щаяся на OGA-алгоритме. Анализ результатов обучения улучшенной нейронной сети подтвердил, что OGANet не только имеет большую скорость обучения, но и преодолевает, в некоторой степени, такой недостаток традиционного обучения нейронных сетей методом обратного распространения ошибки, как склонность к попаданию в "ловушку" локального оптимума.

Практическая значимость. Способности рассматриваемой нейронной сети к нелинейной саморегулирующейся обработке информации позволяют преодолеть недостатки традиционных методов искусственного интеллекта. Данный метод эффективно совмещает преимущества генетического алгоритма и обучения нейронных сетей методом обратного распространения ошибки, предлагает хороший компромисс между глобальным поиском ортогонального генетического алгоритма и обучением нейронной сети.

Ключевые слова: *ортогональный генетический алгоритм, обучение нейронных сетей методом обратного распространения ошибки, оптимизация веса, глобальный поиск, локальный минимум, точность обучения*

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Cheng Zhang,
Hao Peng

Hunan International Economics University, Changsha, Hunan, China, e-mail: 289962526@qq.com

IMAGE EDGE DETECTION BASED ON HYBRID ANT COLONY ALGORITHM

Чен Чжан,
Хао Пен

Хунаньский університет міжнародної економіки, м. Чанша, провінція Хунань, КНР, e-mail: 289962526@qq.com

ВИДІЛЕННЯ КОНТУРІВ ЗОБРАЖЕННЯ НА ОСНОВІ ГІБРИДНОГО МУРАШИНОГО АЛГОРИТМУ

Purpose. With the scientific and technological development as well as the plenty of image information and exchange, the edge detection and automatic identification of the target image have become increasingly intensive. Its practical application problems have raised higher and higher requirements on the image edge detection techniques. The research deals with the problems of detecting the ideal edges and determining every parameter of this algorithm.

Methodology. We combined Ant Colony Algorithm (ACA) and Differential Evolution Algorithm (DE) and used it in the image edge detection. By analyzing the convergence time and optimization capacity of these two algorithms, we found the best method to combine and apply them to the image edge detection.

Findings. We found a way of image edge detection based on ACA and DE. We firstly made a theoretical analysis of image edge detection and found the best combination point of ACA and DE according to their own features. Mainly, it integrated these two algorithms according to the set conditions and included the operating steps of DE in the early phase of image processing followed by the operations of ACA.

Originality. We made a study of image edge detection based on the hybrid ant colony algorithm. We discussed how to detect the ideal edges of an image based on ACA and DE. The research on this aspect has not been found at present.

Practical value. We integrate these two algorithms to extract the complete edge contour in order to make the detected edges continuous and the edge localization accurate. The experimental result shows that the hybrid algorithm not only enhances the adaptive ability and capacity of global optimization but also has excellent edge detection effect, greatly reducing the computation workload and time.

Keywords: *image edge detection, differential evolution, ant colony algorithm, convergence time, optimization capacity, best combination point*

Introduction. The edge is the most fundamental image feature and it contains most of the image information. The research of human visual system demonstrates that the image edge is of particular importance since an object can be identified by only a few rough contours, which are the image edges [1]. Edge detection techniques have been extensively applied in such image analysis and processing field as feature description and image segmentation and it has become a research hotspot in the image processing and analysis technology. Generally, the image recognition and classification techniques include the following phases: image pre-processing, image edge detection, feature extraction and automatic classifier design, among which, the contents and methods of edge detection are extremely important. In practice, the background, the views, the lighting and the size may interrupt edge detection; therefore, it is a significant problem in application research how to extract the feature parameters with excellent edge detection performance and few noise interruptions [2].

As the preliminary phase of vision, image edge detection has a long research history where new theories and methods keep emerging, stressing the importance of the image edge detection research. Together with the development of computer vision and image processing techniques, it is badly in need to make some breakthroughs in the early vision stage and look for excellent edge detection algorithms, however, the edge detection problems of digital image have been resolved perfectly and the noises generated in the image production and transmission will cause false and lost edges in the edge detection. After that, it was found that the optimization algorithm based on swarm intelligence is an effective method to solve image edge detection and it provides new idea and means [3]. Practice has proved that DE is an effective search algorithm with such advantages as easy to understand, fast in convergence and easy to realize. However, it also has its own defects as a new evolution algorithm, i.e. it is slow in convergence when it approximates the optimal solution in the post optimization iteration and it is easy to be trapped in local optimum [4]. ACA has strong capacity in global search but it requires long operating time and it has slow convergence speed in solving the complicated global optimization problems. This paper complements the advantages of these two algorithms, links them together according to the settings and applies it to the image edge detection [5].

This paper firstly makes theoretical analysis of image edge detection, DE and ACA. Based on the above research, it finds the best combination point of these two algorithms according to their own features, mainly including the operating steps of DE in the early image phase, integrates these two algorithms according to the set conditions as well as the operations of ACA. Finally, it is the experimental simulation and analysis.

Image edge detection. Edges are the places in the image with strong intensity contrast. Image edge detection is to detect the image edges through certain techniques, and it works by detecting discontinuities in brightness and filters work essentially by looking for contrast in an image. A parameter controls the degree of smoothing applied, the default value is 1.0; greater values imply less smoothing but more accurate detection, lower values imply more smoothing but less accurate detection. The image edge has two characteristics, direction, and amplitude. The edge of the object is not continuous, which is the most significant part of the local brightness variation, such as texture mutation, gray and color. The image edge detection is mainly based on the derivative calculation, the detection algorithms highlight those points which's gray have significant change in the domain, these methods run by calculating the gradient amplitude generally, but in some images, the gradient amplitude is not the edge point, need to accurately determine the edge position at this time. The traditional edge detection utilizes the edge is the most dramatic feature of the image gray, the edge points are determined by the differential or two order differential of each pixel of the image [6]. The basic steps of image edge detection can be divided into filtering, enhancement, detection and location, the flow of edge detection is indicated in Fig. 1.

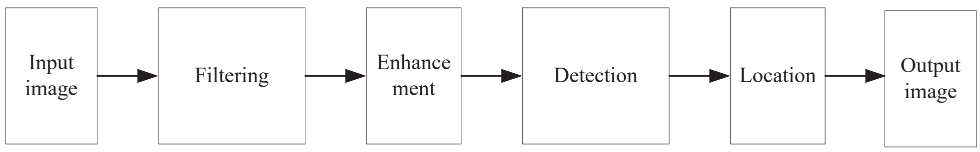


Fig. 1. Flow of image edge detection

The basic principle of differential evolution algorithm. Based on the alternative scheme population, basic DE searches the scheme in the entire search space, evaluates the optimal parameter vector in every generation of the evolution, records the minimization process and realizes through combination on the current schemes of the population through simple mathematical formulas. In this way, it can obtain a result with excellent convergence by using random deviation churn to generate new individuals [7].

1. Initialization

DE uses NP D-dimensional real-value parameter vector as the population of every generationand every individual is represented as

$$X_{i,G}(i = 1,2,\ldots\ldots,\ NP)\,.$$

In this formula, i is the sequence of an individual in the population, G is the evolutional generation and NP is the population size, which remains unchanged in the minimization.

2. Mutation Operation

$$v_{ij} = \begin{cases} v_{i,j},\ if\ (U < CR) \\ x_{i,j},\ otherwise \end{cases}.$$

Here, CR is the crossover probability and U is the variable randomly generated within 0 and 1.

3. Crossover Operation

Crossover operation is to increase the diversity of the individuals in the population through the random recombination of mutation vector v_i and the objective vector x_i. This algorithm generates new crossover vector $u_i = [u_{i,1}, u_{i,2}, \ldots, u_{i,D}]$ with the following formula

$$u_{i,j} = \begin{cases} v_{i,j}, randb \le CR\ or\ j = rand_j \\ x_{i,j}, randb > CR\ or\ j \ne rand_j \end{cases}$$
$$i = 1,\ldots, NP,\ j = 1,\ldots, NP\,.$$

$randb$ is a random number within [0,1] while CR is a constant within [0,1].

4. Selection Operation

$$x_i = \begin{cases} v_i, if\,(f(v_i) < f(x_i)) \\ x_i, otherwise \end{cases}.$$

Here, f is the fitness value and DE uses greedy selection method to guarantee that the population of the next generateon has the vector with better fitness value.

In the early iteration, the mutation operation will help the algorithm have strong global searching ability due to the huge differences among the individuals of the population while in the post iteration; the individuals have few differences when going towards convergence, making the algorithm have the strong local searching capacity [8].

The basic principle of ant colony algorithm. Ant colony algorithm is a swarm intelligence algorithm designed by simulating the principle of ant foraging. The ant will release a pheromone when it moves, with which as the medium, it makes information exchange. In addition, it can sense the density of this substance in the foraging and guide its movement direction. The shorter a certain path is, the more the ants pass this path, the more pheromone is left in the path, the higher concentration the pheromone is and the higher probability of choosing this path, thus constituting a positive feedback process.

Analysis of mechanism of ant colony algorithm. Assume that there are n cities and m ants and make $d_{ij}(i, j = 1,2,...,n)$ as the distance between the cities i, j and $\mu_{ij}(t)$ as the pheromone concentration left in the paths between the cities i, j at the time of t. When ant k moves forward, its next step is determined by the pheromone concentration left in every path. Take $p_{ij}^k(t)$ as the probability for the ant k to move from city i to city j at the time of t and then

$$p_{ij}^k(t) = \begin{cases} \dfrac{\left[\mu_{ij}(t)\right]^\alpha \bullet \left[\nu_{ij}(t)\right]^\beta}{\sum\limits_{s \subset allowed_k} \left[\mu_{ij}(t)\right]^\alpha \bullet \left[\nu_{ij}(t)\right]^\beta}, & if \ j \in allowed_k \\ 0, & otherwise \end{cases}, \quad (1)$$

$allowed_k$ is the city set that ant k can move and table $tabu_k$ is the $tabu$ table of ant k. ν_{ij} is the heuristic factor, meaning the expectation of ant k to move from city i to city j, which is usually the reciprocal of d_{ij} and α, β are the relatively important procedures of pheromone and heuristic factor in the formula respective. After all the ants finish one traversal, update the pheromone of every path according to (2)

$$\mu_{ij}(t+1) = \Delta\mu_{ij} + (1-\sigma) * \mu_{ij}(t); \qquad \Delta\mu_{ij} = \sum_{k=1}^{m} \Delta\mu_{ij}^k. \quad (2)$$

Here, $\sigma (0 < \sigma < 1)$ is the evaporation coefficient, $1-\sigma$ is the persistence coefficient, $\Delta\mu_{ij}$ is the pheromone increment after this iteration and $\Delta\mu_{ij}^k$ is the pheromone left by the kth ant in this iteration [9,10].

Specific realization of algorithm.

Step 1: $nc = 0$ (nc is the number of iterations or the number of searches, the $\mu_{ij}(0) = c$ (constant) in every edge and $\Delta\mu_{ij} = 0$. Put m ants in n vertexes.

Step 2: Put the initial starting points of every ant into the current solution set. Every ant $k(k = 1,2,\ldots\ldots,m)$ moves to the next vertex j at the probability of $p_{ij}^k(l)$ and put the vertex j to the current solution set.

Step 3: After n moments, ant k walks past all the vertexes and finishes one cycle. Calculate the total path length L_k every ant walks past and update the shortest path.

Step 4: Change the trajectory intensity according (2).

Step 5: Put $\Delta\mu_{ij} = 0; nc = nc+1$ in every path.

Step 6: If nc is smaller than the pre-set number of iterations, has no degeneration behaviors, finds the same solution or the evolution trend is significant, then turn to *Step 2*.

Step 7: Output the optimal path.

The flow of ant colony algorithm is indicated as Fig. 2.

Main steps of the hybrid ant colony algorithm on edge detection. Represent the corresponding pixel points in the image with the gray matrix among 0~255. Operate in the 2-dimensional plane. For the digital image, its gray must be among 0～255, therefore, the coding method of every chromosome is set as 8-bit binary coding.

At the early phase, operate DE until the set termination conditions. Select the fitness function. As the criterion of individuals, when selecting the fitness function, the proper standard can be determined according to the practical problems. Perform mutation, crossover and selection operations, $P_m = 0.2$ and $P_c = 0.8$. Convert the current optimal solution from DE as the initial pheromone concentration distribution matrix of ant colony algorithm. Operate ACA until the optimal solution is sought. The design of ACA shall follow the rules below.

1. Perform initial setting on the control parameters of hybrid ant colony algorithm; randomly put the initial starting points of every ant into the current solution set.

2. Calculate the objective function value of processed images according to the distribution of every ant.

3. Select the pixel point to be accessed next, to every artificial ant k, there shall be a set S_k, which is the node set it hasn't accessed yet. U_k is the node set the ant is allowed to access in the next step according to the probability transfer formula. $tabu_k$ is the $tabu$ table, namely the set of those nodes which have been accessed.

$$S_{ij} = \begin{cases} \arg\max_{k \in s_m(i)} \left\{\mu(i,k) \bullet \nu^\beta(i,j)\right\}, & if \ r \le r_0 \\ I, & otherwise \end{cases}.$$

Where, S_{ij} is a state variable obtained from ant colony transfer formula. I is a random variable selected according to the probability given by (1). r is an uniformly distributed random number to determine the relative importance of exploitation versus exploration $r \in [0,...,1]$. r_o is a threshold parameter and the smaller r_o the higher the probability to make a random choice $(0 \le r_0 \le 1)$.

4. Every time when the ant walks past a pixel point, this point will be transferred to the $tabu$ table and deleted from S_k and U_k. If the selected pixel point is not the edge pixel point of the image, then the next pixel point of the image edge will be added to U_k. In the end, the order of the nodes obtained in the $tabu$ table.

5. Update the pheromone concentration of every pixel point, 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. This paper uses Max Min Ant System (MMAS) to update the pheromone, set a pheromone range $[\mu\min, \mu\max]$, and enhance search capacity of hybrid ant colony algorithm on edge detection in global search.

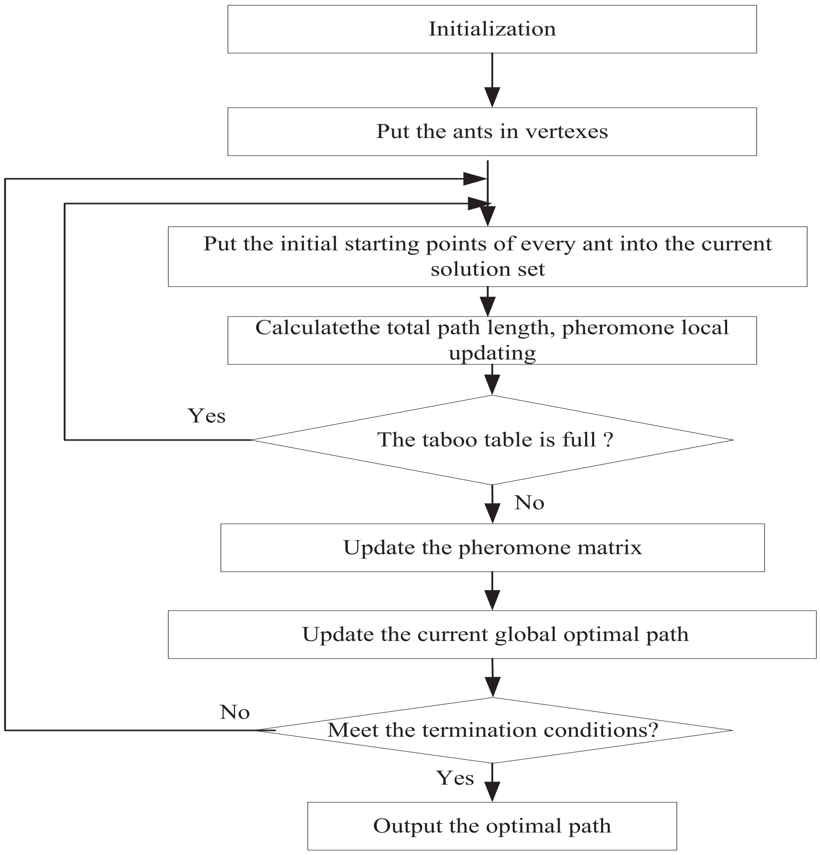
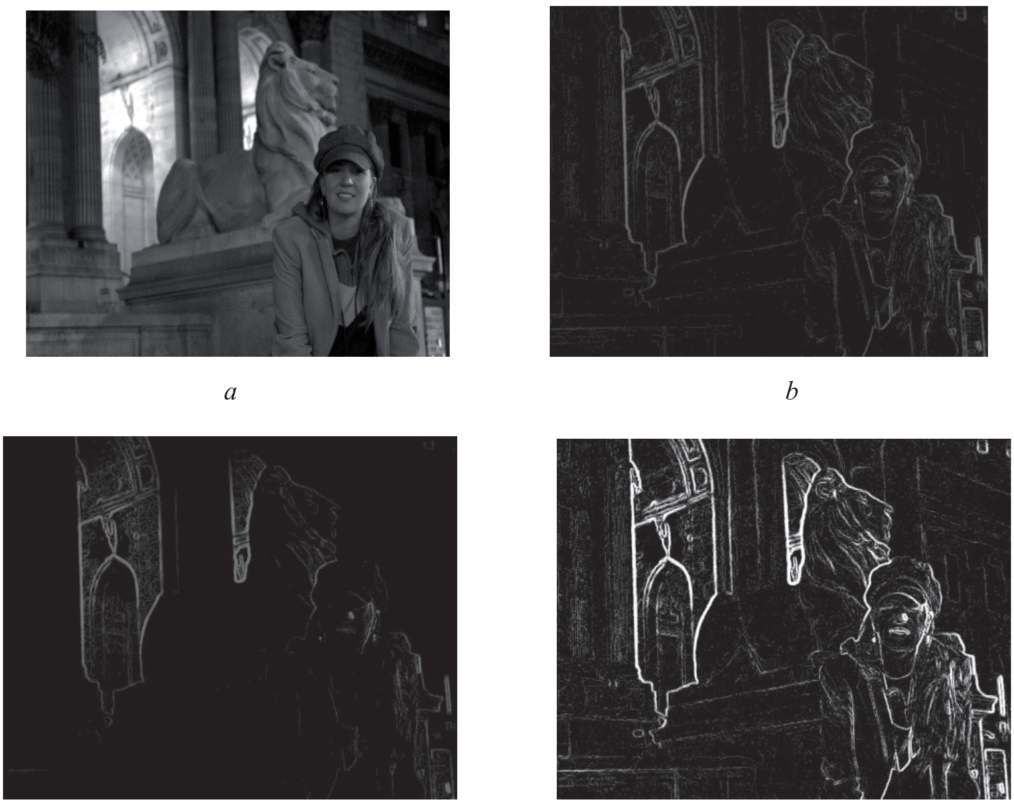


Fig. 2. Flow of ant colony algorithm



a *b* *c* *d*

Fig. 3. Image edge detection comparison: a −original image; b − canny operator method; c − log operator method; d − this paper method

6. If meeting the end conditions, end the program loop, evaluate the current edge and extract the optimal edge of the image. Otherwise, return to Step 3.

Experiment simulation and analysis. The software platform of this paper uses MATLAB2012a in Windows7 operating system. The test image uses Matlab standard image, the hardware platform is Intel (R) Core(TM)i5 2.0 GHz 64-bit processing unit with a memory of 4GB. The Canny operator is the best operator based on the edge detection three criterion, Log operator is the most influential zero crossing edge detection operator, so choose the above two operators and this paper method to compare. Through the simulation comparison of above algorithms, the continuity, refinement and smoothness of the image edge can be determined, as shown in Fig. 3.

In a word, the image edge detection based on Log operator method has the general continuity, bad refinement and smoothness and a short simulation time. The image edge detection based on Canny operator method can display the main image edge information, but the edge contour is not refined and smooth and its long simulation time will also affect the overall algorithm efficiency. The hybrid ant colony algorithm has subjective and objective evaluation reach a high level. This algorithm integrates the advantages such as fast convergence and quick speed of DE and that of global search of ACA, it can not only detect the image edge in a quick and accurate manner, but can also shorten the simulation time and reach the expected effects.

Conclusion. Image edge is the most important image feature and the detection of image edge has always been the most fundamental and significant direction for image processing and pattern recognition. The research of image edge detection based on hybrid ant colony algorithm proposed in this paper detects the ideal edges and how to determine every parameter of this algorithm and increase the algorithm efficiency is worthy of research. At the end, this research analyzes the valuation strategy of every parameter to increase the performance of DE and ACA and it increases the intelligence level of this algorithm through the experiment of the image edge detection.

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Мета. З розвитком науки та техніки, великою кількістю графічної інформації й активним обміном нею, усе більш актуальним стає автоматичне розпізнавання зображень з рішенням завдання виділення їх контурів. Їх практичне застосування обумовлює більш високі вимоги до методик виділення контурів зображень. Розглянуті завдання визначення контурів зображень і параметрів запропонованого алгоритму.

Методика. Мурашиний алгоритм (ACA) і алгоритм диференціальної еволюції (DE) були об'єднані та використані для визначення контурів зображення. На основі аналізу часу обробки та продуктивності цих алгоритмів оптимізації був знайдений найкращий спосіб їх поєднання та використання для визначення контурів зображень.

Результати. Запропоновано спосіб визначення контурів зображень за допомогою мурашиного алгоритму й алгоритму диференціальної еволюції. Проведений теоретичний аналіз визначення контурів і знайдений найкращий спосіб поєднання мурашиного алгоритму та алгоритму диференціальної еволюції, виходячи з їх особливостей. Взагалі, спосіб інтегрує дані алгоритми відповідно до заданих умов і застосовує на початковому етапі обробки зображення процедури алгоритму диференціальної еволюції, а на завершальному етапі – мурашиного алгоритму.

Наукова новизна. Вивчене визначення контурів зображень за допомогою гібридного мурашиного алгоритму. Розглянуте завдання визначення ідеальних контурів зображення на основі мурашиного алгоритму та алгоритму диференціальної еволюції. Раніше даний аспект не був вивчений.

Практична значимість. Дані алгоритми були інтегровані для здобуття цілісного контуру, якому властива безперервність і точність локалізації. Результат експерименту показав, що запропонований гібридний алгоритм не лише покращує адаптивні можливості й продуктивність оптимізації, але й показує відмінний результат у визначенні меж, істотно скорочуючи трудомісткість і тимчасові витрати обчислювальних операцій.

Ключові слова: *визначення контурів зображення, диференціальна еволюція, мурашиний алгоритм, час обробки, продуктивність оптимізації, найкраще поєднання*

Цель. С развитием науки и техники, обилием графической информации и активным обменом ею, все более ак-туальным становится автоматическое распознавание изображений с решением задачи выделения их контуров. Их практическое применение предполагает более высокие требования к методикам выделения контуров изображений. Рассмотрены задачи определения контуров изображения и параметров предложенного алгоритма.

Методика. Муравьиный алгоритм (ACA) и алгоритм дифференциальной эволюции (DE) были объединены и использованы для определения контуров изображения. На основе анализа времени обработки и производительности этих алгоритмов оптимизации был найден наилучший способ их совмещения и использования для определения контуров изображений.

Результаты. Предложен способ определения контуров изображений с помощью муравьиного алгоритма и алгоритма дифференциальной эволюции. Проведен теоретический анализ определения контуров и найден наилучший способ сочетания муравьиного алгоритма и алгоритма дифференциальной эволюции, исходя из их особенностей. В общем, способ интегрирует данные алгоритмы в соответствии с заданными условиями и применяет на начальном этапе обработки изображения процедуры алгоритма дифференциальной эволюции, а на заключительном этапе – муравьиного алгоритма.

Научная новизна. Изучено определение контуров изображений с помощью гибридного муравьиного алгоритма. Рассмотрена задача определения идеальных контуров изображения на основе муравьиного алгоритма и алгоритма дифференциальной эволюции. Ранее данный аспект не был изучен.

Практическая значимость. Данные алгоритмы были интегрированы для получения цельного контура, которому свойственна непрерывность и точность локализации. Результат эксперимента показал, что предложенный гибридный алгоритм не только улучшает адаптивные возможности и производительность оптимизации, но и показывает отличный результат в определении границ, существенно сокращая трудоемкость и временные затраты вычислительных операций.

Ключевые слова: *определение контуров изображения, дифференциальная эволюция, муравьиный алгоритм, время обработки, производительность оптимизации, наилучшее сочетание*

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