Adaptive image enhancement based on artificial bee colony algorithm

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In this paper, image enhancement is realized by using the Incomplete Beta Function (IBF) as the gray transformation curve. The main idea is to employ *Artificial Bee Colony Algorithm* (ABCA) to select the optimal parameters of IBF, which corresponds to the best curve of grayscale transformation. Designing specific fitness function constrains the evolutionary direction of the bees and then better images can be obtained. By comparing among the results of histogram equalization, unsharp masking, and Genetic Algorithm based methods, we come to the conclusion that ABCA is an effective method in image enhancement which is superior to the other three methods, and not only has the better optimizing ability than Genetic algorithm but also it converges quickly.

Keywords: Incomplete Beta Function; Image Enhancement; Artificial Bee Colony Algorithm.

1. Introduction

Image enhancement is one of the important work of image processing. Many methods have been proposed, including Histogram equalization (HE) [1], Unsharp Masking (USM) [2], Gamma correction [3], histogram specification [4], homomorphic filter [5] and gray scale transformation. The first four methods can improve the image contrast, but the enhancement is uncontrollable and unable to use all images. The homomorphic filter can be used to solve the problem of additive noise flexibly, but it can't reduce multiplicative or convolution noise, so the enhancement is not comprehensive. As for the gray scale transformation, such as piecewise linear gray scale transformation based on Genetic Algorithm (GA), since the transformation curve is segmented, may result in part of the pixel value becomes negative or overflow, zero setting and then image information loss. Synthesize all the advantages and disadvantages of these methods, we try to use the artificial bee colony algorithm (ABCA) to enhance images.

The ABCA is a swarm based metaheuristic that was first introduced by Karaboga in 2005 for numerical optimisation [6]. It was inspired by the intelligent foraging behavior of honeybees which is superior to the heuristic algorithm in addressing non-limiting numerical optimization problem. The proposed algorithm was popularized and applied rapidly in the traveling salesman problem, network multicast routing and robot path planning.

In this paper, we proposed an adaptive image enhancement method using ABCA combined with the Incomplete Beta Function (IBF). Proposed method can automatically adjust the gradation transformation curve in the light of image quality and select the optimal parameters of the curve rapidly and overcome the image information loss.

2. Artificial Bee Colony algorithm and Incomplete Beta Function

2.1. *Introduction of ABCA*

In ABCA, each foods positions corresponds to a group of parameters which are possible the optimal; amount of the nectar corresponds to a value of the fitness function designed according to optimization problem. There are three kinds of bees: employed bees, onlookers and scouts. The number of employed bees is equal to the number of onlookers and to that of the whole population of solutions. Bees fly around in a multidimensional search space and search food sources which are possible solutions to the optimization problem. Employed bees always remember the best position and then search for a new location near the best. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. After all employed bees fulfilled the searching task, they share information about the found food sources with the onlookers via the waggle dance. Refer to the information obtained from employed bees, the onlookers select the food sources in accordance with the probability value and search around them to find better food sources. If the nectar amount of a source do not increase after the defined loop count, the scouts tend to randomly search for new food sources [7].

How to design fitness function is the key to optimization problem, secondly, the size of population and the number of iterations also have a direct impact on the stability and convergence time of the algorithm. Designing the fitness function.

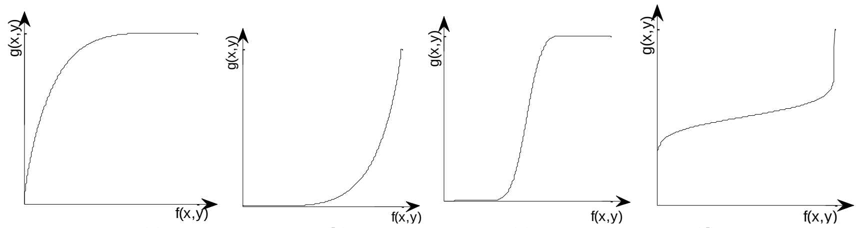
Quality of images can be evaluated based on the human vision or PSNR, image sharpness and image contrast. Considering the quality requirements of images, we introduce image contrast C, image information entropy H and image compactness Z to measure image quality. We come to the fitness function of ABCA for image enhancement. Expressed as follow:

$$Fitness = C \times 10 + H + Z / 100 \tag{1}$$

We multiply image contrast C by 10 and divided image compactness Z by 1000. That is to ensure the three indexes in the same order of magnitude, which controls the consistency of the weight of the image quality assessment. Obviously, the larger the value of Fitness, the better the image quality.

2.2. *Incomplete Beta Function for image enhance*

From the perspective of human vision, low quality images are generally dark, bright or low contrast. Therefore, we need to join characteristics of images into consideration so that we can design the transformation function which suits them best. The typical four types of transformation curves are shown in Figure 1.



(a) (b) (c) (d)

Fig. 1 The four typical curve. (a) Stretch the dull part. (b) Stretch the bright part. (c) Stretch middle part and compress both ends. (d) Stretch both ends and compress middle part

We adopt the IBF proposed by Tubbs to match these four types of curves above, formula is as following:

$$F(u) = \frac{1}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1} d_t} \times \int_0^u t^{\alpha-1}(1-t)^{\beta-1} d_t \tag{2}$$

Where α and β are the variables. Plainly, different variable value corresponds to different curves, so the enhancement of images are also different.

3. Experiments

In order to justify the validity of ABCA, we use the Histogram equalization (HE) method, the Unsharp Masking (USM) method, the Genetic Algorithm (GA) based method and the ABCA to enhance low quality images. Results are as below.

3.1. Dark image experiment

(a) (b) (c) (d) (e) (f)

Fig. 2 Dark image enhance results (a) Original image (b) HE enhancement (c) USM enhancement (d) GA enhancement (e) ABCA enhancement (f) Gray transformation curve of Fig. 2 (e)

The result shows that all these four methods can be used to improve the brightness of low quality test image. Result of USM method and GA based method are slightly darker; Result of HE method has a good brightness but the background and details of image are blurred; ABCA has better effects on details compared with HE method, such as the recovery of the color of girl's hair and details of clothes.

3.2. Bright Image Experiment

(a) (b) (c) (d) (e) (f)

Fig. 3 Bright image enhance results (a) Original mage (b) HE enhancement (c) USM enhancement (d) GA enhancement (e) ABCA enhancement (f) Gray transformation curve of Fig.3 (e)

As we have seen, when the test image is partial bright, the transformation curve corresponds to it is not the same as the result of experiment 1. It means that ABCA can set a suitable transformation curve adaptively in the light of the characteristics of images without user setting. Compared these experiment results we can know, the USM method enhanced the no-loss target details of the image but image contrast has barely increased; HE method and GA based method make the partial bright image clearer but the brightness of result image is low and the background and noise of the image are also enhanced, resulting in a false contour; As for the ABCA, the brightness of result image and the enhancement of the girl's face are better than the other three methods.

3.3. Low Contrast Image Experiment

The transform curve *F (u)* is not the same as the first two experiments which is also the result of the self-adaptability of ABCA. Comparing the experiment results we can find, USM method does not play a significant enhancement effect; HE method lead into too bright images in local area; Result of GA based method is blurry since the method allows the women's face over enhanced, resulting in a slight lumpy image; the ABCA is obviously better than these other three methods in image enhancement, the contrast and brightness of result image are appropriate and the image quality is optimal.

(a) (b) (c) (d) (e) (f)

Fig. 4 Low contrast image enhance results (a) Original image (b) HE enhancement (c) USM enhancement (d) GA enhancement (e) ABCA enhancement (f) Gray transformation curve of Fig.4 (e)

3.4. Quantitative Index Result

In addition to vision observation, we also made a quantitative evaluation of the results above. The fitness value, PSNR, contrast gain and definition gain of the results of these four methods are listed. Shown in Table1.

Tab. 1 Index results of four methods

Image	Treatment	Fitness	PSNR	Contrast gain	Definition gain
Dark	USM	6.8166	24.0665	0.7157	0.8873
	HE	6.9109	28.8748	1.8257	1.7314
	GA	6.9255	25.5652	1.6537	1.4722
	ABCA	7.7331	26.7672	2.2352	1.7494
Bright	USM	6.8583	26.7995	0.0929	0.4656
	HE	7.1064	25.3608	1.4700	0.7573
	GA ABCA	7.8052	25.3608	1.6862	0.7746
		8.1793	25.7477	1.6546	0.9768
Low Contrast	USM	6.9981	25.3493	0.0011	0.0150
	HE	6.9616	25.0989	0.5673	0.3903
	GA	7.5078	25.5205	1.0087	0.5444
	ABCA	7.7208	25.9074	0.9022	0.5530

Compare the result, we find that the maximum of fitness value and definition gain of the three image enhancement experiments are both obtained by ABCA. Where the fitness function of GA is the same as the ABCA. That is to say, ABCA has the better optimizing ability than GA. The fitness value of HE and USM method are both less than the value of these two algorithms. That means, to enhance different low quality images, we can obtaine better results by using intelligent algorithms than traditional image enhancement approaches. The contrast gain of GA in experiment 2 and 3 are both greater than the vaule of ABCA. By comparing the enhanced images, we find that the GA is over enhancing the contrast and lose image details. Such as, in experiment 2, the background of the image color deepened, in experiment 3, the woman's face is blurry. The PSNR value do not appeare apparently characteristics, dealing with dark image, the HE method reaches the maximum value; dealing with partial bright image, the USM method reaches the maximum value; dealing with low contrast image, the ABCA reaches the maximum value. The PSNR shows the mean squared error between the image before enhancing and after enhancing, the larger the value, the less the image distortion. But many experiments suggest that PSNR value can not be exactly the same as human eye visual effects, the sensitivity of the human eye to the errors is not absolute, the visual perception is influenced by many factors [8]. Moreover, the image with trivial distortion may not be the image well enhanced. Therefore, we can come to the conclusion that it is reasonable to introduce the fitness function combined with image contrast, image information entropy and image compactness to constrain the evolutionary direction of the GA and ABCA, the enhanced image results also shows the superiority of ABCA.

4. Conclusions

In this paper, we use IBF as the gray transformation curve which avoids image information loss caused by the traditional segment linear function. We design suitable fitness function to constrain the evolutionary direction of the bees and then obtain optimal image under the consideration of image contrast, image information entropy and image compactness. The same fitness function is used as ABCA to constrain the evolutionary direction of GA and then carry out the image enhance experiments. The experiment shows that whether the dark, bright or low contrast images, results of ABCA are better than that of GA. This proved that ABCA has faster and better result compared with GA, it works better in addressing non-limiting numerical optimization problem. We also use traditional image enhancement approaches, such as the HE method and the USM method to enhance low quality images. Image results shows that proposed method is superior to the traditional method in image enhancing because of their adaptability. Finally, we come to the conclusion that image enhancement based on ABCA not only ameliorates visual effect obviously but also improve image contrast, suppress the noise, keep the useful information of image and improve the image compactness. It lays good foundation for the following-up image processing tasks.

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