

Clustering benefits in mobile-centric WiFi positioning in multi-floor buildings

Andrei Cramariuc, Heikki Huttunen and Elena Simona Lohan
Tampere University of Technology
Tampere, Finland
Emails: {andrei.cramariuc, heikki.huttunen, elena-simona.lohan}@tut.fi

Abstract—In mobile-centric indoor positioning, having a small databases to transfer from the network side to the mobile is of utmost importance. For scalable and low-complexity solutions, various clustering algorithms have been suggested in the literature, either in coordinates or 3D dimension or in the Access Points or Received Signal Strength (RSS) dimension. Typically, the two dimensions were investigated separately. This paper offers a comparative analysis between different clustering methods, together with a novel metric, called the Penalized Logarithmic Gaussian Distance metric which can boost the performance of the clustering. The results are compared based on real-field measurement data in two different multi-floor buildings and they are given in terms of estimation errors, floor detection probabilities and complexity. It is shown that the proposed metric enhances the performance of both 3D and RSS clustering and that the RSS clustering has lower complexity but worse performance than the 3D clustering. We are also providing in open-access the measurement data together with the Python-based implementation of the algorithms to serve as future benchmarks for indoor positioning studies.

I. INTRODUCTION AND STATE-OF-THE-ART

WiFi-based positioning via Received Signal Strength (RSS) information is becoming more and more popular as a complementary positioning tool to GNSS, especially in indoor scenarios. RSS is easily accessible from the application layer on any mobile device, without the need of complex hardware or software changes and RSS-based positioning can work both in network-centric and in device-centric modes. Moreover, with the advent of crowdsourcing data collection [1], [2], large-scale solutions are becoming a reality. In a network-centric mode, the position estimate is computed by the network, based on the fingerprinting databases available at the network side and on the on-line mobile measurements. The amount of data exchange between the network and the mobile is rather low in this case, as only the RSS on-line measurements by the mobile and the final position estimate by the network need to be transferred from each other. The mobile-centric or device-centric solutions on the other hand, while arguably offering more location trace privacy [3], lower latency (as the localization is done locally and there is no need to wait for the network data transfer) and the possibility of reaching a position estimate even in the absence of an Internet connection on the mobile, it does require a larger data exchange between the network and the mobile for the training or offline phase. The fingerprint database or a relevant part of it needs to be transferred to the mobile (e.g., it can be

transferred when an Internet connection is available, then also used when such connection is not active, such as in roaming) and the positioning processing at the mobile side needs to be computationally inexpensive, in such a way that it won't consume a lot of the battery life. Scalability of the solution is also important in order to be able to achieve large-scale positioning solutions.

Minimizing the positioning-related data exchange between the network and the mobile and minimizing the databases sizes stored at the mobile side are thus two important aspects in achieving low complexity fast positioning results in mobile-centric positioning. Traditionally, these two problems have been solved by using probabilistic data models, where a reduced set of parameters, such as the path loss model parameters associated with each Access Point (AP) in the considered geographical area, are computed and transferred to the mobile [4], [5], [6]. Another way of reducing the database sizes and increasing the transfer speed is to preserve only a relevant subset of the heard APs [7]. Yet, a third approach to deal with the data size reduction is the clustering approach, which is the focus of our paper. Clustering can be done in two dimensions, namely the 3D or coordinates clustering [8], [9], [10], and the Access Points (AP) or Received Signal Strength (RSS) clustering [11], [12], [13], [14]. More details about these two clustering types will be given in Section II. Currently, to the best of the Authors' knowledge, there is very limited work comparing the clustering in the two dimensions (i.e., 3D versus RSS clustering). For example in [9], the authors compare k-means 3D clustering and affinity propagation RSS clustering in a reduced measurement environment, with a single corridor on a single floor and only 27 APs. Their conclusion is that affinity propagation clustering works much better than k-means clustering for a low number of clusters (up to 8), and it is much worse than k-means clustering when more than 9 clusters are used. As we will prove with our multi-floor datasets, such a conclusion does not hold for large measurement spaces (e.g., hundreds of APs) and for multi-floor buildings, where the AP clustering is giving worse results than the 3D clustering. The performance of the 3D clustering also proves to be highly dependent on the number of used clusters, with a rapid deterioration of the performance when the number of clusters increases above a threshold. One important contribution of our paper is to compare the 3D clustering with AP clustering in realistic multi-floor indoor

scenarios.

Another significant contribution of the paper is to propose a new Penalized Logarithmic Gaussian Distance (PLGD) metric which takes into account not only the Received Signal Strength (RSS) information of commonly heard AP in the training dataset and the estimation dataset, but it also uses the information carried out by the APs which are additionally heard on one of the two sets (training or estimation). It will be shown that PLGD approach can improve both the 3D clustering and the AP clustering, as well as offering some benefits when used also with the basic fingerprinting.

An additional added value of our work comes from providing our results in open access to the research community, as multi-floor measurement data are still very hard to be found and no current benchmark data exist for indoor 3D positioning to the best of the Authors' knowledge. To the best of our knowledge, the only available indoor WiFi measurements that can be used for positioning can be found in [15], [16], but no positioning algorithm or data analysis tool is provided with that set of measurements, and no benchmark accuracy is offered. For the purpose of offering some benchmark datasets of WiFi RSS data for multi-floor indoor positioning to the research community, we have added our measurement data and the Python-based data analysis via fingerprinting and clustering at [17]. The following sections in the paper are organized as follows: Section II describes the different clustering approaches used in RSS-based wireless localization, Section III describes the new proposed metric, Section IV describes the measurement set-up and the measurement-based results and Section V summarizes the findings.

II. CLUSTERING APPROACHES IN FINGERPRINTING

When clustering the fingerprints, there are two distinct approaches, either partitioning the fingerprints based on their 3D coordinates or based on their RSS vectors. A basic classification of clustering methods can be found for example in [18]. In there, the authors talk, among others issues, about k-means and its variants, such as k-medians and k-medoids. K-means is an clustering method suitable only for Euclidean spaces such as the 3D coordinates of the fingerprints. Due to the RSS vector space not being Euclidean, an approach using a variant of k-means, which selects the most representative element from each cluster as its centroid is more logical. A similar method to k-medians and k-medoids is affinity propagation clustering which also has the advantage of producing better quality clusters [19]. While the terminology used in [18] does not specifically refer to 3D coordinate clustering and AP/RSS clustering, it is clear from their clustering equations that the k-means is used to cluster the data according to their coordinates (i.e., 3D clustering), while affinity propagation is used to cluster the data according to their RSS values (i.e., RSS clustering). By no means is this an exhaustive list, but these are indeed the most encountered clustering methods in WiFi-based positioning. Hierarchical methods are less encountered in WiFi positioning applications. An example can be found

[20], where a Support Vector Machine (SVM)-based hierarchical partitioning was proposed for indoor localization. The classification in [20] was done in two stages: first the visible APs are given some accessibility index, then the visible APs are used for positioning. This method clusters the APs, and not the fingerprinting coordinates, thus belongs to the category of RSS clustering.

A. Fingerprinting without clustering

The method used as benchmark in our paper is the traditional fingerprinting without clustering, explained in what follows. In the online phase the current RSS vector is compared to the fingerprints gathered during the offline phase. Using the Weighted K Nearest Neighbours (WKNN) algorithm, a set of fingerprints is selected as possible candidates for the current location. The weighted average of the positions of these fingerprint will then be the estimate for the current position. The distance metric used in the WKNN algorithm is a variation of the Logarithmic Gaussian Distance (LGD), that has proven to be robust in environments with many fingerprints and APs [5]. The LGD of two RSS vectors \mathbf{p} and \mathbf{r} is

$$\text{LGD}(\mathbf{p}, \mathbf{r}) = - \sum_i \log \max(G(\mathbf{p}_i, \mathbf{r}_i), \epsilon) \quad (1)$$

where $G(p, r)$ is the Gaussian similarity between two values p and r , defined as

$$G(p, r) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(p-r)^2}{2\sigma^2}\right), & \text{if } p \neq 0 \text{ and } r \neq 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

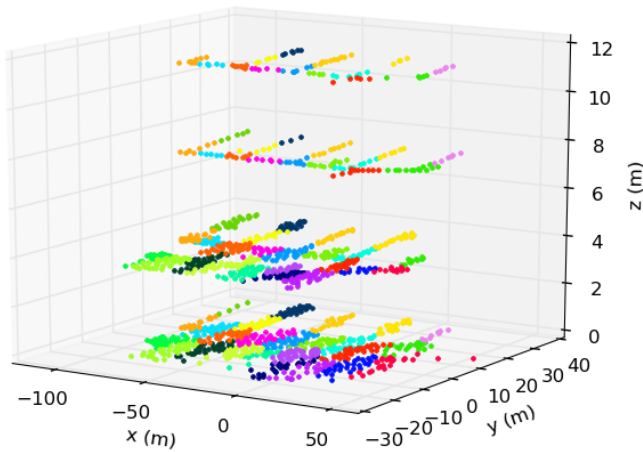
The shadowing variance σ^2 has been studied for example in [21], [22]. It was shown in there that standard deviation values σ between 4 and 10 dB can model quite well the indoor scenarios. In our analysis we used $\sigma = 5$ dB. Small improvements (cm level) can be obtained if σ is pre-computed in the training phase per AP, but the additional computation burden is not justified based on the small performance improvement compared with the case of constant shadowing variance per building. The maximum in Eq. (1) is necessary to avoid logarithm of zero as well as having one APs visibility influence the LGD above a certain threshold.

B. 3D (Coordinates) clustering

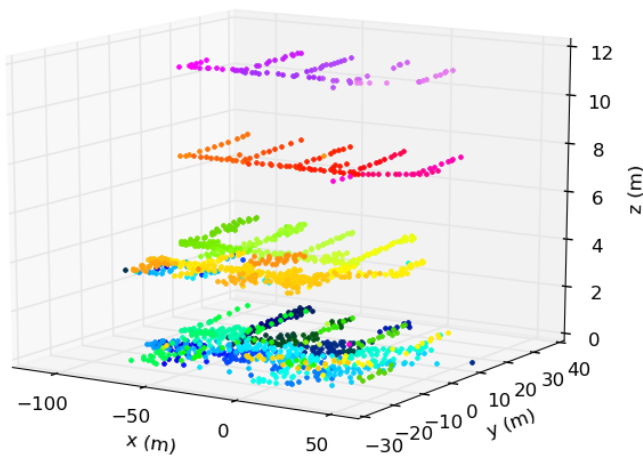
K-means is probably the most well known clustering method when using Euclidean distances and a predetermined number of clusters [18], [23]. For a set of 3D coordinates \mathbf{x} and a set of clusters \mathbf{c} , k-means attempts to minimize the within-cluster sum of squares or in other words

$$\arg \min_{\mathbf{c}} \sum_i \sum_{\mathbf{x}_i \in c_i} \|\mathbf{x}_i - \boldsymbol{\mu}_i\|^2 \quad (3)$$

In Equation 3 $\boldsymbol{\mu}$ represents the mean of the points in the clusters \mathbf{c} . After the initial positioning, only the fingerprints belonging to the closest cluster to the current position estimate as well as its neighbouring clusters will be used to determine the final position using WKNN. The use of the neighbouring clusters is necessary to provide smooth transitions between



(a) 3D coordinate clustering using k-means



(b) RSS clustering using affinity propagation

Fig. 1: Example 3D (upper) and RSS (lower) clusterings of the fingerprints gathered in University 1. Each color represents a different cluster.

clusters as well as accurate position estimates at the edge of a cluster. No clear partitioning of the 3D coordinates of the fingerprints exists that would clearly improve accuracy in another way than by restricting far away points from contributing to the positioning. As this is the only requirement, the uniform and spherical clusters produced by k-means are a good solution to the desired partitioning. An example of a possible 3D clustering of the fingerprints is available in Fig. 1a, where different colors represent different clusters. We can see that the same clusters can split over several floors, for one of the studied buildings, as the floor height is typically smaller than the maximum horizontal distance where an AP is heard.

C. Access Points (RSS) clustering

The most used methods for the AP or RSS clustering are based either on k-means and its variants [10] or on affinity propagation clustering. The affinity propagation clustering method was proposed in [19] and it is based on selecting a set

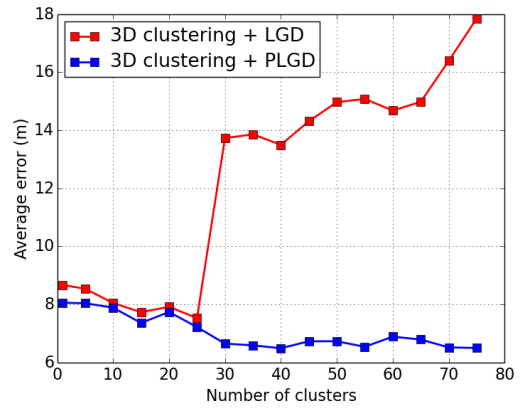


Fig. 2: The average error in relation to the number of clusters used in the 3D clustering with k-means.

of exemplars from the dataset that best represent each cluster. The RSS clustering is done by taking as input the similarity between each data point and exchanging messages between them until a high enough quality set of exemplars emerges. For example, both authors in [13] and [14] use affinity propagation clustering in order to group the APs for increased precision or reduced computation cost. Our studies showed that affinity propagation clustering works slightly better with the RSS clustering than the k-means clustering and it gives exactly the same results as k-medians clustering. For this reason, the results shown here for RSS clustering are based on the affinity propagation algorithm. In this paper we use the LGD as a measure of similarity between points both for the affinity propagation as well as the WKNN algorithm for the fine positioning. In order to determine a subset clusters to be used for the WKNN algorithm the LGD is used to compare the exemplars of the clusters, with the current RSS vector. The resulting clustering for one building can be seen in Fig. 1b, with different colors representing different clusters. We can see that the RSS clustering tends to remain over one floor only, with few exceptions, which usually occurred around open spaces between floors in the building.

III. PROPOSED PENALIZED LOGARITHMIC GAUSSIAN DISTANCE METRIC

One of the short-comings of the LGD is that it only compares the access points that are visible in both RSS vectors (in the training and estimation data), therefore not considering all available information. The proposed distance metric combines the LGD with a linear penalty for the APs that are not visible. The penalty function for the APs visible in \mathbf{p} but not in \mathbf{r} is defined as

$$\phi(\mathbf{p}, \mathbf{r}) = \sum_i T_{\max} - p_i, \text{ for } 0 < p_i \leq T_{\max} \text{ and } r_i = 0 \quad (4)$$

where T_{\max} is an upper threshold for the strength of the visible signal. In our studies we used $T_{\max} = 85$ dB. The threshold is so as to avoid penalizing for measurements that are at the



Fig. 3: An example of the measurement environment.

edge of the measurement range and could either be seen or not seen by chance. The resulting metric will be referred to as the Penalized Logarithmic Gaussian Distance (PLGD) and is defined as

$$\text{PLGD}(\mathbf{p}, \mathbf{r}) = \text{LGD}(\mathbf{p}, \mathbf{r}) + \alpha(\phi(\mathbf{p}, \mathbf{r}) + \phi(\mathbf{r}, \mathbf{p})) \quad (5)$$

where α is a scaling factor dependent on the number of APs. As the number of APs increases the LGD remains relatively constant, while the Penalty Factor increases with the number of APs. To keep the relative importance between the two metrics the alpha factor must be larger when there are more APs. In our studied measurement environments the optimal values were selected empirically, $\alpha = 40$ for University 1 and $\alpha = 10$ for University 2.

One of the pitfalls of using clustering in the 3D coordinate space is that large errors will also affect subsequent estimates, due to the system selecting the wrong cluster. A significant error can sometimes cause the current estimated position to remain stuck inside one cluster while the user moves farther away. An advantage of the penalty function is that it can be used to help determine if the measured RSS vector is outside the currently selected cluster. Because missing APs are more indicative of a bad positioning than the similarity of commonly seen APs the proposed penalty function is a better measure than the LGD at determining if the wrong cluster was chosen. In addition in comparison to the LGD, the proposed penalty function is much faster to calculate for two RSS vectors. If the penalty function is above a certain threshold, a positioning can be attempted using more fingerprints than only those belonging to the nearest cluster. Fig. 2 illustrates that the addition of the penalty function and its thresholding avoids errors from propagating to subsequent estimates, which allows for the use of more clusters.

IV. MEASUREMENT-BASED RESULTS

A. Measurement setup

The WLAN RSS measurements were collected using a Nexus touch-screen tablet with HERE proprietary software. The maps of the building were available at the time of the

TABLE I: Average error [m]

	Method*					
	1	2	3	4	5	6
University 1	8.7	8.1	8.8	8.0	7.6	6.8
University 2	4.0	3.8	4.1	4.0	3.8	3.6

TABLE II: Average floor detection accuracy [%]

	Method*					
	1	2	3	4	5	6
University 1	91	94	89	95	90	93
University 2	97	97	97	97	97	98

TABLE III: Decrease in complexity by a factor of (with respect to methods 1 and 2)

	Method*					
	1	2	3	4	5	6
University 1	1	1	20	20	4.5	5.5
University 2	1	1	25	25	6.5	11

*) Methods

- 1) LGD
- 2) PLGD (proposed)
- 3) RSS clustering (affinity propagation) + LGD
- 4) RSS clustering (affinity propagation) + PLGD (proposed)
- 5) 3D clustering (k-means) + LGD
- 6) 3D clustering (k-means) + PLGD (proposed)

data collection and the measurements were done using a combination of manual and automatic fingerprint collection. The collection process was that first the user set his position on the map through visual software installed on the tablet and afterwards he started the RSS data collection by moving in straight lines across rooms and corridors. At the end of each such line segment the user had to again select his current location using the table. The resulting fingerprints were obtained by linearly interpolating between the endpoints of the line segments assuming constant user speed. The rate of RSS fingerprint collection was three fingerprints per second. The collected fingerprints were then mapped into a 1 m grid by using the mean values. In such a way, the different orientations of the tablet during the data collection were averaged out to some extent. A picture showcasing the measurement environment is visible in Fig. 3.

The fingerprint data was collected from two different university buildings referred to as University 1 and 2. The amount of mapped fingerprints for the two buildings was 1906 and 745, respectively, divided in to a training and test set. The number of visible access points in the buildings was 354 and 309, respectively. We remark that one AP is counted based on the heard MAC addresses, but several APs can be located at the same physical location, as it is the case of the multiple antenna support or multiple BSSID support in WLANs.

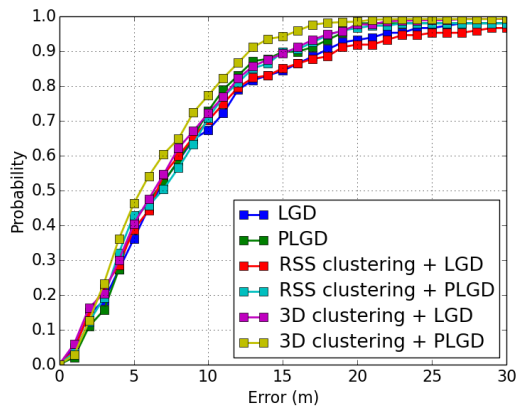


Fig. 4: Cumulative distribution function for the average error in University 2.

B. Positioning accuracy

The average positioning error and the floor detection probability for all the discussed methods are listed in Tables I and II, respectively. In all possible combinations the PLGD has a better accuracy (in both positioning error and floor detection probability) than the LGD. Clustering the datasets also provides a slight increase in accuracy in most of the cases compared to the basic fingerprinting. As it can be seen from the cumulative distribution function presented in Fig. 4, the proposed 3D clustering with PLGD reduces the number of extremely large positioning errors and provides the best accuracy. An example of an estimated test track with the 3D clustering + PLGD method is visible in Fig. 5.

C. Complexity comparison

All the clustering methods trade an increase in the complexity of the offline or training phase for a decrease in complexity during the online or estimation phase. This trade-off is highly beneficial for the mobile-centric positioning, as the training phase takes place at the server side, where the battery consumption is not an issue, while the online phase takes place at the mobile side, where low power algorithms are of utmost importance. Assuming on average that all the clusters have the same number of fingerprints, the decrease in complexity with respect to the basic fingerprinting (methods 1 and 2 from Tables I to III) is proportional to the total number of clusters C_{total} and the average number of clusters used for an individual position estimate C_{used} . The new execution time will therefore be

$$t_{new} = t_{old} \frac{C_{used}}{C_{total}} \quad (6)$$

The average decrease in complexity can be seen in Table III. The higher the factor in Table III, the lower the complexity of the method. Out of the two investigated clustering approaches, the RSS clustering made by affinity propagation (methods 3 and 4) clearly allows for the largest decrease in complexity, while still maintaining an average error below the standard approach of using all the fingerprints (methods 1 and 2). As

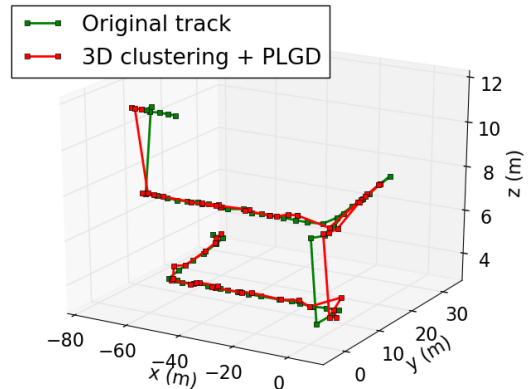


Fig. 5: Example of an original and estimated track inside University 1.

stated previously, the PLGD in combination with k-means allows the use of more clusters than when using just LGD, which is reflected in a decrease in complexity. PLGD combined with the 3D clustering thus offers the best tradeoff between the positioning performance and the complexity.

V. CONCLUSION

In this paper we have compared the two types of clustering used in WiFi positioning: the 3D clustering versus the RSS clustering, and we have also shown the standard fingerprinting results as a benchmark. In addition, we have proposed a new metric, the Penalized Logarithmic Gaussian Distance metric to boost the performance of the existing clustering approaches. It was shown that overall both the 3D coordinate and AP clustering of the fingerprints significantly reduce the execution time compared to the fingerprinting, with some benefits also to the positioning accuracy. The best performance in terms of complexity reduction is achieved with an RSS clustering via affinity propagation (complexity reduction factor of 20). However, the best positioning accuracy both in terms of positioning error and floor detection probability is achieved with a 3D clustering using k-means and PLGD metric. The proposed PLGD metric proved effective in preventing errors from propagating during the cluster selection, which is a major problem because the cluster selection is based on the estimate of the current position. The investigated algorithms have also been made available as an open-source to the research community, in order to offer measurement-based benchmarks in WiFi-based positioning.

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Our measurement data and the Python implementations of the investigated algorithms are now available at [17].

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