UWB 시스템에서 Particle Swarm Optimization을 이용하는 향상된 TDoA 무선측위

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An Improved TDoA Localization with Particle Swarm Optimization in UWB Systems

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요 약

본 논문에서는 UWB (Ultra Wide Band) 시스템에서 PSO (Particle Swarm Optimization)를 사용하는 향상된 TDoA (Time Difference of Arrival) 무선측위 기법을 제안한다. 제안된 기법은 TDoA 파라미터 재추정과 태그 (Tag) 위치 재측정을 수행하는 두 단계로 구성된다. 이들 두 단계에서 PSO 알고리즘은 무선측위 성능 향상을 위해 고용된다. 첫 번째 단계에서 TDoA 추정 오차를 줄이기 위해, 제안된 기법은 전형적인 TDoA 무선측위 방식으로부터 얻어진 TDoA 파라미터를 재추정한다. 두 번째 단계에서 무선측위 오차를 최소화시키기 위해, 첫 번째 단계에서 추정된 TDoA 파라미터를 가지고 제안된 기법은 태그의 위치를 다시 측정한다. 모의실험 결과, 제안된 기법은 LoS (Line-of-Sight)와 NLoS (Non-Line-of-Sight) 채널 환경에서 모두 전형적인 TDoA 무선측위 방식에 비해 우수한 무선측위 성능을 달성하는 것을 확인할 수 있었다.

Key Words : Localization, UWB (Ultra Wide Band), TDoA (Time Difference of Arrival), PSO (Particle Swarm Optimization)

ABSTRACT

In this paper, we propose an improved TDoA (Time Difference of Arrival) localization scheme using PSO (Particle Swarm Optimization) in UWB (Ultra Wide Band) systems. The proposed scheme is composed of two steps: re-estimation of TDoA parameters and re-localization of a tag position. In both steps, the PSO algorithm is employed to improve the performance. In the first step, the proposed scheme re-estimates the TDoA parameters obtained by traditional TDoA localization to reduce the TDoA estimation error. In the second step, the proposed scheme with the TDoA parameters estimated in the first step, re-localizes the tag to minimize the location error. The simulation results show that the proposed scheme achieves a more superior location performance to the traditional TDoA localization in both LoS (Line-of-Sight) and NLoS (Non-Line-of-Sight) channel environments.

Ⅰ. Introduction

Recently, UWB (Ultra Wide Band)[1] has drawn explosive attention as a new type of short range, low power transmission scheme with precise position location capability in indoor wireless

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environments. Unlike the conventional wireless communication systems, UWB systems may transmit a train of pulses called "Gaussian monocycle pulses" or simply "impulses" with a very short duration in the order of nano seconds[2]. In dense multipath environments such as indoor channels, UWB systems provide with very fine multipath resolvability due to the extremely short pulse duration, which makes the UWB suitable for precision ranging and position location applications.

There are a number of recent studies that aim at improving UWB ranging/localization accuracy. The position of a tag can be estimated based on AoA (Angle of Arrival), RSS (Received Signal Strength), ToA (Time of Arrival), and TDoA (Time Difference of Arrival) of received signals. The RSS localization is very simple but it does not provide with precise location performance. All of the AoA, ToA, and TDoA localizations have highly accurate location performance; however, the AoA localization with directional antennas requires a complex system. Also, the ToA localization requires synchronization between beacons and a tag, while the two-way ToA requires long propagation delays[3]. On the other hand, the TDoA localization does not require strict synchronization, long propagation delays, or complex systems; it only requires synchronization among all the beacons. To this end, we focus on the TDoA localization in this paper.

One of the traditional TDoA localizations is the combination of two steps: obtaining TDoA parameters by cross-correlation[4] and localization by a suitable algorithm such as the Chan's method[5]. How to improve the traditional TDoA is an important issue in UWB localization applications. In this paper, we propose an improved scheme with a PSO (Particle Swarm Optimization) algorithm in the UWB systems. The proposed scheme modifies the two steps of the traditional TDoA localization. The fitness functions of the proposed scheme are formulated to reach better solutions in both steps. In addition, the proposed scheme has fast convergence, so it does not require burdensome complexity of the UWB systems. The remainder of the paper is organized as follows: Section 2 defines the signals and system model in UWB multipath channels. Section 3 introduces PSO algorithm which is utilized in the proposed scheme. The proposed TDoA localization scheme is given in Section 4. Simulation results and their analyses are discussed in Section 5, followed by concluding remarks in Section 6.

Ⅱ. Signals and System Model

2.1 UWB Signals in Multipath Channels

We consider the UWB systems utilizing a Gaussian monocycle pulse $p(t)$ with the following form[2].

$$p(t) = 2A\sqrt{\pi e}\left(\frac{t}{\tau_p}\right)e^{-2\pi(t/\tau_p)^2} \tag{1}$$

where A denotes the amplitude and τ_p is the parameter related to the width of the pulse, T_p. By the differentiation property of the antennas, the received pulse $w(t)$ at the receiver may be expressed as[2]

$$w(t) = A'\left(1-\frac{4\pi t^2}{\tau_p^2}\right)e^{-2\pi(t/\tau_p)^2} \tag{2}$$

where A' is an appropriate amplitude constant.

In this paper, the preamble is composed of N -times repetition of a symbol S to acquire timing information. The symbol S is spread by the ternary code[3]. Here, the ternary code C with length $M \equiv 31$ is set to "-10000+10-10+1+1+10 +1-1000+1-1+1+1+100-1+10-100". Hence, the symbol S is formulated as

$$S = C \otimes \delta_L(k) \tag{3}$$

where $\delta_L(k) = \begin{cases} 1, & k=0 \\ 0, & k=1,\cdots,L-1 \end{cases}$ with L is the spreading factor and the operator $\otimes$ indicates a Kronecker product. Note that the length of the symbol S becomes $M \cdot L$ chips. The chip duration is fixed to $T_c (= T_p)$, so that the symbol duration is $T_s = M \cdot L \cdot T_c$.

Assuming that the UWB transmitter begins to transmit the preamble signal at a time stamp $t_0 = 0$, the transmitted preamble signal $s(t)$ is modeled as

$$s(t) = \sum_{i=0}^{N-1} \sum_{j=0}^{M \cdot L-1} s_j w(t - iT_s - jT_c) \qquad (4)$$

where s_j is the j-th chip of the symbol S.

For general UWB multipath channel models, we consider the typical tap-delay-line modeling described in [6] and represent the channel impulse response $h(t)$ as

$$h(t) = \sum_{\ell=0}^{P-1} \alpha_\ell \delta(t - \tau_\ell) \qquad (5)$$

where P represents the number of resolvable paths and α_ℓ denotes the attenuation of the ℓ-th path. Moreover, $\tau_\ell \equiv \tau_0 + \ell T_m$ is the time delay of the ℓ-th path with T_m being the minimum multipath resolvable time and a random variable τ_0 is assumed to be uniformly distributed over a preamble. In order to avoid a partial correlation between the received signals, the pulse duration T_p is assumed to be equal to the minimum resolvable time T_m[6].

Using (4) and (5), the received preamble signal in the UWB multipath channel is obtained as

$$s(t) = \sum_{i=0}^{N-1} \sum_{j=0}^{M \cdot L-1} \sum_{\ell=0}^{P-1} \alpha_i s_j w(t - iT_s - jT_c - \tau_\ell) + n(t) \qquad (6)$$

where $n(t)$ denotes the AWGN (Additive White Gaussian Noise).

2.2 System Model for UWB Localization

Figure 1 shows the system model considered in this paper for UWB localization based on TDoA. There are five beacons which are fixed at known locations, and one tag which is randomly located at an unknown position in a $20\text{m} \times 20\text{m}$ area. A computation center for estimating TDoA parameters and positioning the tag is also included. We assume that all the beacons are synchronized in order to operate localization based on TDoA through wired networks. Here, $r_b(t)$ is the received signal of the beacon B_b $(b = 1, \cdots, 5)$. These received signals are reported to the computation center through the wired cables.

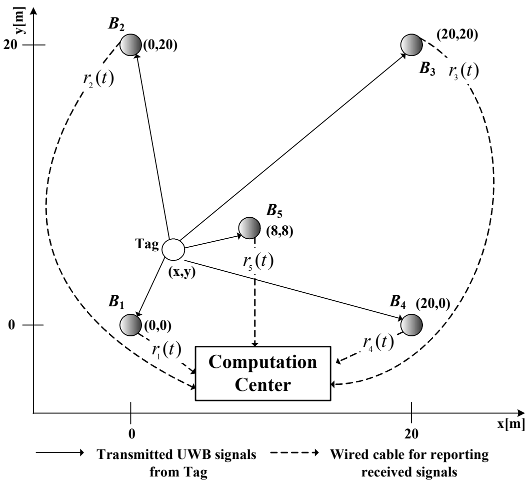


Fig. 1. System model for UWB localization.

Ⅲ. Particle Swarm Optimization

PSO is a population-based search algorithm, proposed by J. Kennedy and R. C. Eberhart in 1995, based on a simulation of the social behavior of birds within a flock[7]. In PSO, individuals referred to as particles, are "flown" through hyper-dimensional search space. Changes to the position of a particle within a swarm are influenced by the knowledge of its neighbors. The PSO algorithm maintains a swarm of particles, where each particle represents a potential solution. Let $\boldsymbol{p}_m(t)$ denote the position of particle m in the n_x dimensional search space at time t. The position of the particle is changed by adding velocity $\boldsymbol{v}_m(t+1)$ to the current position as

$$\boldsymbol{p}_m(t+1) = \boldsymbol{p}_m(t) + \boldsymbol{v}_m(t+1) \qquad (7)$$

For the global best PSO (called "*gbest* PSO" hereafter), the neighborhood for each particle is the entire swarm. The social component of the particle velocity update reflects information obtained from all the particles in the swarm. In this case, the social information is the best position found by the swarm, referred to as $\hat{y}$. The velocity of particle m is updated as

$$\begin{aligned} v_m(t+1) = v_m(t) + c_1 r_1(t)[y_m(t) - p_m(t)] \\ + c_2 r_2(t)[\hat{y}(t) - p_m(t)] \end{aligned} \tag{8}$$

where $v_m(t)$ is the velocity of particle m at time step t, c_1 and c_2 are positive acceleration constants used to scale the contribution of the cognitive and social components, respectively, and $r_1(t)$ and $r_2(t)$ are n_x dimensional vectors whose elements are uniformly distributed in the range $[0,1]$. The personal best position $y_m(t)$ associated with particle m at time step t is the best position that the particle has visited since the first time step. The best position at the next time step $t+1$ is calculated as

$$y_m(t+1) = \begin{cases} y_m(t) & \text{if } f(p_m(t+1)) \geq f(y_m(t)) \\ p_m(t+1) & \text{if } f(p_m(t+1)) < f(y_m(t)) \end{cases} \tag{9}$$

where $f: R^{n_x} \rightarrow R$ is the fitness function. The fitness function measures how close the corresponding solution is to the optimum. The global best position $\hat{y}(t)$ at time step t is defined as

$$\hat{y}(t) = \arg\min_{y_m(t)} \{f(y_1(t)), \cdots, f(y_{n_s}(t))\} \tag{10}$$

where n_s is the total number of particles in the swarm.

The *gbest* PSO algorithm is summarized by the following pseudo code.

For each particle p_m
  Initialize $p_m(0)$
  Initialize the velocity of p_m *with zeros*
  Initialize the personal best position $y_m(0) = p_m(0)$
End
Initialize the global best position the $\hat{y} = y_1(0)$
For $t = 1, \cdots, n_t$ *do* (n_t*: the number of iterations)*
  For each particle p_m *do*
    // Set the personal best position
    If $f(p_m(t)) < f(y_m(t))$
      $y_m(t) = p_m(t)$
    End
    // Set the global best position
    If $f(y_m(t)) < f(\hat{y})$
      $\hat{y} = y_m(t)$
    End
  End
  For each particle p_m *do*
    Update the velocity using (8)
    Update the position using (7)
  End
End

This *gbest* PSO algorithm is utilized in the proposed TDoA localization whose detailed procedure is explained in the next section.

Ⅳ. Proposed TDoA Localization Scheme with PSO

In general, one of the traditional TDoA localizations is the combination of two steps: obtaining TDoA parameters by cross-correlation[4], and localization by, for instance, the Chan's method[5]. However, the proposed scheme modifies the traditional TDoA localization by employing the *gbest* PSO algorithm in both steps. This scheme is composed of the following two steps: first, the re-estimation of TDoA parameters and second, the re-localization of a tag position. The fitness functions of the proposed scheme are formulated to reach better solutions in both steps. In addition, this scheme has fast convergence, so it does not require the burdensome complexity of the UWB systems since the results of the traditional TDoA localization are used for the generation of the initial swarms. Hence, we can expect that the proposed scheme achieves a better location performance than the traditional TDoA localization without much increment of system complexity.

4.1 First step: Re-estimation of TDoA parameters

A simple way to obtain the TDoA parameter is to perform a cross-correlation of the two signals traveling between a tag and the beacons, and then to calculate the time delay corresponding to the largest value of cross-correlation outputs as[4]

$$\hat{\tau}_{ba} = \arg\max_{\tau_{ba}} \left| \int_0^T r_b(t) r_a(t+\tau_{ba}) dt \right| \quad (11)$$

where $r_b(t)$, $r_a(t)$ are the received signals at the beacons B_b and B_a, where $1 \le b \ne a \le N_B$, N_B is the number of beacons, and T is the cross-correlation time.

If d_b is the distance between a tag and a beacon B_b, then $t_b = d_b / c$, where c (=3×10^8 m/sec) is the velocity of light. Without losing generality, assume that

$$t_1 < t_2 < \cdots < t_{N_B} \quad (12)$$

After estimating the TDoA parameters between the received signals of any two beacons, we can obtain TDoA parameters $\hat{\tau} = \left(\hat{\tau}_{12}, \hat{\tau}_{13}, \cdots, \hat{\tau}_{1N_B}\right)$ and a set $\left\{\hat{\tau}_{ba}\right\}$ where $2 \le b < a \le N_B$. The first step of the proposed scheme re-estimates $\hat{\tau}$ to reduce the TDoA estimation error. The set $\left\{\hat{\tau}_{ba}\right\}$ is used in the fitness function of this step.

If there is no measurement error, we have

$$\hat{\tau}_{ba} = (t_a - t_1) - (t_b - t_1) = \hat{\tau}_{1a} - \hat{\tau}_{1b} \quad (13)$$

where $2 \le b < a \le N_B$. Based on (13), we propose a fitness function as

$$f(\tilde{\tau}) = \sum_{2 \le b < a}^{N_B} \left[\hat{\tau}_{ba} - \left| \tilde{\tau}_{1b} - \tilde{\tau}_{1a} \right| \right]^2 \quad (14)$$

where $\tilde{\tau} = \left(\tilde{\tau}_{12}, \tilde{\tau}_{13}, \cdots, \tilde{\tau}_{1N_B}\right)$ is a set of the estimated TDoA parameters of a particle at an iteration. Hence, $f(\tilde{\tau})$ becomes 0 if there is no measurement error.

To lead to fast convergence, we need to generate a particle swarm that is close to the TDoA parameters, which minimizes the fitness function of the first step. For this purpose, a particle swarm of TDoA parameters having $\hat{\tau} = \left(\hat{\tau}_{12}, \hat{\tau}_{13}, \cdots, \hat{\tau}_{1N_B}\right)$ is modeled as

$$\{\boldsymbol{p}_m\} = \left\{\hat{\tau} + \boldsymbol{\sigma}_m\right\} \quad (15)$$

where $m = 1, \cdots, n_s$ with the swarm size n_s. Moreover, $\boldsymbol{\sigma}_m = \left(\sigma_{m1}, \cdots, \sigma_{m(N_B - 1)}\right)$ is uniformly distributed in the range $[-\sigma_t, \sigma_t]$ where σ_t is a given constant.

With both the proposed fitness function of (14) and the generated particle swarm of (15), the first step of the proposed scheme finally applies the *gbest* PSO algorithm to re-estimate TDoA parameters. Hence, we can obtain the re-estimated TDoA parameters as follows.

$$\bar{\tau} = \left(\bar{\tau}_{12}, \bar{\tau}_{13}, \cdots, \bar{\tau}_{1N_B}\right) \quad (16)$$

4.2 Second step: Re-localization

In the second step, the proposed scheme utilizes the *gbest* PSO algorithm with the re-estimated TDoA parameters of (16) in order to compensate for the location errors.

First, we can calculate the coarse location of the tag by the Chan's method[5] where the input values have the parameters of (16).

$$\hat{\boldsymbol{o}} = (\hat{x}, \hat{y}) \quad (17)$$

Here, $\hat{\boldsymbol{o}}$ is the estimated location of the tag and $(\hat{x}, \hat{y})$ denotes the x-axis and y-axis coordinates of the estimated location. In this paper, we use this coarse location to generate the particle swarm in (18).

With the coarse location $\hat{o}$ of (17), the particle swarm of locations is generated as

$$\{p_m\} = \{\hat{o} + \delta_m\} \tag{18}$$

where $m = 1, \cdots, n_s$, $\delta_m = (\delta_{m1}, \delta_{m2})$ is uniformly distributed in the range $[-\delta_l, \delta_l]$, and δ_l is a given constant. For fast convergence, we need to generate a particle swarm that is close to the TDoA parameters, which minimizes the fitness function of the second step.

Next, we employ the fitness function presented in [8] as

$$f(\tilde{o}) = \sum_{b=2}^{N_B} \left(c\bar{\tau}_{1b} - \|X_b - \tilde{o}\|_2 + \|X_1 - \tilde{o}\|_2 \right)^2 \tag{19}$$

where X_b is the location of the beacon B_b and $\tilde{o}$ is an estimated location of the particle at an iteration. The re-estimated TDoA parameter $\bar{\tau}_{1b}$ is obtained from (16). Consequently, by using *gbest* PSO algorithm with both the fitness function of (19) and the generated particle swarm of (18), the second step of the proposed scheme finds the final location $\bar{o} = (\bar{x}, \bar{y})$ of the tag that minimizes the fitness function of (19).

Ⅴ. Simulation Results

In order to compare the performance of the proposed scheme with the traditional TDoA localization, we considered IEEE 802.15.4a UWB channel models[9] in which multipath delays were determined based on the modified Saleh-Valenzuela model with a Poisson distribution, and multipath gains followed a Nakagami distribution. We utilized the Gaussian monocycle pulse with approximated pulse duration T_p of 2 nsec. Also, we simulated the system model presented in Section II. The other parameters considered in this paper are summarized in Table 1. Figure 2 depicts the multipath profiles of IEEE 802.15.4a CM5, CM7 and CM8 channel models[9] considered in this paper. In order to verify simulation results in various channel conditions, we considered these 3 channel models. As shown in Fig. 2, CM7 is a LoS channel with extremely short delay spread ("best" channel), and CM5 is a LoS channel with partial NLoS components ("medium" channel), and CM8 is a fully NLoS channel ("worst" channel)[9].

Table 1. Simulation parameters

Parameter	Value
Chip duration, $T_c(=T_p)$	2 nsec
M, N, L	31, 16, 16
Correlation time, T	15.872 μsec $(N \cdot T_s)$
Swarm size, n_s	50
Iteration number of PSO, n_t	10, 50
σ_t, δ_l	5 nsec, 0.5 m

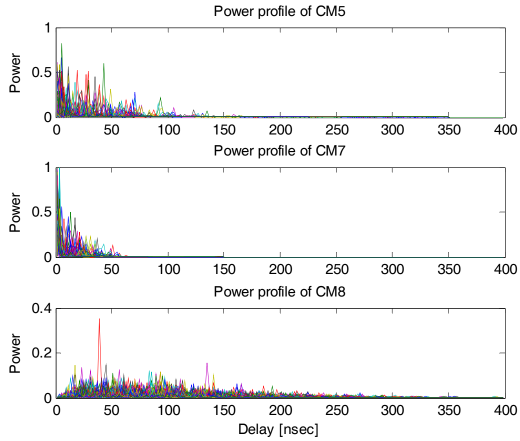
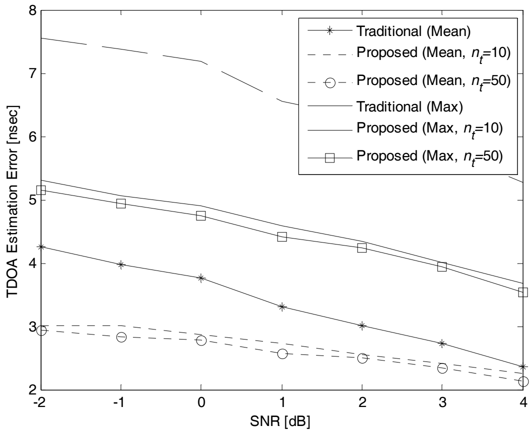


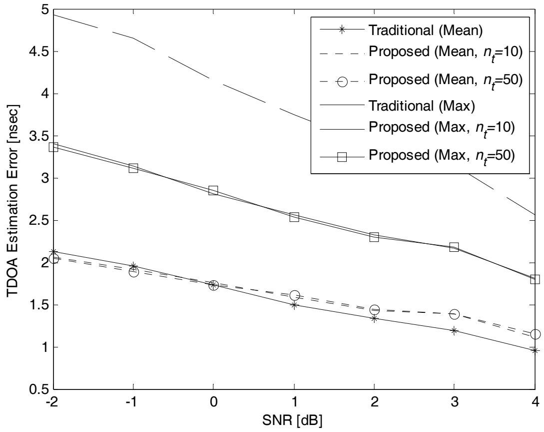
Fig. 2. Multipath profiles of IEEE 802.15.4a CM5, CM7 and CM8 channel models.

Figure 3 shows the TDoA estimation performance of the proposed scheme ("Proposed") according to SNR (Signal-to-Noise Ratio), as compared to the traditional TDoA localization ("Traditional"). These results are only measured in the first step. The "Mean" noted in the figure represents the averaged error of all the estimated TDoA parameters as follows.

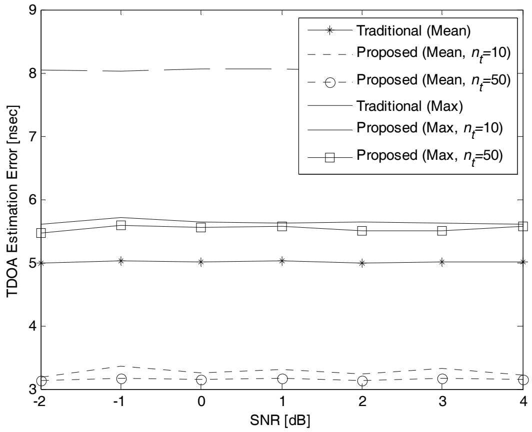
$$e_{avg} = \frac{1}{N_B - 1} \sum_{b=2}^{N_B} |\tau_{1b} - \check{\tau}_{1b}| \tag{20}$$



(a) CM5



(b) CM7



(c) CM8

Fig. 3. The estimation performance of the TDoA parameters in IEEE 802.15.4a channel models.

The "Max" noted in the figure represents the mean of the maximum error of the estimated TDoA parameters. The maximum error is calculated as

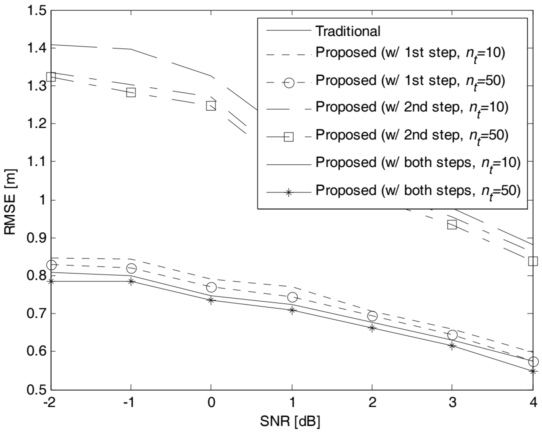
$$e_{\max} = \max\left\{|\tau_{12}-\check{\tau}_{12}|,\cdots,|\tau_{1N_B}-\check{\tau}_{1N_B}|\right\} \quad (21)$$

where $\check{\tau}_{1b}$ is the TDoA parameter estimated by the proposed scheme or the traditional TDoA localization. So, $\check{\tau}_{1b}=\bar{\tau}_{1b}$ in the case of the proposed scheme, or $\check{\tau}_{1b}=\hat{\tau}_{1b}$ for the traditional TDoA localization. From Fig. 3, we observe that the proposed scheme achieves a better TDoA estimation performance than the traditional TDoA localization in most cases, only excepting for the case of the "Mean" TDoA estimation error in CM7 channel model. Even though the "Mean" TDoA estimation error in CM7 is not reduced, the better "Max" TDoA estimation error causes the improvement of the final performance as shown in Fig. 4 (b).

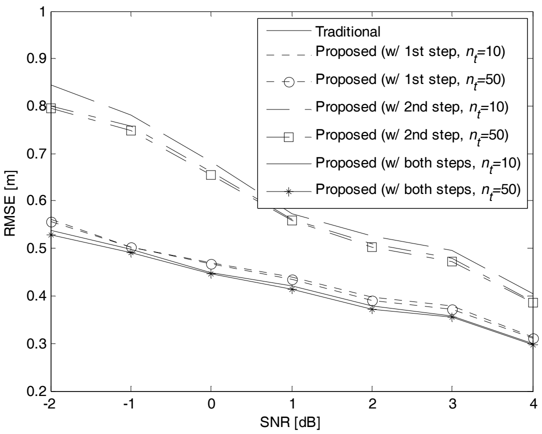
Figure 4 shows the location RMSE (Root Mean Square Error) of the proposed scheme ("Proposed") according to SNR, as compared to the traditional TDoA localization ("Traditional"). Here, the RMSE of location is defined as

$$\mathrm{RMSE}=\frac{1}{I_N}\sum_{i=0}^{I_N-1}\sqrt{(\check{x}_i-x)^2+(\check{y}_i-y)^2} \quad (22)$$

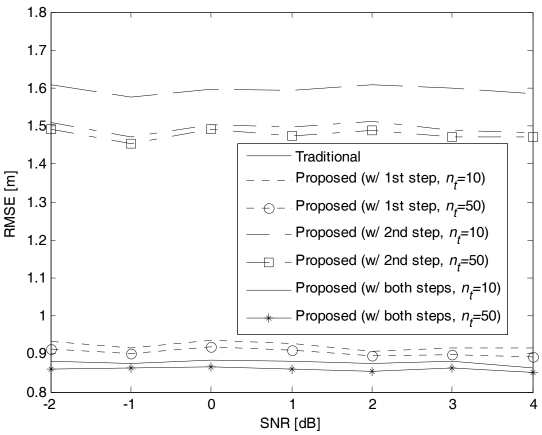
where (x,y) is the actual tag location and $(\check{x}_i,\check{y}_i)$ is the i-th estimated location by the proposed scheme or the traditional TDoA localization. Also, I_N is the number of experiments. In all the cases, the proposed scheme provides with better location performance than the traditional TDoA localization. The proposed scheme with the first step significantly improves the location performance over the traditional TDoA localization. Finally, the proposed scheme with both steps can achieve much superior location performance to the traditional TDoA localization; nevertheless, performance improvement by the second step is not large. Because of the characteristics of the channel models, the



(a) CM5



(b) CM7



(c) CM8

Fig. 4. The location RMSE comparison of the proposed scheme and the traditional TDoA localization in IEEE.802.15.4a channel models.

localization in CM7 gives the best performance. Differently from CM5 and CM7, the performance in CM8 is much more affected by multipath fading than AWGN, it is the reason why the location RMSE is not varied according to SNR.

In both Fig. 3 and Fig. 4, we notice that the proposed scheme with $n_t = 10$ iterations achieves almost the same performance with $n_t = 50$. Hence, we can conclude that the proposed scheme achieves a superior performance to the traditional TDoA localization without much increment of system complexity since it can lead to fast convergence.

Table 2 summarizes the improvement percentage of the location performance as compared to the traditional TDoA localization when $n_t = 50$. The column "With first step only" shows the improvement of the proposed scheme with improving the first step only at SNR -2 dB and 4 dB. Similarly, the columns "With second step only" and "With both steps" show the improvements of the proposed schemes with improving the second step or the both steps. Additionally, we learn from Fig. 4 and Table 2 that the worse localization performance is caused by the channels, the more improvement percentage is achieved.

Table 2. The improvement percentages of the location performance by the proposed scheme.

Channel model	SNR [dB]	With first step only	With second step only	With both steps
CM5	-2	41.16%	6.02%	44.15%
	4	34.58%	4.75%	37.59%
CM7	-2	34.12%	5.77%	37.32%
	4	22.89%	4.41%	26.80%
CM8	-2	43.20%	7.15%	46.46%
	4	43.82%	7.18%	46.42%

Ⅵ. Conclusion

In this paper, we have proposed the improved TDoA localization scheme using PSO in UWB systems. The proposed scheme is composed of two steps: the re-estimation of TDoA parameters and the re-localization of a tag position. In both steps, the PSO algorithm is employed to improve the location performance. The simulation results in

IEEE 802.15.4a UWB channel models show that the proposed scheme achieves a superior performance to the traditional TDoA localization without much increment of system complexity, since the proposed scheme can lead to fast convergence. Especially, the proposed scheme with the first step significantly improves the location performance over the traditional TDoA localization. This scheme is not only for UWB localization systems, but also can be generally applied to other systems as well, as long as the system model and the assumptions considered here hold for those systems.

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