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Indoor localization of wireless emitter using direct position determination and particle swarm optimization

Saeid HASSANHOSSEINI[1,*], **Mohammad Reza TABAN**[2], **Jamshid ABOUEI**[1]
[1]Department of Electrical Engineering, Yazd University, Yazd, Iran
[2]Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran

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Abstract: Many methods are introduced to accomplish determining the position of emitters with respect to known-position receivers in indoor localizations. Among them, the direct position determination (DPD) approach advocates using the received signals by all the base stations together in order to estimate the locations in a single step. However, DPD is not very accurate due to the use of a gridding area, the effect of noise, and the multipath phenomenon. In order to improve the DPD performance, we derive an analytic model based on weighted least square estimation that uses simultaneously the effect of delay, Doppler, attenuation, and angle of reception of the signals. In addition, a new approach to define a cost function based on the analytic model is proposed that is optimized by particle swarm optimization (PSO). A combination of the improved DPD and the proposed PSO-based technique is also used to decrease the computation volume and increase the resolution. Finally, the accuracy of the proposed algorithms is investigated by Monte Carlo computer simulation in a wireless local area network. Numerical results show that the localization by PSO, the improved DPD, and previous DPD are more accurate in that order.

Key words: Direct position determination, particle swarm optimization, indoor localization, wireless sensor networks

1. Introduction

Indoor localization is an attractive issue in the area of signal processing and wireless sensor networks. Noting that GPS systems are inadequate due to the multipath or signal blocked indoors, widespread localization techniques have been used for positioning with wireless access points [1]. The most common techniques are based on measuring the received signal strength indication (RSSI) and methods of fingerprint, time difference delay of arrival signal (TDOA), frequency difference of arrival (FDOA), and angle of arrival (AOA) of signals [2,3]. These methods use a two-stage process to estimate the position but are not necessarily optimal, because in the first stage of these methods the location-dependent parameters are obtained by ignoring the fact that all measurements should be consistent with a single emitter location [4].

Direct position determination (DPD) is a single-stage localization method that centrally processes all received signals to compute a closed-form cost function. The cost function can be minimized using a two-dimensional (2-D) search for an emitter known to be located on a plane or a three-dimensional (3-D) search that has been divided into grids. A grid is a small space obtained by dividing the whole space around the receivers into smaller equal parts, and the probability of the emitter in that space must be checked. The DPD

*Correspondence: s.hoseini@stu.yazd.ac.ir

method estimates the emitter position without the first estimation of intermediate parameters such as Doppler frequency and the time delay [5].

Accordingly, DPD cannot be used as a fine localization method, because the emitter may not be located at the center of grids. However, the cost function is established on the correlation between the intercepted signals from all the receivers, and computes the cross ambiguity function [6,7]. Therefore, the DPD method is inherently vulnerable in the low signal-to-noise ratio (SNR) regime and suffers from fading and multipath receptions [7]. The DPD objective function is often nonconvex, and therefore finding the maximum usually requires an exhaustive search, since gradient-based methods usually converge to local maxima [8]. Recently, some new DPD-based methods have been proposed that provide higher accuracy with a lower computational complexity than classical DPD mechanisms [9]. Many works have been accomplished for DPD algorithm enhancement based on TDOA, AOA, and FDOA, among which the least squares (LS) method has a closed form solution [10].

In this paper, we first develop a formulation of a DPD-based method in order to achieve better accuracy. In this regard, we consider the effect of array antenna processing in receivers, denoise the received signals using the mean filter, and weight received signals by applying the Hamming window. We then optimize a new proposed cost function through proposing the particle swarm optimization (PSO) plan that has been exploited by researchers in localization problems [11]. Most of the previous works have been based on the RSSI measurement [12,13], while the objective function of PSO has been the sum of squares of errors between the estimated and the actual distances. However, the proposed objective function in this paper is based on the vector distance between the estimations of the transmitted signal by all receivers. Accordingly, a combination of DPD and PSO schemes is proposed to reach an acceptable computation time and volume for practical applications, especially in patient tracking problems. The rest of the paper is organized as follows. In Section 2, a brief definition of the localization problem and the DPD solution are presented. The formulation of the DPD method will be more developed and the PSO algorithm will be proposed in Section 3. Section 4 deals with evaluating the performance of the proposed algorithms using Monte Carlo simulations. Finally, the conclusion is provided in Section 5.

2. Problem definition and formulation

We consider an RF emitter sends signal $s(t)$ that is intercepted by L known-position receivers in T seconds. $\mathbf{p}_e = [x\,,\,y]^T$ is the position of an unknown emitter in LOS (Line of Sight) or NLOS (non-LOS) path.[1] All the receivers are equipped with an M-array antenna. Each receiver sent the received signal to a central processing unit in one intercept time. The equivalent low-pass signal observed by lth receiver, located in $\mathbf{p}_l = [x_l\,,\,y_l]^T$, can be measured through

$$r_l(t) = \alpha_l \varpi_l^T \mathbf{a}(\theta_l) e^{-j\omega_l t} s(t-\tau_l) + n_l(t), \quad l = 1, \ldots, L. \tag{1}$$

where $\mathbf{a}(\theta_l) = [e^{-j\frac{2\pi}{\lambda}\frac{M}{2}\Delta\sin(\theta_l)}, ..., 1, ..., e^{j\frac{2\pi}{\lambda}\frac{M}{2}\Delta\sin(\theta_l)}]^T$ is the lth array response to a signal transmitted from the emitter. θ_l is the angle of arrival signal to the lth receiver, M is considered an odd number, and Δ is the distance between the elements of arrays. ϖ_l is considered an $M \times 1$ weight vector [2]. $n_l(t)$ represents noise that is zero mean Gaussian noise with variance σ_l^2. Moreover, interference and multipath in the lth receiver can be represented by $n_l(t)$. α_l is an unknown complex attenuation coefficient of wireless channel related to the

[1] For more generalization $\mathbf{p}_e$ can be considered in 3D coordination

path loss $PL(d) = PL(d_0) + 10n\log_{10}(\frac{d}{d_0}) + \chi_\sigma$, where d is the distance, n is attenuation coefficient, and χ_σ is a zero-mean Gaussian random variable $(0, \sigma^2)$ [14]. $\omega_1 = 2\pi f_l$ is the observed Doppler frequency shift given by

$$f_l = \frac{f_c}{C}\frac{v_l(\mathbf{p}_e - \mathbf{p}_l)}{||\mathbf{p}_e - \mathbf{p}_l||}, \tag{2}$$

where f_c is the carrier frequency and C is the signal propagation speed. We assume that $\tau_l << T$. Each receiver collects N_T samples of the signal with frequency sampling f_s at an intercept time. Then the signal is passed to window processing with N_s samples in each window. Thus, the received signal in the lth receiver can be written as

$$\mathbf{r}_l = \alpha_l \varpi_l^T \mathbf{a}(\theta_l)\mathbf{A}_l\mathbf{D}_l\mathbf{s} + \mathbf{n}_l \tag{3}$$

$$\mathbf{r}_l = [r_l(t_1), r_l(t_2), ..., r_l(t_{N_s})]^T$$

$$\mathbf{s} = [s(t_1), s(t_2), ..., s(t_{N_s})]^T$$

$$\mathbf{A}_l = diag\{e^{-j\omega_l t_1}, e^{-j\omega_l t_2}, ..., e^{-j\omega_l t_{N_s}}\}$$

$$\mathbf{n}_l = [n_l(t_1), n_l(t_2), ..., n_l(t_{N_s})]^T,$$

where $\mathbf{D}_l = \mathbf{D}^{n_l}$, $N_s \times N_s$ matrix , is a shift operator of received signals by $n_l = \lfloor \tau_l f_s \rfloor$ and $\lfloor . \rfloor$ denotes the integer part (or floor) of a number. $\mathbf{D}$ is defined as $([\mathbf{D}_{ij}] = 1, if\, i = j+1\, and\, [\mathbf{D}_{ij}] = 0\; otherwise;\;\; also\, [\mathbf{D}_{1,N_s}] = 1)$. In order to consider the window time, we label the variables of (3) in terms of the interval time index k from $1, ..., K$ as follows:

$$\mathbf{r}_{l,k} = \alpha_{l,k}\varpi_{l,k}^T \mathbf{a}(\theta_{l,k})\mathbf{A}_{l,k}\mathbf{D}_{l,k}\mathbf{s}_k + \mathbf{n}_{l,k},\;\; k = 1, ..., K \tag{4}$$

$$\mathbf{r}_{l,k} = \alpha_{l,k}\mathbf{F}_{l,k}\mathbf{s}_k + \mathbf{n}_{l,k},\;\; k = 1, ..., K, \tag{5}$$

where $\mathbf{F}_{l,k} = \varpi_{l,k}^T \mathbf{a}(\theta_{l,k})\mathbf{A}_{l,k}\mathbf{D}_{l,k}$ [6].

In this section, an appropriate model of received signal from the emitter is considered that can be used to define the cost functions to estimate the emitter position.

3. The proposed emitter localization algorithms

3.1. Direct position determination (DPD) algorithm

In order to find the location of the emitter, we used weighted least square error (WLSE) to minimize the defined cost function below:

$$CF(\mathbf{p}_e) = \sum_{k=1}^{K}\sum_{l=1}^{L} w_{l,k}||\mathbf{r}_{l,k} - \alpha_{l,k}\mathbf{F}_{l,k}\mathbf{s}_k||^2, \tag{6}$$

where $w_{l,k}$s are the weighting coefficients [15]. The path attenuation $\alpha_{l,k}$ that minimizes (6) can be given by

$$\hat{\alpha}_{l,k} = [(\mathbf{F}_{l,k}\mathbf{s}_k)^H(\mathbf{F}_{l,k}\mathbf{s}_k)]^{-1}(\mathbf{F}_{l,k}\mathbf{s}_k)^H\mathbf{r}_{l,k} = \frac{(\mathbf{F}_{l,k}\mathbf{s}_k)^H}{||\mathbf{F}_{l,k}\mathbf{s}_k||^2}\mathbf{r}_{l,k}. \tag{7}$$

Considering $\mathbf{F}_{l,k}\mathbf{s}_k = \varpi_{l,k}^T\mathbf{a}(\theta_{l,k})\mathbf{A}_{l,k}\mathbf{D}_{l,k}\mathbf{s}_k$, since $\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})$ is a scalar, we have $||\mathbf{F}_{l,k}\mathbf{s}_k|| = ||\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|| \times ||\mathbf{A}_{l,k}\mathbf{D}_{l,k}\mathbf{s}_k||$. Since $\mathbf{A}_{l,k}$ is a diagonal matrix with form (3) and $\mathbf{D}_{l,k}$ is a permutation matrix, the effect of

$\mathbf{A}_{l,k}$ and $\mathbf{D}_{l,k}$ on the magnitude of $||\mathbf{A}_{l,k}\mathbf{D}_{l,k}||$ is ineffective. Hence, we have $||\mathbf{F}_{l,k}\mathbf{s}_k|| = ||\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|| \times ||\mathbf{s}_k||$. Without loss of generality, we can assume that $||\mathbf{s}_k||^2 = 1$ and so $||\mathbf{F}_{l,k}\mathbf{s}_k|| = ||\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})||$. Thus,

$$\hat{\alpha}_{l,k} = \frac{1}{|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2}(\mathbf{F}_{l,k}\mathbf{s}_k)^H\mathbf{r}_{l,k}.$$

By substituting Eq. (8) in (6) and simplifications, the cost function can be derived by

$$CF(\mathbf{p}_e) = \sum_{k=1}^{K}\sum_{l=1}^{L} w_{l,k}(||\mathbf{r}_{l,k}||^2 - \frac{|(\mathbf{F}_{l,k}\mathbf{s}_k)^H\mathbf{r}_{l,k}|^2}{|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2}) \tag{8}$$

$$CF(\mathbf{p}_e) = \sum_{k=1}^{K}\sum_{l=1}^{L} w_{l,k}||\mathbf{r}_{l,k}||^2 - \sum_{k=1}^{K}\sum_{l=1}^{L} w_{l,k}\frac{|\mathbf{s}_k^H\mathbf{F}_{l,k}^H\mathbf{r}_{l,k}|}{|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2} \tag{9}$$

Equivalently we can maximize the objective function $OF(\mathbf{p}_e)$, which is as follows:

$$OF(\mathbf{p}_e) = \sum_{k=1}^{K}\sum_{l=1}^{L} w_{l,k}\frac{|\mathbf{s}_k^H\mathbf{F}_{l,k}^H\mathbf{r}_{l,k}|^2}{|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2} = \sum_{k=1}^{K}\mathbf{s}_k^H\mathbf{Q}_{k,p_e}\mathbf{s}_k, \tag{10}$$

where

$$\mathbf{Q}_{k,p_e} = \sum_{l=1}^{L} w_{l,k}\frac{\mathbf{F}_{l,k}^H\mathbf{r}_{l,k}\mathbf{r}_{l,k}^H\mathbf{F}_{l,k}}{|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2} = \mathbf{V}_{k,p_e}^H\mathbf{V}_{k,p_e} \tag{11}$$

$$\mathbf{V}_{k,p_e}^H = \left[\begin{array}{ccc} \sqrt{w_{1,k}}\frac{\mathbf{F}_{1,k}^H\mathbf{r}_{1,k}}{\varpi_{1,k}^T\mathbf{a}(\theta_{1,k})} & \dots & \sqrt{w_{L,k}}\frac{\mathbf{F}_{L,k}^H\mathbf{r}_{L,k}}{\varpi_{L,k}^T\mathbf{a}(\theta_{L,k})}\end{array}\right] \tag{12}$$

The area of localization problem is divided into N_g grid in which $\{\mathbf{p}_j\}_{j=1}^{N_g}$ is the center of the jth grid and can be a possible candidate of emitter location. Therefore, for all grids and in each time interval k, the matrices $\mathbf{V}_{k,p_j}, j = 1, \dots, N_g$ are calculated for all L receivers as

$$\mathbf{V}_{k,p_j} = \left[\begin{array}{ccc} \sqrt{w_{1,k}}\frac{(\mathbf{F}_{1,k}^j)^H\mathbf{r}_{1,k}}{\varpi_{1,k}^T\mathbf{a}(\theta_{1,k}^j)} & \cdots & \sqrt{w_{L,k}}\frac{(\mathbf{F}_{L,k}^j)^H\mathbf{r}_{L,k}}{\varpi_{L,k}^T\mathbf{a}(\theta_{L,k}^j)}\end{array}\right]_{N_s\times L}, \tag{13}$$

where $\mathbf{F}_{l,k}^j$ and $\theta_{l,k}^j$ denote the matrix $\mathbf{F}_{l,k}$ and $\theta_{l,k}$ when the emitter location is assumed to be position $\mathbf{p}_j$; then the $\mathbf{Q}_{k,p_e}$ of candidates are given as

$$\mathbf{Q}_{k,p_j} = \mathbf{V}_{k,p_j}^H\mathbf{V}_{k,p_j} \quad j = 1, \dots, N_g \tag{14}$$

Since $\mathbf{Q}_{k,p_e}$ is Hermitian symmetric, the objective function (10) is maximized by maximizing each term $\mathbf{s}_k^H\mathbf{Q}_{k,p_e}\mathbf{s}_k$. In practice, $\mathbf{s}_k$ is unknown and based on the justification given in [6], and its maximum is the maximum eigenvalue of matrix $\mathbf{Q}_{k,p_e}$ or $\lambda_{max}\{\mathbf{Q}_{k,p_e}\}$. Thus the estimated position of the emitter can be obtained from

$$\hat{\mathbf{p}}_e \equiv \arg\max_{\mathbf{p}_j}(\sum_{k=1}^{K}\lambda_{max}\{\mathbf{Q}_{k,p_j}\}) \tag{15}$$

$\hat{\mathbf{p}}_e$ can be evaluated in just one time interval ($K = 1$). If the emitter moves as time passes, $\hat{\mathbf{p}}_e$ is computed on each time interval using Eq. (15).

To achieve more accuracy in the localization process, the collected signals from all the receivers are buffered. Then a Hamming or Kaiser window is deployed to suppress the discontinuity, and also to reduce the effect of the noise. In addition, a Gaussian mean filter is used to reduce the signal fluctuation. Furthermore, we aim to reduce the computational complexity and to achieve more accurate results. This is possible by first deploying a coarse localization and finding the nearest grid center to the emitter position, and then performing the fine localization during the following procedure at time interval. The DPD method certainly faces a minimum average error that will be less than the half of the grid radius, while the emitter is not exactly located in the center of a grid. On the other hand, to achieve a lower average error, the higher resolution grid leads to a higher computational complexity [16]. The next section includes a given approach, deploying preprocessing of the signal for noise cancelling, and a new approach of exploiting the PSO for high resolution localization.

3.2. The proposed positioning method using PSO

PSO is a numerical method for optimizing a cost function by iteratively trying to find a suitable solution. It was originally proposed by Kennedy and Eberhart [16]. PSO is a well-known algorithm that has been recently used by many researchers in various optimization problems [17].

A brief survey of PSO in wireless sensor networks is presented in [12]. The performance of different PSO variants with different population topologies in wireless sensor networks is investigated in [13]. However, the main factor in applying the PSO algorithm is defining an effective and suitable cost function [11]. In this research, a new cost function is proposed based on the mathematical signal model expressed in section 2. The problem at hand now is to use the observation signals given in Eq. (5) in order to find the location of the emitter. Having the received signal from each receiver, considering (1), and the path loss model of channel, the original signal $s(t)$ can be estimated in each receiver by the following linear model:

$$\mathbf{r}_{l,k} = \alpha_{l,k}\mathbf{F}_{l,k}\mathbf{s}_k + \mathbf{n}_{l,k} \tag{16}$$

Therefore, the weighted least square error estimation of emitted signal $\hat{\mathbf{s}}_{l,k}$ in the lth receiver is obtained as

$$\hat{\mathbf{s}}_{l,k} = [(\alpha_{l,k}\mathbf{F}_{l,k})^H\mathbf{W}_{l,k}(\alpha_{l,k}\mathbf{F}_{l,k})]^{-1}(\alpha_{l,k}\mathbf{F}_{l,k})^H\mathbf{W}_{l,k}\mathbf{r}_{l,k}, \tag{17}$$

where the weighting matrix $\mathbf{W}_{l,k}$ is a diagonal matrix [9]. Considering $\mathbf{F}_{l,k} = \varpi_{l,k}^T\mathbf{a}(\theta_{l,k})\mathbf{A}_{l,k}\mathbf{D}_{l,k}$, since $\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})$ and $\alpha_{l,k}$ are scalar, we have

$$(\alpha_{l,k}\mathbf{F}_{l,k})^H\mathbf{W}_{l,k}(\alpha_{l,k}\mathbf{F}_{l,k}) = |\alpha_{l,k}|^2|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2 \times \mathbf{D}_{l,k}^H\mathbf{A}_{l,k}^H\mathbf{W}_{l,k}\mathbf{A}_{l,k}\mathbf{D}_{l,k} \tag{18}$$

On the other hand, $\mathbf{D}_{l,k}^H\mathbf{A}_{l,k}^H\mathbf{W}_{l,k}\mathbf{A}_{l,k}\mathbf{D}_{l,k}$ is a diagonal matrix with elements as $W_{l,k}^{(i+n_l)modN_s}, i = 1, 2, \ldots, N_s$ where $W_{l,k}^i$ is the ith diagonal element of $\mathbf{W}_{l,k}$ and $n\,modN_s$ denotes the congruent modulo N_s of n. Hence by substituting and some simplifications, (17) can be presented as

$$\hat{\mathbf{s}}_{l,k} = \frac{1}{\alpha_{l,k}|\varpi_{l,k}^T\mathbf{a}(\theta_{l,k})|^2} diag\left\{\frac{1}{W_{l,k}^{(1+n_l)modN_s}}, \frac{1}{W_{l,k}^{(2+n_l)modN_s}}, \ldots, \frac{1}{W_{l,k}^{(N_s+n_l)modN_s}}\right\}\mathbf{F}_{l,k}^H\mathbf{W}_{l,k}\mathbf{r}_{l,k} \tag{19}$$

The main idea behind this approach is that a same signal is transmitted by the emitter to all receivers. Thus, the best estimation of emitter position is where the estimated signals have minimum vector distance to each other. This means that the best global location of the emitter is where the root mean square error between estimated signals gets to its minimum by all the receivers. On the other hand, each receiver assumes that the emitter is located at $\mathbf{p}_e = [x, y]^T$. Then, by knowing the position of receivers and corresponding signals, the channel parameters such as delay, Doppler (and thus $\mathbf{F}_{l,k}$), and attenuation $\alpha_{l,k}$ are computed. According to Eq. (19), each receiver estimates the emitted signal. It is noticed that there are L received signals. Therefore, it is just needed to compare all the 2-combinations from L observed signals together. Therefore, the optimization for localization of the emitter at time k can be carried out as follows:

$$\hat{p}_{e_k} = \begin{cases} \arg\min_{p_e}\left(\sum_{i=1}^{L}\sum_{j=i+1}^{L}||\hat{\mathbf{s}}_{i,k} - \hat{\mathbf{s}}_{j,k}||^2\right) \\ 0 \leq x \leq scale_x \\ 0 \leq y \leq scale_y \end{cases} \tag{20}$$

where $\hat{\mathbf{p}}_{ek}$ is the estimated position of emitter at time k and $scale_x$ and $scale_y$ specify the space of the possible emitter's position. The above equations can also be expanded in three-dimensional space.

The PSO algorithm is used for implementation of the optimization in Eq. (20) at each time interval k. The PSO begins with J number of random particles as population and looks for the optimum cost function point by updating the positions. As it continues, each particle position is updated by two "best" variables. The first one is called local best or pbest. The other "best" variable that is tracked by the particle swarm optimizer is the best value, obtained from every particle in the population. This best value is global best, called gbest [18]. After finding the two best variables, the velocity and position of each particle ith updates through the following equations:

$$\begin{aligned} v_{x,i}(t+1) &= w_x v_{x,i}(t) + r_1^x c_1^x (P_{x,i}(t) - x_i(t)) + r_2^x c_2^x (g_{x,i}(t) - x_i(t)) \\ v_{y,i}(t+1) &= w_y v_{y,i}(t) + r_1^y c_1^y (P_{y,i}(t) - y_i(t)) + r_2^y c_2^y (g_{y,i}(t) - y_i(t)) \\ x_i(t+1) &= x_i(t) + v_{x,i}(t+1) \\ y_i(t+1) &= y_i(t) + v_{y,i}(t+1), \end{aligned} \tag{21}$$

where $\mathbf{p}_{e,i}(t) = [x_i(t), y_i(t)]^T$ and $\mathbf{v}_i(t) = [v_{x,i}(t), v_{y,i}(t)]^T$ are the position and velocity vectors of the ith particle at iteration time t respectively. $[P_{x,i}(t), P_{y,i}(t)]^T$ and $[g_{x,i}(t), g_{y,i}(t)]^T$ are the local best and global best positions respectively. w_x and w_y are inertia weights that define the desired value of a particle to transit from its current location. These values are selected between 0.4 and 0.9. The coefficients c_1^x, c_2^x, c_1^y and c_2^y are individual and global learning factors, selected between 0 and 2. r_1^x, r_2^x, r_1^y, and r_2^y are random variables with uniform distribution between $[0, 1]$ [13].

There are many PSO variants including PSO with inertia weight, compression factor, changed constant, Gaussian dynamic PSO, and logistic dynamic PSO algorithm [19]. In this research the logistic dynamic PSO algorithm is used [20]. The simulation will show that the RMSE of the proposed PSO algorithm is much better than that of DPD. The proposed method has a good implication for the case of tracking a moving emitter; however, using the PSO algorithm involves a large amount of computation, especially in large scale areas. This high volume of computation is needed as a large number of particles should be considered for finding the global optimum of a cost function. This problem can be corrected using a combination of PSO and DPD algorithms.

Suppose that the velocity vector of the emitter is $\mathbf{v} = [v_x, v_y]^T$, and the receivers should collect N_s signal samples at the time interval with length T. The localization algorithm should be applied in each interval, so that the location can be estimated. If the maximum of velocity is known as $\mathbf{v}_{max} = [v_{x_{max}}, v_{y_{max}}]^T$, the search area by a PSO or DPD algorithm could be reduced. Therefore, Eq. (21) could be converted to

$$\hat{p}_e = \frac{1}{K}\sum_{k=1}^{K}\hat{p}_{e_k} \tag{22}$$

$$\hat{\mathbf{p}}_{e_k} = \begin{cases} \arg\min_{\mathbf{p}_e}(\sum_{i=1}^{L}\sum_{j=i+1}^{L}||\hat{\mathbf{s}}_{i,k} - \hat{\mathbf{s}}_{j,k}||^2) \\ \hat{x}_{k-1} - v_{x_{max}}T \leq x \leq \hat{x}_{k-1} + v_{x_{max}}T \\ \hat{y}_{k-1} - v_{y_{max}}T \leq y \leq \hat{y}_{k-1} + v_{y_{max}}T \end{cases}$$

where $\hat{\mathbf{p}}_{e_{k-1}} = [\hat{x}_{k-1}, \hat{y}_{k-1}]^T$ is the estimated position of the emitter in the previous interval time. Finally, the estimated position of the emitter in an intercept time is obtained from the mean of the obtained positions as follows:

$$\hat{p}_e = \frac{1}{K}\sum_{k=1}^{K}\hat{p}_{e_k} \tag{23}$$

This criterion could be used continuously for tracking the moving emitter at each intercept time. As was discussed, the DPD algorithm has a good implication for low resolution estimation. It means that DPD is suitable for the start step of a search algorithm. On the other hand, a large amount of computation is needed to achieve a high resolution of location estimation. Using the PSO algorithm, more resolution in smaller dimensions can be obtained. In the proposed algorithm, the DPD algorithm will be used just at the beginning of the procedure; then the PSO algorithm will be used to optimize Eq. (22). From now on this method is called DPD-PSO.

The simulation results show that the proposed DPD-PSO algorithm outperforms the PSO or DPD algorithms. The proposed DPD-PSO method has an admissible performance in tracking problems too. The steps of the DPD-PSO algorithms are described in Algorithm 1.

4. Simulation results

We examined the performance of the proposed algorithms using the Monte Carlo simulation, which has been used for different scenarios, and the results were compared with each other. We considered a square location with $100 \times 100m^2$, where the receivers were mounted on the floor in the four corners of the location (L = 4). The position of the emitter has been randomly considered in the space. In this simulation, we used a BPSK signal with symbol rate $1 \times 10^8 bps$ and carrier frequency 2.4 GHz. The sampling frequency was 8×10^8 Hz and the number of samples was 2048.

The channel attenuation is considered as $\alpha_l = 1 + \delta_l$, where δ_l is a circular complex Gaussian random variable with zero mean and standard deviation 0.1 that is independent for any receiver. The channel parameters have been adapted from the results of IEEE 802.15 project in reference [14]. In this work, the SNR is considered low and simulation results are compared for SNR between –30 dB and 10 dB. The array weight vector ϖ_l in receivers is considered as a uniform vector.

All simulations have been run in the MATLAB R2013a environment on a computer with a 64-bit processor Core $i7$, 2.2 GHz, and 8 GB RAM. The performance of localization methods has been investigated for different

Algorithm 1 The proposed DPD-PSO algorithm

for t=0,..., $t_{EndofTracking}$ (intercetp times)
  Collect the observation signals from receivers in an intercept time (for example $N_T = 2048$)
  Apply Hamming window in selected time interval. (window length=512 samples with 128 samples in overlap).
  if (t==0)
    Run the DPD algorithm by $Ng = 16$, in order to do a coarse estimation, use Equation (15) with $K = 1$ to estimate $\hat{p}_{e_{t=0}}$
  else,
    for k=1,..K
      Estimate the emitted signal by using Eq. (19).
        Run PSO algorithm around $\hat{p}_{e_{t-1}}$ to optimize the cost function shown in (22)
    End
  Average the estimate position of emitter for all time intervals to estimate $\hat{p}_{e_t}$ Eq. (23).
  End
End

geometries of receivers, but it is obvious that the best performance will be obtained when the entire space is surrounded by receivers. We examined the effect of the proposed algorithm using Monte Carlo computer simulations (with 250 runs each time). The mean of RMSE of every run as the result is computed. Applying a proper window as weighting received samples can improve the performance. The idea behind the WLSE is to normalize the received signals for achieving optimum performance. Thus, $w_{l,k}$ is selected as $\frac{N_s}{\sqrt{\mathbf{r}_{l,k}^H \mathbf{r}_{l,k}}}$ in each time interval and receiver. Although the performance with the WLSE criterion is somehow less than the expected, it outperforms the least square error (LSE) criterion. The method of LSE is a standard approach in regression analysis to the approximate solution of Eq. (6) that has been used in previous works [4–8]. Moreover, the performance of a preprocessing algorithm such as Gaussian noise filtering is shown in Figure 1, which causes canceling of the natural noise in signals. It can be observed that when Gaussian noise filtering and the WLSE criterion are also applied, the RMSE remarkably decreases in low SNR.

The performance of the proposed cost function in (20) has been investigated by PSO algorithm. In Figure 2 the RMSE curves of estimated emitter positions from DPD and PSO methods versus SNR are compared. The simulation results show that exploitation of PSO can decrease the error of estimation to less than 1 m, which results in achieving more resolution in comparison to DPD. Nonetheless, according to Eq. (22), we recommend the DPD-PSO algorithm rather than the PSO algorithm because it would limit the search space and decrease the computation complexity. However, PSO with the proposed cost function can be used in the next processing for fine DPD.

Accordingly, the proposed cost function and localization method can be exploited in the tracking problem. To verify the performance of the proposed algorithm in the tracking problem, it was supposed that an emitter is moving in a path with this given equation

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} v_x & 0 \\ 0 & v_y \end{bmatrix} \begin{bmatrix} t \\ t \end{bmatrix} + \begin{bmatrix} x_0 \\ y_0 \end{bmatrix}, \tag{24}$$

where $[x, y]^T$ is the position and $[v_x, v_y]^T$ is the velocity of the emitter at time t, assumed to be $[2, sin4(\pi \times$

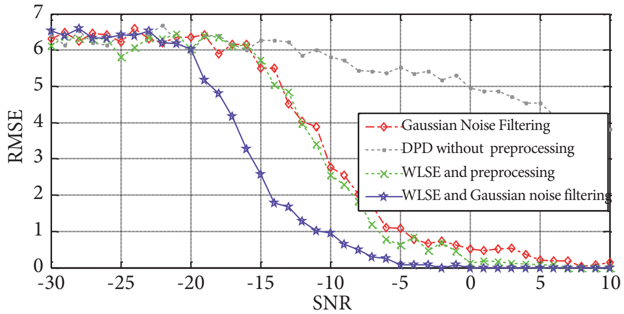

Figure 1. The preprocessing effect on estimating the emitter position.

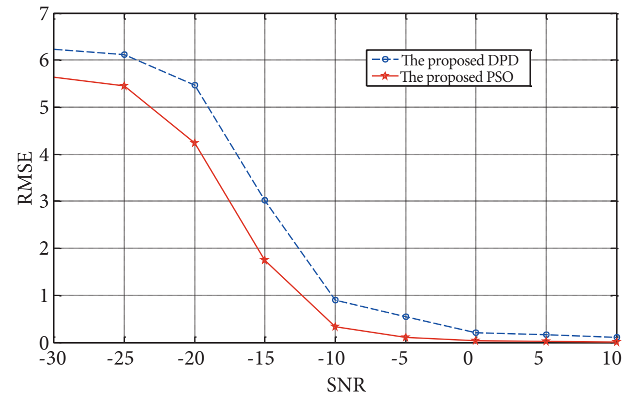

Figure 2. Comparison between the RMSE of DPD and PSO versus SNR.

$t/20)]^T m/s$, and $[x_0, y_0]^T$ is the initial position of the emitter, which is selected as $[10, 10]^T$. The superior accuracy of PSO in comparison with DPD can be shown in Figure 3 for a tracking scenario, and in Figure 4 based on the root mean square error of estimated emitter position at each time interval. As shown, the RMSE of PSO is less than 1 m and is more accurate. However, the time consumed for performing the PSO algorithm is more than twice that for the DPD algorithm.

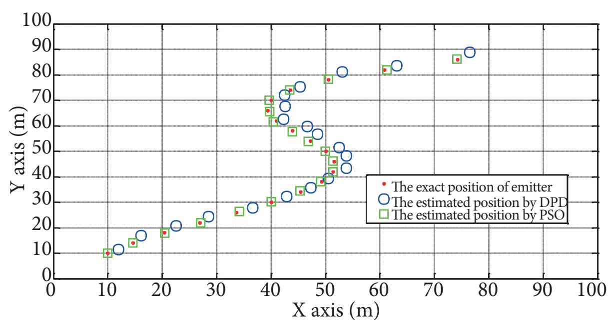

Figure 3. Comparison of DPD and PSO in tracking an emitter in SNR 10 dB.

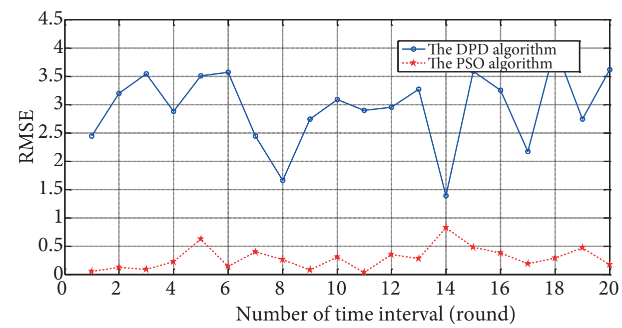

Figure 4. Comparison of RMSE for DPD and PSO in tracking an emitter in SNR –10 dB.

The speed of the PSO algorithm in practical tracking can be improved by recommended approaches. One of them is to decrease the number of population (NOP). Figure 5 shows the RMSE versus NOP in the PSO method with different values of SNR. For values of NOP over than 4, the RMSE decreases close to 0.1. In order to achieve a certain RMSE, it is more suitable to consider a minimum number of NOP. This would insure minimizing the PSO computation. Another approach for improving the speed of PSO is to restrict the search space by estimating the maximum velocity of the emitter, as described in Eq. (22). We have performed some simulations on the defined tracking problem using three algorithms. The first method is based on the previous DPD method in reference [5]. The second method uses the proposed DPD introduced in Eq. (15) and the third method, using the DPD-PSO algorithm implemented according to Eq. (22). The result of the average of the RMSE and the average of the elapsed time is illustrated in the Table. As seen, the average elapsed time for the DPD is much lower than that of the proposed methods, whilst the proposed DPD-PSO is more ideal in terms of the elapsed time and the average of RMSE.

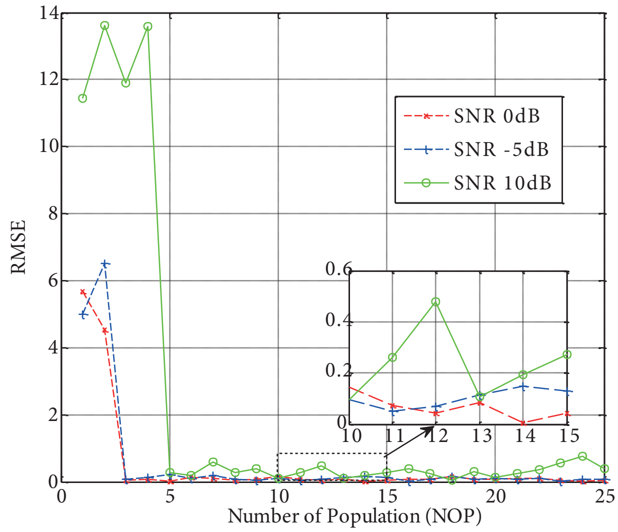

Figure 5. The RMSE of PSO method versus NOP for some various SNR.

Table. Comparison between the proposed algorithms in SNR –10 dB.

Algorithm	Average elapsed time (s)	Average of RMSE (m)
DPD	0.323	3.1342
Proposed DPD	0.671	0.6581
Proposed DPD-PSO	0. 361	0.3246

5. Conclusion

In this work, the problem of indoor localization in WLAN environments was considered. A new approach that uses DPD and PSO was proposed. Preprocessing such as normalization, windowing, and Gaussian noise filtering with considering an array antenna in receivers was applied. Moreover, the DPD method was developed using the WLSE criteria. Exploiting the PSO scheme with a defined proper cost function obtained better results in the RMSE for DPD. The DPD-PSO algorithm had a better performance in the tracking problems. The performance and accuracy of these methods were investigated with various Monte Carlo simulations. The simulation results showed that due to the proposed cost function and the DPD-PSO optimization the RMSE of the localization algorithm can be significantly decreased, especially in noisy channels with SNRs lower than -10 dB, while the time elapse in each interval is still acceptable in indoor applications.

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