Optimal Design of Thinned Array by Using Hybrid Genetic Algorithm

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In this paper, we present a hybrid genetic algorithm for thinning a planar array by combing conventional GA with the moving least square (MLS), which enhances the convergence rate and the global search performance. The MLS is used to estimate local interpolation functions from non-uniform sample data, which are population and fitness in GA, and to find new better populations from the interpolated functions. By adding these better populations into the next generation, the MLS-GA shows better search performance of the global optimum and a faster convergence rate than those of the conventional GA. In order to verify the proposed MLS-GA, we applied the proposed algorithm to thinning a uniformly spaced planar array of 10x10 elements. Thinning objective is to lower the peak SLL and the gain loss.

***Index Terms*—Genetic algorithms, moving least square method, thinned array antenna.**

I. Introduction

THINNING in an antenna array is to switch off some antenna elements with a fixed rate from the full array system without causing major degradation of performances as the gain, the half power beam width (HPBW), and the side love level (SLL). In general, thinned arrays reduce the power consumption and the complexity of the beamforming network [1],[2]. However, the reduction of the number of active elements may lead lower gain or higher SLL compared to full elements.

In recent years, optimization techniques like the genetic algorithm (GA) or simulated annealing (SA), which do not require the gradient information of the objective function, have been applied to thinning array [3],[4]. These methods can find the global optimum in case of smooth objective function or fitness. However, when an objective function has many local optima, these methods tend to converge to one of the local optima. In order to prevent this problem, these methods require more populations and iterations.

In this paper, we propose a new hybrid GA in order to improve the convergence rate and the global search performance by exploiting the moving least square (MLS) method. The MLS constructs the local polynomial function from the non-uniform sample data and interpolates the sample data [5]. By applying the MLS to the population and fitness values, we constructed the interpolated fitness function. Then, from the interpolated fitness function, we obtained the populations that are better than the fittest population of the previous generation and added them to the population of the next generation, which enhanced the rate of convergence and the possibility of the global optimum search.

In order to verify the proposed algorithm, we applied it to thinning a 10x10 uniformly spaced planar array to minimize the gain loss and the peak SLL.

II. Proposed Hybrid GA based on MLS

The MLS is a local approximation method used to estimate the value at the arbitrary point by constructing the local interpolation functions using the scattered data or the non-uniform sample data. A local interpolation function at the local domain D can be represented as [5]

$$\tilde{f}_D(\mathbf{x}) = \sum_{k=1}^{K} p_k(\mathbf{x}) a_{k,D}(\mathbf{x}) = \mathbf{p}^{\mathrm{T}}(\mathbf{x}) \mathbf{a}_D(\mathbf{x}) \tag{1}$$

$$\mathbf{p}(\mathbf{x}) = \{p_1(\mathbf{x}), p_2(\mathbf{x}), \ldots p_K(\mathbf{x})\} \tag{2}$$

$$\mathbf{a}_D(\mathbf{x}) = \{a_{1,D}(\mathbf{x}), a_{2,D}(\mathbf{x}), \ldots, a_{K,D}(\mathbf{x})\} \tag{3}$$

where the subscript D denotes the local domain of estimation, $\tilde{f}_D(\mathbf{x})$ denotes the local interpolation function, $p_k(\mathbf{x})$ denotes the k^{th} basis function, K denotes the number of the basis functions, and $a_{k,D}(\mathbf{x})$ denotes the k^{th} coefficient at the local domain D. Also, $\mathbf{x}$ is the position vector which acts as a population. In general, the basis function for the MLS consists of the polynomial functions. For example, the basis function of the quadratic order is given as $\mathbf{p}(\mathbf{x}) = \{1, x, y, x^2, xy, y^2\}$. To obtain the coefficient vector $\mathbf{a}_D(\mathbf{x})$, we used the weighted least square method [5]. Then, we find the local optimal population by applying the conjugate gradient (CG) method to the local interpolation function in each local domain as shown in Fig. 1.

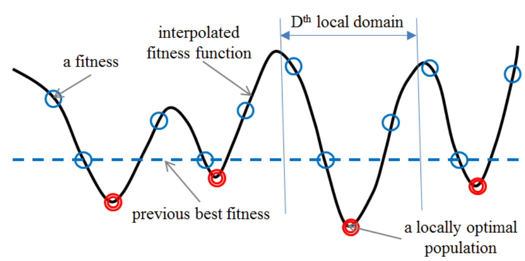

Fig. 1. Interpolated fitness function

If the local optimum at the local domain D is better than the previous best fitness, as shown in Fig. 1, the population becomes a new population-candidate for the parents of the next generation. Fig. 2 shows the flow chart of the proposed MLS-GA. The MLS interpolation is performed once a generation. For computing efficiency, the MLS interpolation is performed only when a new population is generated at the corresponding local domain D.

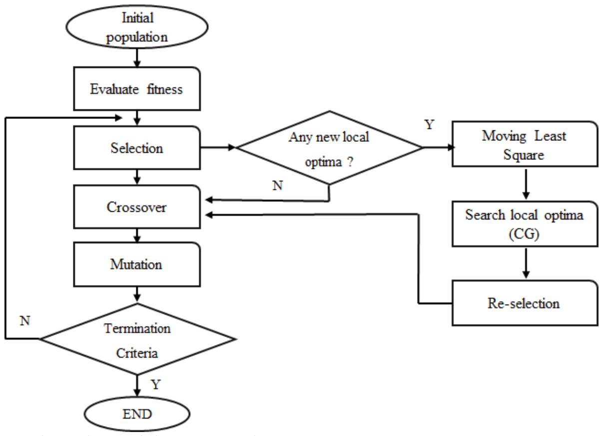

Fig. 2. Flow chart of the proposed MLS-GA

III. Thinning 10x10 Planar Array

In this work, we used a planar antenna array with uniform spacing $d=\lambda/2$ and 10x10 elements. The beam pattern in the planar array can be calculated as [6]

$$F(\theta,\phi)=\sum_{n=1}^{N}\sum_{m=1}^{M} w_{nm}\exp\left[-j\frac{2\pi}{\lambda}\{x_n(u-u_0)+y_m(v-v_0)\}\right] \quad (5)$$

where

$$u=\sin\theta\cos\phi,\ v=\sin\theta\sin\phi \quad (6)$$

For the convenience, we assumed that the planar array has the origin symmetry and designed the 1st quadrant of the planar array. For the GA parameters, we used the number of populations N_P=100, the number of iterations N_G=50, and the probability of mutation P_u=0.05. In this model, thinning objective is to minimize the gain loss and the peak SLL while thinning coefficient is set as 28%. We set the objective function as

$$F(\zeta)=W\left|G_{\text{des}}-G_{\text{cal}}(\zeta)\right|^2+(1-W)\left|PSLL_{\text{cal}}(\zeta)\right|^2 \quad (7)$$

where ζ is a population and W the weighting factor, defined as

$$W=\begin{cases}0\ , & \text{when } G_{\text{cal}}(\zeta)>40\text{dB}\\ 0.8\ , & \text{otherwise}\end{cases} \quad (8)$$

Fig. 3 shows the mean and best value of the fitness according to the generation by averaging the results of 50 trials. To mitigate the effect of the choice of initial populations, we used the same randomized population set for the conventional GA and the MLS-GA. Fig. 4 shows the best thinning quadrant-1 configurations designed by the conventional GA and the MLS-GA, respectively. The gains and peak SLLs designed by the conventional GA and the MLS-GA are compared in Table I. The detail specifications for the application will be represented in the full paper.

IV. Conclusion

In this paper, we propose a new hybrid GA to enhance the convergence rate and the searching performance of the optimal solution based on the moving least square (MLS) method. By using the MLS, we constructed the local interpolation function at each local domain, searched the populations that were superior to those of the previous best fitness, and included them in the new population for the next generation. In order to verify the proposed MLS-GA, we applied it to thinning a uniformly spaced planar array.

Acknowledgments

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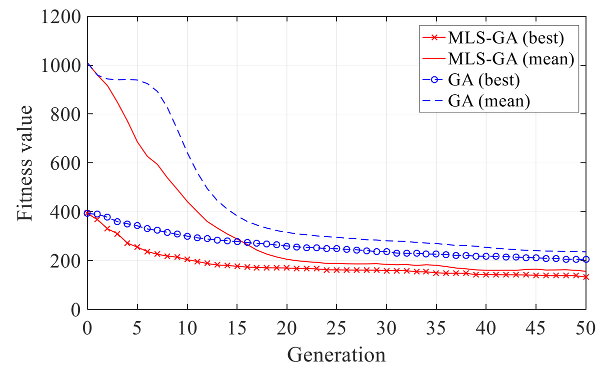

Fig. 3. Average convergence of the GA and MLS-GA over 50 trials

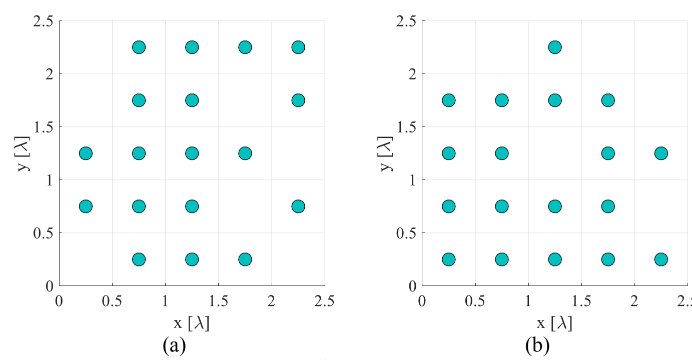

Fig. 4. Best thinning configurations (1st quadrant). (a) GA (b) MLS-GA

TABLE I
Comparison of Gain and Peak SLL

	Gain[dB]	PSLL[dB]
GA	36.86	25.39
MLS-GA	37.89	18.95