Indoor Localization Based on Response Rate of Bluetooth Inquiries

Mortaza S. Bargh
Telematica Instituut
P.O. Box 589, 7500AN Enschede
The Netherlands
+31 (0)53 485 0443
Mortaza.Bargh@telin.nl

Robert de Groote
Telematica Instituut
P.O. Box 589, 7500AN Enschede
The Netherlands
+31 (0)53 485 0445
Robert.deGroote@telin.nl

ABSTRACT
Location is considered as the most important and relevant context information. Bluetooth technology, being a common feature of commercial mobile devices, is a (or the) key technology that is pervasively available nowadays. There has been not much success in using Bluetooth technology for indoor localization, mainly due to the limitation of the technology. Using the Context Management Frame (CMF) infrastructure deployed in our office building, we have designed, implemented and evaluated a Bluetooth based indoor localization solution that determines the locations of stationary mobile users at a room level. The solution is based on the inquiry response rate of Bluetooth technology. This approach does not require establishing any connectivity between Bluetooth devices. Further, since the solution is infrastructure- and network-based, it does not require mobile devices to be upgraded in any way in order to be localized. The results of experiments show that our solution has 98% accuracy in rooms with full Bluetooth sensor coverage, when the target device being stationary for 3 minutes.

Categories and Subject Descriptors
C.2.4 [**Computer-Communication-Networks**]: Distributed Systems – distributed applications

General Terms
Algorithms, Measurement, Performance, Verification

Keywords
Indoor localization, Bluetooth, response rate, office buildings

1. INTRODUCTION
Location based Services (LBSs) have resurrected in recent years due to several important developments like emergence of GPS-capable mobile devices, introduction of Web 2.0 platform, and deployment of wireless broadband wireless services [1]. There are also a number of paradigm shifts that have contributed to resurgence of LBSs, namely: from reactive to proactive (i.e., provoked by predefined events), from single-target to multi-target (i.e., interrelating several targets among each other), from self-referencing to cross-referencing (i.e., other users requesting a user's location), and from content-oriented to application-oriented (i.e., richer applications developed around user location) [1].

Location determination is the main component of the systems that deliver LBSs. For outdoor environments Global Positioning System (GPS) provides an effective solution to determine location of GPS enabled mobile devices. For indoor environments, however, such an effective solution does not exist. As a result, indoor location determination is an active area of research nowadays. In this contribution we consider an indoor localization solution that relies on Bluetooth technology that, being a common feature of mobile devices, is a pervasive technology currently. Most Bluetooth based solutions rely on network characteristics like Received Signal Strength (RSS). Bluetooth RSS, specified as RSS Indicator (RSSI) and Link Quality (LQ), is not a reliable measure considering the heterogeneity of Bluetooth hardware in available devices. This is partly resulting from an imprecise definition of RSS in the Bluetooth standard [2]. Obtaining Bluetooth RSS, moreover, generally requires establishing connectivity between corresponding devices. This requires users to maintain their devices in connectable mode, which is considered unsafe by most users.

Our location determination method is a fingerprint-based localization solution that relies on only the Response Rate (RR) of Bluetooth inquiries. This just requires mobile devices to be in discoverable mode. According to this approach, every location is fingerprinted by Inquiry RRs (IRRs) of Bluetooth sensors installed in a multi-floor building. After obtaining the IRR of a target device to be localized, our system uses relative entropy measure (i.e., Kullback-Leibler function) and its extension (i.e., Jensen-Shannon distance measure) to estimate the location of the target device. We evaluated the performance of the solution by carrying out some experiments in an infrastructure deployed in our entire office building. The accuracy of our location estimation is almost 98% in a room where all neighboring rooms have Bluetooth dongles. Note that this performance was obtained when different device types were used for the fingerprinting of rooms, and the target device to be localized differed from those devices used for room fingerprinting. During our experiments, moreover, the target device was relocated in the test room every hour. Our solution aims at determining location at a room level, which is a meaningful granularity for a wide range of indoor applications. Moreover, our approach does not require any upgrade to mobile

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devices to be localized and it inflicts low power consumption on mobile devices due to its reliance on Bluetooth technology.

The rest of the paper is organized as follows. Section 2 gives some background information over existing localization approaches and our Bluetooth based solution. Section 3 describes our solution in detail. Section 4 provides the results of our evaluation of the proposed solution. Finally Section 5 presents our conclusions and future research directions.

2. BACKGROUND

2.1 Localization Approaches

Localization systems can be divided into two categories: processing based and fingerprint based. Processing based systems use techniques like lateration, angulation, dead reckoning and proximity detection, see [2] for references. For example, the famous GPS uses lateration and angulation techniques to derive the coordinates (i.e., position) of GPS devices. These techniques process different parameters of radio signals like RSS, angle of arrival, time of arrival, and time difference of arrival. Processing based systems generally rely on dedicated software/hardware and they are not much effective indoors. Indoor environments affect the propagation of wireless signals non-deterministically due to sever multi-path effects, dead-spots, noise and interference [3]. As a result, it becomes infeasible to construct a simple and accurate model of indoor signal propagation which is required for the techniques mentioned.

Fingerprint based systems capture fingerprints of all known locations. These fingerprints are (pre-recorded) measurements of network characteristics in the corresponding locations and they can be considered as signatures of those locations. For localization of a target device, the momentary network characteristics of that device are examined with respect to the radio map (i.e., collection of location fingerprints) and most likely location is determined. The network characteristics used for fingerprinting include RSS, access point ID, and RR. A taxonomy of fingerprint based approaches is presented in [2].

RR is one of the network characteristic that is not well-explored for fingerprinting. It is defined as "the frequency of received measurements over time from a given base station" in [2] or "the percentage of times that a given access point was heard in all of the WiFi scans at a specific distance from that access point" in [4]. RR approaches proposed so far are used in combination with RSS for localization with WiFi technology [3][4] and with Bluetooth technology [5]. In this paper we design and evaluate a fingerprint method that relies on only IRR fingerprints of Bluetooth technology.

2.2 Motivation and Principles

Our work is motivated by the design of a location based application called "Colleague Radar" that locates coworkers in our office building. The application aims at locating users at room-level where users are assumed to be stationary for a while (e.g., the person being in her/his room or in a meeting room for a few minutes or more). This means that tracking users (in real-time) is not required for the application.

On the other hand, successful and widely deployable indoor localization systems must integrate smoothly with existing infrastructures (i.e., preferably require no upgrade of user terminals, need no excessive hardware installation, and use existing technologies), impose low power consumption on mobile terminals, and use low cost infrastructure [6]. As mentioned in [6], Zigbee and Bluetooth are two technologies that impose low power consumption on mobile terminals. It is, however, Bluetooth technology that has been deployed pervasively nowadays and it is considered to be "the fastest growing technology since the Internet or the cellular phone", see pp. xiii [7]. Having no mobile terminal upgrade has guided us to adopt an infrastructure-based and network-based approach, as categorized in [2]. In such an approach a target device to be localized must be in discoverable mode and almost all of localization process is delegated to Bluetooth infrastructure (i.e., to Bluetooth access points and the backend server, as described in detail in Section 3).

2.3 Challenge and Opportunity

The process of establishing connectivity between two Bluetooth devices relies on inquiry and paging mechanisms. The inquiry mechanism allows the inquirer to discover the Bluetooth enabled devices in its neighborhood. The inquirer transmits a series of inquiry packets and the discoverable Bluetooth device, which periodically scans for inquiries, eventually replies with a Frequency Hop Synchronization (FHS) packet. The FHS packet contains all information that the inquirer needs to establish a Bluetooth connection with the scanning device (e.g., device class and type). Then, the paging mechanism is used to find out the services that a target device provides. To this end, the inquirer pages the target device using information obtained during inquiry. If the target device scans for paging, it replies. Subsequently a connection is established between the two devices and the inquirer retrieves information about the services provided by the target device. After this the connection is generally shut down. Using the information obtained during paging, the inquirer establishes another connection towards the target device with appropriate quality of service requirements.

Scanning devices can choose for two modes: discoverable and connectable. Being in discoverable mode is enough for the inquiry mechanism. For establishing connectivity, however, scanning devices must choose for connectable mode which implies also being discoverable. The user acceptance barrier to maintain devices in discoverable mode is lower than it is for connectable mode. Therefore, we require for target devices (i.e., those to be localized) to be just discoverable.

Our approach uses inquiry response rate as the sole network characteristic to fingerprint locations and localize target devices. Every T_S = 10 seconds Bluetooth access points (i.e., the inquirers called "dongles" from now on) obtain a list of discovered "object devices". The Bluetooth IRR is defined as "the percentage of inquiry responses to total inquiries, replied by a discoverable target device and sent by a dongle that are located at a specific distance from each other".

Many fingerprinting solutions are based on RSS and access point ID. Recent findings indicate that RSS should be used as a weak indicator of distance for indoors [4]. Cheng et al [4] explored Wi-Fi RR as a new metric for location estimation and found out that there is a strong relation between distance and RR, compare Figures 2 and 3 in [4]. We investigated the relation of IRR and distance for Bluetooth in our office. Our test was carried out in three locations: a room with a dongle, the hall outside the dongle room and a room across the hall. All IRR measurements were carried out at points 2 meters apart on a straight line. Both walls between the rooms and the hall were thin, however, there was a wide metal bookshelf behind the wall between the hall and the room across the hall. Table 1 summarizes the test results and shows how IRR decreases with increasing distance. Each row of Table 1 reports the average and variance of IRR measurements measured every 5 seconds for 20 minutes (thus 240 samples), where every IRR sample is the RR of the last 50 inquiries.

Table 1. Measured IRR with respect to distance

location of the object device	distance of devices	average of IRR	variance of IRR
in the room of the Bluetooth dongle	2 m	97 %	1.8
in the hall outside the dongle room	4 m	97 %	1.2
	6 m	99 %	1
	8 m	94 %	1.4
	10 m	86 %	4.6
	12 m	74 %	9.6
	14 m	67 %	4.6
in room across the hall	16 m	NULL	NULL
	18 m	NULL	NULL

To the best of our knowledge, there is no prior work that bases its location estimation process solely on the IRR parameter. We adopted an IRR based approach for two reasons: (i) RSS in Bluetooth (e.g., RSSI or LQ) cannot be obtained reliably due to the fact that power aspects are not standardized in detail [2]; and (ii) obtaining RRS in Bluetooth v1.1, based on which our dongles were manufactured, requires establishing connectivity between devices, an operation that is against our requirements.

An IRR based approach faces the challenge of a target device being detected by many Bluetooth dongles of the surrounding rooms. In the rest of paper we propose a method that eliminates the location uncertainty imposed by the IRRs of multiple Bluetooth dongles.

3. APPROACH

3.1 Infrastructure and System

Our Bluetooth positioning system was implemented on top of an existing Context Management Framework (CMF). The CMF is a publish-subscribe system where remote machines run so-called context-sources which publish contextual information to central machines that have subscribed to that type of context information. The location determination takes place in a central component called location estimator that subscribes to all Bluetooth context-sources. Bluetooth context-sources run inquiries periodically, and send the results of these inquiries to their subscriber as soon as an inquiry has completed. An inquiry result is a list of Bluetooth addresses that were discovered by every Bluetooth context source. In our setting, inquiries have a fixed length of 5.12s, and are started every T_S=10s.

The system distinguishes between different types of Bluetooth devices: dongles and mobile devices. Bluetooth dongles are the inquiring sensors that are plugged in to the PCs of users. Since these machines have a fixed location (only desktop PCs were used), the locations of these dongles are known. Mobile devices are being discovered by the inquiring dongles, and can be further distinguished into two categories: reference devices and target devices. Reference devices are mobile devices for which the location is known a-priori, since they are known to have been at a particular location at a particular point in time. Target devices are devices for which there is no a-priori location information. It is the task of the Bluetooth positioning system to estimate the location of the target devices by comparing their observed fingerprints with the (pre-recorded) fingerprints of the reference devices. Little homogeneity exists among the Bluetooth mobile devices, while the dongles are all of the same type.

The Bluetooth localization system architecture is shown in Figure 1 schematically. This architecture encompasses the main system components in the central machine and does not include dongles connected to remote PCs. As shown in Figure 1, room fingerprints are derived during training and (pre)stored in a database. On the other hand, the location fingerprint of a target device is detected in real-time and fed to a location estimator that compares it with room fingerprints one by one. The best match determines the location estimate of the target device. This estimate is fed to the Colleague Radar application. Our system determines user locations when the users are stationary for a few minutes. If the target device moves between rooms, our location determination system does not give any particular location as an output, however a subcomponent indicates that the user is moving. This subcomponent is out of scope of this paper.

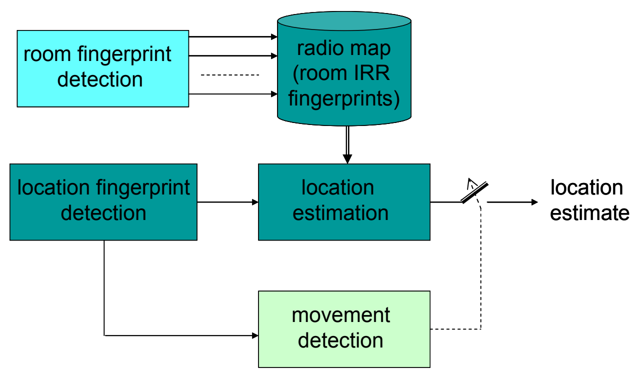

Figure 1. System architecture.

3.2 Solution

Let $\{d_1, d_2, \ldots, d_M\}$ denote the set of the dongles installed on users' PCs. We assume these PCs are located at topological locations (i.e., rooms) of the building, generally one in every room. This constitutes a dynamic sensor network connected through Ethernet. Dynamicity comes from the fact that users' PCs can come and go as users log in and log out their systems.

Fingerprints indicate the spatial density of Bluetooth cells in each room in that, given a room, (a) which subset of dongles detect a discoverable mobile device in the room; and (b) how often they discover the device. These are a function of RSS, the geometry of the building, etc. We have two fingerprint types: training fingerprint T_k associated with Room-k, k=1,…, K, and location fingerprint L associated with a target device.

Let $\{i_{k1}, i_{k2}, \ldots, i_{kM}\}$ be the number of times that in a training window of W_T seconds dongles $\{d_1, d_2, \ldots, d_M\}$ have detected the reference device of Room k. Further, let n_T be number of inquiry done by these dongles in W_T seconds (note that all dongles inquiry at a fix rate of every T_S=10 seconds, thus n_T given W_T is independent of k). Then, the training fingerprint T_k is defined as a vector:

$$T_k = (T_{k1}, T_{k2}, ..., T_{kM}) = (\frac{i_{k1}}{n_T}, \frac{i_{k2}}{n_T}, ..., \frac{i_{kM}}{n_T})$$

Each element T_{km} of T_k, m=1, …, M, can be considered as an empirical binary distribution with parameter i_{km}/n_T . Similarly, let $\{j_1, j_2, \ldots, j_M\}$ be the number of times that in a localization window of W_L seconds dongles $\{d_1, d_2, \ldots, d_M\}$ have detected a target device. Then, assuming the same inquiry rate n_T, the location fingerprint L is defines as:

$$L = (L_1, L_2, ..., L_M) = (\frac{j_1}{n_T}, \frac{j_2}{n_T}, ..., \frac{j_M}{n_T})$$

The location estimation component in Figure 1 determines the location of the target device by finding the room fingerprint that best resembles the observed location fingerprint. This can be considered as a classification problem. The difference measure used in our system is based on the concept of information gain, calculated using the Kullback-Leibler (KL) divergence. For two probability mass functions p(x) and q(x), KL divergence is defined as:

$$D(p(x) \| q(x)) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

The KL divergence or relative entropy has the following interpretation: if a source produces symbols x according to distribution p(x), then a data compression scheme that uses p(x) to compress a sequence of such symbols will result in optimum entropy rate $H(p) = -\sum_x p(x) \log p(x)$ bits per symbol on average. If the data compression scheme uses another distribution q(x) instead of p(x) to compress the same sequence, then the result will have D(p||q) bits more on average. Note that KL divergence is not a “distance” measure in that D(p||q) ≠ D(q||p).

Our approach approximates the location of the target device with the location of the closest room. The output of such a localization process must have minimum deviation or distortion from the real room where the user is physically. The physical/real location is characterized by L, thus our location estimate is Room-k such that $D(L||T_k)$ is minimized, or:

$$\arg\min_k [KL_k] = \arg\min_k [D(L \| T_k)]$$

To calculate KL_k, we assume independence between the binary random variables corresponding to the outputs of dongles given the location of a target device. Then,

$$\begin{aligned} D(L \| T_k) &= \sum_{m=1}^{M} D(L_m \| T_{km}) \\ &= \sum_{m=1}^{M} (\frac{j_m}{n_T} \log \frac{j_m}{i_{km}} + (1 - \frac{j_m}{n_T}) \log \frac{n_T - j_m}{n_T - i_{km}}) \end{aligned}$$

Because in practice we determine location fingerprints using rather small training and localization window sizes (i.e., W_T and W_L), it is possible for some dongles to miss the replies of reference or target devices. This causes the KL measure to deviate enormously. Therefore we have adopted its modified version called Jensen Shannon (JS) divergence [6], defined as:

$$JSD(L \| T_k) = \frac{1}{2}(D(L \| M) + D(T_k \| M))$$

where $M = 0.5(L + T_k)$. Note that, unlike KL divergence, JS divergence is a *distance* measure in that JSD(p||q) = JSD(q||p) [6].

4. EVALUATION

To evaluate the performance of our solution we conducted two tests in two rooms of size 4m×6m in our office building. These rooms are called Room-1 and Room-2 from now on. Our office building has 4 floors and each floor has about 20 rooms. Room-1 was located in floor 2 and surrounded by rooms all with dongles (i.e., rooms on the right, left, top, and below had Bluetooth dongles). Room-2, on the other hand, was located in floor 3 and surrounded by rooms with and without dongles (i.e., rooms on the right and below had no Bluetooth dongles). We refer to Room-1 and Room-2 as rooms with full and partial coverage, respectively.

In each room we put a target device in 6 positions, for about one hour in each position. These positions were at least one meter apart and considered to be the most likely user locations (i.e., of room residences and visitors). The test rooms as well as all the surrounding rooms (12 and 14 rooms in total) were fingerprinted for the duration of the test. These fingerprints were obtained using dedicated reference devices that were (a) other than the target device and (b) of 4 different types: Bluelon BT-002 body tags, HTC-P3300 and 9000 and Nokia E61 and N70.

We carried out location estimations every 5 seconds for the target device in Room-1 or Room-2, using KL and JS divergence measures. The estimation performance is evaluated based on estimation *accuracy* that is defined as the percentage of times in which a method gives the correct location estimate with respect to total number of estimations. The estimation accuracy can be determined for the most likely estimate and for 2 most likely estimates (i.e., that either of the rank 1 *or* rank 2 estimate is correct) and so on. We refer to these accuracy measures as top-1 or top-2 accuracy, respectively.

In Figure 2 two graphs (1^{st} and 3^{rd} from top) show the top-1 accuracy of the KL scheme for the test in Room-1, given two training window sizes of 5 and 30 minutes (i.e., W_T=5’ and 30’) and as a function of localization window size W_L. The training fingerprints for the graphs of Figure 2 were obtained in the beginning of the test day. For $W_L \geq 2$’, the accuracy of the KL method is almost 100%.

The KL method, however, is sensitive to training data and partial dongle coverage, for example, its accuracy becomes about 77-83% if we use a different training data set in each hour or it becomes about 14-45% if we do estimation in Room-2 with partial coverage. Therefore we adopted the JS method whose performance is shown by two graphs (2nd and 4th from top) in Figure 2 for the same training set. As can be seen from Figure 2, the accuracy of JS is slightly lower than that of KL.

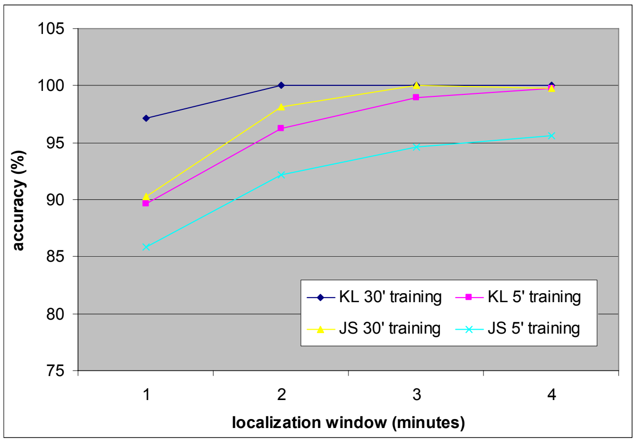

Figure 2. Accuracy of JS and KL methods for training window sizes of W_T = 30 and 5 minutes.

Graphs of Figure 3 show the performance of the JS method when we used fresh training fingerprints obtained in the beginning of every hour. Note that the training data was excluded when doing location estimation. The result shows minor sensitivity of JS method to change of training data, especially for W_T = 30'.

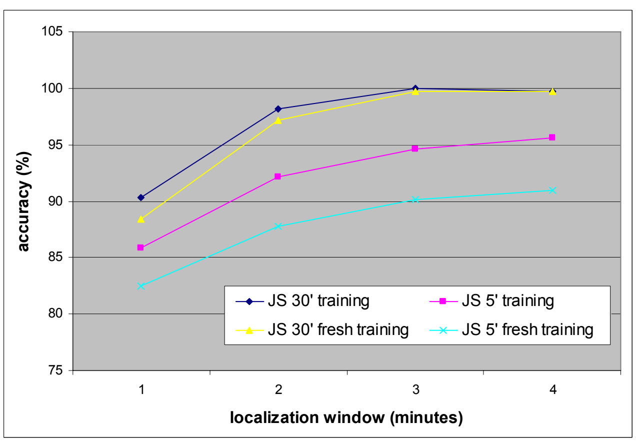

Figure 3. Accuracy of JS method with updated training data for W_T = 30 and 5 minutes.

For the JS method, the effect of partial Bluetooth dongle coverage is shown in Figure 4. This figure, unlike previous ones, depicts accuracy for a localization window size of 3 minutes (i.e., W_L=3') as a function of training window size W_T. The bottom two graphs of Figure 4 show the results of the top-1 estimate for duration of 260 minutes for the tests in Room-1 and Room-2 with full and partial coverage, respectively. For these graphs the training periods are chosen in the beginning of each test day, and the data obtained in the rest of each day is used for location estimation of the target device. As we observe, the accuracy of the JS method for top-1 estimate in Room-1 and Room-2 is 97.82% and 75% for W_L=3' and W_T=10'. For both tests, the accuracy of top-2 estimate is 100%.

In all graphs mentioned so far (i.e., all graphs in Figure 2, Figure 3 and two bottom graphs of Figure 4), we have used two different devices as a reference device to collect training data and as a target data to collect localization data in each room. In our experiments, moreover, the target device was moved every hour with respect to the reference device. If, in addition to training data, we used the rest of the data collected from the reference device for localizing the same reference device –the approach commonly used in literature e.g. [8] – then we would have a top-1 estimate accuracy of almost 100%. Such performance indications are shown by top 2 graphs in Figure 4 for the JS method. Using the same device for training and localization is often not realistic; therefore, we have chosen to present our results based on a realistic case where training and localization devices differ. Should in practice training and localization device be the same, our JS based scheme achieves 100% accuracy of top-1 estimate for both full and partial coverage even if W_T=5' and W_L=1.5'.

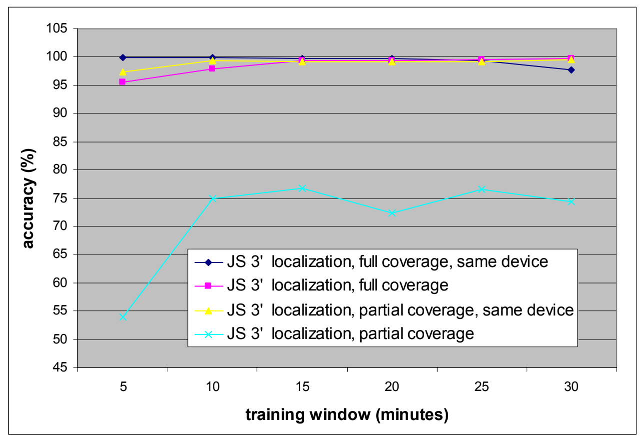

Figure 4. Accuracy of JS method in two rooms with full and partial converge for W_L = 3 minutes.

5. CONCLUSION AND FUTURE WORK

In this paper we proposed a Bluetooth based localization solution that works well when there is a high spatial density of Bluetooth sensors. This means that it is suitable for multi-floor buildings with overlapping Bluetooth cells. The solution is a fingerprinting approach that exploits the inquiry response rate of Bluetooth technology. As such the solution does not require any upgrade of mobile devices and only requires these devices to be in discoverable mode. The solution was implemented and tested. The test results showed that the solution achieves top-1 estimation accuracy of 98% and 75% when there was full sensor coverage and partial sensor coverage, respectively. For this performance, the training and localization window sizes were 3 and 10 minutes, respectively (i.e., WL=3' and WT=10').

Currently we are working on a number of issues and extensions. The impacts of interference and mobility on the RR are needed to be further studied and ways to deal with a time-variant RR are to be investigated. One approach hereto is to obtain and use fresh fingerprints. This solution direction, however, makes sense if one devises localization methods that work well with short fingerprints. The current approach of fingerprinting locations by using dedicated reference devices, moreover, is infeasible when the number of locations is high. A better approach would be to automatically obtain these fingerprints. We are currently investigating whether the dongles used to record the fingerprints can be used as reference devices as well. This basically involves devising a control mechanism (i.e., control protocol and logic) that switches dongles between two modes: a mode where they are inquiring and one where they are discoverable.

Dongles compatible with Bluetooth v1.2 standard are able to provide also the RSS of inquiry responses. It is important to investigate how much our scheme is improved if also the RSS information of Bluetooth inquiries is used for location determination. Another interesting extension to examine further is to fuse the Bluetooth sensor information with other types of sensor data. Since our infrastructure (i.e., CMF) is providing contextual information from multiple sources, combining these sources could aid the location determination. Should this combination allow the system to accurately determine the location of a target device, then the observed fingerprint of the target device could be used as a room fingerprint and added for the already existing fingerprints for that room.

An interesting direction is to get some more insight into the impact of our approach on the mobile phones in terms of power consumption. The power consumption of a mobile device being inquired continuously will increase as the frequency of inquiries or the number of inquirers increases. On the other hand, a higher number of inquirers or a higher inquiry frequency will yield a more responsive system and possibly better (more accurate) fingerprints. An interesting research question is how the estimation accuracy relates to the power consumption of the mobile devices.

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