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Light Linear RSS-Based Sensor Localization with Unknown Transmit Power by Tikhonov-regularization

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ABSTRACT: In this paper, we introduce a new linear received signal strength-based estimator for unknown node localization which its accuracy at low Signal-to-noise ratio (SNR) is better than many linear estimators and can compete with estimators based on the convex optimization, but it is much lighter than convex optimization-based estimators. The main ingredients in our proposed linear position estimator are to reformulate the localization problem in terms of Tikhonov-regularization and introduce a biased noise variable. The way that we apply for this reformulation avoids any possible linear approximation in which target position variables are involved, thus saving fair amount of information. The proposed algorithm is also indifferent to the transmit power and thus, applicable to either known or unknown transmit power scenarios. Simulation results show the efficacy of the proposed algorithm in comparison to the other methods for both typical RSS-based measurement data model and the modified model for indoor application.

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1- INTRODUCTION

Nowadays, a lot of effort is spent on developing more accurate localization methods in sensor networks, such as wireless sensor network (WSN) [1]. This is mainly due to their diverse set of applications, including industrial and health care monitoring, and environmental sensing. The localization systems use different measurements of acoustic and radio signals such as angle of arrival (AOA) [2], time of arrival (TOA) [3], time difference of arrival (TDOA) [4], and received signal strength (RSS) [5] [6], or the combination of these methods [7]. The first three aforementioned methods are more accurate, but require complex hardware. On the other hand, the received signal strength measurement does not aquire expensive antenna or high bandwidth. Node localization based on the RSS measurements should be considered as a fascinating research field. Recently, a lot of scientific research has been undertaken in the field of RSS-based node localization. It serves as an appealing option to be applied for practical applications such as the primary user detection in cognitive radio networks [8] or underwater acoustic localization in wireless sensor networks [9].

The most popular and practical estimators to extract an unknown node position parameter with RSS values is the maximum likelihood estimator (MLE). The MLE is asymptotically efficient, eliciting that its variance attains the Cramer Rao lower bound (CRLB) as the sample size approaches infinity [10]. However, the cost function of MLE for RSS-based localization is highly nonlinear and non-convex and has a large number of local minima. Various methods have been advocated to yield only an approximate solution to this estimator. The Gauss-Newton method may be considered as the first choice for this type of problem [11]. The convergence of any Gauss-Newton method, as an iterative procedure, requires appropriate initial parameter values. Otherwise, the algorithm may get stuck at suboptimal solutions, leading to large estimation error.

Recently, another approach has been derived from considering a class of optimization problems called the convex optimization problems. This approach has been intensively studied since the time of some pioneering papers, such as Beck's paper [12]. The second-order cone programming (SOCP) and semidefinite programming (SDP)-based estimators are some of the most popular algorithms in this class [13] [14]. In this type of estimator, the convex relaxation methods make some approximations of the non-convex cost function and substitutes the cost function with the largest convex function below the cost function. As a result, convergence to the calculated global minimum is guaranteed. In fact, introducing some error is inevitable in the usage of convex relaxation. These methods do not provide a closed form solution for problems, and the solution can be efficiently

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obtained by using the CVX tools [15]. Although it may sound to be computationally demanding.

In this paper, we develop a linear position estimator that is considered to achieve light computation like when so many linear estimators are compared to the convex estimators. As for a WS node with limited process power, this is of merit. Nevertheless, perhaps the most remarkable character of our proposed linear estimator is a specific range of SNR values (low SNRs) for which the accuracy is in the order of convex estimator or even better. The method works from the premise that only the term containing the noise variable is linearly approximated. The term that unknown node position coordinates are included is not approximated. This will prevent loss of certain amount of information contained in nonlinear mapping between coordinates variables in the cost function. The price we pay for getting our new linear estimator is to unrealistically ignore the influence of the bias term of an introduced new noise variable. The price is lowered when the noise power increases. This is where the performance of our proposed estimator surpasses the convex estimators, as simulation results confirm. In addition, the transmit power is not excluded from signal model when its value is not known at an unknown node and obtained as a by-product of the localization process at no cost.

The paper is organized as follows. The typical path loss exponent data model used for RSS-based localization is presented in Section 2. Then This model is modified to more specific application which is the indoor localization. For indoor applications, the propagation path loss model is still valid with some minor modifications which is described in more details. Finally, the problem of position estimation for these types of data models is stated in Section 2. Section 3 introduces our proposed method and discusses our strategy to linearly approximate the nonlinear cost function of the MLE and reformulate it in the matrix format by inspiring the idea of Tikhonov regularization. Section 4 is devoted to the numerical results, indicating the performance of the proposed method compared with some of the well-known localization algorithms, either linear or convex optimization-based estimators. Finally, conclusions and discussions are given in Section 5.

2- DATA MODEL AND PROBLEM STATEMENT

A wireless sensor network comprises of N nodes with prior known positions (anchor nodes), and an unknown node with unknown location which is the subject of the location estimation in a wireless sensor network. The 2D coordinates of the anchor nodes and a node are denoted by vectors of the forms $\mathbf{s}_i = [x_i, y_i]^T \;\; i = 1, 2, ..., N$ and $\boldsymbol{\theta} = [x, y]^T$, respectively.

Since the location of the anchor nodes will surely affect the accuracy of positioning, some research has been done on the placement of the anchor nodes as efficiently as possible [16] [17], although the topic is irrelated to the subject of this paper.

The received signal power in a log-normal shadowing radio propagation environment has the following form:

$$P_i = P_0 - 10\gamma \log_{10} \frac{\|\boldsymbol{\theta} - \mathbf{s}_i\|}{d_0} + n_i, i = 1, 2, ..., N \quad (1)$$

where P_i is the received power of the unknown node (in dBm) from the ith anchor node, P_0 is the received power at (PLE) varies from 1 to 5 in literature models [18], and n_i is a Gaussian random variable with zero mean and variance σ_i^2.

However, it should be noted that assuming a Gaussian shadowing noise does not seem very realistic, and better modeling is of interest based on the Dempster–Shafer theory [19].

It is assumed in this paper that there is no correlation between $n_i, i = 1, 2, ..., N$ variables, though it may no seem realistic. In addition, it has been taken that $\sigma_i^2 = \sigma^2$ for all sensors.

An important point about localization based on the RSS measurements is that the received power is given by averaging instantaneous power for a predetermined period of time. This would cause that the dominant fading for the received power to be large-scaled rather than small-scaled. In other words, the main effective noise term in the average received power is lognormal shadowing. However, as it is mentioned in [20], there are more partitions in an indoor environment, and the model presented in (1) needs to be undergone some modifications to be used as a justifiable model for an indoor environment. Consequently, under an indoor scenario, the model of RSS measurements in (1) may still provide a framework for the node localization, provided that minor adjustments were made to P_0 and n_i as follows [20]

$$P_i = \tilde{P}_0 - 10\gamma \log_{10} \frac{\|\boldsymbol{\theta} - \mathbf{s}_i\|}{d_0} + \tilde{n}_i, i = 1, 2, ..., N \quad (2)$$

where $\tilde{P}_0 = P_0 - n_{\omega,i}\gamma_\omega$ and $\tilde{n}_i = n_i - u_i(t)\Pi_\omega$, and $n_{\omega,i}$ is the number of obstacles or walls that are in the way of the signals through the link between ith anchor node and the node. All of these obstacles are assumed to attenuate the signal with attenuation factor γ_ω. Additionally, $u_i(t)$ is to model the time varying attenuation environment and Π_ω is an indicator function whose values equals 1 when the number of obstacles $n_{\omega,i}$ is more than zero and zero otherwise. It is important to note that $u_i(t)$ is time varying owing to the dynamic propagation environment and it is common to be taken as $u_i(t) = U_i \sin(2\pi t / t_u)$ where $U_i = 5dB$, $\gamma_\omega = 4dB$ and $t_u = 1$ [20]. To assign values for $n_{\omega,i}$, the whole desire area, which is a $20\text{m} \times 20\text{m}$ square, partitioned into four equal smaller squares. If both the unknown node and the anchor node are located in a square, then $n_{\omega,i} = 0$, since there is no wall presented in the line-of-sight (connecting the anchor node to an unknown node). If they are located in adjacent rooms, then $n_{\omega,i} = 1$. This may be illustrated with the help of Fig. 1, in which an unknown node is located in room 1 and the anchor node is located in room 3 and there is only one

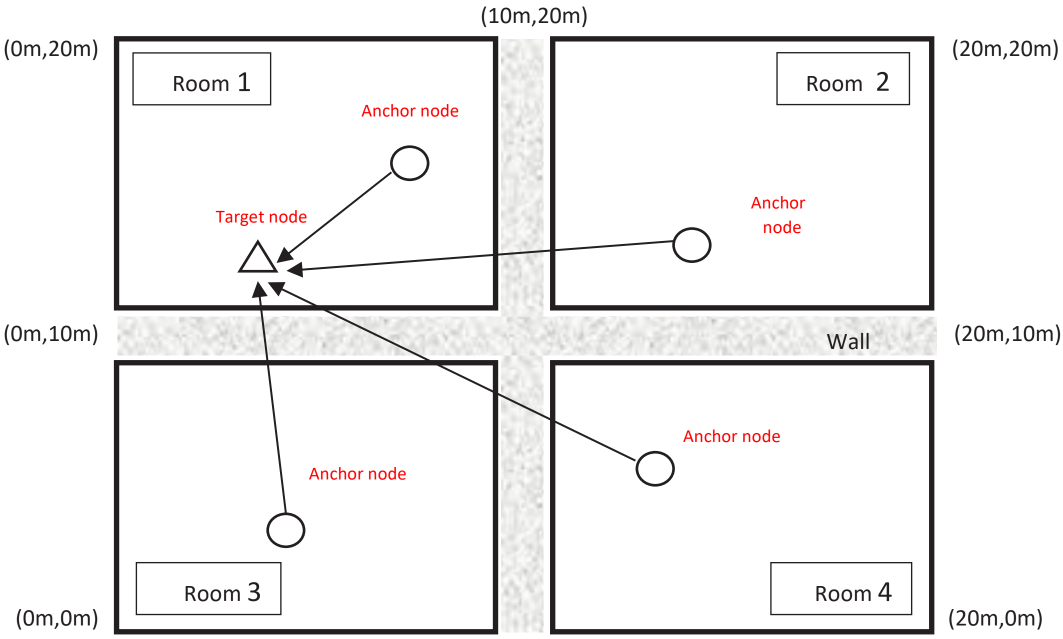

Fig. 1. Illustration of partitioning used for indoor environment modeling of the paper.

wall in line-of-sight with them.

If these two nodes are located in the rooms diagonally opposite from each other, for example an unknown node is in room 1 and the anchor node in room 4, then there are two walls in line-of-sight with them and $n_{\omega,i} = 2$. In other words, to create results of Fig. 5, before setting attributes of $\tilde{n}_i$ and $\tilde{P}_0$ for each pair of an unknown node and the anchor node, their locations are checked according to Fig. 1.

The problem is stated to be the estimation of the unknown node coordinates $\boldsymbol{\theta} = [x, y]^T$ which can be casted as an optimization problem in the maximum likelihood (ML) criterion. The cost function of such optimization problem is shown in (3), [10]:

$$\hat{\boldsymbol{\theta}}_{ML} = \arg\min_{\theta} \sum_{i=1}^{N} (P_i - P_0 + 10\gamma \log_{10} \frac{\|\boldsymbol{\theta} - \mathbf{s}_i\|}{d_0})^2 \quad (3)$$

There is no closed form solution for the nonlinear and non-convex optimization problem in (3). In this paper, this problem is dealt with by utilizing Taylor series expansion and then adopting biased error modeling. Along with a proposed matrix formulation, this leads to a new least squares (LS) estimation. As a result, our estimator has a closed form solution. We also demonstrate that our localization method does not rely on P_0, and we can build an efficient estimator of P_0 soon after the localization.

3- NEW LIGHT LINEAR ESTIMATOR

The basic idea of our approach may be better expressed when the vectorized parameter of the unknown node coordinates $\theta = [x, y]^T$ is treated as the only unknown parameter to be directly estimated.

To eliminate the logarithm from (1), we raise both sides to the same exponent as the base of the logarithm. After some trivial algebra we obtain:

$$10^{\frac{P_i - P_0}{10\gamma}} \frac{\|\boldsymbol{\theta} - \mathbf{s}_i\|}{d_0} = 10^{\frac{n_i}{10\gamma}} \quad (4)$$

To derive the approximate linear estimator, the left-hand side of (4) is approximated by the corresponding first-degree polynomial of Taylor series expansion of RHS of equation (4) centered at $n_i = 0$

$$10^{\frac{P_i - P_0}{10\gamma}} \frac{\|\boldsymbol{\theta} - \mathbf{s}_i\|}{d_0} \approx 1 + \frac{\ln(10)}{10\gamma} n_i . \quad (5)$$

Unlike traditional approach to adopting zero-mean error n_i, such as used in [13]and [14], our suggestion consists of taking the whole RHS terms of (5) as a zero-mean error, ε_i

$$\varepsilon_i = 1 + \frac{\ln(10)}{10\gamma} n_i \quad (6)$$

Needless to say, this way we ignore the biased component of ε_i . However, this ignorance rests on common sense with the high level of noise. Furthermore, allowing this new error modeling is necessary, in order to apply completely linear estimator for the problem defined in (3).

ε_i may also be regarded as the residual modeling errors. Thus, cost function can be expressed as the sum of squared values of ε_i

$$\sum_{i=1}^{N}\varepsilon_i^2=\sum_{i=1}^{N}\left(10^{\frac{P_i-P_0}{10\gamma}}\frac{\|\boldsymbol{\theta}-\mathbf{s}_i\|}{d_0}\right)^2 \tag{7}$$

Considering $\alpha_i=10^{\frac{P_i-P_0}{10\gamma}}/d_0$, (7) is shown as follows

$$\sum_{i=1}^{N}\varepsilon_i^2=\sum_{i=1}^{N}\|\alpha_i\boldsymbol{\theta}-\alpha_i\mathbf{s}_i\|^2 \tag{8}$$

This cost function is sum of the convex functions with nonnegative weights. Therefore, we suggest a corresponding matrix form representation of (8), inspired by the Tikhonov regularization [21].

$$\sum_{i=1}^{N}\varepsilon_i^2=\sum_{i=1}^{N}\|[\mathbf{A}\boldsymbol{\theta}-\mathbf{b}]\|^2 \tag{9}$$

where $\mathbf{A}$ and $\mathbf{b}$ are equal to

$$\mathbf{A}=\begin{pmatrix}\alpha_1 I_2\\ \vdots\\ \alpha_i I_2\\ \vdots\\ \alpha_N I_2\end{pmatrix}_{2N\times 2},\ \mathbf{b}=\begin{pmatrix}\alpha_1 s_1\\ \vdots\\ \alpha_i s_i\\ \vdots\\ \alpha_1 s_1\end{pmatrix}_{2N\times 1} \tag{10}$$

The least squares solution of problem (9) is shown by $\hat{\boldsymbol{\theta}}_{KT-LLS}$ and given by

$$\hat{\boldsymbol{\theta}}_{KT-LLS}=(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b} \tag{11}$$

where the subscript KT−LLS stands for Known Transmit Power-Linear Least Squares. Note that the solution is exact and there is no linearization involved here, which may be understandable in the view of how the state vector is defined as $\boldsymbol{\theta}=[x,y]^T$, containing no nonlinearity. However, it is common in literature of the state vector model to involve some nonlinear terms of x and y, for example, x^2+y^2 [14] [22] [23]. Suppose we define α_i' as

$$\alpha_i'=10^{\frac{P_i}{10\gamma}}, \tag{12}$$

thus $\mathbf{A}$ and $\mathbf{b}$ in (10) can be written as

$$\mathbf{A}=\frac{10^{\frac{-P_0}{10\gamma}}}{d_0}\begin{pmatrix}\alpha_1' I_2\\ \vdots\\ \alpha_i' I_2\\ \vdots\\ \alpha_N' I_2\end{pmatrix}_{2N\times 2}=\frac{10^{\frac{-P_0}{10\gamma}}}{d_0}\mathbf{A}' \tag{13}$$

$$\mathbf{b}=\frac{10^{\frac{-P_0}{10\gamma}}}{d_0}\begin{pmatrix}\alpha_1' s_1\\ \vdots\\ \alpha_i' s_i\\ \vdots\\ \alpha_1' s_1\end{pmatrix}_{2N\times 1}=\frac{10^{\frac{-P_0}{10\gamma}}}{d_0}\mathbf{b}' \tag{14}$$

Now by putting formulas from (12) to (14) in (11), $\hat{\boldsymbol{\theta}}_{KT-LLS}$ is obtained as follows

$$\hat{\boldsymbol{\theta}}_{KT-LLS}=\frac{10^{\frac{P_0}{5\gamma}}}{d_0^{\,2}}(\mathbf{A}'^T\mathbf{A}')^{-1}\frac{10^{\frac{P_0}{5\gamma}}}{d_0^{\,2}}\mathbf{A}'^T\mathbf{b}', \tag{15}$$

$$=(\mathbf{A}'^T\mathbf{A}')^{-1}\mathbf{A}'^T\mathbf{b}'.$$

The result in (16) indicates that $\hat{\boldsymbol{\theta}}_{KT-LLS}$ does not depend on P_0 at all. In other words, $\hat{\boldsymbol{\theta}}_{KT-LLS}$ is not affected by any value of P_0, whether the value is known to the algorithm or not.

Assuming a known true value of P_0 is not realistic in practical sensor localization applications. During the simulation (Section 4), we assume the value of P_0 is unknown to the receiver node. Nevertheless, this would not make any difference to our proposed method. However, the estimate of $\boldsymbol{\theta}$ obtained by our proposed method is referred to as $\hat{\boldsymbol{\theta}}_{UT-LLS}$, where the subscript UT−LLS stands for Unknown Transmit Power-Linear Least Squares. For the rest of the paper, $\hat{\boldsymbol{\theta}}_{KT-LLS}$ is substituted by $\hat{\boldsymbol{\theta}}_{UT-LLS}$. According to (1), the problem of P_0 estimation is equivalent to an estimation of a DC level contaminated by additive Gaussian noise. Here, the signal model is:

$$P_i+10\gamma\log_{10}\frac{\|\hat{\boldsymbol{\theta}}_{UT-LLS}-\mathbf{s}_i\|}{d_0}=P_0+n_i,\ i=1,2,\ldots,N. \tag{16}$$

The left-hand side of (16) can be considered as a received observation. As a classical estimation problem, there is an efficient estimator for P_0 which attains CRLB and is given by [10]

$$\hat{P}_0=\frac{1}{N}\sum_{i=1}^{N}\left[P_i+10\gamma\log_{10}\frac{\|\hat{\boldsymbol{\theta}}_{UT-LLS}-\mathbf{s}_i\|}{d_0}\right] \tag{17}$$

3-1- The computational complexity

We also derive the computational complexity expression of KT-LLS (or UT-LLS) and compare it with the complexity of the existing approaches. Considering the solution presented in (15), the algorithm contains four matrix multiplications and one matrix inversion of size 2 × 2. When one matrix is of size $n\times m$ and another $m\times p$

Table 1. The complexity analysis for different algorithms

Estimator	Complexity
SOCP2[Tomic]	$2 \cdot \mathcal{O}\left(N^4 \log \frac{1}{\epsilon}\right)$
SDP-URSS[Vaghefi]	$2 \cdot \mathcal{O}\left(N^4 \log \frac{1}{\epsilon}\right)$
RSDP[Hu]	$\mathcal{O}\left(4N^{2.5} \log \frac{1}{\epsilon}\right)$
A-BLUE[Hu]	$\mathcal{O}(4N^2)$
LS[Xu]	$\mathcal{O}(4N)$
A-SPM-WIV[Li]	$\mathcal{O}(4N^2)$
UT-LLS	$\mathcal{O}(12N + 12)$

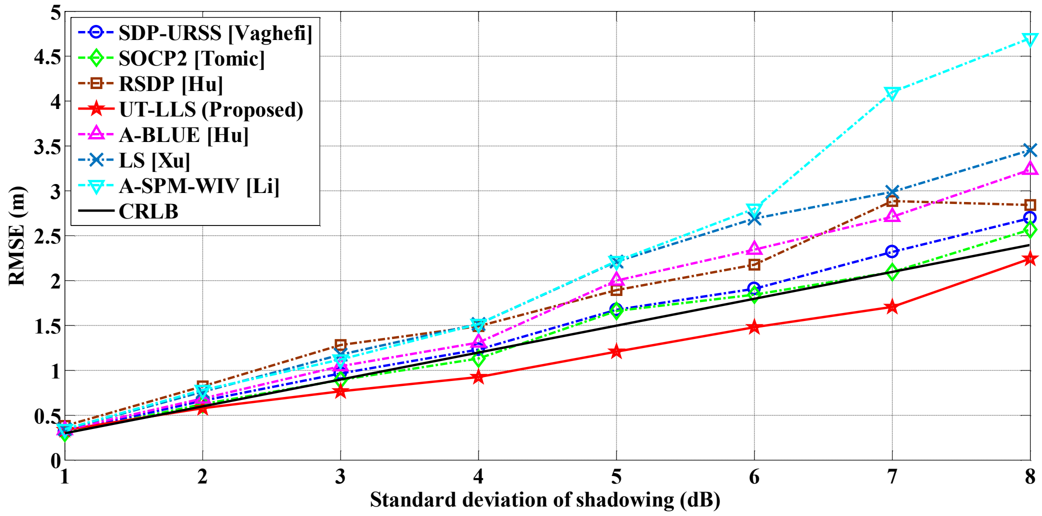

Fig. 2. Performance comparison with different shadowing standard deviation σ and unknown P_0 .

the complexity of a matrix multiplication is $\mathcal{O}(nmp)$. The computational complexity of the matrix inversion of $m \times m$ matrix is $\mathcal{O}(m^3)$. Therefore, the computational complexity of (15) is $\mathcal{O}(8N+4N+8+4)$.

According to [13] and [14], the equations $2 \cdot \mathcal{O}\left(N^4 \log \frac{1}{\epsilon}\right)$ and $\mathcal{O}\left(N^4 \log \frac{1}{\epsilon}\right)$ are used to analyze the worst-case complexities of the SOCP2[Tomic] in [13] and SDP-URSS[Vaghefi] in [14] algorithms, respectively. The ε is the parameter set by the SOCP and SDP solvers (such as SeDuMi in the CVX Toolbox [15]) to obtain the required accuracy. Gazing at the results of the Table 2 in Section 4 confirmes that the computational burden of the SOCP2[Tomic] is about twice as large as that of the SDP-URSS[Vaghefi]. The mathematical complexity of the other methods can be found in their related references and here we only recite: $\mathcal{O}(4N)$ for LS[Xu], $\mathcal{O}(4N^2)$ for both A-BLUE[Hu] and A-SPM-WIV[Li], and $\mathcal{O}\left(4N^{2.5} \log \frac{1}{\varepsilon}\right)$ for RSDP[Hu]. These results are summarized in Table 1.

4- NUMERICAL RESULTS

As stated in the introduction, the sensor position obtained by using the convex optimization is more accurate than that achieved by most current linear methods. In order to demonstrate the superiority of our linear estimator in terms of accuracy for high noise levels, we focus on comparing the results of using our proposed linear estimator and the most well-known methods based on the convex optimization such as SDP-URSS[Vaghefi] [14], RSDP[Hu] [22], and SOCP [13], where the SOCP of unknown transmit power scenario is denoted by SCOP2[Tomic], and denoted by SCOP1 for known transmit power.

We also add two well-known linear localization estimators, A-BLUE[Hu] in [22] and LS[Xu] in [18], which are developed for when the transmit power is unknown. Finally, we compare the results of our proposed algorithm with a new multi-stage localization method developed in [24]. The method is named advanced selective power measurement with weighted instrumental variables (A-SPM-WIV) and denoted by A-SPM-WIV[Li].

The computations are run on a desktop PC with an Intel Core i5 2.3GHz, RAM 6GB, 64bit windows. The software

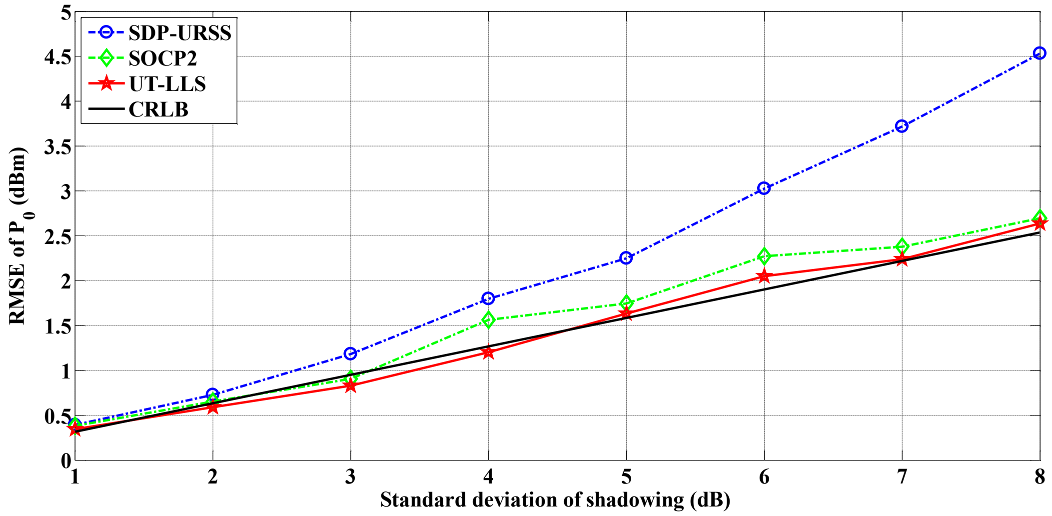

Fig. 3. RMSE of P_0 estimate with different shadowing standard deviation σ where $P_0 = -10dBm$.

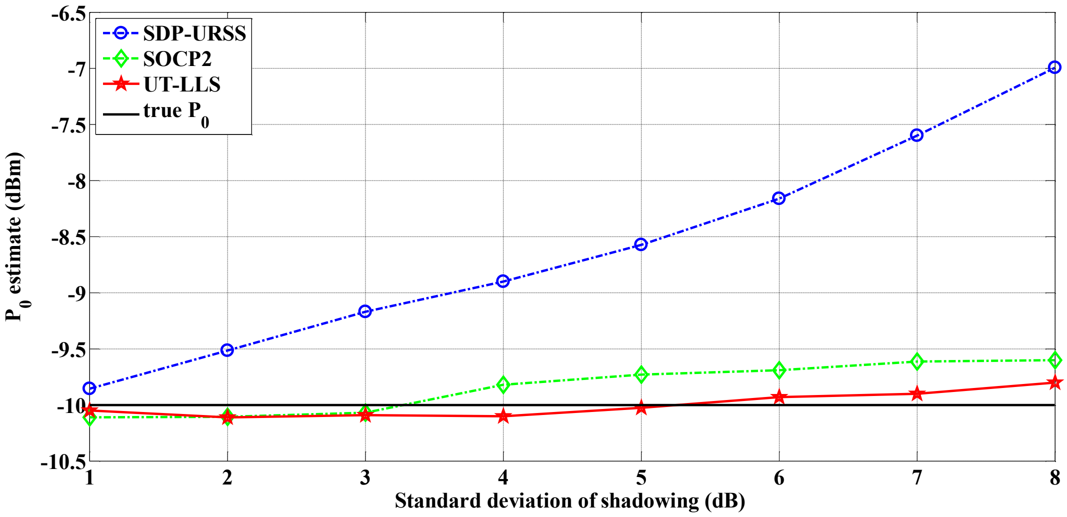

Fig. 4. Mean of P_0 estimate with different shadowing standard deviation σ where $P_0 = -10dBm$.

version is MATLAB 2014a.

RSS measurements are made by $P_0 = -10dBm$, and PLE=3. 10 anchor nodes are deployed, in a square of length 30 m. The node is located at (11,8; 8,4). All performance results are averaged over 200 independent runs.

The value of P_0 is unknown to algorithms. Average RMSE values for our proposed algorithm, as well as SDP-URSS, SOCP, are examined and compared versus the shadowing standard deviation in Fig. 2. In addition, CRLB is presented. For the low values of the shadowing standard deviation, the biased term modeled in (6) is being ignored. As the shadowing standard deviation starts increasing from $\sigma = 1:5dB$ to a high level, the UT-LLS estimator outperforms other algorithms. Fig. 2 demonstrates that the UT-LLS has a superior performance to CRLB at low SNR. This should not be considered as a strange matter, since the CRLB offers a lower bound for only unbiased estimators and the UT-LLS is a biased estimator of a location. As it is evident from Figs. 2, whenever the noise level is simultaneously increasing the A-SPM-WIV [Li] performance further deteriorates. In contrast, our proposed algorithm performs better at low SNRs. The point to note about [24] is, for [24] to reach a set of suitable equations for using BLUE, it aims to linearize the nonlinear terms involving both noise and unknown position coordinates. As mentioned in the abstract and introduction, the main advantage of our method is "The method works from the premise that only the term containing the noise variable is linearly approximated". This causes the performance of our proposed algorithm to be better than [24], when the noise variance is high, for the less approximation used, the less information is discarded. In the simulation results of [24], the RMSE of the positioning error is shown only for very small noises where the upper limit for the standard deviation of shadowing noise is 4 dB, which is an insufficient and small amount. But in our paper,

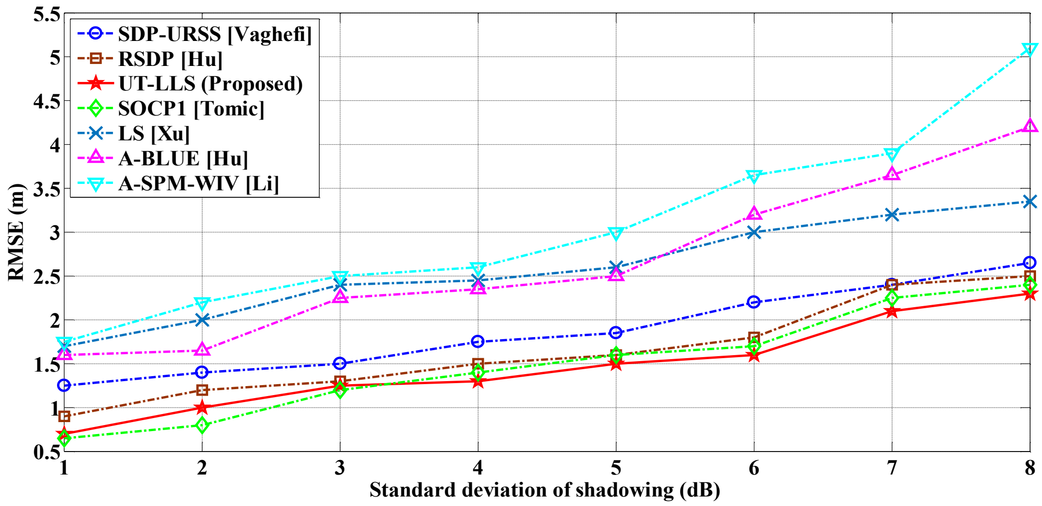

Fig. 5. Performance comparison for indoor environment with different shadowing standard deviation σ and unknown P_0.

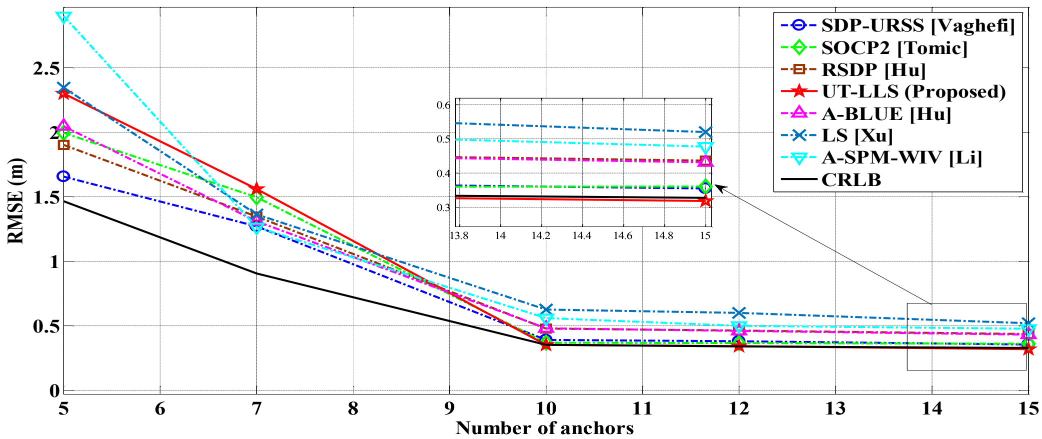

Fig. 6. Performance comparison with different number of anchors and unknown P_0 where shadowing standard deviation σ equals 2 and path loss exponent is 3.

the performance simulation of its algorithm is investigated for also higher values of standard deviation of shadowing noise, and as Figs. 2 and 5 show, the positioning error increases with increasing the noise level.

The next simulation is to evaluate the variance and mean of the estimate of the transmit power P_0 for each algorithm. The results are shown in Fig. 3 and Fig. 4, respectively. As it can be seen, the results of RSDP[Hu], A-BLUE[Hu], LS[Xu], and A-SPM-WIV[Li] are not presented in Figs. 3 and 4. This is due to the fact that only if an algorithm estimates the unknown transmission power, then its performance appear in Figs. 3 and 4. In addition to our proposed algorithm UT-LSS, only the two algorithms SOCP2 and SDP-URSS have this capability. It seems from Figs. 3 and 4 that the SDP-URSS may not be a good candidate in terms of providing an accurate estimate of the unknown transmission power. On the other hand, UT-LSS and UT-LSS show similar satisfactory results in this regard.

The next simulation is about the effect of indoor environment on the accuracy of an unknown node localization. We apply the model introduced in (2), to make the changes that are inherent in an indoor environment and transmitted signals from anchor nodes are undergone. As in [20], we assume $u_i(t) = 5\sin(2\pi t)$ and the attenuation factor $\gamma_\omega = 4$. We also suppose that there are four different rooms where the value of $n_{\omega,i}$ is set accordingly. $n_{\omega,i}$ indicates the number of partitions which the line of sight passes through. Its value varies from 0 to 2 depending on how an unknown node and the anchor node are relatively positioned in the four rooms. The rest of the parameters are the same as in the outdoor environment which is the scenario of the Fig. 2. The results shown in Fig. 5 indicate the superiority of the UT-LLS algorithm. In fact, in Figure 5 the attenuation increases in indoor environment due to the presence of walls, ceilings and other objects, and this attenuation appears as an unknown random loss in the model. This loss is more effective when there are small shadows around zero. However, with increasing shadow noise, its effect decreases, although

Table 2. The average run time per second for different algorithms

Estimator	Run time (s)
SOCP2[Tomic]	0.9461
SDP-URSS[Vaghefi]	0.4517
RSDP[Hu]	0.2717
A-BLUE[Hu]	0.8359e-3
LS[Xu]	0.1693e-3
A-SPM-WIV[Li]	0.9767e-3
UT-LLS	0.131e-3

its value is constant. For this reason, the relative state of performance of the algorithms is similar to the relative state in Fig. 2, at high noise levels.

The behavior of the proposed algorithm and other algorithms toward changes in the number of anchor nodes (N) is shown in Fig 6. The PLE value is 3 and the shadowing noise standard deviation is 2. As the general law, better coverage and more information would be provided to perform the localization with increasing the number of anchor nodes, and therefore the RMSE decreases. Once more, regardless of the number of the anchor node, the performance of UT-LLS is superior at the large noise levels. The two next algorithms which follow are as usual, SOCP2[Tomic] and SDP-URSS[Vaghefi] which are based on the convex relaxation methods.

Additionally, the average run time per second of these algorithms is shown in Table 2. The average run time values taken from Table 2 demonstrate the tremendous time saving offered by using the UT-LLS estimator over using location estimator methods based on the convex optimization.

5- CONCLUSIONS AND DISCUSSIONS

A new linear location estimator, able to work in both known and unknown P_0, is proposed. Firstly, the nonlinear function of the noise term is approximated with a linear function of a biased Gaussian noise for the maximum likelihood estimator cost function. This is against many existing algorithm trends which make approximations based on an unknown signal position. The main advantage of our scheme is in saving a fair amount of information by avoiding any possible nonlinear process that target position variables are involved. Consequently, we replace the nonlinear function of the noise term with linear function of a Gaussian biased noise. Simulation results show that this biased noise is explained for a case where the noise standard deviation is much larger than the noise mean. Later, inspired by the Tikhonov-regularization, linear least squares method is utilized to derive the position estimate of the node. The proposed algorithm is also able to be applied specifically to indoor environments. The way we use to approximate the nonlinear terms leads us to a linear estimator to outperform most convex estimators in terms of both accuracy and speed in high power noise. The other advantage of our scheme is its ability to compute a closed-form expression to estimate P_0 as a by-product.

The idea introduced by this work may be followed by applying the proposed algorithm to the cooperative localization scenarios where is more than one unknown node, and rely information to an anchor or a sink node [13]. In addition, using the new approach introduced in [25], a more appropriate model matching the LS method prerequisites can be applied to increase the accuracy of location.

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APPENDIX

According to [10], to compute the vector parameter CRLB it is required to first compute the Fisher information matrix $\mathbf{I}(\boldsymbol{\theta})$ which is defined as

$$[\mathbf{I}(\boldsymbol{\theta})]_{i,j} = -\mathbf{E}\left\{\frac{\partial^2 \ln p(\mathbf{x};\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_i \partial \boldsymbol{\theta}_j}\right\} \tag{A1}$$

where $\mathbf{x} = [P_1, \cdots, P_N]^T$ and $\boldsymbol{\theta} = [x, y]^T$. The CRLB matrix is $\mathbf{I}^{-1}(\boldsymbol{\theta})$. According to (1) from our paper, the $p(\mathbf{x};\boldsymbol{\theta})$ is a multivariate Gaussian PDF. If $p(\mathbf{x};\boldsymbol{\theta})$ is represented by $\mathcal{N}(\boldsymbol{\mu}(\boldsymbol{\theta}), \mathbf{C})$, then the general formula for the Fisher information matrix for a multivariate Gaussian PDF is given by

$$[\mathbf{I}(\boldsymbol{\theta})]_{i,j} = \left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_i}\right]^T \mathbf{C}^{-1} \left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_j}\right], i, j \in \{1,2\} \tag{A2}$$

For the case of the paper, $\boldsymbol{\mu}(\boldsymbol{\theta})$ and $\mathbf{C}$ are given by

$$\boldsymbol{\mu}(\boldsymbol{\theta}) = \begin{bmatrix} P_0 - 10\gamma \log_{10} \frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_1\|}{d_0} \\ P_0 - 10\gamma \log_{10} \frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_2\|}{d_0} \\ \vdots \\ P_0 - 10\gamma \log_{10} \frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_N\|}{d_0} \end{bmatrix}, \mathbf{C} = \sigma^2 \mathbf{I}_{N \times N} \tag{A3}$$

As a result, $\left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_j}\right]$ is given by

$$\left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_j}\right] = -\frac{10\gamma}{\ln(10)} \begin{bmatrix} \dfrac{\partial \ln\left(\frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_1\|}{d_0}\right)}{\partial \boldsymbol{\theta}_j} \\ \dfrac{\partial \ln\left(\frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_2\|}{d_0}\right)}{\partial \boldsymbol{\theta}_j} \\ \vdots \\ \dfrac{\partial \ln\left(\frac{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_N\|}{d_0}\right)}{\partial \boldsymbol{\theta}_j} \end{bmatrix} \tag{A4}$$

If $\boldsymbol{\theta}_j = x$, then

$$\left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial x}\right] = -\frac{10\gamma}{\ln(10)} \begin{bmatrix} \dfrac{(x - x_1)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_1\|^2} \\ \dfrac{(x - x_2)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_2\|^2} \\ \vdots \\ \dfrac{(x - x_N)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_N\|^2} \end{bmatrix} \tag{A5}$$

If $\boldsymbol{\theta}_j = y$, then

$$\left[\frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial y}\right] = -\frac{10\gamma}{\ln(10)} \begin{bmatrix} \dfrac{(y - y_1)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_1\|^2} \\ \dfrac{(y - y_2)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_2\|^2} \\ \vdots \\ \dfrac{(y - y_N)}{\|\hat{\boldsymbol{\theta}} - \mathbf{s}_N\|^2} \end{bmatrix} \tag{A6}$$

The vector parameter CRLB is calculated as $[\mathbf{I}^{-1}(\boldsymbol{\theta})]_{1,1} + [\mathbf{I}^{-1}(\boldsymbol{\theta})]_{2,2}$.

Nomenclature			
N	Number of anchor nodes	γ_{ω}	Path loss exponent of indoor environment
$\mathbf{s}_i$	Position of the ith anchor	u	Dynamic propagation environment function
x_i , y_i	Length and width of the ith sensor	Π_{ω}	Wall indicator
è	Position of the source	U	Peak power of dynamic propagation environment
γ	Path loss exponent	t	Time
n	Shadow fading	t_u	Period of dynamic propagation environment
P_i	Received signal strength of the ith anchor	ε_i	Localization error
P_0	Received signal strength at d_0	α_i	Parameter
d_0	Reference distance to source	$\mathbf{A}$	System matrix
σ	Standard deviation of shadowing	$\mathbf{b}$	Observation vector
$\tilde{P}_0$	Received signal strength at d_0 in indoor environment	I_2	2×2 identity matrix
$\tilde{n}$	Shadow fading in indoor environment	$[.]^T$	Transpose operator
$n_{\omega,i}$	Number of walls between source and the ith anchor	$(.)^{-1}$	Inverse operator

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