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Evaluating Exposure by MIMO User Equipment at 28 GHz Using Optimization Method

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Abstract

With the wide application of 5G networks, the miniaturization and integration of millimeter-wave antennas make it possible to deploy antenna arrays supporting Multiple-Input Multiple-Output (MIMO) technology in mobile terminals, and it also brings challenges to traditional exposure compliance testing. In this work, several swarm intelligence and evolutionary algorithms are applied using vectorized field values to determine the exposure limit of user equipment (UE) installed with a MIMO antenna operating at 28 GHz. This problem presents a significant challenge due to the difficulty in evaluating all possible configurations of the input values. In the past few years, particle swarm optimization (PSO) and differential evolution (DE) algorithms have been widely used in optimization problems. In this study, based on the traditional DE and PSO algorithms, their hybrid algorithm is proposed to evaluate the exposure limit. The results show that the hybrid DE-PSO algorithm proposed in this experiment shows a good accuracy and high efficiency, i.e., the error is less than 6% and the simulation time is reduced by 98% compared to the results by Monte Carlo (MC) simulations with 100,000 times. The proposed method provides a framework for efficiently characterizing the exposure from millimeter wave MIMO UE.

1 Introduction

MIMO technology can multiply the channel capacity of wireless communication system without increasing the frequency spectrum resources[1]. As the local exposure is highly temporally and spatially variant due to the numerous emission combination, it is a great challenge to efficiently evaluate the maximum exposure of the UE when using the MIMO technique. In theory, a thorough evaluation of all possible combinations of input vectors yields worst-case sPD. However, the time cost of this method can be prohibitive.

Stochastic optimization is a class of algorithms which employ some degree of randomness to find optimal solutions. Genetic algorithm (GA) [2], MC simulation [3] and PSO [4] are often used to study the worst-case exposure of multiple antennas. However, such methods are still time-consuming when applied to exposure assessment, and the results are largely dependent on the specific sampling or the initialization used.

In this work, hybrid DE-PSO algorithms is applied to estimate the maximized peak spatial-average power density (mpsPD) of a MIMO UE[5]. Optimization on different spacing (from 0.2 mm to 2 mm) is investigated in this study because the sampling interval significantly influence the assessment efficiency and denser sampling requires much time for optimization. The proposed method provides an efficient approach for evaluating the worst-case exposure of mmW MIMO UE, which may contribute to the on-going study on averaging surface.

2 Materials and Methods

2.1 Power Density Calculation Based on Vectorized Field Values

The total propagating power density into the evaluation surface, sPD is expressed as[6]:

$$sPD(r_0) = \frac{1}{\hat{A}(r_0)} \int_{A(r_0)} \parallel \Re\{\boldsymbol{S}(\boldsymbol{r})\} \parallel \cdot\, \Xi\{\cos^{-1}[\boldsymbol{n}_R(\boldsymbol{r}) \cdot \boldsymbol{n}_A(\boldsymbol{r})]\} d\hat{A}(\boldsymbol{r}) \quad (1)$$

where

$$\boldsymbol{n}_R(\boldsymbol{r}) = \Re\{\boldsymbol{S}(\boldsymbol{r})\} / \parallel \Re\{\boldsymbol{S}(\boldsymbol{r})\} \parallel \quad (2)$$

$$\Xi(\theta) = \begin{cases} 1, & 0 \le \theta < 85^\circ \\ 1 - \frac{(\theta - 85^\circ)}{5^\circ}, & 85^\circ \le \theta < 90^\circ \\ 0, & \theta \ge 90^\circ \end{cases} \quad (3)$$

where $\boldsymbol{n}$ denotes the unit vector perpendicular to the area A. r is the observation point on the averaging area A. In this article, the averaging area A is a square area of 4cm^2; $\parallel \Re\{\boldsymbol{S}(\boldsymbol{r})\} \parallel$ is the magnitude of the real part of the complex Poynting vector **S** at the location **r**;

Peak spatial-average power density ($psPD$) at a center point $\boldsymbol{r}$ on the evaluation surface S is,

$$psPD = \max_{\mathrm{r}}\{sPD(\boldsymbol{r})\} \quad (4)$$

The evaluation of the mpsPD on the evaluation surface S requires the evaluation of the field amplitudes and phases for all possible antenna configurations of the UE, the mpsPD is determined using Formula

$$mpsPD = \max_{\mathrm{r} \in S}\{psPD(\mathbf{r})\} \quad (5)$$

2.2 UE model and Electromagnetic Field Simulation

The numerical model of a UE with two types of 4-element antenna arrays, namely, the 2 × 2 and 1 × 4 type are developed and shown in Figure 1. The dimensions of the

UE are 150 mm (length), 70 mm (width) and 8 mm (thickness), which is consistent with the sizes of 6-inch screen mobile phones. The major components that induce significant impact on EMF distribution are realized in the device.

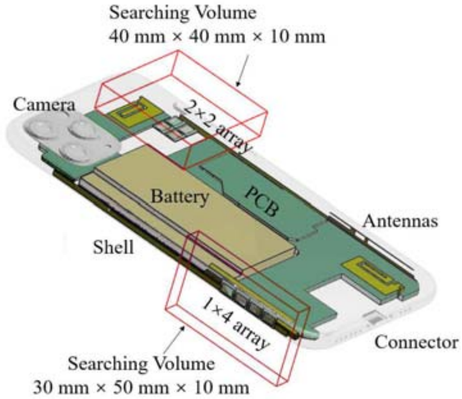

Figure 1. Numerical UE model for 2 × 2 array and 1 × 4 array.

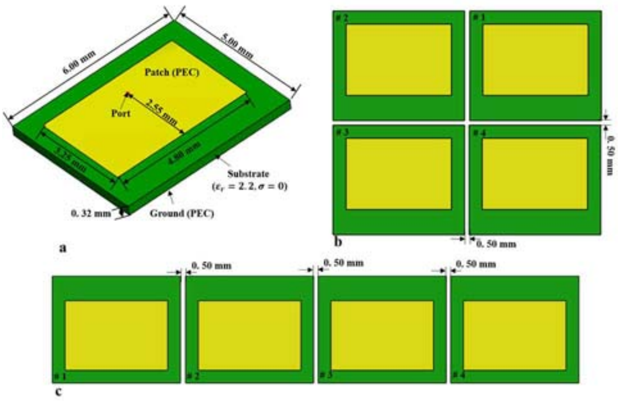

Figure 2. Schematic of the antenna array (a) antenna element, (b) 2 × 2 array, and (c) 1 × 4 array.

The antenna array operates at 28 GHz and is mounted on the back and side of the UE (Figure 2). The simulations are performed with SEMCADX. Finite-difference time-domain method with adaptive grids (varying from 0.05 mm to 0.50 mm, corresponding to 1/200 - 1/20 wavelength in free space) is used to compute the EMF on the evaluate surface. The field of $\boldsymbol{E}(\boldsymbol{r})$ and $\boldsymbol{H}(\boldsymbol{r})$ on the evaluation surfaces for each antenna element are initialized with an incident power of 1 W and a phase of 0°.

2.3 The proposed optimization algorithms

The exposure limit of the MIMO UE can be assessed by determining a suitable combination of variables. As optimization is conducted on the computed $\boldsymbol{E}(\boldsymbol{r})$ and $\boldsymbol{H}(\boldsymbol{r})$, the individuals in a configuration may utilize the calculated electric and magnetic field of various spacing. To demonstrate the performance of the optimizers, MC simulations are conducted to generate the $mpsPD$. To specify, MC simulation using a Latin Hypercube Sampling is repeated 100,000 times.

In the past few years, DE and PSO have emerged as powerful optimization tools for solving complex optimization problems. Both are population-based stochastic search techniques inspired by nature.

DE is an Evolutionary Algorithm proposed by Storn and Price in 1995[7]. In the standard DE, the mutation, crossover and selection operators are three key factors in determining the evolvement of each individual. After these three operators, a newly produced offspring is allowed to the next generation only if it enhances the quality of solution. PSO was proposed in 1995 by Kennedy and Eberhart[8]. It is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality[9]. Each individual in the PSO file is referred to be a particle and assigned a velocity which is dynamically updated based on its own flight memory, as well as those of its companions.

However, both of them have some shortcomings, which sometimes worsen the performance of the algorithm. The main problem is that the lack of diversity leads to suboptimal solutions or slow convergence. In order to improve the performance of these algorithms, we propose a hybrid DE-PSO algorithm. The hybrid algorithms can take either a sequential or a parallel structure.

A. Sequential DE-PSO

This hybrid algorithm is initiated by DE to generate the trial vectors. The generated vector is included in the population if it leads to higher than the parent vectors. Otherwise, the algorithm enters the PSO stage and generates a new candidate solution. The method is repeated iteratively until the required fitness function value is reached. The introduction of the PSO causes perturbation in the population, which in turn helps maintain the diversity of the population. The flowchart of the algorithm is shown in Figure 3.

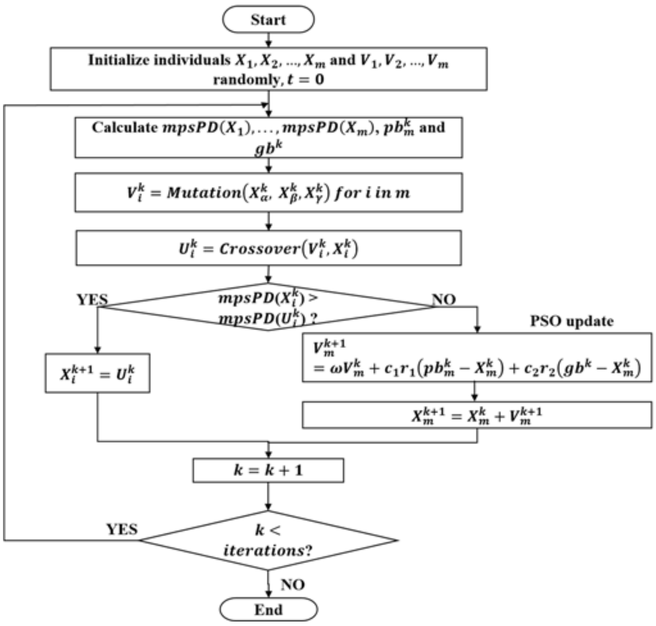

Figure 3. Flowchart of Sequential DE-PSO

B. Parallel DE-PSO

This algorithm initializes N exemplars. DE and PSO algorithms update the exemplars based on their respective protocols. The total updated 2N exemplars are sorted according to their fitness values. The best N exemplars are then chosen as inputs for the next iteration of updates. A flowchart of this algorithm is shown in Figure 4.

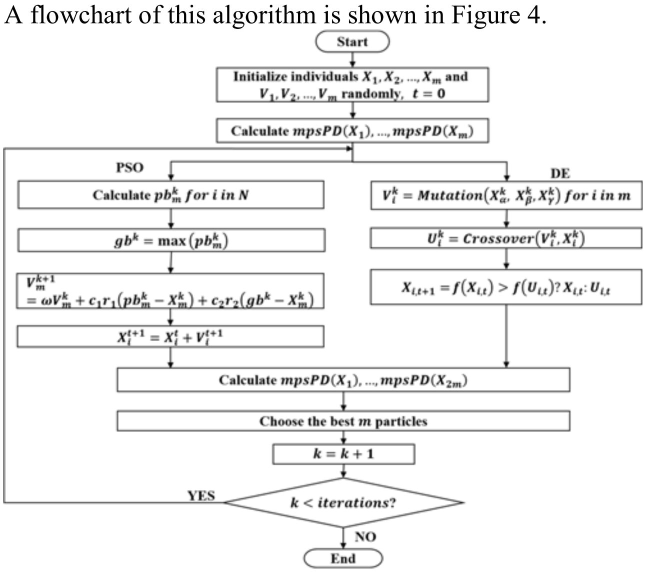

Figure 4. Flowchart of Parallel DE-PSO

3 Results

Figure 5 and Figure 6 compares the mpsPD calculated by various optimizers and at different sampling intervals. The Scheirer-Ray-Hare test [10] reports that there is a statistically significant interaction between optimizer and measurement spacing, i.e., $H = 17.2$, $p < 0.05$ for the 2×2 array while $H = 17.8$, $p < 0.05$ for the 1×4 array. Analyses on main effects show that optimizer and measurement spacing have statistically significant effects on mpsPD for both two kinds of arrays ($p < 0.001$).

For different field spacing, the difference between the mpsPD values obtained by the Sequential DE-PSO algorithm and the Parallel DE-PSO algorithm and the mpsPD obtained by the MC method is not significant. For the 2×2 array, the error of the Sequential DE-PSO algorithm is less than 3% compared with the simulation results of MC method, and the error of the Parallel DE-PSO algorithm is less than 4.5% compared with the simulation results of MC method. For 1×4 arrays, the error of the Sequential DE-PSO algorithm is less than 3.5% and the error of the Parallel DE-PSO algorithm is less than 6% compared with the MC method, and the maximum error occurs when the field spacing is 1 mm.

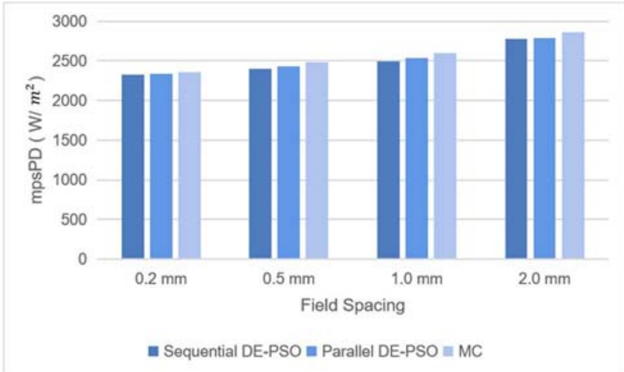

Figure 5. Comparison of the mpsPD of 2×2 array calculated by various optimizers and at different sampling intervals.

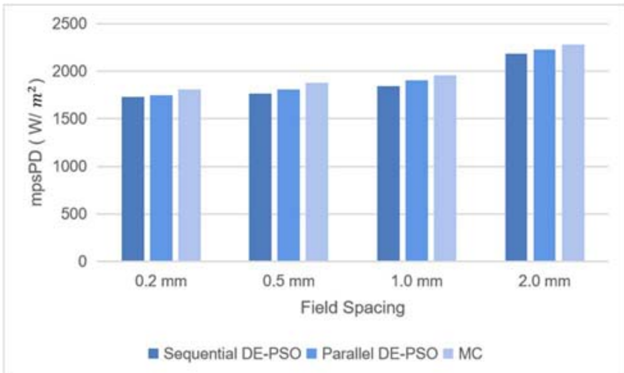

Figure 6. Comparison of the mpsPD of 1×4 array calculated by various optimizers and at different sampling intervals.

A key parameter of the optimizers is the time that the individual operator costs. The number of convergence step for the optimizers is shown in Figure 7 and Figure 8. For 2×2 arrays, there is a significant difference in the number of convergence steps between the Sequential DE-PSO algorithm and the Parallel DE-PSO algorithm. According to the results, it can be found that the number of convergence steps required by the Parallel DE-PSO algorithm is larger than that of the Sequential DE-PSO algorithm, and the difference in the number of convergence steps between the two decreases as the field spacing increases. The maximum difference of 10.2%

occurs when the field spacing is 2 mm and the minimum difference of 1.8% occurs when the field spacing is 1 mm. For 1 × 4 array, the maximum difference in the number of convergence steps between the two algorithms is 9.8% at field spacing of 2 mm and the minimum difference is 3.1% at field spacing of 0.2 mm.

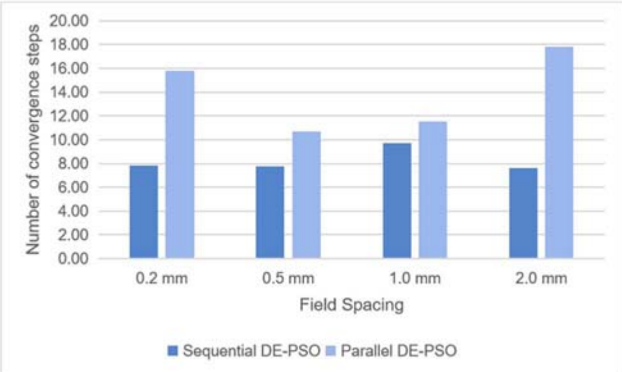

Figure 7. The number of convergence step for the optimizers of 2 × 2 array.

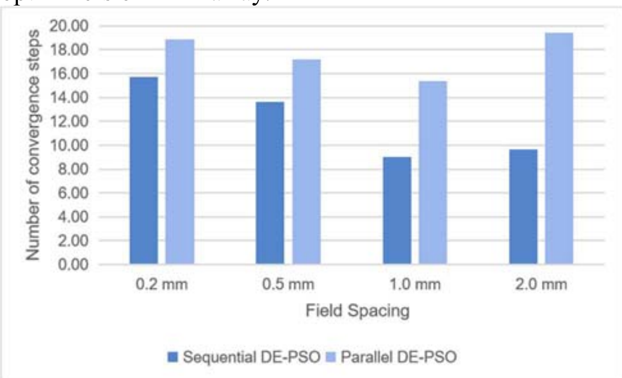

Figure 8. The number of convergence step for the optimizers of 1 × 4 array.

5 Conclusion

Optimizers based on evolutionary algorithms and swarm intelligence are proposed with vectorized field to estimate the exposure limit of mmW MIMO UE. Hybrid DE-PSO algorithm is developed and applied to this problem. The algorithm is found to exhibit superior performance in obtaining the mpsPD. The results show that compared with MC simulation, the error of hybrid DE-PSO algorithm is less than 6%, and the simulation time is shortened by 98%. Sequential DE-PSO algorithm has certain advantages over Parallel DE-PSO in terms of convergence steps. The method fills a gap in the estimation of MIMO UE exposure and provides a feasible optimization scheme that can be used for both simulation and measurement.

Acknowledgements

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