


Improving performance of indoor localization using compressive sensing and normal hedge algorithm

Saeid HASSANHOSSEINI¹, Mohammad Reza TABAN^{2,*}, Jamshid ABOUEI¹,
Arash MOHAMMADI³

¹Department of Electrical Engineering, Faculty of Engineering, Yazd University, Yazd, Iran

²Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran

³Department of Electrical and Computer Engineering, Concordia University, Canada

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Abstract: Accurate indoor localization technologies are currently in high demand in wireless sensor networks, which strongly drive the development of various wireless applications including healthcare monitoring, patient tracking and endoscopic capsule localization. The precise position determination requires exact estimation of the time varying characteristics of wireless channels. In this paper, we address this issue and propose a three-phased scheme, which employs an optimal single stage TDOA/FDOA/AOA indoor localization based on spatial sparsity. The first contribution is to formulate the received unknown signals from the emitter as a compressive sensing problem. Then, we solve an ℓ_1 minimization problem to localize the emitter's position. To combat the nonstationary behavior of wireless channels between sensor nodes, the results of our proposed localization algorithm are finally fused using a novel fusion method based on the adaptive normal hedge algorithm. To improve the accuracy of the estimated location, an optimal set of weighed coefficients are derived through introducing a new loss function. Monte Carlo simulation results show that the accuracy of the proposed localization framework is superior compared to the existing indoor localization schemes in low SNR regimes.

Key words: Wireless sensor networks, indoor localization, direct position determination, compressive sensing, normal hedge

1. Introduction

With the rapid growth of wireless technology for location-based services (LBS), mobile devices and wireless sensors can sense and respond to transmitters in their working surrounding, thereby, can execute sophisticated tasks such as target tracking in indoor/outdoor applications. On the contrary to outdoor positioning services, which exploit GPS signals, indoor localization intends to locate an unknown-position of the emitter in an indoor environment using the received signals which are collected by known-position receivers [1–2]. Numerous researches on the indoor localization services have been performed with a variety of applications such as robotic, target tracking and environmental monitoring [3]. There are also various applications in wireless body area networks (WBANs) such as localization of wireless endoscopic capsule, localizing tumor and patient monitoring [4–5]. The results are useful for physicians to trace accurate positions of patients or implanted sensors inside the human body. One challenge faced for such indoor localization applications is the positioning accuracy. For this purpose, classical location-based methods which have been well matured employ a two step scheme [6].

*Correspondence: mrtaban@cc.iut.ac.ir

In the first step, some measurements such as time difference of arrival (TDOA), frequency difference of arrival (FDOA), angle of arrival (AOA) and/or received signal strength (RSS) are extracted from received signals by collectors inside or around the environment of interest. In the second step, the collection of extracted parameters is employed to estimate the location of emitter. Such two-step methods will not be necessarily optimal from the root mean square error (RMSE) points of view, if estimated parameters in the first step are not accurate enough [7].

On the contrary, single-step method of LBS uses a simple closed-form cost function which can be optimized using a two or three-dimensional search on an indoor environment. Direct-position-determination (DPD) is one of the most efficient single-step localization methods which outperforms even conventional two-step methods under low signal-to-noise ratio (SNR) conditions [8]. The DPD algorithm collects observation signals from all receivers (e.g., the access points or anchor nodes) in sequential intersection times and tries to evaluate the cost function for the candidate places. The DPD belongs to the least squares family if the noise statistics are unknown, while for Gaussian noise, the DPD would be the exact maximum-likelihood estimation of location [9]. In contrast to classical methods which determine the emitter position based on measuring one or more position-dependent parameters from the received signals such as TOA, RSS, FDOA, TDOA and AOA, the DPD method centrally processes all the received signals to estimate the location of emitter finely. In addition, this algorithm can be combined with the minimum variance distortionless response (MVDR) criterion to solve the DPD problem without the prior knowledge of the effective number of emitters [10].

On the other hand, the sparse nature of emitter's locations makes the theory of compressive sensing useful for the indoor localization [11–12]. The sparse vector of emitter's locations is reconstructed by the convex optimization or greedy algorithms [13]. In more recent literature, there have been several approaches presented to localize the emitter using TDOA/FDOA scheme within a sparse representation [14]. The proposed approaches exploit the sparsity of the multi-path channel with the knowledge of the pulse shape of the transmitted signal. A one-step localization approach based on the spatial sparsity of the grid plane has been proposed in [15] which directly estimates the location of the emitter without going through the intermediate stage of the TDOA/FDOA estimation. In [16], a framework is proposed to enhance the accuracy of positioning using the DPD and Normal Hedge (NH) algorithm. In this work, the defined loss function of NH algorithm is presented by the maximum eigen value of cross correlation matrix of the received signals.

Since the accuracy of indoor localization often suffers from the multipath conditions under the low SNR regime, in some methods, the average of estimated positions is considered as an accurate position [17]. Motivated by the above consideration, the main contributions, novelty, and the advantages of our work are summarized as follows:

- In this paper, a novel three-stage framework is developed for the reduction of the RMSE of the emitter's location. The first stage of the framework has extended the traditional DPD algorithms by a new attitude of the signal model. We use a preprocessing stage in which the sampled signals in sequentially intersection times are denoised using a mean filter, and are weighted by applying the Hamming window. On the other hand, we have exploited the weighted least square error (WLSE) with new formulation. In addition, the emitter localization problem is developed using the DPD formulas based on TDOA, FDOA and further more AOA, contrary to other works which use only the TDOA and FDOA scheme [17–18].
- The proposed method exploits the theory of compressive sensing (CS), leads to an accurate recovery of sparse signals by solving an ℓ_1 -minimization problem. In the next stage, the proposed algorithm based on

the spatial sparsity is executed and an ℓ_1 -minimization problem is solved by the basis pursuit denoising algorithm.

- As the proposed algorithm may have different estimations of the emitter’s location for each run in the low SNR regime, the NH algorithm is employed for combining the distribution of emitter’s locations. The NH is a decision-theoretic online learning problem which makes prediction based on some random inputs. The goal here is to sequentially predict the proper weights to fuse the results of the emitter’s position.
- In addition, a new loss function is introduced which causes our algorithm to achieve a better performance than some existing indoor localization schemes, specially in the low SNR regime and small number of receivers. One of the advantages of the proposed algorithm is the fusion of the obtained results by defining a considerable loss function in the adaptive NH algorithm. The loss function related to the results of the last ℓ_1 -minimization, has not ever been used so far for this problem.
- Moreover, the proposed algorithm can use in track a moving emitter and can also estimate the height of the emitter.

Furthermore, modeling in the preprocessing and fusing of postprocessing information, and the combination of methods together has led to a significant reduction in RMSE of position estimate at low SNR. From now on, because of exploiting compressive sensing, TDOA/FDOA/AOA parameters and NH algorithm, the proposed method is called CS-TFA-NH algorithm.

The rest of this paper is organized as follows. The problem definition and the proposed framework are briefly given in Section 2. An overview of ℓ_1 -minimization is discussed in Section 3. In addition, a brief introduction of the NH algorithm is introduced in this section. Later, the performance of the proposed algorithm is investigated by the Monte Carlo simulation in Section 4. In the last section, the results are discussed and compared.

2. Problem formulation

Consider an unknown-position emitter which transmits a narrow band signal $s(t)$ with bandwidth $W \ll f_0$, where f_0 is the carrier frequency. There are L number of known-position receivers (e.g., access points or anchor nodes) around the indoor environment which collect received signals at equal and sequential intersection times with index $k \in \{1, \dots, K\}$ during time interval T . The intersection time refers to the sequential interval time when the received signal is sampled by applying a window function. We denote $l \in \{1, \dots, L\}$ as the index of receivers. In each intersection time k , the signals processing task is performed in a central processing unit. Suppose each receiver is equipped with a uniform linear array antenna with $2M + 1$ elements at a distance Δ from each other. Denoting $\theta_{l,k}$ as the angle of arrival signal to l^{th} receiver at k^{th} intersection time, $\mathbf{a}(\theta_{l,k}) = [e^{-j\frac{2\pi}{\lambda} \frac{M}{2} \Delta \sin(\theta_{l,k})}, \dots, 1, \dots, e^{j\frac{2\pi}{\lambda} \frac{M}{2} \Delta \sin(\theta_{l,k})}]^T$ represents the steering vector corresponding to l^{th} array [19]. The complex baseband of the signal collected by l^{th} receiver at k^{th} intersection time would be as

$$r_{l,k}(t) = \alpha_{l,k} \varpi_{l,k}^T \mathbf{a}(\theta_{l,k}) e^{-j\omega_{l,k} t} s(t - \tau_{l,k}) + n_{l,k}(t), \quad l = 1, \dots, L, \quad (1)$$

where $\alpha_{l,k}$ is the complex attenuation of the communication channel, $\varpi_{l,k}$ is a $(2M + 1) \times 1$ weight vector, $\omega_{l,k} = 2\pi f_{l,k}$ is the Doppler shift effect, $\tau_{l,k}$ is the delay of signal which is considered as $\tau_{l,k} \ll T$, $n_{l,k}(t)$ represents the additive noise and interference with a $\mathcal{N}(0, \sigma^2)$ distribution, where it is assumed that σ^2 is

independent of parameter l . In addition, the Doppler frequency shift $f_{l,k}$ is evaluated by $f_{l,k} = \frac{f_0}{C} \frac{v_{l,k}(\mathbf{p}_e - \mathbf{p}_{l,k})}{\|\mathbf{p}_e - \mathbf{p}_{l,k}\|}$, where C is the light speed and $v_{l,k}$ is the relative velocity between the emitter and receivers, $\mathbf{p}_e = [x_e, y_e, z_e]^T$ and $\mathbf{p}_l = [x_l, y_l, z_l]^T$ denote the positions of the emitter and collectors, respectively.

The path loss and shadowing model for the communication channel is considered as follows:

$$PL(d) = PL(d_0) + 10\eta \log\left(\frac{d}{d_0}\right) + \chi_\sigma, \quad (2)$$

where d_0 and d are the reference distance and the distance between the emitter and the receiver, respectively, η is the path loss exponent and χ_σ (in dB) is a random variable with $\mathcal{N}(0, \sigma_\chi^2)$ distribution which represents the shadowing effect [20].

The sampled version of the signal in (1) with N_s samples is given by

$$\mathbf{r}_{l,k} = \alpha_{l,k} \varpi_{l,k}^T \mathbf{a}(\theta_{l,k}) \mathbf{A}_{l,k} \mathbf{F}_{l,k} \mathbf{s}_k + \mathbf{n}_{l,k}, \quad (3)$$

$$\mathbf{r}_{l,k} = [\mathbf{r}_{l,k}(t_1), \mathbf{r}_{l,k}(t_2), \dots, \mathbf{r}_{l,k}(t_{N_s})]^T, \quad (4)$$

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

$$\mathbf{A}_{l,k} = \text{diag}\{e^{-j\omega_{l,k}t_1}, e^{-j\omega_{l,k}t_2}, \dots, e^{-j\omega_{l,k}t_{N_s}}\},$$

$$\mathbf{n}_{l,k} = [\mathbf{n}_{l,k}(t_1), \mathbf{n}_{l,k}(t_2), \dots, \mathbf{n}_{l,k}(t_{N_s})]^T,$$

and $\mathbf{F}_{l,k} = \mathbf{F}^{m_{l,k}}$ is a cyclic shift operator which is used to shift down the samples of received signals by $m_{l,k} = \lfloor \tau_{l,k} f_s \rfloor$ where $\lfloor \cdot \rfloor$ denotes the integer part of a number. \mathbf{F} is an $N_s \times N_s$ matrix and is defined as $[\mathbf{F}_{ij}] = 1$, if $i = j + 1$ and $[\mathbf{F}_{ij}] = 0$ otherwise, also $[\mathbf{F}_{1,N_s}] = 1$. Indeed, the signal delay $\tau_{l,k}$ in (1) in l^{th} receiver is considered at the shift down operator $\mathbf{F}_{l,k}$. The expression in (3) can be simplified as

$$\mathbf{r}_{l,k} = \alpha_{l,k} \mathbf{H}_{l,k} \mathbf{s}_k + \mathbf{n}_{l,k}, \quad k = 1, \dots, K, \quad (5)$$

where $\mathbf{H}_{l,k} = \varpi_{l,k}^T \mathbf{a}(\theta_{l,k}) \mathbf{A}_{l,k} \mathbf{F}_{l,k}$. There is a procedure to estimate the emitted signal $\hat{\mathbf{s}}_k$ using the weighted least square error (WLSE) to minimize the defined cost function as follow:

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

where $w_{l,k}$'s are the weighting coefficients and can be selected by $\frac{N_s}{\sqrt{\mathbf{r}_{l,k}^H \mathbf{r}_{l,k}}}$ in each receiver and any intersection time. The estimation is generally complicated; nevertheless, we can estimate the emitted signal $\hat{\mathbf{s}}_{l,k}$ in l^{th} receiver and k^{th} slot as

$$\hat{\mathbf{s}}_{l,k} = [(\alpha_{l,k} \mathbf{H}_{l,k})^H \mathbf{W}_{l,k} (\alpha_{l,k} \mathbf{H}_{l,k})]^{-1} (\alpha_{l,k} \mathbf{H}_{l,k})^H \mathbf{W}_{l,k} \mathbf{r}_{l,k}, \quad (7)$$

where $\mathbf{W}_{l,k}$ is a weighting diagonal matrix with elements $w_{l,k}$ [21]. Then the estimation of the emitted signal in k^{th} time intersection can be approximately computed from the average of all receivers. Therefore, the final estimation of the emitted signal can be expressed as

$$\hat{\mathbf{s}}_k = \frac{1}{L} \sum_{l=1}^L \hat{\mathbf{s}}_{l,k} . \quad (8)$$

We assume N_g as the number of candidate positions of the emitter which are randomly generated in the indoor space with the uniform distribution. This assumption is considered in many literatures [9–17]. These positions are supposed to be regularly distributed in the indoor space which forms a set $\mathcal{P} \equiv \{\mathbf{p}_j = [x_j, y_j, z_j]^T; j = 1, \dots, N_g\}$. In k^{th} intercept time, a variable θ_j^k is assigned to j^{th} candidate position and is assumed to be equal to one for the point which is exactly the emitter position. Also, θ_j^k is zero for the rest of points in the indoor space. For the all members of \mathcal{P}_k in k^{th} intercept time, we have $\theta_k = [\theta_1^k, \dots, \theta_{N_g}^k]$. Therefore, the signal vector received by l^{th} receiver can be expressed as

$$\mathbf{r}_{l,k} = \sum_{j=1}^{N_g} \theta_j^k \alpha_{l,k} \mathbf{H}_{l,k} \mathbf{s}_k + \mathbf{n}_{l,k} . \quad (9)$$

The emitter is supposed to be placed in i^{th} position using path loss model in (2). Therefore, $\mathbf{H}_{l,k}^i$, $\alpha_{l,k}^i$, $\hat{\mathbf{s}}_k^i$ can be evaluated for i^{th} position (\mathbf{p}_i). Matrix Ψ_k^i is defined as an operator with respect to all L receivers which can be shown as

$$\Psi_k^i = \left[[\alpha_{1,k}^i \mathbf{H}_{1,k}^i]^T, [\alpha_{2,k}^i \mathbf{H}_{2,k}^i]^T, \dots, [\alpha_{L,k}^i \mathbf{H}_{L,k}^i]^T \right]^T_{LN_s \times N_g} . \quad (10)$$

In addition, vector ϕ_k^i is defined which contains all evaluated received signals by L receivers as

$$\phi_k^i = \Psi_k^i \times \hat{\mathbf{s}}_k^i . \quad (11)$$

Considering all positions in the set \mathcal{P} , the matrix Φ_k is constructed as follows:

$$\Phi_k = \left[\phi_k^1, \phi_k^2, \dots, \phi_k^{N_g} \right]_{LN_s \times N_g} . \quad (12)$$

So, we have

$$\mathbf{y}_k = \Phi_k \times \theta_k + \mathbf{w}_k , \quad (13)$$

where

$$\begin{aligned} \mathbf{y}_k &= \left[\mathbf{r}_{1,k}^T \quad \mathbf{r}_{2,k}^T \quad \dots \quad \mathbf{r}_{L,k}^T \right]^T_{LN_s \times 1} \\ \theta_k &= \left[\theta_1^k \quad \theta_2^k \quad \dots \quad \theta_{N_g}^k \right]^T_{N_g \times 1} \\ \mathbf{w}_k &= \left[\mathbf{n}_{1,k}^T \quad \mathbf{n}_{2,k}^T \quad \dots \quad \mathbf{n}_{L,k}^T \right]^T_{LN_s \times 1} . \end{aligned} \quad (14)$$

\mathbf{y}_k is the total observed vector and Φ_k is the sensing matrix in k^{th} intercept time. In addition, \mathbf{w}_k is an unknown noise vector in all receivers. Since, there is only one emitter in the indoor space at k^{th} intersection

time, θ_k is a sparse vector. A sparse estimation of θ_k can be obtained by solving the ℓ_1 -minimization problem [22]. Toward this goal and in the first contribution of this paper, three methods have been applied to (13) to obtain $\hat{\theta}_k$ and their performance have been examined. These methods are basis pursuit (BP) [23], basis pursuit denoising (BPDN) [24] and Dantzig selector method [25] as follow:

1. **BP**

$$\hat{\theta}_k = \arg \min_{\theta_k \in R^{N_g}} \|\theta_k\|_1, \quad s.t. \quad \mathbf{y}_k = \Phi_k \theta_k \quad (15)$$

2. **BPDN**

$$\hat{\theta}_k = \arg \min_{\theta_k \in R^{N_g}} \|\theta_k\|_1, \quad s.t. \quad \|\mathbf{y}_k - \Phi_k \theta_k\|_2 \leq \epsilon \quad (16)$$

3. **Dantzig selector**

$$\hat{\theta}_k = \arg \min_{\theta_k \in R^{N_g}} \|\theta_k\|_1, \quad s.t. \quad \|\Phi_k^T (\mathbf{y}_k - \Phi_k \theta_k)\|_\infty \leq \mu \quad (17)$$

for carefully chosen $\mu < 1$ and $\epsilon > 0$. Finally, the estimation of the emitter position would be as follows

$$\hat{\mathbf{p}}_{e_k} \equiv \{\mathbf{p}_i : \arg \max |\theta_i^k|\}. \quad (18)$$

Since wireless channels between sensor nodes have nonstationary characteristics due to the multipath and movement of emitter, the position of emitter should be estimated in several times in k^{th} intercept time. In addition, the emitter movement is continuous in indoor environments and has no sudden change. For this reason and in the second contribution of this paper, we use an online learning algorithm to fuse the results of estimation which will be followed in the next section.

3. Proposed CS-TFA-NH framework

To increase the estimation accuracy of the emitter's location, in this section we propose a three-stage processing framework of indoor localization, namely, the CS-TFA-NH scheme, which is shown in Figure 1.

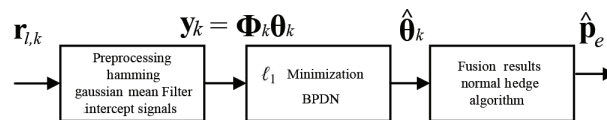


Figure 1. The proposed CS-TFA-NH framework of indoor localization using CS and NH.

In the first stage, receivers collect received signals by their antennas in the intercept time k . For smoothing the truncated autocovariance function in the time domain, it is recommended to use sliding window. Therefore, a hamming window is deployed to decrease the effect of discontinuity in extracted features of the received signal. Since, the main idea of this paper is the improvement of accuracy in low SNR scenarios, a Gaussian mean filter is used. It is quite evident that the noise reduction can play a significant role in improving the localization accuracy, so, the observation vector \mathbf{y}_k is collected. As described in Section 2, a set of candidate points (\mathcal{P}) is uniformly generated in k^{th} intercept time. Then, the sensing matrix Ψ_k is constructed and a linear equation is formed as (13).

In the next stage, the ℓ_1 -minimization algorithm is applied to find the sparsest solution for θ_k corresponding to the lowest $\|\theta_k\|_1$. This can be achieved by first generating a set \mathcal{P} as a coarse localization. Then, the fine localization is performed during the following manner. Let \mathbf{p}_m be m^{th} point of the set \mathcal{P} which satisfies the estimation of the emitter position in (18) and $\hat{\mathbf{p}}_{e_k} \equiv \mathbf{p}_m$. This point is considered as a coarse estimation. In order to perform the fine localization in the following next step, another set \mathcal{P} is randomly generated with the normal distribution. To obtain the best estimation of the emitter's location, the fine localization algorithm is executed several times ($t = 1, 2, \dots, N_t$) and the final outcome is computed using the average results as follows:

$$\hat{\mathbf{p}}_{e_k} = \frac{1}{N_t} \sum_{t=1}^{N_t} \hat{\mathbf{p}}_{e_k}^t, \tag{19}$$

where $\hat{\mathbf{p}}_{e_k}^t$ is the estimation of emitter's location in t^{th} iteration.

3.1. Normal hedge algorithm

Due to the random nature of the proposed algorithm, in each time that the set \mathcal{P} is generated and the ℓ_1 -minimization algorithm is executed, various results are obtained displaying an error with respect to the exact location of the emitter. In order to achieve a more accurate result in complex scenes, an adaptive NH algorithm is used. The NH algorithm uses a set of weighted actions to predict the real location of the emitter [26]. This algorithm is a solution for the decision-theoretic online learning (DTOL) [27] problem which is explained as follows.

At the beginning of estimating the emitter's location, it is assumed that there is a learner who receives the results of N_t actions in k^{th} intercept time. The learner maintains a weight distribution $\Omega_k = \{\omega_k^1, \dots, \omega_k^{N_t}\}$. Each action incurs a loss ℓ_k^t and the learner's expected loss under this distribution is obtained by $\ell_k^A = \sum_{t=1}^{N_t} \omega_k^t \ell_k^t$.

The motivation is that the difference between the estimated and the real values is implied by the loss function. Moreover, the learner attempts to maintain a distribution over actions and to minimize its net loss defined by $\ell_k^{net} = \sum_{k'=1}^k \ell_{k'}^A - \min_t \sum_{k'=1}^k \ell_{k'}^t$. The instantaneous regret to an action t is defined as $r_{k'}^t = \ell_{k'}^A - \ell_{k'}^t$ and the cumulative regret to an action t is obtained by

$$R_k^t = \sum_{k'=1}^k r_{k'}^t = R_{k-1}^t + (\ell_k^A - \ell_k^t). \tag{20}$$

The NH algorithm is based on a potential function with the half-normal distribution which is separately convex in x and c as follows:

$$f(x, c) = \exp\left(\frac{([x]_+)^2}{2c}\right), \quad \text{for } x \in \mathbb{R}, c > 0, \tag{21}$$

where $[x]_+$ denotes $\max\{0, x\}$. The NH algorithm attempts that the average of potential, over all actions at the intercept time, evaluated at R_k^t and c_k , remains constant at e defined as follows:

$$\frac{1}{N_t} \sum_{t=1}^{N_t} \exp\left(\frac{([R_k^t]_+)^2}{2c_k}\right) = e. \tag{22}$$

In this case, the weight is updated for t action as

$$\omega_{k+1}^t = \frac{[R_k^t]_+}{c_k} \exp\left(\frac{([R_k^t]_+)^2}{2c_k}\right). \quad (23)$$

The cumulative regret which depends on the previous values in action t is computed as

$$R_k^t = \lambda_k R_{k-1}^t + (\ell_k^A - \ell_k^t), \quad (24)$$

so that λ_k is considered as

$$\lambda_k = \begin{cases} 1 - \frac{1}{2} \exp\{-\gamma(\ell_k^A - \ell_k^i)^2\}, & \text{if } \ell_k^A > \ell_k^i \\ \frac{1}{2} \exp\{-\gamma(\ell_k^A - \ell_k^i)^2\}, & \text{else} \end{cases} \quad (25)$$

where γ is a constant that controls the shape of the exponential function [28]. Therefore, Eq. (19) can be changed to

$$\hat{\mathbf{p}}_{e_k} = \frac{1}{N_t} \sum_{t=1}^{N_t} \omega_{k+1}^t \odot \hat{\mathbf{p}}_{e_k}^t, \quad (26)$$

where ω_{k+1}^t denotes the vector of weights corresponding to different coordinates of space and \odot represents the hadamard product.

Since, in the localization stage, the ℓ_1 -minimization of θ_k is considered as the suitable criteria, the following loss function is proposed:

$$\ell_k^t = \exp(\|\theta_k^t\|_1). \quad (27)$$

Considering the defined loss function, it can be seen that decreasing $\|\theta_k\|_1$ causes decreasing the loss function in each action. The detailed localization procedure is summarized in Algorithm 1. In this algorithm, the weights and related functions must be evaluated in 2 or 3 dimensions. Thus, these variables are indicated by index z in Algorithm 1.

4. Simulation results

In this section, performance of the proposed algorithm is evaluated and compared with the classical DPD scheme in [7] by Monte Carlo simulations for different scenarios. The patient localization problem is considered by taking into account the IEEE 802.15.6 standard in the wireless body area networks. The simulations are performed on a 64-bit processor Core(TM) i7 , 2.2 GHz and 8 GB RAM and using MATLAB R2013a software. The initial values of basic parameters are shown in Table 1.

Four receivers ($L = 4$) were located in the corner of a 100m \times 100m building. The number of random particles (N_g) has been considered to be 64, the same as [17]. The emitter position has been considered to be random in each round of the Monte Carlo simulation. The proposed algorithms have been repeated 100 times for the range of SNR $\in [-30\text{dB } 10\text{dB}]$. The geometry of the localization problem is shown in Figure 2.

The appropriate channel model for the IEEE 802.15.6 standard is discussed in [29] with CM4 scenario in 2.4 GHz. According to Eq. (2), the parameters $PL(d_0)$, η and σ are selected to be equal to 25.8dB, 2 and 3.6, respectively. Although, there are many considerations for choosing parameters μ and ϵ in statistical models, however, in our proposed algorithm, we consider an appropriate value for these parameters which takes

Algorithm 1 : The Proposed Algorithm based on the NH

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1: procedure
2:   Set initial values:  $k = 0$  ,  $\omega_{z,1}^t = 1/N_t$  for  $t = (1, \dots, N_t)$ ,  $R_{z,0}^t = 0$  ,  $e = e_0$  ,  $\gamma = \gamma_0$ 
3:   topk:  $k \leftarrow k + 1$ 
4:   Collect signals from receivers in time interval  $k$ 
5:   for  $t = 1, \dots, N_t$ 
6:     Generate  $N_g$  uniformly distributed particles ( $\mathbf{p}_j$ ) in the indoor space
7:     Estimate  $\hat{\mathbf{p}}_{e_k}^t$  for all actions using Eq. (18)
8:     Compute loss function  $\ell_{\mathbf{k}}^t = \exp(\|\theta_{\mathbf{k}}^t\|_1)$ .
9:   end
10:   $\hat{z}_{e_k} = \sum_{t=1}^{N_t} \omega_{z,k}^t \hat{z}_{e_k}^t$  for  $z = x$  and  $y$ 
11:  Learner incurs loss  $\ell_{z,k}^A = \sum_{t=1}^{N_t} \omega_{z,k}^t \ell_k^t$  for  $z = x$  and  $y$ .
12:  Compute the adaptive coefficients  $\lambda_{x,k}$  and  $\lambda_{y,k}$  using (25).
13:  Update Cumulative regrets:  $R_{z,k}^t = \lambda_{z,k} R_{z,k-1}^t + (\ell_{z,k}^A - \ell_k^t)$  for  $z = x$  and  $y$ .
14:  Find  $c_{z,k} > 0$  satisfying  $\frac{1}{N_t} \sum_{t=1}^{N_t} \exp \left\{ \frac{([R_{z,k}^t]_+)^2}{2c_{z,k}} \right\} = e$  for  $z = x$  and  $y$ .
15:  Update distribution  $\omega_{z,k+1}^t = \frac{[R_{z,k}^t]_+}{c_{z,k}} \exp \left\{ \frac{([R_{z,k}^t]_+)^2}{2c_{z,k}} \right\}$  for each  $t$  and for  $z = x$  and  $y$ .
16:   $\hat{\mathbf{p}}_{e_k} = \frac{1}{N_t} \sum_{t=1}^{N_t} \omega_{k+1}^t \odot \tilde{\mathbf{p}}_{e_k}^t$ .
17: go to topk.

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Table 1. The simulation parameters

Parameter	Value
f_0	2.4GHz
f_s	8×10^8 Hz
Symbol rate	1×10^8 bps
Modulation	BPSK
C: Light velocity	3×10^8 m/s
Size of area	100×100 m ²
N_s (Number of samples)	2048
L (Number of receivers)	4
M (Number of arrays)	3

a tradeoff between the minimum norm of solution and the required iteration to reach the best answer. Hence, the exact values of ϵ and μ parameters in Eq. (16) and Eq. (17) differ in simulation step, but these parameters are considered about 0.01 and 0.05, respectively.

The RMSE is defined as the average Euclidean distance between the exact position and the estimated position of the emitter for all repetition of algorithm as follows:

$$RMSE = \sqrt{\frac{1}{N_{MC}} \sum_{n=1}^{N_{MC}} \|\hat{\mathbf{p}}_e - \mathbf{p}_e\|^2}, \quad (28)$$

where N_{MC} is the number of Monte Carlo repetitions of the proposed algorithms.

In the first scenario of our simulation results, we start with the ℓ_1 minimization block in Figure 1. We evaluate in Figure 3 the RMSE performance of our proposed indoor localization framework versus SNR for

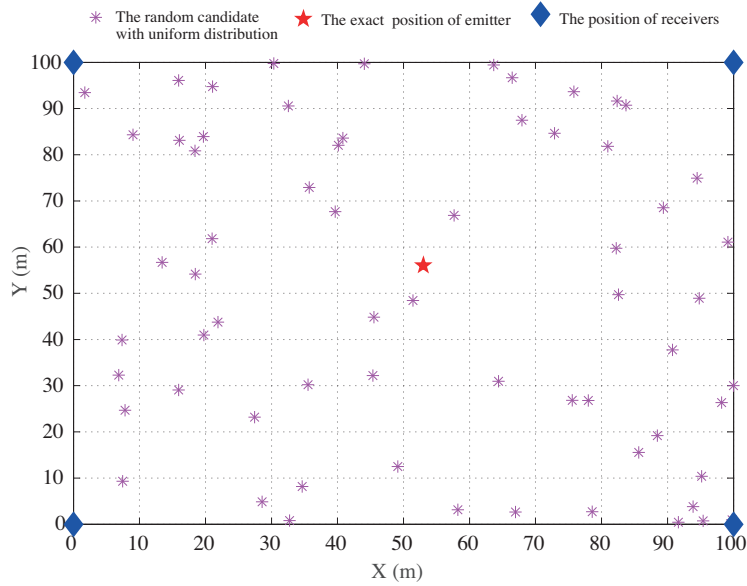


Figure 2. The problem geometry of indoor localization.

the 3 ℓ_1 minimization algorithms, namely BP [23], CS-BPDN [24] and CS-Dantzig [25] selector described in (15)-(17). In this case, we have not applied the adaptive NH algorithm in the proposed framework in Figure 1. The emitter’s location is just estimated using Eq. (19). As shown in Figure 3, the CS-BPDN provides the most accurate approach for solving ℓ_1 minimization in comparison to CS-Dantzig and BP methods. This fact comes from the effect of the noise in the BPDN algorithm. For the convenience of comparing methods, we define CS-TFA as the proposed method of localization based on the ℓ_1 -minimization in (19) and CS-TFA-NH as the proposed algorithm in (26). It should be noted that TFA is the abbreviation of TDOA/FDOA/AOA. The RMSE performance of the proposed CS-TFA-NH algorithm for each time interval is plotted in Figure 4. The plot shows a better accuracy of the CS-TFA-NH method over the CS-TFA, DPD-NH [16], classical DPD, and AP-DPD1 [10], at low SNR regimes. These results show that the proposed algorithms can provide a very effective improvement in the reduction of the RMSE in lower SNRs, whilst the result of reference [10] is ideal in the high SNR regime.

Theoretically, Φ_k in Eq. (12) is a kind of cross ambiguity function which is computed among all receivers. Thus, the correlation of the received signals in low SNRs can indirectly be considered in the next steps of our proposed algorithm. In addition, utilizing the sparsity in the space domain and fusion of the results based on the normal hedge algorithm helps the scheme to reduce the multipath and noise effects, and makes the algorithm capable to reduce the RMSE in low SNRs.

In addition, to verify the performance of the proposed algorithms in tracking problems, we consider a moving emitter whose path is given as follows:

$$\begin{bmatrix} \dot{x}_e \\ \dot{y}_e \\ \dot{z}_e \end{bmatrix} = \begin{bmatrix} v_x \\ v_y \\ 0 \end{bmatrix}, \tag{29}$$

where $[\dot{x}_e, \dot{y}_e, \dot{z}_e]^T$ represents the derivative of the emitter’s position and $[v_x, v_y, 0]^T$ is its velocity. The velocity

is assumed to be $[1 + 0.5\sin(2\pi t/100), 1, 0]^T m/s$ and the initial position of the emitter is selected as $[1, 1, 0]^T$. The total time of tracking and the SNR are considered as 100 s and 0 dB, respectively. By running the tracking simulation, at each time interval, the emitted signal is intercepted by receivers and the proposed algorithms are performed for 100 times. After estimating the emitter's position in the first interval, and to decrease the computation complexity, our proposed algorithm further restricts the searching area in the next intervals. The processor and the algorithm's speed are important for the fast tracking of a moving emitter. However, in this paper, we have focused on wireless body area networks in which the maximum speed will be about 1 to 5 meters per s. Examine for various velocities has the same results as one depicted in Figure 5. It can be seen that the proposed loss function in (27), improves the positioning accuracy in tracking of the emitter. As depicted in magnified area of Figure 5, the position of moving emitter is tracked by the CS-TFA-NH with more accuracy than its counterparts.

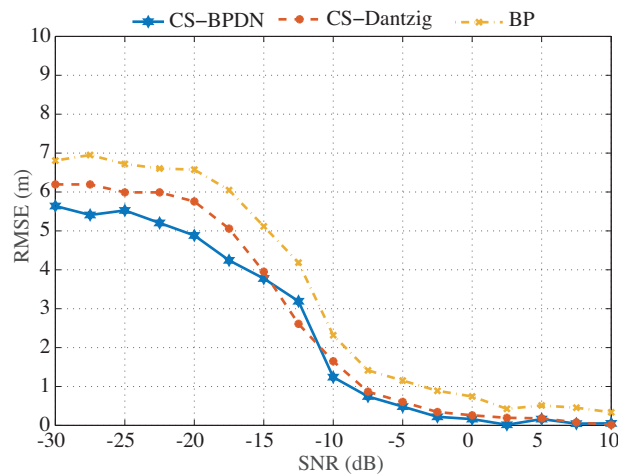


Figure 3. The RMSE performance of the proposed framework versus SNR for various ℓ_1 -minimization algorithms.

A comparison between the methods CS-TFA-NH, CS-TFA, DPD-NH [16], classical DPD and AP-DPD1 [10] in SNR=-10dB is tabulated in Table 2. It is shown that the RMSE for the CS-TFA-NH algorithm is less than the CS-TFA-NH. It is also shown that the average run time for the CS-TFA-NH is slightly longer than the CS-TFA, which is acceptable in applied works. As it can be derived from Table 2, the CS-TFA-NH algorithm has a lower RMSE with the average run time about 0.8 s, while the classic DPD algorithm with large RMSE 3.1402 has an average run time of 0.3251 s. It is worth mentioning that even though the average run time of the CS-TFA-NH algorithm is almost 3 times higher, but it is still acceptable for indoor applications. The complexity of classical DPD algorithm is $\mathcal{O}(L^2N_s^2)$ which is smaller than the proposed algorithm with $\mathcal{O}(L^2N_s^2N_g^2)$. For this reason, the elapsed time for executing the DPD is more less than other algorithms. According to Table 2, the delay for DPD is more less than the proposed algorithm, whilst the RMSE of DPD is not acceptable. Contrary, the RMSE of proposed algorithm is impressive. The effect of the number of collectors and their locations have been examined in a separate study and simulation. These results show that the proposed algorithms can provide a very effective improvement in the reduction of RMSE.

It should be noted that the whole processing tasks are accomplished in a main processor in the central unit which there is no restriction for its resources and power. The wireless sensors play as emitters of their signals. In contrast to energy-constrained WBANs and WSNs in which the main focus is to enhance the energy

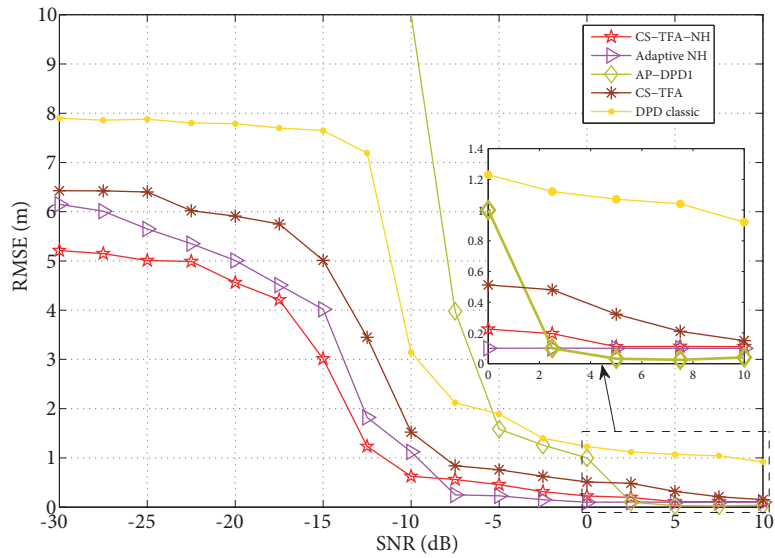


Figure 4. The RMSE of the proposed algorithm versus SNR compared to other DPD algorithms.

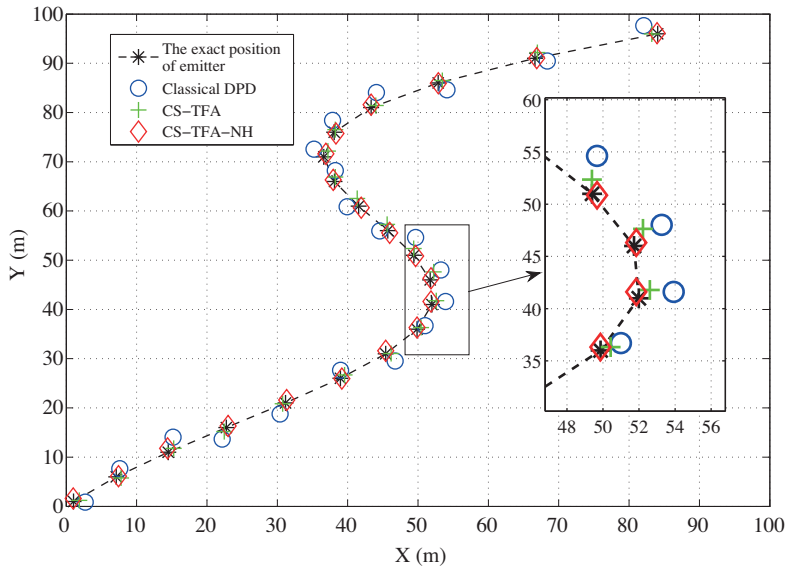


Figure 5. The performance of proposed algorithms in tracking an emitter in SNR 0dB in comparison with the classical DPD.

Table 2. The comparison of the proposed algorithm with DPD-NH and classical DPD based on the RMSE and the average run time in SNR = $-10dB$.

Algorithm	CS-TFA-NH	CS-TFA	DPD-NH[16]	DPD	AP-DPD1[10]
RMSE (m)	0.6241	1.521	1.0170	3.1402	10
Average run time (s)	0.7945	0.762	0.734	0.3251	0.3503

efficiency of the network by targeting the performance metric like first node died (FND) and residual energy, in our work, the main contribution is to execute all processes in a central processing unit. For this reason,

assumptions for the battery life and resources are not considered in the evaluation of the proposed CS-TFA-NH algorithm.

Remark 1: The computational complexity of the first stage of the proposed framework is of order $\mathcal{O}(LN_s \times LN_s N_g^2)$ or equivalently $\mathcal{O}(L^2 N_s^2 N_g^2)$, where L denotes the number of receivers, N_s represents the number of samples, and N_g is the number of grids in 2 dimensional (2D) area. The main process is to compute ℓ_1 -minimization of a compressive sensing equation. It is worth mentioning that the normal hedge algorithm in our problem has very low complexity. According to the expression of the estimated position in Eq. (26), we need to compute the N_t summation of 2D vectors. In this case, the complexity of this part is of order $\mathcal{O}(2N_t)$, which is comparable to the above dominant term. In the normal hedge algorithm which is presented in Algorithm 1, we only need to compute the summation of 2D vectors in N_t iteration which has very low complexity, therefore, the complexity of the proposed algorithm is of order $\mathcal{O}(L^2 N_s^2 N_g^2)$. On the other hand, the complexity of the classical DPD algorithm is of order $\mathcal{O}(L^2 N_s^2)$, which is smaller than that of the proposed algorithm. For this reason, the elapsed time for executing the DPD is much less than other algorithms. According to the results in Table 2, the delay for DPD is much less than the delay of the proposed algorithm, whilst the RMSE of the DPD scheme is not acceptable. Contrary, the RMSE of the proposed algorithm is impressive.

Remark 2: Note that the challenge of locating one unknown-position emitter is considered in many research works (e.g., [1–3]). In most of the proposed algorithms, many receivers may be existed in the environment, e.g., in tracking the patient in the hospital, positioning firefighters in emergency situations and many location base services (LBS), however, 3 or 4 of them are simultaneously necessary for localizing the emitter with the acceptable accuracy. Thus, we do not need to increase the number of receivers (or equivalently, increase the complexity) to achieve a very high accuracy for exact location of patients with a millimeter error. On the other hand, the whole processing are accomplished in a central unit. Thus, the proposed CS-TFA-NH framework can be useful for practical works.

5. Conclusion

In this work, a framework for the indoor localization problem was proposed based on the compressive sensing and the normal hedge algorithm. A method was also developed to address a single-step TDOA/FDOA/AOA indoor localization based on the spatial sparsity in the wireless sensor networks. More specifically, several random points with uniformly distributed in the (x, y) plane are generated, as candidates for the emitter position. A sparse vector was then assigned to indicate the existence of the emitter in these random points. Using ℓ_1 -minimization, the sparsest vector was obtained, which satisfies a linear equation among the observed signals in the receivers and the TDOA/FDOA/AOA sense matrix. The indoor localization methods suffer from multipath reflections in an indoor setting. In addition, since in applied works, such as wireless body sensors, the wireless channel is unstationary, estimated position of the emitter differs in every run of the algorithm. To combat this problem, a novel fusion method was proposed based on the normal hedge algorithm. Finally, a framework was proposed consisting of 3 stages, i.e., preprocessing of the received signals in the first stage, using localization algorithm based on the compressive sensing in the second stage and fusing the results using the normal hedge algorithm in the last stage. Simulation results showed that the proposed framework improves the accuracy and the elapsed time of emitter's localization. It was also verified that with the proposed loss function in the adaptive normal hedge algorithm for fusing the results, the performance of indoor localization and tracking would be improved.

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