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Device Self-Calibration in Location Systems using Signal Strength Histograms

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Received Signal Strength (RSS) fingerprinting is an attractive solution for indoor positioning using WLAN due to the wide availability of WLAN Access Points (AP) and the ease of monitoring RSS measurements on WLAN-enabled mobile devices. Fingerprinting systems rely on a radiomap collected with a reference device inside the localization area, however a major limitation is that the quality of the location information can be degraded if the user carries a different device. This is because diverse devices tend to report the RSS values very differently for a variety of reasons. To ensure compatibility with the existing radiomap, we propose a self-calibration method that attains a good mapping between the reference and user devices with the aid of RSS histograms. We do so by relating the RSS histogram of the reference device, which is deduced from the radiomap, and the RSS histogram of the user device, which is updated concurrently with positioning. Unlike other approaches, our calibration method does not require any user intervention, e.g. collecting calibration data with the new device prior to positioning. Experimental results with five smartphones in a real indoor environment demonstrate the effectiveness of the proposed method and indicate that it is more robust to device diversity compared to other calibration methods in the literature.

Keywords: Wireless networks; Positioning; Signal strength fingerprints; Device calibration; Histograms

1 Introduction

Recent statistics by Strategy Analytics reveal that people spend 80-90% of their time inside buildings, while 70% of cellular calls and 80% of data connections originate from large indoor environments, including shopping malls, museums, exhibition centers, conference venues, airports, etc. This has triggered an increasing interest for indoor location aware services and applications, such as location-enabled advertisements and marketing, in-building guidance and navigation, asset tracking and other. Since satellite-based positioning, e.g. GPS, has low availability inside buildings due to the severe attenuation of the positioning signals, alternative solutions are required for the provision of reliable location information indoors.

WLAN is an attractive positioning technology mainly due to the ubiquity of the relevant infrastructure, i.e. several WLAN Access Points (AP) are already installed in public places and residential areas, and the proliferation of mobile devices that feature integrated WLAN cards for wireless connectivity. These devices have access to different types of location-dependent measurements, such as Received Signal Strength (RSS) values, that can be used to infer location. WLAN RSS fingerprinting is a popular approach, which relies on a radiomap of the localization area that contains vectors of RSS values from the surrounding APs, known as fingerprints. These fingerprints are collected with a reference device at some predefined locations prior to positioning and subsequently location can be determined by finding the best match between the current fingerprint measured with the same device and the fingerprints in the radiomap; see (Honkavirta *et al.*, 2009) and references therein for an overview of fingerprinting methods.

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One of the limitations of such methods is that the user needs to carry the *same* device which was used to build the radiomap to guarantee the best accuracy during positioning. Using a different device is feasible, but the RSS values are not usually compatible with the radiomap, leading to accuracy degradation. In fact, heterogeneous mobile devices may report RSS values from the surrounding APs quite differently, even if they are placed at the same location. This is mainly because the WLAN standard does not specify strictly the range of the RSS Indicator (RSSI), which is used to measure RSS; Figuera *et al.* (2011) provide the details of the measurement process for RSSI according to the WLAN standard. Thus, the actual implementation may differ significantly among various chipsets, leading to diverse measurement accuracy, granularity and dynamic RSS range. Even identical WLAN cards may report RSS values very differently owing to varying antenna gain or different device packaging material (Tsui *et al.*, 2009). Moreover, to make things worse, two WLAN cards may not detect the same number of APs at a specific location, due to variable receiver sensitivity.

Providing adequate accuracy, when a different mobile device is carried during positioning requires a *calibration* step to make the new device compatible with the existing radiomap. Manual calibration is an approach that relies on data fitting to create a mapping between the RSS values collected with different devices (Haeberlen *et al.*, 2004). However, manual calibration implies the collection of a considerable volume of data at several *known* locations prior to positioning, which can be prohibitive in practice. In our previous work, we investigated the manual calibration approach and focused on the amount of data that need to be collected at *known* locations with different devices in order to attain adequate calibration performance (Laoudias *et al.*, 2012). We confirmed that if the localization area is covered by several APs, the manual calibration approach can be effective, even when only a few randomly distributed locations are visited with an uncalibrated device, and provided some analytical results to justify this. Still, the tedious data collection process prior to positioning cannot be avoided, thus rendering this calibration approach unsuitable for real-life applications, where typically the user enters an unknown environment and requests location-based information. To address these limitations, we introduced a calibration method based on RSS histograms that enables a mobile device to be self-calibrated on-the-fly, simultaneously with positioning. In this article, we discuss our self-calibration method in more detail and investigate some variants of the original approach that exhibit lower computational complexity. Moreover, we present extensive experimental results and compare the proposed method against some state-of-the-art device calibration methods.

We outline the related work on device calibration in Section 2. In Section 3, we provide some preliminaries on signal strength fingerprinting, followed by the description of our experimental setup inside a real office environment in Section 4. Section 5 discusses the proposed self-calibration method in detail and in Section 6 we evaluate its calibration performance using experimental data collected during an extensive measurement campaign with five commercial mobile devices. Finally, Section 7 provides concluding remarks.

2 Related Work

Device independent positioning has recently attracted researchers' interest, due to the requirement for the provision of accurate and reliable location estimates regardless of the device carried by the user. Several works try to address this issue, mainly through calibration-free techniques or signal strength data fitting approaches, as outlined in the following.

2.1 *Calibration-free Methods*

The approaches that fall under this category try to remove the device-dependent component in the RSS values through data transformation. The RSS values are given by the log-distance radio propagation model

$$RSS[dBm] = A - 10\gamma \log_{10} d + X, \tag{1}$$

where d denotes the distance between the transmitter (e.g., a WLAN AP) and the receiver (e.g., a mobile device), while the intercept term A provides the RSS value when $d = 1\,\mathrm{m}$ and encapsulates device specific characteristics, such as the antenna gain. The coefficient γ depends on the propagation environment, while $X \sim \mathcal{N}(0, \sigma_n^2)$ is the Gaussian noise disturbing the RSS values.

In this context, differences between RSS values, instead of absolute RSS values, can be used to form the fingerprints. This effectively removes A in (1) and makes the RSS difference fingerprints from diverse devices compatible with each other. The differential fingerprints can be created by taking the difference between all possible AP pairs, i.e. if there are n APs inside the area of interest then the transformed fingerprint contains $\binom{n}{2}$ RSS differences (Mahtab *et al.*, 2007; Dong *et al.*, 2009). However, this method increases dramatically the dimensionality of the fingerprints, especially is areas covered by a large number of APs, thus leading to higher computational complexity compared to the traditional RSS fingerprints. To address this issue, the Signal Strength Difference (SSD) approach creates the fingerprints by subtracting the RSS value of a reference AP from the other RSS values (Mahtab *et al.*, 2013), so that the differential fingerprint contains only the $n-1$ RSS differences that are independent. The reference AP can be selected as the one that exhibits the least average deviation of RSS values over the whole localization area (Mahtab *et al.*, 2010). However, selecting the reference AP is not trivial, especially in large scale setups where the APs do not provide ubiquitous coverage. Moreover, the RSS differences may degrade the positioning accuracy because they exhibit higher noise variance, as explained by Laoudias *et al.* (2012) and Mahtab *et al.* (2013).

The Hyperbolic Location Fingerprinting (HLF) approach combines normalized logarithm ratios of the RSS power from different APs to remove the device-dependent component (Kjærgaard, 2011). However, the resulting RSS logarithm ratios are not totally free from the intercept term A, thus they cannot fully mitigate the hardware variations (Mahtab *et al.*, 2013).

On a different line, RSS ranking methods rely on ranked, rather that absolute, RSS values (i.e., RSS values from a set of APs are ranked from high to low) because the ranking is not affected by device-specific hardware features (Cheng *et al.*, 2005; Machaj *et al.*, 2011). However, ranked-based fingerprints are expected to perform worse, compared to standard RSS fingerprints, because the fine-grain information of the RSS levels is lost when ranks are used.

2.2 *Signal Strength Data Fitting Methods*

The RSS data fitting methods try to create a mapping between different devices and are motivated by the linear relation between the RSS values reported by heterogeneous devices, which has been observed experimentally in several studies (Haeberlen *et al.*, 2004; Kjærgaard, 2006; Ledlie *et al.*, 2012).

One approach referred to as manual calibration (Haeberlen *et al.*, 2004) is to collect a series of RSS measurements at several *known* locations with a pair of devices and subsequently estimate the linear fitting parameters. Essentially, if a sufficient number of colocated RSS pairs (i.e., collected at the same location and time with two different devices) is available, then the linear parameters can be estimated through standard least squares fitting (Haeberlen *et al.*, 2004; Kjærgaard, 2006; Ledlie *et al.*, 2012). Figuera *et al.* (2011) report that the relationship between the RSS values of different devices can sometimes be nonlinear and use a Support Vector Regressor (SVR) and a Generalized Regression Neural Network (GRNN) as learning algorithms. Nevertheless, the manual calibration method requires a considerable data collection effort by the user prior to positioning. Even though the time and labour overhead for calibrating a new device can be significantly reduced when the localization area is covered by several APs, this method still has limited applicability in real-life applications (Laoudias *et al.*, 2012). In a typical scenario, where a user enters an indoor environment, such as shopping malls, airports, etc. carrying an uncalibrated device, he or she has to be guided to specific *known* locations for collecting RSS data. This implies that the user is already familiar with the area, which is usually not the case.

Device calibration with RSS data recorded by the user at *unknown* locations is feasible, but computationally expensive methods are required to obtain the linear fitting parameters. For instance, Haeberlen *et al.* (2004) estimate the parameters by maximizing the confidence value produced by Markov localization, while Kjærgaard (2006) employs a weighted least squares method. We call these quasi-automatic, as opposed to manual, calibration methods.

In automatic calibration, RSS data collected at *unknown* locations are used as in the quasi-automatic case, however the objective is to minimize the user intervention and ideally perform positioning and device calibration simultaneously, while the user walks freely inside the area of interest. To this end, an expectation maximization (EM) algorithm is proposed by Haeberlen *et al.* (2004). Kjærgaard (2006) detects when the user is stationary during positioning in order to divide the data into parts which come from the same *unknown* location and then uses these data with a quasi-automatic calibration approach. The unsupervised learning method of Tsui *et al.* (2009) uses the Pearson product-moment correlation coefficient to label the RSS readings with a rough location estimate, while the user is walking, and then employs EM and neural network learning algorithms to obtain the linear fitting parameters. Kim *et al.* (2012) also assume a linear fitting function and localization is performed when a signal peak is detected, while the location is estimated as the location of the maximum RSS recorded during the training phase. This approach is justified by the fact that the location of the maximum RSS is preserved, even though RSS varies significantly, however a major limitation is that the location can be determined only when a signal peak is detected. Beder *et al.* (2012) assume that the RSS values from heterogeneous devices differ only by a common factor (offset) and incorporate the online estimation of this factor in the likelihood function of their probabilistic localization algorithm.

Regarding the use of RSS histograms, Koski *et al.* (2010) mention the possibility of using histograms for automatic device RSS calibration without implementation details. Misikangas *et al.* (2005) create the empirical cumulative distribution function (cdf) for several devices using the RSS values collected at *known* locations and then use the inverse cdf function, instead of using least squares fitting, to build a database of device models that map the RSS values of the user device to the reference device. However, this method is applicable to a limited number of device pairs, while the selection of the appropriate model during positioning is based on the existence of an easily distinguishable location (e.g., building entrance or exit) that may never be visited by the user.

3 Signal Strength Fingerprinting

Several solutions to the location determination problem using RSS fingerprints have been studied in the literature. These approaches differ in the underlying positioning algorithm, however they all rely on a RSS radiomap that covers the entire area of interest. Fingerprint-based positioning consists of two phases, namely the offline (training) and the online (positioning) phases.

Offline phase: We use a set of predefined reference locations $\{L : \ell_i = (x_i, y_i),\ i = 1, \ldots, l\}$ to collect RSS measurements from n APs using a reference device D_0. A reference fingerprint $r_i = [r_{i1}, \ldots, r_{in}]^T$ associated with location ℓ_i is a vector of RSS samples and r_{ij} denotes the RSS value related to the j-th AP. Usually, r_i is averaged over the multiple fingerprints collected at ℓ_i so that only one fingerprint, i.e. $\overline{r}_i = \frac{1}{M}\sum_{m=1}^{M} r_i(m)$, is stored in the RSS radiomap followed by the physical coordinates (x_i, y_i). With this preprocessing we reduce the effect of noise in RSS measurements and outlier values, while the radiomap is compressed leading to a significant decrease in the location estimation time.

Online phase: During positioning, we exploit the reference data to obtain a location estimate $\widehat{\ell}$, given a new fingerprint $s = [s_1, \ldots, s_n]^T$ measured at the unknown location ℓ by some device $D_i,\ i = 0, \ldots, N_d$. The positioning algorithm tries to find the best match between the currently observed fingerprint s and the reference fingerprints $\overline{r}_i$ in the RSS radiomap. Various positioning algorithms have been presented, such as deterministic and probabilistic approaches (Bahl *et al.*, 2000; Roos *et al.*, 2002; Youssef *et al.*, 2005), assuming that the offline and online phases are performed with the same device D_0. In this work we allow the online device to be *any* device $D_i,\ i = 0, \ldots, N_d$ and focus on the improvement achieved solely by our device self-calibration method, rather than the fingerprint-based positioning algorithm itself. Thus, our results are obtained using the well known Nearest Neighbor (NN) method (Bahl *et al.*, 2000) that estimates location by minimizing the Euclidean distance d_i between the observed fingerprint s and the reference fingerprints $\bar{r}_i$

$$\widehat{\ell}(s) = \arg\min_{\ell_i} d_i, \quad d_i = \sqrt{\sum_{j=1}^{n} (\bar{r}_{ij} - s_j)^2}. \tag{2}$$

All reference locations are ordered according to d_i and location ℓ_i with the shortest distance between $\bar{r}_i$ and s in the n-dimensional RSS space is returned as the location estimate. Note that the proposed self-calibration approach is independent of the underlying positioning algorithm and using more accurate approaches, such as probabilistic methods (Roos *et al.*, 2002), is expected to further reduce the positioning error with respect to the NN method.

4 Experimental Setup

We performed our measurement campaign for collecting RSS data at KIOS Research Center. This is a $560\,\mathrm{m}^2$ typical office environment that consists of several open cubicle-style and private offices, labs, a conference room and corridors (Fig. 1a). We have installed 9 local APs that use the WLAN standard and provide full coverage throughout the floor. Moreover, there is a varying number of neighboring APs that can be sensed in different parts of the floor and in some locations more than 60 APs could be detected. We used 5 different mobile devices for our data collection, namely a HP iPAQ hw6915 PDA with Windows Mobile, an Asus eeePC T101MT laptop running Windows 7, an HTC Flyer Android tablet and two other Android smartphones (HTC Desire, Samsung Nexus S). The data collection for the Android devices was conducted with our Airplace logging and positioning platform (Laoudias *et al.*, 2012). **In particular, we used the Airplace Logger application to collect RSS values from the surrounding APs at several reference and test locations, as follows. The floorplan map is displayed on the Android device within the Airplace Logger user interface, enabling the user to select his/her current location by clicking on the map and then click on-screen buttons to initiate and end the logging process.**

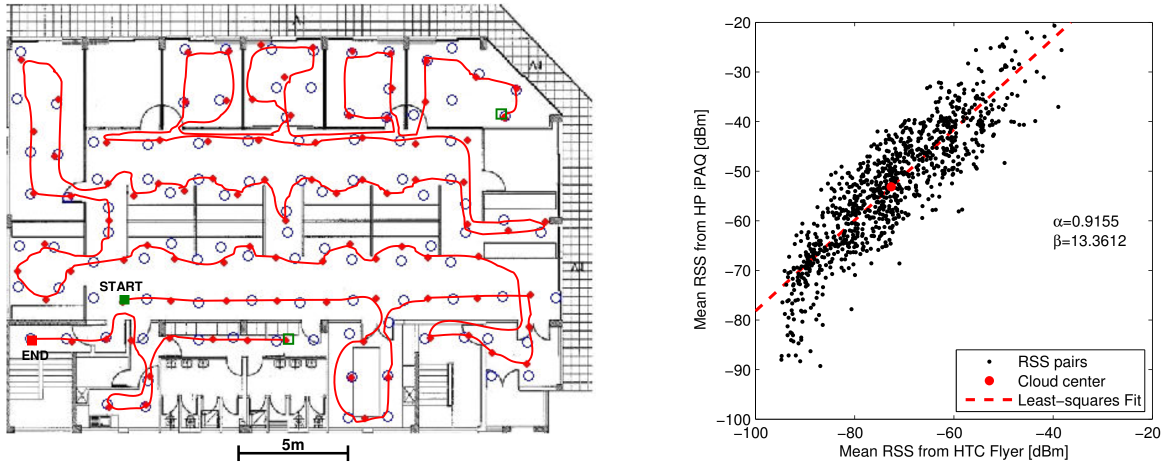
For our training data we recorded fingerprints, which contain RSS measurements from all available APs, at 105 distinct reference locations by carrying all 5 devices at the same time. A total of 2100 training fingerprints, corresponding to 20 fingerprints per reference location, were collected with each device. These data are used to build device-specific radiomaps by calculating the mean value RSS fingerprint that corresponds to each reference location. We point out that the device-specific radiomaps are needed *only* for evaluation purposes. We collected additional test data two weeks later by walking along a predefined route. The route has two segments and consists of 96 locations most of which do not coincide with the reference locations; see Fig. 1a. We sampled the same route 10 times by carrying all devices simultaneously, while one fingerprint was recorded at each test location[1].

5 Device Calibration

In the manual calibration method the linear parameters are estimated through standard least squares, assuming that a sufficient number of colocated RSS pairs (i.e., collected at the same *known* location and time with two different devices) is available. To put it formally, for two devices D_1 and D_2 the RSS data in the respective radiomaps are used to compute the parameters by

$$\bar{r}_{ij}^{(2)} = \alpha_{12}\bar{r}_{ij}^{(1)} + \beta_{12}, \tag{3}$$

[1]The KIOS dataset is available to download at `http://www2.ucy.ac.cy/~laoudias/pages/platform/downloads/KIOSdataset.zip`



(a) (b)

Figure 1. (a) Experimental setup at KIOS Research Center. Reference locations used during the offline training phase are shown with blue circles; the positioning phase route is shown with a red line. (b) Linear fitting for the HP iPAQ – HTC Flyer pair.

where $\bar{r}_{ij}^{(1)}$ and $\bar{r}_{ij}^{(2)}$ denote the mean RSS value at location ℓ_i from the j-th AP for D_1 and D_2 respectively, while α_{12} and β_{12} are the linear parameters for mapping the RSS values from D_1 to D_2. This is demonstrated in Fig. 1b.

As already discussed, the manual calibration approach is not very practical and implies the tedious task of collecting data prior to positioning. Thus, our goal is to exploit histograms of RSS values collected with the reference and user device in order to develop a fully automatic approach that does not require any user intervention.

5.1 *RSS Histograms*

The RSS histograms of three different devices are shown in Fig. 2. These histograms correspond to the mean RSS values from all available APs collected at all 105 reference locations. The first observation is that two histograms may differ significantly with respect to the range of RSS values, as well as the probability of each RSS value, as in the case of HP iPAQ and HTC Flyer. On the other hand, the respective histograms for some device pairs can be quite similar, as in the case of Asus eeePC and HTC Flyer. Note that compared to our previous work (Laoudias *et al.*, 2012), where we considered only the RSS values from the local APs, the histograms considered in this paper are left-skewed because there is a large number of weak RSS values recorded from APs that are located far from the user. This is most evident in the histogram of the iPAQ device, which features a more sensitive WLAN adapter and is able to detect very distant APs (Fig. 2a).

Assuming that the relation between the RSS values reported by diverse devices is linear, there is a simple way to exploit the histograms that are accumulated on each device for some time. Specifically, one can deduce the extreme values from the respective RSS histograms and then obtain the linear fitting parameters from the following system of equations

$$\mathbf{S}^{(2)} = \alpha_{12}\mathbf{S}^{(1)} + \beta_{12}, \tag{4}$$

where $\mathbf{S}^{(1)} = [s_{min}^{(1)}\ s_{max}^{(1)}]^T$ and $\mathbf{S}^{(2)} = [s_{min}^{(2)}\ s_{max}^{(2)}]^T$ denote the vectors that contain the minimum and maximum RSS values in the histograms of devices D_1 and D_2, respectively. This method is very appealing due to its low complexity, however the calibration can be significantly deteriorated under some conditions, as shown by the experimental results in Section 6.

5.2 *Self-calibration Method*

The relation among the RSS histograms of different devices is also reflected in the equivalent empirical cumulative distribution functions (cdf), as shown in Fig. 2d. We have observed that the empirical cdf of the raw RSS values, recorded while walking around with a particular device for a few seconds, resembles the respective empirical cdf of the mean RSS values collected with the same device at several uniformly distributed *known* locations. This implies that we may exploit these empirical cdfs to perform device calibration during positioning. The main idea in the proposed self-calibration method is the use of RSS histograms to obtain a mapping between the reference and various user devices, thus avoiding the bother of the manual calibration method.

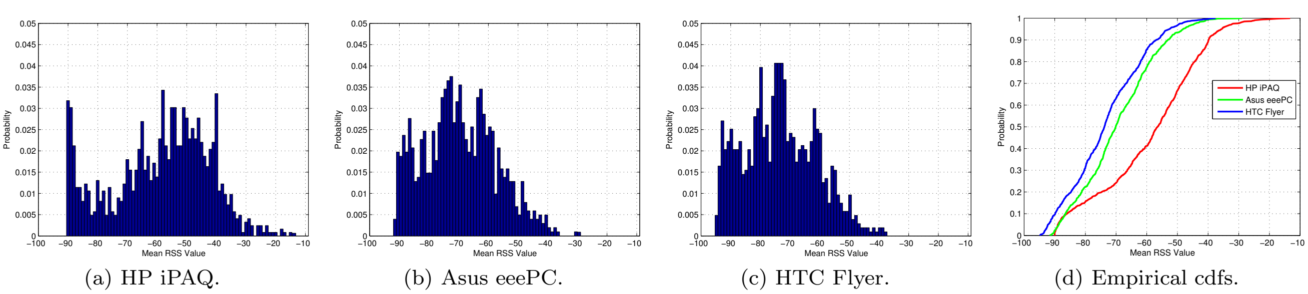
The block diagram of our method is shown in Fig. 3a. First, we use the existing radiomap that contains the mean value fingerprints $\bar{r}_i$ to obtain the RSS histogram of the reference device. Subsequently, when the user enters a building and starts positioning, the RSS values in the currently observed fingerprint $s(k)$ are recorded simultaneously in the background in order to create and update the histogram of raw RSS values for the user device. Then, we use the RSS values that correspond to specific percentiles of the empirical cdf to fit a linear mapping of the form (3) between the user and reference devices. Subsequently, the parameters (α, β) are used to transform the RSS values observed with the user device and obtain the new fingerprint $\tilde{s}(k)$, where $\tilde{s}_j(k) = \alpha s_j(k) + \beta,\ j = 1, \ldots, n$. The fingerprint $\tilde{s}(k)$ is compatible with the radiomap and finally the unknown location $\hat{\ell}(k)$ can be estimated with any fingerprint-based algorithm. The *Device Calibration* component in our method that computes the parameters (α, β) is detailed in the following.

Let $F_r(x)$ and $F_u(x)$ denote the empirical cdfs of the reference and user devices, respectively. In general the cdf $F(x)$ gives the probability of observing an RSS value that is less than x, while the inverse cdf $F^{-1}(y)$ returns the RSS value that corresponds to the y-th cdf percentile. We use the RSS values that correspond to the 10-th, 20-th, ..., 90-th percentiles of the empirical cdf to fit a least squares linear mapping between the user and reference devices and estimate the parameters (α, β) according to

$$F_r^{-1}(y) = \alpha F_u^{-1}(y) + \beta,\ y \in \{0.1, 0.2, \ldots, 0.9\}. \tag{5}$$

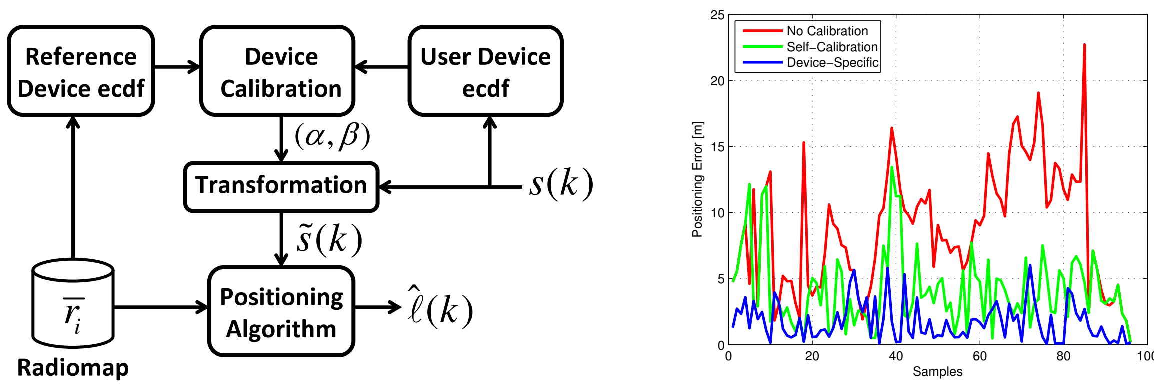
A formal proof on the validity of the least squares mapping (5) that uses the inverse cdf percentile values to reveal the underlying functional relationship between the RSS values collected with different devices can be found in (Laoudias *et al.*, 2012).

A question that arises is how much time is needed in practice until the user device is self-calibrated. While the user is walking, the current fingerprint $s(k)$ contributes only a few RSS values and $F_u(x)$ does not change significantly between two consecutive samples. Thus, it is not necessary to update $F_u(x)$ every time a new fingerprint $s(k)$ is available, but rather one can buffer the RSS values contained in a number of successive fingerprints and then update $F_u(x)$ before performing the linear fitting. We have experimentally found that the buffer size $b = 10$ works well in our setup, i.e. (α, β) are recalculated every 10 seconds. At the beginning, we initialize the parameters to $(\alpha, \beta) = (1, 0)$, i.e. no transformation is performed, to handle the positioning requests until the buffer is full and the parameters are estimated for the first time. Using a lower value for b does not seem to improve the positioning accuracy significantly, while it introduces unnecessary computational overhead. On the other hand, increasing b means that the parameters are not



(a) HP iPAQ. (b) Asus eeePC. (c) HTC Flyer. (d) Empirical cdfs.

Figure 2. Histograms of the mean RSS values from all available APs at all 105 locations and corresponding empirical cdfs.



(a) (b)

Figure 3. (a) Block diagram of the self-calibration method. (b) Positioning error in a single route for the HP iPAQ – HTC Flyer pair.

updated frequently enough and the performance is degraded, especially at the beginning until (α, β) are estimated for the first time.

Calculating the least squares fitting parameters (α, β) is the most demanding task in our self-calibration method in terms of computational power. We propose a modification to address this issue in case such computation is costly for low-resource mobile devices. In particular, we fix $\alpha = 1$, so that we actually fit a unit slope linear mapping and only estimate the parameter β using the following median estimator

$$\beta = \text{med}(F_r^{-1}(y) - F_u^{-1}(y)), \;\; y \in \{0.1, 0.2, \ldots, 0.9\}. \tag{6}$$

This approach is valid because several experimental studies (Tsui *et al.*, 2009; Kjærgaard, 2011; Laoudias *et al.*, 2012) have reported that the α values among different device pairs are usually around 1. With this modification only one parameter, instead of two parameters, needs to be estimated and the computational overhead of the least-squares fitting in (5) is significantly reduced. More importantly, this benefit comes without compromising the performance of the self-calibration method, as the experimental results in Section 6 indicate.

6 Experimental Results

We assess the performance of the proposed self-calibration method using experimental data collected with five devices in a real office environment from all available APs, as described in Section 4. We consider two variants, namely the self-calibration method, denoted SC, that calculates the fitting parameters with (5) and the modified self-calibration method that assumes $\alpha = 1$ and estimates β with (6), denoted SCmed. We also evaluate the histogran-based method in (4) that computes the fitting parameters using only the minimum and maximum RSS values for each device pair, referred to as MM.

In our comparison we also include some state-of-the-art calibration methods, such as the Signal Strength Difference (SSD) method of Mahtab *et al.* (2013), the Hyperbolic Location Fingerprinting (HLF) method of Kjærgaard (2011) and the Rank Based Fingerprinting (RBF) method of Machaj *et al.* (2011). For the SSD method we select the reference AP as the one with the least average deviation of RSS values over the whole localization area (Mahtab *et al.*, 2010) and we apply the same approach to the HLF method. Finally, for completeness we report the positioning accuracy of the Manual Calibration (MC) method that uses the mean RSS values collected with the new device at all 105 locations visited with the reference device (Haeberlen *et al.*, 2004; Kjærgaard, 2006), as well as the two extreme cases of No Calibration (NC) and using a Device Specific radiomap (DS) collected with each device that provide the upper and lower bound on the performance, respectively.

First, we demonstrate the efficiency of the SC method on a single route using the iPAQ radiomap, while the user carries the Flyer device. The performance of our method is illustrated in Fig. 3b, where we have used a buffer size $b = 10$. We observe that in the first 10 seconds the accuracy is not adequate, because the device is still uncalibrated. While the user is walking the raw RSS values are collected in order to build the RSS histogram that will be used for the self-calibration. It is obvious that beyond that point, the user device has been automatically calibrated and the positioning system **delivers accuracy that is considerably better compared to the no calibration case and is much closer to the case of using a radiomap that is created from data collected with the Flyer device.**

Next, we investigate the performance of the SC method in terms of the positioning error attained while the user is walking. In particular, we calculate the mean positioning error $\bar{\epsilon}$ for a single route which is the distance between the estimated and actual user locations averaged over the 96 locations that comprise the testing route. By sampling the testing route 10 times, we calculate the statistics for $\bar{\epsilon}$. These statistics, pertaining to all 10 routes, are depicted as boxplots in Fig. 4 for some indicative device pairs. **Note that on each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, while the whiskers extend to the most extreme values of $\bar{\epsilon}$, except outlier values which are shown individually as red crosses.** The first observation is that positioning without device calibration should be avoided because it may lead to significant accuracy degradation. For instance, for the iPAQ – Desire pair (Fig. 4a) if the Desire device is not calibrated the median of the mean error $\bar{\epsilon}$ is around 10 m compared to 2.2 m in case we use a radiomap collected with the Desire, instead of the iPAQ, device. Both variants of our self-calibration method (i.e., SC and SCmed) are very effective and achieve performance that is very close to the manual calibration approach as shown in Fig. 4a, but with considerably less effort. **Note that for the calculation of the error statistics we have included all the initial location estimates, obtained before the parameters (α, β) have been estimated. Regarding the estimation of the parameters (α, β), the process was restarted at the beginning for each one of the 10 testing routes, i.e. for each route the parameters were initialized to $(1, 0)$ and then estimated using the proposed methodology, to guarantee the same conditions for the 10 experiments. Of course, in real life applications, these parameters can be estimated once when the user walks inside a given indoor environment for the first time and then be stored on the device for future use in this environment.**

Surprisingly, the SSD and HLF methods perform poorly for the iPAQ – Desire pair. It turns out that their performance can be improved, if we consider only the local APs, instead of all the APs in the vicinity, during positioning. This is a strong indication that for small-scale, fully-controlled setups, where the APs provide full coverage, the SSD and HLF methods are adequate. However, in large-scale setups, where the APs provide intermittent coverage, their performance might deteriorate. For other device pairs, the SSD and HLF methods seem to be more robust to device diversity, however they are still both outperformed by the proposed self-calibration method; see for example Fig. 4b and Fig. 4c. Moreover, the performance of the RBF method is also very poor in most scenarios, highlighting that the fine-grain information of the RSS levels is lost when ranks are used.

On the other hand, the simple histogram-based MM method seems to work well in practice for some device pairs and achieves the same level of accuracy as our self-calibration method, as shown in Fig. 4a and Fig. 4b. However, our experimental results reveal that in some cases, relying only on the minimum and maximum RSS values for the device mapping is not a good strategy, as demonstrated in Fig. 4c. For the Flyer – eeePC device pair, the MM method fails to calibrate the eeePC device and the resulting positioning error is almost double, compared to the SC and SCmed methods. In particular, the MM method computes the fitting parameters (α, β) as $(0.76, -27.35)$, while the optimal values attained by the MC method are $(0.89, -11.09)$. This is due to the fact that the eeePC device recorded an outlier maximum RSS value that caused the β parameter to deviate from the optimal, thus leading to poor calibration and consequently high positioning error. Similar behavior was observed for other device combinations, as shown in the following.

The performance of the calibration methods in case the user-carried device is the same as the device used to collect the RSS data for the radiomap is depicted in Fig. 4d. Even though, in many real life applications the positioning system is expected to track mostly diverse devices, there is always the possibility of a user carrying the same device. We observe that the positioning error of the SSD and HLF methods is increased compared to the self-calibration method and in fact it would be better not to employ them at all if this situation can be identified (e.g., the device transmits its brand and model to the positioning system). This

Table 1. Median of the mean error $\bar{\epsilon}$ [m] for different device calibration methods.

	eeePC							Desire						
	SC	**SCmed**	**MM**	**SSD**	**HLF**	**RBF**	**MC**	**SC**	**SCmed**	**MM**	**SSD**	**HLF**	**RBF**	**MC**
iPAQ	3.7	2.8	3.8	4.5	4.6	5.6	2.7	4.2	3.0	3.6	5.5	5.8	5.1	2.9
eeePC	2.2	2.2	2.3	2.7	2.7	3.6	2.2	2.7	2.6	3.6	3.3	3.3	3.7	2.6
Flyer	2.2	2.2	2.7	2.6	2.5	3.6	2.3	2.4	2.3	2.4	3.0	2.9	3.8	2.4
Desire	2.5	2.5	2.5	2.7	3.0	3.8	2.5	2.4	2.3	2.2	2.9	2.9	3.6	2.3
Nexus S	2.3	2.3	2.9	2.9	2.7	3.9	2.4	2.5	2.4	2.7	2.7	2.7	3.8	2.4

Table 2. Median of the maximum error ϵ_{max} [m] for different device calibration methods.

	eeePC							Desire						
	SC	**SCmed**	**MM**	**SSD**	**HLF**	**RBF**	**MC**	**SC**	**SCmed**	**MM**	**SSD**	**HLF**	**RBF**	**MC**
iPAQ	11.6	8.8	11.2	12.0	11.2	20.5	9.7	14.0	13.2	11.2	12.4	13.6	16.5	14.3
eeePC	9.5	9.5	8.9	10.7	10.8	13.0	9.5	8.4	8.8	13.3	10.2	12.1	11.9	9.4
Flyer	7.9	7.7	8.9	7.9	9.4	12.0	7.8	9.0	8.7	8.9	9.1	9.1	11.5	9.6
Desire	8.6	8.9	8.7	8.2	9.3	12.7	8.9	8.2	8.2	8.2	9.3	9.3	10.8	8.2
Nexus S	7.5	7.5	8.9	10.5	10.2	13.6	9.4	9.8	9.6	9.3	8.4	8.6	11.5	9.6

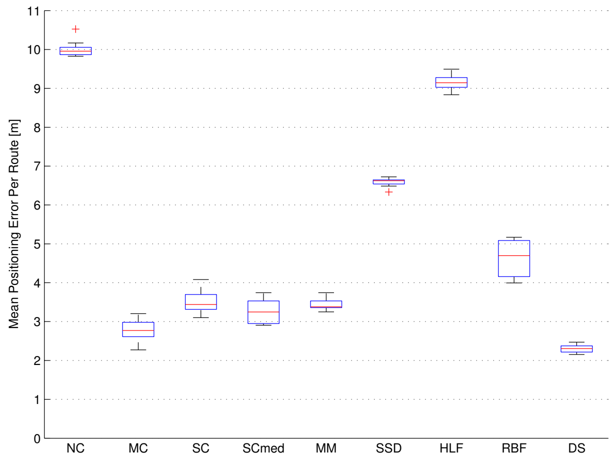
behavior is due to the smaller dimensionality of the SSD and HLF fingerprints, as noted by Mahtab *et al.* (2013). Moreover, transforming the RSS values in SSD and HLF methods reduces the discriminative capabilities of the RSS values at the expense of better accuracy when heterogeneous devices are considered.

The results for five different user-carried devices are summarized in Table 1, where each row indicates the device used during positioning while we assume that the reference device is either the Asus eeePC or the HTC Desire. For every device pair the median of the mean positioning error $\bar{\epsilon}$ is reported for various calibration methods. The calibration performance of MM method seems to be affected in several cases, e.g. the eeePC – iPAQ, the eeePC – Nexus S or the Desire – eeePC device pairs. Looking at these results it is evident that the proposed self-calibration method improves accuracy for all device pairs and provides similar calibration performance with the MC method. Note that the SCmed method attains the same level of performance with the SC method, despite its reduced computational cost, and interestingly it proves to be more resilient to device heterogeneity; see for example the eeePC – iPAQ and the Desire – iPAQ device pairs. **This is probably because the estimated slope parameter α is usually close to 1, so the intercept parameter β is more important to obtain a good fitting. Thus, in practice, the SCmed method seems to perform better than the SC method for some device pairs because it avoids overfitting when the signal strength histograms have not yet converged.**

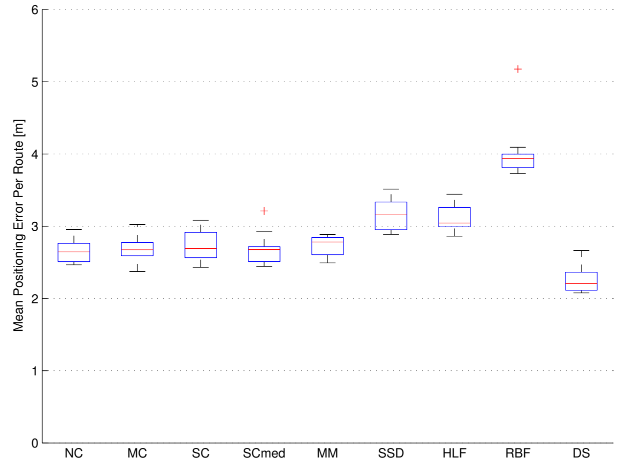
Table 2 tabulates the results on the median of the maximum error ϵ_{max} pertaining to the same 10 testing routes. These results highlight that both self-calibration methods can alleviate high positioning errors for most device pairs, compared to other device calibration methods, while the SCmed method provides a slight improvement over the SC method. Thus, according to our findings, the SCmed method is a good candidate solution that exhibits two highly desirable properties; robustness to device diversity and low computational complexity.

7 Conclusion

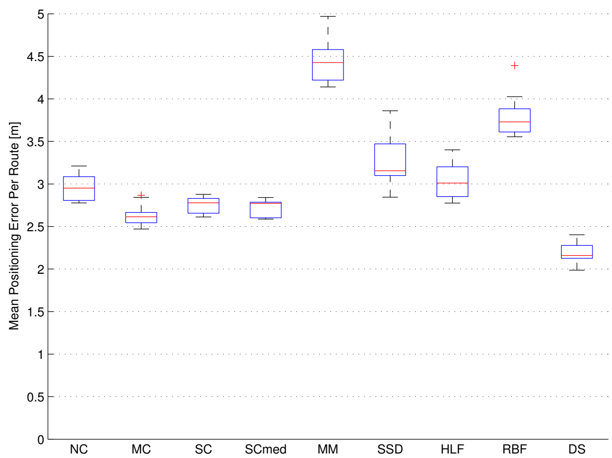
Robust calibration methods that address the device heterogeneity problem effectively are expected to enable the proliferation of RSS-based indoor positioning systems. To this end, we presented a simple, yet very effective calibration method that does not require any user intervention and allows any mobile device to be self-calibrated in short time. Our method exploits the existing RSS radiomap and the RSS values observed while the user is moving freely inside the localization area to create the RSS histograms of the reference and new device, respectively. Subsequently, the new device is self-calibrated, i.e. the observed RSS values become compatible with the radiomap, by fitting a linear mapping between the histograms of these two devices. Contrary to existing RSS data fitting approaches, self-calibration is performed concurrently with positioning and visiting several locations for collecting RSS calibration data is not required.



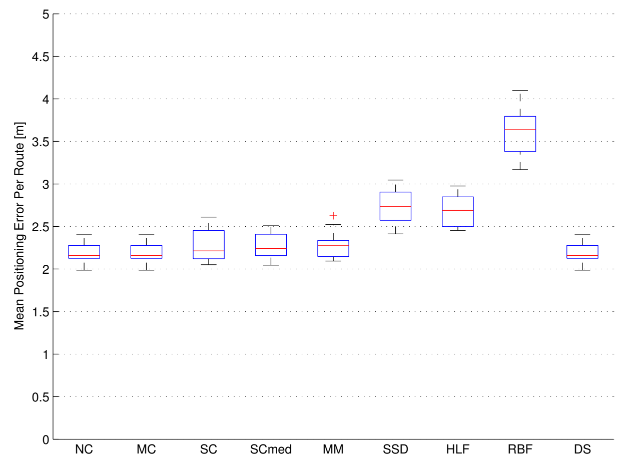
(a) HP iPAQ radiomap – HTC Desire user.



(b) HTC Flyer radiomap – Samsung Nexus S user.



(c) HTC Flyer radiomap – Asus eeePC user.



(d) Asus eeePC radiomap and same user-carried device.

Figure 4. Boxplots of the mean positioning error $\bar{\epsilon}$ for various device pairs.

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