Personal Devices for Contact Tracing: Smartphones and Wearables to Fight Covid-19

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The authors review the current digital contact tracing based on these three components. They focus on two personal devices that are intimate to the user: smartphones and wearables. They discuss the centralized and decentralized networking approaches that are used to facilitate the data flow.

Abstract

Digital contact tracing has emerged as a viable tool supplementing manual contact tracing. To date, more than 100 contact tracing applications have been published to slow down the spread of highly contagious Covid-19. Despite subtle variabilities among these applications, all of them achieve contact tracing by manipulating the following three components: use of a personal device to identify the user while designing a secure protocol to anonymize the user's identity; leverage networking technologies to analyze and store the data; and exploit rich sensing features on the user device to detect the interaction among users and thus estimate the exposure risk.

This article reviews the current digital contact tracing based on these three components. We focus on two personal devices that are intimate to the user: smartphones and wearables. We discuss the centralized and decentralized networking approaches that are used to facilitate the data flow. Lastly, we investigate the sensing feature available on smartphones and wearables to detect the proximity between any two users and present experiments comparing the proximity sensing performance between these two personal devices.

Introduction

2020 will be a long-remembered year to many as the outbreak of a global pandemic has severely affected millions of lives. Besides imposing restriction measures, from small-scale (city-wide) to large-scale (country-wide), many countries started to exploit digital contact tracing to supplement the laborious contact tracing performed manually by human investigators [1, 2]. These digital contact tracing applications exploit rich sensing features from devices that are either carried or worn by users to detect the proximity between users while anonymizing users' identities. Networking technologies are leveraged to facilitate the data flow while identifying potential exposures.

Typical digital contact tracing can be described by three components:
- User devices
- Networking technologies
- Sensing features

The user device should be a device personal to the user and carried by the user most of the time. In other words, we need a personal device that is capable of representing the user uniquely, besides providing rich sensing features and networking capabilities. Two prominent user devices that satisfy the above criteria are smartphones and wearables. Since these devices always contain sensitive data about users, the privacy issue has been the main concern when implementing contact tracing solutions on either of these two devices. Many different privacy-preserving protocols have been designed to anonymize the user's identity while using the personal device to identify a high-risk user who may have been exposed to the virus due to their proximity to an infected patient.

While myriad contact tracing applications have been published in Google Play Store and Apple App Store, the public acceptance of digital contact tracing is quite low, resulting in a low installation rate of these apps. Figure 1 shows the willingness of Canadians to adopt the contact tracing application according to the Canadian Perspectives Survey conducted in June 2020 [3]. Even though many people in Ontario and other regions indicate their willingness to use the application, most of them are only somewhat likely to install it. The young working adult group (aged between 26 and 64) tends not to support the contact tracing initiative due to privacy and performance concerns. For example, they worry about installing a surveillance tool into their device, and they doubt the reliability of the application in measuring proximity.

In view of this, this article studies the current digital contact tracing from the perspective of the three components described above. The objective of this article is to discuss the privacy and performance issues, which are two main concerns that deter users from installing the apps. Experiments are presented to verify the performance issue comparing the contact tracing solution implemented into smartphones and smartwatches. Lastly, a few possible research directions are suggested to improve the digital contact tracing solution so that it can become a mature tool to combat not only Covid-19 but also any highly contagious diseases we may have in the future.

Personal Devices for Contact Tracing

Manual contact tracing, conducted by professional investigators, is time-consuming and not effective considering the short-term memory of human

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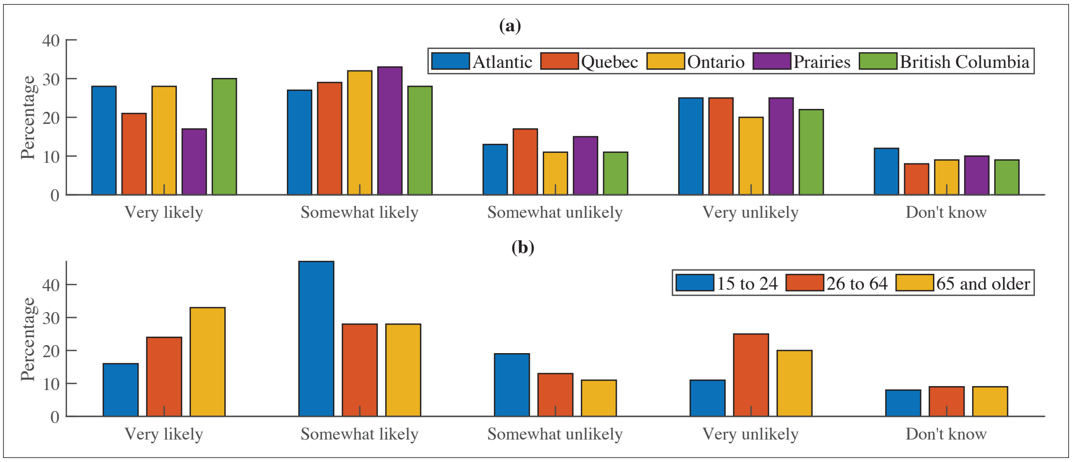

FIGURE 1. The willingness of Canadians to use the contact tracing application: a) by region; b) by age.

Rather than relying on our short-term memory, digital contact tracing relies on users' devices to record daily interactions and store this information into digital-based storage, which can be retrieved automatically once a user is tested positive. As discussed, this device should be a personal device that can represent the user uniquely wherever the user goes.

beings [1]. For example, can you recall who you have talked to when you were doing your grocery shopping, and would you be able to get their contact information? Rather than relying on our short-term memory, digital contact tracing relies on users' devices to record daily interactions and store this information into digital-based storage, which can be retrieved automatically once a user tests positive. As discussed, this device should be a personal device that can represent the user uniquely wherever the user goes.

Digital Contact Tracing with Smartphones

To date, more than 50 countries have launched contact tracing apps, and all of them use the smartphone as the personal device representing the user. Using the approximated downloading data from the Google Play Store, we summarized a few contact tracing applications, as illustrated in Table 1. Since the download action in Google Play Store is equivalent to an install action (i.e., Google Play Store will download and install the app for the user when the user clicks the "get" button), we can use the downloading data to compute the adoption rate. Even though all of the apps have ratings of at least 2.5 (Google and Apple allow users to rate apps according to a rating scale from 1 to 5, in which 1 indicates the least satisfaction and 5 the most satisfaction), users generally commented that they have negative experiences with the apps. Hence, the rating itself might not necessarily reflect the users' satisfaction with the application. Instead, we can examine an app's adoption rate since it was published. Note that the computed adoption rate here is solely based on downloading data from Google Play Store as Apple provides no such information. Even though we only got the adoption rate based on Google Play Store, it should give us a big picture of the general adoption rate as a whole since Android smartphones have the majority of users in the world, and the app downloading trend between iOS and Android devices exhibit a linear correlation.

Table 1 shows that the adoption rate is pretty low even for the application launched in the first half of 2020 (e.g., TraceTogether by Singapore, PeduliLindungi by Indonesia, MorChana by Thailand, COVIDSafe by Australia, Hayat Eve Sigar by Turkey, and Covi-ID by South Africa). Compared to Asia Pacific countries, most European countries only launched contact tracing applications in the second half of 2020. However, some of these apps have a higher adoption rate even though they were launched at a much later date. This is mostly due to the privacy-preserving feature implemented in the appls that gave users a certain assurance about their privacy. Even though these applications have fewer privacy issues, they suffer from performance issues, which causes users to uninstall the applications after an initial attempt.

Digital Contact Tracing with Wearables

Compared to large-scale implementation of contact tracing apps on smartphones, wearable-based solutions focus on a much smaller scale, and most of the time, they mainly trace the interaction of a specific group of users in a specific location. Besides utilizing physiological signals [4] or an activity tracker [5] on a wearable device to detect infection symptoms, many workplaces started to exploit the wearable solution for contact tracing [6]. While almost everybody owns at least a smartphone, the penetration of smart watches is relatively low; that is, only 4 out of 10 people have a smartwatch (in the United States), or about 2 out of 10 people (in developing countries). Hence, the impact of releasing wearable-based contact tracing apps in the application store would be limited since not many people own a smart watch. Rather, most of the current wearable solutions are custom-made and target dense indoor environments like hospitals, shopping malls, and workplaces. For example, [7] uses a wearable tag worn on a user's wrist to track and monitor the healthcare workers working in a hospital or a healthcare center, who are at high risk of exposure to virus infection. Ng *et al.* present a wearable solution based on a commercial off-the-shelf smart watch that can be adopted by any industry toward workplace reopening [8].

While the smartphone-based solution targets each individual, the wearable-based solution targets industrial sectors, expecting them to purchase wearable devices with the contact tracing app installed in bulk and distribute the wearable devices to their workers and customers. Table 2 lists a few industries that have adopted the wearable-based contact tracing solution to protect elders in nursing homes, cadets on academy campuses, players in

Country	App name	Published date	Rating	Approximate downloads	Population (by 2020)	Adoption rate
Singapore	TraceTogether	20 Mar. 2020	3.2	1,000,000	5.850 million	17.09%
Indonesia	PeduliLindungi	10 Apr. 2020	3.9	1,000,000	273.524 million	0.37%
Thailand	MorChana	13 Apr. 2020	4.1	100,000	69.800 million	0.14%
Turkey	Hayat Eve Sığar	18 Apr. 2020	4.2	10,000,000	84.339 million	11.86%
United Arab Emirates	ALHOSN UAE	24 Apr. 2020	4.4	1,000,000	9.890 million	10.11%
Australia	COVIDSafe	26 Apr. 2020	2.8	1,000,000	25.500 million	3.92%
South Africa	Covi-ID	15 May 2020	3.2	500	59.620 million	0.0008%
Poland	STOP COVID-ProteGO Safe	2 June 2020	2.6	1,000,000	37.847 million	2.64%
Germany	Corona-Warn-App	16 June 2020	3.1	10,000,000	83.784 million	11.94%
Japan	COCOA - COVID-19 Contact App	19 June 2020	3.1	5,000,000	126.476 million	3.95%
Canada	COVID Alert	2 July 2020	3.4	1,000,000	37.742 million	2.65%
United Kingdom	NHS COVID-19	24 Sept. 2020	4.0	5,000,000	67.886 million	7.37%
Belgium	Coronalert	30 Sept. 2020	3.5	1,000,000	11.500 million	8.7%
The Netherlands	CoronaMelder	10 Oct. 2020	3.1	1,000,000	17.280 million	5.79%
Hong Kong	LeaveHomeSafe	16 Nov. 2020	3.6	100,000	7.500 million	1.3%

TABLE 1. Contact tracing applications launched by each country.

Contact tracing client	Wearable device	Target froup
CarePredict Senior Home	CarePredict's Tempo bracelets	Elders
U.S. Military Academy	Samsung Galaxy Watch 3	Cadets, students
NFL and NBA Sports	KINEXON SafeTag	Players, coaches
Air Canada	TraceSCAN wearables	Flight attendants, passengers

TABLE 2. Wearable-based contact tracing.

sports centers, and passengers on airlines. In fact, many active companies in IoT and wireless solutions, including Estimote, Radiant, and so on, have launched wearable-based contact tracing solutions. However, the industrial adoption rate is relatively small compared to the multitude of wearable solutions on the market today.

Networking Technologies for Contact Tracing

The second component of contact tracing relies on networking technologies to facilitate the data flow between the user device and the cloud server in either a centralized or decentralized manner.

Centralized Approach

As shown in Fig. 2a, the centralized approach uses a centralized server to store all the data uploaded from users' devices. To preserve privacy, the data are mostly encrypted before being uploaded to the central server for storage. Once a user is diagnosed with the disease, the server will perform the matching computation and only send the alert to a list of users who have been identified as high-risk users who are likely to contract the virus.

An example of contact tracing that uses the centralized approach is the EasyBand [9], in which the data from each wearable device is uploaded to a centralized server for further processing. Besides storing the encrypted data uploaded by the user devices, the centralized server also performs the matching computation to identify a list of high-risk users. The Pan European Privacy-Preserving Proximity Tracing (PEPP-PT) [10] is also a centralized approach focusing on proximity sensing between any two smartphones. PEPP-PT only requires the smartphone to upload the data when it comes into close proximity with another smartphone and stays close for a certain duration. Most of these centralized approaches guarantee users that only encrypted data will be collected, and there is no information regarding the user's location and sensitive information.

Decentralized Approach

The decentralized approach allows each device to store its daily interaction data into its local storage, as illustrated in Fig. 2b. All these data remain in the local storage for 14 to 21 days depending on the design of the application; any expired data (i.e., more than the defined time span) is erased from the local storage. Once a user is diagnosed with Covid-19, he/she can upload his/her daily interaction data to the cloud server, which is responsible for distributing uploaded data to all the user devices that have registered with the cloud server. The data uploading process is subject to a user's consent. If a user declines to upload the data, the data is not uploaded to the cloud. Upon receiving the data, the cloud server broadcasts the data to all registered devices without having each device query the cloud periodically.

Many smartphone-based contact tracing apps developed by European countries (Switzerland, Finland, etc.) mostly apply the decentralized privacy-preserving proximity tracing protocol, known as DP-3T [11]. Inspired by DP-3T, Google and

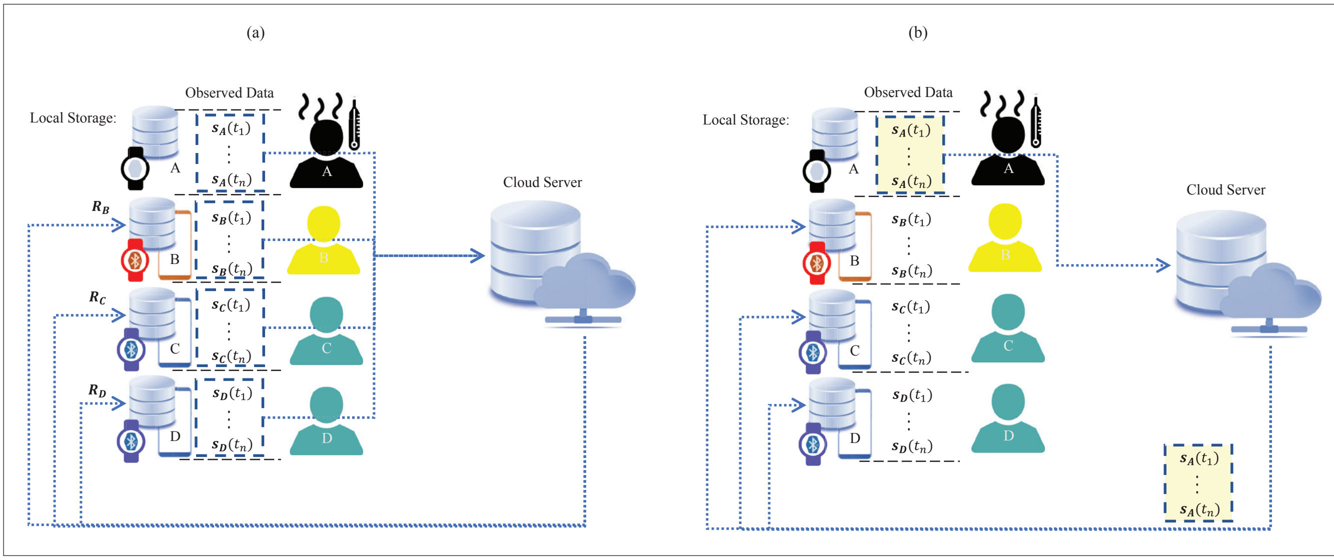

FIGURE 2. Networking technologies in facilitating the data flow: a) the centralized approach uses the cloud to store all the interaction data from all the users; b) the decentralized approach stores the interaction data within the local storage of each individual device, and the cloud is used to broadcast the data from the infected patient to a group of devices that have the app installed.

Apple jointly developed a decentralized exposure notification framework to facilitate the development of contact tracing applications. To date, many countries, including Canada, the United Kingdom, and others, have adopted the Google and Apple framework to provide decentralized-based contact tracing. According to [12], people are more willing to install a contact tracing app when they are assured that the application is developed via the decentralized approach, in which all the data remains in local storage and is erased after a certain time span.

Proximity Sensing for Contact Tracing

Contact tracing records the daily interaction data containing the proximity information, as well as how long two users remain in close proximity. Various sensing features available on smartphones and wearable devices can be used for proximity sensing, including the radio signal, the magnetic signal, the acoustic signal, and so on. This article mainly focuses on the radio signal from Bluetooth Low Energy (BLE) transmission, considering the vast majority of apps listed in Table 1 use BLE as the main sensing feature for proximity detection. Hence, it is crucial to understand the performance issue of using BLE signals for proximity detection.

Fluctuation of Received Signal Strength

Proximity sensing via BLE signals refers to the measurement of smartphones' received signal strengths (RSSs) to estimate their separation. The issue of using RSS for proximity sensing is that RSS is susceptible to environmental dynamics, in which the measurement value fluctuates even though two devices are stationary during the measurement process [13, 14]. Besides the environmental variations, device diversity is another problem affecting the final measurement value. One way to mitigate the problem is to calibrate the model before applying the model to estimate the proximity given the input RSS value. However, such a calibration approach is only applicable if we have obtained sufficient data describing the device characteristics.

Data-Driven Approach

Many works have exploited data-driven approaches to improve proximity sensing with BLE signals. In particular, BLE data are collected to train a classifier that can classify the proximity between any two persons into the following two categories: close or far. The cutoff distance that separates close and far is always based on the social distancing rule suggested by the government. In Canada, any two persons who stand less than 2 m from each other are considered in close proximity. According to Fig. 3, such a direct cutoff distance may produce a lot of misclassification. Suppose that -80 dBm is the cutoff threshold for the distance greater than 2 m. Figure 3 shows that some devices that are very close to each other (i.e., within a distance less than 2 m) can record an RSS value less than –80 dBm. This means that the app will consider users far away from each other, but they are in fact close to each other, resulting in false negatives. Rather than relying on the raw RSS measurements, we can extract more input features, including the time indicating the interaction duration, the device model, and so on, to train a more robust classification.

BLE Dataset from Smartphones and Smart Watches

The lack of comprehensive datasets based on BLE signals is the major drawback preventing further development of machine learning methods for proximity sensing. This article describes two BLE datasets (one based on smartphones and another based on smart watches) collected from our previous works [15], and then discusses the experimental results based on a supervised classification model trained using our datasets. These two datasets are made publicly available to encourage further research, not limited to contact tracing apps, but any IoT apps that deal with BLE signals.

Smartphones Dataset

We collected a large-scale BLE dataset by having smartphones placed in different positions. Specifically, two volunteers were required to stand at a distance from each other while holding the smart-

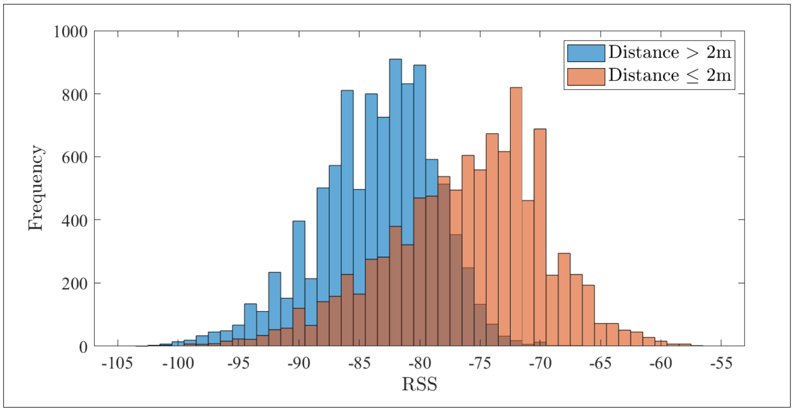

FIGURE 3. RSS distributions for two types of proximity: far (blue color bars) and close (orange color bars).

Approach	Combination	Accuracy
Smartphone	Hand-to-hand	85.82%
Smartphone	Hand-to-pocket	90.75%
Smartphone	Hand-to-backpack	81.44%
Smartphone	Pocket-to-backpack	87.51%
Smartphone	Pocket-to-pocket	87.26%
Smartphone	Backpack-to-backpack	90.85%
Smart watch	Direct	94.16%
Smart watch	Crosswise	90.59%

TABLE 3. Comparison between smartphone and smart watch approaches.

phones in their hands. The ground truth distance was measured using a measuring tape. The app starts the scan when the user presses the scan button. The scan continues until the user presses the button again. We repeated the same data collection procedures for distance from 0.2 m to 2.0 m (with a 0.2 m increment each step), and 3 m to 5 m (with a 1 m increment each step). There were a total of 13 distance points where the measurement was conducted. For each distance, the smartphone was configured to run for at least 60 s. During the 60 s measurement, the user was not subject to any restrictions, so they could check their messages, listen to music, talk to others, and so on.

We repeated the data collection by asking the volunteers to put the smartphone in different positions. Besides hand-to-hand (HH), we also collected the data for five other different position combinations, including hand-to-pocket (HP), hand-to-backpack (HB), pocket-to-backpack (PB), pocket-to-pocket (PP), and backpack-to-backpack (BB). In total, we collected 123,718 data points. We have made our collected dataset publicly available at https://github.com/pc-ng/rss_HumanHuman.

Smartwatches Dataset

We developed a smartwatch app and installed it into Fossil Sport, which is powered by Google's Wear OS, to broadcast and collect the BLE data. We performed the experiment by asking two volunteers to stand at a certain distance from each other, from 0.5 m up to 5 m. The data collection was performed in indoor environments with a lot of interference and at different times with uncontrolled environmental settings so that the dataset could capture the signal distortion subject to the environmental dynamics. During the data collection, volunteer A was asked to wear the smartwatch on her left hand, and volunteer B on her right hand (i.e., left to right, LR). After that, we repeated the same procedures with right hand to left hand (RL), left hand to left hand (LL), and right hand to right hand (RR).

Since LR and RL constitute a direct view between two smartwatches, and LL and RR constitute the crosswise view, we categorize these four hand combinations into two groups: a) direct and b) crosswise. In total, we collected 37,644 data points from all four combinations. We consolidated the data from RR and LL into a single dataset (i.e., the crosswise dataset) and then applied an 80 percent-20 percent splitting rule to split the data into training and testing sets. Similarly, we applied the same splitting rule to the consolidated data from RL and LR (i.e., the direct dataset). The final training and testing data for both sets are shared openly in https://github.com/pc-ng/rsssmartwatch.

Classification Performance

We trained a decision tree classification model given the training data from both datasets and then applied the trained model to the testing data to examine the classification performance. For our experiment, we defined the cutoff distance to 2 m as this is the distancing rule set out by the Canadian Government. Our experimental results in Table 3 show that the best classification result is achieved when the smartphone is held in a similar manner. The accuracy is 90.85 percent when both users put their smartphones inside their backpacks, 90.75 percent when one user held the smartphone in their hand and the other user put the smartphone inside their pocket, and 85.82 percent when both users held their smartphones in their hands. The performance with HH is not good compared to the rest. This can be explained by the subtle hand movements when holding a smartphone. For example, some people might hold their smartphones above their arms, some use two hands to text, some use one hand to open up notifications, and so on. On the other hand, the smartphone is subject to fewer variations when the smartphone is put inside the backpack or pocket. Compared to the smartphone, the smart watch can have better performance most of the time because the smartwatch is always worn on a human's wrist, and there are relatively fewer variations compared to the smartphone. The classification performance is boosted from an average 90 percent with the smartphone approach to approximately 94 percent.

Conclusion

Digital contact tracing can be a prominent solution to slow down the viral spread of the contagious virus if more people are willing to install the apps. This article discusses two personal devices (i.e., smartphones and smart watches) that have been widely exploited for digital contact tracing. Note that smartphone-based and wearable-based solutions target different groups of users for different scenarios. While smartphone-based solutions mostly focus on our day-to-day life, wearable-based solutions are specifically designed to assist in workplace reopening. So far, these two solutions are available to the public independently without any integration. Future work can consider the integration of these two solutions so as to provide continuous contact tracing covering a person's work (based on a wearable solution) and daily life (based on a smartphone solution) routines.

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Biographies

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Konstantinos N. Plataniotis is currently a professor and the Bell Canada Chair in multimedia with the ECE Department, University of Toronto. He is also the founder and the inaugural director-research of the Identity, Privacy, and Security Institute (IPSI), University of Toronto. He was the director of the Knowledge Media Design Institute (KMDI), University of Toronto, from January 2010 to July 2012. He is a Registered Professional Engineer in Ontario. Among his publications in these fields are the books *WLAN Positioning Systems* (2012) and *Multilinear Subspace Learning: Reduction of Multidimensional Data* (2013). His research interests include knowledge and digital media design, multimedia systems, biometrics, image and signal processing, communications systems, and pattern recognition. He has served as the Editor-in-Chief of *IEEE Signal Processing Letters*.

While smartphone-based solutions are mostly focusing on our day-to-day life, wearable-based solutions are specifically designed to assist the workplace reopening. So far, these two solutions are available to the public independently without any integration. Future work can consider the integration of these two solutions.