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Intelligent optimization methods of phase-modulation waveform

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Abstract: With the continuous improvement of radar intelligence, it is difficult for traditional countermeasures to achieve ideal results. In order to deal with complex, changeable, and unknown threat signals in the complex electromagnetic environment, a waveform intelligent optimization model based on intelligent optimization algorithm is proposed. By virtue of the universality and fast running speed of the intelligent optimization algorithm, the model can optimize the parameters used to synthesize the countermeasure waveform according to different external signals, so as to improve the countermeasure performance. Genetic algorithm (GA) and particle swarm optimization (PSO) are used to simulate the intelligent optimization of interrupted-sampling and phase-modulation repeater waveform. The experimental results under different radar signal conditions show that the scheme is feasible. The performance comparison between the algorithms and some problems in the experimental results also provide a certain reference for the follow-up work.

Keywords: waveform optimization, intelligent optimization, phase-modulation, genetic algorithm (GA), particle swarm optimization (PSO).

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1. Introduction

With the continuous development of artificial intelligence, the intelligent level of radar is constantly improving, and various new radars [1−3] are constantly emerging. In response to these new radars, radar countermeasures equipment is also developing towards intelligence. Since 2010, the US military has carried out a series of research and development projects, aiming at realizing radar countermeasure equipment with cognitive ability, such as the behavioral learning for adaptive electronic (BLADE) warfare program [4] based on dynamic countermeasure capability of adaptive communication threat, and the adaptive radar countermeasures (ARC) program [5] for countermeasureing new, unknown, and adaptive radars. Other countries have also carried out related research. However, few details have been published.

Traditional radar countermeasure equipment selects waveform parameters based on a look-up table, and does not have the ability to optimize waveforms. How to intelligently optimize the radar countermeasure waveform in response to complex, changeable, and unknown external threats is a direction that is seldom involved in existing research, but it is also a direction that cannot be ignored. Judging from the literature in similar fields, we find that intelligent optimization algorithms may be a solution. The intelligent optimization algorithm is a modern algorithm to solve similar optimization problems. Compared with traditional optimization methods, the intelligent optimization algorithm has strong universality and lower requirements on target function and constraint conditions. Compared with the exhaustive method, it has a faster search speed. Therefore, it is feasible to solve the optimization problem with strict time requirement in the field of radar-to-radar countermeasure [6]. In the field of radar, tasks scheduling of multi-functional phased array radar and sub-array selection of distributed multi-input multi-output radar system can be realized by using the intelligent optimization algorithm [7−10]. In addition, [11] and [12] used the intelligent optimization algorithm to solve the problem of parameter optimization of missile-borne sythetic apertune radar (SAR) system and waveform design of cognitive radar in Stackelberg game respectively. In the field of radar countermeasures, the intelligent optimization algorithm is used in system resource allocation, aircraft path planning, etc [13−17]. Literature [18] also proposed an intelligent range gate pull-off strat-

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egy based on the intelligent optimization algorithm, which achieves better effect. Jiang et al. transformed the controllability of multiplephase sectionalized modulation signal's antagonistic effect into an optimization problem of antagonistic effect, and a solution is proposed based on the intelligent optimization algorithm [19–21].

An intelligent optimization model of radar countermeasure waveform based on intelligent optimization algorithm is proposed in this paper. The general idea is to add the waveform optimization module to the traditional radar countermeasure system. The module can establish a virtual radar in the system content based on the received radar signals, which can simulate the receiving process of the opposite radar, and evaluate the effectiveness of the countermeasure waveform synthesized by the current parameters. At the same time, under the guidance of the assessment result, using the intelligent optimization algorithm to optimize the parameters of the waveform, enhanced combat performance is achieved. Based on this model, GA and PSO are used to simulate the optimization of intermittent sampling and phase modulation repeater waveform, and some analysis and comparison are made.

2. Phase-modulation waveform

2.1 Interrupted-sampling

Interrupted-sampling is a widely used sampling method to solve the isolation problem of transceiver antennas. Interrupted-sampling repeater signals can generate multiple symmetrically distributed false targets in the distant direction [22]. Assume that the interrupted-sampling function is a rectangular envelope pulse train as shown in Fig. 1. The interrupted-sampling function $p(t)$ can be expressed as

$$p(t) = \mathrm{rect}\left(\frac{t}{\tau}\right) \otimes \sum_{n=-\infty}^{+\infty} \delta(t - nT_s) \tag{1}$$

where τ is the sampling time and T_s is the sampling period.

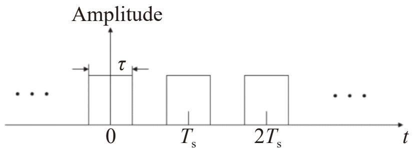


Fig. 1 Interrupted-sampling pulse signals

If the external signal $x(t)$ is sampled interruptedly, the sampled signal $x_s(t)$ can be expressed as

$$x_s(t) = x(t) \cdot p(t). \tag{2}$$

2.2 Periodic repeater

Different effects can be produced by repeating the sampled signal in different ways [23]. The common repeating methods include the direct repeater and the periodic repeater. The periodic repeater means that sampled signals are transmitted several times after one sampling is completed. Its working process is shown in Fig. 2. The direct repeater can be regarded as a special case of the periodic repeater, where the number of transmissions is 1.

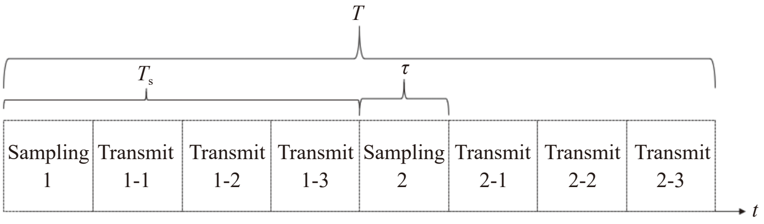


Fig. 2 Schematic diagram of periodic repeater

Assume that the number of transmissions in a sampling period is M. The transmitted signal $x_j'(t)$ can be expressed as

$$\begin{aligned} x_j'(t) &= x_s(t) + x_s(t-\tau) + \cdots + \\ & x_s(t-(M-1)\tau) = \sum_{r=0}^{M-1} x_s(t - r\tau). \end{aligned} \tag{3}$$

2.3 Phase modulation

By phase modulation of the sampled signal, the suppression effect along the distance direction can be formed [24–28]. Pseudo-random sequences is a common modulation signal, and its signal can be expressed as

$$u(t) = \mathrm{rect}\left(\frac{t}{T_c}\right) \otimes \sum_{q=0}^{P-1} c_m \delta(t - qT_c) \tag{4}$$

where T_c is the code width, P is the length of the pseudo-random sequence, and c_m is the code value. For binary pseudo-random sequences, the value of c_m is only ± 1.

Multiply $x_j'(t)$ and $u(t)$, the signal $x_j(t)$ modulated by a pseudo-random sequence can be obtained, and its expression is

$$x_j(t) = x_j'(t) \cdot u(t). \tag{5}$$

2.4 Output of the radar matched filter

According to [22], the result $y_s(t)$ of interrupted-sampling direct repeater signal output by radar matched filter is

$$y_s(t)=\sum_{n=-\infty}^{+\infty}\tau f_s\cdot\operatorname{sinc}(\pi n f_s\tau)\chi(t,-nf_s) \tag{6}$$

where f_s is the sampling frequency, and $\chi(\tau,\xi)$ is the ambiguity function of the radar signal. It is the same as the output result of the radar signal whose Doppler frequency shift is ξ through the radar matched filter. Therefore, the output result of the interrupted-sampling direct repeater signal after the radar matched filtering can be regarded as the weighted synthesis of the matched filtering output signal of the target echo with different Doppler frequency shift $f_d=nf_s$.

Reference [23] pointed out that the output of the periodic repeater signal $x_{j1}(t)$ through the radar matched filter can be regarded as the delayed superposition of the output of the direct repeater signal $x_j(t)$. Thus, the output $y_{j1}(t)$ of the radar matched filter can be expressed as

$$y_{j1}(t)=\sum_{r=0}^{M-1}y_s(t-r\tau). \tag{7}$$

The output of the interrupted-sampling direct repeater signal phase-modulated by a binary pseudo-random sequence through the radar matched filter is given by [24]. Combine (7) and the output of the phase-modulation signal through the radar matched filter. The result is

$$y_j(t)=\sum_{r=0}^{M-1}\sum_{n=-\infty}^{+\infty}\left[a_n\chi(t-r\tau,-nf_s)+\sum_{\substack{l=-\infty\\ l\neq 0}}^{+\infty}b_{nl}\chi\left(t-r\tau,-nf_s-\frac{l}{PT_c}\right)\right] \tag{8}$$

where

$$\begin{cases} a_n=\dfrac{\tau f_s}{P}\cdot\operatorname{sinc}(\pi n f_s\tau)\cdot\delta(f) \\ b_{nl}=\dfrac{\sqrt{P+1}}{P}\cdot\operatorname{sinc}(\pi n f_s\tau)\cdot\operatorname{sinc}\left(\dfrac{l\pi}{P}\right) \end{cases}. \tag{9}$$

It can be seen that the output result of the interrupted-sampling and phase-modulation repeater signal through the radar matched filtering can be regarded as the time-delay superposition of the equally spaced false targets generated by the interrupted-sampling direct repeater signal and the dense false targets generated by the pseudo-random sequence phase modulation generated around the false target generated in the first item.

2.5 Suppression effect

Relevant reception and constant false alarm (CFAR) detection are commonly used radar signal processing techniques, which can improve the signal to noise ratio (SNR) of the received signal and adaptively adjust the target detection threshold [29–32]. Pseudo-random sequence phase modulation waveform can produce dense false targets and achieve suppression effect. This paper measures the suppression effect based on the CFAR threshold.

Since the energy of the target echo is basically concentrated in the detection unit where the target is located, the threshold height is mainly determined by the phase modulation signal in the average unit on both sides of the target. Under self-defense conditions, the delay time of the phase modulation signal relative to the target echo signal is the interrupted sampling time τ. Assume that the arrival time of the target echo is 0. The expressions of the output signal $x_{\mathrm{epc}}(t)$ of the target echo $x_e(t)$ and the output signal $x_{\mathrm{jpc}}(t)$ of the phase-modulation signal $x_j(t)$ through the radar matched filter are respectively

$$x_{\mathrm{epc}}(t)=x_e(t)\otimes x^*(-t), \tag{10}$$

$$x_{\mathrm{jpc}}(t)=x_j(t-\tau)\otimes x^*(-t). \tag{11}$$

At this time, $t=0$ is the target location. Suppose the radar signal bandwidth is B, then the width of each detection unit is $1/B$. With $t=0$ as the center position of one detection unit, the detection units are divided into two sides respectively, and the average value of the phase modulation signal power in the rth unit on the right is recorded as $P_{\mathrm{jpc}}(r)$. Assume that the number of the single-side protection units and the average units are N_1 and N_2 respectively. The expression of the threshold Z of the detection unit where the target is located is

$$Z=\left(P_{\mathrm{fa}}^{-\frac{1}{2N_2}}-1\right)\cdot\left[\sum_{r=-(N_1+N_2)}^{-(N_1+1)}P_{\mathrm{jpc}}(r)+\sum_{r=N_1+1}^{N_1+N_2}P_{\mathrm{jpc}}(r)\right] \tag{12}$$

where P_{fa} is the false alarm probability.

Calculate the difference between the average threshold of N detection units near the target and the target echo pulse pressure peak value. This value can be used as a parameter to measure the suppression effect. If it is taken as the target function, the signal suppression effect can be improved by increasing the target function. The expression of the target function is

$$\text{target} = \frac{1}{N}\sum_{N}[10\lg Z] - 20\lg[x_{\text{epc}}(0)]. \tag{13}$$

3. Optimization model

In the analysis in Section 2, we find that the target function is very complex. When the expression of the radar signal is unknown, the target function cannot even get a specific expression, so traditional optimization methods can not be used. The exhaustive method is extremely time-consuming when the feasible range is large, and it cannot meet the real-time or quasi-real-time requirements in the confrontation environment. Thus, a waveform optimization method based on the intelligent optimization algorithm is proposed

Through analysis and research, it is found that many intelligent optimization algorithms, such as GA [33] and PSO [34–36], have a similar overall structure. Based on this, an optimized model is established. The process of the entire optimization model is as follows:

Pre-step Sample the radar signal. When the samplingofaradarsignalcycleiscompleted,thewaveformoptimization starts. During the sampling period, the countermeasure waveform is generated according to the preset parameters.

Step 1 Generate a set of initial populations according to the preset method. This method can be a combination of optimal parameters under a variety of conditions obtained in advance, but it is better to maintain a uniform distribution in the feasible region.

Step 2 Calculate the fitness function corresponding to the initial population. The fitness function is generally obtained by transforming the target function according to the characteristics of the algorithm. If several algorithms used in this article are the minimum value algorithms, the fitness function can be

$$\text{fitness} = -\text{target}. \tag{14}$$

Step 3 Update the population. Update the existing population according to the population update method of the algorithm used. If there is a better-quality individual in the new generation of population, the parameter combination corresponding to the individual is used to replace the previous optimal parameter combination, and to guide the generation of the subsequent countermeasure waveform.

Step 4 Terminate judgment. When the radar signal changes, the algorithm falls into the local optimum or other preset termination conditions, the current optimization process is stopped and a new round of optimization is started; otherwise Step 3 is repeated.

Externally, the optimization model has a certain degree of intelligence, which can optimize the waveform according to different external environments; internally, the optimization model has a certain universality, that is, it can meet different restrictions and desired effects by changing the constraints of the feasible region and the target function.

4. Simulation experiment

4.1 Optimization parameters

This section mainly conducts simulation experiments on the optimization of the interrupted-sampling and phase-modulation repeater waveform. The selected optimization parameters include the code width of the pseudo-random sequence, the sampling time of the interrupted sampling, the number of periodic repeater, and the time when the transmitted signal is ahead of the target's echo. The constraints set are shown in Table 1.

Table 1 Constraints on optimization parameters

μs

Parameter	Lower limit	Upper limit	Precision
Code width	0.1	4	0.1
Sampling time	1	10	0.5
Forwarding time	1	7	1
Lead time	0	10	0.5
Other constraints	$T_c \leqslant 0.4\tau$		

4.2 Other parameters

The simulation experiment also needs to set the remaining parameters, as shown in Table 2.

Table 2 Remaining parameter settings

Parameter	Detailed parameter
Radar signal 1	LFM (1 MHz, 64 μs)
Radar signal 2	LFM (1 MHz, 128 μs)
Radar signal 3	LFM (8 MHz, 64 μs)
Radar signal 4	PCM (2 MHz, 127 × 0.5 μs)
Radar signal 5	NLFM (8 MHz, 64 μs)
False alarm probability	10^{-3}
Protection unit	4
Average unit	16
Pseudo-random sequence	*M* sequence (511-bit)

4.3 Optimization algorithm

Two typical algorithms, GA and PSO, are mainly used.

And each algorithm is implemented by real number and Gray code encoding respectively. The initialization and termination conditions of all algorithms are the same. The initial population is set to 20, which is generated in a random way. And the initial population used in each optimization is the same. The termination condition is set to 100 iterations or the optimal fitness function does not change for 20 consecutive iterations. The difference lies in how the population is updated. Through the previous comparison of the performance of a variety of operator combinations through simulation experiments, the final selection of the algorithm is as follows:

(i) Real-coded GA

Selection: ternary stochastic tournament model.

Crossover: BLX hybrid crossover with a crossover range coefficient of 0.25 and a crossover rate of 1.

Mutation: single-point Gaussian mutation with a mutation rate of 0.1.

Retention: generation from all individuals after removing duplicate individuals.

(ii) Gray-coded GA

Selection: ternary stochastic tournament model.

Crossover: single-point crossover, two-point crossover, and random crossover with probabilities of 0.1, 0.2, and 0.7 respectively. And the crossover rate is 1.

Mutation: two-point mutation with a 0.2 mutation rate.

Retention: generation from all individuals after removing duplicate individuals.

(iii) Real-coded PSO

Velocity update: adaptive speed update strategy, in which chaotic decreasing inertia weight strategy based on population success rate and learning factor based on inertia weight adjustment are adopted.

Position update: produced by adding the current position to the current velocity.

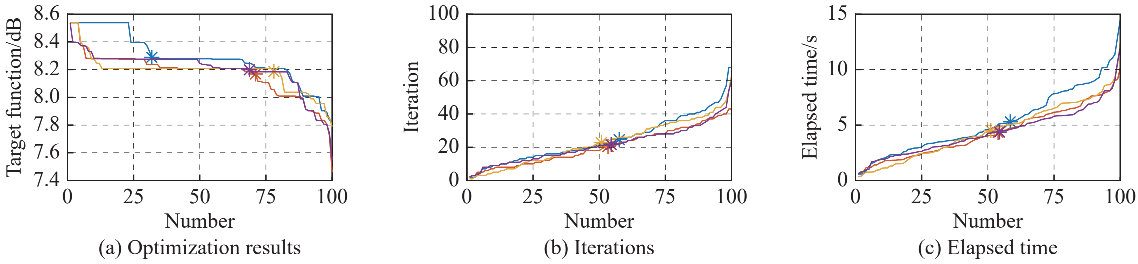
(iv) Gray-coded PSO

Velocity update: inertial weight strategy based on linear decline and velocity mapping based on Sigma function.

Position update: produced by adding the current position to the current velocity.

4.4 Optimization result

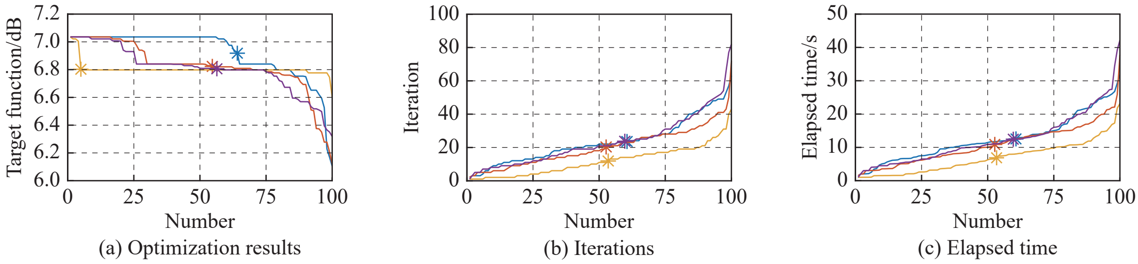
Four algorithms are used to optimize the phase modulation waveform under five signal conditions from 1 to 5, and 100 repeated experiments are performed under each condition. Reorder the obtained experimental data according to the numerical order, and then plot them, as shown in Fig. 3 − Fig. 7. Different colored curves represent the results of different algorithms, and “*” on each curve represents the average value of the data on the curve. Table 3 shows the optimal value of the initial population under each condition and the global optimal value calculated by the exhaustive method.



(a) Optimization results (b) Iterations (c) Elapsed time

—: Real-coded GA; —: Real-coded PSO; —: Gray-coded GA; —: Gray-coded PSO.

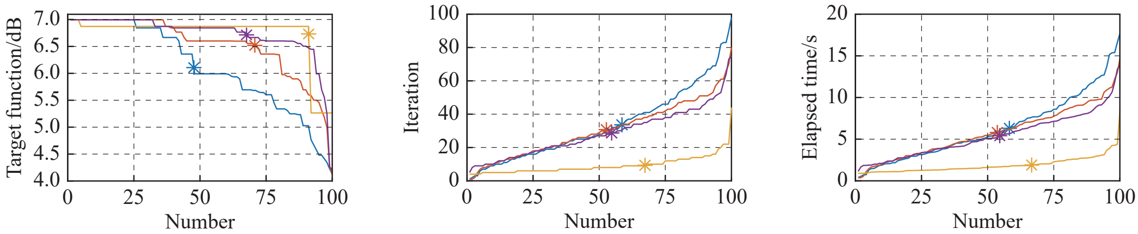
Fig. 3 Optimization results under Signal 1 condition after sorting



(a) Optimization results (b) Iterations (c) Elapsed time

—: Real-coded GA; —: Real-coded PSO; —: Gray-coded GA; —: Gray-coded PSO.

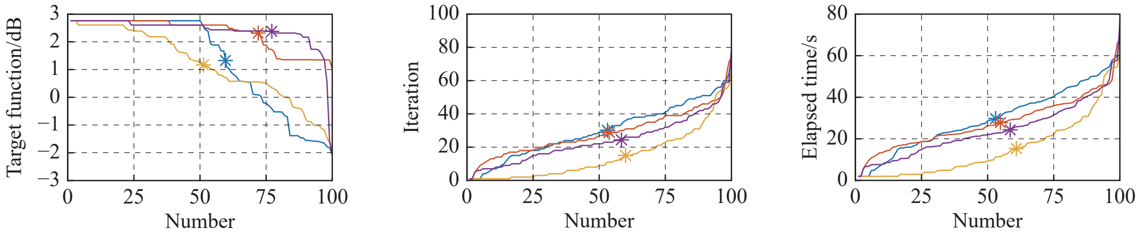
Fig. 4 Optimization results under Signal 2 condition after sorting



(a) Optimization results (b) Iterations (c) Elapsed time

—: Real-coded GA; —: Real-coded PSO; —: Gray-coded GA; —: Gray-coded PSO.

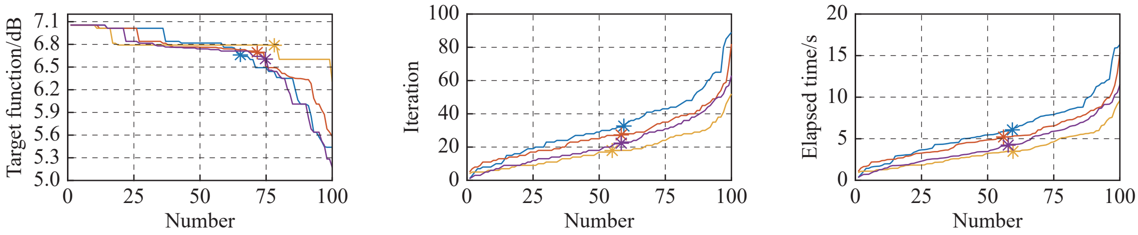
Fig. 5 Optimization results under Signal 3 condition after sorting



(a) Optimization results (b) Iterations (c) Elapsed time

—: Real-coded GA; —: Real-coded PSO; —: Gray-coded GA; —: Gray-coded PSO.

Fig. 6 Optimization results under Signal 4 condition after sorting



(a) Optimization results (b) Iterations (c) Elapsed time

—: Real-coded GA; —: Real-coded PSO; —: Gray-coded GA; —: Gray-coded PSO.

Fig. 7 Optimization results under Signal 5 condition after sorting

Table 3 Initial optimal and global optimal value dB

Signal	Initial optimal	Global optimal
Signal 1	5.83	8.54
Signal 2	5.12	7.04
Signal 3	2.94	7.00
Signal 4	−2.83	2.76
Signal 5	4.59	7.06

From the optimization results, all the four algorithms can optimize the waveform on the basis of the initial population. They all get the global optimal, but they do not get the global optimal in every experiment. Consider the optimization results under five conditions. Although the GA and PSO encoded by gray code may not perform the best under every condition, their overall performance is relatively stable.

From the number of iterations, the real-coded PSO requires the smallest number of iterations when it reaches the termination condition. The real-coded GA is slightly higher than the others, but it is not much different from the two algorithms of gray code encoding. The average number of iterations of the four algorithms under different conditions is less than 40, which is about 1.3% of the feasible solutions. The required target function calculation is much smaller than the exhaustive method.

The distribution of running time is basically the same as the distribution of the number of iterations. It can be seen that the main time consumption lies in the calculation of the target function. At the same time, the running time varies greatly under different signal conditions, which indicates that the calculation amount of the target function set in this paper is greatly affected by the signal characteristics.

5. Conclusions

This paper proposes an intelligent optimization model for radar countermeasure waveforms based on intelligent optimization algorithms. Four algorithms are used to optimize the intermittent sampling and phase modulation repeater waveform, and the performance of different algorithms under different signal conditions is explored. The experimental results show that the optimization model achieves the optimization of radar countermeasure waveforms under different parameters and different styles of radar signal conditions, and improves the countermeasure effect. The feasibility of the scheme is verified preliminarily.

The experimental results also illustrate some existing problems, such as the excessive calculation of the target function under some conditions, and the unstable performance of the algorithm under different conditions. These problems need to be improved in the follow-up study and research.

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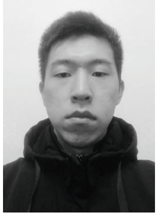
Biographies



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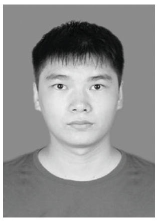

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