

# Auth 'n' Scan: Opportunistic Photoplethysmography in Mobile Fingerprint Authentication

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Recent commodity smartphones have biometric sensing capabilities, allowing their daily use for authentication and identification. This increasing use of biometric systems motivates us to design an opportunistic way to sense user's additional physiological or behavioral data. We define this concurrent physiological or behavioral data sensing during biometric authentication or identification as *dual-purpose biometrics*. As an instance of dual-purpose biometrics, we develop photoplethysmography (PPG) sensing during mobile fingerprint authentication, called Auth 'n' Scan. Our system opportunistically extracts cardiovascular information, such as a heart rate and its variability, while users perform phone unlock of a smartphone. To achieve this sensing, our Auth 'n' Scan system attaches four PPG units around a fingerprint sensor. The system also performs noise removal and signal selection to accurately estimate cardiovascular information. This paper presents the hardware implementation and signal processing algorithm of our Auth 'n' Scan prototype. We also report our system evaluations with 10 participants, showing that, despite a little low precision (a standard deviation of 3–7), estimation of heart rates with high accuracy (under a mean error of 1) is possible from PPG data of five seconds and longer if their baseline information is given. We discuss the feasibility of opportunistic PPG sensing in mobile fingerprint authentication.

**CCS Concepts:** • **Applied computing** → *Health care information systems*; • **Security and privacy** → *Biometrics*; • **Human-centered computing** → *Ubiquitous and mobile devices*; Human computer interaction (HCI);

**Additional Key Words and Phrases:** Dual-purpose biometrics, unobtrusive sensing, cardiovascular sensing, photoplethysmography, fingerprint authentication.

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## 1 INTRODUCTION

Recent identification and authentication systems employ biometrics, physiological, or behavior data that are distinctive among individuals. Such biometric authentication has become commodity in recent computer devices. For instance, it can allow smartphone users to unlock their devices with fingerprints, reducing the effort for entering codes or passwords. Prior work has also revealed that users positively received biometric authentication systems [6, 9]. A report claims that users who own smartphones with a fingerprint authentication capability unlock their devices 80 times a day through biometrics [5]. We believe that future ubiquitous and mobile systems would further integrate biometric authentication/identification, encouraging its use in a daily life.

This increasing use of biometric authentication motivates us to design an opportunistic way to sense user's additional physiological or behavioral data. For instance, when users unlock a smartphone, a system can

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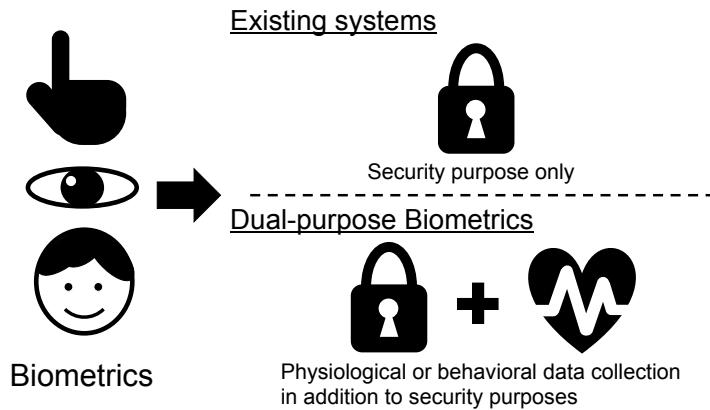
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**Fig. 1.** A concept illustration of *dual-purpose biometrics*. Dual-purpose biometrics enables concurrent physiological or behavioral sensing during biometric authentication or identification. This sensing mechanism offers an opportunistic and unobtrusive way to acquire healthcare information as well as encourages the use of authentication/identification systems through additional applications enabled.

sense physiological data (e.g., vital information, respiration or perspiration) besides fingerprints. Extracted data can benefit a wealth of applications, including life-logging, personal informatics, and healthcare monitoring. We define this concurrent physiological or behavioral data sensing during biometric authentication or identification as *dual-purpose biometrics*. Figure 1 illustrates a conceptual comparison between existing biometric authentication/identification systems and dual-purpose biometrics.

Dual-purpose biometrics can offer unique benefits to existing biometrics systems. Additional applications enabled by dual-purpose biometrics may encourage more use of biometric authentication/identification systems. As dual-purpose biometrics systems perform sensing during authentication or identification, users would not need to perform separate explicit data recording or wear additional devices. This may lead to improved compliance of data collection.

In this work, we demonstrate a system that senses user's cardiovascular data during fingerprint authentication on a smartphone as an instance of our dual-purpose biometrics concept. Our system, called Auth 'n' Scan, utilizes custom-made hardware containing multiple photoplethysmography (PPG) sensors. We design them to surround the fingerprint sensor on a smartphone. In this manner, users can record their cardiovascular data during authentication<sup>1</sup>, and do not need to perform separate explicit measurements. Because our system enables sensing at different times of the day, it can obtain information that otherwise is difficult to infer, such as heart rate changes due to the circadian rhythm [35] and distribution transition in a Poincaré plot (discussed in Section 8.3).

Besides the proposal of dual-purpose biometrics, the main objective of this work is to demonstrate the feasibility of concurrent sensing of fingerprints for authentication and cardiovascular data for healthcare monitoring applications. When users place fingers for unlocking smartphones with their fingerprints for at least five seconds, our system extracts short-term cardiovascular features, such as a heart rate and its variability, with PPG sensors. In addition, the Auth 'n' Scan system reconstructs longer-term features (e.g., a feature in a Poincaré plot) from a series of fragmented measurements if the sensing duration of ten seconds is allowed. Although our current prototype needs at least five seconds of recording for accurate heart rate estimation, the majority of participants in our user study agreed that it is acceptable at the exchange of the benefit by Auth 'n' Scan.

<sup>1</sup>In this work, we mainly refer to authentication scenarios though our concept and system can be applied for identification systems.

The contributions of this work are as follows:

### **Our proposal of the dual-purpose biometrics concept**

We introduce the concept of dual-purpose biometrics. As summarized in Figure 1, dual-purpose biometrics systems enable both authentication/identification and unobtrusive sensing for additional applications. This capability is beneficial for security systems (e.g., encouraging more use of them) as well as sensing (e.g., unobtrusively acquiring users' data).

### **Hardware for concurrent fingerprint and cardiovascular sensing on a smartphone**

We develop custom hardware to attach four PPG units to the periphery of a fingerprint sensor on a smartphone. Our informal evaluation confirms that our hardware design is robust to different finger placement and ambient light conditions.

### **Cardiovascular feature inference from short-term PPG data**

Our algorithm selects a signal among four PPG channels that can best describe cardiovascular information. It then extracts heart rates and peak-to-peak intervals from that signal. In addition, our algorithm attempts to reconstruct a Poincaré plot, comprised of pairs of two adjacent PPIs, from a set of fragmented measurements.

### **System and user evaluations of Auth 'n' Scan**

We conducted system evaluations with 10 healthy adult participants. Our results achieved heart rate estimation from data in the duration of 5 seconds or longer if the baseline heart rate data of each participant is given. More specifically, the estimation error was within 1 and its standard deviation was between 3 and 7. In addition, we confirm that reconstruction of Poincaré plots is possible for some of our participants though a sufficient number of adjacent PPI pairs are necessary. Our participants agreed that a 5-second sensing duration was acceptable because Auth 'n' Scan offers heart rate information.

## **2 DUAL-PURPOSE BIOMETRICS**

Auth 'n' Scan is an instance of *dual-purpose biometrics*, our security system concept proposal. Dual-purpose biometrics represents an identification or authentication system which simultaneously senses users' physiological or behavioral data for additional purposes, such as healthcare monitoring and life-logging (Figure 1). Users frequently engage in activities that require authentication in a daily life (e.g., unlocking a smartphone, opening an office's door, and placing an order in an online system). Various biometrics authentication systems become available in these scenarios. Dual-purpose biometrics exploits these increasing biometrics authentication interactions as sensing opportunities. In this work, we demonstrate cardiovascular sensing in mobile fingerprint authentication for phone unlock as an example of dual-purpose biometrics. Future work should explore a broader area of dual-purpose biometrics (e.g., skin moisture sensing in authentication with fingers or hands; heart rate sensing in face authentication; and throat disorder detection in voice-based authentication).

Dual-purpose biometrics aims to encourage the use of authentication systems by providing additional applications it enables. Sasse and Flechais discussed the role of security systems through the lens of human factor analysis [36]. In a goal-oriented process, there are two types of tasks: *production tasks* (tasks that are necessary to complete to achieve the goal) and *supporting tasks* (tasks that are not directly essential to achieve the goal but would provide value or useful functionality for a production task). This analysis can explain why users often circumvent or disable security systems. According to Sasse and Flechais' argument, security is a supporting task. Although security provides protection value, it does not directly contribute to a production task or offer merits immediately perceivable to users. Thus, security systems may become a burden, resulting in its abandonment. In dual-purpose biometrics systems, authentication can become a production task for the other purposes. For example, a phone unlock would become an interaction to record heart rate information for a healthcare application. In this manner, users can obtain more direct benefits from security systems besides

protection. We hope that dual-purpose biometrics would contribute to further persuasion and penetration of daily security system use.

Dual-purpose biometrics is also regarded as another form of unobtrusive sensing for daily healthcare monitoring. Some existing healthcare monitoring systems involve explicit measurements of physiological data or user activities (e.g., using a blood pressure monitor or making manual annotations upon smoking). Prior work has addressed this issue in the context of experience sampling [18]. Such measurement burden could also degrade user compliance and data reliability in healthcare monitoring applications. One possible solution is unobtrusive sensing, a technology which performs sensing while users are engaging in a main task [23]. Although unobtrusive sensing is promising to reduce user's burden, Korhonen et al. discussed the following three challenges: 1) a requirement for user identification; 2) limitations on continuous monitoring; and 3) constrained sensing capabilities of physiological data. Our dual-purpose biometrics uniquely solves the first and third issues. As dual-purpose biometrics concurrently performs authentication and sensing, user identification can be immediately given under the user's permission. Upon biometric authentication, users are asked to steadily expose part of the body. A system thus has a sufficient opportunity to acquire various physiological data (e.g., cardiovascular information in the Auth 'n' Scan system). Dual-purpose biometrics broadens the field of unobtrusive sensing, and encourages further research in creative exploitation of biometric authentication.

Although it is beyond the scope of this work, dual-purpose biometrics can also contribute to multimodal biometrics [33]. Multimodal biometrics means using multiple physiological or behavioral traits to improve security robustness. Dual-purpose biometrics is different in enabling additional applications instead of reinforcing security. But future dual-purpose biometrics systems could offer unique security enhancement (e.g., ECG data can be another evidence for user authentication [34]).

### 3 RELATED WORK

#### 3.1 Fingerprint Sensing Technology

A fingerprint is a pattern formed by friction ridges observed in epidermis. As fingerprint patterns are considered to be distinctive and immutable, they are widely used in authentication. Fingerprints can be found in several locations of a human body, such as a palm and foot, but those in fingertips are the most common part for security system use. Although prior work has studied various matching methods, a typical approach is to use feature points called minutiae [19]. Minutiae refer to ridge endings and bifurcations in a fingerprint pattern. A typical fingerprint image contains 20–70 minutiae points [19]. Based on the location and orientation of each minutia, a matching algorithm calculates similarity between a given fingerprint and those in a database, and performs identification (i.e., determines who this user is) or authentication (i.e., judges whether this user is really the person who she claims to be) [32].

A broad range of fingerprint sensing approaches exists: optical, capacitive, RF-based (radio frequency), pressure-based, thermal, and ultrasonic sensors [31]. An RF-based method is considered to be the most accurate and reliable [39]. An RF fingerprint sensor consists of a 2D array of tiny antennas each of which produces reading of the depth of a point. Because of the ability to capture fingerprint images beneath the skin, the RF array-based fingerprint sensor technology is robust to different skin conditions, environments, and even minor finger surface contamination [39]. Since Apple integrated this type of sensors into iPhone 5S in 2013, fingerprint authentication on smartphones becomes common. De Luca et al. showed that one of the main decision factors to enable biometrics on smartphones is its usability [9]. Another study reported that people prefer fingerprint authentication to face recognition or traditional password-based approaches for phone unlocking because of its usability [6]. According to Apple's report in 2016, 89% owners of iPhones and iPads with a fingerprint authentication capability regularly used the Touch ID service [5]. This report also showed that they unlocked their devices with Touch ID roughly 80 times a day on average. Recent research has demonstrated broader

applications of mobile fingerprint authentication. Holz et al. developed on-demand biometrics, an alternative way to log into an online service that replaces textual passwords with fingerprint authentication on a user's mobile phone [16]. We believe that fingerprint authentication will be even more common in various devices and systems. Although the present demonstration of Auth 'n' Scan is on a smartphone, our contributions are conceptually applicable to other form-factors.

### 3.2 Fingerprint-based Interaction

HCI research has explored several methods to exploit fingerprints to enable novel interfaces. An early example of fingerprint recognition use for interaction techniques was a fingerprint user interface demonstrated by Sugiura et al. [41]. A contact to their device executed a command uniquely assigned to each finger. Their system utilized a fingerprint authentication mechanism to distinguish user's fingers. RidgePad used fingerprint recognition to improve touch accuracy by identifying a user and estimating her finger posture [14]. Based on the information, it can estimate the user perceived input point which is a little displaced from the actual contact location. In this manner, RidgePad obtained 1.8 times higher accuracy than the conventional touch input. Fiberio is a tabletop touchscreen system that authenticates users during touch interaction with their fingerprints [15]. They used a fiber optic plate which offers both specular reflection and diffuse transmission in order to capture fingerprints and display images simultaneously. This system enables a wide range of tabletop interactions with user identification or authentication.

Although our current main scenario is fingerprint authentication on smartphones, integration of a similar concept to dual-purpose biometrics into the systems above could be possible. For instance, a future FUI [41] could sense cardiovascular data every time a user executes a command. Our work contributes to demonstrating the feasibility of gathering physiological data through a short-time interaction (i.e., authentication in this project).

### 3.3 Unobtrusive Cardiovascular Sensing

Prior work has investigated unobtrusive approaches to sense user's cardiovascular data. Kang et al. developed a mobile electrocardiogram (ECG) monitoring system on a smartphone, called Sinabro [21]. They attached multiple electrodes at the front and back of a smartphone. Sinabro measures the user's ECG when she makes contacts with her left and right body parts. Griffiths et al. integrated an ECG-based heart sensing technique to a chair [13]. Health Chair acquires ECG through electrodes attached to the armrests. One major limitation of ECG sensing is that it requires multiple physical contacts with bare skin. Griffiths et al. found that Health Chair was able to extract user's heart rate information for even shorter than 1% of typical office hours (i.e., 8 hours) in their study. Sinabro requires users to hold a device with both hands, and some users may prefer such bimanual possessing [11]. However, one-handed interaction is also common in mobile touch-screen devices [22]. Thus, sensing opportunities can greatly vary depending on their device holding preferences. Our Auth 'n' Scan system allows cardiovascular sensing during fingerprint authentication, and can co-exist with Sinabro.

Prior research has examined alternative approaches to cardiovascular sensing. One method is to use reflection of radio frequency waves. Adib et al. developed Vital-Radio, which can monitor breathing and heart rates of multiple people without physical contacts with the sensor [2]. Their system can detect respiration and heartbeat changes from signals reflected on users' bodies. BodyScan is a wearable system that recognizes various user's activities and status including heart rates [12]. It consists of a wristwatch-like radio transmitter and receiver with a holster. The system uses the intensity of radio signals to infer user's heart rates.

Research has also investigated vision-based approaches to detecting heart rates. Mauka-Mauka used a Webcam attached to a worker's laptop and confirmed the feasibility of unobtrusive heart rate sensing in a workplace environment [40]. Poh et al. developed a Webcam built-in mirror which detects a user's heart rate while she is looking [30]. Wu et al.'s image processing method, called Eulerian Video, can also extract heart rates and possibly

other cardiovascular information from images of a person taken by an unmodified camera [44]. Although these vision-based methods are very promising, image capturing can be inappropriate or even prohibited at public contexts. Thus, non-vision approaches can be more appropriate for mobile cardiovascular sensing.

Researchers have explored the use of inertial sensors for mobile cardiovascular sensing. Aly et al. developed a respiratory rate estimation system, called Zephyr, using accelerometer and gyroscope sensors of a smartphone [4]. When a user places her smartphone onto her chest, Zephyr captures the chest movements caused by breathing. Mohamed et al. expanded this method to enable heart rate estimation [26]. Their system, HeartSense, also captures users' chest movements using an off-the-shelf smartphone, but it only uses gyroscope sensor data based on observations on heart motion mechanisms. These methods are robust and accurate, and do not require any additional hardware equipment. However, measurements with these systems require users to perform explicit interaction (i.e., users have to be still and keep their smartphone on their chests).

PPG is also an optical approach though image capture and processing are not necessary in general. Another advantage of PPG sensors is that their form-factor can be small (e.g., one pair of an LED and photo-detector). Chigira et al. integrated a PPG sensor into a tumbler [8]. It can detect a user's heart rate during beverage consumption. Poh et al. and Holz et al. demonstrated integration of PPG sensors into an earphone [29] and glasses [17], respectively. These devices enable continuous cardiovascular sensing while users are wearing them. These projects demonstrated a potential of PPG sensors. But PPG sensors are susceptible to ambient light, and use scenarios in the projects above are limited to dark conditions. For example, a user's hand holding the tumbler blocks PPG sensors from ambient light [8]. Effect by ambient light is negligible inside an ear canal [29]. A PPG sensor is a promising approach, but its use under a normal light condition is challenging.

### 3.4 Summary

We discussed the literature about fingerprint-related technology and interfaces as well as unobtrusive cardiovascular sensing. Although much research on these areas exists, one of our contributions is to exploit fingerprint authentication for phone unlock to perform cardiovascular sensing through PPG. Our work is similar to Chigira et al.'s project in terms of exploiting user's frequent activities as a sensing opportunity. As we already discussed in the previous section, our dual-purpose biometrics concept can address two of the major challenges in unobtrusive sensing. This work contributes to broadening the field of unobtrusive sensing and applications of biometric technologies.

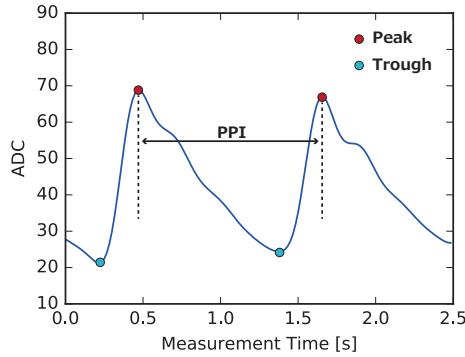
Exploiting phone unlock for data collection has also been investigated. Truong et al. demonstrated an interface to replace an unlock slider with swipe gestures for completing microtasks [42]. This interface design allows smartphone users to participate in lightweight data collection about themselves and their contexts. Vaish et al. explored a similar concept for microtask crowdsourcing [43]. Similar to these projects, Auth 'n' Scan exploits phone unlock for physiological sensing, which would benefit a variety of healthcare applications.

## 4 PHOTOPLETHYSMOGRAPHY (PPG)

We use photoplethysmography (PPG) in the current Auth 'n' Scan prototype. PPG requires physical contacts, but it can be acquired from a single sensing location unlike ECG. Furthermore, its hardware can be simple and easily downsized. This characteristic is desirable in our main use scenario (i.e., phone unlock with fingerprints), and we decided to use PPG in this work though other technologies can be considered in future work. In this section, we explain its principle and physiological information derived from PPG signals.

### 4.1 Sensing Principle

PPG is an opto-electrical and non-invasive measurement technique that can detect blood volume changes in the microvascular bed of tissue [3]. A simple construction of a PPG sensor comprises an LED and photo-detector. A



**Fig. 2.** An example of a photoplethysmography signal with CMS-50E. The output can take a discretized value between 0 and 127. Peaks, troughs, and a PPI are annotated.

periphery of the body, such as a fingertip or earlobe, is a commonly-used contact point for PPG. Light from the LED is partially reflected on the skin, and captured by the photo-detector. When blood volume changes occur, the amount of light absorption varies. The photo-detector then detects this variability as an electrical signal.

One of the most common medical applications of PPG is pulse oximetry which can monitor oxygen saturation as well as heart rates in a non-invasive manner. Oxyhemoglobin and deoxyhemoglobin exhibit different absorption performance of red and infrared light. A pulse oximeter utilizes this phenomenon to determine the proportion of hemoglobin bound to oxygen [7]. We used CMS-50E, an FDA-approved fingertip pulse oximeter, to obtain ground truth PPG signals.

Figure 2 shows a typical waveform gained through CMS-50E with an adult who does not have any major cardiovascular disease. As shown in this figure, a PPG waveform in general demonstrates periodical repetitions. Features in the PPG waveform are denoted as follows:

**Peak** A local maximum in one cycle.

**Trough** A local minimum in one cycle.

**Peak-to-peak interval (PPI)** A time interval between two adjacent peaks.

## 4.2 Physiological information derived from PPG signals

From raw PPG signals, we can obtain the following physiological information beneficial for personal healthcare applications.

**Heart Rate** It is derived from the number of peaks per minute. It is one of the most frequently-used cardiovascular features.

**Heart rate variability (HRV)** It is calculated as the variance of PPIs. It is regarded as a useful feature for assessing an autonomic nervous system.

**Poincaré plot** It is a plot of two adjacent PPI values. The distribution can be indicative of heart dysfunction [20].

**Acceleration plethysmogram** It is the second derivative of PPG signals. It can indicate distensibility of the peripheral artery.

**Respiration rate** It is derived from the frequency of an envelope wave of PPG signals. It is another common cardiovascular feature.

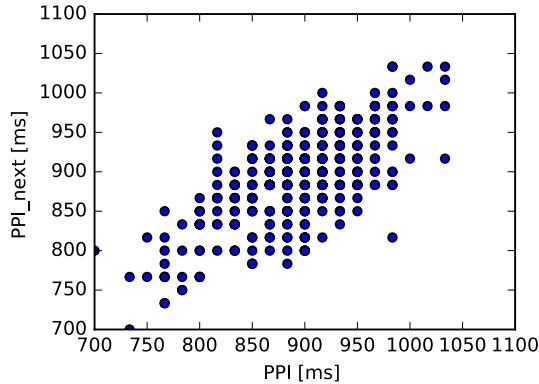


Fig. 3. A Poincaré plot generated from PPI data. The shape of the plot can be indicative of a person's heart functionality.

Heart rate variability (HRV) is traditionally derived from ECG, but medical research shows that HRV is reliably estimated from PPG [38]. HRV is a well-used feature for assessment of autonomic nervous system dysfunction, but this information can lead to additional observations on cardiovascular activities through a Poincaré plot. In this plot, each point represents two adjacent PPI values. Figure 3 illustrates an example Poincaré plot generated from a five-minute long PPG signal with a healthy adult user. A Poincaré plot with healthy users normally demonstrates a distribution that can be approximated as 2D Gaussian [20]. But patients with heart dysfunction can exhibit skewed or dispersed distributions. In general, the creation of a Poincaré plot requires sufficiently-long sampling of PPI, generally for five minutes. Such long sampling is unfortunately impossible in our target application because users would place their fingers for phone unlock only for a couple of seconds. This work examines feasibility to reconstruct a Poincaré plot from a set of short PPG signals.

In a Poincaré plot,  $SD1/SD2$  is considered to be one of the most important features.  $SD1$  is the standard deviation of the differences of two adjacent PPIs.  $SD2$  is the root of the subtract of  $(SD1)^2$  from the variance of PPIs.  $SD1/SD2$  is a ratio of these two values. Medical research shows that this metric varies for people with heart or cardiovascular disease [1], and we examine the feasibility of Auth 'n' Scan to extract this feature.

## 5 SENSOR HARDWARE

### 5.1 Implementation

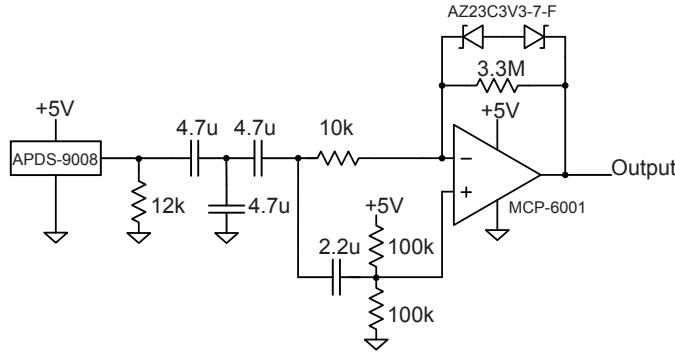
To instantiate the concept of dual-purpose biometrics in mobile fingerprint authentication, we developed a custom PPG sensor circuit. Our circuit is designed to place LEDs and photo-detectors around the fingerprint sensor in a commercially available smartphone. We had the four design considerations in our hardware.

#### **DC-A.** Co-existence with a fingerprint sensor:

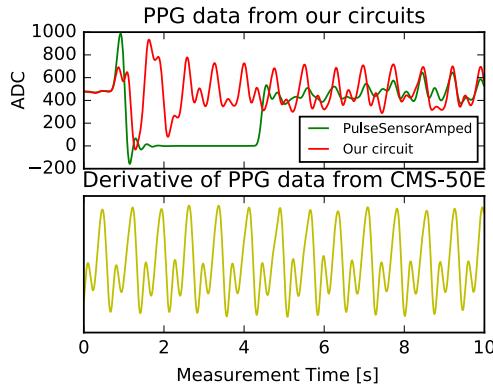
Our system performs physiological sensing during fingerprint authentication. As the main application still lies in authentication, our hardware should not degrade or compromise its performance and accuracy. Existing PPG sensors are designed for users to place fingers at the center, but this would not be feasible in our use case. Thus, our hardware should sense PPG from the side of a user's finger.

#### **DC-B.** Sensing under a normal light condition:

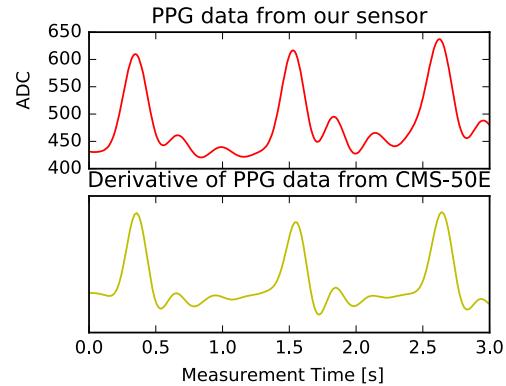
Many PPG sensors function well under sufficiently dark conditions created by finger occlusion or with covers. However, achieving such a dark condition is difficult in typical mobile fingerprint authentication scenarios. Our sensors, thus, have to function even under a normal light condition.



**Fig. 4.** The circuit schematic of our PPG sensor unit. We introduce Zener diodes into negative feedback of an op-amp to avoid signal saturation.



**Fig. 5.** A comparison of an output from our sensor (red), that from the original PulseSensorAmped (green), and the derivative of a PPG signal obtained from CMS-50E (yellow). Note that PulseSensorAmped and a PPG sensing unit in our circuit board return a discretized value between 0 and 1023. The plot of PulseSensorAmped includes negative values caused by a band-pass filter.



**Fig. 6.** A comparison between an output from our sensor (red) and the derivative of a PPG signal obtained from CMS-50E (yellow). The two signals resemble well.

#### DC-C. Noise and individual difference robustness:

Users may put their fingers on a fingerprint sensor differently. For instance, users may use a thumb because it allows one-handed interaction, but others may prefer using an index finger. Such a variation can occur even within the same user (e.g., a person may switch to another thumb for unlock). Even if people use the same finger, placement may be different in each authentication trial. Our hardware thus should be able to acquire PPG signals regardless of the user's finger placement.

#### DC-D. Instant sensing activation upon touch:

Because authentication with fingerprint takes only a couple of seconds, our sensor should acquire PPG signals immediately after users place fingers.

Prior work investigated different PPG sensor hardware designs for accurate signal acquisition [3]. However, no circuit design has achieved consensus among the research community. We decided to utilize the PulseSensorAmped [27] hardware for our sensor design. It is an open source PPG sensor project, and its hardware design achieves reliable signal acquisition even under ambient light noise. This hardware includes a differential amplifier with an op-amp, and a raw signal is normalized at 2.5 V and amplified. However, our preliminary investigation found that PPG signals from PulseSensorAmped were saturated for the first few seconds of sensing. When users place a finger on the sensor, a drastic brightness change occurs, which is the main cause of this signal saturation. This is undesirable because a sensing duration in our use scenario is limited.

To avoid saturation, we added two Zener diodes (AZ23C3V3-7-F, 3.3V) to the feedback loop of the negative input channel of an op-amp. Figure 4 shows the circuit schematic of our PPG sensor. With these Zener diodes, the amplification rate of this circuit becomes zero when the output voltage would become beyond the range of 0–5 V otherwise. In this manner, our circuit achieves an appropriate gain even when drastic changes in light intensity occur. In addition, we maintain the robustness that the original PulseSensorAmped has. Figure 5 illustrates an example observation of PPG signals obtained through PulseSensorAmped and our sensor. We also added a capacitive sensor to the surface of the sensor. This sensor enables instant activation of the PPG sensors. We measured the activation time with an oscilloscope, which turned out to be approximately 300 µsecs. Thus, our hardware design satisfies the design considerations of DC-B and DC-D.

As our circuit and PulseSensorAmped include differential operations, the appearance of the signal from our sensor is different from a wave shown in Figure 2. Figure 6 shows a comparison between our sensor output and the first derivative of a signal obtained from CMS-50E. We did not conduct a formal quantitative analysis on the similarity between two signals. However, our preliminary examination confirmed that peaks in at least one of PPG signals correspond well with those in the ground truth. We report accuracy performance of heart rates and HRV from PPG signals in a later section.

Figure 7 (C, D) shows the circuit board of our sensor. This circuit board has a space at the top center to fit to the fingerprint sensor on a smartphone (Nexus 5X). The fingerprint sensor on Nexus 5X is attached to the backside of the device. For DC-A and DC-C, we place four PPG sensing units to surround the fingerprint sensor instead of installation at a single particular location. Figure 7 (A, B) shows an installation example of our hardware to Nexus 5X. In our current prototype, the sensor is connected to an external computer though more direct integration into a smartphone is possible.

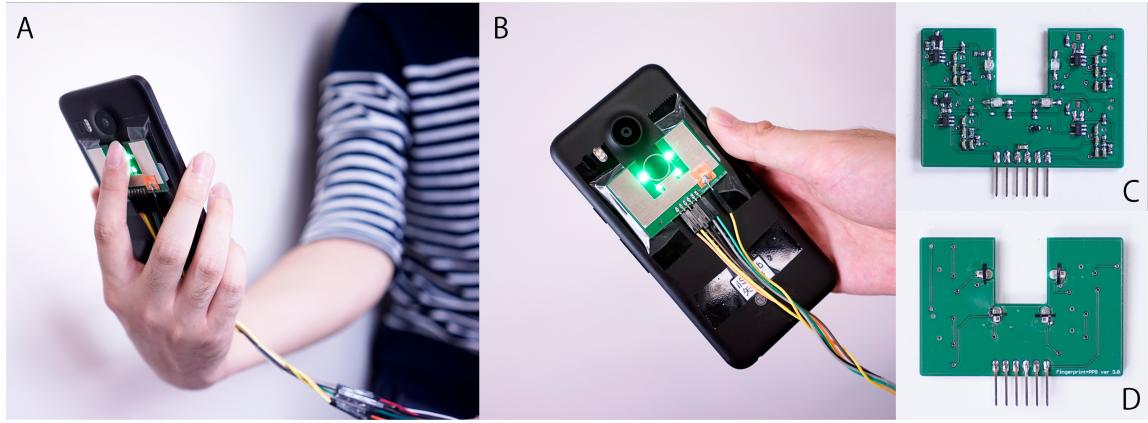
Figure 8 illustrates an example of four PPG signals with our sensor. In this example, Channel 4 demonstrates the most similar waveform to the ground truth (the first derivative of CMS-50E signals). A channel which exhibits the most desirable signal is different depending on how users place a finger. Our signal processing module automatically selects such a signal as well as extracts features from the raw data, which we explain in the next section.

## 5.2 Informal Hardware Evaluation

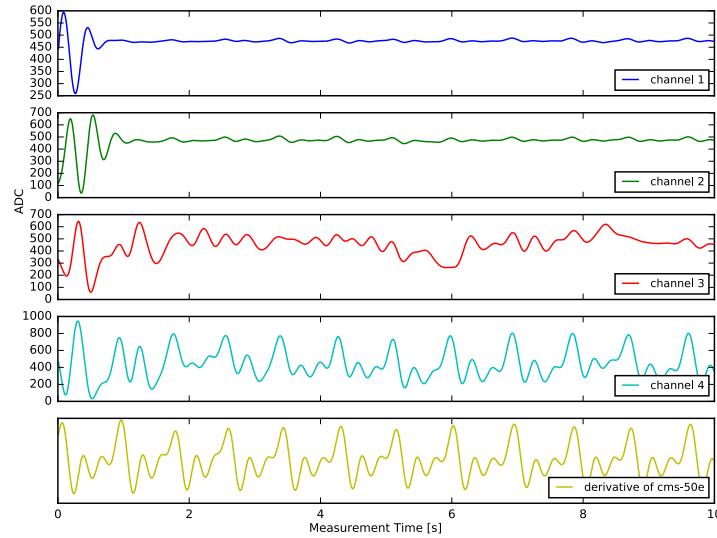
We conducted two informal evaluations to validate the robustness of our sensor against ambient noise and finger placement. We used CMS-50E to obtain ground truth data in each experiment.

**5.2.1 Ambient light robustness.** We recorded PPG signals with our sensor for 10 seconds under the 5 different ambient light conditions. The five conditions included two outdoor and three indoor settings, and the light intensity ranged from 0 to 17280 lux.

Figure 9 shows experimental settings and PPG signals acquired. Signals for the first 1500 ms are removed due to large amplitude fluctuation caused by finger contacts as explained in Figure 8. Our informal test revealed that at least one channel in the sensor demonstrates clear peaks that correspond to the ground truth signal (in yellow) in all conditions. Even under the brightest ambient light condition (the daytime outdoor setting), the peaks in the



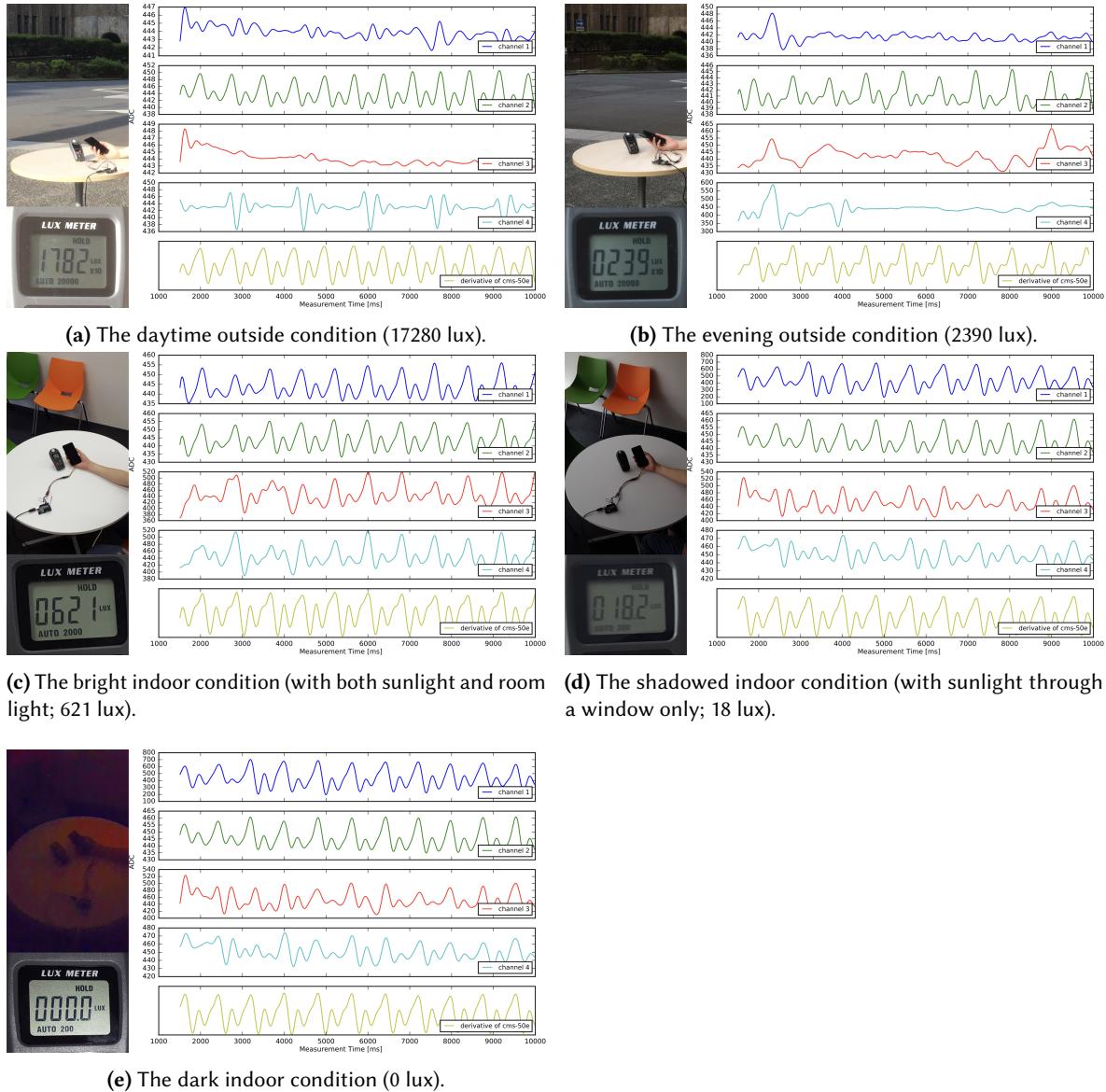
**Fig. 7.** Our Auth 'n' Scan prototype hardware. (A) Our current prototype is designed for Nexus 5X. (B) The back view of the device. The circuit board places four PPG sensing units around the fingerprint sensor. (C) The back of our circuit. (D) The front of our circuit (without the touch sensor). The LEDs and photo-detectors are designed to be exposed.



**Fig. 8.** An example of four PPG signals with our sensor and the first derivative of CMS-50E's output. In this example, the fourth channel (light blue) demonstrates clear peaks that correspond to those in the ground truth signal (yellow) well.

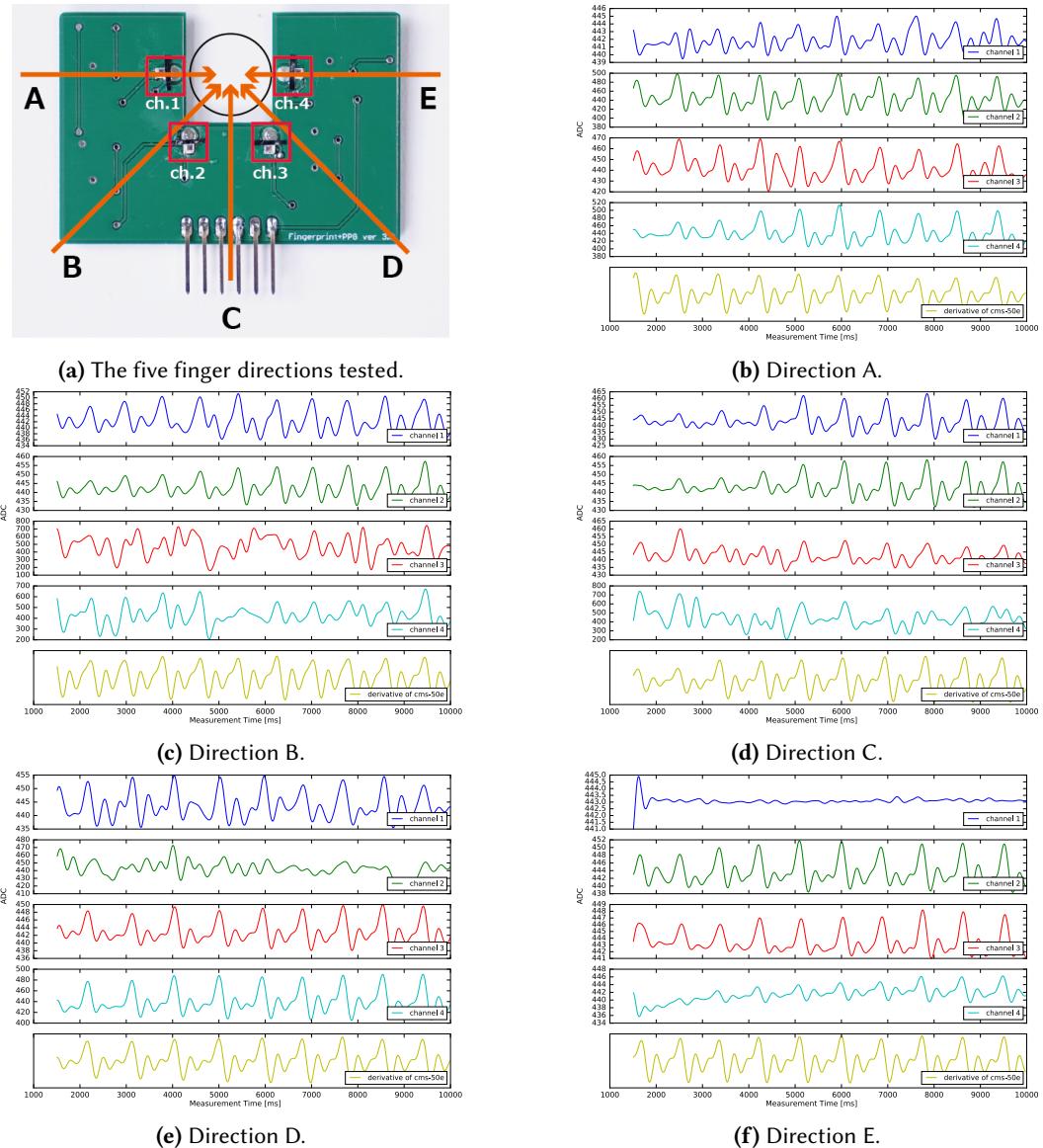
signal in Channel #2 (in green) match well to the ground truth. We thus concluded that our sensors are robust enough under various ambient light conditions.

**5.2.2 Finger placement robustness.** We also tested how different finger placement could impact on PPG signals. Similar to the previous informal evaluation, we recorded PPG signals for 10 seconds with 5 different finger directions illustrated in Figure 10a. We confirmed that the smartphone could be successfully unlocked by fingerprint authentication at all directions. Measurements were performed under a normal indoor light condition.



**Fig. 9.** PPG signals under five different ambient light conditions. At least one channel in the sensor demonstrates clear peaks that correspond to the ground truth signal (in yellow) in all conditions.

Figure 10 (b~f) shows PPG signals acquired under each condition. Again, at least one channel in the sensor shows clear peaks that correspond to the ground truth signal in all conditions. In our current prototype with Nexus 5X, Direction B and D (figure 10c and 10e) are the most likely finger placement for unlocking with fingerprints. As finger directions vary, the channels which exhibit clear peaks also change (Channel #1 and #2 for Direction B



**Fig. 10.** PPG signals under different finger placement conditions. (a): We tested five directions. (b) to (f): Similar to the robustness test against different ambient light, the sensor captured clear peaks at least one channel.

and Channel #3 and #4 for Direction D). This informal study thus validates our sensor design and confirms the robustness against different finger placement.

## 6 SENSING ALGORITHM

Although our hardware enables immediate PPG sensing when finger contacts are made, acquired data may have some noise as seen in Figure 5. In addition, a sensing duration in our target use scenario is limited to at most a few of seconds unlike conventional PPG systems. We thus need novel PPG signal processing; more specifically, our algorithm has to accurately infer a heart rate and HRV given four few-second PPG signals.

We conducted a pilot study to be informed of the algorithm design. We recruited five people and asked them to record PPG data with our hardware from the index finger of their dominant hands. After close examinations on the collected data, we obtained two major findings: 1) at least one of the four channels provided clear peaks and good correspondence with the ground truth; 2) such a channel was consistent during sensing. In this example of Figure 8, Channel 4 exhibits the clearest signal, but the other channels show noisy signals. The channel which offers the clearest signal varies depending on how users place fingers. But our hardware captures seemingly reliable signals at least one of the channels in most cases. In addition, the most desirable channel does not change within one sensing trial. This is because users do not move fingers or hands; otherwise, authentication may fail. Thus, our algorithm needs to choose the most desirable channel which leads to accurate inference of heart rates and HRV. To the end, it executes two kinds of processing within and across the channels: 1) finding the earliest point from when PPG gives most plausible results of heart rates and PPIs within each channel; and 2) choosing a channel that shows most peak points and plausible PPI data. In the following explanation, we suppose that the system has obtained four PPG signals for the duration of  $T$  seconds. We also denote the signal data of Channel # $i$  between time of  $t_1$  and  $t_2$  as  $D_i[t_1, t_2]$  ( $i = 1, 2, 3, 4$ ).

The algorithm first determines the earliest point ( $\tau^i$ ) from which PPG signals provides plausible heart rates and PPI information in Channel # $i$ . Our algorithm applies a bandpass filter between 0.5 and 3 Hz to a raw signal in each channel. This frequency range corresponds to a heart rate between 30 and 180 per minute. The algorithm assumes that major noise caused by initial finger placement occurs at most within the first half (between 0 and  $T/2$  seconds) of the entire signals. With this assumption, it extracts  $D_i[t, T]$  by varying  $t$  from 0 to  $T/2$  by 200 ms (i.e.,  $t \in \{0, 200, 400, \dots, T/2\}$ ).

For each  $D_i[t, T]$ , it then performs peak detection with the Automatic Peak Detection in Noisy Periodic and Quasi-Periodic Signals method [37]. The algorithm calculates the number of the detected peaks ( $P^i(t)$ ) as well as the mean and standard deviation of the observed PPIs. We then derive a relative standard deviation of the observed PPIs, defined as a ratio of the standard deviation over the mean, denoted as  $CV_{ppi}^i(t)$ . We also calculate the relative standard deviation of all the peak height values in  $D_i[t, T]$ , denoted as  $CV_{ph}^i(t)$ .

After statistics for all  $D_i[t, T]$  are calculated, the algorithm next searches  $\tau^i$  using  $P^i(t)$ ,  $CV_{ppi}^i(t)$  and  $CV_{ph}^i(t)$  for each  $t$ . The algorithm calculates the mean and standard deviation from all values of  $CV_{ppi}^i(t)$ . It then removes all  $t$  such that  $CV_{ppi}^i(t)$  is beyond one standard deviation from the mean. As this filtering adaptively changes its threshold, we expect that the system could accommodate data obtained from patients with heart or cardiovascular disease. Similarly, the algorithm removes all  $t$  such that  $CV_{ph}^i(t)$  is beyond one standard deviation from the mean. A large spike is often observed at the time when a user has made a contact on the fingerprint sensor. This filtering aims to remove signals which contain such drastic fluctuations.

In the remaining set of  $t$ , the algorithm further selects  $t$  with which  $D_i[t, T]$  contained the largest number of peaks. The largest value among such a set of  $t$  is chosen as  $\tau^i$ . This is intended to avoid fluctuations that occurred near the beginning of sensing (caused by a finger contact). After choosing  $\tau^i$  for each channel, the algorithm selects a channel which exhibits the lowest value of  $CV_{ppi}^i(\tau^i) \times CV_{ph}^i(\tau^i)/P_{\tau^i}^i$  (i.e., a channel which contains many peaks, and stable PPI and peak height).

**Table 1.** Tasks in each data collection session.

Data collection	Tasks
Session #1	ShortNormal × 6 times LongNormal × 1 time
Session #2	ShortNormal × 6 times
Session #3	ShortHigh × 6 times
Session #4	ShortNormal × 6 times
Session #5	ShortNormal × 6 times
Session #6	ShortHigh × 6 times
Session #7	ShortNormal × 6 times
Session #8	ShortNormal × 6 times LongNormal × 1 time

**Table 2.** Average ground truth heart rates at the beginning of ShortNormal and ShortHigh tasks.

Participant	ShortNormal	ShortHigh
Pf1	69.8	90.6
Pf2	77.4	100.4
Pm1	69.7	67.5
Pm2	65.9	75.1
Pm3	71.0	117.2
Pm4	70.8	120.6
Pm5	66.8	92.0
Pm6	63.0	95.7
Pm7	79.8	99.8
Pm8	66.3	94.6

## 7 SYSTEM AND USER EVALUATION

To quantitatively evaluate the performance of Auth 'n' Scan, we conducted cardiovascular data collection with 10 participants. The following experimental protocol was approved by research ethics committee at our university.

### 7.1 Data Collection Procedure

At the beginning of the data collection, participants were asked to visit our laboratory at the day when they were available throughout the daytime. After they signed a consent form, we explained the protocol and apparatus to be used. We instructed the participants to see the experimenter every one hour (except the lunch time), eight times in total. For instance, if data collection started at 9 am, the eight sessions occurred at 9:00, 10:00, 11:00, 13:00, 14:00, 15:00, 16:00, and 17:00. All participants started the first session at least at 10:30 so that we collected data during the daytime. HRV is known to have some variability throughout the day [45]. Therefore, this session design is important for us to acquire PPG data at different time of the day.

In each session, participants were asked to perform up to two of the following data collection tasks. During data collection tasks, the participants were seated. Table 1 illustrates the design of the eight sessions.

**ShortNormal** Participants unlocked a smartphone equipped with Auth 'n' Scan with their dominant hand, and kept holding fingers for 10 seconds. They also wore CMS-50E on another finger on the non-dominant hand. This data was used for evaluating sensing durations for accurate cardiovascular data inference and reconstructing Poincaré plots. We also recorded if unlock was successful in each trial.

**LongNormal** Participants attached CMS-50E to a finger on their dominant hand, and recorded PPG for five minutes. This data was used to create ground truth Poincaré plots.

**ShortHigh** This is the same task as ShortNormal except that participants engaged in lightweight physical exercise (e.g., climbing up and down stairs) before data collection. This simulated a situation in which users have higher heart rates than normal.

We stored all sensor data for later analysis. Before starting the first session, the experimenter registered the fingerprint of each participant's index finger. All sessions were conducted in an office under a normal indoor light condition.

After completing the last session, they were invited to provide subjective impressions about the Auth 'n' Scan system. We first let the participants experience the Auth 'n' Scan system with sensing duration of five and ten seconds. We then conducted a short semi-structured interview to deepen understanding of their Likert scale

question responses. None of our participants was native in English. We thus conducted interviews in Japanese and translated quotes to English as faithfully as possible for the report in this paper.

## 7.2 Participants

We recruited 10 participants (8 male, Pm1–Pm8; 2 female, Pf1 and Pf2; 22.9 years old on average; 7 right-handed) from our institute for our data collection. None of them claimed to have any known cardiovascular disease, and regularly engaged in intense physical training. All participants were offered approximately 25 USD in a local currency at the end of the data collection.

# 8 RESULTS

## 8.1 CMS-50E heart rate data validation

We obtained 360 and 120 PPG signal data samples in total for the ShortNormal and ShortHigh tasks, respectively. We first created cardiovascular features from the ground truth signals. Although CMS-50E provides its estimated heart rates, we found that those data exhibited non-negligible fluctuations particularly at the beginning of measurements. This fluctuation affected later heart rate measurements for a relatively long time. Figure 11 shows one example measurement observed in our experiment. CMS-50E seems to record a heart rate value every second. However, a log file produced by its accompanying software does not include timestamps, and we were not able to quantitatively validate how much the sampling rate was and how consistent it was. As shown in Figure 11, our informal examination found that 20–40 samples were necessary for stable heart rate measurements (which roughly corresponds to 20–40 seconds). In our ShortNormal and ShortHigh tasks, the sensing duration was up to 10 seconds to make each session as short as possible. However, this means that heart rate values provided by CMS-50E may not be stable or accurate in first several trials. We thus decided to examine the raw PPG signal from CMS-50E and extract the heart rate with our algorithm to create ground truth data.

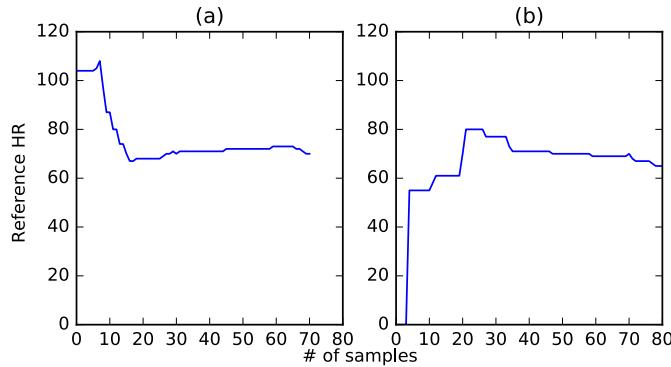
We conducted a comparison to validate whether our algorithm with CMS-50E PPG signal data offered accurate heart rate estimation. In each trial and participant, we had roughly 80 seconds of a PPG signal data from CMS-50E because she was asked to keep placing a finger of the non-dominant hand during a session. We assumed that the participant's heart rate would not drastically change throughout the session, and thus we used the average of last 20 heart rate samples CMS-50E reports as a reference ( $HR_r$ ). We then executed our algorithm on PPG signal data from CMS-50E and estimated heart rates ( $HR_e$ ) for our comparison against the reference values.

Figure 12 shows the plot of  $HR_r$  and  $HR_e$ . We conducted linear regression analysis, and the result yielded to a line of  $HR_r = 0.987 \times HR_e + 2.069$  with  $R^2 = 0.92$ . As the goodness of fit was high, we concluded that our estimation was sufficient to reliably convert  $HR_e$  to  $HR_r$ . In subsequent analysis, we calculated  $HR_r$  given  $HR_e$  extracted from a PPG signal with CMS-50E by using the regression formula above, and regarded it as ground truth heart rate values. Table 2 shows the average heart rate for each participant at beginning of ShortNormal and ShortHigh tasks.

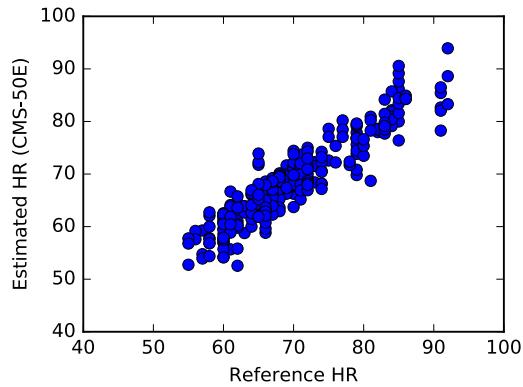
## 8.2 Heart rate estimation

We examined the tradeoff between the sensing duration and accuracy of estimated cardiovascular features. To this end, we created signals with eight different durations (i.e.,  $T \in \{3, 4, 5, 6, 7, 8, 9, 10\}$ ) from original data, and execute our algorithm. We removed clear outliers where the ground truth signals were not reliable. The outliers met at least one of the following criteria: 1) the detected heart rate in ground truth data was above 160; 2) the detected heart rate in ground truth data was 0; and 3) the standard deviation of PPIs in ground truth data was over 200. As a result, 29 data points (about 6%) were excluded.

We considered five different contexts for heart rate estimation: 1) Both ShortNormal and ShortHigh data (without outliers); 2) ShortNormal data only; 3) ShortHigh data only; and 4) ShortNormal data only with the



**Fig. 11.** Typical erroneous heart rate measurements in CMS-50E. Note that the sensor seems to record a heart rate approximately every second though no quantitative evidence is available. As shown in these two plots, it can take time to obtain stable heart rate measurements even if a person is sitting at a desk.



**Fig. 12.** A plot of the reference and estimated heart rate values using CMS-50E. The reference heart rate was the average of the last 20 recording of heart rate values directly produced by CMS-50E. The estimated heart rate is a value our algorithm extracted from the raw CMS-50E PPG signal.

baseline heart rate information for each participant given; and 5) ShortHigh data only with the baseline. The fourth and fifth conditions are considered as a situation where users would perform baseline measurements similar before starting to use the system. Because fingerprint authentication requires registration before its use, such baseline measurements are plausible. We used the average value of the heart rates detected from the ground truth ShortNormal data for the baseline heart rate estimation. We assumed that heart rates in ShortNormal should be within  $\pm 20$  from this normal-condition value (e.g., if a participant had an average heart rate of 60 under a normal condition, estimation below 40 or above 80 would be discarded). After light exercise, heart rates become faster than in the normal context. We thus performed similar filtering for the fifth condition by ignoring data whose estimation was beyond  $\pm 20$  from the addition of 20 to normal-condition values.

Table 3 shows the average differences between the ground truth and estimated heart rates under the five conditions. As expected, a longer duration resulted in higher estimation accuracy. For example, our estimation error can be up to 1.7 even without baseline heart rate information under  $T=10$  seconds. However, the standard

Duration ( $T$ ) [sec]	Without the baseline heart rate information			With the baseline	
	ShortNormal and ShortHigh	ShortNormal	ShortHigh	ShortNormal	ShortHigh
10	1.37 ( 13.3 )	1.69 ( 13.3 )	0.42 ( 13.1 )	-0.92 ( 2.93 )	1.09 ( 7.73 )
9	1.72 ( 14.1 )	2.30 ( 13.7 )	0.03 ( 15.0 )	-0.69 ( 3.07 )	-0.87 ( 7.47 )
8	3.66 ( 18.3 )	4.90 ( 17.2 )	-0.03 ( 20.6 )	-0.39 ( 3.92 )	1.57 ( 6.59 )
7	6.50 ( 22.5 )	8.51 ( 23.0 )	0.56 ( 19.7 )	-0.79 ( 3.90 )	1.45 ( 7.84 )
6	11.5 ( 25.7 )	12.5 ( 25.5 )	8.68 ( 26.0 )	0.01 ( 5.69 )	5.75 ( 15.6 )
5	16.1 ( 30.5 )	17.2 ( 30.5 )	12.9 ( 30.4 )	0.44 ( 6.89 )	5.96 ( 15.3 )
4	30.2 ( 34.2 )	33.7 ( 34.4 )	19.9 ( 31.3 )	1.76 ( 9.81 )	6.40 ( 16.2 )
3	40.2 ( 35.4 )	44.8 ( 35.4 )	26.8 ( 31.6 )	4.14 ( 7.96 )	9.55 ( 18.1 )

**Table 3.** The mean differences of the estimated heart rates from the ground truth data. A positive value represents over estimation. The values in parentheses represent the standard deviations.

deviations were relatively large even under the conditions of  $T=10$ . As  $T$  got shorter, the estimation became further less precise. This result indicates that heart rate estimation without baseline information is challenging.

On the other hand, our estimation was accurate with baseline heart rate information. Even in the case of  $T=5$  seconds, the average difference from the ground truth data was under 1 although the standard deviation was 6.9. In a shorter sensing duration, the average difference did not change greatly but the standard deviation became much larger. The results in the sensing duration of three seconds seemingly showed decent performance. However, we note that many data samples were filtered out in this case. Therefore, we concluded that the best  $T$  in our experiment was five seconds.

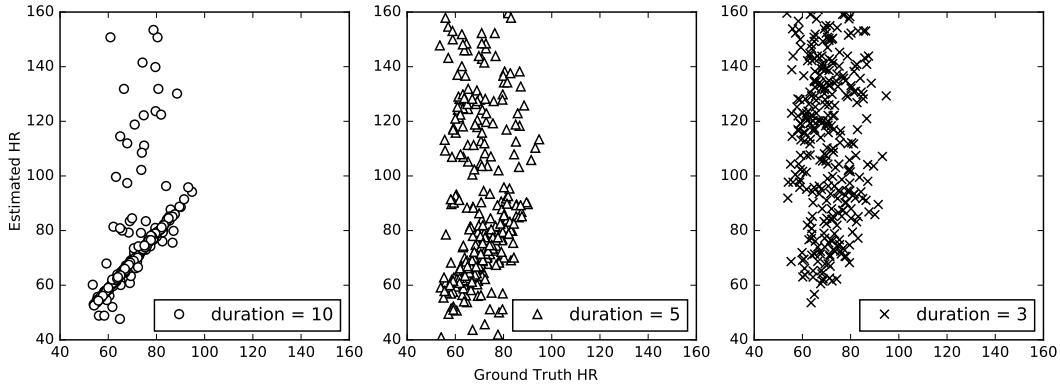
Figure 13 and 14 show a visual comparison of scatter plots between the ground truth and estimated heart rates for three durations (3, 5, and 10 seconds) with and without baseline heart rate information. This comparison clearly illustrates the positive effect of the baseline heart rate information. As shown in Figure 14, filtering successfully maintained many data samples that are highly correlated with the ground truth data. This successful filtering resulted in greatly improved accuracy and precision on heart rate estimation.

Our results also revealed that accuracy of heart rate estimation was not largely different between ShortNormal and ShortHigh under the absence of baseline heart rate information. However, this result differed if the baseline heart rate information was available. The accuracy was improved in both settings, but the standard deviations were much larger with ShortHigh data than ShortNormal. This suggests that heart rate sensing after light exercise is challenging though this work shows a potential.

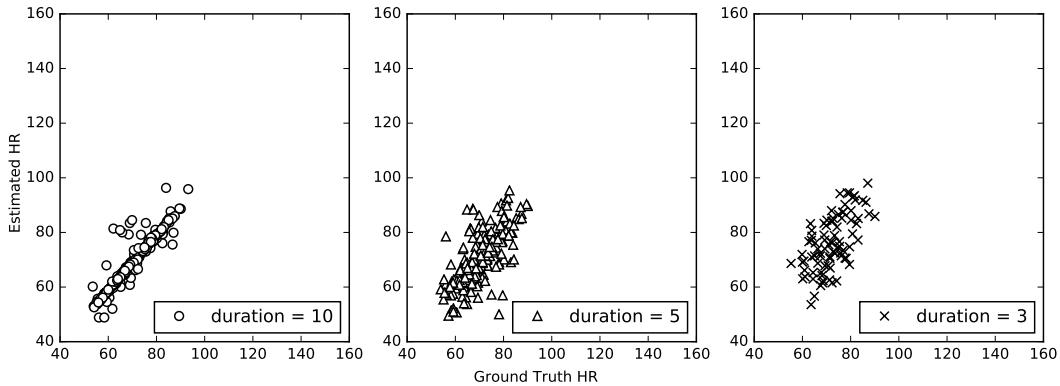
### 8.3 Poincaré plot feature estimation

We examined how accurately we can obtain features in Poincaré plots by reconstructing them from ShortNormal data. We first investigated how many PPIs can be extracted given  $T$ . As a PPI requires two peaks, the necessary sensing duration would be longer than for heart rate estimation. Table 4 shows the mean number of extracted PPIs across different  $T$ . In the heart rate estimation,  $T=5$  was the best; however, this value would result in a limited number of PPI data points. To examine the best estimation performance of Poincaré reconstruction, we decided to set  $T=10$  in this part of our evaluations.

We evaluated differences of  $SD1/SD2$  between the ground truth signal and ShortNormal data with  $T=10$ . Figure 15 and 16 illustrate these differences across all participants. As HRV data can vary throughout the day, we compared estimated  $SD1/SD2$  from all ShortNormal data for each participant with her LongNormal data gathered in the first and last sessions separately. These plots suggest that estimation of  $SD1/SD2$  was fairly accurate for four participants (Pm3, Pm6, Pm7, and Pm8) though not all.



**Fig. 13.** A scatter plot of heart rate estimation from ShortNormal data without the baseline heart rate information. As the sensing duration becomes shorter, more of erroneous data samples are observed.



**Fig. 14.** A scatter plot of heart rate estimation from ShortNormal data with the baseline heart rate information. Compared to Figure 13, erroneous data samples are successfully removed.

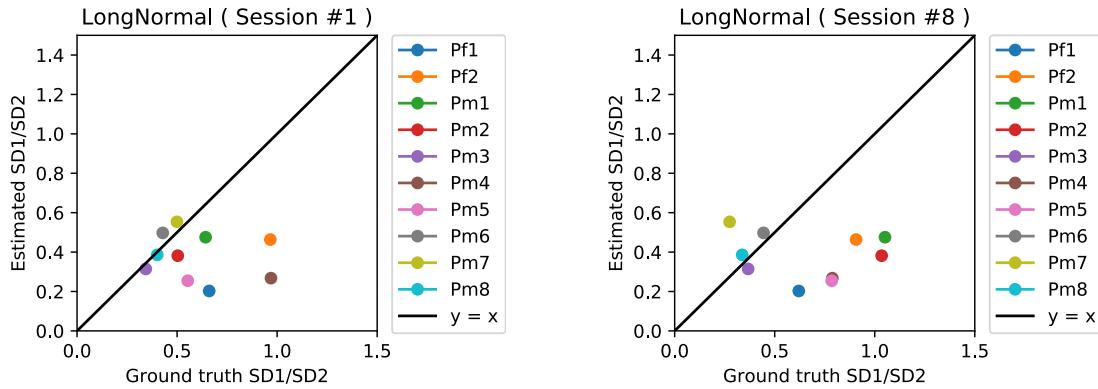
Figure 17 shows the Poincaré plots created with the LongNormal and ShortNormal data for Pm6. In his case, the two Poincaré plots produced with the two LongNormal data were similar (the left and center plots in Figure 17). As a result, reconstruction from his ShortNormal data also yielded to a small difference in  $SD1/SD2$ .

Figure 18 shows the Poincaré plots created with the LongNormal and ShortNormal data for Pm1. His Poincaré plots produced with the two LongNormal data showed different distributions (the left and center plots in Figure 18). The plots moved toward the top right as it became later of the day. This tendency was also observed in the reconstructed Poincaré plot with his ShortNormal data (the right plot in Figure 18). This may be one reason for inaccurate estimation of  $SD1/SD2$ . A future algorithm can be time-sensitive to obtain more accurate reconstruction (e.g., using only data gathered in a particular time period).

In conclusion, although individual differences need to be considered, reconstruction of Poincaré plots from a set of fragmented data can be possible if a sensing duration was long enough (e.g., 10 seconds).

Duration ( $T$ ) [sec]	Mean # of PPI data points
10	135.5 (16.8)
9	100.7 (16.3)
8	70.4 (11.9)
7	45.7 (10.9)
6	26.3 (6.39)
5	11.8 (6.79)
4	1.90 (1.64)
3	0.20 (0.40)

**Table 4.** The mean PPI data points that were able to be extracted in different sensing duration  $T$ . The values in parentheses represent the standard deviations. In later analysis on Poincaré reconstruction, we used  $T=10$  as it provided a sufficient number of samples.

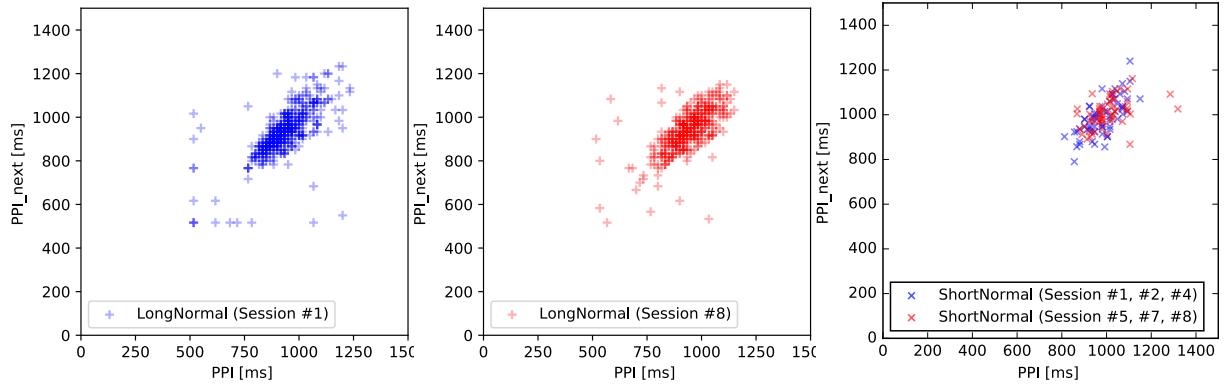


**Fig. 15.** Differences of  $SD1/SD2$  in Poincaré plots between all ShortNormal data and LongNormal of the first session.

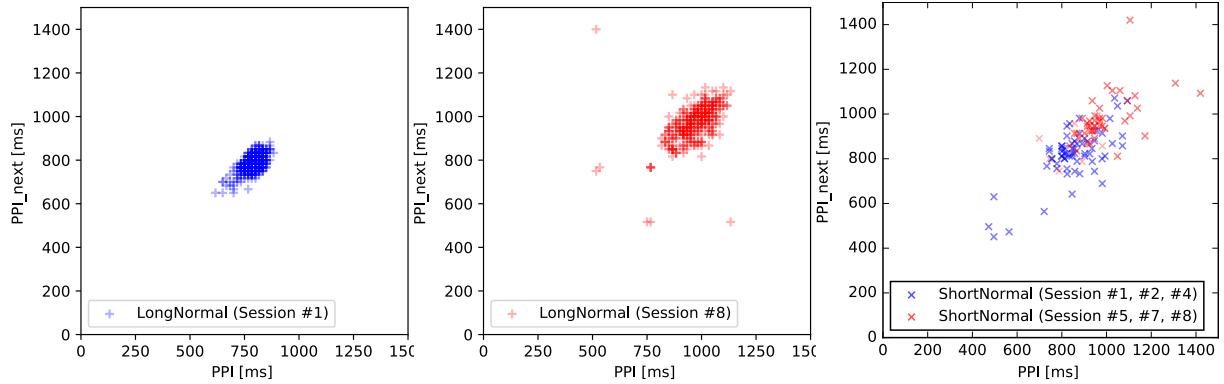
**Fig. 16.** Differences of  $SD1/SD2$  in Poincaré plots between all ShortNormal data and LongNormal of the last session.

#### 8.4 Fingerprint Authentication Success Rate

We also examined how the Auth 'n' Scan hardware can impact on the performance of unlocking with fingerprint authentication. All participants were invited to come back for this part of the study in another day. In each trial, the participants were asked to unlock the phone with their fingerprints. Each participant performed 48 trials with and without the Auth 'n' Scan hardware. We defined a trial in which participants were able to unlock a phone as a success. Table 5 shows the result of unlock success rates with and without Auth 'n' Scan. The mean unlock success rate with Auth 'n' Scan was the same (96.9%) though the standard deviations were different (2.46 and 4.20 for with and without Auth 'n' Scan, respectively). We did not observe clear differences in the handedness and gender (right-handed: 96.7% ( $SD=2.65$ ); left-handed 96.7% ( $SD=2.41$ )); male: 97.4% ( $SD=1.85$ ); and female: 94.8% ( $SD=4.42$ )). We ran mixed effect linear regression against the following factors: *Condition* (1: with and 0: without Auth 'n' Scan); *Gender* (1: male and 0: female); and *Handedness* (1: right- and 0: left-handed). None of the coefficients for the three factors were significant. The estimated coefficients for *Condition*, *Gender*, and *Handedness* were 0.00 ( $SE: 1.58$ ), -0.73 ( $SE: 2.21$ ), and -0.21 ( $SE: 1.94$ ), respectively. Overall, the accuracies were high in both conditions, and we did not see clear degradation on authentication by introducing Auth 'n' Scan.



**Fig. 17.** Poincaré plots for Pm6. Left: the Poincaré plot with the LongNormal data in the first session. Center: the Poincaré plot with the LongNormal data in the last session. Right: the Poincaré plot reconstructed with the ShortNormal data (blue: data in Session #1, #2, #4; red: data in Session #5, #7, #8). In the case of Pm6, variability over time was small, and reconstruction of a Poincaré plot was relatively successful.



**Fig. 18.** Poincaré plots for Pm1. Left: the Poincaré plot with the LongNormal data in the first session. Center: the Poincaré plot with the LongNormal data in the last session. Right: the Poincaré plot reconstructed with the ShortNormal data (blue: data in Session #1, #2, #4; red: data in Session #5, #7, #8). The left and center plots clearly demonstrate variability over time. This variability was clear in the right figure. Although reconstruction using all ShortNormal data was not very successful, this plot suggests that a time-sensitive algorithm could produce an improved result.

## 8.5 Subjective Results

Before the semi-structured interview, we asked each participant to respond to the five 7-point Likert scale questions in Table 6.

**8.5.1 Acceptability of Auth 'n' Scan.** As shown in Table 6, our participants expressed their interests in Auth 'n' Scan for everyday use. Comments from our participants were in line with this result.

*It's not like I want to know health information by wearing wearable devices, but I would want to record it if I can by routine interaction [on a smartphone].* [Pf2]

Participants	With Auth 'n' Scan	Without Auth 'n' Scan
All	96.9% (2.46)	96.9% (4.20)
Right-handed	96.7% (2.65)	97.0% (4.79)
Left-handed	97.2% (2.41)	96.5% (3.18)
Male	97.4% (1.85)	96.1% (4.38)
Female	94.8% (4.42)	100% (0)

**Table 5.** Mean unlock success rate comparison. The values in parentheses represent the standard deviations.

Question	Median	Quartile	Mode	Max	Min
<i>As a dual-purpose biometrics system, how much would you like to use Auth 'n' Scan in a real life?</i> (1: do not want to use at all – 7: want to use it every day)	7	6.25 (1st) 7 (3rd)	7	7	5
<i>How acceptable would it be to wait for 5 seconds when you use fingerprint authentication?</i> (1: definitely unacceptable – 7: definitely acceptable)	5.5	4.25 (1st) 6 (3rd)	6	7	3
<i>How acceptable would it be to wait for 10 seconds when you use fingerprint authentication?</i> (1: definitely unacceptable – 7: definitely acceptable)	2	2 (1st) 3.75 (3rd)	2	6	1
<i>How acceptable did you think the interference by our hardware was?</i> (1: definitely unacceptable – 7: definitely acceptable)	5.5	4.25 (1st) 6 (3rd)	6	7	3
<i>How acceptable would it be to monitor your cardiovascular information with Auth 'n' Scan from the perspective of privacy?</i> (1: definitely unacceptable – 7: definitely acceptable)	7	7 (1st) 7 (3rd)	7	7	7

**Table 6.** Questions and responses about subjective impressions on Auth 'n' Scan.

They also appreciated the unobtrusiveness of sensing by Auth 'n' Scan.

*I would easily give up if I have to do recording by myself. But a system like this would be easy to use because it automatically collects information. [Pm1]*

**8.5.2 Acceptable Sensing Duration.** Our system evaluation found that Auth 'n' Scan would need five seconds for accurate heart rate estimation. The responses from our participants generally showed that this duration was acceptable. Our qualitative results also corroborated with this result.

*I didn't feel (5 seconds) was not that long. I don't want to wait when I am in a rush, but I don't mind either because it's just a little long. [Pm3]*

*Fingerprint authentication does not respond quickly with my finger anyway. So five seconds don't matter to me. [Pm2]*

However, two of the participants (Pm1 and Pm6) expressed that five seconds were slightly unacceptable. Furthermore, when the sensing duration became ten seconds, our participants mostly agreed that it was not acceptable. With this duration, they felt that sensing became rather obtrusive. These results suggest that the sensing duration of five seconds is acceptable though a shorter duration would further improve the acceptability of Auth 'n' Scan.

**8.5.3 Perceived Interference by Hardware.** As shown in Table 6, our participants did not feel that the sensor board strongly interfered with their fingerprint authentication. This result also positively supports our concept. Three of the participants, though, felt a little discomfort due to the thickness of the hardware (2.3 mm thick in the current prototype). However, as we showed in Section 8.4, the installation of the hardware did not significantly degrade the authentication performance.

**8.5.4 Privacy Concerns.** We obtained unanimous strong agreement from the participants that recording cardiovascular information with the Auth 'n' Scan does not raise privacy concerns. Representative reasons were: heart rate information cannot be directly used for identification (3 participants); heart rate information is not sensitive data (3 participants); and it is acceptable as long as data are securely kept (2 participants). Existing mobile apps can also collect heart rate information and potentially more intimate physiological data. Our participants thus did not have strong reluctance for heart rate sensing with Auth 'n' Scan.

## 9 DISCUSSION

Our results on the heart rate estimation found that inference was accurate when baseline heart rate information is available though its precision needs improvements. In particular, a sensing duration of and above five seconds can lead to accurate heart rate estimation. Such baseline measurements are feasible when users are asked to register their fingerprints before the use of an authentication feature. Because our hardware performs PPG sensing from the side of a finger unlike existing systems, accurate heart rate estimation is challenging. In addition, we conducted our evaluations under a normal light condition. Our work, thus, still offers unique contributions for heart rate estimation with a limited sensing duration.

Our evaluations also revealed that the sensing duration should be at least five seconds with our current prototype. This is longer than time users would normally spend for unmodified fingerprint authentication. However, subjective responses from our participants confirmed that the sensing duration of five seconds was acceptable. Their quotes suggested that this positive response was mainly because our system does not require separate explicit measurements of heart rates. Future work should investigate how to improve the acceptability of the system besides shortening the sensing duration. A future system, for example, could offer a quick way to opt in and out opportunistic PPG sensing by pressure-sensitive contacts. When users make a contact with pressure, the system would not execute sensing and simply unlock a phone. Otherwise, it would perform PPG sensing for five seconds (and even longer if users are willing) and execute phone unlock. We admit that future work should further investigate how to shorten the sensing duration. But our work demonstrates sufficient feasibility of opportunistic PPG sensing during fingerprint authentication.

The results confirmed that heart rate estimation becomes unreliable without baseline information. Although the performance degradation was expectable, our results showed its strong effect. In particular, standard deviations of estimated heart rates were large; in most cases without the baseline, they were over ten. Possible factors may have caused this large variance. In some trials, finger placement may not have been close enough and PPG sensing became noisy. We also observed that participants unintentionally performed observable motions, causing large fluctuations in PPG signals (e.g., adjusting their holding of the device). Such motions occurred regardless of the presence of the Auth 'n' Scan hardware, and could have contributed to similar authentication failure rates. Without the baseline heart rate information, our algorithm cannot remove outliers caused by the factors above. This led to large performance degradation.

Our results revealed that heart rate estimation often becomes inaccurate after participants took light exercise. One possible reason for this phenomenon is that jittering of the hand and arm holding the device was observable, potentially caused by harder respiration. Smartphones can easily distinguish whether a person has engaged in light exercise with inertial sensors [24]. Thus, a future system can ignore samples after exercise or perform necessary adjustment on estimated heart rates.

We also examined the feasibility of reconstructing Poincaré plots from a set of fragmented PPI values extracted from our sensor data ( $T=10$ ). The results showed that it can be possible, but future work should examine improvements which handle variability observed over time. As we briefly discussed in the result section, a time-sensitive algorithm may help. A future system could encourage users to unlock a device if enough data samples are necessary for a short period (e.g., deliberately introducing a notification about minor events when users may feel boredom [28]). Future systems should investigate how to exploit user's interruptability for more frequent data collection as well as improve our algorithm in order to obtain reliable estimation results.

Our quantitative examinations also confirmed that integration of Auth 'n' Scan did not degrade fingerprint authentication performance. As none of our participants owned the same smartphone used in Auth 'n' Scan (i.e., Nexus 5X), they did not have prior experience with its particular fingerprint sensor. Some participants also commented that they often could not find finger sensor location precisely because it is on the back of the device. In our tasks, participants were instructed not to re-adjust their finger placement even if they failed to unlock. Thus, our results could be considered as one of the worst performance cases. Nevertheless, the results showed comparable success unlock rates regardless of the presence of the Auth 'n' Scan sensor. We concluded that Auth 'n' Scan did not greatly diminish authentication accuracy upon phone unlock in our experiment.

Subjective responses from our participants also confirmed positive aspects of the current Auth 'n' Scan prototype. Despite the bulkiness of the prototype, the participants did not feel strong discomfort. As future systems may employ thinner hardware or more direct integration into a smartphone, physical interference caused by the hardware could be minimized. The participants unanimously agreed that collecting cardiovascular information through Auth 'n' Scan would not create strong privacy concerns. This is an encouraging result for Auth 'n' Scan and a larger set of dual-purpose biometrics systems. Although additional user studies would be necessary to investigate social acceptability and privacy concerns in a realistic setting, this work demonstrates a potential of the viability of Auth 'n' Scan.

## 10 LIMITATIONS

Our results suggest that opportunistic PPG sensing during fingerprint authentication on a smartphone is feasible. We now discuss several limitations of this work for clarifying its contributions and possible future research.

We employed a naïve heuristics with baseline heart rate information to remove noisy data. Using built-in sensors, smartphones can sense activities which lead to different levels of heart rates (e.g., sitting, walking, and running). However, users may exhibit different frequencies of carrying smartphones [10, 25]. Thus, an assumption that Auth 'n' Scan can adjust heart rate inference using built-in sensors may not hold for some users. Future work should investigate other methods for intelligently calibrating baseline heart rates.

We examined the performance of opportunistic PPG acquisition during fingerprint authentication on Nexus 5X, and the results may change with other smartphones. In particular, the fingerprint sensor in Nexus 5X is on the backside of the device, designed to be interacted using an index finger. However, other devices have fingerprint sensors on the front side, allowing users to interact with a thumb (e.g., an iPhone). A similar hardware design is conceptually applicable to other devices, but its performance should be carefully re-examined.

This work demonstrates opportunistic PPG sensing in a smartphone, and our demonstration can be extended to other fingerprint authentication scenarios. For instance, a fingerprint sensor installed into an office door can perform PPG sensing when an employee is unlocking it. In such a context, more direct integration of PPG sensing into a fingerprint sensor is possible. However, regardless of user context and sensor architecture, users would steadily hold fingers on top of a sensor. Thus, future work can explore a similar idea to this work in other contexts and our results would offer reference performance information.

Our system evaluation did not include patients with heart or cardiovascular disease. Understanding medical implications of extracted cardiovascular features is beyond the scope of this work. We thus do not claim that

our sensing technology would offer professional medical recording. Nevertheless, our results revealed that cardiovascular features extracted by the Auth 'n' Scan system can be close to those from the ground truth signals. In addition, our work has demonstrated a potential to extract longer-term features, such as Poincaré plots, from a series of fragmented PPG data if a sufficient number of PPIs are available. This work thus still shows a strong potential of opportunistic PPG sensing during fingerprint authentication.

Our work did not include a long-term study on user experience of Auth 'n' Scan. Our results found that the sensing duration of five seconds was acceptable though this is still longer than time for unmodified fingerprint authentication. Users might be discouraged to continue to use the Auth 'n' Scan system due to this sensing duration in long-term use. Future work should investigate the user adaptation and experience of Auth 'n' Scan through deployment user studies. The primary focus of this work primarily lies in the system performance of the current Auth 'n' Scan prototype and demonstration of the feasibility of the dual-purpose biometrics concept in mobile fingerprint authentication.

## 11 CONCLUSION AND FUTURE WORK

As the use of biometric authentication is increasing, research can exploit such interaction as a sensing opportunity. We propose a novel security system concept, called dual-purpose biometrics. Dual-purpose biometrics enables concurrent physiological or behavioral sensing during biometric authentication or identification. As an instance of dual-purpose biometrics, we demonstrate Auth 'n' Scan, enabling opportunistic PPG sensing during fingerprint authentication on a smartphone. With our hardware and signal processing algorithm, we achieve heart rate estimation only for five-second sampling if the baseline heart rate of a user is given. Our evaluations also show that a feature observed in Poincaré plots, which in general require long sampling of PPIs, can be potentially inferable from a set of fragmented PPG data. Although further improvements on sensing durations and estimation accuracy would increase the viability of the Auth 'n' Scan system, our work well demonstrates the feasibility of concurrent PPG sensing during mobile fingerprint authentication.

As discussed above, future work should investigate how to improve sensing performance as well as user experience of Auth 'n' Scan. Future work should examine how people would use Auth 'n' Scan in their smartphones through a deployment study. Extending Auth 'n' Scan to other fingerprint authentication scenarios is also an interesting future research direction. We believe that this work serves as a foundation for exploration of a broader context of dual-purpose biometrics.

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