Aether - A Novel Method to Eliminate False Positives in Private Automated Contact Tracing

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***Abstract*— Contact tracing has shown promise to mitigate the negative effects of serious infectious diseases, such as COVID-19. Contact tracing can identify people who have potentially been exposed to COVID-19, as well as to enforce quarantine rules. However, many of these methods store location data, and therefore present privacy concerns. Bluetooth technology provides an effective solution to avoid violating fundamental privacy rights. However, Bluetooth technology does not have a good way of knowing whether devices are on the same level or different levels. In the case of multistory buildings, false positives can occur between two people who are within close proximity but on different floors. This paper proposes a novel solution in which the built-in barometer in mobile devices is used in combination with Bluetooth to avoid false positives. This paper establishes the viability and effectiveness of the solution through various experiments to make the current Bluetooth contact tracing technology even more accurate, which will ultimately save countless lives.**

Keywords*— RSSI, Barometer, Obstruction, Contact Tracing, COVID-19

I. Introduction

The COVID-19 pandemic has impacted millions of people around the world and resulted in over a million deaths worldwide (at the time of writing this paper), and the death toll is expected to grow in the next few months. Health experts and officials believe that contact tracing is essential for controlling COVID-19. One of the ways to achieve contact tracing is to track people using their phones and take appropriate steps to inform people who may have gotten in contact with a person that was diagnosed with COVID-19. This method is acceptable in some countries but is unconstitutional in other countries as it does not preserve the privacy of individuals. To address the privacy issue and still use the contact tracing method, the Massachusetts Institute of Technology (MIT) started an initiative called Private Automated Contact Tracing (PACT). The PACT consortium includes academia, industry, and government agencies. The PACT solution uses Bluetooth signals from phones to detect proximity. Phones store Bluetooth chirps continuously, and whenever a person is diagnosed with COVID-19, other phones that came within six feet of this person in the last fourteen days are alerted.

The goal of Aether is to contribute data and innovative solutions to the Private Automated Contact Tracing (PACT) consortium [1]. The current PACT method relies on Bluetooth Received Signal Strength Indicator (RSSI) values to detect proximity. However, Bluetooth RSSI cannot differentiate between vertical and horizontal distances. This presents a major challenge for multistory buildings. The PACT method cannot tell the difference between two people on the same floor or two people on different floors because the proximity detection is entirely dependent on the Bluetooth RSSI value. As a result, in the case of two people on different floors, a false positive is generated. To address this issue, this paper proposes adding another parameter to the detection method to determine whether the people in "contact" are on the same floor or on different floors. One of the methods to achieve this is to use the barometer built into many phones to detect if people are on the same or different floors and make necessary adjustments to the proximity detection algorithm to avoid false positives. Research work in the field of localization can be used to calibrate phone's embedded barometer to provide accurate results [2] [3]. Indoor localization techniques are documented in past research [4] [5]. The proposed method does not require localization but uses the relative position of phones to figure out the vertical distance between them. To prove the viability of the solution, Bluetooth RSSI data for two Raspberry Pi devices on two different floors was collected. At the same time, the pressure data using the barometer built into phones was also collected. The information above can be used to determine whether an event of proximity detection is a false positive. The specific contributions that this paper makes are:

- Collect data to prove that RSSI value can be used for proximity detection
- Collect data to prove that the current method cannot differentiate between two people on the same floor or different floors, hence resulting in false positives
- Collect data to prove that adding additional data to the PACT proximity algorithm can reduce or eliminate false positives related to people on two different floors

The rest of the paper is organized as follows. Section II describes the methodology used for Aether. Section III details the experiments and data collection. Section IV provides analysis and algorithms. Section V lists implementation details. Section VI concludes the paper.

II. METHODOLOGY

The current method of Private Automated Contact Tracing cannot differentiate between two people that are next to each other on the same floor and two people on separate floors. This means that if one of those people was diagnosed with COVID-19, the current model might alert the other person saying that they had come into contact with someone who had COVID-19, which is a false positive. These false positives in an apartment type environment can be eliminated if pressure information collected from the barometer is used in conjunction with the Bluetooth RSSI data. An evaluation was performed through the use of the barometer, built into most phones, to establish a pressure differential between floors/heights. As part of the testing, four different positions where the phone would be most commonly placed were used: on the floor, in a person's pocket, on a table, and in a person's hand. For my experiments, I used Bluetooth RSSI technology, and the barometer built into most phones. During the experimentation and analysis, I assumed that the current method that uses Bluetooth RSSI provides reasonably accurate information for the proximity detection of two devices [6].

III. EXPERIMENTS AND DATA COLLECTIONS

The combination of experiments 1 and 2 can be used to eliminate a false positive generated by the current PACT model.

TABLE I. EXPERIMENT OVERVIEW

Exp. #	Hypothesis	Reason	Repetitions
1	The current PACT method concludes that two people came into contact even if they are on different floors.	To prove that RSSI data is the same if you are on the same floor or if you are on two different floors.	100 samples for each position of Raspberry Pi-1 and Raspberry Pi-2.
2	The barometer built into most phones can be used to establish a pressure differential between floors/heights.	Confirm that the barometer built into phones is viable to detect an altitude difference.	25 samples for each position of Raspberry Pi-1 and Raspberry Pi-2 (the barometers in iPhones and Android phones were used to measure the pressure)

A. Plan and Execution

For these experiments, four positions where phones are most commonly placed when people are at home were determined. These positions include on the floor, in a pocket, on a table, and in hand. On the floor, in a pocket, on a table, and in hand are zero, two, three, and four feet above the floor, respectively. Fig. 1 illustrates each of these positions on the first and second floors.

Although data is only needed for the sixteen cases, it was decided to collect data at every foot from the floor to the ceiling on the first floor. Data was collected by placing Raspberry Pi-2 (Pi-2) at a fixed position on the second floor and changing the height of Raspberry Pi-1 (Pi-1) by a foot every iteration from the

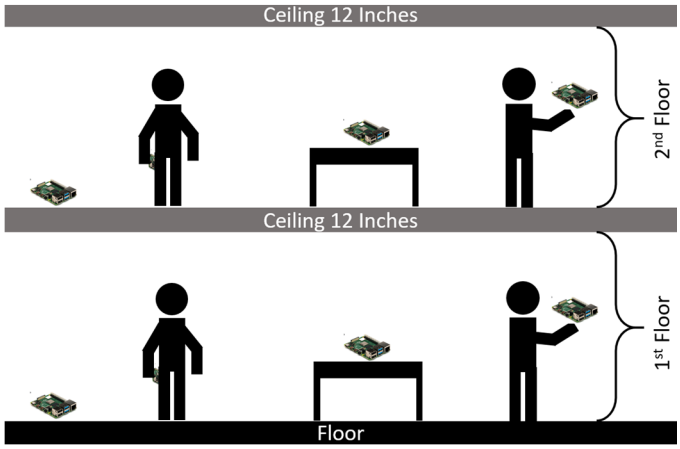

Fig. 1. Different positions where phones are commonly placed

floor to the ceiling. At the same time, pressure data was also collected by placing one phone at the same level as Pi-2 and the second one at the same level as Pi-1. For each measurement, one of the Raspberry Pi devices was configured to be an advertiser and the other as a scanner. One hundred samples of data were stored for RSSI, and twenty-five samples of pressure per iteration to improve accuracy. The difference in altitude of the two devices was calculated using the pressure to altitude conversion method. Then, the position of Pi-2 was changed to in pocket, on a table, and in hand, and the above steps were repeated.

B. Data Relevance

The data that I collected at different heights of Pi-1 and Pi-2 provides a correlation between RSSI and distance. The pressure data that was collected using the barometer in different phones provides an estimation of the altitude. Together, the sets of data are used to validate whether the proposed method is a viable solution to eliminate false positives related to people living on different floors.

C. Examples

Fig. 2 represents 100 RSSI values collected for one of the cases. Fig. 3 represents 25 difference in altitude values collected from the barometer for the same case.

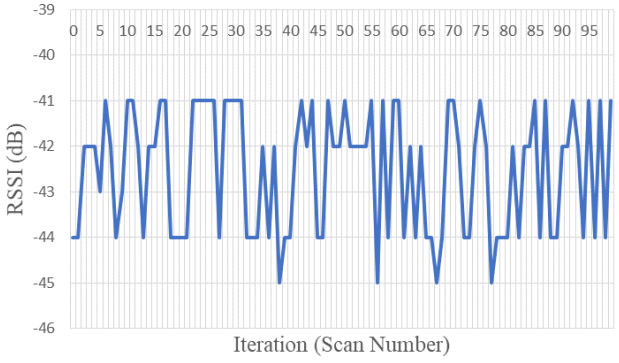

Fig. 2. 100 RSSI Values for the case when Pi-2 is on the floor of the second floor, and Pi-1 is 1 foot away on the first floor.

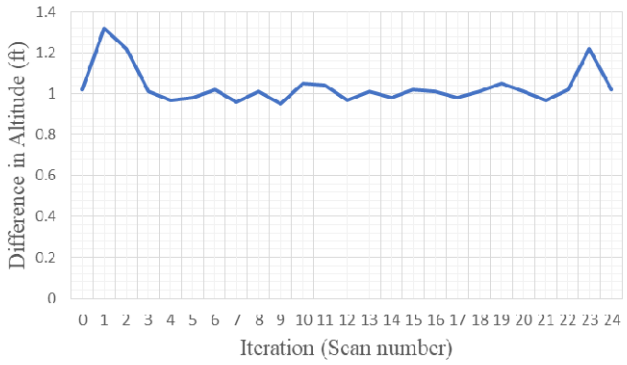

Fig. 3. 25 difference in altitude values from the barometer for the case when Pi-2 is on the floor of the second floor, and Pi-1 is 1 foot away on the first floor.

IV. Analysis and Algorithms

A. Description

Based on the data collected, it is evident that the altitude data computed from the pressure data of the barometer can be used in conjunction with the Bluetooth RSSI to detect potential false positives. This can be based on a policy setting, for example, in the PACT system, if RSSI values indicate that another device is in proximity, the altitude data can be used to determine whether they are on different floors. The policy could be something along the line: if the altitude difference is greater than three feet, the proximity detection algorithm should treat it as not in contact.

B. Results and Examples

Fig. 4-7 show the data collected for the following cases:

- Pi-2 is fixed on the floor of the 2nd floor to simulate a phone placed on the floor. The position of Pi-1 changed from the floor to the ceiling in one-foot increments on the first floor.
- Pi-2 is fixed at a height equal to that of an average person's pocket on the 2nd floor to simulate a phone placed in a pocket. The position of Pi-1 changed from the floor to the ceiling in one-foot increments on the first floor.
- Pi-2 is fixed on a table on the 2nd floor to simulate a phone placed on a table. The position of Pi-1 changed from the floor to the ceiling in one-foot increments on the first floor.
- Pi-2 is fixed at a height equal to that of a person holding a phone in their hand and looking at it on the 2nd floor. The position of Pi-1 changed from the floor to the ceiling in one-foot increments on the first floor.

At each of the positions, one hundred RSSI values were collected and calculated the mean. The mean values were used to plot the graph. Also, regression analysis is performed on the data that was collected. There are outliers in the scan results which skewed the mean. One of the lessons learned was to take a large sample size to reduce the impact of the outlier measurement on the mean value.

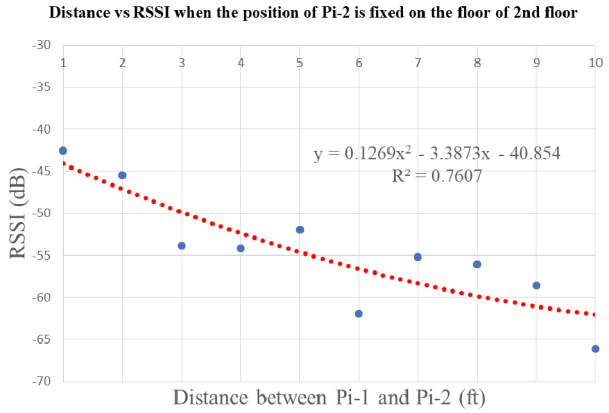

Fig. 4. The distance between Pi-1 and Pi-2 vs. the mean RSSI value. Each point represents the mean of 100 samples. The position of Pi-2 is fixed on the floor of the 2nd floor. The position of Pi-1 is changing on the 1st floor.

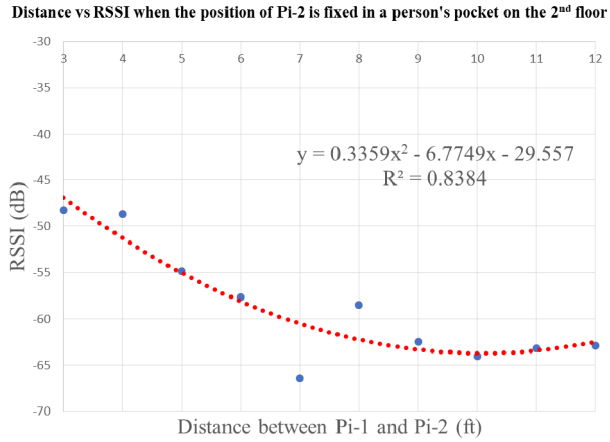

Fig. 5. The distance between Pi-1 and Pi-2 vs. the mean RSSI value. Each point represents the mean of 100 samples. The position of Pi-2 is fixed at a height equal to that of an average person's pocket on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

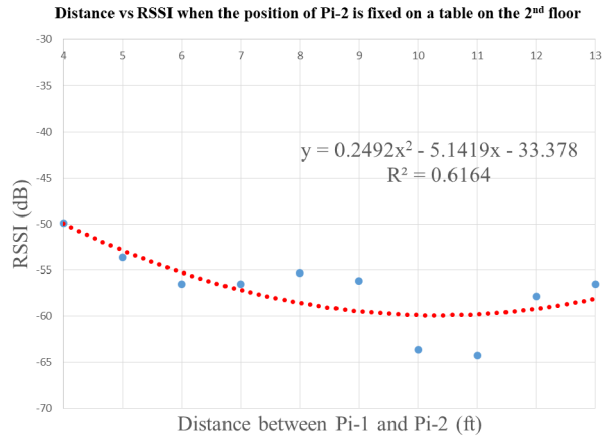

Fig. 6. The distance between Pi-1 and Pi-2 vs. the mean RSSI value. Each point represents the mean of 100 samples. The position of Pi-2 is fixed on a table on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

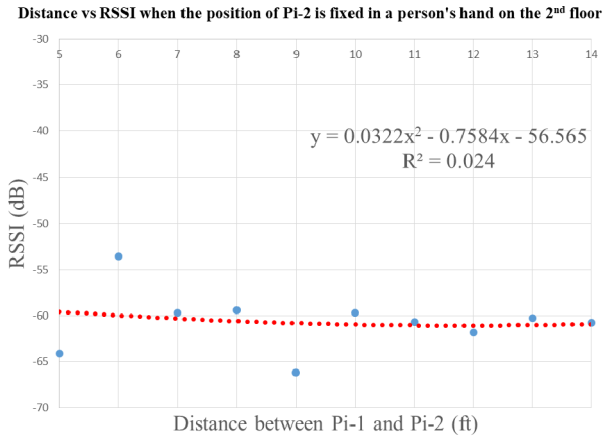

Fig. 7. The distance between Pi-1 and Pi-2 vs. the mean RSSI value. Each point represents the mean of 100 samples. The position of Pi-2 is fixed at a height equal to that of a person holding a phone in their hand and looking at it on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

While collecting the RSSI data, the barometer pressure data was also collected using two different phones positioned next to the Raspberry Pi devices. Fig. 8-11 show the corresponding data collected for the cases shown above in Fig. 4 to Fig. 7. These graphs indicate that the altitude calculation using barometers built into most phones is reasonably accurate for the purpose of eliminating false positives in relation to people living on different floors.

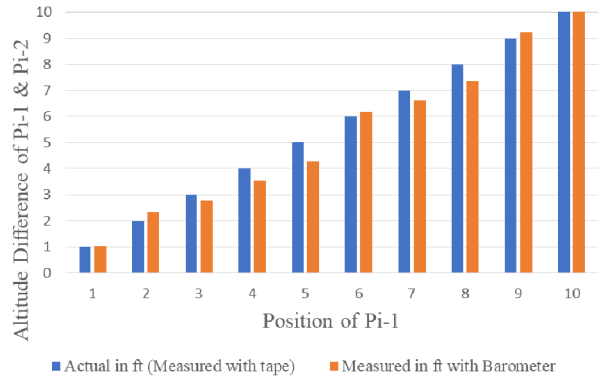

Fig. 8. The actual difference in altitude of Pi-1 and Pi-2 vs. the measured difference in altitude using the barometer. Each bar represents the mean of 25 samples. The position of Pi-2 is fixed on the floor of the 2nd floor. The position of Pi-1 is changing on the 1st floor.

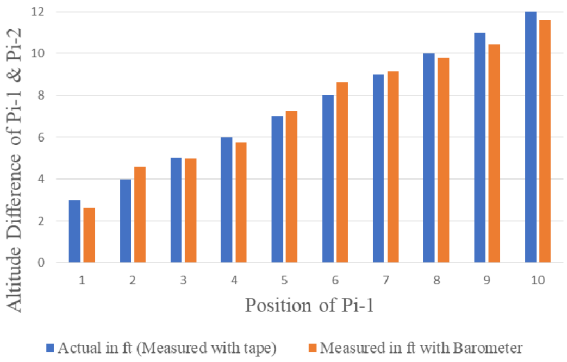

Fig. 9. The actual difference in altitude of Pi-1 and Pi-2 vs. the measured difference in altitude using the barometer. Each bar represents the mean of 25 samples. The position of Pi-2 is fixed at a height equal to that of an average person's pocket on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

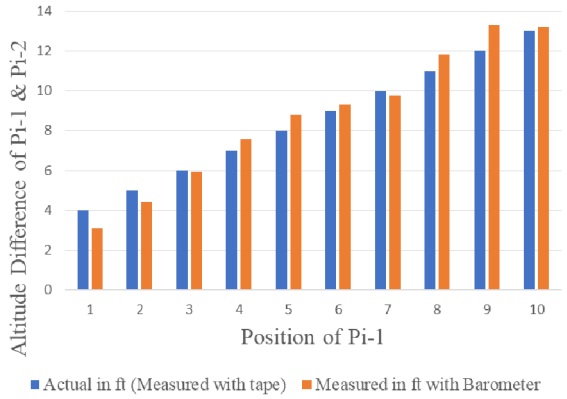

Fig. 10. The actual difference in altitude of Pi-1 and Pi-2 vs. the measured difference in altitude using the barometer. Each bar represents the mean of 25 samples. The position of Pi-2 is fixed on a table on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

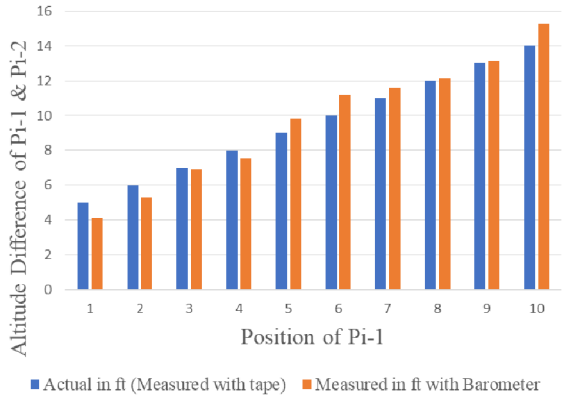

Fig. 11. The actual difference in altitude of Pi-1 and Pi-2 vs. the measured difference in altitude using the barometer. Each bar represents the mean of 25 samples. The position of Pi-2 is fixed at a height equal to that of a phone in hand and looking at the phone on the 2nd floor. The position of Pi-1 is changing on the 1st floor.

V. Implementation

Raspberry Pi devices with Bluetooth support are used to collect RSSI data. Python 3.7.3 running on Raspbian is used to develop code that reads Bluetooth data. iPhones and Android devices were used to collect pressure data. Microsoft Excel was used for regression analysis.

VI. Conclusion

Based on the data presented in section IV, the usage of RSSI data to detect proximity does not account for people on different floors. In addition, based on the data collected, the barometers built into most phones can be used to establish a pressure differential between floors/heights. Furthermore, altitude calculated based on the pressure differential can be used to reduce or completely eliminate false positives related to people living on different floors. Further research for my solution would be to address the situation of open staircases where two people are going up or down the stairs.

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References

[1] Pact.mit.edu. 2020. PACT: Private Automated Contact Tracing. [online] Available at: <https://pact.mit.edu/> [Accessed 12 July 2020].

[2] Dl.acm.org. 2020. Improving Floor Localization Accuracy In 3D Spaces Using Barometer | Proceedings Of The 2015 ACM International Symposium On Wearable Computers. [online] Available at: <https://dl.acm.org/doi/10.1145/2802083.2802089> [Accessed 8 October 2020].

[3] H. Ye, T. Gu, X. Tao and J. Lu, "B-Loc: Scalable Floor Localization Using Barometer on Smartphone," 2014 IEEE 11th International Conference on Mobile Ad Hoc and Sensor Systems, Philadelphia, PA, 2014, pp. 127-135, doi: 10.1109/MASS.2014.49.

[4] I. Constandache, X. Bao, M. Azizyan and R. Choudhury, "Did you see bob?: Human localization using mobile phones" in MobiCom., ACM, 2010.

[5] 17. H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef and R. R. Choudhury, "No need to war-drive: Unsupervised indoor localization" in MobiSys, ACM, pp. 197-210, 2012.

[6] Medium. 2020. Inferring Distance From Bluetooth Signal Strength: A Deep Dive. [online] Available at: <https://medium.com/personaldata-io/inferring-distance-from-bluetooth-signal-strength-a-deep-dive-fe7badc2bb6d> [Accessed 3 June 2020].