Improved Image Thresholding using Ant Colony Optimization Algorithm

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Abstract

The Ant colony optimization (ACO) algorithm is relatively a new meta-heuristic algorithm and a successful paradigm of all the algorithms which take advantage of the insect's behavior. It has been applied to solve many optimization problems with good discretion, parallel, robustness and positive feedback. As an advanced optimization algorithm, only recently, researchers began to apply ACO to image processing tasks. In this paper, an Improved Image Thresholding Method using Ant Colony Optimization Algorithm is proposed. Compared with traditional thresholding segmentation methods, the proposed method has advantages that it can nicely segment the thin, it can efficiently reduce calculation time, and it has good capability and stabilization nature. The results show that using the proposed method can achieve satisfactory segmentation effect.

1. Introduction

Image segmentation plays an important and basic role in image processing and pattern recognition. Its purpose is to separate areas that do not superpose each other and to pick up interesting target. During the past few years, many algorithms for image segmentation have been proposed. The popular technique in image segmentation is the thresholding segmentation because of its simplicity and efficiency. If the target is clearly distinguishable from the background, the histogram of the image will be bimodal and then it can easier get to the threshold by simply choosing the valley bottom as the threshold point. However, in most of real images, there are not clearly distinguishable marks between the target and the background. Otsu's [1] is the typical global thresholding method. It can obtain the optimal threshold using a full search and it needs not preprocess the histogram, but it has the sensitivity for target size and noise. Image segmentation based on Genetic algorithm method [2] has proposed an optimal threshold method to be widely applied. It can overcome the above mentioned trouble, but it needs a mass of calculation time when computing the optimal threshold. Therefore, in order to quickly and effectively obtain optimal threshold, a better method that uses ant colony optimization algorithm is proposed.

The remaining of this paper is organized as follows. Section 2 gives an overview of ant colony optimization algorithm. The material realization for the proposed method is described in Section 3. In Section 4, the experimental results are described. Finally, conclusions are drawn based on the results in section 5.

2. Overview of Ant Colony Optimization Algorithm

Ant Colony Optimization Algorithm (ACO) [3][4] which is a kind of bionic evolution, one was invented by an Italian Scholar M.Dorigo. It was inspired by the observation of real ant colony and used to find an optimal path to food source in the food searching process. In the real world, ants are social insects and live in colonies. Their behavior is directed more to the survival of the colony as a whole than to that of a single individual component of the colony. An important and interesting behavior of ant colonies is their foraging behavior, and, in particular, how ants have the capability to find the shortest paths between food sources and their nest.

In many ant species, individual ants walking to and from a food source deposit on the ground a substance called pheromone. Ants can smell pheromone and follow pheromone with some probability. In this manner, ants can communicate with each other by the medium of pheromone trails and exchange information about which path should be followed. The More the number of ants tracing a given path, the more attractive this path it becomes. Other ants will tend to choose to follow the path and deposit their own pheromone. This autocatalytic and collective behavior results in the establishment of the shortest route. As shown in Figure 1, some ants start from their nest to hunt for food at the

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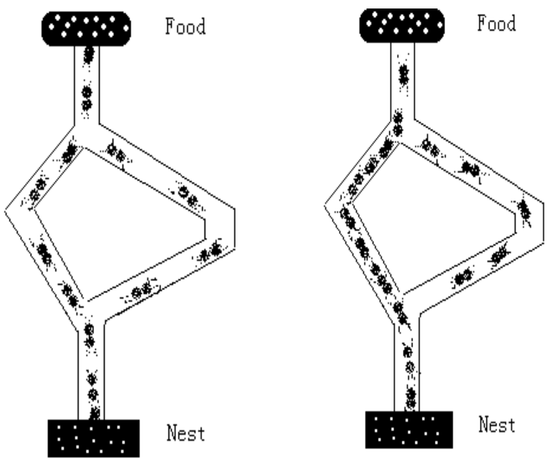
same time toward to two different directions. One group of ants chooses the path that turns out to be shorter while the other takes the longer path. The ants moving in the shorter path go back to the nest earlier and the pheromone density in this path is obviously thicker than what is deposited in the longer path. Other ants in the nest, thus, have high probability to follow the shorter route. These ants also deposit their own pheromone on the path. More and more ants are soon attracted to the path and hence the optimal route from the nest to the food source is established.



(a) (b)

Figure 1. Movement of ant from nest to food and back (a) ants start finding the food and (b) pheromone is more density on the shortest path and most of the ants finally choose the shortest path.

According to the mechanism of movement of ant from nest to food and back, the ACO algorithm description is as in the pseudocode following.

Algorithm 1. The framework of ACO algorithm

```
procedure ACO ( )
 initialize_ant( );
   initialize_pheormone_trails( );
  while (termination_criterion_not_satisfied)
    for m=1 to number_of_ants
      whlie ( current_state!= target_state)
       read_ant_routing_table;
            deposit_pheromone_on_each_route;
        compute_transition_probability;
             do_local_pheromone_adjustment;
             update_pheromone_on_the_visited_route;
             move_to_next_state;
      end while
    do_global_pheromone_adjustment;
    update_pheromone_on _this_circulation;
    update_ant_routing_table;
    end for
  end while
end procedure
```

3. Proposed Image Thresholding Method

3.1. Design of the proposed method

Given one image X, look at every pixel X_i ($i = 1,2,\ldots,N$) as an ant. Every ant is a one-dimensional vector by gray feature. Image segmentation is the process that ants with different feature vector hunt for food source. Moreover, the food source is just the optimal threshold of image segmentation. The proposed method workflow is as follows:

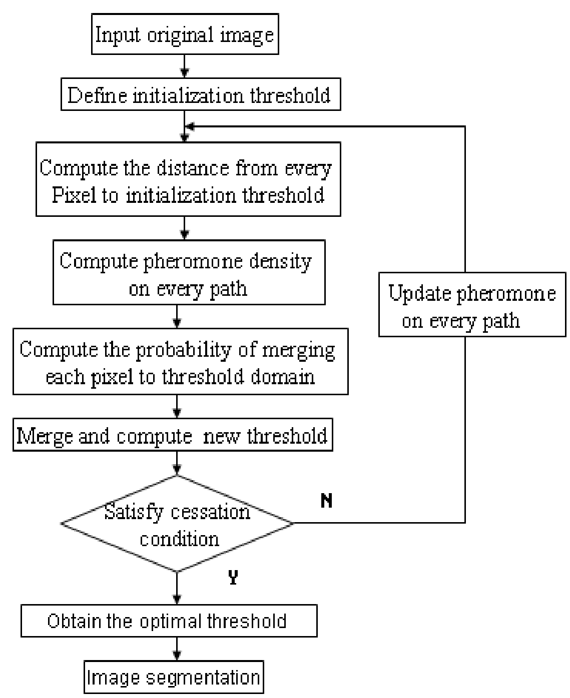


Figure 2. The workflow model of the proposed method

Procedure 1: Initialize threshold

The definition of initialization threshold T adopts the mid-point method between minimum and maximum gray values in the image. We will define T as following:

$$T = \frac{\max value + \min value}{2} \tag{1}$$

Procedure 2: Optimal process

First, according to Euclidean distance formula, the distance d_i of every pixel X_i to initialization threshold T can be calculated as following:

$$d_i = \sqrt{(X_i - T)^2} \tag{2}$$

Second, computing pheromone density τ_i, the pheromone density on every path from each pixel X_i to T can be obtained by the formula in

$$\tau_i(t) = \begin{cases} 1 & d_i \le T \\ 0 & d_i > T \end{cases} \tag{3}$$

Where t is the circulation degree, and when $t = 0$, $\tau_i(0) = 0$.

Third, computing the probability of merging every pixel X_i to threshold domain, the probability of the path X_i to T is p_i as expressed in

$$p_i = \begin{cases} \dfrac{\tau_i^{\alpha}(t) * \eta_j^{\beta}(t)}{\sum_{z \in Z} \tau_i^{\alpha}(t) * \eta_j^{\beta}(t)} & i \in Z \\ 0 & \text{Otherwise} \end{cases} \tag{4}$$

Where $\eta_i = 1/d_i$ is the apocalyptic guidance function; α and β are respectively the apocalyptic factor and the expected apocalyptic factor. They are used to control the influence factor of the accumulated information and apocalyptic guidance function to path selection; $Z = \{X_z \mid d_z \le T, z = 1, 2 \ldots, N\}$ is ambulatory path set.

Fourth, merging and obtaining new threshold, when $p_i \le p_0$ (p_0 is the weight probability factor), X_i is merged into threshold domain. C_j is the whole data set about merging into threshold domain. Viz. $C_j = \{X_i \mid d_i \le T, i = 1, 2, \ldots, J\}$. The new threshold is calculated as following:

$$\bar{T} = \frac{1}{J} \sum_{i=1}^{J} X_i \tag{5}$$

Last, with the ant moving, the pheromone amount on every path changes. Through one circulation, the pheromone amount on every path is adjusted. In this paper, a new method about the pheromone update is adopted according to the following formula expressed in:

$$\tau_i(t) = \left(1 - \frac{n}{m}\rho\right) * \tau_i(t) + \rho \Delta \tau_i \tag{6}$$

Where ρ is the pheromone volatility coeffici ent; n is the pixel number of $d_i \le T$; m is the total number of pixels; $\Delta \tau_i$ is the augmentation of path pheromone amount in a given circulation.

Procedure 3: Cessation condition

The general cessation condition is to set the nu-mber of iterations, but there is the flaw. If the number is too small, the optimization search is not sufficient so that the optimal threshold can not be obtained. Whereas when the number is too big, despite of obtaining the optimal threshold, the calculation time is long to debase efficiency. In this paper, we design a new adaptive method to control algorithm cessation. If the discrepancy between the old threshold T and the new threshold $\bar{T}$ is less than ε (ε is the bias error, and the ε value is set at 0.01)viz. $|T - \bar{T}| \le \varepsilon$, the algorithm will cease, and the $\bar{T}$ is the optimal threshold; Otherwise, step onto procedure2: optimal process.

3.2. Parameters selections

In the proposed method, the selection of the parameters α, β and ρ have pivotal action. The parameter α reflects the accumulated information of the ants in the course of the movement. It plays an important role in ant colony search guiding. The bigger the value is, the bigger the possibility of the ants choosing prevenient traversed path is and the searching randomness weakens. Whereas, when the value is too small, the ant colony search is prematurely immersed in local optimal. The parameter β reflects the apocalyptic information of the ant colony in the course of searching. Its magnitude reflects the optimization process prior and the effect of the uncertainty. The bigger the value is, the bigger the likelihood of the ants choosing the local shortest path on a local point is. The ant colony search is prone to be immersed in local optimal. However, if the value is small, the convergence speed will get slower. The pheromone volatility coefficient ρ directly relates to the global searching capability of the ACO algorithm and the convergence speed. That is, if the value is unduly small, it increases the convergence speed, whereas debases the algorithm global searching capability.

How to set up suitable parameter values? We can use the optimal combination of the "two steps" approach.

1) Rough-tuning parameters: namely adjusting the larger range parameters α and β to get the ideal solution.

2) Fine-tuning parameters: namely adjusting the smaller range parameter ρ to get the ideal solution. Via processing a mass of experiments, the exact parameters are set at α=2, β = 4 and ρ =0.7.

4. Experimental Results

The used images in this paper are the gray images with gray levels of 256. This experiment has implemented the threshold optimization technique using Matlab7.0 program. Examples of the input images are shown in Figure 3. (a), Figure 4. (a) and Figure 5. (a). Figure 3. (b), Figure 4. (b) and Figure 5. (b) use Otsu's method to segment the images. Figure 3. (c), Figure 4. (c) and Figure 5. (c) use Genetic algorithm method to segment the images. Figure 3. (d), Figure 4. (d) and Figure 5. (d) use the proposed method to segment the images.

This paper selects the entropy H, the calculation time S, and the threshold value T to take objective evaluation standards. H is defined as follows:

$$H(\mathrm{x}) = -\sum_{i=0}^{255} p_i \log_2 p_i \tag{7}$$

This H is the measure of the signal resolution [6]. The smaller the H is, the higher the resolution is, and the greater the H is, the lower the resolution is. Therefore, we may take H as one evaluation standard of the image segmentation. If H is smaller, the image detail is clearer; and if H is greater, the image detail is fuzzier.

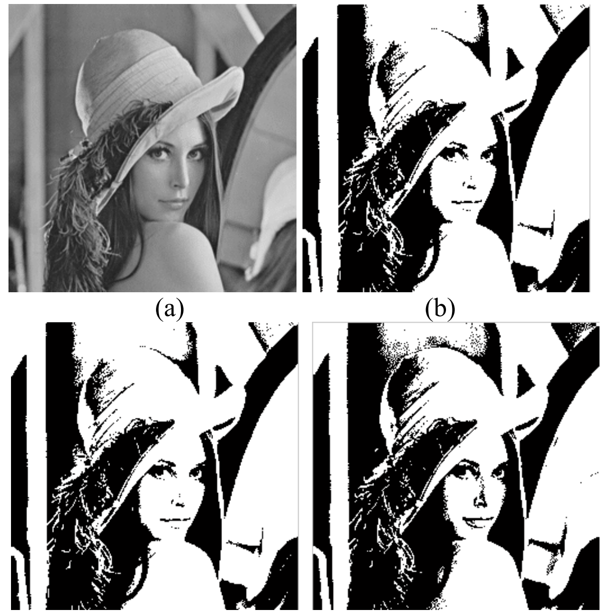


Figure 3. (a) Original image; (b) Result image using Otsu's method; (c) Result image using Genetic Algorithm method; (d) Result image using the proposed method.

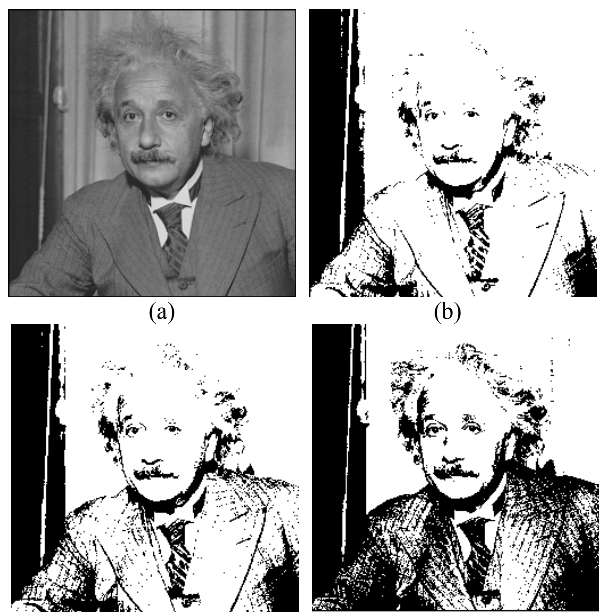


Figure 4. (a) Original image; (b) Result image using Otsu's method; (c) Result image using Genetic Algorithm method; (d) Result image using the proposed method.

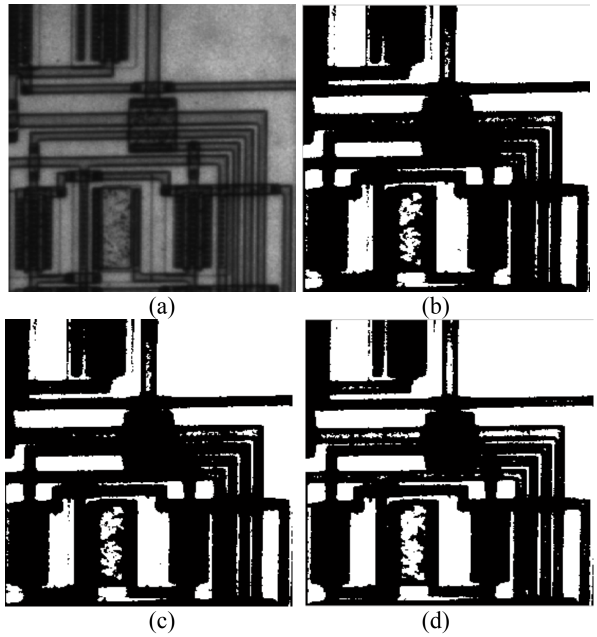


Figure 5. (a) Original image; (b) Result image using Otsu's method; (c) Result image using Genetic Algorithm method; (d) Result image using the proposed method.

The experimental results show that using Otsu's method and Genetic algorithm method, the targets of the segmentation image Figure 3. (b)(c), Figure 4. (b)(c) and Figure 5. (b)(c) can be only segmented assumably from the background. However, as the thin parts such as the face, the hat, the business suit and the tubules, the segmentation effect is extremely poor. Nevertheless, the targets of the segmentation image Figure 3. (d), Figure 4 (d) and Figure 5. (d), based on the proposed method, can be not only segmented greatly from the background, but also, more importantly, the thin parts can be segmented very nicely, and give prominence to the interested regions.

In Table 1, according to the threshold value, the proposed method seems to perform the best. According to the calculation time, the proposed method is the fastest. According to the entropy, the proposed method is better than the other two methods. Therefore, the integrative characteristics show that the proposed method is the best one.

5. Conclusions

Image thresholding is a challenging problem. This paper details a new improved image thresholding method based on the ant colony optimization algorithm. Adopting this method to process image segmentation, not only efficiently segments the target and the background, but also provides the most important success that, it segments thin parts more nicely, and it obtains satisfactory effect. Meanwhile, in the proposed method, that the number of ants need not be set and the cessation condition is uniquely designed only via 2 times cycle to accomplish image segmentation. In this way the calculation time can be consumedly reduced to greatly increase the efficiency.

Table 1. Comparison of the three methods

Method		Figure 3.	Figure 4.	Figure 5.
Otsu's method	Threshold ($\overline{T}$)	115	90	85
	Calculation Time (S)	0.5470	0.6410	0.7650
	Entropy (H)	0.5186	0.5302	0.5281
Genetic Algorithm method	Threshold ($\overline{T}$)	115	97	83
	Calculation Time (S)	2.7970	2.1420	2.5470
	Entropy (H)	0.5186	0.5305	0.5268
The proposed method	Threshold ($\overline{T}$)	123	108	77
	Calculation Time (S)	0.4840	0.4060	0.4530
	Entropy (H)	0.5081	0.5253	0.5201

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