Adaptive Distance Sensing in Contact Tracing Applications Through Indoor/Outdoor Detection

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Abstract. Physical distancing is one of the most effective measures for limiting the spreading of the COVID-19 disease. Smartphones, being carried by their owners most of the time, are particularly appealing for increasing the awareness of people about their closeness to other individuals. Sensing the distance using communications technologies like Bluetooth is known to be affected by the surrounding environment. In this paper, we study the benefits that can be achieved by automatically recognizing if the user is indoor or outdoor and then defining a customized threshold for improving the accuracy of social distancing applications.

Keywords: Smartphone sensors · Distance estimation · Social distancing

1 Introduction

The COVID-19 disease is more likely to spread in crowded places, close-contact settings, and in confined spaces with poor ventilation [20]. The main suggestion from the World Health Organization is to maintain a minimum distance of 1 m between people, in order to reduce the probability of getting infected. Many works focused on the use of smartphones as a means to fight the spread of the virus: being personal devices that are almost always carried by their owners, smartphones are able to detect a wide range of unsafe behaviors. A well-known example is represented by the Exposure Notification (EN) service, a joint effort by Google and Apple to detect close interaction between users. EN relies on Bluetooth Low Energy (BLE). Many apps produced by health authorities include the EN service for tracing the contacts of infected users [3]. One of the key elements of a social distancing app is the capability of correctly estimating the distance between users. This is generally achieved using BLE, as it is a widely available technology and its energy requirements are compatible with prolonged use. In particular, the distance between two devices can be estimated, at the receiver, using the Received Signal Strength Indicator (RSSI), which is related to the distance as follows:

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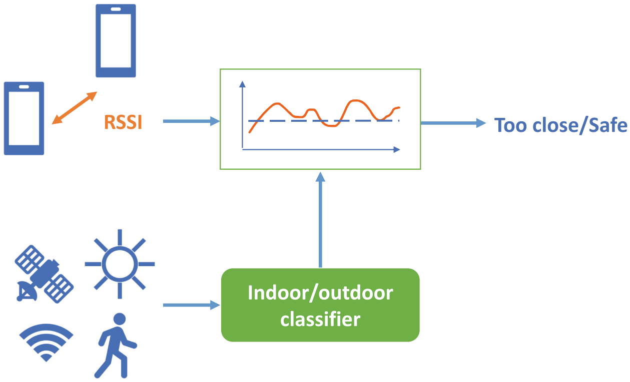


Fig. 1. Overview of the method.

$$RSSI = P_{tx} + G_{tx} + G_{rx} + 20log(\frac{c}{4\pi f}) - 10nlog(d) \quad (1)$$

where P_{tx} is the transmission power, G_{tx} and G_{rx} are the two antenna gains, c is the speed of light, f is the frequency, n is the path-loss coefficient, and d is the distance. Several positioning systems have been based on BLE [1,19]. Unfortunately, estimating the distance with great accuracy is difficult, mostly because of the impact of the surrounding environment (obstacles, walls, furniture, and other physical elements have an impact on the value of n). In this paper, we use the sensors available on common smartphones to automatically detect if the user is indoors or outdoors. This information is then used to recognize users that are too close (< 1 m) or at safe distance (> 1 m) with improved accuracy compared to an environment-unaware approach.

2 Method

Overall, the approach is summarized in Fig. 1: information produced by the sensors available on common smartphones is processed to produce a feature vector; the feature vector is given as input to a previously trained classifier, based on Machine Learning (ML) techniques, which detects the current environment of the user (only two classes are considered: indoor and outdoor); RSSI values are compared to a threshold (S) to understand if the transmitter device, carried by another user, is at safe distance or not. The threshold, used for understanding if the distance between the two devices is safe or not, is set to a value that depends on the current environment: S_{IN} and S_{OUT}, for indoor and outdoor settings respectively.

Indoor/Outdoor Detection. To understand if the user is indoors or outdoors, we use only the information produced by smartphone sensors. In other words, we

Table 1. Features extracted from the Android sensors.

Current luminosity
Mean luminosity (last 30 s)
Mean luminosity (last 30 s before proximity sensor is covered)
Last luminosity value before the proximity sensor is covered
Current proximity
Time elapsed since the last time the proximity sensor was uncovered
Number of Wi-Fi access points currently visible
Number of Bluetooth devices currently visible
Number of GPS satellites in line of sight
Number of fixed GPS satellites
Time elapsed since the last GPS fix
Daylight (night, twilight, daylight)
User's activity (running, walking, still, vehicle, bicycle, on foot, tilting)

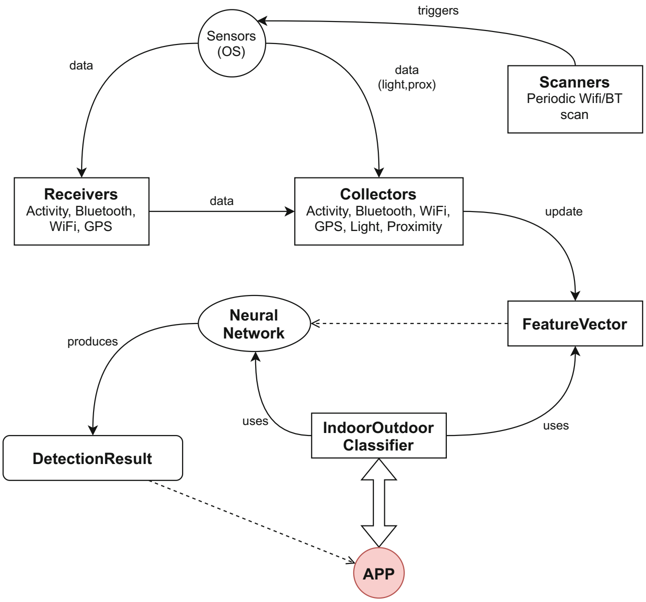


Fig. 2. Structure of the indoor/outdoor detection library.

do not rely on any infrastructure deployed in buildings, streets, etc. The classifier receives as input a vector of 21 elements extracted from the following sensors and communication technologies: light, proximity, GPS, Wi-Fi, Bluetooth. The light sensor is relevant as during daytime outdoor environments are generally characterized by higher values of luminosity. The proximity sensor can be useful to understand if the device is in a pocket or in a backpack. The GPS signals are shielded by buildings, and so they are typically less intense indoors compared to outdoors. Similarly, Wi-Fi access points and Bluetooth devices are generally more abundant indoor compared to outdoor. To foster its reuse, the mechanisms for detecting the current indoor/outdoor scenario have been implemented as an Android library. The library uses a TensorFlow Lite model [8], trained with Python scripts. The model also takes as input the activity of the user as detected by the software sensor included in the Android OS. The features extracted from the information sources are summarized in Table 1. The first 11 features do not need any specific encoding. The last two features, daylight and user's activity, are categorical features and they have been one-hot encoded, increasing the size of the feature vector to 21 elements. The high-level structure of the library is shown in Fig. 2. The receiver classes listen for data produced by sensors (with the exception of luminosity and proximity that are received directly by the collectors). Scanners are used to periodically scan for Wi-Fi AP and Bluetooth devices. The collectors prepare a FeatureVector instance. The IndoorOutdoorClassifier is the main entry point for the applications that want to use the library, and it is responsible for periodically running the neural network with the latest feature vector. The result is an instance of the DetectionResult class which contains the last indoor/outdoor status detected together with its confidence level (i.e. how much the neural network can be trusted about the produced value). The last indoor/outdoor status produced with a confidence greater than a configurable threshold is stored to provide apps with an easy way to retrieve recent information.

Improving the Accuracy in Social Distancing Apps. As mentioned, the distance estimation phase is significantly affected by the current environment. In our approach, we only consider two categories of environments: indoor and outdoor. Depending on the category of the current environment, as detected via ML, the threshold used to distinguish safe distances from unsafe ones is changed. In particular, the RSSI value produced by the BLE packets transmitted by another user is compared with a threshold S that corresponds to the average RSSI observed when two devices are at a distance of 1 m. If RSSI $> S$, the distance between the two users is considered to be unsafe (and vice-versa). Instead of using a universal threshold, the value of S is set to S_{IN} or S_{OUT} depending on the current environment, where S_{IN} and S_{OUT} are the average RSSI values observed when two devices are at a distance of 1 m in indoor and outdoor environments respectively. This is done to improve the accuracy of the system, as the RSSI is known to be influenced by the surrounding environment.

3 Exerimental Evaluation

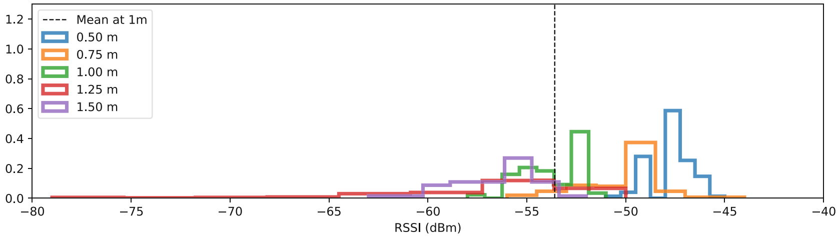
Collection of Data. An auxiliary app was developed to log the above-mentioned data and create an indoor/outdoor dataset. The app was used for two consecutive days by four volunteers. During the data collection phase, the users only had to manually trigger the transitions between indoor and outdoor

Table 2. Indoor/outdoor dataset.

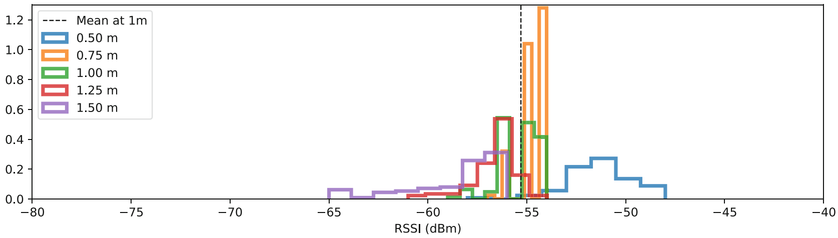
	Indoor	Outdoor
Training set	68190	68190
Test set	1050	1050

settings in order to collect the ground-truth label. Due to the presence of time periods without movements, some repeated values were collected. To limit the bias in the training set, the adjacent duplicates have been discarded. A test set made of completely new data has been collected to evaluate the performance of the classifier. The size of the dataset obtained during the collection phase is reported in Table 2. The trained model was evaluated on the test set, and we obtained 59.4% of accuracy. This non-excellent result is due to the fact that the training set was built using the data collected by three volunteers, whereas the test set was made with the data collected by the fourth volunteer. To better understand the phenomenon, we repeated the training phase now including also 25% of the data collected by the fourth volunteer. The system trained in this way was able to obtain an accuracy of 92.83%. An important lesson can be learned from these results: indoor/outdoor detection can be carried out with high accuracy ($\sim$93%), but only when the training phase includes information about the specific environment where the system is going to operate. While a more diverse and large training set can improve the capacity of the system to generalize beyond the environments provided during the training phase, these preliminary results seem to highlight the benefits of customizing the model according to the specific environment.

Benefits of Adaptation in Social Distancing Applications. We collected 100 RSSI samples using two devices placed at the following distances: 0.5, 0.75, 1.0, 1.25, and 1.5 m. The collection has been carried out in an indoor environment and in an outdoor one. The devices involved in the collection were an iPhone SE 2, used as the transmitter, and a Samsung Galaxy J5, used as the receiver. The empirical pdfs of the RSSI values are shown in Fig. 3. The samples at 1 m distance were used to compute the thresholds S_{IN} and S_{OUT}, represented as dashed lines in the two graphs. As can be noticed, the RSSI values are influenced by the environment where the collection took place. We define the accuracy of the system as the percentage of samples collected at a distance < 1 m that are characterized by an RSSI value higher than S. The same was done for the samples collected at a distance greater than 1 m, but in this case RSSI had to be lower than S. Let's suppose that a single threshold is used for both the indoor and outdoor scenarios and that such threshold has been computed indoor (i.e., $S = S_{IN}$). In this case, the accuracy is equal to 91% for the indoor experiment and 72% for the outdoor one. On the other hand, when using S_{OUT} for the two environments (i.e., $S = S_{OUT}$) the accuracy values for the two environments are equal to 79% and 93%. Obviously, if the S_{IN} threshold is used for the indoor

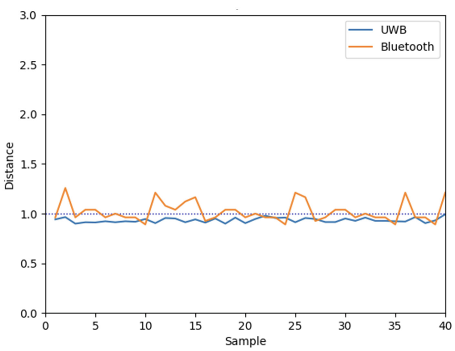


(a) Indoor

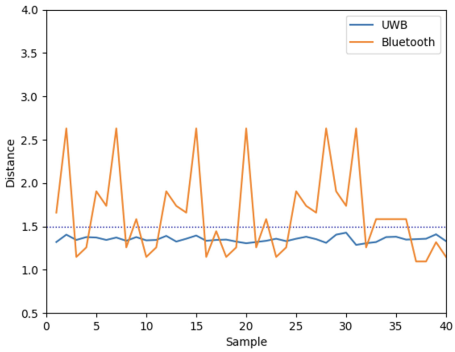


(b) Outdoor

Fig. 3. RSSI values collected at different distances for the indoor and outdoor settings; S_{IN} and S_{OUT} are represented as dashed lines.



(a) 1.0 m



(b) 1.5 m

Fig. 4. Distance estimation using BLE vs UWB. On the x-axis the sample number is reported, whereas on the y-axis the estimated distance.

environment and S_{OUT} is used for the outdoor one, the accuracy values are equal to 91% and 93% respectively.

Overall, a threshold that is environment-specific improves the accuracy of 7–9%, and the technique should be considered for being included in social distancing or contact tracing applications.

Comparison with UWB. UltraWideBand (UWB) is a communication technology increasingly adopted in smartphones. UWB proved to be particularly effective in several applications involving human sensing [4,5,16–18], thanks to its capacity to estimate the distance between a transmitter and a receiver with good accuracy. We carried out a small experimental comparison of distance estimation using BLE vs UWB. For UWB experiments, we used the prototyping boards of a Decawave MDEK1001 kit [6]. For both technologies, we estimated the distance between a couple of nodes in an indoor environment, with four different target distances (0.5, 1.0, 1.5, and 2.0 m). For BLE, we assumed that environment-detection methods allow determining the best n value to be used in the RSSI-to-distance conversion process (Eq. 1). The distances estimated from the two technologies are quite similar for small distances (in the range of 0.5m and 1m). As the distance increases the UWB has a better and more stable estimation accuracy. The results obtained at two of the four considered distances are shown in Fig. 4 (the other results are similar).

4 Related Work

This work lies at the intersection of [11] and [2]. In the former, Liu et al. used Bluetooth for detecting face-to-face interaction between users, as a way to quantitatively assess social relationships. The study, carried out on a campus, highlighted that the sensors commonly available on smartphones, could be used for improving the detection of face-to-face interaction, for instance by recognizing that the device was in a backpack. In the latter ([2]), the authors devised a technique for improving the detection of indoor/outdoor environments. The problem of indoor/outdoor detection was also studied in [13] for logging the life of users, in [14] where the moving direction of the user was included for improving the detection accuracy, and in [10] using just magnetic sensors, light sensors, and cell tower signals. Indoor/outdoor detection for improving the recognition of the activities of daily living was proposed in [15].

5 Conclusion

BLE is a popular communication technology and one of the most convenient means for estimating the distance between people in contact tracing applications, as it works across different vendors and requires a limited energy budget. Unfortunately, its accuracy in estimating the distance between devices, and thus between people, is not particularly accurate [7,9,12]. Methods for automatically recognizing the environment where the users are located (indoor vs outdoor) can help in increasing the accuracy of RSSI-based distance estimation. The detection capability of the current setting (indoor vs outdoor) can also be useful for adapting the allowed physical distance between users. For instance, indoor the safe distance can be set to 2 m because of the poor ventilation, while outdoor a distance of 1 m could be sufficient.

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References

1. Alsmadi, L., Kong, X., Sandrasegaran, K., Fang, G.: An improved indoor positioning accuracy using filtered RSSI and beacon weight. IEEE Sens. J. **21**(16), 18205–18213 (2021). https://doi.org/10.1109/JSEN.2021.3085323
2. Anagnostopoulos, T., Garcia, J.C., Goncalves, J., Ferreira, D., Hosio, S., Kostakos, V.: Environmental exposure assessment using indoor/outdoor detection on smartphones. Pers. Ubiquit. Comp. **21**(4), 761–773 (2017). https://doi.org/10.1007/s00779-017-1028-y
3. Apple: https://covid19.apple.com/contacttracing
4. Bonsignori, C., et al.: Estimation of user's orientation via wearable UWB. In: 2020 16th International Conference on Intelligent Environments (IE), pp. 80–83 (2020). https://doi.org/10.1109/IE49459.2020.9154983
5. Brombin, L., et al.: User's authentication using information collected by smart-shoes. In: Mucchi, L., Hämäläinen, M., Jayousi, S., Morosi, S. (eds.) BODYNETS 2019. LNICST, vol. 297, pp. 266–277. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-34833-5_21
6. Decawave: https://www.decawave.com/product/mdek1001-deployment-kit/
7. Giovanelli, D., Farella, E.: Rssi or time-of-flight for bluetooth low energy based localization? an experimental evaluation. In: 2018 11th IFIP Wireless and Mobile Networking Conference (WMNC), pp. 1–8 (2018). https://doi.org/10.23919/WMNC.2018.8480847
8. Google: https://www.tensorflow.org/lite/
9. Li, G., Geng, E., Ye, Z., Xu, Y., Lin, J., Pang, Y.: Indoor positioning algorithm based on the improved rssi distance model. Sensors **18**(9) (2018). https://doi.org/10.3390/s18092820, https://www.mdpi.com/1424-8220/18/9/2820
10. Li, M., Zhou, P., Zheng, Y., Li, Z., Shen, G.: Iodetector: a generic service for indoor/outdoor detection. ACM Trans. Sen. Netw., **11**(2) (2014). https://doi.org/10.1145/2659466
11. Liu, S., Jiang, Y., Striegel, A.: Face-to-face proximity estimationusing bluetooth on smartphones. IEEE Trans. Mob. Comp. **13**(4), 811–823 (2014). https://doi.org/10.1109/TMC.2013.44
12. Maratea, A., Salvi, G., Gaglione, S.: Bagging to improve the calibration of RSSI signals in bluetooth low energy (BLE) indoor distance estimation. In: 2019 15th International Conference on Signal-Image Technology Internet-Based Systems (SITIS), pp. 657–662 (2019). https://doi.org/10.1109/SITIS.2019.00107
13. Mizuno, H., Sasaki, K., Hosaka, H.: Indoor-outdoor positioning and lifelog experiment with mobile phones. In: Proceedings of the 2007 Workshop on Multimodal Interfaces in Semantic Interaction, pp. 55–57. WMISI '07, Association for Computing Machinery, New York, NY, USA (2007). https://doi.org/10.1145/1330572.1330582
14. Okamoto, M., Chen, C.: Improving GPS-based indoor-outdoor detection with moving direction information from smartphone. In: Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers,

pp. 257–260. UbiComp/ISWC'15 Adjunct, Association for Computing Machinery, New York, NY, USA (2015). https://doi.org/10.1145/2800835.2800939
15. Ouchi, K., Doi, M.: Indoor-outdoor activity recognition by a smartphone. In: Proceedings of the 2012 ACM Conference on Ubiquitous Computing, p. 537. UbiComp '12, Association for Computing Machinery, New York, NY, USA (2012). https://doi.org/10.1145/2370216.2370297
16. Vecchio, A., Cola, G.: Fall detection using ultra-wideband positioning. In: 2016 IEEE Sensors, pp. 1–3 (2016). https://doi.org/10.1109/ICSENS.2016.7808527
17. Vecchio, A., Cola, G.: Method based on UWB for user identification during gait periods. Healthc. Technol. Lett., **6**, 121–125 (2019). https://digital-library.theiet.org/content/journals/10.1049/htl.2018.5050
18. Vecchio, A., Mulas, F., Cola, G.: Posture recognition using the interdistances between wearable devices. IEEE Sens. Lett. **1**(4), 1–4 (2017). https://doi.org/10.1109/LSENS.2017.2726759
19. Viswanathan, S., Srinivasan, S.: Improved path loss prediction model for short range indoor positioning using bluetooth low energy. In: 2015 IEEE Sensors, pp. 1–4 (2015). https://doi.org/10.1109/ICSENS.2015.7370397
20. World Health Organization: https://www.who.int/news-room/q-a-detail/coronavirus-disease-covid-19-how-is-it-transmitted