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Real time localization algorithm based on local linear embedding optimization in mobile sensor networks

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Abstract. Location accuracy of wireless sensor network relies on noise level and connection of non-line of sight. So, Location correcting algorithm based on semi-definite programming is proposed and it is based on edge-semi-definite programming; it is denoted as ESDP_O algorithm and it aims to increase location precision and reduce location time in severe environment. ESDP algorithm is modified and robustness of ESDP_O algorithm in high error environment of distance measurement is increased for ESDP_O algorithm through quoting dithering matrix. ESDP_O algorithm handles high noise and deviation of non-line of sight through seeking low-rank solution. Simulated result indicates that location precision of ESDP_O algorithm is better than algorithms of the same kind and calculation complexity is also reduced in environment of high noise and that most distance measurement is non-line of sight.

Key words. Wireless sensor network, Location, Semi-definite programming, Non-line of sight, Robust.

1. Introduction

Position of sensor nodes plays an important role[1] in application of wireless sensor network, such as detection of abnormal events, induction of fire disaster and objective tracking, etc and these applications all need position information[2-3] of nodes. Position of unknown nodes is further estimated through distance between nodes (anchor node) of known position and themselves in combination with location algorithm to obtain position info9rmation of unknown nodes and distance measurement is the key to location problem of sensor network.

Many different schemes[4-5] are proposed by research personnel pertinent to location problem of sensor network. In the literature [4], the author proposes a kind of location algorithm of time difference based on second-order cone programming and

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position estimation is translated to an issue of second-order cone programming for the algorithm; final position of nodes is estimated with Taylor series development method. Many research personnel also introduce convex optimal relaxation technique to translate non-convex optimal problem to convex optimization problem of location and then achieve position of nodes with Second order cone Programming[6-7] and Semi-definite Programming in convex optimization theory.

However, it is all assumed that distance measurement is line of sight for these location algorithms, namely that communication route among nodes is LOS connection. But this assumption cannot be satisfied in most environments; most connections are in environments of non-line of sight and which connections belong to NLOS and which connections belong to LOS cannot be estimated, thus it proposes challenge for location of sensor nodes.

So, a correcting algorithm ESDP_O of location based on relaxation optimization of Edge-Semi-definite programming is proposed pertinent to noise and severe environment with NLOS. ESDP_O algorithm is based on ESDP algorithm and then pull matrix is introduced to achieve low-rank solution, increase location robustness in severe environment and reduce complexity of the algorithm. Simulated data indicates that proposed ESDP_O algorithm can accurately estimate node position and reduce location complexity in severe environment.

2. Location model and problem description

Suppose sensor network is composed of a series of anchor nodes and common sensor nodes and position of n sensor nodes is known, respectively indicated as $x_1, \cdots, x_n$; position of m anchor nodes is known and respectively indicated as $a_1, \cdots, a_m$. Distance between sensor nodes x_i and x_j is indicated as $d_{s,ij}$; similarly, Euclidean distance between sensor node x_j and anchor node a_k can be indicated as $d_{a,jk}$.

Second-order location problem of wireless sensor network can be simplified as:

$$Find\, \boldsymbol{X} \in \mathrm{Re}^{2\times n}\,. \tag{1a}$$

$$s.t.\, \boldsymbol{Y}_{ii} - 2\boldsymbol{Y}_{ij} + \boldsymbol{Y}_{jj} = d_{s,ij}^2,\, \forall\,(j,i) \in N_s\,. \tag{1b}$$

$$\boldsymbol{Y}_{jj} - 2x_j^T \boldsymbol{a}_k + \|a_k\|^2 = d_{a,jk}^2,\, \forall\,(j,k) \in N_a\,. \tag{1c}$$

$$\boldsymbol{Y} = \boldsymbol{X}^T \boldsymbol{X}\,. \tag{1d}$$

$\boldsymbol{X} = [x_1, \cdots, x_n]$, $N_s = \{(j,i)\,|\,\|x_j - x_i\| < r\}$ and $N_a = \{(j,k)\,|\,\|x_j - a_k\| < r\}$. r is wireless transmission radius.

Convex relaxation technique is an effective method to solve location problem of sensor network. Relaxation algorithm of semi-definite programming is proposed in Literature [2] to translate the non-convex problem in Equation (1) to a convex problem. SDP is modified in Literature [3] to obtain low-rank solution. However, compared with SDP, it still cannot improve location accuracy. These schemes translate limited Equation (1d) to linear inequality LMI, as shown in Equation (2):

$$\boldsymbol{Y} \succ \boldsymbol{X}^T\boldsymbol{X} \to \boldsymbol{Z} = \begin{pmatrix} \boldsymbol{I}_2 & \boldsymbol{X}^T \\ \boldsymbol{X} & \boldsymbol{Y} \end{pmatrix} \succ 0\,. \tag{2}$$

$\boldsymbol{I}_n$ Indicates unit matrix

Besides, compared with SDP, complexity of relaxation algorithm based on ESDP reduces and it has the same location accuracy [8] as SDP. Equation (1) can be solved with ESDP relaxation algorithm, so Equation (1) can be translated to Equation (3).

$$\min_{\substack{\boldsymbol{\alpha}^+,\boldsymbol{\alpha}^-,\boldsymbol{\beta}^+\\ \boldsymbol{\beta}^-,\boldsymbol{Z},\boldsymbol{Y}}} \sum_{(j,i)\in N_s} \left(\boldsymbol{\alpha}_{ij}^+ + \boldsymbol{\alpha}_{ij}^-\right) + \sum_{(j,k)\in N_a} \left(\boldsymbol{\beta}_{jk}^+ + \boldsymbol{\beta}_{jk}^-\right). \tag{3a}$$

$$s.t.\ \boldsymbol{Z}_{(1,2),(1,2)} = \boldsymbol{I}_2\,. \tag{3b}$$

$$\boldsymbol{Y}_{ii} - 2\boldsymbol{Y}_{ij} + \boldsymbol{Y}_{jj} - \alpha_{ij}^+ + \alpha_{ij}^- = d_{s,ij}^2\,. \tag{3c}$$

$$\begin{gathered} \boldsymbol{Y}_{jj} - 2x_j^T\boldsymbol{a}_k + \|a_k\|^2 - \beta_{jk}^+ + \beta_{jk}^- = d_{a,jk}^2 \\ \forall\,(i,j)\in N_s, \forall\,(j,k)\in N_a \end{gathered} \tag{3d}$$

$$\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)} \succ 0,\ \forall\,(j,i)\in N_s\,. \tag{3e}$$

$$\boldsymbol{\alpha}^+, \boldsymbol{\alpha}^-, \boldsymbol{\beta}^+, \boldsymbol{\beta}^- \geq 0\,. \tag{3f}$$

$\boldsymbol{\alpha}^+, \boldsymbol{\alpha}^-, \boldsymbol{\beta}^+, \boldsymbol{\beta}^-$ are respectively errors of squared distance.

$\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)}$ Is sub-matrix of $\boldsymbol{Z}$. Relaxation algorithm of Edge-based Maximum Likelihood is proposed in Literature [9] to increase performance of ESDP relaxation algorithm. However, proposed schemes in Literatures [2-9] are all based on the fact that all nodes have connection of line of sight. But most connections of indoor network especially are NLOS.

Scheme based on SDP is adopted in Literature [10-11] to locate sensor nodes. SDP-M scheme is adopted in Literature [10] to solve node location problem on condition of NLOS connection and it also increases location accuracy. But it is in premise of assuming that NLOS connection is recognizable. However, this hypothesis is unreasonable under conditions proposed by Literature [11]. Location algorithm is proposed in Literature [11] pertinent to the situation that there is no previous information of NLOS and NLOS and LOS connection is not distinguished. Distance measurement model containing error shown in Equation (4) is adopted in Literature [11].

$$\begin{gathered} \hat{d}_{ij} = d_{ij} + G\left(0, \sigma_{ij}^2\right) + b_{ij}, \sigma_{ij}^2{=}K_E d_{ij}^\gamma \\ \forall\,(j,i)\in N_s \cup N_a \cup NL_s \cup NL_a\,. \end{gathered} \tag{4}$$

$\{b_{ij}\}$ is deviation set of unknown NLOS. $\{d_{ij}\}$ Contains $\{d_{s,ij}\}$ and $\{d_{a,jk}\}$. $G\left(0, \sigma_{ij}^2\right)$ is Gaussian distribution of zero mean and variance $\sigma_{ij}^2 = K_E d_{ij}^{\gamma}$. NL_s and NL_a respectively indicates NLOS connection set between sensor node and sensor node, sensor node and anchor node. K_E is scale parameter to determine accuracy of distance measurement, but solution rank of this algorithm is high.

So, optimized robust location algorithm ESDP_O based on ESDP is proposed in this thesis pertinent to environment of high noise and NLOS deviation. ESDP_O can obtain low-rank solution and increase algorithm robustness through introducing new relaxation algorithm based on SDP. Meanwhile, it is assumed that NLOS connection is unknown in ESDP_O algorithm and it is considered that statistics of $\{b_{ij}\}$ is also unknown; it conforms to real environment more in aiming to expand application scene of ESDP_O algorithm and increase location accuracy in severe environment.

3. ESDP_O algorithm

ESDP_O algorithm integrates SDP relaxation technique and aims to increase location performance of location schemes based on SDP in severe environment. Distance measurement is the key to location algorithm. Firstly distance measurement without error is assumed:

$$(\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0})^T \boldsymbol{Z}^{(true)} (\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0})^T = d_{s,ij}^2, \forall (i,j) \in N_s\,. \tag{5a}$$

$$(\boldsymbol{e}_j; -\boldsymbol{a}_k)^T \boldsymbol{Z}^{(true)} (\boldsymbol{e}_j; -\boldsymbol{a}_k) = d_{a,jk}^2, \forall (j,k) \in N_a\,. \tag{5b}$$

$\boldsymbol{Z}^{(true)}$ Indicates matrix without error in matrix $\boldsymbol{Z}$ and $\boldsymbol{e}_i$ is zero column vector.

Equations (5a) and (5b) can be translated to Equation (6) as shown if it is in environment with distance measurement noise in combination with Equations (3c) and (3d):

$$(\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0})^T \boldsymbol{Z}^{(n)} (\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0}) + \alpha_{ij}^+ - \alpha_{ij}^- = d_{s,ij}^2 + t_{ij}\,. \tag{6a}$$

$$(\boldsymbol{e}_j; -\boldsymbol{a}_k)^T \boldsymbol{Z}^{(n)} (\boldsymbol{e}_j; -\boldsymbol{a}_k) + \beta_{jk}^+ - \beta_{jk}^- = d_{a,jk}^2 + \nu_{jk}\,. \tag{6b}$$

$$t_{ij} = 2n_{ij} d_{s,ij} + n_{ij}^2, \forall (i,j) \in N_s\,. \tag{6c}$$

$$\nu_{jk} = 2\delta_{jk} d_{a,jk} + \delta_{jk}^2, \forall (j,k\,.) \in N_a\,. \tag{6d}$$

n_{ij} and δ_{jk} are respectively corresponding noises to $d_{s,ij}$ and $d_{a,jk}$. $\boldsymbol{Z}^{(n)}$ is noise matrix of $\boldsymbol{Z}$.

It is good for location optimization with NLOS distance measurement as upper limit because error caused by NLOS connection is a positive number and it is commonly greater than measurement noise. Besides, thee should be 75% distance measurement at least not greater than sum of mean of $\{\hat{d}_{s,ij}\}$ and $2 \times std(\{\hat{d}_{s,ij}\})$ if thee is LOS connection for a pair of nodes based on in-equation of Chebyshev. Mean value of $\{\hat{d}_{s,ij}\}$ and $std(\{\hat{d}_{s,ij}\})$ in NLOS environment are both far greater than connection in LOS environment.

So, the probability that LOS distance measurement is greater than sum of mean value of $\{\hat{d}_{s,ij}\}$ and $2 \times std(\{\hat{d}_{s,ij}\})$ is very low. Solving space is limited with LOS distance measurement as the upper limit based on Equation (6) and it may increase complexity of optimal matrix. Thus ESDP_O algorithm is used to expand solving space and achieve optimal solution of convergence. In ESDP_O algorithm, more distance measurement is upper limit Equation (7) is introduced as constraint condition of optimization problem in unknown environment of NLOS connection.

$$(\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0})^T \boldsymbol{Z}^{(n)} (\boldsymbol{e}_i - \boldsymbol{e}_j; \boldsymbol{0}) \leq d_{s,ij}^2 \,. \tag{7a}$$

$$(\boldsymbol{e}_j; -\boldsymbol{a}_k)^T \boldsymbol{Z}^{(n)} (\boldsymbol{e}_j; -\boldsymbol{a}_k) \leq d_{a,jk}^2 \,. \tag{7b}$$

$$\left\{\hat{d}_{s,ij}, \hat{d}_{a,jk}\right\} \geq mean\left(\left\{\hat{d}_{ij}\right\}\right) + std\left(\left\{\hat{d}_{ij}\right\}\right) \,.$$

It can be found according to Equations (5), (6) and (7) that distance measurement error can easily cause dithering of matrix $\boldsymbol{Z}$, thus it reduces location accuracy. So matrix $\boldsymbol{Z}$ can be stated as:

$$\boldsymbol{Z}^{(n)} = \boldsymbol{Z}^{(true)} + \boldsymbol{\Delta} \,. \tag{8}$$

Solve Equation (3) with Equations (7a) and (7b) and it can be obtained that:

$$\begin{aligned} \max_{\boldsymbol{S},\boldsymbol{u},\boldsymbol{\omega}} (g(\boldsymbol{u},\boldsymbol{\omega})) &= u_{11} + 2u_{12} + u_{22} \\ &+ \sum_{(i,j)\in N_s \cup NL_s} \omega_{s,ij} \left(d_{s,ij} + n_{ij} + b_{ij}\right)^2 \\ &+ \sum_{(j,k)\in N_a \cup NL_a} \omega_{a,jk} \left(d_{a,jk} + \sigma_{jk} + b_{jk}\right)^2 \,. \end{aligned} \tag{9a}$$

$$\begin{aligned} \text{s.t.} & \sum_{(i,j)\in N_s \cup NL_s} \left\{\omega_{s,ij} (\boldsymbol{0}; \boldsymbol{e}_i - \boldsymbol{e}_j)^T (\boldsymbol{0}; \boldsymbol{e}_i - \boldsymbol{e}_j) + \boldsymbol{S}^{(i,j)}\right\} \\ &+ \sum_{(j,k)\in N_a \cup NL_a} \left\{\omega_{a,jk} (-\boldsymbol{a}_k, \boldsymbol{e}_j)^T (-\boldsymbol{a}_k; \boldsymbol{e}_j)\right\} \\ &+ \begin{pmatrix} u_{11} + u_{12} & u_{12} & 0 \\ u_{12} & u_2 + u_{12} & 0 \\ 0 & 0 & 0 \end{pmatrix} = 0 \,. \end{aligned} \tag{9b}$$

$$\omega_{s,ij} \leq 0, \forall (j,i) \in NL_s, \;\; \omega_{a,jk} \leq 0, \forall (j,k) \in NL_a \,. \tag{9c}$$

$$\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)} \succ 0,\ \forall\,(j,i) \in N_s \cup NL_s\,. \tag{9d}$$

$$\boldsymbol{S}^{(i,j)}_{kl} = 0,\ \forall k \notin (i,j)\ or\ \ell \notin (i,j)\ . \tag{9e}$$

$\boldsymbol{S}, \boldsymbol{u}$ and $\boldsymbol{\omega}$ respectively indicate variables of the problem in Equation (3). NL_s and NL_a contain all nodes satisfying Equation (7). It can be obtained that according to analysis of dithering and sensitivity and Literature [12]:

$$\nabla_{\Delta(1,2,i,j),(1,2,i,j)} f^*\,(0,0,0) = \boldsymbol{S}^{(i,j)^*}_{(1,2,i,j),(1,2,i,j)}\,. \tag{10}$$

Optimal value of Equations (6) and (7) is $f^*\,(\boldsymbol{t}, \boldsymbol{\nu}, \boldsymbol{\Delta})$. $\boldsymbol{S}^{(i,j)^*}_{(1,2,i,j),(1,2,i,j)}$ is optimal value of Equation (9). This means that $f^*\,(\boldsymbol{t}, \boldsymbol{\nu}, \boldsymbol{\Delta})$ will not increase rapidly if absolute value of elements in $\boldsymbol{S}$ reduces on condition of error. So dithering matrix $\boldsymbol{P}$ is used to modify ESDP algorithm:

$$\min_{\substack{\boldsymbol{\alpha}^+,\boldsymbol{\alpha}^-,\boldsymbol{\beta}^+\\ \boldsymbol{\beta}^-,\boldsymbol{Z},\boldsymbol{Y}}} .(3a) \tag{11a}$$

$$\text{s.t} \quad (3b)\,,(3c)\,,(3d)\,,(3f)\,,(7a)\,,(7b)\ . \tag{11b}$$

$$\begin{aligned}&\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)} + \boldsymbol{P}_{(1,2,i,j),(1,2,i,j)} \succ 0\\ &\forall\,(i,j) \in N_s \cup NL_s\,.\end{aligned} \tag{11c}$$

It is noticed that constraint of dual problem of Equation (11) is the same as that of Equation (9). Thus objective function is shown in Equation (12):

$$g\,(\boldsymbol{u}, \boldsymbol{\omega}) - \sum_{(i,j)\in N_s \cup NL_s} tr\left(\boldsymbol{P}_{(1,2,i,j),(1,2,i,j)}\right)\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}\,. \tag{12}$$

Equation (11c) can be slackened so as to obtain solution of Equation (3) and resist dithering of $\boldsymbol{Z}^{(n)}$. It is noticed that eigenvalue in $\boldsymbol{Z}$ is a positive number and eigenvalue of $\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)}$ in Equation (11) is a negative value. Expanding solving space of location problem is to obtain low-rank solution.

Consumed time of WSN location is decided by rank of $\boldsymbol{Z}$. Low-rank solution is helpful to reduce solving time. So the aim of establishing dithering matrix $\boldsymbol{P}$ is to obtain low-rank solution. Suppose $\boldsymbol{Z}$ and $\left\{\boldsymbol{S}^{(i,j)}\right\}$ are solutions of Equation (11) and they are in duality. It can be obtained through this that:

$$\text{rank}\left(\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}\right) + 4 \le 2q \Rightarrow \text{rank}\left(\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)}\right) \le q\,. \tag{13}$$

Proving process of Equation (13) is as follows:

Suppose $\boldsymbol{A} \prec 0$, then Equation (9d) can be translated to:

$$\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)} - \boldsymbol{Z}^T_{(1,2,i,j),(1,2,i,j)}\boldsymbol{A}\boldsymbol{Z}^{\succ}_{(1,2,i,j),(1,2,i,j)}0\,. \tag{14}$$

Then construct Schur complement matrix:

$$\begin{pmatrix} \boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)} & \boldsymbol{Z}^{T}_{(1,2,i,j),(1,2,i,j)} \\ \boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)} & \boldsymbol{A}^{-1} \end{pmatrix} \succ 0\,. \tag{15}$$

Quote lemma [10]: matrix $\boldsymbol{U} \in \mathrm{Re}^{m\times n}$ is offered and $rank\,(\boldsymbol{U}) \leq q$ and there is and merely is $\boldsymbol{V} = \boldsymbol{V}^T \in \mathrm{Re}^{m\times m}$ and $\boldsymbol{W} = \boldsymbol{W}^T \in \mathrm{Re}^{n\times n}$, then:

$$\begin{gathered} rank\,(\boldsymbol{V}) + rank\,(\boldsymbol{W}) \leq q \\ \begin{pmatrix} \boldsymbol{V} & \boldsymbol{U} \\ \boldsymbol{U}^T & \boldsymbol{W} \end{pmatrix} \succ 0 \end{gathered} \tag{16}$$

Proofing is finished.

Deduct and minimize rank of $\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}$ and minimize rank of $\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)}$ similarly. It aims to seek for low-rank solution and $rank\,(\cdot)$ is used for ESDP_O algorithm to conduct normalization. It is well known that if a matrix is symmetrical, positive semi-definite, then its rank can be minimized. So ESDP_O algorithm constructs dithering matrix $\boldsymbol{P}_{(1,2,i,j),(1,2,i,j)}$ to minimize rank of $\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}$, as shown in Equation (17):

$$\boldsymbol{P}_{(1,2,i,j),(1,2,i,j)} = p_{ij}\boldsymbol{I}_4, \forall\,(j,i) \in N_s \cup NL_s\,. \tag{17}$$

So, Equation (12) can be translated to:

$$g\,(\boldsymbol{u},\boldsymbol{\omega}) - \sum_{(i,j)\in N_s\cup NL_s} p_{ij} tr\left(\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}\right). \tag{18}$$

So, rank of $\boldsymbol{S}^{(i,j)}_{(1,2,i,j),(1,2,i,j)}$ can be minimized and rank of $\boldsymbol{Z}_{(1,2,i,j),(1,2,i,j)}$ can be further minimized according to dithering matrix of Equation (17).

Obviously, correctly selecting normative item is the key to ESDP_O algorithm. If normative item is too small, solution of ESDP will not be affected by dithering matrix. Conversely, if it is too big, value of $tr\left(\boldsymbol{Y} - \boldsymbol{X}^T\boldsymbol{X}\right)$ also increases with it to reduce location accuracy. So, selection of parameter p_{ij} should be optimized in combination with network size and information of noise level. Simulated result indicates that selection of normative item changes with distance measurement error in environment with error of distance measurement; meanwhile, location accuracy does not vary with node number.

4. Performance analysis

4.1. Simulated environment

Performance of ESDP_O location algorithm is analyzed through simulated analysis and convex optimization kit in Matlab software is used to solve location problem

(Equation 11). 3.07GHz processor and 8GRAM computer are adopted to implement simulation.

Location performance of the algorithm is measured with average position error and definition is shown in Equation (19).

$$\text{APE} = (1/nL)\left(\sum_{j=1}^{L}\sum_{i=1}^{n}\|\hat{x}_i - x_i\|\right) \tag{19}$$

n is number of sensor node and L is number of noise source. $\hat{x}_i$ and x_i respectively indicate estimation position and actual position of sensor node i.

Besides, limit neighbor number of each node to five. $\{b_{ij}\}$ is subject to exponential distribution and NLOS connection is unknown. For LOS connection, set $E\left[\hat{d}_{ij}^2\right] = E\left[d_{ij}^2\right] + E\left[\xi_{ij}^2\right]$ and $(i,j) \in N_s \cup N_a$ and ξ is error vector of zero mean. So, if the variance of additive noise is bigger, mean of mean square of distance measurement error is bigger. p_{ij} also increases with deviation increase of noise and NLOS. It can be set that p_{ij} is proportional to $E\left[\hat{d}_{ij}^2\right]$ according to this. When $E\left[\hat{d}_{ij}^2\right]$ is less than $0.5r^2$, $p_{ij} = 0$; set value of p_{ij} according to Equation (20) in other situations:

$$\begin{gathered} p_{ij} = 0.05\left(E\left[\hat{d}_{ij}^2/r^2\right] - 0.5\right) \\ \forall\,(i,j) \in N_s \cup N_a \cup NL_s \cup NL_a \end{gathered} \tag{20}$$

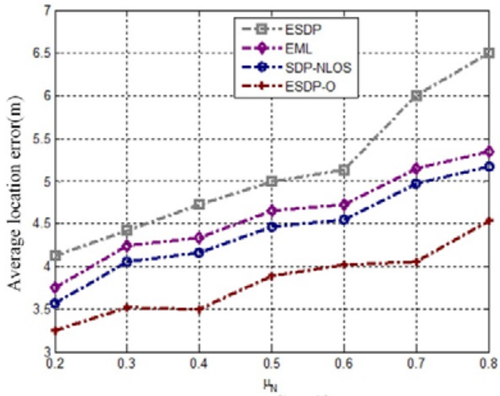
ESDP[8], EML[9] and SDP-NLOS[11] are selected to conduct simultaneous simulation and compare the performance so as to fully analyze performance of ESDP_O location algorithm.

4.2. Simulation result analysis

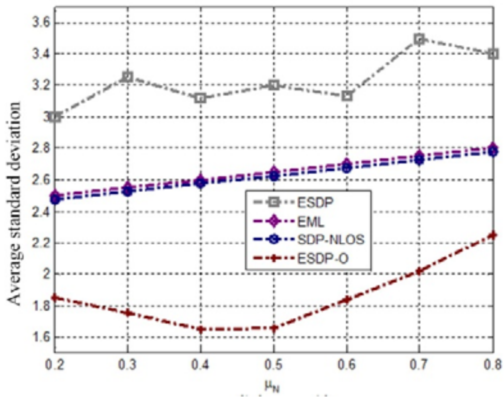
Different application scenes are considered in simulation process; NLOS environment is considered in scenes I and II and LOS environment is considered in scenes III and IV.

Influence of ratio μ_N of NLOS connection number in total distance measurement number on location error and standard deviation of error is mainly investigated in this simulation. Mean values of simulation parameterK_E, wireless transmission radius and NLOS deviation are respectively 0.1, 6m and 5m. Simulation result is shown in Fig. 1.

It can be found from Fig. 1(a) that average location error increases with increase of μ_N and it further indicates that NLOS has negative influence on distance measurement. NLOS connection reduces accuracy of distance measurement and further affects location accuracy. Compared with ESDP, EML and SDP-NLOS algorithms, average location error of ESDP_O algorithm is obviously reduced and the reason is that NLOS environment is fully considered in ESDP_O algorithm and dithering matrix is introduced so as to increase the capacity for the algorithm to handle severe environment. Fig. 1(b) reflects average standard deviation of all algorithms; similar



(a) Average location error



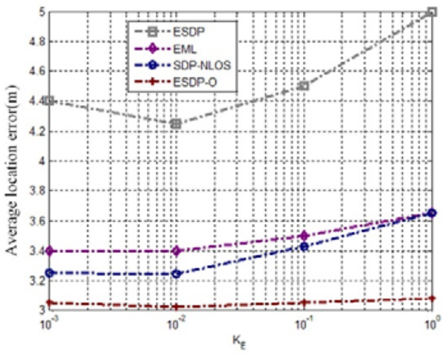
(b) Standard deviation of average location

Fig. 1. Influence of μ_N on location performance

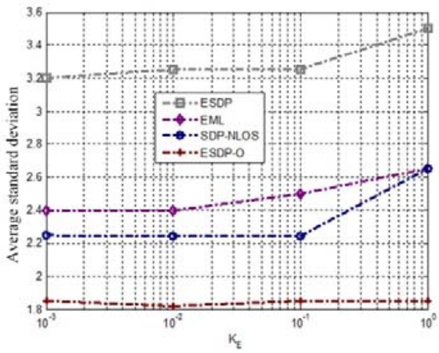
to data of Fig. 1(a), average standard deviation of ESDP_O algorithm is the lowest and standard deviation of ESDP algorithm is the highest.

Influence of K_E on location error and standard deviation of error is investigated in this simulation. As shown in Fig. (4), K_E decides distance measurement error. Noise value $n = 100$ and $\mu_N = 0.4$. There are five anchor nodes and wireless transmission distance is four meters; simulation result is shown in Fig. 2.

It can be found from Fig. 2(a) that increase of K_E reduces location accuracy. However, compared with ESDP, EML and SDP-NLOS algorithms, ESDP_O algorithm is little affected by fluctuation of K_E, which further indicates that K_E can handle NLOS and environment of big noise and it has robustness. Fig. 2(b) describes change curve of average standard deviation with K_E. Average standard deviation of ESDP_O algorithm is the lowest and the fluctuation in change scope of K_E is little. While average standard deviations of ESDP, EML and SDP-NLOS algorithms increase with K_E and they are all higher than that of ESDP_O algorithm. For example, when $K_E = 10^{-1}$, average standard deviation of ESDP algorithm is as high as 3.25m; average standard deviations of EML and SDP-NLOS algorithms are re-



(a) Average location error



(b) Standard deviation of average location

Fig. 2. Influence of K_E on location performance

spectively 2.5m and 2.23m, while average standard deviation of ESDP _O algorithm is only 1.9m.

(3) Scene III

This scene is pertinent to LOS environment, simulation area is and number of anchor node is 15; two types of environment is considered in this simulation: in the first type (**Case1**), noise value is $n = 100$ and wireless transmission distance is $r = 6$m and $K_E = 0.005$; in the other type (**Case2**), $n = 400$ and $r = 4$m and $K_E = 0.5$. Environment of **Case2** is more severe than that in **Case1**. Location errors of all algorithms are shown in Table 1.

Table 1. Average location error in LOS environment

Error Algorithm	ESDP	EML	SDP-NLOS	ESDP_O
Average location error (Case1)	3.19	3.15	3.14	3.19
Average location error (Case2)	4.20	4.12	4.11	3.88

It can be known from Table 1 that in **Case1** environment, compared with ESDP, EML and SDP-NLOS, location performance of ESDP_O algorithm is not improved and it is even slightly higher than that of EML and SDP-NLOS. While in **Case2** environment, location error of ESDP_O algorithm is lower than that of ESDP, EML and SDP-NLOS algorithms. These data indicates that proposed ESDP_O algorithm is more adaptable to severe environment.

(4) Secene IV

This experiment aims to analyze complexity of all algorithms and state it with operation time of algorithm. Experimental parameters: K_E and $r = 6$ are respectively 0.1 and 6m. Number of anchor node is five and all connections are in LOS environment; operation time of all algorithms is shown in Table 2 when $n = 100$, 200, 300 and 400.

Table 2. Operation time of algorithm

Operation time(s) Algorithm	ESDP	EML	SDP-NLOS	ESDP_O
n=100	6.51	9.56	9.78	6.28
n=200	16.13	25.43	24.89	14.84
n=300	34.23	52.42	52.78	30.76
n=400	81.72	119.00	120.60	73.59

It can be found from Table 2 that operation time of proposed ESDP_O algorithm is the least when n change from 100 to 400, so it indicates that its complexity is lower than that of other algorithms. In other words, ESDP_O algorithm increases location accuracy in severe environment, but it does not increase algorithm complexity at the same time. Besides, it can be found from Table 2 that increase of n increases operation time of algorithm and location difficulty.

5. Conclusion

Modified algorithm ESDP_O of location based on relaxation optimization of Edge-Semi-definite programming is proposed pertinent to node location problem of wireless sensor network. Severe environment of non-line of sight and noise are considered in ESDP_O algorithm on focus and low-rank solution is obtained to reduce algorithm complexity, increase location precision in severe environment and strengthen robustness of algorithm through constructing dithering matrix based on ESDP location algorithm. Simulation is conducted pertinent to different scenes and simulation result indicates that complexity and location precision of proposed ESDP_O algorithm is better than those of SDP-NLOS and ESDP algorithms in severe environment.

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