Does BTLE measure up against WiFi? A comparison of indoor location performance

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***Abstract*—Bluetooth low energy(BTLE) is an emerging low-power wireless communication technology which is expected to be of great potential in the next few years. In this paper, we propose several empirical propagation models for BTLE in different conditions: indoor/outdoor, line-of-sight (LOS) / non-line-of-sight (NLOS). Then we compare the propagation characteristics between BTLE and WiFi. It is demonstrated in our experiments that BTLE propagation model can better relate RSSI to range than WiFi, which indicates that BTLE can be more accurate when used in localization scenarios. Extensive experiments in indoor environments have been conducted to explicitly compare the localization accuracy between BTLE and WiFi with nearly identical external environments and conditions. BTLE is proved to be more accurate than WiFi by around 27 percent. We also discuss various underlying reasons why BTLE outperforms WiFi in localization scenarios. We believe that such an accurate and low-cost technique will enable practical and ubiquitous indoor localization.**

Keywords*—*Localization, indoor, BTLE, WiFi, propagation model.

I. Introduction

Accurate indoor localization is an extremely important avenue of research and development, for which no clear solution currently exists. For a particular technological solution to be scalable and widely adopted, it is essential to exploit existing hardware in consumer devices like smartphones. To date, research and development has primarily focussed on the use of WiFi for positioning. However, newer phones are incorporating BTLE (Bluetooth 4.0) which has a number of characteristics that make it attractive for indoor positioning. The major hardware vendors (e.g. Apple, Qualcomm) have recently released frameworks that exploit the Proximity (PXP) mode of BTLE to provide microlocation. This allows the presence/absence of a device within a certain radio range to be detected. Based on this, notifications can be pushed to the user's smartphone, such as special offers.

WiFi is the most widely used approach for indoor positioning, due to the widespread availability of deployed infrastructure. Importantly to note, the infrastructure access points are deployed for reasons of communication/connectivity and not for localization. Localization is thus an opportunistically derived byproduct of an existing infrastructure deployment in a building. Typical indoor WiFi errors range between 3 and 6 m, depending on the experimental protocol, site and technique adopted.

In this paper, we perform direct comparisons between WiFi and BTLE in order to provide an objective overview as to which technology is best suited for indoor localization, through an extensive measurement campaign. We derive channel models in both indoor and outdoor settings, which we expect to be useful to other researchers. Given that both modalities operate in the 2.4 GHz ISM band one would expect similar performance. However, we demonstrate, somewhat surprisingly, that BTLE can outperform WiFi in a like-to-like trial, with an RMS error of 3.8 m compared to 5.2 m, a 27% improvement.

We demonstrate the following contributions in this paper:

- A channel model for BTLE, both indoors and outdoors
- A like-to-like comparison between WiFi and BTLE localization in the same environment
- A discussion on the various reasons for the differing performance between WiFi and BTLE

The remainder of the paper is structured as followed: Section II presents an overview of location techniques in general; Section III discusses the key differences between BTLE and WIFI; Section IV shows the propagation model of BTLE in outdoor and indoor environment and highlights the differences between BTLE and WIFI; Section V contrasts a series of experiments for indoor localization by BTLE/WIFI and analyses the underlying reasons for the results; Finally Section VI concludes the paper.

II. Background

It can be largely claimed that for the majority of use cases, GPS has essentially "solved" the problem of accurate outdoor location. However, due to the RF complex environment of typical indoor spaces, there is no clear solution for indoor location. Due to the potential commercial importance of accurate indoor location, a great deal of research and development has been conducted in this area. There are three broad categories of indoor localization technologies, namely inertial navigation (e.g. using a combination of accelerometers, gyroscopes and magnetometers) [1]–[3], mechanical waves (e.g. ultrasound [4]) and electromagnetic waves (e.g. using the visible, infrared, microwave and radio portions of the EM spectrum). Among all of these technologies, schemes using radio spectrum are very popular. RF techniques use range measurements obtained from multiple anchors to evaluate position through a process of trilateration. Ranges can be

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measured accurately using time-of-flight or inferred through measurements of the received signal strength (RSSI). To date, the latter approach is more common, as RSSI is typically reported as a metric of link quality in any case. However, as many papers have shown, RSSI is impacted greatly by the environment itself, with multipath and scattering leading to large ranging errors.

Technologies used include WiFi [5]–[8], UWB [9]–[11], Bluetooth [12], [13], and ZigBee [14]–[16]. WiFi is the most widely adopted technology for indoor location on smartphones, but typical accuracies are in the range of 3-5 m, which is too coarse for many positioning applications. However, an advantage of WiFi based positioning is that it does not require an additional infrastructure, as APs used for communication are exploited. Approaches for WiFi positioning often use a "fingerprinting" approach as the indoor propagation model is hard to predict accurately. These approaches, including Radar [6] and Horus [17], typically involve an initial map building phase, in which the area is surveyed and the signal strengths received at each location from the various APs are recorded in a radio map. Based on the map, users can use determine their own location by comparing the signal strengths vectors that they receive from APs with those in the map.

Bluetooth has been a common feature on mobile phones for over a decade as protocol for connecting to peripheral devices like handsets and for file transfer. However, the older standards (1.0, 2.1) involved association times of tens of seconds, which precluded their use as a location technology. In fact, this paper states that "Bluetooth is poorly suited to the purpose of fine-grained, low latency location inference due to specification and hardware limitations, and note that the movement speed of mobile devices is an important factor in calculating available bandwidth" [18]. To tackle the major issues of complex protocols, slow association and high power consumption, Nokia developed Bluetooth Low Energy (BTLE) which was previously marketed as Wibree. The use case of BTLE is for smartphones and other devices to be able to connect and interface with low power wearable devices like fitness monitors, which can be powered by coin cells. As an emerging technology, little research has been conducted on the application of BTLE to accurate indoor location. However, a very recent paper shows BTLE has some special characteristics such as high scan rates and very low power operation [19].

III. Comparison between WiFi and BTLE

The two most common technologies that can provide RSSI measurements suitable for the purposes of localization in a consumer grade smartphone are WiFi and BTLE. Table I outlines some key differences between these two modalities, which are expanded on in the following subsections.

TABLE I. Comparison between WiFi and BTLE

	WiFi	BLTE
Bandwidth (MHz)	22	1
Modulation	DSSS/OFDM	GFSK/FH
Tx Power (dBm)	20	1
Typical Scan Rates	1 Hz	30 Hz
Energy Consumption	High (1W)	Low (30mW)
Unit cost	\$30	\$5

A. WiFi

WIFI is currently the most dominant indoor location technology as a result of its widespread deployment as an infrastructure communication service. However, by its very virtue of being a service for communication, the placement of APs is not necessarily optimal for localization. WiFi is a high speed (54Mbps), high power (100mW typical AP power) modality. One major limitation of WiFi for positioning is the low scan rate. This is a combination of the interbeacon time and the dwell time in each channel, which typically results in a scan rate of 1 Hz on typical smartphones. Typical WiFi localization accuracies are in the order of 3-5 m, depending on the technique used to estimate location. For many applications, the performance of WiFi location is not precise enough, which in turn has limited widespread consumer adoption.

B. BTLE

Bluetooth low energy (BTLE) is an emerging low power (1mW typical transmitter output) technology that also operates in the 2.4 GHz ISM band. It has been driven by the need for consumer devices like smartphones to be able to interface with low power sensors (like heart-rate monitors and smart watches) without requiring the long handshake period of classic Bluetooth 2.2. In many ways it is a simpler version of Zigbee in terms of lack of mesh networking functionality. Rather than using correlator based receivers (spread spectrum), BTLE uses GFSK which is much simpler to transmit and decode. Modern smartphones (Apple 5S, Google Nexus 5, Samsung S3 etc) come equipped with BTLE transceivers, resulting in an ever growing user base. BTLE devices are very low power - a device sending beacons at a rate of 10 Hz can run for over a year off a coin cell. In addition they are substantially cheaper than WiFi. The combination of low power and low cost allows for many BTLE transmitters to be installed in strategic locations simply by sticking the devices onto walls, ceilings and other objects.

IV. Propagation Model

In this section, we experimentally derive a wireless propagation model for BTLE and compare it against the propagation model for WiFi, obtained in the same environments. Of key interest is how well each model relates RSSI and distance, as a more predictable and reliable model will yield gains in location accuracy.

A. Attenuation model

We employ the commonly used lognormal attenuation model, which relates the RSSI to distance d with the following function:

$$RSSI(d) = RSSI(d_0) + 10n\log(\frac{d}{d_0}) + X_\sigma \tag{1}$$

where $RSSI(d_0)$ is the RSSI (dBm) at the reference distance d_0, n is the path loss exponent, and X_σ is the zero-mean Gaussian noise with variance σ^2. The path loss exponent has a theoretical value of 2 for unobstructed free space propagation, corresponding to a loss of -20dB/decade. However in real environments path loss typically is much higher due to shadowing and multipath interference.

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B. Experimental Setup

To derive a channel model for BTLE, two experiments were conducted, the first outdoors and the second indoors. The hardware used for both experiments was identical. Transceivers were nRF51882-EK from NORDIC, which provide BTLE functionality through a software stack on top of a configurable GFSK radio. The devices are equipped with chip antennas. A custom firmware image was written which allowed the BTLE transceivers to send and receive beacons at the rate of 50 Hz. The transmitter was powered by a coin cell and the receiver was connected by a USB cable to a laptop which recorded the RSSI measurements. Tranceivers were elevated to a height of 1 m above the ground.

The first experiment was conducted on an open field at the University of Oxford's park. Samples were collected at 50 cm intervals, up to a range of 20 m. The impact of receiver orientation was also investigated, as this is an uncontrolled parameter in positioning applications. At any point, 200 RSSI measurements were collected. The second set of experiments were performed in an indoor office environment, investigating the impact of line-of-sight (LOS) obstructions such as doors and walls. Again, 200 samples were conducted at 50 cm intervals. For comparison, WiFi measurements were also obtained, using a pair of Huawei Ascend mobile phones, placed in the same locations as the BTLE transceivers and at the same height.

The distance and RSSI measurements were used to derive a best-fit model.

C. Results

Outdoor The RSSI measurements from the outdoor experiment are shown in Fig. 1 for three different angles of receiver orientation. The correspondence between RSSI and distance is strong, showing a good trend, but flattening off once the signal level dropped below -80dBm. The orientation angle of the transceiver pair impacts the intercept, with the angle of 90° suffering from the greatest loss. This is because the antennas are not matched in orientation. As the paper [20] has done a lot of work about WiFi signal propagation at 2.4GHz and as the outdoor propagation model contributes little to indoor localization, we only show the BTLE propagation model in the outdoor environment.

The derived best-fit parameters are shown in Table II, where the parameter R^2 denotes goodness of fit to the standard propagation model. Measures of R^2 typically summarize the discrepancy between observed values and the values expected under the model. As a result, the model is better, if the value of R^2 is closer to 1. From the Table II, we can find that the lognormal attenuation model is very suited for BTLE in outdoor environment without shadowing and multipath interference. The results demonstrate that the path-loss exponent for all three orientations varies between 2.47 and 3.00. Similarly, the paper [20] demonstrates that the path-loss exponent for WiFi in free space varies between 2.63 and 3.00, close to the free space prediction.

Indoor

The measurements from the indoor experiment are shown in Fig. 2, with the model parameters shown in Table III.

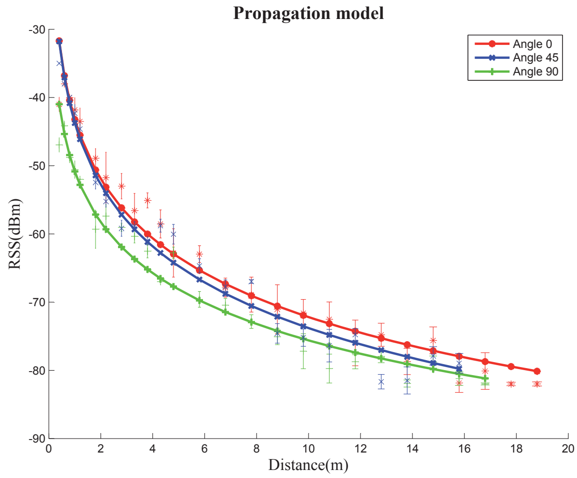

Fig. 1. BTLE propagation model in outdoor environment. There are three propagation models with different angles of receiver orientation, namely 0°, 45° and 90°. The error bar represents 95 percent confidence interval.

TABLE II. DERIVED PARAMETERS FOR OUTDOOR MODEL

Angle	n	$RSSI(d_0)$ (dBm)	R^2
0°	2.89	-43.2	0.9645
45°	3.00	-43.7	0.9638
90°	2.47	-50.0	0.9741

Interestingly, the path-loss exponent for BTLE indoors is lower than outdoors, showing less loss with distance. However, as the intercept corresponds to a much lower reference power, the maximum indoor reception range is lower. The reason for the lower path loss exponent could be that the tests were acquired in offices and corridors that could be acting like a wave-guide, resulting in constructive interference. The WiFi model shows that there is a very big difference in path-loss exponent between the LOS and NLOS case. This large difference makes calculating distance from RSSI relatively inaccurate. What is more, the value of R^2 and variance shows that propagation model for BTLE better relates RSSI to range compared with WiFi.

TABLE III. DERIVED PARAMETERS FOR INDOOR MODEL

Technology	Setup	n	$RSSI(d_0)$ (dBm)	R^2	var(dBm^2)
WiFi	LOS	2.13	-36.1	0.492	20.02
WiFi	NLOS	3.33	-42.7	0.363	5.55
BTLE	LOS	1.98	-52.0	0.775	16.75
BTLE	NLOS	1.35	- 72.3	0.872	4.68

D. Summary

These set of experiments show that as far as the relationship between distance and range is concerned, BTLE is a more suitable technology as the model better relates RSSI to range. This could be due to the lower transmitter power of BTLE which bounds the maximum achievable range in an indoor environment. In addition, the simpler receiver architecture of BTLE could help, as it does not have sophisticated techniques for dealing with multipath such as MIMO or RAKE diversity processing.

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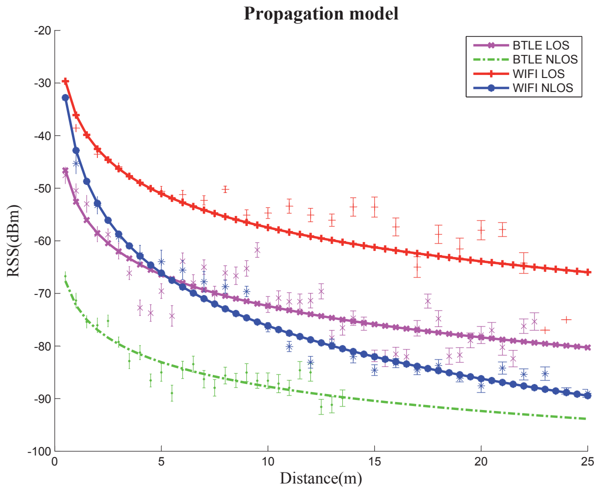

Fig. 2. WiFi/BTLE propagation model in different environment. There are two different BTLE propagation models, namely BTLE LOS and BTLE NLOS propagation model. There are two WiFi propagation models, namely WiFi LOS and WiFi NLOS.The error bar represents 95 percent confidence interval.

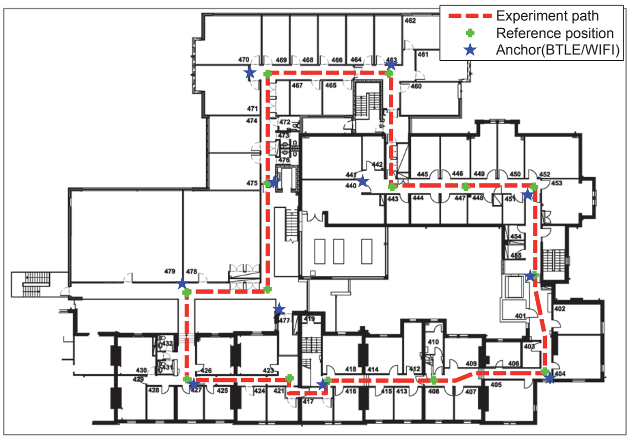

Fig. 3. The locations of the anchors, reference points, and the continuous trajectory at the experiment site (68 $\times$ 48 m^2)

V. Indoor Location Comparison

In this section, we conduct experiments in an indoor office environment to provide a direct comparison between WiFi and BTLE for the purposes of indoor localization.

A. Experimental Setup

These experiments were conducted in the fourth floor of Wolfson building at University of Oxford, as shown in Fig 3. To make explicit comparisons between the BTLE and WiFi performance in indoor localization, we deployed 11 BTLE and the same number of WiFi anchors at exactly the same positions in the experiment site. We randomly chose 14 reference positions at the experiment site to test the accuracy of BTLE and WiFi based localization. In addition, we also generate continuous trajectories in the department to test the responsive tracking performance of both techniques. The location of the anchors, reference positions, and the trajectories are shown in Fig. 3.

We took measures to avoid possible external elements that might interfere the experiments. To avoid the interference of the ground, e.g. wires and possible coupling effects, all 11 BTLE anchors (nRF51882-EK from NORDIC) and WiFi anchors (Huawei U8160) were deployed around 1 meter off the ground. We also kept the antennas of all BTLE anchors and WiFi anchors towards the same orientation during the experiment process to avoid the possible orientaion variations. To further reduce the external interference like people walking around, we simultaneously collected the BTLE data and WiFi data with a Samsung galaxy S3 which is equipped with both BTLE and WiFi receivers.

To fully compare the indoor positioning accuracy of BTLE and WiFi, the experiments in this section were conducted in two steps. The first step is the comparison of static localization performance. In this step, the experimental participants stood still at the 14 reference positions and collected data from both BTLE and WiFi. Trilateration and Gaussian mixtures are employed to derive the estimated locations and then localization accuracy are computed. The second step aims at testing the responsive tracking performance, which requires the participants walking around the building with BTLE/WiFi receiver (Samsung galaxy S3) at hand. Then the collected data were fed into a particle filter with 2000 particles to get the estimated trajectories and corresponding accuracies.

B. Static Localization Performance

In this experiment, in addition to the comparison of accuracy, we also compare the variations of RMS errors with different number samples which reflects another crucial metric in localization with wireless signals – the robustness against multipath effect. To fulfill this task, we collected multiple RSS samples of BTLE and WiFi signals and then computed the localization performance with different number of samples.

As shown in Fig. 4, BTLE outperforms WiFi in terms of both accuracy and robustness in static localization experiments. It is observed that the average RMS error for BTLE with different number of samples is around 3.8m while the average RMS error is 5.3m for WiFi, which indicates almost 40 percent worse in RMS error performance. In addition, the maximum BTLE RMS error is less than 8 m in comparison with over 10 m for WiFi, which is around 25 percent bigger. Since the comparison in this experiment is performed at almost identical external experimental conditions, it is reasonable to claim that BTLE has a better performance in indoor localization in terms of accuracy and robustness.

C. Responsive Tracking Performance

To fully compare the indoor positioning performance, we also conducted experiments to compare the responsive tracking performance of of BTLE and WiFi. The ground truth trajectories in this experiment are shown in Fig 3. Since BTLE samples at 50 Hz compared with WiFi sampling at approximately 1 Hz, to make fair comparisons we merge (average) all the BTLE samples collected during 1 second to estimate one location. Then we fed BTLE and WiFi measurements to two identical particle filters with 2000 particles. In addition, we fused BTLE and WiFi measurements and used this as input to a further particle filter with 2000 particles, to assess if the combination of both modalities would yield performance gains.

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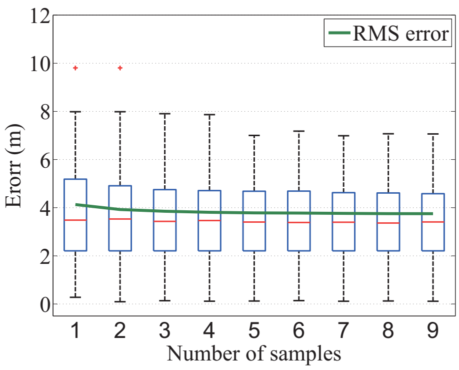
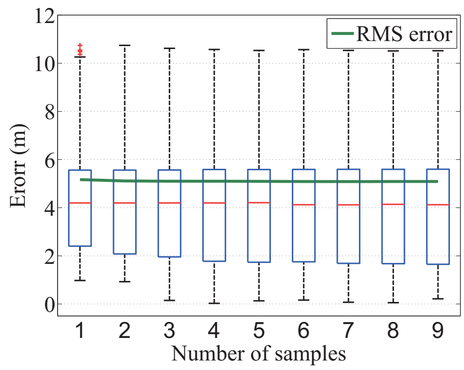
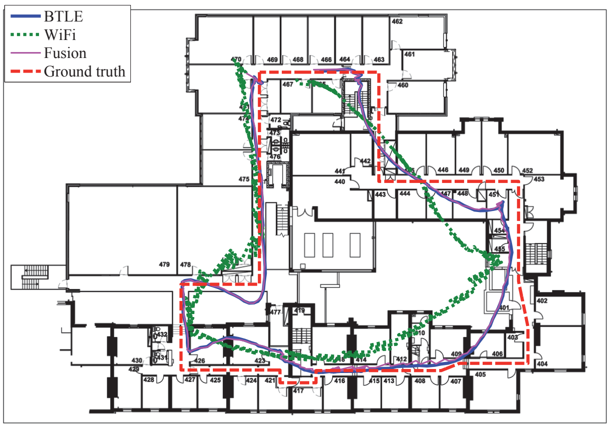


(a) BTLE localization error

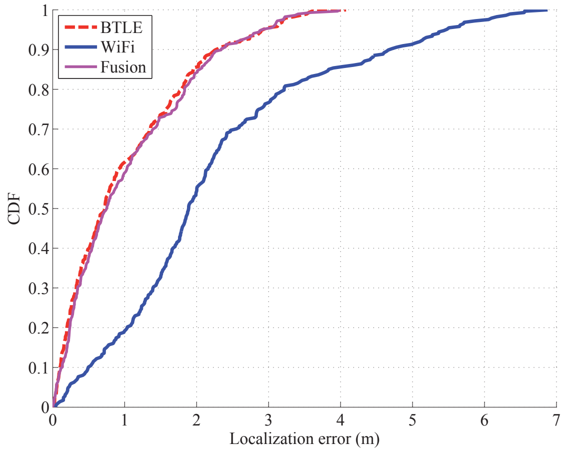


(b) WiFi localization error

Fig. 4. The BTLE outperforms WiFi not only in RMS error (BTLE: 5.2m, WiFi: 3.8m), but robustness against multipath effect as well – smaller variations in RMS error with the same number of samples.



(a) Ground truth and estimated trajctories



(b) RMS error CDFs of BTLE and WiFi

Fig. 5. The results of responsive tracking experiments, showing a) the ground truth and estimated trajectories, and b) the RMS error CDFs of BTLE and WiFi.

The experiment results are shown in Fig. 5. It is apparent from Fig. 5(a) that the trajectory estimated from BTLE is more accurate than the one estimated from WiFi. This is further proved in Fig. 5(b) with cumulative density functions of tracking errors. Meanwhile, the fusion of BTLE and WiFi contributed little to increasing performance beyond BTLE alone, suggesting that errors are correlated between the two technologies.

D. Discussion

It is very interesting and useful to have a discussion on the underlying reasons why BTLE is much better than WiFi in indoor localization while they work within the same spectrum range and similar transmission range.

Generally speaking, the reasons for the superiority of B-TLE in indoor localization over WiFi can be multi-fold. Three major reasons could be that BTLE has a) channel hopping mechanism, b) lower transmission power, and c) much higher sampling rate than WIFi.

The channel hopping, though not as frequent as Bluetooth 2.1, benefits BTLE in the sense of averaging out the interference in a given channel. For instance, if channel 6 has very large interference while other channels do not, then the interfered RSS samples only consist of less than 7 percent of all RSS samples. In addition, if the channel is severely interfered, the BTLE transceivers would hop to the next channel for communication, which completely skip the channel interference. However, WIFi cannot skip the interference becasue it has no channel hopping mechanism. As a result, the RSS of BTLE is “cleaner” than RSS of WiFi, which explains why the R^2 of BTLE model is much smaller than WiFi model in Section IV.

The lower transmission power of BTLE also contributes to the better performance of localization because it can reduce the multipath effect in some scenarios. Since the sensitivity of receivers are almost the same for BTLE and WiFi devices, in an extreme case the receiver can only hear the most powerful signal component, e.g. line-of-sight signal while all others are filtered out.

The benefits of higher sampling rate are apparent. It can

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be observed from the comparison of Figs. 4 and 5 that there is a bigger gap between BTLE and WiFi RMS error in responsive tracking experiments (1.9m) in Section V-C than in static localization experiments (1.5m) in Section V-B. This is because in responsive tracking experiments each RMS error of BTLE is estimated from every 50 RSS samples while each location of WiFi is only derived from 1 sample. A large number of samples make it possible to average out the occasional outliers caused by interference or multipath effect, which improves the tracking accuracy.

E. Summary

The results clearly demonstrate that BTLE is a more accurate technology for indoor location when compared in an equivalent experimental setup. Fusion between WiFi and BTLE did not lead to major gains in overall location performance, demonstrating that errors are correlated in a 1-1 setup. However, this is not to say that fusion will not lead to gains in general, as in a realistic deployment, it is unlikely that WiFi and BT APs will be colocated.

It must be noted that in a typical deployment, WiFi APs are placed at locations that provide good coverage for communication purposes, rather than for location. In addition, placement is also constrained by the availability of mains power.

VI. Conclusion

In this paper, we have presented a comprehensive analysis of the use of BTLE for indoor location, comparing directly with the currently dominant WiFi. It can be seen that BLTE is a more accurate location technology than WiFi, even when AP placement is identical. This is an unexpected finding, as due to their characteristics and frequency of operation it would be anticipated that they would be similar. It would be anticipated that due to the lower variance in signal strength over time, that BTLE will also yield gains over WiFi for positioning techniques based on fingerprinting. BTLE has a number of other advantages, including higher scan rates, lower power and the ability to be deployed unobtrusively on key objects and locations. In addition, BTLE transceivers are inexpensive so dense deployments are feasible. In summary, we expect that BTLE is likely to become the dominant indoor location technology of choice for smartphones in the coming years.

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