Particle swarm optimization-based low-complexity three-dimensional UWB localization scheme

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***Abstract*—To provide a location-based service (LBS), it is needed to obtain an exact location of communication terminals in sensor networks. Because the signal of global positioning system (GPS) cannot be received indoors, a triangulation-based location estimation using ultra-wide band (UWB) signals between more than three reference terminals and the target node is widely used. In particular, a time of arrival (TOA)-based least square (LS) estimation is popular because the balanced performance in terms of calculation complexity and the accuracy is obtained. However, when the height of reference terminals and the target node is close, the three-dimensional LS-based estimation tends to fall into a local-minimum solution and it needs an accurate initial value of search to keep the estimation performance, resulting in the calculation complexity increase. Therefore, in this paper, we adopt a particle swarm optimization (PSO) method which effectively searches in wide-area space and propose an LS-based localization scheme using the combination of PSO and Newton-Raphson method achieving lower calculation complexity. The improved performances are shown by computer simulations.**

Keywords—location-based service; ultra-wide band; least square-based localization; particle swarm optimization; Newton-Raphson method.

I. INTRODUCTION

Location-based services exploiting the location information of communication terminals can provide various new service architectures and their developments are highly expected. Currently, the location information for smartphone by global positioning system (GPS) is widely used outdoors and also the utilization of indoor location information is expected to be developed. For example, a high-resolution location information enables segmented air condition, audio, and lighting supplies which contribute energy-saving and personalized environments. However, because the radio wave of GPS cannot be received in indoor, other measurement schemes are needed. As a popular one, ultra wide band (UWB) radio wave-based triangulation between the target node whose location is unknown and the reference anchor nodes is utilized for centimeter-order localization. As the distance measurement between the target node and the anchor node, there are a few schemes such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS). Among those schemes, TOA has a high measurement resolution and is often used [1]. Using more than three measured distance data the location of target node is estimated, and there are several estimation algorithms from the distance data to the location. The simplest one is the linear least square (LLS) scheme [2] which needs the least calculation complexity. However, for more accurate estimation, it is popular to use the maximum likelihood (ML) scheme or nonlinear least square (NLS or simply LS) scheme [3]. ML scheme provides the most exact location estimation with the requirements of higher calculation complexity and channel parameters. Meanwhile, LS scheme needs less calculation complexity and doesn't need the channel parameters. Hence, the LS scheme is widely used in indoor localization. Thus, in this study we focus on the LS-based localization scheme. There are lots of optimization algorithms applicable for LS-based localization and among them, the full grid search, Newton-Raphson (NR) algorithm, and a nonlinear optimization are often adopted. We have considered a hybrid use of NR and grid search in which a rough grid search is conducted in advance and its result is used as the initial value of NR fine search in the second stage [4]. This scheme can balance the calculation complexity and the accuracy. However, to get the result of NR search converged a relatively exact initial value has to be supplied. In general, the three-dimensional localization tends to need higher complexity [5]. In particular, when the height of the target and anchor nodes is close in three-dimensional localization, more exact initial value is needed to avoid making a local optimal solution output by NR scheme, resulting in the calculation complexity increase in grid search. This happens in the low-height anchor node case which is rather general because the roof of rooms is usually not so high.

To solve this problem, in this paper we adopt a particle swarm optimization (PSO) algorithm [6] in which a wide-range optimization is efficiently conducted and propose a lower-complexity LS-based localization scheme with the hybrid of PSO and NR optimization. As the conventional studies, the PSO localization with RSS signals has been proposed in [7]. However, the estimation error is relatively high because RSS signals are utilized. The TDOA-based exact localization using PSO has been studied in [8,9]. However, those studies are two-dimensional localization and the height problem is not considered. In the proposed scheme, the first estimation results are obtained by the PSO scheme with low calculation complexity, and then, the NR fine search is conducted. By this algorithm, the complexity reduction and the accurate estimation is simultaneously achieved.

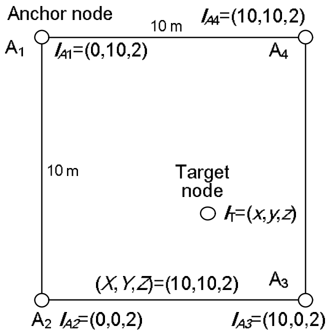


Fig. 1. Three-dimensional sensor field in this study.

In the following, the system model and LS estimation is introduced in Section II, the conventional and the proposed optimization schemes for LS estimation are described in Section III, and the numerical results are illustrated in Section IV. Finally, the conclusions are drawn in Section V.

II. SYTEM MODEL AND LEAST SQAURE LOCALIZATION

Fig. 1 shows the indoor location estimation system in this study. The three dimensional sensor field with $X = Y = 10, Z = 2$ meter is considered and the four anchor nodes whose positions are known are located at the four corners with the height of *Z*=2. The location of ***i***-th anchor node is denoted by $\mathbf{l}_{A_i} = (x_i, y_i, z_i)$, $1 \le i \le N$ where *N*=4 is the number of anchor nodes. One target node whose location is to be estimated exists and it broadcasts an ultra-wide band (UWB) beacon. Four anchor nodes receive it and calculate the distance between each anchor node and the target node in TOA manner, and a central unit estimates the target node location by triangulation using those distance data. The true location of the target node is denoted by $\mathbf{l}_T = (x, y, z)$. Then, the true distance between the anchor node A_i and the target node *T* is denoted by

$$d_i = \left\| \mathbf{l}_T - \mathbf{l}_{A_i} \right\| = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \qquad (1)$$

When it is measured at A_i, the error is added and it becomes $\hat{d}_i = d_i + \varepsilon_i$ where ε_i is the noise component in measurements. It is assumed in this study that the propagation channel between all anchor nodes and the target is in line-of-sight (LOS) environments. According to [10] and [11], in this UWB measurement $\hat{d}_i$ has a Gaussian distribution with the error mean of $\mu_i = \mu_{\mathrm{LOS}} \log(1 + d_i)$ and the variance σ_i^2 . Here, μ_{LOS} and σ_i^2 are the parameters depending on the bandwidth of UWB signal. The probability density function (pdf) of $\hat{d}_i$ is given by

$$p\left(\hat{d}_i \mid d_i\right) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(\hat{d}_i - d_i - \mu_i)^2}{2\sigma_i^2} \right] \qquad (2)$$

Therefore, the accuracy of TOA distance can be raised by the multiple signal measurements at each anchor node. When the anchor node A_i measures the distance *M* times and *k*-th distance is denoted by $\hat{d}_{i,k}$, the measurement results of distance $\hat{d}_i$ is given by

$$\hat{d}_i = \frac{1}{M} \sum_{k=1}^{M} \hat{d}_{i,k} \qquad (3)$$

which is more reliable than a single measurement. Using $\hat{d}_i$, the estimated location of the target node is calculated in the LS manner by

$$\hat{\mathbf{l}}_T = \arg\min_{x,y,z} \sum_{i=1}^{N} \left[\sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - \hat{d}_i \right] \qquad (4)$$

This equation is a nonlinear optimization problem and there are several solution algorithms. Some of typical schemes and the proposed scheme are introduced in the next section.

III. OPTIMIZATION SCHEMES IN LS-BASED LOCALIZATION

The LS estimation of (4) needs less calculation complexity than that of ML estimation. Different from ML scheme, the LS scheme doesn’t need channel parameters in calculation but can obtain relatively good estimation performance. However, it still needs the nonlinear solution search as well as ML scheme. As the conventional algorithm, grid search and the sequential search of gird and NR schemes are introduced here, and the proposed scheme further reducing the calculation complexity is also described.

A. *Grid search*

Grid search is the simplest solution search algorithm. In the grid search, the solution is fully searched at the discrete and equally-spaced grid in the search space in general. For (4), the grid search becomes

$$\hat{\mathbf{l}}_T = \arg\min_{j,k,l} \sum_{i=1}^{N} \left[\sqrt{(j\delta d - x_i)^2 + (k\delta d - y_i)^2 + (l\delta d - z_i)^2} - \hat{d}_i \right] \qquad (5)$$

$$0 \le j \le \lfloor X/\delta d \rfloor \quad 0 \le k \le \lfloor Y/\delta d \rfloor \quad 0 \le l \le \lfloor Z/\delta d \rfloor$$

where δd is the grid interval and $\lfloor x \rfloor$ means the maximum integer less than *x*. The search number of (5) becomes $\left(\lfloor X/\delta d \rfloor + 1\right)\left(\lfloor Y/\delta d \rfloor + 1\right)\left(\lfloor Z/\delta d \rfloor + 1\right)$, and the estimation accuracy and the calculation complexity are increased when δd is smaller.

B. *Seqeuntial search of grid and Newton-Raphson*

NR scheme is an iterative optimal solution search algorithm of equation and it needs an appropriate initial value close to the true solution value to avoid converging to local optimal values. Hence, in (4) calculation, the rough search of Subsection III.A using a relatively large grid is conducted at first, and its result is used as the initial value of NR search. Then, the fine search is conducted by NR search in the second stage. When the object function of LS estimation by NR search is denoted as

$$f(x, y, z) = \sum_{i=1}^{N} \left[\sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - \hat{d}_i \right] \qquad (6)$$

then, the estimation result is obtained by

$$\hat{\mathbf{l}}_T = \arg\min_{x,y,z} f(x, y, z) \, .$$

When a neighborhood solution of $\hat{\mathbf{l}}_T$ is given as $\hat{\mathbf{l}}_T = (\hat{x}, \hat{y}, \hat{z})$, the update equation of NR scheme and the difference parameters are obtained as follows.

$$\hat{\mathbf{l}}_{T,new} = \hat{\mathbf{l}}_T + \delta\mathbf{l}, \quad \delta\mathbf{l} = (\delta x, \delta y, \delta z) \tag{7}$$

$$\begin{bmatrix} \frac{\partial g_1(\hat{\mathbf{l}}_T)}{\partial x} & \frac{\partial g_1(\hat{\mathbf{l}}_T)}{\partial y} & \frac{\partial g_1(\hat{\mathbf{l}}_T)}{\partial z} \\ \frac{\partial g_2(\hat{\mathbf{l}}_T)}{\partial x} & \frac{\partial g_2(\hat{\mathbf{l}}_T)}{\partial y} & \frac{\partial g_2(\hat{\mathbf{l}}_T)}{\partial z} \\ \frac{\partial g_3(\hat{\mathbf{l}}_T)}{\partial x} & \frac{\partial g_3(\hat{\mathbf{l}}_T)}{\partial y} & \frac{\partial g_3(\hat{\mathbf{l}}_T)}{\partial z} \end{bmatrix} \begin{bmatrix} \delta x \\ \delta y \\ \delta z \end{bmatrix} = \begin{bmatrix} -g_1(\hat{\mathbf{l}}_T) \\ -g_2(\hat{\mathbf{l}}_T) \\ -g_3(\hat{\mathbf{l}}_T) \end{bmatrix} \tag{8}$$

$$\begin{cases} g_1(x,y,z) = \dfrac{\partial f(x,y,z)}{\partial x} = 0 \\ g_2(x,y,z) = \dfrac{\partial f(x,y,z)}{\partial y} = 0 \\ g_3(x,y,z) = \dfrac{\partial f(x,y,z)}{\partial z} = 0 \end{cases} \tag{9}$$

Here, (9) is the derivative of (6) and the solution satisfying (9) is searched by (7) and (8). The iterative search is conducted using $\delta\mathbf{l}$ calculated by LU decomposition of (8), and the update of (7) and (8) is iterated from the initial value of rough search results on (5) until

$$f\left(\hat{\mathbf{l}}_{T,new}\right) \geq f\left(\hat{\mathbf{l}}_T\right) \tag{10}$$

is satisfied. Finally, $\hat{\mathbf{l}}_T$ at that point is output as the solution.

C. Proposed search scheme

In the scheme of Subsection III.B, when the heights of the target node z and the anchor node z_i are close, an accurate initial value is required to avoid converging to local optimal value that means the result having large estimation error. As a result, the small δd of (5) was needed and the calculation complexity was increased. Thus, to reduce the calculation complexity while sustaining the estimation accuracy, we propose a sequential search scheme in which the result of rough PSO search is used in NR scheme. The PSO-based LS search is described in the following.

The object function to be minimized is the same as (6) and let N_p as the number of particles. The location and velocity of the particle i at time n are defined by

$$\mathbf{l}^i(n) = \left[x^i(n), y^i(n), z^i(n)\right], \quad 1 \leq i \leq N_p$$
$$\mathbf{v}^i(n) = \left[v_x^i(n), v_y^i(n), v_z^i(n)\right] \tag{11}$$

Then, the personal best of i-th particle is given by

$$\mathbf{p}^i = \left(p_x^i, p_y^i, p_z^i\right), \quad f\left(\mathbf{p}^i\right) \leq f\left(\mathbf{l}^i(n)\right), \quad 0 \leq n \leq n_c \tag{12}$$

where n_c is the current time. The global best of all particles is given by

$$\mathbf{g} = \left(g_x, g_y, g_z\right), \quad f(\mathbf{g}) \leq f\left(\mathbf{p}^i\right), \quad 0 \leq i \leq N_p \tag{13}$$

and the local best $\mathbf{b}^i = \left(b_x^i, b_y^i, b_z^i\right)$ is configured as a ring connection for i-th particle such as

$$f\left(\mathbf{b}^i\right) \leq f\left(\mathbf{p}^j\right), \quad 0 \leq i \leq N_p,$$
$$(i-1+N_p) \bmod N_p \leq j \leq (i+1+N_p) \bmod N_p \tag{14}$$

Then, the update of i-th particle in the x axis is given by

$$\begin{cases} v_x^i(n+1) = w v_x^i(n) + r_1\{p_x^i - x^i(n)\} + r_2\{b_x^i - x^i(n)\} \\ x^i(n+1) = x^i(n) + v_x^i(n) \end{cases} \tag{15}$$

where w, r_1, and r_2 are the behavior control parameters of particle. The location and velocities of other axes v_y^i, v_z^i, y^i, and z^i are calculated in the same way. In this study, by the heuristic adjustment for the sensor field of Fig. 1, these parameters are configured as follows: w of (15) is set as 0.5, r_1 and r_2 are set as $r_1, r_2 \in \mathrm{RND}[0,0.42]$ for x and y axes, and as

$$r_1 \in \mathrm{RND}[0,0.42],\; r_2 \in \mathrm{RND}\left[0, \frac{0.42Z}{X}\right] \tag{16}$$

for z axis because z space is smaller than x and y spaces. Here, RND[a,b] denotes the uniform random number in the range of [a,b]. The initial value of i-th location and velocity is randomly given by

$$\mathbf{l}^i(0) = \left(\mathrm{RND}[0,\mathrm{X}], \mathrm{RND}[0,\mathrm{Y}], \mathrm{RND}[0,\mathrm{Z}]\right)$$
$$v_x^i(0), v_y^i(0), v_z^i(0) \in \mathrm{RND}[0,0.4] - 0.2 \tag{17}$$

The terminating condition is set as $f(\mathbf{g}) \leq 10^{-4}$ which is close to the exact solution and the maximum iteration number is set as $n_{\max}$. In this termination condition, because the iteration reaches $n_{\max}$ in almost all cases, the calculation complexity and the accuracy can be controlled by $n_{\max}$.

In the proposed scheme, the global best solution $\boldsymbol{g}$ of PSO is handed to NR scheme as the initial value and the sequential LS estimation is conducted.

IV. Numerical Results

The performances of calculation complexity and estimation accuracy of the proposed scheme are evaluated by computer simulations. The root mean square error (RMSE) is calculated as the estimation error. Table I shows the simulation conditions. The target node at the location of (x, y, z) sends beacons 30 times (M=30) and the anchor nodes receive them. The RMSE is calculated after 1000 times trial at each target node location. The target node location is changed at every 0.5 m for x and y axes while z=1 m is fixed, and RMSE is calculated on all x-y plane. The UWB signal bandwidth is assumed as 3 GHz and the channel parameter is configured by the experimental results of [10]. As the calculation complexity, the calculation of (6) is defined as one search, and the average number of calculation on one location estimation is compared.

The average RMSE of x-y plane versus average calculation complexity is shown in Fig. 2 where the grid search in Subsection III.A, the sequential scheme of grid and NR in

Table I. Simulation conditions.

Sensor field	X=Y=10 m , Z=2 m
Number of anchor nodes	N=4 (Fig. 1)
Target node location	$0 \leq x \leq X$ and $0 \leq y \leq Y$ on every 0.5 m grid, z=1 m
Number of TOA measurements per one estimation	M=30
Number of simulation for RMSE calculation	1,000 times
UWB bandwidth	3 GHz
UWB channel parameter	$m_{\mathrm{LOS}} = 4.0 \times 10^{-3}, \sigma_i^2 = 4.5 \times 10^{-2}$ [10]
Channel model	Line of sight (LOS)
Number of particles	N_p =10

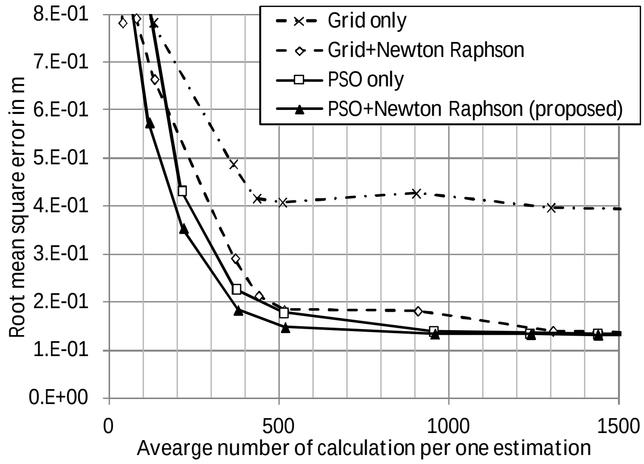


Fig. 2. RMSE performance comparison of the proposed and conventional schemes versus calculation complexity.

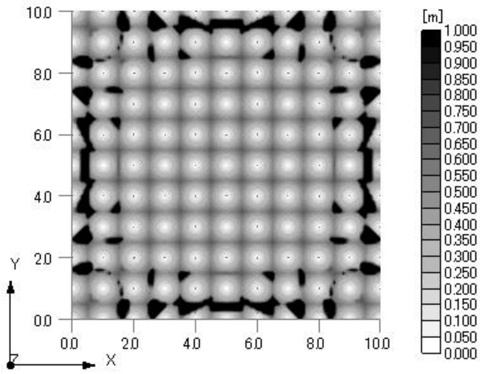
Table II. Relationship between parameter settings and required calculation complexity.

	average number of calculation			average number of calculation	
dd m	grid	grid+NR	n_{max}	PSO	proposed PSO+NR
8.0	4	9.6			
3.0	32	37.6			
2.0	72	77.3	5	62	66.9
1.5	128	131.6	10	112	117
1.0	363	368.6	20	212	217
0.9	432	437.4	36	372	376.7
0.8	507	512.5	50	510.5	515.4
0.7	900	905.0	100	950.7	955.1
0.6	1296	1302.0	150	1232	1236.9

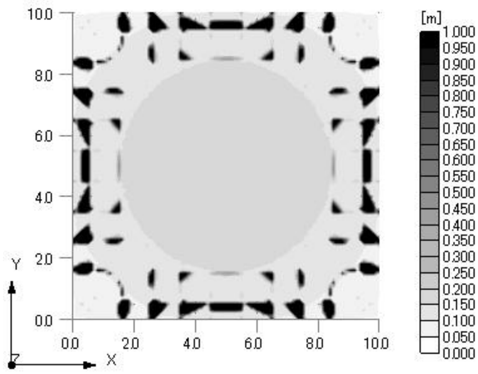
Subsection III.B, and PSO scheme are compared as the conventional schemes. Here, the relationship between the average number of calculation and the grid width dd or the maximum number of iteration n_{max} in PSO is listed in Table II. The result of Fig. 2 shows that the RMSE performances are improved according to the calculation increase in all schemes. This is because the calculated location approaches to the true location with a small grid dd in the grid-based search, and the each particle become easier to converge into the true location with the increased n_{max} in PSO scheme. When compared with other schemes, the grid scheme has the worst performance and it needs further calculation complexity with much smaller dd for improvement. The hybrid scheme of grid and NR has better performance than the grid scheme because of the fine search of NR scheme. However, the RMSE is increased when the accuracy of initial value is not good. On the other hand, PSO-based scheme needs relatively less calculation complexity to obtain the same RMSE that means the effective particle search is valid in the LS-based localization. It can be seen that over 1300 calculation the RMSE of PSO scheme becomes the same as the hybrid scheme of grid and NR, and that the PSO scheme has better performance below that calculation complexity. In addition, the proposed scheme has the best RMSE performance of four schemes and the RMSE is converged to lower bound with the calculation complexity of 500, a half of the hybrid scheme of grid and NR. This means the PSO scheme effectively produces a good initial value to NR scheme with less complexity. Hence, the proposed scheme achieves an accurate LS estimation with lower complexity.

Next, the RMSE performances of four schemes on *x*-*y* plane at $dd = 1.0$ or n_{max}=36 whose calculation complexity becomes around 370 as shown in Table II are compared. The results of Fig. 3 show that there are irregular and relatively large errors in Fig. 3(a) due to the grid-based search. In Fig. 3(b), the center area is improved thanks to NR fine search but there still exists a large error in the side area because the initial value is not sufficiently accurate. On the other hand, as shown in Figs. 3(c) and (d), PSO schemes have averagely good RMSE performances in all areas and the proposed scheme has the best performance.

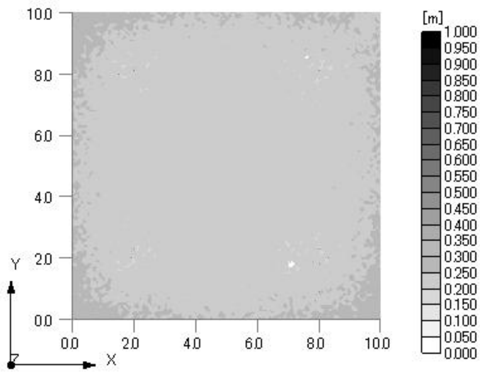
Then, the average RMSE on *x*-*y* plane versus the *z* height ($0 \le z \le 2$) of the target node when the calculation complexity



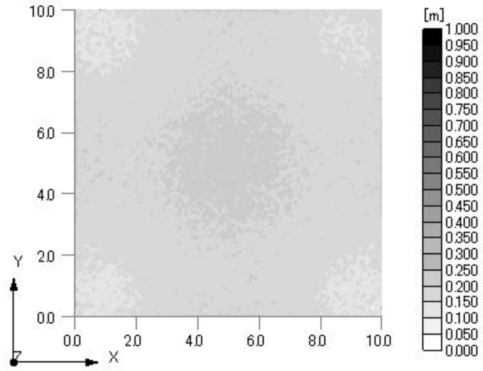
(a)



(b)



(c)



(d)

Fig. 3. RMSE performances on *x*-*y* plane at calculation complexity of 370; (a) grid search, (b) hybrid search of grid and NR, (c) PSO scheme, (d) proposed hybrid search of PSO and NR.

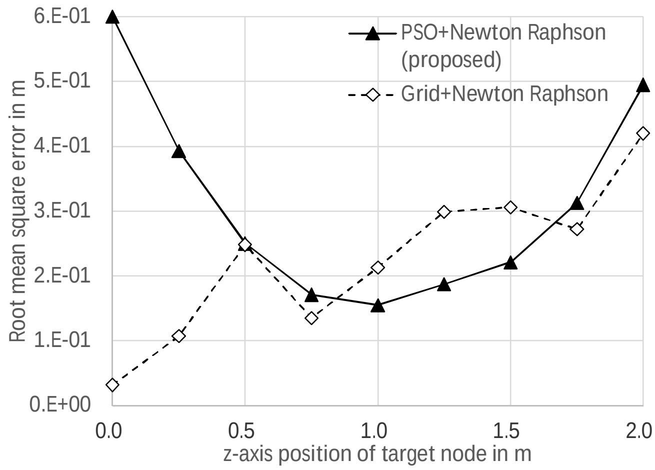


Fig. 4. RMSE performance comparison at calculation complexity of 500 versus the height of target node.

is fixed at 500. The results of Fig. 4 shows that the proposed scheme has similar or better RMSE performance at z ³ 0.5 m. In particular, RMSE at the height between 1.0 and 1.5 m, which is a practical height of the target node in indoor environments like the configuration of Table II, is improved. The reason why the performance at both ends of the height z (floor and roof) is degraded in the proposed scheme is that the estimation error in the z direction is increased. This may come from the inconsistency of PSO control parameters w, r_1, and r_2 for z-axis. It will be improved by further parameter adjustments.

Consequently, it was shown that the proposed scheme could accurately estimate the location with less calculation complexity in three dimensional LS localization even when the height of the target and anchor node are close.

V. Conclusion

In this study we proposed the hybrid scheme of PSO which effectively searched in wide areas and NR which could conduct fine search for three-dimensional LS-based localization. Because the NR scheme sometimes terminates at local optimal solution, the high-complexity accurate grid is needed in the conventional scheme, while the proposed scheme achieves less-complexity and accurate estimation by adopting PSO rough search. By numerical results it was shown that the least RMSE of estimation could be obtained with a half calculation complexity compared to the conventional hybrid scheme of grid and NR.

In future studies, the application of the proposed scheme to non-line-of-sight (NLOS) environments and the further improvement of RMSE performance will be considered.

Acknowledgments

This work is partially supported by the Telecommunications Advancement Foundation (TAF). The authors wish to thank for their support.

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