Evaluation of Calibration Methods Applied to Fingerprinting-Based Radiolocalization using Machine Learning

Douglas T. R. P. Silva and Daniel C. Cunha

***Abstract*— One of the main problems of fingerprinting (FP)-based radiolocalization systems is the heterogeneity of mobile devices. This problem usually causes variations in the collected radio frequency (RF) signals due to a set of heterogeneity elements, such as RF chipsets, antennas, hardware drivers, and operating systems, resulting in larger location prediction errors. This work proposes a combined calibration method to correct discrepancies in the RF signal levels collected, helping to reduce the prediction errors of the FP-based localization systems. The combined calibration method presented better performance than its component methods in all cases of the generalized and homogeneous scenarios and partially in the heterogeneous scenarios. The results showed that, in generalized scenarios, the FP-based localization system using the combined calibration method reduced the average prediction error in the range of 7 to 22%.**

***Keywords*— Fingerprinting, indoor localization, machine learning, free-calibration methods.**

I. Introduction

The evolution of wireless technology, with its variety of mobile devices, has expanded the possibilities of localization techniques for wireless networks [1]. In this context, global navigation satellite systems (GNSS), such as global positioning systems [2] and Galileo [3], play a fundamental role in consolidating localization techniques for outdoor environments. However, concerning indoor environments, the GNSS signal is often attenuated or becomes unavailable due to physical obstacles that can block or reflect the radio frequency (RF) signals. Given that, radiolocalization based on fingerprinting (FP), a localization method based on the similarity between RF signal levels, is a cost-effective solution to estimate the user's positioning [4], [5].

One of the main obstacles faced by the FP-based localization technique is device heterogeneity [6]–[9]. This problem occurs due to variations in RF signal levels collected from different wireless devices, even when they are positioned in the same physical location. These variations are caused by a set of heterogeneous elements in mobile devices, such as different RF chipsets, receiver antennas with distinct sensitivities, hardware drivers, and operating systems, resulting in larger location prediction errors [10]. In the face of this challenge, calibration methods are employed with the aim of normalizing or correcting discrepancies of the variations in RF signal levels, which, in turn, indirectly helps to reduce the distance prediction errors of the localization systems [11]. In this way, calibration methods contribute to a more reliable location, seeking to adjust the collected data considering the individual particularities of each wireless device.

Considering the device heterogeneity problem and the use of machine learning (ML) models to implement a localization solution, we can define some scenarios in the context of the supervised ML algorithms. A *heterogeneous* scenario is defined when the ML model is trained with data from one type of device, and the testing data is acquired from different wireless devices in terms of manufacturers, brands, or models. When the testing set is formed by data obtained from exactly the same type of device used to generate the training data, we call this scenario a *homogeneous* one. Finally, when we have testing data extracted from several devices, including the one that was used to compose the training set, this is a *generalized* or *joint* scenario. Calibration methods are usually used in generalized and heterogeneous scenarios, presenting good results, such as, for example, the received strength signal certainty (RSC) method [11]. On the other hand, there are calibration methods that are not efficient in heterogeneous scenarios, but promote benefits when applied to homogeneous scenarios, such as the weight-received strength signal (W-RSS) method [10]. Finally, it is important to highlight that, in homogeneous scenarios, the use of calibration does not always result in performance improvements, thus harming a certain number of users.

In view of the above, the motivation for proposing the new calibration method is based on the idea of combining the RSC method, which demonstrated good performance in heterogeneous scenarios, with the W-RSS one, which presented satisfactory results in homogeneous scenarios. Thus, the main objective of the proposal is to mitigate discrepancies in the RF signal levels collected from different mobile devices, considering different scenarios.

The rest of the paper is organized as follows. Section II presents a brief description of the proposed calibration method. In Section III, numerical results are accomplished, and the proposed method is compared to RSC and W-RSS calibration approaches. Finally, conclusions are drawn in Section IV.

II. Proposal of Calibration Method

The proposed calibration method consists of the integration of the RSC and W-RSS methods and will be denoted by

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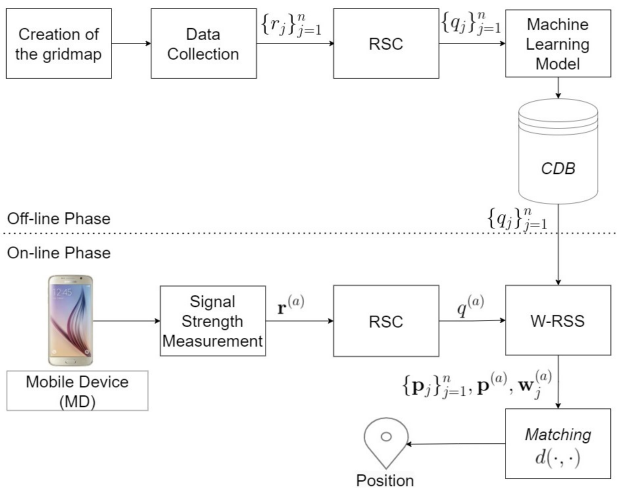
Fig. 1. Diagram of the fingerprint-based radiolocalization technique considering the insertion of the RSC/W-RSS calibration method.



RSC/W-RSS. The main idea of the proposal is to investigate the benefits that the joint use of the RSC and W-RSS methods provides to the FP technique, in heterogeneous, homogeneous, and generalized scenarios. When applied alone, the RSC method increases accuracy in heterogeneous scenarios, however diminishes it in homogeneous ones. On the other side, the W-RSS method also raises accuracy in heterogeneous scenarios and simultaneously maintains or improves accuracy in homogeneous ones. It is worth highlighting that the RSC, W-RSS, and RSC/W-RSS calibration methods were used together with the ML models k-nearest neighbors (k-NN) [12], support vector regression (SVR) [13], and random forest (RnF) [14] to compose the localization technique.

Fig. 1 illustrates the architecture of an RF fingerprinting-based localization technique, considering the insertion of the calibration method, that can be divided into two stages: offline and online [4]. In the offline stage, the radio map of the region of interest is produced by merging RF measurements and a grid map [1] composed of regular squares (also called cells) that cover all the location areas. The main objective of the offline stage is to establish, for each grid map cell, a vector that uniquely identifies it. These vectors are named reference fingerprints.

In this work, we will denote by $\mathbf{z}_j$ the reference fingerprint of the received RF signal at the center of the j-th grid cell on the grid map, whose Cartesian coordinates are (x_j, y_j), being x_j and y_j expressed in meters. Thus, the reference fingerprint is given by

$$\mathbf{z}_j = [\mathbf{r}_j; (x_j, y_j)] \ , \tag{1}$$

where $\mathbf{r}_j = [r_j^i]$, $i = 1, \ldots, m$, represents the vector of RF signal levels, obtained from the access points (APs) existing in the coverage region, that is composed of n grid cells. Each component r_j^i of $\mathbf{r}_j$ means a signal level measurement from the i-th AP at the j-th grid cell, while m expresses the number of APs in the localization area.

After building the radio map, the next step is to calibrate the RF signal measurements collected in the field. In this context, the block "RSC" processes the set of vectors $\{\mathbf{r}_j\}_{j=1}^n$ transforming them into $\{\mathbf{q}_j\}_{j=1}^n$, such that each component q_j^i of the vector $\mathbf{q}_j$ is given by

$$q_j^i = \frac{r_j^i}{\sum_{k=1}^m r_j^k} \ . \tag{2}$$

At this point, it is worth noting that not all grid map cells may be accessible for collecting measurements[2]. A possible solution to this problem is the use of ML algorithms, such as k-NN, neural networks, RnF, and SVR, to predict the values associated with inaccessible cells, allowing correlation database (CDB) to become complete [15]. Finally, all reference fingerprints (collected, predicted and calibrated) along the coverage region are stored in the CDB, which in turn is contained on a localization server. This location server acts as a central management and coordination point, receiving location data from mobile devices and providing responses to location requests.

The second stage of the fingerprint-based localization technique is the online phase, whose objective is to estimate the position of the mobile device to be located. To do this, initially, only the RF signal levels of the mobile device are collected from all the APs of the coverage region to compose the so-called target fingerprint vector, denoted by $\mathbf{r}_{td}$. Similar to $\mathbf{r}_j$, the vector $\mathbf{r}_{td}$ is also processed by the block 'RSC', represented by (2), to derive the vector $\mathbf{q}_{td}$. In this way, the RSC method creates a new signal level tuple by refining the original signal level data, aiming to reduce the uncertainty associated with the measurements [11].

Subsequently, the W-RSS method uses the vectors $\{\mathbf{q}_j\}_{j=1}^n$ and $\mathbf{q}_{td}$ as input parameters, generating in its output the set of vectors $\{\mathbf{p}_j\}_{j=1}^n$, the vector $\mathbf{p}_{td}$ and the vector of weighted signal levels between $\mathbf{p}_j$ and $\mathbf{p}_{td}$, denoted by $\mathbf{w}_j^{(td)}$. Each vector $\mathbf{p}_j$ is expressed by

$$\mathbf{p}_j = [(q_j^1; I(q_j^1)), \ldots, (q_j^i; I(q_j^i)), \ldots, (q_j^m; I(q_j^m))] \ , \tag{3}$$

where q_j^i is the certainty value vector of the received signal levels defined by (2), and $I(q_j^i)$ represents the index of q_j^i after the descending ordering of the components of $\mathbf{p}_j$. The vector $\mathbf{p}_{td}$ is obtained in a similar way as $\mathbf{p}_j$, but assuming $\mathbf{q}_{td}$ as input. Finally, the vector $\mathbf{w}_j^{(td)}$ is such that

$$\mathbf{w}_j^{(td)} = [w_{1,j}^{(td)}, \ldots, w_{i,j}^{(td)}, \ldots, w_{m,j}^{(td)}], \tag{4}$$

where $w_{i,j}^{(td)}$ is given by

$$w_{i,j}^{(td)} = 1 - \frac{|I(r_{i,j}) - I(r_i^{(td)})|}{\max(I(r_{i,j}), I(r_i^{(td)}))}, \ 1 \leq i \leq m \, . \tag{5}$$

Once the vector $\mathbf{w}_j^{(td)}$ is obtained, a matching algorithm is applied using $\mathbf{w}_j^{(td)}$ in the calculation of Euclidean distances

[1]Irregular grid maps can also be used in RF fingerprinting-based localization. Nevertheless, such grids are not within the scope of this work.

[2]This is a very common situation in outdoor environments, in which some regions are, for example, private properties.

between $\mathbf{p}^{(td)}$ and each of the vectors $\mathbf{p}_j$, such that

$$d(\mathbf{p}_j, \mathbf{p}^{(td)}, \mathbf{w}_j^{(td)}) = \sqrt{\sum_{i=1}^{m} w_{i,j}^{(td)} (r_{i,j} - r_i^{(td)})^2} \,. \quad (6)$$

After all, the purpose of the matching algorithm is to find a reference fingerprint in CDB that presents the largest similarity with the fingerprint target [4]. The Cartesian coordinates of the selected reference fingerprint are then assigned to the searched mobile target.

III. Results

The database used in this work is made up of Bluetooth signal level measurements collected in an area of approximately 176 m^2. These Bluetooth signal level measurements were obtained from three different mobile devices, identified as SM_1 (Samsung Galaxy A5 2017), SM_2 (BQ Aquaris X5 plus), and SM_3 (Samsung Galaxy S6) [16]. In the training stage, 560 measurements were used from a single mobile device to build the CDB. In the testing stage, 420 observation points were employed from three different mobile devices, with a third (140 samples) corresponding to the device used in the training stage. The remaining 280 samples were extracted from the other two devices, with 140 samples from each one.

For the three ML algorithms, a parameter adjustment step was carried out using the grid search method, aiming to optimize the results. The K-fold cross-validation method was also used to guarantee the generalization capacity of the ML algorithm in the localization technique. Cross-validation aims to reduce the impact of randomness when splitting training and testing data. At each iteration of the K-fold technique, the calculation of the average prediction error for the j-th fold of validation is performed using the Euclidean distance $d_j[(x, y), (\hat{x}, \hat{y})]$, such that

$$d_j[(x, y), (\hat{x}, \hat{y})] = \frac{1}{n} \sqrt{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} \,, \quad (7)$$

where n represents the total number of samples in the j-th validation fold, while (x_i, y_i) and $(\hat{x}_i, \hat{y}_i)$ correspond, respectively, to the Cartesian coordinates of the real and predicted positions of the i-th sample. After the end of the iterations, the distance prediction error is obtained through the mean value of the Euclidean distances, denoted by $\bar{\epsilon}$, obtained in all K folds, such that

$$\bar{\epsilon} = \frac{1}{K} \sum_{j=1}^{K} d_j \,. \quad (8)$$

We adopted three metrics to evaluate the performance of the localization systems presented in this work. The first one is the average distance error prediction of all samples present in the test set and defined by Eq. (8). The second metric is the precision of the technique, given by the standard deviation of the distance error prediction. Later, the third metric is based on the time required for the localization technique to perform calibration, training of the ML algorithm, and prediction of the coordinates of the test samples.

TABLE I

Average distance prediction error ($\bar{\epsilon}$) and precision (σ) of the FP-based radiolocalization technique with and without the use of free-calibration methods. Training data: Mobile device SM_1. Calibration methods: RSC, W-RSS, RSC/W-RSS, and NC (no calibration).

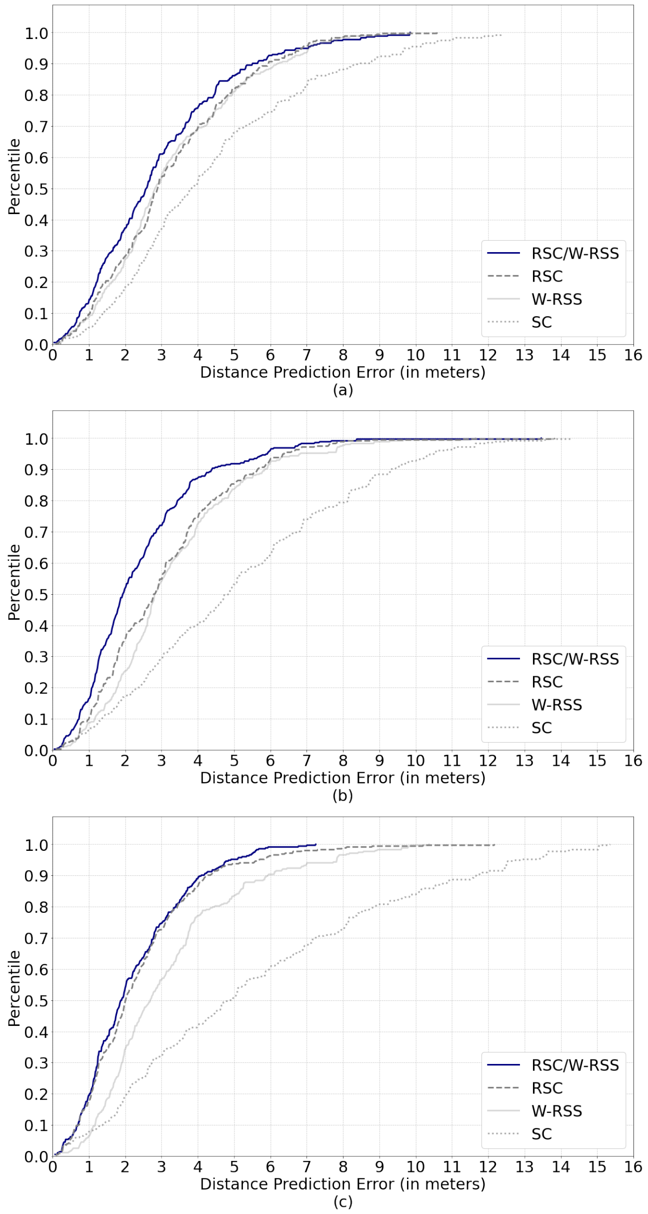
ML	Calib. Method	Metric	Joint	SM_1	SM_2	SM_3
k-NN	RSC	$\bar{\epsilon}$	3.25 m	3.44 m	**3.14 m**	**3.17 m**
		σ	1.91 m	2.16 m	1.74 m	1.82 m
	W-RSS	$\bar{\epsilon}$	3.29 m	2.42 m	3.82 m	3.61 m
		σ	1.96 m	1.29 m	2.14 m	2.03 m
	RSC/W-RSS	$\bar{\epsilon}$	**2.91 m**	**1.75 m**	3.48 m	3.48 m
		σ	1.96 m	1.17 m	2.02 m	2.02 m
	NC	$\bar{\epsilon}$	4.40 m	3.34 m	5.17 m	4.65 m
		σ	2.70 m	2.22 m	2.86 m	2.65 m
SVR	RSC	$\bar{\epsilon}$	3.04 m	3.47 m	3.04 m	2.63 m
		σ	1.89 m	2.18 m	1.74 m	1.63 m
	W-RSS	$\bar{\epsilon}$	3.28 m	2.54 m	3.83 m	3.44 m
		σ	1.91 m	1.32 m	2.27 m	1.77 m
	RSC/W-RSS	$\bar{\epsilon}$	**2.38 m**	**1.74 m**	**2.86 m**	**2.51 m**
		σ	1.69 m	1.21 m	1.94 m	1.63 m
	NC	$\bar{\epsilon}$	5.12 m	3.68 m	6.35 m	5.27 m
		σ	3.03 m	2.45 m	2.97 m	3.02 m
RnF	RSC	$\bar{\epsilon}$	2.37 m	3.15 m	2.19 m	**1.80 m**
		σ	1.67 m	2.20 m	1.32 m	0.95 m
	W-RSS	$\bar{\epsilon}$	3.17 m	2.65 m	3.78 m	3.04 m
		σ	2.01 m	1.25 m	2.45 m	1.95 m
	RSC/W-RSS	$\bar{\epsilon}$	**2.20 m**	**2.56 m**	**2.17 m**	1.88 m
		σ	1.40 m	1.65 m	1.35 m	1.06 m
	NC	$\bar{\epsilon}$	5,60 m	3.49 m	7.33 m	5.90 m
		σ	3.82 m	2.72 m	3.77 m	3.84 m

Tab. I illustrates the average distance error prediction and precision of the FP-based radiolocalization technique considering the use of free-calibration methods and no calibration (NC). The experiment was performed assuming a training database composed of RF measurements from the device SM_1 [3]. The test set was built with data collected in four different scenarios. The first one contemplates measurements from all three mobile devices (SM_1, SM_2, and SM_3) and is represented by the column "Joint". The other three scenarios only consider individual data from each mobile device and are identified by the columns "SM_1", "SM_2", and "SM_3". With this in mind, the columns "SM_2" and "SM_3" illustrate heterogeneous scenarios, while the column "SM_1" represents a homogeneous one. Finally, the column "Joint" depicts a generalized scenario.

As can be seen in Tab. I, the RSC/W-RSS method led to a reduction in the average prediction error in the range of 7 to 22%, for all ML algorithms, when compared to the RSC method in the joint scenario, that is, when the testing set was composed of data from all mobile devices considered. Concerning the homogeneous scenario, the RSC/W-RSS method presented reductions of 27.7%, 31.5%, and 3.4%, considering the k-NN, SVR, and RnF, respectively, in relation to the W-

[3]Similar results were acquired for training sets built from the mobile devices SM_2 and SM_3. However, due to lack of space, they will be omitted from this work.

Fig. 2. Cumulative distribution function of the average distance prediction error for training data extracted from the mobile device SM_1, considering the use of free calibration (RSC/W-RSS, RSC, and W-RSS) and no calibration (NC). ML algorithms: (a) k-NN. (b) SVR. (c) RnF.



RSS calibration. Finally, in the heterogeneous scenario, the RSC/W-RSS method outperformed the RSC one in half of the cases. Nonetheless, even in cases where the prediction error of the RSC/W-RSS method increased relative to the RSC one, the magnitude of its increase did not exceed 10.8%. In spite of that, the RSC/W-RSS method showed smaller distance prediction errors compared to the NC case for all scenarios considered in this work. Therefore, the RSC/W-RSS method is a viable calibration option since the overall performance of the system in the joint scenario was not damaged, even with an increase in the distance prediction error in specific heterogeneous cases. Last but not least, it is noteworthy that the precision of the localization techniques was improved with the use of calibration methods.

A typical way to evaluate the precision of localization techniques is through the cumulative distribution function (CDF) of the distance prediction error [17]. The CDF is the probability that the localization error takes on a value less than or equal to x meters. Figs. 2(a), 2(b), and 2(c) illustrate the CDFs of the distance prediction error of localization techniques for k-NN, SVR, and RnF algorithms, respectively, considering all the calibration methods as well as the NC system. The steeper the curve, the better the precision of the localization system. So we can see that the precision of the calibrated systems is superior to the precision of the NC one. Furthermore, the performance of the system depends directly on the ML algorithm used. For example, as can be seen in Figs. 2(a), 2(b), and 2(c), the curves of the RSC/W-RSS calibration using SVR and RnF algorithms are steeper than the k-NN case. At the same time, the use of the RnF algorithm makes the performance of the RSC method very close to the RSC/W-RSS one.

TABLE II

NORMALIZED VALUES OF THE TOTAL RUNTIME OF THE LOCALIZATION TECHNIQUE (CALIBRATION, TRAINING, AND TESTING). CALIBRATION METHODS: RSC, W-RSS, RSC/W-RSS, AND NO CALIBRATION (NC).

ML Algorithm	NC	RSC	W-RSS	RSC/W-RSS
k-NN	2.4	2.8	4.9	7.3
SVR	1.0	1.6	3.1	6.2
RnF	1.9	2.1	3.5	3.9

Tab. II indicates the normalized values of the total runtime of the localization technique, including calibration, training, and testing steps. The SVR-based localization technique using no calibration was adopted as a benchmark. As expected, the runtime of the RSC/W-RSS-based localization method increased compared to the other isolated calibration methods and the system with no calibration. Considering the homogeneous scenario and depending on the ML model, the total runtime of the RSC/W-RSS method was 1.1x to 2x larger than the entire runtime of the W-RSS localization technique. For the generalized scenario, the increasing of the runtime was 1.8x to 3.8x larger than the runtime of the RSC-based method. In spite of that, it is important to point out, as previously mentioned, that the proposed calibration method promoted a performance gain in the range of 7 to 22% for generalized scenarios and 3 to 31% for homogeneous cases.

IV. CONCLUSIONS

In this work, a combined calibration method was proposed to investigate the benefits that the joint use of the received strength signal certainty (RSC) and the weight-received strength signal (W-RSS) methods provides to the performance of fingerprinting (FP)-based radiolocalization systems in a variety of mobile device scenarios. For this, a Bluetooth database containing RF signals from three different mobile devices was used for analysis. To compose the localization technique, we consider three machine learning (ML) models: k-nearest neighbors (k-NN), support vector regression (SVR), and random forest (RnF). Finally, experiments were executed considering heterogeneous, homogeneous, and generalized mobile device scenarios.

The FP-based localization system using the proposed calibration method presented better results than the system with no calibration in all scenarios investigated. In heterogeneous scenarios, the results indicated that the RSC/W-RSS method outperformed the RSC method in half of the cases analyzed. Considering the situations in which the RSC/W-RSS method failed to overcome the RSC one, the increase of location prediction error did not exceed 10.8%. In the homogeneous scenario, the combined method outperformed the W-RSS one in all cases. Finally, with regard to global performance (generalized scenario), the RSC/W-RSS method managed to reduce the average prediction error in the range of 7 to 22%. This decreasing occurred due to the better performance in the homogeneous scenario, despite the increasing of prediction error in specific heterogeneous scenarios. In spite of the increase in processing runtime, the proposed calibration method proved to be a good alternative, depending on the ML model used, something that needs to be further investigated in search of new solutions to the problem of device heterogeneity.

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