Improving Proximity Classification for Contact Tracing using a Multi-channel Approach

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Abstract—Due to the COVID-19 pandemic, smartphone-based proximity tracing systems became of utmost interest. Many of these systems use Bluetooth Low Energy (BLE) signal strength data to estimate the distance between two persons. The quality of this method depends on many factors and, therefore, does hardly deliver accurate results. We present a multi-channel approach to improve proximity classification, and a novel, publicly available data set that contains matched IEEE 802.11 (2.4 & 5 GHz) and BLE signal strength data, measured in four different environments. We utilize these data to train machine learning models. The evaluation showed significant improvements in the distance classification and consequently also the contact tracing accuracy. However, we also encountered privacy problems and limitations due to the consistency and interval at which such probes are sent. We discuss these limitations and sketch how our approach could be improved to make it suitable for real-world deployment.

Index Terms—Contact Tracing, Proximity Classification, Bluetooth Low Energy, COVID-19, IEEE 802.11

I. INTRODUCTION

The scale and impact of the COVID-19 pandemic spurred governments and society to look for easy ways to automatically track contacts between individuals in order to trace chains of infection. Several countries and technology companies came up with software-based solutions implemented on smartphones. One such approach, which is deployed by many countries, is Google/Apple Exposure Notification (GAEN) [3]. This method is based on logging potential contacts using Bluetooth Low Energy (BLE) advertisements. This approach to contact tracing is used by many countries and implemented as mobile applications by the national and federal health agencies. Well-known examples are Germany, Ireland, Italy, the Netherlands, South Africa, and several states in the US.

The risk of exposure is assessed using a distance approximation based on signal strength information (RSSI and TX Power). Such distance approximations tend to be noisy and error-prone [23], [33]. Studies, e.g., by Leith and Farrell [19] or the calibration trial for the Singaporean contact-tracing app [16] show how challenging this approach can be. There are many factors that can affect the signal strength of a BLE signal, for example antenna design, Bluetooth stack implementation, or sending power. Equally, the quality of classifications can be influenced by the environment through common factors that always exist when it comes to radio wave propagation: attenuation, shadowing, reflection, scattering, diffraction, and refraction. Due to these limitations, almost no infectious contacts were detected in [19]. Even if some contacts, at a proximity that is relevant for infections, were detected by the application, the results showed high false-positive rates.

To deliver on the promise of automated contact tracing, it is important that the accuracy of distance classification is improved. We argue that the combination of IEEE 802.11 broadcast messages (2.4 GHz and 5 GHz) with BLE advertisements will significantly improve the classification of the proximity between two devices. Our core contributions of this paper are as follows:

- We introduce a multi-channel proximity classification technique for contact tracing applications based on a combination of BLE with IEEE 802.11 probe requests in the 2.4 and 5 GHz bands.
- We evaluate our approach in four different scenarios (outdoor, office, and two public transport settings on a bus and a train) and make our measurement results available as open access data.
- We show that our approach significantly outperforms GAEN in terms of accuracy of distance classification.

Moreover, we evaluate several machine learning models for the use case of proximity classification. Besides this use case, our approach could also be used in other fields where accurate proximity classification is a major issue, such as localization, indoor navigation, or beaconing products. Finally, we provide suggestions on how our approach can be incorporated into existing contact tracing solutions to reduce the number of false-positives and false-negatives.

The remainder of this paper is structured as follows. Section II provides background information on wireless proximity classification and current approaches to contact tracing. Next, Section III discusses related work, followed by a detailed discussion of our approach in Section IV. In Section V, we provide information on the data set we recorded and used for evaluation. We continue in Section VI by presenting the evaluation of our approach, and end with conclusions and future work in Section VII.

II. BACKGROUND

A. Bluetooth Low Energy Advertisements

Bluetooth Low Energy (BLE) was introduced in Bluetooth specification 4.0. It includes advertisements, which are broad-
cast messages that are delivered to all clients in signal range. It was originally developed for Internet of Things (IoT) use cases, for example to deliver sensor data energy efficient between several sensor nodes, or to implement beacons for localization purposes. Being available in almost every smartphone, these advertisements were then quickly utilized in contact tracing solutions. Most of the contact tracing frameworks send out messages with randomized advertising addresses (AdvA) [8]. The advertisements are only sent on 3 of the 40 BLE channels, the three Adv CHs are channel 37 (2402 MHz), channel 38 (2426 MHz), and channel 39 (2480 MHz). These three frequencies were selected in an attempt to minimize interference with IEEE 802.11 b/g/n channels 1, 6, and 11. Even though the Adv_CHs have been chosen to have low interference rates, studies show that channel 37 and 38 are still significantly affected by noise and interference from IEEE 802.11 [26]. This causes variation in signal strength, which is later used to determine the proximity between two devices.

B. Google/Apple Exposure Notification (GAEN)

The Google/Apple Exposure Notification (GAEN) framework is used by at least 15 EU member states and several other countries and regions around the world to implement their proximity tracing solution [24]. The GAEN concept derives from the Decentralized Privacy-Preserving Proximity Tracing (DP-3T) proposal, which was presented after a wide discussion on privacy in contact tracing frameworks [29]. A BLE advertisement sent out by GAEN carries its information in the payload field. A 16 byte Rolling Proximity Identifier (RPI) is used to warn a user, followed by 4 bytes of associated encrypted metadata. The metadata contains information of the framework version and the transmission power (TX_power) level. The RPIs are used to detect potential contacts. When a potential match is found, the metadata gets decrypted and a risk assessment will be done by estimating the distance to the infectious individual and the duration of a possible exposure [5]. To estimate the distance between the two individuals, this formula is used:

\[ \text{Attenuation} = \text{TX_pwr} - (\text{RSSI}_{\text{measured}} + \text{RSSI}_{\text{corr}}) \] (1)

In this formula TX_power is obtained from the metadata, RSSI_measured from the local log, and RSSI_correction from a vendor-supplied list of correction values for various smartphone models. Since version 1.5 of the API and on smartphones with Android 9 or higher, for each scan window the minimum and average attenuation values are available. Due to the fact that the three Adv_CHs may have different noise levels, that result in various Received Signal Strength Indicator (RSSI), it is recommended to use the minimum attenuation for further risk assessment, as this reflects the best signal transmission situation over the three channels.

The next step depends on the implementation of the actual proximity tracing app, as different thresholds for calculations are used. In essence, the framework calculates a weighted risk score using these thresholds. It first classifies the attenuation as very close, for distances less than 1.5m, with an attenuation value \( < d_{vc} \text{ dB} \), close, for distances greater than or equal 1.5m and less than or equal 3m, with an attenuation value \( \leq d_c \text{ dB} \) and safe distances for all higher values. These classified attenuation durations can also be obtained by querying the API. As an example, the thresholds in the German Corona Warn App (CWA) are \( d_{vc} = 55 \text{ dB} \) for very close and \( d_c = 63 \text{ dB} \) for close, with any values higher than that classified as safe.

Next, the time is added up for the two close cases using the following formula:

\[ ES = B1 + 0.5B2 \] (2)

In this formula, \( B1 \) is the time of exposure in minutes in the very close category, so less than 1.5m and \( B2 \) the time in minutes of exposure at close distance, so greater than or equal 1.5m and less than or equal 3m. If the resulting value is at least 15 minutes, the user will be warned by the application and informed about further steps to take (e.g., getting a test etc.) [28]. The attenuation thresholds vary, depending on the country-specific implementation by the health authorities.

C. IEEE 802.11 probe requests

IEEE 802.11 probe requests are messages that are sent out via broadcast, in order to detect which IEEE 802.11 networks are around. Depending on the device, the messages are sent out with a randomized MAC address via 2.4 GHz and/or 5 GHz periodically, when the devices are not connected to a network [1]. Many smartphones send these messages when they have screen-on-time, e.g., when a user is interacting with the phone, in order to connect to a network to save on cellular data. By entering a network interface into monitor mode, it is also possible to capture these packets on conventional client hardware. When the packets are captured, the RSSI can be captured and information on which specific frequency a packet was sent is also available [14].

Compared to BLE advertisements, where it is unclear on the receiving side which Adv_CH was used, this information being available for IEEE 802.11 broadcasts is a significant benefit, since more specific path-loss-models can be computed if the actual frequency is known [15].

D. Signal propagation

The transmission of radio signals is affected by several factors, that make it hard to model the propagation of a radio signal. These factors have strong influence on the power with which a signal is received. The energy lost on the transmission path is called path loss. The most general issue of path loss is attenuation. When a signal is sent through a medium, it loses power proportional to the distance that the signal needs to travel through a medium. Signal propagation in general, but especially indoors, is mainly affected by four effects [6], [7]: Reflection, diffraction, scattering and multi-path propagation.

These effects make it hard to model signal strength according to the distance and to derive a distance from a given signal strength. Models such as the two-ray-ground model take factors like the ground reflection into account.
For varying situations and environments, with unknown height levels and orientations of receiver and transmitter, as well as low information grades as we have for BLE advertisements (no frequency information), it is almost impossible to obtain an accurate model for estimating a distance. To illustrate this issue, we combined measured data in an indoor and an outdoor environment in a plot, together with the log-normal-shadowing-model (LNSM) and two-ray-ground model (TRG), illustrating the discrepancy and difficulty between modelled and real signal propagation.

III. RELATED WORK

A. Evaluation studies on proximity tracing

One of the first studies, after GAEN was announced, was carried out by Leith and Farell [19], [20]. They deployed smartphones in a tram and in a bus, placed the devices at various distances and collected GAEN advertisements and let them run through the risk assessment process. The results were computed for the German, Swiss, and Italian attenuation thresholds. Almost no alerts were triggered using these thresholds, even though the devices were at a critical distance. In later work [18], they assessed the correlation of RSSI and distance with a comparison of various environments. The authors pointed out that device orientation, human bodies in the line of sight (LOS), or the position of the device, e.g., whether it is in a pocket, play an important role and have crucial influence on the RSSI.

Zhao et al. [32] evaluated a set of proximity tracing applications, surveyed their broadcasting behaviour, the underlying calculations for proximity estimation, and tuning possibilities to the RSSI measurements. They showed that there are different internal factors in software and in hardware that can affect the RSSI. For example, chipset and antenna of the smartphone, or the operating system running on a smartphone that is adjusting the levels of transmission power. Moreover, they briefly mentioned issues of signal propagation like obstacles and interference of other signals.

In the field of indoor navigation and positioning, many studies show how challenging it is to perform accurate proximity classification, especially in indoor environments. Even with complex preprocessing pipelines and sophisticated approaches for the removal of propagation effects, these approaches achieved results that still had an error of at least 1 m [9], [11]. Approaches that showed better results were only fitted to a single environment, e.g., an office [12], [27]. Such approaches are not applicable for contact tracing purposes, as this requires the approaches to work in a variety of environments in real-life scenarios and environments. Lui et al. [22], proposed a smartphone based device to device distance estimation based on the RSSI BLE, as it is done by most contact tracing solutions. In their study, they achieved a 1.5−2.5 m accuracy, which is also not sufficient in pandemic tracing applications, where the critical distance is at 1.5 m.

Regarding the specifics in signal propagation of the three BLE ADV_CHs, Nikoukar et al. [26] collected data in various indoor and outdoor scenarios. In line with the other results, a trend of RSS against distance can be obtained from outdoor scenarios, but it is quite hard for indoor applications. They explained these with reflections, multi-path effects, interference by IEEE 802.11 networks inside, and antenna anisotropy. Moreover, they state that among these three channels, channel 39 is facing less interference and the measured values have less variance due to smaller IEEE 802.11 interference.

A number of studies evaluated the use of IEEE 802.11 signals in a device-to-device setup, these studies showed that IEEE 802.11 2.4 GHz signals can achieve more accurate results than BLE signals [10], [31]. Additionally, a study by Terán et al. [31] evaluated the combination of BLE and IEEE 802.11 2.4 GHz signals in a kNN classifier. They were able to obtain an accuracy of 0.75 in a resolution of 1 m, which was a better result than using a single signal type in isolation. However, except for this study, less prior work can be found when it comes to combine the RSSIs of BLE and IEEE 802.11 signals, as we do, to achieve a better distance estimation.

B. Approaches improving proximity tracing

Various studies try to improve BLE-only proximity classification approaches. The NIST issued a contest for AI researchers to develop approaches to improve the accuracies of currently used proximity tracing products. The winners of this contest stated that it is very challenging to derive a distance from the RSSI of a BLE signal. Therefore, they utilized other sensors from a smartphone, such as Inertial measurement unit (IMU) and magnetron, in order to detect the environment and the orientation of a device [17]. The proposed neural networks have a high computational complexity and have to be trained for each device type. Therefore, the approach is not directly applicable for a wide deployment.

Besides the NIST challenge, Clark et al. [13] suggested the usage of a network localization algorithm. This approach showed good results, but it requires a central instance that
collects all RSSI values received from all devices to compute the algorithm, which will result in a privacy issue.

Gentner et al. [15] try to determine on which of the three channels the packet was received. The proposed approach is timing-based and runs on the application level in Android. Their results showed an accuracy of about 100% in determining the correct BLE channel. This information makes it possible to use more specific models, but still, this information does not help to model propagation issues.

### IV. Approach

The main question that we want to answer in this paper is: *Is it possible to improve the accuracy of proximity classification?* To answer this question, we hypothesize that improvement is possible by using a multi-channel approach, combining IEEE 802.11 and BLE signals. Our assumption for this hypothesis is, that IEEE 802.11 signals have different signal propagation characteristics. Even for both signal types on 2.4 GHz, the IEEE 802.11 signals on 2.4 GHz are sent with higher transmission power and using different modulation methods. Moreover, these signals, especially on 5 GHz band, tend to suffer less from interference by noise. Having multiple RSSI values for more than one signal type, and having exact frequency information from the IEEE 802.11 signals results in an information gain that should enable a classifier to make more accurate distance classifications between two smartphones.

In order to prove that our hypothesis is correct, we present a novel data set of BLE and IEEE 802.11 signals captured in various settings, at a variety of distances, and with three different devices in Section V. In our data set we trigger regular sending of IEEE 802.11 probe requests. This technique is already available and current proximity tracing deployments could be extended, in a way that also IEEE 802.11 probe requests are sent and captured for proximity classification. We use this data set to train various machine learning models and evaluate these models with typical machine learning metrics. The models predict, whether a signal was sent in very close ($d < 1.5$ m), close ($d \leq 3$ m and $d \geq 1.5$ m) or safe ($d > 3$ m) distance.

At first, we evaluate each signal type separately. Our goal is to determine the differences and the contributions of a single signal type to a distance classification. Especially, the BLE threshold based approach is assessed here to provide an empirical evaluation of the classification quality. Due to the fact, that we use machine learning approaches for the other signal types, we also do train two models on BLE signals only, to have an adequate comparison. Otherwise, advantages or disadvantages may have a bias due to the different classification approach.

Secondly, we create models that take all three signal types into account. We follow two different approaches:

1) A combination of specialized classifiers that utilize a single signal type to predict the proximity. Thus, three models (BLE, 802.11 2.4 GHz band, and 5 GHz band), get their specific input and predict the distance class. Then, all three results are combined to an overall result.

2) One general classifier to build a model that utilizes all features (RSSIs of all three signals and frequencies for IEEE 802.11) directly as an input to perform a classification.

Overall, we test 13 models with different features (RSSIs and frequencies) for our approach. All 13 models are listed in Table I. Besides the threshold based BLE classification, we also evaluate Decision Tree (DT) and Random Forest (RF) classifiers, implemented using scikit-learn\(^1\), for certain signal types. We decided to use only DT-based classifiers and RF, as a more sophisticated combination of trees in a first step. Our goal is to test if there are advantages in general of our multi-channel approach, due to the high explainability of the results. Moreover, it is possible to derive thresholds for the new signal types, from the highest nodes of a Decision Tree. Having this, it would be possible to follow the same approach as GAEN uses for BLE also for the IEEE 802.11 features. The parametrization of the models was done using grid search. We optimized the maximum depth of trees using grid search. We identified, that the improvements do become significantly small at a depth of 8 or more, and deeper splits would only contain less than 100 samples. Therefore, we used a max depth of eight in our models, which also allows plotting the resulting DTs in order to get an understanding on the models decision.

In order to make the combined special approach clearer, we describe model 9 as an example: it is a weighted combination of models 2, 4 and 6. It is described in equation (3):

$$0.25 \text{BLE} + 0.25 \text{WiFi 2.4 GHz} + 0.5 \text{WiFi 5 GHz} \quad (3)$$

It uses the results from the Decision Tree or Random Forest single signal model. These weighting factors are chosen to consider both bands, the two 2.4 GHz signals and one 5 GHz signal, equally. Tests on various weights combinations on our data, showed that this is a robust combination. Moreover, to us, it was important in this model to equally weight both frequency bands, in a way that the average on both bands could compensate issues in one of the single bands.

\(^1\)https://scikit-learn.org/
V. DATA SET

To the best of our knowledge, there is no publicly available data set that contains signal strength values per distance for BLE and IEEE 802.11 signals. Therefore, we captured such a data set ourselves in various environments. In this section, we present information on the data set. The data set is publicly available on GitHub.

A. Data collection setup

In order to collect data, we utilized two measurement setups. One for measuring ground truth data, visualized in Figure 2a, and a second one to measure real-life scenarios, presented in Figure 2b. The main difference between the two setups is that in the ground truth setup only one device is sending out signals, with a constant device orientation over all iterations. In the scenario measurements, these could be multiple devices with varying orientations.

We use three different devices for transmission. These devices are a Raspberry Pi 4b, a OnePlus Nord N10 5G, and an Apple iPhone 6S. With this selection we want to represent the differences between Android and iOS devices. On the two smartphones we use the German Corona-Warn-App to generate BLE advertisements. On the Raspberry the advertisements are sent using the bluez sample advertising script. The 802.11 probe requests are sent by triggering network scanning regularly. On the receiver side, which is a Raspberry 4b too, the wireless interface is put into monitor mode using the nexmon kernel patch, to sniff the 802.11 probe requests and a sniffer script for BLE advertisements is developed based on the Rust bluez crate.

B. Measurement environments

The measurements are carried out in the following four environments:

1) Office room, with a size of 26 m²
2) An articulated public transport bus
3) Outdoors in an empty parking lot, being at least 3 m away from the next building
4) On a train, in wagon with open compartments (Deutsche Bahn Intercity Train)

Except for the train environment, we capture data with both the ground truth setup and the scenario setup. For the train environment only scenario measurements is taken. The data is collected during a normal journey. We had no exclusive wagon just for the measurements. However, since we had a very realistic environment, with other devices from passengers that also sent Bluetooth signals, we include these measurements in our data set, too. Moreover, we measure the exact distance of our deployed devices. In the other three environments, we measure at least 15 minutes per distance using the ground truth setup. The distances under measurement are in the range of 50 cm to 400 cm and increased by 50 cm after each iteration. In the bus and outdoor sets, we also measure the distances 500 cm and 600 cm to have more than two distances in the safe category. The office space is too small to accommodate these distances as well. We show an example of our bus measurement setup in Figure 3. While measuring the scenario sets we used different combinations where the devices are placed on seats, to establish realistic scenarios of a bus journey, for example. Additional information on the scenarios is provided in the data set repository.

C. Calibration

We need to perform a calibration, as the thresholds used by GAEN are based on attenuation and not on a device-specific RSSI. In the actual implementation a list of calibration factors by Google is used. This list is based on a calibration procedure designed by Google [4]. In our study, we used a Raspberry Pi 4b, a OnePlus Nord N10 5G, and an Apple iPhone 6S. For these devices no calibration values are available in the list, and the calibration method of Google is not usable, because it is based on a Pixel 4 device, which is not available for our experiments. To overcome this issue, we take the average RSSI per distance for all devices in all environments we measured, and use these values in a linear program. The program is implemented with the python package ortools. We use constraints, in a way that the very close distances have to stay below the threshold of 55 dB. We relax the variables for

5https://developers.google.com/optimization

6https://github.com/laptou/bluez-rs

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(a) Ground truth collection
(b) Scenario measurements

Fig. 2: Setup for measurements

(a) Exterior view
(b) On-board setup

Fig. 3: Bus measurement environment
VI. EVALUATION

In this section, we present the evaluation of our hypothesis. We utilize our novel data set containing BLE and IEEE 802.11 data. Before evaluation, we perform a preprocessing step on the data to balance between distances and environments, and to split the data into training, testing, and evaluation data. The preprocessing and the data flow will be briefly described first. Next, we discuss the selection of the metrics used for evaluating the models. Finally, we present the results, with insights into the ground truth data, such as a comparison of all three signal types and the classification performance using the GAEN approach with thresholds of the German implementation.

A. Data processing

The number of samples per data set is not equal, due to varying distances measured using the scenario setup. Thus, a balancing of the data is needed to avoid overfitting. The overall data flow that is used to capture the samples up to the classifier and the evaluation is illustrated in Figure 4. In the first step, the recorded BLE and IEEE 802.11 data needs to be merged. In both sets, traces of random MAC addresses need to be identified to match the data, the data is available in single measurement runs, that are used for the matching process. This ensures stable distances for matching the three different signals. We use a timing based approach on the BLE data to identify the new MAC address after an address and payload roll. All previously seen MAC addresses before the roll and all seen 30 seconds after the roll are filtered, resulting in most cases in only a single address, which is the new MAC address. In collision cases, when two devices roll at the same time, we use the mean RSSI to identify which address belongs to the address under inspection. Using this method we are able to find all packets sent out by a certain device using GAEN. For the IEEE 802.11 probe requests, we use a fingerprinting-based approach. We identify the devices based on their features and transmission rates supported, sent in the probe request frames [30]. Due to the small number of devices in our recorded data, this approach is very accurate, as comparison to a manual MAC address trace extraction shows. Next, we match BLE packets with IEEE 802.11 probe requests, based on the time sent, resulting in a CSV file containing both data sources. Then, the data for each distance in each environment is upsampled, having every class label (very close, close, and safe) and environment equally represented in the set. From this set, a random sample for each class label of 100,000 is taken, stratified by distances. This overall set is split into a training, test, and evaluation set. The training set consists of 60% of the samples, and the test and evaluation set of 20% each (cf. [25]). These sets are then used for training, testing, and evaluating the various machine learning models. From the upsampled data set, except for the train data, we leave data captured in measurements using the scenario setup (multiple devices sending in real-life like scenarios) out. These raw samples are later used to also evaluate the classifiers against completely unseen samples.

B. Metrics

We use common metrics from the field of machine learning, such as $F_1$-score, precision, recall, accuracy, and confusion matrices, to evaluate the performance of our models [2]. For
better readability, we do not present a confusion matrix for every classifier. Instead, we sum up the accuracies and the $F_1$-scores for each class in tables.

C. Ground truth data for BLE and IEEE 802.11

As an example, Figure 5 shows the ground truth data measured in the meeting room using the OnePlus for sending. For a better overview we connected the average values per 50 cm in a line plot. As described in the signal propagation background (II-D), the BLE signal is affected more strongly by fades, e.g. caused by ground reflection. In comparison, for the 2.4 GHz Wi-Fi signals a correlation of RSSI and distance can be derived, unlike for BLE. The 5 GHz signals seem to be less distorted. There is only a single stronger outlier at 400 cm. Evaluating the BLE threshold-based approach, which is also used in GAEN, on our data, the distance prediction performance is equally poor as reported in other studies [18].

A confusion matrix for the OnePlus is shown in Table IV. The accuracy of this method is almost at 0.6, and worse using other senders (cf. Table II). E.g., for the iPhone, more than every second sample is falsely classified. From the clearer RSSI trends for the IEEE 802.11 signals, on both bands, shown in Figure 5, we expect a better performance and better base for estimating distance.

D. Classification performances

The complete result of the model evaluation on our data set is listed in Table II. Our evaluation shows that the Random Forest models, using only a single signal type, performed similar to the Decision Trees. Moreover, the models that combined three single classifiers (models 8-11) did not perform better than a single classifier. The weighted version’s performance is comparable to that of the 5 GHz model, but in most cases a few points worse. Our assumption that IEEE 802.11 signals will form a better base for distance classification, appears to hold true. These models performed better than the two BLE models in every case. Apart from the clearer trend of RSSI vs. distance, the IEEE 802.11 models also utilized the frequency as a feature. Thus, better differentiations are possible. Visualizations of the Decision Trees show that having this information brings good information gain and enables the model to perform better splits. The clear winners are the two models that utilize all available features/signal types in a single classifier, with the Random Forests slightly outperforming the Decision Trees. Overall, regardless of the sender, our multi-channel approach delivers excellent results in the evaluation with our ground-truth data set. Even if the evaluation subset has not been seen by the models before, the data set can be relatively homogeneous due to upsampling. To ensure that the models do not overfit, we performed additional evaluations with our measurement data from the scenario measurements. We sum up the evaluation data for all data sets in Table III. Except for the parking lot set using the Raspberry Pi for sending, our multi-channel approach delivers excellent results in the evaluation with our ground-truth data set. Even if the evaluation subset has not been seen by the models before, the data set can be relatively homogeneous due to upsampling. To ensure that the models do not overfit, we performed additional evaluations with our measurement data from the scenario measurements. We sum up the evaluation data for all data sets in Table III. Except for the parking lot set using the Raspberry Pi for sending, our multi-channel approach outperforms the threshold-based BLE-only approach. The Raspberry Pi outlier may be explained by the setup, where the Raspberry Pi is the only device that is on the backside of the receiver. Moreover, most of our training data is measured in indoor environments (which is one of the main use cases for contact tracing). This results in a slight specialization of the model. Generally, our approach improves the classification performance on average by more than 0.3, regardless of the device that is used for sending.

VII. Conclusions & Future work

In this paper, we presented a method to improve the accuracy of the distance classification used in privacy-preserving contact tracing systems. Our own measurements confirm results from other studies that showed using BLE signals with thresholds for proximity classification is an error-prone approach. To overcome this issue we proposed an approach of adding signal strength information of IEEE 802.11 signals,
for both the 2.4 GHz and 5 GHz bands, to perform a more accurate proximity classification. Our approach outperformed the GAEN, BLE threshold based, approach significantly. We proved this for three different devices in several environments. This leads to the conclusion that the availability of signal strength information from different channels allows better distance classification.

In our study, we used IEEE 802.11 probe request frames as broadcast messages on IEEE 802.11 in order to combine them with the BLE advertisements. We used these packets to achieve an easy deployment. Unfortunately, there are several limitations when using such probe requests. For example, there are many cases where these messages are not sent, which results in a difficult mapping of the signal types. Moreover, when a smartphone is connected to a network, the monitor mode can not be used, otherwise the connection needs to be interrupted. In addition, probe requests contain information that make it easier to identify a device or user. The combination of probe requests and BLE advertisements, will result in an increased risk to user privacy. As we found out during our study, by using a simple timing based approach combined with probe request fingerprinting, we were able to match IEEE 802.11 probe requests with the GAEN BLE advertisements. Even though, that this risk gets smaller when more devices are around that lower the accuracy of the timing based approach, it could be applied in daily scenarios in less crowded places. This brings in privacy risks, that usually come in with probe requests and fingerprinting of such requests, e.g., making it easy to identify a device by the capability and data rates fields [30], or to identify a certain user when his or her phone looks for the usual used SSID set. To overcome this privacy risk, we propose the use of a customized data frame. Such a data frame should contain the same payload that is used for the BLE advertisements, so essentially the RPI. This new custom frame would also solve the issue of matching BLE signals with IEEE 802.11 signals. Such frames need to be sent immediately after or before sending the BLE signal, to ensure that both signals hold a stable distance to the receiver. This is especially important in moving scenarios.

Moreover, in future work, a calibration method for IEEE 802.11 signals is needed. This will enable the training of just a single machine learning model instead of device-specific models as we them. Another issue is power consumption. Periodically sending and receiving IEEE 802.11 signals consumes more power than doing this with BLE only. One way of solving this could be the utilization of an opportunistic sending approach, such as the Trickle algorithm [21]. This would save battery power, but also enables a better proximity classification when other clients are detected via the BLE advertisements. One last point to mention is the issue of device orientation, occlusions, and movements. This can highly influence the signal strength. Therefore, a promising way could be the utilization of IMU or gyro sensor data, to detect such situations, to apply correction factors.

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