Protecting Health Care Workers from Infectious Diseases using Physical Proximity Networks (PPN)

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***Abstract*—The COVID-19 pandemic is a major global health threat, and Health Care Workers (HCWs) may have an increased risk of infection through occupational exposure. In the case of hospital outbreaks, contact tracing of close physical interaction needs to be performed. In this article, we propose an IoT-connected contact tracing system based on Bluetooth Low Energy (BLE) beacons for subject identification and data transmission. The proposed system consists of BLE receivers, BLE wearable tags, an edge gateway and a cloud server. The system records interaction information such as entering/exiting time of an HCW to isolation rooms in the hospital. The collected data will be further analyzed to inform infection prevention policies. The performance of the proposed system is assessed through qualitative and quantitative experimental results. Finally, the capabilities of the current system and future research directions are briefly discussed.**

***Index Terms*—Contact Tracing; BLE; Internet of Things; COVID-19**

I. Introduction

The current COVID-19 pandemic is causing substantial global disruption, and as yet there are no effective vaccines or therapies. Therefore the only way of preventing infections is to reduce transmission. One strategy is to perform contact tracing, where we identify and quarantine people who have been in contact with the infection. Several methods are presented to address these solutions such as mobile apps for contact tracing, using common sense, and rough distance estimations to maintain a safe distance and some devices to alarm when a person attempts to touch the face [1]. Recently several mobile apps were introduced to trace the COVID-19 infection through Bluetooth wireless connectivity, including TraceTogether and COVIDSafe [2][3]. Quick battery drainage, performance reduction due to the app running continuously in the background, interruption in Bluetooth connectivity when using wireless devices such as headphones, and corruption of file transmission are some of the issues that users have raised. Moreover, turning Bluetooth always-on on personal devices is not safe because of the possibility of breaching privacy-related information [4][5]. Finally, many researches have shown that people like HCWs should not carry their mobile phones with them all the time to prevent contamination [6][7].

Protecting HCWs from infectious diseases is of paramount importance to ensure their safety and maintain the capacity of the hospital system to treat patients. Healthcare authorities defined several scenarios as ‘physical proximity’ e.g. remaining within 6 feet for more than 10 minutes with a subject [5][8] infected by an infectious disease such as COVID-19, face-to-face interaction for more than 15 minutes, or sharing a confined space for more than 2 hours [9].

Recent advancement in IoT technologies has provided various solutions for indoor and outdoor tracking applications, such as ZigBee and RFID. BLE is another promising short-range IoT protocol that is gaining more and more research and commercial interests in the indoor localization field. For instance, BLE beacons can be used in retail advertisement applications to provide the location-based advertisement to users [10]. Interaction and notification can also be realized by BLE protocols [11]. Due to its compact size, low power, low cost, better interaction supported, and wide availability among various devices, BLE is selected as the enabling technology in this work.

To protect the HCW from infectious diseases, this article proposes an IoT-connected contact tracing system. The BLE receivers scan for the BLE advertising packets broadcasted by wearable BLE tags of HCWs. These advertising packets are used for subject identification and room entering/exiting activity recognition. Aforesaid data will be forwarded using Long Range (LoRa) integrated BLE receivers to an edge gateway. Interaction data prepossessing, time data correction and hardware parameters (such as battery levels) monitoring are performed by exploiting the so-called edge computing [12] in the gateway. The final information is sent to the cloud for storage, analysis and visualization over the web interface and mobile applications which helps to mitigate disease spreading to protect HCWs.

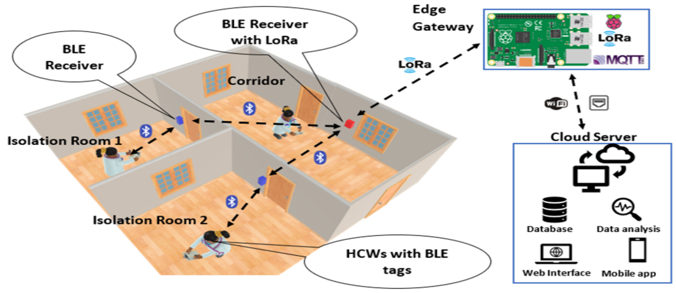

Fig. 1. The architecture of the proposed HCW interaction IoT tracing system.

II. SYSTEM ARCHITECTURE

The overall system architecture of the proposed HCW contact tracing system is demonstrated in Fig. 1, which includes wearable BLE tags, BLE receivers, BLE receivers with LoRa and an edge gateway.

A. BLE Receiver

The core device of this system is the BLE receiver, which performs the tasks of identifying HCW ID, record entering and exiting data along with timestamps and interaction time and forwarding to data to the gateway via BLE receivers with LoRa connection.

Hardware: Fig. 2 demonstrate the block diagram of the BLE receiver. It consists of a BLE module (Nordic nRF52840) as shown in Fig. 2(b), that supports BLE 5.0 for localization-based information collection and wireless data communication which forwards data to the BLE receiver with LoRa. Its connection has a LoRa module (RFM95) additionally, to forward the data to the gateway via LoRa. The two proximity sensors (VL53L0X time of flight laser range modules) are used to identify the entering and exiting activities. Depending on the sequence of sensor activations, the direction of the HCW movement is determined.

Firmware: BLE receiver is the front end of the proposed HCW interaction tracing system. The BLE receiver scans the HCW wearable ID, identifies different subjects, recognizes entering and exiting activities, captures entering timestamp, calculates interaction time of HCW with the patient and forwards the data to the gateway through BLE receivers with LoRa. The BLE receiver scans the surrounding BLE tags which are advertising. Relative distances to tags are determined on the Received Signal Strength Indicator (RSSI) values. However, RSSI values are highly susceptible to interference from surrounding objects and people, which results in high-frequency noise addition. To filter out the noise and smoothen the RSSI values, a low-cost averaging and smoothing algorithm is used [13]. The algorithm takes a window of (n = 7) RSSI values in a short duration and discards the maximum and minimum values, then calculates the average of the remaining values (m = 5). Furthermore, to reduce the computations and the error rate, only the devices in close proximity are considered, by filtering only the advertising packets with an RSSI of -60 dBm or higher.

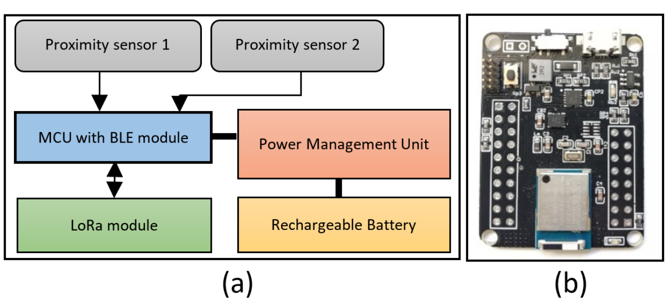

Fig. 2. (a) Block diagram of BLE receiver; (b) BLE module.

B. Wearable BLE Tag

The wearable BLE tag consists of a BLE module (nRF52840) and a rechargeable battery. The BLE module works as a portable BLE beacon that continuously advertises information of the HCW who holds it. Advertising packets of all BLE tags has a common universally unique identifier (UUID). BLE receivers use this UUID to filter out other BLE devices in the surrounding. Moreover, each tag has a unique device name that is used for identification, such as “D123” for Doctor 123 and “N123” for Nurse 123. The current prototype of the wearable BLE is an identification card-sized electronic device which can be worn on the chest area.

C. Edge Gateway and Cloud

The gateway is based on a Raspberry Pi Model 3 B+ which is a low-cost single-board computer with a low form factor and high performance. In the developed system, the edge gateway mainly performs five types of functionalities including IoT device management, data processing, local database management, local user interface and network connection. The IoT device management block is responsible for registering the IoT devices as well as collecting data from them through the different wireless technologies. A Python script running in the Raspberry Pi performs these tasks. The data processing block is in charge of filtering, pre-processing and encryption of data that results in low-latency feedback with a reduced requirement of bandwidth. Python, JavaScript and SQL are employed for performing the data processing operations while the open-source relational database management system MySQL is used for data storage and management.

The data forwarded by the edge gateway is stored in an external cloud server for further processing, analysis and visualization. In this work, the MySQL database is used in a cloud server for data storage and the phpMyAdmin software tool is utilized to handle the database. To ensure the data integrity and real-time system operability, the concept of transaction-based data handling is utilized where every data generation event is regarded as a transaction. A simple web application is implemented to visualize the information in real-time.

III. EXPERIMENTAL RESULTS

A series of qualitative and quantitative experiments have been conducted in a mock isolation room scenario, for the performance validation of the proposed systems. The experimental setup consisted of a BLE receiver inside the isolation room close to the entrance, a BLE receiver with LoRa connection in the corridor. This setup was used to simulate the scenarios in a hospital isolation ward. During the tests, wearable BLE tags were worn on the chest of the subjects and entering and exiting activities were performed repeatedly at normal walking speed. To evaluate the performance of the proposed system, four test cases were considered as follows:

- Case 1: One HCW enters to an isolation room when there are no other HCWs inside the room
- Case 2: One HCW leaves from the isolation room when there are no other HCWs inside the room

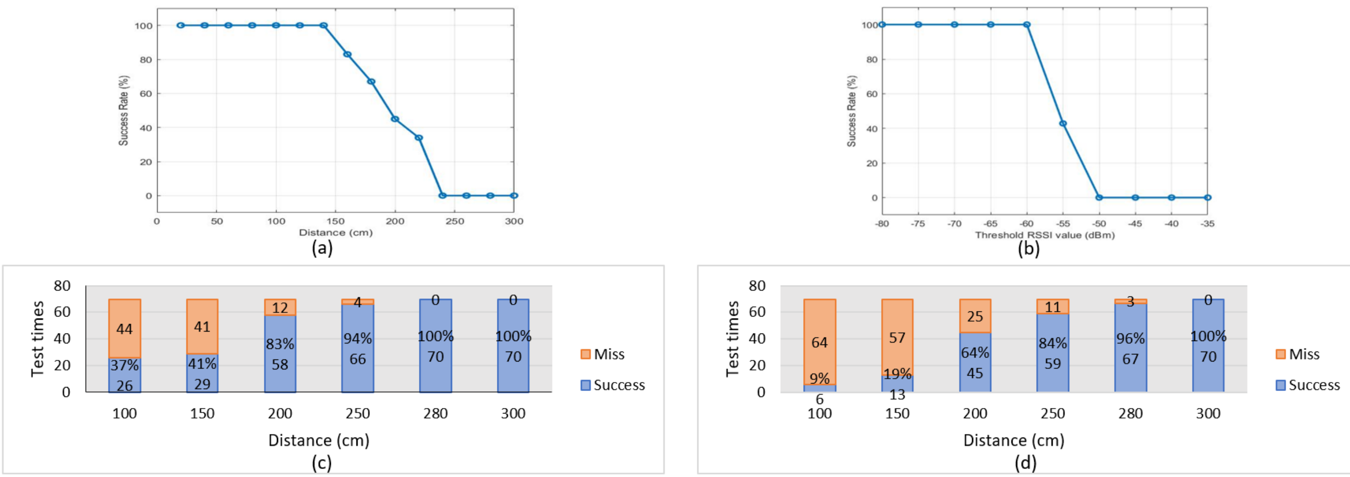

Fig. 3. Experimental results: (a) success rate with varying distance between BLE receiver and BLE tag; (b) success rate with varying threshold RSSI values; (c) results for case 3 scenario with varying distance between other HCWs inside the room and the BLE receiver; (d) results for case 4 scenario with varying distance between other HCWs inside the room and the BLE receiver.

- Case 3: One HCW enters to an isolation room when another HCW is already inside the room
- Case 4: One HCW leaves from an isolation room when there is another HCW inside the room

To demonstrate the HCW's tag identification performance and to define a boundary with a good accuracy of identification, case 1 and case 2 were considered. The transmitting power of the wearable BLE tags was maintained in -4 dBm to limit the range of signal transmission and to avoid misidentifications when more than one HCWs are in the isolation room or the corridor. An experiment was performed by varying the distance between the BLE receiver and the pathway of the HCW enters or exits from the isolation room. According to the results of the experiment which performed fifteen times for each distance value as shown in Fig. 3(a), the size of the entrance should not be more than 1.5 m to achieve a 92% success rate in HCW identification and entering-exiting activity recording.

To evaluate the effective value of RSSI thresholding for identifying a wearable tag, an experiment was conducted. The RSSI thresholding value is used for filtering purposes that can limit the advertising packets by considering only the signals having an RSSI greater than or equal to a certain value. In the experiment, BLE signal RSSI was collected at varying RSSI thresholding values while the distance between the BLE receiver and the wearable tag was fixed at 1.5 m. A subject with a chest-mounted wearable tag passes through a door repeatedly, and RSSI data were collected for different RSSI thresholding values ranging from -80 dBm to -35 dBm. The experiments for each RSSI thresholding value are repeated fifteen times to reduce random error. Fig. 3(b) illustrates the output of this evaluation that indicates the tag identification success rate at different RSSI thresholding values. According to the figure, the developed system achieves a success rate of 100% for the RSSI thresholding values less than or equal to -60 dBm. It also demonstrates that the system could not detect the tag when the RSSI thresholding value was -50 dBm or more. Thus, this experiment assisted to empirically find out the best RSSI thresholding value, which can balance both the tag detection range and the application-specific requirement for this particular application scenario.

In a typical hospital environment, usually more than one HCWs care for the patient. So, the systems' ability to identify multiple tags and recording their activities were tested using case 3 and case 4 test scenarios. In the case 3 scenario, there was one BLE tag inside the mock isolation room and one subject with a BLE tag entered to the room while varying the distance between the tag inside the room and the BLE receiver. Fig. 3(c) illustrates the results of this evaluation that indicates the tag identification success rate is greater than 94% when a distance of more than 2.5 m is maintained between the BLE receiver and the BLE tag inside the room. Similarly, another experiment was performed when two subjects are inside the room and one subject leaves the room. Fig. 3(d) shows the results of this experiment and the identification rate is 96% when a distance of more than 2.8 m is maintained between the BLE receiver and the subjects inside the room. From both aforementioned results, it is shown that the HCWs should maintain at least 2.8 m distance from the BLE receiver to identify the subjects with acceptable accuracy.

IV. Conclusion and Future Work

In this article, an autonomous HCW interaction tracing is presented that can be used to protect HCWs from infectious disease spreading. The proposed system helps to trace the contacts between patients and HCWs, in case of an HCW got infected or a patient is confirmed with an infection. Furthermore, this helps to monitor the total interaction time between a particular HCW and patients. This data can provide valuable information on HCWs interaction time distributions with patients, and hospital administration can make decisions using this information to minimize and control infection outbreaks.

References

[1] C. T. Nguyen, Y. M. Saputra, N. Van Huynh, N.-T. Nguyen, T. V. Khoa, B. M. Tuan, D. N. Nguyen, D. T. Hoang, T. X. Vu, E. Dutkiewicz *et al.*, "Enabling and emerging technologies for social distancing: A comprehensive survey," *arXiv preprint arXiv:2005.02816*, 2020.

[2] M. B. Weiss and S. Mehta, "Tracetogether," 2020.

[3] G. Greenleaf and K. Kemp, "Australia's 'covidsafe app': An experiment in surveillance, trust and law," *Trust and Law (April 30, 2020)*, 2020.

[4] R. Canetti, A. Trachtenberg, and M. Varia, "Anonymous collocation discovery: Harnessing privacy to tame the coronavirus," *ArXivorg*, vol. 2003, no. 13670, 2020.

[5] J. Chan, S. Gollakota, E. Horvitz, J. Jaeger, S. Kakade, T. Kohno, J. Langford, J. Larson, S. Singanamalla, J. Sunshine *et al.*, "Pact: Privacy sensitive protocols and mechanisms for mobile contact tracing," *arXiv preprint arXiv:2004.03544*, 2020.

[6] Y. C. Foong, M. Green, A. Zargari, R. Siddique, V. Tan, T. Brain, and K. Ogden, "Mobile phones as a potential vehicle of infection in a hospital setting," *Journal of occupational and environmental hygiene*, vol. 12, no. 10, pp. D232–D235, 2015.

[7] Y. Cavari, O. Kaplan, A. Zander, G. Hazan, Y. Shemer-Avni, and A. Borer, "Healthcare workers mobile phone usage: A potential risk for viral contamination. surveillance pilot study," *Infectious Diseases*, vol. 48, no. 6, pp. 432–435, 2016.

[8] L. Maccari and V. Cagno, "Do we need a contact tracing app?" *arXiv preprint arXiv:2005.10187*, 2020.

[9] "DHHS Department about coronavirus (covid-19)," https://www.dhhs.vic.gov.au/victorian-public-coronavirus-disease-covid-19how-do-you-define-close-contact, accessed: 2020-07-10.

[10] K. E. Jeon, J. She, P. Soonsawad, and P. C. Ng, "Ble beacons for internet of things applications: Survey, challenges, and opportunities," *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 811–828, 2018.

[11] P. C. Ng, J. She, and S. Park, "Notify-and-interact: A beacon-smartphone interaction for user engagement in galleries," in *2017 IEEE International Conference on Multimedia and Expo (ICME)*. IEEE, 2017, pp. 1069–1074.

[12] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE internet of things journal*, vol. 3, no. 5, pp. 637–646, 2016.

[13] T. Chowdhury, M. Rahman, S.-A. Parvez, A. Alam, A. Basher, A. Alam, and S. Rizwan, "A multi-step approach for rssi-based distance estimation using smartphones," in *2015 International Conference on Networking Systems and Security (NSysS)*. IEEE, 2015, pp. 1–5.