ISSN : 2347 - 8446 (Online)
ISSN : 2347 - 9817 (Print)

Multiple Threshold Based Method With Data Smoothing and Atmospheric Pressure Using Bluetooth on Smartphones

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Abstract

The communications of always-on has tremendous implications with people to interact socially. In particular, sociologists ask the question whether pervasive access increases or decreases face-to-face interactions. The proximity estimation problem is complicated for the measurement and it can cover the wide variety of environments. Existing approaches of GPS and Wi-Fi triangulation is insufficient to meet the requirements of accuracy and flexibility. But Bluetooth, which is commonly available on most smartphones, provides a persuasive alternative for proximity estimation. This paper proposes a proximity estimation model to identify the distance based on the RSSI values of Bluetooth and Atmospheric Pressure Sensor in different environments. This paper presents Bluetooth proximity estimation on Android with respect to accuracy and power consumption.

Keywords

Bluetooth, RSSI, Proximity estimation model, smartphone, Face-to-face proximity

I. Introduction

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 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 research questions whether such digital social interactions are modifying the nature and frequency of human social interactions. A key metric for sociologists is whether these networks facilitate face-to-face interactions or whether these networks impede face-to-face interactions.

The 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. The increasing availability of data in logs generated by smartphones, there are tremendous opportunities for collecting data automatically. 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 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.

Face-to-Face interactions, the approximate distance between individuals in casual conversation is within 0.5 to 2.5 meters. One of the solutions would seem to be location based calculation which relies on location technologies such as Wi-Fi triangulation, cell phone triangulation GPS or a combination of all three. However, none of these solutions are ideal or sufficient. Although Wi-Fi triangulation can present a reasonable degree of accuracy, its accuracy in all but the dense Wi-Fi deployments is insufficient, ranging on the order of 3 to 30 meters. Similarly, cell phone triangulation suffers from an even worse accuracy. Moreover, while Wi-Fi is reasonably pervasive, Wi-Fi tends to generally be sparser in green spaces, i.e. outdoor spaces. Notably, GPS suffers from both an accuracy shortcoming (5-50m) as well as a lack of viability indoors.

Face-to-Face interaction does not demand an absolute position as offered by the previously mentioned schemes but rather requires a determination of proximity. With that important shift of the problem definition, Bluetooth emerges as a straightforward and plausible alternative, offering both accuracy (1-1.2m) and ubiquity (most modern smartphones come with Bluetooth). Although some prior work has attempted to use the detection of Bluetooth to indicate nearness it is not enough for the face-to-face proximity estimation.

II. System Overview

A. Bluetooth Proximity Estimation

The viability of using Bluetooth for the purposes of face-to-face proximity estimation and propose a proximity estimation model with appropriate smoothing and consideration of a wide variety of typical environments. The relationship between the value of Bluetooth RSSI and distance based on empirical measurements and compare the results with the theoretical results using the radio propagation model. The energy efficiency and accuracy of Bluetooth compared with WiFi and GPS via real-life measurements. The 'Phone Monitor' which collects data such as Bluetooth RSSI values on Android-based phones. Based on the data collection platform the proximity estimation model provides several real-world cases to provide high accurate determination of face-to-face interaction distance.

Wi-Fi is quite costly, especially keeping the information up to date, as tower positions, etc. are updated on an annual basis. Without calculating absolute location, Near Me explores the algorithm for detecting proximity using Wi-Fi signatures (Wi-Fi APs and signal strengths), allowing it to work with no priori setup. Most GPS proposals for such services give low accuracy guarantees and incur high communication costs.

B. Multiple Thresholds

The objective to describe the approaches of relative distance between indoors and outdoors determination. Afterwards, the data collecting system built on smartphones is documented. The results of empirical tests are evaluated and compared. Based on these practical results, a proximity estimation model with smoothing and environment differentiation is proposed. The data in different

ISSN : 2347 - 8446 (Online)
ISSN : 2347 - 9817 (Print)
Vol. 2 Issue Special 1 Jan-March 2014
International Journal of Advanced Research in Computer Science & Technology (IJARCST 2014)

real-world cases are analyzed by using the model.

Wi-Fi triangulation can present a reasonable degree of accuracy. Its accuracy in all but the densest Wi-Fi deployments is insufficient, ranging on the order of 3 to 30 meters. Moreover, while Wi-Fi is reasonably pervasive, Wi-Fi tends to generally be sparser in green spaces, i.e. outdoor spaces. GPS suffers from both an accuracy shortcoming (5-50m) as well as a lack of viability indoors.

Bluetooth emerges as a straightforward and plausible alternative, offering both accuracy (1-1.2m) and ubiquity most modern Smartphone's come with Bluetooth. Although some prior work has attempted to use the detection of Bluetooth to indicate nearness. To deploy an application 'Phone Monitor' this collects data such as Bluetooth RSSI values on Android-based phones. Based on the data collection platform the proximity estimation model across several real-world cases to provide high accurate determination of face-to-face interaction distance occurs.

C. System Architecture for Bluetooth on Smartphones

The smart phone is taken and the application for it is modeled. The first one is to enable the application and it will turn on the Bluetooth application then it asks whether to display the listed pair device. If list paired device button is pressed then the list of paired device is displayed. Then select one device and if the device is near the coverage area then it displaces the RSSI value i.e., distance between the devices. The obtained RSSI value is calculated by using the propagation formula. After that in future the pressure sensor is used to detect whether the smart phone is in indoor or outdoor location.

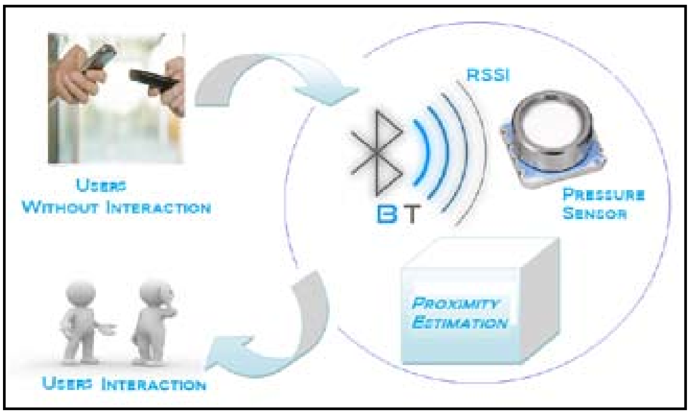

Fig. 1: System Architecture

D. Data Collection System

The application named Phone Monitor collects Bluetooth data including the detailed values of RSSI, MAC address, and Bluetooth identifier (BTID). The data is recorded in SD card once the phone detects other Bluetooth devices around. In addition to Bluetooth, data points from a variety of other subsystems (light sensor, battery level and etc.) are gathered in order to compare and improve the proximity estimation. Separate threads are employed to compensate for the variety of speeds at which the respective subsystems offer relevant data. It also record the location data reported by both GPS and network providers (either WiFi or cell network). 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) during the daytime, we keep track of the light sensor data. The battery usage percentage is recorded for the energy consumption comparison.

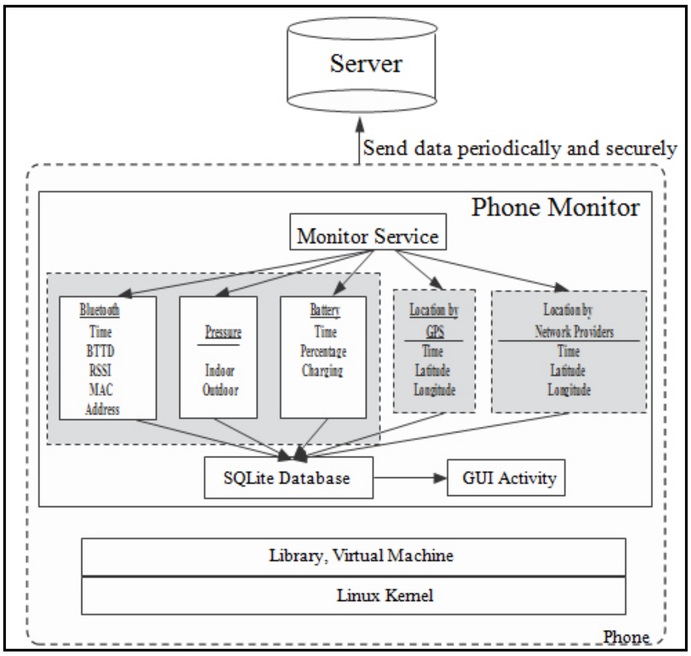

Fig. 2: Software Architecture

III. Methodology

A. RSSI Value Calculation

Digital calculation of an RSSI (Reduced Signal Strength Indicator) value begins by digitally calculating a magnitude of a signal (e.g., a received RF signal or representation thereof). The process then continues by filtering the magnitude of the signal to produce a filtered magnitude signal. The process then continues by determining a coarse RSSI value of the filtered magnitude signal, wherein the coarse RSSI value indicates a sliding window of RSSI values. Once the coarse RSSI value is obtained, the process continues by determining a fine RSSI value within the sliding window of RSSI values. The process concludes by summing the fine RSSI value with the coarse RSSI value to produce a digital RSSI value. Bluetooth received signal power level is converted to distance estimate using simple propagation model

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

Where P_{TX} is the transmit 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*108m/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).

B. Pressure Sensor Working

Accurate location of mobile devices will be the key enabler for many emerging Location-Based Services (LBS), which are widely expected to be the next wave of 'killer applications' in the mobile world. The challenge is to provide the means of identifying the location of the mobile device in three dimensions in a way that meets a variety of conflicting constraints including spatial resolution, reliability, physical size, robustness, and cost. MEMS Pressure Sensor technology is used.

1. Power Comparison

Energy is one of the most important considerations for applications

ISSN : 2347 - 8446 (Online)
ISSN : 2347 - 9817 (Print)

on smart phones. Compared to a PC, the energy of mobile phones is quite limited. Therefore it is essential to utilize an energy saving method in the system. The experiment was run on the same phone within several days. For each type of technologies, the application collects the signal strength data and the default update interval is 30 seconds. The application starts to run when the phone is fully charged and stops when the phone is out of battery. It is the only application running on the phone and collects the data of one technology at once. The battery level was recorded periodically (every half an hour) in order to obtain the results. The phone running Bluetooth almost has twice the battery life than the one with Wi-Fi. Moreover, when the time granularity of Bluetooth update becomes larger, the battery can even last longer.

Table 1: Different Proximity Estimation Techniques Comparison

	Bluetooth	WiFi	GPS
HW costs	Medium	High	High
Coverage	High	High (Indoor)	High (Outdoor)
Power Usage	Medium	High	High
Accuracy	1-4m	2-30m	5-50m
Security	High	High	Not Applicable

2. Bluetooth RSSI vs. Distance

Due to reflection, obstacles, noise and antenna orientation, the relationship between RSSI and distance becomes more complicated. The experiment is carried out in several ways such as Initial indoor RSSI values with different distances, Bluetooth RSSI vs. distance - theoretical, indoor, outdoor, Bluetooth RSSI vs. Distance indoor case, Symmetric RSSI values, Bluetooth RSSI vs. Distance outdoor case. Based on these indoor and outdoor results, there are two main environmental factors that may affect the RSSI values: inside/outside building and inside/outside a backpack. Besides those factors, it is also necessary to take multiple-phones scenario into consideration since phones with Bluetooth around may have interference on Bluetooth RSSI values.

3. Single Threshold

RSSI value (-52dBm) of direct communication distance (152cm) based on the indoor measurements was used as a threshold to estimate whether the individuals were in proximity. Accordingly, values less then -52dBm were considered as not in face-to-face proximity and labeled as a wrong estimation. It was found that both of the outdoor and backpack parts have extremely high error rates. After switching the threshold value to -58dBm which is the outdoor RSSI values with 152cm distance, the error rate was improved but still high. To reduce the error rate we go multiple thresholds with data smoothing and different environmental effects.

4. Multiple Threshold-Based Methods with Data Smoothing

Smoothing on the data collection to avoid environmental fluctuation effects and there are several ways to achieve it. One way is using simple window function and each value RSSIi at time i is modified using the following function

$RSSI_i = a * RSSI_{i-1} + b * RSSI_i + c * RSSI_{i+1}$ (2)

For the values of the parameters (a, b and c), several combinations such as (0.4, 0.6, 0), (0.3, 0.4, 0.3) and (0.2, 0.6, 0.2) are used in the following comparisons.

Another smoothing method is to utilize EWMA (exponentially weighted moving average) to analyze the dataset. Let Ei be the EWMA value at time i and s be the smoothing factor. The EWMA calculation is as follows

$E_i = s * RSSI_i + (1 - s) E_{i-1}$ (3)

Based on real-world data, Combine the data smoothing method with signal threshold filter to analyze the effects of data smoothing and select the best smoothing function. In while the combination (0.3, 0.4, 0.3) exhibits good improvement of error rate in different scenarios, the EWMA methods with smoothing factor 0.5 is the best among the five options and we use it in the proximity estimation model.

5. Multiple Threshold-Based Method Different Environmental Effects

The Bluetooth RSSI values are much smaller than the indoor ones when the phone is in the backpack or outdoors. One of the observations is that it is possible to treat the light sensor data as an indicator of the environment. Light sensor data distribution in different settings: during the daytime when the phone is inside the building the light sensor returns values between 225 to 1280 while this value comes up to larger than 1280 when phone is under daylight. When the phone is in the backpack, the light values are typically around 10. Therefore, when the light sensor value is in a range that indicates the phone is in a specific corresponding environment. Variations due to time of day (day vs. evening) may be accounted for using the Smartphone time. Inevitably, accuracy will decrease during evening hours.

6. Multiple Threshold-Based Method Atmospheric Pressure

During the nighttime, only the data reported by light sensor is not reliable. One possible method to solve this problem is to take atmospheric pressure into consideration to determine whether the phone is indoor or outdoor. There are significant differences in air pressure between the interior and exterior of a building envelope and between lower and upper levels of multi-storey buildings. Though the location is different and the pressure may vary. This atmospheric pressure sensor is used for environmental detection.

IV. Conculsion and Future Work

The proposed work validates the usage of Bluetooth as a tool for face-to-face proximity detection. The relationship between Bluetooth RSSI values and distances for indoors and outdoors settings are explored carefully. The impacts of different environment settings are also analyzed. Based on the experiment results, there are two methods to estimate proximity: single threshold and multiple thresholds. In the latter approach the atmospheric pressure sensor and smoothing can be employed to yield reasonable approximations for proximity. Then the proposed proximity estimation model by combining Bluetooth RSSI value, Pressure sensor data as well as data smoothing together. Compared with the method of collecting all devices around, the accuracy of utilizing proximity estimation model to estimate whether two devices are in a direct communication distance is improved dramatically. The comparison between the battery usage and accuracy of our method with other different location methods such as WiFi triangulation and GPS. The results demonstrate that Bluetooth offers an effective mechanism that is accurate and power-efficient for measuring face-to-face proximity.

For future work, intend to improve the threshold algorithms with data mining. The thresholds used in the proximity estimation model are based on the experiment results on Nexus S 4G phones. For different phones, such thresholds may be different. Therefore, a more general method is necessary to determine the relationship between Bluetooth RSSI values and the face-to-face proximity.

References

[1] A. K¨upper and G. Treu, "Efficient proximity and separation detection among mobile targets for supporting location-based community services," ACM SIGMOBILE Mobile Computing and Communications Review, vol. 10, no. 3, pp. 1–12, 2006.

[2] A. P. Nathan Eagle and D. Lazer, "Inferring social network structure using mobile phone data," Proc. of the National Academy of Sciences (PNAS), vol. 106, no. 36, pp. 15 274–15 278, September 2009.

[3] N. Eagle and A. Pentland, "Social serendipity: Mobilizing social software," IEEE Pervasive Computing, vol. 4, no. 2, pp. 28–34, 2005.

[4] H. Falaki, R. Mahajan, S. Kandula, D. Lymberopoulos, R. Govindan, and D. Estrin, "Diversity in smartphone usage," in Proceedings of the 8th international conference on Mobile systems, applications,and services. ACM, 2010, pp. 179–194.

[5] V. Otsason, A. Varshavsky, A. LaMarca, and E. De Lara, "Accurate GSM indoor localization," UbiComp 2005: Ubiquitous Computing, pp. 903–921, 2005.

[6] V. Zeimpekis, G. M. Giaglis, and G. Lekakos, "A taxonomy of indoor and outdoor positioning techniques for mobile location services," SIGecom Exch., vol. 3, pp. 19–27, December 2002.

[7] S. Zhou and J. Pollard, "Position measurement using Bluetooth," Consumer Electronics, IEEE Transactions on, vol. 52, no. 2, pp. 555–558, May 2006.

[8] A. O. M. Raento and N. Eagle, "Smartphones: An emerging tool for social scientists," Sociological Methods Research, vol. 37, no. 3, pp. 426–454, 2009.

[9] S. Liu and A. Striegel, "Accurate extraction of face-to-face proximity using smartphones and Bluetooth," in ICCCN'11. IEEE, 2011, pp. 1–5.

[10] M. Bilgi, M. Yuksel, and N. Pala, "3-d optical wireless localization," in GLOBECOM Workshops (GC Wkshps), 2010 IEEE. IEEE, 2010, pp. 1062–1066.

[11] J. Krumm and K. Hinckley, "The nearme wireless proximity server," UbiComp 2004: Ubiquitous Computing, pp. 283–300, 2004.

[12] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, vol. 37, no. 6, pp. 1067 –1080, November 2007.

[13] J. Figueiras and S. Frattasi, "Mobile positioning and tracking," Wiley Online Library, Tech. Rep., 2010.

[14] K. Truong, J. Kientz, T. Sohn, A. Rosenzweig, A. Fonville, and T. Smith, "The design and evaluation of a task-centered battery interface," in Ubicomp'10. ACM, 2010, pp. 341–350.

[15] D. Ferreira, A. Dey, and V. Kostakos, "Understanding humansmartphone concerns: a study of battery life," Pervasive Computing, pp. 19–33, 2011.

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