Accurate Extraction of Face-to-Face Proximity Using Smartphones and Bluetooth

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***Abstract*—The availability of "always-on" communications has tremendous implications for how people interact socially. In particular, sociologists are interested in the question if such pervasive access increases or decreases face-to-face interactions. Unlike triangulation which seeks to define precise position, the question of face-to-face interactions reduces to one of proximity, i.e. are the individuals within a certain distance? Moreover, the problem of proximity estimation is complicated by the fact that the measurement must be quite precise (1-1.5m) and can cover a wide variety of environments. Existing approaches such as GPS and WiFi triangulation are insufficient due to those constraints. In contrast, Bluetooth, which is commonly available on most smartphones, provides a compelling alternative for proximity estimation. In this paper, we demonstrate through experimental studies the efficacy of Bluetooth for this exact purpose. We present several real world scenarios and explore Bluetooth proximity estimation on Android with respect to accuracy and power consumption.**

***Index Terms*—Bluetooth, smartphone, proximity estimation, face-to-face interaction, RSSI**

I. Introduction

In recent years, the presence of portable devices ranging from the traditional laptop to fully fledged smartphones has introduced low-cost, always-on network connectivity to significant swaths of society. Network applications designed for communication and connectivity provide the facility for people to reach anywhere at any time in the mobile network fabric. Digital communication [1], such as texting and social networking, connect individuals and communities with ever expanding information flows, all the while becoming increasingly more interwoven. There are compelling societal questions whether such digital social interactions are modifying the nature and frequency of human social interactions. A key metric for researchers in this area is whether these networks facilitate face-to-face interactions or whether these networks impede face-to-face interactions.

Sociological studies have shown that collecting occurrences of communications based on self-reporting, where subjects are asked about their social interaction proximity, is unreliable since the accuracy depends upon the recency and salience of the interactions [2]. With the increasing availability of data available in logs generated by smartphones, there are tremendous opportunities for collecting data automatically [3]. The critical technical challenge is how to measure face-to-face interactions, i.e. are two or more individuals within a certain distance that could afford such interactions?

Interactions are not limited to any particular area and can take place at a wide variety of locations, ranging from sitting and chatting in a Starbucks coffee shop to walking and chatting across a college campus. For most face-to-face interactions, the approximate distance between individuals in casual conversation is within 0.5 to 2.5 meters[1]. The natural solution would seem to be either WiFi triangulation [4], cell phone triangulation [5], GPS or a combination of all three. However, none of the solutions nor the combination of the solutions are ideal nor sufficient. Although WiFi triangulation can present a reasonable degree of accuracy, its accuracy in all but the most dense WiFi deployments is insufficient, ranging on the order of 3 to 30 meters [4]. Similarly, cell phone triangulation suffers from an even worse accuracy [5]. Moreover, while WiFi is reasonably pervasive, WiFi tends to generally be sparser in green, i.e. outdoor spaces. Notably, GPS suffers from both an accuracy shortcoming (5-50m) as well as not being viable indoors [6].

However, it is important to note that face-to-face interaction does not demand an absolute position as offered by the previously mentioned schemes but rather simply requires a determination of *proximity*. With that shift of the problem definition, Bluetooth emerges as a plausible alternative, offering both accuracy (1-1.2m) [7] and ubiquity (most modern smartphones come with Bluetooth) [8]. While there has been prior work that has utilized the existence of Bluetooth to ascertain proximity, we will argue later that such mechanisms are wholly insufficient. The question addressed by this paper is to what extent Bluetooth can be an accurate estimator of such proximity. Beyond its social implications, we believe that face-to-face proximity could also imply how media content is likely to be consumed (share phone versus load on own phone) and engaged.

To summarize, our work makes the following contributions:

- We demonstrate the viability of using Bluetooth RSSI with appropriate smoothing for the purposes of face-to-face proximity estimation and evaluate the accuracy across several real-world scenarios.
- We study the relationship between the value of Bluetooth RSSI and distance based on empirical measurements and

[1] Section IV presents empirical evidence supporting this claim.

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radio propagation model.

- We discuss the construction of a data collection platform using Bluetooth on Android-based smartphones.
- We explore the energy efficiency of Bluetooth compared with WiFi and GPS via experimental measurements.

II. Related Work

For most position techniques which aim to deliver on absolute position, distance/angle estimation techniques are used to calculate the distances and then the locations are plotted based on the known reference locations with the help of triangulation or trilateration [4]. Different methods can be used to estimate such information which include time of arrival/time difference of arrival (ToA/TDoA), angle of arrival (AoA) and RSSI [9]. In TDoA, the difference in arrived signal time and transmitted signal time gives estimated distance. TDoA is efficiently used by GPS and has the potential for very high accuracy. The method of angle of arrival (AoA) uses an array of antennas to measure the angle of the signal received and is combined with TDoA to reduce error rate.

In contrast to TDoA and AoA techniques which tend to require a much costlier implementation and infrastructure, RSSI-based techniques rely on the theory that the received signal strength is inversely proportional to the square of the distance. RSSI-based method is one of the most commonly implemented techniques, due to its practicality, low cost and availability. Numerous works have been explored in the literature leveraging WiFi [4] and Bluetooth [7]. Theoretically, a known radio propagation model can be used to convert the signal strength into distance. However, in real world environments, the indicator is highly influenced by noise, obstacles and the type of antenna, which make it difficult to calibrate.

Antti et al. present the design and implementation of a Bluetooth Local Positioning Application (BLPA) [10]. BLPA converts the received signal power level to distance estimate according to a simple propagation model, then BLPA compute 3-D position estimate on the basis of distance estimates. The accuracy of BLPA is reported to be 3.76 m. However all the results are based on the propagation model which is only suitable for specific controlled environments as we will show in the later indoor versus outdoor comparisons. Moreover, we also show that the method by which the device is carried (in backpack vs. in pocket or in hand) can play a significant role in mapping RSSI to distance.

From a specific work prospective, the works of Nathan et al. [3] [2] are highly relevant to the paper. In those studies, the authors use the ability to detect Bluetooth signals as indicators for people nearby within the Bluetooth range (around 10m). In contrast to the Nathan work, our work focuses on a finer grain of proximity detection in order to remove potential ambiguities in face-to-face detection. While the presence of Bluetooth or the usage of multiple detections can operate as an effective superset of all potential interactions, the techniques introduce inaccuracy, particularly in environments such as college campuses. For instance, consider the example of a large lecture hall or a campus dining hall with a large set of geographically spread seating locations. By default on most smart phones, Bluetooth can be detected at ranges approaching 10m+. In contrast, face-to-face interactions are only 1-1.5m. Thus, there exists a significant false detection rate. For example, students may be seated at different tables in the dining hall but yet the simpler technique posed by Nathan would detect those students as interacting in a face-to-face manner incorrectly. Due to the heavy usage of such facilities by college students (as in our studies), the detection of such face-to-face interactions is essential.

III. System design and implementation

A. System design

The goal of our work is to estimate the proximity between two users with Bluetooth RSSI values logged on smartphones. We now present the software architecture of the system. The application collects Bluetooth data including the detailed values of RSSI, MAC address and Bluetooth identifier (BTID). In addition to Bluetooth, data points form a variety of other subsystems (WiFi, GPS, light sensor and battery level) are gathered in order to compare and improve our proximity estimation. Separate threads are employed to compensate for the variety of speeds at which the respective subsystems offer relevant data. For WiFi, the data of access point(AP) name, RSSI as well as MAC address are logged. For GPS, the locations of phones are collected for the later distance calculation. In order to determine whether the phone is sheltered (e.g. inside a backpack or in hand) and the surroundings (e.g. inside or outside buildings), we keep track of the light sensor data. The battery usage percentage is recorded for the energy consumption comparison.

We designed a application which starts automatically when the phone powers on and runs passively in the background on HTC Nexus One (with Broadcom chip BCM4329EKUBG) using Android OS version 2.2 (Froyo). The Android platform was selected for its customization capabilities with respect to hardware-level interactions, be those capabilities through normal API or rooted/customized interfaces. The system contains a Graphic User Interface (GUI) which allows users to check details of the collected data. All the data management including saving and query relies on SQLite database. With current Android APIs, each kind of data is invoked through the corresponding function calls. The default sensing granularity in terms of updating time interval for Bluetooth is 10 seconds. Intuitively, larger time intervals can help save energy, so we also enable the changing of such sensing interval in order to explore its impact on the energy consumption. The generated data files on phones are sent to servers periodically with RSA security for backup and analysis.

Unfortunately, in order to protect users from people trying to hack into their phones, phones by default do not allow Bluetooth to always be discoverable. Thus we must root the phone in order to enable Bluetooth to be discoverable all of the time while in the experiments. The root process does not overwrite the shipped ROM on the device. During the development another consideration about Bluetooth is the difference of Bluetooth discovery and pairing. Since in our tests there is no need to create Bluetooth connections among phones, we simply call the method of $startDiscovery()$ to return the found devices instead of sending pairing request to other phones.

B. Power Comparison

Energy is one of the most important considerations for applications on smartphones. Compared to PC, the energy of mobile phones is relatively low and limited. So it is essential to utilize an energy saving method in the system. Before we reveal the relationship between Bluetooth RSSI values and the distance, we first compare the energy consumption of Bluetooth, WiFi and GPS in order to ensure that Bluetooth is suitable for proximity estimation on smartphones. In order to test the energy consumption of Bluetooth, WiFi and GPS, they are separately run on three identical phones with full charged battery and the updating time interval is 30 seconds. The battery level is recorded periodically (every half an hour) in order to get the precise results. The light sensor values are also collected in the Bluetooth application at the same time. The test results are showed in Figure 1 and obviously Bluetooth application has the best capability of energy saving. When the time granularity of Bluetooth update becomes larger, the battery can even last longer.

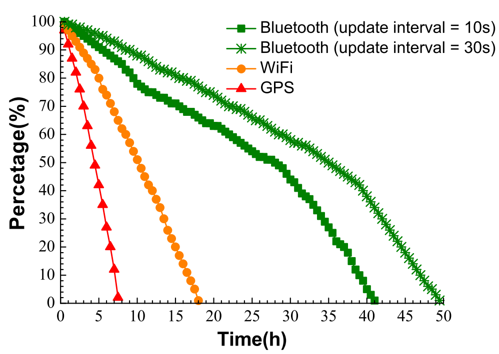

Fig. 1. Energy consumption of Bluetooth, WiFi and GPS

IV. Experiments & Evaluation

Before doing distance estimation with RSSI values, we first explore the relationship between Bluetooth RSSI and distance. We then improve the estimation accuracy based on the different experimental results and comparisons in fixed scenarios. Finally we compare the accuracy results based on Bluetooth, WiFi and GPS.

A. Bluetooth RSSI vs. Distance

Since the unit of RSSI returned by the Android phone interface is dBm, there is no need to convert RSSI to received signal power level like in BLPA [10]. In theory, distance can be measured based on the radio propagation model and power level. The model can be described as follows:

$$\begin{aligned} RSSI &= P_{TX} + G_{TX} + G_{RX} + 20\log\left(\frac{c}{4\pi f}\right) - 10n\log(d) \\ &= P_{TX} + G - 40.2 - 10n\log(d) \end{aligned} \tag{1}$$

where P_{TX} is the transmitted power; G_{TX} and G_{RX} are the antenna gains; G is the total antenna gain: $G = G_{TX}+G_{RX}$; c is the speed of light ($3.0*10^8 m/s$); f is the central frequency (2.44 GHz); n is the attenuation factor (2 in free space); and d is the distance between transmitter and receiver (in m). d is therefore:

$$d = 10^{[(P_{TX}-40.2-RSSI+G)/10n]} \tag{2}$$

However, such model can only be utilized as a theoretical reference. Due to reflection, obstacles, noise and antenna orientation, the relationship between RSSI and distance becomes more complicated. Our challenge is to assess how much impact these environmental factors have on Bluetooth RSSI values. Therefore, we carry out several experiments to understand how the Bluetooth indicators fade with distance with environmental influences.

Figure 2 presents indoor, outdoor, and theoretical results for Bluetooth across a variety of distances (0-5 meters). The theoretical values are predicted by the propagation model with $P_{TX} = 2.9\ dBm, n = 2$ and $G = -4.82\ dBi$ [10]. Indoor experiments were conducted in a noisy hallway in the campus engineering building. Outdoor experiments were conducted in the open area outside the building. In the measurement there were no obstacles between the two phones and the antennas of the phones were aligned towards each other. In such a way, we tried to build up a relatively simple and “ideal” environment where the possible impact factors are reflection and noise only. We repeated the measurements over the period of half an hour with the distance being increased by 0.5 meters between each result. The average RSSI value was calculated over 150 samples for each position. The inside results were relatively close to the theoretical values. However, the results outside the building were somehow farther away from the theoretical reference and imply that these two kinds of environment should be differentiated for later measurements.

Next we perform the experiments focusing on the inside case but with different antenna orientation(e.g. in the same direction) and obstacles (e.g. put in a backpack or partitioned by cubicle) in order to discover the influence of these possible factors. Figure 3 illustrates the different impacts. First, the change in orientation turns out to have little impact on the final results. As many smart phones cannot predict phone orientation, antenna design is typically optimized to account for this fact. Second, although we placed two phones on each side of a cubicle, such an arrangement did not affect RSSI significantly. Third, the most important environment issue came from the backpack. It may because the signal of Bluetooth is disturbed or shielded in such a closed environment. As many individuals would be likely to carry their phone in a purse or backpack (particularly on a college campus), the backpack setting bears

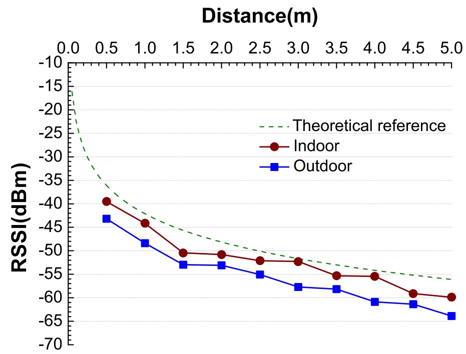

Fig. 2. Bluetooth RSSI vs. Distance - Theoretical, Indoor, Outdoor

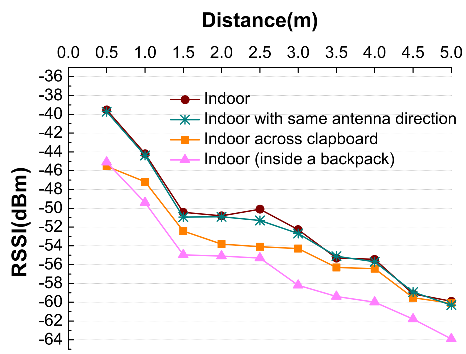

Fig. 3. Bluetooth RSSI vs. Distance Inside Case

further investigation.

Using the same method, we measured the RSSI values outside with the consideration of the influence of a backpack. Figure 4 shows the results from those experiments. Similarly, the RSSI values become lower when the phones are in the backpack so it is a non-ignorable elements in the following estimations, further reinforcing that detection of such an arrangement may be critical for proper distance resolution.

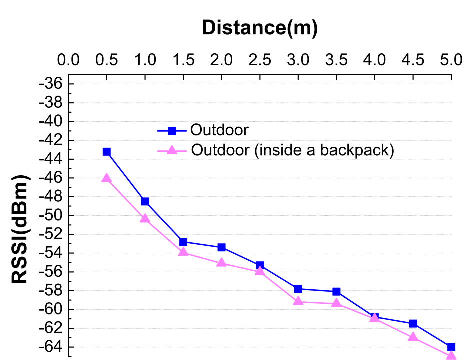

Fig. 4. Bluetooth RSSI vs. Distance Outside Case

Therefore, it is not trivial to draw a definite conclusion about the relationship between Bluetooth RSSI and distance. Based on these inside and outside results, two environmental factors may affect the RSSI values: inside/outside building and inside/outside a backpack.

B. Proximity estimation

As mentioned at the beginning, the objective of the paper was to provide an accurate proximity estimation for face-to-face communication. This raises a question: what is the face-to-face communication distance? In this subsection, we first define the face-to-face distance and then use the indoor results to do estimation. Since the error rate turns out to relatively high, we explore the possible reasons and remodel the estimation method with the introduction of light sensor values.

Distance of face-to-face communication: When we have dinner with our friends sitting at the same table, the conversion among us is called face-to-face communication; or when we talk with someone side by side, the distance between us is also called face-to-face communication. In other words, face-to-face communication happens when people are close enough to have conversations in a convenient way. People typically have such communication when they are sitting or walking together. Thus, we calculate the distance for this kind of communication by measuring distances across the campus (such as diagonal of desk in dinning hall, distance between desks in classrooms and etc.) and the average value is equal to 1.52m.

Base assessment: To conduct an initial evaluation of the raw accuracy of Bluetooth, we constructed a scenario that draws upon several likely occurrences in normal campus interactions. The scenario blends each of the earlier test cases and provides a ground truth to assess the accuracy in a real-world setting.

The measurement is conducted as follows: two people with two phones walked side by side from Cushing Hall to Grace Hall and then returned back.The whole process took 30 minutes and individuals were always within the distance for face-to-face communication. During the first five minutes (phone in hand) and last five minutes (phone inside a backpack) they were inside Cushing Hall. While individuals were outside (the duration was 20 minutes), in the first 10 minutes individuals held the phones in their hand and then put phones in backpack for the later 10 minutes. After the data collection, the corresponding RSSI value (-50dBm) of direct communication distance (152cm) from results (Figure 3) was used as a threshold to estimate whether the individuals were in face-to-face proximity or not. Based on the ground truth, the values less then -50dBm are considered as wrong estimations. The second column in Table I shows the results and error rate of this naïve method. It was found that the outside parts have especially high error rates and the reasons may include: i) indoor relationship was used to estimate the distance outdoors without differentiation; ii) the influence of backpack was not taken into consideration; iii) each RSSI value was not smoothed allowing for environmental fluctuations.

TABLE I
ORIGINAL AND IMPROVED ERROR RATE AGAINST GROUND TRUTH

Total samples	174	Improved
Total error rate	42.5%	13.8%
Inside error rate (0 - 5 mins)	14.3%	10.7%
Outside error rate (5 - 15 mins)	56.1%	14.0%
Outside (inside a backpack) error rate (15 - 25 mins)	58.3%	16.7%
Inside (inside a backpack) error rate (25 - 30 mins)	10.3%	10.3%

Accuracy Improvement: In order to distinguish those different circumstances, we propose a solution based on the following concepts: when phones are inside the building, the light sensor return values between 225 to 1280; while this value comes up to larger than 1280 when phones are under daylight. When the phones are in the backpack or anything of shelter, the light values are always under 10. Thus, we use the light sensor to improve the accuracy of distance estimation.

As mentioned in Section III, light values are collected in our system. The improved method is described as follows: when the light value is under 10 meaning it is in backpack, the threshold value equals to -55dBm; when the light value is larger than 1280 which means the phone is outdoor, the threshold changes to be -53dBm; when the light value is between 10 and 1280, the phone is thought to be inside buildings and the threshold kept to -50dBm. We also do smoothing on the data collection to avoid environmental fluctuation effects and each value $RSSI_i$ at time i is modified using the following function:

$$RSSI_i = 0.3 * RSSI_{i-1} + 0.4 * RSSI_i + 0.3 * RSSI_{i+1} \tag{3}$$

We employ the improved method on the dataset and the error rate is decreased to 13.8% showed in the third column of table I.

C. Comparisons

WiFi triangulation/trilateration is a widely used method to do location indoors while GPS is perhaps the most popular way to do location outdoors. As summarized in Section II, both of them have their own advantages and disadvantages. Here we use WiFi and GPS and try to estimate the distance between two phones in order to compare the accuracy of them with the Bluetooth method we proposed. Together with the power consumption comparison in Section III, the method of Bluetooth is proved to be an effective and efficient way in both aspects of accuracy and power usage.

In order to get the relative distance between two phones, we first use trilateraion to get the location of each phone with the knowledge of AP locations. When each phone's location is known, the relative distance as well as the accuracy is simple to calculate. Based on our experimental results, the accuracy of WiFi turns out to be 10 meters and the one with GPS is about 10-15 meters. Table II summarizes the comparison results of accuracy and power consumption which is the total time to exhaust the phone battery form a full charge invoking each method as fast as possible. These results are consistent with the data in table II and Bluetooth can definitely fulfill the requirements of proximity estimation in our system.

TABLE II
ACCURACY AND POWER CONSUMPTION COMPARISONS

	Accuracy	Power consumption	Number of samples
Our method	1.5 meters	41 hours	4630
WiFi	10-15 meters	18 hours	8640
GPS	10 meters	8 hours	1892

V. Conclusion and Future work

In summary, our presented work validates the usage of Bluetooth as a tool for face-to-face proximity detection. We carefully explored the relationship between Bluetooth RSSI values and distances for indoors and outdoors settings. We also analyzed the impacts of different environment settings. We showed how the light sensor and smoothing can be employed to yield reasonable approximations for proximity. We believe that Bluetooth offers a good mechanism that is accurate and power-efficient for measuring face-to-face interactions.

For our future work, we intend to farther explore real-world scenarios including small scale experiments with five to ten phones. We further intend to improve our threshold algorithms with data mining and include considerations for atmospheric pressure and night.

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