Location Fingerprinting With Bluetooth Low Energy Beacons

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Abstract—**The complexity of indoor radio propagation has resulted in location-awareness being derived from empirical *fingerprinting* techniques, where positioning is performed via a previously-constructed radio map, usually of WiFi signals. The recent introduction of the Bluetooth Low Energy (BLE) radio protocol provides new opportunities for indoor location. It supports portable battery-powered beacons that can be easily distributed at low cost, giving it distinct advantages over WiFi. However, its differing use of the radio band brings new challenges too. In this work, we provide a detailed study of BLE fingerprinting using 19 beacons distributed around a $\sim$600 m^2 testbed to position a consumer device. We demonstrate the high susceptibility of BLE to fast fading, show how to mitigate this, and quantify the true power cost of continuous BLE scanning. We further investigate the choice of key parameters in a BLE positioning system, including beacon density, transmit power, and transmit frequency. We also provide quantitative comparison with WiFi fingerprinting. Our results show advantages to the use of BLE beacons for positioning. For one-shot (push-to-fix) positioning we achieve < 2.6 m error 95% of the time for a dense BLE network (1 beacon per 30 m^2), compared to < 4.8 m for a reduced density (1 beacon per 100 m^2) and < 8.5 m for an established WiFi network in the same area.**

Index Terms—**Indoor positioning, location fingerprinting, bluetooth positioning, bluetooth low energy positioning, iBeacons.**

I. Introduction

GLOBAL Navigation Satellite Systems (GNSS) have enabled accurate, ubiquitous positioning outdoors but the inability of these signals to penetrate buildings means other techniques must be found for indoor positioning. Today the most common consumer technology used in the absence of GNSS is WiFi. Coarse WiFi positioning is tightly integrated into many mobile platforms, providing urban localization on the scale of tens of meters. The algorithms are essentially proximity-based, relying on the relatively short spatial range of WiFi transmitters and a signal survey. WiFi pattern matching, or *fingerprinting*, is the de-facto localization technique for indoor positioning on consumer devices today.

Other candidates for radio fingerprinting on consumer devices are cellular and Bluetooth signals. Cellular sources are typically too sparsely distributed to provide good indoor fingerprints, while practical issues have limited the value of Bluetooth tracking, most notably the very lengthy scan times. However, the recent introduction of the Bluetooth 4.0 specification has potentially addressed these problems via the Bluetooth Low Energy (BLE, also known as Bluetooth Smart) subsystem [4], [14]. Already supported on a major proportion of deployed devices, BLE is designed for machine-to-machine communication with the "Internet of Things" in mind. BLE devices are small, inexpensive and designed to run on batteries for many months or years and it is expected that many buildings will contain a high density of BLE devices in the near future.

As a result BLE poses a challenge to the dominance of WiFi for indoor positioning: it already has comparable market penetration since it is supported by all recent smartphones, and deployed devices are fundamentally cheaper, smaller, more portable and less power hungry. However, they are also more susceptible to fast fading interference, as we show.

In this paper we examine the unique properties of BLE signals and study the application of fingerprinting to locate BLE devices in an environment with BLE beacons. Many BLE beacons will be deployed for communication and advertising purposes by third parties, and so their use in fingerprinting will be *opportunistic*. There are many beacon parameters that can and will be variable in this case, and we assess the impact on positioning performance of each of these factors. We therefore also provide a guide for ensuring good positioning performance from a set of *dedicated* BLE positioning beacons.

A. Motivating BLE for Fingerprinting

BLE uses 40 channels, each 2 MHz wide, spanning the unlicensed 2.4 GHz radio band that is also used by WiFi—see Fig. 1. The protocol uses very short duration messages to reduce battery consumption [14]. These messages are either *data* messages or *advertisement* messages. The latter are broadcast messages that are used like WiFi beacon frames for device discovery, although they carry a payload that can be used to broadcast changing information such as sensor state. Regardless of the application, advertisements are needed to enable any form of communication and they are therefore the natural choice for both dedicated and opportunistic positioning. They are the basis for the *proximity profile* defined in the specification and the proprietary proximity profiles such as Apple's iBeacon. For fingerprinting, the received signal strength of each advertisement can be used to form a signature for each location.

Given that WiFi and BLE occupy the same radio frequency bands, one might expect little to choose between them when fingerprinting and thus little motivation to change from the

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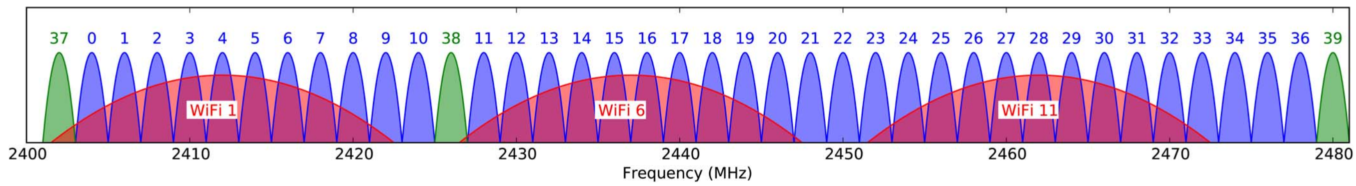


Fig. 1. The 40 BLE channels and the three most commonly populated WiFi channels. BLE advertising only occurs on channels 37, 38 and 39.

incumbent, ubiquitous system (WiFi). Although we will demonstrate there *are* subtle but important differences at a technical level, it is useful to highlight that WiFi fingerprinting faces a growing number of challenges regardless of BLE:

- The increasing duration of *passive* WiFi scans—where the device waits for a Service Set IDentifier (SSID) broadcast from each access point—limits the update rate. With over 50 WiFi bands now available in the 2.4 GHz and 5 GHz bands and a typical SSID broadcast interval of 100 ms, a single scan can take multiple seconds, giving a very low positioning update rate. As an example, a Samsung Galaxy S4 smartphone produced a scan rate of just 0.25 Hz; a Nexus 4 smartphone marginally faster at 0.32 Hz (note that a rate of 1.3 Hz was achievable on this handset when limiting the channels to 2.4 GHz only. We exploit this capability in a later section).
- WiFi access point sightings are buffered and reported via a single aggregate report. So long scan durations not only limit the update rate but also *smear* the radio fingerprints across space if the user is moving. Note that the majority of fine-grained WiFi positioning systems to date have been based on short (~1 s) 2.4 GHz-only WiFi scans, so this issue has received little attention.
- The use of frequent *active* WiFi scans, where the device to be positioned broadcasts a query, increases network traffic and hence reduces WiFi throughput, as well as reducing privacy.
- Not all mobile platforms allow access to the WiFi scan data. Apple's iOS, for example, allows only RSS readings from the connected access point, which prevents third-party WiFi fingerprinting.
- The WiFi specification does not require the signal strength value (on which fingerprinting depends) to be reported in any specific unit. Consequently cross-device positioning can be challenging if the devices do not share a frame of reference for the fingerprint values.

By contrast, BLE suffers none of these problems: advertisement packets are reported immediately and the specification demands that all are reported by the platform in standard units of dBm. BLE offers further potential benefits:

- We have found that the power draw at the mobile device (primarily associated with regularly radio scanning) is lower for BLE than WiFi. For a Samsung Galaxy S4 running Android 4.4.2 with a baseline power draw of 816 mW with the screen on at constant brightness and a CPU wake lock held, continuous WiFi scans increased the draw to 1224 mW, while continuous BLE scanning was associated with a draw of 1028 mW. The difference can be attributed to the simpler protocols of BLE and its optimization for the scan operation (WiFi was not designed with continuous scans in mind).
- BLE beacons are more easily deployed (especially if battery powered) and not constrained by the need to provide uniform communications coverage. WiFi access points are deployed first for communication, and this means minimal range overlap. No consideration is typically given to WiFi access point geometry for positioning.

B. Approach and Contributions

We evaluate a BLE-only fingerprinting system that assumes static BLE beacons distributed throughout the environment and contrast it with a comparable WiFi system. We used BLE beacons advertising at very high advertising rates (50 Hz) and high transmission powers. By post-processing with dropped packets and manually attenuated raw data, we investigate the rate and transmission power needed for good positioning.

The fusion of other location-related sensors (e.g., inertial) would be expected to improve both systems, albeit at the cost of extra battery drain. Nonetheless the characteristics of the pure BLE system we detail here are sufficient to enable the use of BLE signals as a fusion input. Our contributions to the state of the art are:

1) the first experimental test of fine-grained BLE positioning using fingerprinting;
2) a detailed study into the key parameters for accurate indoor positioning using the BLE radio signals;
3) the discovery that the use of three widely spaced but narrow band advertising channels leads to severe RSS variations if the BLE channel number is not reported to the system (this can be seen as a weakness in the current BLE specification);
4) the testing of mitigation schemes to protect against this problem;
5) detailed experimental validation; and
6) a series of recommendations for the developers of BLE-based positioning systems.

II. Related Work

Indoor positioning is a mature research field, with many proposed technologies and techniques—comprehensive overviews can be found in [2], [18], [19]. Here the focus is on radio positioning, specifically using the empirical fingerprinting techniques [3], [15], [17], [22] that avoid the need to model the complex radio propagation environment indoors by pattern-matching to a previously surveyed map of radio signal strengths. Although applied to different radio technologies, these techniques have been developed primarily with WiFi in mind.

Positioning with Bluetooth Classic (pre specification 4.0) has used various techniques from proximity [5], [12] to trilateration [7], [21] to fingerprinting [6], [21]. However, the limiting factor was usually the time taken for a mobile handset to scan the nearby Bluetooth beacons. The specification allows for a scan to take in excess of 10.24 s, during which time the user could travel 15 m or more. It is possible to retrieve RSSI values more promptly from devices connected in a Bluetooth piconet but this is not a scalable solution [12]. Consequently, positioning using Bluetooth Classic has not proved popular.

The latencies that plague Bluetooth Classic for positioning are not present in BLE. The standard itself incorporates the notion of "micro-location" [4], which is a re-badged proximity technique. To our knowledge this is the first study of fingerprinting using BLE RSS values.

The most recent literature in fingerprinting has fused WiFi fingerprints with other sources to form hybrid systems, many of which are based on the idea of Simultaneous Localization and Mapping (SLAM) [10], [16] being applied to pedestrian dead reckoning [13]. SLAM provides an auto-surveying capability by exploiting machine learning to periodically correct the user's path through an environment during navigation. Of particular interest is the work of Ferris *et al.* [11], who used Gaussian Process regression (a form of non-parametric data fitting) to estimate continuous signal maps from discrete WiFi RSS data. This approach is superior to traditional surveying methods and we apply it to pure RSS data in this work.

III. From WiFi to BLE

For WiFi, each access point uses a particular radio channel (of width at least 20 MHz) on which it broadcasts its identifier (SSID). In contrast BLE advertisements are broadcast on three much narrower (2 MHz) advertising channels in quick succession. These channels are nominally labelled 37, 38, and 39 and are widely spaced at 2402 MHz, 2426 MHz and 2480 MHz, respectively (see Fig. 1). These frequencies are chosen to minimize interference with common WiFi deployments.

The receive device adopts a scan cycle that cycles over the three advertising channels, pausing to listen for advertisements on each. The precise cycle and pause time are unspecified, but we have found recent smartphone implementations switch listening channel after a few milliseconds. Therefore listening for a significant fraction of a second could produce advertisements on any or all of the three channels.

A BLE scan continues indefinitely and each advertisement is reported as it is received. Consequently, we must form each fingerprint from the observations within a time window. If the window is greater than the beacon interval, multiple sightings of that beacon will be reported (some current mobile operating system report each *connectable* beacon only once per scan. In this work we use *non-connectable* beacons to avoid this issue). We show in this work that this redundancy is important to robust fine-grained BLE positioning and that there are therefore constraints on the windowing length.

Note that *the BLE specification for an advertisement report does not include the channel on which it was received*. This information *is* available when using iOS 7 or above, but a general solution must not assume the channel information is available. Indeed, an advertisement report on a strictly standards-compliant device cannot be mapped back to a channel. In this work we use an iPhone to investigate the value of the channel information, using it to develop schemes that do not require it and can thus be deployed on a strictly standards-compliant device.

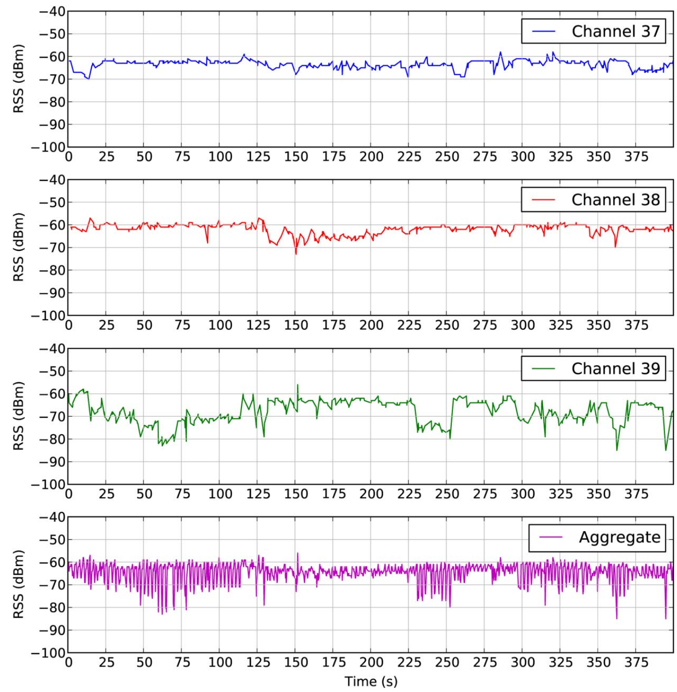


Fig. 2. RSS variation with time (static devices).

Fig. 2 shows the RSSI values recorded for a 50 Hz BLE beacon, collected using a static iPhone approximately three meters away. The measurements are separated by channel number (as reported by iOS 7) and also presented as an aggregate signal, representative of what would be seen on a generic BLE standards-compliant device. We make two key observations.

Firstly, the mean levels of the three separated signals are different ($37 : -63.7 \pm 1.9$ dBm, $38 : -61.9 \pm 2.3$ dBm, $39 : -67.7 \pm 5.0$ dBm). Two factors cause this: uneven channel gain and multipath interference. The former occurs because embedded antennas rarely have a flat response across the entire 2.4 GHz band. WiFi's use of a single 20 MHz channel renders this a non-issue, but BLE's use of frequencies at either band limit results in different responses even without multipath interference. The addition of multipath interference causes further differences and changes over time with signal fading in cluttered environments.

Fig. 3 further demonstrates BLE fading. Here, the iPhone was moved 3 m towards the BLE beacon using a custom mechanical system. The test was performed out of working hours to give a more stable radio environment. Deep multipath fades are evident in all three channels, with 30 dB drops in power across just 10 cm. Importantly, the *different channels exhibit fades at different spatial positions* due to their different centre frequencies—we make use of this observation in constructing our positioning system.

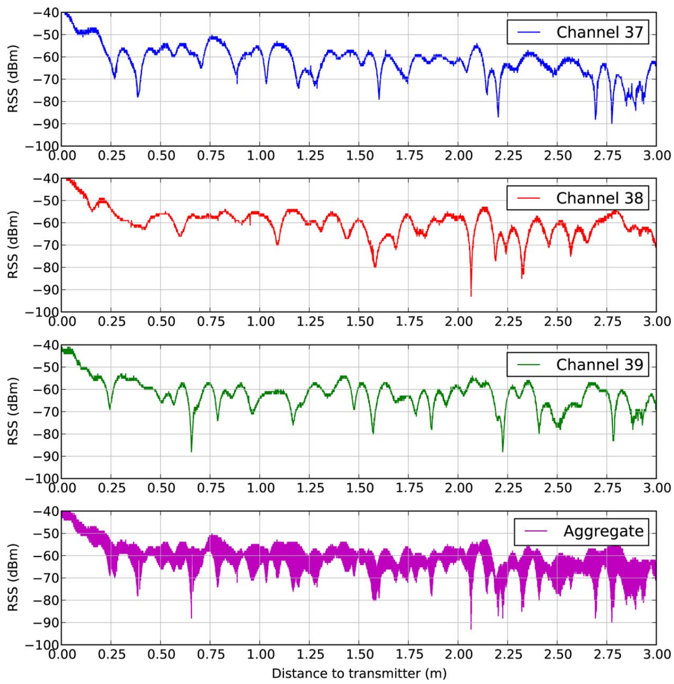


Fig. 3. RSS variation with distance (receiver moving).

In the context of BLE fingerprinting, radio channel gains and fast fading are both serious concerns, especially if a receiver does not segregate the measurements it provides into three separately-reported channels. In this case, the BLE signal will appear to suffer an artificially-high, non-white signal noise (shown by the "Aggregate" plots in Figs. 2 and 3) that reduces the performance of positioning systems. Fading is still an issue for devices that report the channel information—the deep fades just become unambiguously clear. Crucially, *these effects are far less evident in WiFi positioning because a given access point typically uses one fixed 20 MHz channel*. Increasing the signal bandwidth can reduce the RSS fluctuations caused by fast fading, and this is evident when comparing WiFi and BLE fading characteristics [9].

So, for BLE fingerprinting we seek to exclude faded data. Sharp (fast) fades will be naturally removed at the map creation stage through the application of regression. This leaves maps that predominantly represent the free space loss and the shadowing loss from objects. However, the problem remains during the online (map matching) phase where a single reading may find itself in a sharp fade.

IV. Positioning Algorithms

A. Fingerprint Construction

Since BLE advertisements are reported immediately, we must form an RSS fingerprint by taking a time window of BLE measurements. The choice of the width depends on many factors, including:

- **The movement rate**. If the receiver is moving during the fingerprint collection, the fingerprint will be formed from measurements at different spatial positions. The movement rate puts an upper bound on the maximum acceptable window length—if the window is too long, the large spatial extent (*smearing*) of the fingerprint will limit successful matching.
- **The presence of fast fades**. A very short window limits the spatial extent of the fingerprint but increases the risk that the fingerprint measurement is taken within a fast fade null on at least one channel.
- **The beaconing rate**. We define the *receive rate* to be the rate at which BLE advertisements are reported within the application. This value is a lower bound on the beaconing rate since specific advertisement messages may be dropped or missed. Clearly, a lower receive rate requires a longer fingerprint window to build the same fingerprint dimensionality.

The average human walking pace is approximately 1.5 ms^{-1}. On this assumption, and the desire for meter-level positioning, the time window should not exceed 1 s during movement and should ideally be less than this. By a similar argument, the window should not fall below 0.1 s since fast fades occur at a spatial separation of around half the signal wavelength (around 12 cm) or longer. This lower bound on the window size ignores the advertisement transmission rate of the beacons—we return to this shortly.

To address the different RSS values that result from the different channels we take a window of advertisements from each beacon to form each fingerprint. We filter this window to provide an RSS value to insert into the fingerprint. The filters we consider here are the mean, median and maximum. To gain maximal benefit from the filtering, each fingerprint window should contain at least one reading on each of the three advertising channels. This has two important consequences:

- when using a standards-compliant device (which does *not* require the reporting of advertisement channel information) we cannot know whether the window has captured samples from multiple channels. We must choose a window that guarantees that the handset has listened on all three channels and hope that the collected samples span the channels. Longer windows clearly increase the likelihood of this occurrence.
- we must collect at least three samples per window per beacon. For a window of length w, this implies a minimum beaconing rate of $\frac{3}{w}$. At the limit of $w = 1$ s discussed above, this requires 3 Hz beaconing. This is easy to ensure with a dedicated deployment, but is unlikely for an opportunistic system (other BLE applications are not so dependent on high receive rates and application designers will prefer to optimize for battery lifetime). In such contexts the best positioning result is likely to be achieved by forcing the user to remain still and position using longer time windows.

B. Map Construction

Previous work has constructed RSS maps by visiting a series of survey sites and manually taking readings at each. However, because our testbed offered high-accuracy ground truth position, we chose to construct the maps using data collected during the experiments. Each fingerprint was linked to a true position and we used Gaussian Process regression to generate a signal strength map per source. We constructed a separate database for each set of fingerprint construction parameters (i.e., window length and filter algorithm).

C. Position Computation

To position a device on a subsequent walk we used a Bayesian estimator. The entire area of interest was divided into grid cells of side 1 m and the probability of a given fingerprint corresponding to each cell was determined for each epoch. To do this we require a way of evaluating the "distance" between the set of signal strength values in a map cell and the current fingerprint measured by the device being tracked. The most commonly used metric in the literature is the Euclidean distance:

$$distance(B, m, M) = \sqrt{\sum_{i=1}^{N} \frac{(m(b_i) - M(b_i))^2}{N}}, \qquad (1)$$

for current fingerprint m containing RSS measures for beacons $B = \{b_1, \ldots, b_N\}$ and the set of beacon survey maps, M. We used this metric throughout this work.

This metric was used to generate a score for each cell. That score was then weighted using a Gaussian kernel to generate a probability for that cell which accounted for the uncertainty in both the map estimate and the current fingerprint measurement. The variance data within the Gaussian Process survey maps were thresholded such that map cells with moderate or high variance were ignored completely (not trusted) during these calculations. The resulting function across all cells was the Bayesian Likelihood function. Each cell was assigned a probability according to

$$p = \exp\left(-\frac{distance^2}{2\sigma^2}\right), \qquad (2)$$

where σ is the standard deviation associated with the fingerprint measurement noise.

In terms of usage scenarios, we consider both *one-shot*, where the user wishes to have a single position fix given no prior information, and *tracking*, where the user wishes to be tracked around an environment continuously and the position history can be used to constrain the prior. For one-shot positioning the prior was taken to be uniform across the test area at each epoch. For tracking, the posterior function from the previous position estimate was used as the prior for the new calculation, i.e., we assumed the user had only moved within a single map cell (one meter square) or to an adjoining cell between measurement updates. For high beacon rates of many Hertz this is an appropriate assumption. For example at 10 Hz update rates a user is expected to move 15 centimeters between beacon measurement epochs.

Once a posterior distribution was calculated, we estimated the position (and hence the error) using the distribution maximum (i.e., maximum a-posteriori (MAP) probability, P_{max}). We also compared this to a weighted mean of all positions (i.e., Minimum Mean Square Error (MMSE) or P_{mean}) to assess which metric provided better positioning against the ground truth reference. However, for clarity and brevity we present only the P_{max} results since there was rarely any significant difference and P_{max} is cheaper to compute.

V. Experimental Method

When deploying a BLE positioning system, there are many parameters to consider, including: fingerprint construction algorithm; beacon rate; transmit power; antenna orientation; beacon mobility; beacon geometry; beacon density; etc. Many of these parameters are inter-dependent—e.g., reducing the transmit power may require altering the beacon density to maintain coverage. Performing an exhaustive search of the parameter space is infeasible, involving constant beacon redeployment. Furthermore, the results would be highly environment-specific.

Instead, our approach was to deploy an over-specified set of beacons with parameters set to give good results without consideration of real-world issues such as power consumption. This allowed us to bound the possible performance and to look at the effects of the parameters by post-processing the data many times. To explore the parameter space we focus on one-shot positioning since any improvements should be reflected in the tracking performance (tracking can be viewed as a filter on top of one-shot positioning, so improving one-shot performance typically improves tracking). Having explored the parameter space we propose a realistic beacon setup and deployment and evaluate both its one-shot and tracking performance.

Since our positioning algorithms are based on mapping RSS values, it is important to consider the temporal stability of these values. We use data collected over a few weeks, during which time we observed little, if any, significant change in the signal RSS values. We attribute this to the nature of the testbed—an office space that was rarely crowded or changed. As such our results provide a valuable upper bound to positioning performance. Further work will be needed to evaluate the extent to which environmental changes affect the positioning performance in highly variable environments such as retail spaces. Prior work by the authors has suggested that fingerprint complexity decreases in such open retail spaces, further impacting fingerprinting performance for indoor positioning applications and suggesting that these environments will be the most challenging [8].

VI. Experimental Testbed

Our testbed covered approximately 600 m^2 and was an office environment in normal daily use at the William Gates Building, Cambridge, UK. The area had an existing WiFi network, with three access points within the testbed, plus more that could be heard from adjacent areas and floors.

Deployed Beacons: Nineteen BLE beacons were deployed as shown in Fig. 4. They were were installed on top of window ledges or desks in offices or attached to the wall or convenient devices (printer, water cooler) in the corridor. Most of the

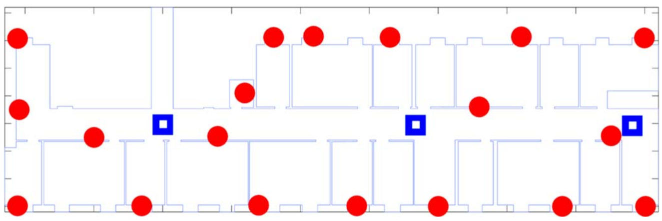


Fig. 4. The locations of the BLE beacons (circles) and WiFi access points (squares) in the test area. The test area is approximately 50 meters by 15 meters. Signals from 6 other WiFi sources located in other regions of the building were also received in this area and included in the fingerprints.

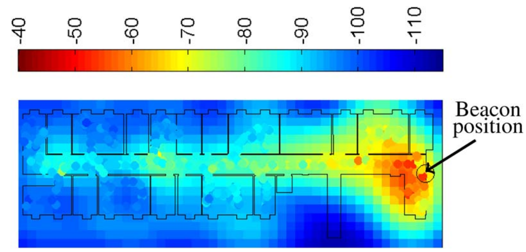


Fig. 5. Sample BLE signal strength map for iPhone E_1 data. The area shown is approximately 50 metres by 15 metres.

beacons were installed a height of approximately 1 m from the floor and oriented such as to provide maximum response in the horizontal plane (to coincide with users holding smartphones approximately parallel to the ground during interactions with them). Each was set to beacon at 50 Hz with an output power of 0 dBm.

Handset Logging: The iPhone logged the BLE advertisement events to local storage using an application supplied by CSR Ltd. We also used a Nexus 4 Android 4.4.2 device to simultaneously capture WiFi beacons. In the experiments the tester carried one phone in each hand, held in front as if navigating.

Ground Truth Location: The Active Bat system [1] was available throughout the testbed and was used to provide ground truth position. This system is a low error (less than 3 cm in 3D 95% of the time), high-infrastructure location system capable of estimating positions at around 15 Hz. The data from it were post processed and smoothed to remove spurious positions.

Synchronization: The Active Bat system, the iPhone and the Nexus 4 each ran on independent clocks. Before each experiment, each clock was manually synchronized using a Network Time Protocol (NTP) server [20].

VII. Results

The parameter exploration presented here is based on data gathered in a series of four walking experiments, referred to as $E_1, \ldots, E_4$. The walks lasted between 5 and 18 minutes and covered the entire test bed where the Active Bat ground truth was active. The routes were not predetermined and areas were visited multiple times. The collection included periods with and without walking movement.

A. Baselines

To contextualize the fingerprinting results we provide three baseline positioning accuracies; two based on using the BLE signals without prior survey; and one applying the same fingerprinting algorithms to WiFi. We refer to the two baseline BLE algorithms as "proximity" and "kNN," and note that they both require knowledge of the beacon positions. The proximity algorithm selects the beacon with the strongest received signal at a given time and co-locates the user with it. The kNN algorithm used $k = 3$ and took the three strongest signals and produced a weighted mean of the corresponding beacon positions. The weight applied was $\frac{1}{|r_i|}$, where r_i was the RSS for beacon i in dBm.

The WiFi baseline was derived from 2.4 GHz WiFi fingerprints collected at approximately 1.3 Hz during the E_1 walk and applied during the E_2 walk (a walk conducted a week later) using the tracking mode. As previously mentioned, we used the WiFi access points already installed in the building, the geometry of which was arguably sub-optimal for positioning (access points were located along the corridors, not in the corners of the building). Note that the decision to use only 2.4 GHz WiFi signals enabled faster scan rates on the test handset we used. Combined with the use of the tracking mode, this presents WiFi in its best light for our testbed.

B. Sample BLE Signal map

Fig. 5 gives a sample RSSI signal strength map for a beacon, generated using the iPhone data in E_1 and applying Gaussian Process regression.

C. Fading Mitigation: Maximum vs Median vs Mean vs Raw

We constructed a set of signal strength maps from the data in E_1, using three fading mitigation schemes (maximum, median and mean). These maps and the same schemes were then used to position the iPhone in datasets E_2 and E_4.

For comparison we included a *Raw* scheme that represented no fading mitigation at all. This used no windowing during the map generation (each advertisement was assigned a position and fed to the regression directly). However, the online position computation still required a window of measurements to form a useful fingerprint (a single advertisement alone would provide a highly-ambiguous position estimate). Since our maximum observed receive rate was around 25 Hz, we used a window of 0.05 s to provide the Raw dataset. In the rare case where multiple sightings of a beacon were observed within one window, the latest reading was used.

The effect of the multipath mitigation on positioning performance can be viewed directly in Fig. 6. The left hand image shows a position fix without multipath mitigation, the right shows the same position fix with a 0.5 s median filter applied to the BLE input data. The left hand image shows three distinct regions of highly-probable user location (green regions). We observe that the multipath mitigation step (which has been applied to both the survey data and the tracking data on the right hand image) has significantly reduced the complexity of the posterior distribution.

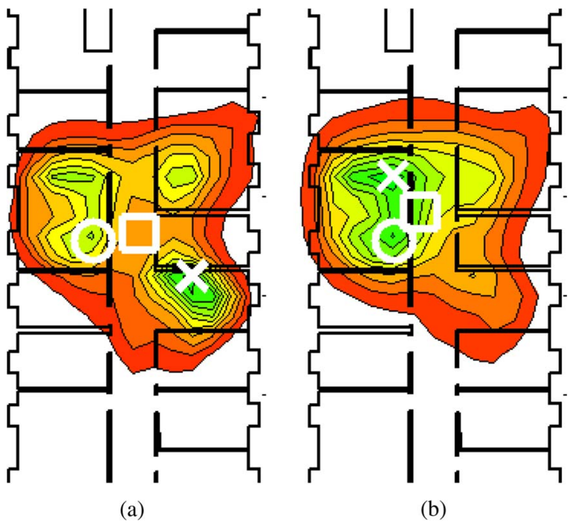


Fig. 6. BLE fingerprinting with a 0.5 s median filter (right) enabled, compared to the baseline (left). In these images the true receiver location is marked by the circle, P_{max} is shown by the cross, and P_{mean} is shown by the square. The area shown is 25 meters by 15 meters. (a) Without multipath mitigation. (b) With multipath mitigation.

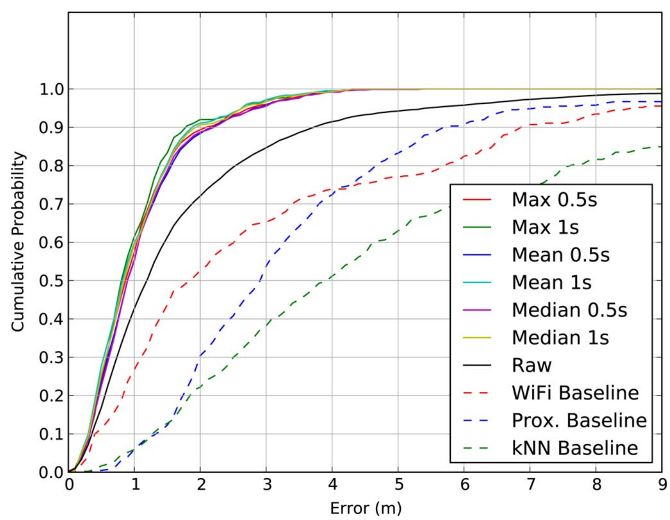


Fig. 7. Positioning error for E_2 iPhone data using E_1 iPhone map positioning.

The overall cumulative error is shown in Fig. 7 for windows of 0.5 s and 1.0 s—a more detailed look at window size is given in the next section. The results clearly show that any of the mitigation schemes vastly outperform the raw scheme, with errors less than 3 m 95% of the time versus less than ∼6 m 95% of the time, respectively. The choice between mean, median and maximum is not so clear, however, with all three producing very similar results. The maximum appears to give the best results and is the cheapest to compute. However, we have experimented with other handsets and observed occasional spurious high RSS values that skew the performance of the maximum [9]. The median and mean both filtered these out. Given a moderate sampling rate, we expect the median score to be the most robust to large outliers (i.e. both spurious high values and very deep fast fades which may distort the mean) for a device-agnostic positioning scheme, and so we favour this in this work. Nonetheless, we note that the other schemes are viable choices.

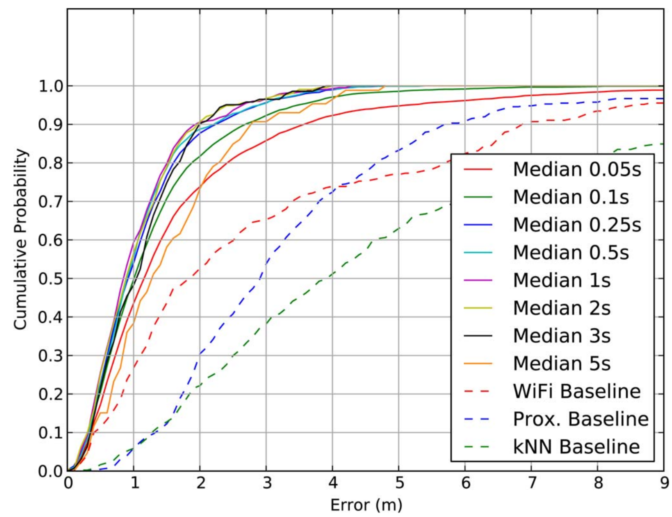


Fig. 8. Positioning error dependency on window size for E_2 iPhone data using E_1 iPhone map positioning.

D. Window Selection

The window duration is a balance between ensuring sufficient samples are taken for multipath mitigation; obtaining sufficient dimensionality in the fingerprint; and minimising spatial smearing from handset movement. In any specific implementation, this will depend on the expected receive rate and the degree of user motion. Fig. 8 shows the positioning errors associated with applying a median scheme with varying window sizes to the data used in the previous section. We observe that window sizes of around 0.5 to 2 s seem to provide the best performance, corresponding to a pedestrian covering approximately 0.7–3.0 m while walking. The performance in this range is very similar, with an error of less than 3 m 95% of the time. This suggests that core features of radio fingerprinting, such as measurement noise and typical slow-fading correlation scales, intrinsically limit the accuracy to this level, and hence smearing at the same scale has little effect. For shorter windows, multipath mitigation is not as effective; for longer windows the smearing error dominates.

E. Effect of Beacon Advertising Period

The beacons used in this work transmitted at a very high rate of approximately 50 Hz. This is far higher than would be expected in any opportunistic system, and would significantly reduce the lifetime of battery-powered nodes in any dedicated system (as a guideline, our beacons were each powered by two AA batteries and exhibited a lifetime of approximately six months at 50 Hz advertising). We therefore studied the effect of downsampling the BLE signals.

Fig. 9 shows the positioning result using different synthesized frequencies, including those more typical in an opportunistic system. Where the rate allowed multiple samples of the same beacon per (1 s) window, we applied median-based fading mitigation. We observed decreasing error with increasing rate, albeit with diminishing returns. The error achieved at 20 Hz (approximately 2.6 m at the 95% confidence level) was negligibly different from that at 10 Hz. Note that at 0.5 Hz, the

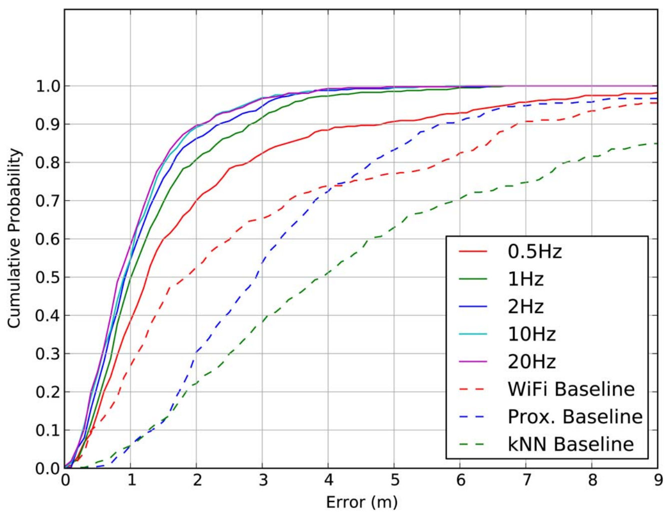


Fig. 9. Positioning error with synthesized data rate.

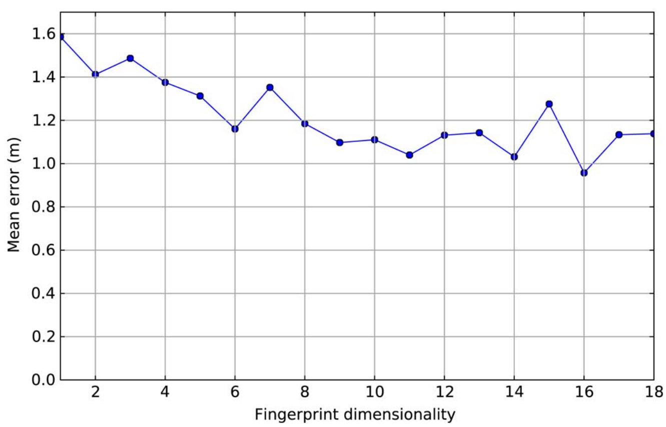


Fig. 10. Mean error variation with fingerprint dimensionality.

beaconing interval was double the fingerprint window duration. Consequently we observed a long tail in the cumulative probability plot associated with fingerprints of lower-than-expected dimensionality. This confirms the need for longer windows when using slow-rate opportunistic beacons.

F. Fingerprint Dimensionality

The number of beacons detected by a receiver (and so the number of elements in the fingerprint for that position fix) is expected to have an effect on positioning accuracy. In this experiment we artificially reduced the number of beacons detected per epoch and measured the effect on the positioning accuracy. The results are shown in Fig. 10 as a mean position error per number of beacons within a fingerprint. They showed a steady improvement in mean accuracy up to around 8–10 beacon measurements per fingerprint, at which point the positioning accuracy levelled off and a higher density of beacons produced diminished returns.

G. Reduced Beacon Density

Following the finding of the previous experiment, we studied the effect of moving from a test bed of 19 beacons, with all

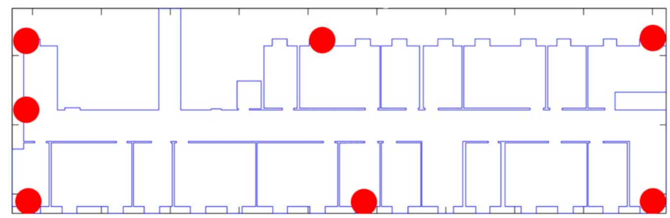


Fig. 11. The reduced BLE beacon set. The test area is approximately 50 meters by 15 meters.

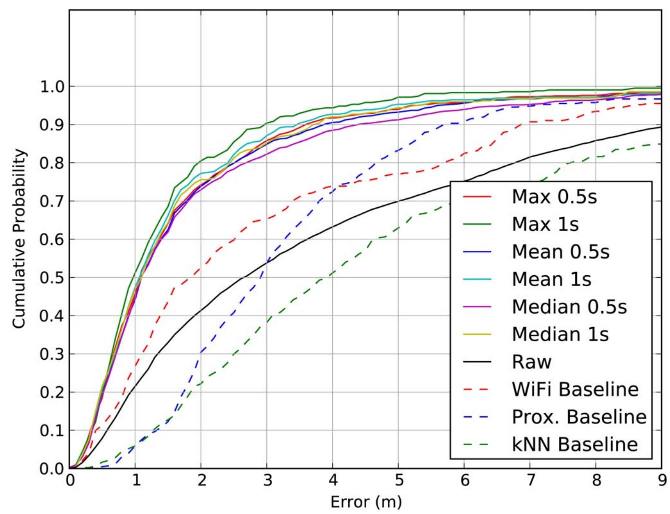


Fig. 12. 7 beacons for E_2 iPhone data using E_1 iPhone map positioning.

fingerprints exceeding the dimensionality boundary of 8–10, to just seven beacons in the environment. The seven were manually selected to be distributed approximately uniformly as shown in Fig. 11—a representative layout for tracking devices within an enclosed region with BLE beacons attached to perimeter walls. This layout was expected to result in most fingerprints containing measurements from only 3–5 beacons. The positioning results are shown in Fig. 12. We observe very similar performance to the 19-beacon set up to the 66% confidence interval, but increased errors for the seven beacon distribution for the remaining data (moving from less than ∼2.5 m to less than ∼5 m 95% of the time). On examining the data for signal availability we confirmed that this layout and beacon power setting resulted in a relatively even spread of fingerprint dimensionality of 2–6.

H. Transmit Power

The previous results were collected with the BLE beacons transmitting near the top of the BLE specification range (0 dBm). This inevitably resulted in fingerprints of greater dimensionality since a given beacon has a much greater range. Very low power results in short range, isolated beacons and regions of no positioning coverage, but as the power is increased and beacon coverage patterns start to overlap, we expect to see diminishing returns in terms of positioning accuracy as power increases further still. To investigate this, we artificially attenuated the BLE readings for our datasets, discarding any that fell below the empirically-determined noise floor for the smartphone of −115 dBm.

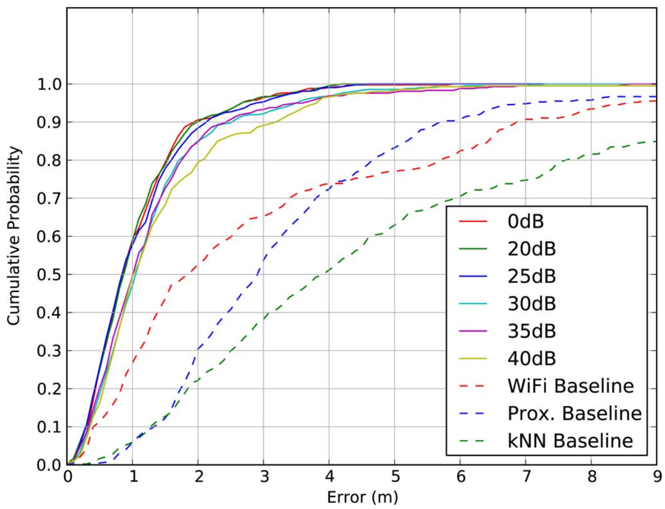


Fig. 13. Effect of artificially attenuating 19 beacon signals on E_2 iPhone data with E_1 iPhone maps. The legend gives the applied attenuation.

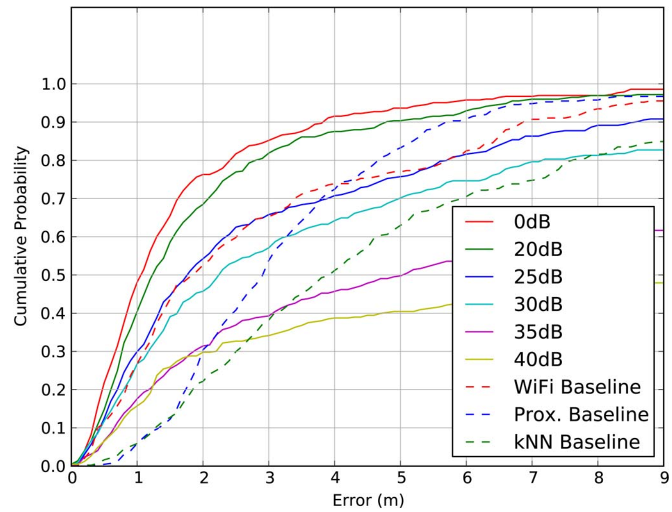


Fig. 14. Effect of artificially attenuating the seven beacon subset on E_2 iPhone data with E_1 iPhone maps. The legend gives the applied attenuation.

Fig. 13 shows the positioning result for the full set of 19 beacons. As expected, reducing the power initially makes little difference. This indicates that the beacon power setting was unnecessarily high for the deployment—in fact an attenuation of 25 dB would have had little effect on the positioning. For attenuations of 30 dB and above, we see the positioning performance decline. By 40 dB the error has grown approximately 50% at the 95% confidence level. However, we note that even with a 40 dB attenuation applied, there was 100% availability of positioning (i.e., there was always a signal to position with, regardless of the error it resulted in). Further attenuation would be expected to lead to availability less than 100% as the beacons became small proximity "islands." However, such attenuations are unlikely in a real deployment.

Instead we consider reducing the density to the seven beacons of Section VII-G. As Fig. 14 shows, the availability was less than 100% for attenuations greater than 20 dB, falling to just 50% for 40 dB. This density of beacons provides a good compromise between minimizing the deployed infrastructure and still ensuring fingerprints of sufficient dimensionality from beacons with good positioning geometry.

I. Evaluating a Realistic Dedicated Deployment

Having explored the parameter space we analyzed a balanced consumer system that traded off good positioning performance for realistic deployment numbers. From the previous section, a seven beacon deployment can provide 100% coverage of our testbed. Using a transmit power in the range −10 to −20 dBm has little impact on accuracy. Table I shows the published capabilities of a series of commercially available BLE beacons, from which we select a transmit power of −12 dBm to match the default of the popular Estimote beacons.

We processed the data from six different walks and trialled both the one-shot positioning and tracking modes for a range of beacon rates. The results are shown in Fig. 15. They illustrate that the system is rarely worse than the deployed WiFi system with its error of < 8.5 m (3.1 m) 95% (66%) of the time, even when using 1 Hz beaconing (as might be expected when using opportunistic rather than dedicated beacons). Beaconing rates of 10 Hz provide a significant boost, with tracking accuracies < 4.8 m (1.3 m) at the 95% (66%) confidence level (equivalent one-shot accuracies of < 6.5 m and < 1.6 m, respectively).

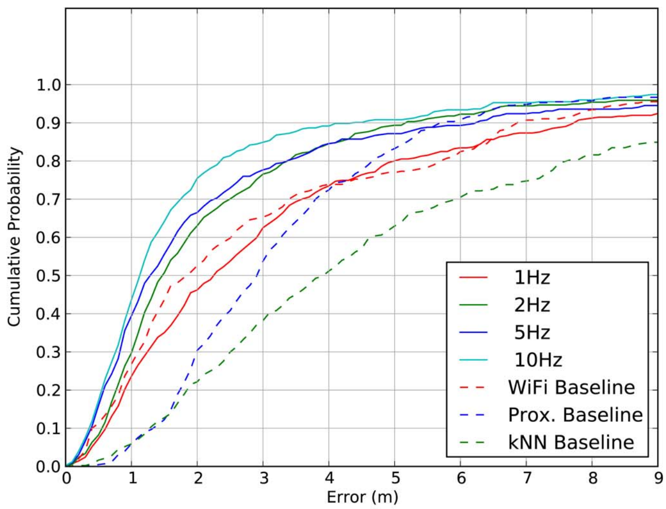
TABLE I
CONSUMER BLE BEACON PROVIDER SETTINGS

Provider	Power (dBm)	Advertising rate (Hz)
CSR	-18 to +4 (default -18)	0.1 to 50 (default 4)
Estimote[1]	-30 to + 4 (default -12)	0.5 to 20 (default 5)
Kontakt [2]	-20 to +4 (default -16)	0.1 to 50 (default 2)

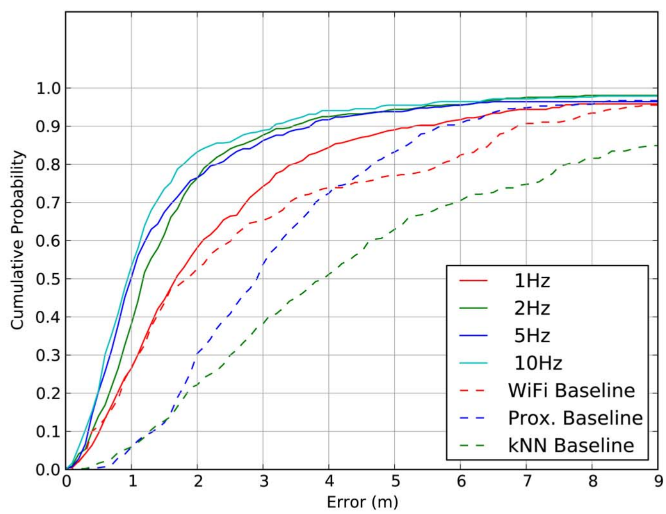
VIII. Conclusion and Further Work

This paper has explored the use of Bluetooth Low Energy (BLE) beacons for fingerprint positioning. We have shown that significant positioning improvement over WiFi is possible even using a relatively sparse deployment of beacons once the characteristics of BLE signals are accounted for. We have achieved tracking accuracies of < 2.6 m 95% of the time using a dense beacon distribution (1 beacon per 30 m^2) and < 4.8 m using a lower density distribution (1 beacon per 100 m^2) in an environment where WiFi achieved only < 8.5 m 95% of the time. Our key conclusions are:

1) The three BLE advertisement channels are associated with different gains and multipath effects due to their narrow width and wide spacing. Thus a BLE RSS measurement without channel information may be tri-modal at any given point, making a single measurement of the RSS—as per WiFi fingerprinting—insufficient.
2) Batch filtering multiple beacon measurements per fingerprint is necessary for BLE fingerprinting. This requires longer fingerprint listening periods or faster beaconing rates. Rates of multiple Hertz are required when the subject is moving to eliminate fingerprint smearing, and as such slow-rate opportunistic beacons are unlikely to support accurate tracking of moving users.



(a)



(b)

Fig. 15. One-shot and tracking performance for a balanced system. (a) One shot, P_{max}. (b) Tracking, P_{max}.

3) Diminishing returns were observed for beaconing rates above 10 Hz using a 1.0 s filtering window.
4) Positioning error decreased as the number of beacons per fingerprint increased, up to a threshold of around 8–10 beacons. Beyond this there was no further improvement in positioning accuracy. Combining this information with the desired beacon power level will steer the beacon density required for maximum positioning performance.
5) Beacon transition powers around -15 dBm provided good coverage for a reasonably low density of beacons in our office environment.

Our deployment of one beacon per 30 m^2 gave accuracies of < 2.5 m 95% of the time. Lowering the density to one beacon per 100 m^2 degraded this result to < 5.5 m. However, this is still a significant improvement compared to positioning via the established WiFi network in the same area, which achieved only < 8.5 m error 95% of the time.

We intend to extend this work by deploying a larger BLE-based positioning system over a large building. This will allow us to investigate the ease of estimating the current floor a device is on and the possibilities that ubiquitous tracking within a building offer.

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