Energy Consumption and Proximity Accuracy of BLE Beacons for Internet of Things Applications

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***Abstract*—In the Internet of Things (IoT) era, with millions of connected devices to the internet, indoor location services regarding room discovery and resource identification/tracking are among the most popular applications for smart homes and smart buildings. Bluetooth Low Energy (BLE) beacons are a promising solution to improve the scalability and accuracy of indoor localization applications. They are low cost, configurable, small transmitters designed to attract attention to a specific location. In this paper, we investigate three popular BLE beacon devices available on the market and compare them in terms of energy consumption and proximity accuracy for indoor localization services. In addition, two state-estimation filters are developed for the Android mobile platform in order to improve the proximity accuracy when using smartphone devices. Specifically, a static Kalman filter and Gaussian filter are implemented.**

I. Introduction

Lifespan and accuracy are critical characteristics of any Internet of Things (IoT) applications. Current battery technologies have come a long way, but in order to manage a large network of various wireless nodes, a low power solution is required. With the increase in wireless nodes and competing networks in all environments, the level of contention will drastically affect accuracy.

Bluetooth Low Energy (BLE) beacons have emerged as a popular wireless device, predominantly due to their simplicity and low cost. They are small devices which transmit their unique identity, as well as any telemetry data collected from additional sensors that may have been added by the manufacturer. They are readily available in today's market and have become a popular means of providing indoor localization, using Received Signal Strength Indicator (RSSI) techniques [1]. Their scalability and ease of integration with smartphone devices are additional attributes that ensure homogeneity for indoor localization applications. BLE beacon deployment continues to grow and is projected to reach 400 million deployed devices globally by the year 2020 [2]. However, the transmitted signals are subject to noise and physical interference. As the number of wireless networks and devices grow, or as the complexity of the environment increases, the level of accuracy diminishes and the need for filtering techniques increases.

Research has proven that the addition of post-process filtering techniques improves the precision of RSSI readings from BLE beacon packets. These filters are generally predictive/ estimation filters, such as the Kalman, Gaussian, or particle filters [3], [4]. These filters are often implemented on a server [4]. Further research regarding prediction and accuracy improvements has expanded into machine learning, with such models as the K-Nearest Neighbor (KNN) [5].

This paper compares the accuracy and energy consumption characteristics of three BLE beacon devices through experimentation. Each beacon is chosen for its variations in power sources and cost. The accuracy of each device is compared in its raw form and with two separate filtering techniques; Kalman filter and Gaussian. The implications of the results in relation to IoT integration is also discussed.

The rest of this paper is organized as follows; In Section II, an overview of the related works regarding BLE beacon devices is discussed, followed by Section III that introduces the experimental procedure and methodology. Section IV discusses the experimental results and its implications. The conclusion is in Section V.

II. Related Works

Smartphones and their wide range of integrated technologies facilitate a lot of the growth in IoT, supporting multiple mechanisms for indoor localization, as discussed in [6]. Multiple techniques and technologies have been adapted to provide indoor location information, all of which attempt to overcome the noise and dynamics of a complex and dynamic indoor environment. Such indoor localization models may be based on a visual system, as in [7]. This model is capable of accurate indoor localization through sophisticated feature recognition but requires pre-processed data of the environment and increased hardware costs. Other implementations attempt to use existing Wi-Fi infrastructure to provide indoor localization services. The work in [8], utilizes a fingerprinting approach to achieve accurate location, but suffers from more noise in the environment and high energy consumption.

BLE beacons are cheap, simple, and a very scalable means of implementing indoor localization services. In recent years, BLE technology has grown in popularity and much more research has been developed in using it for indoor localization and resource identification/tracking [3], [9]. The fundamental operation of these beacons for localization purposes is based on RSSI techniques [10], [11], where the RSSI value is translated into a distance by using a best curve-fit signal propagation model. BLE beacon protocols, such as iBeacon [12] and Eddystone [13], provide the necessary information and configuration capabilities for micro-location [1] and integrate easily with the vast majority of mobile devices on the market.

As the number and variation of devices increases in any environment, susceptibility to noise and interference becomes especially important. To overcome the effects of noise and dynamic changes to the physical environment, many filtering techniques have been implemented. One of the most common filter implementations is the Kalman filter as detailed in [3]. This filter may provide a reasonably accurate state estimation. Other filters such as the particle filter are used. Particle filters can be highly accurate but at the cost of greater computational complexity. Hence the need for a client-server based model, as outlined in [4].

One of BLE's critical characteristics in Indoor Positioning Systems (IPS) is its low power consumption. BLE requires less energy than Wi-Fi [14], while some beacons even operate on solar power, as discussed in detail in [15]. The works presented in [16] explore the power consumption of alternate BLE devices. They introduce some basic IoT applications that utilize the BLE protocol, giving insight to the energy requirements of BLE devices.

This paper expands on the previous work in [17], comparing the performance of the Kalman filter to the performance of the proposed Gaussian filter for RSSI distance estimation. This paper also explores the energy consumption of 3 different BLE beacon devices in the interest of understanding the varying power characteristics of beacons offered by different manufacturers.

III. Experimental Procedure and Methodology

This section introduces the characteristics of all system components, which includes the three beacons, the receiving device, and the measuring tools used in the experiments. Furthermore, the experimental procedures used to measure accuracy and energy consumption is explained in detail.

A. Equipment

Three BLE beacons are used in the following experiments: Estimote [18], Kontakt [19], and Gimbal Series 10 [20]. The three beacons are chosen for their variations in design, price, power source, and features. The goal is to compare the performance with respect to the vast variety of BLE beacon devices that are available on the market by using three very different yet popular beacon devices.

The Estimote beacon contains many additional sensors, such as humidity, lux, air pressure, and motion. It runs on 4 CR2477 3V batteries, organized in a series pair to provide the required 6V input for operation. The Kontakt beacon is a simpler beacon that runs on 2 CR2477 batteries in a parallel configuration. The Gimbal Series 10 beacon is the simplest and cheapest beacon of the three and requires a single CR2032 battery. All beacon devices are able to implement either Apple's iBeacon, or Google's Eddystone protocol. The receiving device is a Google Nexus 5 smartphone running Android OS version 6.0.1. The power measuring device is a Monsoon power monitor.

B. Filtering techniques

Two filtering techniques were implemented in the experiments in order to achieve better accuracy. Specifically, a static Kalman filter and Gaussian filter. These filters were chosen due to their simplicity, aptness, and ease of implementation in mobile software. The Kalman filter is a linear quadratic estimator that uses a sequence of measurements over time to produce estimates that also considers statistical noise, making is a great suitor for RSSI-based localization techniques. The Gaussian filter is a great filter for sequential measurements with inherently small delay, making it computationally manageable for a smartphone-based implementation. Alternative filtering algorithms, such as the particle filter, would have been too power consuming and computationally expensive to implement on a smartphone.

Static Kalman filter (KF-ST). The static Kalman filter is following the work in [17]. The static Kalman filter works in two stages; prediction, then update. A Kalman gain modifies the predicted value and is calculated based on a constant measurement noise parameter, set in the algorithm. This parameter is chosen based on the environment it is being used in, and for RSSI measurements, is often chosen to be between 2 and 4 for most environments.

Gaussian filter. The Gaussian filter can be defined by the following equations and is implemented in a similar fashion to [3].

First, an array of previously obtained RSSI values is created. This array is used to calculate two essential parameters; the mean, (μ), and the standard deviation, (σ). For the purposes of these experiments, the array size is kept as the latest 10 values (including the current state).

The mean is calculated as;

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

To calculate σ, the variance needs to be calculated.

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

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.

$$\sigma = \sqrt{var} \tag{3}$$

In reference to algorithm 1, notice that the first **if** statement determines if σ is greater than 0. It assumed that the standard deviation always takes the positive root, but if the value is zero, the alternate standard deviation is set to 1 so that it has no effect on the rest of the calculation. Next, the algorithm determines which side of the distribution the value is on so that it can appropriately add or subtract the determined Gaussian distribution value.

Algorithm 1 Calculate Gaussian Filtered RSSI

if $\sigma > 0$ **then**
  if $newSignal - \mu > 0$ **then**
    $RSSI = newSignal - (\frac{1}{\sqrt{2 \cdot \pi} \cdot \sigma} \cdot \frac{-(newSignal-\mu)^2}{2 \cdot \sigma^2})$
  else
    $RSSI = newSignal + (\frac{1}{\sqrt{2 \cdot \pi} \cdot \sigma} \cdot \frac{-(newSignal-\mu)^2}{2 \cdot \sigma^2})$
else
  if $newSignal - \mu > 0$ **then**
    $RSSI = newSignal - (\frac{1}{\sqrt{2 \cdot \pi}} \cdot \frac{-(newSignal-\mu)^2}{2})$
  else
    $RSSI = newSignal + (\frac{1}{\sqrt{2 \cdot \pi}} \cdot \frac{-(newSignal-\mu)^2}{2})$

C. Room selection

The performance of beacons can be affected by the environment. To examine the performance of each beacon and the filtering techniques, two rooms of different sizes were selected for the accuracy experiments. Room 1 – a lab room of size 5.65 x 10.30 meters and Room 2 – a meeting room of size 4.5 x 5.0 meters. The first room is a wireless laboratory while the second was a smaller meeting room, with beacons being the only BLE transmitting devices in the area during the experiments. These rooms were chosen for their difference in size, physical layout, and noise characteristics. The RSSI data is expected to vary between these environments, thus allowing us to compare and contrast filter performance and distance estimation accuracy in different environments.

IV. Experimental Results

We examine the performance of the three beacons in terms of energy consumption and accuracy.

A. Energy Efficiency

The lifespan of every IoT network is a critical factor in its performance and development/ maintenance costs. In this experiment, the average power and current consumption are measured and compared for all three beacons.

1) Experimental Setup: To compare the energy efficiency of each beacon, the average power and current consumption is measured over a period of 4 minutes. To access the beacon devices, each beacon was taken out of its shell so that the positive and negative terminals could be accessed.

Each beacon is set to have the same transmit interval and transmission power, of 3 seconds and -12 dBm respectively. To measure the average power and current consumption, the Monsoon power monitor is used. It measures these parameters at a rate of 5000 samples per second, thus providing a highly accurate result.

2) Energy Results and Discussion: The average current and power consumption of the three BLE beacons are shown in Fig. 1. As it can be seen, under identical conditions, the Gimbal beacon has the highest current draw and power consumption. This is then followed by the Estimote, and the Kontakt beacons.

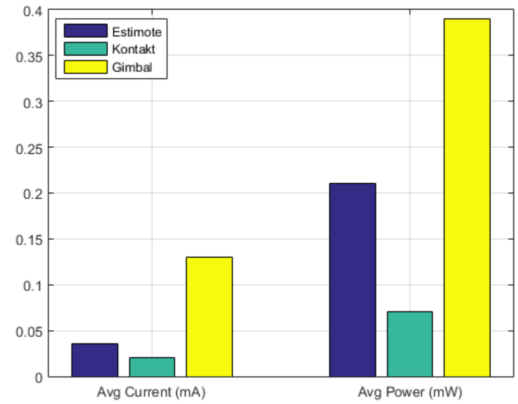


Fig. 1. Average current and power consumption.

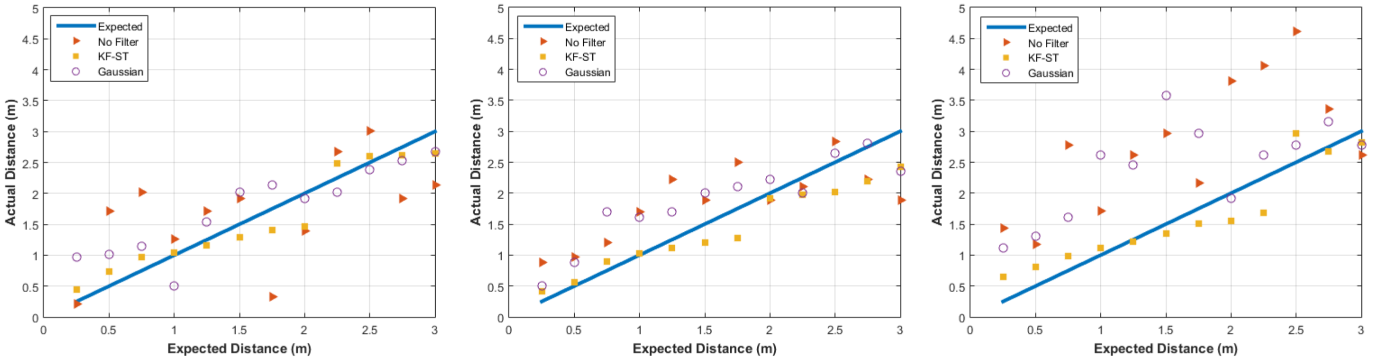
The differences in power consumption are due to the differences in circuit design and additional sensors integrated with the various beacons. The Gimbal beacon is, in fact, the cheapest beacon of the three, and as a result, the engineering behind power management is reflected in its results. The Estimote beacon, though much more expensive, has the most additional sensors as previously outlined, which causes the increase in power consumption. The Kontakt beacon is the clear choice of the three with regards to greatest lifespan. Note that the Kontakt beacon supports 2 CR2477 button cell batteries in parallel, drastically increasing its lifespan.

B. Accuracy

Each beacon device contains varying hardware components, specifically transceivers, that will influence its behavior and accuracy in a given environment. In this experiment each beacon is tested in the two rooms, the wireless laboratory (Room 1) and the meeting room (Room 2) and over multiple set distances, to compare their accuracy in a simple indoor localization application. The rooms are selected based on their different environmental characteristics as described in section III-C.

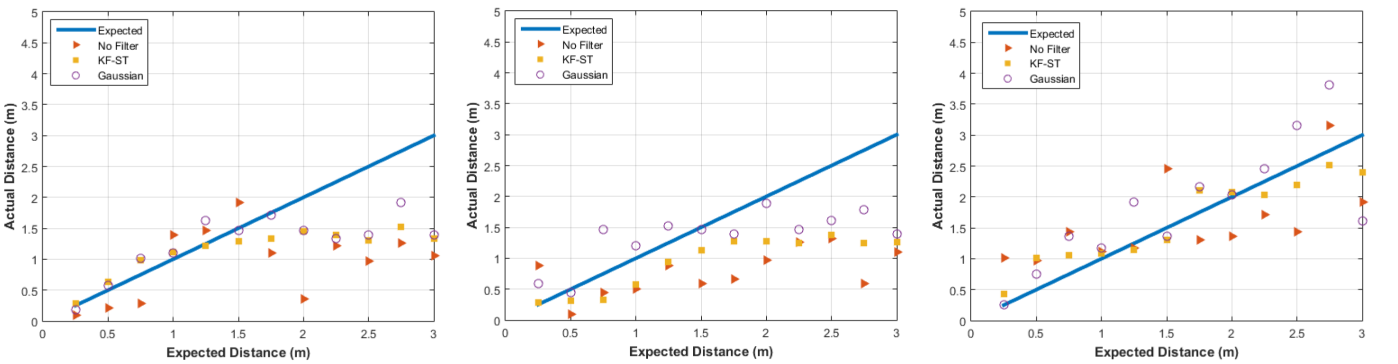
1) Experimental Setup: Each beacon undergoes three iterations of the experiment; the first takes 12 RSSI measurements in its raw form, i.e. no additional filters, the second takes the same 12 measurements under the employment of a static Kalman filter (KF-ST), and the third makes use of a Gaussian filter. To measure the RSSI values, the beacon is placed at a fixed point and the Google Nexus 5 is moved to the 12 set distances; 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. Similar to the energy consumption experiment, each beacon is set to have the same transmission power of -12 dBm. Also consider that in this particular experiment, the transmit 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 distance estimation because it cannot progress at a rate that can accommodate for the dynamic changes in the noise of the environment.

The receiving device (Google Nexus 5) implements an open source application *Beacon Scanner* [21], to read the iBeacon



(a) Estimote. (b) Kontakt. (c) Gimbal.

Fig. 2. Room 1: Distance estimation.



(a) Estimote. (b) Kontakt. (c) Gimbal.

Fig. 3. Room 2: Distance estimation.

TABLE I
ROOM 1: STANDARD DEVIATION IN m.

	NoFilter	KF-ST	Gaussian
Estimote	0.84	0.27	0.40
Kontakt	0.60	0.28	0.41
Gimbal	0.76	0.33	0.68

TABLE II
ROOM 2: STANDARD DEVIATION IN m.

	NoFilter	KF-ST	Gaussian
Estimote	0.84	0.63	0.63
Kontakt	0.74	0.54	0.67
Gimbal	0.71	0.32	0.61

packets, transmitted by the beacons. It utilizes the *AltBeacon* library to support the BLE packet decoding. The application code is altered to append the Kalman and Gaussian filtering algorithms to the logic and UI.

2) Accuracy Results and Discussion: Figures 2 and 3 depict the distance measurement results of all 3 beacons in the two test environments and Tables I and II detail the standard deviation of each beacon from its expected distance values for both test environments. The translated distance estimation is calculated as the best curve fit for the receiving device's hardware. Take into consideration that each BLE beacon has a calibrated RSSI value that is expected to be seen at 1m. This value is used for distance calculations, and this parameter is sent with every packet as per the iBeacon protocol [12].

It can be seen from the graphs and tables that the KF-ST and Gaussian filters result in a significant improvement in accuracy over the raw data. The signal noise and competing 2.4GHz channels in both testing environments appeared to have a significant effect on the accuracy. The filtered results are much closer to the true value in the first environment as compared to the second, likely due to interference caused by the closer proximity of the beacons to a wireless router. Additional causes for the variation in results is likely due to the difference in environmental layout, where beacon signal interference may have a greater impact on each other in Room 2 versus Room 1. This may also explain the underestimation at distances greater than 1.5 meters for the Estimote and Kontakt beacons respectively. This effect is not seen with regards to the Gimbal beacon and may be attributed to changes in signal noise in the environment at the time of testing. Further analysis into the noise levels of interfering signals and their effects on beacon performance could expand on this research. Without any filtering, the beacons achieved a standard deviation no better than 0.6m from the expected proximity, as shown in Table I. An improvement of over 50% was obtained in the case of the Estimote beacon, under the influence of the Gaussian filter, and over 67% improvement in accuracy under the influence of the KF-ST. Both filters are a viable means of improving accuracy, but the KF-ST shows consistent superiority over the Gaussian. This is because the Kalman filter is tuned for the particular environment in which it is used [17], while the Gaussian filter relies only on the standard deviation, arithmetic mean, and the current measurement to produce an estimation of the true distance.

Testing of each filter, given the deployment environment, is needed to make an appropriate decision on which filter to implement. The difference in environmental layout and noise may cause one filter to perform better than the other. Even with 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 or Gaussian filter.

V. Conclusion

This paper explored two critical characteristics, energy consumption and accuracy of BLE beacons. The three beacons in this experiment are representative of a larger market of beacon manufacturers. The Estimote, Kontakt, and Gimbal beacons were subject to two experiments. The first measured average current and power consumption, and the second measured RSSI/distance proximity, comparing raw values with those under the enforcement of a mobile software implemented Kalman and Gaussian filters.

It was shown that beacon devices can vary drastically in expected life and that scalable and improved BLE based positioning systems can be created with a combination of parameter tuning and mobile software defined filters algorithms. There are clear trade-offs and trends that are observed when comparing the cost and features of each beacon. The simpler devices with lower cost may behave sufficiently in terms of accuracy, but fall short in terms of energy consumption, and the beacons with more sensors show obvious increases in power consumption. If the application must be highly scalable (i.e. large number of nodes), then beacons such as the Gimbal series 10 would optimize the budget. For applications that require additional sensing and longer lifespan, more expensive options such as the Estimote beacon may be the optimal choice. Future studies and analysis would be focused on a more in-depth energy characterization of several popular beacon devices, as well as an analysis on the effects of noise and obstacles on distance estimation.

BLE beacons are a popular choice for a growing number of IoT applications including indoor positioning, resource/asset tracking and location discovery. With the addition of low power sensors, BLE beacons have a wide range of capabilities and applications in IoT. In an effort to improve the convergence of IoT in heterogeneous environments, the research and experimental results presented in this paper suggests that in order to select an ideal beacon, an extended characterization of power and proximity accuracy of available beacons should be carried out. A simple decision matrix comparing accuracy, power consumption, and cost may be sufficient in selecting the ideal beacon given the application requirements.

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