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Sinabro: Opportunistic and Unobtrusive Mobile Electrocardiogram Monitoring System

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ABSTRACT

In this paper, we propose Sinabro, an opportunistic and unobtrusive mobile electrocardiogram (ECG) monitoring system that monitors the user's ECG opportunistically during daily smartphone use. Daily ECG monitoring will open up an unprecedented opportunity for pervasive healthcare applications. It will enable the daily detection and prevention of heart problems and also allow inferences about stress, emotion, and even sleep quality. Despite its huge potential, daily ECG monitoring still has not become reality due to its obtrusiveness. In this paper, we first study the potential opportunity to capture ECGs from daily use of smartphones, without requiring the user's explicit attention. Based on such an opportunity, we present a prototype ECG sensor that allows neat integration with a smartphone and the Sinabro system to provide ECG-related physiological status. We show the basic feasibility of our approach, based on daily smartphone usage through phone usage analysis and prototype-based experiments.

Categories and Subject Descriptors

K.8 [**Personal Computing**]: General; C.3 [**Special-Purpose and Application-based Systems**]: Real-time and embedded systems.

General Terms

Measurement, Design, Human Factors.

Keywords

Opportunistic sensing, Unobtrusive sensing, ECG, Sensor.

1. INTRODUCTION

Daily ECG monitoring will open up an unprecedented opportunity for pervasive healthcare applications. Primarily, it will enable the daily detection and prevention of heart problems such as arrhythmia and heart attack [9][12]. Also, an ECG can serve as an indicator to infer stress, affective state, and even sleep quality for a person [6][8][9][10]; heart movement is controlled by an electric signal generated by the autonomous nervous system, which also influences such physiological factors. The core on which to build the applications is to monitor ECGs in everyday situations. Despite active efforts, such daily monitoring of ECGs still does not come into our reality.

A key barrier to daily ECG monitoring lies in its obtrusiveness. Fundamentally, ECG monitoring requires the stable contact of two body parts that show a certain level of bio electric potential difference for a certain time duration, e.g., up to several seconds to minutes depending on the purpose. This hard requirement has inevitably caused obtrusiveness in previous ECG or heart monitoring systems. A popular approach is to employ a wearable device, which requires low user attention while measuring physiological signals [3][6][12]. However, the monitoring is only possible when users wear the device, which is not yet widely accepted among most common users. Thus, the approach is often limited to specific situations, such as monitoring for clinical and fitness purposes. For example, people wear commercial heart rate monitors such as chest strap-type devices [3], during exercise. Another approach is to integrate such functionality into prevailing smartphones [1][2]. However, this requires the users' explicit initiation and attention for a while. For example, a smartphone application to monitor heart rate based on a phone camera requires users to start the application, gently place their finger on lens, and hold still for 10 seconds or more [2]. Requiring conscious effort makes consistent and long-term monitoring challenging. Users are likely to forget and have other priorities.

Our primary approach is to address such obtrusiveness by overlaying the sensing of physiological signals onto daily smartphone usage, e.g., phone calls, texting, and gaming; sensing is performed opportunistically while users do such activities with their smartphone. Such opportunistic monitoring will lower the barriers to daily ECG monitoring for ordinary users who are interested in their heart-related status but reluctant to use the aforementioned obtrusive approaches. Moreover, it will enable many new, useful applications without user intervention. For example, an application can notify users of the stress levels of conversation partners via phone vibrations when talking over the phone and allow them to respond appropriately, as they do naturally during face-to-face conversation; our system can capture ECG signals without attracting the user's attention while the user is on the phone and extract stress levels from the signal.

While previous works have studied ECG monitoring based on wearable sensors and smartphones [3][6][12], the opportunistic sensing approach based on daily smartphone use has hardly been considered before. To make such an opportunistic approach feasible in daily situations, we need to address several new research challenges. First, due to the nature of the opportunistic

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approach, it is unknown whether we will have enough ECG monitoring opportunities to capture one's heart status, e.g., heart rate. Even if ECG sensing is possible, whether such intermittent information could be utilized meaningfully by applications and how we could abstract such information into a meaningful set of APIs have not been studied. Second, under such an opportunistic approach, it is difficult to capture the signal reliably, even when the users touch the phones with two body parts, such as when gaming or during a phone call. They may use the phone with active gestures when playing a game, and this could increase the noise during heart rate detection or even make it impossible.

We propose an unobtrusive mobile ECG monitoring system, Sinabro, which monitors a user's ECG discretely during daily smartphone use. First, we investigate the potential opportunity to capture ECGs from only daily usage of smartphones. Based on this opportunity, we design an ECG sensor in the form of a phone case that can be integrated with a smartphone for unobtrusive sensing. Specifically, we attached multiple electrodes at the corners, front, and back of the smartphone (see Figure 3), which could allow maximal opportunities for ECG measurement when a user touches the phone with two body limbs during daily use, such as two hands when sending a text message or an ear and a hand when making a phone call. Also, we present the Sinabro system, which handles unstable daily ECG signals and extracts diverse heart-related information, such as heart rate (HR) and stress, to expose a set of APIs upon which useful, everyday healthcare applications can be developed and executed.

While there are a number of research challenges in building Sinabro into a fully-functioning daily ECG monitoring system, we make the initial step towards this direction in this paper. The contributions of this paper are summarized as follows. First, we have built an unobtrusive, smartphone-based ECG monitoring system that captures the user's ECG opportunistically during daily smartphone use. Second, through smartphone usage analysis and prototype-based experiments, we show that 1) such potential opportunities do exist, in terms of app usage time, which may involve simultaneous contact by two body limbs (e.g., more than an average of 20 opportunities for tens of seconds); 2) given the opportunity, our prototype system can capture the ECG signal and derive HR (up to 99.2% of peak detection accuracy and more than 99.7% of HR estimation accuracy for typing and calling cases); and 3) from 32% up to 92% of the time duration for potential opportunities lead to actual reliable sensing opportunities.

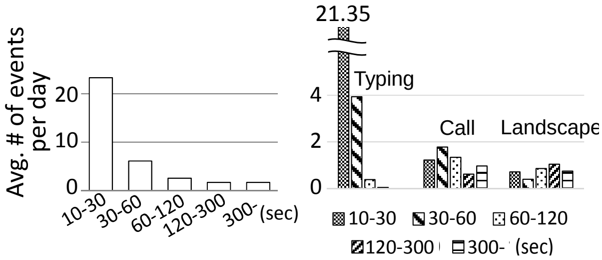
2. OPPORTUNISTIC ECG SENSING

2.1 Opportunities in Practice

We investigate the potential opportunities for ECG monitoring during daily smartphone use. Our study is intended to answer the following questions.

- How many potential opportunities exist per day?
- How long does each opportunity last?
- How reliably can we capture ECG signals, given the opportunity?

For this study, we recruited 14 smartphone users (male/female: 10/4, age: 23–34) on the KAIST and SNU campus and collected their smartphone usage logs for 6 days, on average (4–12 days). We analyzed the collected logs to calculate the number of ECG sensing opportunities and their time durations. We focused on opportunities from three major smartphone use activities: (1) calling without using earphones or a speakerphone; (2) keyboard typing; and (3) gaming and taking a picture in landscape mode. ECG signals can be captured with two electrodes during these activities, i.e., with two hands or one hand and an ear. Users often hold their smartphone with two hands while using instant messaging and typing messages, playing mobile games, and taking pictures. While talking over the phone, they usually hold it with one hand and touch it to their ear. Note that this analysis does not present the actual opportunities where ECG signals could be measured. Instead, we intended to investigate the potential feasibility for this study.



(a) Different time durations (b) Different use cases

Figure 1. Average number of potential opportunities.

To collect the logs of smartphone use, we developed a tool to log a range of user interaction data, i.e., start/end times of call events, touch events for typing, landscape view events, and app use events. To analyze typing duration, we considered consecutive typing events within 5 seconds as typing sessions and measured their time duration; there are some time intervals between typing events, e.g., when chatting with a messenger, users often wait for a response from their friends before responding again.

We classified these events into five groups by time durations, considering different conditions for features to compute and the purpose of analyses based on previous literature. The time durations include 10–30 seconds for HR, 30–60 seconds for ultra-short term heart rate variability (HRV) analysis [10], 1–2 minutes for the high-frequency HRV components [9], 2–5 minutes for the low-frequency HRV components [9], and 5 or more minutes that is typically recommended duration for HRV analysis [8][9].

Sensing Opportunity: A number of potential opportunities for unobtrusive ECG monitoring exist throughout the day, as shown in Figure 1. The average number of potential opportunities varied from about 1.7 to 23, depending on the time durations (Figure 1 (a)). The number of opportunities to obtain HRs was more than 20 per day. Also, there were about 6 potential opportunities for ultra-short term HRV analyses (30–60 sec.) per day. The number of opportunities varied largely, depending on the users. However, there were avg. 8.5 events for the user who had the fewest number of opportunities. For the users who used their phones frequently, three of them showed more than 80 opportunities on average. 11 users had more than 20.

The average number of potential opportunities varied depending on the type of use cases (see Figure 1 (b)). The typing case had the largest number of opportunities. The call case had the second most, but there was no remarkable difference, compared to the landscape case. In the typing case, the number of short time durations was relatively larger, compared to other two cases. There might be a number of opportunities for HR and ultra-short term HRV analysis. In the call and landscape cases, the number of opportunities for larger time durations increased since it is more likely that phone calls and gaming last for minutes. They might be opportunities for analysis with more than 2 minute-ECG recordings.

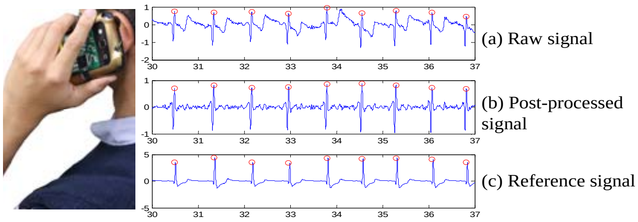


Figure 2. ECG signals for a call case

Sensing Reliability: We checked if we could detect the ECG signal reliably, in comparison with a signal measured with a medical reference device. We collected ECG signals from our prototype sensor device attached to the test smartphone and from the reference device (see Section 4 for details), while assuming the phone call case. As shown in Figure 2, it was possible to capture ECG signals that were quite close to the reference signal (Figure 2 (c)) after post-processing (Figure 2 (b)).

2.2 Application Scenarios

Daily opportunistic ECG monitoring will open up a new opportunity for ECG-enabled applications based solely on daily phone use. We discuss example scenarios of such applications.

Personal Anti-stress Advisor: Stress is a key factor that affects physical and mental health [5][6], and often causes depression and even heart attacks. Although one can easily find generic advice to mitigate stress, such as regularly doing meditation, it is not straightforward to find and apply a personal anti-stress strategy that works and is well-integrated into one's own lifestyle. A personal anti-stress advisor (PAA) attempts to find personalized anti-stress strategies that are readily available in the user's daily routines. The PAA can be personalized with the opportunistic ECG sensing results from the user that have been collected for weeks or months, as well as the accompanying context monitoring data. The PAA spots the records in which the user's stress level becomes lower than average and empirically finds the frequent contextual factors that contribute to such mitigation. For example, PAA may advise the user that "I recommend listening to Beethoven Violin Sonata No. 5 as one of your personal stress relievers." Such advice would be much easier for users to accept and apply to their daily lives because the causes and effects are observed and derived from each user's own lifestyle.

Beat-aware Chat: This application allows users to be aware of the status (e.g., emotion or stress) of conversation partners such as close friends or a spouse, when talking over the phone or texting and to respond appropriately. Considering user's concern on exposing personal status, it provides users with an option with which they can control the status sharing, e.g., when and to whom.

Hearty Tamagotchi: Inspired by Tamagotchi, a world-famous digital pet game, Hearty Tamagotchi is a game in which the user nurtures a virtual pet that lives in the user's smartphone. The user's heart status is used as inputs to raise the pet. The pet also sympathizes with the user; for example, when the user is stressed, the pet feels sympathy for it and cheers up the user. Moreover, Hearty Tamagotchi attempts to complement opportunistic ECG sensing, i.e., to allow sensing in a more regular and predictable basis. While living in the background most of the time, the pet occasionally signals hunger several times a day or more through notification interfaces, and the user has to feed the pet as soon as possible in such events to get more scores. The user interface to

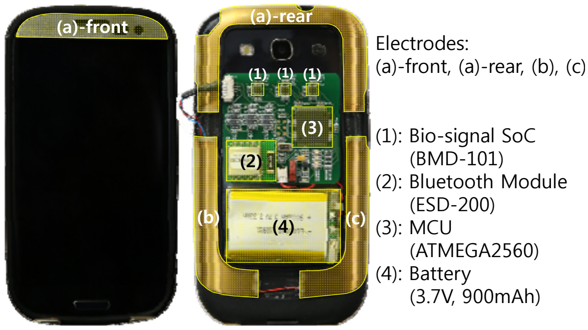


Figure 3. Sinabro sensor

feed the pet is carefully designed so that the user naturally holds the phone with two hands in landscape mode. By pre-scheduling the feeding cycles carefully, reliable ECG-sensing opportunities at desired times are yielded throughout the day, while keeping the user experience natural, enjoyable, and unobtrusive.

Besides the scenarios above, the users' physiological or emotional statuses can be used as the inputs for the mobile system. Such information could be a knob to prioritize applications or schedule resources suitably for a user's status at the OS level, as discussed in [13]. For instance, the system can delay notifications for work-related emails or messages when a user is stressed at home. Also, it would be possible to change the look and feel of the smartphone, such as the wallpaper and theme of the Android launcher.

3. SINABRO DESIGN AND PROTOTYPE

We design Sinabro to fully leverage opportunities for unobtrusive ECG sensing during natural smartphone use. Sinabro is a collaborative system that includes the phone-case sensor and the smartphone middleware. The sensor reliably measures ECG data and transfers it to the middleware. The middleware delivers diverse ECG-derived contexts to multiple apps with Sinabro APIs.

We first custom-designed a reliable and durable smartphone-cover sensor to sense ECGs during daily smartphone use. Figure 3 shows a prototype. As shown in the figure, we placed multiple metal electrodes to capture bio electric signals naturally when the user touches the phone with two different body limbs, e.g., the right and left hands. An electrode is bent smoothly to adhere to the skin naturally. Also, we used thick stainless steel as the electrode material for reliable sensing; it has high conductivity for measuring tiny bio electric signals and small artifacts against external force. Also, the material is highly durable against sweat and humidity. A key consideration of the prototype sensor design is to make the sensors in the form of a smartphone case, so that users can easily adopt it onto their smartphone, if needed. Making the sensor design feasible for commercial products would require further in-depth studies on usability, aesthetic aspects, and other engineering issues, which is beyond the scope of this work.

The current sensor design targets three main modes of daily smartphone usage: phone calls, landscape mode-holding (e.g., gaming, picture taking), and portrait mode-holding (e.g., typing, gaming). To capture such moments, we carefully placed three electrodes in the back and one in the front. During phone calls, a signal is captured by the electrode (a)-front that touches the ear and the electrode (b) that touches the hand. For the portrait mode-holding, the signal is captured by the electrode (b) and (c). Also, landscape-holding is covered by the electrode (a)-rear and (b), or (a)-rear and (c).

Table 1. Key APIs

Monitoring HR and HRV	*registerHRListener* (callback(HR), condition) *registerHRVListener* (callback(HRV), condition) * condition = TARGET_APP | TARGET_MODE class HR { long timestamp; int HR; } class HRV{ long timestamp; float LF; float HF; float LF/HF; float RMSSD; float SDNN; …};
Monitoring HR-/HRV-derived contexts	*registerContextListener*(callback(Context), condition, type) * type = STRESS | AFFECTIVE_STATE | …

The sensed signal is preprocessed by a sensor-side processing module, and delivered to the smartphone through a Bluetooth interface (2). The major sensor-side processing is performed by a BMD-101 SoC (system on chip) (1). It filters out low-frequency fluctuation over the sensed analog signal, and the signal is converted into digital data. The digitalized data is further clarified with the power noise filter and the 100Hz low-pass filter. We integrated three BMD-101s to handle three combinations of electrodes ((a)-(b), (a)-(c), and (b)-(c)). The processed data are delivered to an Atmega2560 MCU (3) via USART interfaces and then wirelessly forwarded to the smartphone. The processing and communication modules are turned on when an ECG is likely to be available to save energy. The sensor consumes 124.52mW for sensing and transmission and only 25.52mW in standby mode.

The smartphone middleware detects a potential opportunity to get a reliable signal given the user's smartphone usage, and sends the sensor a command to trigger sensing, along with a proper channel (a combinatinon of electrodes) to get data from. During the opportunity, it receives raw ECG signals, extracts useful features and contexts, and delivers them in real-time to multiple applications using Sinabro APIs. To make reliable context inferences, raw ECGs are processed through a series of processing modules. First, the preprocessor applies a digital band-pass filter (5Hz–35Hz) to further clarify the QRS peaks in the ECG signals and to remove power noises and EMG noises once again. Second, QRS peaks are detected from the filtered signals. For reliable peak detection, we employ an efficient algorithm, which has been developed by the SNU research group. Third, the QRS peak corrector further removes false-positive peaks that the detector may have mistakenly added; false positives are filtered out when their power value is less than a certain threshold and their interval to the previous/next peak is too small. Then, the missing peaks are interpolated using a Piecewise-Cubic-Hermite interpolation method. Finally, HR and HRV are calculated from the peaks obtained [9], and other data, such as stress and affective state, are further derived based on HR and HRV [8][10].

Table 1 shows the key APIs that Sinabro provides to support diverse daily healthcare and wellbeing applications. First, the two primitives are *registerHRListener*() and *registerHRVListener*(), with which applications can trace HR and HRV on-the-fly. Once the former is registered, Sinabro can notify applications of the user's HR if available. Applications may designate specific use cases with a condition argument, e.g., a messenger may want to leverage heart rate when the user communicates with a friend. Second, applications can retrieve physiological contexts derived from HR and HRV using *registerContextListener*(), which currently provides stress and affective state. We adopted existing methods to derive such contexts [8][10], and we can easily incorporate additional processing logics. Besides real-time monitoring, Sinabro supports applications to query historical data with *getHistory*(), e.g., "Let me know the HR and stress value when I was in a subway train to the office" It provides a SQL interface to support the easy querying of stored information.

4. PRELIMINARY EVALUATION

Here, we present the preliminary evaluation of the Sinabro prototype. We perform the evaluation in two steps. First, we investigate how accurately Sinabro can monitor ECG signals and derive related features, given actual sensing opportunities. For the potential opportunities we consider in Section 2, we assume that users touch the electrodes with two body parts, and ECG sensing can thus be done during such usage. In this study, we assess which opportunities are useful for the valid operation of Sinabro. Second, we investigate how many potential opportunities can lead to actual sensing opportunities. For this, we analyze sensing data from four users during free smartphone use for one hour.

4.1 Evaluation in Actual Sensing Opportunity

Setting: We recruited 13 participants from Seoul National University (male/female: 9/4, avg. age: 25.1, SD: 3.1). We asked them to use our prototype phone under predetermined use cases, i.e., while texting, gaming, and calling. Also, we collected data when the participants held the phone still with two hands for 10 seconds, both in portrait and landscape mode, which can be considered to be an upper-bound scenario. We used Galaxy S3 for the prototype. The raw ECG and detected QRS peak data were acquired during smartphone use. The HRV parameters calculated by the Sinabro middleware were also acquired. For evaluation, we collected the ground-truth data from the bio-signal acquisition system, the BIOPAC MP150 ECG module, with Ag/AgCl electrodes, which were attached to the left and right forearms.

The detailed settings for the different use cases were as follows. In the texting case, the participants were asked to hold the phone naturally in portrait mode with their two hands, so that they touched the electrodes and there was a valid sensing channel. They were asked to type text messages naturally using a mobile messenger for 5, 10, and 15 seconds, respectively. In the gaming case, they were asked to play two different games for 1 and 5 minute(s), respectively. We selected the games because both are played with two hands in landscape mode. One was the highly interactive action game, *Touch fighter for Kakao*, which incurs frequent and strong inputs (at least 1–2 inputs per second, up to 5). The other was the low interaction baseball game, *Perfect Inning 2013*, which involves relatively less frequent, gentler inputs (avg. 0.5 per second). For calling, they had a conversation with the experimenter for 1 and 5 minute(s), respectively. They were asked to hold the phone with their left hand and touch it to their left ear.

As evaluation metrics, we used the QRS peak detection ratio (PDR) and the error rate of the HRV parameter. The PDR is the number of correctly detected QRS peaks from Sinabro divided by the number of QRS peaks detected manually by the experienced expert from the ground-truth ECG signals. The interpolated peaks were excluded from the calculation of the PDR. The error rate of the HRV parameter was calculated by comparing the HRV parameter obtained from the QRS peak intervals after the interpolation process with that from the intervals that were manually detected by the experienced expert from the ground-truth data. The HRV parameters that we used include time-domain HRV parameters, mean HR, SDNN, and RMSSD, and frequency-domain parameters, LF, HF, nHF, nLF, and LF/HF [9].

We calculated the errors in the mean HR for all measurements, while we measured those in the other HRV parameters for the gaming and calling cases with 5-minute measurements.

We did not include a case of texting in landscape mode as a sensing opportunity. All participants only used their thumbs when typing while holding the phone with two hands. They hardly held it in landscape mode for typing, since it was not comfortable.

PDR: We could see that the QRS peaks were almost all correctly detected while typing in portrait mode and calling, whereas there were relatively more missed peaks in the other cases. As shown in Figure 4, the PDRs for the 10-second holding cases were quite close to 100%; only one peak was missed for several participants. The PDRs for calling and portrait typing were also nearly 100%; avg. 99.2% and 98.7% for 1-minute and 5-minute calling, respectively, and avg. 99% for typing. For the gaming cases, the average PDRs varied from 84.5% (high, 1 minute) to 89.5% (low, 1 minute), and their SDs were quite large (14–21%). We observed that 4–5 of the participants showed quite low PDRs (e.g., 31, 47, 66%) while the rest of them showed PDRs larger than 92%. During gaming, the participants moved their thumbs frequently to press buttons. Such movements can result in rubbing or weak contact between the electrodes and the hands, thereby causing noise in the ECG signal. From these results, we could see that the gaming cases should be utilized selectively for meaningful sensing opportunities depending on the user. Also, it will be necessary to spot the valid sensing segments among the whole measurement for an opportunity, in order to exploit the opportunity effectively.

Error Rates of the HRV Parameters: There were negligible errors or small errors in the mean HR, depending on the use cases. As shown in Table 2, the mean HRs were almost correct for the typing and calling cases. The gaming cases show relatively larger average errors due to some of the participants' results, similar to the previous PDR result. However, more than half of the participants showed less than 1% error, which is almost completely accurate heart rate estimation. The other HRV parameters showed somewhat noticeable errors, depending on the use cases, e.g., LF: 1–5.1%, RMSSD: 7.8–102.9%. They were sensitive to errors in the QRS peak intervals due to missed and incorrectly interpolated peaks. A more detailed investigation into the causes of the errors and an elaboration of the peak detection and correction algorithms are ongoing to improve performance.

4.2 Potential to Actual Chance

Setting: In this small-scale study, we analyzed whether potential opportunities resulted in actual sensing opportunities that allowed QRS peaks to be detected reliably. For this purpose, we recruited 5 participants (4 students and a researcher), at the KAIST campus (all male, avg. age: 26.4). They were all Android users, including 3 Galaxy S3 users, 1 Galaxy S4 user, and 1 Nexus 5 user. We attached the prototype sensor case onto the users' phones and asked all but the Nexus 5 user to use it. The Nexus 5 user used our prototype. Before the study, we conducted a test to check if their phones, which were equipped with the sensor, worked well. During the test, we observed that one of participants held his phone in such a way that he hardly touched the electrodes with his hands, so that the sensing signals could not be captured reliably. Thus, we conducted the study with the 4 participants other than him. They were asked to sit down on a chair and freely use the apps they use frequently in their free time for an hour. We allowed the Nexus 5 user who used our prototype to install his

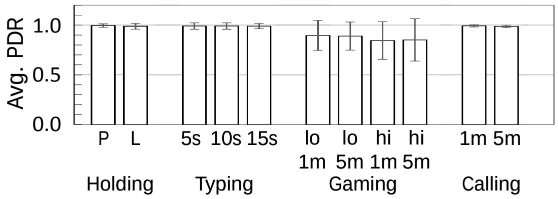
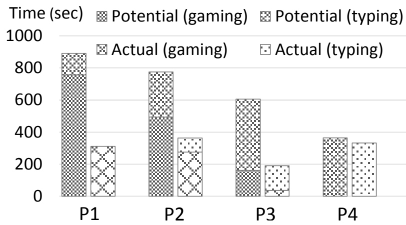


Figure 4. Average PDRs for different use cases
- the error bars represent standard deviations

Table 2. Average error rate of mean HR

Use cases	Typing			Gaming				Calling	
	5sec	10sec	15sec	Low, 1min	Low, 5min	High, 1min	High, 5min	1min	5min
Error rate of mean HR avg. (std.)	0.10% (0.10%)	0.16% (0.24%)	0.12% (0.13%)	11.6% (19.8%)	1.61% (2.49%)	5.78% (9.95%)	6.98% (18.1%)	0.28% (0.38%)	0.13% (0.16%)

	# of events (gaming, typing)	
	Potential	Actual
P1	12(5, 7)	5(5, 0)
P2	14(1, 13)	6(1, 5)
P3	17(1, 16)	7(1, 6)
P4	15(0, 15)	13(0, 13)



(a) Number of opportunities **(b) Time duration**
Figure 5. Actual sensing opportunities

favorite apps and keyboard before the study. We recorded them on video to check their phone holding posture, as well as when and how long they held their phones with two hands and how their hands contacted the electrodes.

Results: A reasonable number of potential opportunities led to actual sensing opportunities where the QRS peaks could be detected reliably; we considered sensing signals to be reliable when more than 95% of peaks could be detected. In terms of the number of opportunities, 41–87% of potential opportunities led to actual sensing opportunities (Figure 5(a)); we included use cases, such as typing, lasting for more than 10 seconds as potential opportunities. The distribution of potential opportunities was different, depending on the participants, since their app usages were different, e.g., P1 frequently played a game, and used a messenger and SNS apps, while P4 did not play a game and frequently used a messenger, a browser, and a news reader app. We observed that the different holding postures of the participants affected the results for actual opportunities. Also, they sometimes changed their holding posture, e.g., holding the phone with two hands or with one hand for their convenience. While all of the participants often used two thumbs to type on the keyboard, P1 did not provide actual opportunities from any of the typing cases. P1 used one hand to hold up the phone and slightly touched the phone with his other hand when typing with his thumbs. Thus, the electrodes were not contacted stably. However, the other three participants could utilize the typing cases as actual opportunities, although their sensing reliability varied, depending on their holding posture. Intriguingly, P4 showed considerably reliable sensing results. In terms of time duration, 32–92% of the time for potential opportunities resulted in actual opportunities (Figure 5(b)). We observed that the full duration of many of the typing cases became the actual sensing duration, while the time durations for gaming partially became the actual sensing duration.

In addition, we observed that other use cases, such as browsers or SNS apps led to actual sensing opportunities as long as the users' two hands contacted the electrodes stably when holding the phone. It would be helpful to develop a method to efficiently detect and exploit such moments for opportunities. We plan to conduct more extensive feasibility studies in real-life smartphone usage with a wider variety of participants, as well as over a longer period.

5. RESEARCH ISSUES

Among a number of research issues to build a fully-functioning daily ECG monitoring system, we discuss four of them here.

Extending Sensing Modality. We will extend the current Sinabro prototype by applying the opportunistic health monitoring approach to other sensing modalities. We consider three potential cases. First, Sinabro can integrate a GSR sensor, which can be used to detect stress levels by analyzing skin conductance [5]. When users hold their phones with one hand, their skin conductance can be automatically measured and analyzed. Second, sound data from a microphone are a useful signal that can be obtained opportunistically to detect health-related statuses, e.g., stress detected from human voice [5] and coughs. Phone calls can be opportunities to get such sound signals. Third, a thermometer can be integrated into earphones. When a user uses earphones to listen to music, body temperature can be measured.

Augmenting Contextual Information. Contextual information about the situation in which sensing data are obtained can provide important cues for analyzing the data from diverse daily situations, e.g., heart rate may be high right after running in a hurry, but low when a user sits down for an hour. To handle such cases, the interpretations of sensing data should incorporate appropriate contextual data. Utilizing contextual data also may enable users to understand the changing trends in their status under different conditions, e.g., comparing heart rate or stress level at home with that in the office. The user's text data or voice can be analyzed to further investigate the cause of and response to stress.

Handling Signal Noise. Since Sinabro collects ECG signals during smartphone usage, the contact between hands and the electrodes can be unstable, which can result in motion artifacts. Motions during touch inputs on a keyboard and on buttons can cause noise and corresponding errors when detecting QRS peaks. Moreover, different users may have different behaviors such as holding posture and touch intensity. Proper processing for noise detection and error compensation should be incorporated.

Expanding Sensing Opportunities. Sinabro can be extended to incorporate other wearable sensors and sensors integrated with household equipment, such as a chair or a bed [11], to increase sensing opportunities. For example, Sinabro can incorporate a bed-embedded ECG sensor and exploit expanded opportunities. The sensor would allow not only heart rate and stress to be obtained but also sleep quality and stages while the user is asleep.

6. RELATED WORK

There have been research efforts to monitor physical and mental health status and provide in-situ intervention based on mobile phones, such as for physical health (e.g., heart [1][12], sleep duration [4]), mental health (e.g., stress [5][6]), and wellbeing [7]. Some have used external sensors along with a mobile phone to monitor health status, e.g., ECG monitoring with a wearable device [12] and stress detection with a range of sensors such as ECG, GSR, and accelerometer sensors [6]. While using additional devices may be helpful to monitor diverse physiological parameters and investigate enriched statuses, it would also be intrusive to users. Thus, others have employed an approach that only uses a mobile phone for unobtrusive monitoring. StressSense [5] has developed a voice-based stress classifier by using phone-embedded microphones. In [4], the authors propose a sleep duration estimation approach. While the proposed system also goes in the direction of unobtrusive daily health monitoring, it further enables physiological sensing, such as ECG that cannot be achieved with the currently available smartphone sensors by exploiting opportunities during daily smartphone use.

7. CONCLUSION

In this paper, we presented an unobtrusive mobile ECG monitoring system that monitors the user's ECG opportunistically during daily smartphone use. We first studied the potential opportunity to monitor ECG from daily smartphone use alone. Based on this opportunity, we proposed a design for the system and built an early prototype. We plan to conduct further research to build a fully-functioning opportunistic monitoring system and evaluation including comprehensive experiments in the wild.

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