Modified Differential Evolution Algorithm for Time-Modulated Linear Array Antenna

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Abstract — A modified differential evolution (MDE) algorithm based on a novel mutation strategy and adaptive adjustment strategy of parameter crossover rate (CR) is proposed to improve the population diversity and to avoid frapping in local optima. Also the simplified quadratic interpolation is employed to accelerate the convergence rate. Benchmark functions have been provided to verify the MDE algorithm. Compared with other improved evolutionary algorithms, experiment results reveal that the MDE has a promising performance in the convergence rate and the exploration ability. Finally, the proposed algorithm is proved to realize accelerating the optimization of time-modulated arrays (TMA).

Index Terms — Crossover rate, differential evolution (DE) algorithm, mutation strategy, time-modulated array (TMA).

I. INTRODUCTION

The differential evolution algorithm (DE) is an evolution algorithm based on the theory of swarm intelligence. It intelligently directs and optimizes searching via cooperation and competition between individuals in the population [1-2]. Compared with other algorithms, it lowers the complexity of evolution operation by adopting differential-based simple mutation operation and one-to-one competitive survival strategy with real number encoding and fewer controlling parameters. However, DE algorithm also has significant drawbacks in practical situations, for example, in solving complicated optimization problems, it would meet the problems such as being trapped in local optima easily, slow convergence in later period, searching blindness and determining control parameter with difficulty. To deal with the aforementioned problem, many scholars have been delving into three control parameters (population size NP, crossover rate CR, differential scale factor F) and mutation strategy of DE algorithm [3-6], and propose some empirical methods of selecting control parameters and mutation strategy. The three control parameters and evolution strategy of early DE algorithm are fixed. However, fixed mode of parameter setting would degrade the algorithm to reach the optimal convergence performance, so the parameter adaptive and evolution strategy adaptive method of modulation are proposed successively. Liu and Lampinen propose a fuzzy logic adaptive differential evolution (FADE) algorithm, which uses fuzzy logic controller to modulate mutation and crossed factor by inputting individuals of consecutive generations of population and corresponding functional value [7]. Two new probability factors τ_1 and τ_2 are introduced by Brest et al. to control F and CR of each individual, which are automatically modulated and updated during evolution [8]. The evolution strategy of offspring individual and setting of corresponding control parameters of the self-adaptive differential evolution, which proposed by literature [9], are all produced adaptively by learning excellent individuals in all generations and their parameter value.

The time-modulated array (TMA) was proposed firstly by Shanks in 1959 [10-20]. Each antenna element is connected to a RF switch in the TMA. The array introduces the new variable, time, by controlling the on off cycle of RF switch. The time modulation would make the dynamic range of antenna array feeds much smaller than that of common array and also make control more precise, convenient and rapid, hence low side-lobe array can be easily realized [10-11]. Yet due to the introduction of time variable, part energy of TMA would be radiated from sideband in the form of harmonic. Usually the sideband level (SBL) is regarded as useless and needing to be repressed to reduce energy loss. Therefore, the problem of designing time-modulated array itself is

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a complicated problem of array optimization and integration. Presently, the optimization and integration of TMA can hardly obtain satisfactory solution if traditional evolution algorithm is used.

Based on the above analysis, this paper proposes a modified differential evolution algorithm to rapidly and efficiently optimize TMA. According to the diversity of each generation of population, it adopts different adaptive strategies for CR and mutation strategy of individuals of the next generation, which improves the later population diversity of the algorithm and avoid the algorithm being trapped in local extremum. Besides, the simplified quadratic interpolation method is adopted to expedite the convergence of algorithm. This algorithm can perfectly suppress SBL of TMA by optimizing feed amplitude of array element and switching period of TMA. In comparison with optimization result of other algorithms, it proves that this algorithm can optimize and integrate the TMA more rapidly, stably and perfectly.

II. MODIFIED DIFFERENTIAL EVOLUTION ALGORITHM

In DE algorithm, the crossover rate CR determines the proportion of the individuals produced by differential mutation and original individuals in test vector, which is key to algorithm convergence rate and diversity of population. The span of CR is generally [0,1]. The larger the CR value is, the larger the proportion of individuals produced by differential mutation in test vector is, and the wider the searching scope of individuals produced is. Contrarily, the smaller the CR value is, the larger the proportion of parent individuals in test vector is, and the quicker the velocity of local search is. In addition, assorted mutation strategies have been proposed since DE algorithm appeared. However, currently there is no mutation strategy that can obtain optimum solution in solving all optimization problems. The population diversity of some mutation strategies is well kept while rate of convergence is slow, such as DE/rand/1. Some mutation strategies have quick local convergence rate yet with limited search scope, such as DE/target-to-best/1.

In the standard DE algorithm, the early populations of algorithm are generated randomly, and populations have high diversity. The mutation strategy with smaller CR value and wide search domain does not influence the diversity of populations and can expedite convergence of algorithm. In later period of algorithm, the individual differences become smaller and diversity of populations becomes lower, making the algorithm easily trapped in local extreme value. While adopting larger CR value can increase the proportion of mutated individuals, thus favorable for algorithm to escape from local extreme value. Besides, the mutation strategy with rapid rate of convergence can improve overall convergence rate of the algorithm.

Based on the above analysis on CR and mutation strategy, this paper proposes a modified algorithm in which the CR and mutation strategy adjust adaptively on the basis of population diversity. Wherein, the population diversity is judged by calculating population variance *v*. After substantive calculation and experiments, the threshold for judgment of population diversity is set as: v_0 = 1E-2. The CR in the algorithm is no longer a fixed value, and a CR_i, G is set for each individual in the population, where G represents number of evolution generation, *i* represents individual number. The concrete adaptation steps are as follows:

Firstly, the adaptation steps of CR are provided: when $v>v_0$, calculate,

$$\mu_{CR} = (CR_1 + CR_2 + \cdots + CR_5)/s \,, \tag{1}$$

and generate:

$$CR_{i,G} = randn_i(\mu_{CR}, 0.1) \,. \tag{2}$$

Where, CR_1, CR_2, …, CR_s represent the crossover rates corresponding to s test vectors that successfully enter the next generation of population, μ_{CR} is the mean of these crossover rates, with its initial value being generally set as 0.5. The $CR_{1,G}$, $CR_{2,G}$,…, $CR_{NP,G}$ in each generation are all generated randomly via normal distribution function with expectation of μ_{CR} and variance of 0.1. Such modified algorithm can inherit the CR of excellent individuals and expedite the convergence of algorithm.

When $v<v_0$, which indicates the population diversity is low, then $CR_{i,G}$ values are all set as 0.9 to raise the proportion of mutated individuals in test vector to expand the search scope of algorithm, and avoid the algorithm being trapped in local solution.

Secondly the adaptation steps of mutation strategy are provided:

$$\begin{cases} DE/rand/1 & when \quad rand < m_0 \\ DE/target-to-best/1 & \text{otherwise} \end{cases} . \tag{3}$$

Where, $m_0 \in (0,1)$ is the judgment factor. The mutation strategy judges by generating a uniform average number in (0,1). If rand< m_0, mutation strategy of DE/rand/1 is selected; contrarily, the mutation strategy of DE/target-to-best/1 is selected. In early period of algorithm, generally $v>v_0$. Preceding analysis shows that DE/rand/1 strategy is a good choice, so $m_0 \in (0.5,1)$, with m_0 recommended to be 0.8. Contrarily, when $v<v_0$, the algorithm generally has entered the end stage, adopting strategy of E/target-to-best/1 can accelerate the local convergence of algorithm, so m_0 is set as 1- m_0. The adjustment of m_0 can enable the DE algorithm to select more proper strategy in different periods to expedite convergence rate of algorithm and guarantee precision of the solution.

Lastly, in an effort to further effectively utilize population information and improve operational performance of algorithm, the modified DE algorithm adds simplified 3-point quadratic interpolation (SQI) operator after the step of selection, with mathematical expression as follows:

$$P_i = 0.5\frac{(X_{2i}^2 - X_{3i}^2) f(X_1) + (X_{3i}^2 - X_{1i}^2) f(X_2) + (X_{1i}^2 - X_{2i}^2) f(X_3)}{(X_{2i} - X_{3i}) f(X_1) + (X_{3i} - X_{1i}) f(X_2) + (X_{1i} - X_{2i}) f(X_3)} \quad i = 1,2\cdots,D \quad . \tag{4}$$

The flowchart of the MDE is shown in Fig. 1. To verify the performance of the modified adaptive DE algorithm proposed in the last section, the paper adopts 10 standard testing functions to test the standard DE algorithm, hybrid differential evolution algorithm (DESQI), jDE algorithm and modified algorithm. The 10 testing functions are as shown in Table 1.

It is observed from Table 2 that the modified adaptive DE algorithm mentioned in this chapter has superior performance. Except that it is slightly inferior to jDE algorithm in optimizing function F5 and function F8, the modified adaptive DE algorithm outperforms standard DE algorithm, DESQI algorithm and jDE algorithm in convergence rate and solving precision.

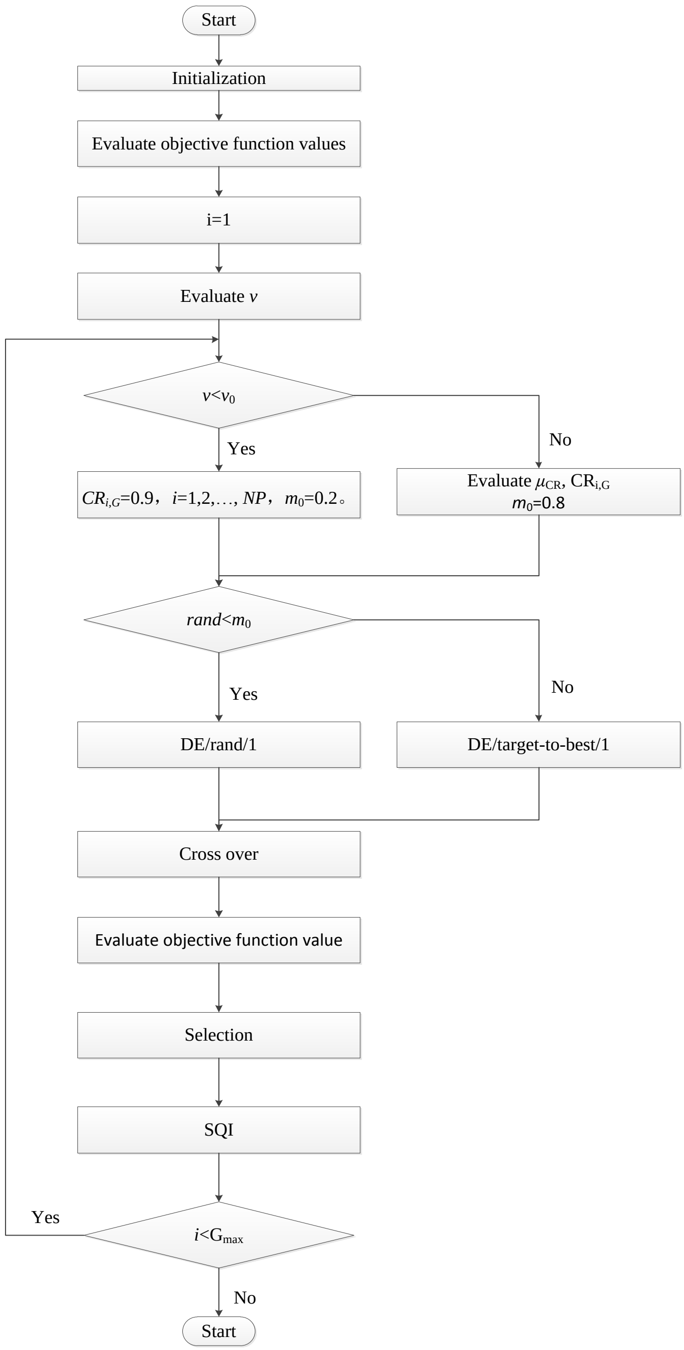


Fig. 1. The flowchart of the MDE.

Table 1: Standard testing functions

SN	Testing Function	Dimension Di(D)	Variable	Minimum Value
F1	$f_1(x)=\sum_{i=1}^{D} x_i^2$	30	$[-100,100]^D$	0
F2	$f_2(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$	30	$[-10,10]^D$	0
F3	$f_3(x)=\sum_{i=1}^{D}\left(\sum_{j=1}^{i} x_j\right)^2$	30	$[-100,100]^D$	0
F4	$f_4(x)=max_i\{\lvert x_i\rvert,\quad 1\le i\le D\}$	30	$[-100,100]^D$	0
F5	$f_5(x)=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	30	$[-30,30]^D$	0
F6	$f_6(x)=\sum_{i=1}^{D}(\lfloor x_i+0.5\rfloor)^2$	30	$[-100,100]^D$	0
F7	$f_7(x)=\sum_{i=1}^{D} i x_i^4+random[0,1)$	30	$[-1.28,1.28]^D$	0
F8	$f_8(x)=\sum_{i=1}^{D}[x_i^2-10cos(2\pi x_i)+10]$	30	$[-5.12,5.12]^D$	0
F9	$f_9(x)=-20exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i\right)+20+e$	30	$[-32,32]^D$	0
F10	$f_{10}(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	30	$[-600,600]^D$	0

III. INTEGRATION AND OPTIMIZATION OF TIME-MODULATED LINEAR ARRAY

This section adopts the modified DE algorithm proposed in previous section to quickly optimize and integrate time-modulated linear array. A time-modulated linear array is assumed, which contains N isotropic units with interval of half-wavelength. Each unit is connected to a high-speed RF switch to control operation cycle of unit. Define x=(τ_1/Tp, τ_2/Tp,…, τ_n/Tp, I_1, I_2,…, I_n), then the array factor of TMA can be expressed as:

$$AF_n(\theta,x)=\sum_{i=1}^{N}\alpha_{n,i}\cdot e^{j(i-1)\pi\sin\theta}. \tag{5}$$

Where, $\alpha_{n,i}$ is complex amplitude,

$$\alpha_{n,i}=\tfrac{I_i\tau_i}{T_p}\cdot\mathrm{sinc}(\pi n f_p\tau_i)\cdot e^{-j\pi n f_p\tau_i}. \tag{6}$$

The array factors at center frequency f_0 (n=0) and the first side-band f_1 (n=1) are:

$$AF_0(\theta,x)=\sum_{i=1}^{N}I_i\frac{\tau_i}{T_p}\cdot e^{j(i-1)\pi\sin\theta}, \tag{7}$$

$$AF_1(\theta,x)=\sum_{i=1}^{N}I_i\frac{\tau_i}{T_p}\cdot\mathrm{sinc}(\pi f_p\tau_i)\cdot e^{j(i-1)\pi\sin\theta-j\pi f_p\tau_i}. \tag{8}$$

Take x=(τ_1/Tp, τ_2/Tp,…, τ_n/Tp, I_1, I_2,…, I_n) as optimizing variable of the algorithm, then the peak side-lobe level (PSLL) at center frequency and the peak level for the first side-band (PSBL) can be expressed as follows:

$$\mathrm{PSLL}(x)=20\log\left\{\max_{\theta\in Y}\left[\frac{AF_0(\theta,x)}{AF_0(\theta_{\max},x)}\right]\right\}, \tag{9}$$

$$\mathrm{PSBL}(x)=20\log\left\{\max_{-\frac{\pi}{2}\le\theta\le\frac{\pi}{2}}\left[\frac{AF_1(\theta,x)}{AF_0(\theta_{\max},x)}\right]\right\}. \tag{10}$$

Where, θ_{max} is the angle corresponding to the largest radiation direction for the array at center frequency f_0. $\theta\in$ Y represents minor lobe zone of array corresponding to the position of center frequency x. Finally the optimization model of time-modulated linear array is:

$$\begin{aligned}&\text{minimize}\quad f(x)=\omega_1*\mathrm{PSLL}(x)+\omega_2*\mathrm{PSBL}(x)\\&\text{subjet to}\,\mathrm{HPBW}(x)\le 6^\circ\ .\end{aligned} \tag{11}$$

Where, ω_1 and ω_2 are weight factors, which are all set as 1. HPBW(x) represents half-power beamwidth of array pattern corresponding to the position of center frequency x. Setting the condition of HPBW≤6° is to guarantee directivity factor of array does not largely reduce after optimizing PSLL and PSBL. The penalty function method is adopted to process array's constraint condition when the algorithm is operating. When the HPBW(x) of individual is greater than 6°, the objective function value of this individual is set as a maximum value to make this individual unable to enter the next generation of population via the operation of selection. Following will adopt modified DE algorithm, standard DE algorithm and DESQI algorithm to optimize TMA, and compare the result. The control parameters of the algorithm are NP=100, G_{max}=1000, CR=0.9, F=0.5. Each algorithm operates for ten times with result recorded. The comparison result after optimization is as shown in Table 3.

Table 2: Performance comparison of algorithms

Function	Evolutional Generation	Average Value of Modified DE (Standard Deviation)	Average Value of DE/rand/1/bin (Standard Deviation)	Average Value of DESQI (Standard Deviation)	Average Value of jDE (Standard Deviation)
F1	1500	4.22E-41 (9.44E-41)	5.14E-14 (4.39E-14)	2.05E-23 (2.02E-23)	1.1E-28 (1.0E-28)
F2	2000	3.77E-43 (4.59E-43)	3.78E-10 (1.96E-10)	7.02E-16 (3.31E-16)	1.0E-23 (9.7E-24)
F3	5000	1.82E-44 (4.07E-44)	2.92E-11 (2.45E-11)	6.65E-18 (1.58E-17)	3.1E-14 (5.9E-14)
F4	5000	00E+00 (0E+00)	1.62E-01 (4.29E-01)	2.17E-20 (3.07E-20)	00E+00 (0E+00)
F5	20000	4.46E+01 (3.18E+01)	00E+00 (0E+00)	00E+00 (00E+00)	00E+00 (0E+00)
F6	1500	00E+00 0E+00)	00E+00 (0E+00)	00E+00 (0E+00)	00E+00 (0E+00)
F7	3000	1.1E-03 (2.26E-04)	4.80E-03 (1.30E-03)	1.50E-03 (4.91E-04)	3.15E-03 (7.5E-04)
F8	5000	1.78E-15 (1.78E-15)	7.29E+01 (3.08E+01)	2.29E+01 (1.97E+01)	00E+00 (0E+00)
F9	1500	6.41E-15 (3.18E-15)	5.90E-08 (2.16E-08)	1.58E-12 (7.28E-13)	7.7E-15 (1.4E-15)
F10	3000	00E+00 (0E+00)	2.46E-04 (1.3E-03)	00E+00 (0E+00)	00E+00 (0E+00)

Table 3: Comparison of result of design optimization by the three algorithms

	Modified DE	DE/rand/1	DESQI
PSLL (dB)	-34.22	-36.18	-45.26
PSBL (dB)	-63.42	-17.23	-14.63
Objective function value (dB)	-97.64	-53.41	-59.89

The evolution curves of the three algorithms in Fig. 2 show that compared with SDE algorithm and DESQI algorithm, the MDE algorithm has quick convergence rate and can avoid being trapped in local extremum. The optimization result by the modified DE algorithm far outperforms other two algorithms. The array pattern result after optimization by the three algorithms is as shown in Fig. 3 and Table 3. It is observed that despite that the modified algorithm has larger PSLL, yet PSBL optimized by it is equal to -63.42 dB, which is obviously superior to other two algorithms. By synthesizing the optimized PSLL and PSBL result, it is found that the modified algorithm generally delivers better optimization performance. From the numerical results it can be seen that the PSLL and PSBL are restricted. Ideal result can be get quickly by choosing appropriate weight factors ω_1 and ω_2.

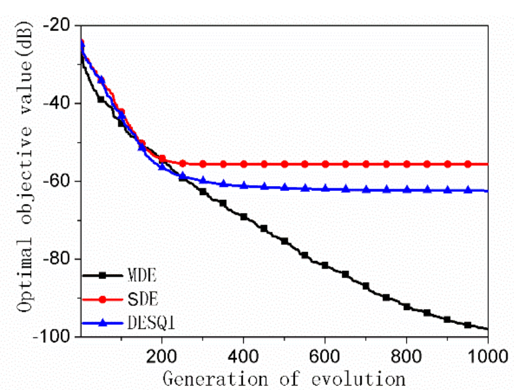
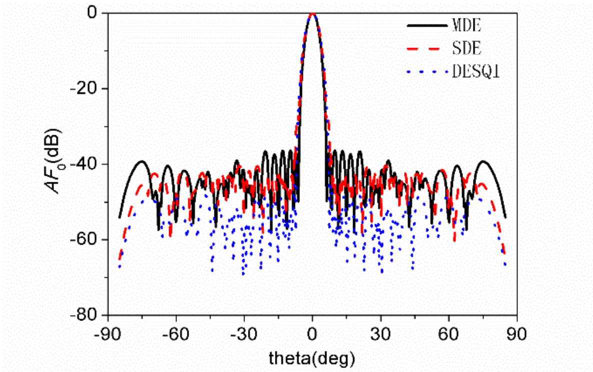
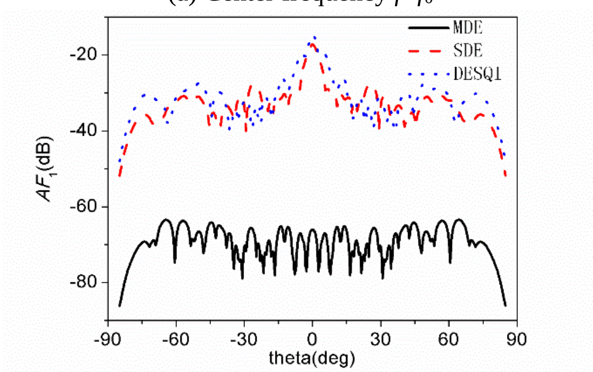


Fig. 2. Evolution curve of time-modulated linear array using the three kinds of algorithm optimization.



(a) Center frequency f=f_0



(b) The first side band f=f_1

Fig. 3. Comparison of array radiation patterns obtained by three kinds of algorithm optimization. (a) Center frequency f=f_0, and (b) the first side band f=f_1.

Table 4: Evolution generation when the three algorithms meet end condition

Times of Independent Operation	Evolution Generation when the Algorithm Ends		
	Modified DE	Standard DE	DESQI
1	365	314	341
2	345	433	416
3	298	362	406
4	281	399	467
5	299	465	508
6	379	414	421
7	363	491	406
8	323	494	387
9	323	437	504
10	314	469	456
Average value	329	427.8	431.2
Standard deviation	32.77	57.01	52.48

To further verify the performance of the algorithm, the population scale is set as NP=500, and the end condition of algorithm is set as PSLL<-30dB and PSBL<-30dB. The evolution generation when the algorithm meets terminal condition is recorded, with concrete result as shown in Table 4. The modified adaptive DE algorithm averagely needs 329 times, which is far fewer than the evolution generations needed by standard DE algorithm and DESQI algorithm to meet calculation conditions, and the standard deviation of its result is 32.77, the smallest among the three algorithms. The numerical result speaks volume for superiority of modified DE algorithm in convergence rate and robustness of calculation in optimization design of TMA antenna.

VI. CONCLUSION

The paper presents a modified differential evolution algorithm based on population diversity, which adopts the variance value of the last generation of population as judgment standard to adaptively evolve crossover rate CR and mutation strategy of each generation. This algorithm realizes perfect balance between search span and search depth by correcting CR value and mutation strategy. Besides, it expedites convergence rate of algorithm by adopting simplified quadratic interpolation strategy. Comparison with other evolutionary algorithms shows that this algorithm has higher convergence rate and better quality of solution. Then the time-modulated linear array is designed using modified DE algorithm. The numerical result shows that the modified DE algorithm is more rapid in solving the optimal solution in optimization design of TMA antenna with satisfactory stability, hence it can serve as an effective design method to optimize time-modulated array antenna.

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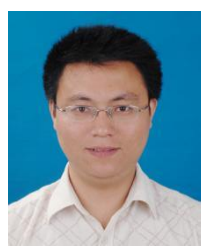

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