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1. Introduction

The World Health Organization (WHO) declared Coronavirus COVID-19 a pandemic on March 11, 2020. According to Ref. [1], protective measures are necessary to avoid peaks in the number of daily cases that can lead to overpass the health care system capacity, which would mean that patients who require care cannot be cared for and put their lives at risk. As shown in Fig. 26.1, the application of protective measures helps to flattening the curve of daily cases.

One of these protective measures is to maintain social distancing. It’s a simple and effective way to fight COVID-19, but in practice, it’s not always respected. Ref. [2] recommends that the social distancing between people to maintain protection from COVID-19 is at least 1 m. A comprehensive survey of the technologies for social distancing was elaborated by Ref. [3]. Among the emerging technologies are: artificial intelligence, computer vision, ultrasound, inertial sensors, and thermal. Regarding wireless technologies, it mentions Wi-Fi, Cellular, Bluetooth, Ultra-wideband, GNSS, Zigbee, and RFID. The use of smartphones to maintain social distancing brings many advantages, as mentions [4], such as: ubiquity, convenience, low-cost, and portability. In addition, smartphones have many built-in sensors such as accelerometer, gyroscope, magnetometer, Wi-Fi, Bluetooth, Cellular Radio, GPS, camera, microphone, proximity sensors, environmental light sensors, and temperature sensors. From the mentioned sensors, there are three that stand out to make a solution of social distancing: Wi-Fi,
Bluetooth, and global positioning system (GPS). GPS has an accuracy of 3–15 m in outdoor environments, but it has a poor indoor performance. Bluetooth it is suitable for low consumption because its active energy use is less than 40 mW, unlike Wi-Fi and GPS, which vary between 50 and 300 mW [5]. Besides that, Bluetooth is cost effective, and has deployment flexibility [6]. Among the best known distance estimation, techniques between two nodes are: Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival, and received signal strength indication (RSSI). According to Ref. [7], Bluetooth cannot handle efficiently ToA or TDoA techniques because of its narrow band signals, so RSSI is the more reliable option. Since RSSI has an inversely proportional relationship to squared distance, different radio propagation models to estimate the distance between two nodes based on RSSI were used and are mentioned by Refs. [8,9] and being these: Link Budget model, Log-Distance model, Log-Normal Shadowing model, ITU Indoor Path Loss model, Two-Ray Ground Reflected Path Loss model, Experimentally Derived Signal Strength Distance Relation model. The aim of this research is to build an RSSI-based mobile application to comply with social distancing using Bluetooth signals from smartphones. We use Bluetooth technology to maintain the social distancing between two people as shown in Fig. 26.2.

FIGURE 26.1 Effect of protective measures to flattening the curve of daily number of cases.

FIGURE 26.2 Bluetooth to maintain the social distance.
Instead of using traditional techniques to estimate the distance based on radio propagation models, we use a simpler and more effective approach based on determining if the social distance of at least 1 m is met as a binary classification problem. The rest of the paper is organized as follows. Section 2 presents a literature review of other solutions for social distancing using other technologies, indoor localization systems and its relation with RSSI, factors that affect the measurements of RSSI, and RSSI filtering techniques. In Section 3, we describe an experiment overview explaining the methodology for measurements and the collection of data. In Section 4, we make an analysis of data and build an embedded machine-learning model on the smartphone that determines if the social distancing is met, as well as an operation of the application is shown. In Section 5, we discuss the results of Section 4. Finally, conclusions and future work are given in Section 6.

2. Literature review

2.1 Other solutions for social distancing using other technologies

Enabling technologies for social distancing were mentioned by Ref. [3] and were divided into the following categories:

- Emerging technologies: Artificial Intelligence (AI), Computer Vision, Ultrasound, Inertial Sensors, and Thermal.
- Wireless technologies: Wi-Fi, Cellular, Bluetooth, Ultra-wideband, GNSS, Zigbee, and RFID.

Also, it mentions the open issues and future research directions:

- Security and privacy-preserving in social distancing.
- Real-time scheduling and optimization.
- Incentive mechanism to encourage social distancing.
- Pandemic mode for social distancing implementation.

As an example, a computer vision application was implemented by Ref. [10]. It proposes the use of real-time surveillance video analytics to automate the task of monitoring social distancing. It uses the YOLO v3 object detection model and a Deepsor approach to track people. This application is based on the application released by landing AI. The commitment of companies to find solutions to social distancing shows its importance to fight this pandemic.

Another example was developed by Ref. [11]; he uses a smartphone-based Wi-Fi fine time measurement that can measure the distance between two nodes named “Initiator” (the smartphone) and a “Responder,” reaching a root mean squared error (RMSE) of 1.10 m.
2.2 Indoor localization systems and its relation with Received Signal Strength Indication

Indoor Localization systems is a very active research field of study because it is needed in different applications like asset tracking, people tracking, autonomous robotics, navigation, etc.

Ref. [4] elaborates a diagram of indoor localization techniques, which is as follows:

- Pedestrian reckoning
- Fingerprinting
  - Magnetic fingerprinting
  - RSSI fingerprinting
- Trilateration
  - RSSI distance estimation
  - Time of arrival ranging
  - Time difference of arrival
- Proximity estimation
- Visual localization
  - Visual recognition
  - Scene analysis

As you can see, the RSSI approach is used for fingerprinting and trilateration.

In the case of fingerprinting, it consists of five stages as mentions [12]: planning, collecting, preprocessing, training, and positioning. For planning stage, an area is selected and splits. Then collects, preprocess, and store RSSI signals as a fingerprint data characteristic of each split area. After that train a model to predict location based on the RSSI signals measurements. Finally, in the positioning stage, collect in real-time the RSSI measurement and infer your position. In this approach, the aim is to predict where your location is. In Ref. [13], it was implemented an RSSI fingerprint based on Bluetooth Low Energy 4.0 beacon for a localization mechanism in an area split on 15 sectors using a smartphone and a Raspberry Pi with a BLE4.0 antenna.

In the case of trilateration, it consists basically of four stages: collecting, preprocessing, distance estimation, and positioning. For collecting stage, data are collected and filtered. Then in distance estimation stage, the radio propagation model parameters are tuned. Finally in positioning stage, trilateration is applied, and consists of select the best three RSSI sources, estimate the distance from device to source with the model, and applies a geometric method to estimate the position. In Ref. [14], an indoor application with a positioning accuracy of 0.2–0.5 m based on Bluetooth low energy beacons and a mobile device was developed.

The different location techniques mentioned before can also be used together. In Ref. [15], a hybrid method was used to improve positioning in a dense Bluetooth environment; the trilateration algorithm and the dead reckoning algorithm (make calculations of the position based on velocity and direction) were applied to estimate the
indoor position. The RMSE of the three methods used are trilateration (2.330 m), dead reckoning (0.823 m), and hybrid method (0.757 m), proves that the hybrid method has improved the accuracy of the positioning. In Ref. [16], WiFi RSSI filtered data were collected to use trilateration algorithm together with the data of the inertial navigation system (INS) was fused using a Kalman Filter to make an indoor positioning system.

### 2.3 Factors that affect the measurements of Received Signal Strength Indication

As mentioned by Ref. [17], there are three basic mechanisms that rules radio propagation (see Fig. 26.3):

- Reflection: occurs when the radio wave collides with an obstruction, and this wave is completely reflected, so they can interfere constructively or destructively at a receiver.
- Diffraction: occurs when the radio wave collides with an obstruction, but instead of be reflected it manages to pass through it.
- Scattering: occurs when the radio wave collides with an obstruction, and this causes that the radio wave to be reradiated in several different directions.

According to Refs. [18,19], there exist two other factors that affect RSSI measurements: smartphones itself (hardware characteristics) and environment (physical obstacles between smartphones, smartphone orientation, distance between smartphones, radio interference from other sources, humidity, and temperature).

It can be concluded that RSSI measurements are unstable and behaves as a noise signal. Even if you take several measurements in the same position and with the mobile device, values fluctuates significantly. As Ref. [20] mentioned, work with RSSI raw data is impossible, but it could be possible with RSSI average data or with RSSI data that has been filtered from noise. For this reason, it is necessary to review RSSI filtering techniques.

![FIGURE 26.3 Radio propagation mechanisms: reflection, diffraction, and scattering.](image-url)
2.4 Received Signal Strength Indication filtering techniques

RSSI signals are not sufficiently stable to do an estimation base in just one measurement. After reading several authors, it was found that the following techniques are used to filter RSSI signals:

- Low pass filter [20].
- Window moving average filter [8,14,21–24].
- Autoregressive moving average filter [25].
- Median filter [6,12,25].
- Exponentially weighted moving average filter [8,15,23,25].
- Span thresholding filter [8,23].
- Kalman filter [12,14,16,22,24–29].
- Extended Kalman filter [30].
- Alpha trimmed mean [22].
- Belief condensation filtering [31].
- Gaussian filter [27].
- Particle filter [24].
- Discrete bayes filter [29].
- Adaptive-bounds band-pass moving-average filter [32].
- Nonparametric information (NI) filter [29].

Some authors also use outlier detection techniques like Ref. [28] that combined Chebyshev outlier detection with Kalman filter. A single direction outlier removal was used by Ref. [14] because RSSI have tendency to decline and then uses Kalman filter.

As can be concluded from the review, many authors use Kalman filter, window moving average filter, exponentially weighted moving average filter, and median filter.

3. Experiment overview

The experiments were carried out using two smartphones: a Xiaomi Redmi 7A (A) as a Bluetooth RSSI source and a Huawei CAM-L03 (B) as a Bluetooth RSSI signal scanner.

3.1 Methodology for measurements

- People hold their cell phones in front of them horizontally, as if they were using it.
- There are no physical obstacles between people.
- There is little or no radio interference.
- Measurements were taken in the afternoon and night at 23 and 19°C, respectively.
The user with the smartphone “A” used as the RSSI Bluetooth source remains fixed while the measurements are made. The user with the smartphone “B” used as the RSSI Bluetooth scanner moves when taking measurements statically around the other user, rounding him up by making circles at different distances (Fig. 26.4).

3.2 Collection of data

- Measurements within a 1 m radius of the user are labeled “1,” indicating that social distance has been breached. While measurements outside the user’s 1 m radius are labeled “0,” indicating that social distance has been met (Table 26.1). A total of 1612 data points were collected and saved in a.csv file.
- An application was developed to collect the data (Fig. 26.5).

| Received Signal Strength Indication (dBm) | Social distance label |
|-----------------------------------------|-----------------------|
| −38                                     | 1                     |
| −56                                     | 0                     |
| −40                                     | 1                     |
4. Analysis of results

4.1 Descriptive analysis

Because of its simplicity and ease of implementation, the average and median filters were used in a size mobile window of 10 because that would be a reasonable smartphone sampling capacity.

- Raw data for breach of social distance is shown in Fig. 26.6.
- Raw data for compliance of social distance is shown in Fig. 26.7.
- Mean data for breach of social distance is shown in Fig. 26.8.
- Mean data for compliance of social distance is shown in Fig. 26.9.
- Median data for breach of social distance is shown in Fig. 26.10.
- Median data for compliance of social distance is shown in Fig. 26.11.
- Raw dataset was divided based on its labels “1” and “0,” then descriptive statistics were performed such as count of data, mean, standard deviation, minimum, maximum, and 25%, 50%, 75% percentiles (Fig. 26.12A and B).
FIGURE 26.6 Raw data when social distance is less than 1 m.

FIGURE 26.7 Raw data when social distance is greater than 1 m.
FIGURE 26.8 Mean data when social distance is less than 1 m.

FIGURE 26.9 Mean data when social distance is greater than 1 m.
Mean dataset was divided based on its labels “1” and “0,” then descriptive statistics were performed such as count of data, mean, standard deviation, minimum, maximum, and 25%, 50%, 75% percentiles (Fig. 26.13A and B).

Median dataset was divided based on its labels “1” and “0,” then descriptive statistics were performed such as count of data, mean, standard deviation, minimum, maximum, and 25%, 50%, 75% percentiles (Fig. 26.14A and B).

- FIGURE 26.10 Median data when social distance is less than 1 m.
- FIGURE 26.11 Median data when social distance is greater than 1 m.

- Received signal strength 493
FIGURE 26.12 Descriptive statistics of raw dataset. (A) Social distance is breached (<1 m), (B) Social distance is met (>1 m).

FIGURE 26.13 Descriptive statistics of mean dataset. (A) Social distance is breached (<1 m), (B) Social distance is met (>1 m).

FIGURE 26.14 Descriptive statistics of median dataset. (A) Social distance is breached (<1 m), (B) Social distance is met (>1 m).
The raw dataset was shown in Fig. 26.15. As can be seen below, there is a lot of overlap of the measurement values. This is mainly because of two reasons:
- RSSI signals are very susceptible to environmental conditions as mentioned, so the variance in the measurements is large.
- Another reason occurs when the measurement of the RSSI is performed behind the user in the case of breach of social distance, since the user’s body becomes a physical obstacle that alters the measurement of the signal.

The mean dataset was shown in Fig. 26.16 because of the three datasets it is the one with the least variance, and it will be the one to work with. As can be seen, the mean filter helps a lot to reduce the overlapping zone.

### 4.2 Machine learning model

Determining whether or not social distance is met is a binary classification problem. So, four models were tested: simple logistic regression, support vector machines, random forest, and neural networks. The model selected was neural networks because it returns the best accuracy. The architecture and hyperparameters of the model will be detailed below.

- One dense hidden layer with one neuron using a “relu” activation function.
- One output neuron using a sigmoid activation function.
- Binary cross entropy loss function.
- Adaptive moment estimation (Adam) optimization algorithm.
- 200 epochs.
The results when training the model using the raw data reaches an accuracy of 83.37%, and when is trained with the filtered mean data, it reaches an accuracy of 89.89%.

1000 random numbers from 0 to 100 (representing the RSSI values in -dBM) were randomly generated as input values to the model that makes the inference, returning the probability that the social distance is breached as shown in Fig. 26.17.
4.3 Embedding a machine learning model in a smartphone using TensorFlow Lite

According to Ref. [33], TensorFlow Lite is “an open source deep learning framework for on-device inference.” It has the following main characteristics that make it interesting to work with mobile devices: lightweight, low-latency, improved power consumption, no internet connection required.

It has two main components:

- “Converter” that transform a TensorFlow model into a TensorFlow Lite format using optimizations to reduce model size and which makes it easy to read by the “Interpreter.”
- “Interpreter” runs on your mobile device and deals with the inference of these converted models.

4.4 Operation of the application

As shown in Fig. 26.18A–C, the model input is the Bluetooth RSSI scan (in dBm) and returns the probability of social distancing breach.

![Image](image.png)

**FIGURE 26.18** Probability of social distancing breach calculated by the application. (A) High probability, (B) 50% probability, (C) Low probability.
5. Discussion

After having analyzed 1612 raw data points (1592 filtered data points because of the windows size of 10) to embed a machine-learning model in the smartphone so that it can detect whether the social distance was breached or not. Our experiments suggest that:

- All measurements made when the social distance when the mean filter is applied is greater than 1 m as seen in Fig. 26.16 never fall below $-48 \text{ dBm}$. Furthermore, as seen in Fig. 26.13A, being closer to the source, the measurement of the data is more consistent since it has less variance. This allows us to affirm with certainty that one breach social distance automatically if values less than $-48 \text{ dBm}$ are entered into the model that runs the application, returning a probability greater than 50% as seen in Fig. 26.18A.

- The overlap area of the signal measurements varies in a range from $-59$ to $-48 \text{ dBm}$ (Fig. 26.16), this is mainly because of:
  - The nature of radio frequency means that RSSI measurements can vary significantly even if conditions are apparently maintained as they may be sensitive to small changes in the environment.
  - Measurements made just behind the user (Fig. 26.16) could mislead the model as the user behaves like a physical obstacle that would cause the signal to drop significantly and confuse it with a drop because of a greater separation distance. This would indicate that the measurements of the overlapping zone are those made just behind the user.

- The model as shown in Fig. 26.17 determined a limit to determine whether the social distance is breached. This limit is $-53 \text{ dBm}$, corresponding to a probability of approximately 50%.

- The application of the filter is important because it helps to narrow the overlapping zone noticeably.

This study is important in the context of COVID-19 since the conditions of the measurements that were established are very similar to those that occur when people go out to the street: they have the smartphone in their hands, little radio interference, and without physical obstacles between users. So the model predictions as mentioned could reach 89.89% accuracy. Our study helps the developers of applications to integrate an alarm when the social distance is breached because many times other people get too close to users without caring about their safety, and the user does not complain, either for fear or other reason too can help when queuing. Since when people have the application, the alarm of those who do not comply with social distance would sound and automatically try to distance themselves.

A limitation of the study is that it can fail the prediction when the measurement is just behind the other user, although the probability of getting COVID-19 decreases when you are behind the user since the droplets produced by coughing or sneezing would not fall directly on the user. As mentioned in Ref. [34], the operation of the Bluetooth signals is better face-to-face.
6. Conclusions and future work

In this study, we have explored if a Bluetooth RSSI-based mobile application can be developed to detect if the social distance recommended by the WHO of 1 m as a measure to fight against COVID-19 is met or not.

After examining 1612 collected data points, our statistical analysis concluded that RSSI measurements less than $-48 \text{ dBm}$ breach the social distance with great certainty, also exists a measurement range from $-59 \text{ to } -48 \text{ dBm}$ where the signals for labels “1” and “0”, that indicates if the social distancing is breached, are overlapped.

A machine learning model was created using a simple neural network for binary classification, then this was transformed into a TensorFlow Lite format using a “Converter,” with the purpose that using an “Interpreter” the smartphone can run the model and do inference. The model achieved 89.89% accuracy, and a limit of $-53 \text{ dBm}$ to determine whether the social distance is breached.

As future work recommendation: test different smartphone’s location such as user’s pockets, test different environment’s temperatures, test with more smartphones and radio interferences, test with different smartphone’s models, use of a time windowing approach to measure signals, other filters, etc.

Source code is at https://github.com/alvaro-martin/data-sience-for-covid19.

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