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Hybridization of Genetic Algorithm and IBMUSIC applied to DOA estimation under coherent signals

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Abstract: This paper introduces a new hybrid of genetic algorithm (GA) and iteration beamspace multiple signal classification (IBMUSIC) suitable for making direction-of-arrival (DOA) in coherent signals. In general, the problem of estimation the DOA in coherent signals is more difficult to solve and conventional DOA estimation methods such as minimum variance distortionless response (MVDR) and multiple signal classification (MUSIC) algorithm produce mistake results owing to the existence of coherent terms. In this situation, we adopt the method of conjugate with a GA for selecting the initial search angle of IBMUSIC estimation. Moreover, the received data is projected onto the steering vectors of signal complement space by GA estimation, and then the coherent terms can be decrease. We use this tool to estimate the DOA in coherent signals to achieve low computational complexity and an excellent performance. Finally, numerical example was analyzed to illustrate the design procedure and confirm the performance of the proposed method.

Keywords: Genetic Algorithm, Direction-of-Arrival (DOA), Multiple Signal Classification (MUSIC)

1 Introduction

Array signal processing has been a very attract topic for several decades. Conventional adaptive beamformers are found to achieve high output signal-to-interference-plus-noise ratio (SINR) as long as the signal are uncorrelated to each other and the errors in the steering vector are small. In many practical applications, the coherent signals with can result in performance degradation in beamformer designed for point sources [1-4]. A number of direction-of-arrival (DOA) estimation algorithms have been developed, including multiple signal classification (MUSIC), rotational invariance technique (ESPRIT), minimum variance distortionless response (MVDR), and linear constrained minimum variance (LCMV). However, their searching DOA estimators algorithms, their performance will dangerous caused by coherent signals and therefore the estimation may be biased. Furthermore, their searching complexity and estimating accuracy strictly depends on the number of search grids used during the search. It is time consuming and the required number of search grid is not clear to determine.

In this paper, the design procedure is divided into two steps. The first step is based on a GA to search the neighborhood of the signal direction to rebuild receive data is by projected onto the signal complement space, and then the coherent terms can be removed [5-6]. In the second step, utilizing a first-order Taylor series approximation to the spatial scanning vector in terms of estimating deviation results in and reduces to a simple one-dimensional optimization problem [7] and applied to the IBMUSIC algorithm estimator.

Generally, the genetic algorithm (GA) is stochastic optimization algorithms, which applies

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operators inspired by the mechanics of natural selection to the population of binary strings that encode the parameter space. The underlying principles of GA have been suggested by Goldberg (1989) [8] could find the more details about GA. In addition, a number of experimental studies show that GA's exhibit impressive efficiency in practice. While classical gradient search techniques are more efficient for problems which satisfy tight constraints, GA's consistently outperform both gradient techniques and various forms of random search on more difficult (and more common) problems, such as optimizations involving discontinuous, noisy, high-dimensional, and multimodal objective functions. It is a parallel global search technique that emulates natural genetic operators, such as reproduction, crossover, and mutation. At each generation, it explores different areas of the parameter space, and then directs the search to the region where there is a high probability of finding improved performance. Since the GA is able to explore several points in the search space simultaneously, thereby reducing the chance of convergence to local optima. It is able to recombine structural information to locate new points in the search space with expected improved performance.

An estimation approach for coherent signals with adaptive search grid based on the observed receiving data is has long been an attractive solution to DOA [5]. Utilizing a first-order Taylor series approximation to the spatial scanning vector in terms of estimating deviation results in and reduces to a simple one-dimensional optimization problem [5]. Correcting factor is self-tuned and fast adaptively corrected from the iteration previous stage in spite of how well the initial guess is performed. Thus, we also proposed conjunction with a GA for selection initial search angle of IBMUSIC estimator. Moreover, the received data is projected onto the steering vectors of signal complement space by GA estimation, then the coherent terms can be remove [6]. Thus, the hybridize GA and IBMUSIC not only selected features from GA and IBMUSIC to achieve weak dependence on initial parameters and fast convergence but also can close unbiased DOA estimation.

The rest of this paper is organized as follows. Section 2 briefly outlines the problem description. Section 3 presents GA-based, IBMUSIC, and GA/IBMUSIC estimators to DOA estimation. Simulation example for showing the effects of the proposed estimator is presented in the Section 4. We conclude this paper in Section 5.

2 Problem Description

Consider a DOA scenario in a baseband system with P users impinging on an M sensors uniform linear array with unknown DOAs $\theta_1, \theta_2, \ldots, \theta_P$. All are assumed to be narrowband signal sources in the far field. The input data vector to the array sensors can be expressed as

$$\mathbf{x}(t) = \sum_{i=1}^{P} \mathbf{a}(\theta_i)\mathbf{s}_i(t) + \mathbf{n}(t) = \mathbf{A}(\theta)\mathbf{s}(t) + \mathbf{n}(t), \tag{2.1}$$

where $t = 1, 2, \ldots, N_s$, N_s is number of snapshots, $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_P(t)]^T$ is the $P \times 1$ vector of signal amplitudes, superscript T is transposition, and $\mathbf{A}(\theta) = [\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \ldots, \mathbf{a}(\theta_P)]$ is the $M \times P$ composite steering matrix. Let $a_m(\theta) = \exp[-j2\pi d(m-1)\sin\theta / \beta]$ denote 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 is the wavelength of the signal carrier. $\mathbf{a}(\theta_p) = [a_1(\theta_p), a_2(\theta_p), \cdots, a_M(\theta_p)]^T$ is the response vector of the pth user signal with direction angle θ_p. The sensor noise $\mathbf{n}(t)$ is assumed to be a zero-mean spatially white Gaussian process and uncorrelated with all the source signals. Then the noise is unknown diagonal covariance matrix given by

$$\mathbf{R}_{nn} = E\{\mathbf{n}(t)\mathbf{n}(t)^H\} = \sigma_n^2 \cdot \mathbf{I}_M, \tag{2.2}$$

where $E\{\cdot\}$ and the superscript H denote the expectation and complex conjugate transpose, respectively, σ_n^2 is noise power, and $\mathbf{I}_M$ is the identity matrix with size $M \times M$. The array covariance matrix is given by

$$\begin{aligned} \mathbf{R}_{xx} &= E[\mathbf{x}(t)\mathbf{x}^H(t)] \\ &= \mathbf{A}(\theta)E[\mathbf{s}(t)\mathbf{s}^H(t)]\mathbf{A}^H(\theta) + E[\mathbf{n}(t)\mathbf{n}^H(t)] \\ &= \mathbf{A}(\theta)\mathbf{R}_{ss}\mathbf{A}^H(\theta) + \sigma_n^2 \cdot \mathbf{I}_M, \end{aligned} \tag{2.3}$$

where $\mathbf{R}_{ss} = E[\mathbf{s}(t)\mathbf{s}^H(t)]$ is the source signal covariance matrix. For finite received signal's samples, the received signal correlation matrix $\mathbf{R}_{xx}$ is replaced by the estimated sample average $\hat{\mathbf{R}}_{xx} = (1/N_s)\sum_{k=1}^{N}\mathbf{x}(k)\mathbf{x}^H(k)$. The eigendecomposition of matrix (2.3) can be expressed as

$$\begin{aligned}\mathbf{R}_{xx} &= \sum_{m=1}^{M}\lambda_m \mathbf{e}_m \mathbf{e}_m^H \\ &= \sum_{m=1}^{P}\lambda_m \mathbf{e}_m \mathbf{e}_m^H + \mathbf{E}_n \mathbf{\Lambda}_n \mathbf{E}_n^H,\end{aligned} \qquad (2.4)$$

where $\lambda_1 \ge \lambda_2 \ge \cdots \lambda_P \ge \lambda_{P+1} = \cdots = \lambda_M = \sigma_n^2$ are the eigenvalue of $\mathbf{R}_{xx}$ and $\mathbf{e}_m$ denotes the eigenvector associated with λ_m for $m = 1, 2, \cdots, M$. Moreover, $\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_P$ and $\mathbf{E}_n = [\mathbf{e}_{P+1}, \cdots, \mathbf{e}_M]$ are orthogonal. $\mathbf{\Lambda}_n = \sigma_n^2 \mathbf{I}_{M-P}$ is the noise eigenvalue matrix. Furthermore, $\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_P$ spans the same signal subspace as that spanned by $\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \cdots, \mathbf{a}(\theta_P)$. Thus, the MUSIC estimator is also estimates the DOA of the desired user from the highest peak of the following spectrum [3]:

$$J_{MUSIC}(\theta) = \max_{\theta} \frac{1}{|\mathbf{a}^H(\theta)\mathbf{E}_n\mathbf{E}_n^H\mathbf{a}(\theta)|}. \qquad (2.5)$$

It is noted that the DOA estimation is to finding the maximum of the spectrum cost function. In general, $J_{MUSIC}(\theta)$ is a very highly nonlinear function of the probability θ.

3 GA/IBMUSIC Estimators

3.1. GA-based Estimator

The DOA estimation problem in (2.5) is a highly nonlinear function of θ, and many local maxima may exist. In this paper, a GA-based method is adopted to find the global solution to the maximum problem.

The GA consists of three operations [8-9]: (1) reproduction, (2) crossover, and (3) mutation, which are implemented by copying strings, exchanging portions of strings, and changing the state of bits from 1's to 0's or vice versa, respectively. These operations ensure that the “fittest” members of the population survive, so that their information is preserved and combined to generate even better offspring. The result is an improvement in the next generation's performance. Therefore, GAs are better suited to the maximum likelihood estimation problem than most search algorithms.

In the most conventional searching techniques, a single point is considered based on some decision rule. These methods can be dangerous in multimodal (many peaks) search spaces because they can converge to local optima. However, genetic algorithms work with a population of binary strings, searching many peaks in parallel. By employing genetic operators, they exchange information between the peaks, hence reducing the possibility of ending at a local optimum. This is why we use genetic based algorithm as the first stage to reach the neighborhood of DOA estimation problems. Let us denote the fitness value as.

$$Fit(\theta) = J_{MUSIC}(\theta). \qquad (3.1)$$

Then the GA tries to generate better offspring to improve the fitness. Using the above components, a standard GA procedure for solving the optimal power flow problem is summarized in the diagram of the Fig. 1. Now, let us describe the operation of the three basic operators

(1)Reproduction: Reproduction is based on the principle of survival of the fitness. The fitness Fit_i of the ith string is assigned to each individual string in the population where a higher Fit_i implies a better fitness. These strings with a large fitness have a large number of copies in the new generation. For instance, in roulette wheel selection, the i^{th} string with high fitness values Fit_i is given a proportionately high probability of reproduction P_i . The distribution of P_i can be presented as follows:

$$P_i = \frac{Fit_i}{\sum_{t=1}^{T} Fit_t}, \qquad (3.2)$$

where T is size of population. Once the strings are reproduced or copied for possible use in the next generation in a mating pool, they wait for the action of the other two operators: crossover and mutation.

(2) Crossover: If the chromosomes are operated only by reproduction, they search for the optimum existing individual and do not create any new individual. Crossover provides a mechanism for strings to mix and to match the desirable qualities through a random process. After reproduction, simple crossover proceeds in three steps. First, two

newly reproduced strings are selected from the mating pool, as produced by reproduction. Second, a position with the two strings is uniformly selected at random. Though as a random walk through the search space. Crossover is an effective mean of exchanging information and combing portions of high-quality solutions, when combined with reproduction.

(3) Mutation: Reproduction and crossover yield genetic algorithms with most of their searching power. The third operation, mutation, enhances the ability of genetic algorithms to search for the optimal solution. Mutation is the occasional alternation of a value at a particular string position and an insurance policy against the permanent loss of any simple bit. It is applied with a low probability that is chosen so that, on the average, one string in the population is mutated, the mutation operation simply flips the state of a bit from 0 to 1. Mutation should be used sparingly because it is a random search operation. With high mutation rates, the algorithm should become little more than a random search.

3.2. IBMUSIC Estimator

As it was mentioned in Eq. (2.5), which the estimation will exit bias by coherent signals. To achieve an unbiased estimation and a significant reduction in computational time, researchers proposed a so-called IBMUSIC estimator, which first projects the original data into a subspace (i.e., the beamspace [5-6]) and then processes the beamspace data by using iteration MUSIC algorithm. Let $\mathbf{A}_1=\left[a(\hat{\theta}_1) \quad a(\hat{\theta}_2) \quad \cdots \quad a_p(\hat{\theta}_p)\right]$, the outputs of these can be written as [5-6]

$$\mathbf{y}(k)=(I_M-\frac{\mathbf{A}_1\mathbf{A}_1^H}{\|\mathbf{A}_1\|})\mathbf{x}(k). \qquad (3.3)$$

Similar to element space domain, in the beam domain, the covariance matrix can of $\mathbf{y}(k)$ be written as

$$\begin{aligned}\mathbf{R}_y &= \mathrm{E}\left[\mathbf{y}(k)\mathbf{y}(k)^H\right] \\ &= \sum_{m=1}^{M}\kappa_m\mathbf{b}_m\mathbf{b}_m^H,\end{aligned} \qquad (3.4)$$

where $\kappa_1\ge\kappa_2\ge\kappa_3\cdots\ge\kappa_P\ge\kappa_{P+1}=\cdots=\kappa_M=\sigma_{n_b}^2$ are the eigenvalue of $\mathbf{R}_y$ and $\mathbf{b}_m$ denotes the eigenvector associated with κ_m for $m=1,\ 2,\ \cdots,\ M$. $\mathbf{B}_y=[\mathbf{b}_{P+1},\ \cdots,\ \mathbf{b}_M]$. The beam MUSIC(BMUSIC) estimator power spectrum in beamspace domain can be written

$$J_{BMUSIC}(\theta)=\max_{\theta}\frac{1}{|\mathbf{a}^H(\theta)\mathbf{B}_y\mathbf{B}_y^H\mathbf{a}(\theta)|}. \qquad (3.5)$$

The performance of the abovementioned spectral searching estimators are governed by the scanning grid size and the number of search grids while implementing the high-resolution DOA estimation. In this paper, it can be applied to iteratively search for the correct DOA by maximizing the spectrum with respect to the DOA estimating deviation. A first-order Taylor series approximation to the spatial scanning vector in terms of the estimating deviation results in and reduces to a simple one-dimensional optimization problem. The correcting factor is self-tuned and fast adaptively corrected from the iteration previous stage regardless of the accuracy of the initial guess. Then it contributes to enhance the convergence rate of the conventional spectrum-search estimator.

From (3.5), the BMUSIC spectrum cost function, we know that finding out the maximum is equivalent to finding out the minimum of the denominator (null spectrum) of this cost function, i.e.,

$$\min_{\theta}\mathbf{a}^H(\theta)\mathbf{B}_y\mathbf{B}_y^H\mathbf{a}(\theta). \qquad (3.6)$$

In a small region $\Delta\theta$ about the assumed initial angle-of-arrival θ_0, $\mathbf{a}(\theta)$ can be approximated by a first order Taylor series

$$\begin{aligned}\mathbf{a}(\theta) &= \mathbf{a}(\theta_0+\Delta\theta) \\ &\cong \mathbf{a}(\theta_0)+\Delta\theta\,\mathbf{a}'(\theta_0),\end{aligned} \qquad (3.7)$$

where $\mathbf{a}'(\theta_0)=\frac{d}{d\theta}\mathbf{a}(\theta)|_{\theta=\theta_0}$. Substituting (3.7) into (3.6) results in

$$\begin{aligned}&\min_{\Delta\theta}\ [\mathbf{a}(\theta_0)+\Delta\theta\,\mathbf{a}'(\theta_0)]^H \\ &\mathbf{B}_y\mathbf{B}_y^H[\mathbf{a}(\theta_0)+\Delta\theta\,\mathbf{a}'(\theta_0)],\end{aligned} \qquad (3.8)$$

which is a simple one-dimensional optimization problem. And, it can be easily shown that the optimum $\Delta\theta_o$ is given by

$$\Delta\theta_o = -\frac{\mathrm{Re}[\mathbf{a}^H(\theta_0)\mathbf{B}_y\mathbf{B}_y^H\mathbf{a}'(\theta_0)]}{[\mathbf{a}'(\theta_0)]^H\mathbf{B}_y\mathbf{B}_y^H\mathbf{a}'(\theta_0)} \quad (3.9)$$

where $\mathrm{Re}[\cdot]$ denotes the real part of the complex quantity. The optimum spatial response vector can then be found by substituting (3.9) into (3.8). If the estimating deviation $\Delta\theta$ is very small, the spatial response vector obtained from (3.9) is equivalent to the real response vector with actual desired signal's DOA. However, if the estimating deviation is quite large, then we require an iterative algorithm that updates the estimating deviation toward to the actual value. The iteration BMUSIC (IBMUSIC) estimator is formed as following steps:

1. Given the received data $\mathbf{x}(k)$, ε, and initial θ_0.
2. Compute the $\Delta\theta$ from (3.9).
3. If $\Delta\theta > \varepsilon$, then renew the $\theta = \theta + \Delta\theta$ and repeat the procedure from step (2) to step (3) until $\Delta\theta \le \varepsilon$, the suitable θ is obtained.

3.3. GA/IBMUSIC Estimator

In order to associate the weak dependence on initial parameters of GA with the initial fast convergence and the unbiased estimation of IBMUSIC, we combined both methods. The combined GA/ IBMUSIC always start the search procedure as a pure-GA and ends as a pure-IBMUSIC. The transition from GA to IBMUSIC occurs when the following condition is satisfied. The fittest individual remains the same for L_i iterations [7]. This condition is satisfied whenever the algorithm converges to an intermediate solution. The solution thus constitutes a good initial guess to IBMUSIC and decrease coherent signal effect.

Based on the above analysis, the design procedure of GA/IMUSIC direction angle θ estimation is divided into the following steps:

1. Given the received data $\mathbf{x}(k)$, and generate a random population θ of T chromosomes
2. Compute the corresponding fitness value Fit from (3.1).
3. Use the GA operators (reproduction, crossover, and mutation) to produce chromosomes of next generation.
4. Repeat the procedure from step 2 to step 4 until the fittest individual remains the same for L_i iterations.
5. Given the best chromosome θ are the initial IBMUSIC values and rebuild received data by Eq. (3.3).
6. Compute the $\Delta\theta$ from (3.9).
7. If $\Delta\theta > \varepsilon$, then renew the $\theta = \theta + \Delta\theta$ and repeat the procedure from step 6 to step 7 until $\Delta\theta < \varepsilon$, the suitable θ is obtained. The flowchart of GA/IBMUSIC procedure is present in Figure 1.

4 Design Example

In this section, computer simulations are presented to illustrate the feasibility of applying the proposed method to DOA estimation of coherent signals. Simulation results were used to compare the performance of the proposed estimation method with to the MUSIC [3], GA [9], and IMUSIC [7]. We consider a ULA with $P=2$, $M=8$ omnidirectional elements spaced half a wavelength apart. The desired signals are located on the array broadside ($\theta = \begin{bmatrix}-3^\circ & 3^\circ\end{bmatrix}$) are presented. The additive background noise is assumed to be spatially and temporally white complex Gaussian distribution with zero-mean and unit variance. The deviation precision is $\varepsilon = 0.01^\circ$ and searching grid size for the spectrum searching MUSIC [3] is set at 0.01°. The parameters of the GA-based estimator are defined as follows [10]:

$$T = 50, p_m = 0.1, p_c = 0.8, l = 15, \quad (4.1)$$

where T is the population size of the GA, p_m is the mutation probability, p_c is the crossover probability, and l is the length of the genetic.

The root mean square error (RMSE) is used as the performance index, and the RMSE of DOA estimation is defined as

$$\begin{aligned}\mathrm{RMSE} &= \sum_{i=1}^{P}\sqrt{E\left(\left(\hat{\theta}_i - \theta_i\right)^2\right)} \\ &= \sum_{i=1}^{P}\sqrt{[\frac{1}{S}\sum_{j=1}^{S}(\hat{\theta}_{i,j} - \theta_i)^2]},\end{aligned} \quad (4.2)$$

where S indicates the independent simulation runs. Every simulation result is presented after $N = 200$ data bits were processed and it is averaged by 100 independent runs with independent noise samples for each run. Table 1 gives the DOA estimates and search number of these four estimators. From Table 1, the GA/IBMUSIC DOA estimation is high accuracy and fast convergence with weak dependence on initial parameters. Figure 2 depict the RMSE performance of these four estimators versus different correlation coefficient with SNR is 5dB. From this Figure, it is clear that the performance of GA/IBMUSIC estimator has been improved, especially in signal of high coherent environments. The RMSE of DOA estimation versus different SNR is shown in Fig3. The result shows again that the proposed GA/IBMUSIC estimator not only retains the benefits iterative searching process, but also gains the improvement in DOA estimation accuracy.Logic coverage criteria are mainly used for formal specification-based testing [3]. It generates test cases by analyzing the predicates and literal truth value relationship. The formal specification is constituted by a series of states and transitions. Long-term practice shows that the system boundary is most likely to make system wrong. Boundary state is a state that at least one of those state variables can be taken to the extreme value of its sub-domain state. Aim at the logic coverage criteria with little regard to the boundary, this paper proposes a series of logical boundary coverage criteria based on paper [1] and [2].

5 Conclusion

The IBMUSIC method is gradient search method approach to create efficient DOA estimators for coherent signals. The IBMUSIC method seems to converge more rapidly than the MUSIC, but its performance depend on initial value and the relation of coherent signals. In this paper, we combine the selected features form GA and IBMUSIC to achieve weak dependence on initial values, high accuracy, and fast convergence. Simulation result indicated that the GA/IBMUSIC method behaves well even in cases with high relation of coherent signal environments. It is obvious that the performance is improved significantly if the relations of coherent signals are considered in the proposed design procedure

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Estimators	Correlation coefficient	Initial Angle	Iterations	RMSE
MUSIC	*0*		180001	0.2832
	0.8		180001	1.8320
IMUSIC	*0*	$(-10^o,0^o)$	136	2.7880
	0.8		157	7.7674
GA	*0*			2.9144
	0.8			8.6591
GA/IBMUSIC	*0*		13	0.1207
	0.8		35	0.6014

Table 1: Estimated DOA and number of searches based on the proposed method, MUSIC estimator, GA-based estimator, and IMUSIC estimator.

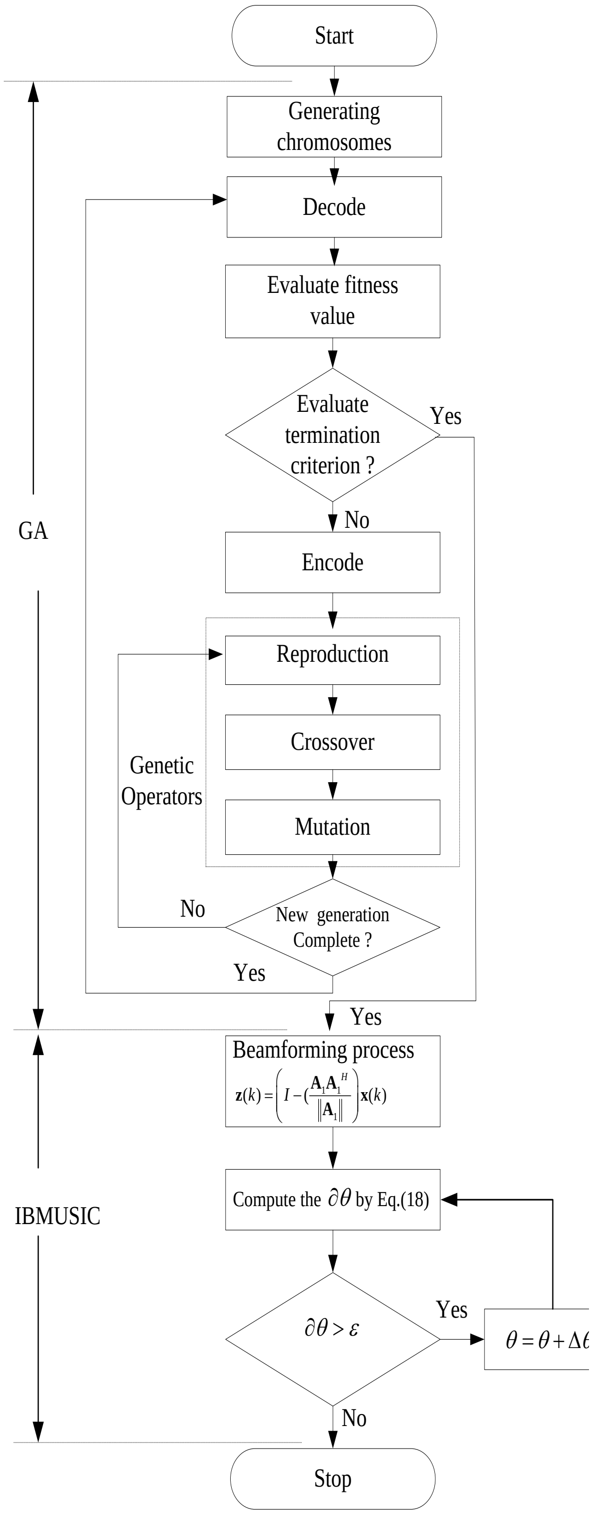

Figure 1: The flowchart of the GA/IBMUSIC estimator.

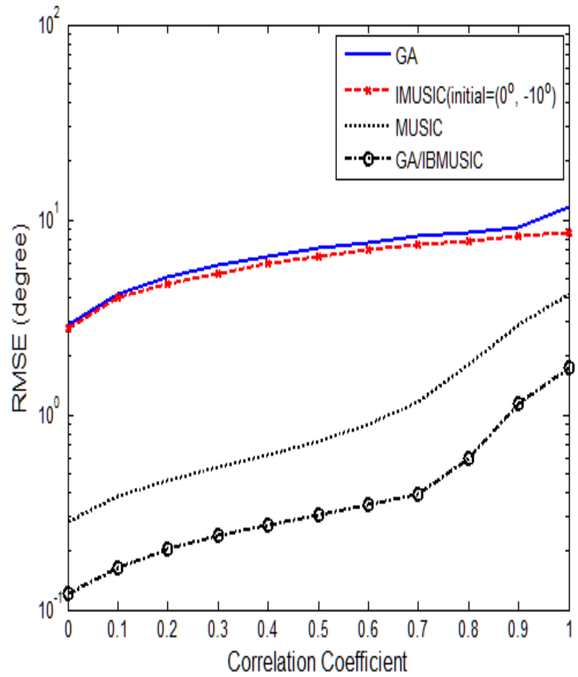

Figure 2: RMSE of DOA estimation versus the correlation coefficient.

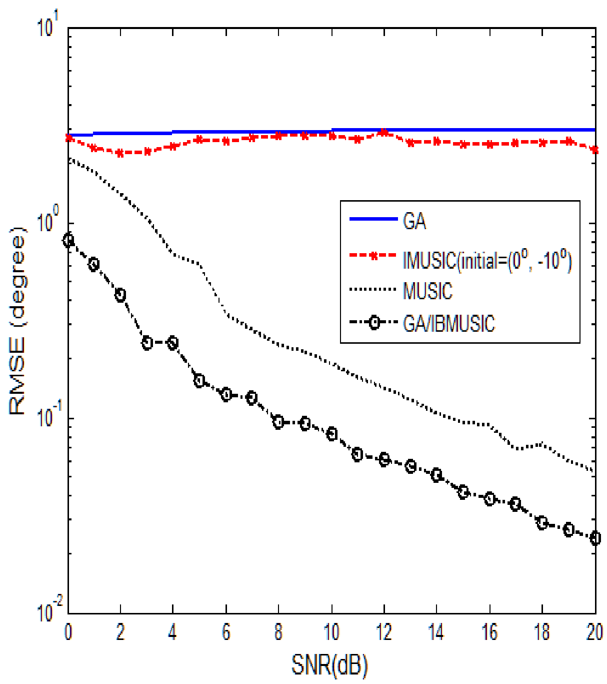

Figure 3: RMSE of DOA estimation versus the SNR .

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