ISSN 2395-1621

Proximity evaluation app for Face-to-Face Proximity evaluation Using Bluetooth on Smart phones

#1Madhuja Bhole ,#2Radhika Kale, #3Suchitra deokate ,#4Prof. Milind Hegade

1pooja.eknathbhole@gmail.com
2 radhikakale145@gmail.com
3deokate.suchitra@gmail.com
4 milindhegade@gmail.com

#1234Department of Computer Engineering JSPM's
Bhivarabai Sawant Institute of Technology& Research,
Wagholi,Pune-412207

ABSTRACT

An programmed system for human face recognition in a real time background for a company to mark the attendance of their workers. So smart presence using Real Time Face Recognition is a real world solution which comes with day to day actions of management employees. The task is very difficult as the real 'time background subtraction in an copy is still a experiment. To detect real time human face Haar cascade is used and a simple fast Principal Component Breakdown is used to identify the faces detected with a high accuracy rate. The matched face is then used to mark presence of the workers. Addition to positive or rejecting leaves and replies for all requests. This product gives much more solutions with correct results in user cooperating manner rather than existing attendance and leave management system

ARTICLE INFO

Article History

Received :15th October 2015

Received in revised form :

16th October 2015

Accepted : 19thOctober , 2015

Published online :

21th October 2015

***Keywords*- Bluetooth, RSSI, proximity estimation model ,Smartphone, face to face proximity**

I. INTRODUCTION

The accessibility of "dependably on" correspondences has colossal ramifications for how individuals communicate socially. Specifically, sociologists are occupied with the inquiry if such pervasive access expands or abatements up close and personal communications. Not at all like triangulation which looks to exactly characterize position, the subject of eye to eye collaboration decreases to one of nearness, i.e., is the people inside of a certain separation? In addition, the issue of vicinity estimation is entangled by the way that the estimation must be truly exact (1-1.5 m) and can cover a wide assortment of situations. Existing methodologies, for example, GPS and Wi-Fi triangulation are lacking to meet the necessities of precision and adaptability. Conversely, Bluetooth, which is ordinarily accessible on most cell phones, gives a convincing distinct option for nearness estimation. In this paper, we exhibit through trial studies the viability of Bluetooth for this accurate reason. We propose a closeness estimation model to focus the separation taking into account the RSSI approximations of Bluetooth and light sensor information in diverse situations. We display a few certifiable situations and investigate Bluetooth vicinity estimation on Android as for precision and force utilization.

Connections are not restricted to any specific territory and can occur at a wide assortment of areas, running from sitting and talking in a Starbucks coffeehouse to strolling and visiting over a school grounds. As will be investigated later in the paper, for most vis-à-vis connections, the rough separation between people in easy going discussion is inside of 0.5 to 2.5 meters (Section 4 presents observational proof supporting this case.). One of the arrangements would appear to be area construct figuring which depends with respect to area advances, for example, Wi-Fi triangulation, PDA triangulation, GPS, or a blend of each of the three. On the other hand, none of these arrangements are perfect or adequate. In spite of the fact that Wi-Fi triangulation can exhibit a sensible level of precision, its exactness in everything except the most thick Wi-Fi arrangements is deficient, going on the request of 3 to 30 meters. So also, mobile phone triangulation experiences a far more detestable precision. Besides, while Wi-Fi is sensibly pervasive, Wi-Fi tends to by and large be sparser in green spaces, i.e., outside spaces. Outstandingly, GPS experiences

both an exactness weakness (5-50 m) and also an absence of practicality inside

II. LITERATURE SURVEY

[A] Perfect Mining of Direct Immediacy Consuming Smart phones and Bluetooth, The availability of "always-on" communications has marvelous implications for how people interact socially. In particular, sociologists are interested in the question if such universal access increases or decreases face-to-face interactions. Unlike triangulation which seeks to define exact situation, the question of face-to-face interactions reduces to one of proximity, i.e. are the individuals within a convinced 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 inclusive variety of environments. Existing approaches such as GPS and Wi-Fi triangulation are unsatisfactory due to those constraints. In contrast, Bluetooth, which is commonly available on most smart phones, provides a convincing alternative for proximity estimation. In this paper, we demonstrate through experimental studies the efficiency of Bluetooth for this exact purpose. We present several real world scenarios and discover Bluetooth proximity estimation on Android with respect to correctness and power consumption.

[B] Final Social Network Meeting Using Movable Phone Data, Data collected from mobile phones have the potential to provide understanding into the relational dynamics of individuals. This paper compares observational data from mobile phones with average self-report examination data. We find that the information from these two data sources is overlapping but diverse. For example, self-reports of physical proximity depart from mobile phone records conditional on the regency and salience of the interfaces. We also determine that it is likely to correctly infer 95% of friendships created on the observational data alone, where friend dyads validate distinctive temporal and spatial patterns in their physical proximity and calling patterns. These behavioral patterns, in turn, allow the prediction of individual-level outcomes such as job satisfaction

[C] Gauging Social Relations with Multiple Datasets, Because people have different levels of meeting with each other, gagging social relations is difficult. In this work, we propose a method of measuring common relations with many datasets and demonstrate the variances with pragmatic evidence. Our empirical findings demonstrate that publics use different letter media channels differently. Therefore, we suggest that in order to understand social erections, one should use numerous kinds of data sources and not just depend on a single dataset. Our datasets include traveling phone data assembled with handset-based measurements and data from OtaSizzle online communal media services. By means of communal network analysis, we show that the online social media facilities have a different friendship network than the nets based on mobile phone message. The mobile phone communication networks, however, have a very similar construction. These results are hopeful as previous research also indicates differences in the communication networks.

III. PROPOSED SYSTEM

In recent years, the attendance of movable devices ranging from the traditional laptop to fully fledged smart phones has presented low-cost, always-on network connectivity to significant swaths of society. Network applications designed for communication and connectivity provide the capacity for people to reach anywhere at any time in the mobile network fabric. Digital message, such as texting and social networking, connect individuals and communities with ever expanding info flows, all the while becoming progressively more intertwined. There are compelling research questions whether such digital social interfaces are changing the nature and frequency of human community relations. A key metric for sociologists is whether these networks help face-to-face communications or whether these networks impede face-to-face interactions.

We demonstrate the feasibility of using Bluetooth for the purposes of face-to-face proximity estimation and propose a closeness estimation model with appropriate smoothing and consideration of a wide variety of typical surroundings. We education the association between the value of Bluetooth RSSI and distance based on empirical dimensions and compares the results with the hypothetical results using the radio propagation model.

We explore the energy effectiveness and accuracy of Bluetooth compared with Wi-Fi and GPS via actual capacities. We organize an application “Phone Monitor” which assembles data such as Bluetooth RSSI values on 196 Android-based phones. Based on the data collection platform, we are able to use the propinquity estimation model across several real-world cases to provide high accurate determination of face-to-face interaction distance.

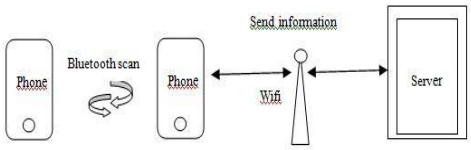

Fig 1: System Architecture

Algorithm

Bluetooth RSSI versus Distance

Kotanen et al. presented the strategy and execution of a Bluetooth Local Positioning Application (BLPA) [28] in which the Bluetooth received signal power level is converted to distance estimate according to a simple propagation model as follows:

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

where PTX is the transmit power; GTX and GRX are the antenna gains; G is the total antenna gain: G ¼ GTXþGRX; c is the speed of light (3:0 108 m/s); f is the central frequency (2.44 GHz); n is the reduction factor(2 in free space); and distance between teller and receiver (in m). d is therefore

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

However, such a model can only be utilized as a academic location. Due to reflection, obstacles, noise and antenna orientation, the connection between RSSI and distance becomes more complex. Our challenge was to assess how much impact these conservation influences have on Bluetooth RSSI standards. Therefore, we carried out several experiments to understand how the Bluetooth indicators fade with detachment under these environmental effects.

Algorithm 1 Estimate probability p_i of face-to-face proximity with Bluetooth RSSI value x_i and light sensor value y_i

$x_i \leftarrow a * x_{i-1} + b * x_i + c * x_{i+1}$
determine the scenario depending on y_i
if x_i *is in positive zone* **then**
  $p_i \leftarrow 1$
else if x_i *is in probability zone* $[B_{min}, B_{max})$ **then**
  $p_i \leftarrow (x_i - B_{min})/B_{range}$
else
  $p_i \leftarrow 0$
end if

A)SOFTWARE DESIGN AND IMPLEMENTATION

The goal of our work is to estimate the proximity amongst two or more users with Bluetooth RSSI values recorded on smartphones. In this section, we current the software architecture of data collection system, describe the data we get and compare the battery ingesting by consuming dissimilar location methods on smartphones.

B) Data Collection System

As illustrated in Fig. 1, an request named Phone Monitor assembles Bluetooth data including the complete values of RSSI, MAC talk, and Bluetooth identifier (BTID). The data is recorded in SD card once the phone detects other Bluetooth devices everywhere. In adding to Bluetooth, data points from a variability of other subsystems (light sensor, battery level and etc.) are grouped in order to compare and improve the proximity estimation. Separate threads are employed to reward for the variety of speeds at which the respective subsystems offer relevant data. We also record the location data reported by both GPS and system providers (either Wi-Fi or cell network). In order to decide whether the phone is protected (e.g., inside a backpack or in hand) and the backgrounds (e.g., inside or outside buildings) during the daytime, we keep track of the light sensor data. The battery custom ratio is noted for the energy ingesting comparison.

The application starts mechanically when the phone command is turned on and runs passively in the background on Samsung Nexus S 4G using Android OS version 2.3 (Gingerbread). The Android platform was selected for its customization capabilities through normal API or rooted/ modified boundaries with respect to hardware-level interactions. We keep the data records in a native SQLite databank on the phone and upload them to MySQL database on the servers periodically with AES security for backup and analysis. With current Android APIs, each kind of data is invoked through the corresponding function calls. The defaulting detecting granularity in terms of updating time interval for Bluetooth is 30 seconds. Intuitively, larger time intervals can help save energy, hence we also enable the changing of such sensing interval in order to explore its impact on the energy consumption.

Unfortunately, in order to shield users from people trying to hack into their phones, phones by default do not allow Bluetooth to continually be discoverable in Android 2.3. Thus we must root the phone and flash CyanogenMod in order to enable Bluetooth to be discoverable all of the period while in the experimentations. The root process does not overwrite the shipped ROM on the stratagem. During the development another consideration about Bluetooth is the difference between Bluetooth detection and union. Since in our tests there is no need to create Bluetooth connections among phones, we simply call the method of start Discovery to return the found devices with RSSI values instead of sending pairing request to other phones.

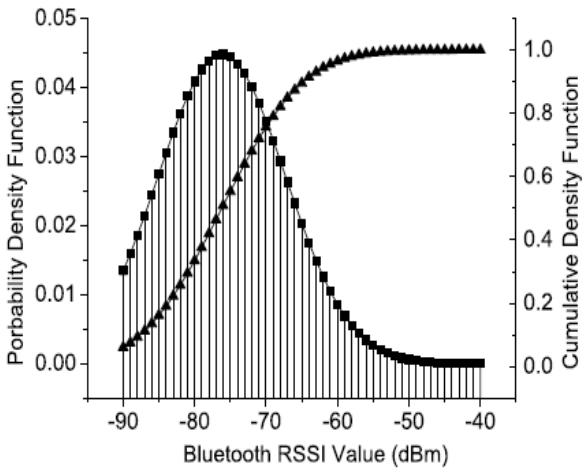

Fig. 2. Bluetooth distribution in one week.RSSI values

There are more than one million Bluetooth records collected per week. Fig. 2 shows the distribution of the Bluetooth RSSI values composed from 196 phones in one week (more details will be discussed in Sections 4 and 5). The data collected includes both indoor and outdoor environments. As it shows, the most prevalent value is around _76 dBm which indicates much more than 5 m indoor and closely 5 m outdoor as will be shown later. Therefore, an unfiltered detection method such as , is not enough to estimate the face-to-face proximity and we use a more correct method in Section 4 to resolve this problem. Moreover, we introduce various smoothing properties and take advantage of empirical observations to function crosswise a wide variety of typical environment.

C)Power Comparison

Energy is one of the most imperative considerations for applications on smartphones. Compared to a PC, the energy of mobile phones is quite limited. Therefore it is vital to use an energy valid method in the system. Before we reveal the relationship among Bluetooth RSSI values and the distance, we compare the energy consumption of Bluetooth, Wi-Fi and GPS in order to guarantee that Bluetooth is appropriate for proximity estimation on smartphones.

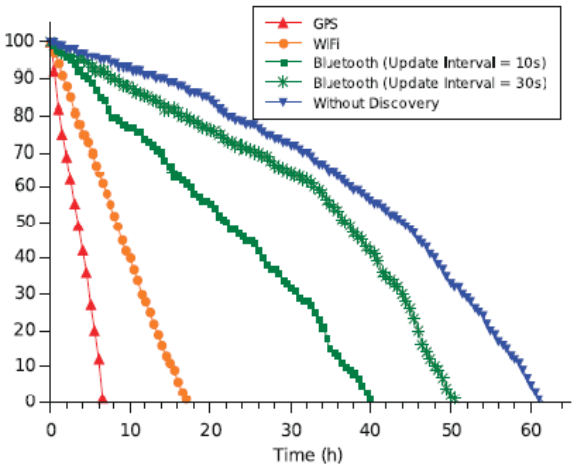

Fig. 3. Energy consumption of Bluetooth, Wi-Fi and GPS.

There are three ways to measure the energy consumption on the smartphone. One is to use a model introduced in Android 2.0 to check the battery each application is attractive. However, the numbers are normalized and it does not provide the detailed power measurement. Another way is battery simulator such as Monsoon. Such expensive way measures the accurate power usage but it goes far elsewhere our requirement. The third way to measure energy consumption is to write an app to log the battery level and export the record to computer for analysis. It is widely used in both Symbian and iOS energy analysis . We used this method and Fig. 3 shows that such method is good enough for comparison of the energy consumption among changed wireless technologies. The experiments remained run on the same phone within several days. For each type of technologies, the application assembles the signal strength data and the defaulting inform break is 30 seconds. The application starts to track when the phone is fully charged and stops when the phone is out of battery. It is the only application consecutively on the phone and collects the records of one technology at once. The battery level was recorded periodically (each half an hour) in order to obtain theresults. The log shows that Bluetooth evidently having the greatest capability for energy saving. The phone running Bluetooth almost has twice the battery life than the one with Wi-Fi logging. Moreover, when the time granularity of Bluetooth update becomes larger, the battery can even last longer.

IV. CONCLUSION & FUTURE SCOPE

In synopsis, our exhibited work accepts the utilization of Bluetooth as an instrument for up close and personal nearness recognition. We painstakingly investigated the relationship between Bluetooth RSSI values and separations for inside and outside settings. We likewise examined the effects of distinctive environment settings. Taking into account the test results, we condensed two strategies to gauge vicinity: single limit and various edges. In the last approach we demonstrated how the light sensor and smoothing can be utilized to yield sensible close estimations for closeness. At that point we proposed the closeness estimation model by joining Bluetooth RSSI worth, light sensor information and in addition information smoothing together. By creating and conveying the application "PhoneMonitor" on 196 telephones, we recorded information reported from gadgets in diverse events. We connected the closeness estimation model on the reasonable information and dissected the closeness among the members and in addition the symmetry of nearness. Contrasted and the system for gathering all gadgets around, the exactness of using vicinity estimation model to gauge whether two gadgets are in an immediate correspondence separation is enhanced drastically. We too looked at the battery utilization and precision of our strategy with other distinctive area systems, for example, Wi-Fi triangulation and GPS. The outcomes shows that Bluetooth offers a compelling instrument that is exact and power efficient for measuring up close and personal vicinity.

REFERENCE

[1] S. Liu and A. Striegel, “Accurate Extraction of Face-To-Face Proximity Using Smartphones and Bluetooth,” Proc. 20th Int’l Conf.Computer Comm. and Networks (ICCCN ’11), pp. 1-5, 2011.

[2] A. Mitra, Digital Communications: From E-mail to the Cyber Community. Chelsea House Publications, 2010.

[3] A. Pentland, N. Eagle, and D. Lazer, “Inferring Social NetworkStructure Using Mobile Phone Data,” Proc. Nat’l Academy of Sciences USA, vol. 106, no. 36, pp. 15274-15278, Sept. 2009.

[4] N. Eagle and A. Pentland, “Social Serendipity:

Mobilizing SocialSoftware," IEEE Pervasive Computing, vol. 4, no. 2, pp. 28-34, Apr.2005.

[5] M.N. JuusoKarikoski, "Measuring Social Relations with MultipleDatasets," Int'l J. Social Computing and Cyber-Physical Systems,vol. 1, no. 1, pp. 98-113, Nov. 2011.

[6] H. Falaki, R. Mahajan, S. Kandula, D. Lymberopoulos, R.Govindan, and D. Estrin, "Diversity in Smartphone Usage,"Proc. Eighth ACM Int'l Conf. Mobile Systems, Applications, andServices, pp. 179-194, 2010.