Discrete Fireworks Algorithm for Welding Robot Path Planning

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Abstract. Welding robots are widely used in manufacturing industries, and reasonable welding path planning is an important issue in production efficiency. Welding robot path planning aims to arrange the sequence of weld joints and find the optimal welding path for the robot, which is essentially a combinatorial optimization problem. With the development of artificial intelligence, swarm intelligence algorithms shed new light on this problem. Fireworks algorithm (FWA) is a newly proposed swarm intelligence algorithm, simulating the process of fireworks explosion producing sparks to find the optimal solution. It has shown excellent performance in continuous optimization problems. In this paper, a discrete fireworks algorithm (DFWA), is proposed to solve the welding robot path planning problem. We introduce some operations to the framework of traditional FWA. In DFWA, 2-opt local search and crossover operator are applied on the explosion sparks. A new way of fireworks quality judgment is designed. Mutation operator is implemented for the generation of Gaussian sparks, and the selection strategy is improved. Simulation experiments have been made to verify our method and compare its performance with other current swarm intelligence algorithms. Experimental results show that the proposed method performs well with good convergence, stability and accuracy. It is effective for welding robot path planning.

1. Introduction

In the manufacturing industries such as automobile and shipbuilding, welding robots have been widely used to greatly increase productivity. In practical applications, the number of weld joints in a welding task is very large. Therefore, properly planning the welding sequence of these weld joints plays an important role in saving time and reducing production cost. Traditional path planning methods are mostly based on experiences of welding engineer, and cannot ensure the optimal solution. In recent years, with the rapid development of artificial intelligence (AI), more and more swarm intelligence algorithms have been born and widely used in optimization. These algorithms have provided new ways to robot path planning. Yang and Tang [1] proposed a particle swarm optimization (PSO) with quantum mechanics to realize welding path optimization. Shen [2] combined genetic algorithm (GA) and ant colony optimization (ACO) to solve the contradiction between the convergence speed and the optimization accuracy. Wang et al. [3] presented a double global optimum GA-PSO approach based on two populations to improve optimization effects of welding robot path planning.
Inspired by the natural phenomenon of fireworks explosion, Tan and Zhu [4] proposed fireworks algorithm (FWA) in 2010. FWA is a newly swarm intelligence algorithm in AI field, and performs multiple simultaneous explosion searches by simulating fireworks explosion at night. It shows high performance and efficiency in solving complex optimization problems. FWA has gradually gained attentions and follow-up researches. So far, it has been applied for solving practical optimization problems, including digital filters design [5], spam detection [6], power system reconfiguration [7], and improved in studies [8], [9], [10]. However, for the application on discrete optimization problems, e.g. path planning, the current research on FWA is in the early stage, and this direction is still a new topic. In this paper, a novel discrete FWA (DFWA) method is proposed, which combines with 2-opt local search and GA operators, in order to solve the problem of welding robot path planning efficiently.

2. Description of welding robot path planning
The welding robot path planning problem can be summarized as obtaining a reasonable sequence of weld joints for the welding robot. It is briefly described as: given N weld joints and the distance between any two joints, the manipulator starts from an initial position and returns the initial position after finishing all the assigned weld joints. The goal is to find a shortest possible route, in which each joint is welded once and only once.

The mathematical description is as follows:
Considering N weld joints \( C = \{c_1, c_2, ..., c_N\} \), the distance between each pair of joints is denoted by \( d(c_i, c_j) \). Welding robot path planning aims to find a permutation \( X = \{x_1, x_2, ..., x_N\}, x_i \in \{1, 2, ..., N\} \) to minimize the total path length of route \( X \).

\[
f(X) = \sum_{i=1}^{N-1} d(c_{x_i}, c_{x_{i+1}}) + d(c_{x_N}, c_{x_1})
\]

where \( f(X) \) denotes the distance when the welding sequence is \( X \).

3. Discrete fireworks algorithm

3.1 Standard fireworks algorithm
In FWA, a firework or a spark is considered as a feasible solution in the solution space of the optimization problem. The process of fireworks explosion producing a certain amount of sparks is regarded as a neighbourhood searching process. Similar to other swarm intelligence algorithms, FWA is based on population and evolution. The optimal solution is generated through a series of iterative processes. In each iteration, the fireworks undergo explosion operations, Gaussian operations, mapping rules, and selection strategies to form the fireworks for next generation. Finally, the population converges to an optimal solution.

3.1.1. Sparks explosion. The core of the FWA is the explosion operation, which simulates the behaviour of natural fireworks exploding in the sky. The fireworks with better fitness (quality) produce more sparks in a smaller range. On the contrary, the fireworks with poorer fitness (quality) produce less sparks in a larger range. Suppose that for a D-dimensional optimization problem, \( n \) denotes the number of fireworks, \( x_i = \{x_{i1}, x_{i2}, ..., x_{id}\} \) represents the position of the \( i \)th \((i = 1, 2, ..., n) \) firework, and the explosion amplitude and sparks number are calculated by:

\[
A_i = \hat{A} \cdot \frac{f(x_i) - y_{\text{min}} + \epsilon}{\sum_{i=1}^{n}(f(x_i) - y_{\text{min}}) + \epsilon}
\]

\[
s_i = m_s \cdot \frac{y_{\text{max}} - f(x_i) + \epsilon}{\sum_{i=1}^{n}(y_{\text{max}} - f(x_i)) + \epsilon}
\]
where $f(x_i)$ represents the function value of the $i$th firework, $A_i$ and $s_i$ are the explosion amplitude and the number of sparks of the $i$th firework. $\hat{A}$ and $m_s$ are constants, controlling the maximum explosion amplitude and the total number of sparks. $y_{\text{min}} = \min(f(x_i))$, $y_{\text{max}} = \max(f(x_i))$. $\epsilon$ is a very small constant, used to prevent the denominator being zero.

To avoid the overwhelming effects of outstanding fireworks, the bounds of sparks number are defined by:

$$s_i = \begin{cases} \text{round}(am_s), & \text{if } s_i < am_s \\ \text{round}(bm_s), & \text{if } s_i > bm_s, \ a < b < 1 \\ \text{round}(s_i), & \text{otherwise} \end{cases}$$

(4)

where $a$ and $b$ are constants to control the maximum and minimum of sparks.

3.1.2. Gaussian sparks explosion. Another type of sparks named Gaussian sparks are based on the Gaussian distribution, in order to increase the diversity of sparks. Suppose the position of the $i$th individual on the $d$th dimension is denoted by $x_i^d$, the Gaussian sparks are calculated as:

$$x_i^d = x_i^d \cdot g$$

(5)

Note that $g$ is a Gaussian-distribution random number with a mean of 1 and a variance of 1, that is:

$$g \sim N(1,1)$$

(6)

3.1.3. Mapping rules. In the explosion operations and Gaussian operations, sparks may be outside the range of feasible domains. When spark $x_i$ exceeds the boundary on dimension $d$, it will be mapped into the new location by the following mapping rules:

$$x_i^d = x_{\text{min}}^d + \left| x_i^d \right| \% (x_{\text{max}}^d - x_{\text{min}}^d)$$

(7)

where $x_{\text{max}}^d$ and $x_{\text{min}}^d$ represent the upper and lower boundaries of the $d$th dimension respectively, and $\%$ represents a modular operation.

3.1.4. Selection. In order to retain excellent information in the fireworks population and pass it to the next generation, after the explosion sparks and Gaussian sparks generated, a certain number of individuals (all fireworks, explosion sparks and Gaussian sparks) will be selected as the fireworks for next iteration. The individual with the best fitness is always kept for the next iteration, and the remaining $n - 1$ individuals will be selected based on their distance to other individuals. Individuals that are further away from other individuals have more chance to become the fireworks of next iteration. This selection strategy ensures the diversity of the population.

3.2 DFWA

The basic FWA is mainly applied on continuous optimization problems, however, their rules cannot be directly used to deal with discrete problems. Compared with continuous space, the objective function of discrete problems is discontinuous, and the function fitness of adjacent spaces often varies greatly. The welding robot path planning belongs to the discrete combinatorial optimization problem, so the discretization of the traditional FWA is one of the most important parts.

First, the representation of the solution of the FWA is the same as the definition of welding path, which is the sequence of weld joints. The vector $X = (x_1, x_2, ..., x_N)$ is used to represent the sequence of weld joints in the path, and $x_i$ is the number of the $i$th weld joint in the path. There is one and only
one chance that each weld joint is passed. Our goal is to find an arrangement $X$ such that its path length $f(X)$ is the shortest.

Secondly, this paper redesigns the searching process of FWA while maintaining the traditional FWA framework. For the explosion operator, we introduce two new explosion methods. For the generation of Gaussian sparks, we use mutation operators which are suitable for discrete field. Moreover, the mapping rules are removed, because the solutions of discrete FWA would not exceed the definition domain of the path planning problem. Finally, the selection strategy is also adjusted. The framework of our algorithm is shown in figure 1.

![Figure 1. Framework of DFWA.](image)

### 3.2.1. Modified explosion operator
The process of generating explosion sparks is an important part in FWA, which plays a role of local search and global search. Fireworks with good fitness produce more sparks in a smaller range, meaning that a local search is applied within a promising area. In the contrast, fireworks with poor fitness produce fewer sparks in a larger range, meaning that a global search is implemented.

For good fireworks, in other words, the sequence of weld joints with a short total distance, adequate exploitation is needed near their locations. Based on this idea, we use $k$-opt method to enhance the local search for fireworks with good fitness. As for poor fireworks, inspired from genetic algorithm (GA), we use crossover operator to deal with them. This is because the crossover damages the original gene (path), and the generated gene (path) is very different from the original. It is consistent with the idea of global search.

$k$-opt is a basic local search heuristic algorithm, in which core idea is to randomly select $k$ edges and perform iterative optimization on them. When breaking $k$ edges, there are $(K - 1)! \cdot 2^{K-1}$ ways to reconnect this path, and each new combination is a valid solution. For example, in 2-opt method, 2 edges are removed and reconnected to search better solution (Figure 2).
Figure 2. An example of 2-opt. The left is original path, and the right is a path possibly generated.

Increase of $k$ gets better optimization while increases time complexity. Due to this, simple 2-opt operation is used, and it stops iterating when the maximum number of iterations is reached. $MaxItCount$ represents the maximum number of iterations set in this paper. The method using 2-opt for one robot path mainly contains following steps:

step 1: Suppose the current path $X_k$ to be optimized (e.g. [1, 2, 3, 4, 5, 6]) is the shortest path, the path length $f(X_k)$ is calculated according to equation (1).

step 2: Randomly select two positions in the path and reverse the sub-path between the two positions, then a new path $X_{new}$ is obtained. For example, if we randomly select the position 2 and position 4, the new path is [1, 4, 3, 2, 5, 6], as shown in figure 2.

step 3: If $f(X_{new})$ is shorter than $f(X_k)$, set the new path $X_{new}$ to be the shortest path $X_k$. Then return to step 2.

GA treats a solution (path) as a chromosome. In GA, crossover is a main operation. In this paper, partial mapping crossover operator is used, and the current firework randomly intersects with the rest of the fireworks to create a new solution.

After redesigning the explosion operations of different fireworks, how to judge the qualities of fireworks is a special problem in discrete optimization. In accordance with the principle that the good fireworks produce a large number of sparks, we select the top 20% of fireworks as the excellent fireworks according to the calculated number of sparks, and generate their sparks through 2-opt local search. The sparks of remaining fireworks are produced by crossover operator of GA.

3.2.2. Modified Gaussian sparks generation. In the problem of combination, the Gaussian random number does not play its role. After the generation of explosion sparks, all sparks are selected to perform the mutation operator of GA, which are called mutation sparks. Corresponding to the effect of Gaussian sparks in traditional FWA, the population diversity is further enhanced.

3.2.3. Selection mechanism. After fireworks producing explosion sparks and mutation sparks, selecting a specified number of individuals to go to the next iteration is needed. In traditional FWA, the selection strategy is based on distance metrics. The individuals (fireworks and all sparks) with lower density have higher probability to be selected, in order to ensure the diversity of the population. However, this selection strategy needs to construct the Euclidean distance between any two individuals, which will lead to large time consumption and high computational cost. Therefore, in DFWA, roulette strategy is adopted, where the probability of each individual being selected is based on the fitness. It can avoid trapping in the local optimum, and has a great help to the convergence of the whole population.

3.2.4. Algorithm steps. By means of 2-opt local search and genetic algorithm (GA), a discrete fireworks algorithm (DFWA) is proposed. The specific steps of DFWA are given as follows:

step 1: Initialize control parameters.

step 2: Randomly select $n$ locations for fireworks.
step 3: For each firework $X_i$, calculate the number of sparks of the firework $s_i$ according to equation (3) and equation (4).

step 4: Evaluate the qualities of fireworks, and generate explosion sparks by 2-opt local search and crossover operator.

step 5: Generate mutation sparks through mutation operator.

step 6: Select the best individual and n – 1 individuals by roulette mechanism to compose fireworks for next generation.

step 7: Determine whether the algorithm stop criteria is reached. If answer is no then go to Step 3, otherwise the algorithm ends.

4. Simulation experiments
In the actual welding process, joints are welded by manipulator in the order. And the proposed path planning is to provide a reference welding sequence for the robot. In order to test the performance of DFWA for welding robot path planning, 26 weld joints are selected for welding robots and the joint distribution is shown in figure 3. Figure 4 shows the path planning result of the DFWA algorithm.

Figure 3. The distribution map of weld joints. Figure 4. The optimal welding path based on DFWA.

Particle swarm optimization (PSO), genetic algorithm (GA), simulated annealing (SA) and our DFWA are applied on this example of 3-dimension path planning to show the performance of these swarm intelligence algorithms. They are respectively operated for 30 times. The parameters are given as follows. Iterations are set to 1000 for PSO and GA, inertia weight, self-learning factor and social learning factor in PSO are 0.8, 0.5 and 0.7. Crossover probability and variation probability in GA are 0.95 and 0.05. In SA, temperature $T_0 = 1000$, $p = 0.9$. In DFWA, $n = 5$, $m_s = 50$, $a = 0.04$, $b = 0.8$, and MaxItCount = 10. The experimental results are shown in table 1.

| Algorithm | Optimal (mm) | Mean (mm) | Maximum (mm) | Mean Iterations |
|-----------|--------------|-----------|--------------|-----------------|
| PSO       | 5155.77      | 6472.51   | 7509.79      | 30.30           |
| GA        | 4960.01      | 5335.90   | 9196.97      | 102.10          |
| SA        | 4960.01      | 5352.03   | 6640.13      | 39.20           |
| DFWA      | 4960.01      | 5050.65   | 5980.48      | 13.00           |

And the convergence curves of these 4 swarm intelligence algorithms are shown in figure 5.
Figure 5. Comparison of convergence curves among PSO, GA, SA and DFWA.

It can be seen that DFWA performs well in convergence speed, stability and accuracy of the optimization.

Overall, the DFWA proposed in this paper is feasible and effective. It provides a new idea for the research of FWA on discrete problems. In addition, the DFWA develops a reasonable welding sequence and is significant to welding robot path planning application.

5. Conclusion
A novel discrete fireworks algorithm (DFWA) is proposed for welding robot path planning. The DFWA algorithm combines 2-opt local search and operators in GA to discretize the searching process of the FWA. As the experimental results indicate, the discrete method for FWA is very effective for welding robot path planning, and it can be applied to more discrete optimization problems.

Acknowledgments
This paper was supported by National Key R&D Program of China (2017YFB1303300).

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