Array Calibration using hybrid PSOGSA approach under array position errors

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***Abstract*— In this paper, an array calibration method using hybrid population-based algorithm (PSOGSA) with the combination of particle swarm optimization (PSO) and gravitational search algorithm (GSA) is proposed. We consider the problem of estimating the direction-of-arrival (DOA) based on maximum likelihood (ML) criteria of code-division multiple access (CDMA) signals under sensor position errors. ML function is a complex non-linear, multimodal function that features high dimensional problem spaces. However, when the random array position errors exist that the performance degradation is very fast. In this paper, the main idea is to integrate the ability of exploitation in PSO with the ability of exploration in GSA to synthesize both algorithms' strength. However, the proposed technique offers a much faster convergence compared to the PSO and GSA. The proposed method has no requirement for calibration sources while the sensor position errors as well as the DOAs of the incident signals can be estimated simultaneously. Computer simulations are conducted to show the validity and feasibility of the proposed method.**

***Keywords*— DOA, position errors, PSOGSA, ML.**

1. INTRODUCTION

The code-division multiple access (CDMA) system is the most promising multiplexing technology for cellular telecommunication services, such as personal communications, mobile telephony and indoor wireless networks [1,2]. Users identify personal data transmissions according to customized pseudo-noise in the CDMA system. The advantages obtained by employing different user-specific code sequences for these services include superior operation in multipath environments. With the advantage of code-matched filter inherent in CDMA systems, it has been contributed to solve the limitation that the number of array elements must be more than the number of impinging sources. However, source direction-of-arrival (DOA) estimation using an array of spatially distributed sensors is an essential and difficult task in a variety of applications. The problem has been an active research area for decades, and many high resolution methods have been proposed and analyzed, such as multiple signal classification (MUSIC) [3], estimation of signal parameters via rotational invariance technique (ESPRIT) [4] and maximum likelihood (ML) [5]. The ML method gives superior statistical performance compared to other methods when the SNR is small, the numbers of samples are small and the sources are coherent. However, array steering vector cannot be obtained precisely because of the presence of array phase and gain errors, mutual coupling and sensor position errors, which will badly degrade the performance of high-resolution techniques [6-8]. For array calibration with sensor position errors based on ML functions, a number of methods have been proposed. In [9], genetic approach (GA) is used to estimate the sensor positions as well as the DOAs of incident signals, but as we known it, its implementation is somewhat cumbersome due to slow convergence. Moreover, particle swarm optimization (PSO) algorithm is also presented to resolve the array calibration with sensor position errors for maximum likelihood (ML) estimation [10]. In this paper, we explore an improved hybrid PSO and Gravitational search algorithm (GSA) algorithm for optimizing ML functions to accurately estimate source DOA in linear arrays. The proposed method is used to determine the optimal solution and simultaneously estimate the DOA and perturbations of sensors. Unlike [11], it has no requirement for calibration sources. Computer simulations are conducted to show the validity of this method and the results show that it has a good performance in estimate of the sensor position errors and the DOAs of incident signals.

GSA is a relatively new nature based optimization algorithm based on the law of gravity [12]. It is characterized as a simple concept that is both easy to implement and computationally efficient. In GSA, the individuals, called agents, are a collection of masses, which interact with each other based on the Newtonian gravity and the laws of motion. All agents move to a new place, their velocities determine the direction and distance. The agents share information using the gravitational force to guide the search toward the best location in the search space. By changing the velocities over time, the agents are likely to move toward the global optima. Combination of PSO and GSA (PSOGSA) has been proposed in [13] and it has been shown that the PSOGSA can provide improved results for general mathematical functions. Moreover, it has been specifically applied to solve the problem of sidelobe minimization in collaborative beamforming [14]. In this paper, an PSOGSA is proposed to solve the DOA for the CDMA signal problem.

2. PROBLEM FORMULATION

2.1. SIGNAL MODEL

Consider a DOA estimation scenario in a CDMA system with P users. Let the bit duration T_b be equal to the processing gain L times the chip duration T_c. Let $a_m(\theta)=\exp[-j2\pi d(m-1)\sin\theta/\beta]$ denotes the response of the mth sensor array to a signal with unit amplitude arriving from the direction angle θ, where $j=\sqrt{-1}$ and β are the wavelength of the signal carrier. After demodulating and chip sampling, the received signal vector across a ULA with M elements and element spacing d at the kth bit interval can be represented as

$$\mathbf{x}(k)=\sum_{p=1}^{P} s_p(k)\mathbf{a}(\theta_p)\mathbf{c}_p^T+\mathbf{N}(k), \quad (1)$$

where $s_p(k)=\sqrt{Q_p}b_p(k)$, Q_p is the received signal power of the pth user, and $b_p(k)\in\{-1,1\}$ is the kth data bit of the pth user spreaded by a pseudo-noise (PN) codeword $\mathbf{c}_p$. Let θ_p is the angle-of-arrival of the pth received signal. Then, $\mathbf{a}(\theta_p)=[a_1(\theta_p),a_2(\theta_p),\cdots,a_M(\theta_p)]^T$ is the response vector of the pth user signal with direction angle θ_p. $\mathbf{N}(k)$ is the spatially and temporally white complex Gaussian noise with zero mean and variance σ_n^2. For convenience, we will assume that the user of interest is $p=1$. After passing through the code-matched filter, the despreaded signal at the kth bit interval is given by

$$\begin{aligned}\mathbf{r}_1(k)&=\mathbf{x}(k)\mathbf{c}_1\\&=Ls_1(k)\mathbf{a}(\theta_1)+\sum_{p=2}^{P}s_p(k)q_{p1}\mathbf{a}(\theta_p)+\mathbf{n}_1(k),\end{aligned} \quad (2)$$

where $q_{p1}=\mathbf{c}_p^T\mathbf{c}_1$ and $\mathbf{n}_1(k)=\mathbf{N}(k)\mathbf{c}_1$. The second term of (2) can be viewed as the interference noise. Thus we can put it into the noise term $\mathbf{n}_1(k)$ and the composite vector is replaced by a new nomenclature as $\mathbf{n}_1'(k)$ with zero mean and variance $\sigma_{n_1'}^2$. Then, (2) can be rewritten as

$$\mathbf{r}_1(k)=Ls_1(k)\mathbf{a}(\theta_1)+\mathbf{n}_1'(k). \quad (3)$$

The ensemble correlation matrix of $\mathbf{x}_1(k)$ is obtained by

$$\begin{aligned}\mathbf{R}_1&=E\{\mathbf{r}_1(k)\mathbf{r}_1^H(k)\}\\&=L^2Q_1\mathbf{a}(\theta_1)\mathbf{a}(\theta_1)^H+\sigma_{n_1'}^2\mathbf{I}\end{aligned}, \quad (4)$$

where $E\{\bullet\}$ and the superscript H denote the expectation and complex conjugate transpose, respectively. $\mathbf{I}$ is the identity matrix. For finite received signal's samples, the received signal correlation matrix $\mathbf{R}_1$ is replaced by the estimated sample average $\hat{\mathbf{R}}_1=(1/N)\sum_{k=1}^{N}\mathbf{r}_1(k)\mathbf{r}_1^H(k)$ and N is the total bits of observation.

2.2. RANDOM ARRAY POSITION ERRORS

When performing high-resolution DOA estimations, problems with uncertain sensor positions reduce the effectiveness of estimations. To address this issue, a PSO-based search strategy is proposed, which involves minimizing the ML adaptive function during each iteration to identify solutions.

Considering array elements may encounter stochastic positional perturbations, omnidirectional sensor array elements with identical unit gains also experience stochastic positional perturbations in the x-y direction. For sensors experiencing stochastic positional perturbations, the quantity of stochastic positional perturbation for the mth element can be expressed as follows:

$$\Delta u_m(\theta_p)=[\Delta x_m,\Delta y_m][\sin(\theta_p),\cos(\theta_p)]^T \quad (5)$$

where Δx_i is the horizontal error quantity of the ith sensor, and Δy_i is the vertical error quantity of the ith sensor. The positional error $[\Delta x_m,\Delta y_m]$ is a two-dimensional vector that possesses identical variance σ_p^2. The quantity of positional perturbation is generally assumed to be an unchanging constant. Therefore, the mth sensor response can be expressed as

$$\tilde{a}_m(\theta_p)=\exp(j\frac{2\pi}{\lambda}\Delta u_m(\theta_p))a_m(\theta_p) \quad (6)$$

Then, based on the aforementioned element positional perturbations, vectors of the received data arrays can be expressed as

$$\mathbf{x}=\sum_{q=1}^{P}\mathbf{U}_q\mathbf{a}(\theta_q)s_q+\mathbf{n} \quad (7)$$

where $\mathbf{U}_q=diag\{e^{(j\frac{2\pi}{\lambda}\Delta u_1(\theta_q))},e^{(j\frac{2\pi}{\lambda}\Delta u_2(\theta_q))},\cdots,e^{(j\frac{2\pi}{\lambda}\Delta u_M(\theta_q))}$. Therefore, the array signal vector $\hat{\mathbf{y}}_p$ obtained by the pth user after despreading and sampling can be expressed as

$$\begin{aligned}\hat{\mathbf{y}}_p&=\mathbf{x}\mathbf{c}_p\\&=Ls_p\mathbf{U}_p\mathbf{a}(\theta_p)+\sum_{q=1,q\neq p}^{p}s_q\mathbf{U}_q\mathbf{a}(\theta_q)+\mathbf{n}_p\end{aligned} \quad (8)$$

The correlation matrix generated using (8) can be expressed as

$$\begin{aligned}\hat{\mathbf{R}} &= E\{\hat{\mathbf{y}}_p \hat{\mathbf{y}}_p^H\} \\ &= L^2 \pi_p (\mathbf{U}_p \mathbf{a}(\theta_p))(\mathbf{U}_p \mathbf{a}(\theta_p))^H + \pi_{np} \mathbf{I}_M\end{aligned} \tag{9}$$

Based on (7), the positional shift of elements ($\mathbf{U}_p$) is influenced by the signal directions and element positional perturbations. However, the correlation matrix generated using (7) no longer exhibits a Toeplitz structure. In addition, because of perturbations, a portion of the noise subspace exceeds the true noise subspace. Therefore, when array experience positional shifts, the DOA estimation performance also declines.

2.3. ML ESTIMATOR

We derive the ML estimate of DOAs and array position perturbations to minimize the likelihood function with respect to all unknown real parameters. The ML criterion function can be given as

$$\begin{aligned}S_{ML}(\theta) &= \arg\{\max_{\theta}\ L(\theta)\} \\ &= \arg\{\max_{\theta}\ tr\{\mathbf{P}_{\mathbf{A}(\theta)}^{\perp} \hat{\mathbf{R}}\}\},\ p = 1,\ 2,\ \cdots,\ P\end{aligned} \tag{10}$$

where $tr[\cdot]$ is the trace of the bracketed matrix, $\mathbf{P}_{\mathbf{A}(\theta)}^{\perp} = \mathbf{I} - \mathbf{A}(\theta)(\mathbf{A}^H(\theta)\mathbf{A}(\theta))^{-1}\mathbf{A}^H(\theta)$ is the projection operator onto the space spanned by the columns of the matrix $\mathbf{A}(\theta) = [\mathbf{U}_1\mathbf{a}(\theta_1), \mathbf{U}_2\mathbf{a}(\theta_2), \cdots, \mathbf{U}_P\mathbf{a}(\theta_P)]$ for sensor positional errors, which are the $M \times P$ source direction matrix. Apparently, the maximization of the log-likelihood is computationally expensive. If nominal sensor positions differ from the actual sensor positions, the estimates fail. In order to reduce computational complexity and improve system convergence speed, we introduce the PSO and GSA algorithms as follows.

3. THE PROPOSED METHOD

3.1. PSO-ML ESTIMATOR

In this subsection, the PSO is employed to solve the DOA estimation for the CDMA system under array position errors. We can search both the array position errors and the DOA at the same time. Each particle can be treated as a point in the *J*-dimensional problem space and a swarm consisting of *D* random particles and then searches for best position (solution) by updating iterations. Consider the effect of position errors, the position of the *i*th particle is represented as $\boldsymbol{\theta}_i = [\Delta x_{i1}, \Delta x_{i2}, \cdots, \Delta x_{iM}, \Delta y_{i1}, \Delta y_{i2}, \cdots, \Delta y_{iM}, \theta_{i1}]$, where Δx_{im} and Δy_{im} are the unknown coordinates position errors of array *m*, then the estimate of array position errors and DOAs with respect to *Q*= 2*M* + 1 unknown real parameters can be converted to the problem of optimization. The rate of the position change (velocity) for *i*th particle is represented as $\mathbf{v}_i = [v_{i1}, v_{i2}, \cdots, v_{iQ}]$. The best previous position of the *i*th particle, which gives the best fitness value, is recorded as $\mathbf{p}_i = [p_{i1}, p_{i2}, \cdots, p_{iQ}]$. And, the index of the best particle among all the particles in the population is represented by $\mathbf{p}_g = [p_{g1}, p_{g2}, \cdots, p_{gQ}]$ and called global best location. In every iteration, the local bests and global bests are determined through evaluating the fitness values of the current population of particles. Two factors characterize a particle status on the search space: its position and velocity. The *q*th position for the *i*th particle in the *k*th iteration can be denoted as $\theta_{iq}(k)$. Similarly, the velocity for the *i*th particle in the *k*th iteration can be described as $v_{iq}(k)$. The velocity and the position of the *i*th particle at the (*k*+1)th iteration for $i = 1,\ 2,\ \cdots,\ D$ and $k = 1,\ 2,\ \cdots,\ k_{\max}$ are updated according to the following equations:

$$\mathbf{v}_i(k+1) = w(k)\mathbf{v}_i(k) + c_1\mathbf{r}_1(\mathbf{p}_i - \boldsymbol{\theta}_i(k)) + c_2\mathbf{r}_2(\mathbf{p}_g - \boldsymbol{\theta}_i(k)) \tag{11}$$

$$\boldsymbol{\theta}_i(k+1) = \boldsymbol{\theta}_i(k) + \mathbf{v}_i(k+1) \tag{12}$$

where c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward $\mathbf{p}_i$ and $\mathbf{p}_g$ positions. $\mathbf{r}_1$ and $\mathbf{r}_2$ are *Q*-dimensional vectors consisting of independent random numbers with uniform distributed between $[0,\ 1]$, which are used to stochastically vary the relative pull of $\mathbf{p}_i(k)$ and $\mathbf{p}_g(k)$ in order to simulate the unpredictable component of natural swarm behavior. The inertia weight $w(k)$ based on the linear decreasing strategy is considered critically for the convergence behavior of PSO, which is selected to decrease during the optimization process. Thus, PSO tends to have more global search ability at the beginning of the run while having more local search ability near the end of the optimization. Given a maximum value $w_{\max}$ and a minimum value $w_{\min}$, $w(k)$ is updated as follows:

$$w(k+1) = w_{\max} - k(w_{\max} - w_{\min}) / k_{\max}, \tag{13}$$

where $w_{\max}$ and $w_{\min}$ are chosen as 0.9 and 0.4 respectively in this work as in [15]. All parameters of the *Q*-dimensional particle positions, either initialized or updated during search, must be limited to $[\theta_{\min}, \theta_{\max}] = [-90^{\circ},\ 90^{\circ}]$, avoiding infeasible particle positions that can lead to slow PSO search. The new particle position is calculated using (12).

A particle position vector is converted to a candidate solution vector in the problem space through a suitable mapping. The score of the mapped vector evaluated by a ML function is regarded as the fitness of the corresponding particle. The DOA estimation problem in this paper is to find the particle position. At the end of iteration, the final global best position $\mathbf{p}_g(k_{\max})$ is taken as the search angle for the ML estimator.

3.2. GSA-ML ESTIMATOR

GSA starts with randomly placing all agents in search space. Suppose a system with D agents and θ_i^q represent the position of ith agent, where q denotes the qth dimension of agent. Then during all iterations, the gravitational force from agent j on agent i at a specific iteration k is defined as follow [12]:

$$F_{ij}^q = G(k)\frac{M_{di}(k)\times M_{aj}(k)}{R_{ij}(k)+\mu}(\theta_j^q(k)-\theta_i^q(k)) \tag{14}$$

where $i \neq j = 1, 2, \cdots, D$ and $k = 1, 2, \cdots, k_{\max}$. M_{aj} is the active gravitational mass related to agent j, M_{di} is the passive gravitational mass related to agent i, $G(k)$ is gravitational constant at time k, μ is a small constant, and $R_{ij}(k)$ is the Euclidian distance between two agents i and j. The $G(k)$ is calculated as

$$G(k) = G_0 e^{-\beta\frac{k}{k_{\max}}} \tag{15}$$

where G_0 and β are initial value of gravitational constant and descending coefficient. The total force that acts on agent i at iteration k is calculated as

$$F_i^q(k) = \sum_{j=1, j\neq i}^{D} rand_j F_{ij}^q(k) \tag{16}$$

where $rand_j$ is a random number in $[0,\ 1]$. According to the law of motion, the acceleration of an agent is proportional to the result force and inverse of its mass, so the acceleration of all agents should be calculated as

$$acc_i^q(k+1) = F_i^q(k) / M_{ii}(k) \tag{17}$$

where M_{ii} is the mass of agent i. The updating formula of gravitational and inertial masses of agent i follows as bellow:

$$m_i = \frac{Fitness_i^q(k) - worst^q(k)}{best^q(k) - worst^q(k)} \tag{18}$$

where $Fitness_i^q(k)$ is the fitness value of the agent i at time k. Then, $worst^q(k)$ and $best^q(k)$ are defined as follows:

$$\begin{cases} best^q(k) = \max\limits_{j\in\{1,\ldots,D\}} Fitness_j^q(k) \\ worst^q(k) = \min\limits_{j\in\{1,\ldots,D\}} Fitness_j^q(k) \end{cases} \tag{19}$$

For simplify, let $M_{ai} = M_{di} = M_{ii} = M_i$, and $M_i(k) = m_i(k) / \sum_{j=1}^{D} m_j(k)$. The velocity and position of agents are calculated as

$$v_i^q(k+1) = rand_i \times v_i^q(k) + acc_i^q(k+1) \tag{20}$$

$$\theta_i^q(k+1) = \theta_i^q(k) + v_i^q(k+1) \tag{21}$$

where $rand_i$ is a random number in the interval $[0,\ 1]$. Unfortunately, both of the PSO and GSA suffer from the local minimum searching problem and leads to a degradation of the effectiveness of the ML estimator. In this paper, we present a more feasible and efficient hybrid PSOGSA algorithm for enhancing performance of the ML estimator.

3.3. THE PROPOSED PSOGSA

The hybridization of PSO and GSA in [13] is categorized as low level teamwork hybrid algorithm. It is considered as a low level hybrid as it combines the functionality of two existing algorithm. The algorithm is also teamwork based since the algorithm is combined as one and runs in parallel. While the particle update for PSO and GSA is similar, as shown in (9), the velocity update for both the algorithms differ and PSOGSA algorithm in [13] replaces the local search of the original PSO with the GSA's acceleration, which is essentially a local best and worst aware search function. Hence, the proposed algorithm is:

$$\mathbf{v}_i(k+1) = \mathbf{v}_i(k) + c_1 r_1 \mathbf{acc}_i(k) + c_2 r_2 (\mathbf{p}_g - \boldsymbol{\theta}_i(k)) \tag{22}$$

$$\boldsymbol{\theta}_i(k+1) = \boldsymbol{\theta}_i(k) + \mathbf{v}_i(k+1) \tag{23}$$

From (10), the ML cost function, we can find out the maximum of the denominator of this cost function, i.e.,

$$\max_{\theta}\ tr\{(\mathbf{I} - \mathbf{A}(\theta)(\mathbf{A}^H(\theta)\mathbf{A}(\theta))^{-1}\mathbf{A}^H(\theta))\hat{\mathbf{R}}\} \tag{24}$$

In PSOGSA, at first, all agents are randomly initialized. Each agent is considered as a candidate solution. After initialization, Gravitational force, gravitational constant, and resultant forces among agents are calculated using (14), (15), and (16) respectively. After that, the accelerations of particles are defined as (17). In each iteration, the best solution so far should be updated. After calculating the accelerations and with updating the best solution so far, the velocities of all agents can be calculated using (22). Finally, the positions of agents are defined as (23). The process of updating velocities and positions will be stopped by meeting an end criterion.

SIMULATION RESULTS

In this section, we present several simulation examples to illustrate the DOA estimate performance of the proposed estimator for CDMA signals. The stage involved ML estimator with the traditional MUSIC and evaluating and comparing their performance when encountering issues of array stochastic position errors. CDMA possessed six-element sensor arrays with ULA of 0.5λ apart. Additionally, eight randomly and uniformly distributed source signals were transmitted from $[-90^\circ,\ 90^\circ]$ to the sensor arrays. Unless otherwise specified, all users possessed identical power, a signal-to-noise ratio (SNR) of 10 dB, and zero mean white Gaussian background noise. The scan resolution of the MUSIC algorithm was set to 1° and 0.1°. Comparison results with other estimators, including the PSO and GSA are also presented. The root-mean-squared error (RMSE) is defined as $\mathrm{RMSE}_{\hat{\theta}_1} = [(1/F)\sum_{j=1}^{F}(\hat{\theta}_{1,j} - \theta_1)^2]^{0.5}$, where F indicates the independent simulation runs. All CDMA signals were generated with BPSK modulation and PN codes of processing gain 31. For this study, the PSO and GSA algorithms' parameters were set as $c_1 = c_2 = 2$, $G_0 = 1$, $\beta = 20$ and $D = k_{\max} = 30$. All PSO algorithms underwent random initialization, and this process is terminated when the maximum iteration number $k_{\max}$ is attained or global optimal solution position is not iteratively updated for more than 10 times. The parameters of GSA estimators are set as [12]. All PSO and GSA start with random initializations and are terminated if the maximum iteration N_S is reached, or the global best fitness value is not updated in 100 successive iterations. The quantity of stochastic positional perturbations in the sensor was a Gaussian distribution of $2\Delta = [0,\ \ 0.2]\lambda^2$. The simulation results are obtained by averaging 200 independent Monte Carlo runs and 100 bits.

Consider CDMA signals P = 6 and an 8-element ULA with half-wavelength. Five interferers are impinging on the array with random impinging angles of uniform distribution in $[-90^\circ,\ 90^\circ]$. The desired user is impinging on the array with directional angle of 0.55°. For MUSIC, the searching grids are set to 1°, 0.1°, and 0.01°. The convergence of the RMSE for PSOGSA is shown in Fig. 1. Note that the proposed PSOGSA searching approaches can achieve fast convergence. Fig. 2 depicts the sensitivity in terms of RMSE versus the magnitude of position errors. Let four interferers have equal power with SNR $= 20$ dB and desired user's $\mathrm{SNR} = 0$ dB. As shown in Fig. 2, the ML estimation method was used as hybrid approach to demonstrate the effectiveness of various algorithms under the condition of array stochastic positional perturbations. The magnitude of the perturbations Δ was altered to observe the effectiveness of the various algorithms on DOA estimating RMSE. The simulation results showed that with increased perturbation, all the estimation methods exhibited greater estimation deviations. However, in this study, using the hybrid strategy to estimate the positional perturbation of the array sensors and the signal incident angles achieved a lower RMSE than that of the PSO, GSA and scan methods.

As shown in Fig. 3, the ML estimation method was used as hybrid approach to verify the effectiveness of various methods, which were subsequently compared with the MUSIC DOA method. When the interference-to-noise ratio (INR) was fixed at 10 dB, the number of sensor stochastic perturbations was 0.075λ. Next, the SNR of the desired signals was altered to analyze RMSE estimated using DOA with various algorithms. The PSO, GSA and scan methods yielded an approximate RMSE when simultaneously estimating the number of array sensor positional perturbations and the incident angle of the desired signal. By using a hybrid strategy, a lower RMSE than that of the scan method was achieved.

CONCLUSION

In this letter, we have presented a hybrid PSOGSA-based DOA estimator for CDMA signals under array position errors. The PSOGSA-based method is one of the efficient solving techniques than the PSO and GSA to search optimum solution and it also shows great potential for the application of ML function in real systems. Moreover, the proposed method incorporates with the features of the PSO and GSA algorithms to convert the estimate of array position errors and DOAs to the search for optimal solution. Then the array position errors and DOAs can be estimated simultaneously. Computer simulations were used to demonstrate the effectiveness of the proposed estimator under large SNR.

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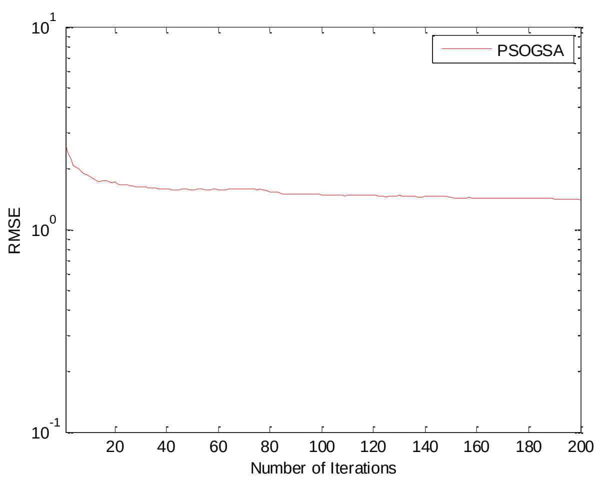

Fig. 1 RMSE versus the number of iterations.

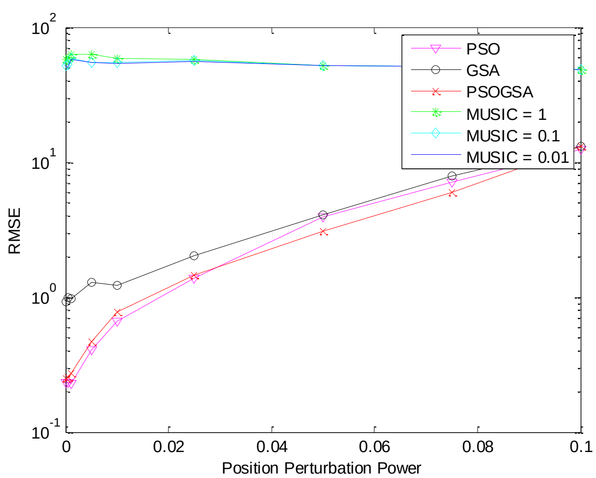

Fig. 2 RMSE versus the magnitude of position errors.

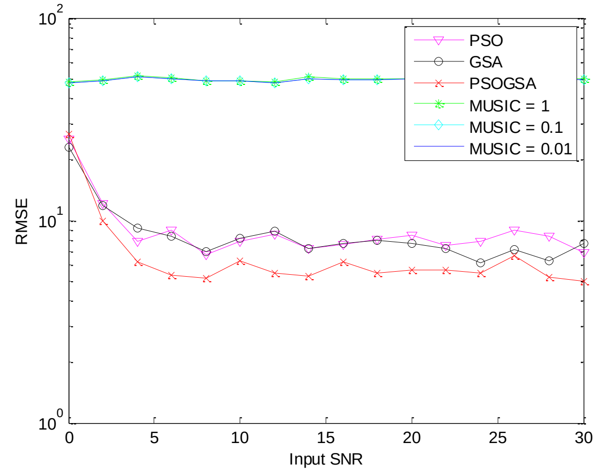

Fig. 3 RMSE versus the SNR of desired user.