Combining Scalability and Resource Awareness in Wireless Sensor Network Localization

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***Abstract*—Wireless Sensor Networks (WSNs) have been shown to be most suitable for monitoring large and possibly inaccessible areas. To assign measured values to certain positions as well as for complex network algorithms, localization represents a required basic capability. By splitting a costly localization calculation into *precalculation* and *postcalculation*, Distributed Least Squares (DLS) has been introduced as an efficient approach of fine grained localization.**

Since the development of DLS, basically two advancements of DLS have been introduced. On the one hand, scalable DLS (sDLS) enabled the use of DLS in large WSNs, making the cost independent from network size. On the other hand, Resource Aware Localization Algorithm (RAL) simplified calculation and improved accuracy by use of a different linearization approach.

The aim of this work is to combine the before mentioned advancements. Therefore, a new algorithm called scalable RAL (sRAL) is introduced. This newly introduced algorithm has been compared to its sDLS counterpart by use of a WSN simulator with real world channel model. The results have been further investigated by use of a more idealistic simulation, using laboratory conditions.

***Keywords*-wireless sensor networks; localization; scalability**

I. Introduction

The ongoing trend of miniaturization of microcontrollers, radio modules and sensor technology has been enabled the fusion of sensoric, communication and computation, building a new class of devices, called sensor nodes. Working together in a Wireless Sensor Network (WSN), these devices are most suitable to observe large and inaccessible areas. In those WSNs each node acts autonomously, senses its environment, computes simple tasks and exchanges data with other nodes. For a meaningful interpretation of captured data, each nodes' location is mandatory in many applications. Furthermore, location-awareness serves as a precondition for location based algorithms like geographic routing [1][2] or clustering [3].

Due to limitations in terms of size, financial cost and energy consumption, local positioning within the network is preferred over utilizing Global Navigation Satellite Systems (GNSSs) like GPS [4]. Commonly, local positioning algorithms make use of a couple of location-aware nodes, called beacon nodes, to localize the remaining nodes, referred to as blind nodes. With the help of these known positions and the distances to these anchor points, commonly estimated by use of communication, blind nodes become able to estimate their own position.

While coarse-grained localization like Adaptive Weighted Centroid Localization (AWCL) [5] requires less computation and communication, fine-grained approaches are typically based on distance estimations and costly computations. A combination of high precision and relativly low complexity has been introduced with Distributed Least Squares (DLS) [6]. It splits the costly localization calculation into *pre-* and *post-calculation*. Independent from a specific blind node, the complex precalculation is performed on a high performance sink, while the remaining less complex postcalculation is performed on resource-constrained blind nodes.

A fundamental drawback of DLS is its limitation to small networks. Caused by the use of only one global precalculation, its size depends on the network size, i.e. the number of beacon nodes, which causes costly postcalculations comprising beacon nodes, inaccessible to the blind node. This restriction has been addressed by scalable DLS (sDLS) [7] and its successor sDLS with normal equation (sDLS^{ne}) [8], providing costs of computation and communication, incurred on blind nodes, which are independent from network size.

A further drawback of DLS is its dependence on a single node, referred to as linearizer, which is used to linearize the system of equations. The choice of linearizer has deep impact on the resulting accuracy. By use of a different linearization scheme, Resource Aware Localization Algorithm (RAL) [9] addressed this limitation and further simplified the postcalculation.

The present work aims to combine both advancements of DLS within a new algorithm, called scalable RAL (sRAL). The given algorithms, i.e. DLS, sDLS^{ne}, RAL and sRAL, will be analysed and compared to each other in terms of costs as well as in terms of accuracy.

The remainder of the paper is organized as follows. Section II covers basic informations about DLS, sDLS^{ne} and RAL. In Section III, the new combined approach referred to as sRAL is presented. Section IV covers performed simu-

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lations as well as simulation results. Finally, the presented work is summarized in Section V.

II. Related Work

A. DLS

The DLS algorithm as well as the following algorithms base on system of equations, composed of distance equations as given in equation (1). Here x and y indicate the unknown position of a blind node. The known position of a beacon node is denoted as x_i and y_i. The distance between both nodes is given as r_i. The number of beacon nodes utilizable for localization is given as m.

$$(x-x_i)^2+(y-y_i)^2 = r_i^2 \quad (i \in I; I = \{1,2,\dots,m\}) \tag{1}$$

To linearize this system of equations DLS makes use of a linearization tool [10], using one beacon node as linearizer, denoted with index L. After restructuring, the system of equations consists of equations as given in equation (2), where r_L denotes the distance between blind node and linearizer, r_i is the distance between blind node and beacon node and d_{iL} denotes the distance between linearizer and beacon node.

$$\begin{aligned} b_{iL} &= (x-x_L)(x_i-x_L)+(y-y_L)(y_i-y_L) \\ &= \frac{1}{2}\left[r_L^2 - r_i^2 + d_{iL}^2\right] \end{aligned} \tag{2}$$

After further restructions, the system of equations matches the matrix form $\mathbf{A}\mathbf{x} = \mathbf{b}$, using $\mathbf{A}$, $\mathbf{x}$ and $\mathbf{B}$ as given in equation (3).

$$\begin{aligned} \mathbf{A} &= \begin{pmatrix} x_{k_1}-x_L & y_{k_1}-y_L \\ x_{k_2}-x_L & y_{k_2}-y_L \\ \vdots & \vdots \\ x_{k_n}-x_L & y_{k_n}-y_L \end{pmatrix}, \\ \mathbf{x} &= \begin{pmatrix} x-x_L \\ y-y_L \end{pmatrix}, \mathbf{b} = \begin{pmatrix} b_{k_1L} \\ b_{k_2L} \\ \vdots \\ b_{k_nL} \end{pmatrix} \end{aligned} \tag{3}$$

Here, beacon nodes, used for localization, are denoted with indices $K = \{k_1, k_2, \dots, k_n\}$ with $K = \{I \setminus L\}$. While matrix $\mathbf{A}$ only consists of beacon position data, calculations on this matrix build one part of the precalculation.

By use of normal equations, the localization task is to solve equation (4a), splitted into precalculation (4b), performed on the sink, and postcalculation (4c), performed on blind nodes. Figure 1 gives an algorithmic representation of DLS.

$$\mathbf{x} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\frac{1}{2}\left[r_L^2 - \mathbf{r}^2 + \mathbf{d}^2\right] \tag{4a}$$

$$\begin{aligned} \mathbf{A}_p &= \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T \\ \mathbf{d}_p &= \mathbf{d}^2 \end{aligned} \tag{4b}$$

$$\mathbf{x} = \mathbf{A}_p\frac{1}{2}\left[r_L^2 - \mathbf{r}^2 + \mathbf{d}_p\right] \tag{4c}$$

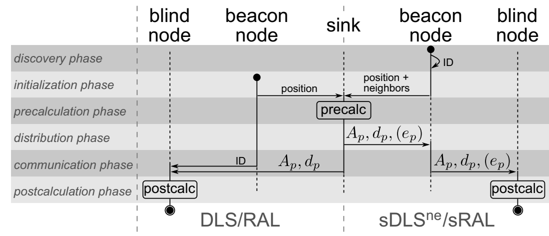


Figure 1. Algorithmic comparison of DLS/RAL and sDLS^{ne}/sRAL

B. sDLS

sDLS^{ne} as the latest variant of sDLS keeps the idea of splitting the calculation into precalculation and postcalculation, but uses multiple, individual precalculations with smaller size. Each beacon node provides its own precalculation, using its own position as linearization tool. Blind nodes are expected to choose the precalculation of the closest beacon node, according to their distance estimation. Due to this condition, the distance towards the linearizer is much smaller than distances between linearizer and beacon nodes outside the blind nodes's communication range, given by the precalculation (4b). Therefore, the sum of both distances can be used as distance estimation towards those beacon nodes, as shown in figure 2.

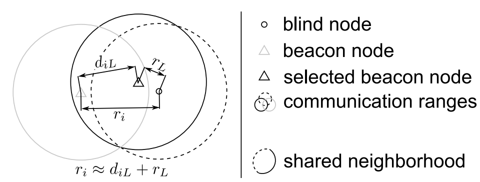


Figure 2. Approximation of a distance between blind node and inaccessible beacon node

Considering $\mathbb{G}$ as the global set of all beacon nodes within a WSN and $\mathbb{L}_i \subseteq \mathbb{G}$ as a local set of beacon nodes within the communication range of beacon node i, sDLS^{ne} uses individual precalculations for all beacon nodes, i.e. $|\mathbb{G}|$ precalculations using equation (3) with $K = \{\mathbb{L}_i \setminus L\}$, $L = i$, $\forall i \in \mathbb{G}$. In contrast, DLS made use of only one precalculation, including all beacon nodes, i.e. equation (3) with conditions $K = \{\mathbb{G} \setminus L\}$ and $L = 1$. Therefore, the sDLS^{ne} algorithm starts with an additional discovery phase to find other beacon nodes in one hop distance, as illustrated in figure 1. While DLS needs an explicite communication with all beacon nodes during the communication phase for distance estimation, this is implicitely performed by sDLS^{ne} as each blind node receives precalculations from beacon nodes in its own communication range.

C. RAL

While the enhancements of sDLS^{ne} are mainly achieved by changes of the algorithmic part, RAL changed the math behind DLS to achieve its advancement and left the algorithm unchanged as given in figure 1. Instead of using a linearization tool, RAL uses a substitution to linearize the system of equations. Based on equation (1), RAL starts with resolving the binomial formulas followed by the substitution $x^2 + y^2 = w$, which results in equation (5).

$$b_i = -2x_i x - 2y_i y + w = r_i^2 - x_i^2 - y_i^2 \tag{5}$$

The resulting matrix form $\mathbf{Ax} = \mathbf{b}$ holds three unknown parameter and one more column in matrix $\mathbf{A}$ as given in equation (6).

$$\mathbf{A} = \begin{pmatrix} -2x_{k_1} & -2y_{k_1} & 1 \\ -2x_{k_2} & -2y_{k_2} & 1 \\ \vdots & \vdots & \vdots \\ -2x_{k_n} & -2y_{k_n} & 1 \end{pmatrix}, \quad \mathbf{x} = \begin{pmatrix} x \\ y \\ w \end{pmatrix}, \mathbf{b} = \begin{pmatrix} b_{k_1} \\ b_{k_2} \\ \vdots \\ b_{k_n} \end{pmatrix} \tag{6}$$

However, when solving this system of equations using linear least squares, similar to DLS, w does not need to be calculated in the postcalculation (7b) for localization and the corresponding row of the precalculation, given in equation (7a), does not have to be transmitted.

$$\begin{aligned} \mathbf{A}_p &= \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T \\ \mathbf{d}_p &= \left(x_i^2 + y_i^2\right)_{i\in K} \end{aligned} \tag{7a}$$

$$\mathbf{x} = \mathbf{A}_p\left(\mathbf{r}^2 - \mathbf{d}_p\right) \tag{7b}$$

As it can be seen in equation (6), one advantage of RAL is that the unknown position, given in $\mathbf{x}$, is determined directly. Second advance is the absence of an outstanding beacon node, known as linearizer in DLS, which affects the localization accuracy. In [11], the accuracy of various localization algorithms have been analyzed. Particularly, it has been shown that the linearization tool, used in DLS, leads to higher localization errors, causing an error ellipse in line with the linearizer's direction. Therefore, RAL outperforms DLS in terms of accuracy and reliability.

III. The sRAL Approach

As RAL relies on the same basic idea as DLS, it also shares the same problem of unreachable beacon nodes and costs, growing with the number of beacon nodes. Having the before mentioned enhancements of DLS in mind, i.e. sDLS and RAL, the idea of sRAL almost suggests itself. In a few words, sRAL aims to combine the linearization method, used in RAL and the algorithmic approach of individual precalculations, promoted by sDLS.

In spite of the given similarities of DLS and RAL, there is one major difference, which needs to be taken into account, when applying the idea of sDLS onto RAL. RAL takes it advance from waiving of a linearization tool. This affects the precalculation, given in equation (7a), which does not include any distance information. In contrast, to avoid costly matrix updates, sDLS^{ne} used the given distances between linearizer and beacon nodes for distance approximation as mentioned in figure 2. To fully apply this idea of sDLS^{ne} onto RAL, the precalculation of sRAL, given in equation (8a), had to be extended by a distance vector $\mathbf{e}_p$, holding the euclidean distances e_i between the beacon nodes of the precalculation and the beacon node that provides the precalculation. Except from its size, the postcalculation of sRAL (8b) is similar to RAL.

$$\begin{aligned} \mathbf{A}_p &= \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T \\ \mathbf{d}_p &= \left(x_i^2 + y_i^2\right)_{i\in K} \\ \mathbf{e}_p &= \left(e_i\right)_{i\in K} \end{aligned} \tag{8a}$$

$$\mathbf{x} = \mathbf{A}_p\left(\mathbf{r}^2 - \mathbf{d}_p\right) \tag{8b}$$

IV. Simulations

A. Field Based Simulation

As previously done with sDLS, all mentioned algorithms has been simulated in a realistic WSN, using the MATLAB® based network simulator Rmase [12]. Radio communication is modeled by use of log-normal fading with pathloss 2 and shadowing variance 1.7, which corresponds to an outdoor open area. Especially distance estimations on blind nodes have been performed by use of the received signal strength (RSS), given by the simulator's radio communication model. Simulated field size has been varied from $50m \times 50m$ to $200m \times 200m$. The mean number of randomly chosen beacon nodes, as well as blind nodes was set to $0.005/m^2$. The mean communication range of a node was about $30m$. For multi-hop communication, a simple spanning tree routing is applied. All simulations have been repeated 100 times, performing all localization approaches concurrently. In each simulation, one of the randomly deployed nodes has been chosen as sink.

First results are dealing with the amount of communication. Therefore, each transmitted float value has been counted as 4 bytes, while an integer value, e.g. an ID, has been counted as 2 bytes.

Besides the before mentioned data, i.e. $\mathbf{A}_p$, $\mathbf{d}_p$ and $\mathbf{e}_p$, an additional vector $\mathbf{b}_{ID}$ which relates the IDs of used beacon nodes to the precalculation is transmitted. In case of DLS and sDLS also the linearizer's ID ID_L and position P_L need to be transmitted. Table I provides an overview of the amount of data per precalculation based on n beacon nodes.

Although the amount per precalculation is similar in most approaches, there are differences due to the number and size of genererated precalculations. Furthermore, in case of sDLS, linearizer information needs not to be transmitted from sink to beacon node but only from beacon node to blind node. Figure 3 shows the mean data transmitted per

Table I
SIZE OF DATA PER PRECALCULATION, BASED ON n BEACON NODES

data	type	DLS	RAL	sDLS^{ne}	sRAL
$\mathbf{A}_p$	float	$[2 \times n-1]$	$[2 \times n]$	$[2 \times n-1]$	$[2 \times n]$
$\mathbf{d}_p$	float	$[n-1 \times 1]$	$[n \times 1]$	$[n-1 \times 1]$	$[n \times 1]$
$\mathbf{e}_p$	float	-	-	-	$[n \times 1]$
$\mathbf{b}_{ID}$	integer	$[n-1 \times 1]$	$[n \times 1]$	$[n-1 \times 1]$	$[n \times 1]$
ID_L	integer	$[1 \times 1]$	-	$[1 \times 1]$	-
P_L	float	$[2 \times 1]$	-	$[2 \times 1]$	-
sum of bytes		$14*n-4$	$14*n$	$14*n-4$	$18*n$

node. Therefore only routing nodes and beacon nodes have been taken into account. It can be seen that, using DLS and RAL, a one and the same high amount of data has to be transmitted by each node. In contrast, sDLS^{ne} leads to lower data transmission per node, similar to sRAL which needs slightly more data.

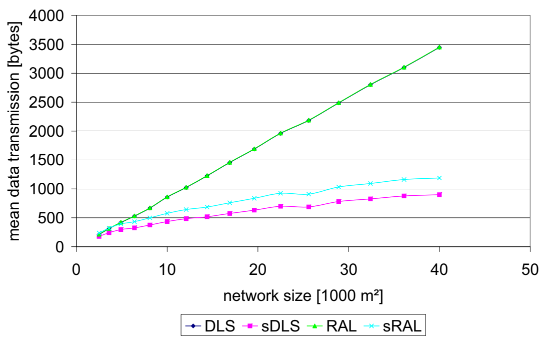


Figure 3. Mean amount of data transmission

Second results, given in figure 4, investigate the number of floating point operations, which have been performed on a blind node in order to estimate its position, including postcalculation and distance approximation. Once again it can be seen, that DLS and RAL show similar performance, using a high number of operations. By use of sDLS^{ne} and sRAL, the number of operations is much smaller. As theoretic analyses show that a postcalculation of n beacon nodes takes $7*n-5$ operations in case of DLS and only $6*n-2$ operations in case of RAL, RAL based approaches take less operations than DLS based approaches.

The most interesting results regard the mean localization error, measured as distance between estimated position and real position. Therefore distances to unreachable beacon nodes have been approximated as desribed in Section II-B also in the case of DLS and RAL. It can be seen in figure 5 that in the case of a high number of inaccessible beacon nodes RAL falls back to a mostly constant localization error. Caused by the used distance approximation, this error is close to a nearest-beacon approach. Due to the strong impact

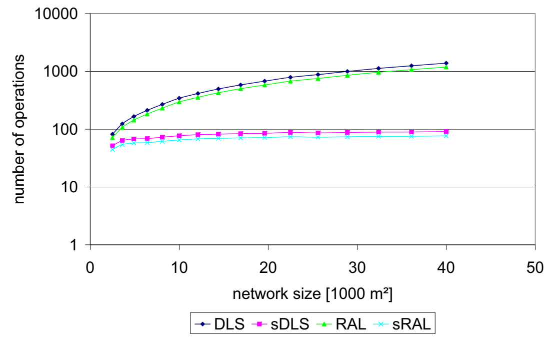


Figure 4. Mean number of operations on blind nodes

of the linearizer, DLS leads to a quite higher localization error.

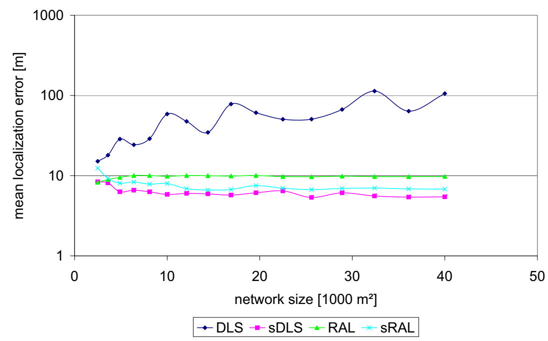


Figure 5. Mean localization error

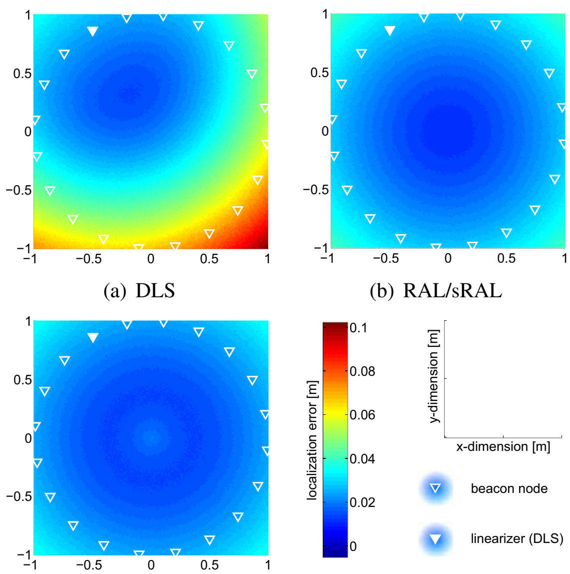
A contrary result can be observed concerning sDLS^{ne} and sRAL. Both approaches provide higher localization accuracy than their antetypes. Although sRAL could have been expected to provide higher accuracy than sDLS^{ne}, it is outperformed by sDLS^{ne}. Supposably, this is caused by the linearizer which is chosen close to the blind node's position. This aspect is further investigated in the following subsection.

B. Idealistic Simulation

The following simulations have been inspired by simulations, used in [11], which identified RAL as more accurrate than DLS. As previously done in [11], a number of beacon nodes have been arranged in a circle. In contrast to the original simulations the blind node has not been set to the center of the circle, but has been moved around in the given field. The number of beacon nodes as well as the variance, used to distort measured distances, has been varied.

The idealistic character is given by the assumption, that beacon nodes and blind nodes are always within each others communication range. Therefore, sDLS only differs from DLS in the fact that the linearizer node is chosen close to the blind node. Concerning RAL and sRAL, there are no differences. All simulations has been repeated 2000 times, applying each algorithm on the same sets of distorted distances.

Firstly, figure 6 shows a network of 20 beacon nodes. At each point, a blind node estimated its position, using one of the algorithms, and calculated its localization error, indicated by the colorbar. For distance distortion a variance of 10% has been used. It is shown in figure 6(a), that DLS is strongly influenced by the linearizer. Blind nodes will be localized best, if they are located in a certain region between linearizer and center. In contrast, as shown in figure 6(b), RAL/sRAL is not influenced by a certain beacon node, achieving best localization in the center. Using sDLS, a blind node always choses the closest beacon node. Therefore, sDLS also shows a circular error distribution. In contrast to RAL/sRAL, best localization is achieved within a ring around the center, as illustrated in figure 6(c). Close to the border, sDLS is even better than RAL/sRAL.



(a) DLS

(b) RAL/sRAL

(c) sDLS

(d) legend

Figure 6. Distribution of mean localization error

To illustrate the regions where sDLS outperforms RAL/sRAL and vice versa, the localization error of sDLS has been substracted by the localization error of RAL/sRAL, i.e. positive values indicate that RAL/sRAL outperforms sDLS and vice versa. Figure 7 illustrates this difference, using several parameter sets. A white borderline outlines where both algorithms provide the same localization error. Within this borderline, sRAL performs allways better than sDLS. On the one hand, it can be seen that the region within sDLS performs better is as larger as less beacon nodes are used, and does not depend on the variance, applied to measured distances. On the other hand, the difference itself depends on the variance. While both algorithms perform similar if a low variance is assumed, the difference between both algorithms is larger if a high variance is assumed.

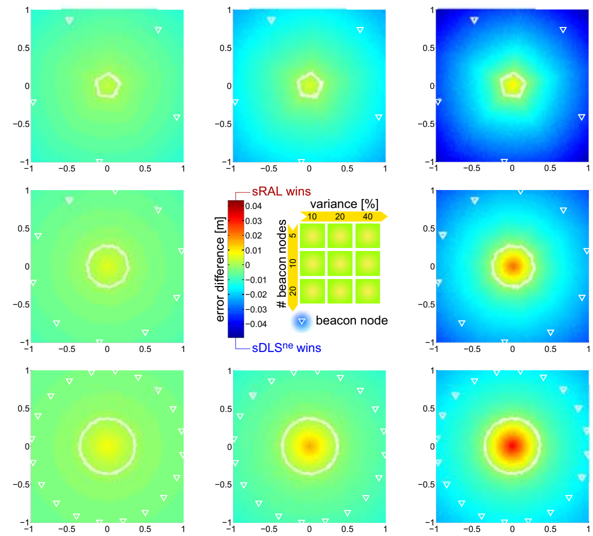


Figure 7. Difference of mean localization error of sDLS and RAL/sRAL

These results are underlined by figure 8 and 9, also showing the difference of the mean localization error of the two algorithms. For these simulations, a blind node has been moved from one side of the circle, i.e. the position of the linearizer in case of DLS, to the opposite side.

Figure 8, illustrating the impact of the number of beacon nodes, shows that only in case of a small number of beacon nodes sDLS significantly outperforms RAL/sRAL within a large area. In contrast, having a high number of beacon nodes, sRAL becomes more beneficial, significantly outperforming sDLS in a wide range. Although there is still a region within sDLS outperforms sRAL, the gain in this outer region is much less than the gain of sRAL near the center.

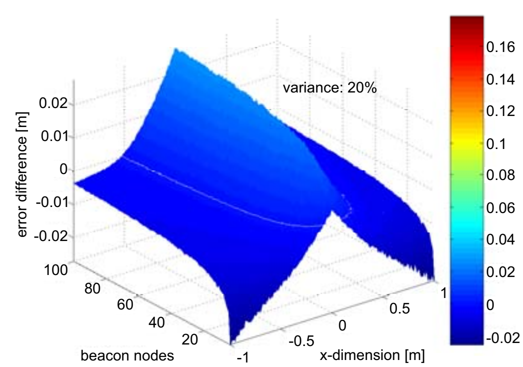


Figure 8. Difference of mean localization error (sDLS - RAL/sRAL) versus number of beacon nodes. Blind node traverses the circle of beacon nodes along the x-axis ($y = 0$).

Figure 9, which illustrates the impact of the variance applied on measured distances, shows that there is no influence on the apportionment of the found regions. The difference between the algorithms increases as the variance increases. In the given case of 20 beacon nodes, RAL/sRAL copes better with high variance than sDLS.

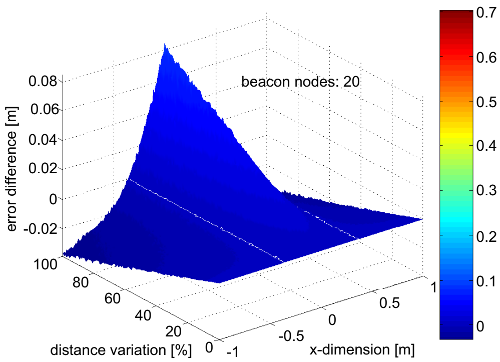


Figure 9. Difference of mean localization error (sDLS - RAL/sRAL) versus distance variation. Blind node traverses the circle of beacon nodes along the x-axis ($y = 0$).

On the one hand, the results of the idealistic simulation support the field based results, presented before, proving that under certain conditions, the linearization tool can also have possitive influence on the localization. In the field based simulation a blind node used a mean number of 13 beacon nodes. On the other hand, the results show that sRAL is more reliable in case of high distance variantions. In addition, sRAL profits much more from a higher number of beacon nodes than sDLS.

V. Conclusion

In this work, a new localization approach, called sRAL, has been introduced with the aim to combine efficiency and accuracy of RAL with the scalability of sDLS^{ne}. Field based simulations have shown that this new approach greatly outperforms the initial RAL. Compared to sDLS^{ne} it is more efficient in terms of computation but slightly outperformed in terms of accuracy. Idealistic simulations underlined, that under certain conditions the linearization tool, used in sDLS^{ne}, has positive influence on the accuracy. Nevertheless, it has been shown that sRAL is more stable against high variations in distance estimation, and profits from a high number of beacon nodes. As both algorithms provide low localization error, it depends on the network design goal which algorithm is preferred. sRAL needs to be preferred if computation is an important criterion. Especially in case of high number of beacon nodes as well as in case of highly distorted distance estimations, sRAL is the best choice, as it provides a reliable efficient localization.

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