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PSOGSA-Explore: A new hybrid metaheuristic approach for beampattern optimization in collaborative beamforming

S. Jayaprakasam*, S.K.A. Rahim, Chee Yen Leow

Wireless Communication Centre, Universiti Teknologi Malaysia (UTM), Johor 81310, Malaysia

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ABSTRACT

A conventional collaborative beamforming (CB) system suffers from high sidelobes due to the random positioning of the nodes. This paper introduces a hybrid metaheuristic optimization algorithm called the Particle Swarm Optimization and Gravitational Search Algorithm-Explore (PSOGSA-E) to suppress the peak sidelobe level (PSL) in CB, by the means of finding the best weight for each node. The proposed algorithm combines the local search ability of the gravitational search algorithm (GSA) with the social thinking skills of the legacy particle swarm optimization (PSO) and allows exploration to avoid premature convergence. The proposed algorithm also simplifies the cost of variable parameter tuning compared to the legacy optimization algorithms. Simulations show that the proposed PSOGSA-E outperforms the conventional, the legacy PSO, GSA and PSOGSA optimized collaborative beamformer by obtaining better results faster, producing up to 100% improvement in PSL reduction when the disk size is small.

1. Introduction

Collaborative beamforming (CB) has been receiving favourable attention in the research community, especially for the energy constrained and throughput gain centred networks [1–5]. In transmit CB, decentralized nodes act as a distributed antenna array and adjust the initial phases of their carriers to form a beam collaboratively towards an intended receiver [1].

In many practical scenarios, the collaborating nodes will have random locations, thus forming a random antenna array. The randomness of the nodes' locations results in high and asymmetrical sidelobes in the sample beampattern [1,6]. High sidelobe is undesirable in a beamformer as it will cause interferences to unintended users.

Sidelobe suppression problem has been widely discussed by researchers in the context of centralized antenna array [7–19]. Metaheuristic algorithms such as genetic algorithm (GA) [14], particle swarm optimization (PSO) [17,16,15] and evolutionary algorithm (EA) [18,11,19] are popular approaches that has been undertaken to solve this problem in the past. However, most of these researches exploit the array's geometry to achieve beampattern with reduced sidelobe, whereas position of the nodes in CB scenarios usually cannot be arranged.

A node selection algorithm to control the sidelobe in CB has been proposed in [20] but the proposed algorithm is feasible only when large number of nodes is available for collaboration. A collaborative null steering beamformer is presented in [21]. The peak sidelobe (PSL) reduction method in this paper suggests careful positioning of the BS/AP, and does not suit practical scenarios where the nodes' geometries are fixed. Moreover, it is more desirable to reduce the overall sidelobe value rather than nulling at a certain direction as the directions of unintended users are usually unknown.

Gravitational search algorithm (GSA) is a relatively new nature based optimization algorithm based on the law of gravity [22]. Combination of GSA and PSO has been proposed in [23] and it has been shown that the hybrid of PSO and GSA can provide improved results for general mathematical functions. However, both [22,23] are presented as generic algorithms and has not been specifically applied to solve the problem of sidelobe minimization in CB.

This paper proposes a metaheuristic approach called Particle Swarm Optimization-Gravitational Search Algorithm-Explore (PSOGSA-E) to optimize the beampattern of collaborative beamforming. While previous researchers considered optimizing the array geometry, this new version of hybrid GSA and PSO focuses on optimizing the weight vector of the beamformer to achieve lower sidelobes. The proposed technique combines the search method of particle swarm optimization (PSO) and gravitational search algorithm (GSA) with enhanced exploration ability to achieve lower PSL and is more cost effective to tune compared to the legacy optimization methods.

* Corresponding author. Tel.: +60 125554990.
E-mail address: suhanya.jayaprakasam@gmail.com (S. Jayaprakasam).

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The novel contributions in this paper are as follows:

1 This is the first time any variant of the metaheuristic algorithm PSOGSA is applied to solve the sidelobe reduction problem in collaborative beamforming.
2 A new and simpler version of PSOGSA called PSOGSA-E is proposed in this paper. Only one parameter need to be tuned in this proposed version as compared to at least three parameters in the legacy PSO and PSOGSA.
3 The proposed algorithm utilizes both exploration and exploitation to find the global optimum and successfully avoids the problem of premature convergence.

The rest of the paper is organized as follows. System models and the objective function of the problem are introduced in Section 3. Section 2.2 discusses the recent works in the field of beampattern optimization in CB and also the existing hybrid PSOGSA algorithms. Section 4 details the flow of PSO, GSA and the PSOGSA. The proposed PSOGSA-E algorithm is explained in detail in Section 5. The performance of the proposed technique is studied in Section 6. This is finally followed by conclusions in Section 7.

2. Related works

2.1. Beampattern optimization in collaborative beamforming

Very few literatures exist on beampattern optimization in distributed beamforming. Most initial studies on distributed beamforming focus on carrier and phase synchronization issues. Beampattern optimization in distributed array has only recently gained attention. In [17], a simple 1-bit feedback from the receiver is used to allow distributed nodes to iteratively perturb their phases until nulling is achieved at the directions of interferences. Yet another nulling scheme for distributed beamforming has been suggested in [9] for WSN application. According to this scheme, available nodes are divided into subsets and a control node will pick a suitable subset to achieve nulls at predetermined interference directions. This scheme, however, can only be applied for cases where there are a very large number of nodes available for beamforming.

In practical cases of distributed beamforming, though, the directions of interferences are usually unknown. Therefore, it is more useful to achieve lower overall sidelobes rather than just nulls at certain directions.

The author in [16] has recently proposed a quasi-circular node selection method to reduce the PSL in distributed beamforming using a variation of the PSO algorithm. Similarly, node selection method based on uniform space linear array was done using GA for PSL minimization in [24]. Both papers adopt node selection method, which is basically the array synthesis method to achieve PSL reduction. Using node selection method on distributed beamforming which has fixed destination position will cause some nodes to be used more often than others. Not all the nodes will be utilized and the network might exhaust the energy of certain frequently used nodes.

PSL minimization in distributed beamforming has also been adopted by using GA based weight synthesis method [25,26]. However, it has been noted in [25]that the minimization of PSL comes at the cost of wider beamwidth.

2.2. Recent works on hybrid PSOGSA

The hybrid PSOGSA algorithm was first introduced by Mirjajili et al [23]. The algorithm combines PSO and GSA by replacing the local search scheme in PSO with the local search based acceleration of GSA-which takes into account both the local best and worst during every iteration-during the velocity update step. Thus, the paper integrates the exploitation ability of PSO with the exploration ability of GSA, and the proposed PSOGSA outperforms most benchmark optimization functions compared to the conventional PSO and GSA.

The interest in further exploring and applying the PSOGSA gained attention only in these past couple of years. The algorithm proposed in [23] has been used directly for solving optimal reactive power dispatch problem in [27] and provided better power loss compared to the conventional GSA and multiobjective evolutionary algorithm. It has also been successfully applied to find the optimal parameters in fuzzy controller tuning [28,29] and to identify the best placement and size of distributed generation units that satisfies multiple objectives [30].

Several other works have resorted to introducing their own version of hybrid PSOGSA to solve their optimization problem. Unlike [23], the work in [31] retains the local search scheme of PSO and introduces the GSA based acceleration as an additional element during the velocity update. This new version of algorithm is used to solve a dual objective problem to produce optimal collision free trajectory for mobile robots and provides faster convergence compared to the legacy PSO and GSA. The work in [32] adopted the original velocity update suggested by [23], however included a fuzzy logic controlled maximum velocity constraint to avoid divergence in the PSOGSA method. Promising results were obtained when the algorithm was applied to solve economic dispatch problems with valve point effect.

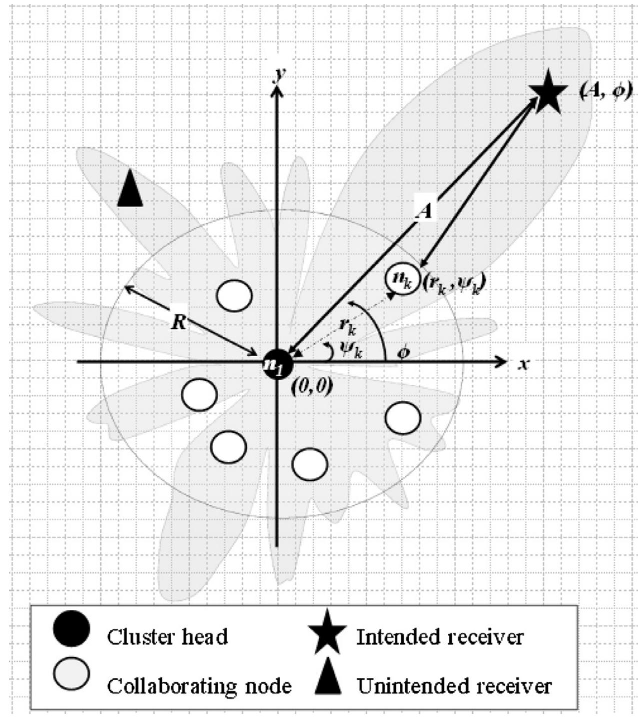

Fig. 1. Geometrical configuration of nodes in collaborative beamforming.

3. System description and problem formulation

Consider a network with K number of nodes located randomly following a uniform distribution in a disk area of R, as shown in Fig. 1. One of the collaborating nodes is chosen as the reference node, known as the cluster head (CH). The node locations are represented in polar coordinates where $\mathbf{r} = [r_1, r_2, \ldots, r_K] \in [0, R]$ and $\boldsymbol{\psi} = [\psi_1, \psi_2, \ldots, \psi_K] \in [-\pi, \pi]$. The location of the node $k = [1, 2, \ldots, K]$ is therefore denoted as (r_k, ψ_k). The azimuth angle of the