EEG Signal Radio Frequency Control Wheeled Robot Based on Bi-objective Chaotic Particle Swarm Optimization Algorithm

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Abstract: Aiming at the EEG signal radio frequency control problem of EEG signal radio control wheeled robot traversing multiple objective points, a new method of EEG signal radio frequency control that integrates the bi-objective chaotic particle swarm optimization (BCPSO) is put forward. This method transforms the selection of objective points into the EEG signal radio frequency control problem and makes optimization by using the ant colony algorithm. The EEG signal control function between the two objective points is defined, and the particle swarm optimization algorithm is applied for optimization. Given the premature phenomenon of particle swarm optimization algorithm, the inverse learning strategy is introduced into the particle swarm optimization algorithm, and the inertia weight and learning factor of the particle swarm optimization algorithm are improved. The performance test results show that the bi-objective chaotic particle swarm optimization algorithm can effectively prevent the premature particle phenomenon and improve the optimization capacity and stability of the particle swarm optimization algorithm.

1. Introduction

Ant colony optimization (ACO) is a heuristic evolutionary algorithm evolved from ant foraging behavior. The ant colony algorithm has presented superiority in solving the TSP problem. The particle swarm optimization algorithm (PSO) is a swarm intelligence algorithm that is evolved from the bird's foraging behavior [1]. Compared with the general swarm intelligence algorithm, PSO has memory characteristics, which can obtain more information through self-learning and learning from others. Due to the advantages of fewer parameters and convenient calculation, PSO is widely applied in optimization problems and has achieved very excellent results. With the development of the EEG signal radio frequency control wheeled robot technology, domestic and foreign scholars have carried out a lot of studies on the EEG signal radio frequency control of the EEG signal radio frequency control wheeled robot, such as the multi-robot EEG signal radio frequency control [2-4], the free floating robot trajectory planning [5-7] and other application areas [8-9]. PSO is widely applied in EEG signal radio frequency control, and ACO is effective in solving the TSP problem. Hence, the combination of the two algorithms is very suitable for solving the multi-objective point EEG signal radio frequency control problem of the EEG signal radio frequency control wheeled robot [10-12].

In a space that contains obstacles, the PSO algorithm is used to control the EEG signal from the starting point to the objective point and between each objective point and the objective point. The
starting point, the objective point and the obstacle position are known, but which route to be selected is unknown. In order to determine which path will be selected, ACO is applied to traverse the starting point and all objective points to obtain the shortest path through all points. In order to avoid premature PSO and improve the efficiency of the algorithm, a particle swarm optimization algorithm with fast convergence is put forward. The experimental results have verified the effectiveness of the hybrid algorithm and the superiority of the bi-objective chaotic particle swarm optimization algorithm.

2. Bi-objective chaotic particle swarm optimization algorithm

2.1. Iterative evolution process
The time when the particle identifies the optimal solution in the problem space is proportional to the distribution in the space when the particle is initialized. The particle near the optimal position identifies the optimal solution faster than the particle with the optimal position. However, particles are randomly distributed in the problem space, and the position of each particle relative to the optimal solution is unknown.

Combined with the above analysis, the introduction of the reverse learning strategy in the initialization of the bi-objective chaotic particle swarm optimization algorithm is conducive to the particle in identifying the optimal solution. Upon the initialization, firstly, the fitness value of the particle and its inverse particle fitness value are calculated, and their values are compared to select the particles with relatively good fitness value. Secondly, the particles with the optimal fitness value are selected from the population as the initial population.

2.2. Iterative evolution process
In the standard PSO algorithm, the inertia weight affects the global search and local search ability of the particle, and the learning factor affects the capacity of the particle to acquire information. In the process of evolution, the global search ability and local search ability should also change, that is, from global search to local search, to ensure that the particle can identify the optimal solution to the problem. Similarly, the particle should also be gradually enhanced social skills for the transition from “self” learning to learning from “others”, so as to acquire more useful information.

According to the above analysis, the inertia weight should be kept dynamically changing during the optimization process. When the value taken for $\omega$ is relatively large, the global search ability of the particle is relatively strong; when the value taken for $\omega$ is relatively small, the local search ability of the particle is relatively strong. In the process, it will gradually approach the optimal point, and the inertia weight of the particle should change adaptively with the optimization process. Hence, the inertia weight update formula of the particle is $\omega_{max}$:

$$\omega = \omega_{max} - \left( \omega_{max} - \omega_{min} \right) \left( 1 - \frac{dist_i}{\max_dist} \right)$$

(1)

In the above equation: $\omega_{max}$ and $\omega_{min}$ stand for the maximum and minimum values of the particle inertia weight, respectively; $dist_i$ stands for the euclidean distance from the i-th particle to the global optimal particle; $\max_dist$ stands for the maximum distance from the particle to the global optimal particle. Hence, the expressions of $dist_i$ and $\max_dist$ are as the following:

$$dist_i = \left( \sqrt{ \sum_{d=1}^{D} \left( g_{best_d} - x_{i,d} \right)^2 } \right)^{\frac{1}{2}}$$

$$\max_dist = \arg \max_i \left( dist_i \right)$$

(2)

The learning factor $c_1$ and $c_2$ control the relative influence between the particle’s own memory and the companion memory: when the value of $c_1$ is relatively small, it is presented that the self-cognitive
ability is insufficient; when the value of $c_2$ is small, it is presented that the social ability is insufficient.

In order to ensure that the self-cognition and social ability of the particle can vary from time to time in the iterative process, and the particle learning factor update formula is as the following:

$$
c_1 = c_{1\text{max}} \times \left( \frac{c_{2\text{min}}}{c_{1\text{max}}} \right)^t
$$

$$
c_2 = c_{2\text{min}} \times \left( \frac{c_{2\text{min}}}{c_{1\text{min}}} \right)^t
$$

In the above equation: $c_{1\text{max}}$ and $c_{2\text{max}}$, as well as $c_{1\text{min}}$ and $c_{2\text{min}}$ stand for the maximum and minimum values of the learning factors $c_1$ and $c_2$, respectively; $t$ stands for the current number of iterations; $T_{\text{max}}$ stands for the maximum number of iterations.

### 2.3. Implementation process of the algorithm

Once the algorithm falls into premature, chaotic particle swarm optimization will search in the region around the optimal solution to replace some of the particles in the original population, leading the population to jump out of the local optimum. A chaotic variable has the following characteristics in a certain range: randomness, that is, its performance is as disorderly as random variables; ergodicity, that is, it can go through all States in space without repetition; regularity, the variable is derived from the determined iteration equation. Chaotic optimization is a novel optimization method, which uses the ergodicity of chaotic system to achieve global optimization, and it does not require the continuity and differentiability of the objective function.

In this paper, two different chaotic search spaces are used, one is to search in the neighborhood of space with global optimum gbest as the center and $R$ as the radius, as shown in Formula (4); the other is to search in the spatial domain with origin as the center and $R'$ as the radius, as shown in Formula (5).

$$
R = \eta \text{gbest}
$$

$$
R' = \rho(x_{\text{max}} - x_{\text{min}})
$$

Among them: $\eta$ is chaotic search coefficient, take 1.5; $X_{\text{max}}$ and $X_{\text{min}}$ represents the upper bound and lower bound of the position vector respectively, $\rho$ is the shrinkage factor of chaotic search, which decreases linearly in the iteration process of the algorithm to reduce the scope of chaotic search and increase the search accuracy, taking 1.0-0.3 linear decline. The steps are as follows:

Step1: Initialize parameters, set the total number $N$, the maximum number of iterations, replacement probability, etc.

Step2: Update the velocity and position of the $i^{th}$ particle. Calculate the fitness value $f_i$ of the $i^{th}$ particle.

Step3: Calculate the inverse solution of the position and velocity of the $i^{th}$ particle: $\bar{x}_i = a_i + b_i - x_i$, $a_i = \min(x_i)$, $b_i = \max(x_i)$

Step4: Calculate the fitness value of the inverse solution

Step5: Select the particle with the best fitness to form the population

Step6: Update the velocity and position of the $i^{th}$ particle

Step7: Determine whether it falls into local optimal. If it gets stuck at the local optimum, it creates chaotic particles. In Step7, D dimensional chaotic vector is generated according to formula (1), where $P$ is the replacement probability, and the chaotic vector is linearly mapped to the set solution space to randomly replace the original population particles.

Step8: Determine whether the algorithm satisfies the termination condition, if so, terminate the algorithm and proceed to Step2 to continue execution.
3. Experimental results and analysis

3.1 BCPSO performance test

In order to verify whether the performance of the bi-objective chaotic particle swarm optimization algorithm is improved, the author compares it with other improved algorithms on four fitness functions. The four fitness functions are the Sphere function, Rastrigin function, Grewank function and Schaffer function, respectively, and the test function parameter settings are shown in Table 1 as the following.

| Function    | Value range | Optimal point | Optimal solution |
|-------------|-------------|---------------|------------------|
| Sphere ($f_1$) | [-100,100]  | (0,0)         | 0                |
| Bastrigin ($f_2$) | [-5.12,5.12] | (0,0)         | 0                |
| Grewank ($f_3$)  | [-600,600]   | (0,0)         | 0                |
| Schaffer ($f_4$) | [-100,100]   | (0,0)         | 0                |

The BCPSO algorithm parameters are set as the following: the particle swarm size 40, the spatial dimension is 2, $\omega = [0.4, 0.9]$, $c_1 = [1.25, 2.75]$, $c_2 = [0.5, 2.25]$, and the maximum number of iterations is 100.

In Table 2, the mean value of the BCPSO algorithm on the four test functions is smaller than the values of the other three algorithms, especially in the Sphere function and the Rastrigin function. From the data in Table 2, it can be observed that the BCPSO algorithm has better convergence performance, and the solution thus obtained is more superior. The data in Table 3 reflects the stability of the improved algorithm. Comparison between the BCPSO algorithm and the IAPSO algorithm, between the IPSO algorithm and the WPSO algorithm shows that the improved algorithm has better performance in the stability.

| Function | BCPSO | IAPSO | IPSO | WPSO |
|----------|-------|-------|------|------|
| $f_1$    | 0     | 0.132790 | 0.020476 | 0.034939 |
| $f_2$    | 0     | 0.066379 | 0.066331 | 0.297488 |
| $f_3$    | 0.002153 | 0.031692 | 0.017342 | 0.018080 |
| $f_4$    | 0.003273 | 0.005328 | 0.006179 | 0.017561 |

| Function | BCPSO | IAPSO | IPSO | WPSO |
|----------|-------|-------|------|------|
| $f_1$    | 0     | 0.714775 | 0.009423 | 0.006733 |
| $f_2$    | 0     | 0.248174 | 0.248186 | 0.455948 |
| $f_3$    | 0.004418 | 0.087505 | 0.021595 | 0.019151 |
| $f_4$    | 0.0045600 | 0.004699 | 0.004650 | 0.032801 |

From the data in Table 2 and Table 3, it can be known that the reverse learning strategy has improved the diversity of the population, increased the probability of particle optimization success and saved the particle optimization time; the linearly varying inertia weight guarantees the particle from global search to local search. The linear transformation suppresses the premature phenomenon of the particles; the change of the learning factor ensures that the particles can fully complete the self-learning and social behavior and improve the convergence speed of the particles.

3.2 Performance comparison of EEG radio frequency contro

In order to verify the practicability and effectiveness of the new method, the author conducted the experiment in the simulation environment. The simulation experiment environment is set in an 18x16 two-dimensional rectangular space, which is further set into a simple environment and a complex environment. In the first experiment, the parameters of the BCPSO algorithm are set as the following:
\( \omega_{\text{max}} = 0.9, \quad \omega_{\text{min}} = 0.4, \quad S = 10, \quad c_1 = 2.75, \quad c_2 = 2.25, \quad c_3 = 1.25, \quad c_4 = 0.5, \quad v_{\text{max}} = 1.9, \quad v_{\text{min}} = 0 \), the safety distance in the repulsive field \( d = 2, \quad k = 2.7, \quad \lambda = 0.25, \quad \mu = 0.25 \), and the maximum number of iterations is 100. The experiments for the above two tasks are repeated 10 times, and the mean value is obtained. The time consumption and moving distance performance of the multi-objective point EEG signal radio frequency control in the EEG signal radio frequency control wheeled robot are shown in Table 4 as the following.

| Environment          | Algorithm | Moving distance/m | Time consumed/s |
|----------------------|-----------|-------------------|-----------------|
| Simple environment   | BCPSO     | 40.943            | 8.866           |
|                      | IAPSO     | 41.749            | 10.257          |
|                      | IPSO      | 42.865            | 10.625          |
| Complex environment  | BCPSO     | 44.942            | 18.583          |
|                      | IAPSO     | 43.127            | 23.265          |
|                      | IPSO      | 45.336            | 25.183          |

From the data in Table 4, it can be concluded that with the increase of task complexity, BCPSO, IAPSO and IPSO are also increasing in time consumption. The more complex the task is, the more time it takes. However, when performing the same task, BCPSO takes time and IAPSO. In terms of moving distance, the moving distance of BCPSO is shorter than the other two comparison algorithms in simple tasks. In the complex task, although BCPSO has a longer moving distance than IAPSO, it is shorter than IPSO algorithm; in terms of the path security, the BCPSO algorithm is superior to the other two comparison algorithms. As the objective function of the EEG signal radio frequency control is designed, not only the path shortest problem is considered, but the safety problem is also taken into consideration. Hence, the experimental results can be obtained by combining the two environments. The comprehensive performance of the BCPSO algorithm is stronger than the IAPSO algorithm and the IPSO algorithm.

Figure 1 shows the convergence curves of the BCPSO algorithm, IAPSO algorithm and IPSO algorithm on the objective function in a simple environment. It can be observed that the BCPSO algorithm can be applied in the multi-objective point brain when iteration is performed for about 72 times. The optimal path is identified in the radio frequency control of the electrical signal, and the IAPSO algorithm and the IPSO algorithm still fail to obtain the convergence value of the BCPSO algorithm when iteration is performed for 100 times.

In summary, under the same task, the comprehensive performance of BCPSO algorithm is superior to that of the IAPSO algorithm and the IPSO algorithm. With the change of task complexity, BCPSO algorithm can effectively and properly complete the movement distance and time consumption and security performance, which indicates that the BCPSO algorithm can effectively and properly complete the multi-objective point EEG signal radio frequency control effect of the EEG signal radio frequency control wheeled robot.

![Figure 1. Comparison of BCPSO and IAPSO and IPSO objective function convergence curves](image-url)
4. Conclusions
In this paper, a new method of multi-objective point EEG signal radio frequency control for the EEG signal-based wheeled robot based on the combination of ACO algorithm and BCPSO algorithm is put forward, and the feasibility of the new method is verified by experiments. The ACO algorithm presents relatively good superiority in the TSP problem. Hence, the ACO algorithm is applicable to the objective point selection problem of the EEG signal radio controlled wheeled robot. The BCPSO algorithm has not only inherited the simple calculation characteristics of the PSO algorithm but also introduced the reverse learning strategy during initialization to ensure the particle. In the iterative process, the BCPSO algorithm has suppressed the premature of the particles and improved the convergence speed. Four performance parameters are applied to evaluate the performance of the BCPSO algorithm, and excellent test results are obtained. The experimental results under the simulation experiment and real environment suggest that the new method proposed in this paper is a valid multi-objective point EEG signal radio frequency control method. The application of the new method proposed in this paper to the EEG signal multi-objective point EEG signal radio frequency control of the wheeled robot in the dynamic environment is the research content in the next step.

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