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Overcoming Radio Map Degradation in Wi-Fi-based Positioning Systems

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***Abstract*—Wi-Fi-based positioning systems, particularly the ones based on Wi-Fi fingerprinting, rely on a Radio Map (RM) which represents the radio environment at the time when it was collected. Over time, phenomena such as the propagation effects or adding/removing Access Points (APs) from an indoor environment may lead to significant variations in the radio environment, thus leading to errors in estimated positions. Although it is common knowledge that RMs degrade over time, it is difficult to predict and detect when degradation causes large errors. In this paper, we propose a method that continuously monitors the radio environment and uses Radial Basis Functions (RBF) interpolation to automatically enrich an old RM with new information. Before enriching the RM, AP selection is performed to remove APs that disappeared and mobile APs from the old radio map. Then, the analysis of the radio environment is performed to select newly detected APs to enrich the radio map, based on predefined criteria. Our experiments with real-world data show a significant improvement over 100% in mean error when using the enriched RM. This approach presents a promising solution to overcome the RM degradation in Wi-Fi fingerprinting, with potential applications in indoor positioning and location-based services.**

***Index Terms*—Radio Map Degradation; RSS Interpolation; Radial Basis Functions; Indoor Positioning; Wi-Fi fingerprinting.**

I. Introduction and Motivation

One of the main drawbacks of Wi-Fi fingerprinting [1], assumed as common knowledge by the research community, is the need to update the RM to maintain the performance of the system over time, as demonstrated in [2]. Typically, the RM is a representation of the radio environment at the time it was collected, it can be considered a snapshot of the radio environment containing the detected APs and respective signal strength levels at each reference point. Therefore, the RM is usually static, thus being a representation of the radio environment, restricted to that point in time. RMs are prone to degradation since Wi-Fi signals in indoor environments are affected by the addition or removal of APs [2], interference, people [3]–[5], humidity, or alterations in the indoor layout.

RMs have associated downsides such as the need to perform manual site surveys to collect signal strength data at Reference Points (RPs). To address this issue, numerous research works have proposed novel methods to improve radio map construction [6]–[12]. Although radio environments are constantly changing, we cannot predict when the radio environment has changed in such a way that it hinders the Indoor Positioning System (IPS). Since the RM is usually static, it may not be capable of withstanding long-term variations (over months or even years) and maintaining the same positioning performance over time.

In this paper, we propose an approach to overcome RM degradation by continuously monitoring the radio environment and enriching an old RM with new information over time. This is achieved by exploring several anchors placed in known locations. These devices continuously monitor the radio environment to detect APs that have moved and new APs, which were not present when the RM was created. We apply several metrics to determine which APs should be removed from the old RM, before enriching it, and to determine whether the newly detected APs are suitable for enriching the RM, e.g., the AP must have been detected for a few days, and it must be a fixed AP (not a hotspot or an AP that was moved). Finally, the old (filtered) RM is enriched with interpolated signal strength values, using RBF, which considers measurements taken by the anchors and interpolates signal strength values at the positions where the old RM was collected. The main contributions of this paper are as follows:

- A set of metrics that can be used to detect variations in radio signals indoors and to detect mobile APs;
- AP selection criteria, to determine which APs should be filtered out of an old RM and which new APs should be considered to enrich it;
- A method to overcome RM degradation, by enriching an old RM with new information, based on RBF interpolation.

II. Related Work

Several works have tackled how to deal with RM degradation. Eisa *et al.* [13] perform AP selection to remove useless APs from fingerprints and optimise the RM. The authors defined a set of rules to select which APs were useful to keep in the RM, based on Received Signal Strength Indicator (RSSI) signal distribution, the AP observation frequency (whether AP is missing in many fingerprints), and RSSI standard deviation. Results showed that it is possible to simplify the RM without significant degradation in the positioning performance.

Anagnostopoulos and Kalousis [14] proposed a data augmentation scheme, creating new fingerprints based on crossover and mutation operators of genetic algorithms, to reduce positioning error. Fingerprints spatially close are used

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as input to generate new original ones. Results obtained with a public dataset (Sigfox) demonstrated an improvement of 6% in the mean error, in comparison to the baseline. Sun *et al.* [15] proposed an approach based on Gaussian Process Regression (GPR) for RM augmentation. This approach works by applying an GPR based RSSI prediction model for signal strength distribution modelling, which augments the data of a sparse RM, increasing its resolution. The advantages of this approach are that it does not require additional manual calibration or additional infrastructure. Experiments conducted in a building with 25.6×23.2 m demonstrated that the enriched RM reaches an improvement of $\approx 26\%$ in the localisation error in comparison to the original RM.

Several approaches can be explored for building/updating the RM alternatively to manual methods. Simultaneous Localisation and Mapping (SLAM) techniques have been applied to automatically map the radio environment whilst providing also a localisation method in [6]. Crowdsourcing is also one of the most used techniques where users collaboratively contribute to updating the RM [10], [11]. Interpolation techniques are often explored for building and/or updating RMs automatically without additional human effort, e.g., Inverse Distance Weighted (IDW) [8], RBF [9], Voronoi tesselation [7] and Kriging [12], among others. Most interpolation techniques require data samples from a few locations, often collected by anchors (fixed devices placed in known locations), which then apply a technique to interpolate RSSI values at the radio map RPs.

In this paper, in addition to removing useless APs, we aim to select the APs more suitable for positioning based on a set of criteria and then apply an interpolation technique to automatically update an old RM.

III. Enriching an old radio map with new data

Keeping a radio map constantly up-to-date is challenging due to the unpredictable and inevitable degradation of the radio map. To address this issue, we propose an approach that involves exploring an initial radio map (site survey), filtering out useless APs, and enriching it with new information collected by anchors deployed in the space. The key benefit of this approach is that it enables the radio map to be updated with the latest information anytime without any additional configuration, manual calibration, or human effort. Since the radio environment is constantly changing, it is essential to analyze the radio environment to determine which APs are best suited to enrich the radio map.

Figure 1 shows the pipeline of enriching a radio map:

- **Step 1**: metrics are computed on data collected by the anchors (see Section III-A for details).
- **Step 2**: AP selection process (Section III-B) involving two stages. First, the APs that should be removed from the initial RM (e.g., those that disappeared or moved) are selected. Second, the best-suited APs that were not previously detected when the initial RM was built are selected to enrich the RM.
- **Step 3**: filtering is applied to the initial RM to remove the selected APs from the previous step.
- **Step 4**: applying the RBF interpolation (Section III-C) to estimate the RSSI values of selected APs for the same RPs as those present in the initial RM.
- **Step 5**: the output of this process is the enriched RM, which combines the filtered initial RM with the interpolated data from the RBF interpolation module.

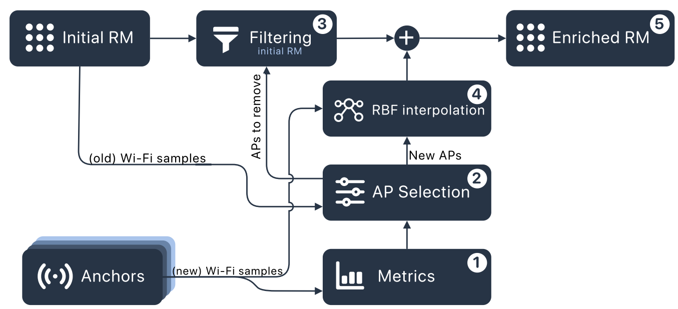


Fig. 1: Pipeline of the process to enrich the radio map.

A. Metrics

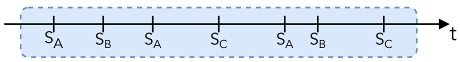
After deploying anchors, variations of the RM can be evaluated through a set of metrics that measure different parameters related to Wi-Fi signals. These metrics are necessary to perform AP selection (Section III-B) and are based on analysing AP's signal strength and observation frequency, as well as estimating the APs positions to detect whether they moved between two time instants.

Metrics can be perceived in two ways, global and local. Global metrics characterise the overall radio environment of the building. Local metrics are related to signals, observed in specific areas of the building, where an anchor is deployed. Each anchor, installed in a known position collects Wi-Fi samples. A Wi-Fi sample S_x^t is an observation of the radio environment obtained at time instant t by anchor x and comprises the set of n detected APs, and is defined as:

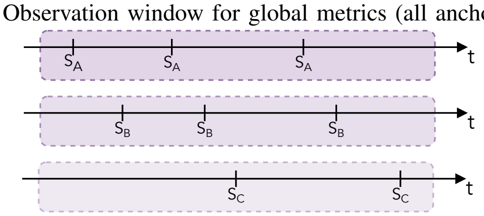
$$S_x^t = \{AP_1, AP_2, ..., AP_n\} \tag{1}$$

where $AP_i = (RSSI_i, MAC_i, SSID_i, channel_i)$.

In order to obtain the global metrics, Wi-Fi samples from all anchors deployed in the building should be considered. Since the Wi-Fi samples are not synchronised between anchors, it is necessary to consider an observation window that is a time interval considering Wi-Fi samples from all anchors. This is depicted by the example shown in Figure 2 (a), where the observation window for global metrics considers samples collected by all anchors (A, B and C). Local metrics consider an observation window with the same duration as the global, but in this case it considers samples from only one anchor. Figure 2 (b) shows the local observation windows that considers only Wi-Fi samples collected by each device. The purpose of using observation windows is to aggregate data collected by anchors and synchronise them in time when considering the global metrics. In the case of local metrics, using an observation window allows to reduce several measurements into an aggregated value, e.g., the average RSSI or the RSSI standard deviation.



(a) Observation window for global metrics (all anchors).



(b) Observation window for local metrics (one anchor).

Fig. 2: Examples of observation windows for metrics.

1) Local Metrics: First, we introduce the **mean RSSI**, which is the central RSSI during an observation window:

$$\langle RSSI \rangle = \frac{1}{n}\sum_{i=1}^{n} RSSI_i \qquad \text{[dBm]} \tag{2}$$

where n is the number of samples where the AP was detected in the observation window, and $RSSI_i$ represents the i-th signal strength value. A similar approach may be applied to determine the **RSSI standard deviation**, which defines the range of values around the mean RSSI.

The **observation frequency** of an AP is defined as the ratio of its detected occurrences:

$$OF = \frac{\sum_{i=1}^{n} f\left(S^i, AP_x\right)}{n} \tag{3}$$

$$f\left(S^i, AP_x\right) = \begin{cases} 1, & \text{if } AP_x \in S^i \\ 0, & \text{if } AP_x \notin S^i \end{cases} \tag{4}$$

where S^i represents the i-th Wi-Fi sample, n denotes the number of Wi-Fi samples collected during the observation window, and the numerator represents the number of times AP_x was detected within the observation window.

2) Global Metric – AP Displacement: When considering data from all anchors, taking advantage of the local metrics at those locations, one can leverage a global perception of the radio environment in the building. This allows obtaining more information about the Wi-Fi infrastructure, aiming to detect removed APs, new APs that appear in the building and whether the existing APs have moved into a new position. As demonstrated in [2], RM degradation is mostly caused by changes in the Wi-Fi infrastructure by adding, moving, and removing APs, hence the objective of detecting these APs. Thus, we propose the global metric **AP Displacement**.

Moving an AP to another position can affect a RM because when an AP is moved, the RM changes in the area where the AP was removed and in the area where the AP was moved into. Usually, APs remain in the same position where they were deployed. However, sometimes they are moved to other locations due to maintenance, or in the case of mobile hotpots, they do not have a fixed position.

A way of detecting the AP mobility is to compare the AP's positions (that need to be estimated) in two times and measure the distance (displacement) between those positions. To achieve that we propose an approach that combines data from all anchors to determine the RSSI rankings of APs, and then apply the k–Nearest Neighbour (k–NN) algorithm to estimate the APs positions.

Typically, when interference is low and when the radio signal is not obstructed, APs closer to the anchors are detected with the highest RSSI values while other APs, further from an anchor are detected with lower RSSI values. Hence, if the RSSI rankings of an AP significantly change over time it may indicate that the AP changed position. Let us consider the example in Figure 3, where AP_1 changes location. Initially, AP_1 is closer to anchor A, which detects AP_1 with the highest RSSI values among all anchors. Consequently, anchor C registers the lowest RSSI because it is the furthest from the location of AP_1. When the AP is moved to a new position, the new RSSI rankings have changed because it is now closer to anchors B and C, and further away from anchor A. For this particular example, the RSSI rankings of AP_1 are:

$$\mathcal{V}_{AP1_{t=i-1}} = \left(\langle RSSI \rangle_A, \langle RSSI \rangle_B, \langle RSSI \rangle_C\right)$$
$$\mathcal{V}_{AP1_{t=i}} = \left(\langle RSSI \rangle_C, \langle RSSI \rangle_B, \langle RSSI \rangle_A\right)$$

where $\langle RSSI \rangle_A > \langle RSSI \rangle_B > \langle RSSI \rangle_C$ in $t = i-1$ and $\langle RSSI \rangle_C > \langle RSSI \rangle_B > \langle RSSI \rangle_A$ in $t = i$.

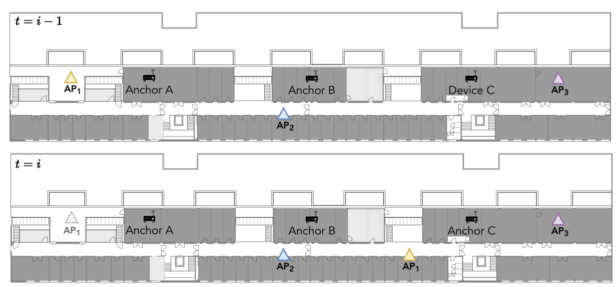


Fig. 3: AP position change between two time instants.

Following, the general formula that defines the RSSI rankings of an AP is presented:

$$\mathcal{V} = \left(\langle RSSI \rangle_1, \langle RSSI \rangle_2, ..., \langle RSSI \rangle_n\right) \tag{5}$$

where $\mathcal{V}$ is the ordered set of mean RSSI values measured at each anchor during an observation window, for a total of n anchors. The mean RSSI is then converted into a rank value, as follows: $\mathcal{V}_{rank} = (r_1, r_2, ..., r_n)$, where $r = \{1, 2, ..., n\}$.

The following step is to estimate the AP's position based on the rankings. A rough estimate of the AP's position can be provided using a weighted centroid approach. Anchors that register higher RSSI values have higher ranks while anchors that register lower RSSI values have lower ranks. By associating weights to the rankings, one can use a weighted average to estimate the positions of APs. Higher weights are attributed to positions of anchors that registered higher RSSI values, conversely, lower weights are attributed to positions of anchors that registered lower RSSI values.

Only top anchors matter when calculating the AP's location, using a parameter $\mathcal{R}$ to specify the number of anchors to consider. Thus, the APs' positions can be estimated as follows:

$$AP_{pos}(x,y) = \begin{cases} x = \frac{\sum_{i=1}^{\mathcal{R}} w_i x_i}{\sum_{i=1}^{n} w_i} \\ y = \frac{\sum_{i=1}^{\mathcal{R}} w_i y_i}{\sum_{i=1}^{n} w_i} \end{cases} \tag{6}$$

where w_i represents the weight of anchor i, $\mathcal{R}$ represents the number of considered anchors. The weight is defined as $w = \mathcal{R} - (\mathcal{A}_{rank} - 1)$, with $\mathcal{A}_{rank}$ representing the anchor's rank, such that a higher weight is assigned to anchors with better rank. Changes in the AP's position results from changes in the RSSI rankings of an AP, which may come from situations, such as, change in the AP's position, presence of obstacles that obstruct the signal, changes in the building's indoor layout, among others. Independently of the case, when AP's position changes significantly, it means that the radio map samples from that AP are not useful for positioning.

B. AP Selection

The metrics presented in the previous section can be used to perform AP selection in two ways. First, to select which APs should be filtered out from the initial RM. Second, to select which new APs should be used to perform RBF interpolation to enrich the RM.

1) APs to remove from initial RM: Since the radio environment undergoes constant variations and the initial RM is static, it is important to identify the APs that have a negative impact on fingerprinting-based IPSs. These include the APs that were removed from the space and are no longer detected, and those that have moved to a different position in the environment. In Wi-Fi fingerprinting, APs that are missing, either in the RM sample or the test sample, are usually penalized with a default RSSI value, such as -120 dBm. If these APs are detected, this penalization is not required. Wi-Fi fingerprinting assumes that APs remain static; otherwise, the radio map would not be useful. Thus, detecting which APs have moved and removing them from the initial RM should result in improved performance.

These two types of APs are detected based on the previously described metrics. If an AP from the initial RM is no longer detected in the metrics, it means that it has been removed. APs that have moved are identified using a distance threshold (d_{th}), which is defined in meters. If the distance between the AP's position when the initial RM was created and the AP's position at a given time is greater than this threshold, the AP is selected to be removed from the initial RM.

2) APs to enrich the RM: As time passes after building the initial RM, new APs may be detected, some of which may be useful to enrich the RM, while others may be problematic for positioning. For example, in large buildings frequented daily by many people, such as schools or malls, many mobile APs (hotspots) may be detected since they are carried by users. So, it is important to filter out mobile APs because they are not useful and can degrade the positioning performance.

When refreshing the RM with updated information, it is necessary to select which new APs should be used for RBF interpolation. We refer to new APs as the ones that were detected by anchors and not present when the initial RM was built. To select the new APs more suitable for positioning, we defined the following criteria that were applied to the metrics considering the δ *days* prior to enriching the RM: the AP must be fixed (distance between AP positions $< d_{th}$); the AP must be detected by at least one anchor with observation frequency higher than a threshold, OF_{th}; the highest RSSI of the AP must be higher than a threshold, rss_{hi}, which defines the highest detected RSSI of the AP in the past δ *days*.

C. RBF Interpolation

Considering that only a limited number of anchors are deployed inside the building and that the RM contains many RPs, an interpolation technique should be used to estimate APs' RSSIs at the RPs locations. This process is performed after selecting the APs to be in the enriched RM. Despite the existence of many interpolation techniques, RBF [9] has several advantages for interpolation of radio signals, e.g., it does not depend on the knowledge of the APs positions, neither the floor plan information to estimate RSSI values.

Generally, RBF networks have an input layer, a hidden layer with radial basis functions and an output layer. When applying this interpolation method it is necessary to select the kernel function. We opted for the Gaussian kernel function, which is suitable for interpolation of RSSI values [9]. Interpolated values follow a Gaussian curve, having higher signal strength in areas where the AP was observed with stronger signals.

Algorithm 1 details the process to estimate RSSI values of selected APs. As input, a radial basis function takes: $\mathcal{D}$, the set of RSSI values measured by anchors; $\mathcal{P}$, the set of RPs where RSSI values will be estimated (can be the RPs from the initial RM); rss_{min}, value assigned to samples where an AP is missing; ϵ, parameter necessary to define RBFs.

Algorithm 1: Pseudocode - RBF RSSI Interpolation

1 **input** $\mathcal{D}$, $\mathcal{P}$, rss_{min}, ϵ
2 Pre-process inputs (assign min. RSS, and convert to positive value)
3 $\mathcal{D}^+ = \{\}$
4 **for** $i = 1$ *to* $|\mathcal{D}|$ **do**
5   **if** $D_i = \emptyset \quad || \quad D_i < rss_{min}$ **then**
6         $rss_i = rss_{min}$
7     $rss^+ = rss_i - rss_{min}$
8     $\mathcal{D}^+ = \mathcal{D}^+ \cup rss^+$
9 Create model with Gaussian RBFs
10 $rbf = RBF(\mathcal{D}^+$, ϵ, function=$Gaussian)$
11 **for** $i = 1$ ***to*** $|\mathcal{P}|$ **do**
12   Obtain estimated RSSI and convert to negative value
13     $rss_i^+ = rbf(p_i.x, p_i.y, p_i.z)$
14     $rss_i^- = rss_i + rss_{min}$
15 Return: Estimated RSSI values.

The algorithm starts with data pre-processing (ln.2-10), by assigning the rss_{min} in case the AP was not detected or if its signal strength is lower than rss_{min} (ln.5-6). Then

RSSI values are converted to a positive data representation (ln.8-9). This conversion is necessary because when using the Gaussian kernel function, interpolated values far from the anchor's location tend rapidly to zero, due to the shape of the Gaussian function. Following, the RBF model is created (ln.12) and used to estimate one RSSI value for each RP (ln.13-17). The estimated values are converted back to negative data representation (ln.16) and returned at the end. The process to enrich the RM is completed after repeating this algorithm for each selected AP.

The resulting enriched RM is composed of the initial RM and the synthetic samples obtained from the RBF interpolation process. Obtaining the enriched RM can be repeated whenever there is new data from the anchors, allowing to continuously keep the radio map up to date.

IV. Experiments

We used a long-term database collected over the course of 2+ years, which is composed of Wi-Fi samples continuously collected by 7 anchors, as well as 12 manual site-survey datasets [16], [17]. Fig. 4 shows the locations where anchors (Raspberry Pi) were deployed (1 anchor per ≈264 m^2) as well as the RPs where Wi-Fi samples were collected in site surveys.

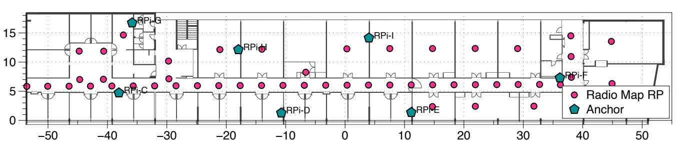


Fig. 4: Locations of anchors and radio map RPs.

In order to compute the metrics for this entire period, we considered an observation window of one day for local and global metrics, thus having the information regarding the radio environment every day for over two years.

As the initial RM, we considered the site survey from 2019-03-25 with averaged samples (the ones collected in the same RP). Ten subsequent site surveys, until 2021-04-23, were used as test datasets and the performance of the IPS was assessed with k–NN fingerprinting, with $k = 1$, Manhattan distance (city-block). A default RSSI was assigned to missing APs (either on the RM sample or the testing sample), defined as the minimum RSSI found in the RM minus 1 dBm.

Regarding AP selection, we used $\mathcal{R} = 5$, $\delta = 5$ days, and $OF_{th} = 0.8$. RBF parameters used were $rss_{min} = -120$ dBm, and $\epsilon = 15$. Usually, ϵ is defined based on the distance between the points where samples are collected, in this case, it is the distance between the anchors. The average distance between anchors is 7.77 m, but since the building is large, we opted for a larger value.

A. Results

We evaluated the Wi-Fi fingerprinting performance between the initial RM and the enriched RMs with different AP selection parameters. The idea is to explore AP selection

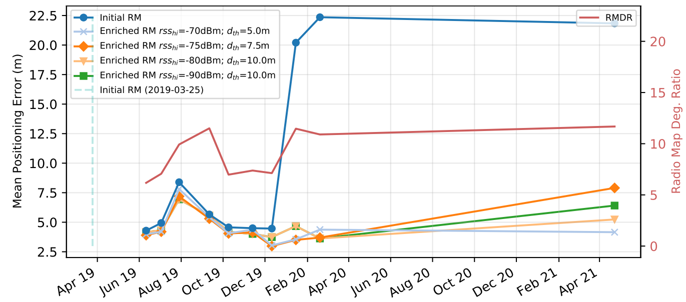


Fig. 5: Wi-Fi fingerprinting comparison between the initial RM and enriched RMs with different parameters and Radio Map Degradation Ratio (RMDR) on the right side y-axis.

criteria, such as stricter criteria (higher rss_{hi} and smaller d_{th}) or more lenient criteria (lower rss_{hi} and larger d_{th}).

Figure 5, depicts the mean error obtained for each RM version at different testing dates (scatter points). Degradation caused the mean error to significantly increase (>20 m) at the beginning of 2020 when using the initial RM, created on 2019-03-25 (blue plot line). Other plot lines represent the performance when using the enriched RMs, demonstrating that they are capable of overcoming the degradation that started in 2020, keeping the mean error bellow 8 m in all cases. As explained in [2], the significant degradation that started in 2020 was caused by changes in the Wi-Fi infrastructure, where many APs were moved, and new ones were installed in the building. Fig. 5 also shows the RMDR, a metric that measures the variations in signal strength between two Wi-Fi datasets [2]. In this case, the RMDR is computed between the initial RM and all subsequent dates when the RM was evaluated, to assess how much it degraded since it was created.

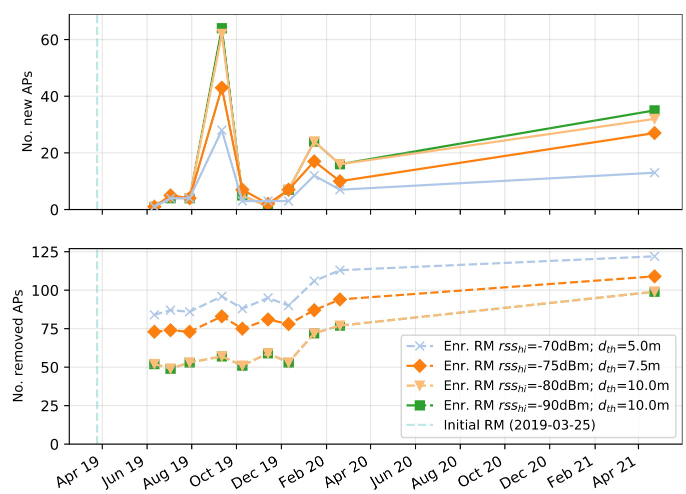


Fig. 6: Number of new and removed APs in enriched RMs.

Figure 6 presents the number of new APs considered in enriched RMs at each testing date, as well as the number of APs that were removed from the initial RM in the filtering process, before obtaining the enriched RM. As expected, when increasing the rss_{hi} parameter, the number of new APs considered decreases because it filters out APs whose highest signal strength was lower than this value. Similarly, when decreasing the d_{th} parameter, the number of new APs considered is also lower because it limits the number of APs to those that have not moved far from their original position. The peak in the number of new APs added to enriched RMs around Sept. 2019 was caused due to tests conducted in the Wi-Fi infrastructure where many new APs were detected, and removed about a month later [2]. The number of removed APs varies mostly depending on the d_{th} parameter, because when this value is low, e.g., $d_{th} = 5$ m, a higher number of APs are removed from the RM.

Table I compares the mean error between the initial RM and the enriched RMs, in dates when the RMDR was higher than 10, i.e., when radio map degradation was significant.

TABLE I: Mean error (in metres) of initial RM against enriched RMs on dates when $RMDR > 10$.

rss_{hi} [dBm] / d_{th} [m]	-70 / 5.0	-75 / 7.5	-80 / 10.0	-90 / 10.0	Init. RM
2019-09-11	5.42	**5.30**	5.56	5.56	5.66
2020-01-15	3.55	**3.51**	4.67	4.67	20.20
2020-02-19	4.37	3.70	**3.62**	**3.62**	22.36
2021-04-23	**4.16**	7.90	5.23	6.41	21.84
Overall	**4.38**	5.10	4.77	5.07	17.51

In 2019-09-11, the degradation of the initial RM was not significant as it achieves 5.66 m of mean error, with equivalent performance to the enriched RMs. The initial RM was not affected by this degradation, because this was a period when many new APs were detected, but the vast majority of APs from the initial RM was still available, as can be seen in Fig. 6. After 2020, the initial RM degraded significantly because many APs were removed from the building and new ones were installed [2], which is demonstrated in Fig. 6, both in the number of new APs and removed APs. Results demonstrate a clear improvement in enriched RMs, which overcome this issue. Overall, the configuration with the best results is $rss_{hi} = -70$ dBm, $d_{th} = 5$ m, with an improvement of ≈120% against the initial RM (4.38 m vs 17.51 m).

V. Conclusions and Future Work

In fingerprinting solutions RM degradation is unavoidable and cannot be predicted. In the long-term, alterations in the Wi-Fi radio environment cause worse positioning performance when using an old RM. Continuously monitoring the radio environment proposes several advantages, mainly the ability to detect when APs are removed, when new APs are detected and also when APs are relocated, causing dramatic changes in the radio environment. We use this information to filter out APs from an old RM and to select which new APs are better to enrich it using an interpolation method. This approach can be applied at any time to generate an updated radio map with data from just a few anchors placed in known positions.

Obtained results from a long-term experiment in the real world, demonstrated that our AP selection method and data augmentation technique based on RBF allow to use an old RM (enriched with new information) even after it is clearly affected by RM degradation, achieving similar performance to the one achieved before degradation occurred. Consequently, there is no need to update the RM manually, as this approach automatically keeps it up to date.

Future work aims to enhance APs selection based on other metrics and identify when the initial RM must be replaced.

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