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Low complexity metaheuristics for joint ML estimation problems

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ABSTRACT

Joint maximum likelihood (ML) estimation of multiple parameters is an important problem with wide-spread relevance in many domains. The high computational complexity involved in joint ML problems has led to the search for more efficient methods. Efficient heuristic algorithms for joint ML problems can be developed by exploiting the characteristics of the objective functions used in the estimation problem. This paper proposes a novel reformulation of existing heuristic algorithms, which considerably reduces their computational complexity with significant improvement in performance. The method is applicable for joint maximum likelihood estimation problems, with cost functions that exhibit asymptotic separability with increase in observation vector size. The proposed method is adopted to five recently discovered heuristic algorithms and consequently applied to a relevant recent signal processing problem in wireless communication. It is found that the reformulated algorithms deliver both reduced computational complexity as well as better mean square error (MSE) performance. The significant features of the proposed method are substantiated through extensive computer simulation studies.

1. Introduction

Metaheuristic algorithms comprise a major domain of stochastic optimization methods that make use of a heuristic of learned randomness to move forth towards an optimal solution to an estimation problem. They provide a way to tackle problems that are NP-hard as well as for other problems that cannot be addressed through classical optimization techniques. Also, the chance of getting trapped into local optima values is very less for metaheuristic algorithms due to the wide random searches employed in them. Many of these algorithms are biologically inspired, which mimic natural phenomena [1,2]. Recently there had been a proliferation of such algorithms [3,4].

Metaheuristic algorithms are found to have widespread applications in diverse domains. Typical areas in which metaheuristic algorithms find applications include machine design [5], communication engineering [6], wireless sensor networks [7], satellite image processing [8], speech recognition [9], data mining [10], digital signal processing[11], optics [12], chemical engineering [13–15], biochemical processes [16] etc. They are of interest in multimodal optimization problems [17] and joint maximum likelihood (ML) estimation problems for various cutting-edge signal processing requirements.

ML optimization in real-valued search spaces may have a prohibitively high computational complexity. Hence, there had been attempts to find out low-complexity suboptimal approximations to ML problems [18] and also to nonlinear least

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square problems [19]. Many of these algorithms are based on developing certain projection matrices to project the objective functions into low-dimensional subspaces. Typically an M-dimensional search problem is converted into a sequence of 'M' one-dimensional problems. But the calculation of projection matrices involve a significant computational overhead in each cycle. Approximations to reduce the computational burden significantly reduce the MSE performance [20].

In this paper we formulate a low-complexity general modus applicable to several heuristic algorithms that can be used for joint ML problems. There has been attempts to reduce the computational burden of metaheuristic algorithms. Proper initialization is one way of improving the performance of algorithms. Thus the algorithm will be able to explore the search space in a more efficient manner and discover better solutions. In [21], the nonlinear simplex method is used to initialize the swarm of the PSO algorithm. Experiments with well-known benchmark problems demonstrate that better convergence and success rates can be obtained through this approach.

The work outlined in [22] proposes a continuous tabu simplex search (CTSS) method based on the Nelder–Mead simplex algorithm. The method is effective in accelerating convergence towards a minimum within a detected promising region. The paper [23] introduces a directed tabu search (DTS) for non-linear global optimization. The Nelder–Mead method is applied at every non-improving trial point obtained by the TS neighborhood search. The Cyber Swarm Algorithm (CyberSA) in [24] combines PSO and a scatter search/path relinking (SS/PR) template. An external memory, containing a reference set of the best solutions observed throughout the evolution history is used to improve the performance. The search capability of CyberSA is improved in [25] by incorporating additional ideas from TS and SS/PR. Multi-level (short term, middle term, and long term) memory manipulations are designed to reinforce the search process.

In [26], the convergence rate of harmony search algorithm is improved by fine-tuning certain parameters through successive generations. The efficacy of the method is demonstrated through various practical examples. The method outlined in [27], makes use of the velocity information of the particles in a particle swarm optimization (PSO) algorithm for adaptive parameter finetuning. In the algorithm proposed in [28], search experience from previous generation is used to generate a search-direction matrix that gives impressive exploration and exploitation capabilities in the search space.

Compared to all these methods, the distinguishing feature of the work outlined in this paper is that it derives a method that significantly reduces the computational effort and improves performance through faster convergence and lesser MSE for joint ML problems. It should be noted that none of the methods reviewed above considers the joint ML premise that is extremely relevant in contemporary applications. We frame our method in the context of objective functions that exhibit the property of separability with increase in observation vector size called asymptotic separability. To substantiate the importance of this formulation, we apply it to a very relevant estimation problem in fourth generation (4G) wireless communication, which is the joint estimation of carrier frequency offsets (CFO) of multiple users in an orthogonal frequency division multiple access (OFDMA) uplink [29].

The paper is organized as follows. Section 2 presents a general signal model for joint ML estimation of multiple parameters. In Section 3, we introduce five metaheuristic algorithms that can be used for such estimation problems. In Section 4, we develop a new initialization to such algorithms, which can drastically reduce their computational complexity in the context of an important contemporary problem in wireless communication, viz. joint CFO estimation in the OFDMA uplink. In Section 5, we give the details of the simulation studies and performance evaluation. Section 6 gives the conclusions.

2. A signal model for joint ML estimation of multiple parameters

Consider the signal model given below.

$$\mathbf{r} = \mathbf{A}(\boldsymbol{\varepsilon})\xi + \mathbf{v} \tag{1}$$

where, $\mathbf{A}(\boldsymbol{\varepsilon}) = [\mathbf{A}(\varepsilon_1), \mathbf{A}(\varepsilon_2), \ldots, \mathbf{A}(\varepsilon_M)]$. This is a signal received at a suitable receiving system. $\mathbf{A}(\boldsymbol{\varepsilon})$ could be the steering matrix in a direction of arrival (DOA) estimation problem corresponding to M unknown DOAs, represented by the vector $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_M]^T$. In such a case, we can consider $\boldsymbol{\xi} = [\xi_1, \xi_2, \ldots, \xi_M]^T$ as the $M \times 1$ vector of unknown target complex amplitudes. Both these vectors need to be estimated. Alternatively, $\mathbf{A}(\boldsymbol{\varepsilon})$ could be the augmented matrix of the signal components of M users in an OFDMA uplink system, $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_M]^T$ is the CFO vector to be estimated and $\xi = [\xi_1^T, \xi_2^T, \ldots, \xi_M^T]^T$ is the augmented vector of the unknown channel impulse responses of the M users. $\mathbf{v}$ is the additive noise. Assuming $\mathbf{v}$ to be white Gaussian with zero mean and variance σ^2, the likelihood function based on (1) is,

$$\psi(\boldsymbol{\varepsilon}, \xi) = \frac{1}{(\pi\sigma^2)^N} \exp\left\{-\frac{1}{\sigma^2}[\mathbf{r} - \mathbf{A}(\boldsymbol{\varepsilon})\xi]^H[\mathbf{r} - \mathbf{A}(\boldsymbol{\varepsilon})\xi]\right\}. \tag{2}$$

Maximizing this likelihood is equivalent to minimizing

$$\Lambda(\tilde{\boldsymbol{\varepsilon}}, \tilde{\xi}) = \|\mathbf{r} - \mathbf{A}(\tilde{\boldsymbol{\varepsilon}})\tilde{\xi}\|^2, \tag{3}$$