A System for Monitoring Social Distancing Using Microcomputer Modules on University Campuses

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***Abstract*—We propose a system for monitoring social distance on university campuses to prevent the spread of COVID-19 infections. In our proposed system, mobile nodes are distributed to students as permits for entering the campus. Distances between students are measured by periodically sending and receiving BLE advertising packets between nodes. Locations of nodes on the campus can be roughly estimated by using signals from the university Wi-Fi network. Information collected by mobile nodes is sent to a monitoring server. We partially implement the proposed system using an ESP32-based microcomputer module as a mobile node. We evaluate fundamental performance of the implemented system, especially regarding BLE communication between nodes.**

***Index Terms*—Social distancing, M5StickC, BLE, Wi-Fi, COVID-19, University campus**

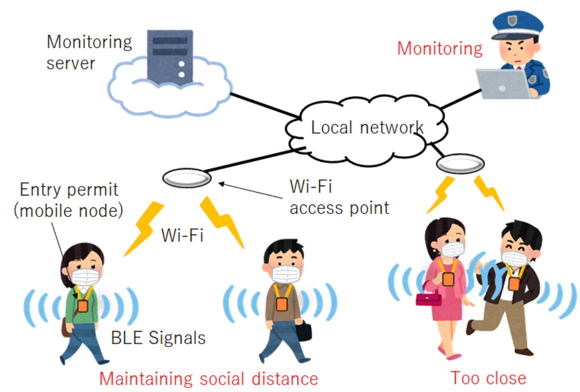


Figure 1. Overview of the proposed system.

1. Introduction

Various efforts toward preventing the spread of COVID-19 infections are underway worldwide. The Japanese government announced in early April 2020 a state of emergency, which was lifted at the end of May 2020. However, university campuses are an environment posing high risk of infection, so universities have implemented campus entry restrictions and other regulations.

Maintaining social distance is one effective countermeasure against COVID-19 infections. After the state of emergency was lifted, the main campus of our university, Kindai University, restricted the number of students allowed to enter per day as a congestion avoidance measure. University staff first measure the body temperature of students wishing to enter the campus. After receiving permission to enter, students tap their ID card against a RFID reader. However this method does not allow tracking of student behavior after entrance or determination of places where congestion occurs. Monitoring congestion sites on a university campus facilitates avoidance of crowded environments, campus infrastructure improvements that will encourage students to change their behavior, and class planning.

In this paper, we propose a system for monitoring social distance on university campuses. Figure 1 shows an overview of the proposed system, in which mobile nodes are distributed to each student as a permit for entering the campus. The node can be worn from the neck with a neck strap. Distances between students are measured by periodically sending and receiving Bluetooth low-energy (BLE) advertising packets between nodes. Locations of nodes on the university campus can be roughly estimated by using signals from Wi-Fi access points on a campus-wide Wi-Fi network, through which information collected at each node is sent to a monitoring server. Nodes further notify users who are at risk of close contact. In this study, we partially implemented our proposed system using an ESP32-based microcomputer module (M5stickC; M5Stack Technology Co., Ltd.) as the mobile node. We evaluated fundamental performance of the implemented system, especially regarding BLE communication between nodes.

2. Related work

Even before the COVID-19 pandemic, there was extensive research on using cameras [1]–[3], sensors [4]–[6], and Wi-Fi devices [7]–[9] to monitor numbers of persons and degrees of congestion. However, these studies did not consider distances between people (social distancing), the monitoring and management of which has become an important aspect of countermeasures for preventing the spread of COVID-19 infections.

There have, however, been some studies regarding the use of cameras [10], smartphones [11], [12], and dedicated devices [13], [14] to monitor social distancing. In June 2020, the Japanese Ministry of Health, Labour and Welfare released a smartphone application called the COVID-19 Contact-Confirming Application (COCOA) [11]. Based on the Exposure Notification Framework, this application uses Bluetooth to measure distances between smartphones. If smartphones are within one meter from each other for more than fifteen minutes, this proximity information is recorded. Therefore, in the unlikely event that an infected person is discovered, it is possible to identify their close contacts. To maintain privacy protection, however, this application does not collect location information.

Smartphone-based approaches are inexpensive and quick to deploy, because most students have smartphones. However, students have different smartphone models and carry them in different ways, such as holding them or carrying them in pockets or handbags. Radio-wave propagation environments around the smartphone therefore differ by student, possibly affecting the accuracy of distance measurements. Our proposed system for monitoring social distance thus assumes students wearing the same model of mobile node on a neck strap.

Some studies have investigated the use of dedicated devices to monitor social distancing [13], [14]. In June 2020, the Singapore government announced plans to distribute a device called the Trace Together Token [13]. This token has Bluetooth functions that record information about contact with other tokens. As in smartphone-based approaches, it is possible to identify close contacts after determination of an infection. This token does not have Internet connectivity or GPS functions, and user data is deleted after twenty-five days to maintain privacy protection.

Safe Spacer [14] is another wearable device for measuring social distance. It alerts Safe Spacer users coming within six feet of each other. This device is worn on a wristband or hung from the neck with a strap, and distances are measured using ultra-wideband radio. These devices are less affected by interference than are Bluetooth devices, and allow distance measurements as short as 10 cm. In contrast to these systems, our system monitors both contact information and contact locations.

3. Proposed system

Figure 1 shows an overview of our proposed social distance monitoring system for university campuses, in which mobile nodes (hereinafter, nodes) are distributed to students as a permit for entering the campus. These nodes are supposed to be worn using a neck strap. As of July 2020, the Kindai University campus gate has restricted entry to one person at a time. We thus assume that nodes can be distributed at the time of entry and collected upon exit.

Nodes have both BLE and Wi-Fi functions, and are assumed to be connected to the campus network via a campus-wide wireless LAN. The campus-wide wireless LAN at the Higashi-Osaka Campus of Kindai University comprises 1,000 installed access points. We assume that nodes utilize Network Time Protocol to maintain the correct time.

Nodes periodically broadcast BLE advertising packets, which include the MAC address of the sender node and a Universally Unique Identifier (UUID) for system identification. We assume that the MAC address is not randomized during the service period.

When a node receives from a neighboring node a BLE advertising packet including the proposed system's UUID, the receiving node records in internal memory the reception time, the source MAC address of the packet, the received signal strength indication (RSSI), and the basic service-set identifier (BSSID), which is the MAC address of the currently connected Wi-Fi access point. The BSSID is used to estimate the approximate node location. At regular intervals, this information is collected at the monitoring server via the campus-wide wireless LAN. The server then visualizes campus congestion sites based on the collected information.

When a node receives a BLE advertising packet, it uses RSSI to estimate the approximate distance between nodes. If this distance is below a threshold value for more than a designated time, the node displays an alert on a monitor. In addition, for more precise location estimation, the node compiles a list of campus LAN access points that are accessible from that location, along with the RSSI of beacon signal transmitted from each Wi-Fi access point, and sends that information to the server. The Japanese National Institute of Infectious Diseases exemplifies "close contact" as being within one meter of a COVID-19 patient for more than fifteen minutes without taking necessary infection prevention measures [15]. We refer this values when setting distance and time thresholds.

4. Experimental evaluations

To verify the feasibility of our proposed system, we implemented a prototype focusing on between-node BLE communications and conducted a fundamental evaluation.

4.1. Implementation

We used M5StickC devices as nodes in our implemented system (Fig. 2). M5StickC is based on the ESP32-PICO microcontroller, which supports Wi-Fi (IEEE 802.11b/g/n) and Bluetooth (classic and BLE). An M5StickC has dimensions $24 \times 24 \times 14$ mm and weighs 33 g. It has a 80×160 pixel LCD display, a six-axis inertial measurement unit (MPU6886), and an 80 mAh battery.

Nodes in the implemented system send a BLE advertising packet every second. The M5StickC cannot change its transmission power. Up to 31 bytes of advertising data can be included in each BLE advertising packet. Adverting packets in our implemented system include a flag, a 16-byte service UUID, and two bytes of battery voltage information used for power consumption evaluation and debugging. The overall size of an advertising packet, including its header, CRC, etc., is 43 bytes.

The following sections present evaluations of our implemented system, especially for between-node BLE communication. There have been many previous studies measuring RSSI in BLE communications, but here we measure social

Figure 2. Mobile node used in our prototype system.

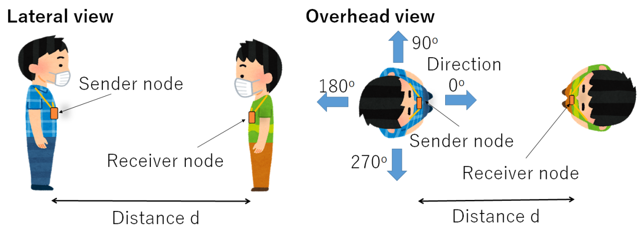


Figure 3. Experimental settings.

distances using BLE communication between M5StickC devices hanging from the neck.

4.2. Effects of social distance on receiver-node RSSI

We first evaluated the effect of node distance on receiver-node RSSI. We performed these experiments with two subjects on the third-floor elevator hall of Building 38 at Kindai University. One subject wore a sender node that periodically broadcasts only BLE advertising packets, and the other subject wore a receiver node that only receives advertising packets (Fig. 3). The direction of the subject wearing the sender node is defined as 0°, and the between-subject distance was varied in a range of 0.5 to 5 m in 0.5 m increments. The sender node broadcasts 100 BLE adverting packets at each distance. All nodes were powered by wired cables to avoid effects due to remaining battery power.

Figure 4(a) shows the RSSI distribution, average, and median at each distance. Here, 0 m indicates two terminals immediately adjacent to each other. As this figure shows, there are RSSI variations even at the same distance, but RSSI averages and medians decrease with distance. Therefore, it is possible to roughly estimate social distances by transmitting and receiving BLE advertising packets between sender and receiver nodes some number of times and acquiring average or median values. The consulted guideline for COVID-19 close contacts [15] stipulates not only distances but also contact durations exceeding fifteen minutes. Therefore, for estimation of close contact, we can use the results of a certain number of packet transmissions and receptions.

We also investigated distances at which nodes can receive BLE advertising packets. The results of this evaluation indicated that sender nodes can deliver BLE advertising packets to receiver nodes from distances up to 20 m. Therefore, even if a BLE advertising packet is received, it cannot be determined whether people are in close contact.

We should note here that we obtained these evaluation results under limited conditions. In future work, we will perform additional evaluations by changing conditions including combinations of nodes, combinations of people, postures of persons wearing monitors, and the environments in which measurements are performed.

4.3. Effects of body orientation on receiver-node RSSI

We next evaluated the effects of body orientation on receiver-node RSSI. In these experiments, we fixed the distance between subjects to 2 m, and varied the orientation of the subject wearing the sender node in 90° increments (Fig. 3). At each orientation, the sender node broadcasted 100 BLE adverting packets.

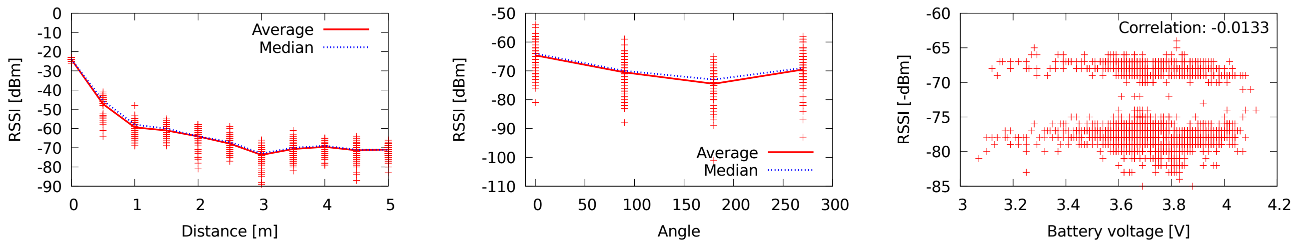
Figure 4(b) shows the RSSI distribution, average, and median at each orientation. As the figure shows, there were variations in RSSI even among same orientations. However, the average and median RSSI decreased with orientation. Compared to the case where both subjects faced each other (defined as 0°), RSSI decreased by about 5 dBm at sender-node subject orientations of 90 and 270°, and by about 10 dBm at 180°. There will likely be situations where students sit side-by-side on campus, so it is necessary to estimate close contact with a margin of about 5 dBm.

Here, as an outlier, Fig. 4(b) also shows a point at which RSSI exceeded -100 dBm at a 180° orientation. The influence of such outliers can be reduced by using median values when estimating social distancing.

4.4. Effects of sender-node battery level on receiver-node RSSI

To evaluate any effects of sender-node battery levels on receiver-node RSSI, we conducted experiments with two nodes at a fixed distance of 1 m. In these experiments, receiver nodes were powered with a wired cable and sender nodes were powered by its internal battery. Two nodes were fixed on a laboratory workbench, because we expected measurement times to be long.

We found that the M5StickC battery voltage fell below 3.0 V after the sender node transmitted 2130 BLE advertising packets, after which the M5StickC shut down. Figure 4(c) shows the relation between battery voltage and RSSI as a scatter diagram. As the figure shows, we found no correlation between battery voltage and received signal strength. The calculated correlation coefficient was -0.0133. We therefore conclude that in our implementation, there is no need for considering effects of sender-node battery voltage on RSSI. Accordingly, it is not necessary to include battery voltage information in advertising packets.



(a) RSSI against social distance (b) RSSI against body direction (c) Relation between battery voltage and RSSI

Figure 4. Experimental evaluation results.

5. Conclusions and future work

We proposed a social distance monitoring system for university campuses. The proposed system estimates social distances by using BLE packets among dedicated mobile nodes, collecting their data on a monitoring server via a campus-wide wireless LAN. We partially implemented the proposed system using M5StickC devices and conducted fundamental evaluations for between-node BLE communications. The results confirmed that it is possible to roughly estimate distances by using average or median RSSI values, that there are variations in RSSI depending on the orientations of persons wearing the monitor, and that sender-node battery power does not affect RSSI.

Evaluations in this study considered only very simple situations, so in future studies it will be necessary to perform evaluations in larger and more varied university campus environments. It is also necessary to consider mechanisms for reducing node power consumption.

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