Bluetooth Distance Estimation for COVID-19 Contact Tracing

Guenther Retscher, Pajtim Zariqi, Ana Oliva Pinilla Pachon, José Pablo Ceballos Cantu, Sasanka Madawalagama

Department of Geodesy and Geoinformation, Engineering Geodesy,
TU Wien – Vienna University of Technology, Vienna, Austria

Abstract. Because of the covid-19 pandemic, Bluetooth is widely adopted for contact tracing Apps to keep and prove social distancing. If two persons are close at a short distance as defined for a period of usually at least 15 minutes, then the contact should be automatically detected using Bluetooth Low Energy (BLE) measurements on the mobile devices of the two persons. For that purpose, usually the signal strength of the Bluetooth signals, referred to as Received Signal Strength Indicator (RSSI), is measured and converted into a distance using path loss models. Logarithmic models are thereby commonly employed. In this study, the feasibility of the use of BLE for this type of application is investigated. A test field in an indoor environment has been defined and measurements taken with different smartphones serving either as signal broadcaster, the so-called advertisers, or as scanners recording the BLE signals from the advertisers. From the RSSI measurements, distances are estimated and aerial distributions in the form of interpolated radio maps (or heat maps) derived. Experiments were conducted in three scenarios where the smartphones were either placed unobstructed in free space on chairs, put into backpacks or handbags and into the trousers pockets of the users. The results indicate that a meaningful relationship between the RSSI values and models based on an approximation with a logarithmic path loss model can be derived in most cases especially at a very close range (> 1 m). This is very promising if we consider the contact tracing application. From the radio maps of the whole test area, it could be seen that the results of the distribution of RSSI in the main free space and backpack experiments were coherent to the distance from each selected advertiser. The results of the trousers pocket experiment, however, showed unexpected distributions due to the low granularity in the sampling points.

Published in "Proceedings of the 16th International Conference on Location Based Services (LBS 2021)", edited by Anahid Basiri, Georg Gartner and Haosheng Huang, LBS 2021, 24-25 November 2021, Glasgow, UK/online.

https://doi.org/10.34726/1748

Keywords. Bluetooth Low Energy (BLE), Received Signal Strength Indicator (RSSI), Path Loss Model, Radio Map Interpolation

1. Introduction

Contact tracing for covid-19 is an important tool for reducing the number of infections (Apple and Google, 2020). Its goal is to reduce the number of infections by identifying the cases through contacts with infected people and provide early detection, guidance, and treatment (Bay et al., 2020; Leith et al., 2020; Nguyen et al., 2020). Using Bluetooth Low Energy (BLE) for estimating distance between users of mobile devices is a potential alternative which is evaluated in this study by measuring the Received Signal Strength Indicator (RSSI) in three different scenarios. We measured firstly in a free space, secondly in a scenario with the selected advertisers inside bags, and finally we measured the effect on RSSI caused by the human body by locating a cell phone in a trouser pocket. In this contribution the experiment design, statistics, distance estimations, leading to a derivation of radio maps (or heat maps) of RSSI distributions, are presented. A variety of smartphones serving either as so-called advertising mobile devices (short advertisers) broadcasting BLE signals or as scanning devices (i.e., the scanners) to scan for the RSSI of the advertisers were used in the tests. Distance estimation is supported by graphs that show each selected advertiser alongside the sampling points and the expected distance. Radio maps display the distribution of RSSI in each scenario per selected advertiser.

Thus, the main objectives of the study are:

- Understand better how Bluetooth signal interaction between different devices in order to asses better the effectiveness of using BLE technology as a contact tracing tool;
- Long-term Bluetooth observations in different scenarios, such as device is held in hand, in trousers pocket, backpack, handbag, etc.

2. Test Set-up and Design

The indoor experiments were designed to acquire data from different mobile devices at different scenarios: (1) unobstructed in free space (2) inside bags or backpacks and (3) inside trousers pockets. In order to get a good data range eight control points and 20 observation points are established in an open room as shown in Figure 1. After establishing the control points and observation points on the ground with chain surveying methods, identical plastic chairs were placed above each control point and advertiser phones were placed on these chairs at the eight locations A to H. Figure 2 shows impressions from the set-up in the room.

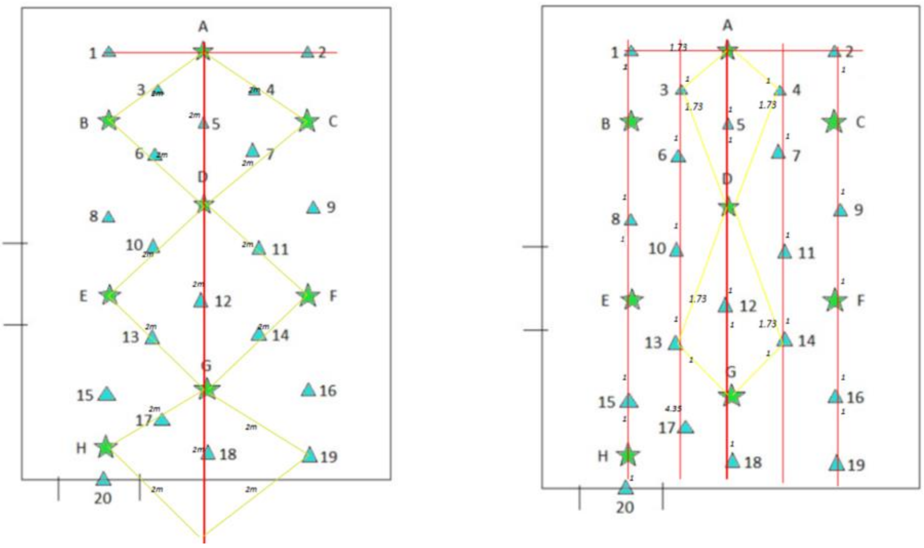


Figure 1. Layout of control points A to H and observation points 1 to 20.

Figure 2. Experimental set-up.

Eight different mobile devices were used in the test. Their specifications are summarized in Table 1. The Apple iPhone SE 2020 was used as the scanner for all the experiments and the other phones were configured as advertisers. The open source nRF connect App developed by Nordic Semiconductor was used to collect the RSSI data (Nordic Semiconductor, 2020). nRF Connect for Mobile is a powerful generic tool that allows to scan and explore Bluetooth devices, communicate with them, and acquire data about the signal. RSSI data were recorded in CSV format and exported for post processing. Pre-processing of the observed RSSI data was done to remove outliers and calculate average RSSI for each observation points. This was done with a code written in Python using the Pandas package.

Location	**Device**	**Bluetooth specification**
A	iPad pro 2018	5.0, A2DP, LE, EDR
B	Samsung Galaxy S7	4.2, A2DP, LE, aptX
C	LG Nexus 5x	4.2, A2DP
D	Google Pixel 5	5.0, A2DP, LE, aptX HD
F	Sony Xperia Z3	4.0, A2DP, aptX
G	Samsung Galaxy S8	5.0, A2DP, LE, aptX
H	One Plus 7	5.0, A2DP, LE, aptX HD
moving scanner	iPhone SE 2020	4.2, A2DP, LE

Table 1. Specifications of the used mobile devices and their usual location on the control points A to H. A2DP stands for Advanced Audio Distribution Profile, LE for low energy, EDR for Enhanced Data Rate, aptX for audio processing technology and HD for high definition.

Bluetooth Low Energy (Bluetooth LE, colloquially BLE, formerly marketed as Bluetooth Smart) is a wireless personal area network technology designed and marketed by the Bluetooth Special Interest Group (Bluetooth SIG) aimed at novel applications in the healthcare, fitness, beacons, security, and home entertainment industries. The original specification was developed by Nokia in 2006 under the name Wibree, which was integrated into Bluetooth 4.0 in December 2009 as Bluetooth Low Energy. Bluetooth 2.0+EDR (Enhanced Data Rate) and Bluetooth 2.1+EDR are specifications for short-range wireless data exchange. Both Version 2.0 and 2.1 support EDR, a faster PSK (Phase Shift Key) modulation scheme capable of transmitting data 2 or 3 times faster than previous versions of Bluetooth. The audio processing technology aptX is a proven technology that compresses and then decompresses audio as it travels from a source device like a phone, to a receiving device like a wireless speaker, in a way that it can be transmitted over Bluetooth without damaging the quality. This ensures that you get the very most from your audio.

3. Distance Estimation from BLE RSSI

Path loss models can be applied to convert the recorded RSSI to distances between the mobile devices. Usually a logarithmic path loss model for the relationship is employed. Such a model is a simple way to estimate distance with RSSI (Phunthawornwong, 2018). It can be expressed using the following equation:

$$d = 10^{\left(\frac{A-RSSI}{10\beta}\right)} \tag{1}$$

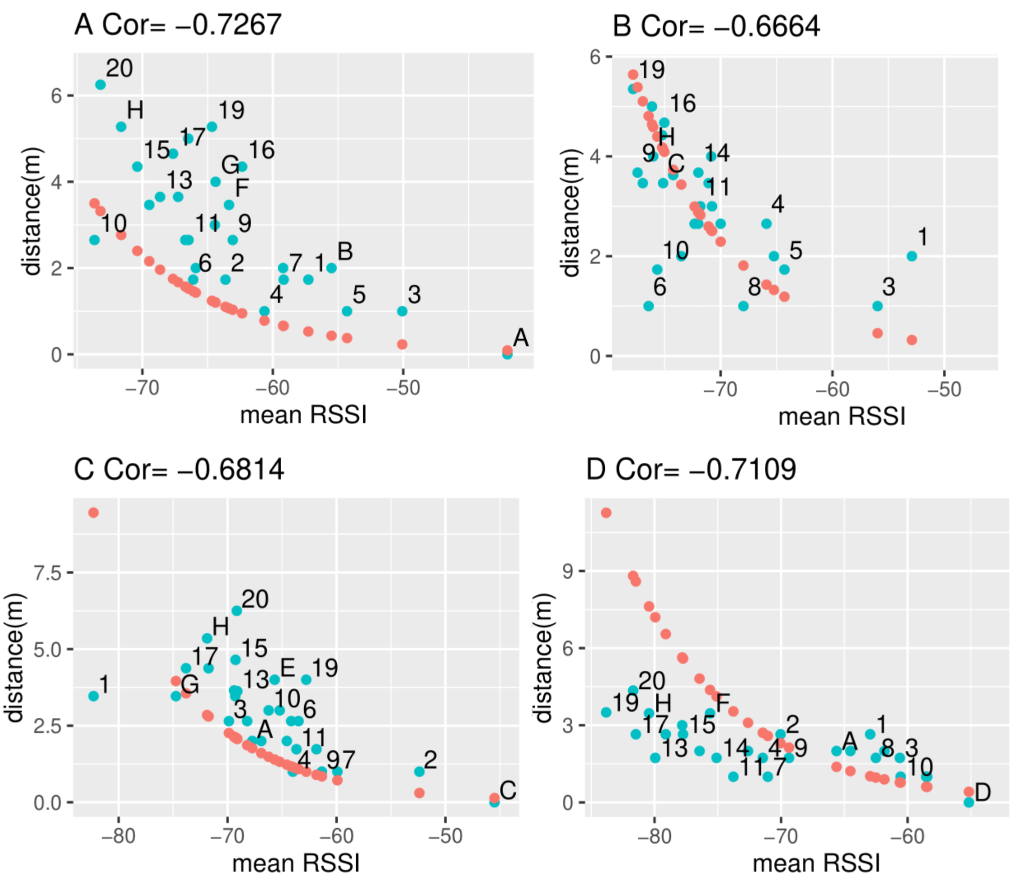
where d is the distance between the reference node and any nodes in [m], A is the RSSI at reference distance (1 m) and β is a propagation constant (in free space = 2).

A was determined as the average of all RSSI measurements taken at a 1 m distance and the propagation constant β was also set as 2 since the experiment was conducted at a free space between the phones.

After derivation of the estimated distance, a comparison with the true distance is performed and analysed how the model deviates from reality. The results were plotted for all phones and the resulting distance from equation (1) were compared with the true distance that the phones had from each other. The graphs in Figure 3 present these comparisons for the different mobile devices. Thereby the title letter corresponds to a specific phone and all sampling points are referenced on the scatter plot.

As part of the results, a logarithmic equation was estimated for each phone with an r^2 to indicate the correlation that each equation has to the ground truth data. The results are presented in Table 2. For the estimated equations the following applies: x → ||RSSI||, y(x) -> d(m).

As can be seen from Figure 3 some smartphones follow the logarithmic path loss model even at long distances. An example is the Samsung Galaxy S7 which has a very similar trend as the theoretical model and the data correlates somewhat fairly at -0.664. On the other side of the spectrum, there is the Sony Xperia Z3 phone whose RSSI values do not reflect at all the true distance of the phone and have a very low correlation coefficient at -0.055. Some phones clustered in the mid-regions such as the Samsung Galaxy S8 and the LG Nexus 5x which shows that some phones have somewhat reliable RSSI at specific regions but deviate in other regions. Similar results for these smartphones were obtained by Retscher et al. (2021) in a similar test set-up. As for the estimated equations (see Table 2), it can be seen that the iPad pro 2018 and the Google Pixel 5 fit very well on the logarithmic model while the One Plus 7 and the Sony Xperia Z3 have a very poor fitting. Even though the One Plus 7 seems to show a somewhat similarity to the loss model. Lastly, something important is that all phones had a good RSSI estimation at a very close range (> 1 m) which is promising if we consider the contact tracing application. We can see that in all graphs with the exception of the Samsung Galaxy S8 (G) the model and the true distance match. This results have been achieved for smartphones unobstructed lying on the chairs in the testing room. In the following section, results are presented where smartphones are placed in backpacks, handbags and in trouser pockets.



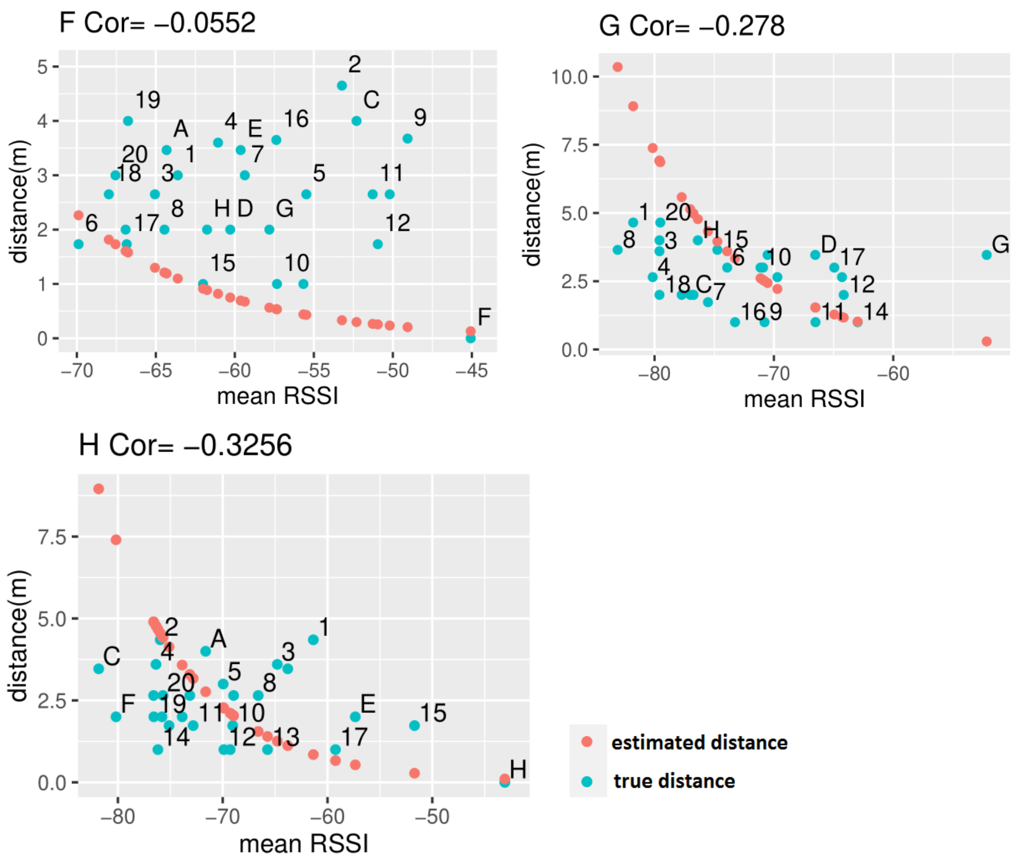


Figure 3. Distance comparison for each phone where the sampling points (blue) are plotted alongside the true distance (red) illustrating the deviation from the logarithmic path loss model.

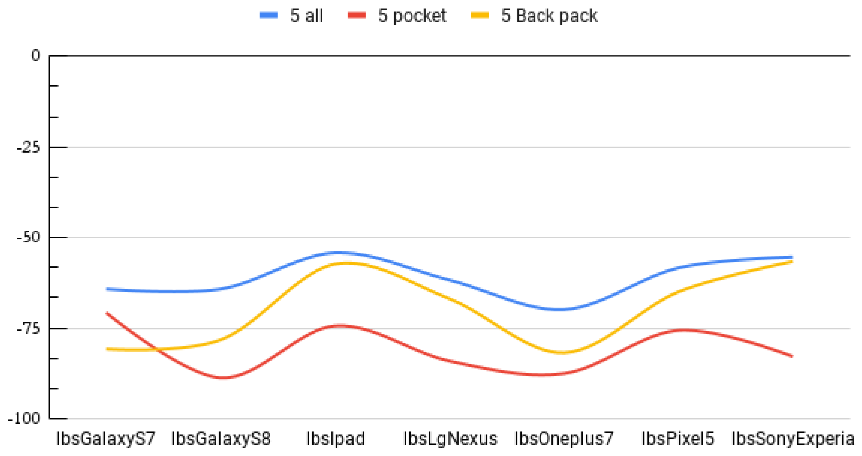
Location	Smartphone	Equation	r²
A	iPad pro 2018	-35.2 + 9.2 ln x	0.513
B	Samsung Galaxy S7	-23.6 + 6.26 ln x	0.397
C	LG Nexus 5x	-35.2 + 9.09 ln x	0.470
D	Google Pixel 5	-19.5 + 5.09 ln x	0.496
F	Sony Xperia Z3	-0.191 + 0.668 ln x	0.005
G	Samsung Galaxy S8	-7.87 + 2.5 ln x	0.048
H	One Plus 7	-19.5 + 5.09 ln x	0.121

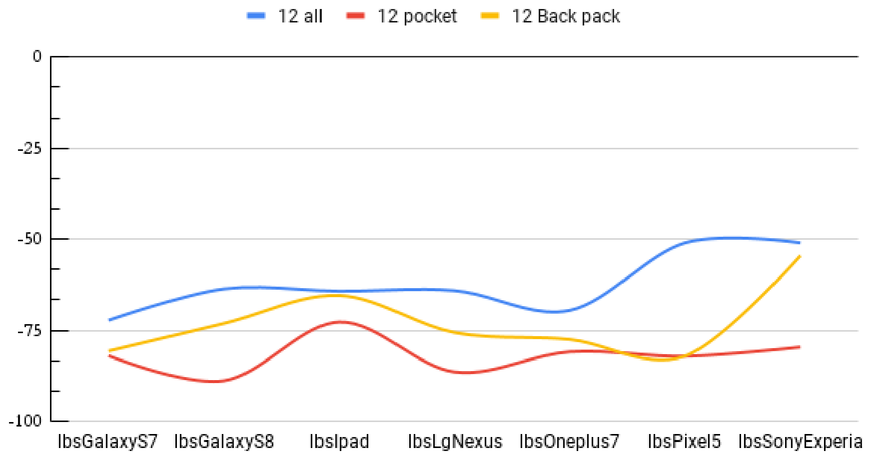
Table 2. Logarithmic equation relationships and their respective correlation coefficients r^2.

4. Different Smartphone Placement Scenarios

Figure 4 shows comparisons of different scenarios where several phones were put into a backpack each or trousers pocket of the user. In these three plots the sampled points of each experiment are compared with each other to see how the change in condition affected the RSSI recorded. The difference in signals between the seven devices is obvious.

As can be seen clearly in the three plots in Figure 4, the placement of phones affects the RSSI significantly. For the observation points 5 and 12 the RSSI of the backpack is stronger than the one of the trousers pocket and for location 18 there is some similarity between the backpack and pocket scenarios but a similar trend can be inferred where the backpack scenario has stronger RSSI's.





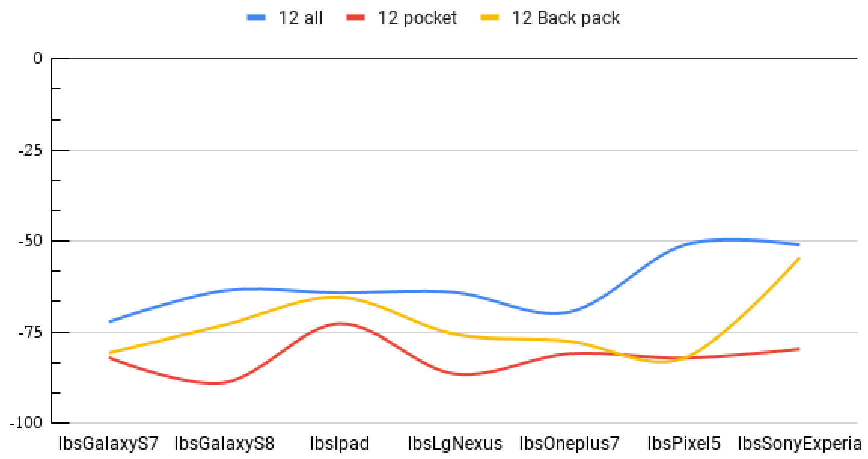


Figure 4. Different placement scenarios of smartphones on the observation points 5, 12 and 18 (see Figure 1 for their location in the test field).

5. Derivation of Radio Maps in the Test Field

Heat maps can be employed to show the distribution of the RSSI in the test field. In the case of RSSI distributions, these maps are usually referred to as radio maps. These maps were generated using the inverse distance weighted (IDW) interpolation method. This method determines the values of unknown points by assigning a weighted average of values from the known points depending on their distance from the unknown point (see Figure 5) (Qgis, n.d.). The known values closest to the unknown values have more influence, thus, a higher weight than the points farther away (Esri, n.d.).

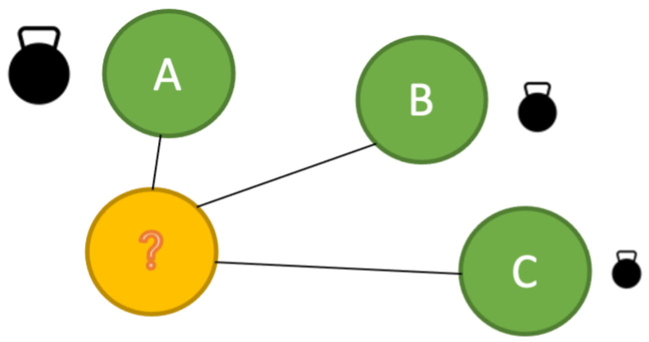


Figure 5. Illustration of the inverse distance weighted (IDW) interpolation method where the relative weights are assigned to each known point to determine the value of the unknown point.

Weights are proportional to the inversed distance raised to the power value p that in this case was 2 for all the maps. Figure 6 shows the variation in distance depending on the value of p. For $p = 0$, there are no changes in the distance so the values of the unknown points would be the mean of all the know values. The greater p is, the faster the weight assigned is decremented (see Figure 6) (Esri, n.d.). For this experiment, each known value represents the mean value of RSSI calculated for each advertiser position (A, B, C, D, F, G, and H).

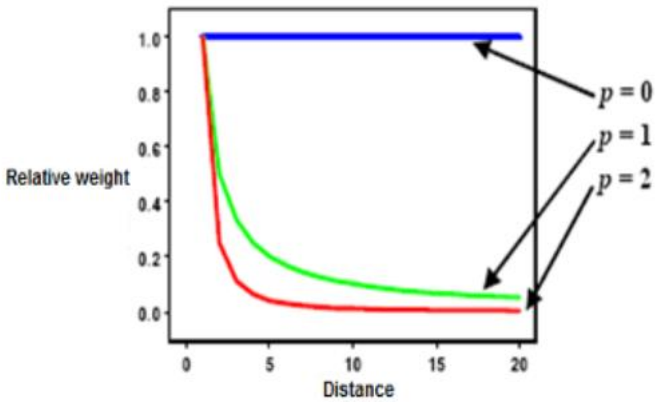
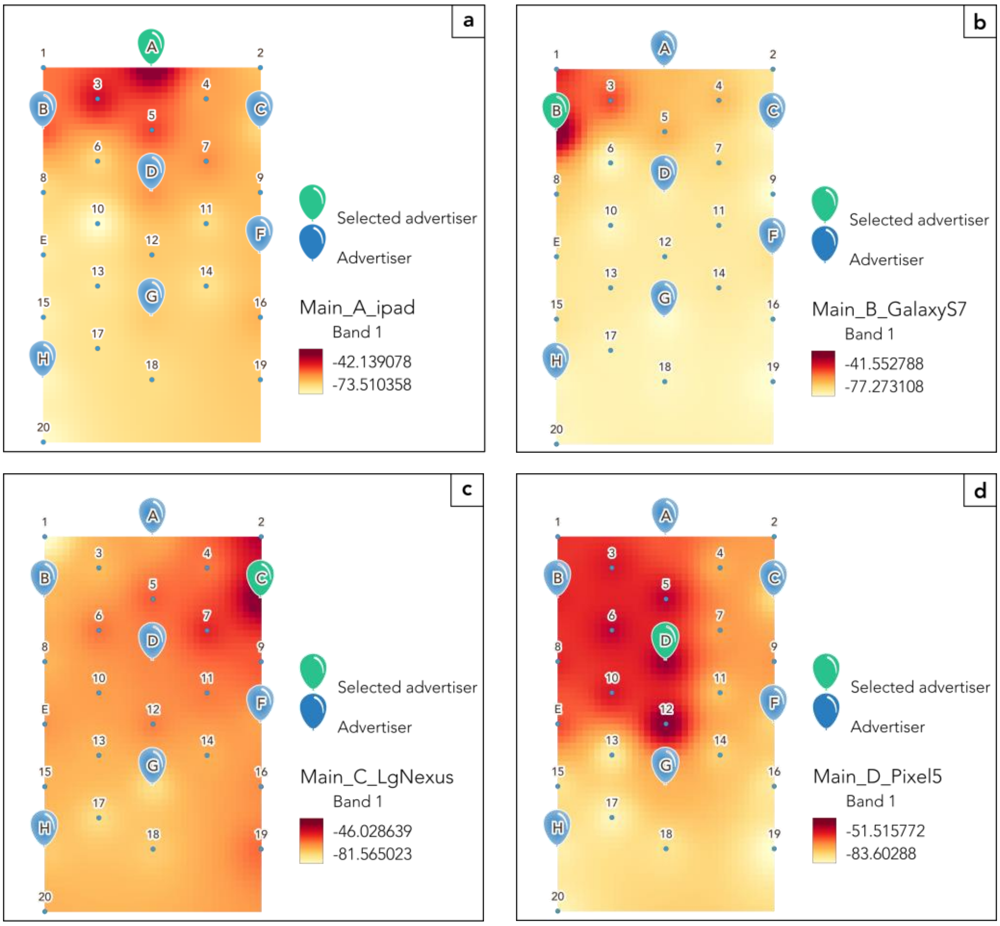


Figure 6. Decrease of weight with distance (https://pro.arcgis.com/en/pro-app/2.7/help/analysis/geostatistical-analyst/how-inverse-distance-weighted-interpolation-works.htm).

Figure 7 presents the radio maps for the main experiment where the smartphones were placed on the chairs. Figure 8 and 9 present examples of the radio maps for the scenarios where the smartphones were placed in backpacks or trousers pockets of the user sitting on the chairs, respectively. As can be seen from a cross-comparison between Figure 7 with Figures 8 and 9, the granularity of the RSSI values is higher than the represented for the experiments where the phones have been put in backpacks and trouser pockets. The RSSI for each selected advertiser in the main experiment (see green balloons with labels A, B, C, D, F, G, and H in Figure 7) is displayed by representing the mean RSSI from each point in the scenario (from 1 to 20 and from A to H). Figure 7 shows a clear distribution of the signal strength concerning the distance from the selected advertisers (see A, B, C, D, F, G, and H green balloons in Figure 7). However, there are some differences in the distribution of the RSSI. For instance, the RSSI for the selected advertiser C (Figure 7c) shows higher RSSI values in the whole scenario compared to the values of RSSI in Figures 7a and 7b. Since D is along the line in the middle of the test area between A to G (referred to as middle baseline; compare Figure 1), it is expected that the distribution of

RSSI to the right and left of it should be similar, however, the RSSI values on the left are higher than those on the right. For Figures 7e, 7f, and 7g, there is a clear distribution of the signal strength in respect to the distance from the selected advertiser.

Respect to the backpack and trouser pocket scenarios, the granularity is lower compared to the main experiment. For these two experiments (backpack and pocket), the measured points were only taken at stations 5, 12 and 18. Even though, most of the radio maps for these two experiments show a coherent distribution in respect to the distance from the selected advertiser, there are two unexpected results for the trousers pocket experiment. In both cases (see Figures 9a and 9c), the distribution is opposite to the expected. It could be cause to the low number of measured points for these two experiments.



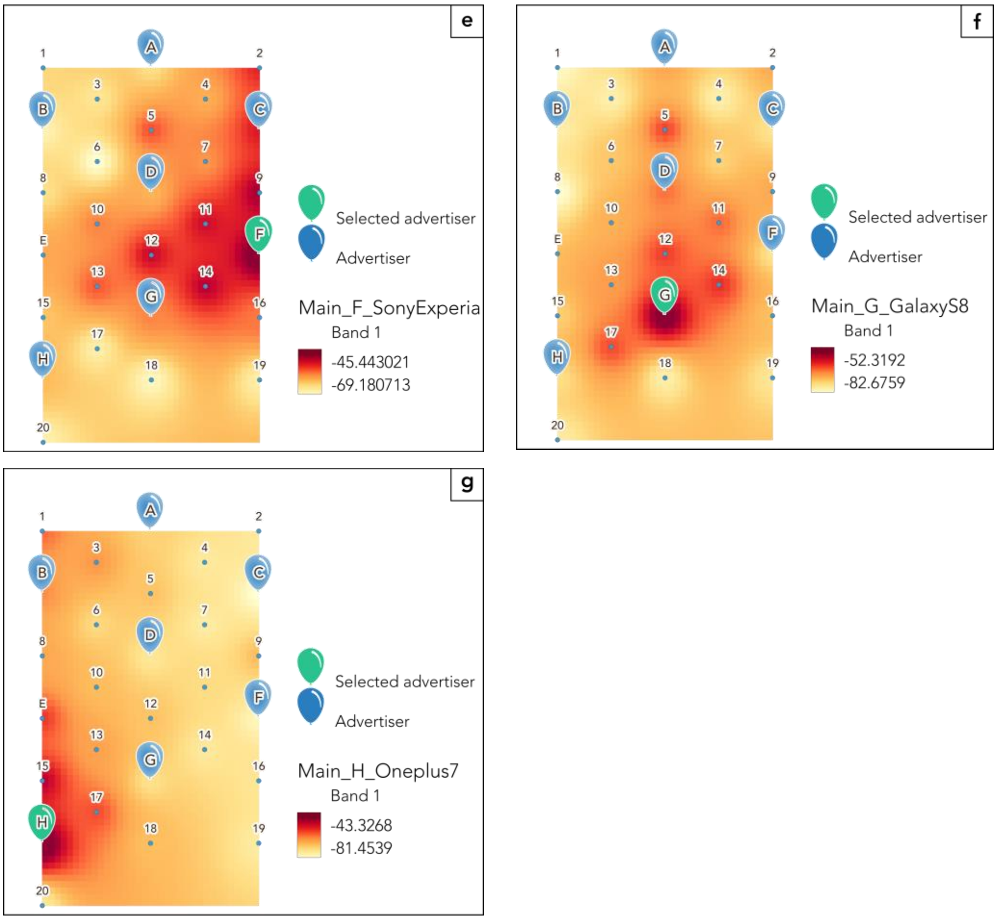


Figure 7. Radio maps of the RSSI distribution showing the results of the IDW interpolation method for the main experiments made for every point in the following positions: (a) point A, (b) point B, (c) point C, (d) point D, (e) point F, (f) point G, and (g) point H.

6. Conclusions

In this study, the usage of BLE RSSI measurements was investigated. From the experiments it can be concluded, that a relationship between the RSSI values and models based on an approximation with a logarithmic path loss model can be derived. In respect to the distance estimation from the measured RSSI values, some of the selected smartphones used in this study are following the predicted logarithmic model and some other phones deviate entirely. The trousers pocket scenario has the most impact on the obtained RSSI strength. If one looks at the radio maps derived from RSSI values in the whole test area, it can be seen that the results of the distribution of RSSI in the main and backpack experiments were coherent to the distance from each selected advertiser. On the other hand, the results of the trousers pocket experiment showed unexpected distributions due to the low granularity in the sampling points.

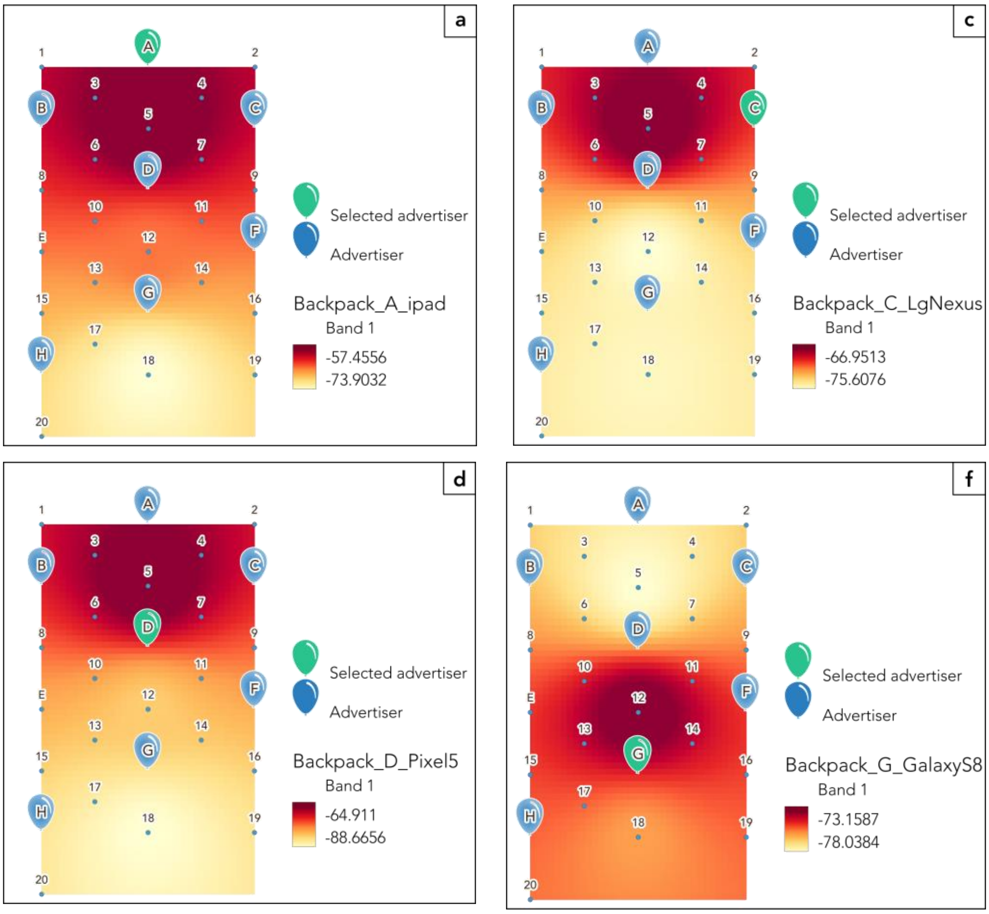


Figure 8. Selected radio maps of the RSSI distribution along the middle baseline ((a) point A; (d) point D and (f) point G) as well as point C (c) on the side for the experiments where the phones were in the backpacks.

References

Apple and Google (2020) Exposure Notification – Bluetooth Specification. Version 1.2, https://covid19.apple.com/contacttracing. Accessed 8 April 2020

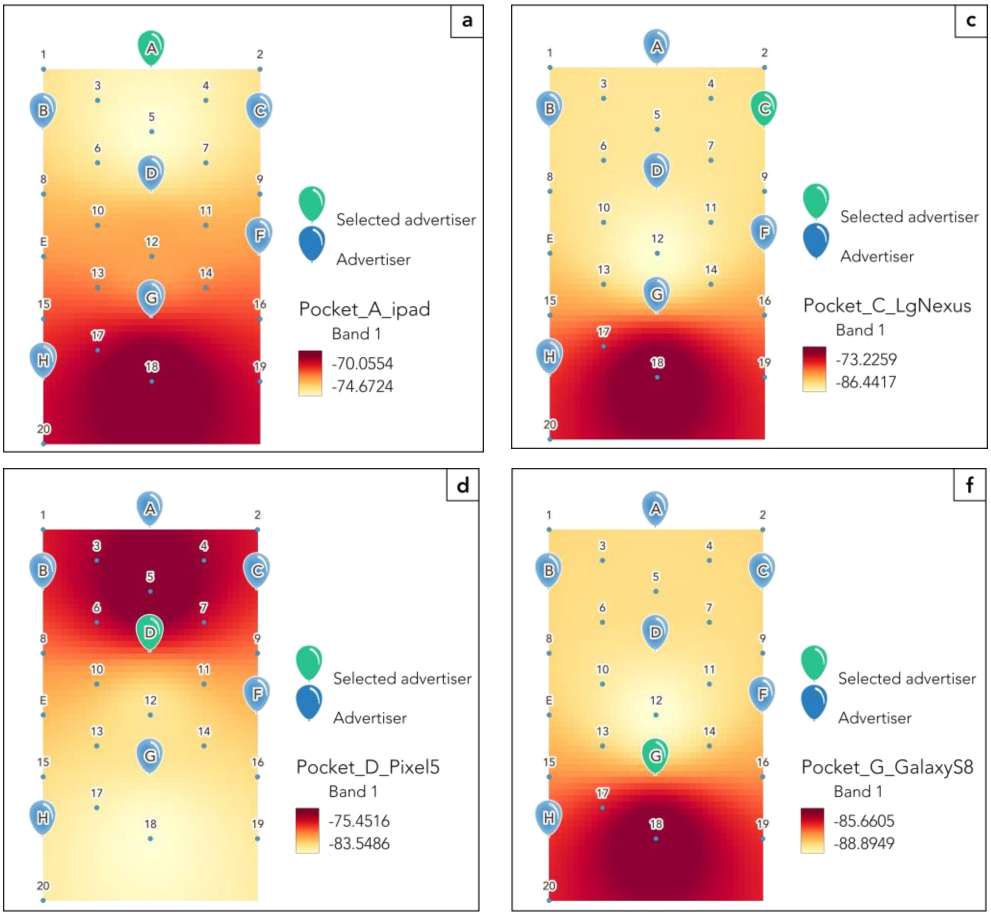


Figure 9. Selected radio maps of the RSSI distribution along the middle baseline ((a) point A; (d) point D and (f) point G) as well as point C (c) on the side for the experiments where the phones were in the trousers pocket.

Bay J, Kek, J, Tan A, Sheng Hau C, Yongquan L, Tan J, Anh Quy T (2020) BlueTrace: A Privacy-preserving Protocol for Community-driven Contact Tracing Across Borders. Government Technology Agency Singapore, Technical Report, 9 pgs

Esri (n.d.) How Inverse Distance Weighted Interpolation Works. https://pro.arcgis.com/en/pro-app/2.7/help/analysis/geostatistical-analyst/how-inverse-distance-weighted-interpolation-works.htm. Accessed 28 June 2021

Leith D J, Farrell S (2020) Coronavirus Contact Tracing: Evaluating The Potential Of Using Bluetooth Received Signal Strength For Proximity Detection. arXiv.org, eess, arXiv:2006.06822; 11 pgs

Nguyen K. A.; Luo Z.; Watkins C.; 2020. Epidemic Contact Tracing with Smartphone Sensors. Journal of Location Based Services, 14:2, 92-128, DOI: 10.1080/17489725.2020.1805521.

Nordic Semiconductor (2020) nRF Connect for Mobile. https://www.nordicsemi.com/Software-and-tools/Development-Tools/nRF-Connect-for-mobile. Accessed 8 April 2020

Phunthawornwong M, Pengwang E, Silapunt R (2018) Indoor Location Estimation of Wireless Devices Using the Log-Distance Path Loss Model. 2017 Proceedings of TENCON 2018 - 2018 IEEE Region 10 Conference

Qgis. (n.d.) Spatial Analysis (Interpolation). https://docs.qgis.org/2.18/en/docs/gentle_gis_introduction/spatial_analysis_interpolation.html. Accessed 28 June 2021

Retscher G, Zariqi P, Gartner G (2021) Analyses of Bluetooth Distance Measurements for Digital Contact Tracing. International Symposium on Geospatial Approaches to Combating Covid-19. Florence, Italy, 13-14 December, 2021 (accepted)