Poster Abstract: Proactive Privacy-Preserving Proximity Prevention through Bluetooth Transceivers

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ABSTRACT

Many activities in laboratories at Purdue require user movement that cannot be carefully orchestrated or planned out, e.g., in our hardware, manufacturing, or propulsion labs. In such environments, it is challenging for users to consciously maintain the required safe social distance. This project provides a technical approach to proactively monitor the distance between users utilizing the Bluetooth transmission-reception signal strength (RSSI). We use a lightweight machine learning model to map the signal strength to the distance and infer the direction of motion between any two users. The technology builds on a long line of research in the area of wireless signals, some of which has been carried out in our lab. It is lightweight (can be easily carried as a lanyard worn by users), low cost (less than \$15 when produced in bulk), privacy preserving (no data need to be shared to any other organizations), proactive (provides warning messages prior to approaching unsafe distance). We have shown its effectiveness in our preliminary experiments.

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1 TECHNICAL PROBLEM

In many laboratory and other learning environments at Purdue, it is challenging for individuals to constantly monitor and maintain a safe distance from others. This problem appears in learning laboratories and research laboratories alike, where users are mobile and

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distancing while engrossed in their laboratory activity. We therefore wish to use wireless signals that are low power and already ubiquitous in our environments (Bluetooth) to monitor the distance between users and provide a warning signal (visual and/or audible) proactively when the safe distance is predicted to be violated. Further, there are laboratory surfaces that are regularly touched by users, and a safe amount of time needs to elapse before another user should touch the same surface. This is hard to keep track of in a manual way for shared apparatus with high frequency of different users, as is common in many of our educational labs. Thus, low-power Bluetooth transceivers (transmitters and receivers) with some memory built into them can provide an indication of when a surface will be safe to touch by another user. Though commercial solutions exist, their current offerings lack the flexibility to be customized to meet our stakeholders' demands. While some would prefer a centralized database of proximity records, others are more concerned with user privacy and ensuring none of their data leaves the devices. Additionally, depending on the environment, different types of proximity alerts are required. In a noisy manufacturing environment, this alert needs to be stronger and perhaps more multidimensional than in a quiet laboratory.

their movements cannot be precisely planned out or orchestrated. It is onerous for individual users to constantly be aware of safe

2 SOLUTION APPROACH

We want to use wireless communication beacons and the measurement of RSSI at the receiving device to determine the distance of separation between any two people. We will estimate the trend of the distance (increasing, decreasing, staying constant) and if the trend becomes of concern, the device will provide an alarm before an unsafe situation occurs. The wireless signal to use should be low power, completely safe for the users, suitable for a small form factor that can be easily worn (say as a lanyard), and low cost for widespread deployment. We have manufactured a Bluetooth-based transceiver that satisfies all these conditions. Such a transceiver will be worn on the body of the users, such as a lanyard, and will be unobtrusive. The distance measurement will happen without any active involvement of the users and will thus be deployable in a widespread way. For surfaces that need monitoring for touch, we

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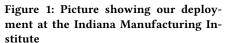




Figure 2: The signal strength (RSSI) separates the distance less than 6 feet from greater than.



Figure 3: RSSI is not predictive of distance when there are obstacles between transceivers.

will customize the transceiver with memory that will keep track of the time when a user had last interacted with the surface. If a different user comes close to the surface and wishes to touch it, then a proactive alarm will be presented. While there has been significant technology development around the world on the broad topic of contact tracing, most of this is commercial, closed-source, expensive, and not customizable to our university environment. For example, in a privacy-preserving mode for inter-user proximity tracing, we may not want the data to leave the user's device. On the other hand, for laboratory asset surface monitoring, we may want to create a central database at the department so as to take mitigation actions, like determining the schedule for cleaning. Our proposed solution approach is customizable in both these and several other dimensions, including the intrusiveness of the alert (such as blinking LED or low or loud buzz).

3 RELATED WORK

This technology is based on a long line of research that has been carried on in the field of wireless technology (specifically, wireless signals) [4] and applied machine learning (specifically, models to deduce physical environmental characteristics from wireless signals) [3]. In prior work in the PI Bagchi's lab, we have demonstrated how wireless signal capture can be done even in noisy or insecure environments and have derived robust intelligence from such signals [1, 5]. PI Iyer [2], in his recent book, has summarized smart technology that can assist manufacturers in recovery from Covid-19 and the role of Bluetooth-based technologies in ensuring safe operations.

4 EXPERIMENTAL DETAILS/RESULTS

The data we have gathered from experiments at the Indiana Manufacturing Institute (IMI) has shown the effectiveness of using RSSI as a means of discriminating a safe distance of approximately 6 feet from an unsafe distance. In one experiment, tests were conducted at distances ranging from 2 to 15 feet, each over a 90 second period, and the results are shown in Figure 2. As the plot shows, while mapping RSSI to an exact distance is difficult due to environmental noise, there is a significant difference between < 6 feet proximity and greater distances of separation.

Other tests revealed the limits of RSSI to distance mapping. For example, Figure 3 shows data collected from tests conducted where the transceivers were placed on opposing sides of a closed door. In cases such as these, it may be difficult to detect proximity between users until the door is opened and the users' safety is compromised.

This explains why in our design each transceiver is also equipped with an accelerometer, whose data can be crossed with RSSI to provide more robust proximity predictions in noisy, obstacle-filled settings.

5 RESEARCH PLAN AND PRELIMINARY RESULTS

Currently, we have created a PCB (Printed Circuit Board) design with the requisite hardware that will be manufactured into a form factor of a credit card, which can be conveniently carried on the body of the user. Next, we will collect measurements from a wide set of laboratories and create a machine learning model that will enable us to map signal strength and accelerometer measurements to a distance and direction of motion. Finally, we plan to deploy to about 100 students and researchers in a variety of laboratory settings and do a thorough evaluation of the accuracy of the technology. We expect that we will adjust the software parameters and the machine learning model in response to the evaluation with two spirals of refinement during a 90-day period (roughly till the end of the Fall semester here). It will then be trialed in the manufacturing sector, which has the concept of VSMI (Value Stream Mapping with an Infection Layer). VSMI improves manufacturing processes by ensuring that employees maintain safe distance and only touch surfaces after acceptable quarantine intervals.

6 ONLINE RESOURCES

Here is the link to a video of one of our testing environments: https://youtu.be/2z5WYfnrnGM

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