THERMAL CONTROL SYSTEM BASED ON ANT COLONY ALGORITHM

by

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In order to improve the accuracy and speed of solving the inverse problem of source-seeking heat conduction, the paper proposes a correlation-based ant colony optimization algorithm for the inverse problem of source-seeking heat conduction based on the characteristics of the influence of the heat source position on the boundary temperature distribution in the heat conduction problem. This method is used to construct the corresponding heuristic information value for each co-ordinate of the heat source location, which can reflect the degree of similarity between the temperature curve of the calculated measuring point and the temperature curve of the real measuring point, namely the correlation degree. The ant colony optimization algorithm the medium path selection mechanism and the structure of the objective function have been improved. The paper replaces the actual experiment with numerical calculation obtain the temperature of the measuring point, and performs computer programming experiment on the inverse problem. The calculation results show that the calibration method of this heuristic information value and the objective function the construction method can distinguish the quality of the path well, thereby increasing the speed of the ant colony converging to the best path. The computational efficiency is improved by 18-60% compared with the ant colony algorithm that does not consider the correlation.

Key words: *ant colony optimization, inverse problem of seeking heat conduction, path construction, thermal control system, objective function*

Introduction

Engineering thermal equipment design, metal non-destructive testing, medical tumor diagnosis and treatment*, etc.* can be abstracted into the problem of identifying the location of the heat source of an object with an internal heat source, that is, the inverse problem of source tracing and heat conduction. The application of inverse heat conduction problems is very wide. For example, cutting and welding of metals, development and application of new materials, development of transient calorimeters, precision temperature measurement*, etc.* Because this problem is non-linear or ill-posed, it is difficult to solve.

Italian scholar Dorigo [1] proposed a new bionic optimization algorithm-ant colony optimization (ACO) algorithm. This algorithm has great advantages in solving complex optimization problems, and has become a hot spot for scholars at home and abroad. The application objects of group algorithm in recent years have mainly focused on traveling salesman problem (TSP), ordering problem, generalized assignment problem, multiple knapsack problem, network routing problem and dynamic TSP*, etc.* [2]. This article attempts to construct the path,

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heuristic information value selection and goal start with the construction of the function, find a reasonable path construction method and the form of the objective function suitable for the source-finding heat conduction problem, so as to speed up the search speed of the ants and improve the accuracy of the algorithm, and avoid the occurrence of local optima.

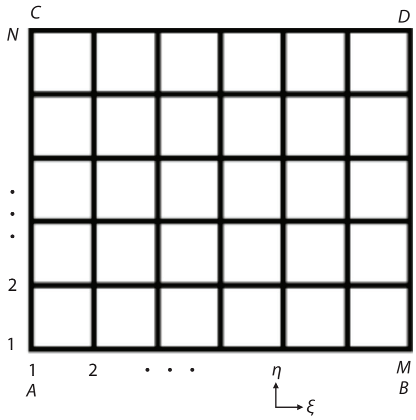

Figure 1. The 2-D physical model of heat conduction problem

Mathematical model of inverse heat conduction problem

Physical model

The paper selects a 2-D steady-state heat conduction problem with an internal heat source with a computational domain of 0.1 m × 0.1 m as an example to verify the effectiveness of the path construction method and objective function selection in the ACO algorithm, as shown in fig. 1. The physical parameters are shown in tab. 1. The computational domain is divided into a 100 × 100 structured grid [3]. The point heat source is arranged in a grid at (0.0405, 0.0305), and the measuring points are arranged on the boundary of $y = 0$ and $x = 0.1$. The measuring points are arranged as shown in the points on the boundary in fig. 1, and the specific positions of the measuring points are shown in tabs. 2 and 3.

Table 1. Basic parameters

Parameter	Parameter value
Thermal conductivity, λ [Wm^{-1}K^{-1}]	1.3
Wall temperature, T_0 [K]	310.15
Air temperature, T_f [K]	297.15
Convection heat transfer coefficient h, [Wm^{-2}K^{-1}]	13
Uniform heat source intensity, Q_0 / (W·M^{-3})	50
Point heat source intensity, Q [W]	72

Table 2. The $y = 0$ boundary measurement point location and its real temperature (obtained by numerical calculation)

Location / m	(0.0005, 0)	(0.0035, 0)	(0.0105, 0)
Temperature [K]	310.07	310.32	311.55
Location [m]	(0.0295, 0)	(0.0355, 0)	(0.0405, 0)
Temperature [K]	315.55	316.36	316.66
Location [m]	(0.0415, 0)	(0.0455, 0)	(0.0515, 0)
Temperature [K]	316.67	316.57	316.02
Location [m]	(0.0725, 0)	(0.0985, 0)	(0.0995, 0)
Temperature [K]	312.3	308.34	308.22

Table 3. The x = 0.1 Boundary measuring point location and its true temperature

Location [m]	(0, 0.0005)	(0, 0.0085)	(0, 0.0155)
Temperature [K]	308.22	309	309.51
Location [m]	(0, 0.0215)	(0, 0.0275)	(0, 0.0315)
Temperature [K]	309.81	309.97	310.01
Location [m]	(0, 0.0335)	(0, 0.0395)	(0, 0.0465)
Temperature [K]	310.01	309.91	309.64
Location [m]	(0, 0.0555)	(0, 0.0885)	(0, 0.0995)
Temperature [K]	309.12	306.39	305.46

Mathematical model

The differential equation describing the 2-D steady-state heat conduction problem:

$$\frac{\partial}{\partial x}\left(\lambda \frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(\lambda \frac{\partial T}{\partial y}\right)+S=0 \tag{1}$$

where λ is the thermal conductivity, T – the temperature, and S – the source term. The boundary conditions:

$$\begin{gathered}
-\lambda \frac{\partial T}{\partial x}\bigg|_{x=0,1}=h\left(T\big|_{x=0,1}-T_f\right) \\
-\lambda \frac{\partial T}{\partial y}\bigg|_{y=0,1}=h\left(T\big|_{y=0,1}-T_f\right) \\
-\lambda \frac{\partial T}{\partial y}\bigg|_{y=0}=h\left(T\big|_{y=0}-T_f\right) \\
T\big|_{x=0}-T_0
\end{gathered} \tag{2}$$

Improved ant colony optimization algorithm based on the inverse problem of sourcing heat

Since the possible positions of the heat source are discretely distributed in a certain grid divided, the simplest method is to place the heat source in these grids at a time, calculate the temperature value of the measuring point, and then compare it with the actual temperature value of the measuring point. Comparison determine the true location of the heat source. However, due to the large number of grid divisions and the long time spent in each numerical calculation, it will become impractical to bring the heat source to all possible positions for calculation in turn.

How the path is constructed

Ant colony algorithm is usually used in actual path search problems, for example, the TSP, the path refers to the real path. For the inverse problem of sourcing and heat conduction, the definition of the path becomes very abstract. The computational domain is divided into $100\times1\,00$ grids, and the position of the point heat source is distributed in the center of one of the grids [4]. This article is called a certain co-ordinate axis the possible selected co-ordinate value is a path. For this example, there are 100 paths on the x-axis and 100 paths on the y-axis. Each path on the x-axis and the path on the y-axis constitute the ant find the complete path to the heat source.

Improvement of heuristic information value

For the inverse heat conduction problem, it is very important to find an evaluation standard that can accurately reflect the quality of the path, that is, to find a calculation method that can accurately and effectively calibrate the heuristic information value on each path, so as to guide the ants to quickly and accurately find the best path. For traditional problems solved by ant colony algorithm, the length of the path is a known quantity. Usually, the reciprocal value of the path length is used as the heuristic information value of this path, and the ants will use this heuristic value according to the probability to choose the path [5]. Obviously, a shorter path corresponds to a larger heuristic value, that is, the probability of being selected by the ant is greater. But as far as the heat conduction problem is concerned, the quality of the path is not known in advance, that is, the ant must first randomly choose a complete path.

Obtain the co-ordinate value x_i, y_j of a point heat source, and then substitute it into the positive problem for calculation. The quality of the path can be determined only after the calculated temperature value of the measuring point is compared with the real temperature value of the measuring point. This makes it possible to find a suitable path the calibration method of heuristic information value becomes particularly important.

The usual processing method is to use the reciprocal $1/\sum(T_t - T_r)^2$ of the sum of squared difference between the measured temperature and the real measured point temperature as the path heuristic information value to reflect the path quality. Among them, T_t and T_r are the calculated measured temperature and the measured point temperature, respectively [6]. The x_i path and the path influence each other, that is, after the same x_i path is selected, the path change of y will affect the change of the boundary temperature, resulting in a great change in the value of $1/\sum(T_t - T_r)^2$. If this value is used as the heuristic information value of the x_i path, it will cause the uncertainty of the heuristic information value calibrated on a certain path and unreality. This effect can be clearly seen from fig. 2. The solid line in the curve shown in fig. 2 is the temperature distribution curve on the $x = 0.1$ boundary calculated from the point heat source arranged at the real position (0.0405, 0.0305), other the three curves keep the y-co-ordinate value of the point heat source unchanged, and only change the x-co-ordinate value to calculate the temperature distribution curve on the $x = 0.1$ boundary. From the curve in fig. 2, it can be seen that if $1/\sum(T_t - T_r)^2$ is used for calibration the quality of the path, then, when only the x-co-ordinate is changed, the distance between the calculated temperature curve and the true temperature curve is very different. If this value is used to calibrate the heuristic information value on the path $y = 0.0305$ where the real heat source is located, it will inevitably cause this the probability of the path being selected is reduced, which is not conducive for the ants to find the true heat source location.

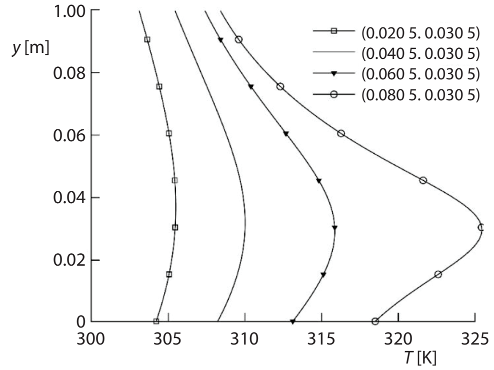

Figure 2. The *y*-co-ordinate remains unchanged, only the calculated *x*-co-ordinate is replaced

Based on the previous reasons, it is necessary to find a heuristic information value calculation method that has less mutual influence and can distinguish the quality of the path to calibrate the quality of the path, so that the ants can better recognize the quality of the path, so as to find the best path faster. Optimal path [7]. This article uses a method that reflects the degree of similarity between the calculated temperature value of the measuring point and the trend of the real temperature value, that is, the degree of correlation construct the heuristic information value of the path. The calculation formula:

$$\rho_{T_{x,r},T_{x,t}} = \frac{\sum\left(T_{x,r} - \bar{T}_{x,r}\right)\left(T_{x,t} - \bar{T}_{x,t}\right)}{\sqrt{\sum\left(T_{x,r} - \bar{T}_{x,r}\right)\left(T_{x,t} - \bar{T}_{x,t}\right)^2}} \tag{3}$$

$$\rho_{T_{y,r},T_{y,t}} = \frac{\sum\left(T_{y,r} - \bar{T}_{y,r}\right)\left(T_{y,t} - \bar{T}_{y,t}\right)}{\sqrt{\sum\left(T_{y,r} - \bar{T}_{y,r}\right)^2 \sum\left(T_{y,t} - \bar{T}_{y,t}\right)^2}} \tag{4}$$

Equations (3) and (4), respectively calculate the correlation between the temperature of the calculated measuring point and the temperature of the real measuring point on the two boundaries parallel to the two co-ordinate axes, that is, the degree of similarity of the temperature distribution curve, $\rho \in [-1, 1]$. If the value of ρ is higher close to 1, the higher the similarity between the two curves, the better the path.

The benefits of using correlation in the paper can be observed from fig. 2. Although the two temperature distribution curves are very different from the true temperature distribution curve, they are very similar, that is, the trend is the same [8]. This shows that when a certain path remains unchanged, when only changing another path, the obtained temperature curves are all similar. Therefore, if the method that reflects the degree of correlation between the calculated temperature curve of the measuring point and the temperature curve of the real measuring point can be used to calculate the heuristic value of the path, it can reduce the influence caused by the change of another co-ordinate. In order to increase the discrimination of path quality, this article does not directly use the value of correlation ρ, Instead, $\tan(\pi/4(1 + \rho) \in [0, +\infty]$ is used to calculate the heuristic information value of the path. However, even if the correlation principle is used to construct the path, the influence of another co-ordinate cannot be completely eliminated. Therefore, this paper calculates its weighted average while using the correlation degree, to reflect the heuristic information value of the path, thereby further reducing the influence of the two co-ordinates of the path, and ensuring the stability of the path heuristic information value. The calculation method of the path heuristic information value η_p:

$$\eta_p = \frac{\sum \tan\frac{\pi}{4}\left(1 + \rho_{T_{p,r},T_{p,t}}\right)}{k_p} \tag{5}$$

where p is a path, which is a certain co-ordinate x_i or y_i, k_p – the heat source in this paper and it is the number of times the path p is selected by ants. Based on the aforementioned reasons, two points must be observed when selecting a temperature measurement point: first, when selecting a measurement point, try to make the temperature of the measurement point truly reflect the trend of the temperature curve of this boundary; this is very important; use infrared heat imager detection can easily solve this problem and second, for 2-D problems, corresponding to the cartesian co-ordinate system, the temperature of the measuring points must be arranged on the left or right boundary of the object and the upper or lower boundary of the object, only then the correlation between each path on the x-axis and each path on the y-axis can be calculated separately. However, in actual engineering applications, it is often limited by the surrounding environment, and sometimes it is impossible to measure the temperature on the two sides separately. Therefore, for the case where the temperature on only one boundary can be measured, this paper also gives the calculation path heuristic information value methods [9]. If the measuring points cannot be arranged on the $y = 0$ boundary, the measuring points can only be arranged on the $x = 0.1$ boundary, Then, the path heuristic information value on the $y = 0$ boundary:

$$\eta_{x_i} = \frac{\sum \left[\sqrt{\frac{\sum \left(T_{y,r} - T_{y,t} \right)^2}{n_y}} \right]^{-1}}{k_{x_i}} \tag{6}$$

where k_{xi} is the number of times the path is selected by the ants, n_y – the number of measurement points on the boundary parallel to the y-axis, in this paper, n_y – the number of measurement points on the $y = 0$ boundary. Similarly, when $x = 0.1$ the boundary cannot be placed. When point, calculate the path heuristic information value of $x = 0.1$ boundary:

$$\eta_{y_j} = \frac{\sum \left[\sqrt{\frac{\sum \left(T_{x,r} - T_{x,t} \right)^2}{n_x}} \right]^{-1}}{k_{yj}} \tag{7}$$

where k_{yj} is the number of times the path y_i is selected by the ants, n_x – the number of measurement points on the boundary parallel to the x-axis, in this paper n_x – the number of measurement points on the boundary of $x = 1$. Equations (6) and (7) are the numerator of reflects the closeness of the calculated temperature at the measuring point to the real temperature at the measuring point. As can be seen from fig. 2, if the position of x is closer to the true temperature curve, then the calculated temperature will be closer to the true temperature. Therefore, the eqs. (6) and (7) can reflect the quality of the path on the temperature boundary without measuring point.

Improvement of objective function

In the ACO algorithm, ants update the pheromone on the path according to the calculated value of the objective function, so a directional objective function cannot only ensure the accuracy of the calculation, but also make the pheromone value on the path. It has a stronger orientation and guides the ants to find the optimal path quickly [10]. The calculation value formula of the objective function in this article introduces the correlation ρ. Objective function:

$$Te\left(x_i, y_j\right) = \tan\frac{\pi}{4}\left(1 + \rho_{T_{x_i,r},T_{x_i,t}}\right)\tan\frac{\pi}{4}\left(1 + \rho_{T_{y_j,r},T_{y_j,t}}\right)\left[\sqrt{\frac{\sum\left(T_r - T_t\right)}{n}}\right]^{-1} \tag{8}$$

where n is the total number of measuring points:

$$Te\left(p\right) = \tan\frac{\pi}{4}\left(1 + \rho_{T_{p,r},T_{p,t}}\right)\left[\sqrt{\frac{\sum\left(T_r - T_t\right)}{n}}\right]^{-1}, \quad p = x_i \text{ or } y_i \tag{9}$$

This objective function construction method not only considers the closeness of the temperature curve of the calculated measuring point to the real temperature curve of the measuring point, but also reflects the similarity, which can better indicate the quality of the path and speed up the convergence of the ants to the best path speed.

Pseudo-random ratio path selection mechanism with variable probability

According to the characteristics of the inverse problem of source search, if the ants choose a better path, then there may be a better path around this good path, that is, the closer to the heat source, the better the path quality. According to with this feature, this paper proposes a pseudo-random ratio path selection mechanism with variable probability, that is, the probability q_0 of the ants choosing the current optimal path varies with the degree of the search process. The specific path selection mechanism:

$$p = \begin{cases} p_P, & q \le q_0 \\ p_{\text{best}} & \text{other} \end{cases} \tag{10}$$

$$p_{P_j} = \frac{\tau_{p_j}^a \eta_{p_j}^\beta}{\sum_{i=0}^{99} \tau_{p_i}^a \eta_{p_i}^\beta}, \quad p = x \text{ or } y, \quad j = \in [0, 99] \tag{11}$$

$$p_{\text{best}} = \begin{cases} A, & q_b \le q_{0,b} \\ B, & \text{otherwise} \end{cases} \tag{12}$$

where p is the path, p_P – the path selected according to the probability according to eq. (11), A – the current best path or the path around it, p_{best} – the current best path, q_0 – the current best path around path, B – the percentage of the number of path selections made by the ant colony to the total number of selections, q – the random number of 0-1, p_{P_j} – the probability of path p_j – being selected, τ – the pheromone concentration on the path, α and β are visibility index determines the relative importance of the heuristic information value and the pheromone concentration on the path, respectively. In this article, α and β are both 1, which means that the path heuristic information value and the pheromone concentration are equally important, $q_{0,b}$ – the current number of ant colonies' path selection the percentage of the total selection times, and the maximum value of $q_{0,b}$ does not exceed a random number with 0.6, q_b being 0-1.

Local pheromone update strategy based on correlation

After each ant completes the path search, the local pheromone must be updated. The update method:

$$\tau_p(k+1) = (1-\xi)\tau_p(k) + \xi Te, \quad p = x \text{ or } y \tag{13}$$

where τ is the pheromone concentration, the subscript p is a certain path, ξ – the local volatilization coefficient of the pheromone $0 < \xi < 1$, and k – the number of times the ant chooses. The local pheromone update formula in this article is different from that. Directly in this article the value of the objective function is selected to update the local pheromone. Since the objective function contains the concept of correlation, the quality of the two paths can be better considered when the pheromone is updated, which further enhances the path. When matched with the initial value of pheromone of appropriate size, this update formula cannot only reduce the pheromone concentration on low quality paths, making these paths difficult to find by ants, but also increase the information on high quality paths. The concentration of prime elements, thereby increasing the probability that this path is selected by ants, makes it easier for the ant colony to converge to the optimal path. This update method cannot only improve the convergence speed of ants, but also effectively avoid the occurrence of local optimal. A large number of calculations show that, the initial value of the path pheromone should be set between 400-500.

Global pheromone update strategy

When all the ants in the ant colony have completed a search, the pheromone will be updated globally on the best path. The update method:

$$\tau_p\left(kr+1\right)=\left(1-\xi\right)\tau_p\left(k_r\right)+\xi\left[\sqrt{\frac{\sum\left(T_r-T_t\right)^2}{n}}\right]_{\text{best}}^{-1} \tag{14}$$

where ζ is the global volatilization coefficient of the pheromone, $0<\xi<1$ and k_r – the number of rounds selected by the ant colony, the subscript best represents the current optimal path.

Basic algorithm flow

The calculation process of the aforementioned improved algorithm is shown in fig. 3. In the calculation, there are a total of 100 ants in the ant colony, and the ant colony performs a total of 15 loop searches, that is, a total of 1500 path searches are performed, and the final optimal path is used as the calculation result. After calculation, 1500 path searches are enough, and the ants will basically concentrate on the same path after the 600th search.

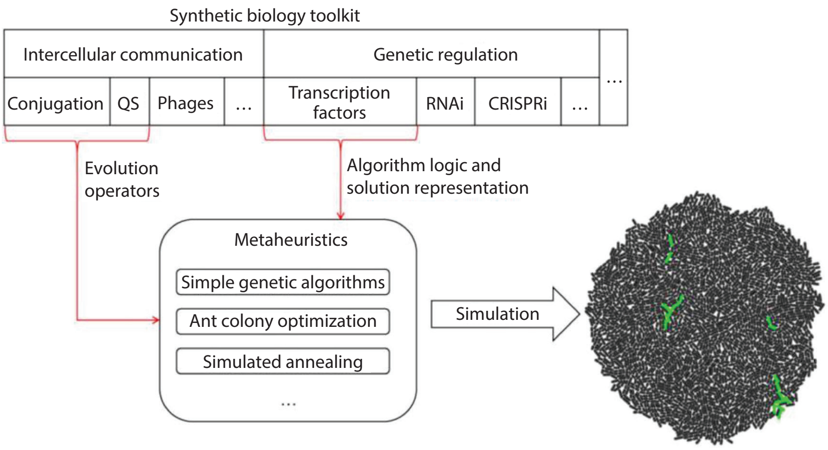

Figure 3. Algorithm flow chart

Calculation verification

Aiming at the calibration method of the path heuristic information value proposed previously, the construction method of the objective function, the path selection mechanism and the pheromone update mechanism, the C language is used for computer programming calculation. In the judgment of the merits of the calculation results, due to the compilation and the operating environment is different. Therefore, the program running time is not used as the criterion, but the number of calculations of the positive problem in each inverse problem calculation process is selected as the criterion. In an inverse problem calculation process, the algorithm with good convergence corresponds to the relative fewer forward problem calculation times. Since the ACO algorithm is a probability-based solution method, the calculation result of an inverse problem (the number of calculation times for the positive problem in the inverse problem) does not explain the problem [11]. Therefore, this article focuses on arranging measuring points on the boundary of $y = 0$ and $x = 0.1$, arranging measuring points only on the boundary of $x = 0.1$, and arranging measuring points only on the boundary of $y = 0$. Inverse problem calculations were performed 200 times, and 200 the average result of this calculation is compared with the calculated result. The location of the measuring point on the $y = 0$ boundary and the boundary of $x = 0.1$ and the corresponding measuring point temperature are shown in tabs. 2 and 3, respectively. Figure 4 shows the values at $x = 0.1$ and the calculation result when the measuring points are arranged on the $y = 0$ boundary. The abscissa a is the calculation of each inverse problem test. The ordinate d represents the number of calculations of the positive problem in each inverse problem calculation. The curve c represents the calculation of the positive problem so far average number of times. It can be seen from fig. 4 that when the inverse problem is calculated multiple times, the average number of positive problems calculated in each inverse problem will stabilize at 60 times.

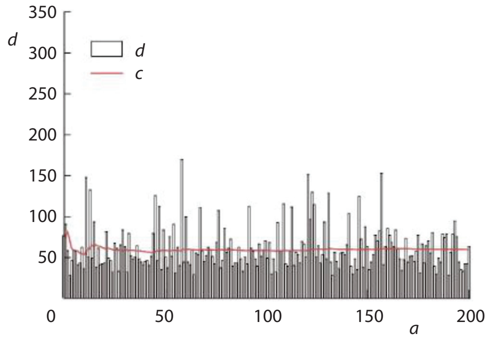

Figure 4. The calculation results of the measurement points arranged on the boundary of $x = 0.1$ and $y = 0$

Figures 5 and 6, respectively show the calculation results when the measuring points are only arranged on the $y = 0$ boundary or $x = 0.1$ boundary. The calculation times of the positive problem in each inverse problem are stable at 137 and 135, respectively. The calculation results are obviously secondary the measurement points are arranged on both borders. This is because the temperature of the measurement point on the border is missing, and the correlation method cannot be used to calibrate the heuristic information value of the border path, which affects the ants' recognition of the path quality, which is not conducive to the ant colony converges to the best path.

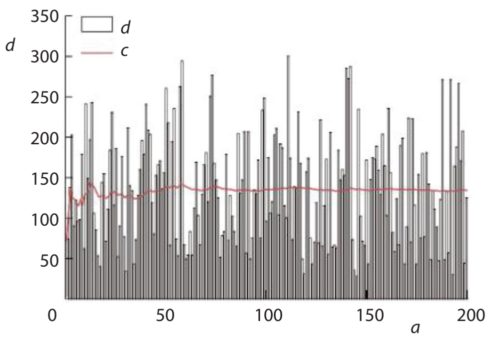

Figure 5. Calculation results of measuring points arranged on the $y = 0$ boundary

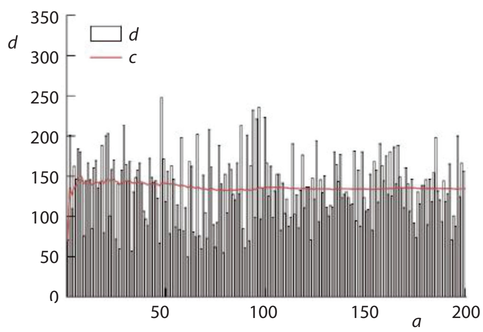

Figure 6. The calculation results of the measuring points arranged on the boundary of $x = 0.1$

Table 4 compares the calculation results with the results using the method in this paper. It can be seen that the improved method described in this article can increase the calculation efficiency by about 60% when the measurement points are arranged on both boundaries. In fact, the method in this article can also increase the calculation efficiency by nearly 20%. It can be seen that we use the method of correlation calibrate the path heuristic information value and build the objective function based on it. It can indeed effectively reduce the amount of calculation and improve the calculation efficiency and calculation accuracy.

Table 4. Summary of calculation results

Lay-out of measuring points	Average positive problem calculation times	Correct rate [%]	Improved efficiency compared with literature [%]
Lay-out of measuring points on both boundaries	60	100	64
The $y = 0$ boundary lay-out measuring points	137	100	18
The $x = 0.1$ boundary layout measuring points	135	100	19
Literature results	167	–	–

Conclusion

Aiming at the characteristics of the heat conduction problem, the paper improves the ACO algorithm to make it suitable for the inverse problem of sourcing heat conduction. The paper establishes a calibration method that uses the correlation value between the temperature of the measuring point and the temperature of the real measuring point as the path heuristic information value. The concept of relevance is used to construct the objective function, using a pseudo-random ratio path selection mechanism and a local pheromone update strategy based on relevance. Through computer programming calculations, the paper verifies the effectiveness of the improved ant colony algorithm. The calculation results show that on both sides when the measuring points are all arranged, the calculation efficiency of the ACO algorithm using the correlation degree is about 60% higher than that of the ACO algorithm without the correlation degree. When there is only one side of the measuring point, the calculation efficiency is also close to 20%. The improvement. It shows that the ACO algorithm using correlation degree can significantly accelerate the convergence speed of the ant algorithm in the calculation of the inverse problem of source-finding heat conduction, thereby improving the calculation efficiency and calculation accuracy.

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