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Trajectory Optimization of Industrial Welding Robots based on Artificial Hummingbird Algorithm

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Abstract

In industrial welding scenarios, the smoothness of welding trajectories, uniformity of energy distribution, and control of thermal deformation directly determine weld quality and production efficiency. Traditional trajectory planning algorithms struggle to balance robustness, real-time performance, and executability under multi-objective constraints, exhibiting problems such as unstable convergence and a tendency to fall into local optima. This paper proposes the application of the Artificial Hummingbird Algorithm (AHA) and its improved variants to the trajectory optimization of industrial welding robots, constructing a multi-objective optimization framework to achieve closed-loop optimization of weld feature perception - trajectory generation - execution. By introducing chaos mapping in the population initialization phase, the global search capability and convergence stability of the algorithm are enhanced. A simulation model is built based on the Matlab platform, combining visual perception and robot kinematic models to model and optimize high-dimensional multi-objective constraints (smoothness, heat input, energy distribution, etc.). The research results show that the improved Artificial Hummingbird Algorithm can effectively enhance the smoothness of welding trajectories and the uniformity of energy distribution, reduce thermal deformation and residual stress, improve the consistency of weld quality and production efficiency, and provide an efficient and concise trajectory optimization scheme for industrial welding in complex environments.

Keywords

Artificial Hummingbird Algorithm; Industrial Welding Robot; Trajectory Optimization; Multi-objective constraint; Chaos Mapping.

1. Introduction

With the continuous development of technology, in traditional industrial welding scenarios, the smoothness of welding trajectories, energy distribution, and thermal deformation directly affect weld quality and production efficiency. Traditional trajectory planning often struggles to simultaneously balance robustness, real-time performance, and executability under multi-objective constraints. This study intends to take the Artificial Hummingbird Algorithm (AHA) as the core optimizer, construct a multi-objective optimization framework for welding trajectories, and realize closed-loop optimization of weld feature perception - trajectory generation - execution. The Grasshopper Optimization Algorithm (GOA) proposed by Li Guikui et al. has been applied in solving numerous optimization problems due to its advantages of strong operability, few adjustable parameters, and fast convergence speed, achieving effective solutions to various optimization problems[1,2]. Therefore, this also provides a new method choice for welding robot path planning. However, on the one hand,

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the population initialization in the basic GOA algorithm is determined by a random method, which may lead to uneven distribution of the initial population, thereby affecting the next step of convergence; on the other hand, the GOA algorithm regulates the search ability of the algorithm in the early and late stages through a linearly decreasing parameter, but in fact, the linearly decreasing parameter cannot achieve a good balance. Therefore, it is necessary to improve the above problems to enhance its effect in welding robot path planning. The Wolf Pack Algorithm (WPA) proposed by Gong Zheng et al.has good convergence and robustness and can be applied to different welding paths, so WPA is selected for welding path planning[3]. However, WPA also has shortcomings such as low precision, a tendency to fall into local optima, and long search time [4,5]. Hu et al. proposed a multi-strategy improved Artificial Hummingbird Optimization Algorithm (IAHA), which improves algorithm performance through three improvement granularities: introducing chaos mapping (Logistic-Tent) in the population initialization phase to improve diversity; introducing the Lévy flight strategy in the guided foraging phase to expand the search range; introducing the adaptive spiral migration strategy in the migratory foraging phase to balance convergence speed and global search ability [6]. However, the mathematical theoretical foundation of AHA is relatively weak. Research on its convergence proof and parameter adjustment is not in-depth enough. Although AHA usually exhibits extremely fast convergence speed and high solution accuracy when searching for global optimal solutions, in some problems, the convergence speed may be slow, especially for high-dimensional or extremely complex objective functions, and the obtained results may have unstable convergence speed. Through the research on the trajectory optimization of industrial welding robots based on the Artificial Hummingbird Algorithm, meta-heuristic optimization (AHA) is introduced into the field of welding trajectory optimization, enriching the algorithms for trajectory optimization and promoting the research on global-local optimization collaboration under multi-objective constraints [7]. This study explores the multi-module coupling optimization of visual perception, kinematics, and force control, and promotes the development of cross-modal optimization theory between simulation and real domains. This paper mainly improves the smoothness of welding trajectories, shortens the welding path, enhances the consistency of weld quality and appearance, improves productivity and automation level, reduces the demand for manual intervention, and lowers the costs caused by energy consumption and process fluctuations through the low cost of the Hummingbird Algorithm. At the same time, it can provide a concise method for machine welding in different environments.

2. Hummingbird Algorithm

The Artificial Hummingbird Algorithm imitates three foraging strategies of hummingbirds: Guided Foraging, Territorial Foraging, and Migratory Foraging. It conducts efficient exploration and exploitation within a territory while avoiding excessive repeated searches at the same location, and allows hummingbirds to jump out of the current local optimum and explore potential better solutions in farther areas to enhance global search ability. In addition, various flight skills used in foraging strategies are modeled, such as axial, diagonal, and omnidirectional flights, to richly express the trade-off between exploration and exploitation, as well as the adjustment of step size and direction in different dimensions. At the same time, a Memory Access Table imitating the extraordinary memory ability of hummingbirds is constructed to guide hummingbirds to perform global optimization in the algorithm.

2.1 Guided Foraging

Axial flight, diagonal flight, and omnidirectional flight represent problems of different dimensions, allowing hummingbirds to reach different food sources.

$$D^{(i)} = \begin{cases} 1, & if i = \mathrm{randi}([1, d]) \\ 0, & else \end{cases}, \quad i = 1,2,\dots,d \tag{1}$$

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$$D^{(i)}=\begin{cases}1, & i=p(j),\ j\in[1,k],\ P=\text{randperm}(k),\ k\in[2,\lfloor d-2\rfloor+1],\ i=1,2,\dots,d \\ 0, & \text{else}\end{cases} \tag{2}$$

$$D^{(i)} = 1, \quad i = 1,2, \dots, d \tag{3}$$

Randi([1, d]) is a random integer between 1 and d, and randperm(k) represents a random permutation of integers from 1 to k, indicating different positions.

The formula indicates that hummingbirds in axial flight can fly straight along any coordinate axis; diagonal flight allows hummingbirds to fly along the diagonal of a rectangle, determined by any two of the three coordinate axes; hummingbirds in omnidirectional flight can fly along the space diagonal in space.

Guided foraging behavior and candidate food sources

$$v_i(t+1) = x_{i,tar}(t) + a \cdot D \cdot (x_i(t) - x_{i,tar}(t)), \quad a \sim \mathcal{N}(0,1) \tag{4}$$

Where α is the guiding coefficient, which follows a normal distribution.

Update of food source position

$$x_i(t+1) = \begin{cases} x_i(t), if \quad f(x_i(t)) \le f(v_i(t+1)) \\ v_i(t+1), if \quad f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{5}$$

By comparing efficiency, hummingbirds are helped to make the best choice when facing different food sources.

2.2 Territorial Foraging

$$v_i(t+1) = x_i(t) + b \cdot D \cdot x_i(t) \tag{6}$$
$$b \sim N(0,1)$$

b is the territorial coefficient. After hummingbirds find new food sources and better paths, the access table is updated.

2.3 Migratory Foraging

To prevent resource depletion caused by frequent foraging, hummingbirds will change their paths.

$$x_w(t+1) = \text{Low} + r \cdot (U_p - \text{Low}) \tag{7}$$

X_ω: is the food source with the worst efficiency.

Low: The lower boundary of the search space.

Up: The upper boundary of the search space.

2.4 Initialize the Access Table

The access table records the time when each hummingbird last iterated to a food source, so the access table is updated in each iteration. Among food sources with the same number of visits, hummingbirds prefer to visit the food source with the highest nectar replenishment rate, which is the optimal choice of path. Each hummingbird in the limited population can find the target food source by reading the access table. During initialization, a limited number of hummingbirds are randomly arranged on the same number of food sources.

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3. Improved Hummingbird Algorithm

In the AHA algorithm, the population initialization is determined by a random method, which is prone to uneven initialization of the population within the solution space, thereby affecting the next step of convergence. This problem can be solved by introducing chaos mapping to complete population initialization. The Tent chaos mapping has better traversal uniformity, simple structure, piecewise linearity, and good robustness within a certain range.

$$x_i(t+1) = \begin{cases} \frac{x_i(t)}{a}, & x_i(t) < a, \\ \frac{1-x_i(t)}{1-a}, & x_i(t) \geq a, \end{cases} a \in (0,1). \tag{8}$$

In the formula, the value range of α is (0, 1), i = 0, 1, 2,....

Here, α = 0.5, and the following formula is obtained after Bernoulli shift transformation of the Tent chaos mapping:

$$x_{i+1} = (2x_i)\, mod 1 \tag{9}$$

Algorithm flow diagram for the improved method:

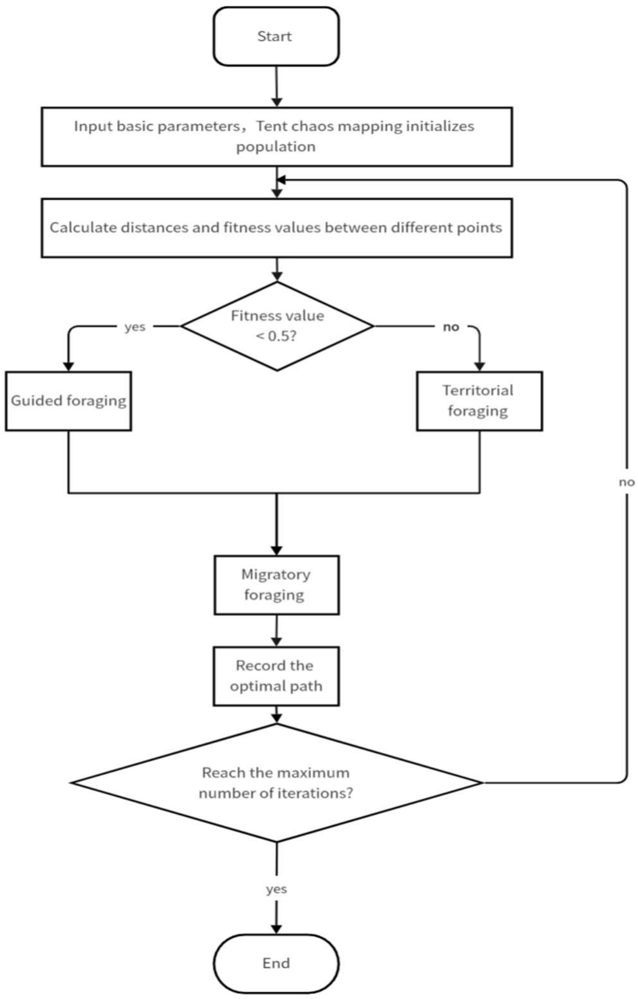

Figure 1. Flow Charts

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4. Simulation Experiments

4.1 Experimental Environment

A simulation system is built based on the Matlab R2023b platform for simulation experiments.

4.2 Obstacle Point Coordinates

Table 1. Obstacle point

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
x_1	250	350	450	550	280	900	850	600	650	800
y_1	280	320	250	380	450	400	650	950	450	700
z_1	190	190	190	190	190	160	160	160	160	160

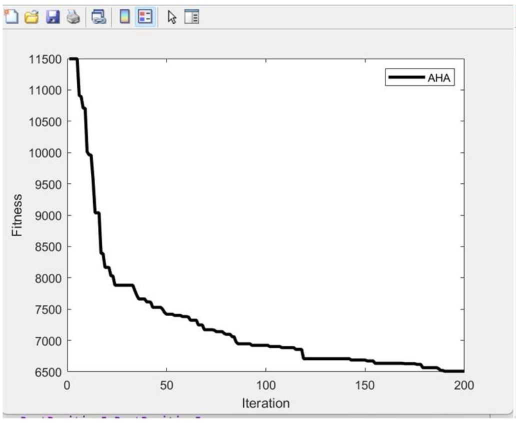

Figure 2. Before Optimization

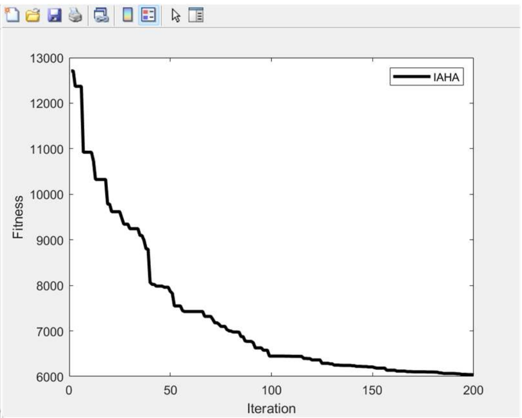

Figure 3. Optimized

The simulation experiment sets the population size to 50 and the maximum number of iterations to 200. Each obstacle point coordinate is brought into the algorithm. According to the simulation results, it can be analyzed that the standard Artificial Hummingbird Algorithm is slower than the improved algorithm in terms of search speed, and the improved Artificial Hummingbird Algorithm has better simulation results.

5. Conclusion and Prospects

The improved AHA effectively solves the problems of uneven initial population distribution and easy falling into local optima of traditional algorithms through chaos mapping initialization. Under multi-objective constraints, it can achieve global optimal optimization of welding trajectories, balance multiple objectives such as path length, and improve welding quality and production efficiency. This paper proposes the application of the improved Artificial Hummingbird Algorithm to the trajectory optimization of industrial welding robots, constructs a multi-objective optimization framework, and verifies the effectiveness of the algorithm through simulation experiments. The main conclusions are as follows: the improved AHA adopts chaos mapping initialization, which improves population diversity and convergence stability, and has higher solution accuracy and faster convergence speed. The established multi-objective optimization model can effectively balance trajectory smoothness, shorten the path length by 4%-5.6%, reduce welding costs, and provide an efficient and feasible method for the trajectory optimization of industrial welding robots.

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This research still has some shortcomings: first, the mathematical theoretical foundation of the algorithm needs to be further improved, and the convergence proof needs in-depth research; second, simulation experiments are different from actual experiments, and uncontrollable factors in the actual welding process are not considered.

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