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Review Paper

Geometric Configuration Optimization for Baseline Interferometry

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Abstract

One of the necessary parts for settlement of baseline interferometric arrays which are used in radio astronomy is to design geometric configuration of the array in a way that most effective results could be achieved. In VLBI imaging the uv plane coverage is a key factor for obtaining better sampling of signals. In this paper the configuration of antenna arrays are optimized by means of PSO and its multi-population version MPSO. By presenting some simulation results, effectiveness of methods, especially for MPSO will be shown.

Keywords: Baseline interferometry, antenna array optimization, particle swarm optimization.

Introduction

Observation of distant astronomic objects has always motivated the people to invent and utilize high tech systems performing in outer space or on the Earth. Modern radio astronomy is not only based on single location telescopes, but it vastly uses the interferometric methods for arrays of antennas. VLBI (Very Large Baseline Interferometry) is the technique of obtaining samples of radio signals from astronomic objects by distant antennas on Earth-based array. This makes it possible to have a larger eye on the sky by means of calculating correlation between signals from various couples of antennas. However the data samples are often not spatially rich, but the effect of Earth rotation is to obtain broader region of observation. It could be shown that the visibility function V (u, v) in uv plane is the Fourier transform of radio source image I (x, y) in the xy plane[1].

$$V(u, v) = F[I(x, y)] \quad (1)$$

However the effects of sampling, gain and noise of the channel should be mentioned as convolution of main visibility function by an overall measurement function B (u, v).

$$V_{dirty}(u, v) = V(u, v) * B(u, v) \quad (2)$$

The dirty visibility function could be inverse Fourier transformed to give the dirty image I_{dirty}.

$$I_{dirty}(x,y) = F^{-1}\{V_{dirty}(u,v)\} \quad (3)$$

One of the main tasks to be done after collecting observation data is to deconvolve dirty signals to obtain estimation for source signal. Various methods for deconvolution of VLBI images are introduced in literature. The most basic and utilized one of those method is CLEAN algorithm[2], in which the result estimated image is obtained by iterative processes on dirty signals. This method often needs some manipulations by human user. Some other deconvolution methods are also proposed based on the concept of entropy maximization[3]. Entropy based methods are suitable mostly for data of high quality and enough number of samples to estimate the probability density of data appropriately. By estimating source signal in a way maximizing some entropy measure, the deconvolution task could be done. Some recent methods based on compressive sensing are proposed especially for the case of sparse data[4,5].

Another task for increasing the performance of baseline interferometry is to optimize the configuration of antenna array in a way that broader regions of uv plane could be observed and the final estimated result have the most similarity to the picture of radio source object. The task of configuration optimization is often a pre-settlement operation for baseline interferometry. But for the case of space borne interferometric astronomy, the configuration of spacecrafts could be changed on demand.

For optical telescopes array, the optimal configuration problem is studied in Mugnier *et al.*[6] Since the optimal selection of parameters for deep space network arrays is considered to be a complex problem, Jones[7] has surveyed some constraints on the array configuration. Considering some sort of criteria such as compactness of configuration, minimum and maximum aperture, and flexibility, some requirements are obtained for the optimum array design. By using multiobjective optimization, Cohanim *et al.*[8] developed a design method for array of radio telescopes, which considers the imaging performance and cable length as its main objectives. In that paper, some well known array topologies are assumed and then some improvements to them are obtained. A *sieving* algorithm for optimization of array configuration is proposed in Su *et al.*[9]. The sieving algorithm removes elements form array to fit the resulted uv coverage to a predefined sketch in the coverage plane. To remove the points, some weights are assigned to the points in each iteration and those weights are used to determine the points to be removed.

There is also recent interest in utilization of search based algorithms in designing arrays of antennas. Jin and Rahmat-

Samii[10] introduced PSO (particle swarm optimization) method for designing various configurations of radio antenna arrays to obtain maximum coverage and minimum sidelobe level of the synthesized beam. A comparative study of three different approaches for the task of radio antenna array optimization is presented in Oliveri *et al.*[11]. The three methods includes GA (genetic algorithm), ADS (almost difference sets) and PSO.

In this paper it is shown how to improve PSO in a way that optimum solutions of problem could be found faster and more accurately. The main improvement in PSO used here, is to define multiple subpopulations of particles rather than only one population. The method is used to find locations of antennas to have an optimum coverage, and satisfaction of some constraints on problem. In section 2, the PSO and its improved multi-population version are discussed, then the procedure of solving optimal configuration problem by those methods are described and simulation results are presented in section 3.

PSO and MPSO

Particle swarm optimization is one of the vastly used search based optimization algorithms and proposed by Kennedy and Eberhart[12]. In recent years, PSO is utilized to solve many optimization problems in various applications[13]. The conventional PSO is based on swarm intelligence of some number of simulated particles which search the space of possible solutions and share the information about their location fitness with other particles in population. By means of some simple updating equations, the positions of particles change in each iteration and converge to some optimum solution in search space. The main procedure of PSO is as follows. The fitness function of the problem is defined to assign a fitness measure to every position (solution) in parameter space. Several particles are positioned randomly in the search space. The best position due to fitness function among all particles is named as *gbest* and for every particle i, the best previous position is named as $pbest_i$.

Then the updated velocity of particles are calculated from those information as below:

$$v_i\,(t+1) + w\,v\,(t) + r_1 c_1\,(gbest - x_i(t)) + r_1 c_1\,(\rho best_i - x_i(t)) \qquad (4)$$

In this equation, w is inertia factor, r_1 and r_2 is random numbers and c_1 and c_2 are some constant numbers. After updating velocity vectors for each particle, the new position of particles are calculated by adding the velocity vector to current position.

$$x_i\,(t+1) = x_i\,(t) + vi\,(t+1) \qquad (5)$$

The procedure continues iteratively till some criteria (such as exceeding some predefined number o iterations) is met.

In conventional PSO, all the particles are assumed to be from a single population and share information with all other ones. But it might be appropriate for some problems to have more than one population, independent to each other or having some kind of information sharing. In MPSO (multi-population PSO), for each subpopulation k there is a $gbest_k$. A particle in a subpopulation is affected only by information within that same subpopulation. In this paper it is shown that MPSO could be more effective than conventional PSO for the problem of optimal geometric configuration of baseline interferometric antenna arrays.

Optimization of Array Configuration

In this section the geometric configuration of an example array is optimized by PSO and MPSO. The locations for antennas in a square area should be determined in a way that best *uv* plane coverage could be achieved. The Earth rotation effects are also considered.

For the first case, the problem is to decide locations of four antennas in a limited area. This problem is solved by means of both PSO and MPSO. The geometric configuration and corresponding *uv* plane coverage as solved by PSO are depicted in figures 1 and 2 respectively.

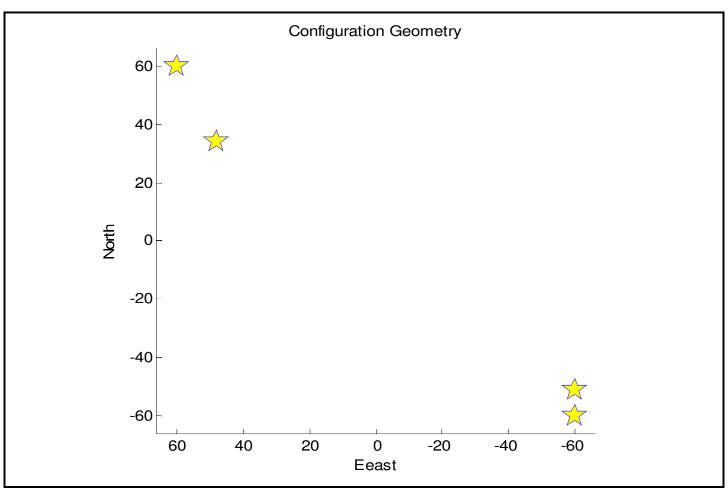

Figure-1
Configuration Geometry for four antennas determined by PSO

The same problem is also solved by means of MPSO with equivalent parameters. The results are shown in figures 3 and 4. The *uv* coverage as resulted by utilizing MPSO shows better characteristics of covering more areas in *uv* plane. To show how MPSO could find the solution faster than PSO, in figure 5 convergence curves of the two methods are shown. This two curves show that the MPSO method has found the solution that minimizes objective function faster than PSO.

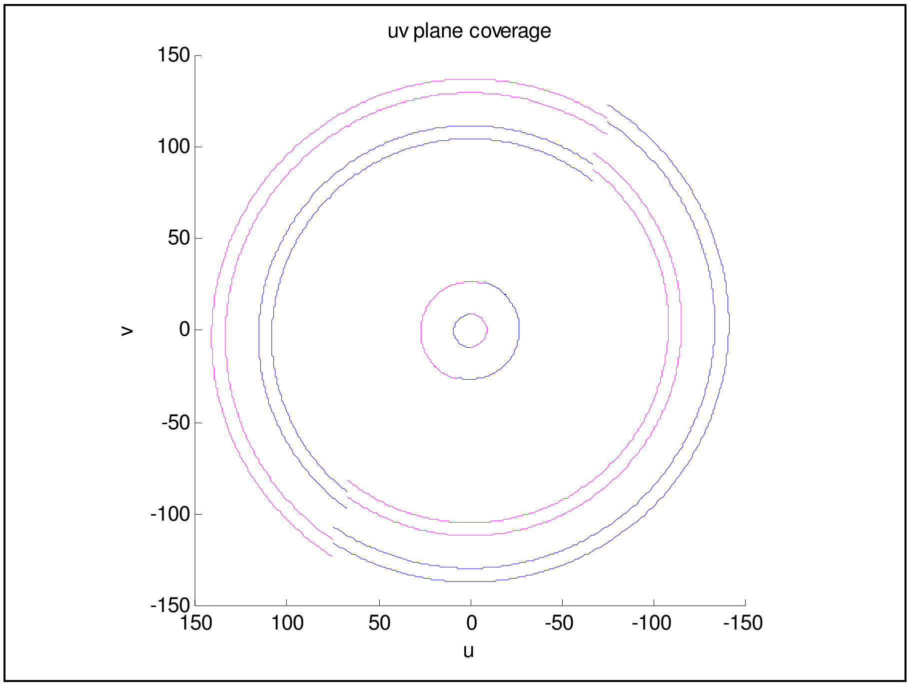

Figure-2
Resulted *uv* coverage for configuration shown in figure 1

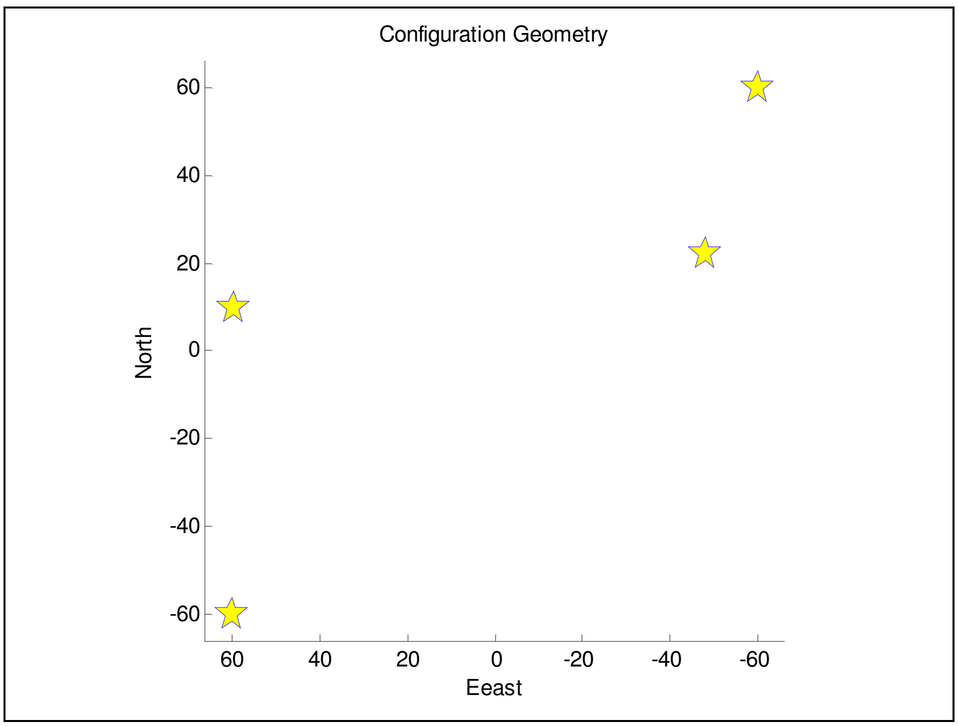

Figure-3
Configuration Geometry for four antennas determined by MPSO

For another case, the problem of choosing locations for ten antennas is also solved by means of MPSO which shows good results as seen by *uv* coverage characteristics. The resulted configuration and corresponding *uv* coverage are shown in figures 6 and 7.

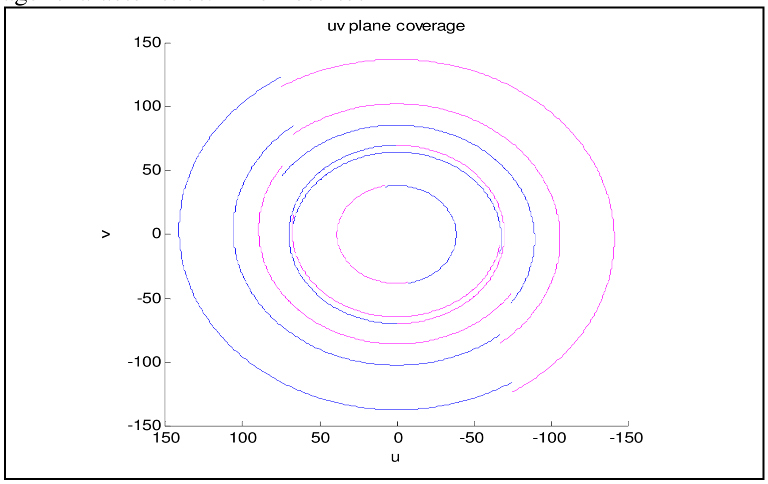

Figure-4
Resulted *uv* coverage for configuration shown in figure 3

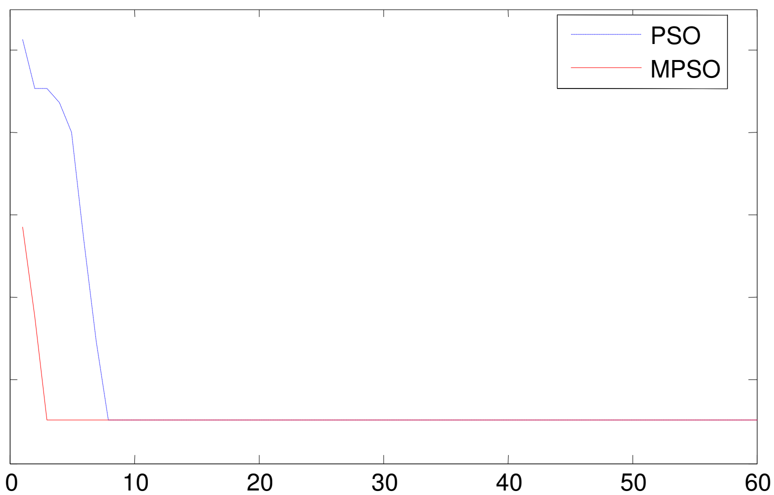

Figure-5
Convergence curves (Objective in each iteration) for PSO and MPSO

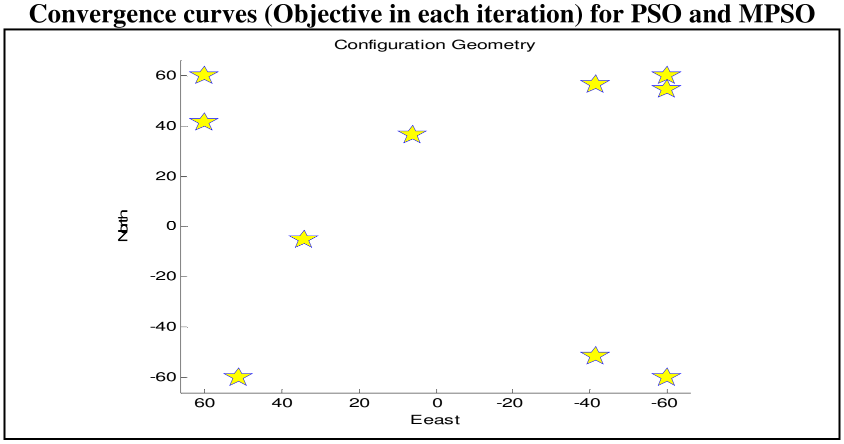

Figure-6
Configuration Geometry for ten antennas determined by MPSO

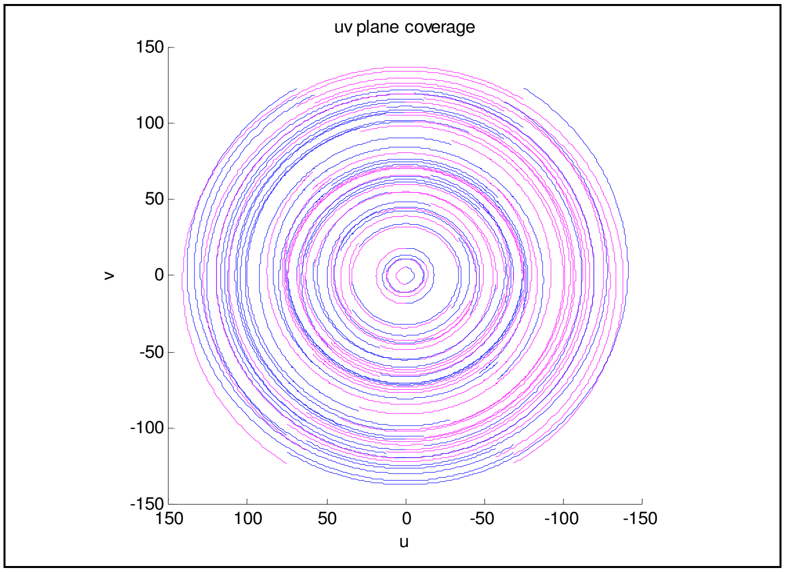

Figure-7
Resulted *uv* coverage for configuration shown in figure 6

Conclusion

In this paper the problem of optimizing array configuration for baseline interferometry is addressed and solved by means of PSO and MPSO. Simulation results showed that both PSO and MPSO could be used appropriately for selecting optimal locations for antennas in order to obtain good characteristics of *uv* plane coverage. The results showed that MPSO could be more effective than PSO as it is faster in finding better solutions.

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