RSS-based Localization for Directional Antennas

Anetta Nagy, Thomas Bigler, Albert Treytl
Department for Integrated Sensor Systems
Danube University for Continuing Education
Viktor Kaplan Straße 2-E, A-2700 Wr. Neustadt, Austria
{firstname.lastname}@donau-uni.ac.at

Roland Stenzl, Stefan Wilker, Thilo Sauter
TU Wien
Institute of Computertechnology
Gußhausstraße 27-29/E384, 1040 Vienna, Austria
{firstname.lastname}@tuwien.ac.at

***Abstract*— With increasing deployment of wireless devices also localization gets a consequential boost in industrial and other IoT environments. Localization so far in most cases assumes omni-directional antennas. This paper investigates a generalized Received Signal Strength (RSS) fingerprinting localization algorithm for antennas with arbitrary radiation patterns in order to include IoT devices with directional antennas in localization.**

Focus is set on the recursive algorithm which improves performance of the traditional fingerprinting methods. First a machine-learning aided analysis of the overlapping reception areas of the antennas is conducted for quickly determining possible initial positions of the nodes to be localized. Then, for reaching higher resolution, different up-scaling techniques and gradient search is applied. In particular, the localization accuracy vs. computational efficiency is investigated which is an important trade-off for many applications.

***Index Terms*—RSS fingerprinting, position estimation, directional antenna, clustering**

I. Introduction

Wireless communications are getting increasingly popular not only in IoT applications but also in more conservative industrial environments. This is owed to the advances in their real-time capabilities and reliability by introducing redundant wireless links and by careful antenna selection: For example, in order to increase power efficiency and robustness against disturbances (but also to spatially separate the wireless signals of the increasing number of nodes) often directional antennas are employed.

Although industrial wireless communications were at first mainly seen as a point-to-point connection replacement, nowadays they are employed in a wide range of applications, especially in those involving mobile nodes. However, the freedom of mobility often comes with the cost of localization. Current localization schemes are mostly based on omni-directional antennas and use trigonometric or hyperbolic mathematics to calculate the position by using arrival angles, signal strength, or propagation time, often in combination with post-processing approaches such as fingerprinting [1], [2]. The rare approaches using directional antennas solely pursue the goal of estimating the Direction of Arrival (DoA).

The research presented in this paper aims at using nodes deployed in the field (e.g., stations along a conveyor line) for localization purposes fully supporting antennas with arbitrary characteristics. This includes (highly) directional antennas, but also antennas with limited omni-directional radiation patterns. To improve the performance, our Received Signal Strength (RSS) fingerprinting approach calculates the position in an iterative manner refining it to the requested resolution. Several position refinement algorithms were implemented applying either different up-scaling techniques or a gradient search. Common for all of them is that the RSS fingerprints at the up-scaled sampling points are obtained by calculations, which requires models of the angle dependent antenna gains. We rely on a numerical modeling approach already discussed in [3] based on actual, high-resolution antenna radiation patterns. Furthermore, as the iterative position refinement introduces additional computation costs, we mitigate this by a fast initial position estimation algorithm. This initial step is based on creating clusters over the RSS fingerprint map which represent areas where certain signal conditions are met. A comparison of clustering algorithms based on their suitability for the initial position determination was already presented in [4].

In this article we present the first implementation of an overall system and the evaluation of different scenarios typical for industrial applications. Focus is set on the investigation of accuracy vs. efficiency being an important trade-off for many applications. Section III presents the clustering-based initial position determination idea and multiple recursive position refinement algorithms. Section IV describes the proof-of-concept implementation and the results of an evaluation based on simulations and first measurements including issues of noise influence on the location accuracy.

II. Related Work

The basic idea of localization is that the node to be localized (the target node) needs to be within range of several receivers (anchor nodes). The anchors observe distance-relevant parameters (field strength, propagation time or angle-of-arrival). In the case of self-localization the target node observes these parameters itself.

Although the RSS can be directly converted to the distance (thus position) using radio propagation models, the simpler way of determining a target's position is based on fingerprinting techniques. The idea behind RSS fingerprinting is to measure (or compute) the RSS at certain sampling points over the area of interest and later compare the actual measured RSS with the pre-measured (computed) RSS fingerprints. A well-known example is the RADAR system [5]. However, conducting actual measurements over a large localization area is a time consuming and expensive process. Therefore, algorithms to reduce the effort for fingerprinting have been researched extensively. Reducing the number of measured fingerprints and calculating the rest of them by interpolation has been proposed in [6]. In [7] an automatic approach is proposed to both build a radio map and to assess the best system calibration that fits the required positioning quality. In summary, with these fingerprinting approaches, for many cases sufficiently accurate methods for indoor localization can be achieved.

Most RSS-based systems use omni-directional antennas, due to the fact that the assumption of a uniform antenna gain in all directions allows (theoretically) simple algorithms [1]. Nevertheless, this assumption is not always valid, especially for cheap patch antennas in modern portable devices. The usage of directional antennas for RSS-based localization has also been discussed in several publications. In [8] the propagation characteristics of such directional antennas are analytically investigated for angle-of-arrival (AoA) applications. It also covers the effects of multipath propagation and none-line-of-sight (NLOS) situations, which are particularly important for localization tasks. Nevertheless, most of the practical approaches described in literature use directional antennas in a sectoral manner only, either through rotating antenna platforms or (switched) antenna arrays.

In [9] a rotating directional antenna is mounted on a moving beacon. By adding a GPS receiver on the moving node it acts as a reference that allows position estimation with a range-free approach. This means that the signal strength is not used to calculate the distance directly. Rather, the current position and angle of the rotating antenna together with the AoA estimation of the response signal from the static node can be used to determine an absolute position. Instead of a rotating antenna, the authors of [10] use a setup with two perpendicular antennas per node. The position of the transmitter can be determined by comparing the RSS values at the antennas and then calculating the intersection. Similarly, in [11] several planar antennas are combined into a three-dimensional unit so that direction and position of a transmitter in the room can be estimated by switching between the individual directional antennas. The principle behind this method is, therefore, the combination of multiple angular information similar to triangulation. An interesting feature of this work is that it is possible to determine the position with only one node by an appropriate arrangement of the patch antennas. This approach can also applied in combination with fingerprinting, which was shown in [12], where a spherical setup of directional antennas was used.

A general trend in the field of localization systems is also the use of machine learning and neural networks. This is for example shown in [13], where the K-Means clustering algorithm is used to create a more accurate fingerprinting map. In this paper, the clustering algorithm is used to mitigate environmental effects, such as multipath propagation and shadowing, and basically acts as filter that performs better than standard averaging operations. Similarly, in [14] a convolutional neural network (CNN) is applied to first train a model in the offline phase using the collected RSS data, which is subsequently used for localization in the online phase. In [15] this is further refined by combining multiple machine learning algorithms which results in an increased robustness. Generally, machine learning approaches and neural networks can be rather processing time intensive, especially in the online phase. Therefore, the authors in [16] investigated the offloading of the localization system to a Field Programmable Gate Array (FPGA).

III. Proposed Concepts

RSS fingerprinting has been the most prevailing indoor localization method in the past and has been extensively studied. The major drawback concerning manual RSS measurements is tackled either by reducing the number of measured sampling points and using interpolation (often combined with modern machine learning algorithms) or entirely skipping them by the usage of profound propagation models. Attempts to re-calibrate the RSS map in the position determination phase are also made, e.g., to mitigate disturbances. RSS is well known to be prone to error caused by various environmental effects, however, these can reduced by careful antenna selection and RSS map planning. In one of our previous works [17] we approached this issue for the first time by using directional antennas for RSS fingerprinting.

A second drawback of basic RSS fingerprinting consist in a balance between accuracy and performance. Low resolution RSS sampling points lead to low positioning accuracy, while high resolution increase computational expenses. This is especially evident in industrial applications, with potentially a high number of target nodes. Instead of searching for the best matching fingerprint over the entire RSS map, we propose to first quickly identify a rough initial solution of the target and then refine it, substantially reducing CPU time without any degradation in accuracy. This concept has been already adopted in some localization systems regardless of the underlying radio technology employed (e.g. [18] where sensor nodes are localized by a single drone), but we determine the initial position by a novel RSS map analysis method: (1) during initialization, the RSS map is created and analyzed based on machine learning algorithms by clustering the fingerprints resembling similar signal conditions; (2) in the position determination phase, the RSS values that are measured can be quickly assigned to best matching cluster; and (3) the (iterative) position refinement is conducted from the cluster's midpoint by up-sampling of the RSS values within the selected cluster.

A. *RSS Map Building for Directional Antennas*

Our RSS map building concept was introduced in our previous works [3], [4] and will be discussed here only briefly. Unless intention is to obtain the entire RSS map by means of measurements, profound models of the radio signal propagation, the environment and antennas are a must. When it comes to directional antennas, often simplified models are used not representing the full characteristics of the radiation pattern. In [3] we already discussed a numerical modeling approach by storing the measured antenna gains within look-up tables as (angle; gain) pairs. The look-up table can be created (based

TABLE I
DEFINED SIGNAL STRENGTH LEVELS [19]

RSS [dB]	Expected quality	Quality level
-30	Maximum signal strength	Excellent (E)
-50	Excellent signal strength	Excellent (E)
-60	Good and reliable signal strength	Good (G)
-67	Reliable signal strength	Medium (M)
-70	Weak signal strength	Weak (W)
-80	Unreliable signal strength	Weak (W)
-90	Connection loss	Connection Loss (CL)

on specification or measurements) with any resolution, again depending on the trade-off between the accuracy (of the model) and the needed effort for creating the look-up table. Since the angle between an anchor and sampling point can be calculated by simple trigonometry, the directional antenna gain can be easily included for generating the RSS values at every sampling point in the map.

This approach has a second advantage: it enables us to detect overlapping areas of practically any number of antennas and with any types of patterns. When it comes to localization, at least 3 anchors are needed. To detect the overlapping area, it is sufficient to iterate through the RSS map and at each sampling point analyze the RSS fingerprint. We have done this by selecting the three highest RSS values and converting them to the corresponding three RSS levels as defined in table I.

Then, the 3 RSS levels are converted to a class number which represents a combined signal quality. With 3 RSS values per sampling point, and with the 4 signal levels, we end up having 20 classes (calculated using combinations with repetition). The additional connection loss (CL) class contains all the sampling points with insufficient number of anchors in reach.

B. RSS map Clustering

Once the RSS fingerprints are all converted to a signal quality class number, the ones belonging to the same class are further processed. We run a clustering algorithm over the them to divide the RSS map into smaller areas with known signal quality classes, center points, and sizes. The resulting clusters heavily depend on the chosen clustering algorithm. In our previous work [4] we conducted a detailed analysis on K-means and Mean-Shift with focus on the cluster quality and suitability for our application. K-means is a well-documented algorithm and widely used for clustering data. It excels by a low computational time but has a crucial drawback: k, the number of clusters to be formed, is unknown beforehand. Since we want a highly automated system, we tried to find the best number of clusters by iterative repetition until some threshold is met. As shown in [4], a robust solution is an iteration until all clusters fall under a specific size. Opposite to this, the Mean-Shift algorithm finds the best number of clusters itself, hence it does not require additional calculations. Its drawback is that it is computationally expensive ($O(n^2)$) and often produces larger clusters, hardly dividing the RSS map, which is not optimal for our application.

While working with real antennas, arbitrarily shaped and differently sized clusters could provide the best results. This could lead to problems when working with a parametric algorithm such as K-means. Therefore, with an eye on the future use of hardware, we extended the work with Affinity Propagation and HDB-Scan. Affinity Propagation is a high-speed algorithm, especially when working with a large number of clusters, which is feasible in large scale scenarios. HDB-Scan is a popular algorithm, too, especially due to its noise-canceling abilities.

C. Fast Initial Position Estimation

The signal quality class based clustering of the RSS map provides several advantages for initial position estimation. First, the computed cluster centers can be seen as a new RSS map with a reduced number of carefully selected sampling points. Second, during position calculation, the measured RSS values can be converted to a class number using the same principle. Hence, we can limit the initial position search within that particular class. Finally, as a cluster identifies a small area, the initial position is estimated with a (relatively) high accuracy.

In the future we also intend to extend the computed clusters with a additional information (as e.g. a list of the anchor nodes in range) for furthermore optimizing the initial position search algorithm.

D. Position Refinement Algorithm

Once a best matching cluster is found, the position needs to be refined to increase the localization accuracy. With the cluster center point taken as the initial position, the simplest approach is to define the (refinement) search area as a square with a side length equaling the cluster's diameter. We considered multiple algorithms based on up-sampling the cluster and one algorithm based on a gradient search.

1) Algorithms based on up-sampling: The up-sampling algorithms are implemented in an iterative manner: the cluster (search area) is first sampled with lower resolution, and the best matching fingerprint is determined, e.g., using the Root Mean Square Error (RMSE) measure. Then, a smaller sub-area is defined around the selected fingerprint, which is then sampled with higher resolution in order to find a better match. This can be then repeated until the desired resolution is achieved.

Beside this simple recursive algorithm (SREC), a couple of variants of the algorithm have been implemented, both using the same principle. The goal of the first variant is to further increase accuracy by using the K-Nearest Neighbor (KNN) classification method. Here several most best-matching fingerprints are chosen instead of one, and the target position is calculated as a mean (simple or weighted) of the selected fingerprints. In the second variant the sampling points are generated using the Latin Hypercube Sampling (LHS) method, which generates near-random sampling points. In a two-dimensional case the result of the LHS algorithm is a square grid, where in each row and column only one sample position exists. The idea behind this is to reduce the number of generated samples, hence improve computation time without significant accuracy impairment.

Figure 1 shows the principle of the up-sampling algorithms: On the left-hand side the simple recursive algorithm is depicted with the sampling points driven all over the entire search area around the initial position. By contrast, the right-hand side of the figure shows a Latin Hypercube sampling-based (LHS) algorithm with the decreased number of sampling points.

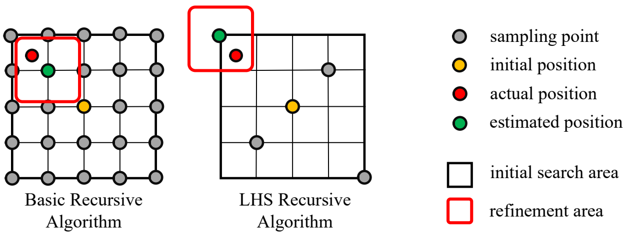

Fig. 1. Principle of the basic recursive and recursive LHS algorithm

Figure 2 illustrates the resulting position refinement cycles of a single position calculation. The triangles numbered from 1 to 4 are the anchor nodes, the green dot stands for the target's actual position, and the numbered red dots are as follows: (1) is the initial position (in this case was simply selected as the geometrical midpoint of the anchor node positions), (2) thew intermediate refined position, and (3) the final refined position after reaching the defined (in this case 0.25 m) sampling point resolution.

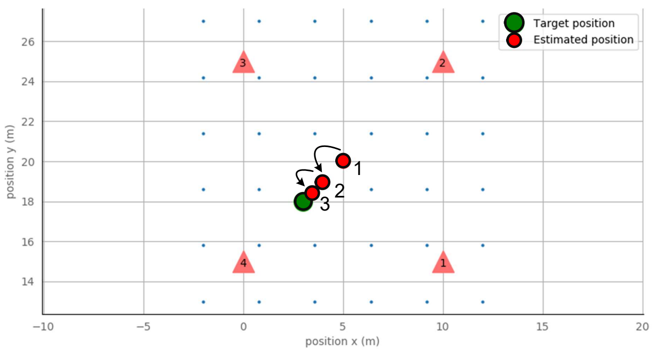

Fig. 2. A single position calculation cycle of the SREC algorithm

2) Gradient search based algorithm: Beside the recursive algorithms relying on the up-sampling principle, we have also implemented a gradient search-based algorithm using this well-known optimization technique. In our implementation the algorithm computes 8 neighbor fingerprints around the initial position and selects the best matching one. The procedure is repeated with respect to best matching neighbor, until no better match is found. The principle of our gradient search algorithm is shown in figure 3. The weak point of the gradient search is that it is a local optimization algorithm. If there are multiple local minima on the RSS map, the gradient search can reach a false local minimum and does not reach the position closest to the actual position.

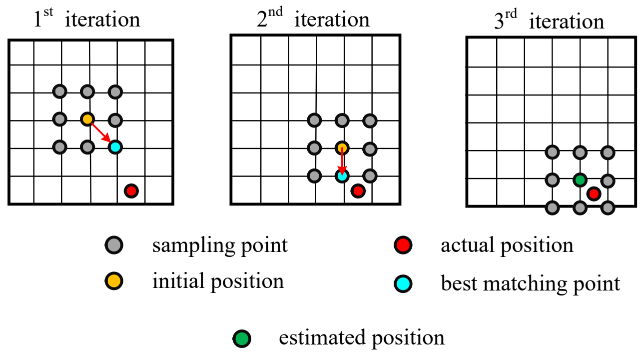

Fig. 3. Gradient search of target position

IV. Proof of Concept

In order to validate our concepts, all of the discussed concepts have been implemented in Python. The section is organized as follows: First, a comparison of our selected four clustering algorithms is presented which was done based on algorithm evaluation criteria recommended in the literature. Second, the position determination algorithms are evaluated based on a selected simulation setup with primary focus on the computation time vs. localization accuracy.

A. *Clustering algorithms evaluation*

The requirements for cluster algorithms are different for each application, and therefore the evaluation of the cluster quality is a very individual task. To get some general directions we followed on the recommendations in [20] and used three scoring algorithms: (I)Silhouette analysis, (II)Calinski Habarasz score and (III)Davies Bouldin score. Each of them is designed to determine the ideal number of clusters, but focuses on a different aspect of clustering, allowing us to view the issue from different perspectives. The silhouette analysis evaluates for each data sample, how similar it is to its own cluster compared to the other clusters, and provides a score between [-1, 1]. A high value indicates a well-formed cluster, i.e., that the samples were assigned to an appropriate cluster. The Calinski Harabasz score is defined as the ratio between the within-cluster dispersion and the between-cluster dispersion. The higher the value, the better the formed clusters are. Davis Bouldin score evaluates intra-cluster similarity and inter-cluster differences and indicates well-formed clusters by the lowest value converging to zero.

To evaluate the quality of the clusters, we used the same method as previously in [4]. Fifty localization scenarios were generated, and the three scores were calculated. The result are listed in table II.

Our analysis lead us to the following conclusions:

Even though each of the algorithms has a different computational complexity, all of them had similar process times. This

TABLE II
CLUSTER ALGORITHM COMPARISON

	K-means	MS	HDB-Scan	AP
Time [ms]	3.903	4.071	3.808	3.716
Silhouette-Analysis	0.395	0.555	0.449	0.475
Calinski-Harabasz score	231.1	161.4	155.3	193.0
Davies–Bouldin score	0.640	0.532	2.180	0.617

leads us to the conclusion that for small data-sets like ours, the choice of cluster algorithm does not affect the processing time a lot. The Silhouette-score of all 4 algorithms were close to 0.5 which is a rather good score. Our cluster size-dependent version of K-Means was preferred by the Calinski-Harabasz-algorithm. The clustering done with HDB-Scan is rated poorly overall, especially by the Davies-Bouldin method leading us to the assumption that HDB-Scan creates many densely packed clusters.

Moreover, since the idea is to use the center of the clusters as an initial starting point for the localization, the actual form of the clusters is important. Both Affinity Propagation and HDB-Scan do not create spherical clusters predominantly, which means that the centers of these clusters could be located outside the clusters. This would automatically lead to a wrong initial position since the cluster defines the high probability area of the target's location. Based on the evaluation, it was decided to restrict further research to the K-means and Mean-Shift algorithms and test first our clustering-based initial position estimation aided RSS fingerpinting concept. Nevertheless, in the future we will consider to use HDB-Scan for post-processing the computed positions, as its excellent noise handling could indeed bring advantages.

B. Position determination algorithms estimation

The aim of the section is to compare the different localization algorithms in combination with several possible initial position determination algorithms. Figure 4 depicts the simulation use-case. It is a 54 meter times 29 meter area, which is a realistic size for an industrial environment. We have placed 16 anchors with 15 dBi 60 degrees sector antennas. As our intention is to illustrate the algorithms and compare the accuracy vs. computation time, the simulations have been based on free space propagation with a path-loss model for the 2.4 GHz carrier frequency. In order to include noise and interference from reflections or multipath propagation we added noise to these simulated RSS values as described in section IV-D4.

The 16 anchors have been placed such as to represent different actual installation situations on factory floors and allow us to evaluate situations with different requirements. It should be noted that our antenna placement is in some cases deliberately not optimized for localization performance to show the effects of such existing situations. Optimal (additional) anchor placement for localization is not within the scope of this paper. The area with trajectory T1 and anchors A10 to A14 is an area where precise position estimation is required, e.g., due to safety issues, hence, the area of interest is covered by all four main lobes. The area with trajectory T2 and anchors A1 to A10 could be used for localizing targets moving along, e.g., a conveyor belt, with different wireless stations positioned only according to the production tasks having antenna orientations not optimized for localization. Finally, anchors A15 and A16 are envisioned as point-to-point wireless communication replacement, but are able to take part in the position determination along trajectory T3.

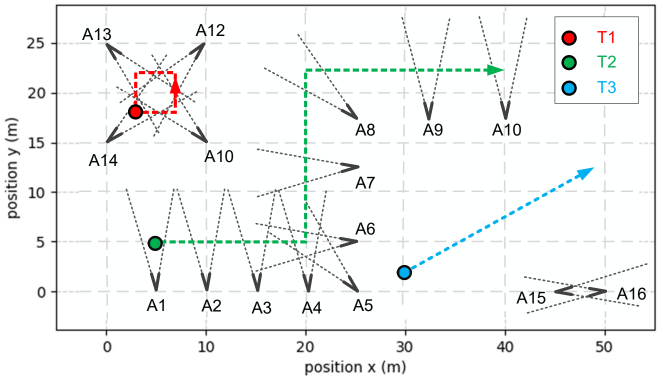

Fig. 4. Scenario setup with simplified drawing of main antenna lobes

The first step in the simulation is to create the RSS map and convert the RSS fingerprints to the signal quality classes as explained in section III-A. Figure 5 shows the quality classes of the simulation scenario. The points in the heat map resemble the combined signal quality value of the three strongest RSS fingerprints measured by the anchors in reach. As the figure suggests, the trajectory T1 resides in an area which is well suited for localization with strong combined signal quality in most of the points. Trajectory T2 passes through areas with diverse combined signal quality with sharp transitions. Finally, at trajectory T3 the combined signal quality is more uniform.

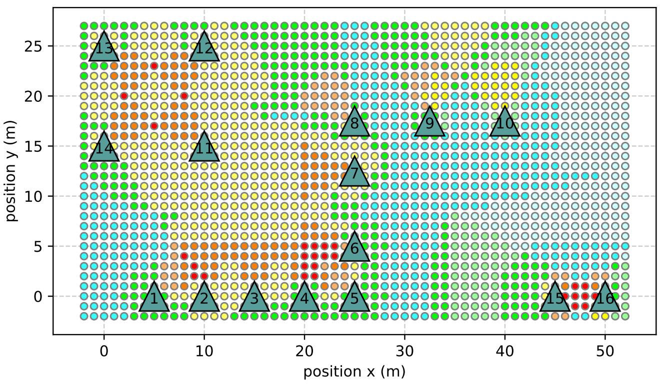

Fig. 5. Signal quality class-based RSS map of the test simulation setup

C. Basic RSS fingerprinting algorithm

As the goal was to reduce computation time by reducing the number of sampling points, we first tested how the resolution of the sampling points affects the accuracy and the computation time which was measured by using the default timer from the timeit library. In the first run, the resolution was set to 1 m, which equals 1650 sampling points in total. In the second run it was set to 2 m (420 points) and finally to 3 m (190 sampling points). Table III lists the simulation results of the basic RSS fingerprinting algorithm as reference. Although there is no linear dependency, we could very roughly say, that by lowering the resolution of the sampling points by a meter, the accuracy dropped at least half a meter. Concerning the CPU time, there is a clear relationship between the number of sampling points and the measured run times: The 1 m resolution means 8.68 times more sampling points compared to the 3 m resolution. Accordingly, the average CPU time is as well approximately 8.5 times higher. Finally, the 2 m resolution has 2.2 more sampling points and twice the execution time.

TABLE III
BASIC ALGORITHM RESULTS

Trajectory	*Resolution* [m]	*Mean* [m]	*Variance* [m]	*Runtime* [ms]
I	1	0.345	0.023	93
	2	1.039	0.07	22
	3	1.39	0.78	11
II	1	0.92	1.41	95
	2	1.47	1.16	22
	3	1.93	2.12	9
III	1	0.73	0.32	95
	2	1.36	1.2	21
	3	2.27	2.36	9

D. Fast initial position computation algorithms comparison

To validate our clustering-based initial position estimation scheme, we ran several tests with different possible initial position estimation options. The up-sampling algorithms were configured to a highest resolution of 0.25 m, which equaled the step size in the gradient search.

1) Simple initial position estimation algorithm: In this scenario the basic RSS fingerprinting algorithm with the low, 3 m resolution was used for computing the initial position, and then the 3 types of up-sampling and the gradient search algorithms were applied. Table IV shows the corresponding results. The initial position run time ($CPU_{init-pos}$) is the average CPU time needed for the initial position determination, whereas the (CPU_{refine}) is the CPU time needed for the position refinement in ms. Compared to the basic algorithm with 3 m resolution, an improvement of the accuracy can be noticed with just a few ms overhead. At the same time, the accuracy is higher compared to the 1 m resolution basic algorithm.

2) Signal Quality Class-based simple initial position estimation: In this second run we created a 1 m resolution RSS map and converted the RSS fingerprints to the signal quality class numbers. However, we did not apply any clustering algorithms, hence each of the 20 classes contained a relatively long list of sampling points. The results of the simulation run are listed in table V. In general, there is a significant improvement of the accuracy while having just a minor overhead in CPU time (up to 3.5 ms, which is lower than 4 % or 30 % of the CPU time of the high- or low resolution algorithms, respectively).

TABLE IV
SIMPLE INITIAL POSITION ESTIMATION ALGORITHM

Trajectory	*Alg.*	*Mean* [m]	*Var* [m]	$CPU_{init\text{-}pos}$ [ms]	CPU_{refine} [ms]
I	GRAD	1.00	0.31	12	1.3
	SREC	0.61	0.24	14	3.8
	LHS	0.63	0.27	12	3.5
	KNN	0.41	0.05	13	3.1
II	GRAD	1.32	2.4	12	1.5
	SREC	1.26	2.29	14	3.8
	LHS	1.34	2.39	12	4.7
	KNN	1.36	2.9	13	3.1
III	GRAD	1.35	2.73	12	1.3
	SREC	1.66	3.21	14	3.8
	LHS	1.74	3.69	12	3.3
	KNN	1.78	3.64	13	3.3

TABLE V
RSS CLASS-BASED INITIAL POSITION ESTIMATION

Trajectory	*Alg.*	*Mean* [m]	*Var* [m]	$CPU_{init\text{-}pos}$ [ms]	CPU_{refine} [ms]
I	GRAD	0.18.	0.04	12.5	1.3
	SREC	0.25	0.03	12.5	3.0
	LHS	0.18	0.02	13	3.5
	KNN	0.14	0.02	13	3.1
II	GRAD	0.61	2.3	12	1.5
	SREC	0.62	1.53	12	3.1
	LHS	1.68	1.55	13	3.5
	KNN	0.62	1.72	12	3.2
III	GRAD	0.52	0.37	12.5	1.3
	SREC	0.39	0.19	12.5	3.2
	LHS	0.53	0.37	12.5	3.3
	KNN	0.46	0.31	12.5	3.3

3) Clustering-based initial position estimation: In this simulation run we applied the clustering algorithms as suggested on our high (1 m) resolution RSS map. In the first case we selected K-means. The algorithm parameters were configured in such a manner to obtain a higher number of smaller clusters (up to 2 m in diameter). Table VI shows the simulated results. Compared to the 1 m resolution basic algorithm, there is a major improvement in the measured times and a further improvement in the localization accuracy. Finally, we tested the Mean-Shift clustering algorithm. For our particular scenario the algorithm yielded a rather low number of larger clusters. The results are shown in table VII. Compared to the basic algorithm with high resolution, there is a degradation in accuracy (roughly 0.5 m), but at the same time a substantial improvement of the computation time.

4) Preliminary measurement results: At the current stage of the project the simulation setup from the previous section has not yet been verified by actual measurements. So far first steps toward setting up the system and antenna model gain measurements have been made. The measurements were done to verify the specified radiation pattern and (if necessary) calibrate our models. Three simple 60 degrees horn antennas were tested. The antennas were placed in a straight line, with

TABLE VI
K-MEANS WITH HIGH NUMBER OF CLUSTERS CLASS-BASED INITIAL POSITION ESTIMATION

Trajectory	*Alg.*	*Mean* [m]	*Var* [m]	$CPU_{init\text{-}pos}$ [ms]	CPU_{refine} [ms]
I	GRAD	0.53	0.19	4	1.6
	SREC	0.30	0.03	5	3.1
	LHS	0.28	0.04	4	3.8
	KNN	0.22	0.02	5	3.3
II	GRAD	0.75	1.3	4	1.6
	SREC	0.77	1.67	5	3.2
	LHS	0.73	1.51	4	3.8
	KNN	0.69	1.54	5	3.5
III	GRAD	0.74	0.4	4	1.8
	SREC	0.61	0.4	4	3.2
	LHS	0.61	0.29	5	3.6
	KNN	0.62	0.37	4	3.2

TABLE VII
MEAN-SHIFT ALGORITHM WITH LOW NUMBER OF CLUSTERS

Trajectory	*Alg.*	*Mean* [m]	*Var* [m]	$CPU_{init\text{-}pos}$ [ms]	CPU_{refine} [ms]
I	GRAD	0.78	0.42	1.8	2.5
	SREC	0.53	0.17	1.7	3.6
	LHS	0.52	0.13	1.7	4.6
	KNN	0.51	0.14	1.6	3.6
II	GRAD	1.55	6.02	1.8	2.5
	SREC	1.48	5.55	1.6	3.6
	LHS	1.41	5.32	1.7	4.5
	KNN	1.45	5.33	1.6	3.6
III	GRAD	1.07	1.03	2	2.6
	SREC	1.09	0.91	1.7	3.6
	LHS	1.13	1.11	1.7	4.6
	KNN	1.12	1.03	1.6	3.6

0.4 m distance between them. The RSS(i) was measured for around 80 s at 1 m distance from the middle antenna. Based on the mean value of the measured RSS and the path loss propagation equation the actual antenna gains were computed.

Besides calculating the actual antenna gains, we used the data to test our refinement algorithms. We defined a 12 m x 12 m search area around the anchors and computed the RSS map using the path-loss propagation model. The mean value and variance of the estimated position error were calculated based on the unfiltered values. The measured RSS values were filtered by a median filter. The results are listed in table VIII. As expected, the KNN refinement algorithm reached the highest accuracy (with just 0.21 m)

TABLE VIII
LOCALIZATION ERROR BASED ON THE MEASURED RSS DURING ANTENNA CALIBRATION

Name	*Mean [m]*	*Var. [m]*	*CPU total [ms]*
Basic (1 m)	0.49	0.10	12.7
SREC	0.39	0.07	4.0
KNN	0.21	0.14	4.1
LHS	0.43	0.12	3.8
Grad	0.36	0.11	3.2

In order to evaluate the simulation use-case in the presence of noise, but due to the lack of measurements at the current state, we decided to extract the measured noise from the antenna calibrations and feed it to the simulated RSS values. The mean value of the noise at the anchors were 0.1 dB, 0.2 dB and 0.65 dB, respectively, the variance 0.7 dB, 0.65 dB and 1.11 dB. We tested our most successful algorithm (the KNN up-sampling in combination with the K-means) against the basic 1 m and 3 m resolution algorithms. The results are listed in table IX.

TABLE IX
LOCALIZATION ERROR IN PRESENCE OF NOISE

Trajectory	*Alg.*	*Mean [m]*	*Var [m]*	*CPU time [ms]*
I	Basic 1 m	0.57	0.06	90
	Basic 3 m	1.44	0.27	11
	KNN	0.37	0.02	7
II	Basic 1 m	1.33	3.31	91
	Basic 3 m	2.12	2.63	11
	KNN	1.19	1.56	7
III	Basic 1 m	2.01	1.59	90
	Basic 3 m	2.72	3.73	11
	KNN	1.54	1.69	7

As expected, the accuracy dropped, but again the KNN algorithm outperformed the basic algorithm, both in terms of accuracy and CPU time. For a final visualization figure 6 shows the simulation setup. The green line denotes the actual trajectory of the targets, the blue line the trajectory calculated by the 1 m resolution basic algorithm and finally, the orange line marks the trajectory obtained by KNN up-sampling algorithm. Both algorithms performed well in terms of accuracy for trajectory T1. The calculated T2 and T3 trajectories show some major deviations from the actual ones. However, as the intention was to compare the localization algorithms solely, we deliberately show "raw", unprocessed calculated positions. Typically such outliers are easily detected and removed by means of filtering.

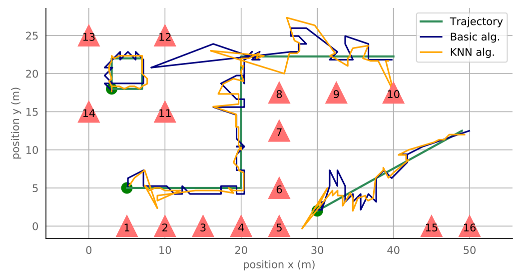

Fig. 6. Target trajectory results: basic low resolution vs. the KNN up-sampling

V. CONCLUSION AND OUTLOOK

This paper introduces a localization approach based on optimizing the search through the RSS fingerprint map for anchors using antennas with any type of radiation patters. We proposed a clustering-based algorithm for efficiently finding a suitable initial solution which is then refined to the desired resolution in an iterative manner. Several initial position estimation algorithms in combination with the refinement algorithms were compared against the traditional (basic) fingerprinting method.

Using the basic algorithm there is a clear trade-off between accuracy and CPU time: higher resolution RSS maps lead to higher accuracy, but are computationally expensive and vice versa. Our proposed algorithms allow us to reach higher resolution (thus achieving potentially higher accuracy) and at the same time significantly shorten the execution times. Based on simulation and first measurement results, we showed that the clustering-based initial position estimation algorithm provides good estimates. The size of the clusters plays a significant role: a higher number of small clusters means a more accurate initial position estimate, hence, choosing the right clustering algorithm was essential.

Concerning the position refinement, the results show that the up-sampling algorithms perform better in terms of accuracy over the gradient search algorithm. In particular, the K-Nearest Neighbor based algorithm achieves the highest accuracy. Opposite to our expectations, the Latin Hypercube Sampling (LHS) based algorithm brought no further improvement of the run time. On the one hand, the algorithm does reduce the number of sampling points, but in the other hand, introduces overhead due to generating the pseudo-random distribution.

Further midterm activities are focused on the influence of noise on the localization accuracy which we want to assess both by means of simulation and measurements. Simulation will focus on the comparison of omni-directional vs. directional antennas for optimal anchor placement and experiments will be conducted to extract statistical parameters for calibrating the simulation models. We also intend to investigate the best number of anchors taken for position estimation in over-determined systems. Although taking the minimal required 3 (for two-dimensional) or 4 (for three-dimensional localization) anchors which measured the highest RSS values seems a logical choice (which is at the same time computationally the least expensive), parameters such as raw RSS- and estimated distance variance, the quality of the antennas, etc. can be used to weight the anchors to further improve accuracy. Moreover, the position of anchors relative to each other (and the targets) could significantly influence the accuracy (due to geometrical dilution of position and the environment itself). All these facts ask for a more profound anchor selection algorithm. Finally, post-processing of the calculated positions is required, hence different approaches based on filtering and weight adding to the coordinate calculation of the target nodes (as for example proposed in [21] for WSNs) will be investigated.

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