# Indoor Localization with Bluetooth Low Energy Beacons

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## 1. Abstract (1/4 page)

Indoor localization has not yet been deployed to large scale commercial applications. While extensive research has been done on it, there are still numerous precision issues that makes its use in commercial application with widely available technology unfeasible. In this paper, we examine the use of Bluetooth Low Energy (BLE) localization with the use of trilateration and heuristics in order to localize in indoor environments. We present a scheme that employs the use of Received Signal Strength Indicators (RSSI) from several anchors in order to estimate the distance to those anchors. From there, we use heuristics in order to estimate the location of a target.

## 2. Introduction (1 page)

Indoor localization has been a problem that researchers have been trying to address for a while. It can be beneficial for individuals trying to navigate complex indoor environments. For example, if an individual was navigating an art museum, indoor localization can be used to play audio clips when the individual was in front of a particular artwork. Additionally, if someone is trying to find a particular store in an indoor mall, it would be ideal to have technology in place for them to quickly navigate via their phones, similarly to how they navigate outdoors currently. Localization in general has been proven in commercial settings, primarily with the use of Global Positioning Systems (GPS).

GPS has been great for many outdoor environments. It uses four satellites to localize a target, and has been accurate up to a couple of meters. This has made its use in navigation systems preveliant. A majority of phones and cars can now accurately localize outdoors. However, indoor localization has been a continued problem. GPS is completely unreliable indoors due to the signal attenuation through walls. In a basement, it is completely impossible to use GPS. Additionally, even when the target is outdoors in dense urban environments, GPS can become unreliable. Therefore, other methods for localization have been explored.

The primarily mentality behind indoor localization is to bring the beacons indoors into the environment that one is localizing in. This prevents weak signals being lost when they attenuate through the concrete of walls. A lot of techniques primarily rely on the use of existing infrastructure in order to provide a low-cost solution. For example, they use wireless cards in phones and access points in buildings. These already are in place, making implementation far easier. However, these techniques have been shown to lack reliabilty. Other alternatives, such as the use of Ultra-Wide Band (UWB) have been shown to yield far more precise results, sometimes even with centimeter accuracy. However, UWB is not compatible with most smart phones, making its potential use in commercial settings far less.

Another common technology used in indoor localization is Bluetooth Low-Energy (BLE). This is the technology that we will use in our research. It is compatible with most phones, and transmitters are quite cheap, making its use in indoor localization feasible. However, there are still a lot of issues with using BLE in a commercial setting to localize. For example, there is a lot of noise in the channel, and most complex environments are rapidly changing. BLE requires setup and calibration for each environment that one is trying to localize in. If the environments shift rapidly, it can render previous calibration useless, thus making its reliability questionable.

Our project was centered on seeing if we could use trilateration with a received signal strength indicator (RSSI) in order to accurately localize within a specific environment. In addition to this basic approach, we also analyzed various filters, filter frames, and heuristics to optimize our accuracy within the environment.

## 3. Motivation and background (2-3 pages)

One of the primarily difficult parts of indoor localization is the need for high precision coupled with a very noisy environment that shifts. In addition, for commercial applications, there is a need for the technology to be cheap and scalable. This has lead to poor overall adoption of indoor localization in commercial settings. The technology and approaches have to balance all of these factors at once, and as shown, most cannot do that.

### 2.1 Types of Technology

There are primarily three different types of indoor localization technologies that are used. The first, BLE, is great due to its low energy output compared to that of WiFi. The primary way to localize using BLE is to gather RSSI values from the target to the anchors. This can be coupled with a few other techniques that we will discuss later. The primary issues with BLE include the large susceptibility to noise. Signal strength is not always an accurate indicator of distance. There can be objects in the way, or interference from other devices emitting similar frequencies. BLE also faces multipath issues, where a high density of objects can cause a wave to interfere with itself. In addition, when applied in a commercial settings, BLE anchors will be needed to be set up and calibrated. This makes it slightly harder to scale than the next technology we will discuss. In most settings, BLE based localization has been shown to be accurate up to 3 meters [4].

Another technology that can be used is WiFi. One of the primary benefits of WiFi compared to BLE is the fact that a majority of buildings actually have a plethora of WiFi access points. This makes scalability far less of an issue for WiFi than BLE. However, one of the primary disadvantages of WiFi is the high energy cost, especially compared to that of BLE or UWB. Like BLE, WiFi uses RSSI as its primary way to localize. Its accuracy is also fairly similar to that of BLE, which is within a few meters. It faces the same issues of noise and dynamic environments [5].

Finally, the last major technology we examined is ultra wideband. UWB has many advantages over WiFi and BLE. First, it sends a short impulse. This makes it very easy to distinguish over noise. In addition, due to its low frequency range, it can easily travel through walls, which can remove another barrier that face other technologies. Even if new obstacles were introduced into the environment, UWB would be able to propagate through them. UWB also samples across a wide band of frequencies and channels. This means that if a few channels have poor readings, the overall reading will still be sound. Finally, UWB can utilize RSSI as well as time of arrival [6]. This yields a far greater accuracy than that of BLE or WiFi. In fact, UWB can consistently yield an accuracy of up to 5cm. The primary setback of UWB is the fact that the hardware is not present in most modern smartphones. This means that its use in commercial settings will be limited until this constraint is no longer relevant.

### 2.2 Types of Approaches

In addition to different technologies and devices that can be used to localize, there is also a wide variety of approaches that can be taken to localize. The first and most commonly used one is called trilateration. Trilateration is the use of a few predicted distances in order to localize a particular target. In trilateration, there is usually at least three anchors and one target. Based off of the predicted distances with each anchor, we can predict the location in a two dimensional area. This approach usually uses RSSI in order to predict the distance. Based off of the rate of attenuation in the signal, we can predict that distance that signal traveled. This approach uses a free space path loss model ( $RSSI = -10 n log d - C$ ). In this model, n is the path loss exponent and C is the environmental variable. Finally, d is the distance. The variables n and C need to be calibrated per environment, but once they are, you can establish a direct relationship between RSSI values and distance. Once you have the distance that is predicted, you can localize like in Figure 1. One of the biggest issues with this approach is in the case that the three distances do not meet at one intersection point. In this case, one has to use the least square approximation method in order for determining the most probably location. In addition, RSSI's units are in decibel form, which is on a logarithmic scale. RSSI values are also in integer form. Because of this, there can be a lack of precision at long distances.

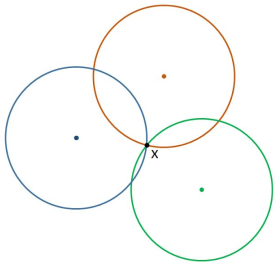



Fig 1. Trilateration

Another approach that is widely used is called fingerprinting. The idea behind fingerprinting is to generate large amounts of RSSI readings from many anchors coupled with the targets location. Once enough of this data is generated, one can localize by comparing the current RSSI vector with the database to find the closest fingerprint [2]. The main motivation behind this approach is to account for obstacles. By using trilateration, there is an assumption that the signal will attenuate at a consistent rate. However, in the real world, this is not always the case. There could be a column or obstacle in between the anchor and target, which will be impossible to accurately calibrate. With fingerprinting, as long as one gathers data all around the object, it will be possible to account for this environment. However, there are several issues with fingerprinting. First, it assumes a fixed environment. The second a new obstacle is introduced in the environment, all of the fingerprints will shift. In addition, momentary noise can still cause inaccuracies. In fact, a misreading can mean that one is localized to the completely opposite side of the environment if the fingerprint more closely resembles those on that side. There are also performance issues that arise from utilizing a large database of fingerprints.Finally, it is not a scalable technique. One will need to calibrate the environment with large amounts of data which can be very time consuming, especially if this calibration can be rendered useless.

Another method is often used to augment trilateration and fingerprinting is dead reckoning. Dead reckoning is the use of other sensors that smartphones employ in order to augment predictions from trilateration and fingerprinting such as the accelerometer. One can see how this approach can make predictions more accurate by generating predictions on an individual's movement over time. If noise disrupts one momentary prediction, dead reckoning can realize that mistake. For example, if noise shifts the RSSI values to predict the individual is on the other side of the environment, dead reckoning can detect this if the movement is not feasible for an individual to make in the elapsed time.

## 4. Approach (1-2 pages)

Our approach was to use BLE devices in order to localize indoors. This choice was made due to the low energy needs of the devices as well as the prevalence of the technology in smartphones. We first started by programming the receivers and transmitters. We decided to fix the channel that the transmitters sent advertisements at. This choice was made in order to prevent issues which hoping between channels. Each channel employs a different frequency, which means that it will attenuate at a different rate. If the transmitters are all advertising on different beacons, it will make it difficult to calibrate precisely. In addition, the channel characteristics could be different as well, such as different levels of noise or fading.

After we decided to fix the channel, we had to choose an appropriate beacon interval. Based on best practices, probability of interference, and other factors, we decided to send advertisements at 100ms. This would give us frequent enough RSSI readings. We also had to decide the power level of the transmitters. This decision was arrived based on empirical and theoretical speculation. If the power level was too high, it would be hard to localize as near distances because of the logarithmic nature of RSSI values. In addition, if the power level was too low, the RSSI values would be more susceptible to noise. In the end, we decided on a -4 dBm level.

Another decision we decided to make was to fix our localization to only one dimension. As seen in the next section, there was too much noise and multipath issues to accurate localize in two dimensions. We decided to localize within a hallway, so our primary goal was to predict where the target was along the hallway (the width or height of the target was not relevant for real world applications in this scenario). We decided to hand three anchors from the ceilings in the hallway. This was primarily to avoid any multipath effects with any walls or vents that the device would rest on.

We attempted to use tin foil to cover all of the wires. We suspected that these wires would cause significant interference with the RSSI readings. After a couple of experiments, we realized that tin foil did not have a significant impact on RSSI readings, and we no longer employed its use in covering wires. In addition, if we were to wrap our wires with tin foil (the wires that hung from the ceiling), it could interfere with other advertisements from the other beacons.

We decided to use a filter in order to mitigate noise. If there is a sharp deviation in the RSSI reading, the filter can account for this. It was also important to select a small enough filter frame so that the RSSI readings did not take into account channel fading. We also decided to use a median filter instead of an average filter. This was due to the fact that a sharp change in RSSI value will have less of an effect on a median filter than an average filter.

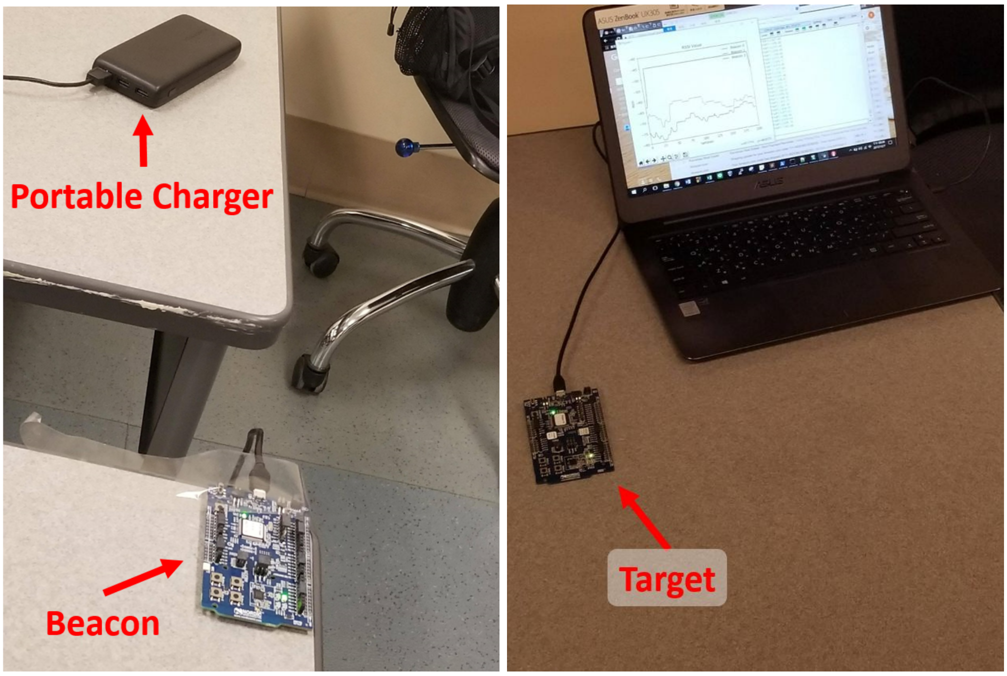
Once we set up, we started to calibrate. We decided to calibrate each device individually, instead of collectively. We reasoned that this would yield more accurate results because of the unpredictability in each device and its set up. The antennas may not be consistent from device to device.

Finally, we also decided to employ heuristics in order to localize more accurately. This was due to consistently poor results from traditional trilateration and least square approximation. The heuristics employed will be described in detail in the next section.

We created a python script in order to display the raw RSSI readings so that we can access the environment in real time. In addition, we encoded in this python script the functions necessary to localize using both trilateration with least square approximation as well as our heuristic method, and eventually created a data visualization to show the localization in real time.

## 5. Implementation/Evaluation (3-4 pages)

We used one Nordic nRF51 Development Kit board (PCA10028) v1.1.0 as our target/receiver and three Nordic nRF52 Development Kit boards (PCA10040) v1.1.1 as our beacons. Every beacon used portable chargers as power source. Target development board was connected to our laptop to display data and location simultaneously. Implementation setup is shown in Figure 2.




(a) Beacon setup (b) Target setup

Fig. 2. Implementation Setup

4.1 Beacons settings

From the free space path loss model as follow,

$$FSPL = \left(\frac{4\pi df}{c}\right)^2$$

where $d$ is distance, $f$ is frequency and $c$ is light speed, there is a frequency component in the model. Since beacons can broadcast advertisement in three channels, which are 37, 38 and 39 with different frequency, we fixed the advertising channel to only 37 to exclude the influence of frequency.

Beacons power consumption is related to advertising interval and transmit power. Advertising interval can be set in scales from milliseconds to seconds. Every time the advertising interval is met, beacons advertise messages from antennas. Such interval can have huge influence on battery lifetime. The longer the advertising interval is, the less power is consumed. However, with shorter intervals, the device can receive advertisement more frequently, allowing localization to be more reactive and precise. Samely, the lower transmit power results in low power consuming, but with high transmit power the device can localize itself at further distance from beacons. Therefore, there is a tradeoff of advertising interval and transmit power as battery lifetime, which depends on what the requirement of accuracy and durability is.

We used 100 milliseconds for advertising interval and -4 dBm for transmit power from experimental result. These gave us enough speed to gather advertising data and reliable RSSI values in the distance under 6 meters.

Every beacon transmits advertisement containing following data.

- 6 bytes MAC address
- 16 bytes Universal Unique Identifier (UUID)
- 2 bytes major value
- 2 bytes minor value

We used device name as identifier to differentiate beacons for convenience, which is also one well-defined data field in advertising data.

## 4.2 Filter

One of the most critical key for positioning accurately is to mitigate fluctuation of RSSI values. There are many factors causing RSSI values to fluctuate, including environment noise, moving people or objects, non-line-of-sight (NLOS) propagation and multipath effect. Even under stable and line-of-sight (LOS) environment without noise, RSSI values might still vary due to inconsistent RF or IF signals under hardware factors such as uneven signal strength from antennas. Those with large deviation might lead to great distortion of localization.

Thus, given such a varying RSSI, we tried to filter the fluctuation and obtain more reliable RSSI values. We experimented at fixed distance with two filter types, average filter and median filter, as in Figure 3. We can see that raw RSSI data has significant variation. The maximum deviation is even up to 18 percent. However, applying either one of two filters gives a much more steady values with the deviation less than 4.5 percent. This are huge improvement of data quality.

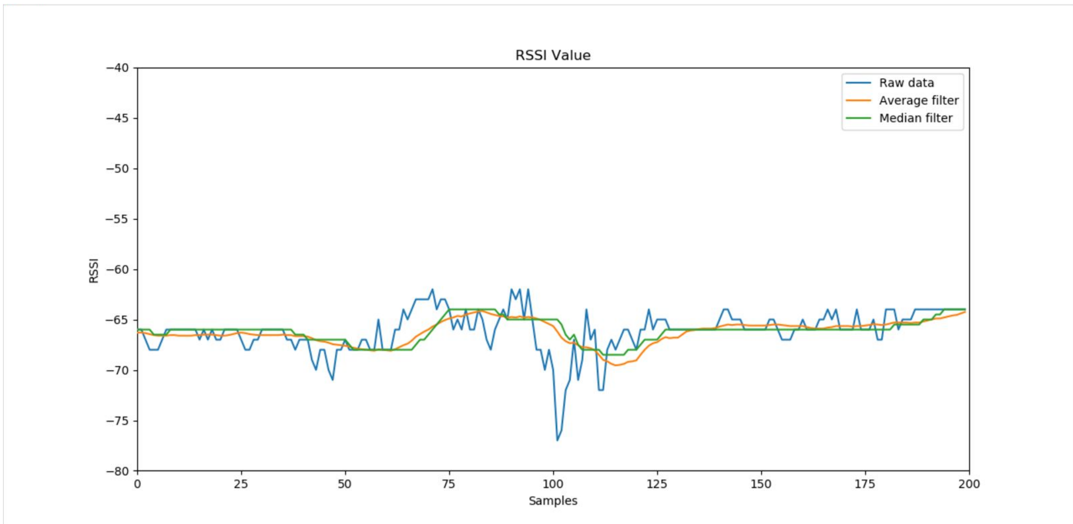



Fig. 3. RSSI without filter and with different filter types

In Figure 3, near the 100$^{th}$ samples, RSSI dramatically drops. At certain samples afterward, both RSSI values with average and median filter drop slightly. But notice that RSSI with median filter has less deviation than one with average filter. The filter generates estimated data from current value along with pass information, but however, while there is a great variation coming in, it reflects on output through average. In other hand, median filter only shift to the value next to the previous data when some peak values take place. Thus, median filter is more robust than average filter given a sudden great changes on RSSI. And in this project we apply median filter to mitigate the variation.

Filter frame size decides how many pass values are taken into consideration. The larger the filter frame is, more pass information is included to the output values, and RSSI values are more resistant to fluctuation. However, large filter frame can cause less reactivity when target changes position. When target moves, It needs more samples to stabilize RSSI values. This is a tradeoff between robustness of RSSI and reactivity.

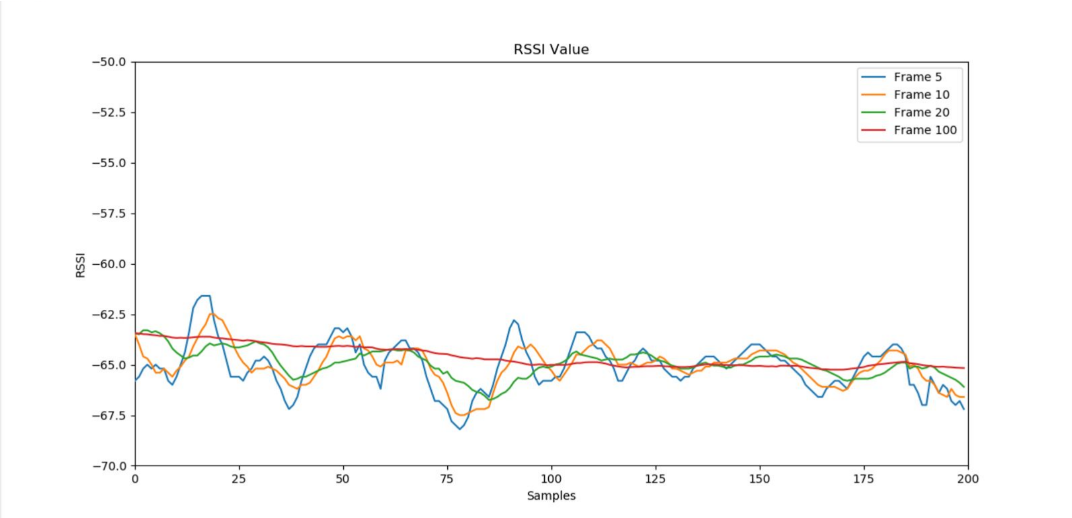



Fig. 4. RSSI with median filter under different filter frame sizes

In Figure 4, we experimented with different filter frame sizes, 5, 10, 20 and 100. With the larger filter frame, RSSI is more stable than those smaller frames, which meets with our expectation. In this project, we use 3 as our frame size, giving us not quite perfectly steady RSSI but more reactive to position movement.

4.3 Calibration

First, we calibrated our system at the hallway on third floor in Siebel Center, which is only one dimension. Three beacons were used although it only required two beacons to locate in one dimension and each beacon was calibrated separately with others keeping advertising. We hung three beacons from the ceiling in the air in order to make sure line-of-sight. The calibration results is shown in Figure 4. Beacon 0 and 2 shows in great accordance with the relationship of RSSI and distance, which both coefficient of determination ( $R^2$ ) is up to 0.8. To be noticed, both Beacon 0 and 1 have similar path loss exponent ( $n$ ) and environment constant ( $C$ ). However, Beacon 2 shows quite large path loss and lower constant value than other two. We inferred that hardware discrepancy such as development boards or height we place beacons really influenced calibration. That's also why it is better to calibrate each beacon.

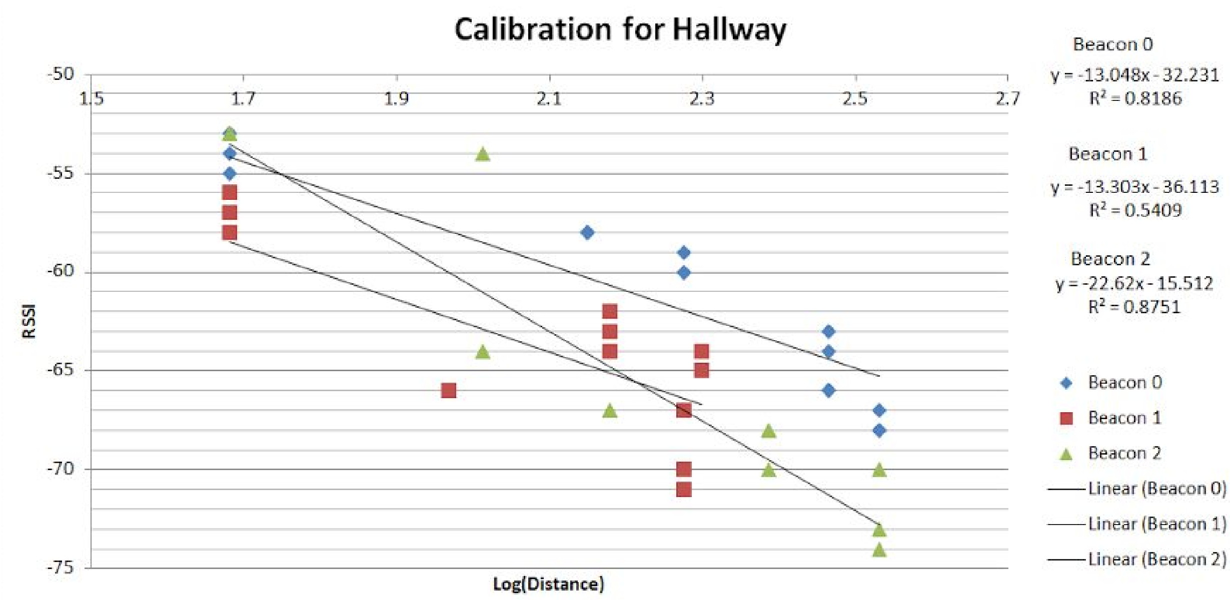


Fig. 5. Calibration at hallway (one dimensional)

We also tried to calibrate in Room 1302 in Siebel Center, which was a two dimensional experiment, with three beacons in nonlinear location. Beacons were placed on tables to ensure those on the same plane, alse, with antennas facing inward. The target was measured with the antenna in fixed direction during the whole experiment. The calibration result is show in Figure 6. We can see that neither a beacon had RSSI value in obvious relation to distance. Since we found that while the target in one position changed the direction of the antenna, RSSI values from some beacons would vary dramatically, thus, we inferred that orientation of either the beacons or the target significantly affected received signal strength.

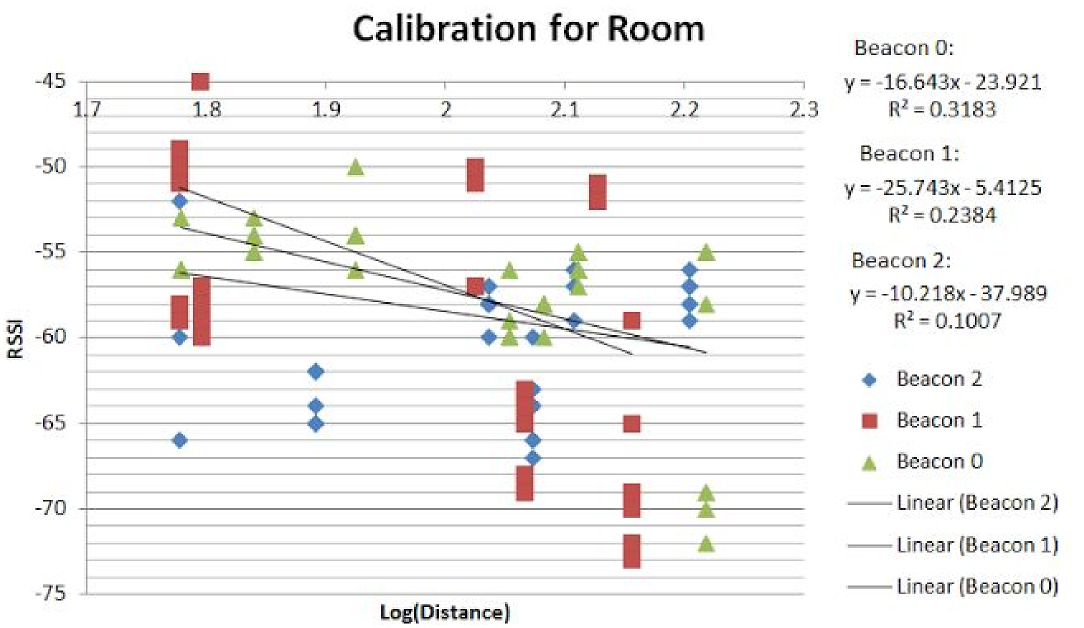



Fig. 6. Calibration in room (two dimensional)

4.4 Heuristics

After analysis of some preliminary tests in the hallway, it became clear that trilateration alone was not a reliable method for us to localize in this environment. Therefore, we settled on the use of some heuristics in order to better localize. The first heuristic we employed was that if any of the RSSI values were greater than -48 dB, we would automatically localize the target to that anchor. This is because we empirically discovered that only at the beacon were values this strong possible. The second heuristic we employed was to “bucket” the target into one of four intervals if all the RSSI values were weaker than -49 dB.

We determined that there were 4 possible intervals as illustrated in the Figure 7. If the difference between the two strongest RSSI values was 8 or less, we placed the target in the interval between the two anchors (interval 2 or 3). If the RSSI values were not, and the strongest RSSI value was that of beacon 0, we placed it in interval 1. If the strongest RSSI value was beacon 2, we placed it in interval 4. Our reasoning was that if it was in interval 1 or 4, the RSSI values between beacons 0 and 1 or 1 and 2 will be greater than 8 because there will be a far greater distance between the target and beacon 1 than the target and beacon 0 or 2. If the target was in interval 2 or 3, the distance between the target and beacon 1 and the target and beacon 0 or 2 should be similar, and thus the RSSI values should be closer together.


Fig. 7. Heurstic Interval Setup

Finally, once we placed the target in the correct interval, we needed to predict where along that interval the target was at. This is where we employed the use of the distance estimations from our RSSI readings. We computed the predicted location in the interval (i.e. the distance away from the beacon), and then averaged the two locations together.

### 4.5 Localization

After the use of heuristics, our localization became far more accurate. Figure 8 is a graph that displays our tests. We tested ten different points in different intervals and locations throughout the hallway. Figure 9 shows the error at each of these positions.

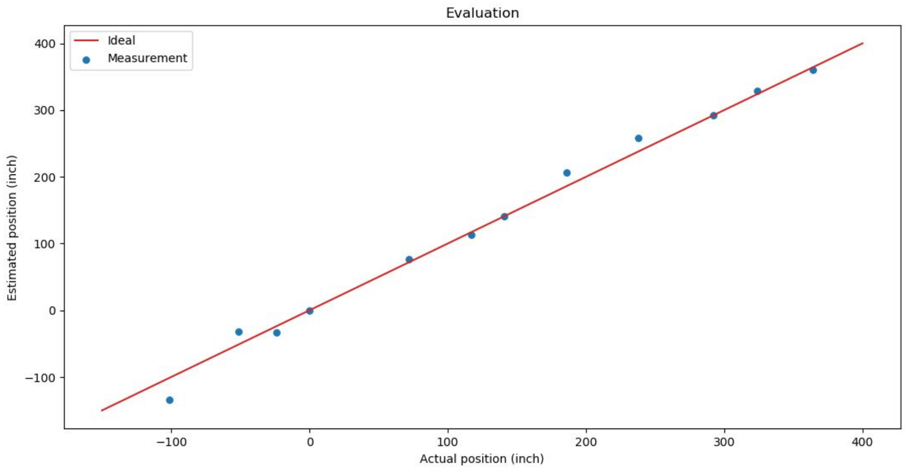



Fig. 8. Localization measurement

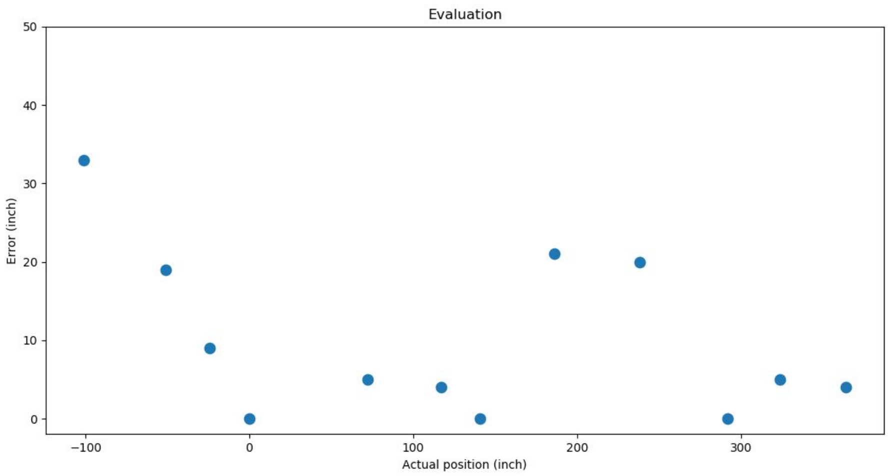



Fig. 9. Error evaluation

From the graphs, we can see that the use of heuristics in this environment yielded very accurate results. Our average error was roughly 10in. While this was very accurate compared to many of the research papers we have seen, it clearly has its limitations. First, the anchors were relatively close together. In addition, we were only localizing along one dimension, and not two like most of the research papers. Finally, the heuristics we crafted were hand selected for this particular environment, and likely would not generalize to most environments or two dimensional localization.

## 6. Conclusions and future directions (½ page)

In this project, we implement RSSI-based indoor localization with Bluetooth Low Energy devices. Exploiting the relationship between signal strength and attenuation while traveling in air, we are able to obtain the distance between beacons and the target through path loss model. Furthermore, applying trilateration gives the location of target. We use median filter with frame size 5 to mitigate the fluctuation from noise and other factors. Filter gives us a significant improvement of stable RSSI.

Calibration is the most important key to localization. We calibrated each beacons in the system separately but under all beacons advertising. The result in one dimension gave us reliable path loss exponent and environment constant. However, we could not calibrate in two dimension properly since it was significantly affected by orientation of the beacons and the target.

In localization step, we combined heuristics and trilateration. First, determine in which interval the target is from RSSI values and also the N-nearest beacons. Second, calculate the distance from those beacons and then apply trilateration to localize the target. This method only takes those nearby beacons with more accurate RSSI values into consideration of trilateration. Our approach showed pretty great localization accuracy in one dimension with error only 10 inches in average.

RSSI-based localization is susceptible to noise and multipath effect, and thus, it is not a great choice to localize in precise scale of meters. However, it is implemented with low complexity compared with another most commonly used technique, time-of-arrival (ToA), which requires time synchronization of all devices. Besides, RSSI-based technique is power saving, which is in favor of IoT development.

In the future, we will try to improve the localization accuracy. Eliminate the significant RSSI difference between beacons led by orientation of beacons and direction of target antennas, especially in two dimension. Furthermore, to optimize indoor localization, we can combine with other distinct techniques, such as dead reckoning, and use data fusion algorithm like Kalman Filter to obtain a hybrid estimated location. Besides, from the experiment, we are able to get quite stable RSSI values. Therefore, it is potential that fingerprinting would get accurate localization. This project is now in the experimental stage. In the future work, it will be implemented in practical application.

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