Experimental Comparison of Energy Consumption and Proximity Accuracy of BLE Beacons

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***Abstract*—As technology gets cheaper and wireless networks grow, more efforts have been put into developing smart buildings and homes. A key characteristic of these smart buildings is to provide indoor navigation and localization services to its occupants. As this demand increases, simple, scalable solutions are sought after. Current localization technologies, such as GPS, do not work in indoor environments, nor does it provide the level of accuracy required for an effective indoor navigation solution. This paper explores the feasibility of a wireless indoor location system based on Bluetooth Low Energy beacons (BLE). Five popular BLE beacon devices are compared in terms of energy consumption and proximity accuracy. Experiments are conducted in three different rooms and three filtering techniques are also examined, to improve the performance of each beacon. According to experimental results, a proper selection of the filtering technique can help to improve their proximity estimation.**

I. Introduction

Among the critical characteristics of a wireless indoor localization system, the achievable lifespan and accuracy will define its behaviour, effectiveness, and most importantly its feasibility. Current battery and energy harvesting technologies have, and will continue to improve. These developments, such as improved battery capacities, and effective solar harvesting power sources have been adapted to fit many wireless devices, although there is much demand for improvement. Following this, the accuracy of wireless devices, for the purposes of indoor localization, changes drastically between technologies [1], [2]. Popular technologies such as Wi-Fi [3], [4] have high accuracy for indoor localization. Wi-Fi nodes can achieve under 1m error in positioning, however, they use over 200mW [5].

Bluetooth Low Energy (BLE) beacons, simply known as beacons, are growing in popularity and research potential [6]. They are fully wireless devices that implement Bluetooth Special Interest Group's Bluetooth Low Energy technology, which was developed for the purposes of low power consumption for devices that require minimal data throughput. Beacons are largely popular for their small size, low cost, fully wireless form factor, and relatively long lifespans. It is projected that 400 million beacons will be deployed globally by the year 2020 [7]. They are also an attractive solution for indoor localization services, using techniques that utilize the received signal strength indicator (RSSI) [8]. Their small size provides a means of increased scalability and their BLE functionality establishes simple integration with smartphone devices, making them a viable selection for indoor localization applications.

A main drawback of using beacons for localization is their susceptibility to any physical interference and noise. With the increased number of wireless devices for every individual, environmental, contention rises. In addition, beacons are sensitive to their environment, so as the physical characteristics of the environment changes.

There are a number of state estimation filtering techniques that can be implemented to improve the precision and accuracy of RSSI readings from BLE beacon signals. Popular filters to implement are generally state prediction/ estimation filters, i.e. the Kalman, Gaussian, or particle filters [9], [10], [11]. The more computationally complex filtering algorithms must be implemented on a server [11], but simpler RSSI filters have been implemented on the receiving device [12], [13].

This work expands on our previous work [14] and compares the energy consumption and proximity accuracy of five BLE beacon devices for the purposes of indoor localization. Each beacon varies in size, power source requirements, and cost. To improve the performance, three filtering techniques are used; a static Kalman filter, a Kalman filter with a dynamic process noise component, and Gaussian filter, against its unfiltered raw form. The experiments took place in three rooms with different size. According to the experimental results, BLE beacons can be a promising solution for indoor localization. The experimental results are available online [15].

II. Related Works

In recent years, BLE technology has grown in popularity due to the explosion of IoT applications [6]. Much research has emerged in using and improving these devices for indoor localization, and navigation based services [13], [10], [16], [17], [12], [18]. The primary use of BLE beacons is for proximity based location services, based on RSSI techniques, where the received RSSI value is translated into an approximate distance. Specifically for BLE beacons, multiple packet formats have been developed; Apple's iBeacon [19], and Google's Eddystone [20], are the 2 most common BLE beacon packet formats. They provide the necessary information and configuration capabilities for micro-localization, and indoor navigation systems. The advantages of beacons, primarily the low power consumption, small size, and fully wireless design make them highly scalable for most indoor environments.

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Many works attempt to improve the signal accuracy of BLE beacons with filtering techniques. Some of the common techniques are Kalman [13], Gaussian [10], and particle filters [11]. These filtering techniques are not new, but the application and design of these filters for beacon based indoor positioning is more current. Alternate methods for localization have also been adapted for beacons. The Pedestrian Dead Reckoning (PDR) approach as used in [21], exploits the smartphone sensors to track user steps, direction, and pace and combines this information with RSSI from the beacon devices. More advanced positioning algorithms such as the K-Nearest Neighbour [22], [23] have been applied to beacons for the purpose of indoor positioning. All of the techniques have shown improvement over the base RSSI location accuracy, although with any improvements it is still necessary to test the accuracy of beacon devices before use. BLE was developed specifically for lower power consumption than alternative wireless technologies, such as Wi-Fi [24]. In [25], it explores the power consumption of BLE peripheral devices in a star network topology. The model uses a smartphone as the receiving node.

This paper provide extensive experimental results with five beacons from three environments and can serve as reference for researchers or developers who wish to implement their own BLE beacon-based indoor location system.

III. Filtering Algorithms

State filtering algorithms improve accuracy by utilizing prior information about the state to make an estimation that is likely closer to the true state. In this case, the state is proximity. filtering is necessary with beacons since not all observed RSSI values are accurate due to interference and dynamic changes in the environment. Three filtering algorithms are compared, to examine their effect on the proximity accuracy of each beacon.

A. Static Kalman Filter (KF-ST)

A Kalman filter is considered to be a predictive filter in which it makes use of previous states to make predictions on the current state. This particular filter is static because it does not take into account any dynamic noise changes in the environment. The Kalman filter is executed in two stages; prediction and update. Similar to [13], it is defined as follows;

Stage 1: Prediction

State prediction:

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

System error and noise covariance prediction:

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

Stage 2: Update

Kalman gain:

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

State update:

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

System error and noise covariance update:

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

Parameter k is defined to be the time/ current state, Q is the process noise covariance. In the static Kalman filter, Q is set to zero as it is assumed that all experiments are conducted in an environment with low contention, and all measurements are static and maintain direct line of sight. R is the configurable parameter that alters the Kalman gain, and should be optimized for the environment. As in [13], an R value of 2 is used for all of the experiments.

B. Dynamic Kalman Filter (KF-DN)

The Dynamic Kalman filter is too, a predictive filter computed in two stages. The differentiating factor between the two is that in the dynamc Kalman filter, a dynamic process noise component, parameter Q is recursively calculated. Here, Q is describes as the process noise covariance matrix. Since this system is one dimensional, and we are only concerned with the RSSI values, the covariance matrix transforms into just the variance. In this filter implementation, the latest 10 states, including the current, are maintained, and with this the variance is calculated. This acts as a sliding window behaviour to the standard static Kalman filter, to make up for dynamic changes in process noise in the environment.

C. Gaussian Filter

The Gaussian filter is a filter that utilizes an impulse response to create a Gaussian distribution. The filtered value is then chosen to lie on one side of the distribution, determined by the variance and mean.

The Gaussian filter is implemented similar to [10], [14]. An array of previously obtained RSSI values is created and used to calculate two parameters; the mean and the standard deviation (σ). In this experiment, the array size was 10.

The mean is calculated as;

$$\mu = \frac{\sum_{i=1}^{n} RSSI}{n} \tag{6}$$

To calculate σ, the variance needs to be calculated.

$$var = \frac{\sum_{i=1}^{n} (RSSI - \mu)^2}{n} \tag{7}$$

where n is a set number of previously obtained RSSI values (including the current state), and μ is the mean of these values.

The σ parameter is calculated as the square root of the variance.

$$\sigma = \sqrt{var} \tag{8}$$

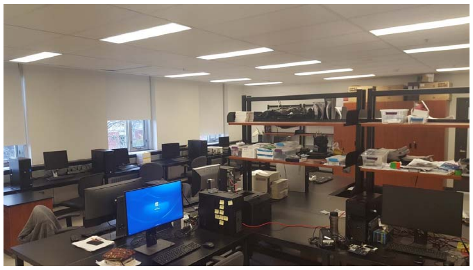
IV. Experimental Procedure

A. Equipment

In this work, five BLE beacons are used:

i) BlueCat [26] which is powered by 2-AA batteries,
ii) Gimbal S10 [27] which uses a single CR2032 battery,
iii) Cyalkit-E02 [28] which is a powered beacon,
iv) Kontakt [29] which requires two CR2477 batteries and
v) Estimote [30] which needs four CR2477 batteries.

(a) Room 1 - Laboratory room.



(b) Room 2 - Laboratory room.

(c) Room 3 - Meeting room.

Fig. 1. Different environments for proximity experiments.

All the beacons implement Apples iBeacon protocol. A Google Nexus 5 smartphone running Android OS version 6.0.1 was used as the receiving device and the power measurements are obtained using a Monsoon power monitor.

B. Environment

The accuracy experiments took place in three rooms; a lab room of size 5.65 x 10.30 meters (Room 1), a second lab room of size 9.10 x 17.50 meters (Room 2), and a meeting room of size 3.40 x 4.00 meters (Room 3), shown in Fig. 1. It is important to note that the first and third rooms are chosen based on difference of dimension, and remained isolated from other BLE beacons during the experiments, while the second room, similar in size to the first, is chosen to compare the accuracy of the beacons in a busy/ noisy environment. In particular, 14 other BLE beacons were transmitting in the same room while the experiment took place.

C. Energy efficiency experimental setup

Each beacon is set to have the same transmit interval of 3 seconds and the same transmission power of -12dBm respectively, except for the case of the BlueCat beacon, as it has predefined transmit powers. The closest configurable transmission power was -10dBm, so in the following experimental results, the BlueCat beacon transmits at a level 2dBm higher than the rest. The 3 second transmission interval is chosen for fair comparison between beacon devices, as the Cyalkit solar beacon can only achieve a maximum transmission interval of 3 seconds. The -12dBm was chosen as it proved to be sufficient for all three test environments given their size and the testing procedure. The average power and current consumption of each beacon is measured over a period of 4 minutes. Monsoon power monitor was use

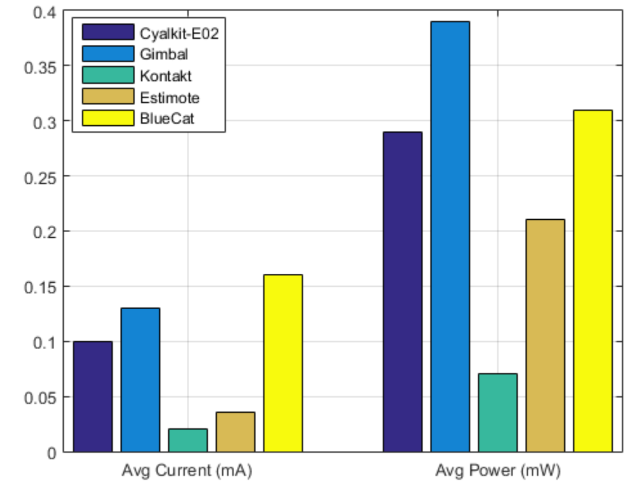


Fig. 2. Current and Power characteristics of beacons.

D. Proximity accuracy experimental setup

In the proximity accuracy experiment, the effect of the filters is also examined. Initially, 12 distinct RSSI measurements are collected in their raw form, i.e. no additional filters. Then, one of the three filters is applied at the same 12 measurements. The distance between the beacon and the smartphone is predefined at; 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75 2.00, 2.25, 2.50, 2.75, and 3.00 meters.

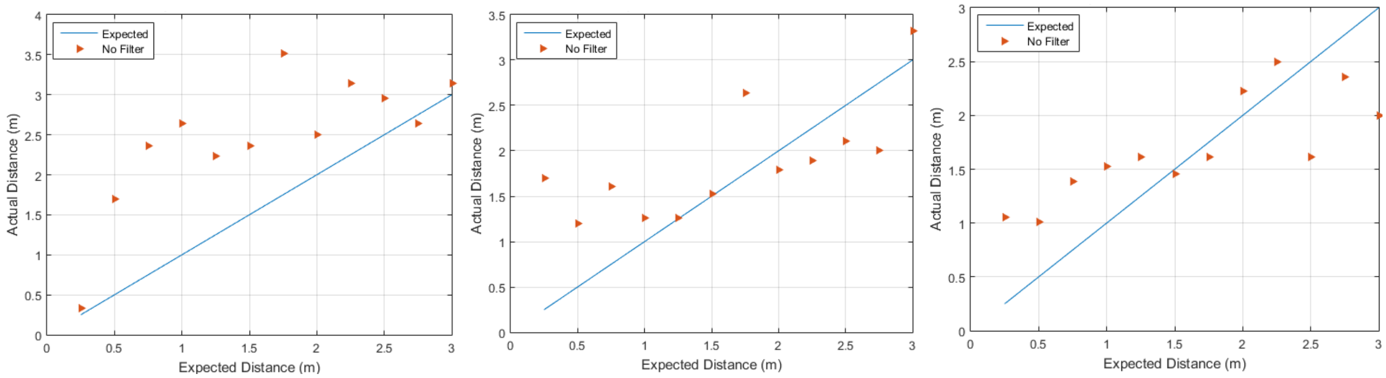
As in the energy consumption experiment, aside from the BlueCat, each beacon is set to have the same transmit transmission power of -12dBm. In this experiment, the transmission interval is set to 300ms. The change in transmission interval is due to the fact that if the beacons transmit only every 3 seconds, the Kalman and Gaussian filters have little to no effect on the RSSI/distance estimation because it cannot progress at a rate that can accommodate for the dynamic changes in process noise of the environment.

It is important to note that the Cyalkit-E02 beacon can only transmit at a maximum rate of every 3 seconds, reliant on that the environment has sufficient light. For this reason, the results of the filters are not included for this beacon as they are the same as the raw measurements. This is a major shortfall in this particular beacon's performance, and should be noted.

V. Experimental Results

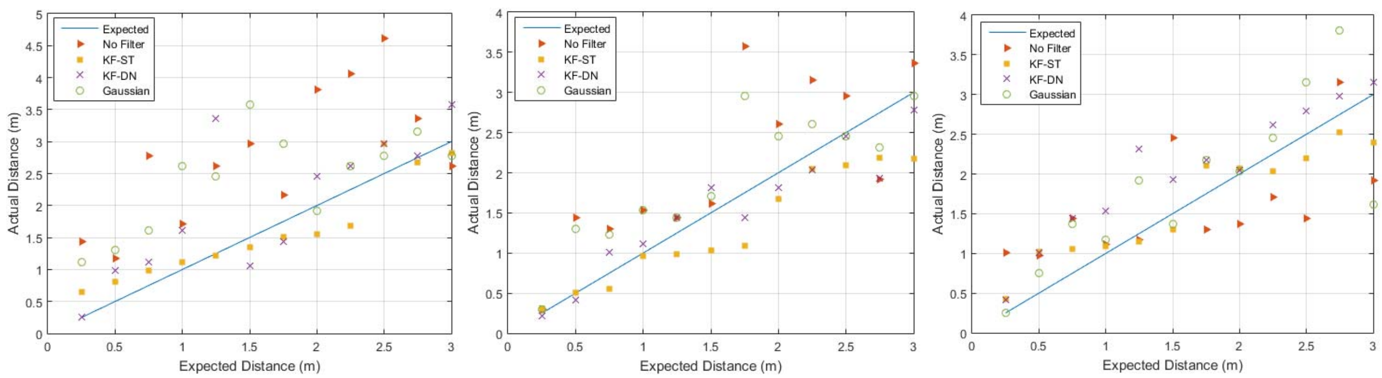
A. Energy results and discussion

The experimental results are available online [15]. The average current and power consumption of the five BLE beacons is shown in Fig. 2. It can be seen that under identical conditions,



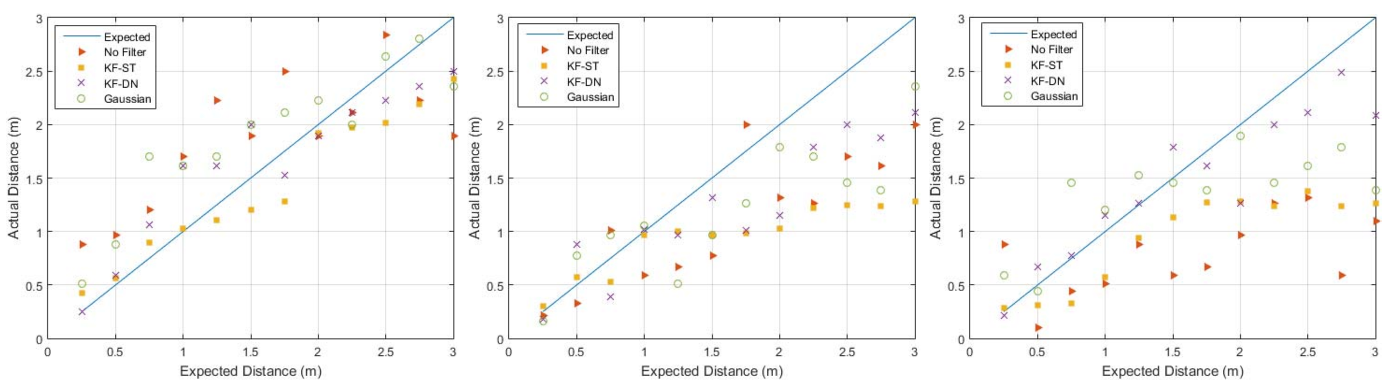
(a) Room 1 (b) Room 2 (c) Room 3

Fig. 3. Cyalkit E02 - Proximity estimation results.



(a) Room 1 (b) Room 2 (c) Room 3

Fig. 4. Gimbal - Proximity estimation results.



(a) Room 1 (b) Room 2 (c) Room 3

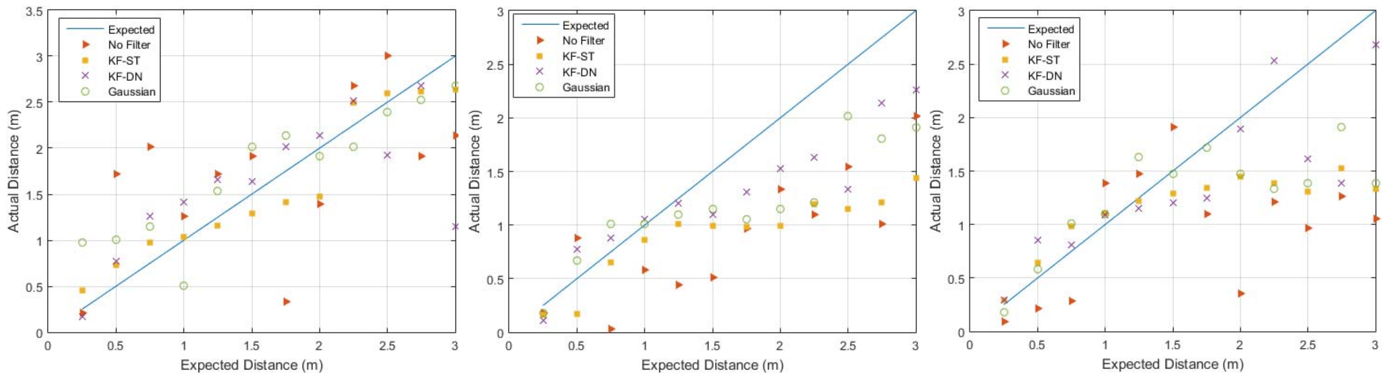
Fig. 5. Kontakt - Proximity estimation results.

the Gimbal beacon has the highest power consumption. It is then followed by the BlueCat, Estimote, Cyalkit-E02, and the Kontakt beacons. The differences in power consumption can be due to the differences in circuit design.

The Kontakt beacon has the best performance in terms of power consumption. It supports 2 CR2477 button cell batteries in parallel, which can increase its lifespan drastically. On the other hand, the Gimbal beacon might have higher energy requirements, but it is the cheapest beacon of the five. The BlueCat beacon seems to implement a simple circuit and power source (2-AA batteries), which in conjunction with the slightly higher transmission power, may attribute to its poor energy consumption performance. The Estimote beacon has a good energy consumption performance, when the additional sensors are not used. The E02 can be a great beacon for longevity due to its solar cells, allowing it to charge its super capacitor [31].

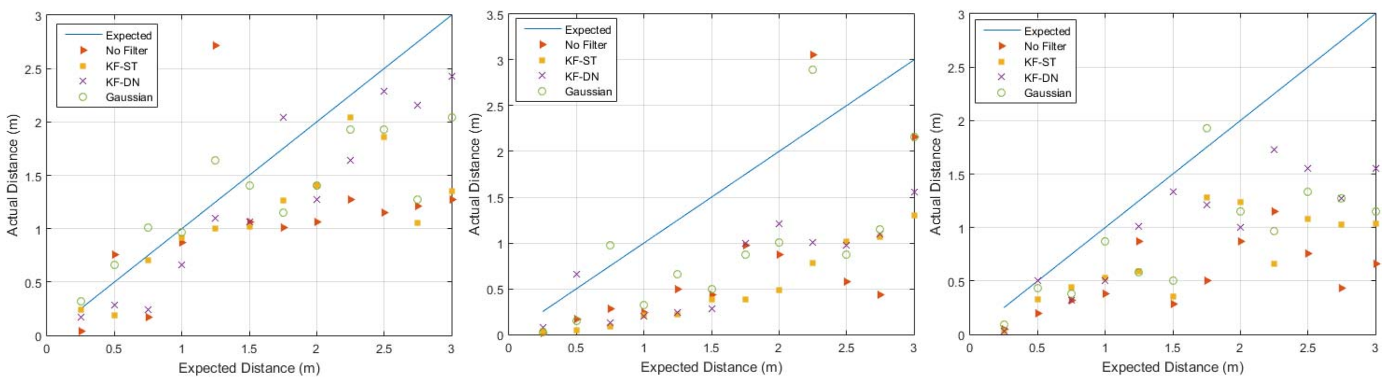
B. Accuracy results and discussion

The experimental results of all five beacons, across all three test environments are shown in Fig. 3 to Fig. 7. Each



(a) Room 1 (b) Room 2 (c) Room 3

Fig. 6. Estimote - Proximity estimation results.



(a) Room 1 (b) Room 2 (c) Room 3

Fig. 7. BlueCat - Proximity estimation results.

graph depicts a scatter plot of the measurements while the solid line represents the expected value at each point. As discussed, the E02 measurements under the influence of the KF-DN, KF-ST, and Gaussian filters were not included as it had no effect due to the long transmission intervals. In fact, during experimentation, it was observed that in the tested environment, the E02 would transmit approximately every 60 seconds, making it hard to be used in real indoor localization applications that needs updates more often. The standard deviation of each beacon from its expected distance in each room is shown in Table I, II and III.

According to the experimental results, the KF-ST, KF-DN, and the Gaussian filters, in all cases, show a great improvement in accuracy over the raw measured data. The electrical noise and competing 2.4GHz channels in the test environment did appear to have a significant effect on the achievable accuracy.

In the first test environment, the use of the static Kalman filter achieved an error standard deviation of 0.36. The second test environment, in which 14 other BLE beacons were transmitting during experimentation, the dynamic Kalman filter prevailed, as expected. The dynamic component of the filter was able to make up for the dynamic changes in noise that was being produced by the additional beacons in the region. As it is shown in Table II, an average standard deviation of 0.42 was achieved under the influence of the dynamic Kalman filter. In the final test environment the dynamic Kalman filters performed better, on average.

In all of the results, all three filters are a viable means of improving accuracy, but one can not be chosen to have definitive superiority over the others. In noisy environments, it can be seen that the dynamic Kalman filter achieves better accuracy over its static counterpart, but this may not be true in all scenarios. Testing of each filter, given the deployment environment, is needed to make an appropriate decision on which filter to implement. Even with electrical noise and contention in the test environment, it is important to note that the experiment was conducted with direct line of sight (LOS) and no physical environmental changes. These factors will have a large effect on the accuracy of real world implementations, even with the assistance of the KF-ST, KF-DN or Gaussian filter.

VI. Conclusion

This paper examines the energy consumption and proximity accuracy of BLE beacons. Five beacons are used in extensive experimentation in three unique environments. Three filtering techniques are also used to improve the proximity estimation.

According to experimental results, the expected life of beacon devices can vary drastically and significant improvement in localization performance can be achieved with filtering. BLE beacons are likely to continue to be a popular choice for

TABLE I
ROOM 1: STANDARD DEVIATION IN m.

	NoFilter	KF-ST	KF-DN	Gaussian
Cyalkit-E02	0.64	N/A	N/A	N/A
Gimbal	0.76	0.33	0.64	0.68
Kontakt	0.60	0.28	0.36	0.41
Estimote	0.84	0.27	0.65	0.40
BlueCat	0.87	0.57	0.29	0.55
Average	0.74	**0.36**	0.48	0.51

TABLE II
ROOM 2: STANDARD DEVIATION IN m.

	NoFilter	KF-ST	KF-DN	Gaussian
Cyalkit-E02	0.64	N/A	N/A	N/A
Gimbal	0.63	0.27	0.31	0.43
Kontakt	0.48	0.62	0.40	0.50
Estimote	0.54	0.57	0.42	0.48
BlueCat	0.80	0.50	0.54	0.67
Average	0.62	0.49	**0.42**	0.52

TABLE III
ROOM 3: STANDARD DEVIATION IN m.

	NoFilter	KF-ST	KF-DN	Gaussian
Cyalkit-E02	0.58	N/A	N/A	N/A
Gimbal	0.71	0.32	0.27	0.61
Kontakt	0.74	0.54	0.36	0.67
Estimote	0.84	0.63	0.49	0.63
BlueCat	0.75	0.63	0.49	0.64
Average	0.72	0.53	**0.40**	0.64

indoor localization and navigation applications. The research presented in this paper enforces the need to test and compare the options, given the application requirements, as there is no single beacon device that is superior to the rest. The experimental results are available online [15].

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