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Novel Mechanisms for Location-Tracking Systems

Giuseppe Destino and Giuseppe Abreu
University of Oulu, Centre for Wireless Communications
Finland

1. Introduction

The need of location information is rapidly emerging in many wireless application scenarios Hightower & Borriello (2001); Poslad (2009); Vossiek et al. (2003). For instance, in home and office environments, location-based services are developed to improve the efficiency of the working environment, to localize printers, mobile-phones, people, etc. In warehouse, industrial and hospital application scenarios, location information can be used to track assets and persons. In military and rescuing applications, positioning technologies can be utilized for real-time monitoring of soldiers in the troop, track machines and cars Destino & Abreu (2009a); Destino et al. (2007).

Location-information, however, is also emerging as a requirement for the next generation of wireless communication technologies. For instance, for mobile networks, the 23rd of September 2010, the Federal Communications Commission (FCC) unanimously approved new rules for the use of unlicensed TV white space spectrum. It was stated that devices will be able to access to the TV white space spectrum if they will able to determine their locations and to identify the unused channels at that location. Yet another emerging area where positioning will play a major role is the Internet-of-things (IoT) Scott & Benlamri (2010). In this case, context and location-awareness will be fundamental for the development of smart technologies that will allow "Things" (computer, mobile-phones, objects, sensors, actuators, etc.) to be autonomous and energy-efficient.

Motivated from all the above, a lot of researches are devoted to the development of accurate positioning technologies based on satellite radios like the Global Positioning System (GPS), or short- and medium-range radio technologies such as Wi-Fi, Bluetooth and Ultra-wide band (UWB). In particular, UWB technology has seen a strong surge of interests because of its high accurate ranging capabilities and energy efficiency Dardari et al. (2008.); Gezici et al. (2005); Yihong et al. (2004).

This chapter is intended as a survey on current state-of-the-art localization techniques for large-scale and single-hop networks, and for the latter case, a dedicated section will be also devoted for Non-Line-of-Sight (NLOS) mitigation mechanisms. Finally, considering a low-data-rate impulse radio (LDR-IR) UWB ranging model Denis et al. (2007), the performance of the described algorithms will be shown for Line-of-Sight (LOS) and mixed LOS/NLOS channel conditions in both single-hop and multi-hop network topologies.

2. Modeling of the localization problem

Consider a network of N nodes deployed in the η-dimensional space. We shall assume that N_{A} nodes are anchors and N_{T} nodes are targets, where an anchor is a node whose location is known *a priori*, while a *target* is a node whose position is yet to be determined.
Denote by $\mathbf{p}_i \in \mathbb{R}^{\eta}$ the position (Euclidean coordinates) of the i-th node such that $\mathbf{p}_i \triangleq \mathbf{a}_i$ and $\mathbf{p}_i \triangleq \mathbf{z}_j$ for $1 \leq i \leq N_A$ and $N_A + 1 \leq i \leq N$, respectively.
The Euclidean distance between the i-th and the j-th node is defined as

$$d_{ij} \triangleq \|\mathbf{p}_i - \mathbf{p}_j\|_{\mathrm{F}}, \tag{1}$$

where $\|\cdot\|_{\mathrm{F}}$ is the Frobenius norm, while a measurement (ranging) of d_{ij} is given by

$$\tilde{d}_{ij} = \begin{cases} d_{ij} + b_{ij} + n_{ij}, & \text{if either } \mathbf{p}_i = \mathbf{z}_i \text{ or } \mathbf{p}_j = \mathbf{z}_j, \\ d_{ij}, & \text{if both } \mathbf{p}_i = \mathbf{a}_i \text{ and } \mathbf{p}_j = \mathbf{a}_j \end{cases} \tag{2}$$

where n_{ij} and b_{ij} indicates small(noise) and large(bias) errors.
Extensive measurement campaigns can be found in the literature in order to characterize the statistics of n_{ij} and b_{ij} for different radio-technologies Gentile & Kik (2006); Joon-Yong & Scholtz (2002); Mao et al. (2007); Patwari et al. (2003). In the case of Low-Data-Rate Ultra-Wideband (LDR-UWB) we adopt the model proposed in Denis et al. (2007), which summarizes as follows.
Define the biased distance d'_{ij} as $d'_{ij} \triangleq d_{ij} + b_{ij}$ and consider such a variable as a random variate conditioned upon the true Euclidean distance d_{ij} and governed by the probability density functions p_C

$$p_C(d'_{ij}|d_{ij}, C) = \frac{G_C}{d_{ij}\sqrt{2\pi}\sigma_C} \exp\left(\frac{\left(\frac{d'_{ij}}{d_{ij}} - 1\right)^2}{2\sigma_C^2}\right) + \lambda_C E_C \frac{1_{d'_{ij} > d_{ij}}}{d_{ij}} \exp\left(\frac{-\lambda_C(d'_{ij} - d_{ij})}{d_{ij}}\right), \tag{3}$$

where $1_{d'_{ij} > d_{ij}} = 1$ if $d'_{ij} > d_{ij}$ and 0 otherwise, $\{G_C, \sigma_C\}$ and $\{E_C, \lambda_C\}$ are the weights and parameters of Gaussian and Exponential mixture components and $C \triangleq \{\mathrm{LOS}, \mathrm{NLOS}, \mathrm{NLOS}^2\}$ refers to a ranging error model without bias (LOS), with small bias (NLOS) and large bias (NLOS^2). Furthermore, consider that the channel C is also a function of the distance d_{ij}, and the probability of LOS, NLOS or NLOS^2 can be computed as

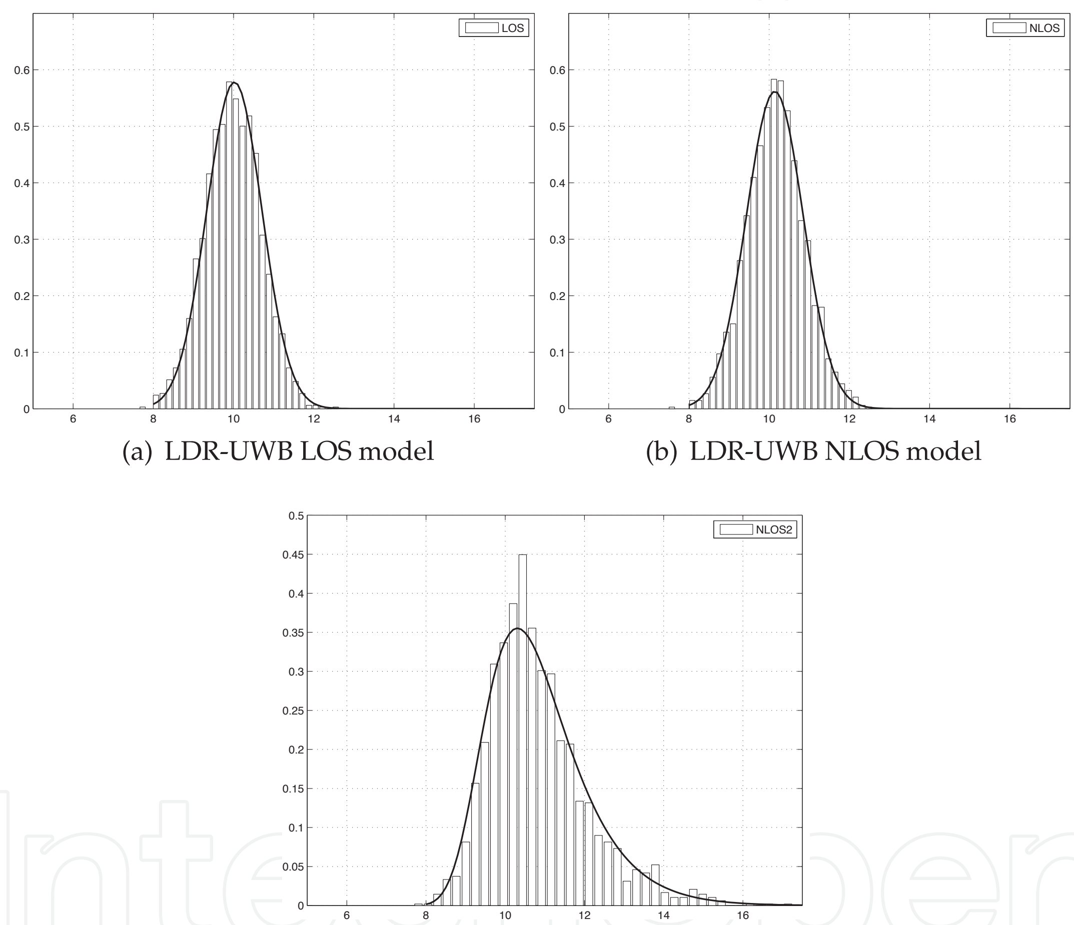
$$W_C(d_{ij}) = \frac{\xi}{\sqrt{2\pi}\varsigma_C} \exp\left(\frac{-\left(d_{ij} - d_0\right)^2}{2\varsigma_0^2}\right), \tag{4}$$

where d_0 and ς_0 are reference values (typical $d_0 = 10$ and $\varsigma_0 = 4.6$) and ξ ensures that $W_{LOS}(d_{ij}) + W_{NLOS}(d_{ij}) + W_{NLOS^2}(d_{ij}) = 1$ (for instance ξ is 10 when $d_0 = 10$ and $\varsigma_0 = 4.6$).
Once, the biased distance in computed, then the distance measurement $\tilde{d}_{ij}$ is obtained as in equation (2), where n_{ij} is a zero-mean Gaussian random variable with variance σ_{ij}^2.

In figure 1 we exemplify the LDR-UWB ranging model and we show the histograms and pdfs of $\tilde{d}_{ij}$ obtained for $d_{ij} = 10$, $\sigma_{ij} = 0.7$ and bias-distance parameters $\{G_C, \sigma_C\}$ and $\{E_C, \lambda_C\}$ given by

	G_C	σ_C	E_C	λ_C
LOS	0	0.0068	0	0
NLOS	0.31	0.0102	0.69	47.013
NLOS^2	0.26	0.0129	0.74	8.4331

Table 1. Setting of the parameters for the UWB-LDR ranging model given in equation (3)



(a) LDR-UWB LOS model (b) LDR-UWB NLOS model

(c) LDR-UWB strong NLOS model

Fig. 1. Example of the biased distance d'_{ij} in different channel conditions.

In many application scenarios, however, it is assumed that the ranging model is unknown and it cannot be accurately estimated because of scarcity of information. Therefore, we consider non-parametric localization methods such as the minimization of a Weighted Least Square (WLS) objective function,

$$\min_{\hat{\mathbf{Z}} \in \mathbb{R}^{N_{\mathrm{T}} \times \eta}} f_{\mathrm{R}}(\hat{\mathbf{Z}}), \tag{5}$$

with

$$f_{\mathrm{R}}(\hat{\mathbf{Z}}) \triangleq \sum_{ij\in\mathcal{H}} w_{ij}\left(\tilde{d}_{ij}-\hat{d}_{ij}\right)^2 = \sum_{ij\in\mathcal{H}} w_{ij}\left(\tilde{d}_{ij}-\|\mathbf{a}_i-\hat{\mathbf{z}}_j\|_{\mathrm{F}}\right)^2 + \sum_{ij\in\mathcal{H}} w_{ij}\left(\tilde{d}_{ij}-\|\hat{\mathbf{z}}_i-\hat{\mathbf{z}}_j\|_{\mathrm{F}}\right)^2, \quad (6)$$

where $\mathcal{H}$ is the set of indexes related to connected links, $\hat{d}_{ij} \triangleq \|\hat{\mathbf{p}}_i-\hat{\mathbf{p}}_j\|_{\mathrm{F}}$ is the distance obtained from the estimates of the i-th and j-th nodes, and w_{ij} is a weight Costa et al. (2006); Destino & G. (2009) related to the "concern" Boyd & Vandenberghe (2004) over the term $(\tilde{d}_{ij}-\hat{d}_{ij})$.

In the localization problem posed as in equation (5), several challenges are met and the one that has attracted a large research community is the design of efficient minimization techniques Costa et al. (2006),Biswas, Liang, Toh & Wang (2006),Ding et al. (2008),Destino & Abreu (2009c),Wymeersch et al. (2009). In the sequel, this issue will be addressed and the most effective state-of-the-art solutions will be described in details.

2.1 WLS localization methods in large scale networks

Rewrite the objective function given in equation (6) as

$$f_{\mathrm{R}}(\hat{\mathbf{Z}}) = \left\|\mathbf{W}\circ\left(\widetilde{\mathbf{D}}-\mathcal{D}(\hat{\mathbf{P}})\right)\right\|_{\mathrm{F}}^2, \quad (7)$$

where the ij-th element of $\mathbf{W}$ is the weight w_{ij}, $\circ$ is the Hadamard product and

$$\hat{\mathbf{D}} = \mathcal{D}(\hat{\mathbf{P}}) \triangleq \sqrt{\mathbf{1}_N\cdot\mathrm{diag}\left(\hat{\mathbf{P}}\cdot\hat{\mathbf{P}}^{\mathrm{T}}\right)^{\mathrm{T}} + \mathrm{diag}\left(\hat{\mathbf{P}}\cdot\hat{\mathbf{P}}^{\mathrm{T}}\right)\cdot\mathbf{1}_N^{\mathrm{T}} - 2\cdot\hat{\mathbf{P}}\cdot\hat{\mathbf{P}}^{\mathrm{T}}}, \quad (8)$$

where $^{\mathrm{T}}$ indicates transpose, $\mathbf{1}_N$ is a column vector of N elements equal to 1, and $\mathrm{diag}(\cdot)$ indicates a column vector containing the diagonal elements of its argument Dattorro (2005).

The localization problem given in equation (5) can then be approached in two different manners Dattorro (2005); Destino & Abreu (2009c); So & Ye (2005). The first one, which is the basis for the later described Classical Multidimensional Scaling (CMDS) Cox & Cox (2000) and Semidefinite Programming (SDP) methods, is to consider $\widetilde{\mathbf{D}}$ as the observation of a multidimensional variable $\hat{\mathbf{D}}$. Therefore, the optimization problem can be formulated as matrix proximity optimization problem, in which the objective is to estimate the closest Euclidean Distance Matrix (EDM) $\hat{\mathbf{D}}$ to the observed EDM-sample $\tilde{\mathbf{D}}$. In so doing, the optimization problem benefits from the fact that the space of the EDM, denoted by $\mathbb{EDM}^N$, is related to the space of symmetric positive semidefinite matrixes, denoted by $\mathbb{S}_+^N$ with the linear relationship

$$\mathbf{K} \triangleq \mathcal{K}(\mathbf{D}) = -\frac{1}{2}\mathbf{J}\cdot(\mathbf{D})^{\circ 2}\cdot\mathbf{J}^{\mathrm{T}}, \quad (9)$$

where $^{\circ 2}$ indicates the element-wise square and

$$\mathbf{J} \triangleq \mathbf{I}_N - (\mathbf{1}_N\cdot\mathbf{1}_N^{\mathrm{T}})/N. \quad (10)$$

The search of the optimum matrix can therefore be constrained either to $\mathbb{S}_+^N$ or to $\mathbb{EDM}^N$, such that two different methods can be formulated. The first method is to solve the optimization problem as

$$\min_{\hat{\mathbf{K}}} \left\|\mathcal{K}(\mathbf{W} \circ (\tilde{\mathbf{D}} - \hat{\mathbf{D}}))\right\|_F^2, \quad (11)$$
$$\text{s.t. } \mathcal{K}(\hat{\mathbf{D}}) \in \mathbb{S}_+^N,$$

and the second method is to formulate the problem as

$$\min_{\hat{\mathbf{D}}} \left\|\mathbf{W} \circ (\tilde{\mathbf{D}} - \hat{\mathbf{D}})\right\|_F^2. \quad (12)$$
$$\text{s.t. } \hat{\mathbf{D}}^2 \in \mathbb{EDM}$$

For the sake of illustration, in figure 2 we show the logic of the two approaches with an Euler diagram. The black and red arrows indicate the linear mapping from $\mathbb{S}_+^N$ to $\mathbb{EDM}^N$ given by equations (8) and (9) and viceversa, respectively. The yellow cicle describes the method 1 (optimization in $\mathbb{S}_+^N$) and the blue arrow method 2 (optimization in $\mathbb{EDM}^N$). In the following subsections we describe two state-of-the-art solutions based on method 1 and 2, namely the algebraic Classical Multidimensional Scaling (CMDS) technique and the Semi Definite Programming (SDP) method.

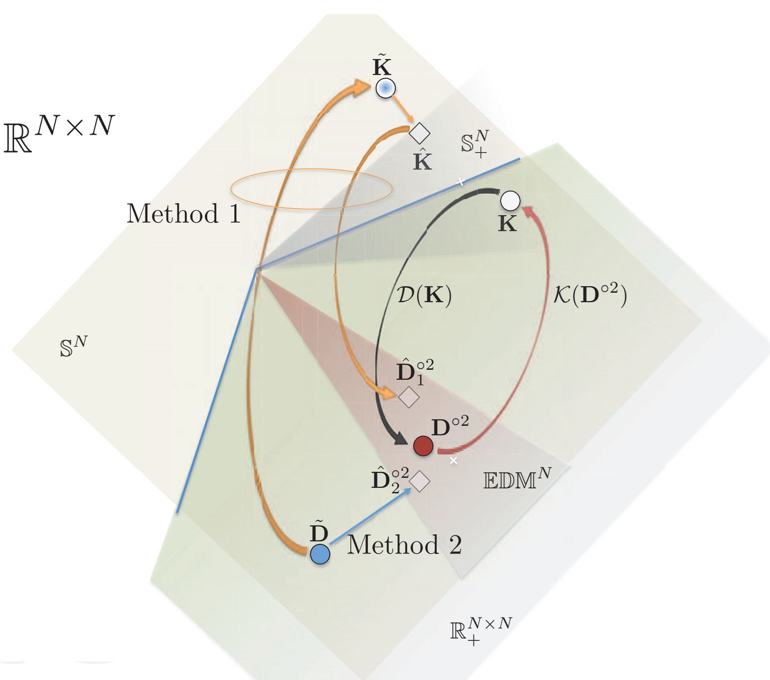


Fig. 2. Illustration of the matrix proximity problem with and Euler diagram. The notations $\mathbb{R}^{N\times N}$, $\mathbb{R}_+^{N\times N}\mathbb{S}^N$, $\mathbb{S}_+^N$ and $\mathbb{EDM}^N$ indicate the real, real-positive, real-symmetric, real-positive semidefinite and Euclidean Distance Matrix spaces.

As mentioned above, however, the WLS-based localization problem can also be approached in a different manner than a matrix proximity problem. The alternative indeed is to solve equation (5) directly over the unknown variables $\mathbf{z}_i$'s Gezici (2008). In this approach, the major difficulty is to handle the multiple minima with robust optimization methods. To this end, indeed, several techniques can be found in the literature which are proposed either as distributed or centralized algorithms. Amongst all, we will describe two algorithms that can benefit of a very low-computational cost, namely the Stress-of-a-MAjorizing-Complex-Objective-Function (SMACOF) Cox & Cox (2000) and the Range-Global Distance Continuation (R-GDC) Destino & Abreu (2009c); More & Wu (1997).

2.2 Classical Multidimensional Scaling (CMDS)

The CMDS is an algebraic technique to solve the localization problem posed as in equation (11). Specifically, the CMDS algorithm relies on the $\mathbb{EDM}^N - \mathbb{S}_+^N$ relationship given in equation (9) Schoenberg (1935) and it can be concisely summarized as

$$\hat{\mathbf{P}}_o = \left([\mathbf{U}]_{\mathrm{UL}:N\times\eta} \cdot [(\mathbf{\Lambda})^{\frac{1}{2}}]_{\mathrm{UL}:\eta\times\eta}\right)^{\mathrm{T}}, \tag{13}$$

where $\hat{\mathbf{P}}_o$ is a representation of the desired estimates coordinates $\hat{\mathbf{P}}$ up to rigid motions (rotation, mirroring and shifting) and scaling, $[\cdot]_{\mathrm{UL}:n\times q}$ denotes the n-by-q upper-left partition and the matrices $\mathbf{U}$ and $\mathbf{\Lambda}$ are the eigenvector and eigenvalue matrices (both in decreasing order) of $\tilde{\mathbf{K}} \triangleq \mathcal{K}(\widetilde{\mathbf{D}})$.

Notice however, that the CMDS performs optimally only if all pairwise links are observed and all weights are unitary. In the other cases, the accuracy of the solution computed via CMDS can be very poor and not sufficient for any location-based application. Furthermore, it is imperative to remind that the real nodes' location estimates $\hat{\mathbf{P}}$ are computed from $\hat{\mathbf{P}}_o$ applying a procrustes operation, which calculates the scaling, rotation, mirroring and shifting factors based on the location of the anchors.

2.3 Semi-definite Programming (SDP)

The SDP method is one of the most powerful algorithms for network localization and it is able to handle incomplete and imperfect data Biswas, Liang, Toh, Wang & Ye (2006). The fundamental idea of the SDP method is to find the EDM-estimate $\hat{\mathbf{D}} \triangleq [\hat{d}_{ij}]$ of rank at most $\eta + 2$ closest to the observed EDM-sample $\tilde{\mathbf{D}}$, in the Frobenius norm sense. Because of the rank-constraint, the optimization problem is not convex, nevertheless, a rank-relaxation can be adopted such that the final optimization problem is

$$\begin{aligned}
&\min_{\hat{\mathbf{K}},\{\hat{\mathbf{B}}_{ij}\}} \sum_{ij\in\mathcal{H}} w_{ij}\,\varepsilon_{ij} \\
&\text{s.t.}\quad [-\tilde{d}_{ij} \quad 1]\,\hat{\mathbf{B}}_{ij}\,[-\tilde{d}_{ij} \quad 1]^{\mathrm{T}} = \varepsilon_{ij},\ \ \forall ij \\
&\qquad [\mathbf{0}_\eta \quad \mathbf{e}_i - \mathbf{e}_j]\,\hat{\mathbf{K}}\,[\mathbf{0}_\eta \quad \mathbf{e}_i - \mathbf{e}_j]^{\mathrm{T}} = \nu_{ij},\ \ i,j \ge N_A \\
&\qquad [\mathbf{a}_i \quad -\mathbf{e}_j]\,\hat{\mathbf{K}}\,[\mathbf{a}_i \quad -\mathbf{e}_j]^{\mathrm{T}} = \nu_{ij},\ \ i \le N_A,\ \forall j \\
&\qquad \hat{\mathbf{B}}_{ij} \triangleq \begin{bmatrix} 1 & b_{ij} \\ b_{ij} & \nu_{ij} \end{bmatrix} \succeq 0 \\
&\qquad \hat{\mathbf{K}} \triangleq \begin{bmatrix} \mathbf{I}_\eta & \hat{\mathbf{Z}}^{\mathrm{T}} \\ \hat{\mathbf{Z}} & \hat{\mathbf{Y}} \end{bmatrix} \succeq 0
\end{aligned} \tag{14}$$

where $\mathbf{0}_\eta$ is a vector of zeros and $\mathbf{e}_i \in \mathbb{R}^{N_T}$ the only non-zero element is a 1 at the i-th element. The SDP formulation can be optimally solved using standard convex SDP optimization software, such as SDPA, CSDP, SDPT3, SeDuMi[1], however, the computational complexity grows quickly with the number of variables and constraints.

2.3.1 SMACOF

The SMACOF technique is another optimization method, that in contrast to the SDP and C-MDS algorithm, operates on the space of the variables $\hat{\mathbf{z}}_i$'s. The fundamental idea in SMACOF is to find the minimum of a non-convex function by tracking the global minima of the so-called majored convex functions $\mathcal{T}(\hat{\mathbf{P}}, \mathbf{Y})$. As illustrate in figure 3 the majorinzing function is computed from from the original objective and a given point $\hat{\mathbf{P}} = \hat{\mathbf{X}}$. Mathematically, such a function is given by

$$\mathcal{T}(\hat{\mathbf{P}}, \mathbf{Y}) = \sum w_{ij}^2 \cdot \tilde{d}_{ij}^2 + \mathrm{tr}\left(\hat{\mathbf{P}}^{\mathrm{T}} \cdot \mathbf{H} \cdot \hat{\mathbf{P}}\right) - 2 \cdot \mathrm{tr}\left(\hat{\mathbf{P}}^{\mathrm{T}} \cdot \mathbf{A}(\mathbf{Y}) \cdot \mathbf{Y}\right), \tag{15}$$

where $\mathrm{tr}(\cdot)$ denotes the trace, $\mathbf{Y} \in \mathbb{R}^{N \times \eta}$ is an auxiliary variable and the entries of $\mathbf{H}$ and $\mathbf{A}(\mathbf{Y})$ are given by

$$h_{ij} = \begin{cases} \sum\limits_{\substack{i=1 \\ i \neq j}}^{N} h_{ij}, \ i = j, \\ -w_{ij}^2, \ i \neq j, \end{cases} \tag{16a}$$

$$a_{ij} = \begin{cases} \sum\limits_{\substack{i=1 \\ i \neq j}}^{N} a_{ij}, \ i = j, \\ w_{ij}^2 \cdot \dfrac{\tilde{d}_{ij}}{\|\mathbf{y}_i - \mathbf{y}_j\|_2}, \ i \neq j. \end{cases} \tag{16b}$$

The SMACOF algorithm, therefore, consists of an iterative method that converges to a solution $\hat{\mathbf{P}}$ that depends on the initial estimate $\hat{\mathbf{P}}^{(0)}$. The main advantage is that at the n-th iteration the global minimum $\hat{\mathbf{P}}_{\min}^{(n)}$ of the majored function $\mathcal{T}(\hat{\mathbf{P}}, \mathbf{Y})$ with $\mathbf{Y} = \hat{\mathbf{P}}_{\min}^{(n-1)}$, can be computed in closed form via the Guttman transform,

$$\hat{\mathbf{P}}_{\min}^{(n)} = \mathbf{H}^{\dagger} \cdot \mathbf{A}\left(\hat{\mathbf{P}}_{\min}^{(n-1)}\right) \cdot \hat{\mathbf{P}}_{\min}^{(n-1)}, \tag{17}$$

where † denotes the pseudoinverse and $\mathbf{A}\left(\hat{\mathbf{P}}_{\min}^{(n-1)}\right)$ is the matrix with elements a_{ij}.

2.3.2 Nearly optimum WLS minimization

Recently, in Destino & Abreu (2009c) a novel low-complexity algorithm was proposed to solve the WLS optimization problem with nearly optimal performance. The minimization method, hereafter referred to as the R-GDC algorithm, is based on the global continuation method proposed in More & Wu (1997), which can be summarized as the iteration of three fundamental steps: *smoothing*, *minimization* and *continuation*. In the smoothing step the entire

[1] SeDuMi runs in Matlab©and uses the Self-Dual method for solving general convex optimization problems, etc.

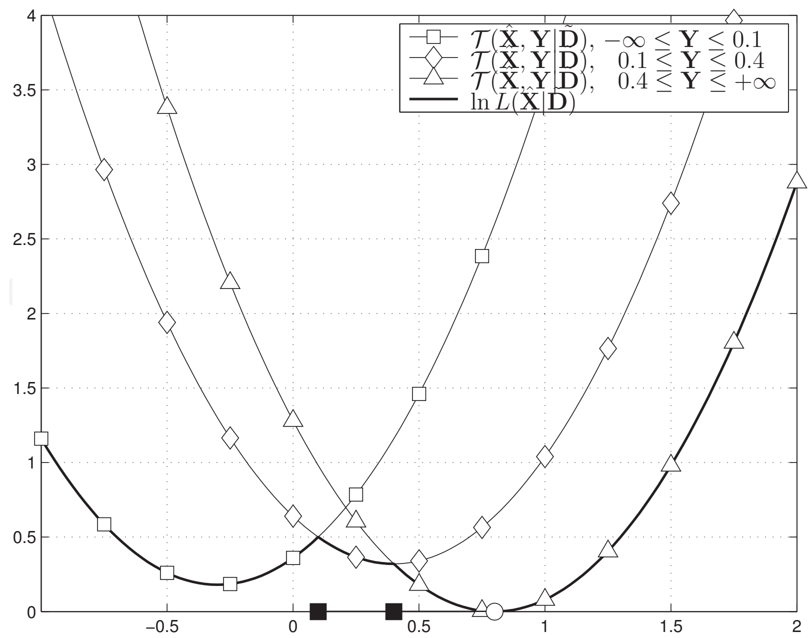


Fig. 3. Illustration of the majorizing functions $\mathcal{T}(\hat{\mathbf{P}} = \hat{\mathbf{X}}|\mathbf{Y}, \mathbf{D})$ in the optimization of WLS-objective function related to a source-localization problem in $\eta = 1$ dimension. The function $\ln L(\hat{\mathbf{X}}|\mathbf{D})$ is the WLS-objective with $\tilde{d} = d$. On the x-axis, we have plotted the network, where the anchors and the target are indicated with a black square and a white circle, respectively.

objective is approximated by function with a higher degree of differentiability (smoothed), obtained by means of a convolution of the original function with a Gaussian kernel $g(x;\lambda)$

$$g(x;\lambda) = \exp\left(-\frac{x^2}{\lambda^2}\right), \tag{18}$$

where the parameter λ controls the smoothing degree.
In the minimization step each of these smoothed functions is minimized using a conventional Newtonian algorithm Nocedal & Wright (2006). Finally, the continuation refers to the process of tracing the global minimum, which in practice is typically performed by initializing the minimization of the next smoothed objective with the latest solution.
In figure 4, for instance, an illustrative example of the GDC method is shown, where the non-convex objective function $s(x)$ is given by the sum of Gaussian functions. The dark and the thin lines indicate the original and the smoothed objective functions, respectively. The smoothed functions are obtained via the convolution of the original objective $s(x)$ with the Gaussian kernel $g(x;\lambda)$ given in equation (18). The algorithm starts with the minimization of the most smoothed function (largest λ), from which a new iteration will be initiated. This process is then repeated until $\lambda = 0$, from which the solution of the optimization problem is obtained.
In the context of network localization, this technique consists of

$$\hat{\mathbf{Z}}^{(k)} = \min_{\hat{\mathbf{Z}} \in \mathbb{R}^{N_{\mathrm{T}} \times \eta}} \langle f_{\mathrm{R}} \rangle_{\lambda^{(k)}} (\hat{\mathbf{Z}}), \, 1 \leq k \leq K, \tag{19}$$

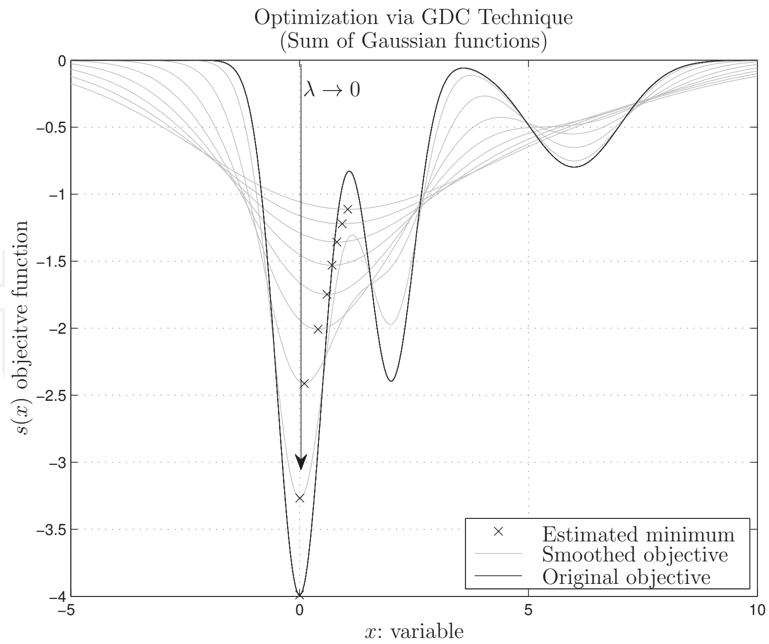


Fig. 4. Illustration of the GDC method. Starting from the original objective (dark line) and give a set of smoothing parameters λ, smoothed versions (thin line) of the original objective are computed. Iterating the process smooth-minimize-continue, the global optimum of the original objective can be found with high probability when the last minimization with $\lambda = 0$ is performed.

where $\langle f_{\mathrm{R}} \rangle_{\lambda^{(k)}}(\hat{\mathbf{Z}})$ is the smoothed variation of $f_{\mathrm{R}}(\hat{\mathbf{Z}})$ and it is given by

$$\langle f_{\mathrm{R}} \rangle_{\lambda}(\hat{\mathbf{Z}}) = \frac{1}{\pi}\int_{\mathbb{R}^{\eta}} \sum_{ij\in\mathcal{H}} w_{ij} \left(\tilde{d}_{ij} - \|\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j + \lambda\mathbf{u}\|_{\mathrm{F}} \right)^2 \exp(-\|\mathbf{u}\|_{\mathrm{F}}^2)\, \mathrm{d}\mathbf{u} \tag{20}$$

$$= \sum_{ij\in\mathcal{H}} w_{ij} \cdot \left(\lambda^2 + \tilde{d}_{ij}^2 + \hat{d}_{ij}^2 - \lambda\sqrt{\pi}\tilde{d}_{ij}\, {}_1F_1\left(\frac{3}{2};1;\frac{\hat{d}_{ij}^2}{\lambda^2}\right) \exp\left(\frac{-\hat{d}_{ij}^2}{\lambda^2}\right) \right), \tag{21}$$

where $\Gamma(a)$ is the gamma function and ${}_1F_1(a;b;c)$ is the confluent hypergeometric function Abramowitz & Stegun (1965)., which can be efficiently evaluated as

$${}_1F_1\left(\frac{3}{2};1;s\right) = 1 + \sum_{m=1}^{+\infty} \left(s^m \cdot \prod_{t=1}^{m} \left(\frac{1}{2t^2} + \frac{1}{t} \right) \right), \tag{22}$$

and (Abramowitz & Stegun, 1965, Eq. 13.5.1, pp. 508)

$${}_1F_1\left(\tfrac{3}{2};1;s\right) = \frac{2e^s}{\sqrt{\pi}} \sum_{p=0}^{P-1} \frac{s^{\frac{1}{2}-p}}{p!} \prod_{t=0}^{p-1} \left(t - \tfrac{1}{2}\right)^2 - \frac{s^{-3/2}}{2\sqrt{\pi}} \sum_{m=0}^{M-1} \frac{(-s)^{-m}}{m!} \prod_{t=0}^{m-1} \left(\tfrac{3}{2} + t\right)^2 + \mathcal{O}(|s|^{-M}) + \mathcal{O}(|s|^{-P}) \tag{23}$$

The minimization step is then performed with a very low-complexity mechanism, namely the Broyden-Fletcher-Goldfarb-Shanno (BFGS), in which the gradient of the smoothed objective can be computed as

$$\nabla_{\hat{\mathbf{Z}}} \langle f_{\mathrm{R}} \rangle_{\lambda} (\hat{\mathbf{Z}}) \triangleq \sum_{ij \in \mathcal{H}} w_{ij} \left(2 - \frac{\sqrt{\pi} \tilde{d}_{ij}}{\lambda} \exp\left(\frac{-\hat{d}_{ij}^{2}}{\lambda^2} \right) {}_1F_1 \left(\frac{3}{2}; 2; \frac{\hat{d}_{ij}^{2}}{\lambda^2} \right) \right) \times \left(\mathbf{e}_{ij} \otimes (\hat{\mathbf{z}}_j - \hat{\mathbf{z}}_i) \right),$$

where $\otimes$ indicates the Kronecker product and $\mathbf{e}_{ij} \in \mathbb{R}^{N_{\mathrm{T}}}$ are row-vectors with the i-th and the j-th element equal to 1 and -1 respectively.
Although any decreasing sequence of λ can be selected, the general rule-of-thumb is to compute $\lambda^{(0)}$ such that $\langle f_{\mathrm{R}} \rangle_{\lambda^{(0)}}$ is convex and then decreases λ linearly for K steps until $\lambda^{(K)} = 0$. In the specific case of $\langle f_{\mathrm{R}} \rangle_{\lambda}$ given by equation (21), the initial value $\lambda^{(0)}$ can be selected as

$$\lambda^{(0)} = \frac{\sqrt{\pi}}{2} \max_{ij \in \mathcal{H}} \tilde{d}_{ij}. \tag{24}$$

2.4 Enhanced LS-based localization methods for NLOS conditions

The NLOS problem, that is the presence of large errors in the ranging measurements, is yet a remaining challenge in the context of network localization, especially when multiple targets are localized simultaneously like in the algorithms described above. In this regard, only little articles tackle this problem and few algorithms are proposed to solve effectively this challenge Denis & Daniele (2004); Destino & G. (2010); Guvenc et al. (2007); Venkatesh & Buehrer (2007); Yu & Jay Guo (2008). For instance in Destino & G. (2009) a weighing strategy was derived in order to associate a lower weight to those measurements affected by bias and more weight to those ranging that are considered very reliable. To the best of our knowledge, however, the most effective localization techniques that compensate for the bias in a non parametric manner are the Sequential-Quadratic-Programming (SQP) and the Distance Contraction (DC) described in Yu & Jay Guo (2008) and Destino & Abreu (2009b); Destino & G. (2010), respectively.
In the remaining subsections, these algorithms are discussed in details. For the sake of convenience, hereafter, we simplify the notation such that the j-th index will be omitted in any subscript pair $_{ij}$. For instance, the symbol d_{iN_T} that refers to the Euclidean distance between the i-th anchor and the target will be simply denoted by d_i.

2.5 Sequential-quadratic-programming method

The SQP algorithm was proposed in Yu & Jay Guo (2008), and it consists of a constrained variation of the minimization problem given in equation (5). Specifically, the authors consider the bias errors as variables to be estimated. In essence, the SQP formulation of the source localization problem in NLOS conditions is given by

$$\begin{aligned} \hat{\mathbf{z}} \;=\; & \min_{\hat{\mathbf{z}} \in \mathbb{R}^{\eta}, \hat{b}_i \in \mathbb{R}^{+}} \sum_{i=1}^{N_{\mathrm{A}}} \left(\tilde{d}_i - \hat{d}_i - \bar{h}_i \hat{b}_i \right)^2, \\ & s.t.\ \hat{d}_i \leq \tilde{d}_i,\ \forall i. \\ & \quad \hat{b}_i \leq \min_{j=1,\ldots,N_{\mathrm{A}}} \{ \tilde{d}_i + \tilde{d}_j - d_{i,j} \}, \\ & \quad \hat{b}_i \geq 0 \end{aligned} \tag{25}$$

where $d_{i,j}$ is the distance between the i-th and the j-th anchor and $\bar{h}_i$ is equal to 1 when it is assumed the presence of a bias and $\bar{h}_i = 0$ otherwise.
The effectiveness and the accuracy of this method depends on: $a)$ the size of the feasibility region $\mathcal{I}$, which is obtained from the set of constraints $\hat{d}_i \leq \tilde{d}_i$, $\forall i$; b) the tightness of the bias upper bounds $\{u_i = \min_{j=1,\ldots,N_\mathrm{A}} \{\tilde{d}_i + \tilde{d}_j - d_{i,j}\}\}$; c) the exactness of assumptions on the presence/absence of bias. Specifically, $a)$ implies that the smaller is the size of the feasibility region, the more restricted is the domain of $\hat{\mathbf{z}}$ and therefore the more accurate is the solution; $b)$ implies that the tighter are the bias upper-bounds, the more accurate are the estimations of the variables $\hat{b}_i$; $c)$ implies that the larger is the number of exact h_i, the more appropriate are the bias corrections.
Because of these conditions, the SQP approach is somewhat heuristic and it leaves room to further improvements which can be achieved with the modification of the constraints in the optimization problem.

2.6 Least-square with distance contraction method

In this subsection, a completely novel technique for bias mitigation will be described. The method is based on "distance contractions" Destino & Abreu (2009b); Destino & G. (2010), which in plain words is the mechanism to contract (correct) the distance measurements such that $\tilde{d}_i < d_i$. This mechanism has the following advantages

a) it can improve the convexity of the objective function,

b) it relaxes the requirements on the ranging precision,

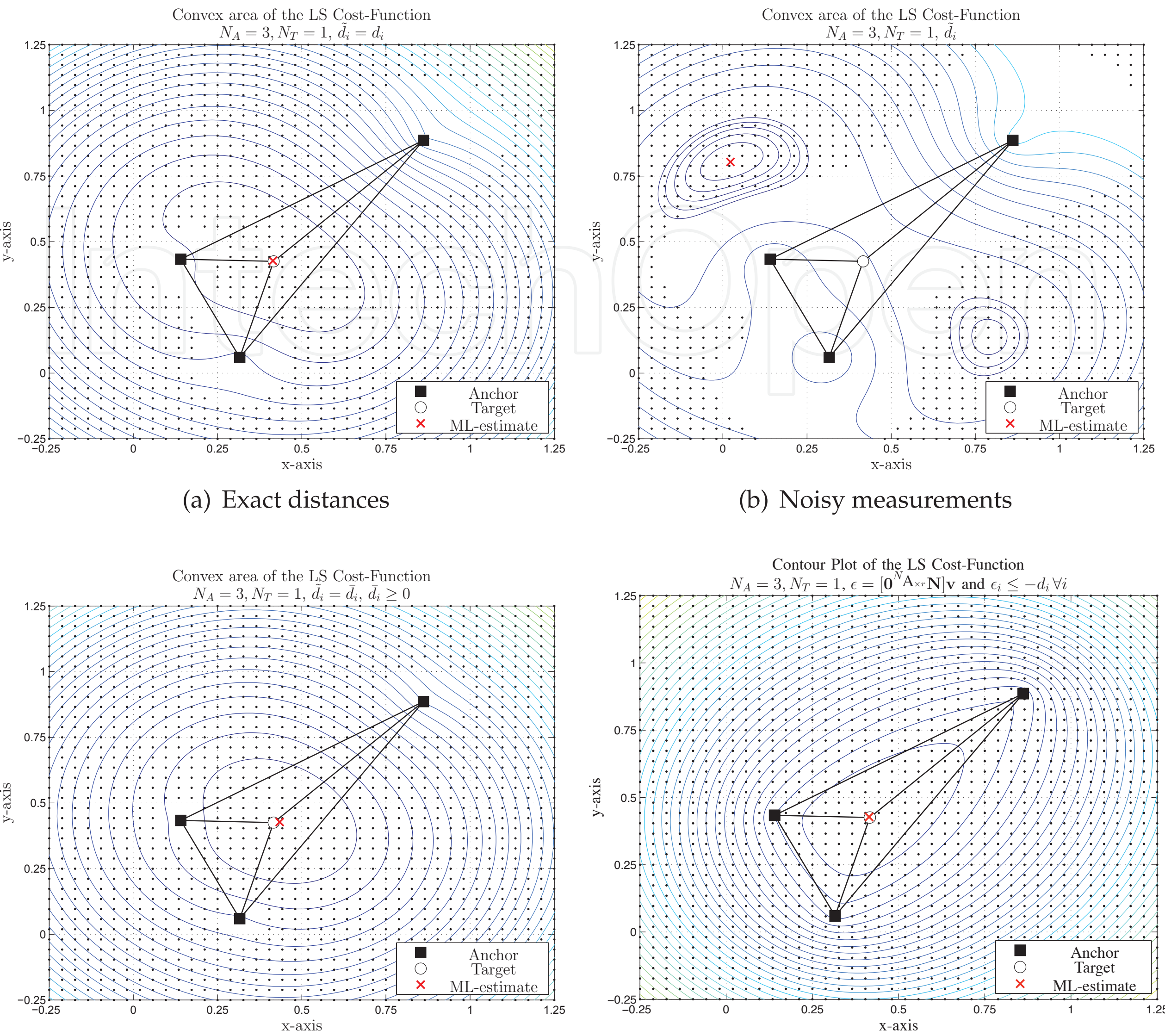
c) it can provide accurate location estimates,

d) it is low-complexity.

It was also shown that corrections can be made such that the WLS-objective function always convex and with minimum in the real target location. Such corrections relate to the geometry of the network and, it can be studied by observing the null space of the angle kernel matrix

$$\mathbf{\Omega} \triangleq \begin{bmatrix} 1 & \cos(\theta_{1T2}) & \ldots & \cos(\theta_{1TN_\mathrm{A}}) \\ \cos(\theta_{1T2}) & 1 & \ddots & \cos(\theta_{2TN_\mathrm{A}}) \\ \vdots & \ddots & \ldots & \vdots \\ \cos(\theta_{1TN_\mathrm{A}}) & \cos(\theta_{2TN_\mathrm{A}}) & \ldots & 1 \end{bmatrix}, \tag{26}$$

where θ_{iTj} is the angle between the (i, j) pair of anchors seen by the target. The example proposed in figure 5 illustrates the aforementioned concepts. Specifically, in the subfigure 5(a), the LS objective function is studied under the assumption of exact distance measurements, i.e. Visualizing the contour levels (lines) together with the convex area (dots) of the function, we can observe that, for the specific example, only one minimum exists. In the subfigure 5(b), the same type of study is carried out, but in contrast, the measurements are now assumed with positive bias (typical for NLOS channel conditions). In this case, the WLS objective function results with two minima, and both correspond to very inaccurate node location estimate. In addition, it is observed that the convex area is drastically decreased such that it is no longer convex where the real target location is. In the subfigure 5(c), the contraction mechanism is applied such that the ranging measurements are shorter than the true distances. It is



(a) Exact distances (b) Noisy measurements

(c) Contracted distances (d) Negative contracted distances

Fig. 5. Illustrative example of the distance contraction theory.

observed, that with these simple contractions the convex area is expanded around the true target location and the minimum is very close to the true location. Finally, in the subfigure 5(d), we show that with negative measurements and structured errors the objective function is convex everywhere and the minimum is exactly the true target's location.

In practice, however, there are several difficulties to deal with while utilizing the aforementioned distance contraction method, and perhaps, the largest one is the estimation of the angle kernel matrix $\mathbf{\Omega}$ especially, if only distance measurements are available.

Nevertheless, suboptimal and yet practical solutions can be considered via simply exploiting the fact that $\tilde{d}_i < d_i$ can improve on the optimization of the WLS-objective function. In Destino & G. (2010), for instance, a distance contraction based method was proposed, and thereby, the idea was to utilize the knowledge of the feasibility region in order to make the contraction. Specifically, the contracted distance of $\tilde{d}_i$, hereafter denoted by $\bar{d}_i$, is found as the distance between the nearest point $\bar{\mathbf{x}}_i \in \mathcal{I}$ to $\mathbf{a}_i$, which can be computed as

$$\bar{\mathbf{x}}_i = \max_{\hat{\mathbf{x}} \in \mathcal{I}} \left(\tilde{d}_i - \|\mathbf{a}_i - \hat{\mathbf{x}}\|_{\mathrm{F}}\right)^2, \tag{27}$$

$$\text{s.t.} \qquad \tilde{d}_i - \hat{d} \geq 0, \ \forall i.$$

Repeating the optimization above for all anchor-target distance measurements, a set of contracted distances $\bar{d}_i$'s is obtained, which will be utilized in the WLS optimization problem as

$$\hat{\mathbf{z}} = \min_{\hat{\mathbf{z}} \in \mathbb{R}^{\eta}} \sum_{i=1}^{N_{\mathrm{A}}} \left(\bar{d}_i - \hat{d}_i\right)^2. \tag{28}$$

3. Results

In this section we compare the performance of the nearly optimum ML (R-GDC), the SQP and DC algorithms in LOS and mixed LOS/NLOS channel conditions utilizing the LDR-IR UWB ranging model described in section 2. The results will be shown for both cases of a single-hop and a multi-hop network topology.
In particular, we shall measure the localization error

$$\epsilon \triangleq \|\mathbf{P} - \hat{\mathbf{P}}\|_{\mathrm{F}}^2, \tag{29}$$

and study its statistics via the location error probability

$$\Pi \triangleq \Pr\{\epsilon \leq \xi\}. \tag{30}$$

In figures 6 and 7 the results related to the single-hop scenarios are shown. We considered a network with 4 anchor nodes, which are placed at the corner of a square with edge 20 meters. The target is then randomly located within the convex-hull of the anchors.
The results obtained in LOS conditions show that all algorithms have similar performance. To mention some relevant figures, for instance, the localization error is below 40 cm with probability 0.5, and below 1 meter the 90% of the cases.
The performance degrades, although not significantly, when the LOS/NLOS channel conditions are considered. In this case, indeed, the SQP and DC are the best performing methods, which can provide a localization error of 1 and 3 meters with a probability of 0.5 and 0.9, respectively.
The next type of study is the evaluation of the proposed algorithms in a mesh(multi-hop) network. In this regard two approaches are considered, namely a full centralized (cooperative) and a multi-hop (target-centric) methods which are sketched in figures 8(a) and 8(b), respectively. The full centralized approach consists of collecting all information at the anchors and process this information jointly in order to estimate the location of the target. In the target-centric approach, instead, the objective is to exploit only the paths that link each anchor to the target and use those distance measurements to estimate the target's location.

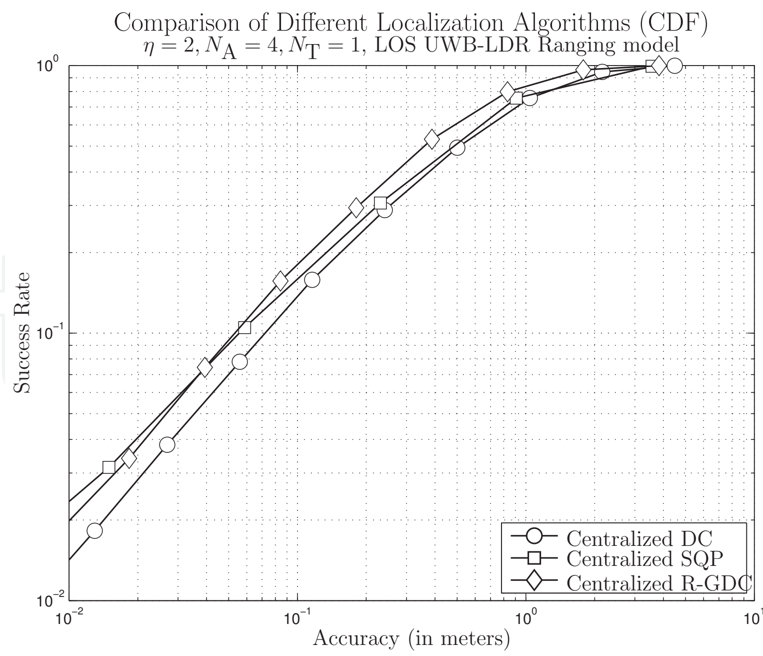


Fig. 6. Comparison of the localization accuracy achieved by different algorithms for the case of a single-hop scenario in LOS conditions.

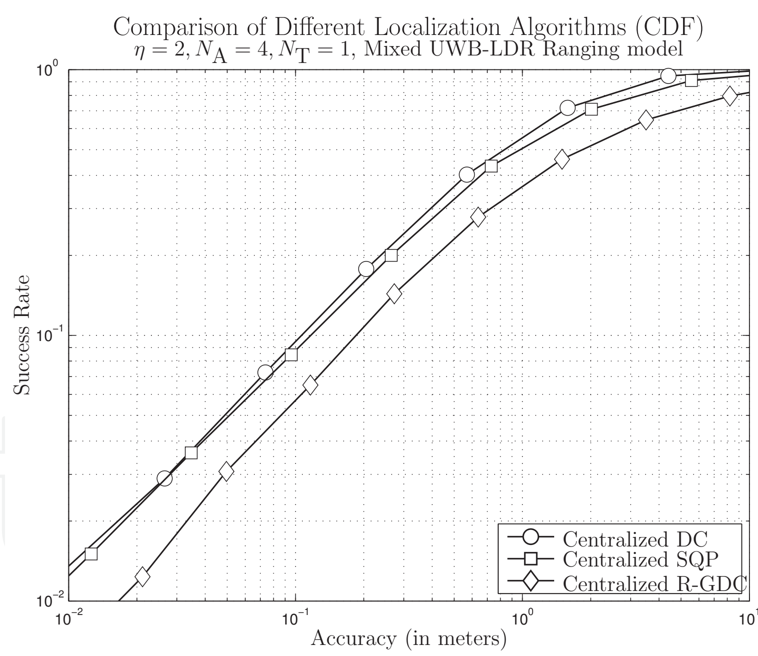


Fig. 7. Comparison of the localization accuracy achieved by different algorithms for the case of a multi-hop scenario in mixed LOS/NLOS conditions.

In figures 9 and 10, the results related to considered studies are shown. In the LOS conditions, the full centralized approach is the best performing method with an average localization accuracy per node of 50cm and 1m with probabilities 0.5 and 0.9, respectively.

In the mixed LOS/NLOS conditions, where distances are affected by bias errors, the SQP and DC are the best performing methods and amongst the latter, the DC can achieve the

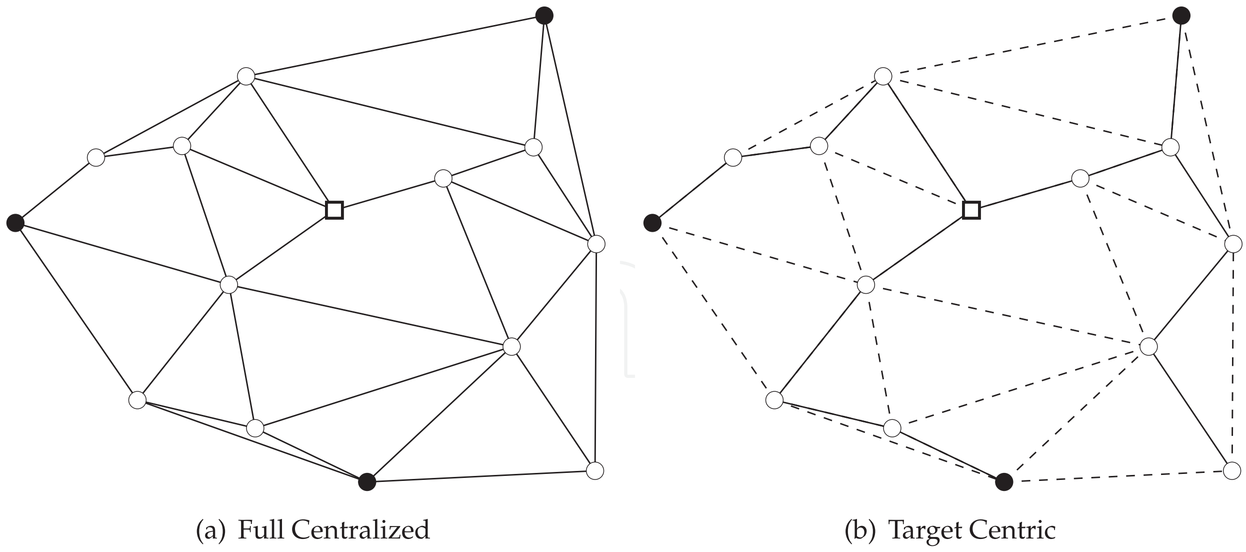


Fig. 8. Illustration of two different approaches for network localization.

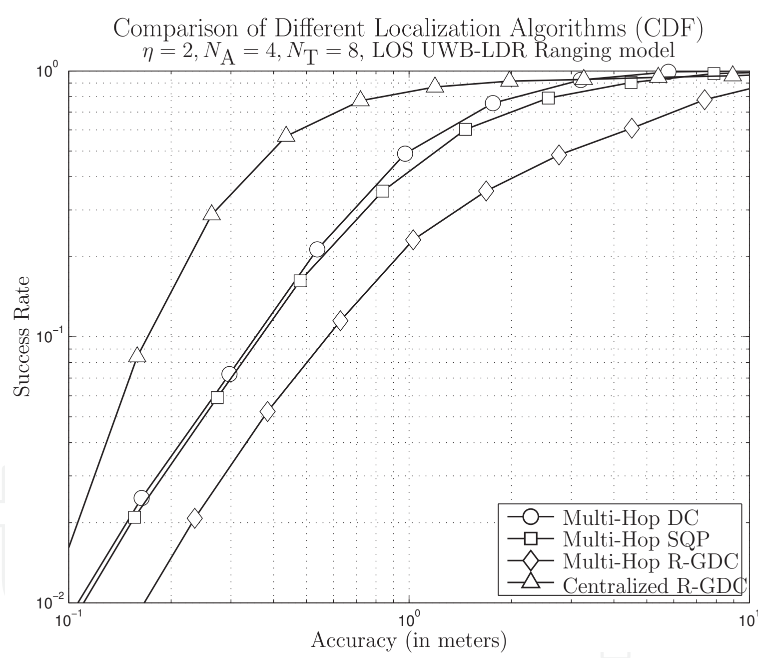


Fig. 9. Comparison of the localization accuracy achieved by different algorithms for the case of a multi-hop scenario in LOS conditions.

highest accuracy. Notice, moreover, that in this simulation set up, the target-centric approach can generally achieve a better accuracy than the centralized one. The reason is that in the target-centric approach minimizes the impact of wrong measurements and poor connectivity onto the localization error since, the problem to be solved is always a "single-hop" type positioning.

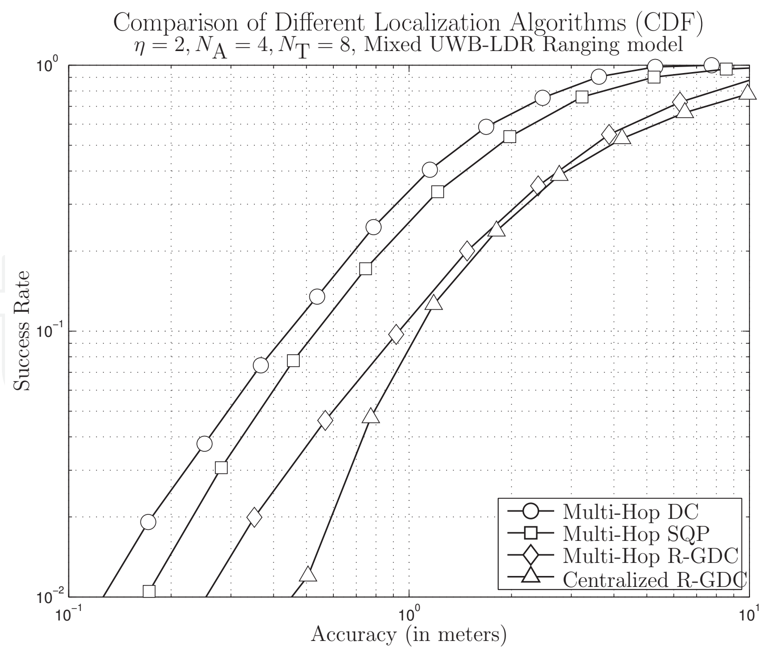


Fig. 10. Comparison of the localization accuracy achieved by different algorithms for the case of a multi-hop scenario in mixed LOS/NLOS conditions.

4. Conclusions

In this chapter, we have seen the most effective optimization-based localization methods described in the literature. We distinguished them in methods for large-scale and single-hop networks. We also addressed the NLOS problem and, we provided effective solutions for the single-hop scenario. In the simulation section, we also described a novel approach for network localization in NLOS conditions, which basically relies on a combination of a multi-hop routing with a single-hop localization method.
It was observed that such a technique can provide accurate location estimates, especially in the case of mixed LOS/NLOS conditions.

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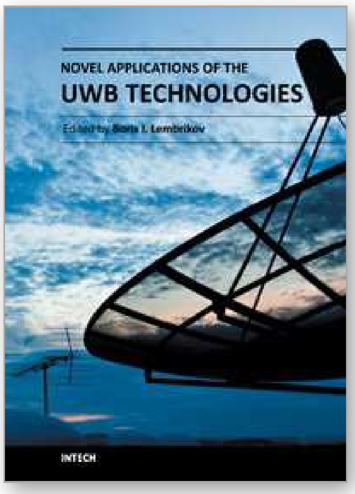

Novel Applications of the UWB Technologies

Edited by Dr. Boris Lembrikov

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Ultra wideband (UWB) communication systems are characterized by high data rates, low cost, multipath immunity, and low power transmission. In 2002, the Federal Communication Commission (FCC) legalized low power UWB emission between 3.1 GHz and 10.6 GHz for indoor communication devices stimulating rapid development of UWB technologies and applications. The proposed book Novel Applications of the UWB Technologies consists of 5 parts and 20 chapters concerning the general problems of UWB communication systems, and novel UWB applications in personal area networks (PANs), medicine, radars and localization systems. The book will be interesting for engineers and researchers occupied in the field of UWB technology.

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