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Combining genetic algorithm and iterative MUSIC searching DOA estimation for the CDMA system

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ABSTRACT

This paper deals with direction-of-arrival (DOA) estimation based on iterative MUSIC searching technique for the code division multiple access (CDMA) system. It has been shown that the iterative searching technique suffers from the local maximum searching problem, causing acquisition errors in DOA estimation. In conjunction with a genetic algorithm (GA) for selecting initial search angle, we present an efficient approach to achieve the advantages of iterative DOA estimation with fast convergence and more accuracy estimate over existing conventional spectral searching methods. Finally, several computer simulation examples are provided for illustration and comparison.

1. Introduction

Code division multiple access (CDMA) techniques have adopted as a standard for the third-generation cellular network and attracted increasing attention recently in wireless applications for efficient use of available bandwidth, resistance to interference, and adaptability to variable traffic pattern. In CDMA systems, several independent users are simultaneously active in the same transmission medium and distinguishable at the receiver by different user-specific code sequences (Liu, 2000). Due to the imperfect orthogonality among the different code sequences, multiple-access interference (MAI) is a major limitation to the system capacity. Adaptive array techniques have been developed for enhancing the performance of CDMA systems (Liberti & Rappaport, 1994). They can provide accurate localization of user terminals (Caffery & Stuber, 1998), which are of interest in advanced handover schemes, public safety services and intelligent transportation systems. In all these applications, estimation of the direction-of-arrival (DOA) of the desired signal is required. Array outputs aligned with code-matched filter can make the multiple sources DOA estimation equivalent to that of a single source localization problem in a noisy environment. With the advantage of code-matched filter inherent in the CDMA system, it has been proved that the traditional multiple signal classification (MUSIC) algorithm can obtain an unbiased DOA estimation with low mean-square-error (MSE) (Chiang & Chang, 2003). It also contributes to solve the limitation that the number of array elements must be more than the number of impinging sources. But for the conventional spectral searching DOA estimators such as minimum variance distortionless response (MVDR) (Capon, 1969) and MUSIC (Schmidt, 1986) algorithms, their searching complexity and estimating accuracy strictly depend 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. For the purpose of efficient DOA estimation, a highly efficient approach (Rao & Hari, 1989) has been proposed that is implemented on polynomial rooting rather than spectral searching. However, this rooting method is suboptimal in the presence of the noise and MAI. The improper root-selection due to local minimum/maximum problem often results in serious bias in the signals' parameter estimation, especially in low SNR environments (Rao & Hari, 1989). A major problem of MUSIC type algorithms is heavy computational load incurred with spatial spectral search when root finding schemes are not applicable. The application of root finding schemes is only suitable for uniform linear array (ULA). The estimation of signal parameters via rotational invariance technique (ESPRIT) may manifest significant performance and computational advantages, but a translation invariance structured array is required, and the estimation variance is large. This prompts development of another class of eigenvalue decomposition (EVD) based DOA estimation algorithms which does not require conventional spectral search.

Generally, the genetic algorithm (GA) is stochastic optimization algorithms, which applies 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 Holland (1962) and the more details about GA could be found in Goldberg (1989). In addition, a number of experimental studies show that GAs exhibit impressive efficiency in practice.

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While classical gradient search techniques are more efficient for problems which satisfy tight constraints, GAs 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. In particular, it does not need to assume a differentiable or continuous search space, and can also iterate several times on each datum received. Recently, the application of GA has been applied to deal with antenna arrays (Haupt, 1994; Sharman & McClurkin, 1989; Stoica & Gershman, 1999; Tennant, Dawoud, & Anderson, 1994; Yan & Lu, 1997; Yeo & Lu, 1999). A typical example of which is GA for the global maximization of likelihood function (Sharman & McClurkin, 1989; Stoica & Gershman, 1999). This approach can keep the risk of false DOA estimate low, at the expense of a significant increase in the computational burden that may not be always acceptable. Haupt (1994) uses a GA to optimize a thinned array and a planar array to produce patterns with lowest sidelobe level, while Tennant et al. (1994) demonstrate its use in null steering in a phased and adaptive array. An improved GA based on Yan and Lu (1997) is also applied to array-failure corrections (Yeo & Lu, 1999).

In this paper, we present an efficient DOA estimation approach for CDMA signals with adaptive search grid at each iteration based on the observed receiving data. First, by employing GA to treat our optimization problem of the desired signal direction angle θ, first coded to be a binary string called a chromosome. In each generation, three basic genetic operators, that is, reproduction, crossover, and mutation, are performed to generate a new population with a constant population size. The chromosomes that remain after the population is reduced by the principle of the survival of the fittest produce a better population candidate solution. Although empirical evidence indicates that GA can sometime find good solution for complex problems. A rigid and comprehensive analysis for GA is difficult. However, the convergence of the proposed GA-based DOA estimator scheme can be guaranteed via the theorem of the schema discussed by Goldberg (1989). The DOA, obtained by the proposed GA-based estimator, converges to the optimal or near optimal solution. Secondly, 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 (Er & Ng, 1994). Correcting factor is self-tuned and fast adaptively corrected from the iteration previous stage in spite of how well the initial guess is performed. We also present the iterative noise subspace with eigenvalue shaping (IMUSIC) estimator. The IMUSIC is a serial search method, unlike the GA, which is a parallel search method. Finally, in conjunction with a GA for selecting initial search angle, we present an efficient approach to achieve the advantages of iterative DOA estimate with fast convergence and more accuracy estimate over existing conventional spectral searching methods. Comparing GA and IMUSIC, we can find that GA exhibits fast initial convergence, but its performance deteriorates as it approaches the desired global extreme. Interestingly, IMUSIC shows a complementary convergence pattern, in addition to high accuracy. We combine the selected features from GA and IMUSIC to achieve weak dependence on initial parameters, parallel search strategy, fast convergence and high accuracy (Requena-Pérez, Albero-Ortiz, Monzó-Cabrera, & Díaz-Morcillo, 2006; Tam & Cheung, 2000). The resultant approach is referred to as a GA/IMUSIC estimator which starts the search procedure as a pure-GA and ends as a pure-IMUSIC. The transition from GA to IMUSIC occurs when the fittest individual remains the same for L_g generations (Zacharias, Lemes, & Dal Pino, 1998). Simulation results show that the proposed GA/IMUSIC estimator is very suitable to treat the DOA estimation under CDMA signals.

This paper is organized as follows. Section 2 briefly outlines the problem description. Section 3 presents GA-based, IMUSIC, and GA/IMUSIC estimators to DOA estimation. Several simulation examples for showing the effectiveness of the proposed estimator are presented in Section 4. We conclude this paper in Section 5.

2. Problem description

2.1. Signal model

Consider a DOA scenario in a baseband CDMA system with P users. Let the bit duration T_b be equal to the processing gain L times the chip duration T_c. After demodulating and chip sampling, the received signal across a ULA with M elements and sensor spacing d at the kth bit interval can be represented as

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

where $r_p(k) = \sqrt{Q_p} b_p(k)$. 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 $\mathbf{c}_p$. $\mathbf{N}(k)$ is the spatially and temporally white complex Gaussian noise with zero mean and variance σ_n^2. 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. $\mathbf{a}(\theta_p) = [a_1(\theta_p), a_2(\theta_p), \ldots, a_M(\theta_p)]^T$ is the response vector of the pth user signal with direction angle θ_p. 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

$$\mathbf{y}(k) = \mathbf{x}(k)\mathbf{c}_1 = L r_1(k)\mathbf{a}(\theta_1) + \sum_{p=2}^{P} r_p(k) q_{p1} \mathbf{a}(\theta_p) + \mathbf{n}_1(k), \tag{2}$$

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 (Chiang & Chang, 2003). 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 $\sigma_{n_1'}^2$ (Chiang & Chang, 2003). Then, (2) can be rewritten as

$$\mathbf{y}(k) = L r_1(k)\mathbf{a}(\theta_1) + \mathbf{n}_1'(k). \tag{3}$$

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

$$\mathbf{R} = E\{\mathbf{y}(k)\mathbf{y}^H(k)\} = L^2 Q_1 \mathbf{a}(\theta_1)\mathbf{a}(\theta_1)^H + \sigma_{n_1'}^2 \mathbf{I}_M, \tag{4}$$

where $E\{\cdot\}$ and the superscript H denote the expectation and complex conjugate transpose, respectively. $\mathbf{I}_M$ is the identity matrix with size $M \times M$. For finite received signal's samples, the received signal correlation matrix $\mathbf{R}$ is replaced by the estimated sample average $\widehat{\mathbf{R}} = (1/N)\sum_{k=1}^{N} \mathbf{y}(k)\mathbf{y}^H(k)$ and N is the total bits of observation. The eigen decomposition of matrix (4) can be expressed as

$$\mathbf{R} = \sum_{m=1}^{M} \lambda_m \mathbf{e}_m \mathbf{e}_m^H = \lambda_1 \mathbf{e}_1 \mathbf{e}_1^H + \mathbf{E}_n \mathbf{\Lambda}_n \mathbf{E}_n^H, \tag{5}$$

where $\lambda_1 \geq \lambda_2 = \lambda_3 = \cdots = \lambda_M = \sigma_{n_1'}^2$ are the eigenvalues of $\mathbf{R}$ and $\mathbf{e}_m$ denotes the eigenvector associated with λ_m for $m = 1, 2, \ldots, M$. Moreover, $\mathbf{e}_1$ and $\mathbf{E}_n = [\mathbf{e}_2, \ldots, \mathbf{e}_M]$ are orthogonal and span the signal and noise subspace corresponding to $\mathbf{R}$, respectively. $\mathbf{\Lambda}_n = \sigma_{n_1'}^2 \mathbf{I}_{M-1}$ is the noise eigenvalue matrix. Furthermore, $\mathbf{e}_1$ spans