Indoor Localization with Low Complexity in Wireless Sensor Networks

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***Abstract*— Autonomous localization of nodes in wireless sensor networks is essential to minimize the complex self organization task consequently enhancing the overall network lifetime. Recently, precise indoor localization is impeded by multi path propagation of signals due to reflections at walls or objects. In this paper we partly overcome some of these problems by methods like frequency diversity and averaging multiple measured data. Received radio signal strength (RSS) in combination with weighted centroid localization, featuring low communication overhead and a low complexity of *O(n)*, is our basis of a localization on the energy constrained sensor nodes. We first analyze the RSS-characteristics on a specific sensor node platform in different rooms. Next, we describe methods to improve these characteristics to reach best localization results at minimized complexity. Finally, in a practice indoor localization we achieve a small localization error of only 14% for 69% of all test-points that was enhanced to at least 8% in average by simple optimizations. For that, no hardware modifications as well as time consuming RSSI-maps or complex signal propagation models are required.**

***Index Terms*—indoor localization, approximate algorithms, received signal strength indicator, low complexity**

I. Introduction

Hundreds of tiny electronic devices, able to sense the environment, compute simple tasks and communicate with each other, form a huge wireless sensor networks (WSN). Gathered information (e.g. temperature, humidity etc.) is transmitted in a multi hop fashion over direct neighbors to a data sink, where the data is interpreted [1]. With methods like self configuration and self organization the network reacts to node failures. Wireless Sensor Networks enable new possibilities for timely detection of wood fire, monitoring of artificial dikes along a river, and "Precision Farming". Due to the desired nodes size of only some millimeters, the dimensions of the communication module and the battery are critical. Consequently, the scarcest resource within a network is the available energy [2]. Therefore, achieving a long lifetime of the sensor network requires low power hardware and algorithms. Beside the measuring task every sensor node must be able to forward packets and to compute different subtasks like CRC-checking or data aggregation.

This paper briefly analyzes an approximate indoor localization with a weighted centroid approach combined with signal strength measurements. We partially overcome some of the problems resulting by indoor signal propagation. Our approach achieves a good precision without the need of time consuming creation of RSSI-maps or complex probability models.

This paper is subdivided as follows. In Section II, we give a basic overview about the methods for localization in wireless sensor networks. Then a more detailed description about common methods in indoor localization follows. We continue explaining the "Weighted Centroid Localization" algorithm (WCL) in Section III. Next, in Section IV, the received signal strength characteristic of our used hardware-platform is analyzed and optimized. Followed by an adjustment of WCL, we continue showing the results of our practical indoor localization in Section V. After a detailed discussion of them in Section VI we finally conclude the paper in Section VII.

II. Localization in Sensor Networks

After deploying the sensor network over an area of interest, initially the sensor nodes have no position information. For several reasons a node's position is very important:

- Measurements without a location where they were gathered are generally useless.
- Full covered sensor networks enable energy aware geographic routing.
- Self configuration and self organization are key mechanisms for robustness and can easily be supported by position information.
- In many applications the position itself is the information of interest.

At present a mobile device can be tracked outdoor and limited indoor by the "Global Positioning System" (GPS). However, this system requires line of sight to some satellites, consumes additional energy and is too expensive to get integrated on hundreds of energy constrained sensor nodes. For this reason a small number of existing localization methods assume that some sensor nodes already know their own position. These nodes are called beacons or anchors. All other nodes in the network, without known positions, are further called unknowns. With known distances and/or angles between beacons and unknowns, the localization process starts. We classify algorithms into exact and approximate methods for localization.

A. Exact Localization

Exact localization of an unknown features high precision and is based on solving a linear system of equations with coordinates of the beacons and distances to them. With at least three beacons, required in 2-dimensions, unknown nodes estimate their positions via trilateration. More beacons than required result in an over determined system of equations that must be solved with e.g. a least-squares method (multilateration). Due to complex and memory consuming calculations, exact methods are not suited to run on resource and energy constrained sensor nodes [3]. Nevertheless, Savvides et al. describe different approaches (Atomic, Iterative, Collaborative Trilateration) for exact or also called fine-grained localization in wireless sensor networks [4].

B. Approximative Localization

Considering energy constraints in sensor networks created the group of approximate algorithms that consumes less power but estimates a position with a higher localization error. Different approximate (also called coarse grained) localization approaches exist in the literature.

Tian et al. completely avoid distances in their approach [5]. First, triangles are combined with all beacon coordinates in the field. Then every unknown checks by a "point in triangulation-test" (PIT-test) on

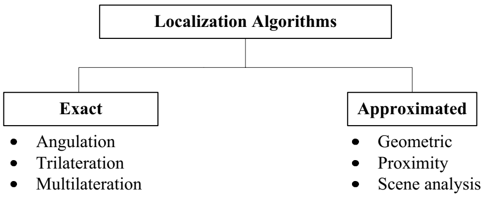

Fig. 1. Basic classification of localization algorithms

which triangle surface it is. In this PIT-test only neighbor relations are used. A following intersection test with all filtered triangles shrinks the region where the unknown is probably located.

In another approach by Bulusu et al. every unknown maintains a list with all beacons in transmission range. The beacons are deployed on a grid of points with same distances to each other [6]. With all received positions sent by the beacons, unknowns calculate the centroid as its own position. Further approaches introduce constraints [7] or a relative coordinate system [8].

C. Measuring Observations

With only few exceptions localization methods require observations to deduce distances from. These observations are gathered by different measuring techniques like e.g. time of flight, received signal strength, and differences of the phase. Signals can be either radio, infrared [9] or ultra sound [10]. Reading the received signal strength indicator (RSSI) is supported by almost every transceiver-hardware that makes this to a beneficial solution. Transmitted signals are attenuated in the communication channel between sender and receiver. Thus, the RSSI determined by the receiver is lower then the emitted signal by the sender. This dependency can be described among other models with the log-normal-shadowing model:

$$RSSI(d) = P_T - PL(d_0) - 10\eta \log_{10} \frac{d}{d_0} + X_\sigma \tag{1}$$

P_T = `Transmit Power`
$PL(d_0)$ = `Path loss for` d_0
d_0 = `Reference distance`
η = `Path loss exponent`
X_σ = `Gaussian random variable`

Unfortunately, the received signal strength measurements are highly error-prone due to the following reasons:

- Reflections of radio waves at obstacles cause multi path propagation.
- Other electrical fields in the environment interfere the transmitted radio waves.
- The resolution of the received signal strength indicator can be limited by the transceiver hardware.
- The required line of sight between nodes can not be guaranteed.
- Node mobility influences the measurement.

D. Indoor Localization with Received Signal Strength

1) Problem Statement: The described multi path effect leads, especially indoor, to high measurement errors. Reflections of electromagnetic waves at walls, objects or persons produce high fluctuations of the received signal strength. There exist different methods to reduce these errors.

First, high redundant measuring is one of the basic procedures to eliminate outliers. Second, there are two possibilities to reduce errors caused by reflections - antenna diversity or frequency diversity.

Antenna diversity means using two antennas that are placed 1/2 wavelength apart. Because the extension of the "null" in space is restricted to a fraction of the wavelength, the probability for two nulls 1/2 a wavelength apart are very small. The receiver must switch between both antennas and use the one that at any time measures the strongest signal.

Frequency diversity means that the message is transmitted at two different frequencies separately. If there is a destructive interference at one frequency, it is not very likely that it will be destructive also at the other one. For the reason, that our used hardware platform supports two frequencies, we will gather information for two frequencies.

2) Related Work: Zhou et al. analyzed the effects of signal propagation in indoor environments and described different techniques to reduce the error [11]. Furthermore, Elnahraway et al. tested different algorithms for localization in a typical IEEE 802.11 network infrastructure with RSSI [12]. One of the most well known localization systems with signal strength in literature is RADAR [13]. A very comprehensive overview about different localizations systems gave Lymberopoulos et al. in [15].

Two approaches are commonly accepted in literature - RSSI-maps and Signal Propagation Models. Many RSSI-measurements at different locations in a building form a so called RSSI-map which is stored on a node or on a base station [14], [16], [17]. An unknown estimating its position compares the measured RSSI-values with the entries in the RSSI-map. The position with the most equal entry is then chosen. Although the precision of this technique is relatively high, movements of objects or persons enforce a recreation of the map, which is very time consuming.

As an alternative the Signal Propagation Models have been established [12], [18], [19]. The effects of indoor signal propagation are mapped in numerous propagation models. The measured RSSI by the unknown is transformed by a formula to a corresponding distance. Advantageously, the complex premeasurement is not needed, but the mapping of a real environment to a model is very difficult and not always appropriate. Approaches with self learning algorithms enhance classical Propagation Models and increase the overall precision [21]. However, these models require complex calculations on the unknown node. In our approach, we neither use RSSI-maps nor Propagation Models. We first analyze the RSSI-characteristics for our specific hardware at different locations. Then, we reduce the location-dependent errors and adapt the curves to WCL.

III. Background: Weighted Centroid Localization

The following reasons motivated us to choose WCL as the algorithm for indoor localization [3]:

- Low memory allocation.
- Low complexity $O(n)$ allows distributed computation on every sensor node.
- High input errors (e.g. defective RSSI or beacon coordinates) slightly decrease the precision.

Further, we describe the procedure of WCL. In order to do so, we define some variables. A sensor network with a total number of k nodes consists of u sensor nodes and b beacon nodes ($b \ll u$). Beacons are equipped with more efficient hardware and a localization system (e.g. GPS), whereby they are able to determine their own position. If the positions cannot be determined via GPS, which is in indoor scenarios more realistically, we deploy the beacons at known positions in the building. The algorithm is divided into two phases.

A. Initialization Phase

In the first phase, all beacons broadcast their position $B_j(x, y)$ to all unknown sensor nodes within their transmission range. Ideally, the transmission range is small enough to reach many unknowns. While receiving the packets, every unknown measures the received signal strength and stores it together with the position of the beacon.

B. Distributed Computation Phase

After all positions are gathered, the unknown estimates its approximate position $P(x_{iapp}, y_{iapp})$ by a weighted centroid determination for all n positions of the beacons in transmission range:

$$P(x_{iapp}, y_{iapp}) = \left(\frac{\sum_{j=1}^{n} \left(w_{ij}(d) x_{B_j} \right)}{\sum_{j=1}^{n} \left(w_{ij}(d) \right)}, \frac{\sum_{j=1}^{n} \left(w_{ij}(d) y_{B_j} \right)}{\sum_{j=1}^{n} \left(w_{ij}(d) \right)} \right) \quad (2)$$

$w_{ij}(d)$ = Weight between sensor node i and beacon j
n = Number of beacons in range

The weighted centroid determination considering distances $d_{i1}...d_{i4}$ results in the approximated position $P_i(x_{i_{app}}, y_{i_{app}})$. Figure 2 shows that distance d_{i1} is higher weighted than d_{i4} and significantly more weighted than distances d_{i2} and d_{i3}. Consequently, the approximated Position moves considerable to B_1,B_4 and slightly to B_2,B_3 as well as to the exact position $P_i(x_{exact}, y_{exact})$ and thus the estimation error $f_i(x, y)$ decreases.
We postulated that distances are attained by observation values. Due to interferences, obstacles, and hardware restrictions, the obtained distances are very noisy. Hence, WCL uses distance information as a weight w_{ij}. Small distances to neighboring beacons lead to a higher weight than to remote beacons. Further, every coordinate of a beacon's position obtains a weight depending on the distance $w_{ij}(d_{ij})$. The calculation of a weight by an RSSI-value and their optimization is described detailed in Section IV-A.2.

The localization error $f_i(x, y)$ is defined as distance between exact position $P_i(x_{exact}, y_{exact})$ and approximated position $P_i(x_{app}, y_{app})$ of sensor node i:

$$f_i(x, y) = \sqrt{(x_{exact} - x_{app})^2 + (y_{exact} - y_{app})^2} \quad (3)$$

Figure 2 shows the exact $P_i(x_{exact}, y_{exact})$ and the approximated $P_i(x_{i_{app}}, y_{i_{app}})$ position of a sensor node determined by a weighted centroid calculation with positions of four beacons $B_1...B_4$. In different publications we analyzed the adjustment of the most important parameters in a multi hop case [21].

IV. Evaluation

This section describes extensive analyzes of the signal strength characteristics of a sensor node platform in different environments in order to use RSSI as input for a Weighted Centroid Localization.

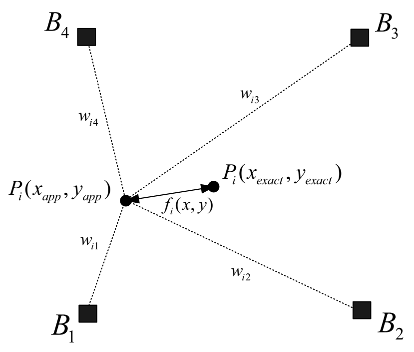

Fig. 2. Weighted centroid localization with 4 beacons ($B_1...B_4$) and one unknown; closer beacons "pull" the unknowns position P_i more to its own position because of the higher weight w_{ij} in the calculation process.

Fig. 3. Encapsulated evaluation module CC1010EM in a chassis with additional hardware and batteries to work autonomously.

A. Hardware Platform

1) Chipcon CC1010 Sensor Node Platform: As node platform we used modules of the type CC1010 (868/915MHz) from Chipcon. These modules feature low power consumption and a low transceiver sensitivity of typically -107dBm. The integrated 8051-micro-controller allows simple calculations and the control of the transceiver hardware. We attempted to reduce transmitter/receiver variability and different antenna characteristics using the same standard antenna on every module. The evaluation modules (CC1010EM) supported revision 3.0 and the evaluation boards (CC1010EB) revision 4.0. We encapsulated the CC1010EM circuits in a chassis with additional modules and batteries to allow free movement (see Figure 3).

2) Send Power Levels: The transceiver allows configuration of different output powers, by writing to the "Output Power Control Register" (PA_POW = 0xE2). A table with the relation between the register values and their corresponding output powers is given below [1].

TABLE I
DIFFERENT SEND-POWER-LEVELS OF THE CC1010.

PA_POW $[hex]$	Output Power $[dBm]$	PA_POW $[hex]$	Output Power $[dBm]$
0x2	-19	0xA	-9
0x3	-17	0xB	-8
0x4	-15	0xC	-7
0x5	-14	0xD	-6
0x6	-13	0xE	-6
0x7	-12	0xF	-5
0x8	-11		

3) Received Signal Strength Indicator: The evaluation module features measurement of the received signal strength in form of an RSSI within the interval $-50dBm \leq RSSI \leq -110dBm$. The RSSI is determined by an analogue digital converter which converts the measured voltage over a $27k\Omega$ resistor (50dB/V) which is in the interval $0V \leq RSSI \leq 1.2V$. We investigated that the sensor modules do not depend on the input voltage that makes the localization process more robust.

4) Frequency Switching: The Chipcon modules feature a simple frequency switching by software between 868.28MHz and 915.03MHz. We gathered sample data for both frequencies under the same test conditions.

[1]Higher output power ($> -5dBm$) is supported by the hardware but produced no additional information in our test scenarios. The RSSI always reached its maximum at -50dBm.

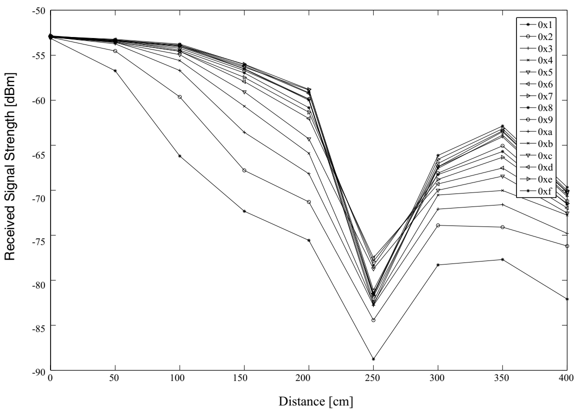

Fig. 4. RSSI over distance curves of beacon 77 on a straight line in room 1 (output power levels are shown as register values).

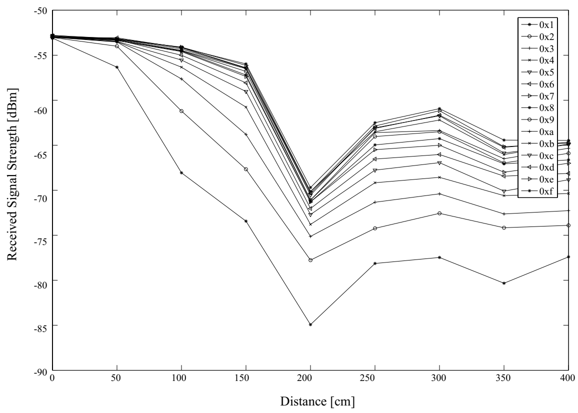

Fig. 5. RSSI over distance curves of beacon 89 on a straight line in room 1 (output power levels are shown as register values).

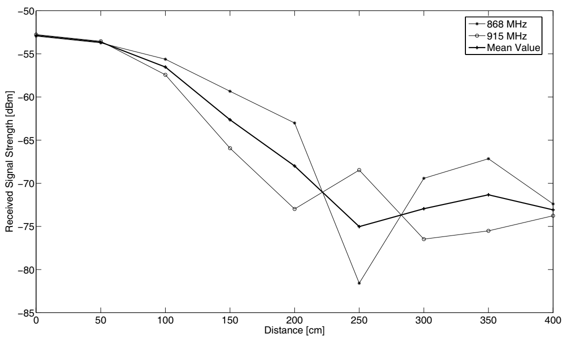

Fig. 6. Averaged curves over the different output power levels; outliers were decreased by averaging (room 1).

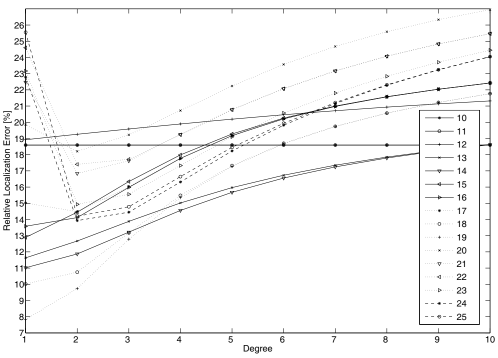

Fig. 7. Relative localization error over the degree; every curve represents different RSSI-boundaries.

B. Analyzing and Optimizing RSSI-Measurements

To get an idea of the RSSI characteristics, we first gathered sample data in different measurement series. For that purpose, we mounted 5 evaluation modules on the evaluation boards. Every node was given a specific identification number[2] (ID). In all test setups node ID 94 represents the unknown and node ID's 63,77,78,89 represent the beacons. First of all, we measured the RSSI on a straight line at different distances. To be able to detect location dependencies, we measured in 2 different rooms with different floor materials and objects within. The modules were placed on the ground, that was made of carpet (room 1) and linoleum (room 2). Both rooms had a size of 7×5 meters. The measurement process at every distance step consists of RSSI-data:

- at 2 frequencies (868MHz, 915MHz),
- with 15 different output send powers,
- and 30 repetitions to calculate mean and standard deviation.

The results for 2 beacons (sender) and always the same unknown (receiver) are illustrated [3] in the Figures 4 and 5. Every figure shows the obtained RSSI-curves over the distance at 15 power levels. The characteristics approximately correlate with the expected signal path loss curves to be obtained by (1). An increasing output power level at the sender results in an increasing RSSI-value at the receiver. Reflections in the room produce high outliers e.g. in Figure 4 at 250cm or in Figure 5 at 200cm. The outliers do not vary at the different power levels.

The measured data scatter in a specific probability interval. The scattering depends among others on the already introduced influences. To determine the "best" value out of the stochastic values within the measurement interval there exist different operators for averaging.

$$RSSI_{av}(d) = \frac{\sum_{i=1}^{s} \left(\sum_{j=1}^{t} RSSI_{ij}(d) \right)}{(s \cdot t)} \quad (4)$$

s = Number of different power levels
t = Number of repetitions

We decided to calculate the arithmetic mean in (4) to obtain the optimal RSSI-value per distance. The standard deviation as an indicator for the quality of a measurement was not considered at present, because we do not need this value in the localization process. After averaging the curves for both frequencies, we derived 8 RSSI-curves. To illustrate, Figure 6 shows the averaged curves for beacon

[2] The ID originates from the last two numerics of the explicit hardware identification number.

[3] It is important to annotate that the standard deviation of all curves is marginal and was left out in the figures. Moreover, we connected the resulting RSSI samples to a line, which is indeed mathematically not correct, because every point is only a snapshot of the curve. Both changes shall improve the viewers perspective.

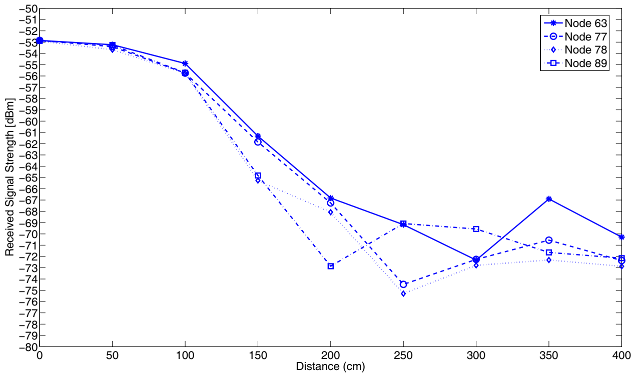

Fig. 8. Averaged curves over different power levels and two frequencies for all four test nodes in room 2.

77. Although the outliers still exists, averaging both curves (for 868MHz and 915MHz) yield in more linear curves with less extreme outliers then before. This method was repeated for all nodes in both rooms resulting in one characteristic RSSI-curve for every beacon-unknown combination (see Figure 8).
Summarized, relations between RSSI and distance are qualified for localization input in the first room between 1cm and 350cm and in the second room between 1cm and 200cm. A differentiation of the RSSI after these distances is almost impossible.
Recapitulating, the defective RSSI-characteristics were enhanced by gathering more measurements and a simple averaging. So far, no hardware modification or complex computations were required. Following, we consider the findings for a transformation of the RSSI as weight in WCL.

C. Adjustment of the weight in WCL

In [3] we described an optimal weight for exact and for defective distances. Now, we want to convert the RSSI-values into a weight by starting to convert the original scale[4] ranging from -110dBm to -50dBm into a standardized scale[5] ranging from 1 to 61:

$$RSSI_{stand}(d) = -RSSI(d) + 49 \tag{5}$$

The weight $w_{ij}(d)$ must be inversely proportional to the standardized RSSI-value because closer beacons to an unknown must have a higher weight then farther ones. In [21] we introduced a degree q to additionally vary the weights.

$$w = \frac{1}{RSSI^q} \tag{6}$$

D. Realization of an Indoor Localization

In the previous sections we defined the basics for a practice indoor localization. Next, the initial test setup will be described. Our test field was quadratic with side length $w = 300cm$ and build up in room 2. The sensor nodes were placed on the ground consisting of linoleum. Some furniture (tables, chairs) stood next to the walls. The four beacons $(ID = 63, 77, 78, 89)$ were placed at the four corners of the field with the positions $B_{63}(1, 1)$; $B_{77}(300, 1)$; $B_{78}(1, 300)$; and $B_{89}(300, 300)$. The unknown node $(ID = 93)$ was placed at 13 different positions (see Figure 10). At every position the unknown run the measuring process described in Section IV-A.2 (2 frequencies, 15 power levels, 30 RSS-indicators) for all 4 beacons. Followed by the averaging process, described in Section IV-C, the unknown estimated its position via WCL.
In further simulations we tried to enhance the precision by introducing RSSI-boundaries. The reason for that is the insufficient differentiation after 200cm in room 2. Thus, all RSSI-values above a specific boundary were set to zero. There exist 52 RSSI-values in the test scenario, arising from the corresponding distances from 13 test-points to 4 beacons. Summarized, the RSSI-value between a test-point and a beacon that is above the boundary indicator-value was not considered in the localization process. The boundary ranged in simulations between 10 and 25.

[4]The value -110dBm represents a long distance between sender and receiver, complementary the value -50dBm means a small distance.

[5]After converting, 1 stands for small and 61 for long distances.

V. Experimental Results

Over degree $q > 3$ the relative localization error rised nearly linear. The localization error varied between $7.8\% \le f \le 26\%$ at different degrees ranging from 1 to 3 (Figure 7). The RSSI-boundaries influenced the characteristics of the curves for $q < 3$ very strongly and controlled the number of RSSI-values used in the localization.
Figure 9 illustrates the number of RSSI-values used in the localization process, the minimal relative localization error, and the optimal degrees over different RSSI boundaries. At a very low boundary, $RSSI_{bound} = 12$, less than 15 out of 52 RSSI-values were involved in the localization. With an increasing boundary an increasing number of RSSI-values got involved. At $RSSI_{bound} = 19$ and degree $q = 1$ the minimal relative localization error of $f = 7.9\%$ was achieved. This optimal configuration used the half of all possible RSSI-values. At $RSSI_{bound} = 20$ the error reached its maximum. At the end of the curve, $RSSI_{bound} > 25$, all RSSI-values got involved in the localization and so the error stayed constant at $f = 14.009\%$ $(f = 14.7851\%)$ at a degree of $q = 2$ $(q = 3)$. Whereas a degree of $q = 1$ dominated at lower boundaries, at higher boundaries the degree $q = 2$ dominated.

VI. Discussion

The experimental test setup basically showed the efficient function of WCL in an indoor environment. Higher degrees "pulled" the unknowns too close to the beacons with short distances. On the other hand, if the degree was too small (e.g. $q = 1$), the estimated position moved in the centroid.
A significant enhancement of the localization was reached by involving boundaries. This originated by the heavy defective RSSI-values after 200cm (Figure 8). The optimal configuration of all parameters, where the localization error reached its minimum, was determined at $RSSI_{bound} = 19$ and degree $q = 1$. At this point most of the RSSI-values in the localization process are accurate. It was shown in

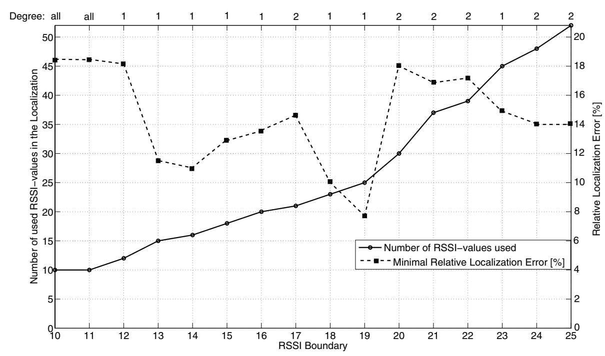

Fig. 9. Number of RSSI-values used in the localization process (left axis) and the minimal obtained relative localization error (right axis) over the different RSSI-bounds; for every boundary the optimal degree is shown at the top where the highest precision was reached.

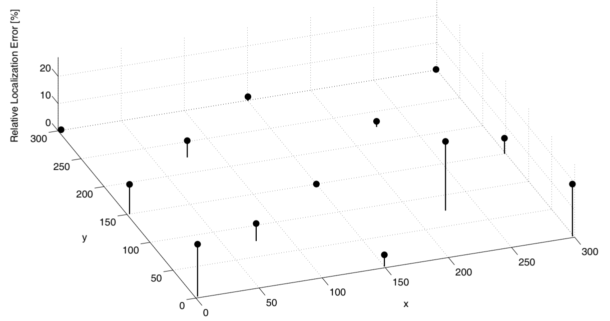

Fig. 10. Relative localization error over the experimental sensor field with 13 test-points in room 2 with optimal settings $RSSI_{bound} = 19$ and degree $q = 1$.

[3] that a high number of beacons with good RSSI-values achieved the highest precision. Summarized, a smaller error $f = 14.16\%$ was achieved for 69.23% of all test-points without optimization. Additionally, the enhancement with boundaries decreased the relative average error to at least $f = 7.9\%$. The resulting error field is shown in Figure 10. The error can be decreased with more beacons. Especially one beacon in the centroid is very effective, because it can reach almost all unknowns under the 200cm boundary. Further, the neighboring unknowns can interchange RSSI-values to detect outliers.

VII. Conclusion

We showed in this paper that the approximate "Weighted Centroid Localization"-algorithm in combination with received signal strength achieved in indoor environments a small localization error of 14% for 69% of all test-points. With optimization the averaged error was decreased to only 8%. This result was obtained without the need of time and memory consuming RSSI-maps or probability models. We first analyzed the characteristic RSSI-curves for different indoor environments for 2 different frequencies (868MHz, 915MHz). Then, we reduced the location dependent errors and introduced a boundary under which the sampled data was qualified for localization. The WCL-algorithm features a low complexity of $O(n)$. Hence, WCL can be computed on energy constrained sensor node without exploiting them.

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