Gray Image Edge Feature Extraction Based on Differential Ant Colony Optimization

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Abstract
As the foundation of image understanding and analysis, image edge feature extraction of a topic worthy of research in the field of image processing. This paper combines differential evolution and ant colony optimization, uses the combined algorithm in the gray image edge feature extraction, finds the best combination point of these two algorithms and designs the algorithm according to the image edge features. At the beginning, the algorithm of this paper operates the steps of differential evaluation. If the changes of the fitness function value are within the error range, terminate the algorithm, convert the current optimal solution as the matrix distribution of the initial pheromone concentration and operate ant colony optimization. After the optimization is over, output the edge image. This paper compares the advantages and disadvantages as well as the applicability of different algorithms in the gray image edge feature extraction through theoretical analysis and experimental simulation.
Key words: EDGE FEATURE EXTRACTION, DIFFERENTIAL EVOLUTION, ANT COLONY OPTIMIZATION

1. Introduction

Image edge is one of the most fundamental image features and it is of great significance in the research of human vision and machine vision. Edge feature extraction is one of the basic contents and a hot topic in image processing and analysis, in the meanwhile, it is also one of the problems to be resolved[1]. Due to the restrictions of shooting environment and conditions, there will always be some irrelevant interruptions to the objective in the image. So far, many algorithms have been raised in edge feature extraction and how to increase the accuracy and signal to noise ratio has become a difficult problem. therefore, an excellent edge extraction method has always been a research focus for numerous scholars as well as what we should work hard on[2].

As the elementary phase, image edge feature extraction has a very long research history when many new theories and methods keep emerging. With the development of computer vision and image processing technology, it is in a desperate need to find a good edge feature extraction algorithm[3]. Artificial intelligence is an approximate optimization algorithm arising in the 1980s, which has been widely applied in the research of dispatch. Such heuristic algorithms as ant colony optimization, differential evolution, tabu search and simulated annealing have been developed there after. Differential Evolution (DE) is an evolutionary algorithm based on population differences. As a simple algorithm with fast convergence speed and little knowledge, it is suitable to solve complicated optimization problems, however, it is easy to get trapped in local optimum[4]. Ant colony optimization is a highly efficient intelligent optimization which is developed in recent years. This algorithm has strong capacity of global optimization, excellent robustness and powerful convergence ability, but it requires complicated computation and long operation time, therefore, the best combination point of differential evolution and ant colony optimization can be found and the algorithm can be designed in accordance with the features of the image edge[5].

This paper firstly discusses the theoretical analysis of image edge feature extraction, differential evolution and ant colony optimization. Based on the above research, it finds the best combination of these two algorithms and designs an algorithm according to the edge features of the gray image. The final part is the experimental simulation and analysis.

2. Image Edge Feature Extraction

Image edge feature extraction is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge feature extraction is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. Image edge feature is the most fundamental and one of the important image features because it usually carries the majority information of an image. Generally, an object can be identified from some rough contours, which are the image edges[6]. Edges provide a number of derivative estimators, each of which implements one of the definitions above. For some of these estimators, you can specify whether the operation should be sensitive to horizontal edges, vertical edges, or both edge returns a binary image containing 1's where edges are found and 0's elsewhere. Normally, there are four types of image edges: slope edge, step edge, roof edge and line edge, which are indicated as Figure 1.

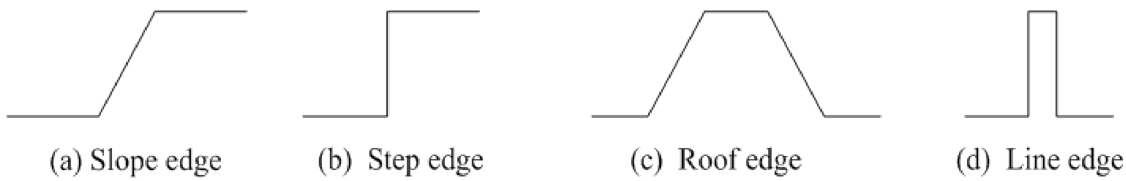


Figure 1. The types of edge

It is also possible for an edge to have both step and line characteristics, but if the surface has a specular component of reflectance and if the surface corner is rounded, there can be a highlight due to the specular component as the surface orientation of the rounded corner passes the precise angle for specular reflection. There are also edges associated with changes in the first derivative of the image intensity. Edges are important image features since they may correspond to significant features of objects in the scene. For the gray image, if a pixel is located in the edge of a certain object, then its neighborhood will become a region of gray changes. To such change, two of the most useful features are the change rate and direction of the gray, which are represented by the amplitude and direction of gradient vector[7].

3. Basic Differential Evolution Algorithm

The basic idea of DE is to recombine the differences of the individuals in the current population to obtain the intermediate population and use the competition between the offspring individual and parent individual to get a new generation of population. DE is a random parallel and direct search algorithm. It minimizes the non-linear, in-differential and continuous space function and succeeds in many fields with its usability, robustness and global optimization capacity[8].

Assuming that f is the minimum fitness function, it takes a candidate plan as the parameter in the form of real vector and gives a real number as the output fitness value of the candidate plan. The purpose is the find m to make $f(m) \le f(p)$ after searching all the plans p and maximization is to find an m to make $f(m) \ge f(p)$.

(1) Mutation operation

As any objective vector x_i in the parent population, generate the mutation vector v_i according to the following formula:

$$v_i = x_i + F \bullet \left(x_{i_2} - x_{i_3}\right) \quad (1)$$

$$v_i = x_{i_1} + F \bullet \left(x_{i_1} - x_{best}\right) + F \bullet \left(x_{i_2} - x_{i_3}\right) \quad (2)$$

Here, $F > 0$ is the real constant to control differential mutation, i_1, i_2, i_3 are the individuals randomly selected from the population and x_{best} is the current optimal solution[9].

(2) Crossover operation

Crossover operation is introduced in order to increase the diversity of the interference parameter vectors and the test vector will become:

$$u_{i,G+1} = (u_{1i,G+1}, u_{2i,G+1}, \ldots, u_{Di,G+1}) \quad (3)$$

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & if\ randb(j) \le CR\ or\ j = rnbr(i) \\ X_{ji,G+1} & if\ randb\ (j) > CR\ or\ j \ne rnbr(i) \end{cases}$$

$$(i = 1,2,\ldots\ldots,\ NP;\ j = 1,\ 2,\ldots\ldots,\ D) \quad (4)$$

Here, the jth estimated value of the random number generator is generated by $randb(j)$ within [0,1], $rnbr(i) \in 1,2,\ldots,D$ is the selected sequence to ensure that at least one parameter will be obtained from $u_{i,G+1}$, CR is the crossover operator with its value range within [0,1].

(3)Selection operation

The selection operation of DE is a greedy selection mode. When and only when the fitness value of the new vector individual u_i is better than that of the objective vector individual x_i, u_i can be accepted by the population, otherwise, x_i will still be preserved in the population of the next generation and it will have mutation and crossover operations as the objective vector in the next iteration. Assuming that the optimization problem is $\min f(x)$, selection operation can be described by the following formula:

$$x_i^t+1=\begin{cases} u_i, f(u_i)<f(x_i^t) \\ x_i^t, else \end{cases} \tag{5}$$

The selection operation of DE is have the parent individuals and the newly-generated individuals compete with each other, making the offspring individual always superior to or equal to the parent individuals and the population evolve towards the optimal solution.

The most novel feature of DE is its mutation operation. When an individual is selected, the algorithm will complete mutation through the weighted difference of two individuals and this individual. Such novel mutation operation makes this algorithm have incomparable advantages compared with other similar methods in resolving functional optimization problems[10].

4. Analysis of Mechanism of Ant Colony Optimization

Ant colony optimization has strong capacity to find the solution in solving combinatorial optimization problems and it has such advantages of distributed computation and strong robustness so that it presents high flexibility and robustness in dynamic environment. The ants will leave what is called pheromone in the paths they pass and they always walk towards the direction with high pheromone concentration, therefore, the collective foraging comprised by numerous ants shows a positive feedback on pheromone[11]. The ants can sense the pheromone concentration in the paths, select the path with higher concentration at higher probability, approximate the optimal path gradually and select the optimal path, which is indicated as Figure 2.

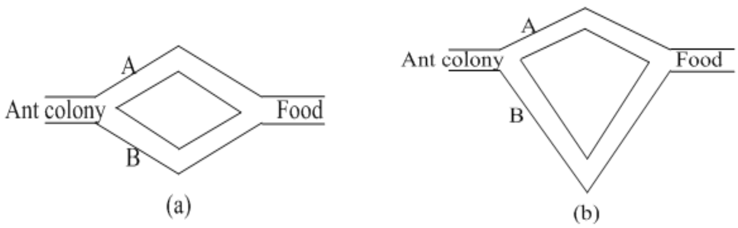


Figure 2. The demonstration for the path-selection process of the ants

The ant will select the next path at the corresponding probability according to the pheromone concentration in the path in the movement, ignore the paths it has passed and use a data structure to control this point $(tabu_k(k=1,2,\cdots,m))$. After finishing one cycle, it will release the pheromone of corresponding concentration according to the entire path length and update the pheromone concentration of the path it has passed[12]. The flowchart of ant colony optimization is indicated in Fig.3 and the main steps are as follows:

Step 1: $nc=0$ (nc is the number of iterations or searching times), Initialize τ_{ij} and $\Delta\tau_{ij}^k$ and put m ants in n vertexes.

Step 2: Put the initial starting points of every ant to the current solution set $tabu_k(s)$, move every ant $k(k=1,\cdots,m)$ to the next vertex j at the probability of p_{ij}^k and put j in $tabu_k(s)$.

Step 3: Calculate the objective function value $Z_k(k=1,\ldots\ldots,m)$ of every ant and record the current optimal solution.

Step 4: Update the pheromone concentration $\tau_{ij}(t+n)$ of every edge.

Step 5: For every edge (i,j), make $\Delta\tau_{ij}^k=0, nc=nc+1$.

Step 6: If $nc<$the preset number of iterations $NCMAX$, turn to Step 2; otherwise, output the shortest path and terminate the entire procedure[13].

Step 7: Output the current optimal solution.

5. Main Procedures of Differential Ant Colony Optimization

(1) Determine the encoding mode of DE and the initial parameters of ant colony optimization.

(2) Operate the DE, randomly generate a group of feasible solution population. Initialize, define the

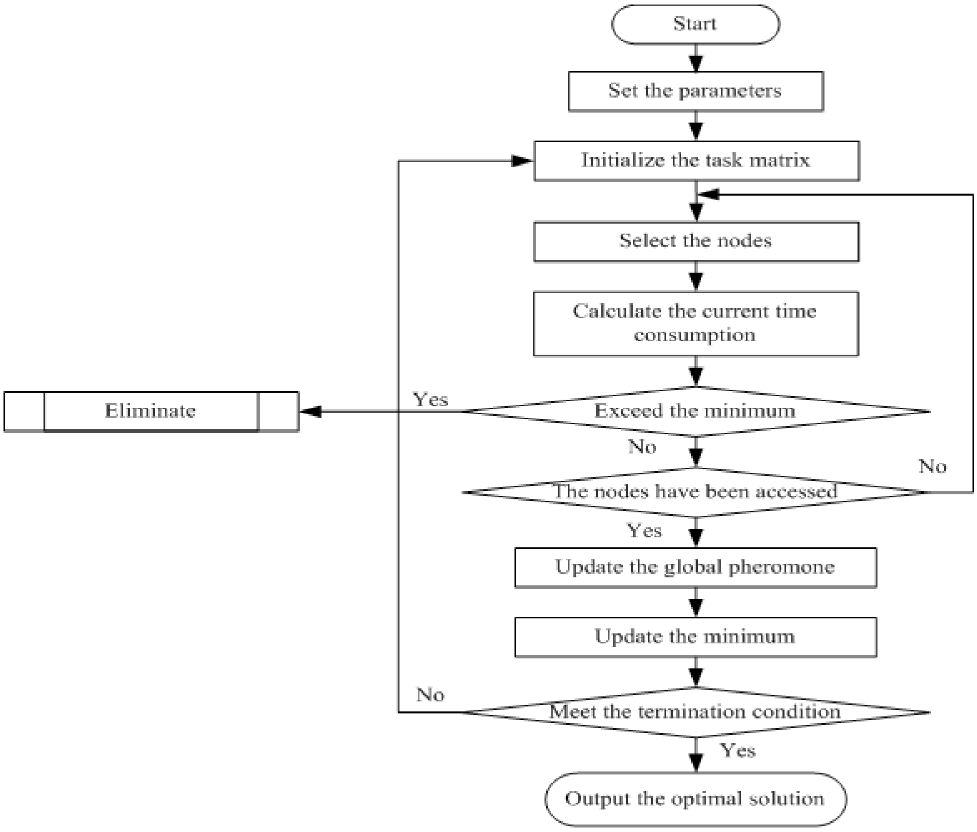


Figure 3. Flowchart of ant colony optimization

fitness function, the population size, the maximum number of iterations $cMax$ and the parameters.

(3) Perform selection operation and copy the optimal individual in the population to the next generation. Perform crossover operation, generate a pair of new nodes and calculate the fitness. Perform mutation operation, select a node according to the mutation probability, generate new individuals and calculate the fitness.

(4) Select N good individuals from the newly-generated population.

(5) Operate the ant colony optimization and obtain the optimal solution. Initialize the parameters and convert the previous good individuals into the nodes distribution at the early phase of ant colony optimization.

(6) Randomly put m artificial ants in n nodes.

(7) Initialize the accessed table of the ant, the un-accessed table and the accessible table.

(8) According to the accessibility of the pixel point, determine the next pixel point to be accessed and update the pheromone of the pixel point and the table of every pixel point.

(9) Evaluate the current edge and extract the optimal edge of the image.

The flowchart of the image edge feature extraction based on differential ant colony optimization is as follows[14,15]:

6. Experiment Simulation and Analysis

The parameters are set as follows: the population size of DE is: $f = a \times b$, the crossover probability is: $p_c = 0.8$, the mutation probability is: $p_m = 0.2$, the size of ant colony optimization is: $f' = a \times b$, the heuristic factor of pheromone is: $\alpha = 2.0$, the expected heuristic factor is: $\beta = 4.0$ and the pheromone polatility is: $\rho = 0.5$.

In the experiment, 20 simulations are performed on every algorithm and select the best effect as the final result. The following images represent the simulation results of different algorithms respectively.

It can be seen from the above results that the image edge feature extraction based on DE is just so-so and has bad refinement, but it includes some major and simple information of the image, as indicated in Fig.5(b) while that based on ant colony optimization has good continuity, refinement and smoothness and it contains the edge information, as indicated in Fig.5(c). The image edge feature extraction based on differential ant colony optimization has integrated the advantages of the advantages of these two algorithms and obtained significant edge feature details and excellent continuity, as indicated in Fig.5(d). The edge presentation is complete and has reached the expected objective.

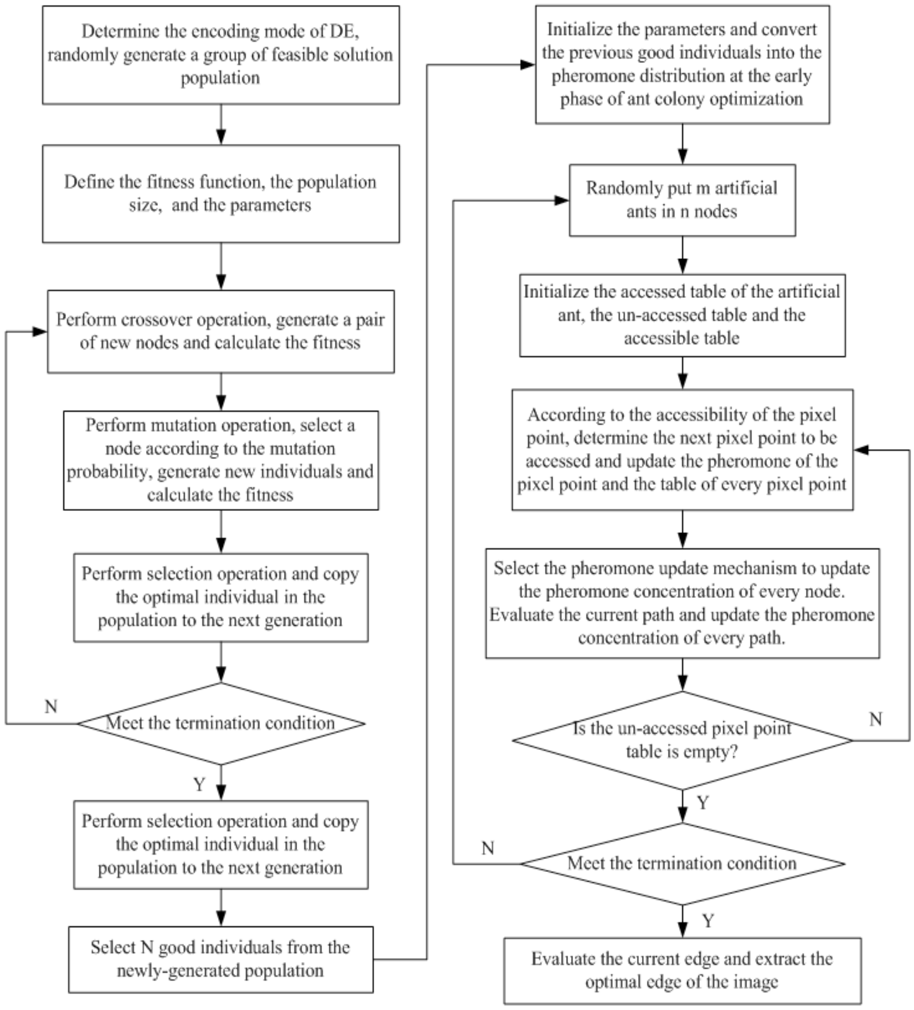
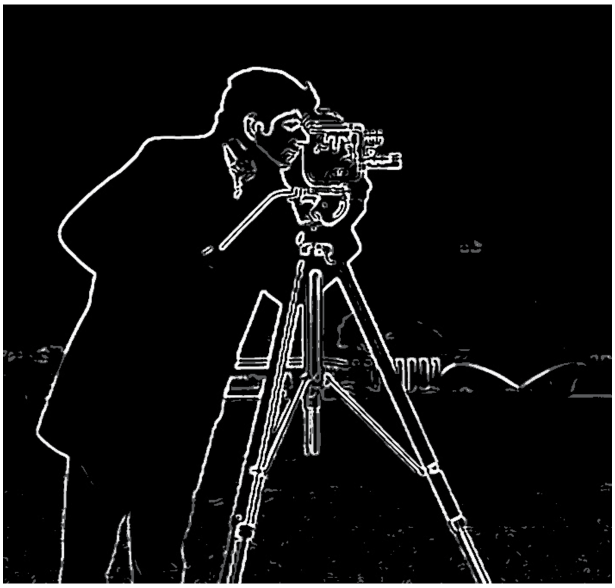


Figure 4. Flowchart of image edge feature extraction based on differential ant colony optimization

(a) Original image

b) Differential evolution algorithm



(c) Ant colony optimization

(d) The algorithm of this paper

7. Conclusions

Image edge is the most important feature of the image. On the basis of the summarization of some traditional and newly-emerging image edge feature extraction methods, this paper has done some creative and exploratory work on the edge extraction of gray image and made some improvements on the combination of ant colony optimization and differential evolution in light of the problems in the image edge feature extraction. In the initial phase of the proposed differential ant colony optimization, it uses the operating steps of differential evolution. If the changes of the fitness function value are within the error range, terminate the algorithm, convert the current optimal solution as the matrix distribution of the initial pheromone concentration and operate ant colony optimization. After the optimization is over, output the edge image.

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Decision Classification Tree Based Track and Field Athletes Training Evaluation Model

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Abstract
For the features of nerve type are often the key factors that decide athlete's emotion regulation ability to face competition and the performance of competitive level on spot, which ultimately affects the success or failure of the final game. This paper discusses the relationship and laws between the neural types of athletes and high level sports, and obtains track and field athlete nerve type group index test data from the "Athlete Nerve Type Group Index Database". Secondly, it applies the data mining decision tree algorithm and association rules analytical test data to identify the correlation index feature between the nerve type of athletes and the sports they are engaged in, to build the track and field athlete nerve type group traits evaluation model. The experimental results show the validity of the model, which can provide evaluation for the training of track and field athletes.
Key words: NEURAL TYPE, TRACK AND FIELD ATHLETE, DATA MINING, DECISION TREE ALGORITHM, INDEX FEATURE, EVALUATION MODEL