An image threshold segmentation method based on multi-behaviour global artificial fish swarm algorithm

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Abstract

Firstly, this paper describes how the histogram analysis method pre-processes the images to be segmented. Then is makes a detailed analysis of the working principles and behaviour pattern of basic artificial fish swarm algorithm (AFSA); dissects the defects of AFSA in principle and proposes an improved AFSA with global convergence. Finally, it presents the main steps of image threshold segmentation method based on AFSA; compares the performances of AFSA with those of other intelligent algorithms and proves that this improved AFSA makes all-around improvements on image segmentation.

Keywords: Image Threshold Segmentation, Artificial Fish Swarm Algorithm

1 Introduction

Image segmentation divides an image into several mutually-disjoint areas according to certain rules and every area meets the consistency under the rules for convenience of the subsequent target measurement as well as classification and identification. Image segmentation needs to divide the input image into two or more sub-regions, which is exactly the top priority encountered in the design and realization of image analysis, the text character identification and automatic target acquisition. Nowadays, there have emerged several image segmentation methods, including threshold segmentation method, statistic segmentation method and clustering segmentation, however, none of them is a universal image segmentation method. Therefore, it plays a significant influence on the entire performance of the segmentation method whether the appropriate image segmentation method is chosen.

Swarm intelligence is the intelligent behaviour of a group, which is formed by the individuals with no or simple intelligence in certain way and the individuals in this group show complicated intelligent behaviours through collaboration. For example, when the small fish with limited capacities are attacked by big fish, they usually hold together to form a fish swarm quickly and move around the swarm center continuously to withstand the attack and minimize the loss. In case of lack of centralized control and understanding of global situation, swarm intelligence can accomplish complicated and difficult tasks, which provides a clue for people to solve large-scale and complexly-distributed problems [1]. In image-processing applications, swarm intelligent optimization algorithm is relatively weak in mathematical theoretical foundation and it lacks the theoretical analysis in a general sense. When different swarm intelligent optimization algorithms are used in specific image processing, the parameters involved in these algorithms are usually determined by experience without any specific theoretical basis.

In order to improve the various shortcomings of AFSA, this paper has come up with an improved multi-behaviour AFSA with excellent global convergence after analysing and investigating the research results of other scholars. This algorithm has absorbed the advantages of other improved algorithms [2]. For instance, it optimizes the step size and horizon by using self-adaptive theory; increases the artificial fish behaviours such as jump and devour and makes distinct and all-around improvements over the basic AFSA. Therefore, it enhances the self-adaptive ability and convergence precision, accelerates the convergence time and avoids local extremum in searching global optimum [3].

2 The image pre-processing

Due to digital image acquisition and channel transmission, the images we obtain usually have noises, which may interfere the ornamental value of the images and even directly affects the subsequent image characteristics extraction, target measurement and target identification. Considering the influence of image noise, we reconstruct the images by using the characteristic of wavelet domain after multi-level wavelet transform, namely “the highest low-frequency coefficients and high-frequency coefficients have fewer noises”, and so we can obtain enhanced noise-suppressing images of the original images. Then, the segmentation threshold to be determined shall be located between the two peaks of the

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enhanced image histogram and its value shall be similar to the segmentation threshold of the enhanced image.

Assuming that the two peak values of the enhanced image histogram are *a* and *b*, narrow the distribution range of the threshold and design the objective function of threshold segmentation according to the following steps.

(1) Decompose the image to be segmented with three-level sym5 wavelet and proceed wavelet reconstruction by the decomposed 3rd-level low-frequency and high-frequency coefficients to obtain the noise-suppressing enhanced image.

(2) Analyze the histogram of the enhanced image; calculate the average grey level $\bar{c}$ and get the grey level a with the biggest possibility within $[0,\bar{c}]$ and the grey level b with the biggest possibility within $[\bar{c}+1, L-1]$. Then the threshold distribution range is $[a,b]\in[0,L-1]$ and $L=256$ is the grey level of the grey-level image[4].

(3) Segment the objective function by using OTSU according to the two-dimensional histogram information of the enhanced image and neighbourhood mean-value image.

3 The improved mechanism of fish swarm algorithm

Although AFSA has the merits like undemanding objective function value, greatly random parameter determination and quick convergence rate, improvements need to be made somewhere. When the optimization region of the algorithm is big or the change is relatively flat, the algorithm searching speed is becoming slow and the convergence performance decreases; the convergence speed is quick in the initial stage and it becomes slow in the later phase; optimization precision is subject to the randomness of horizon and step size so that it is difficult to get precise solutions [5].

3.1 THE IMPROVEMENTS OF ARTIFICIAL FISH SWARM BEHAVIORS

In the basic AFSA, assuming that there are N artificial fish in the search region and the i-th represents a feasible solution vector, $X_i=\left(x_1^i,x_2^i,\ldots,x_D^i\right)$ (D is the dimension). Then assuming that $X_i\left(t\right)$ is the current state of the artificial fish and (t+1) is the next status, the artificial fish will implement one of the four behaviours according to the current status in every iteration; update its ego state and add an added vector $\Delta X_i(t+1)$ on the basis of the original status $X_i(\mathrm{t})$; therefore, the position update formula of the artificial fish in AFSA is described by using the following formula:

$$\Delta X_i\left(\mathrm{t+1}\right)=\mathrm{Rand()}\bullet\mathrm{Step}\bullet\left[X_{next}\left(\mathrm{t+1}\right)-X_i\left(\mathrm{t}\right)\right], \tag{1}$$

$$X_i\left(\mathrm{t+1}\right)=X_i\left(\mathrm{t}\right)+\Delta X_i\left(\mathrm{t+1}\right). \tag{2}$$

In the above formula, Rand() is a random number within 0 and 1 and Step is the step size of the artificial fish. After every iteration, the artificial fish update the ego status according to the above formula [6].

3.1.1 The improvements of feeding

Assuming that (t) is the current status, $Y_i(t)$ is the function value of the current status $X_i(t)$; the next status is $X_i(\mathrm{t+1})$ and $X_j(\mathrm{t})$ is a randomly chosen status of its horizon. And the expression formula is as follows:

$$X_j\left(\mathrm{t}\right)=X_i\left(\mathrm{t}\right)+Visual\bullet Rand(). \tag{3}$$

In searching the minimal value, if $Y_i(\mathrm{t})>Y_j(\mathrm{t})$, then the artificial fish moves towards the vector sum direction of X_j and the global optimal position and the expression formula is as follows:

$$X_i\left(\mathrm{t+1}\right)=X_i\left(\mathrm{t}\right)+Visual\bullet Rand(). \tag{4}$$

3.1.2 The improvements of clustering

Assuming that (t) is the current status of the artificial fish, search the number of its companions n_f and the central position $X_c(t)$ within its horizon. If $Y_c(t)n_f<\delta Y_i(t)$, it is indicated that its neighbourhood centre has higher food concentration and low congestion degree and the artificial fish moves a step size towards the vector sum direction of the global optimal position X_{best} and the central position. If (t) $n_f>\delta Y_i(t)$, then the artificial fish implements the feeding [7].

3.1.3 The improvements of rear-end

Assuming that X_i is the current status of the artificial fish, search the smallest companion $X_k(\mathrm{t})$ among the companions $Y_k(\mathrm{t})$ within horizon. If $Y_K\left(t\right)\bullet n_f<\delta\bullet Y_i\left(t\right)$, it is shown that the status of the companion $X_k(\mathrm{t})$ has higher food concentration and low congestion degree and then the artificial fish moves one step towards the vector sum of $X_k(\mathrm{t})$ and the global optimal position X_{best} with its expression as follows. If not, the artificial fish implements feeding.

$$X_i\left(\mathrm{t+1}\right)=X_i\left(\mathrm{t}\right)+\left(\frac{\left(X_k\left(\mathrm{t}\right)-X_i\left(\mathrm{t}\right)\right)+\left(X_{best}-X_i\left(\mathrm{t}\right)\right)}{\left\|\left(X_k\left(\mathrm{t}\right)-X_i\left(\mathrm{t}\right)\right)+\left(X_{best}-X_i\left(\mathrm{t}\right)\right)\right\|}\right)\bullet Step\bullet Rand(). \tag{5}$$

3.1.4 The introduction of jumping

After several continuous iteration, if the objective function value of the optimal artificial fish is smaller than the pre-set value eps, then randomly choose some artificial fish and set their parameters with the expression formula as follows:

$$X_i\left(\mathrm{t+1}\right)=X_i\left(\mathrm{t}\right)+\beta\bullet visual\bullet Rand(). \tag{6}$$

In this formula, β can be either a parameter of a mutation function.

3.1.5 The introduction of devouring

We have increased a new fish swarm behaviour, devouring. In this new fish swarm movement mode, the artificial fish with low objective function value are usually considered as weak artificial fish because they have little influence on the algorithm performance. These weak artificial fish will be eliminated by the system after some iteration, which is just like they are devoured by big fish. Because these artificial fish which are eliminated are weak, they have little influent on the optimization capacity of the algorithm; thus reducing its complexity.

The specific behaviour description is as follows: in calculating the minimum, if the objective function value of a certain artificial fish is bigger than the set function value T_value after n continuous iteration, then the system will automatically release the system space occupied by this artificial fish and reduce the total amount of the artificial fish. Therefore, this artificial fish will not involve the subsequent iteration. Likewise, the maximum can be calculated [8].

3.2 THE IMPROVEMENTS OF PARAMETERS

The horizon and step size of the artificial fish in the basic AFSA are always fixed, which may lead to the slow convergence speed due to the undersized step size in the initial phase and the oscillation phenomenon caused by the oversized step size in the precise convergence in the later phase. In order to solve this problem, we have introduced self-adaptive step size with the specific behaviour description as follows.

Set $X_i(t)$ as the current status of the artificial fish, then $Y_i(t)$ is the function value of the current status $X_i(t)$; set $X_i(t+1)$ as the next status of the artificial fish and $X_v(t)$ is the next status searched by the artificial, then $Y_v(t)$ is the function value with the formula as follows:

$$X_v(t) = X_i(t) + Visual \bullet Rand(), \tag{7}$$

$$X_i(t+1) = X_i(t) + \frac{X_v(t) - X_i(t)}{\| X_v(t) - X_i(t) \|} \bullet \left| 1 - \frac{Y_v(t)}{Y_i(t)} \right| \bullet Step \ \left(\text{Minimization problem}\right). \tag{8}$$

From the above formula, it can be seen that the movable step size in the algorithm is determined by the current status and the sensing status within horizon.

4 The noisy image threshold segmentation based on afsa

The main idea of the noisy image segmentation method based on AFSA is: consider the threshold of the noisy image as the individual fish in the fish swarm; the threshold distribution range $[a,b]$ is the feeding space of the fish swarm and find the optimal segmentation threshold through the chemotaxis, reproduction and elimination-dispersal with Formula 1 as the behaviour guide of fish feeding, namely the fitness function of AFSA.

The main steps are:

(1) Read in the image to be segmented;

(2) Decompose the image to be segmented with three-level sym5 wavelet and proceed wavelet reconstruction by the decomposed 3rd-level low-frequency and high-frequency coefficients to obtain the noise-suppressing enhanced image;

(3) Determine the threshold distribution range based on the histogram of the enhanced image;

(4) Get the fitness function of AFSA through Formula (1) by using the two-dimensional histogram of the enhanced image and its neighbourhood mean-value image;

(5) Set the control parameters in AFSA;

(6) Calculate the fitness of every individual fish and record the fish with the biggest fitness as well as its fitness;

(7) Chemotaxis operation: firstly, the fish overturns according to the following formula:

$$P(i, j+1, k, l) = P(i, j, k, l) + C(i) \times \Delta(i). \tag{9}$$

In this formula, $P(i, j, k, l)$ is the position of i-th fish in the l-th elimination-dispersal, the k-th reproduction and the j-th chemo taxis; $P(i, j+1, k, l)$ is the overturn new position of the i-th fish in the l-th elimination-dispersal, the k-th reproduction and the j-th chemotaxis; $C(i)$ is the step size of the i-th fish and $\Delta(i)$ is a random vector among [-1,1];

Then, compare whether the fitness of the fish after the overturn has been improved. If the fitness is improved, then the fish moves forward according to the below formula:

$$P(i, j+1, k, l) = P(i, j, k, l) + C(i) \times \Delta(i). \tag{10}$$

Otherwise, add 1 to the number of chemotaxis j; when $j < N_c$, the fish repeats the chemotaxis operation in this step. If not, the fish turns to Step (8).

Finally, compare the fitness after the fish moves forward and the biggest fitness recorded in this bulletin board to make the biggest fitness and the corresponding position are always kept in the board;

(8) Reproduction operation: calculate the fitness cumulative sum in the chemotaxis:

$$SumFitness(i)=\sum_{j=1}^{Nc+1}Fitness(i,j,k,l)\,. \tag{11}$$

Rank the fitness accumulative sum of the fish in the descending order. Make the weak fish to get the position and step size of the optimal fish and add 1 to the number of reproduction k. If $k<N_{re}$, turn to Step (7); otherwise, turn to Step (9);

(9) Elimination-dispersal Operation: the fish is dispersed to any random position in the solution space with the possible P_{ed} and add 1 to the number of elimination-dispersal. If $l<N_{ed}$, implement Step (7); otherwise, turn to Step (10);

(10) Output the optimum in the bulletin board and end the entire feeding process;

(11) Obtain the segmented image according to the following formula:

$$bw(x,y)=\begin{cases}0,\text{当}0\le f(x,y)+g(x,y)\le s+t\\ 1,\text{当}f(x,y)+g(x,y)>s+t\end{cases}. \tag{12}$$

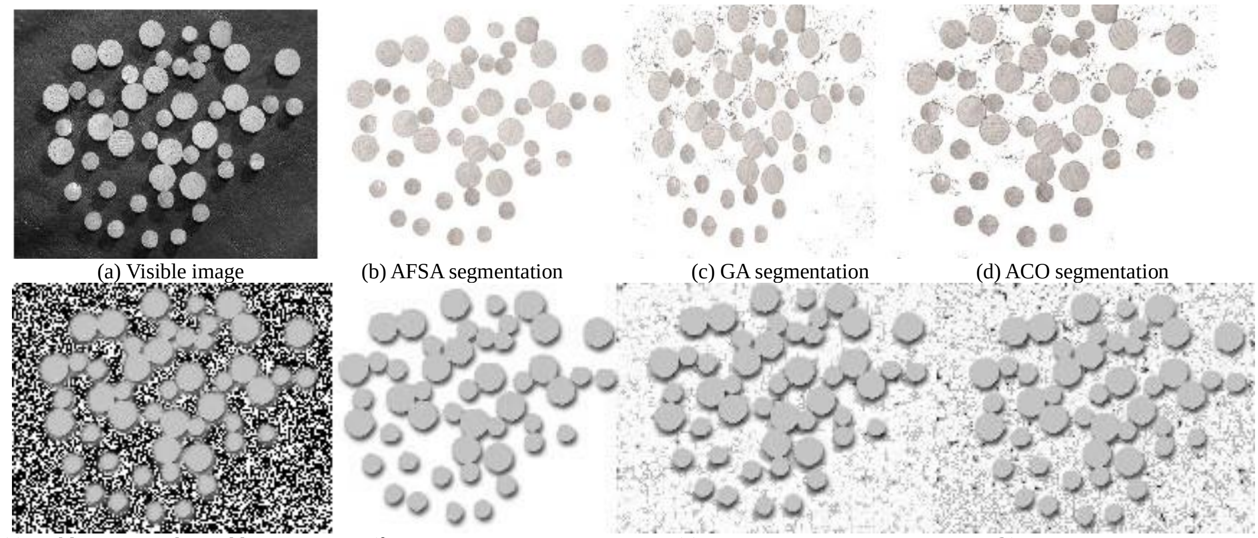
In this formula, $f(x,y)$ is the grey level of pixel (x,y); $g(x,y)$ is the average grey level of its 3×3 small neighbourhood pixel and $bw(x,y)$ is the grey value of pixel (x,y) after segmentation.

5 The experimental result and performance analysis

The following experiments are conducted in order to verify the effectiveness of the segmentation methods of AFSA.

5.1 THE COMPARISON OF SEGMENTATION EFFECTS

Segment the visible image and the visible image with speckle noise by using AFSA, genetic algorithm and ant colony optimization algorithm and the results are indicated as Fig.1. After conducting histogram analysis pre-processing on the images to be segmented, the threshold distribution range of Fig.1(a) is [103, 221] and that of Fig. 1(e) is [106, 218].



(a) Visible image (b) AFSA segmentation (c) GA segmentation (d) ACO segmentation
(e)Visible image with speckle noise (f) AFSA segmentation (g) GA segmentation (h) ACO segmentation

FIGURE 1 Image segmentation result comparison with different optimization algorithms

When using the segmentation method of AFSA, the segmentation result is clear-cut and intact with optimal performance.

5.2 THE COMPARISON OF SEGMENTATION SPEED

In order to test the segmentation speed of this method, the following table has presented the segmentation time and segmentation threshold by using AFSA segmentation methods, GA, ACO and PSO to segment Fig.1(a), as indicated as Table 1.

From Table 1, it can be seen that the segmentation time order of the above methods is: the method in this chapter<ACO<PSO<GA. The reason is that the new method adopted in this paper, on one hand, can reduce the search range of the threshold by conducting histogram pre-processing on the image to be segmented and on the other hand, quickly find the optimal threshold of the image to be segmented by introducing the parallel search mechanism of AFSA.

TABLE 1 The results by using different segmentation methods to segment fig.1

Optimization Algorithm	Fitness Function	Threshold	Run Time/S
AFSA	Two-Dimensional Maximum Between-Cluster Variance	68	5.047
GA	Two-Dimensional Conditional Entropy	131	8.372
ACO	Two-Dimensional OTSU Improved	63	6.846
PSO	Two-Dimensional Grey Entropy	153	7.478

6 Conclusion

This paper has proposed an improved AFSA image threshold segmentation method. Use histogram analysis techniques; design the trace of two-dimensional histogram scatter matrix of OTSU as the fitness function and instruct the search direction of the fish swarm in AFSA. Then, narrow down the threshold distribution range by enhancing the histogram information of the enhanced image and reduce the search range of the fish swarm in AFSA. Finally, with AFSA as the parallel threshold search strategy, accelerate the segmentation process and find the optimal threshold of the image to be segmented. The experimental results demonstrate the effectiveness of the new method, which can search the optimal threshold quickly and exactly.

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