# An Analysis of the Accuracy of Bluetooth Low Energy for Indoor Positioning Applications

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**ABSTRACT**
This study investigated the impact of Bluetooth Low Energy devices in advertising/beaconing mode on fingerprint-based indoor positioning schemes. Early experimentation demonstrated that the low bandwidth of BLE signals compared to WiFi is the cause of significant measurement error when coupled with the use of three BLE advertising channels. The physics underlying this behaviour is verified in simulation. A multipath mitigation scheme is proposed and tested. It is determined that the optimal positioning performance is provided by 10Hz beaconing and a 1 second multipath mitigation processing window size. It is determined that a steady increase in positioning performance with fingerprint size occurs up to 7 ±1, above this there is no clear benefit to extra beacon coverage.

## I. INTRODUCTION

The introduction of low-cost, low-power Bluetooth Low Energy (BLE) beacons for proximity detection also provides a new signal of opportunity with which to perform more fine-grained positioning. This paper provides a comparison of WiFi and BLE fingerprinting with representative hardware in a large indoor space with a highly-accurate (3 cm in 3D at 95% confidence) ultrasonic ground truth referencing system.

Indoor positioning systems based on WiFi fingerprinting schemes [1, 2, 3] are now well established due to the ubiquity of WiFi signals and are known to provide positioning accuracy of a few metres given a well-surveyed environment and dense WiFi coverage. However, access points are rarely deployed with the ideal density and geometry for positioning, and WiFi is a power-hungry protocol. Bluetooth Low Energy (BLE) uses the same 2.4 GHz ISM radio band as WiFi, and addresses many of these shortcomings. It was designed primarily as a short range energy-efficient machine-to-machine communication protocol characterised by very short messages with minimal overhead. The standard defines many core capabilities, including simple proximity sensing. Targeted advertising and simple "near-me" applications are already exploiting these capabilities. However for most traditional indoor positioning applications such as asset tracking, route guidance, unrestricted navigation and rapid localisation, the indoor positioning system needs to be available at every possible location within the environment, not just when in close proximity to BLE beacons. Therefore the impact on unrestricted indoor positioning of introducing BLE beacons into an environment needs to be assessed to determine whether BLE can have a significant impact on solving the larger "indoor GPS" problem.

### Bluetooth Low Energy

Bluetooth Low Energy [4] devices operate in the 2.4 GHz licence-free band, and so share the same indoor propagation characteristics as 2.4 GHz WiFi transceivers. The beaconing, or *advertising* mode, permitted in the BLE standard enables a very short, unsolicited message at very flexible update rates. These messages can be used to allow a device to detect close proximity to a specific location based on the Received Signal Strength (RSS). In this way, location specific triggers, adverts, vouchers and information can be provided to the user.

BLE advertising beacons are particularly attractive to retailers because of the promise of long battery lives of many years, and so low maintenance requirements. Long battery lives are expected to require low radio power output and/or low beaconing rates. While this does not affect their use for proximity detection it does affect their usefulness for providing fingerprint-based positioning throughout an entire indoor environment.

**Fingerprinting**

Fingerprinting is currently the state-of-the-art indoor positioning scheme readily available on standard smartphones. A fingerprint refers to the pattern of radio signal strength measurements recorded at a given location in space and consists of a vector of signal identity information (such as cellular Cell-IDs, or WiFi MAC addresses) and a corresponding vector of Received Signal Strength (RSS) values.

Typically WiFi signals alone provide the fingerprints, but cellular measurements and data from a magnetometer can also be used [5]. WiFi signals exhibit greater dynamic range and anisotropy throughout a building than the RSS from the external, and often very distant, signal sources such as the cellular network. Magnetometer data provide a high dynamic range on a very fine scale but can only provide a single contribution to the fingerprint vectors, which will be dominated by the many WiFi and cellular measurements available in a typical metropolitan indoor environment.

As a receiver moves through a complex signal environment, such as a building full of walls and objects, the RSS of any non-line-of-sight signal can vary rapidly on a fine spatial scale (metre level) as that signal penetrates different media and interacts with different objects as it moves along different paths through the building. Fingerprinting relies on these RSS values varying rapidly on the spatial scale, but only very slowly over time, such that a receiver coming back to a fingerprint location in the future should record the same RSS measurements, within the limits of measurement noise.

In reality fingerprints inevitably degrade over time as environmental changes occur – the density of people within the building at different times, the positions of furniture, even the positions of walls and partitions. This means that traditional fingerprinting schemes require regular re-surveying to ensure the accuracy of the system. WiFi fingerprints are also affected by the position of the user's body during the measurements, as the human body is typically a good attenuator at WiFi frequencies. This is of course also the case for BLE (see Figure 1) as both technologies operate at 2.4 GHz.

## II. BLE RANGING PRECISION

One of the simplest ways to achieve metre-level accuracy in specific zones is by a proximity measurement. The measurement of distance using received signal strength is very accurate when within a metre or so of a transmitter because the signal strength decreases as the inverse square of the distance to the source, and there are rarely any signal obstructions. It is therefore easy to detect close proximity to a BLE device, and hence confidently trigger a location-based event. However the ranging performance rapidly drops off with range, as shown in Figure 1. If we were to assume a modest measurement noise such as 3 dBm, this would result in a ranging uncertainty of the same order of magnitude as the distance to the source; within a metre of the transmitter a positioning uncertainty of only a few centimetres would be possible, however, at 10 m the ranging error would be around 5 m.

The human body also attenuates 2.4 GHz radio signals, further complicating the range estimation. Figure 1 shows the output from a short set of static tests moving away from a BLE beacon in an open environment. The experiment demonstrates that a ~10 dB reduction in RSS caused by this body effect will still result in a reasonable proximity measurement when within 10 cm of the transmitter (the receiver will still be estimated to be within a metre of the transmitter), whereas out at 1 metre the body effect can result in a range estimate of 5-10 m.

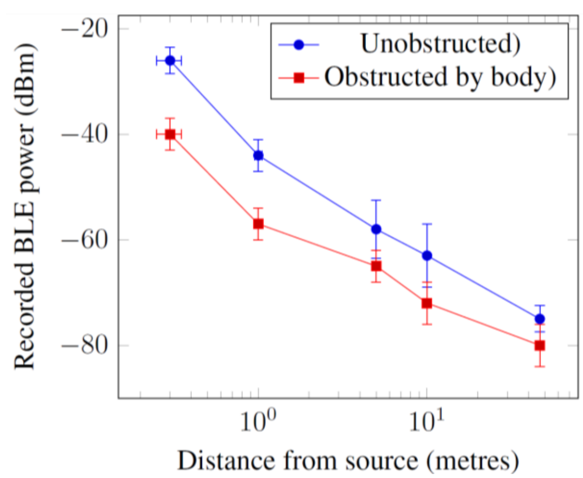


*Figure 1 shows the experimentally-derived RSS reduction with range from a BLE source, with and without body attenuation*

## III. CHANNEL BANDWIDTH

WiFi access points communicate on a radio channel that is at least 20 MHz wide, broadcasting their identifier (BSSID) on the same channel. BLE follows Bluetooth classic in using frequency hopping to communicate. It has 40 channels, each of width 2 MHz. It moves between these channels pseudorandomly to transmit data in short chunks. However, BLE uses only three of these channels to broadcast (advertise) its identifier. This is an energy compromise (the receiver needs to do less work if it only needs to monitor three channels). The BLE advertisement channels are nominally labelled 37, 38, and 39 and are centred on 2402 MHz, 2426 MHz and 2480 MHz, respectively (see Figure 2). Each advertisement is repeated on each of the three channels in quick succession. The receiving device adopts a scanning process that cycles over the advertising channels, pausing to listen for advertisements. The precise time spent by the tuner within each channel is unspecified in the Bluetooth standards, but we have found that recent smartphone implementations switch between channels every few milliseconds.

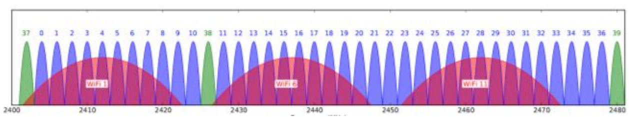

*Figure 2 shows the 40 BLE channels within the 2.4 GHz band. The green channels are the advertising channels used by BLE beacons. Three WiFi channels are shown for comparison (red).*

A BLE scan continues indefinitely and each advertisement is reported as it is received. If a scan lasts longer than the beacon interval, multiple sightings of that beacon will be reported. Some current mobile operating systems report each *connectable* beacon only once per scan. In this work we used *non-connectable* beacons to avoid this issue. For micro-location (proximity) applications all that is required is to listen for advertisements and take the strongest advertisement over some arbitrary period as coming from the nearest beacon. Importantly, 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, and we exploit this here to provide extra insight into the behaviour of BLE signals indoors. Note that a device agnostic solution must not assume this channel information is available.

**Fast Fading Effects**

Figure 3 demonstrates BLE fading due to interference in the spatial domain. The iPhone was moved across a 3 m length, away from a BLE beacon and two WiFi access points using a simple conveyor belt in a small room. The test was performed out of working hours to give a more stable radio environment. The cluttered space contained many surfaces from which signals could reflect, including walls, the floor and ceiling, the conveyor belt, furniture and miscellaneous objects.

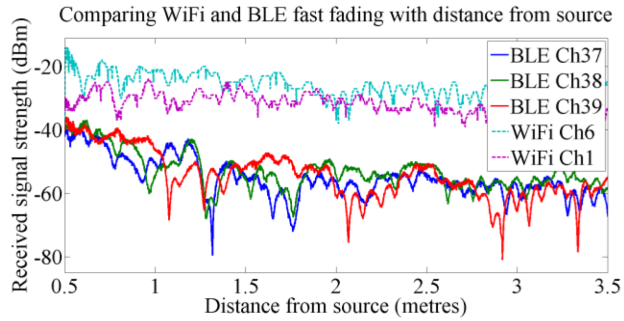


*Figure 3 shows the RSS variation over both time and distance for an iPhone moving on a slow conveyor belt away from a BLE beacon and two WiFi Access Points. The motion was so slow (around a millimetre per second) that velocity Doppler effects can be ignored.*

Deep multipath fades are evident in all three BLE channels, with 30 dB drops in power across just 10 cm of movement. Importantly, the different channels exhibit fades at different spatial positions. The exact distances travelled by reflected signals to cause destructive interference is dependent on the signal wavelengths and so fades occur at difference positions for different advertising channels, with their significantly different centre frequencies. The fades are notably less severe for WiFi.

From a signal fingerprinting perspective, deep fades present a challenge since the RSS can vary so dramatically over a spatial range that is smaller than the expected positioning accuracy of the system. The problem is amplified if the receiver does not report the channel on which an advertisement is received. In that case the reported BLE RSS is effectively drawn randomly from one of the three advertising channels, resulting in an apparent high noise level and very rapid fluctuations in signal power, even for a static environment. Understanding and dealing with these large fluctuations is thus key to producing an accurate BLE fingerprinting system.

To investigate this we used a ray-tracing simulator and a simple 3D model of the environment. Only first-bounce reflections were simulated. The signals were constructed by considering a set of monochromatic waves with random initial phase spread across the desired bandwidth and the total power in the channel was determined by summing up the total power of all of these individually-interfering carriers. An example output from this simulator is shown in Figure 4, comparable to the experimental output shown in Figure 3.

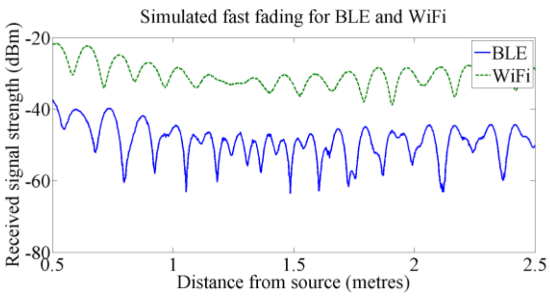


*Figure 4 shows a simulated conveyor belt experiment for a single WiFi channel and a single BLE channel*

The fact that signal fading at a given spatial location varies with frequency explains why the depth of fades in the overall reported signal strength reduces as the bandwidth increases. This is demonstrated in Figure 5, which shows the output of a simple simulated experiment where only one reflecting surface exists. An arbitrary point has been selected along the path that contains both the line of sight and the reflected signal, and the radio spectrum across the entire 80MHz band measured at that location is plotted. Some frequencies experience constructive interference, and some destructive. As the simulation is of a simple single-reflection experiment there is a sinusoidal transition between these states. The wavelengths in this band range from 12.1 cm to 12.5 cm. Therefore once the signal has propagated about 2 metres from the source the frequencies at the extreme ends of the spectrum are out of phase (2 metres represents 16.5 wavelengths for 2.4 GHz and 16 wavelengths for 2.48GHz). Therefore if two copies of the signal interfere, one having travelled 2 metres further, there will be constructive interference at one end of the spectrum and destructive at the other.

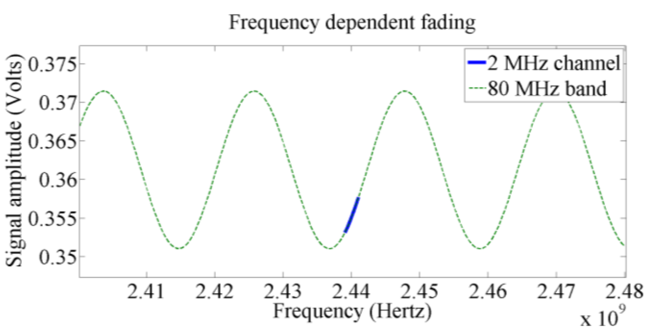


*Figure 5 shows the spectrum of the received signal amplitude across the 2.4 GHz ISM band for a simple multipath interference event (a reflection coming straight back along its original path). An example channel occupied by a BLE beacon is highlighted in blue.*

As we extend this idea to longer path length differences the number of constructive and destructive events through the spectrum increases, Figure 5 is based on a reflector 7 metres from the source. As we can see from Figure 5, if the entire band is used to calculate the total signal power, then small motions will have no effect on the overall calculated power, as the average is taken over many oscillations of the sinusoid. Narrow channels, such as the 2 MHz BLE channel, will however report an average power that is highly dependent on the current locations of these peaks and troughs through the spectrum. The path length differences of interfering signals need to exceed 75 metres before the oscillations in the radio frequency spectrum are shorter than 2 MHz, and the BLE bandwidth starts to provide a level of multipath resilience.

For most typical indoor environments, the path length differences caused by reflectors (walls, ceiling and floor) are usually large enough to dampen the frequency selective fading phenomena for the 20 MHz and 40 MHz WiFi channels (and future 5G WiFi will makes use of 80 MHz and 160 MHz channels, which will improve matters further). However, the coherence length of the 2MHz BLE channels is much longer than these typical length scales. Hence we expect to see much larger fluctuations from fast fading multipath interference with BLE indoor positioning than WiFi, as observed above.

**Corridor test**

A BLE beacon (set to 20Hz advertising rate) and WiFi access point were placed at the far end of a 45 metre corridor (see Figure 10) and two smartphones (an iPhone and an Android-based Samsung S4) were mounted to a pedestrian who walked away from the devices at a slow pace, and then turned around and slowly walked back. BLE data were logged with both devices; WiFi could only be logged using the S4. The WiFi data and iPhone BLE data is shown below in Figure 6. As expected from the previous analysis, the WiFi data exhibits lower apparent measurement error than the BLE data as it provides great resilience to fast fading in environments of typical indoor dimensions.

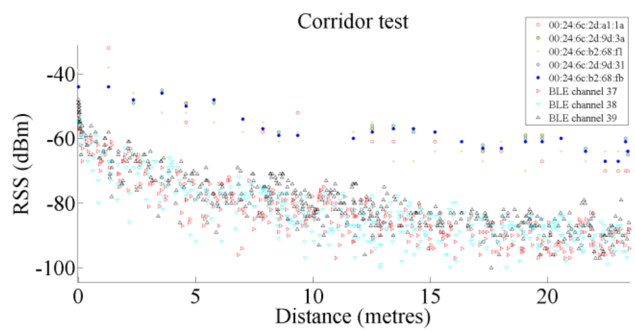


*Figure 6 shows the WiFi RSS data (circles) and the iPhone BLE data separated out by channel number (triangles) as the user moved away from the transmitters.*

The S4 BLE data displayed the expected fall and subsequent rise in RSS for the roundtrip walk (see Figure 7). However, we also observed a small but significant set of spurious measurements approximately 20 dB higher than expected. After some investigation we discovered that turning the simultaneous WiFi scanning off removed these outliers (see Figure 8).

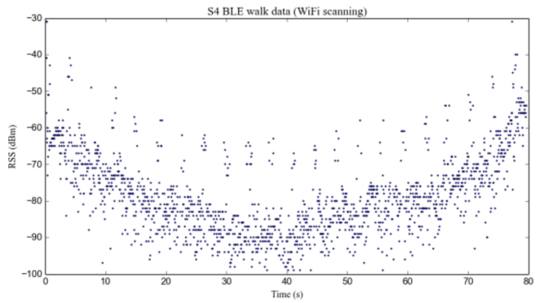


*Figure 7 shows BLE data for a walk away from, then back towards, a beacon using the S4 handset with WiFi constantly scanning*

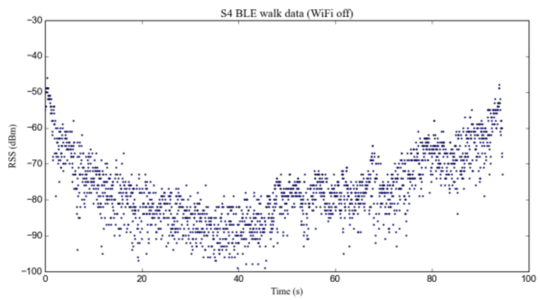


*Figure 8 shows a repeat of the experiment shown in Figure 7 but this time with WiFi scanning disabled*

These spurious values would be highly detrimental to fingerprinting if not filtered from the data. The issue appears to stem from the use of active Wi-Fi scanning (rather than passive) in the latest version of Android (4.4.4). A conclusion that can be drawn at this point is that it may be useful to switch off all radios that are not being used while RSS fingerprint measurements on a particular radio band are being recorded.

**Multipath Mitigation**

To aid accurate BLE fingerprinting performance we need to ideally reduce the large measurement variation to the levels of WiFi (or better). Smoothing could be achieved by taking the mean or median of a batch of data, with a choice driven by the asymmetry of the distribution of samples around the true value. The batch size is also limited by many factors such as the beaconing rate, the receiver speed and the desired positioning accuracy.

In order to assess the effect of window size on the BLE RSS error data from the corridor tests was examined. The data was segmented into batches of consecutive samples and the mean value calculated. The difference between pairs of consecutive mean values was recorded and the standard deviation of this new distribution calculated. Different window sizes were tested. As the RSS is expected to vary smoothly down a corridor in line of sight conditions once fast fading multipath interference has been mitigated, then this standard deviation should tend to a small value as multipath errors are removed. The result of this analysis is shown in Figure 9.

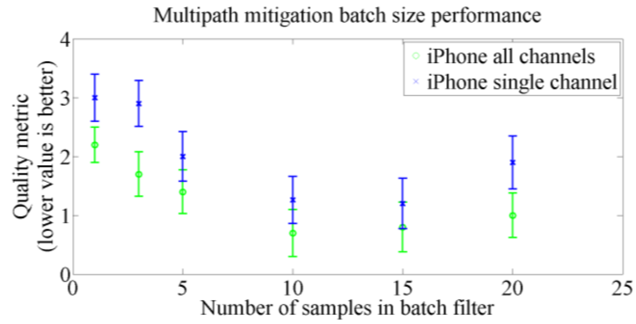


*Figure 9 shows the effect of batch window size on multipath mitigation performance for iPhone data*

The test suggests that batch smoothing exhibits noticeable improvement up to a batch size of around 10 samples, without noticeable improvement above this value. If the batch is allowed to become too large then the user motion will be appreciable during the windowing process, smearing the measurements across a distance larger than the potential accuracy of the system for static batch measurements. Processing data from all channels shows an improvement over single channel processing, this may due to the fact that the batch window can be populated three times faster if all channels are used, therefore the receiver moves a much shorter distance during the smoothing process.

The batch size that is most appropriate in practice depends on the beaconing rate and the speed of the user (slower users can exploit lower beaconing rates to gather the same number of samples in unit distance travelled). The beaconing rate affects the battery life of the BLE beacon, and for most iBeacon purposes will typically be set to an advertising rate of a few Hertz. For positioning purposes it is clear that good multipath mitigation is highly dependent on the properties of the receiving device and the beaconing rate. During our experiments we determined that 10 Hz beaconing and 1 second batch processing of median or mean values produced the best (smooth and repeatable) RSS profiles.

It was observed that taking the mean or median of the iPhone datasets to provide a single RSS metric produced very similar results. The highly skewed S4 data was filtered better by taking the median of a batch window than the mean.

## IV. GEOMETRY

An advantage of BLE over WiFi is the flexible deployment options it provides. BLE beacons are very small (typically the battery dominates the volume of the beacon) and can be placed anywhere, unlike WiFi access points, which are typically located near power sources and are generally much bulkier than BLE beacons. Since WiFi access points are also usually located in order to maximise signal coverage for minimal infrastructure deployment, they are seldom located ideally for radio positioning. For example, given a large square open area such as a canteen, a WiFi Access Point may be located in the centre of the ceiling for best coverage, whereas optimal radio positioning performance would instead by provided by a set of transmitters distributed around the perimeter of the region. BLE has the flexibility and portability to allow good signal geometries for radio positioning to be provided as needed.

## V. FINGERPRINTS AND MAPS

WiFi measurements are returned by smartphones at a rate of around 1Hz or slower as a batch of data representing the full scan of the whole band. BLE measurements are returned individually as soon as they are detected. Fingerprints are a batch of data that identify the region of space where they were recorded, and so the BLE measurements must be batched together intentionally to form an RSS fingerprint. The choice of the width depends on a series of factors, including movement rate, fast fading and beaconing rate. The desire for metre-level positioning suggests that the windows should not exceed 1 second, as a pedestrian will walk further than 1 metre in this time. 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.

If the channel information is unavailable (as per the official BLE specification), then we must aim to sample data from all three advertising channels for each beacon in each window. We choose a window that provides the handset with a chance to scan across all three channels, and hope that we have received samples on each. This requires a minimum of three samples per beacon per window, but of course the more samples we have the more likely we are to achieve a good result. This places a constraint on the beaconing rate correlated with the expected walking speed of the user being track. Since it is easy to remove data manually in post processing but not to add more, we set a high beaconing rate of 50Hz and a fingerprint window size of 100 ms in order to satisfy all of these constraints.

Fingerprint databases are commonly constructed by manually visiting a series of survey sites and manually taking readings at each. However, because the Active Bat system [6] offers high-accuracy ground truth position, we chose to construct the maps using data collected during the walking experiments. It is also possible to construct fingerprint maps using Simultaneous Localisation and Mapping [5]. Each fingerprint was assigned a position using the ground truth and we used Gaussian Processes regression [7] to generate a continuous signal strength map per source. For BLE, fingerprints were formed using the various fast-fade and smearing mitigation techniques described in the previous section. Note that we selected an offline time window and fast-fade mitigation scheme that matched the online algorithm— i.e. the maps were based on the same fingerprint construction technique as they were used for.

**Positioning**

A Bayesian estimator provided the positioning solution on subsequent walks. The operating region was divided into a grid with square cells of length 1 m or smaller and the probability of a given fingerprint corresponding to each cell was determined for each epoch using the Euclidean distance:

$$F = \sqrt{\frac{\sum_{i=1}^{N}(R_i - M_i)^2}{N}} \qquad \textit{Equation 1}$$

for current fingerprint $R$ containing RSS measures for $N$ beacons and the value $M$ extracted from the coordinate of interest from the signal strength map for the corresponding beacon.

This fingerprint distance 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

$$L = e^{-\frac{F}{2\sigma^2}} \qquad \textit{Equation 2}$$

where $\sigma$ is the standard deviation associated with the fingerprint measurement noise. The Gaussian kernel is well suited to the error distributions following the use of a multipath mitigation scheme.

Two priors were tested, a uniform prior at every epoch, and a prior based on the previous epoch's posterior, to enable a tracking mode. The uniform prior carried no correlations through time, and so represents the performance of an acquisition position estimate at every epoch. This is referred to as "one shot" positioning. The tracking mode reduces the effects of sporadic errors in the fingerprint measurements pulling the user far from the true location, as it is assumed that the new posterior distribution will be close to and overlap with the previous one. Note that this tracking mode is only appropriate for high beacon rates and good signal coverage such that it is a valid assumption that the user moves only a small fraction of the length scale of the posterior distribution between measurement epochs.

Once a posterior distribution was calculated, we estimated the position (and hence the error) using the maximum value (i.e. maximum a posteriori (MAP) probability) and also the weighted mean of the posterior (i.e. Minimum Mean Square Error (MMSE)). In general the results were very similar, except when the posterior was multi-modal, or described a sickle shape.

## VI. FINGERPRINTING COMPARISON - EXPERIMENTAL SET UP

An analysis of the performance of indoor positioning using signal fingerprinting was conducted within the Computer Laboratory at the University of Cambridge. The experiment provided a comparison between WiFi and BLE fingerprinting using the Active Bat positioning system as a ground truth reference. Active Bat provides a 3D positioning accuracy of around 3 centimetres and provides a position estimate at a 3Hz update rate.

The experiments were carried out in the 45m by 12m section of the building that had Active Bat coverage. We made use of the established WiFi access point deployment, with access points positioned at the two ends of the experimental area, and one halfway down the corridor. There was also weak WiFi signal coverage from access points in other. We deployed 19 BLE beacons in the same area (Figure 10). An attempt was made to locate the BLE beacons in realistic locations for a typical commercial use case, i.e. mounted close to objects or items of interest, rather than being uniformly distributed specifically to ensure maximum signal coverage in a cellular fashion.

BLE RSS measurements were collected using both an Apple iPhone running IOS 7 and an LG Nexus 4 handset running Android 4.4.2. The former also provided channel information for each received advert, which was not available in Android; the latter recorded WiFi RSS at approximately 1 Hz, which was not available in iOS. The experiments consisted of a two lengthy (5—18 minute) walks in the test area, along routes that were not predetermined. The two walks were taken approximately one week apart.

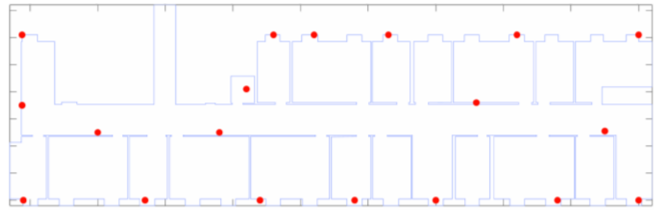

*Figure 10 shows the locations of the BLE beacons within the test area*

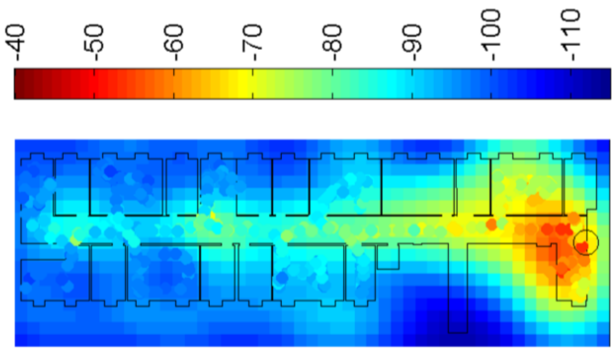


*Figure 11 shows an example BLE signal strength map using Gaussian Processes Regression. The training data can be seen as coloured circles. The black circle shows the location of the BLE device, that information is not needed to produce the coverage map. The colour bar scale is in units of dBm.*

The experimental 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. As a typical desire for indoor positioning using fingerprints is good acquisition performance (rather than relying on continuous tracking) we considered the performance provided by “one shot” fixes, as well as by a separate tracking solution.

## VII. FINGERPRINTING COMPARISON – RESULTS

We used data collected in the first walk data to generate a WiFi fingerprint map that was then used to estimate the user’s position for the data from the second walk. This formed a baseline to compare BLE against. For reference the positioning error for a WiFi tracking scheme was less than 8.5 m 95% of the time, this performance was limited by the poor signal geometry afforded by the existing WiFi infrastructure available in our laboratory. The advantage of BLE lies in the ability to freely locate beacons to provide good signal geometry.

Repeating this analysis with BLE data rather than WiFi achieved an accuracy of less than 2.6 m 95% of the time. The boosted accuracy is in part due to the greater density of beacons, their fast beaconing rate, their high power output, and their better geometry. However, we argue that the density and geometry would be expected to be much higher than WiFi in a BLE beacon rollout. We have post-processed the data using reduced beacon rates and transmission powers and found that near-optimal results were possible had we used 10 Hz beacons and power levels around -20 dBm for the 19-beacon deployment. Slower rates and lower power degrade the positioning result significantly, although rarely below the WiFi baseline (which we again attribute to the density and geometry)

Figure 12 illustrates the value of our multipath mitigation when positioning with BLE signals. The left hand image shows a position fix without multipath mitigation, the right shows the same position fix with a 0.5 second median filter applied to the BLE input data (each batch processing window contained 10 measurements). It is clear that the multipath mitigation improves the ambiguity in the posterior distribution.

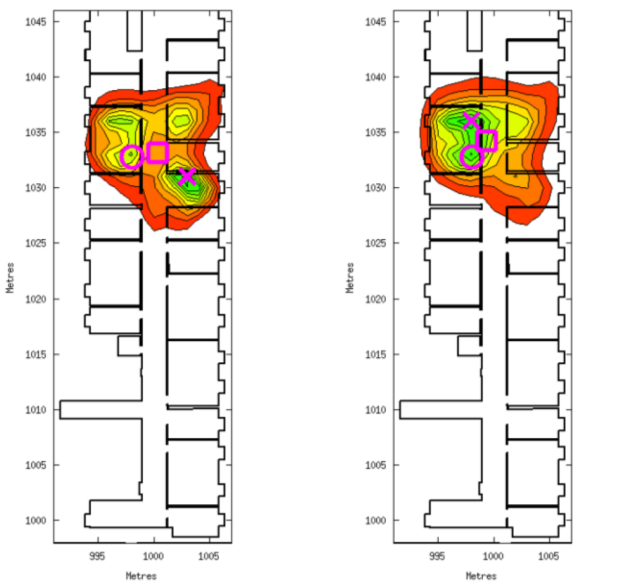


*Figure 12 shows the benefit of multipath mitigation processing on BLE positioning. The left image is without multipath mitigation and exhibits multimodality and reduced positioning performance compared to the right image. The true location is shown by the pink circle, the pink square and pink cross show the Bayesian MMSE and MAP estimators respectively.*

The high transmission powers and dense deployment also allowed us to asses the effect of fingerprint size on positioning performance (see Figure 13) and it was determined that there is little benefit in having more than 6-8 beacons available for a given fingerprint (assuming that they are not co-located).

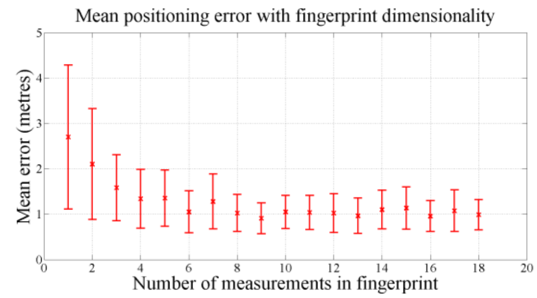


*Figure 13 shows the effect of fingerprint size on position error for BLE experiments. The error bars represent two standard deviations from the mean.*

## VIII. BLE DEPLOYMENT DENSITY

Our testing has demonstrated that smartphones reliably report BLE measurements with RSS values as low as -100 dBm. This sensitivity should be taken into account during a large scale beacon deployment, since it potentially allows for a lower density than might be expected. We concentrated our studies on the effects caused by interior walls and any associated fittings (shelving, cupboards, etc). Latapy [8] has previously proposed that one should assume 1 dB of attenuation per metre of an indoor office/residential environment (accounting for furniture and walls) for broadcasts of similar frequency (cellular) to BLE

The data shown in Figure 14 were generated by placing a beacon in the end office of the test area and recording the measurements at known locations in each office along the corridor, increasing the number of internal walls between the receiver and source by one per measurement. We observe that each wall led to an additional loss of around 2 – 3 dB.

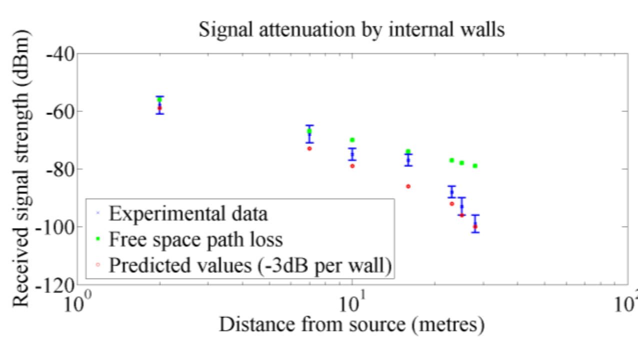


*Figure 14 shows the experimental and predicted loss per interior partition wall in our office environment.*

We propose the following rule of thumb to determine BLE beacon ranges indoors:

$$D = 10^{\frac{P_{min} + P_{Tx} - W \times A_{wall}}{20}} \qquad \textit{Equation 3}$$

The range ($D$) in metres depends on the minimum detectable power ($P_{min}$), the transmission power ($P_{Tx}$), the number of interior partition walls $W$ and the loss per wall, $A_{wall}$. A value of 3dBm per wall was appropriate for our office building. The power and loss values are in base-10 logarithmic units.

## IX. CONCLUSIONS 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 that available from existing WiFi infrastructure is possible even using a relatively sparse deployment of beacons once the characteristics of BLE signals are accounted for.

1. The low bandwidth of BLE makes it is more susceptible to fast fading, and so large RSS fluctuations, than WiFi. The use of three advertising channels by a BLE beacon, combined with frequency-dependent fading, can result in RSS measurements varying across a much wider range than the measurement noise for very small changes in the signal path length. This was confirmed in both simulated and experimental tests.

2. Smoothing the BLE RSS measurements by batch filtering multiple beacon measurements per fingerprint is necessary to account for the bandwidth and channel hopping issues. The batch window is determined by the user velocity, and best performance is provided by gathering a batch of measurements across a metre of user motion. Assuming typical walking pace, this leads to batch windows of 0.5 to 1 second in length.

3. Positioning accuracy increases with the number of beacons per fingerprint, up to a threshold of around 6–8. Beyond this there is no further improvement in positioning accuracy. Combining this information with the desired beacon power level steers the beacon density required for maximum positioning performance.

4. A rule of thumb has been provided to permit users to estimate their beacon ranges depending on transmit power and the number of interior walls.

5. There is some evidence to suggest that active Wi-Fi scanning and Wi-Fi network access can cause errors in BLE signal strength measurements. Careful consideration of the use of the Wi-Fi radio in a smartphone is required during BLE fingerprinting.

## ACKNOWLEDGMENTS

The authors would like to acknowledge the technical and financial support of the project sponsors, CSR Limited. They are also grateful to Reinoud Erhorst, who developed the conveyer belt apparatus and collected the associated data (Figure 3).

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