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Comparing the effect of different smartphone on the accuracy of wi-fi based proximity estimation approaches in an outdoor setting

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Abstract

Proximity estimation is a task that estimates the distance between a reference point and a selected object. Proximity estimation allows the possibility of creating applications that are based on proximity from the reference point. With the increased penetration of smartphone with multiple sensors, it is possible to utilize one of the many built-in sensors for proximity estimation such as Global Positioning System (GPS), Bluetooth Low-Energy (BLE), and Wi-Fi approaches in proximity estimation. The paper explores the approaches before expanding on utilization of Wi-Fi approaches to proximity estimation in a practical outdoor field test on multiple smartphone and mobile devices to examine the suitability and issues that may arise when utilizing the approach.

Keywords: Proximity Estimation, Wi-Fi, Received Signal Strength Indication, Smartphone

1. Introduction

Proximity estimation is a task that estimates the distance between a reference point and a selected object. Proximity estimation and the distance that is estimated from the reference point and selected object could be used for many potential real-world applications that exhibit group or flocking behaviors. One such application that could use the proximity estimate between the reference point and selected objects could be tour guide application. In this application, it would be possible to set the reference point at the tour guide, and use tourists in the group as selected objects. With this application it would be possible to check if the tour group are within a certain proximity range.

As smartphones and mobile devices have become ubiquitous and have a multitude of sensors, it is possible to use one of the various built-in sensors to estimate the proximity between the reference point and selected objects. Typical smartphones and mobile devices come embedded with many different sensors. Within the range of sensors available in those devices, a number of sensors could potentially be used for proximity estimation such as global positioning system (GPS), Bluetooth, and WiFi. Each of the sensors could be used for proximity estimation, but are suitable for different tasks and ranges depending on the nature of the sensors. For example, the GPS approach is suitable for estimation of long ranged proximity in an outdoor setting. GPS based approaches suffers from the fact that it is not suitable for indoor purposes, has a high error rate, and cannot be used in certain environmental conditions such as cloudy and overcast skies. For indoor usage, Bluetooth approaches and WiFi approaches are more suitable than GPS approaches due to the different nature of the approach. For Bluetooth approaches, based on the Bluetooth 4.0 specifications [1], it could be utilized as a beacon and any connecting Bluetooth enable device can register with the beacon and also be used to estimate the proximity to the device. One major advantage is that these devices can operate indoors. Though Bluetooth is suitable for proximity detection, it is geared mainly towards shorter range transmission. WiFi is an alternative that could be used to detect the proximity between the reference point and selected objects. WiFi is not as commonly used as Bluetooth approaches in proximity estimation. However, there is potential to explore the WiFi based approaches in proximity estimation usage in greater details due to the prevalence of WiFi devices, the potential longer range

$$d = acos[(sin(lat_2) * sin(lat_1) + cos(lat_2)) \dots * cos(lat_1) * cos(\Delta long_{21})] * R \quad (1)$$

of WiFi, and the possibility of setting up proximity estimation applications with existing infrastructure without requiring additional hardware [2]. Though there are potential benefits, it will come at the cost of higher power requirements and potentially lower accuracy in proximity estimation.

In this study, WiFi approaches in proximity estimation are explored in greater detail. The study aims to figure the effect of different smartphone and mobile devices and whether the WiFi embedded sensors of each of the devices have any effect on the accuracy of proximity estimation, and to explore additional issues that may arise when utilizing WiFi in proximity estimation applications. To control the effect of environmental parameters and its effect on the accuracy of proximity estimation via WiFi approaches, the experiment has been setup in an outdoor scenario.

2. Background

In the background section, proximity estimation approaches are explored in further details. Global Positioning System (GPS) approaches, Bluetooth approaches, and WiFi approaches are explored. For each of the approaches, the examination of the approaches required for proximity estimation where first explored, before discussion about the pros and cons of each approach when compared with each other.

2.1 GPS approaches

Using GPS sensors is one approach that could be used to calculate the proximity estimation between the reference object and the selected object. The GPS could be used to find the longitude and latitude which is the GPS coordinate of the reference object and of the selected object. By using one of the various distance formula calculation from two sets of GPS coordinates such as haversine [3], spherical law of cosines, or equirectangular approximation could be used to approximate the distance between the two selected points. Equation 1 contains the calculation for the spherical law of cosines. In the equation, the d is the distance in meters, whereas R contains the radius of the Earth which is approximated as 6,731,000 meters. The equation allows a quick approximation between two GPS coordinates with a few meters of error if the GPS coordinates are accurate.

Though GPS coordinates can be used for proximity estimation between the reference object and the selected object, there are a number of issues that GPS cannot address [4]. One of the issue is that GPS depends on satellite reception, and only works optimally in outdoor scenarios where the sky is clear. Another issue is that the GPS coordinate calculated depends on the quality of the GPS sensors [5] coupled with environmental conditions. The combination of the factors can lead to a high error between the detected GPS coordinate and the actual coordinate. One of the symptoms of the high error is that the calculated position can be off by many kilometers, and the results can be a significant distance when both the positions were not accurate. The phenomenon of the error is displayed in Figure 1, in which visually displays the GPS coordinates received over a period of time of a single non-moving subject which is highly erroneous. Coupled that with the fact that the GPS distance calculation approaches does not have a high degree of accuracy and granularity, makes the GPS approach unsuitable for proximity estimation for shorter distances. It has been reported that error rates on the best rates are from 5-50m [6], though the proximity estimation error can be far worse.

2.2 Bluetooth approaches.

Bluetooth technology is another popular approach in proximity estimation. With Bluetooth 4.0 specification or Bluetooth Low-Energy (BLE), there is the beacon technology [7] that can be used for proximity estimation. By placing a beacon at a certain spot, any Bluetooth enabled device can easily detect the beacon when in range and estimate the distance and proximity from the beacon to the Bluetooth device. Bluetooth proximity estimations have been explored on smartphones [8], in which reports good results.

For Beacon based devices, there are many types of devices. Typical Beacon devices are low-powered devices that are typically designed to operate on battery power. To increase battery-life, it is possible to set the device's transmission at low-power settings, which comes at cost of maximum range. For a typical beacon, the proximity range for is from 0-30m, though the range may be as short as 10m if the device is set to normal use as opposed to high power transmission. There are longer-range beacons in which can operate with a farther range though at the trade-off of higher power requirements. Long-range beacons that can transmit further are available, but less popular in the market. The rationale why long range beacon are less popular is that it is a specific device that is target mainly for close range proximity applications [9].

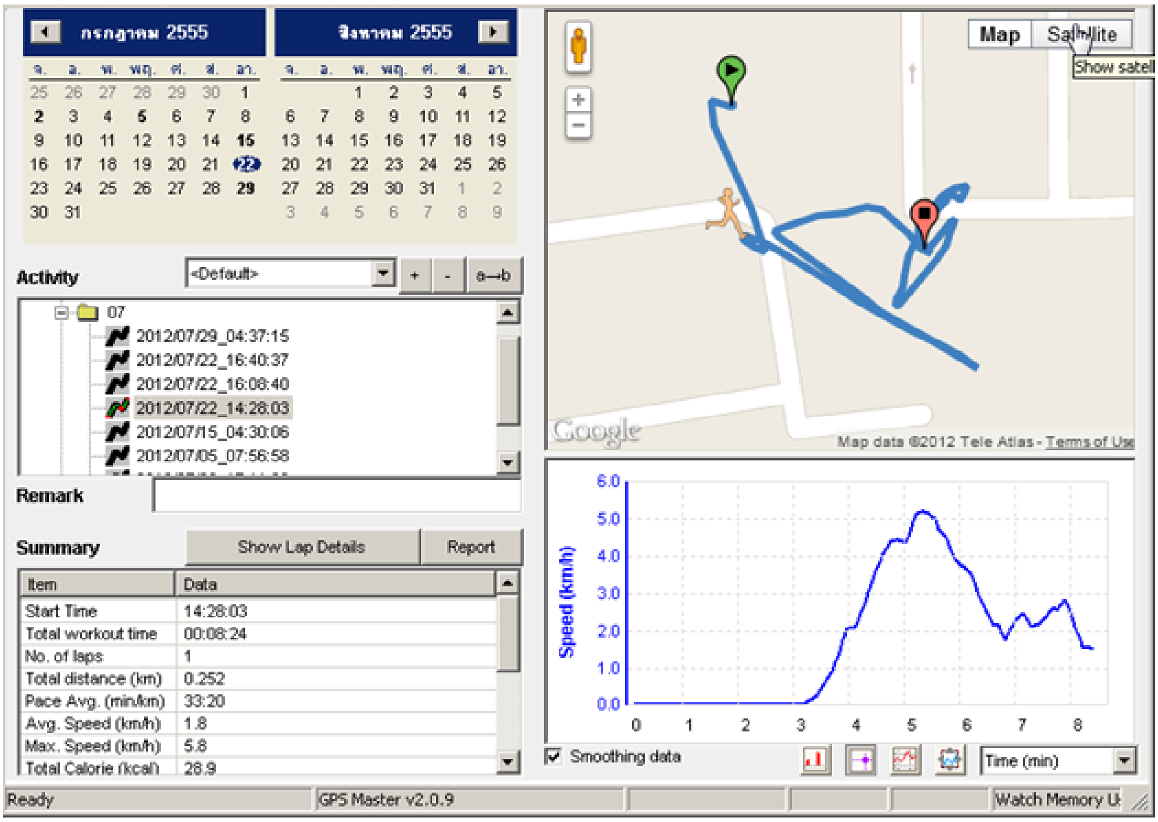

Figure 2. Example of GPS Positional Error.

2.3 WiFi approaches

WiFi can be used in proximity estimation. It is possible to estimate the distance from the signal of the WiFi access point from a selected WiFi device by a number of approaches. One of the approach is to utilize triangulation of the WiFi devices [10] to detect the distance and position. However in proximity estimation, heading is not required. In the example of proximity estimation, using the received signal strength indicator (RSSI) level is an approach that can be used. The RSSI level degrades with increased distance between the access point and the receiver. Based on the RSSI degradation via distance, it is possible to estimate the distance from the RSSI level that is detected on the mobile device.

In the example of proximity estimation, a simplified RSSI distance estimation [11] could be used, which is denoted by Equation 2. In the equation n denotes signal propagation constant, d denotes the distance in meters, and A is the received signal strength at 1 meter distance. This equation provides a quick estimation of the distance, though it requires calibration by exploring the RSSI level at the 1m distance from the access point.

$$RSSI\ (dB) = -10n \log_{10}(d) + A \tag{2}$$

Another approach is to utilize the concept of free space path loss (FSPL) [12] which is based on observing the loss in signal strength of an electromagnetic wave through distance. With the equation, it is possible to estimate the distance from the transmitter to the device. The FSPL equation is denoted by Equation 3. In the equation, f is the frequency in GHz and d is the distance in Km. By working the equation it is possible to estimate the distance from the settings of the access point. This approach it is more generalized than the simplified RSSI distance estimator and requires less setup, though it may be slightly less accurate. The reason for the lowered accuracy is that in practical applications, FSPL estimates do not directly translates into RSSI levels directly, though are related.

$$FSPL\ (dB) = 10 \log_{10}\left((\tfrac{4\pi}{c} df)^2 \right) \tag{3}$$

Based on the previous discussions, it is observed that proximity estimation is possible with WiFi approaches. However instead of using one single smartphone or mobile device as the test case, the experiment aims to explore the practical usage of varied devices in proximity estimation using WiFi approaches.

3. Experiment setup

To test the viability of using WiFi for proximity estimation an experiment was setup. For the reference point, a WiFi access point is required. As it is in an outdoor setting, the usage of a WiFi access point that can potentially be mobile is recommended as there exists certain proximity estimation applications in which the reference point can be moving. In the experiment, TP-Link Model No. TL-MR3040, a portable battery powered WiFi router was selected as the access point due to fulfilling the requirements stated earlier. The specifications of the access point is displayed in Table 1.

For the experiment, channel 11 was selected and the access point is broadcasting at 2.462 GHz. Regarding the placement, to allow the least interference to the experiment, the selected access point is placed in the perimeter of the the football field. The rationale behind selecting the football field is that it is the most secluded area in the campus when considering WiFi coverage. With the less access points in the vicinity, the experiment could be setup with the least amount of channel conflict and interference from other access points. The setup is also in an outdoor area, in which other factors such as walls and other obstacles do not have to be considered.

A measuring rope that contains distances that are marked with one meter intervals from 0-100 meters was procured. This measuring rope is then set at the access point which serves as the reference point and is spread over the range along the length of the football. To make the distance markers more accurate, the rope is fixed to the field so that wind and other factors do not affect the distance.

Table 1. Characteristics of wastewater derived after conducting the COD-test

Features	Specifications
Wireless Standard	802.11b, 802.11g, 802.11n
Frequency	2.4-2.4835 GHz
Signal Strength	<20 dBm
Signal Range	150 m
Antenna Type	Internal
Weight	94 g
Power Supply	Internal 2000 mAh rechargeable battery

Table 2. Mobile Devices Selected in the Experiment (15)

Manufacture	Model	Type	Price	Year
Samsung	Galaxy Note 5	Phablet	620 €	2015
Wiko	Ridge 3G	Smartphone	130 €	2015
Oppo	Joy 3 A11W	Smartphone	130 €	2015
LG	L Bello D335	Smartphone	100 €	2014
Huawei	Ascend MATE 7	Phablet	250 €	2014
Asus	Zenfone 6	Phablet	250 €	2014
Lenovo	A3000	Tablet	180 €	2013
Sony Ericsson	Experia LT18A	Smartphone	210 €	2012

To test the viability of proximity estimation with WiFi, a varied selection of smartphones and tablets are used to reflect the diversity of smartphone and mobile devices configurations in the market. The selection range from hi-end flagship mobile devices to entry level devices, and were first manufactured between 2012-2015. All the devices used in the testing are installed with applications that allow to receive the received signal strength indication (RSSI) level. The RSSI level could be used in proximity estimation in theory, but it is ideal to examine by practical field tests and to examine other related issues such as device specific factors and environmental factors that can affect such applications.

Initially the experiment aims to utilize the widest range of mobile devices, and aims to explore the three most popular smartphone platforms, which are Android, iOS, and Windows Phone. However after exploring the devices, it is discovered that many devices that cannot be used for the experiment due to the limitation of the OS, application ecosystem, and/or API support provided by the respective software development kit. One of the AppStore requirements of Apple is that applications that report RSSI levels are not permitted [13]. Due to that, it is not possible to install any RSSI level reporting applications on Apple devices which includes all variants of the iPhone and iPad product line. Though it is technically possible to jailbreak the machine and install custom apps, it is not considered due to EULA purposes. Windows Phone devices are also excluded from the experiment due to the lack of API support in the SDK. Windows Phone 8.1 devices and earlier iterations does not have API support [14]in their respective SDKs that allows access to hardware level values of the network sensors including WiFi. With that limitation, it is not technically possible to access the RSSI levels with Windows Phone devices until the latest iteration of Windows 10 Mobile. Due to the limitations, only Android devices could be selected and install with applications that can monitor the RSSI level from the access point. The list of the devices and a selection of specifications that have been selected are listed in Table 2. The mobile devices are later placed at the distance markers between 1-100m and then later checked for their RSSI level. As the reported RSSI levels can fluctuate widely, the devices were placed at the interval for a specific period of time before the level is examined and recorded. The values are recorded for all mobile phones at 1m intervals from 1-50m and at 5m intervals from 50-100m. To emulate a real working scenario, the first value recorded by the device is saved. The RSSI level of each of the smartphone and mobile devices are recorded and saved for later analysis.

4. Results and discussion

The results of the experiment and the recorded RSSI level of each devices are plotted against FSPL for each of the smartphone and mobile devices. Figures 2-9 displays the graph of each of the individual devices and the FSPL estimate at the specific distance. A composite graph is shown at Figure 10.

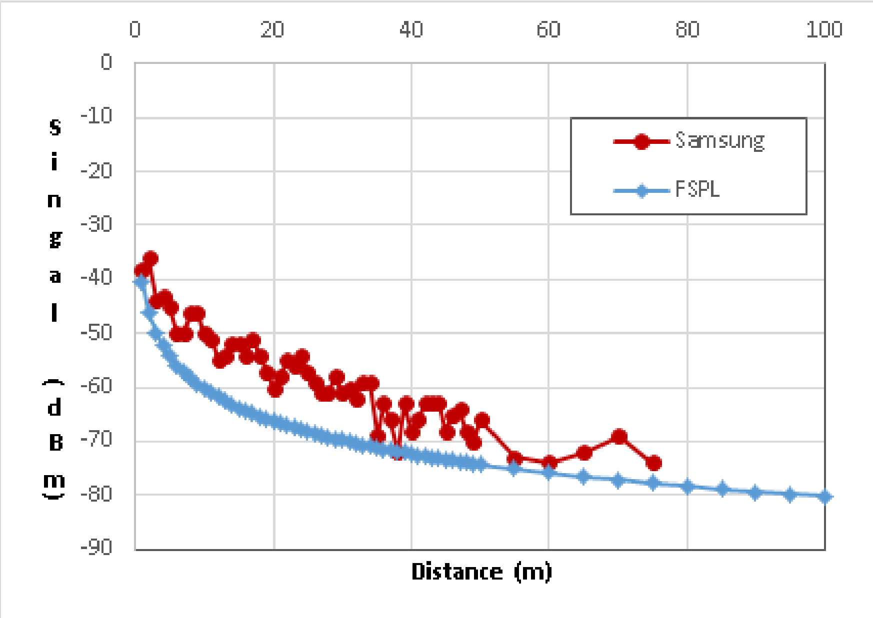

Figure 2. Measuring Samsung Galaxy Note 5 vs FSPL.

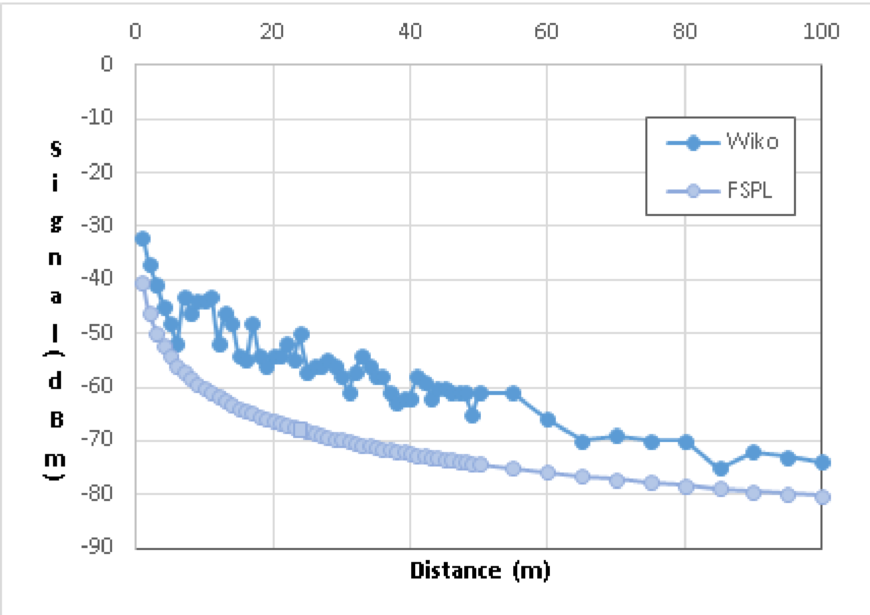

Figure 3. Measuring Wiko Ridge 3G vs FSPL.

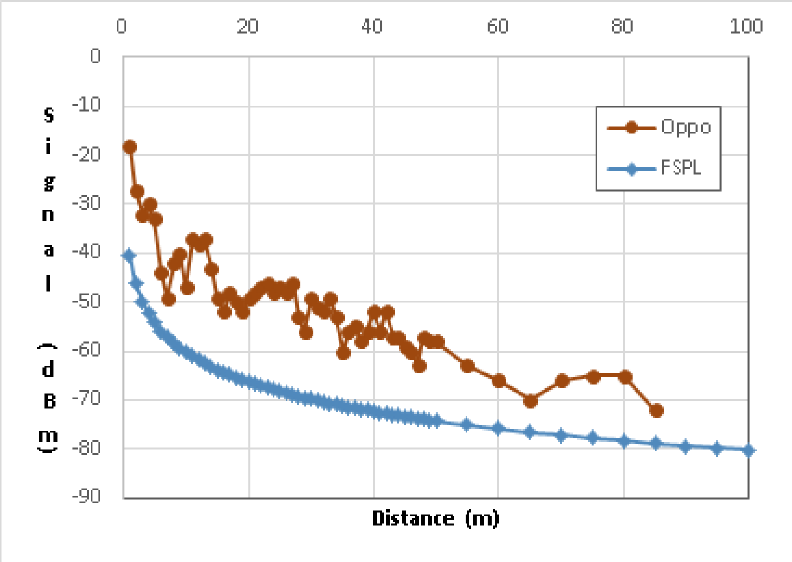

Figure 4. Measuring Oppo Joy 3 vs FSPL.

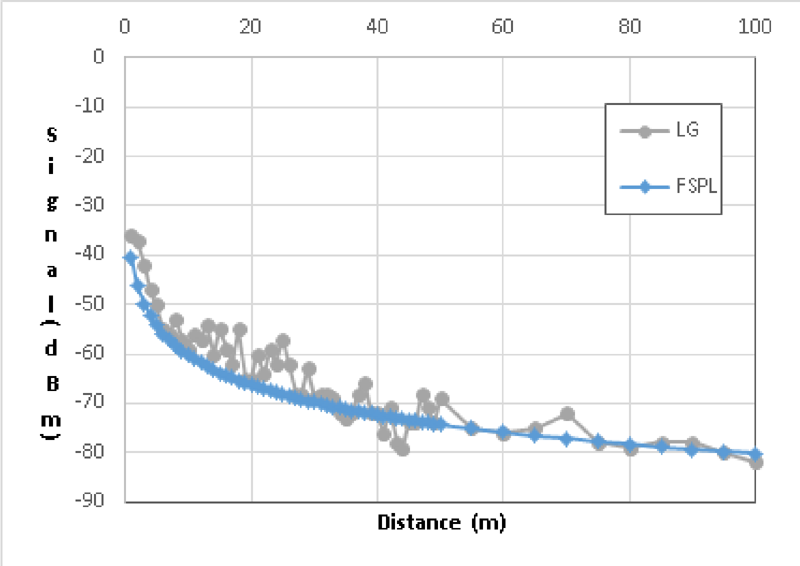

Figure 5. Measuring LG L Bello vs FSPL.

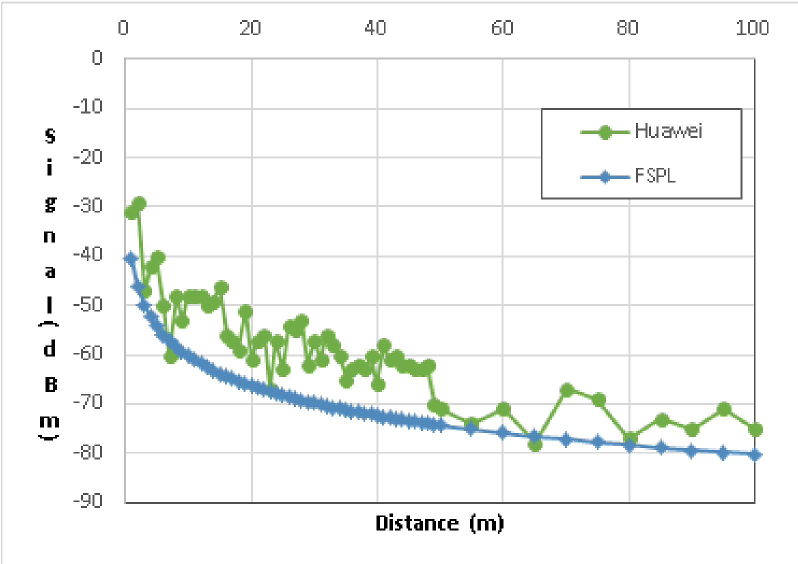

Figure 6. Measuring Huawei Ascend Mate7 vs FSPL.

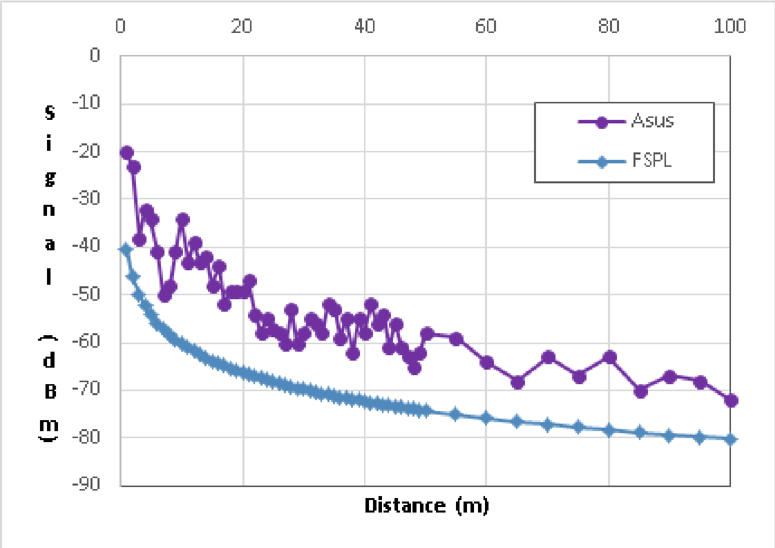

Figure 7. Measuring Asus Zenfone 6 vs FSPL.

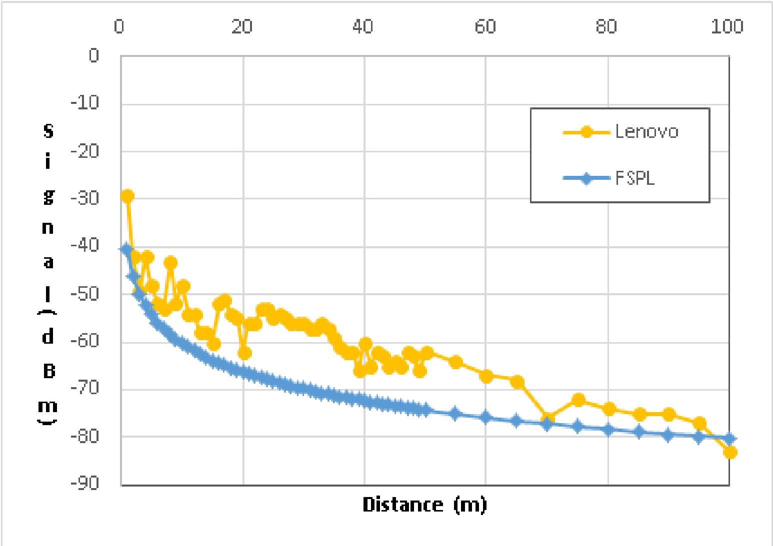

Figure 8. Measuring Lenovo A3000 vs FSPL.

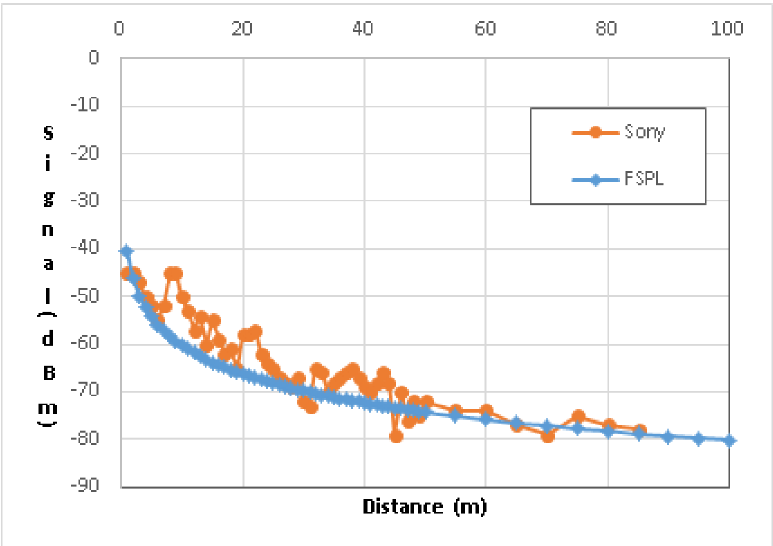

Figure 9. Measuring Sony Ericsson Experia LT18A vs FSPL.

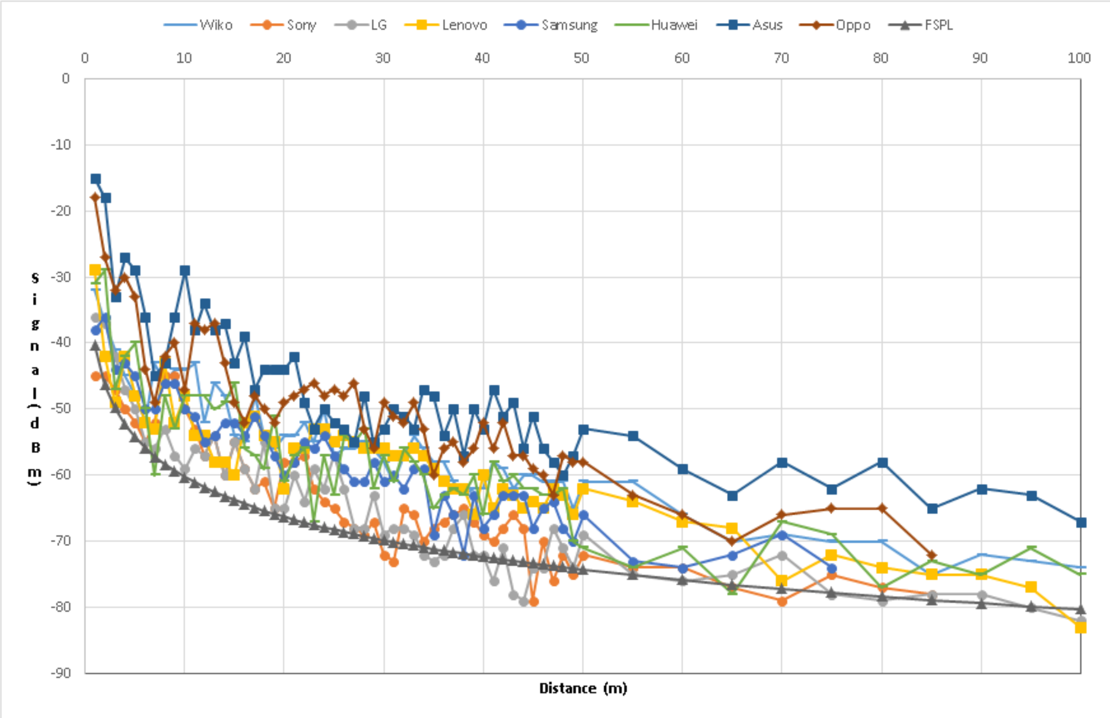

Figure 10. Composite Diagram of Devices Compared with FSPL.

One of the observation from the experiment is that the theoretical outdoor range of access point that is based on the 802.11n WiFi protocol is approximately 250m [16]. Though the theoretical range is 250m, the experiment has recorded that a number of devices have not been able to reach close to the theoretical limit. In the test, there were a number of devices that could not be detected within the 100m range in the experiment. Samsung Galaxy Note 5 (Figure 2) cannot detect the access point after the distance of 80m. Sony Ericsson Experia LT18A (Figure 9) and Oppo Joy 3 (Figure 4) cannot detect the access point after the distance of 90m. It is reported that RSSI levels can fluctuate and this behavior is replicated by other researchers [11 & 17]. In the experiment by examining the graph of the RSSI level of each mobile device, the fluctuation of the RSSI levels was observed. Even though the device was allow to stabilize before recording the RSSI level at each of the interval, the phenomenon is observed.

To further examine the results in the area of the displacement between the FSPL estimates and the recorded RSSI levels, further calculation is done. The average displacement is calculated from averaging the absolute displacement between the reported RSSI level and the FSPL estimate for all of the test intervals excluding intervals that cannot be reported by certain devices and is calculated by Equation 4. The standard deviation of the displacement is also calculated for all the devices and is calculated by Equation 5. The summary of the results are displayed in Table 3.

$$\overline{\Delta dBm} = \frac{\sum_{i=1}^{n}(|RSSI_i - FSPL_i|)}{n} \tag{4}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(|RSSI_i - \overline{\Delta dBm}|)}{(n-1)}} \tag{5}$$

For certain devices, it is observed that the reported RSSI level and the FSPL estimate displays high displacement. This is observed as devices can display different behaviors depending on the WiFi receiver, in which the values when uncalibrated can be significantly different from the FSPL estimate. This behavior is observed in the Oppo Joy 3 and Asus Zenfone 6 as the initial reported RSSI levels are significantly lower. At the remaining distances, the behavior is consistent decaying in a logarithm fashion. Due to that, by providing a calibration for the FSPL estimate, it may be possible to get more accurate results. Alternatively, examining the simplified RSSI distance estimation that requires calibration of the level at the 1m interval is a possibility to explore.

Table 3. Displacement of RSSI Level with FSPL Estimate

Mobile Device	AVG	STDEV
Samsung Galaxy Note 5	8.35	3.25
Wiko Ridge 3G	11.53	3.35
Oppo Joy 3 A11W	16.70	4.37
LG L Bello D335	3.46	2.95
Huawei Ascend MATE 7	9.35	4.27
Asus Zenfone 6	14.86	4.33
Lenovo A3000	9.28	3.95
Sony Experia LT18A	4.21	3.16

5. Conclusion and future work

Based on the results from the experiment, it is observed that proximity estimation is possible with WiFi on smartphones and mobile devices in an outdoor scenario. The results are relatively accurate, though it is observed that there are a number of issues. Similarly to Beacon based approaches, at high distance, there is a delay before the device can receive the RSSI level from the reference point. This issue can be remedy by allowing a few seconds for the device to receive the signal for the calculation of the RSSI level. Another issue is that it is observed that different mobile devices receive different values though at the same distance interval. It is observed that the cost of the device does not have a relationship with the quality of WiFi reception, and the most expensive device in the experiment has the worst WiFi reception out of all the devices in the test list. The reason behind this is likely to be down to the design of the mobile device. Material type and the placement of the WiFi receptors is has a higher relationship with the WiFi quality of the device. Since the RSSI level can vary between mobile devices due to the issues listed earlier, it is possible to the accuracy of the proximity estimation of the devices by fine-tuning the proximity estimation approaches to fit with the mobile device profile.

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7. References

[1] Bluetooth Low Energy specification adopted document., 2014. [WWW Document]. URL https://www.bluetooth.com/specifications/adopted-specifications. (access 9. 6. 16).

[2] Yang, C., Shao, H. R., 2015. Wifi-based indoor positioning. IEEE Communication Magazine 53, 150-157.

[3] Sinnott, R. W., 1984. Vitues of the haversine. Sky and Telescope 68.

[4] Lee, L., Jones, M., Ridenour, G. S., Testa, M. P., Wilson, M. J., 2015. Investigating and Comparing Spatial Accuracy and Precision of GPS Enabled Devices in Middle Tennessee. Springer Berlin Heidelberg, 215-224.

[5] Park, M., Gao, Y., 2008. Error and performance analysis of mens-based inertial sensors with a low-cost gps receiver. Sensors 8, 2240-2261.

[6] Zeimpekis, V., Giggles, G. M., Lekakos, G., 2002. A Taxonomy of indoor and outdoor positioning techniques for mobile location services. SIGecom Exch 3, 19-27.

[7] Newman, N., 2014. Apple beacon technology briefing. Journal of Direct, Data and Digital Marketing Practice 15, 222-225.
[8] Liu, S., Jiang, Y., Striegel, A., 2014. Face-to-face proximity estimation using bluetooth on smartphones. IEEE Transactions on Mobile Computing 13, 811-823.
[9] Deepest, P. C., Rath, R., Tiwari, A., Rao, V. N., Kanakalata, N., 2016. Experience with using beacons for indoor positioning. Proceedings of the 9th India Software Engineering Conference: 2016, 184-189, New York, USA, ACM: 2016.
[10] Lim, C. H., Wan, Y., Ng, B. P., See, C. M. S., 2007. A real-time indoor WiFi localization system utilizing smart antennas. IEEE Transactions on Consumer Electronics 52, 618-622.
[11] Liu, E. E. L., Lee, B. G., Lee, S. C., Chung, W. Y., 2008. Enhanced RSSI based high accuracy real-time user location tracking system for indoor and outdoor environments. International Journal on Smart Sensing and Intelligent System 1, 534-548.
[12] Sklar, B., 2001. Digital Communications: Fundamentals and Applications. 2nd ed. Prentice Hall.
[13] Apple Developer Program Terms and Agreement., 2014. [WWW Document]. URL https://developer.apple.com/terms (accessed 9. 6. 16).
[14] Device Networking Information Class (WP 8.1)., 2015. [WWW Document]. URL https://goo.gl/FnTESB. (accessed 9. 6. 16).
[15] GSM Arena., 2016. [WWW Document]. URL https://www.gsmarena.com/ (accessed 9. 6. 16).
[16] Halepovic, E., Williamson, C., Grader, M., 2009. Wireless data traffic: a decade of change. IEEE Transaction on Networking 23, 20-26.
[17] Alippi, C., Panini, G., 2006. A RSSI-based and Calibrated Centralized Localization Technique for Wireless Sensor Networks. In: PERCOMW 06. Proceedings of the 4th Annual IEEE International Conference on Pervasive Computing and Communications Workshops, 305