Performance Evaluation of Beacons for Indoor Localization in Smart Buildings

Andrew Mackey and Petros Spachos
School of Engineering, University of Guelph
Guelph, Ontario, Canada, N1G 2W1
Email: mackeya@uoguelph.ca, petros@uoguelph.ca

***Abstract*—Enforced by the concept of Internet of Things, indoor location services using Bluetooth Low Energy beacons has become a growing reality. Many systems of which, propose the use of Received Signal Strength Indicator based location methods. The unpredictable propagation of these signals, in combination with surrounding signal noise and variable environmental conditions, makes it difficult to implement such systems as a simple entity. With the multitude of beacons on the market, it may be difficult to develop an optimal indoor positioning system for the desired application. To help address this issue, this paper compares three popular beacons, presents a simple mobile application based Kalman filter, and explores the correlation between transmit power and desired Kalman filter parameters.**

***Index Terms*—Indoor localization, beacons, smart buildings**

I. Introduction

The emergence of Internet of Things (IoT), and specifically smart buildings and homes has generated an increased desire for indoor location services. This has subsequently led to the growth in popularity of Bluetooth Low Energy (BLE) beacon devices. BLE beacons are generally small, low cost, and configurable wireless devices that work by repeatedly broadcasting packets using either Apple's iBeacon protocol, or Google's Eddystone protocol.

There are other solutions that present viable means to support indoor location services, such as Wi-Fi [1] and ultrasound [2]. Though, unlike these solutions, BLE provides the benefit of fully wireless hardware that does not rely on an external power source. BLE was specifically developed for novel applications that lie under the umbrella of IoT, with a focus on low power consumption. In addition, due to the small size of the average BLE beacon and the capabilities of BLE in most of the current mobile devices on the market, these systems can be easily implemented and scaled in a manner that does not pose a significant impact on current infrastructures. This makes BLE beacons a popular choice for indoor location services.

A common range-based method of indoor positioning with beacons is to use the Received Signal Strength Indicator (RSSI). This information can be translated into a determined distance based on the comparison between the received signal strength and the expected signal strength at 1m. Each beacon transmits this information along with each packet it broadcasts. Although popular, the application of RSSI for indoor location services is inherently inaccurate due to noise in the system. This is true for Wi-Fi, BLE, and the like. Thus, the addition of hardware and software support are required to make the beacons more accurate. This often includes the addition of more beacons for added points of reference and software defined filters to eliminate noise.

This paper provides insight on a beacon's ability to provide proximity based location services, how to improve the performance with simple Kalman filter solutions implemented in mobile application software, and the correlation between Kalman filter accuracy, beacon transmit power, and the effects of the surrounding environment for three popular beacons.

The rest of this paper is organized as follows: In Section II, an overview of the related work is given, followed by Section III with the system overview. Section IV presented the experimental procedure and the experimental results. The conclusion is in Section V.

II. Related Work

This section introduces the multiple experimental studies regarding the evaluation and effectiveness of iBeacon based Indoor Positioning Systems (IPS).

A. *Position Accuracy Enhancements*

Filters are a common and effective means to improving indoor location accuracy. In [3], particle filters are implemented to enhance iBeacon based micro-location. Through two experiments, using Gimbal 10 series beacons, it is shown that with optimal particle and beacon number selection, the accuracy of iBeacon based IPS is greatly improved. The experiments were conducted in unobstructed rooms and in real world scenarios the importance of beacon placement at high altitudes to avoid obstacle interference was noted. In addition, a simple Android tracking applications that implement a Kalman filter for improved accuracy have been created. One particular application provides real time remote tracking capabilities, and through multiple experiments it was concluded that room to room accuracy is attainable within the order of meters [4]. Similarly, in [5], the effectiveness of three popular filtering techniques; Kalman filters, Gaussian filters, and a hybrid of the two are compared. Three real world experiments were conducted with the use of a Texas Instruments CC2540 serving as an iBeacon base station. The Kalman-Gaussian Linear filter proved to be the most effective at reducing noise and improving indoor location accuracy. Other works experiment with the raw accuracy of BLE RSSI signals for location purposes, and suggest averaging/ smoothing the incoming RSSI signals to obtain better accuracy [6].

B. Positioning Algorithms

The placement/ utilization of BLE nodes and the approach to calculating distance may also have a significant effect on IPS. One approach compares the effectiveness of two position detection algorithms, nearest neighbor vs. k-nearest neighbor, using the iBeacon protocol [7]. It is shown that the nearest neighbor algorithm resulted in the lowest average error (approximately 1m). In [8], the positioning accuracy of indoor location using the Pedestrian Dead Reckoning (PDR) approach is described. The experiment utilizes Estimote beacons to fix the inherent drift in the PDR approach, which finds user position by utilizing three essential variables; step detection, walking length, and walking direction. The system relies on smartphone sensors and strategically placed beacons to provide the needed variable information and calibration zones respectively. Future research includes multi-floor location using the smartphone barometer.

The relation between beacon arrangement and positional accuracy in an indoor environment is also analyzed [9]. Four arrangements, corresponding to; triangular, square, pentagonal, and hexagonal are compared. It is determined that arrangements with additional beacons (up to a threshold) improve location accuracy. Two-dimensional positioning algorithms are common in IPS. Expanding on this research, the exploration of indoor positioning in three-dimensions using the three-ball positioning algorithm is conducted [10]. The 3-dimensional positioning experiment is executed in a 7m x 5m x 3m room and resulted in a peak error of 1.2m.

C. Applications and User Acceptance

User acceptance of IPS is a critical factor in the growth of IoT and continued research into iBeacon based location systems. A vast overview of the current technologies, techniques and services associated with IoT equipped smart buildings is discussed in [11]. Tenant services, disaster management, marketplace applications, and user security are explored in length to provide us with knowledge regarding the current problems and potential solutions with regards to each topic. Experimental models such as [12], utilize a simple Android application for room detection using incremental rule learning. The decisions made by the application can be edited by the user of the application to improve its effectiveness and accuracy. The experiment proves to be effective for room discovery applications, and its general simplicity may aid in the acceptance of other iBeacon indoor location systems. To enhance the security of iBeacon based location systems, the detection of physical attacks against iBeacon transmitters is proposed and explored in [13]. Hidden Markov Models are used to be able to identify four common physical attacks patterns; broken, moving, switch and duplication. The solution provides a detection accuracy of 85%. All detection algorithms are implemented on a server, eliminating the need to update smartphones and reduce power consumption of smartphone devices [13].

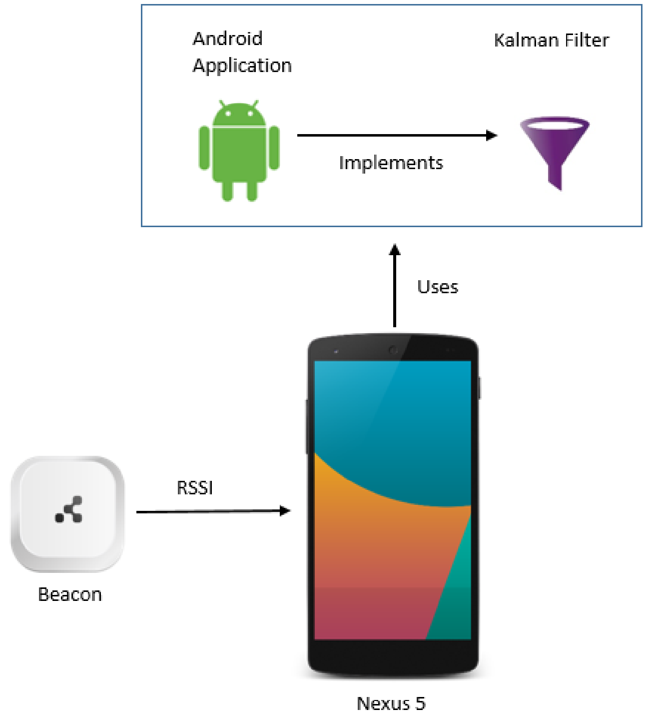


Fig. 1. Overview of the system that uses RSSI from beacons for indoor localization.

This paper focus on the comparison of three popular iBeacon hardware devices and the development of a simple IPS model, which describes how to improve the accuracy of each beacon in a particular environment, with the addition of a simple Kalman filter implementation on mobile application software.

III. System Overview

A. Topology and communication

All experiments were conducted in a single room, a lecture hall of size 9m x 11m. The room is laid out with a series of tables and chairs. In this system, the beacon was placed at the edge of a table in the center of the room. The beacon would remain stationary, while the smartphone (Google Nexus 5) would move along the table(s) at each defined distance, away from the beacon.

Each beacon transmits an iBeacon packet containing the Universally Unique Identifier (UUID), major, and minor values, along with some basic telemetry data depending on the additional sensors included with each beacon. The smartphone reads the iBeacon packet to be able to identify the beacon(s) it sees. It then collects the RSSI value of the particular beacon and utilizes this signal to calculate a corresponding distance. All information regarding beacon ID, RSSI, and final distance results are displayed to the user through a simple user interface. An overview of the system can be seen in Fig. 1.

B. Kalman filter

A simple Kalman filter is implemented in the Android application, computed in two stages; prediction and update. These stages are needed as the filter makes predictions on the received RSSI signal, based on the previously determined RSSI value, and finally updates the variables before its next iteration. The algorithm is executed in the order of the following equations, similar to [5].

Prediction:

State prediction at time k:

$$x(k|k-1) = x(k-1|k-1) \tag{1}$$

System error & noise covariance prediction at time k:

$$P(k|k-1) = P(k-1|k-1) + Q \tag{2}$$

Where Q is the process noise covariance. Q is set to zero as it is assumed that all experiments are conducted in a controlled environment with static measurements in direct line of sight. Values used for the prediction stage are maintained using a simple hash map.

Update:

Kalman gain:

$$G(k) = \frac{P(k|k-1)}{P(k|k-1) + R} \tag{3}$$

where R is the Kalman value, optimized for the environment.

State update at time k:

$$x(k|k) = x(k|k-1) + G(k) * [y(k) - x(k|k-1)] \tag{4}$$

System error & noise covariance update at time k:

$$P(k|k) = [1 - G(k)] * P(k|k-1) \tag{5}$$

C. Distance Calculations

The distance calculations are implemented using the calculations provided by the `AltBeacon` Android library. It is computed as follows:

First, the ratio between RSSI and transmit power (Tx) is calculated:

$$ratio = \frac{RSSI}{Tx} \tag{6}$$

If the ratio <1.0 then

$$distance = ratio^{10} \tag{7}$$

else

$$distance = c_1 * ratio^{c_2} + c_3 \tag{8}$$

where c_1 = 0.42093, c_2 = 6.9476, and c_3 = 0.54992.

All distance calculations are in meters. The values of c_1, c_2, and c_3 correspond to a specific mobile phone model. The values seen above correspond to the Google Nexus 5 used in these experiments. All three values were provided by the `AltBeacon` library. The different values are likely attributed to the differences in Bluetooth hardware between smartphones.

(a) Estimote [14]. (b) Kontakt [15]. (c) Glimworm [16].

Fig. 2. Beacons used in the experiments.

IV. Experimental Procedure & Results

In this section, the experimental set up is described followed by a brief discussion on the results.

A. Experimental Setup

Each beacon consists of three important layers; iBeacon capable hardware, environment/ conditions and Android application software. To effectively evaluate and compare three different beacons, multiple experiments were conducted with each.

1) Equipment: Beacon hardware from three popular manufacturers were used in the experiments: Estimote [14], Kontakt [15], and Glimworm [16] shown in Fig. 2. The measuring and calculating device was a Google Nexus 5 running a simple Android application that utilizes the `AltBeacon` Android library. A measuring tape was used to provide accurate distance placements in the experimental procedure.

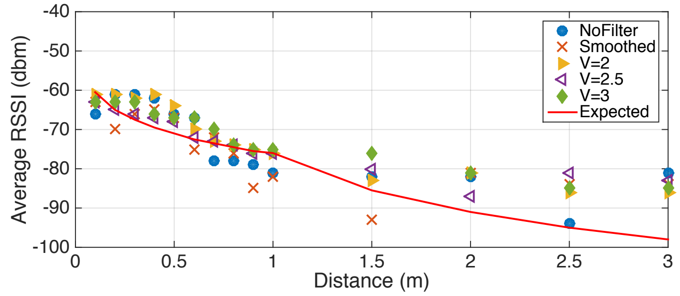
2) Conditions: As previously stated, the experiments were conducted in a single 9m x 11m room (lecture hall). Minimal obstructions were in the room aside from tables and chairs. It is important to note that no other BLE beacons aside from the one being tested was in the room at a given time during experimentation to avoid interference.

B. Procedure

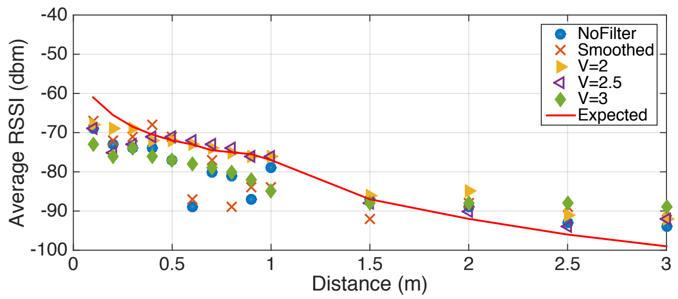
Each beacon was tested five times. The first iteration is to obtain the raw RSSI values and resulting distance calculations without any form of smoothing and/ or filtering. The second iteration attempts to smooth the incoming RSSI values over a twenty second interval, eliminating the top and bottom 10% of values. Iterations three through five measure the incoming RSSI signals and apply a simple Kalman filter of varying Kalman values (2, 2.5, and 3). Within each iteration, 14 measurements are taken. The beacon remains still on a table, while the smartphone moves along the table at the following set of distances: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.5, 2.0, 2.5, 3.0 meters. At each distance, the RSSI and corresponding distance is recorded. All measurements are given 20 seconds to calibrate before recording.

C. Results

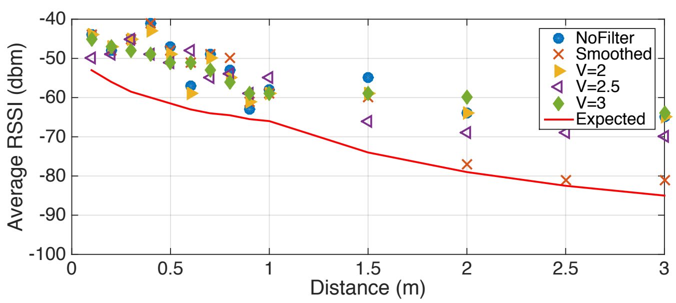
The results of the different beacons are shown in Fig. 3. In the case of all three beacons, it can be seen that the accuracy of any given filter method tends to be closest to the expected results within the first 1 - 1.5m. Distances greater than 1.5m



(a) Estimote.



(b) Kontakt.



(c) Glimworm.

Fig. 3. Average RSSI value of the beacons with the use of different filtering techniques.

show a drastic change in accuracy/ closeness to the expected result depicted by the red line. This is likely a result of a weaker signal due to the increase in distance as well as the effects of noise in the environment. Among all the three beacons, the Kontakt beacon Fig. 3b, under the aid of a filter, appears to perform the best at distances greater than 1.5m.

The standard deviation of the average RSSI with filtering in comparison with the expected value is shown in Table I. As expected, measurements obtained without any form of filtering performed poorly. Furthermore, from these results, it can be seen that smoothing the incoming RSSI values may not necessarily improve the accuracy, as the standard deviation is higher in the case of Estimote and Kontakt. In addition, it can be seen that for beacons with similar expected transmit power of -76dBm and -77dBm at one meter, for Estimote and Kontakt respectively, the accuracy is optimal under the same Kalman filter with a Kalman value of 2. For that value the average error in all the distances for Estimote and Kontakt is 0.3 and 0.19 respectively.

TABLE I
STANDARD DEVIATION IN dBm.

	NoFilter	Smoothed	V=2	V=2.5	V=3
Estimote	6.54	7.18	4.22	5.22	4.47
Kontakt	5.79	7.09	3.76	4.25	6.46
Glimworm	5.65	5.46	4.91	3.41	5.17

Similarly the results show that as the transmit power increases, so does the optimal Kalman value. This can be seen in the case of the Glimworm beacon, where the expected transmit power at 1m is -66dBm and the corresponding optimal Kalman value is 2.5. For this value, the average error is 0.46. Also note that non-optimal Kalman values result in poor filter performance, and subsequently, poor beacon accuracy.

In all experiments, it was clear that each beacon performed better with the addition of a Kalman filter. From a purely accuracy based standpoint, the Glimworm beacon was able to obtain the smallest standard deviation I with respect to the the expected values, making it the ideal candidate of the three for indoor proximity-based location services. Note that different conditions, i.e. noise and physical environment, may produce different results. It is under the conditions of these experiments that the Glimworm performed adequately, but this may not be the case in all scenarios.

V. CONCLUSION

This paper presents an experimental study of three popular beacons for indoor localization. The beacons were tested for their accuracy in a simple indoor environment. Further filtering applied to the results to improve the beacon accuracy. According to the experimental results, filtering is necessary to improve the performance. However, the environment is also important for the selection of the proper filtering method. For the experiments in this work, a Kalman filter seems to improve the accuracy while also proving to be easily implemented in a smartphone.

REFERENCES

[1] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for wlan location fingerprinting," in *The First Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004.*, Aug 2004, pp. 14–23.

[2] H. L. P. S. B. Ben-Moshe, A. Dvir, "Indoor positioning using time of flight fingerprinting of ultrasonic signals," in *2013 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2013, pp. 1–6.

[3] F. Zafari and I. Papapanagiotou, "Enhancing ibeacon based micro-location with particle filtering," in *2015 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2015, pp. 1–7.

[4] A. Ozer and E. John, "Improving the accuracy of bluetooth low energy indoor positioning system using kalman filtering," in *2016 International Conference on Computational Science and Computational Intelligence (CSCI)*, Dec. 2016, pp. 180–185.

[5] K. Zhang, Y. Zhang, and S. Wan, "Research of rssi indoor ranging algorithm based on gaussian - kalman linear filtering," in *2016 IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, Oct. 2016, pp. 1628–1632.

[6] M. Kaczmarek, J. Ruminski, and A. Bujnowski, "Accuracy analysis of the rssi ble sensortag signal for indoor localization purposes," in *2016 Federated Conference on Computer Science and Information Systems (FedCSIS)*, Sept. 2016, pp. 1413–1416.
[7] C. Takahashi and K. Kondo, "Accuracy evaluation of an indoor positioning method using ibeacons," in *2016 IEEE 5th Global Conference on Consumer Electronics*, Oct. 2016, pp. 1–2.
[8] Z. Chen, Q. Zhu, H. Jiang, and Y. C. Soh, "Indoor localization using smartphone sensors and ibeacons," in *2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)*, June 2015, pp. 1723–1728.
[9] M. S. Aman, H. Jiang, C. Quint, K. Yelamarthi, and A. Abdelgawad, "Reliability evaluation of ibeacon for micro-localization," in *2016 IEEE 7th Annual Ubiquitous Computing, Electronics Mobile Communication Conference (UEMCON)*, Oct. 2016, pp. 1–5.
[10] L. Yang, Q. Wang, and G. Wang, "Positioning in an indoor environment based on ibeacons," in *2016 IEEE International Conference on Information and Automation (ICIA)*, Aug. 2016, pp. 894–899.
[11] F. Zafari, I. Papapanagiotou, and K. Christidis, "Microlocation for internet-of-things-equipped smart buildings," *IEEE Internet of Things Journal*, vol. 3, no. 1, pp. 96–112, Feb. 2016.
[12] S. Bobek, O. Grodzki, and G. J. Nalepa, "Indoor microlocation with ble beacons and incremental rule learning," in *2015 IEEE 2nd International Conference on Cybernetics (CYBCONF)*, June 2015, pp. 91–96.
[13] C. Liu, P. Zhao, K. Bian, T. Zhao, and Y. Wei, "The detection of physical attacks against ibeacon transmitters," in *2016 IEEE/ACM 24th International Symposium on Quality of Service (IWQoS)*, June 2016, pp. 1–10.
[14] Estimote. [Online]. Available: https://estimote.com/
[15] Kontakt. [Online]. Available: https://kontakt.io/
[16] Glimworm. [Online]. Available: https://glimwormbeacons.com/