Bluetooth Low Energy (BLE) for Covid-19 Contact Tracing Using Smartphones in Four Different Scenarios

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Key words: Bluetooth Low Energy (BLE) positioning, RSSI; covid-19, contact tracing, low cost technology

SUMMARY

This work deals with the effectiveness of developed smartphone Apps for contact tracing for covid-19 that are based on Bluetooth LE (low energy) to detect contacts. Many applications based on BLE technology were developed in the past year to track the contact of people. Applications are based on how close two people are in accordance with the distance derived from the received signal strength indicator (RSSI). The paper is a more detailed study based on different types of smartphones, analysing the different factors that affect the value of the RSSI records. Thus, it describes a method and analysis for determining whether two phones, carried by humans, were in persistent contact from up to 6 meters for 5 minutes using Bluetooth LE signals. In this aspect, too, numerous methods for positioning smartphones were used so that the effectiveness of the study is as clear and precise as possible, but also to highlight the quality of intelligent devices. Experiments were carried out in four scenarios, in which the smartphones were either placed unhindered in open space on chairs, stowed in backpacks or handbags, in the user's trousers pockets and behind a wall. The results of the analyses show that several factors have a decisive influence on the signal quality. While Bluetooth technology has proven to be very useful, it is not always easy to convert Bluetooth RSSI measurements into distances between different mobile devices. The results also indicate that in most cases, especially in the near range between the devices a meaningful relationship between the RSSI values and models based on an approximation with a logarithmic path loss model can be derived. Sensitivity and specificity are also two parameters that were part of the analysis. These parameters are usually used in medicine to see if a patient is ill or affected. Therefore the sensitivity and specificity methods were used for better analysis and result for correct positive and negative cases. In most cases, the true positive and negative cases could be detected. However, the results of the trousers pocket experiment showed unexpected distributions due to the low granularity of the sampling points.

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1. INTRODUCTION

Contact RSSI (Received Signal Strength Indication) measurements and social distancing are two similar but distinct ideas that are often utilized in discussions about preventing covid-19 transmission. However, in different situations, social distance and contact RSSI have distinct uses and advantages. Ensuring a safe gap between oneself and other people in order to minimize the danger of viral transmission is known as social distancing. Two meters are usually considered a minimal distance to prevent individuals from being infected and to reduce or stop the transmission of infectious illnesses (Chen et al., 2021). Social distancing techniques aid in monitoring whether the safe distance is maintained, but they may be inadequate to safeguard individuals in offices or industrial environments. Contact tracing, on the other hand, assists in identifying individuals who have had close contact with the infected so that they may be quarantined or tested promptly. When it comes to avoiding covid-19 breakouts in workplaces, significant sanitization reactions, and maintaining employee well-being, contact tracing is critical.

Firstly, a hype in the development of contact tracing Apps based on the estimation of the distances between users could be seen to stop the spread of covid-19. But the acceptance of such Apps by the public was very low. Nevertheless in this study it is investigated how ranges between Bluetooth devices can be estimated from RSSI measurements. This is not only useful for contact tracing but also for other applications where RSSI to range conversion has to be carried out.

This paper is organized as follows: In section 2 the theoretical background of the operation of Bluetooth Low Energy (BLE) is briefly reviewed followed by a discussion of contact tracing using BLE in section 3. Section 4 discusses the state-of-the-art of Bluetooth contact tracing Apps whereas section 5 introduces the operational principle of the RSSI to range conversion. Then two parameters for the identification of infected individuals, the sensitivity and specificity parameters, are introduced and applied to the conducted experiments. This discussion of the experimental results is followed by final concluding remarks in section 7.

2. THEORETICAL BACKGROUND OF BLUETOOTH LOW ENERGY (BLE)

Bluetooth is basically a technology which operates wirelessly and transfers data between the devices compatible to this technology. It works on short distances only and uses radio waves (UHF) and bands (ISM) of two different frequencies, i.e., 2.402 and 2.48 GHz. Bluetooth

Low Energy (BLE) is a technology, extremely energy-saving wireless technology for short and medium ranges of up to 50 meters, based on Bluetooth Classic. BLE was specially designed for low-power solutions in the field of control and monitoring applications. BLE is a low energy version of Bluetooth specified in the version 4.0. BLE is used in many different areas such as the healthcare system, consumer electronics, smart energy and security. Bluetooth has a much higher data rate than BLE, but BLE has a slightly higher range, although the energy consumption is significantly lower. There are two types of BLE, the first one is single mode and the other is dual mode. Devices with single mode only use BLE and therefore have a very low power requirement. These devices, such as beacons, have chips without complicated functionalities. Dual-mode devices have a classic Bluetooth chip that has BLE integrated. These include, for example, smartphones, tablets, computers, etc. The iPhone 4S was the first device to support BLE in 2011. All current smartphones, tablets, etc. are now BLE-capable.

Proximity detection can be performed with BLE with a simple mechanism. Each BLE-equipped device can be operated in two states, i.e., the broadcaster and the observer. The broadcaster sends a broadcast beacon message on three default channels every 'advertising interval'. The observer instead wakes up every 'scan interval' and listens to beacons for a 'scan window' time. When the observer receives the beacon, it estimates the distance from the broadcaster using the RSSI. In the BLE protocol definition, 40 channels, each 2 MHz wide, around the 2.4 GHz radio band are used to transmit messages. The duration for transmitting messages is extremely short to save battery power. Among these 40 channels, there are three channels (i.e., 37, 38, and 39) for broadcasting advertiser messages. The RSSI from these three channels can be used for estimating the target's location. The BLE advertising rate can be set up to 50 Hz. The transmission power for BLE beacons is also set from 0 to 40 dBm. To reduce power consumption, BLE advertising rate and transmission power are usually set to less than 10 Hz and 16 dBm, respectively. Comparing with Wi-Fi localization, BLE localization has the following advantages:

- BLE RSSI signals can have a higher sampling rate than Wi-Fi RSSI signals, i.e., 0.25 ~ 2 Hz);
- BLE consumes less power than Wi-Fi;
- BLE RSSI signals can be obtained from most smart devices, while Wi-Fi RSSI signals cannot be provided by Apple portable devices; and
- BLE beacons are usually battery powered, which are more flexible and easier deployed than Wi-Fi.

3. CONTACT TRACING USING BLE

Bluetooth Contact Tracing is a system that monitors real-time and previous contacts between people in order to determine who was in direct contact with an infected individual (Becker and Paar, 2007). It allows Bluetooth tracing-enabled cellular phones to exchange anonymously random keys with other phones in their vicinity. If a contact tracing App user in the neighborhood was diagnosed positive for covid-19, a Bluetooth alert may be issued to inform any other App user with whom they have been in touch. This allows to keep communities secure without invading anyone's privacy (Cunche et al., 2020).

The operation principle of BLE contact tracing is described in the following steps. First of all, a BLE tag or enabled smartphone is given to an individual. The portal light gateway constantly analyzes BLE signals from these tags or devices and transmits pertinent data to the Kontakt.io cloud. The Kontakt.io cloud then interacts with the Kontakt.io contact tracer App to deliver tagged people’s anonymized location information. If an individual experiences initial signs or a diagnosis, an authorized person, such as a human resource manager in the case of a company or institution, may observe inside the App who this person was in contact with and where he/she was traveling about.

It is claimed that Bluetooth contact tracing offers a strong privacy protection system (Raskar et al., 2020). No personally identifying information or users’ data is collected; explicit user permission is needed. The list of individuals you were in contact from never leaves your phone. Positive test results are not visible to other users, Google, or Apple. The contacts will only be utilized for contact tracing by healthcare practitioners in the event of a covid-19 epidemic. However, privacy concerns about the usage of Bluetooth contact tracing were not widely accepted (Bay et al., 2020) leading to very low acceptance rates of BLE contact tracing Apps by the public. As reported in The New York Times (Zhao et al., 2020) the major reason for the low acceptance is its implementation inside the Android operating system which can possibly still gather GPS data. This data might be used to identify the user’s position, despite public statements that Google and Apple’s Bluetooth contact-tracing tools would not monitor users’ whereabouts. The problem is caused by the operating system's device location setting, which must be activated for the system to search for additional Bluetooth devices. According to a Google official who talked to the newspaper, this restriction has been in place since 2015 since certain applications would utilize Bluetooth to understand the user’s position. Google may utilize the enabled option to determine a user’s position via non-cellular connections such as Wi-Fi and Bluetooth beacons. According to a business spokesperson, applications developed using contact-tracing technologies do not have access to this data without user consent. Apple and Google have developed a method to track interaction between people who may be infected with the illness. The concept is straightforward because the technology of BLE keeps on scanning continuously for other pair-able devices. So, it can be easily told that one mobile was in contact or near with other Bluetooth enabled devices. If a person is positive for covid-19, then the application in his/her cellular phone will notify the other smart phones in contact with that mobile by using the Bluetooth (New York Times, 2021). In fact, however, obtaining the correct and required set of information using Bluetooth may be a sophisticated and challenging process answering questions like ‘How near do you need to be to a person and for how long to be at risk?’, but even collecting precise readings from signals of Bluetooth is problematic.

4. STATE-OF-THE-ART OF BLE CONTACT TRACING APPS

Contact tracing can be considered a more selective isolation measure targeted to the population most likely to have the infection (Eames and Keeling, 2003). Nevertheless, as shown with the covid-19 pandemic, if the basic reproductive number is large and most infected individuals are asymptomatic, contact tracing must be efficient and rapid in order to be effective. As a result, several governments started taking all feasible precautions to contain the virus's transmission until an authorized cure or vaccine could be developed. This presents a significant difficulty for health experts in many nations to investigate any possible interaction with persons who have screened positive for the infection. As a result, a procedure is known as 'contact mapping' was developed to identify persons who had intimate contact with the positive screening subject (Eames and Keeling, 2003). Rather than implementing drastic measures like isolation and quarantine, contact tracing allows for a more targeted approach that separates the individual who is far more likely to become sick. In summary, phone contact tracing employs capabilities like Geolocation, Wi-Fi, and Bluetooth to store the users' whereabouts and contact numbers so that, if they become affected, this data may be used to track their contacts back to the beginning of the incubation.

TraceTogether is among the first smartphone applications to employ a Bluetooth system to detect connections in immediate contact, and it was used by Singapore's authorities to combat covid-19 transmission. The location and temporal information are shared anonymously among users who have previously downloaded the App. It is a centralized design that makes use of the BlueTrace communication. CovideSafe (AU), like TraceTogether, is an Australian mobile App that uses the BlueTrace technology to track down acquaintances. The variation between them is the duration of each smartphone's temporary ID established by the service. Developers from Germany and France collaborated on the ROBust and privacy-presERving (ROBERT) closeness Tracing technology, which is comparable to BlueTrace but stores information anonymously on the webserver (Rosenkrantz et. al., 2021). StopCovid is a French App that employs a centralized framework to track interactions using the ROBERT interface. These Apps, on the other hand, rely on a centralized server, which is seen as a data loss, and would pose major security and privacy concerns that consumers may not embrace (Stevens and Bhadra Haines, 2020). MIT has also suggested Private Automated Contact Tracing (PACT) as a framework for decentralized architecture, in which essential functions are transferred from the computer to the cellphone, giving consumers additional anonymity (Montagni et al., 2021).

Another smartphone-based contact tracing system called 'Tracy' that supports self-investigation is built on a dynamic architecture that protects consumers' confidentiality while also allowing health experts to analyze data. The system contains three main parts: (1) a smartphone-based intelligent software, (2) a data processing infrastructure, and (3) a webpage on which the various functionalities of those elements are linked to deliver the contact RSSI software's needed services. To minimize the Bluetooth range estimate ambiguity, a unique technique for accurately detecting the user's effective locations together with their time stamps may be kept on the smartphone (Rowe et al., 2020). Another engine just allows for self-investigation for connections with compromised people. The system also allows for effective connection with the primary healthcare council in order to get evaluations, health advice, and preventive steps to those that have conducted their own inquiry and determined they may have come into contact with covid-19 affected individuals. There are four types of contact tracing: first-order, single-step, iterative and retrospective (Elmesalawyet al., 2020; Vivanti et al., 2020):

- First-order tracing only identifies those people the patient immediately came into contact with:
- Single step contact tracing identifies all people that the infected person came into contact with;
- Iterative contact tracing continues to track and re-apply the relevant diagnostic test to contacts iteratively before their infection may even be detected through symptom screening; and
- Retrospective contact tracing follows the same process as either single-step or iterative with the addition that it also operates in reverse by considering the people with which the infected patient had been in contact with in their recent past, with the goal to identify who it was that infected the patient.

Because of the critical function of contact tracing Apps on cellphones, which take advantage of existing digital techniques to offer a rapid and exact identification of persons who may have come into contact with an infectious cause, their acceptance by the public was very low. When a large amount of the population would have used these Apps, it could have largely limited the effects of the covid-19 infection (Rivest et al., 2020).

5. BLE RSSI TO DISTANCE RELATIONSHIP

In principle, the quantity of signal power is related to distance, thus it may be used to determine how far apart the two cellphones are. A strong signal indicates that the phones are near together; a weak signal indicates that they are further away. As a result, a certain signal intensity between two phones might signify a ‘contact event’ between their respective owners. Mostashari told Newton (Bengio et al., 2020) that one issue with such a system is that it may produce a lot of false positives. ‘If I'm out in the open, my Bluetooth and your Bluetooth may ping each other even if you’re much farther away than six feet,’ he explained. ‘You might be in an apartment across the hall from me, and it could ping that we’re having a proximity incident. It might ping even if you are on a different floor of the building. You might be riding past me in broad daylight, and it could ping.’ There are several more possible sources of inaccuracy. For instance, if one smartphone is trying to stand up inside one pocket—in portrait rather than landscape mode—the quantity of received power might alter dramatically. That alone might make it appear as if someone across the room is only a few feet away from another person (Bengio et al., 2020).

By taking advantage of the signal strength of BLE, distance can be estimated (Hatke et al, 2020). There are several path loss models to estimate distance from RSSI for indoor environment, such as Free Space Friis Model, and Linear Approximation Model, etc. (Chowdhury et al., 2015). It is worth noting that, as a BLE scan will also reveal the RSSI, which roughly indicates how far away the nearby peripheral phones are, we could estimate the distance using the well-known inverse square law of physics, that is, the signal intensity is inversely proportional to the square of the distance from a signal transmitter (Narkhede, 2018). The distance between the tracker and the receiver can be obtained using the path loss model. 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 (Chowdhury et al., 2015).

This model is based on that RSSI follows a log-normal distribution over distance and it is applied inside a building or densely populated areas. Once the average RSSI values of all positions for all phones are determined, a theoretical distance estimation based on a logarithmic loss model can be made. This model is a simple way to estimate distance with RSSI. After having the estimated distance, it is compared with the truth distance and seen how the model deviates from reality (Phunthawornwong et al., 2018). So, the path loss model is expressed as:

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

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

After derivation of the estimated distance d, 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. As an example, the graphs in Figure 1 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 a correlation coefficients R^2 to indicate the correlation that each equation has to the ground truth data. For the estimated equations the following applies:

$$x \rightarrow \|\mathrm{RSSI}\|,\ y(x) \text{ -> } d(\mathrm{m}). \tag{2}$$

As can be seen from Figure 1 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 -0.798. But we can conclude that in general all the phones that were employed in this experiment have a similar trend as the theoretical model, making perhaps a very small difference from the others is the phone Samsung Galaxy S8 with correlation coefficient at -0.558.

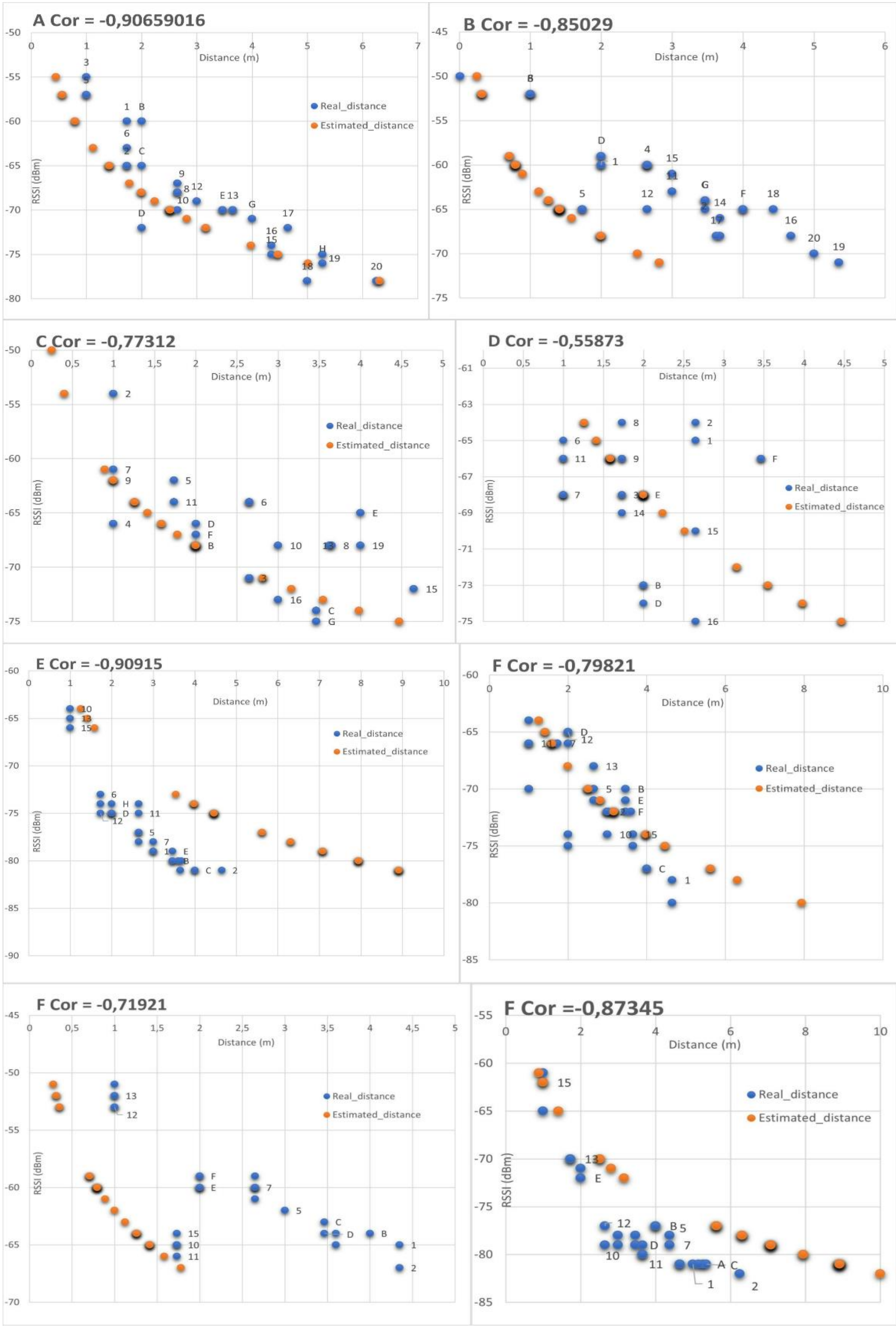

Figure 1. Sampling points (blue) and the estimated distance (orange) of six smartphones indicating the deviation from the logarithmic path loss model

As for the estimated equations (see Table 1), it can be seen that the Samsung Tablet A6, Sony Xperia Z3, Samsung Edge 6 and Google Pixel 3, fit very well on the logarithmic model while the Samsung Galaxy S8 have a poor fitting. 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 the model and the true distance match. These results have been achieved for smartphones unobstructed lying on the chairs in the testing room.

Position	Phone	Equation	R^2
A	Samsung Tablet A6	y = 12.611 log(x) – 50.088	$R^2 = 0.8146$
B	Sony Xperia Z3	y = 12.386 log(x) – 48.259	$R^2 = 0.7618$
C	LG Nexus	y = 11.011 log(x) – 43.543	$R^2 = 0.6452$
D	Samsung Galaxy S8	y = 8.0456 log(x) – 31.888	$R^2 = 0.4125$
E	Samsung Edge S6	y = 9.2312 log(x) – 37.253	$R^2 = 0.7413$
F	Samsung Galaxy S7	y = 10.631 log(x) – 42.537	$R^2 = 0.6499$
G	Sony Xperia Z5	y = 10.006 log(x) – 38.629	$R^2 = 0.5889$
H	Google Pixel 3	y = 11.734 log(x) – 47.331	$R^2 = 0.7247$

Table 1. Logarithmic equation relationships and their respective correlation coefficients R^2

6. SENSITIFITY AND SPECIFICITY AS PARAMETERS FOR IDENTIFICATION OF INFECTED INDIVUDALS

Sensitivity and specificity mathematically describe the accuracy of a test which reports the presence or absence of a condition:

- Sensitivity (True Positive Rate) refers to the proportion of those who have the condition (when judged by the ‘Gold Standard’) that received a positive result on this test; and
- Specificity (True Negative Rate) refers to the proportion of those who do not have the condition (when judged by the ‘Gold Standard’) that received a negative result on this test.

In a diagnostic test, sensitivity is a measure of how well a test can identify true positives and specificity is a measure of how well a test can identify true negatives. For all testing, both diagnostic and screening, there is usually a trade-off between sensitivity and specificity, such that higher sensitivities will mean lower specificities and vice versa (Heinrich, 2020).

Mathematically, the two parameters can be expressed as:

$$\begin{aligned} \text{sensitivity} &= \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}} \\ &= \frac{\text{number of true positives}}{\text{total number of sick individuals in population}} \\ &= \text{probability of a positive test given that the patient has the disease} \end{aligned} \tag{3}$$

and

$$\begin{aligned}\text{specificity} &= \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}} \\ &= \frac{\text{number of true negatives}}{\text{total number of well individuals in population}} \\ &= \text{probability of a negative test given that the patient is well}\end{aligned} \tag{4}$$

In the experiments it was investigated how different locations of the smartphone advertisers and scanners have an impact on the resulting two parameter sensitivity and specificity. In scenario 1 one scanning smartphone as well as smartphone advertisers were distributed in a classroom on chairs. This scenario is described as unobstructed scenario in the following. Figure 2 on the right shows the respective location of the advertising phones on the points A to H. It is also illustrated in the sketch which scanner locations are less than 2 m or more than 2 m apart. The 2 m distance limit describes the social distance. A distance of less than 2 m means that both phone users were in close proximity and an infection with covid-19 can occur. As an example, Figure 2 shows the RSSI recordings with one scanning smartphone (Samsung S9) on test point 1 and their resulting values in [%] for the sensitivity and specificity. The results are quite satisfying in the unobstructed scenario with this cellphone on the chair as the specificity resulted in 100%. The lower sensitivity value of around 75% was caused by the fact that the RSSI was in the range of 2 m for two advertiser phones placed on points A (Tablet A6) and B (Sony Xperia Z3), although at less than 2 m away from the test point 1. This, however, is still a satisfactory result because the sensitivity value is 100%. Lower values for sensitivity and specificity were usually obtained due the age of the cellphones or some older version of operating system. Table 2 summarizes the statistical parameters for sensitivity and specificity over all test measurements in the unobstructed scenario.

In the second scenario investigated the scanning phone was put into the trousers pocket of the test user who was sitting on the chair of each test point. The location of the phone in the trousers pocket had the biggest influence on the measured signal strengths and the results for sensitivity and specificity. As can be seen in Figure 3 the RSSIs show high fluctuations with high noise. The RSSI values are also significantly lower than in unobstructed scenario. Figure 3 shows the most representative example in this scenario because the equal division of phones was with distances shorter and larger than 2 m. The resulting sensitivity was only around 40% and the specificity 46%. Table 3 summarizes all statistical parameters for sensitivity and specificity over all test measurements in the trouser pocket scenario.

Further scenarios investigated were that the scanning phone was put into a backpack or handbag and was located behind a thick wall. These two scenarios should much better results than if the phone is placed into the trousers pocket of the user. Further information about these scenarios might be found in Retscher et al. (2021).

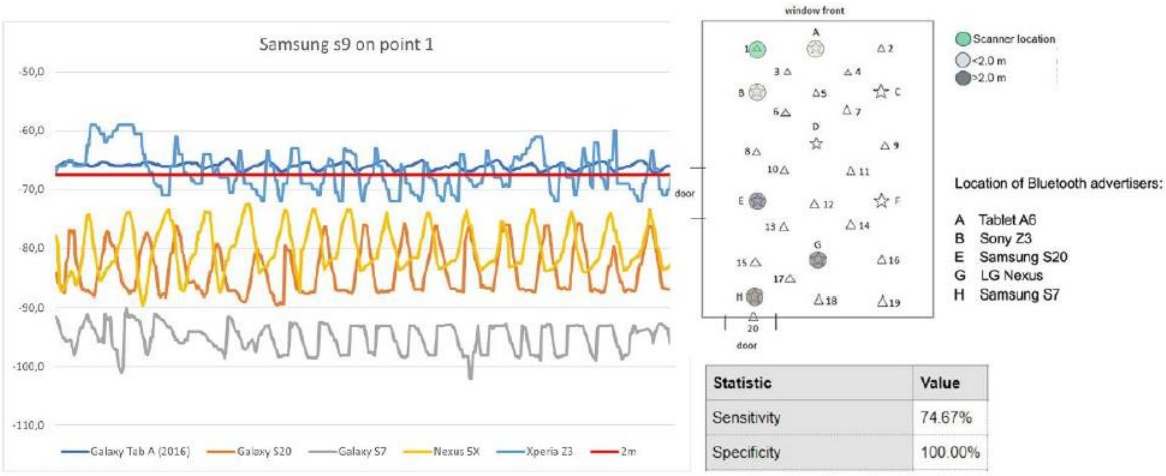

Figure 2. RSSI recordings with Samsung S9 on test point 1 in the unobstructed scenario and resulting sensitivity and specificity

	Sensitivity	Specificity
Median	92.00	88.00
Average	83.27	83.00
Standard Deviation	20.44	15.81
Mode	1.00	1.00
Minimum	18.00	20.00
Maximum	100.00	100.00
Skewness	-1.43	-2.30

Table 2. Statistical characteristics of the sensitivity and specificity in [%] in the unobstructed scenario where the cellphones were placed on chairs

7. CONCLUSIONS

In this study the usability and practicability of BLE for contact distance estimation between different mobile devices was investigated. This technology was proposed for digital contact tracing in respective to disease control such as in the covid-19 pandemic. Using different experiments the feasibility for the conversion of the measured Bluetooth RSSIs into ranges between the advertiser and scanning smartphones was tested and analyzed. Thereby it was seen that in the unobstructed scenario where the phones are in contact with each other without any obstruction provided reasonable and useable results. In an obstructed scenario, however, where the smartphone of the RSSI scanner was placed into the trousers pocket of the user many false predictions for determination of the social distance can occur. Further scenarios investigated where that the scanning and/or advertising phones were placed into backpacks or handbags or behind a wall. These scenarios proved that meaningful distance estimation is also possible in these cases. For the investigation of the correct positive and negative prediction, the two parameters sensitivity and specificity know in medicine for determination of infected cases were used.

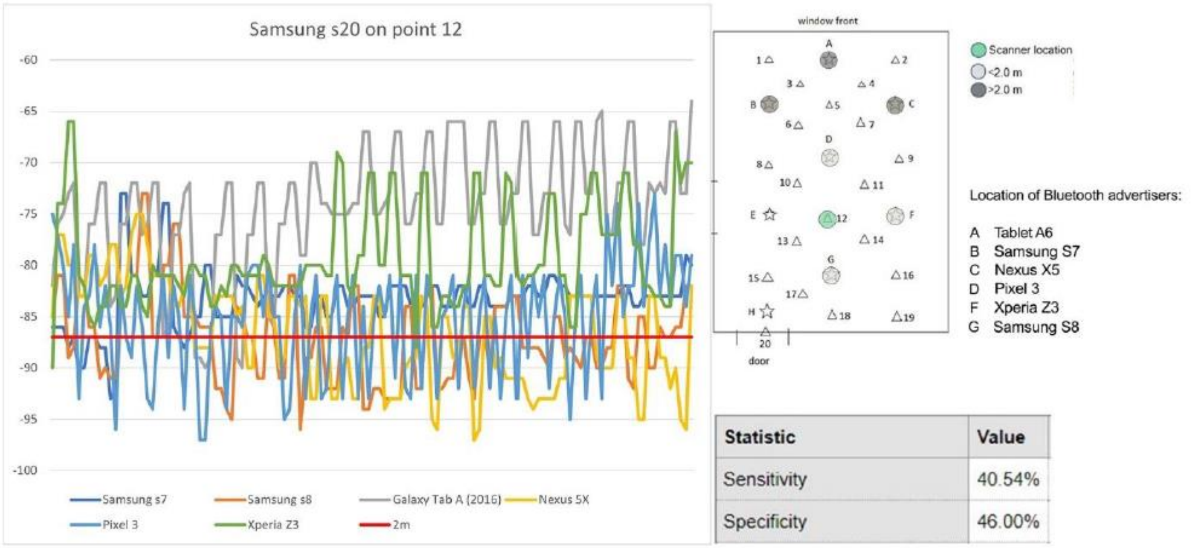

Figure 3. RSSI recordings with Samsung S20 on test point 12 in the trousers pocket scenario and resulting sensitivity and specificity

	Sensitivity	**Specificity**
Median	62.50	65.00
Average	59.41	65.46
Standard Deviation	13.53	10.87
Mode	1.00	1.00
Minimum	10.00	38.00
Maximum	82.00	89.00
Skewness	-1.32	-0.25

Table 3. Statistical characteristics of the sensitivity and specificity in [%] in the trousers pocket scenario

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BIOGRAPHICAL NOTES

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