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# Design RF Diplexer by Directional Immune Clonal Selection Algorithm

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***Abstract*—Based on the clonal selection theory of the immune system, a novel optimal algorithm, called a directional immune clonal selection algorithm (DICSA), is proposed to design RF diplexer. In DICSA, antibody is proliferated and divided into a set of subpopulation groups. In the antibody's updating, the clonal mutation is applied to avoid premature convergences. The clonal selection realizes the information communication between the subpopulation groups so as to improve the search efficiency. DICSA is applied to a practical problem, designing RF diplexer. The results show that DICSA has stable performance during the optimization process with a satisfactory result.**

***Keywords*—computer-aided design(CAD), RF diplexer, artificial immune system, directional search, global optimization**

## I. INTRODUCTION

The increasing development of communication systems has encouraged the need of high-selectivity diplexers for base stations and millimeter-wave point-to-point radio links. Although synthesis technology of microwave filter has been already mature [1, 2], the design of microwave diplexers is still widely based on optimization [3, 4]. The difficulty of this approach is that due to the complexity of the circuit and the large number of optimization variables with high correlations, the landscape of optimization is very multimodal and most conventional optimization algorithms will trap into a local minimum. In [5], Nader Damavandi and Safieddin Safavi-Naeini modified the Evolutionary Programming method (EP), which is hybrided with clustering algorithm to design complex RF diplexer circuit. Unfortunately, the hybrid EP is still hard to avoid the premature phenomena while the number of optimization variables with high correlations is increasing. Furthermore, the optimization course is very tedious.

In this paper, an innovative approach to objective function of designing microwave diplexer is presented. Based on this objective function, an improved artificial immune system algorithm based on the clonal selection theory and the idea of directional learning, Directional Immune Clonal Selection Algorithm (DICSA) is proposed to perform the optimization process. The new algorithm has a fast convergence speed to some extent, and can be easy to realize.

## II. PROBLEM DEFINITION

In this letter, we concern a device to be employed in GSM 1800MHz mobile communications base-stations. The structure of the diplexer is shown in Fig.1. It has following characteristic:

RX filter: 9poles, passband1710-1785MHz, RL=-20dB;

TX filter: 9poles, passband1805-1880MHz, RL=-20dB.

The optimization goal of RF diplexer is to minimize the common port return loss (CPRL). As is well known, at the heart of any circuit optimizer is an efficient analysis routine. The transmitter-receiver isolation performance would almost not be changed during the optimization process, so it should be given to the design of the filter.

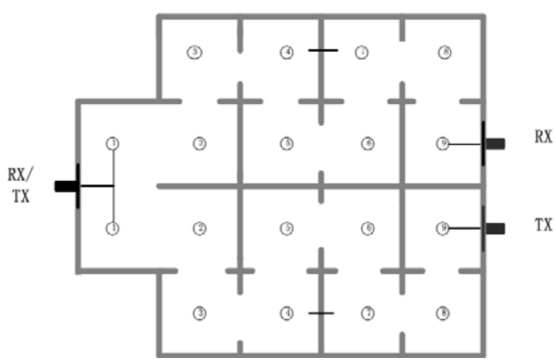
In this problem, the guard band is about 25% of the design bandwidths. So the coupling matrices of the corresponding channel filter should be synthesized with the singly terminated prototype There are two types of object functions for this problem, one is the Least square type (L2) and the other is Minimax type (MINIMAX).

For the Least square type, the objective function is defined as:

$$\min \quad U = \sum_{j=1}^{m} F_j^2 \tag{1}$$

Where $F_j$ denotes a set of differences between the simulated response and the specifications. L2 is a classical defining method of objective function, which is widely used. But obviously, for the problem in this letter, the points less than threshold value is looked as equal to the points more than threshold value by L2 type. While what we need is the situation that all the points less than or equal to threshold value. That means faulted diagnosis of some fine candidate solutions,

Figure 1 Top view of the diplexer




Which will leads to non-equiripple solution.

For the minmax approach, the objective function is formulated as:

$$\min \quad U = \max\left(RL\right) \tag{2}$$

Where

$$RL = 10 * \lg\left(\left|S_{11}\right|^2\right) \tag{3}$$

Where $S_{11}$ is the reflectance of the input port. Different to L2, minmax approach only takes the worst points into consider. Therefore, it will result in inaccuracy evaluate of solutions. During the optimization process, maybe most points are less than the threshold value, only few points are still worse, which just need fine adjustment. The situation will be identified as worse result and be ignored.

To overcome above problems, a novel objective function is proposed. The features of this method are:

1. Only takes the points more than threshold value into consider.

2. Based on 1, introduce L2 to define objective function.

For this type, the objective function is defined as follows:

$$\min. \quad U$$

$$U = sum\left(\left(\left(sign\left(RL+25\right)+1\right)/2\right)*\left(RL+25\right)\right) \tag{4}$$

Where, RL is shown in (2).It should remarked that we set the optimization goal to -25dB rather than the required -20dB.As a result, even the goal can't be satisfied, we still could obtain an acceptable solution.

## III. Directional Immune Clonal Selection Algorithm

### A. Directional Operator

The purpose of directional operator is to determine the search direction for each antibody in a population. Assume $x_i$ ( $x_i \in R, x_i = \left[x_{i,1}, x_{i,2}, \cdots x_{i,m}\right]$ ) is a point in the search space of a problem. The directional operator is denoted as (e.g. to seek the minimum value):

$$\begin{aligned} & s(x_i) = (fit(min_i) - fit(x_i)) / abs\left(fit\left(\min_i\right)\right) \\ & dir\left(x_i\right) = sign\left(x_i - \min_i\right) * s\left(x_i\right) \\ & sign\left(x\right) = \begin{cases} 1 & x \geq 0 \\ -1 & others \end{cases} \end{aligned} \tag{5}$$

Where $fit(min_i)$ is the current minimum affinity value, $fit\left(x_i\right)$ is the affinity value of antibody $x_i$ .

### B. The procedures of the algorithm

Based on Clonal Selection Theory of the immune system Licheng Jiao proposed a clonal selection algorithm for optimization and learning, termed as the Immune Clonal Selection Algorithm (ICSA) [6-10]. Concretely, ICSA is to implement three steps including clone, clonal mutation and clonal selection on the antibody population, and a new antibody population will be obtained after iteration. The evolvement process can be denoted as follows:

$$A(k) \underrightarrow{clone} A^{(1)}\left(k\right) \underrightarrow{mutation} A^{(2)}\left(k\right) \underrightarrow{selection} A\left(k+1\right) \tag{6}$$

Inspired from the clonal selection mechanism and the thought of gradient, a novel algorithm, called Directional Immune Clonal Selection Algorithm is put forward. The novel algorithm can be implemented as follows:

- Step 1 k=0; Initialize the population randomly, set the algorithm parameters.
- Step2 Through Inversion Operation, Clonal Operation, Recombine Operation, Clonal Mutation Operation, Clonal selection operation, a new population is formed.
- Step3 According to the affinity distribution, divide the population into three parts. Part1 concludes antibodies with a affinity value better than best affinity saved. Antibodies with a affinity value between the best affinity and the worst affinity belong to part2.Others are contained in part3. Because individuals with better fitness are more likely to be in basins of attraction of good local optima, it needed to make a difference among different individuals.

- Step4 Assume $x_i$ is a point in the search space of a problem which will move to a new point $x_j$ .The directional operator is applied to the antibodies in part1as:

$$x_j = x_i + dir(x_i) * \lambda_k \tag{7}$$

Where, $\lambda_k$ is the iteration step which is 0.1 here. the max number of iteration is 100.

For the antibodies in part2, the directional operator is applied to them with probability 0.05~0.065, step is 0.1, the max number of iteration is 60.

If $fit(x_j) \geq fit(x_i)$ or the max number of iteration is reached, the directional operator is applied to them with probability 0.01~0.035, step is 0.1, the max number of iteration is 30.

- Step5 k = k + 1; Check the halted condition. If the halted condition is satisfied, the algorithm is terminated, otherwise, return to Step2.

*C. Convergence of DISCA*

**Definition 3.1** let $X(t) = (x_1(t), x_2(t), \cdots, x_n(t))$ in $S^n$ be the population at time *t* and for $X(t)$, defined:

$$M = \{\bar{X} \,|\, f(\bar{X}) = \max\{f(X_i(t)), i \leq n\}\} \tag{8}$$

$$M^* = \{\bar{X} \,|\, f(\bar{X}) = \max\{f(X), X \in S^n\}\} \tag{9}$$

$M$ is called the satisfied set of population $X_t$ and $M^*$ is defined as the global satisfied set of state $S^n$.

**Definition 3.2** supposes arbitrary initial distribution, the following equation satisfies:

$$\lim_{t \to \infty} P\{M \subseteq M^*\} = 1 \tag{10}$$

Then we call the algorithm is convergent.

**Theorem 3.1** the population series of DICSA $\{pop(t), t \geq 0\}$ is finite homogeneous Markov chain.

**Proof:** Like the evolutionary algorithms, the state transfer of DICSA are processed on the finite space, therefore, population is finite, since

$$pop(t+1) = T(pop(t)) = T_C \circ T_D \tag{11}$$

$T_C, T_D$ indicate the operators belong to Immune Clonal Selection Algorithm used in this paper and directional operator respectively. Note that, $T_C, T_D$ operators have no relation with *t*, so $pop(t+1)$ only relates with $pop(t)$. Namely, $\{pop(t), t \geq 0\}$ is finite homogeneous Markov chain.

**Theorem 3.2** the $M$ of Markov chain of DICSA is monotone increasing, namely

$$\forall t \geq 0, f(pop(t+1)) \geq f(pop(t)) \tag{12}$$

**Proof:** Apparently, the individual of DQICA does not degenerate for our adopting holding best strategy in the algorithm.

**Theorem 3.3** The Directional Immune Clonal Selection Algorithm is convergent.

**Proof:** For Theorem 3.1 and Theorem 3.2, the DICSA is convergent with the probability 1.

## IV. EXPERIMENT

The response of optimized diplexer at global solution found by Directional Immune Clonal Selection Algorithm (DICSA)is shown in Fig. 2. In DICSA, the size of initial population is 10, the clonal sizes is 5, pr (Probability of Recombine)=0.5, and pm (Probability of Mutation)=0.35. In GA, the size of initial population is 100, the pc(Probability of Cross)=0.7, pm=0.08. The parameters in HEP are as shown in [5]. $S_{11}$ is the reflectance of the input port 1(RX/TX), $S_{21}$ is the transmission coefficient form the input port to output port 2(RX). $S_{31}$ is the transmission coefficient form the input port to the output port 3(TX). For the diplexer in this work, between1710-1785MHz, the target value of $S_{11}$ is under -20dB and $S_{21}$ is 0dB. Between 1805-1880MHz, the target value of $S_{11}$ is under -20dB and $S_{31}$ is 0dB. As can be seen it satisfies the required specifications very well. The response also shows an equiripple behavior at this global solution. Experimental data are the statistical results of 50 times independent running. The variations of best fitness value in different generation are shown in Fig.3. It is can be seen that with the use of the DICSA, faster convergence of the evolution process can be achieved and more excellent value of object function can be obtained. The final values of optimization variables are shown in (13).

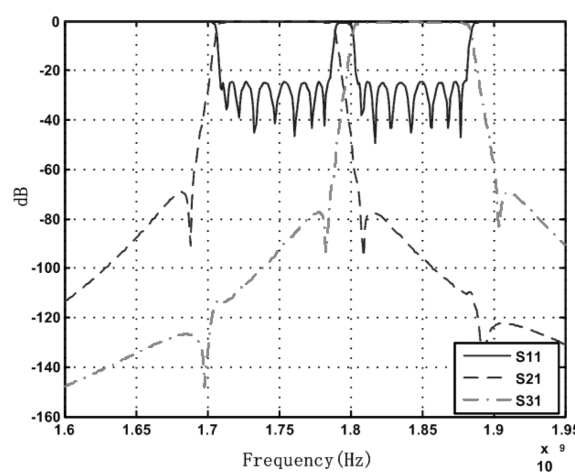



Figure 2 Response of optimized diplexer at global solution.

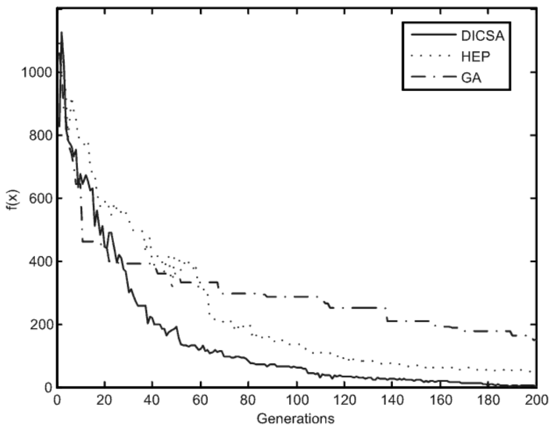



Figure 3 Fitness versus generation in trials of RF diplexer optimization

$$M1=\begin{bmatrix} 0 & 1.6016 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1.0616 & 0.4933 & 0.7837 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.7837 & 0.0728 & 0.5755 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.5755 & 0.02 & 0.5377 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5377 & 0.0109 & 0.5189 & 0 & -0.09 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.5189 & 0.0069 & 0.614 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.614 & 0 & 0.5372 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.09 & 0 & 0.5372 & 0 & 0.5927 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5927 & 0 & 0.8579 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8579 & 0 & 1.0441 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.0441 & 0 \end{bmatrix}$$

$$M2=\begin{bmatrix} 0 & 1.066 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1.066 & -0.499 & 0.779 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.779 & -0.0654 & 0.5726 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.5726 & -0.0117 & 0.536 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5360 & -0.0025 & 0.517 & 0 & -0.09 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.517 & -0.0003 & 0.614 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.614 & 0 & 0.5372 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.09 & 0 & 0.5372 & 0 & 0.5927 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5927 & 0 & 0.8579 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8579 & 0 & 1.0441 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.0441 & 0 \end{bmatrix} \quad (13)$$

## V. CONCLUSION

In this paper, a novel approach to defining objective function to designing RF microwave diplexer by optimization is presented. Directional operator is also adopted to determine the search direction during optimization process. By the improving strategy, the computation of finding the optimal return loss of its common port is significantly reduced. The results show the efficiency of the proposed method.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