Accelerated current-driven multi-objective topology optimization for compact ultrawide-band MIMO antenna design

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ABSTRACT

In this work, an accelerated current-driven multi-objective topology optimization method is proposed for compact high-isolation ultrawide-band (UWB) multiple input multiple output (MIMO) antenna design. The proposed method takes the current Pareto solutions as the centers to perform fuzzy clustering (FC) and then drives the evolution of individuals in each cluster according to the current distribution characteristics of the clustering centers. Individuals in each cluster purposefully generate antennas with expected performance, thereby accelerating the process of optimization design. The proposed method uses about half the computational cost of traditional algorithms to design a compact (20 × 18 mm²) and high-isolation (>20 dB) UWB MIMO antenna. The proposed method provides a new way for accelerating multi-objective topology optimization with a high design degree of freedom. Also, the optimized antenna is a competitive candidate solution for UWB applications.

1. Introduction

With the development of wireless communication technologies, antenna design is required to consider more performance indexes, and multi-objective evolutionary algorithms (MOEAs) have become an effective alternative to traditional antenna designs using parameter scanning based electromagnetic (EM) simulation tools [1, 2, 3, 4]. Different MOEAs, such as NSGA [5], MOEA/D [6], and MOEA/D-GPSO [7], have been successfully used in antenna size optimization problems where the initial antenna geometry is almost determined and only the dimension parameters are to be optimized. The antenna size optimization highly depends on the design experiences of antenna engineers and also limits the diversity of antenna geometries.

The topology optimization based on binary MOEAs opens a new door for antenna designs because it needs little information on the initial antenna geometry and reduces the reliance on antenna designer's expertise. The topology optimization, also known as pixel optimization, discretizes the design space into small pixels represented by a matrix with “1” (conductor) and “0” (air). Different binary MOEAs in [8, 9] were used to find diverse antenna geometries satisfying the given performance indexes with a high design degree of freedom. However, these design methods are the simple combination of binary MOEAs and EM simulations, and their computational cost will increase with the number of iterations and populations.

The antenna design using the surrogate model reduces the computational burden to a certain extent. However, the collection time of the training and testing datasets for the surrogate model is not negligible. In antenna design, data sets can only be obtained through physical measurement or EM simulation, either way is very time-consuming. Furthermore, the size of the dataset for training the surrogate model is related to the number of variables for which the antenna is to be optimized. Generally, the more variables, the larger the dataset required. Dong et al. used 200 sets of data to train and test BPNN to optimize 10 design variables of the antenna [10] and collected 220 sets of data to train and test the radial basis function neural network (RBFNN) to optimize 10 design variables for the antenna in [11]. Dhaliwal et al. used 40 sets of data to train ANN to optimize the compact fractal antenna with two design variables [12]. Koziel et al. found that 400 sets of training data were appropriate for training kriging surrogates to optimize a triple band uniplanar dipole antenna and a quasi-Yagi antenna with ten design variables [13]. From the above-mentioned results of antenna size optimization based on the surrogate model, the size of the training dataset is tens of hundreds of times the number of optimization variables. In antenna topology optimization, the number of design variables is usually tens or even hundreds, and the number of training sets will also increase greatly, which is a very huge computational cost. Therefore, it is currently not feasible to train surrogate model with fewer data sets for antenna topology optimization.
In this work, an accelerated circuit-driven multi-objective antenna topology optimization method is proposed, which incorporates a priori knowledge of the current distribution into the iterative search process for the first time in order to improve the antenna design efficiency. Specifically, the idea of fuzzy clustering (FC) is firstly introduced into a newly arising MOEA optimizer, i.e., binary multi-objective grey wolf optimizer (BMOGWO) [14, 15], for the population division. MOGWO has demonstrated its superior optimization performance compared with the classical multi-objective particle swarm optimizer (MOPSO) [16] and multi-objective evolutionary algorithm based on decomposition (MOEA/D) [17] due to its social leadership and hunting technology [14]. Then, the current distribution of the cluster centers drives the update of the individuals in the iterative process.

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The experimental results show that the proposed method has a better convergence and only spends nearly half of the time on obtaining the satisfactory design compared to some classical MOEAs. Also, the resulting UWB MIMO antenna has a compact size of 20 mm × 18 mm, an ultrawide working band operating from 2.85 to 12.5 GHz, and good isolation higher than 20 dB.

### 2. Current-driven multi-objective antenna topology optimization

Although MOEAs have brought many conveniences, a priori knowledge of antenna design is seldom considered in the MOEA-based optimization process. In traditional antenna design, the current distribution is of vital importance in determining antenna performance. Therefore, in our proposed method, the influence of the current distribution on antenna structure is integrated with the multi-objective optimizer. First, we divide the population into three clusters based on FC to gather individuals with the same characteristics. Then the current distribution of cluster centers drives the update of the individuals in the iterative process.

### Table 1. Comparison of computational cost between the proposed method and traditional binary MOEAs.

| Method type   | Optimization approach | Number of EM simulation | CPU Time/h* | Total | Relative (%) |
|---------------|-----------------------|-------------------------|-------------|-------|--------------|
| Traditional   | BMOPSO                | 30 × 50                 | 20.8        | 98.1  |              |
| Traditional   | NAGA-II               | 30 × 50                 | 20.7        | 97.6  |              |
| Traditional   | BMOGWO                | 30 × 50                 | 21.2        | 100   |              |
| Traditional   | NAGA-III              | 30 × 47                 | 20.1        | 94.8  |              |
| Current-driven| Proposed method       | 30 × 28                 | 11.5        | 54.2  |              |

* Each electromagnetic (EM) simulation runs on a PC equipped with a 64-bit operating system, 16 GB RAM, 3.7 GHz i5 processor. The PC supports parallel computing of four particles.
2.1. Population division based on FC

Dividing the population can help individuals obtain some potential information that is conducive to evolution from the characteristics of each cluster. Compared with hard clustering methods such as K-means, FC-means [18] provides more flexible clustering results. Regarding the fusion of FC and multi-objective topology optimization (i.e., BMOGWO in this paper), we set the three optimal solutions \( x_j (j = \alpha, \beta, \delta) \) of MOGWO as cluster centers to form three clusters \( C_j (j = \alpha, \beta, \delta) \). Thus, three clusters with \( \alpha, \beta, \) and \( \gamma \) as the center are formed, and the degree of membership of each individual belonging to each cluster can be described as follows:

\[
    u_{ij} = \frac{1}{\sum_{k=\alpha,\beta,\delta} \frac{|x_i - x_j|}{|x_k - x_j|}} \tag{1}
\]

where \( u_{ij} \) represents the membership degree of the \( i \)-th individual (\( x_i \)) belonging to the \( j \)-th cluster (\( C_j \)) and \( \sum_{j=\alpha,\beta,\delta} u_{ij} = 1 \). * is the distance between \( x_i \) and \( x_j \), \( m \) is the number of clusters and \( m = 3 \). The cluster to which each individual belongs is determined by the calculated \( u_{ij} \). For each individual \( x_i \), if \( u_{i\alpha} > u_{i\beta} > u_{i\delta} \), then \( x_i \) belongs to cluster-\( \alpha \).

The influence of \( \alpha, \beta, \) and \( \delta \) on \( x_i \)'s update is changed from the original equivalent to the influence ratio determined by \( u_{ij} (j = \alpha, \beta, \delta) \), which can be described mathematically as follows:

\[
    x_i(t+1) = u_{i\alpha}X_1 + u_{i\beta}X_2 + u_{i\gamma}X_3 \tag{2}
\]

where \( t \) is the number of iterations. The weights of \( X_1, X_2, \) and \( X_3 \) are determined by the degree of membership of \( x_i \) to the three clusters, and their mathematical description can be seen in [14].

2.2. Current-driven evolution mechanism

In the past antenna topology optimization based on binary MOEAs [6, 7], a priori knowledge of antenna design is rarely considered. As an important factor affecting antenna design, current distribution is introduced by us for the first time in multi-objective topology optimization to promote individual evolution.

The characteristics of each cluster after FC are reflected by the cluster centers \( x_j (j = \alpha, \beta, \delta) \), therefore, the current distribution of the antenna structures mapped by the \( x_j (j = \alpha, \beta, \delta) \) has a guiding significance for the evolution of each individual in the cluster. In the traditional antenna design, changes in the antenna structure in areas with strong currents and nearby has a greater impact on the performance of the antenna. In this way, individuals can be updated based on the cluster center, which is specifically manifested in that in the dimension where the current of the cluster center is relatively strong, the individual has a certain probability of variation. This process can be mathematically modeled as follows:

Figure 4. Surface current distribution when port 1 is excited. (a) 3.5 GHz, (b) 6.5 GHz, (c) 9.5 GHz.

Figure 5. Photo of measurement experiment.

Figure 6. The simulated and measured S-parameters of the optimized UWB MIMO antenna and the comparison with the original antenna (\( d_1 = 1.4, d_2 = 0.6, w = 8.7 \)).
where $r_{ij}^{\text{dim}}$ is a random matrix that determines the change of $x_i$ and $x_i$ belongs to $C_j$. $\text{dim}$ indicates the area where the current distribution of $\alpha, \beta,$ and $\delta$ is strong (Different antennas have different standards for the division of strong current areas. The reference value is about half of the maximum current.) and the surrounding dimensions. $\text{randsc}$ is a random function, which produces "$0" with a probability of $p_j$ and "$1" with a probability of $1 - p_j$. The value of $p_j$ is determined by the number of individuals in each cluster and $p_j = M_j/N_{\text{pop}}$, where $M_j$ is the number of cluster $j$ and $N_{\text{pop}}$ is the number of population size. To maintain the diversity of the population, we select some individuals ($p_j/N_{\text{pop}}$) from each cluster to implement the current-driven evolution mechanism according to the proportion and others evolve normally. Eqs. (1), (2), and (3) mathematically describe the update process of individuals in a population. The accelerated current-driven multi-objective antenna topology optimization method is illustrated in Figure 1.

3. Compact high-isolation UWB MIMO antenna design

UWB technology has received widespread attention due to its high transmission rate and strong anti-interference ability [19]. However, UWB communication systems suffer from the multipath fading problem. Multiple input multiple output (MIMO) technology can effectively solve this problem, but the placement of multiple antennas in a limited space will cause strong mutual coupling. Then many schemes have been proposed to solve this problem, including decoupling network, neutralization line, slotting, and so on [20, 21, 22]. In this section, the accelerated...
current-driven multi-objective topology optimization is used to design a compact high-isolation UWB MIMO antenna. The geometries of both antennas and the decoupling structure are optimized simultaneously to meet the multiple performance requirements, which lead to a high design degree of freedom. The initial antenna geometry is shown in Figure 2. It consists of a quasi-self-complementary half-slot structure, fed by a coplanar waveguide (CPW) structure and fabricated on a 0.8 mm-thick FR4. The multi-objective topology optimization of this antenna can be mathematically described as (4):

\[
\begin{align*}
\text{Find: } & \quad x^* = \arg \min \{ F_1(x), F_2(x) \} \\
& \quad F_1 = \max(S_{11}(f_{\text{num}})) \\
& \quad F_2 = \max(S_{22}(f_{\text{num}}))
\end{align*}
\]

where \(x\) is a group of variables to be optimized, including 72 binary parameters and 3 continuous parameters. It is a matrix representation of an antenna structure. \(F_1\) and \(F_2\) are two objectives and they are designed to make the antenna meet the UWB working frequency band and achieve the highest possible isolation with a compact structure. \(S_{11}(f_{\text{num}})\) and \(S_{22}(f_{\text{num}})\) are the return loss and isolation of \(n\)-th frequency points in the bandwidth respectively. For all the experimental algorithms, the parameters are set as follows: the maximum iteration \(N_{\text{iter}} = 50\), and the population size is \(N_{\text{pop}} = 30\). The convergence condition is to reach the \(N_{\text{iter}}\) or \(S_{11} < -10 \text{ dB} \) & \(S_{22} < -20 \text{ dB}\).

### 3.1. Numerical Results

It can be seen from Figure 3 that the proposed method has met the design requirements at the 28th iteration. However, the benchmark algorithms, binary MOPSO (BMOPSO) [16], NSGA-II [23], and BMOGWO, have not reached the convergence condition \(S_{22} < -20 \text{ dB}\) when the \(N_{\text{iter}}\) is reached. Although NSGA-III [24] has reached the design goal, it is inferior to our proposed method in terms of Pareto curve and optimization time. Moreover, our objective is that the smaller the \(S\)-parameters, the better, that is, the lower left of the Pareto curve, the better. Table 1 shows the comparison of the calculation costs of the three methods. The comparison results show that the computational cost of the proposed method is only about half of that of traditional MOEAs. Therefore, it can be concluded that our proposed method obtains the optimal Pareto curve at a faster speed. The surface distribution, at 3.5, 6.5, and 9.5 GHz, of the optimized UWB MIMO antenna is depicted in Figure 4. As it is seen, a longer current path excited on the radiating patch reduces the resonance frequency and attain a more compact size for UWB MIMO antenna as compared to the literature [22, 25, 26, 27]. Moreover, it can be found that a large amount of current is concentrated on the left half of the ground plane, and the isolation structure obtained by topology optimization effectively blocks the current flowing to the adjacent port through the connection plane. Therefore, the structure obtained based on the current distribution driving multi-objective topology optimization not only supports a more compact size, but also reduces the mutual coupling of the two ports.

### 3.2. Antenna Performances

To evaluate the effectiveness of current-driven multi-objective topology optimization, the optimized antenna (i.e., “Final result” in Figure 3) was fabricated and measured using the vector network analyzer and the microwave anechoic chamber. Figure 5 shows the measurement environment. Figure 6 presents the simulated and measured S-parameters of the optimized antenna and the reference antenna (i.e., the initial antenna in Figure 2). The simulation results and the measurement results are in good agreement. The optimized working frequency band of the antenna is 2.85–12.5 GHz, which not only broadens the bandwidth of the reference antenna but also satisfies the working frequency band of the UWB antenna.

The 2-D radiation pattern is plotted in Figure 7 and the simulation and measurement results are in good agreement. The optimized antenna almost achieves quasi-omnidirectional radiation on the H-plane, and there is almost no deterioration at high frequencies. Also, some complementary characteristics for the two-element patterns are observed at the same frequency, indicating pattern diversity ability for combating multipath fading. Envelop correlation coefficient (ECC) is also an important parameter that describes the degree of isolation or correlation of different communication channels. For the obtained antenna, the ECC can be calculated as (5):

\[
\text{ECC} = \frac{|S_{11}S_{12} + S_{21}S_{22}|^2}{(1 - |S_{11}|^2)(1 - |S_{22}|^2)}
\]

From the results in Figure 8, the simulated and measured ECC values of the optimized antenna are all below 0.01 in the entire working frequency band, which indicates a desirable diversity capability is achieved by the optimized UWB MIMO antenna. Figure 9 shows the group delay variation over the UWB range which gives the time domain information of the proposed UWB MIMO antenna. Group delay (m, n) describes the delay from port m to port n. The characteristics of group delay (m, n) and group delay (n, m) are the same because the MIMO antenna elements are identical with symmetrical spacing, where m ≠ n. According to the results in Figure 9, it is shown that the delay in the operating frequency band is less than 0.1 ns between all ports. Table 2 shows the comparison between the optimized antenna and the previously published work. Although the gain of our proposed antenna is lower than that of the design in [22] with a similar size due to larger loss of the dielectric substrate, it can be found that our optimized antenna is very competitive in terms of bandwidth, isolation and ECC. We provide a suitable antenna for portable UWB applications with a small computational cost. The UWB MIMO antenna design example in this section verifies the effectiveness of our proposed method, and further experiments are needed for the wider application of the current-driven topology optimization method.
4. Conclusion

This work presents an accelerated current-driven multi-objective antenna topology optimization method for the design of UWB MIMO antennas. In this method, the idea of FC is first used to divide the population, and then the current distribution information related to the cluster centers is used to drive the evolution of other individuals in the iterative process, thereby accelerating the convergence of MOEAs. The experimental results show that the proposed method only takes nearly half of the time on obtaining the satisfactory design of UWB MIMO antennas compared to other classical MOEAs. The optimized antenna has a compact structure, a ultrawide working band, and high isolation, indicating that the antenna is a good choice for portable UWB communication systems. It can be concluded that the current-driven multi-objective topology optimization method is efficient to a certain extent for solving computationally expensive antenna design problems. In the future, we will further test the effectiveness of the proposed method in different types of antennas.

Declarations

Author contribution statement
Xia Yuan: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Meng Wang: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.
Jian Dong: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement
Data included in article/supp. material/referenced in article.

Declaration of interest’s statement
The authors declare no conflict of interest.

Additional information
No additional information is available for this paper.

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