BlueEye – A System for Proximity Detection Using Bluetooth on Mobile Phones

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Abstract
Interesting applications of crowdsensing include measurement of crowdedness at public places and evaluating the extent of social interactions between people, at large gatherings. These require enabling the accurate estimation of proximity between two or more people. Since mobile phones have emerged as the most ubiquitous sensing and computing platform, carried by almost all people close to their body, it is logical to use the same for proximity detection. Further, in order to motivate people to use such application, it is necessary to estimate distances accurately, using only short blocks of sampled signal strengths. In this paper the authors present a mobile based proximity detection system, codenamed BlueEye which is based on Bluetooth. To achieve better distance estimates, BlueEye proposes a new form of path loss model which takes into account the relative orientation of mobile phones. The results show enhanced distance estimates when the separation between devices is less than 8 feet.

Author Keywords
Proximity detection; wireless propagation channel model; RSSI features; mobile crowdsensing

ACM Classification Keywords
H.1.2 [Information Systems]: User/Machine Systems – Human Information Processing; C.2.1 [COMPUTER-

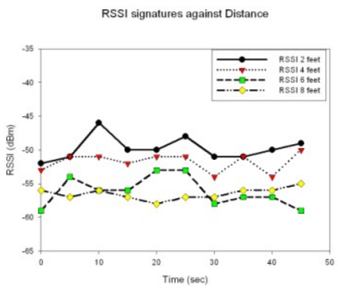

Figure 1. RSSI variation with space and time

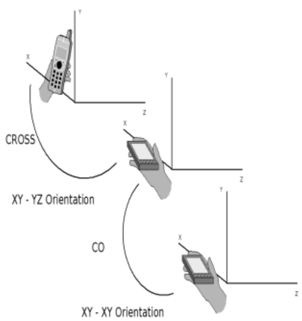

Figure 2. Relative Orientations

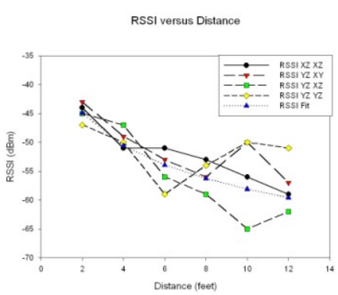

Figure 3. Effect of Orientation on RSSI

COMMUNICATION NETWORKS]: Network Architecture and Design - Wireless communication

General Terms

Human Factors; Experimentation; Measurement

Introduction

One important use-case where principles of crowdsensing can be applied to a great extent is the estimation of crowdedness at public places especially at transit points which allow Intelligent Transportation Systems to size their commutes and manage the traffic accordingly. Toyosawa et al. [1] approached the problem of crowdedness measurement using infrastructure based sensing, but it makes the solution cost ineffective. Liu et al. [2] makes an attempt to detect crowded spots in a city traffic using participatory sensing of vehicles. However crowd and large queues are also a routine part of public transportation in large cities, which can be detected and managed using crowdsensing. Though the primary part of crowdedness measurement involves sensing of the location, sensing of proximity also plays very important part in determining people density. Also, for extraction of social and community context, one important aspect is the capturing of face-to-face interaction between people, which provides an indication of offline interactions for social behavior modeling. Liu et al. [3] describe face-to-face interactions and the importance of proximity.

Since mobile phones have become the most popular pervasive computing platform of today, it's only logical to attempt the proximity detection problem using mobile phones. Mobile crowdsensing has been discussed in various literatures including [4]. Since users normally carry their mobile phones pretty close to their body like in pocket or a hostler or carry case etc., detecting proximity would mean detecting distance between two mobile devices. Mobile devices are equipped with multiple radio communication protocols, out of which Bluetooth and WiFi, both use 2.4GHz, ISM (Industrial Scientific and Medical) band working in peer-to-peer mode that can be used for such measurements. However, phone WiFi often works in infrastructure mode only which makes it improbable for true peer-to-peer applications. Also, a larger number of mobile phones have some version of Bluetooth compared to the number of WiFi equipped phones. This prompts us to choose Bluetooth as the favored technique for proximity detection in project BlueEye. The use of Bluetooth for detection of proximity between people has also been proposed by [3, 5]. The authors of [3] clearly state that "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 to meet the requirements of accuracy and flexibility". Madan et al. [5] mention that "Due to API limitations with Windows Mobile 6.x, signal strength was not available to the sensing application." However with the advent of Android™ Smartphone platforms, the API (Application Programming Interface) to read RSSI (Received Signal Strength Indication) has been opened and we have based our work in BlueEye on the same. However, there are specific challenges in accurate distance measurement from Bluetooth RSSI as pointed out by [6, 7], especially in indoor environments due to noise generated by multipath. Such attempts have stated that the noise is random and primarily

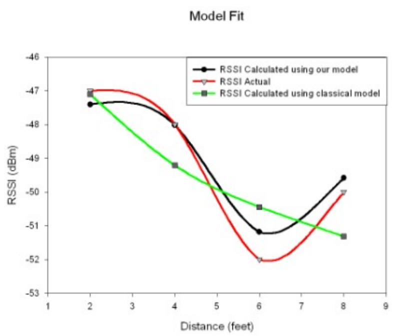

Figure 4. Fitting of our model vs. the power decay model on real data

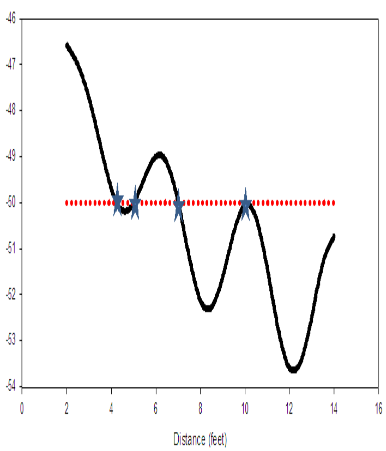

Figure 5. Zero Crossing Points for a RSSI measurement using our model

used statistical methods to minimize the same. However as [8] points out, having huge training data sets may not be feasible for participatory mobile applications, since users are unlikely to give consent to the use of their personal phones (for such application) if the energy consumption of these are found to be high. Hence, a potential success of BlueEye also demands that the measurement and evaluation are performed in a short time using a limited number of samples. Prior approaches have reported an accuracy of around 1 meter (~3.08 feet) when reporting distances. This may be good for localization but as Liu et al. [3] point out that the average distances for face-to-face interactions between two people is 1.52 meters, hence an accuracy of 1m range is not good enough for such applications. The authors have used a modified path loss model that reduces error to 13.8% over a variety of regions. Intuitively, it can be understood that the maximum distance for such interactions should not exceed 3 meters. Our initial results using BlueEye show an average error of around 5% over short distances, which comes to ±0.16 meters accuracy for 3 meters distance.

Based on the above facts, we decided to remodel the wireless propagation channel for Bluetooth operation over close distances, using only Smartphones. In this paper we present BlueEye a system for proximity detection, based on a modified channel propagation model for ISM band radio signals, which provides better than foot level accuracy over short distances. The system works with limited number of RSSI measurements by using a method based on k-means clustering [9]. Also every environment needs to be calibrated only once since spiky noise is canceled by choosing group medians of RSSI values. The foundation of the proposed model is based on work by Liberti et al. [10], where the channel model is considered to be a power decay function and the multipath noise is modeled as lognormal distribution with standard deviation of σ (dB). Based on the conclusions drawn from extensive measurements and published literature, the path loss exponent is remodeled so that the model closely follows the damped sinusoidal nature of real profile seen for close distances (<3m typically).

The measurement of crowdedness at a particular location is actually the measure of people density at that location. One way to achieve this can be counting the number of mobile devices at a location by estimating their positions. However, some intelligent measurement technique is required due to the diversity in environment and phones. In outdoor environment, Smartphones can report their location using GPS, whereas in indoors, the same can be achieved using means of indoor localization using WiFi etc. However, there is a substantial population in developing nations, where overcrowding is a major problem, who use feature-phones (for example Nokia X series phones). These phones do not have WiFi or GPS; however they have coarse localization using GSM triangulation. They do however have Bluetooth radio and also these phones can be kept in discoverable mode forever. Hence if a Smartphone application can detect the number of Bluetooth peers in near vicinity, it has a much comprehensive measure of crowdedness. Kjeldskov et al. [17] provides a method whereby Bluetooth peers are counted at a location, while this shall provide the notion of presence; it shall not provide the density factor accurately. However if the same Bluetooth signal, meaning Received Signal Strength Indicator (RSSI) can be used to estimate the distance that separates the

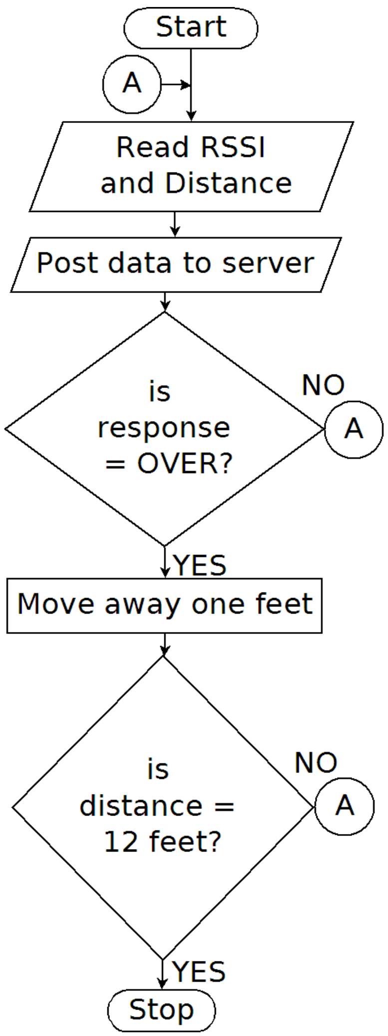

Figure 6. Client side calibration

persons, it can be used to estimate the density factor much better along with presence. This method can also be extended to estimate face-to-face interaction between people in offices, malls etc. Banerjee et al. [18] provides a similar application and mentions a median error of 0.9 meters in field testing. However using our model we have found a mean error of ~ 0.2 meters for distances up to 3 meters which is good for discovering peers in crowded environments.

Basic Theory

The Modified Wireless Path-loss Model

In the light of the problem statement, it is understood that a better modeling of the indoor propagation path, at Bluetooth's operating frequency 2.4GHz, is imperative. Indoor propagation modeling is a formidable job, given that fact that a number of phenomena like scattering, reflection, diffraction etc. gives rise to multipath effects resulting in uncertainty in signal strength estimation at a given location [12]. A number of experimental observations and potential models have been described in [13, 14].

Using the standard free-space radio propagation formulation, it is possible to represent the measured received signal strength indicator ($RSSI_M$) as

$$RSSI_M = RSSI_0 - 10.n.\log_{10}(d_E) + X_\sigma \tag{1}$$

In equation 1, n = 2 for free-space and n > 2 (empirically adjusted) for RF challenged environment like office indoor, as example. In typical path loss model [10], n takes multiple values, for office buildings, ranging from 2.76 to 4.33, based on location type. In addition, the term X_σ was introduced in Rappaports path loss model to account for slow-fading phenomenon in RF challenged environment like office setup with cubicles. X_σ is a zero-mean lognormal distributed random variable with σ (dB) ranging from 4.3 to 12.8 for different location in office premises. The range of σ is somewhat different at 2400 MHz.

If results of [3,10,14, 15,16] are closely observed, for close distances (< 5m) between transmitter and receiver, the path loss profile in dB displays 'hidden' spatial periodicity, on which random variations (in signal strength) are superimposed. Authors in [16] have presented simulation (2-D ray tracing model) based results at 2400MHz. Chethan at al. [15] presented similar line-of-sight (LOS) measurements with antenna height of 1.2m. These are also measured in narrow, confined office space. Moreover, [15] demonstrates that if RSSI measurements taken for multiple polarizations are combined, it leads to a much improved propagation model. Comparing the results presented in [15, 16], we also estimate the possible implications of antenna height on received signal strength. At lower heights [16], the RSSI measurements are less than free-space prediction by 16- 30dB; whereas at moderate heights [15] such difference is 8 – 12dB. Measurements were carried out to investigate (a) the effect of relative orientation between the two Smartphones (Tx & Rx) carried by two persons (b) signal strength variations with finer granularity. All the measurements were carried out while the Smartphone was being carried by a person. Figure 1 shows one set of RSSI measurements that depict typical temporal variations in a dense cubicle based office floor: 4th floor of a multi-floor building. These include measurements for different relative orientations between the two Smartphones. The notion of "relative orientation" between

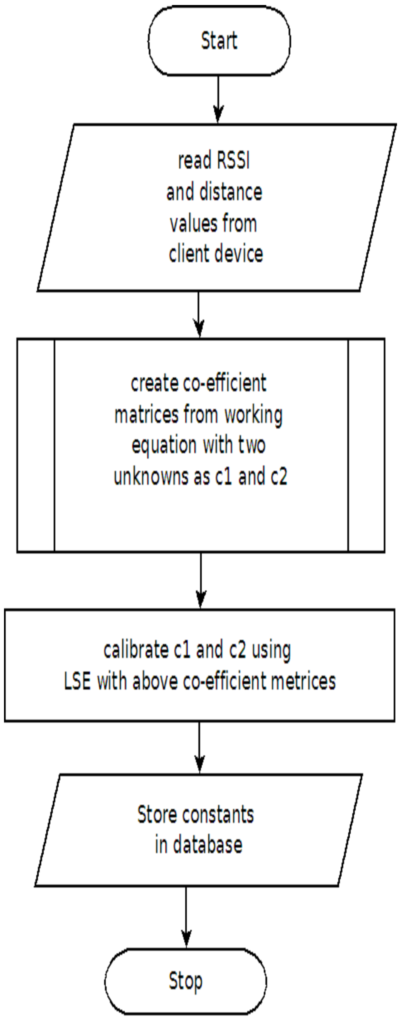

Figure 7. Server side calibration

the transmitter and receiver is depicted in Figure 2, whereby if two phones are kept screen-flat on the palm with Y axis in same direction, it shall be a "CO" and if one is flipped 90 degrees, the orientation becomes cross. Figure 3 displays the RSSI measurement carried out for different relative orientations. We found that for a given static environment, the spatial variation measurement can be repeated. Hence, we propose a new form of statistical model in equation 2 for propagation path based on regression analysis on measured data. We consider the path-loss exponent as similar in nature to a weakly stationary process and model it in terms of harmonic components; the random nature (of signal strength) is incorporated in the phase component. The path-loss exponent, therefore, is location dependent and also, it attributes the variance with a given harmonic component. It is to be noted that the proposed model is considered valid only for LOS measurements.

$$RSSI_M = RSSI_0 + \gamma(d).\log_{10}(d_E) \qquad (2)$$

Where

$$\gamma(d) = \{\sum_m c_m \sin(2\pi m.d / \Omega + \theta)\}^2 + c_n \qquad (3)$$

Where,

c_m and c_n stand for constants which are properties of a given environment. For the present case, we consider the dominant mode only i.e. m =1. Going forward, we denote $c_m = c_1$ and $c_n = c_2$. Greater accuracy will be obtained if the higher order modes are also considered. Ω stands for spatial wavelength of the channel (approximately determined from a limited set of measurements). θ is a random phase lag introduced due to relative orientation of receiver and transmitter, with value ranging from $0<\theta<\pi/2$. Using the above equations and adjusting the values of 'c_1' and 'c_2' for a given location, we get a reasonable good fit of the RSSI function with indoor multipath effects for distances up to ~ 10-12 feet, Ω, the spatial frequency accounts for the effect of multipath on propagation loss for a given RF antenna polarization and environment. We have found the variation to follow a near sinusoidal profile. Our findings are entirely empirical and the observation is obtained from repeated measurements under various indoor environments. The value of Ω is seen to be varying between 7.8 – 8.2 feet and the variation does not have significant effect on the results obtained. This model fits the experimentally captured data better than the classical model given by equation 2. The result is shown in Figure 4. However, it is imperative to note that due to the sinusoidal nature of the curve, it is not possible to directly estimate the distance from an $RSSI_M$ value as there will be multiple values of distances satisfying the equation as shown in Figure 5. To overcome this problem we use a statistical technique to determine the distance as detailed in the next sub-section.

Determination of Distance from RSSI

In order to estimate the distance between two persons using Bluetooth, we need to obtain all possible solutions of equations 2 & 3. Such solutions, gathered from a number of consecutive RSSI measurements are used as input to k-means clustering [9] module because for mostly static environment, majority of solutions will occur near the actual distance between the devices. Hence the centroid of the most populous cluster shall provide us with the distance estimate. This becomes the working principle of the application which is described in the next section.

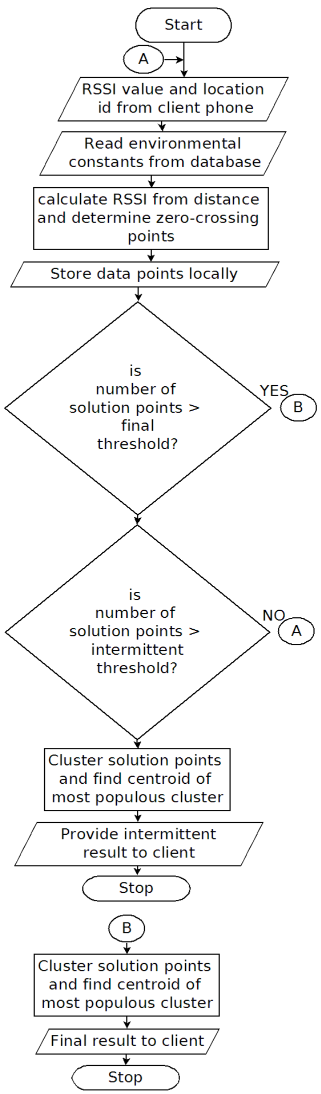

Figure 8. Distance Estimation

Application Details

System Components

The application also has two entities involved, one is an Android smartphone that reads the RSSI values and sends them to a backend server, and a backend server that performs the complex analytics and provides the results back to the client.

Method Details

THE CALIBRATION MODE

In the calibration mode, the constants for an environment are determined. In order to achieve this, ground truth is collected for that environment whereby the user annotates RSSI readings for distances from 1 – 8 feet at the concerned location. Since RSSI readings often contain unwanted "spikes" and "troughs" owing to interference and channel hopping etc. we take readings in groups of 5 for each annotated distance and use only the median value of those 5 observations for our calculation. Since we take multiple measurements and in known orientations ($\theta = 0$), and we have only two undetermined constants as per our proposed model, it becomes typically over-determined with more equations than unknowns. Hence we use a Least Square Estimate (LSE) based method to determine the constants. The client side application logic is summarized in Figure 6, whereas the server side logic is captured in Figure 7.

THE DETERMINATION MODE

In the determination phase, for every value of RSSI received, the application uses the c_m and c_n values stored for that room id to calculate the possible distances with value of θ set at $\pi/4$ (to average out the errors due to random and unknown relative orientations). Using environmental constants in the model we determine the possible values of distances from the observed value of RSSI. However, one value of RSSI shall produce multiple values of distance. So we accumulate all values for distances between 2 and 10 feet by solving equation (2). We call these values as "zero crossing points (ZCP)". For distance estimated similarly from subsequent RSSI values, k-means clustering is used to determine intermittent and final distance estimates as shown in Figure 8.

Results

A number of experiments were conducted in different type of indoor spaces (mostly office spaces) and BlueEye was used to estimate distance from observed RSSI values, for each distance we have taken a series of RSSI measurements; estimate distance from each measured value of RSSI and then clustered to find the distance estimate as per application logic. The experiments were carried out using a the following phones: transmitters - Apple iPhone, Nokia E63 and Samsung Corby, receivers - Intel Xolo 800, Samsung Galaxy Y and Samsung Galaxy Tab 2, all running Android^{TM}. The results were gathered over a period of time as mentioned in the tables to show that there was little temporal effect on the method.

Experimental Setup

Three different locations were chosen for validating the application. The three rooms are denoted as LOC I, LOC II and LOC III. LOC I is depicted in Figure 9 as an open indoor environment which is a lab room setup with one door and three lab benches (desks) placed along the three walls; the fourth wall is equipped with a white-board and hence it is free from furnishings. The readings were taken in the vacant space at the center of the room. The second location, named LOC II is an

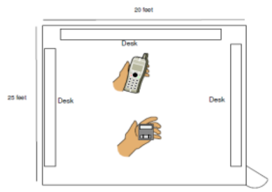

Figure 9. Location I

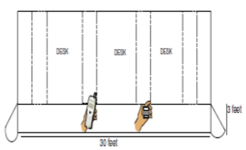

Figure 10. Location II

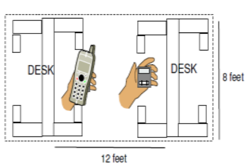

Figure 11. Location III

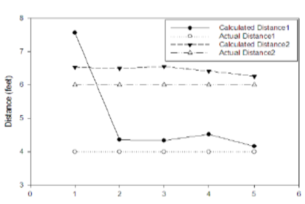

Figure 12. Convergence

office corridor which is a long open space with close bounds breadthwise as depicted in Figure 10. The corridor is the passage to an array of office spaces and walk paths along its length. The experiments were carried on in the length of the passage. The passage is equipped with two doors on either end lengthwise. The third and final location named LOC III is a typical office room space with cubicle like arrangement which is a near close space as shown in Figure 11. The room is an enclosure of work desks with a small vacant space in the middle where the experiments were carried out. The phones were also allowed to migrate to the walk paths from the central location as they are of comparative dimensions.

Calibration Mode

Using our application, the three locations described in previous section have been calibrated to train the model accordingly. Table 1 show the results for the calibration phase which ends with the determination of c_1 and c_2 for that environment using Least Square Estimation technique.

Determination Mode

In the determination phase we illustrate how using our approach the distance estimate made through the model converges with iterative clustering. Figure 12 shows this convergence phenomenon. Table 2 shows results taken for various distances in a fixed indoor location, with various Number of Iterations (NOI) of clustering. Table 3 provides the error of estimation in close distances across the three locations that have been described in Experimental Setup section. The error percentage increases with distances ~ 10 feet as shown in Table 4.

NOI	**2 feet**	**4 feet**	**6 feet**	**8 feet**
1	1.56 (2012-11-30 12:30:10)	4.95 (2012-11-19 19:18:16)	7.39 (2012-11-17 13:43:53)	11.18 (2012-12-12 16:28:48)
2	1.74 (2012-11-30 12:30:14)	3.32 (2012-11-19 19:18:18)	5.55 (2012-11-17 13:44:32)	10.05 (2012-12-12 16:29:09)
3	2.17 (2012-11-30 12:30:16)	4.06 (2012-11-19 19:18:20)	6.84 (2012-11-17 13:45:05)	9.24 (2012-12-12 16:29:12)
4 (final cluster)	1.95 (2012-11-30 12:30:20)	4.04 (2012-11-15 19:18:36)	6.41 (2012-11-17 13:45:05)	8.29 (2012-12-12 16:29:24)

Table 2. Distance Estimates for Known Distances (Using Consecutive Iterations of RSSI Measurements, Each Iteration Consists of 5 RSSI Values)

Conclusion and Future Work

In this paper we have shown that BlueEye can be effectively used to detect proximity between people. We have also outlined that the distances estimated using BlueEye are more accurate than those provided by previous approaches in indoor environments. Our future work includes extending the model to outdoor spaces. Also by reducing the time taken for detecting proximity, BlueEye can be coupled with inertial navigation systems (INS) [11] and provide a comprehensive social interaction and crowdedness measurement model using principles of crowdsensing. Finally and most importantly a comprehensive

Location-n ID	LOC I	LOC II	LOC III
c_1	1.88	0.52	1.23
c_2	-1.25	-10.7	-2.12
Time stamp	2012-11-15 10:26:53	2012-11-17 13:42:00	2012-11-17 13:42:49

Table 1. Calibration Results

Location ID	LOC I	LOC II	LOC III
Actual Distance(ft)	2	4	6
Estimated Distance (ft)	1.95	4.16	6.27
% Error	2.5	4.12	4.4

Table 3. Distance Estimation Results

Location ID	LOC I
Actual Distance(ft)	10
Estimated Distance (ft)	11.3
% Error	13

Table 4. Distance Estimation > 8 ft.

application layer is required which can detect crowdedness and social interactions using the back-end server.

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