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Image Edge Feature Extraction and Refining Based on Genetic-Ant Colony Algorithm

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Abstract

Edge is composed by a collection of its nearby pixels which has a step change or changes in roof, an image is an information system and most of its information comes from the edges. This paper gives a brief overview of the status and the importance of image edge detection and introduces the research status of the image edge detection. After that, it introduces the basic principle and the main steps of the genetic algorithm and ant colony algorithm. On the basis of these, the paper proposed a new hybrid algorithm for the image edge extraction and refining, which combined the genetic algorithm and ant colony algorithm. Through the analysis of the time-speed graph of the genetic algorithm and the ant colony algorithm, we can find the best fusion point between the genetic algorithm and the ant colony algorithm. The experiment indicated the proposed hybrid algorithm can make the full use of the image information, the simulation time is shorter, the image edge is more continuous, and preserved the outline of original image more completely.

Keywords*: image edge detection, genetic algorithm, ant colony algorithm*

1. Introduction

Edge refers to the collection of pixels the gray level of the surrounding pixels of which has step change or roof change. Edge is the important information in the image as well as a significant clue of visual perception. Actually, it can not only convey most of the image information, but it is also an important foundation of image analysis and machine vision. An image is an information system and a great deal of its information is provided by its contour edges. Therefore, edge feature extraction and detection play a significant role in image processing [1]. Although active research has been made on edge detection algorithm in the long term, the edge detection methods increase day after day and numerous edge extraction operators have been come up with gradually, the traditional Roberts operator and Sobel operator have been rarely used alone [2]. Currently, an increasing number of scholars have applied bionics algorithm in image edge detection.

In bionics algorithm, the edge detection based on genetic algorithm and that based on ant colony algorithm have their own advantages and disadvantages. In the operation of genetic algorithm, it can be found that the individuals of the population have a relatively rapid iteration speed at the initial stage; however, as the algorithm proceeds to the later period, redundant iteration emerges obviously and the iteration speed at this time is very slow [3]. As for ant colony algorithm, in its early phase, the convergence speed of the system is slow due to the lack of pheromone; nevertheless, the convergence speed accelerates on account of the positive feedback of the algorithm at the late phase and ant colony algorithm has excellent parallelism and global search ability.If the advantages of genetic algorithm are to be integrated with those of ant colony algorithm, the performance of genetic-ant colony hybrid algorithm can be improved [4],[5].

This paper mainly applies genetic-ant colony hybrid algorithm into the image edge feature detection and refining. Through the analysis of time-speed curves of genetic algorithm and ant colony algorithm, it can be found out the optimal combination of genetic algorithm and ant colony algorithm and then designs the algorithm for image edge detection, including the operation steps of genetic algorithm at the early stage; the integration of genetic algorithm and ant colony algorithm according to the setting conditions and the operation of the later ant colony algorithm. At the beginning of the proposed genetic-ant colony hybrid algorithm, it adopts the operation steps of genetic algorithm and ends it within the scope of its genetic iterations. Then it

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transforms its current optimal solution as the matrix distribution of the initial pheromone concentration of ant colony algorithm and operates ant colony algorithm. After the algorithm ends, output the edge image.

2. Image Edge Detection

Most important information of the image exists in the image edge, which is the most prominent in the image local changes. It reflects the feature differences within theimage local areas and it is indicated as certain discontinuity of the image information [6]. Edge mainly exists between objective and objective, objective and background as well as area and area (including different colors) and it is animportant foundation of the image analysis such as image segmentation, texture features and shape features [7]. Edge is mainly expressed as the discontinuity of image local characteristics and it contains the relatively severe gray level changes in the image, that is, the place withsingular changes in the signal. The gray level change of singular signal becomes increasingly dramatic along the edge. We generally divide the edge into two types: step and roof, which are indicated in Figure 1 and Figure 2 [8].

(a) Step, namely the image intensity has significant differences between the pixel gray levels of two discontinuous positions [9].

(b) Roof, namely the image intensity suddenly changes from one value to another and then returns to the original value after maintaining a small schedule [10].

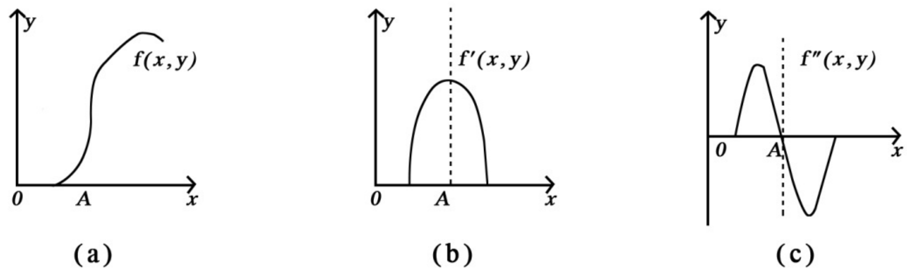

Figure 1. Step edge

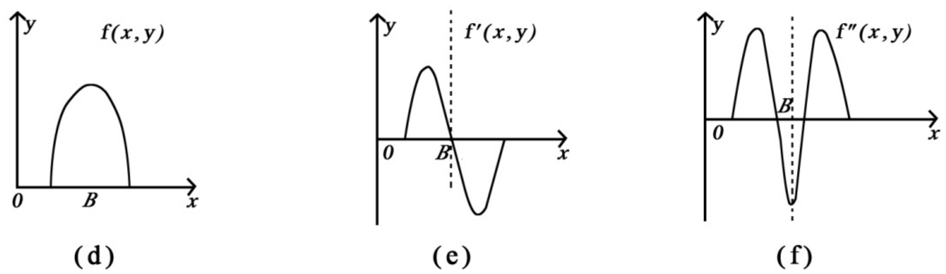

Figure 2. Roof edge

The image edge detection directly affects the effects of the entire image processing.The traditional edge detection methods are normally based on such single feature asfirst-order or second-order derivative of the edge neighborhood and they are not sensitive to the image with fuzzy edges. Besides, the uncertainty of the object boundary in the image is usually fuzziness [11].

3. Feasibility Analysis of Integration of Genetic Algorithm & Ant Colony Algorithm

3.1. Principle of Genetic Algorithm

As a random and high-efficient global search method to solve problems, genetic algorithm needs no prior knowledge of its search space, instead, it approximates the optimal solution step by step through the information exchange between individuals, by randomly generating the initial population in the search space and with the help of the objective function [12].

(i) The codes can perform corresponding coding on the problems to be settled. Since the image gray level value is between 0-255, the code of every chromosome is an 8-digit binary code.

(ii) If the population model has excessive populations, the amount of calculation of every generation of fitness value is huge; however, if the population is small, it is difficult to demonstrate species diversity. Therefore, set the population number reasonably.

(iii) Fitness function is the standard to evaluate every individual and it needs to be selected to show the evolution trend. Here, choose the fitness function as the basis for ant colony parameter selection.

(iv) Completely copy the individuals with high fitness function in the population to the next-generation population. Set a random function and select the copied individuals with the widely-used selection method, namely Roulette wheel selection in the ant colony algorithm to make it as the selected operator.

(v)Crossover uses the method of single-point crossover. Select two chromosomes. Set a random function to determine a common point of these two chromosomes randomly as the crossover point of these chromosomes. After the crossover, keep the positions of the nodes of these two chromosomes from the source point to the crossover point unchanged the interchange the node positions from the crossover point to the destination point.

(vi) Mutation determines the local searching ability of genetic operation.

The flowchart of genetic algorithm is as follows[13],[14].

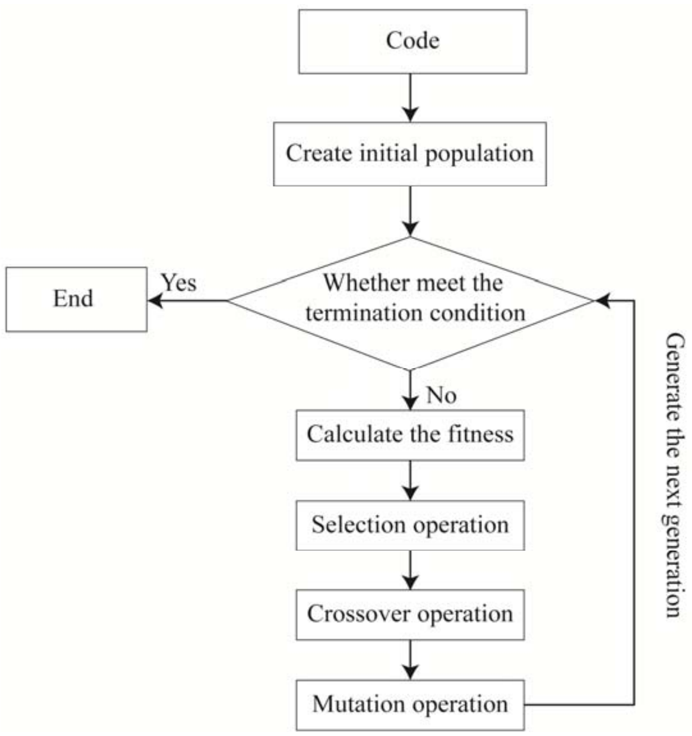

Figure 3. The flowchart of genetic algorithm

3.2. Concrete Realization of Ant Colony Algorithm

Many kinds of ants release pheromone and pheromone direction in food foraging. Deneubourg explains this kind of path selection mode based on self-organization with a simple test model. In this mode, a bridge with two bypasses of equal length separates the ant nest and the food. At the beginning, the ants select from these two paths according to the same probability since there is no pheromone distribution in the paths. With the introduction of random fluctuation, more ants will choose one path, which increases the pheromone concentration of this path; therefore, it will attract more ants to select this path.

In Deneubourg's experiment, the left-over pheromone concentration on the path is in direct proportion to the number of ants and no pheromone volatilization is taken into account. In this simplified model, the ant chooses a path according to the total quantity of the ants passing this path. Assume that A_i and B_i are the numbers of ants to select path A and B respectively after the ith ant crosses the bridge, then the probabilities of the $(i+1)th$ than t to choose path A and B are

$$P_A = \frac{(k+A_i)^n}{(k+A_i)^n + (k+B_i)^n} = 1 - P_B \quad (1)$$

Formula(1) has quantized this selection mode. Parameter n determines the non-linearity of the selection function. When n is bigger, the pheromone concentration of one path is only a little higher than that of the other path, then the probability for the next ant to choose the previous path is bigger. Parameter k reflects the attraction of the unmarked path. If k is bigger, then it has higher requirements on the necessary pheromone concentration to perform non-randomized selection. This kind of probability expression form is actually inferred from the actual ant path selection experiment. The parameters suitable for experiment are $n = 2$ and $k = 20$. If $A_i >> B_i \,\&\, A_i >> 20$, then $P_A = 1$, if $A_i >> B_i$ but $A_i < 20$, then $P_A = 0.5$. The dynamic selection result of the system is determined by the following formulas

$$A_{i+1} = \begin{cases} A_i + 1, & if \quad \delta \le P_A \\ A_i, & if \quad \delta > P_A \end{cases} \quad B_{i+1} = \begin{cases} B_i + 1, & if \quad \delta > P_A \\ B_i, & if \quad \delta \le P_A \end{cases} \quad (2)$$

Here, $A_i + B_i = i$ and δ is a random variable uniformly distributed within [0,1].

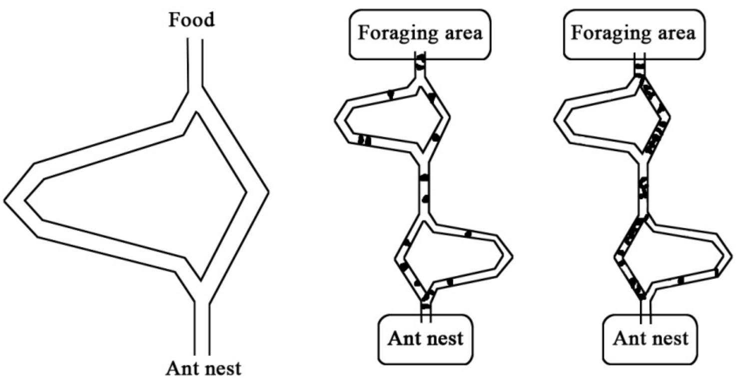

Figure 4. Principle of ant path search

This experiment designed on equi-arm bridges can also be extended to non-equi-arm bridges. As indicated in Fig.4, the method for the ant to select the path is basically the same with the above process. Among the ants from the ant nest, the ants passing by the shorter path will reach the food source and go back to the nest earlier. Then the pheromone on the shorter path will be enhanced at a shorter time, causing more ants to choose this shorter path [15].

The above circumstances haven't taken the constitution, placement and volatilization of pheromone. There are various diversified actual pheromone left-over methods in the natural environment. The research personnel has only obtained some fundamental features of pheromone through experiment, including, volatilization rate, absorption rate and diffusion coefficient. The research proves that pheromone can be preserved on the path for a long time, which has a close relationship with the type, population rule and environmental conditions of ants.

3.3. Feasibility Analysis

Genetic algorithm is a universal method to solve optimization problems, which has been widely used in various optimization problems. However, because of its strong universality, it has relatively bad flexibility. For lack of infinite application range, although it can ensure that it has global convergence ability on most problems, local degeneration is difficult to avoid and it fails to process the feedback information of the system. The calculation efficiency reduces when huge inefficient and redundant iterations repeat when searching to a certain degree. Ant colony algorithm achieves the purpose to converge to the optimal path through the accumulation and updating of pheromone and it has distributivity, parallelism and global searching ability; nevertheless, it is short of pheromone at the early stage and its solving efficiency is not high. In order to complement each other's advantages of these two algorithms, it can be found from the research of these two algorithms that they present the Speed-Time Curves in Fig. 5 in solving problems [16].

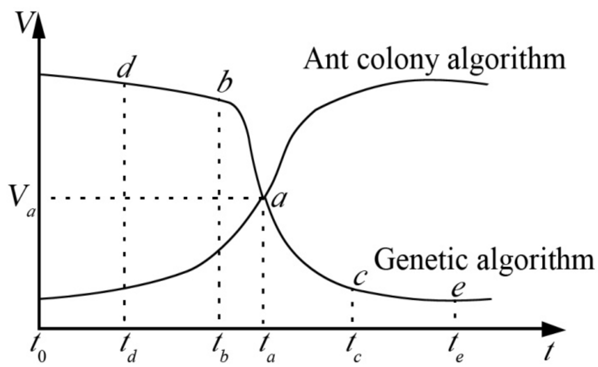

Figure 5. Speed-time curve of ant colony algorithm and genetic algorithm

The genetic algorithm has a fast solving speed at the early solving period (during $t_0 \sim t_a$), but it can be seen that after t_a, the speed drops quickly. On the contrary, the ant colony algorithm (during $t_0 \sim t_a$) is slow in its searching due to the relative shortage of pheromone at the initial searching and the long pheromone accumulation time; however, when the pheromone is accumulated to a certain degree (after t_a), it accelerates its convergence to the optimal solution. The basic principle of the integrated algorithm is: generate the initial pheromone concentration through genetic algorithm before the optimal integration point (point a); fully use the rapidness, randomness and fast convergence of genetic algorithm and after the optimal point, utilize the parallelism, positive feedback and high solving efficiency to seek the optimal solution to the problem.

4. Strategy of Mutual Integration of Genetic Algorithm and Ant Colony Algorithm

It is the key for the algorithm of this paper to seek the optimal connection time for genetic algorithm and ant colony algorithm and the following dynamic integration strategy can achieve the purpose of dynamically mutual integration of genetic algorithm and ant colony algorithm.

At the beginning of genetic-ant colony hybrid algorithm, conduct genetic algorithm till the set termination condition. Transfer the current optimal solution from genetic algorithm as the distribution matrix of the initial pheromone concentration of ant colony algorithm. Implement ant colony algorithm until the optimal solution is sought.

In this paper, max-min ant-colony algorithm(MMAS) is adopted to update the pheromone. When setting the initial pheromone of ant colony algorithm, set the initial value of the pheromone on every path as the maximum value $t_{\max}$ and the initial value δ_0 can be set as a fixed number, namely 100.According to the distribution of the initial pheromone transferred from the previous genetic algorithm, we can set the initial value of the pheromone in resource i as:

$$\delta_i^s(t) = \delta_0 + \delta_i^G(t) \tag{3}$$

In Formula (3), δ_0 is a constant of pheromone, equal to $t_{\max}$ in MMAS. $\delta_i^G(t)$ is the pheromone value transferred from the second-best solution obtained from the early genetic algorithm.

The realization steps of genetic-ant colony hybrid algorithm are as follows:

(i)The construction of the initial population

We have expressed every parameter with 16-digit binary coding and we have had a group of parameters (4 parameters) for every individual; therefore, we indicate every individual in the initial population with 64digit binary coding. 1 to 16digit is the value of pheromone impact factor α of state transfer probability; 17 to 32digit is the value of the impact factor β of heuristic direction function, 33 to 48digit is the value of the pheromone volatilization coefficient λ while 49 to 64digit is the number of iterations N .

(ii)The design of objective function

Randomly put m artificial ants in n pixels and evaluate the effects of the final edge extraction image generated by every individual with objective function. When a corresponding group of parameters to the individual obtains the final edge image through edge extraction and if the iterative edge image has small difference with the original image, namely that the two images are basically the same, it proves that the edge of the objective object has been found. Therefore, we introduce the similarity $std2$ value of two images for evaluation.

The objective function is expressed as $Objv = std2(u)$. Here, u is the energy difference between the iterative edge image and the original image, namely $u = I_1 - I_2$.

(iii)The selection of the next pixel to visit

To every artificial ant, G_k is the collection of nodes which haven't been visited before. S_k is the collection of nodes which allow to be visited in the next step according to probability transfer formula. $tabu_k$ is the search $tabu$ table, which is the collection of nodes which have been visited before.

$$Cij = \begin{cases} \arg\max_{j \in allowed} \left\{ \delta(i,j) \bullet \eta^{\beta}(i,j) \right\}, if \quad q \le q_0 \\ 0, \quad otherwise \end{cases} \tag{4}$$

In Formula (4), C_{ij} is a state variable which is obtained from the transfer formula of ant colony, q_0 is a constant with its value range within0~1 and q is a random number and $q = (0,1]$,it is generated randomly when the ant colony selects the next pixel. When q is smaller than or equal to q_0 , transfer by selecting the next shortest pixel; when q is bigger than q_0 , select according to Formula (5).

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\delta_{ij}(t)]^{\alpha}\bullet[\eta_{ij}(t)]^{\beta}}{\sum\limits_{s\subset allowed_k}[\delta_{ij}(t)]^{\alpha}\bullet[\eta_{ij}(t)]^{\beta}}, & if\ j\in allowed_k\\ 0, & otherwise\end{cases} \tag{5}$$

In Formula (5), α is the pheromone heuristic factor, β is the impact factor of heuristic direction function; $allowed_k$ is the next pixel allowed to visit and $p_{ij}^{k}(t)$ is the probability that ant k moves from pixel i to pixel j at moment t.

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(iv) Updating of the pheromone concentration of every pixel

The pheromone on the path between two pixels is not accumulated infinitely. This paper updates the pheromone with MMAS by setting a pheromone scope $[\delta_{\min},\delta_{\max}]$ to prevent the algorithm from being trapped in local convergence because of the infinite increase of local pheromone.

(a)The updating mechanism of global pheromone

$$\delta_{ij}=(1-\lambda)\times\delta_{ij}(t)+\lambda\times Q \tag{6}$$

Here, λ is the pheromonevolatilization coefficient with its value range within0~1. Q refers to the value of the initial pheromone. $Q=\delta_{\max}$ in order to increase the searching scope at the beginning.

(b)The updating mechanism of local pheromone

For the kth ant, the pheromone increment δ_{ij} on the path it passes by is:

$$\delta_{ij}(t+1)=\lambda\times\delta_{ij}(t)+\Delta\delta_{ij}(t+1) \tag{7}$$

$$\Delta\delta_{ij}(t+1)=\begin{cases}\dfrac{Q}{T_{\min}^{k}}, & if\ (i,j)\ on\ the\ optimal\ path\\ 0, & otherwise\end{cases} \tag{8}$$

Here, λ is the pheromone volatilization coefficient and $1-\lambda$ is the pheromone coefficient remained between iterationst and iterations $t+1$. Q is a constant of the remaining trajectory number. $T_{\min}^{k}$ is the shortest operation time after the ant has gone through all the walking steps. In the initial moments, $\delta_{ij}=0$.

(v) If it meets the established end conditions, exit the algorithm, otherwise, return to Step (3).

Decode the initial population (namely every individual) randomly generated from genetic algorithm. Then conduct ant colony algorithm evolution on the edge extraction according to a corresponding group of parameters to every individual. Finally, get the final result of an iteration, namely the image edge detection result.

The realization flowchart of the algorithm of this paper is as follows [17].

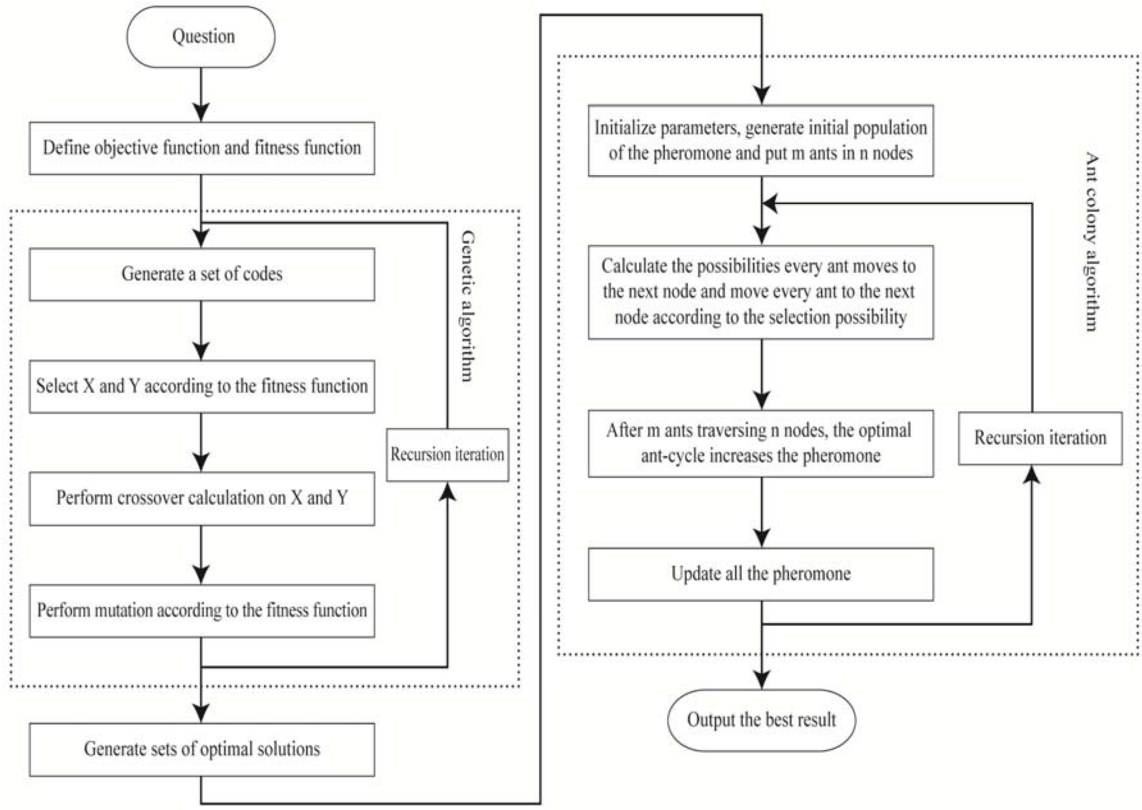

Figure 6. Flowchart of genetic-ant colony hybrid algorithm

5. Experiment Simulation & Analysis

Simulate this experimental result and data in the environment of Windows 7 with Intel (R) Core2CPU 1.33G and a memory of 2.5G through Matlab R2012a.

For the convenience of comparison, compare the genetic-ant colony hybrid algorithm proposed in this paper with single genetic algorithm and single ant colony algorithm with the same parameters. The algorithm parameters are set as follows: the population size of genetic algorithm is $g = n \times m$, the crossover probability is $p_c = 0.8$, the mutation probability is $p_m = 0.05$,the size of ant colony algorithm is $h = n \times m$, the pheromone heuristic factor is $\alpha = 3$, impact factor of heuristic direction function is $\beta = 1$ and the pheromone volatilization coefficient is $\lambda = 0.1$

The experiment will conduct 5 analog simulations to the edge detection of every algorithm and choose the optimal effects as the final results. Figure 7 reflects the simulation results by different algorithms.

It can be seen from the above experiment simulation that the image edge feature extraction based on genetic-ant colony hybrid algorithm has a higher level in its objective effects and excellent continuity, refining and smoothness. It can demonstrate the main edge features of the image; contains the main edge information of the image and its edge lines are quite refining and smooth. In one word, it has reached the expected effects.

(a) Original image (b) Genetic algorithm

(c)Ant colony algorithm (d)Genetic-ant colony algorithm

Figure 7. Image edge feature extraction results by different algorithms

6. Conclusion

As the most fundamental feature, edge carries the majority of the image information. This paper analyzes the advantages and disadvantages of genetic algorithm and ant colony algorithm; integrates the advantages that genetic algorithm has fast convergence speed in the early phase and that the ant colony algorithm has strong global searching ability and applies it in image edge feature extraction and detection.As shown in the experiment simulation result, genetic-ant colony hybrid algorithm can detect the image edge quickly and accurately with obvious edge details, excellent continuity and complete edge expression to reach the expected objective.

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