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Investigating the RSSI-based Distance Classification using Median Confidence Interval in a Multi-Device BLE Environment

Jille Anne R. VERANO
Mapúa University

Doreen Marie S. SORONGON
Mapúa University

Febus Reidj G. CRUZ
Mapúa University

Abstract: As the COVID-19 global pandemic occurred in 2020, there has been an increase in interest in using Received Signal Strength Indicator (RSSI) for strict implementations of social distancing. Bluetooth Low Energy (BLE) has been mainly used as an option for it is cost-effective and can be integrated with IoT for a wide range of applications. For a multiple-device BLE environment, the devices were calibrated, and parameters of the distance estimation were estimated using linear regression. For each device, RSSI values were acquired in various directions and distances. A confidence interval of 90% was used to create a prediction range for distance classification using the acquired RSSI. Using the range of median, BLE combinations at various distances and positions yield less than 50% of the data when classifying received RSSI values to distances of 1, 2, 3, and 4m. Irregularities from acquiring the RSSI value for various distances have been observed and can affect the classification of distance with the RSSI values. Further study is needed on other methods for the basis of interval range and minimization of irregularities.

Keywords: Social distancing, Bluetooth, Distance estimation, Confidence interval, Signal strength

Introduction

COVID-19 is an infectious disease that can spread from an infected person through small aerosols or large droplets discharged when they talk, cough or sneeze. It is mainly transmitted through respiratory discharges and can potentially spread on a large scale within communities. Due to this possibility, countries like the Philippines have declared a state of public health emergency to address concerns about its transmission. Monitoring and strict observation of regulation are physically and time demanding without the use of automation and robotics. Having tremendous access to a wireless network, sensors, and knowledge on machine learning, deep learning, and the internet of things (IoT), other studies explored various methods of reducing the transmission (Alsaeedy & Chong, 2020; Degadwala et al., 2020). Cellular networks, IoT devices for location tracking, contact, and symptom tracking, social distancing alert devices, and deep learning models for real-time monitoring are currently used risk detection methods (Alsaeedy & Chong, 2020; Degadwala et al., 2020). For establishments, several proposed automated systems ensure proper observation of social distancing. These systems primarily detect motion using image processing and background reduction to indicate human presence (Ahamad et al., 2020). Apart from this, several other detection algorithms exist, such as the pre-trained convolutional neural network (CNN) based models (Ahamad et al., 2020; Teles de Menezes et al., 2020). CNN-based models contribute to the automation filtering and feature extraction process of deep learning algorithms for object detection and classification (Teles de Menezes et al. (2020). Several deep object detection algorithms such as You Only Look Once (YOLO), Single Shot Detector (SSD), Faster Region-based Convolutional Neural Network (Faster R-CNN), and Region-based Fully Convolutional Neural Network (R-FCN) were already studied for monitoring the adherence of the people to social distancing (Ahamad et al., 2020; Bhambani et al., 2020). Aside from the increasing interest in deep learning models as a monitoring system, IoT devices such as smart wearables have also been increasingly gaining attention in the field. IoT provides systems that are low-cost and user-friendly yet an excellent indicator of the adherence to preventive measures using ultrasound, magnetic fields, and Bluetooth Low Energy (BLE) as proximity sensors (Jeon et al., 2018; Stojanović et al., 2020). The use of AI systems and specific proximity sensors in IoT have certain limitations. With AI systems, although it provides high accuracy of proximity detection, the concern on the user's privacy arises as the exact location and appearance of the user can be observed (Bhambani et al., 2020; Jeon et al., 2018). Magnetic fields yield high accuracy and robustness; however, challenges to their portability, such as size minimization and low power design and privacy concerns, need further improvement (Bello, et al., 2020; Bian et al., 2020). The use of beacon technology in BLE allows proximity detection by using the contextual information generated by the beacons (Jeon et al., 2018; Lubis & Basari, 2020).

Emerging low power wireless technologies, such as BLE, have enabled dynamic wireless communication between devices and paved the way for IoT applications in automation, health, tracking, etc (Lubis & Basari, 2020; Polonelli et al., 2021). BLE is particularly suited to power-constrained applications, and its beacon technology offers efficient location-based services, which can be used in unmanned proximity-based applications (Jeon et al., 2018; Lubis & Basari, 2020; Polonelli et al., 2021). The neighbor discovery process (NDP) of BLE is used in proximity-based applications, where devices send information in the form of advertising packets over advertising channels to be discovered by scanners (Song et al., 2019). BLE architecture has several layers, including the Generic Access Profile (GAP), which provides different device roles such as a broadcaster, peripheral, observer, and central. BLE uses two modes of advertising PDU, one requiring an established connection and the other not requiring it (Ng et al., 2021). Moreover, proximity estimation relies on Received Signal Strength Indicator (RSSI), and filters are needed to increase its accuracy due to the factors affecting the RSSI's behavior (Cruz et al., 2018).While outdoor applications using filtered RSSI resulted in effective and efficient proximity tracking, the distance is inversely relative to the maximum distance for optimal functionality (Cruz, Garcia, et al., 2018).

Received Signal Strength Indicator (RSSI) is an indication of the power of the signal that is received from a transmitter. For distance estimation, a formula equation based on the power loss during signal propagation was used to acquire distance using transmitted power and RSSI (Amft et al., 2020; Zhang et al., 2016). Previous studies have used formulas that can estimate the distance between a transmitter and receiver using the Log-Distance Path Loss Model below: (Ivanic & Mezei, 2018; Jones et al., 2020; Onofre et al., 2016; Song et al., 2019; Tiwari et al., 2020; Zhang et al., 2016):

$$d = 10^{\left(\frac{(A-RSSI)}{10\cdot n}\right)} \qquad (1)$$

Wherein the d is the estimated distance from the transmitter and receiver, A is the signal strength from a fixed distance of d from the transmitter and n is the path loss exponent depending on the surrounding environment. Due to the instability of RSSI, identification of the parameters in the estimation of distance varies on varying RSSI. Several studies have shown that by using known values of RSSI and its relative distance, unknown parameters such as the A and n can be acquired using the linear regression model (Ivanic & Mezei, 2018; Zhang et al., 2016). Furthermore, the model features a good distance estimation for a line-of-sight propagation (Ivanic & Mezei, 2018).

An ideal antenna radiates uniformly in all directions. However, it is not practically possible in real-life application as some antennas radiate more power in certain directions. For the antennas, the (RSSI) is the measure of the power of the radio signal received by an antenna. When the RSSI is not equal when measured at various directions, it means that the power of the received signal is not distributed equally in all directions. This non-uniform distribution of power is affected by various factors, including the performance and elevation of the antenna and the environmental conditions in which the signal is transmitted (Fang et al., 2010). Therefore, for ranging purposes, it is important to consider the non-isotropic nature of the RSSI and the factors that influence it.

In proximity detection, the data of RSSI is used to identify the user within the proximity range. However, local implementations of this, such as in a closed area, need further improvements on its proximity detection, signal detection, and battery consumption (Lubis & Basari, 2020). Furthermore, beacon technology only employs one as transmitter and the other as the receiver with or without connection (Lubis & Basari, 2020). This technology is mostly employed for social distancing purposes. However, current BLE technology supports a dual role on a single device and therefore can be explored for device communication that does not require a connection. For most social distancing wearables, the device is only tested using the one device to one device set-up. A one device to many device set-up is more efficient to minimize the spreading of the COVID-19 disease within crowded places because this set-up limits close face-to-face contact with two or more people (Alhmiedat & Aborokbah, 2021).

Despite the increasing interest in the usage of BLE technology of ranging, there is lack of research conducted on ranging for multiple devices in an environment. This paper will include acquiring the RSSI around each transmitter and based on the acquired results, a distance classification was done using the confidence interval median. The paper investigates RSSI to distance matching using the created interval from confidence interval and the RSSI values of devices in a multi-device environment.

Method

Hardware Development

Figure 1 shows the overview schematic diagram of the wearable. The wearable would have the ESP32 module as its main component for processing and acquisition of the RSSI values. For the BLE configuration, devices would be configured as BLE broadcasters and observers. The configuration does not need to establish a connection to relay information from one another. The advertising packet of the broadcaster will be set to ADV_NONCONN_IND which does not allow connection requests and does not allow additional data to be advertised that is not included in the advertising packet. The advertising packet was configured to include the local device name, UUID, and TX power.

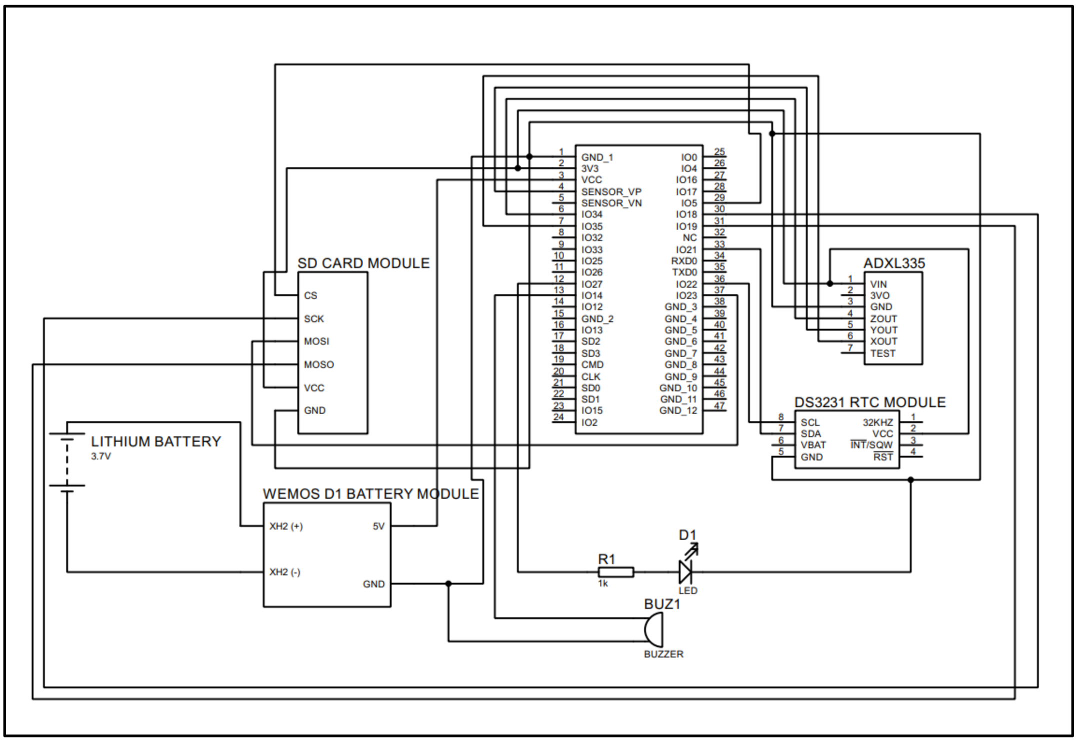

Figure 1. Schematic diagram of the hardware

RSSI Calibration and Parameter Estimation

Calibration is essential when dealing with RSSI that is susceptible to environmental interferences. According to a study (Fang et al., 2010), the RSSI value can be calibrated by means of acquiring the average deviation from the receivers. For the consistency of the power being transmitted from the transmitter for the 5 devices, 40 samples of raw RSSI values were measured at a fixed height and fixed distance of 1m direct line of sight from the transmitter using another receiving device. The five devices would take turns being the transmitter, and the acquired values would be compared to those obtained from an application that measures the RSSI in units of dBm. From the specification of the ESP32, the RSSI values acquired are in units of dBm. The average RSSI value from the application was then used to adjust the raw RSSI values. The difference between the raw RSSI with the RSSI from the application will be the offset values. For the estimation of the path loss model parameters at line of sight, different raw RSSI from different distances of 0.5, 1, 1.5, and 2m from a transmitter was acquired. Linear regression would then be applied to acquire the unknown parameters from the equation (1).

The linear regression has the equation,

$$y = mx + b \qquad (2)$$

During a signal propagation, the attenuation is expressed by the received power in the form of signal strength with the distance. From the given formula in a study (Zhang et al., 2016), this can be rearranged in the form,

$$P_d - P_{d0} = -10log(\frac{d}{d_{d0}}) \qquad (3)$$

Where d is the distance between a transmitter and receiver, d0 is a fixed reference distance from the transmitter, Pd the signal strength at d and Pd0 is the signal strength at the reference distance. Letting the dependent variable y to be the signal strength, RSSI, and the independent variable x the log-distance,

$$y = P_d - P_{d0} \qquad (4)$$
$$x = log(\frac{d}{d_{d0}}) \qquad (5)$$

Then the m from the linear regression would then be,

$$m = -10n \qquad (6)$$

Acquiring the y and m from the linear regression analysis would be done to obtain an ideal value for A and n for the given environment.

RSSI Ranging and Matching

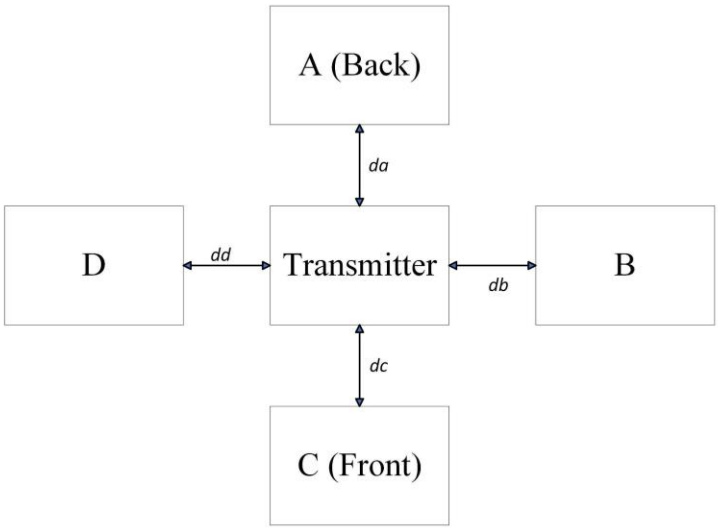

Figure 2. Location A, B, C, and D positions

The RSSI around each device being a transmitter was acquired. The considered locations for the placement of the receiver is shown in Figure 2 where location C is where the receiving device is at the front of the transmitting device, A is at the back, and B and D are at its sides. The *da*, *db*, *dc*, and *dd* correspond to the distances of the devices at positions A, B, C, and D respectively. For each device, RSSI values are stored onto the SD card at various positions. The interval will be created from the acquired RSSI values from the five devices. For the matching of distance with the position, confidence interval is used to acquire the range in which a parameter, RSSI, of a population would most likely fall. In here, the range was acquired using the formula,

$$NQ \pm z\sqrt{NQ(1-Q)} \tag{7}$$

Wherein *N* is the sample size, Q is 0.5 for median (quantile interest), and *z* the z-critical value. From the data, the *N* has the value of 205 and 90% confidence would be used where the $z = 2.58$. The range for the various distances from the transmitter at position A, B, C, and D is shown in Table 2.

Results and Discussion

Figure 3 represents the RSSI values at position A within distances 1m, 2m, 3m, and 4m from each device. For the 1m distance, the highest median RSSI value is at device 2. As for the distances 2m, 3m, and 4m, the highest median value of the RSSI was device 1. Although it can be observed that there are existing differences in the RSSI median values between each device, the median of each device in various distances is also observed to be like one another when looking at each box at different devices at position A. In addition the IQR or the Interquartile Range of the RSSI values is observed to be narrow. The interpretation is that the RSSI values were not spread and relatively towards a narrow range when measured at position A.

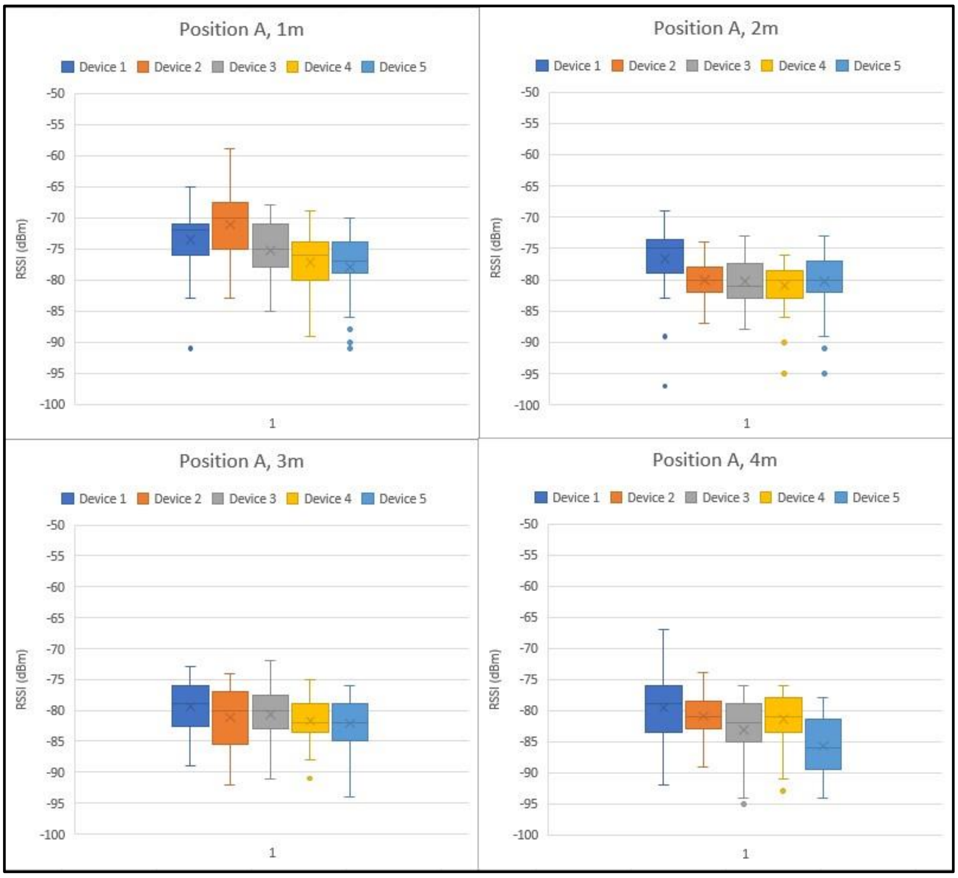

Figure 3. Box plot of RSSI values at position A

On the other hand, additional observations of the differences from the graph for the different devices for position B shown in figures 4, at 1m, devices 2-5 shared relative median RSSI values. As for 2m, the median RSSI values vary from one another for the devices except for device 3 and device 5 which remained close to one another. At 3m, the group of devices are resulted to have relative RSSI median values, such as for device 2 and device 4, and devices 1, 3, and 4. At 4m, the same behavior of the RSSI median values was observed, except for device 1 which had an entirely different RSSI median value when compared to other devices. With this, it can be observed that the devices at some distance can either have relative or non-relative values of the RSSI median. Moreover, the lengths of the box are not similar which means that the RSSI of some devices are highly variable.

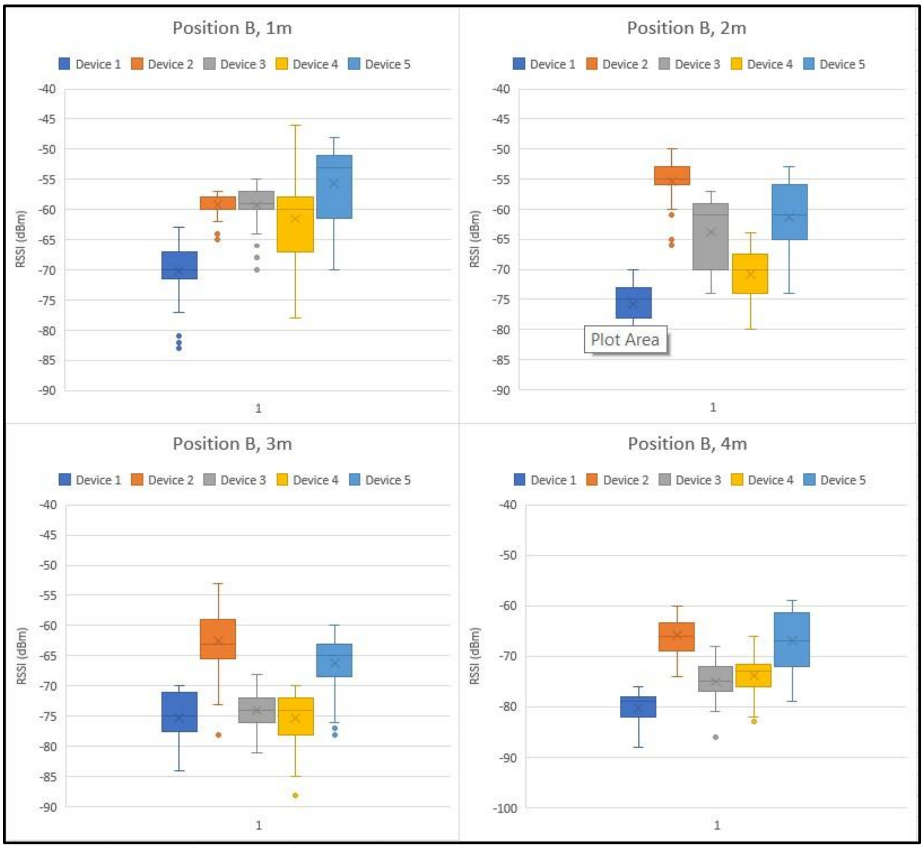

Figure 4. Box plot of RSSI values at position B

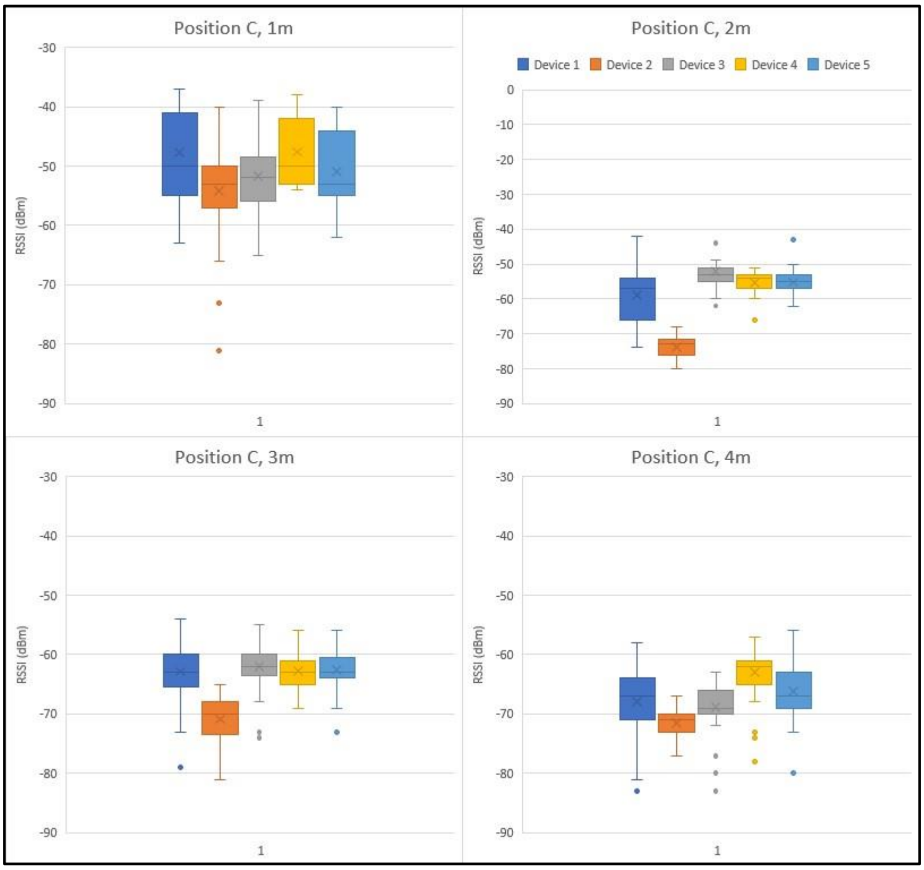

Figure 5. Box plot of RSSI values at position C

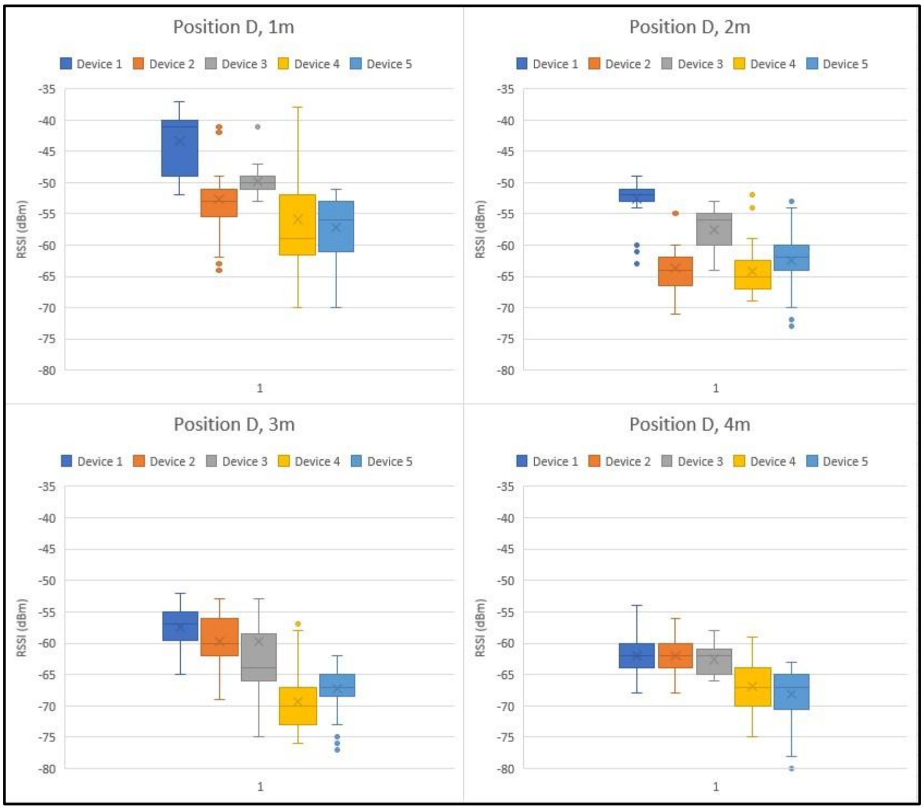

Figure 6. Box plot of RSSI values at position D

The median RSSI values at 1m are close to one another when looking at figure 5. However, comparing the box plot length in position A, a distinction between the two can be observed. Some box plots are not narrow as observed for devices 1, 4, and 5 in which the RSSI values from these devices at position C have large variability when compared to devices 2 and 3. Moreover, aside from distance 1, the RSSI median value from device 2 is not close to the median of other devices. Not only at position C but also in position D, show in figure 6, that highly variable RSSI values are observed for distance at 1m and 2m from the transmitter. Close median values of RSSI are only observed at 4m for position D.

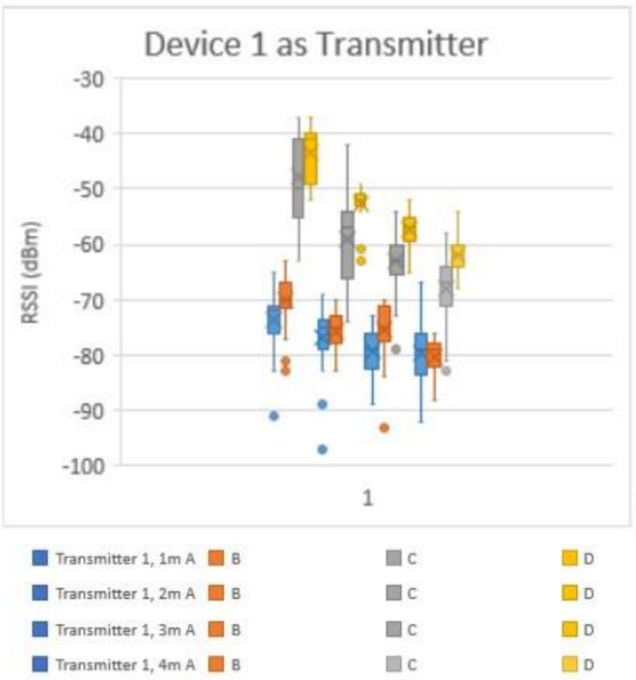

Figure 7. RSSI values from transmitter device 1.

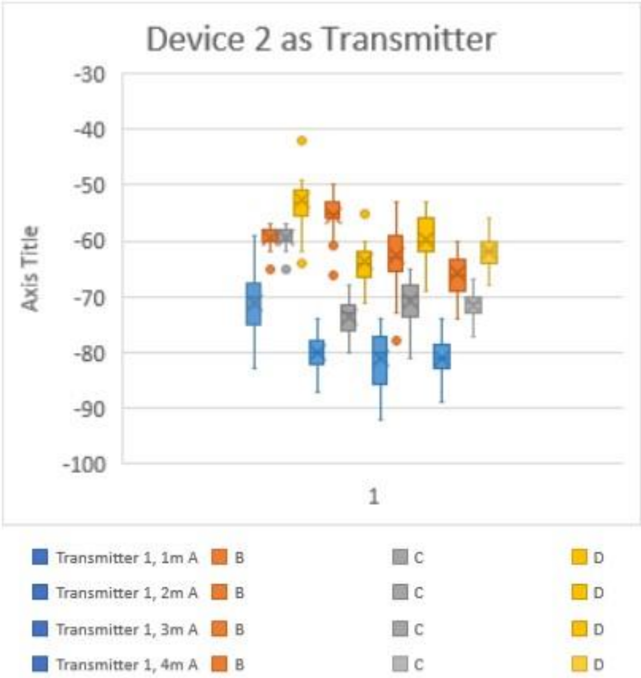

Figure 8. RSSI values from transmitter device 2.

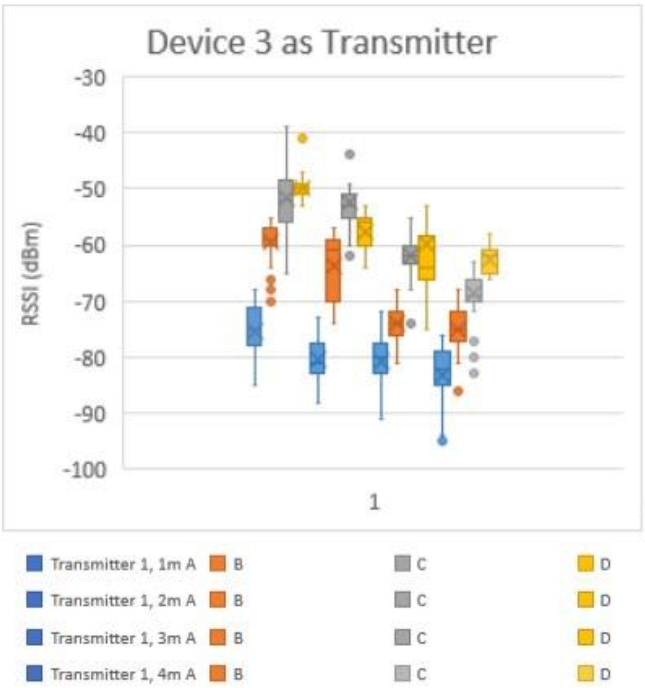

Figure 9. RSSI values from transmitter device 3.

The signal strength from the 5 devices figure 7, 8, 9, 10 and 11 shows the relationship between distance. Based on the trend of the graph, the relationship between the distance and signal strength can be observed where RSSI values at farther distances have lower RSSI values compared to near distance such as 1m. In signal propagation, attenuation is experienced due to the presence of external factors which results in loss of energy and low signal strength values received by the devices. This characteristic of signal can be observed on the acquired RSSI values where the median of the RSSI keeps decreasing as the distance from the transmitter changes from 1 to 4m for some devices. However, some devices do not exhibit the trend and can be due to the factors that influence the RSSI.

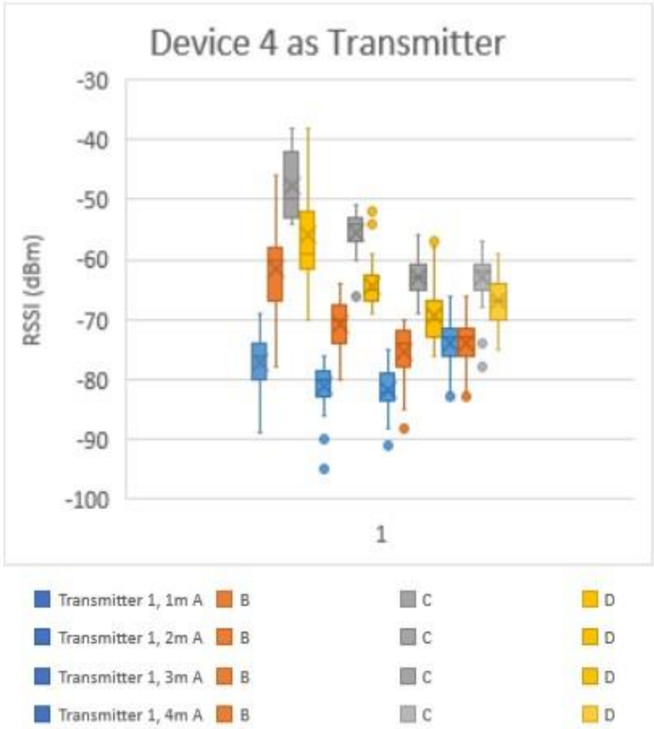

Figure 10. RSSI values from transmitter device 4.

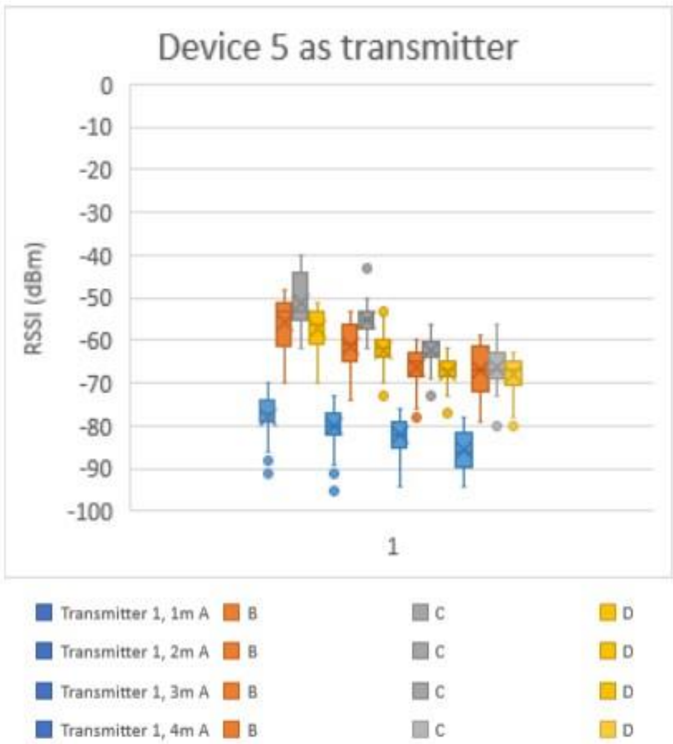

Figure 11. RSSI values from transmitter device 5.

Overall, some RSSI values acquired by the devices are highly variable at some distances. The variability observed from the set of data acquired can be due to the uncontrolled conditions such as environmental factors or factors present in the hardware such as lack of calibration of the battery level voltage of the different devices. In a study (Mitralexis & Goumopoulos, 2015), one factor that can affect the signal strength is the battery level of the device. Decreasing the battery level affects the signal strength, a weaker signal strength is received from the transmitter (Mitralexis & Goumopoulos, 2015). Therefore, a constant supply of power to the module is crucial to the usage of an RF module.

RSSI Matching based on Position

The relationship between the RSSI and distance can be observed from the combined received RSSI values at various positions as shown in Figure 12 and 13. At the various positions, observations are made by using measures of central tendency such as the median or mean to describe the RSSI values. In Figure 12 and 13, a sharp drop on the RSSI values can be observed in position B using the mean as the measure. At position C, the RSSI values are much lower compared to the D RSSI values for distance 3 and 4m. The sharp drop if RSSI values for position B can be due to the lower acquired RSSI values of Device 1 as shown in Figure 4 compared to the other devices. For low RSSI values at position C for distances 3 and 4m, this can be due to the RSSI values acquired by Device 2 where the RSSI values were close to a lower median value for all distances except at 1m shown in Figure 5.

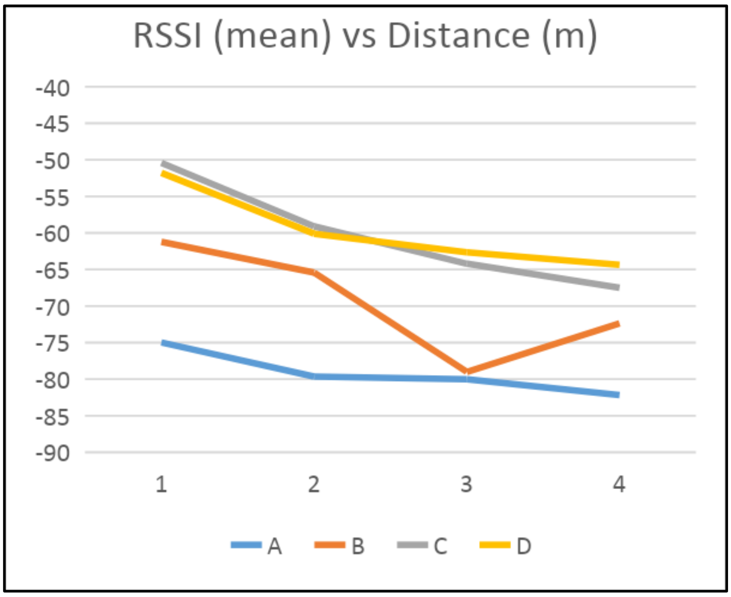

Figure 12. RSSI (mean) vs Distance at various positions

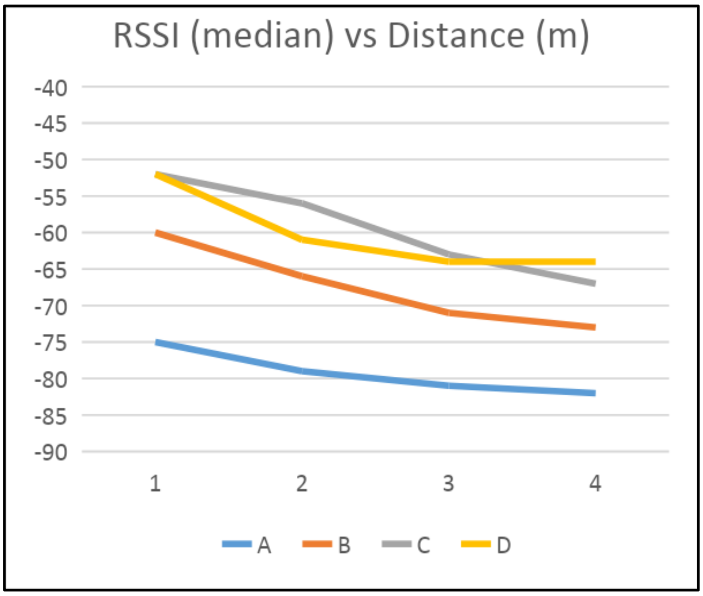

Figure 13. RSSI (median) vs Distance at various positions

RSSI (median) and RSSI (mean) have a similar trend shown, however, the graph of the RSSI (median) produces a much smoother line compared to RSSI (mean). The difference can be due to the nature of the RSSI where it is susceptible to influences and it is highly variable when there are presence of outliers in the gathered data. From the data acquired, the distinction can be due to the suspected potential outliers found from the data. Therefore, representation of the RSSI values that are not susceptible outliers can be achieved by using RSSI (median).

Table 1. Interval for various positions and distances

Position	Distance	Lower bound	Upper bound
A	1	-76	-74
	2	-80	-79
	3	-82	-79
	4	-83	-81
B	1	-60	-59
	2	-69	-63
	3	-73	-71
	4	-74	-72
C	1	-53	-51
	2	-57	-55
	3	-65	-63
	4	-69	-66
D	1	-53	-51
	2	-62	-60
	3	-65	-62
	4	-65	-63

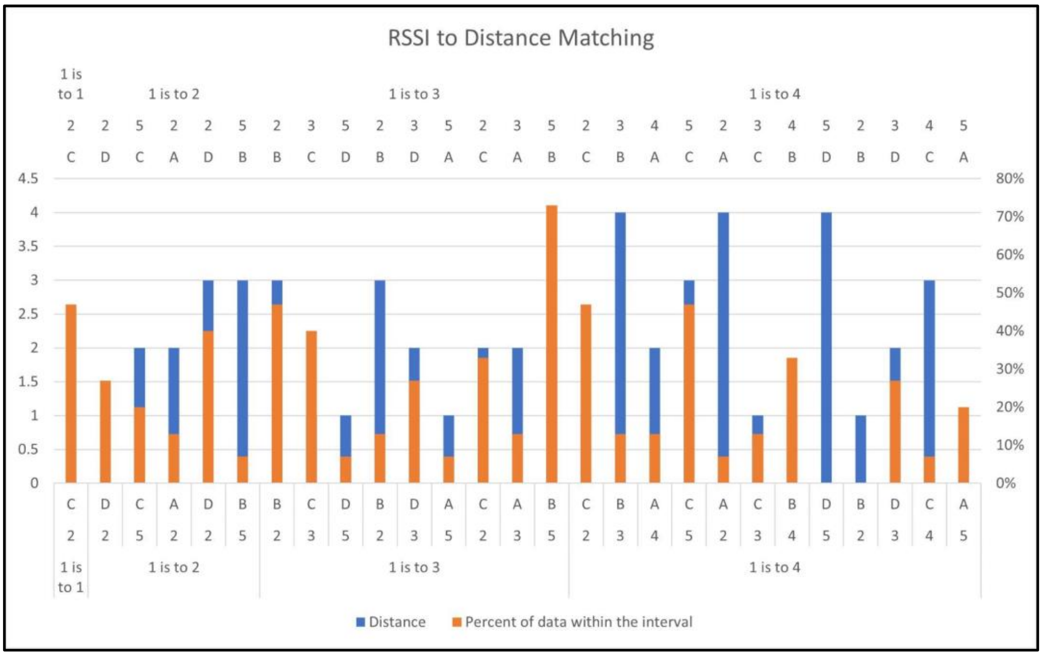

Figure 14. Percent of RSSI data within the interval

The acquired range using the confidence interval was then used to the acquired raw RSSI values from various distances and positions. Table 1 shows the various combinations of the devices where aside from the position and distance, the number of devices within the perimeter was also considered. For most of the combinations, the data falls less than 50% using the created range as shown in Figure 14. The created range was formed using the initial RSSI observations from the five devices. The low percentage from the various combinations can be due to the reliance on the individual performances of the devices, the RSSI data it gathered. As aforementioned, irregularities on the RSSI values on some of the devices were observed. The formation of irregularities can be from uncontrolled factors that affect the signal strength such as the battery level and environmental interference. It can also be due to the method used in creating the range where other methods can be considered for solving the confidence interval. Exploring improvements on the gathered data or range for it was compared might improve the matching of RSSI values to the various distances.

Conclusion

In real-life applications, antennas radiate more to certain directions than others. Observations with multiple devices in the environment show variations on the RSSI transmitted with the other devices. Using a confidence interval-median, most of the BLE combinations have less than 50 % of the data fall within the interval. The resulting low percentage might be due to the irregularities observed from the devices. Other factors affecting RSSI should be considered and controlled as it can improve the use of the prediction range when estimating the distance.

Recommendations

The future researchers recommended to perform much stricter calibration of the devices and consider more factors that influence the RSSI. In addition, exploring other methods of creating the confidence interval range might improve the distance classification.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

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Author Information

Jille Anne R. Verano
Mapúa University
Manila, Philippines
jarverano@mymail.mapua.edu.ph

Doreen Marie S. Sorongon
Mapúa University
Manila, Philippines

Febus Reidj G. Cruz
Mapúa University
Manila, Philippines

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