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Color Image Enhancement Based on Ant Colony Optimization Algorithm

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Abstract

In the collection, transmission, decoding process, the images are likely to produce noise. Noise makes the image color distorted and the articulation dropped, and also affects the image quality. Due to different causes, there are different types of noise, and the impulse noise is most common among them which exert great influence on the image quality. This paper, according to the characteristics of the color image, combines the ant colony algorithm and weighted vector median filter method to put forward an algorithm for the impulse noise removal and the color image enhancement. This method finds the optimal filter bank parameter by ant colony optimization (ACO) and processes image points polluted by the noise to achieve the purpose of image enhancement and protect the image details and edge information. Simulation experiment proves the correctness and validity of this method.

Keywords*: ant colony optimization, weighted vector median filter, image enhancement*

1. Introduction

Noise can be understood as various factors interfering with people's understanding or analysis of image source information received by people's visual organ or system sensors. The common noise is the unpredictable random signal and it can only be known by means of the probability statistical method. Noise is very vital for the image processing and affects each image processing step such as the input, collection and processing and the output result [1]. The noise removal has become a very important step in image processing. The comparison between the gray image and color image shows that the gray image processing method development is more mature, while, the color image more worth studying with the rapid development of computer information processing technology [2].

Because the color image is multichannel signal, namely the multidimensional signal, which makes the noise removal become more complex. The impulse noise is a very common and typical noise which has a very big impact on the image [3]. One of the effective methods removing the impulse noise is the vector median filter (VMF), however, just as the median filter algorithm, the vector median filter still faces shortcomings, and, because of the color image signal's multichannel property, such limiting factor becomes increasingly more and more, therefore, there still exist great potential to improve the vector median filter [4].

This paper, based on above requirements, studies the application of the vector median filter technology in the impulse noise removal of the color image. This paper applies ACO to the color image's vector filtering method and finds optimal filter bank parameter by ACO to achieve the purpose of image enhancement. At first, this paper analyzes the characteristics of the impulse noise, the image's weighted vector filter method, and then studies the ant colony algorithm principle and basic idea, based on this, puts forwards the implementation steps of color image filter enhancement based on ACO algorithm, and finally the experimental simulation and the result analysis.

2. Color Image Filtering Enhancement Methods

Color image filtering aimsto simultaneously achieve the following three objectives: weakening noise, maintaining tones and protecting edges or details. The three-dimensional space is required when expressing a color pixel. Color space or Color model or Color coordinate

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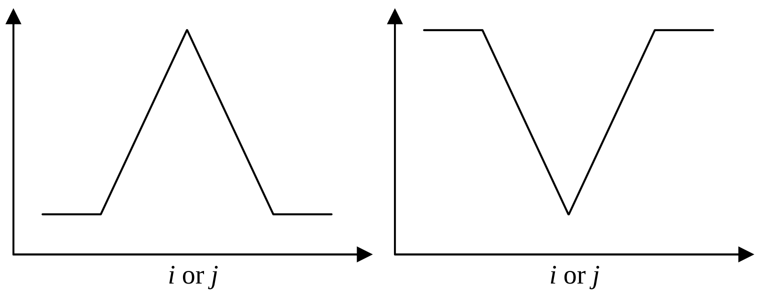
system is the three-dimensional description of the color perception. Each color can be represented by a dot in the color space.

2.1. Characteristics of Impulse Noise

In image processing, impulse noise, that is, salt-pepper noise, will cause black and white dots in the image, especially, in parts where are very dark or very bright. Generally speaking, the pixel grayscale value in the image is a continuous gradation. The grayscale of the impulse noise dot is the superposition of the normal grayscale of this dot and the noise grayscale.

When a pixel in the image is interfered by the impulse noise, its grayscale value will differ greatly from those of the adjacent pixels. When the noise grayscale is positive, it appears in the image as an isolated bright dot. When the impulse noise grayscale is negative, it appears as an isolated dark dot. Impulse noise dot and the typical variation characteristics of the neighborhood pixel grayscale of are shown in Figure 1 (a) and (b):



(a) (b)

Figure 1. Impulse noise model

2.2 Weighted Vector Direction Distance Filteringof the Image

The natural image is non-stationary. The premise of filtering operation is that the image can be divided into several smaller areas, and each area can be regarded as stationary. The smaller image area is determined by the support window. Filter window is an important part of spatial filtering, which is related to the size of the window, directionality and partition, etc. All the pixels $W = \{x_1, x_2, \cdots, x_N\}$ in a window around the center pixel, is shown in Figure 2:

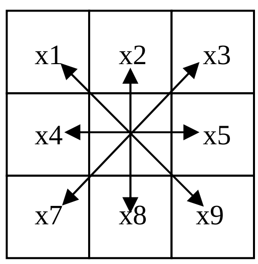


Figure 2. Pixels in the window

In 1993, Trahanias put forward the Basic Vector Directional Filter (BVDF), which is a method based on the direction information in color vectors. In 1995, Karakos put forward the Directional-distance Filters (DDF), which integrates the methods of Vector Median Filter (VMF) and BVDF. They have a common drawback, that is, they all neglect that the pixels in the filter window are also related to space distance. This crucial point will affect the result of image filtering. However, weighted vector direction distance filter can make up this drawback. Weighted vector filter means that each pixel in the weighted vector filter has a corresponding weight value. The filter result is represented through the space distances between the pixels in the filter window [5].

In weighted vector direction distance filter, each pixel in the same filter window has two corresponding weight value, which concerns two factors, one is vector direction, and the other is vector distance. In the filter window, suppose there are k pixels $Z_1^{(p,q)}, Z_2^{(p,q)}, \cdots, Z_{(K+1)/2}^{(p,q)}, \cdots Z_K^{(p,q)}$, using $w_1, w_2, \cdots w_K$ to represent the coefficient of the vector distance weight value, using $w_r \left(r \in \{1, 2, \cdots, K\} \right)$ to represent the real number, whose range is [0,1], multiplying weighted vector distance with weighted angle distance, whose produce can be represented with $\phi_r^{(p,q)}$, $\phi_r^{(p,q)}$ represents the weighted vector direction distance, as shown in the following:

$$\phi_r^{(p,q)} = \left(\sum_{\substack{r_1=1 \\ r_1 \neq r}}^{K} w_{r1} \left\| z_r^{(p,q)} - z_{r1}^{(p,q)} \right\|^{y_1} \right)^{1-\delta} \square \left(\sum_{\substack{r_1=1 \\ r_1 \neq r}}^{K} w_{r1} A\left(z_r^{(p,q)}, z_{r_1}^{(p,q)} \right) \right)^{\delta} \quad r \in \{1, 2, \cdots K\} \tag{1}$$

In the filter window, using δ represent vector distance and vector angle, that is, the output. If each pixel $z_r^{(p,q)} \left(r \in \{1, 2, \cdots K\} \right)$ in $\Phi_{p,q}$ is sequenced in an ascending order according to the vector distance $\phi_r^{(i,j)}$ in (1), and gain the result after sequencing $\left\{ z_{(1)}^{(p,q)}, z_{(2)}^{(p,q)}, \cdots, z_{((K+1)/2)}^{(p,q)}, \cdots z_{(K)}^{(p,q)} \right\}$, then $Y_{p,q} = z_{(1)}^{(p,q)}$ represents that the filter keeps calculating till gaining the correct result. Therefore, such filtering is called weighted vector direction distance filtering [6].

3. Principle and Application of Ant Colony Algorithm

3.1. Basic principle and idea of ant colony algorithm

(1) Basic idea

Ant colony algorithm is the imitation of ant foraging behavior in the nature. During the ant foraging process in the nature, although there are many barriers between ant nest and food source, ants have always been able to bypass obstacles and find the shortest path between the nest and source to acquire food. When the exterior environment is changed, the ants can quickly adapt to such change to find new optimal path. The main reason lies in the mechanism of communication among the ants. This mechanism is the pheromone which is an important channel for ants to communicate with each other, which at the same time also makes ants always tend to select the path with higher pheromone density in the process of searching for food.

(2) Ant's path search

Such a positive feedback mechanism will also occur when ants meet obstacles. As shown in the following Figure 1, assume that A is the ant nest and D the food source, when the ant reaches B from A, the ant will reach C by selecting randomly to pass E or F, and leave pheromones along the way. At first, with the same probability, all ants will select E or F to bypass the obstacle, in this way, the pheromone density on path BE and BF are same in a short period of time. But with the passage of time and the pheromone volatility, pheromone density on path BE is relatively low than BF due to the path BE is longer than path BF. In selecting the path, subsequent ants will tend to select path BF, and in this way, the pheromone density on path BF will further increase, while, the pheromone density on path BE will sharply decrease due to the ant number selecting path BE decreases, and then the ant number selecting such path will sharply reduce, thus a new positive feedback mechanism will be formed and finally all ants tend to select one shortest path to bypass obstacles in order to reach the food source [7].

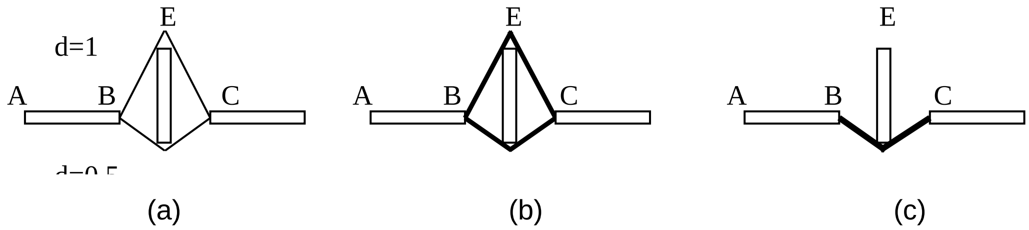


Figure 3. Ant colony foraging sketch map

We can see that during the foraging process, all ants coordinate with each other. Although, the ant number in the entire ant colony is numerous, the entire ant colony reflects the self-organizing characteristic, and following principles should be met to complete such characteristic:

(1) Search range

The individual ant is very tiny and its perceptive range is very limited. Usually, the range that one ant is able to observe is a checkered world. This range is the 3*3 check with 8 directions and its advancing distance of only 1. The ant step search is only within such a small range.

(2) Ant search environment

The environment where artificial ants are in is a virtual world in which the ant will also encounter obstacle when searching, and this obstacle is also a kind of visual existing forms. In order to make the ants have large search range possibly, we assume a volatile mechanism for the pheromone released by ants during the moving process to make the virtual environment more close to the ant's environment in the nature possibly.

(3) Search rule

Search whether there is any food in the range that can be perceived by each ant, and get over if there is food, otherwise, check whether there is any pheromone. Select the point with the most pheromones within the range that can be perceived and move to this point with larger probability, that is to say, each ant will make mistakes in small probability and does not always move towards the point with the most pheromones. The rule that ants finding the nest is similar to the above, but it only responds to nest pheromones.

(4) Move rule

Each ant moves towards the direction with the most pheromones in larger probability, but when there is no pheromone to guide, the ant will move on according to the original move direction and there may be small random disturbance along the move direction. In order to avoid circling around, the ant can remember and avoid the position where it has gone when moving.

(5) Obstacle avoidance rule

If there are obstacles blocking the direction where the ant is to move, the ant will randomly choose another direction, and will move according to the rules of foraging behavior under the guidance of the pheromone.

(6) Disseminating pheromone rule

The pheromone disseminated by each ant at the time when it finds the food or the nest is the most, which becomes fewer and fewer as the moving distance increases.

According to these few simple rules, there is no direct relationship among ants, but each ant interacts with the environment and is associated together by the pheromone bond[8,9].

3.2. Basic ant colony algorithm applied to TSP

According to the pheromone update strategy, the principle that the ant-cycle algorithm is applied to TSP problems is as follows:

First, randomly place m ants in n cities, and each ant $k\left(k=1,2,\cdots,m\right)$ generates one action path with $n-1$ steps $T^k\left(t\right)$ according to rules of probability transformation, and its length is $L^k\left(t\right)$. m paths will be generated when all ants have completed the travel around for one time. The shortest path $T^{+}(t)$ will be gained after comparing lengths of m paths. Update pheromones on m paths after an iteration, and conduct such iterative process for N times to finally get the global shortest path T^{+}. Problems should be paid attention to during the iterative process are as follows:

(1) Ant memory function

Ants in the artificial ant colony system has the memory function called Tabu List which is used to remember the city set J_i^k that has been visited by number k ant. With this list, the ant's repetitive visit of one same city will be avoided.

(2) Pheromone and heuristic guidance function

The pheromone τ_{ij} on the path represents the intellectual desire by transferring from city i to city j, which reflects the experience accumulation of the ant in the problem solving process, and this parameter is dynamic and changeable in the process of algorithm iteration. Heuristic guidance function η_{ij} also called the visibility function represents the heuristic desire of the ant k from city i to city j, which is used to guide the ant search, and its definition is related to practical problems, and it is defined as the reciprocal $\eta_{ij}=1/d_{ij}$ of the distance between cities in the TSP problems[10].

(3) Transfer rule

The transfer rule on which the ant based to select the path from city i to city j is shown in Formula (1):

$$p_{ij}^{k}(t)\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum\limits_{l\in J_i^k}\left[\tau_{il}(t)\right]^{\alpha}\left[\eta_{il}\right]^{\beta}} & j\notin J_i^k\\ 0 & j\in J_i^k\end{cases} \tag{2}$$

In which, α and β are two parameters that can be adjusted, which are respectively weight factors of the pheromone strength and heuristic guidance function to the ant path selection [11].

(4) Pheromone update

After the number t iteration, the ant k will disseminate certain pheromone $\Delta\tau_{ij}^{k}(t)$ on the path (i,j). The calculation formula of $\Delta\tau_{ij}^{k}(t)$ is shown in Formula (2):

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}Q/L^{k}(t) & (i,j)\in T^{k}(t)\\ 0 & (i,j)\notin T^{k}(t)\end{cases} \tag{3}$$

In which, $T^{k}(t)$ is the path passed by number k ant during the number t iteration, and $L^{k}(t)$ is the length of this path and Q is a preset parameter [12].

If there is no volatile mechanism of the pheromone, the initialization random fluctuation will be caused to further enlarge, thus, the algorithm converges to the non-optimal solution. In order to guarantee the full search of the solution space, similar to the real ant colony, we introduce the pheromone volatile mechanism. Introduce the pheromone volatile coefficient $\rho(0<\rho<1)$ in the algorithm to simulate the volatile process. The pheromone volatile rule of each path is as shown in Formula (3):

$$\tau_{ij}(t)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{4}$$

In which, $\Delta\tau_{ij}(t)=\sum\limits_{k=1}^{m}\Delta\tau_{ij}^{k}(t)$

In order to make the ant search successfully start, the pheromone initial value on each path can not be zero. During the specific initialization, the pheromone on each path can be set as one small positive constant τ_0.

Ant colony algorithm flow chart is shown in Figure 4:

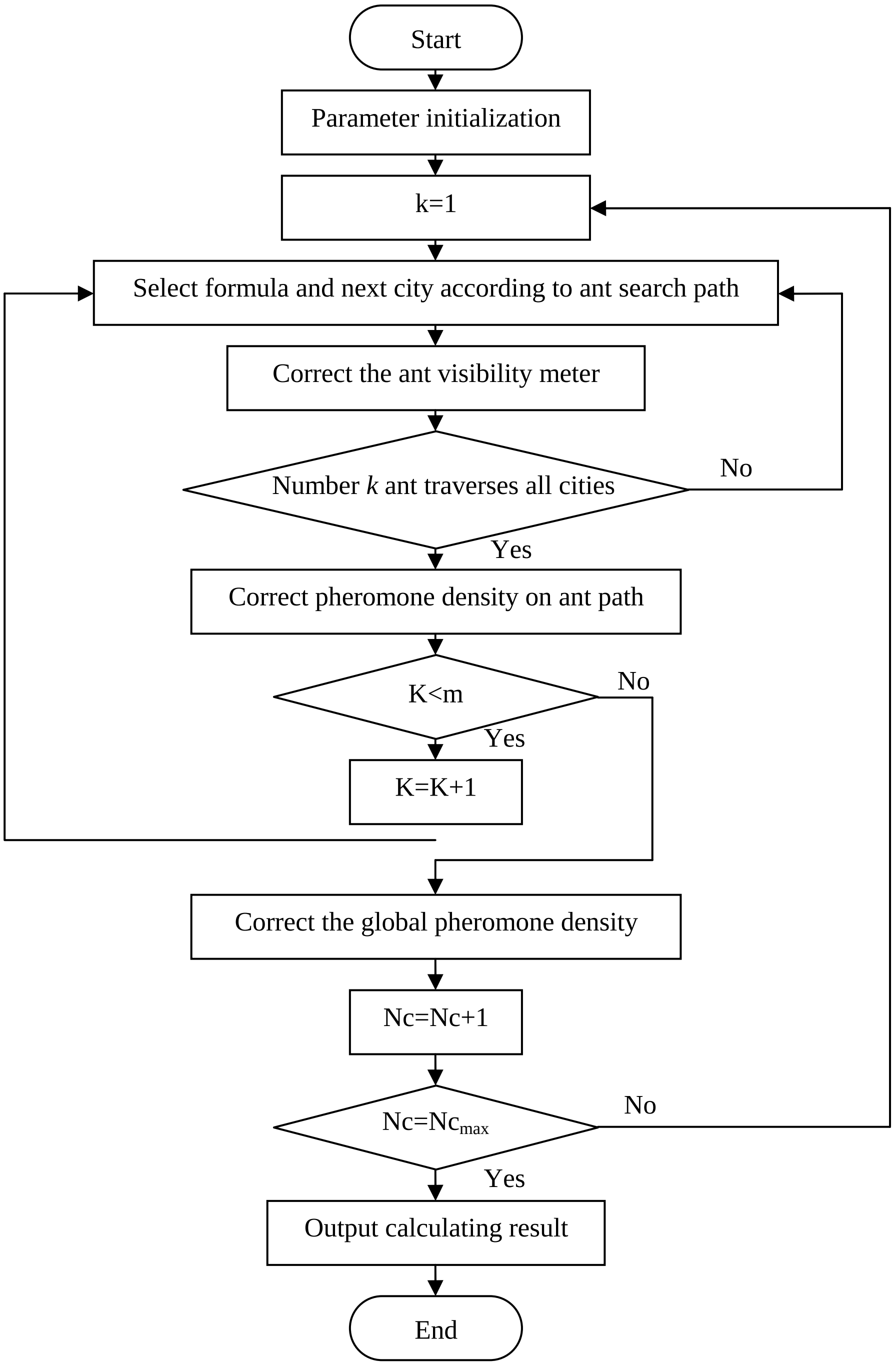


Figure 4. Ant colony algorithm flow chart

4. Color Image Filtering Enhancement Based on ACO Algorithm

The basic thought of this paper is to using ACO algorithm to optimize the weight value coefficient vector of the filter in the weighted vectors, so as to find the optimized filter parameter to eliminate the noise.

4.1. Population design

Using K *to represent* the size of the median filter window, then, the search is K dimensional, in other works, there are K weighted coefficient vectors in the median filter to be optimized, which forms an ant individual in ACO. A set of weight value corresponds an ant individual to be optimized. Different filters are represented by different weight value combinations of real number code, here, $0 \le w_r \le 1$ refers to the range of the weight value.

4.2. Fitness function

Mean Absolute Error (MAE) and Mean Square Error (MSE) are frequently used color image quality evaluation functions. Equation (5) refers to MAE, and equation (6) refers to (MSE).

$$MAE = \frac{1}{3PQ}\sum_{r=1}^{3}\sum_{i=1}^{PQ}\left|o_{ir} - y_{ir}\right| \tag{5}$$

$$MSE = \frac{1}{3PQ}\sum_{r=1}^{3}\sum_{i=1}^{PQ}\left(o_{ir} - y_{ir}\right)^2 \tag{6}$$

The MAE or MSE of the original noiseless image and the filtering output image can be regarded as the target function. The minimum of the target function is the search target of the ant algorithm. The fitness function Fit_i is shown in equation (7), which is the fitness function after normalization.

$$Fit_i = 1 - \frac{MAE_i}{MAE_{\max}} \tag{7}$$

Fit_i refers to the fitness value of individual i. MAE_i refers to the mean absolute error between the weighted image and the original noiseless image of individual i. $MAE_{\max}$ referd to the mean absolute error between the noise image and the original noiseless image. The larger the Fit_i, the better the image filtering result.

4.3. Algorithm procedure

The algorithm procedure is as follows:

(1) initialization: the median filter window size is K, the individual dimension is K. The individual position and velocity are randomly initialized real numbers in within [0, 1].

(2) calculate the vector distance and angle distance: calculate the vector distance and angle distance between any vector in the median filter window and other vector.

(3) calculate the individual fitness: fitness function Fit_i is calculated through equation (7), according to step(2) calculate the vector distance and angle distance, calculate individual fitness through equation.

(4) gain the current optimal of the individual and the ant group through comparison.

(5) update the individual position and velocity.

(6) algorithm completion condition: if the corresponding solution of the overall optimal $\hat{y}$ is figured out, that is the final optimized weight coefficient $w = \{w_1, w_2, \cdots w_K\}$, then, the algorithm is completed, otherwise, turn to step(2), and continue the calculation.

(7) gain the optimized filtering output image.

4.4. Simulation experiment

Under the Matlab environment, we applied autumn.tif to test the image, and added 10% impulse noise to the image, then adopted the ACO parameter optimization put forward by this paper to conduct weighted vector median filtering operation. The gained filtering results are shown in Figure 5.

(a)

(b)

(c)

Figure 5. Image filtering results

It can seen from the above figure that the method put forward by this paper can effectively adjust the filtering weight to process the impulse noise image. Its mean absolute error and mean square error deviation are relatively smaller. It can reduce or eliminate the noise in the image to achieve the optimized filtering and gain better color image enhancement effect.

5. Conclusion

This paper applies ACO to the parameter optimization of the weighted vector median filter. Method put forward in this paper can better adjust the filter weights to process the noise image, further improves the image quality to better achieve the purpose of the color image enhancement with relative small mean absolute error and mean square error. Simulation experiment shows that the method in this paper has good detail and chromaticity-keeping effect.

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