Improved Weighted Centroid Localization in Smart Ubiquitous Environments

Stephan Schuhmann[1], Klaus Herrmann[1], Kurt Rothermel[1], Jan Blumenthal[2], Dirk Timmermann[2]

[1] University of Stuttgart, Germany
Institute of Parallel and Distributed Systems (IPVS)
Email: {firstname.lastname}@ipvs.uni-stuttgart.de

[2] University of Rostock, Germany
Institute of Applied Microelectronics and CE
Email: {jan.blumenthal,dirk.timmermann}@uni-rostock.de

Abstract. Location-awareness is highly relevant subject in ubiquitous computing, as many applications exploit location information to provide adequate services or adapt to a changing physical environment. While GPS provides reliable outdoor localization, indoor positioning systems present a bigger challenge. Many indoor localization systems have been proposed. However, most of them rely on customized hardware or presume some dedicated infrastructure. In this paper, we focus on WLAN-based localization in smart ubiquitous environments. We propose an improved scheme of the *Weighted Centroid Localization* (WCL) algorithm that is robust and provides higher location accuracy than the original WCL algorithm. The improvements are based on the use of dynamic weighting factors that are solely dependent on the correlation of the Received Signal Strength Indicators of the received beacon signals. Compared to the original WCL scheme, our approach does not increase requirements to the environment. Real-world experiments in a typical environment that we report on in this paper confirm that the increased location accuracy determined in previous calculations is reproducible in a realistic noisy environment. This provides a simple, cost-efficient, and battery-conserving, but yet adequate technique for getting the accurate location information of mobile devices.

1 Introduction

Location-awareness is an essential service for many wireless ubiquitous computing scenarios, as many applications integrate location information to increase context knowledge. However, ubiquitous computing environments have specific characteristics which limit the approaches that are applicable to maintain location-awareness. For instance, pervasive applications have to deal with fluctuating availability of devices due to mobility and network failures. Thus, environmental contexts are highly dynamic. Furthermore, processor performance and available energy of mobile nodes in ubiquitous computing scenarios are often limited. Therefore, intensive communication and computation tasks are not feasible. In this context, algorithms are subject to strict requirements covering reduced memory consumption, communication, and processing time. In Smart Environments, available infrastructure devices can provide additional support for mobile devices.

Determining the position of nodes in wireless networks, particularly in noisy environments, represents a real challenge. To identify the exact coordinates of a device (also called *Station Of Interest*, or *SOI*) requires measuring a distance, e.g., measuring Time of Arrival (ToA) or Time Difference of Arrival (TDoA). Difficulties concerning time measurements result from synchronization of involved devices as well as the high computational effort to calculate the position. Measuring the Received Signal Strength Indicator (RSSI) offers a possibility to realize distance determination with minimal effort.

A good localization algorithm should calculate a position as fast as possible and should be resistant to environmental influences as well as imprecise distances. However, it is desirable to use standard off-the-shelf consumer products without the necessity for far-reaching customization as this reduces the effort necessary for setting up the positioning system. Thus, our approach of combining the Weighted Centroid Localization (WCL) [1] with standard Wireless LAN technology has high practical relevance in typical environments.

The main contribution of this paper is an improved Weighted Centroid Localization scheme that uses weighting factors of dynamic degrees to increase location accuracy in smart ubiquitous environments. Therefore, we derived optimal dynamic weighting factors through theoretical calculations and approximated the obtained weighting factors by a power function using the least-squares method. Furthermore, we evaluated the improved localization scheme in an office room that represents a typical noisy ubiquitous computing environment. The measurements confirmed that our approach increases location accuracy almost to the best possible value for weighted centroid schemes.

The paper at hand is divided into six sections. The second section discusses the requirements to be met by the localization scheme and the environment. Section 3 gives a broad survey of existing localization approaches. In Section 4, we at first describe the original WCL scheme. Following, we derive an improved WCL scheme that uses dynamic weighting factors and increases location accuracy. We present our theoretical and practical evaluation results in Section 5. This is followed by the conclusion and a brief outlook to future work in Section 6 which closes this paper.

2 Requirements

In this paper, we focus on indoor localization for resource-restricted devices in smart ubiquitous environments. This requires to avoid high battery consumption, as mobile devices like PDAs or smart phones are equipped with limited battery and computation power. Hence, we aim at minimizing the requirements for the localization devices as well as the infrastructure to allow applicability to a wide range of scenarios. This means we want to provide a flexible solution for indoor localization. Thus, our system has to maintain the following properties:

- **Minor environmental requirements:** The environment solely has to provide infrastructure nodes with fixed positions that send periodic beacon signals. Many realistic ubiquitous scenarios fulfill this property, as they include 802.11 WLAN Access Points (APs), for example. These devices have to know their exact position and notify other devices of their location, e.g. within the beacon signals which needs slight adaptations to the APs. If changes to the APs are undesired, AP positions can be received by queries to a location server that provides the clients with AP locations.
- **Minimal costs:** Additional hardware costs should be avoided by relying on standard components that are available in typical ubiquitous scenarios, both on the client and on the infrastructure side. For instance, the localization scheme ought to integrate existing infrastructure devices without the need of large changes in their configuration. To minimize costs, we rely on exactly four beacon nodes in this paper. These beacons are placed at the edges of a rectangular plain, as common rooms typically have a rectangular base. This AP positioning enables nodes to localize themselves in the whole region.
- **Minimal communication needs on the client devices:** Since power supply is critical for small mobile devices, the clients should avoid any additional communication during the localization process to maximize battery lifetimes. So, only the infrastructure devices should send beacons needed for the localization process, while the mobile devices have to exploit the information provided by these beacons. As localization is supposed to be executed in various scenarios in real-time, a solution that demands prior configuration of the client devices is not feasible, as this limits the use of the system.
- **Applicability in realistic ubiquitous scenarios:** Contrary to laboratory environments, realistic scenarios often suffer from effects like multi-path propagation or interferences with other wireless networks operating on the same frequency spectrum. This can significantly influence the accuracy of the localization. A localization scheme must be able to cope with this interference in order to provide accurate localization nevertheless.

3 Related Work

In this section, we investigate several related localization approaches concerning the above requirements to confine WCL from these approaches, and we clarify why they prove inadequate in our scenarios. In Figure 1, we provide a classification of proposed schemes. At first, these schemes can be divided into those that are based on coordinates and those that are coordinate-free.

Coordinate-free schemes, as presented by Fekete et al. [2], focus on an abstract way of location-awareness. These schemes aim at achieving consistent solutions by the use of geographic clustering. Unfortunately, they rely on rather dense sensor networks to achieve adequate accuracy and, therefore, are not usable here. Thus, we focus on coordinate-based approaches that can further be divided

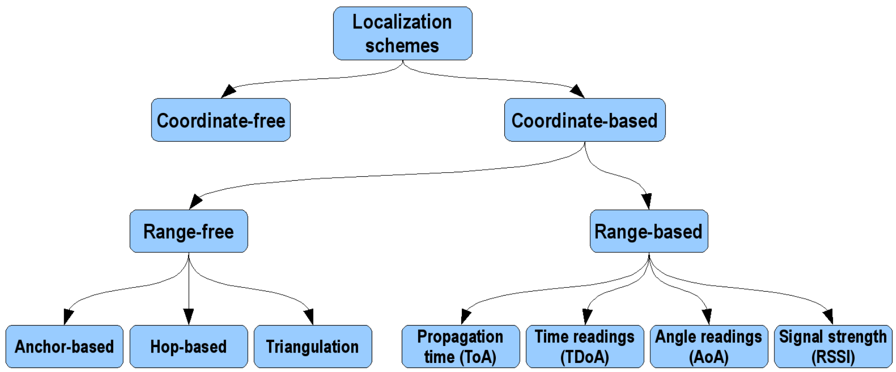

Fig. 1. Classification of proposed localization schemes

into range-free and range-based schemes. Range-free schemes comprise implicit distance measurements, while range-based schemes use explicit distances for localization. Regarding range-free schemes, there exist three main approaches:

- **Anchor-based approach:** This approach uses anchor beacons, containing two-dimensional location information (x_i, y_i), to estimate node positions. After receiving these beacons, a node estimates its location using a specific formula. Besides a scheme proposed by Pandey et al. [3], another anchor-based approach is Centroid Localization (CL), proposed by Bulusu et al. [4]. In this approach, the SOI calculates its position as the centroid of the coordinates from the stations whose beacons are received. While CL performs only averaging the coordinates of beacons to localize SOIs, the Weighted Centroid Localization (WCL) algorithm [1] uses weights to ensure an improved localization and, hence, represents a direct advance over CL.
- **Hop-based approach:** In this type of localization scheme, the SOI calculates its position based on the hop distance to other nodes [5],[6]. This scheme delivers an approximate position for all nodes in networks where only a limited fraction of nodes have self-positioning capability. Through this mechanism, all nodes in the network (including other anchors) get the shortest distance, in hops, to every anchor. However, this approach only works well in dense networks and relies on flooding of messages which produces high communication overhead that is undesired in our scenarios.
- **Area-based approach:** Area-based schemes [7],[8] perform location estimation by isolating the environment into triangular regions between beaconing nodes. The presence inside or outside of these triangular regions allows a node to narrow down the area in which it can potentially reside. Area-based approaches normally perform particularly well in heterogeneous networks with high node density. Unfortunately, this condition does not hold in our case and, thus, area-based approaches cannot be used here.

Besides range-free schemes, a couple of approaches exist that are based on the transmission ranges of the nodes. Range-based approaches can be subdivided into the following approaches:

- **Signal propagation time**: The Time of Arrival (ToA) technology is commonly used as a means of obtaining range information via signal propagation time. This approach is used by satellite navigation systems [9]. Though this approach guarantees high precision and can be globally used, it suffers from several major drawbacks as this scheme can only be used outdoors, needs expensive hardware, and the receivers consume much energy. Thus, ToA approaches are inapplicable in our case.
- **Localization by measuring signal propagation time differences and arrival angles**: This technology is based on measurements of the Time Difference of Arrival (TDoA) [10], or the Angle of Arrival (AoA) [11]. While TDoA estimates the distance between two communicating nodes (this is also called *ranging*), AoA allows nodes to estimate and map relative angles between neighbors. Like ToA technology, TDoA and also AoA rely on special hardware that is expensive and energy consuming. Thus, these approaches are unsuited here.
- **Simple signal strength measurements**: This approach uses the Received Signal Strength Indicator (RSSI) of incoming beacon signals and has been proposed for hardware-constrained systems. Contrary to techniques like ToA, TDoA or AoA, RSSI is the only feature that is measurable with reasonably priced current commercial hardware. RSSI techniques use either theoretical or empirical models to translate signal strength into distance estimates where each point is mapped to a signal strength vector [12], or to a signal strength probability distribution [13]. This technology suffers from problems such as background interference or multi-path fading, which make range estimates inaccurate, as shown in [14]. Furthermore, many signal strength based approaches rely on special hardware, like small infrared badges [15], magnetic trackers [16], or multiple cameras [17], which usually are not included in typical environments and mobile devices.
  Some approaches do not use client-based, but sniffer-based localization [18]. However, this technique cannot be used here as it assumes that the access points can localize other devices which induces major changes in the APs.
  Many approaches use location fingerprinting for localization in wireless networks [12],[13]. This method consists of a training phase and a positioning phase. Unfortunately, this approach needs additional preconditioning and the creation of a training database for several environments beforehand, which makes it inapplicable in our case.

In summary, one can see that most approaches cannot be chosen since they rely on extensive special hardware, need additional preconditioning to build a training database, use sniffer-based localization, or depend on high node densities to perform well. This narrows the huge field of localization schemes to few anchor-based approaches. Among those, Weighted Centroid Localization uses more fine-grained parameters than CL to weight the received beacon signals, as CL simply uses binary weighting (weight 1 for those APs whose beacons were received, weight 0 for the others). This ensures higher location accuracy for WCL.

4 Improved Weighted Centroid Localization

After a short introduction to the original WCL scheme with static weighting factors [1], we propose an advanced scheme that uses dynamic weighting factors which are based on the correlation of the received RSSI values.

4.1 Static Degree Weighted Centroid Localization (SWCL)

We assume that the network consists of SOIs that want to localize themselves, and n beacons. In our case, beacons are WLAN access points whose position is assumed to be known exactly. We depend on a small number of $n = 4$ beacons, placed at the edges of a rectangular plain. The SOIs are mobile devices that initially do not know their own position.

Algorithms such as CL use centroid determination to calculate a device's position [4]. In the first phase, each beacon B_j sends its position (x_j, y_j) to all nodes within its transmission range, which can simply happen through the periodically sent beacon signals. In the second phase, the SOI P_i calculates an approximation (x'_i, y'_i) of its real position (x_i, y_i) by a centroid determination from all n positions of the beacons in range (1).

$$(x'_i, y'_i) = \frac{1}{n} \sum_{j=1}^{n} (x_j, y_j) \tag{1}$$

The localization error f_i for the SOI P_i is defined as the distance between the exact position (x_i, y_i) and the approximated position (x'_i, y'_i) of P_i (2).

$$f_i = \sqrt{(x'_i - x_i)^2 + (y'_i - y_i)^2} \tag{2}$$

While CL only averages the coordinates of beacon devices to localize SOIs, WCL uses weights to ensure an improved localization. In CL, all weights of received beacon signals are implicitly equal to 1. WCL represents a generalization of this scheme since it introduces variable weights w_{ij} for each device P_i and each beacon B_j. These weights depend on the distance between the two as it will be explained later in this section. In the more general WCL equation, the number of beacons n is replaced by the sum of weight factors w_{ij}, and each beacon position (x_j, y_j) is multiplied by its weight factor w_{ij}. Hence, Equation 1 is expanded to the WCL formula (3) yielding the new approximation (x''_i, y''_i) for P_i's position.

$$(x''_i, y''_i) = \frac{\sum_{j=1}^{n} w_{ij} \cdot (x_j, y_j)}{\sum_{i=1}^{n} w_{ij}} \tag{3}$$

The weight w_{ij} is a function depending on the distance and the characteristics of the SOI's receivers. In WCL, shorter distances cause higher weights. Thus, w_{ij}

and d_{ij} (the distance between beacon B_j and SOI P_i) are inversely proportional. As an approximation, the correlation is equivalent to the function $1/d_{ij}$. To weight longer distances marginally lower, the distance is raised to a higher power h. For a concentric wave expansion with a linear characteristic of the receiver and a uniform density of the beacons, we form (4).

$$w_{ij} = \frac{1}{(d_{ij})^h} \tag{4}$$

The degree h has to ensure that remote beacons still impact the position determination. Otherwise in case of a very high h, the approximated position moves to the closest beacon's position and the positioning error f_i increases. There exists a minimum of f_i where h is optimal [19]. However, as the next section clarifies, this use of a static value for h leads to suboptimal accuracy if you compare it with the use of adapted dynamic weight factors that are based on the correlation between the received RSSIs from several APs.

According to Friis' free space transmission equation (5), the detected signal strength decreases quadratically with the distance to the sender.

$$P_{rx} = P_{tx} \cdot G_{tx} \cdot G_{rx} \cdot (\frac{\lambda}{4\pi d_{ij}})^2 \tag{5}$$

P_{tx} = Transmission power of sender
P_{rx} = Remaining power of wave at receiver
G_{tx}, G_{rx} = Gain of transmitter and receiver
λ = Wave length
d_{ij} = Distance between sender and receiver

In embedded devices, the received signal strength is converted to the RSSI which is defined as ratio of the received power to the reference power (P_{ref}). Typically, the reference power represents an absolute value of $P_{ref} = 1\ mW$. The actually received power P'_{rx} can be obtained by the RSSI and vice versa, as denoted in the following equations.

$$P'_{rx} = P_{ref} \cdot 10^{\frac{RSSI}{20}} \quad \Longleftrightarrow \quad RSSI = 20 \cdot log_{10} \frac{P'_{rx}}{P_{ref}} \tag{6}$$

An increasing received power results in a rising RSSI. Thus, distance d_{ij} is indirect proportional to P'_{rx} and Equation 7 with power g ($\neq h$) is formed.

$$w_{ij} = (P'_{rx})^g \tag{7}$$

So, it can be seen that the knowledge of d_{ij} is not necessary, as the algorithm can simply use the received power P'_{rx} or, alternatively, the RSSI. In this paper, we use the RSSI, i.e. we take Equations 6 and 7 and form Equation 8.

$$w_{ij} = (P_{ref} \cdot 10^{\frac{RSSI}{20}})^g. \tag{8}$$

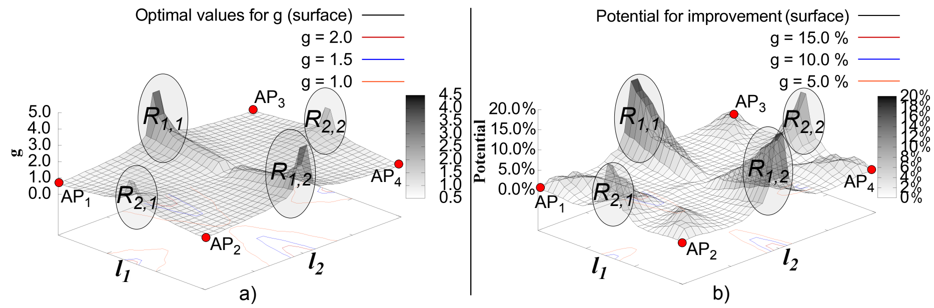

Fig. 2. a) Distribution of optimal g at a rectangular plain ($p = \frac{4}{3}$), b) Potential for improvement of location error at a rectangular plain ($p = \frac{4}{3}$), relative to longer side l_1

In practical scenarios, the ideal distribution of P_{rx} does not hold, because the radio signal propagation is interfered with many influencing effects, like reflection on objects, diffraction at edges, or superposition of electro-magnetic fields. Thus, P_{rx} and P'_{rx} represent different values which yields localization errors.

4.2 Dynamic Degree Weighted Centroid Localization (DWCL)

Using an optimally chosen static degree g_s, as original WCL does, results in improved location accuracy, compared to CL [1]. However, the degree g_{opt} that leads to minimal error can significantly differ from g_s in some regions, as this section will clarify. Therefore, we used Equations 5 and 6 and put $P_{rx} = P'_{rx}$ to calculate the expected RSSI in various positions within an idealized region under observation. Following, we used the WCL algorithm with different powers g to determine the optimal g_{opt} which yields highest location accuracy at a particular place in the region.

Figure 2a shows the distribution of the factors g_{opt} in a rectangular region where the proportion p of the length l_1 of the longer side divided by the length $l_2(\leq l_1)$ of the shorter side is $p = \frac{l_1}{l_2} = \frac{4}{3}$. It can be seen that the distribution of g_{opt} is very uneven. The values at the regions $R_{1,1}$ and $R_{1,2}$ exactly between two adjacent anchors with a distance of l_1 to each other (e.g., AP_1 and AP_3) are relatively high (up to 5.0), as well as at those regions $R_{2,1}$ and $R_{2,2}$ between two anchors with a distance of l_2 to each other (e.g., AP_1 and AP_2), where the maximum g is approximately 2.5. In the special case of a quadratic plain ($l_1 = l_2$, i.e. $p = 1$), the distribution of g_{opt} is symmetric to the center of the region.

By selecting the determined optimal dynamic powers shown in Figure 2a, the mean error could be decreased by about 30 % (compared to WCL with an optimal static weight factor of $g_s = 0.87$ in a region with $p = \frac{4}{3}$) to the best possible value for WCL. Thus, it is obvious that there is huge potential for improvements by using dynamic weight factors. Figure 2b shows this potential which represents the difference between the error if g_s is used, and the minimum possible error if the optimal g_{opt} is used. This figure clarifies that the potential for improvements is alike very unevenly distributed. Particularly the regions $R_{i,j}$ $(i, j \in \{1, 2\})$

offer an enormous potential of more than 10 % of l_1 for improvements, which corresponds to the noticeably increased optimal weight factor at these regions, as Figure 2a shows. It is obvious that the influence of the two farthest access points was too high there, as the value of g_{opt} was chosen too low. This shifted the calculated position near the centre of the region.

The proceeding of DWCL to obtain the optimal dynamic weighting factor g_d is the following: At first, the SOI has to identify the approximate subregion it is located in. Then, it has to lookup subregion-specific parameters. Now, the SOI can at first calculate the value of a balancing function and, based on this result, the approximated actual dynamic weight g_d and its location within the whole region under observation. We will focus on these steps in the following.

Subregion determination First of all, a SOI has to determine the approximate subregion in which it is located. This has to happen by solely regarding the RSSIs of incoming beacon signals. Figure 2a suggests to define four different subregions, as there exist four peaks for the optimal values of g. A simple way to divide the region in adequate subregions is using the perpendicular bisectors of the sides from AP_1 to AP_4 and from AP_2 to AP_3, as illustrated in Figure 3. A SOI then can easily determine in which of the emerging subregions $C_{1,1}$, $C_{1,2}$, $C_{2,1}$, and $C_{2,2}$ it is located. This is performed by simply comparing the RSSIs pairwise, as denoted in Table 1.

RSSI constraints	**Relevant subregion**
$(RSSI(AP_1) > RSSI(AP_4)) \wedge (RSSI(AP_3) > RSSI(AP_2))$	$C_{1,1}$
$(RSSI(AP_4) > RSSI(AP_1)) \wedge (RSSI(AP_2) > RSSI(AP_3))$	$C_{1,2}$
$(RSSI(AP_1) > RSSI(AP_4)) \wedge (RSSI(AP_2) > RSSI(AP_3))$	$C_{2,1}$
$(RSSI(AP_4) > RSSI(AP_1)) \wedge (RSSI(AP_3) > RSSI(AP_2))$	$C_{2,2}$

Table 1. Determination of subregions

Determination of subregion-specific parameters After determining the subregion it is located in, a SOI needs to obtain further parameters which we will derive in this paragraph. Regarding the beacon signals received in $R_{i,j}$, their RSSIs have several special characteristics:

- The RSSIs of the two strongest received signals are almost equal, as the distances from the SOI to the corresponding access points, respectively, are almost the same. The same holds for the two weakest signals.
- At those points within $R_{i,j}$ where the optimal g_s is maximal, the quotient Q_i ($i \in \{1, 2\}$) of the distance to the close APs by the distance to the far APs can be calculated by Pythagoras' formula, as depicted in Figure 3.

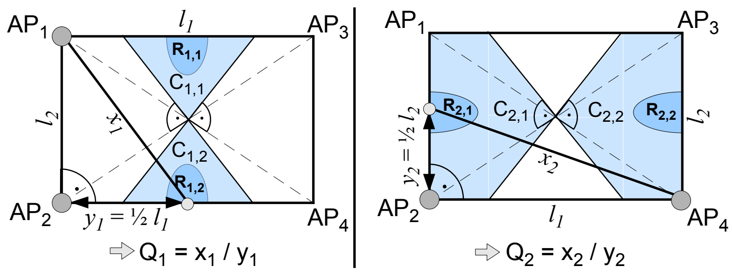

Fig. 3. Calculation of parameters Q_1 and Q_2

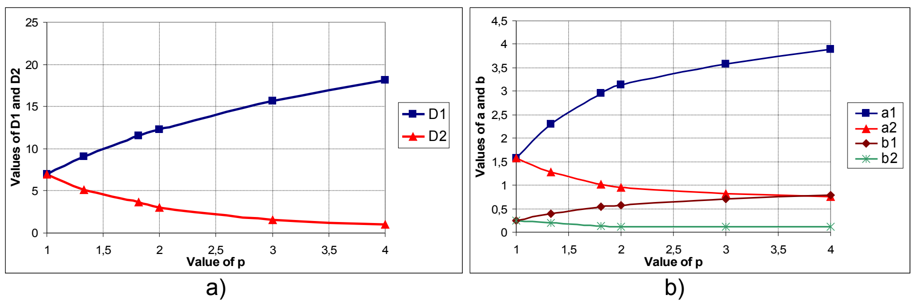

Fig. 4. Typical values in common rooms a) for D_1 and D_2, b) for a_1, b_1, a_2, and b_2

$$Q_1 = \frac{x_1}{y_1} = \frac{\sqrt{l_2^2 + (\frac{1}{2}l_1)^2}}{\frac{1}{2}l_1}; \quad Q_2 = \frac{x_2}{y_2} = \frac{\sqrt{l_1^2 + (\frac{1}{2}l_2)^2}}{\frac{1}{2}l_2} \tag{9}$$

According to Equation 6, the RSSI differences between the received signals from the corresponding APs are

$$D_i = 20 \cdot log_{10}\, Q_i. \tag{10}$$

Thus, a SOI only needs to know l_1 and l_2 to achieve the parameters Q_i and D_i. The values of l_1 and l_2 can easily be obtained by the fixed AP positions. The SOI has to use D_1 if it is situated in region $C_{1,1}$ or $C_{1,2}$ and D_2 if it is situated in $C_{2,1}$ or $C_{2,2}$. Otherwise, it has to choose D_2, as it is situated in region $C_{2,1}$ or $C_{2,2}$ then. Common values for D_i are shown in Figure 4a. For example, in a region with $p = \frac{4}{3}$, the calculation results for D_i are $D_1 = 9.0908$ dB and $D_2 = 5.1188$ dB.

The differences between the received RSSIs can generally be expressed as follows:

$$\Delta_i = RSSI_i - RSSI_{i+1}, i \in \{1, 2, 3\}$$

where $RSSI_i$ represents the i-th strongest received RSSI. Within regions R_1 and R_2, the values of Δ_1 and Δ_3 are typically very low (close to 0), while those of Δ_2 are close to D_1 (in $R_{1,j}$) or D_2 (in $R_{2,j}$).

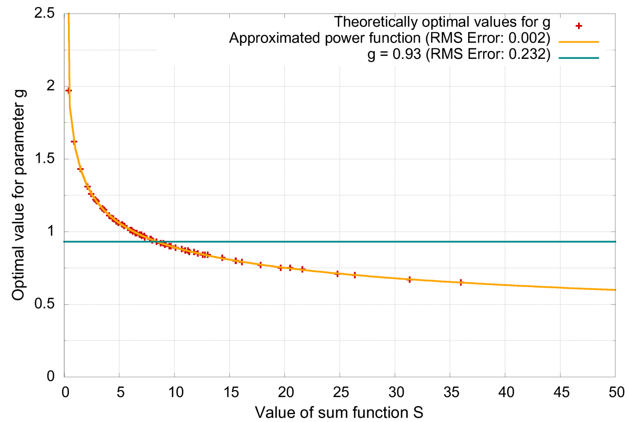

Fig. 5. Distribution of calculated $g(S)$ in theory ($p = 1$, i.e. $g_1(S) = g_2(S)$)

Balancing function To differ if a SOI is located in $R_{i,j}$ where g_{opt} is considerably high, we decided to define the following balancing function S that is based on the special RSSI characteristics in $R_{i,j}$ that were mentioned above:

$$S = \Delta_1 + |D_i - \Delta_2| + \Delta_3,\ i \in \{1, 2\} \tag{11}$$

As already mentioned, Δ_1 and Δ_3 are close to zero within $R_{i,j}$, while Δ_2 depends on the parameter p and is around D_i in $R_{i,j}$. Thus, $(D_i - \Delta_2)$ is around zero in $R_{i,j}$. Following, S is minimum within $R_{i,j}$ and increases outside of these regions. Hence, the use of S helps to state more precisely the location of the SOI.

Approximation We calculated S for various positions in the whole region, and compared the values with those of the optimal g at this position. The distribution of S dependent on g is shown in Figure 5 and suggests to approximate $g(S)$ by the power function that is denoted in Equation 12.

$$g_d = g_i(S) = \frac{a_i}{S^{b_i}}, i \in \{1, 2\} \tag{12}$$

with the unknown parameters a_1 and b_1 if the SOI is within $C_{1,1}$ or $C_{1,2}$, and with a_2 and b_2 if the SOI is located in $C_{2,1}$ or $C_{2,2}$. Now, we approximated the power functions with the least-squares method for various values of p and got the parameters a_i and b_i as denoted in Figure 4 that yield minimum root mean square (RMS) errors. For example, for $p = 1$, we got $a_1 = a_2 \approx 1.580$ and $b_1 = b_2 \approx 0.248$ which led to a very small RMS error of only 0.002 which is a small fraction of the RMS error of SWCL with optimal static weight.

5 Evaluation

First, we present the theoretical results of DWCL and compare them with those of SWCL. Then, we concentrate on the indoor tests with 802.11 WLAN access

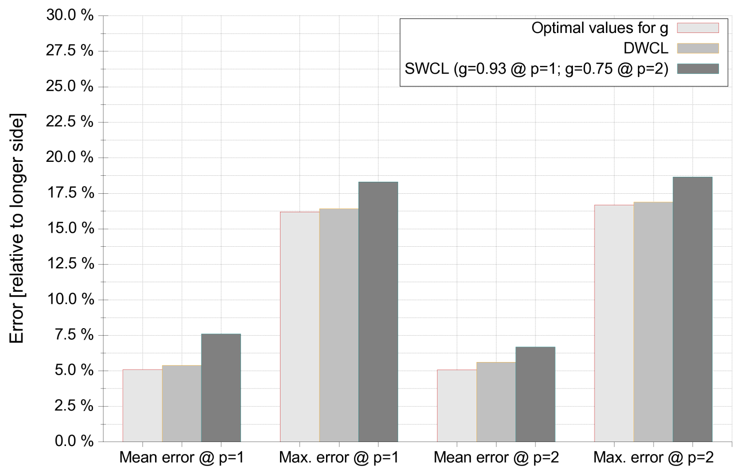

Fig. 6. Evaluation results of theoretical calculations

points, operating at a wavelength of $\lambda = \frac{f}{c} = \frac{2.44 \cdot 10^9 Hz}{3 \cdot 10^8 \frac{m}{s}} \approx 0.123$ m, and compare our practical results with the calculated ones.

5.1 Theoretical results

We compared the calculated location accuracies of DWCL and SWCL with the results we got by choosing the optimal g_{opt} at each position within the observed region. The results are shown in Figure 6. The mean error of SWCL at a quadratic room ($p = 1$) is 7.6 %, while the mean error of DWCL is 5.3 % and, hence, very close to the best possible WCL value of 5.1 %. Regarding the maximum error within the region, DWCL and the WCL optimum are almost equal, while SWCL's accuracy is worse by 2.5 percentage points. The results for a value of $p = 2$ are quite similar, even though DWCL's mean gain decreases a bit.

5.2 Indoor WLAN tests

We implemented the WCL scheme on a common smart phone[3] which served as a client device. The infrastructure beacons are represented by standard 802.11 access points[4]. The transmission power was put to the maximum possible value of 50 mW with a fixed bandwidth of 11 Mbits/s at 802.11b mode. According to [20], this provides a maximum range of about 67 meters in indoor scenarios.

Figure 7a shows the setting for our indoor tests. We used four beacons, A_1 to A_4, which were placed in the corners of a quadratic plain of 4.8 m x 4.8 m (i.e., $p = 1$) in a first test, and a rectangular plain of 5.8 m x 3.2 m (i.e., $p \approx 1.81$) in

[3] T-Mobile$^{\mathrm{TM}}$MDA Pro with PXA 270 CPU (520 MHz), 48 MB RAM, IEEE 802.11b

[4] Cisco$^{\mathrm{TM}}$Aironet 1200, [20]

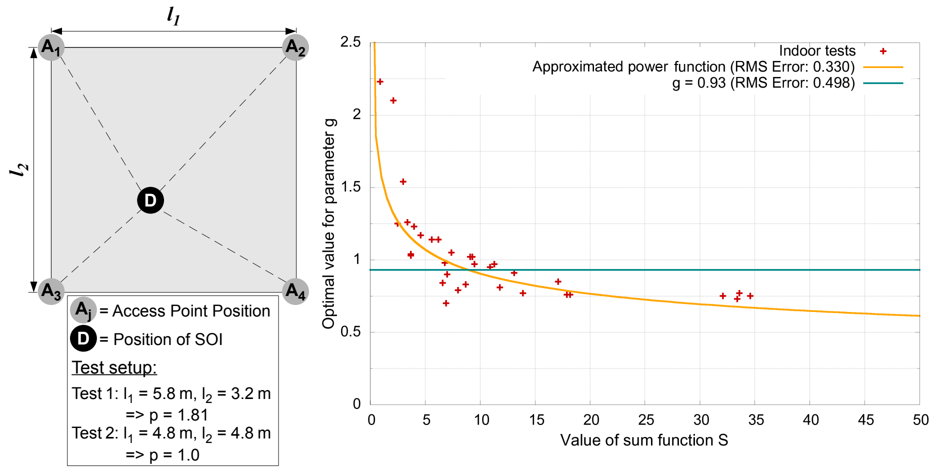

Fig. 7. a) Indoor test setup, b) Distribution of calculated $g(S)$ at indoor tests ($p = 1$)

a second test. The tests have been performed in a wall-enclosed office within a building where interferences with other WLANs occured. Furthermore, typical office furniture like chairs, desks, and a flip chart were available in the room. The SOI and the APs were placed on a plain table. We deactivated rate shifting on the APs to guarantee fixed transmission powers and performed 20 localization processes at various positions within the region, respectively. Then, we compared the averaged calculated positions with the real ones to determine the location errors.

Figure 7b displays the values of the balance function S at the test positions and the approximated power function for $p = 1$. The mean square error (0.330) is higher than in theory as the signals suffered noise and reflections. However, this error is still about 33.7 % lower than that of SWCL with $g_{opt} = 0.93$.

Figure 8 presents a comparison of the mean errors of DWCL, SWCL, and calculations with optimal values of g in these tests. It states that for $p = 1$, DWCL performs about 0.7 percentage points worse than the theoretical WCL optimum, but at the same time about 2.3 percentage points better than SWCL regarding the mean error, which implies it uses most of the existing potential for improvements. Concerning worst cases, DWCL's difference to the optimum in accuracy is close to zero, while SWCL performs about 4.2 percentage points worse than the optimum. These results confirm the increased location accuracy by dynamic weighting factors, particularly worst case accuracies in rooms that are almost quadratic where DWCL chooses nearly optimal values for g.

6 Conclusion and Outlook

In this paper, we proposed an improved Weighted Centroid Localization scheme called DWCL in combination with 802.11 access points as a simple, cost-efficient, applicable, and accurate localization scheme for ubiquitous computing scenarios.

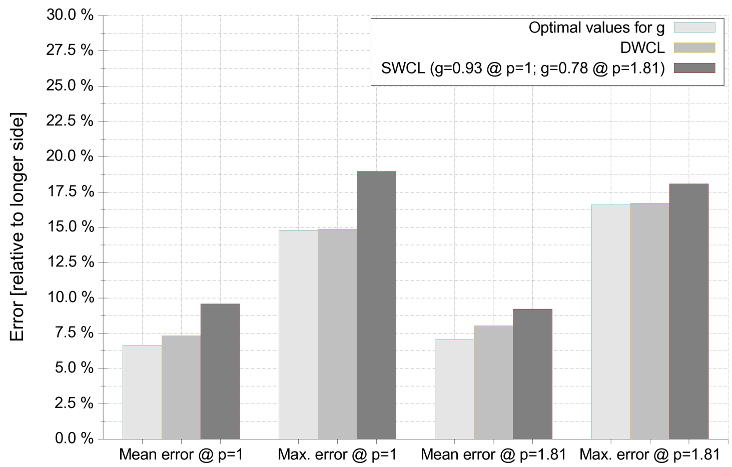

Fig. 8. Evaluation results of indoor tests

We introduced the problem domain, discussed the requirements, and presented the original WCL scheme with static weight factors (SWCL). Following, we developped an improved WCL scheme called DWCL that uses dynamic weighting factors which depend on the RSSIs to increase location accuracy. From our experiments, we conclude that DWCL represents a very effective and yet simple method for indoor localization, as it implies almost optimal location accuracy for weighted centroid schemes with rectangular anchor positioning. It does not pose additional requirements for clients as well as the infrastructure in the environment. Standard WLAN access points suffice for achieving acceptable localization errors, and the computational burden put on mobile client devices is mild. Due to the fact that WLAN-based WCL can be used in environments with off-the-shelf WLAN hardware, it is appropriate for achieving ad hoc localization in many ubiquitous smart environments with minimal prior setup efforts.

The research group at the University of Stuttgart currently investigates if this improved WCL scheme is applicable for localization across several rooms with larger distances between the access points, and alternative positionings of the access points. The research team at the University of Rostock concentrates on the reduction of the positioning error that is mainly caused by border effects. Current focus is the adaptation of weight functions according to the number of known beacons and the adjusted transmission range of the beacons.

Acknowledges

This work is funded by the German Research Foundation within Priority Programme 1140 - Middleware for Self-organizing Infrastructures in Networked Mobile Systems.

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