, S. Kwon, C. Yoo, S. Seo, K. Park, J. Song, et al., "Sinabro: opportunistic and unobtrusive mobile electrocardiogram monitoring system," in Proceedings of the 15th Workshop on Mobile Computing Systems and Applications, 2014, p. 11.

[6] MP150, Biopac, USA, http://www.biopac.com/ [Online].