OSTU image segmentation algorithm of fruit fly optimization algorithm

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Received 1 May 2014, www.cmnt.lv

Abstract

Traditional OSTU algorithm has the disadvantages of a large amount of calculation and low calculating speed. Based on the combination of Fruit Fly Optimization Algorithm and OSTU algorithm, an image segmentation algorithm is created from Fruit Fly Optimization Algorithm to improve OSTU, stressing the basic principles and calculation procedures of this revised algorithm. In order to verify the validity of this algorithm, the work compared the quality of image segmentation, segmentation speed and algorithm stability of 4 sets of standard test images. The simulation results show that the segmentation speed of revised OSTU algorithm is much faster than that of traditional OSTU algorithm when Fruit Fly Optimization Algorithm is applied to improve OSTU algorithm. Meanwhile, the quality of image segmentation is also more stable under the same condition of time limit.

Keywords: OSTU algorithm, image segmentation, Fruit Fly Optimization Algorithm, grey value, stability

1 Introduction

Image segmentation is the key technology of computer image visual processing. It has received extensive attention from researchers since it was proposed. So far, there are nearly one thousand kinds of image segmentation algorithm [1-3]. However, these algorithms are poor in versatility and are only applicable to some specific image segmentation issues rather than all images segmentations.

Based on the characteristics of large amount of calculation and low calculation speed of traditional OSTU algorithm, the work combined Fruit Fly Optimization Algorithm and OSTU algorithm and proposed an improved OSTU image segmentation algorithm by Fruit Fly Optimization Algorithm. Meanwhile, the work also compared the improved algorithm and OSTU, showing that both the segmentation quality and speed are superior to that of the traditional OSTU

2 OSTU method (also known as OSTU algorithm)

OSTU method is to set threshold value according to the sequence of grey value, and then classify images into 2 categories. Then, obtain the interclass variance through calculating the pixel and average grey-value of each category. In the end, set the threshold value as the final segmentation threshold when OTSU reaches its maximum. The calculation method of segmentation image is as follows [4-5]:

Classify the pixel of one digital image $f(x,y)$ into C_0 and C_1 by threshold T according to its grey levels. That is: $C_0=\{f_1(x,y)\mid f_{\min}\le f(x,y)\le T\}$, $C_1=\{f_2(x,y)\mid f_{\max}\ge f(x,y)>T\}$.

Here, $f_{\min}$ and $f_{\max}$ are respectively the minimum and maximum of the grey level of image $f(x,y)$. If N_{i} is set as the pixel when grey value is i ($f_{\min}\le i\le f_{\max}$), the total pixel of image $f(x,y)$ is $N=\sum N_{\mathrm{i}}$. Therefore, the probability of the occurrence of each grey level is $P(i)=N_i/N$ and the total probability of the occurrence of C_0 is [6-7]: $P_0=\sum_{i=f_{\min}}^{T}P(i)$.

Its mean value is: $\mu_0=\sum_{i=T+1}^{T} iP(i)\Big/P_0$.

The total probability of the occurrence of C_1 is: $P_1=\sum_{i=T+1}^{f_{\max}}P(i)$.

Its mean value is: $\mu_1=\sum_{i=T+1}^{f_{\max}} iP(i)\Big/P_1$.

The mean value of image $f(x,y)$ is: $\mu=\sum_{i=f_{\min}}^{f_{\max}} iP(i)=\sum_{i=f_{\min}}^{T} iP(i)+\sum_{i=T+1}^{f_{\max}} iP(i)=P_0\mu_0+P_1\mu_1$.

Define the interclass variance of the two categories is $\sigma^2(T)$: $\sigma^2=P_0(\mu-\mu_0)^2+P_1(\mu-\mu_1)^2$.

OSTU takes the interclass variances of the two categories as the determine evidence of selecting threshold value. It suggests that the best threshold value T^* should be the one when interclass variance $\sigma^2(T)$

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gets its maximum. That is: $T^* = \left\{ T^* \mid \sigma^2\left(T^*\right) \geq \sigma^2\left(T\right), \forall T \in \left[f_{\min}, f_{\max} \right] \right\}$.

3 Fruit fly optimization algorithm

3.1 OVERVIEW OF FRUIT FLY OPTIMIZATION ALGORITHM

Pan Wenchao [13], a young teacher in Taiwan, proposed Fruit Fly Optimization Algorithm (FOA), which is a new evolutionary calculation method. Fruit fly has the superiority on the senses of smell and visual, shown as Figure 1. Fruit fly can find food through searching the food sources in air, keenly locate food and its companions through its exquisite visual and finally fly to the food. Therefore, this method suggests that fruit fly usually determines an approximate position of food through its sense of smell and then locates the exact position of food through its sense of visual. This new method is for global optimization deduced from the action of fruit flies searching for food.

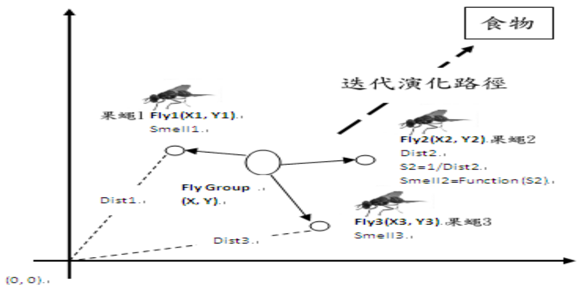


FIGURE 1 Fruit Flies Iteratively Search for Food

3.2 PROCEDURES OF FRUIT FLY OPTIMIZATION ALGORITHM

Fruit Fly Optimization Algorithm contains 7 steps. The specific procedure is as follows:

(1) As shown in Figure 1, initialize the location of fruit fly group and set the initialization results as $InitX\_axis$ s and $InitY\_axis$.

(2) When searching direction RV_x and RV_y are set, the stochastic searching distance of individual fruit fly can be obtained through the following formula:

$$Xi = Init\ X\_axis + RV_x,\ Yi = Init\ Y\_axis + RV_y. \quad (1)$$

(3) Estimate the distance $Disti$ between the current location of individual fruit fly and its original location because the location of food is unknown. Then, calculate the determination value of taste concentration S_i. Determination value of taste concentration equals the reciprocal of distance.

$$Disti = \sqrt{Xi^2 + Yi^2},\ Si = 1/Disti. \quad (2)$$

(4) Apply the determination value of taste concentration into determination function of taste concentration to calculate the taste concentration of this fruit fly at current location.

$$Smelli = Function(Si). \quad (3)$$

(5) The best taste concentration of fruit fly group can be calculated through the following formula:

$$[bestSmell\ bestIndex] = \max(Smelli). \quad (4)$$

(6) Keep the best taste concentration value of fruit fly group as well as its corresponding X coordinate and Y coordinate. At this time, fruit fly group can locate the food source according to their sense of visual and then fly to the food position.

$$\begin{aligned} &Smellbest = bestSmell, \\ &X\_axis = X(bestIndex), \\ &Y\_axis = Y(bestIndex). \end{aligned} \quad (5)$$

(7) Enter the iterative optimization step. Repeat iterative step (2) to (5) and determine whether the taste concentration is better than that of the previous iteration at the same time. If it is, then perform step (6).

4 USTO image segmentation of fruit fly optimization algorithm

4.1 DESCRIPTION OF THE ALGORITHM

When applying initialization, certain amount of fruit flies will be created at random. Calculate corresponding variance of the grey level of each fruit fly and find the maximum of variance among fruit flies. Then, update the location of fruit flies according to fruit flies optimization algorithm principles and procedures. When getting the set algebra, take the corresponding grey value of the maximum variance as the optimal threshold value to achieve image segmentation [8-9].

Specific procedure of the algorithm is as follows:

Step 1: Initializing the location of fruit flies and set the iteration times and the size of fruit fly group at the same time;

Step 2: Calculating the corresponding variance of the grey level of each fruit fly and compare the historical optimal value of individual and that of fruit fly group. Keep the location of current value and update the historical optimal value if the variance is superior to the historical optimal value of individual or fruit fly group; whereas, keep the current optical value;

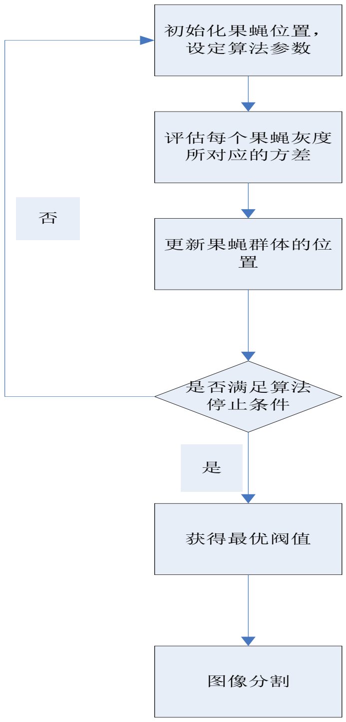
Step 3: Updating and changing the location of fruit fly according to the fitness value of fruit flies;

Step 4: If the iteration times $Iteration < Maxgen$, searching optimization completes; whereas, return to Step 2;

Step 5: Obtaining optimal threshold value and applying it to achieve image segmentation.

4.2 ALGORITHM FLOW CHART

The flow chart of Fruit Fly Optimization Algorithm improving OSTU algorithm is shown as Figure 2:



Initiate the location of fruit lies and set the parameter of the algorithm

Evaluate corresponding variancefor each grey value of fruit flies

Update the location of fruit fly group

Whether it meets the conditions to stop the calculation

Yes

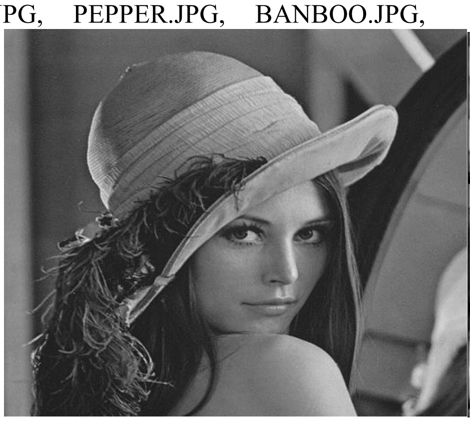
Obtain the optimal threshold value

Segment the images

FIGURE 2 OSTU Segmentation Method of Fruit Fly Optimization Algorithm

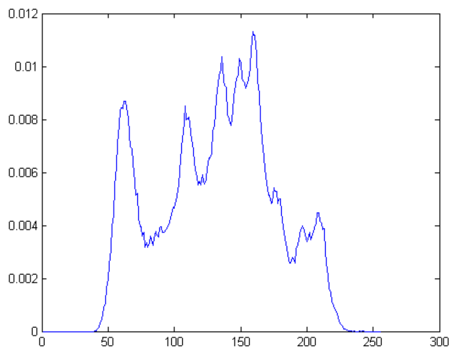
5 Algorithm test

Based on four standard images as test images [10-12], namely LENA.JPG, PEPPER.JPG, BANBOO.JPG, HUNTER.JPG, the work compared the segmentation effect of OSTU algorithm and FOAOSTU algorithm. The test images are shown as Figure 3:

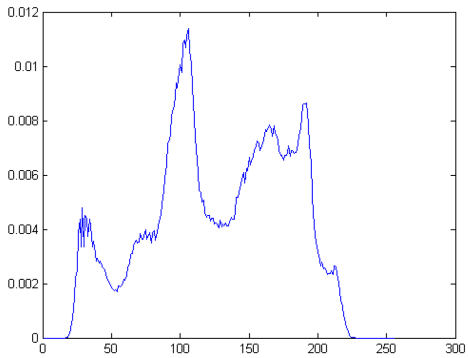


(a) LENA.JPG

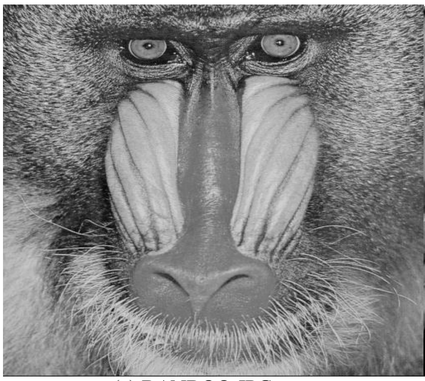
(b) PEPPER.JPG



(a’) LENA.JPG histogram

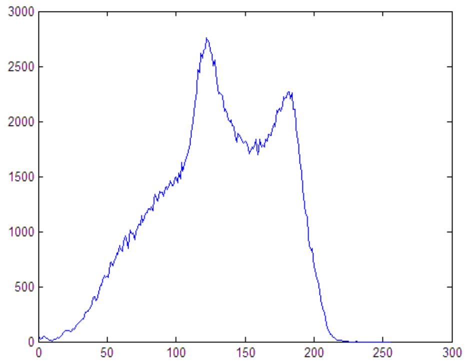


(b’) PEPPER.JPG histogram

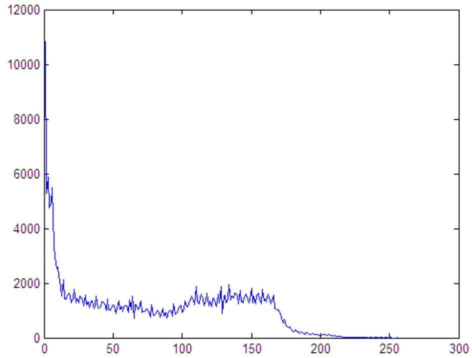


(c) BANBOO.JPG

(d) HUNTER.JPG



(c') BANBOO.JPG histogram



(d') HUNTER.JPG histogram

FIGURE 3 Test Images and Corresponding Histogram

5.1 COMPARISON OF SEGMENTATION QUALITY

Figure 3 shows test images and the corresponding histograms. The segmentation comparison results of OSTU algorithm and improved OSTU algorithm by Fruit Fly Optimization are shown as Figure 4:

(1) OSTU

(1') FOAOSTU

(2) OSTU

(2') FOAOSTU

(3) OSTU

(3') FOAOSTU

(4) OSTU

(4') FOAOSTU

FIGURE 4 Comparison pictures of segmentation results of OSTU and FOAOSTU

Figure 4 shows that the segmentation of FOAOSTU algorithm is superior to that of OSTU algorithm, which ensures the segmentation speed and effect when achieving the edge information of images.

5.2 COMPARISON OF STABILITY

In order to compare the stability of OSTU algorithm and improved OSTU algorithm, the work applied formula (6) to evaluate the astringency [14-15] of the algorithm results:

$$std = \sqrt{\sum_{i=1}^{n} (\sigma - \tilde{\sigma}) / n} \, . \tag{6}$$

In the above formula, n refers to the times (set as 100 in the work) of repetitive computation of the algorithm; σ means the optimal solution obtained from every computation of the algorithm, and $\tilde{\sigma}$ refers to the average value of σ. Therefore, formula (6) is considered as the standard deviation of σ, which is labelled as std. Under the same condition, the bigger std is, the more unstable the algorithm is; whereas, it means the algorithm is more stable.

TABLE 1 Comparison results of the standard deviation of OSTU algorithm and FOAOSTU algorithm

Images	Standard Deviation	
	FOAOSTU	*OSTU*
LENNA	0.0912	6.8173
PEPPER	0.4738	3.3477
BANBOO	0.3015	5.3859
HUNTER	0.0968	3.9608

Table 1 shows that the stability of FOAOSTU algorithm is superior to that of OSTU algorithm, but its standard deviation is much smaller than that of OSTU algorithm.

5.3 COMPARISON OF SEGMENTATION SPEED

Table 2 shows that the segmentation speed of FOAOSTU algorithm is superior to that of OSTU algorithm, but its segmentation time is shorter than that of the OSTU algorithm.

TABLE 2 Comparison results of the segmentation speed of OSTU algorithm and FOAOSTU algorithm

Images	Segmentation Speed (Unit: Second)	
	FOAOSTU	*OSTU*
LENNA	0.32	0.75
PEPPER	0.38	0.67
BANBOO	0.43	0.82
HUNTER	0.56	0.79

6 Conclusions

According to the disadvantages of large amount of calculation and low calculation speed of traditional OSTU algorithm, the work applied fruit fly optimization algorithm to improve it and then segment images after obtaining optimal threshold value through this algorithm. The work carried out comparisons on image segmentation quality, segmentation speed and algorithm stability for 4 sets of standard test images. The simulation results show that when fruit fly optimization algorithm is applied to improve OSTU algorithm, and the segmentation speed of the improved algorithm is much faster than that of traditional OSTU algorithm. Meanwhile, the segmentation quality is also more stable under the same condition of time limit.

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