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Image Fuzzy Enhancement Based on Self-Adaptive Bee Colony Algorithm

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Abstract

In the image acquisition or transmission, the image may be damaged and distorted due to various reasons; therefore, in order to satisfy people's visual effects, these images with degrading quality must be processed to meet practical needs. Integrating artificial bee colony algorithm and fuzzy set, this paper introduces fuzzy entropy into the self-adaptive fuzzy enhancement of image so as to realize the self-adaptive parameter selection. In the meanwhile, based on the exponential properties of information increase, it proposes a new definition of fuzzy entropy and uses artificial bee colony algorithm to realize the self-adaptive contrast enhancement under the maximum entropy criterion. The experimental result shows that the method proposed in this paper can increase the dynamic range compression of the image, enhance the visual effects of the image, enhance the image details, have some color fidelity capacity and effectively overcome the deficiencies of traditional image enhancement methods.

Keywords*: image enhancement, bee colony algorithm, fuzzy set*

1. Introduction

Image enhancement is mainly aimed to improve the visual quality of image. Image enhancement selectively highlights the interesting characteristics or suppresses (covers) some unnecessary characteristics in the image to make the image match visual response characteristics and get a more practical image or transform into an image more suitable for human or machine to perform analytical processing by adding some information or changing data. Image enhancement doesn't analyze the reasons to image degradation and the processed image may not be closed to the original image [1],[2].

After years' research, image enhancement technology has made significant progress and it has formed multiple theoretical algorithms by now. According to the different spaces where enhancement is located, it can be divided into the algorithm based on spatial domain and the algorithm based on frequency domain [3]. The former algorithm directly operates on the image grayscale while the latter conducts certain correction on the transformation coefficient value of image within certain image transformation domain, which is an indirect enhancement algorithm. It should be pointed out that these traditional image enhancementtechnologies haven't considered the fuzziness of image, on the contrary, it only simply changes the contrast or suppresses noise of the entire image [4]. It weakens the image details in the noise suppression; it inevitably causes serious negative effects and it has certain limitations [5].

So far, the image enhancement based on fuzzy theory has achieved significant results and the main advantage of image fuzzy enhancement is that it can preserve the image details [6]. The parameter selection such as membership and enhanced operators in the image fuzzy enhancement play an important significant on the enhancement effects while artificial bee colony algorithm has the advantages of simple computation, ease to realize and few control parameters. Considering the parallelism of artificial bee colony algorithm, as the fitness function of bee colony algorithm, the new definition of fuzzy entropy proposed in this paper has favorable robustness, introduced fidelity and enhances the stability of the algorithm and the ability to maintain details. This paper firstly systematically introduces the basic idea, differences and application characteristics of the common methods of image enhancement. Then, it integrates artificial bee colony algorithm and fuzzy sets and introduces fuzzy entropy into the self-adaptive fuzzy enhancement of image so as to realize the self-adaptive parameter selection. In the meanwhile, it raises a new definition of fuzzy entropy based on the indicial response of information increase and it realizes the self-adaptive contrast enhancement of image by using

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artificial bee colony algorithm in the maximum entropy criterion. Finally, it realizes the self-adaptive fuzzy enhancement of image through simulation experiments.

2. Image Enhancement Techniques

Image enhancement is a method to highlight some information in an image and weaken or get rid of some unnecessary information according to some specific requirements. Its purpose is to enhance the clarity and contrast of image in certain specific applications to improve the image quality and make the processed results more consistent with human visual sensory system or easier to be recognized by machines [7].

The current common-used enhancement technique is divided into technique based on spatial domain and technique based on transformation domain.The former technique directly processes in the space of the image while the latter processes in the transformation domain of the image.The common-used transformation space is the frequency domain space, namely the Fourier transform. The enhancement methods based on spatial domain include: the grayscale transformation to enhance image through per pixel points, the histogram transformation to change the image contrast globally or locally and the spatial transformation to process the neighborhood pixels of image through template or masking [8]. Figure 1 demonstrates two common transformation functions of spatial-domain image enhancement.

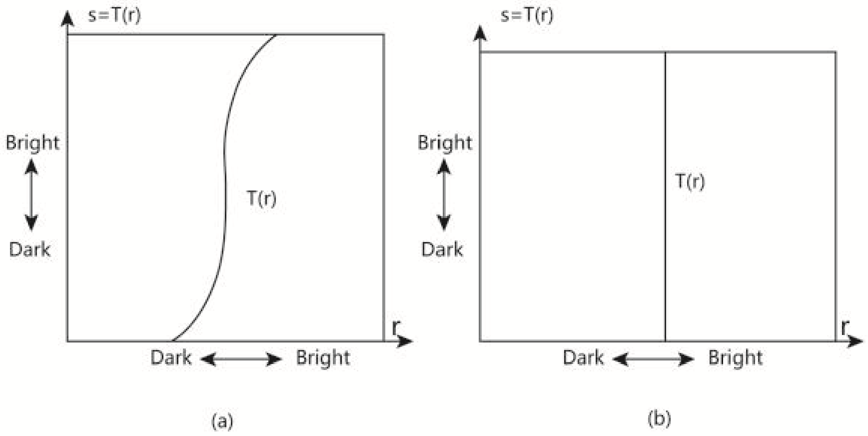

Figure 1. Transformation functions of contrast enhancement

The enhancement of frequency domain space is realized through different frequency components in the image. The image frequency spectrum gives global characteristics of the image; therefore, the frequency-domain enhancement is not implemented per pixel and it is not as direct as the spatial-domain enhancement. The frequency-domain enhancement is realized through the filter and the frequency filtered by different filters and the reserved frequency differ from each other; therefore, it can get different enhancement effects.

3. Artificial Bee Colony Algorithm

3.1 The Principleof Artificial Bee Colony Algorithm

The honey-collecting process of the bee (namely to find high-quality honey sources) is similar to the process to search the optimal solution to the problem to be optimized in the evolutionary computation. The honey collection is realized through the communication, the transformation and the collaboration among different bees. The process for the bee colony to collect honey includes three basic parts and two basic behaviors. The three parts are: foods, employed bees and unemployed bees and the two behaviors are to recruit and abandon certain foods [9].

The essence of artificial bee colonyalgorithm is to search optimal solution through the random but targeted evolution on the group formed by the candidate solutions. In every circulation, the numbers of leaders and followers are the same and there is only one or no scouter. The solution evolution is completed by the above-mentioned three kinds of bees: (1) Employed bee conducts local search in the neighborhood domain of its corresponding foods and updates its foods when finding new foods optimal to the current foods; (2) According to the food information provided by the employed bee, the follower chooses the food through certain selection method; makes local search near the selected food sources; informs corresponding employed bee to the current foods and updates the foods when finding more excellent new foods. When the follower chooses the foods, excellent foods (solutions with high fitness) can attract more followers. With several searches in the neighborhood domain and these foods have more evolution opportunities. (3) In the stagnation of the termination solution of scouter, namely when the solution evolution stagnates, the un-employed bee abandons the current foods and becomes a scouter. Then it randomly searches and generates a feasible solution as a new food and conveys the relevant information to the employed bee. Through the collaboration of the above-mentioned three kinds of bees, ABC algorithm gradually converges and obtains the optimal solution or approximate optimal solution in the feasible solution space [10].

3.2 Mathematical Descriptionof Artificial Bee Colony Algorithm

Consider optimization problem(P):

$$\min\{f(x): x \in S \subset R^d\}$$

f is the objective optimization function; $X = (x_1, x_2, \cdots x_d)$ is the variable to be optimized; S is the solution space and $S = \{(x_i^{\min}, x_i^{\max}) \mid j = 1, 2, \cdots, d\}$.

The set formed by the feasible solutions to Problem (P) can be abstracted as the foods of a bee colony. The position (feasible solution) of every employed bee in the colony corresponds to a food, which is determined by the function value of the objective function and the number of employed bees and followers is the same as that of foods (solutions). Therefore, the position of a certain food can be expressed with the vector $X_i = (x_{i1}, x_{i2}, \cdots x_{id})$.

Firstly, initialize with ABC algorithm. Randomly generate an initial population with SN solutions according to Formula (3); every solution is $X_i = (x_{i1}, x_{i2}, \cdots x_{id})$ and SN is a d-dimensional vector.

$$\begin{aligned} &x_{ij} = x_j^{\min} + rand(0,1) \times (x_j^{\max} - x_j^{\min}) \\ &i = 1, 2, \cdots, SN,\ j = 1, 2, \cdots, d \end{aligned} \tag{3}$$

Then, the bees begin to conduct cyclic search for the foods and the cycle time is $Gen(Gen = 1, 2, ..., MAX\_Gen)$ until it reaches to the specified precision or the maximum iterations MAX _Gen. The employed bee searches corresponding foods, namely randomly choose a different bee as a neighbor and randomly chooses a dimension as its search guide direction. The search process is conducted according to Formula (4) and (5).

$$v = r \times (x_{ij} - xneighbour.j) \tag{4}$$

$$x_{ii}^{new} = x_{ii} + v \tag{5}$$

Among the two formulas, v is the search direction and step length.

$meighbour \in \{1, 2, \cdots SN\}$ and $neighbour \neq i,\ j \in \{1, 2 \cdots, d\}$ are randomly selected and r is a random number among [-1,1]. If x_{ij}^{mew} exceeds the solution space range, transform it into the boundary value according to Formula (6):

$$x_{ij}^{new} = \begin{cases} x_{ij}^{\min}, x_{ij}^{new} < x_{ij}^{\min} \\ x_{ij}^{\max}, x_{ij}^{new} > x_{ij}^{\max} \end{cases} \quad (6)$$

If the quality (fitness) of the searched food (solution) x_i^{new} is better than the current food, replace the new food with the current food; otherwise, keep the food unchanged.After the search of all employed bees, they go back to the dancing area in the honey comb and share the food information with the unemployed bees in the comb through waggle dance and the followers judge the return rate of every food according to the information obtained and collect honey through roulette wheel selection.The return rate is expressed with the fitness value of the solution and the fitness and selection possibility are computed according to Formula (7) and (8).

$$fit_i = \begin{cases} \frac{1}{1+f_i}, f_i > 0 \\ 1+|f_i|, f_i \le 0 \end{cases} \quad (7)$$

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \quad (8)$$

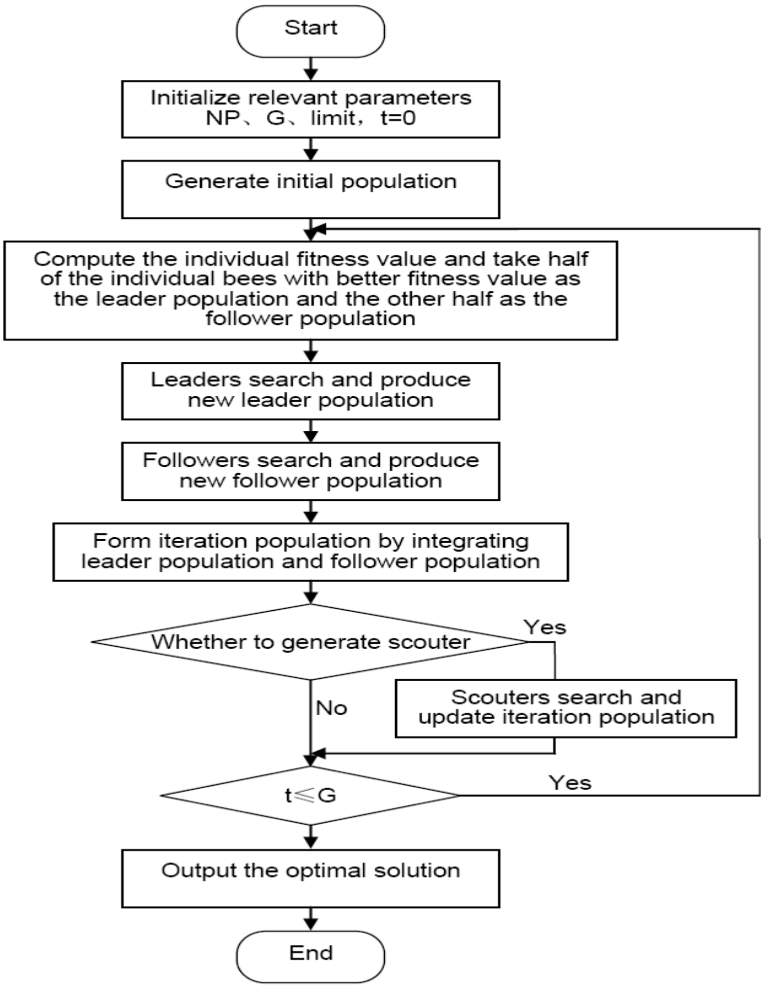

Figure 2. ABC Algorithm flow chart

In the above two formulas, f_i is the function value of the ith solution; fit_i is its corresponding fitness value and SN is the number of solutions. Obviously, based on the roulette wheel selection, good foods can attract more followers and it has higher possibility for evolution and it can accelerate the convergence rate of algorithm. After the followers choose the foods, search the neighborhood domain of the foods according to Formula (4) and (5); adjust the foods according to Formula (6); conduct greedy selection to the newly-searched positions and maintain the better solutions [11],[12].

If a food stagnates in a certain position for more times than the pre-set time limit, it demonstrates that this solution is trapped in the local optimal solution and the corresponding honey-collecting bee become a scouter and it abandons the food and randomly generates a new food (solution) to replace the abandoned food (solution) in Space S according to Formula (3). The limit here is the boundary parameter to judge whether a certain solution jumps out from the current stagnation status [13].

The flow chart of ABC Algorithm is shown as Figure 2.

4. Conduct Image Fuzzy Enhancement with Artificial Bee Colony Algorithm

4.1 Definition of Fuzzy Entropy

Fuzzy entropy quantificationally reflects the fuzzy degree of an image and is the average difficulty level to determine whether a pixel can be seen as an element of a fuzzy subset.

(i) According to different enhancement purposes and images, set the membership parameters $(F_e, F_d, g_{\max})$ in Formula (9); the plane formed by all μ_{mn} is the fuzzy characteristic plane; $g_{\max}$ is the maximum pixel value; F_e and F_d are exponential and reciprocal fuzzy factors and their values will directly affect the fuzziness of the fuzzy characteristic plane. Therefore, in fuzzy enhancement processing, to choose good fuzzy parameters F_e and F_d is an important step to get a satisfactory enhanced image.A particular grayscale meeting $\mu_{mn} = G(g_C) = 0.5$ is called crossover point. The selection of fuzzy parameter is related to the selection of crossover point g_C and the crossover point meets the following requirements:

$$G_{mn} \begin{cases} < 0.5 & g_{mn} < g_C \\ = 0.5 & g_{mn} = g_C \\ > 0.5 & g_{mn} > g_C \end{cases}$$

Therefore, after determining the crossover point g_C, F_d can be determined through Formula (9) when F_e is determined.

(ii) Transform the image from the spatial domain to the fuzzy domain through Transformation G;

$$\mu_{mn} = G(g_{mn}) = [1 + \frac{g_{\max} - g_{mn}}{F_d}]^{-F_e} \tag{9}$$

(iii) Modify the membership $(\mu_{mn} \to \mu'_{mn})$: through the following transformation, namely the regression of the fuzzy enhancement operator (INT);

$$T(\mu_{mn}) = \begin{cases} 2 \cdot [\mu_{mn}]^2 & 0 \le \mu_{mn} \le 0.5 \\ 1 - 2 \cdot [1 - \mu_{mn}]^2 & 0.5 \le \mu_{mn} \le 1 \end{cases} \tag{10}$$

The key of fuzzy enhancement is to use the fuzzy enhancement operator to reduce the membership value smaller than 0.5 by increasing the membership value μ_{mn} bigger than 0.5 so as to reduce the fuzziness of G. The fuzzy enhancement opeartor generates another fuzzy set in the fuzzy set G.

$$\mu'_{mn} = T^{(r)}(\mu_{mn}) = T(T^{(r-1)}(\mu_{mn})), r = 1, 2, \cdots, \infty \tag{11}$$

In the formula, $T^{(r)}$ is defined as the multiple calling of T. In the extreme case, when $r \to \infty$, $T^{(r)}$ generates a two-grayscale (two-value) image. In order to avoid the loss of detail information and the deficiency of fuzzy image enhancement, r chooses 1, 2 and 3 according to different enhancement purposes and images.

(iv) New grayscale g'_{mn} is generated through inverse transformation G^{-1} so as to transform the data from fuzzy domain to the spatial domain of the image:

$$g'_{mn} = G^{-1}(\mu'_{mn}) = g_{\max} - F_d \left((\mu'_{mn})^{\frac{-1}{F_e}} - 1 \right) \tag{12}$$

4.2 Choose The Optional Fuzzy Parameter By Using Bee Colony Algorithm

Considering the exponential properties of information increase, we have proposed a new definition of fuzzy entropy to conduct self-adaptive fuzzy enhancement of the image based on the above-mentioned analysis and its definition is as follows:

$$K(A, N, M, \mu_A) = \frac{1}{N} \sum_{i=1}^{N} [P_P(A_i) e^{\{1-P_P(A_i)\}} + \{1 - P_P(A_i)\} e^{P_P(A_i)}] \tag{13}$$

and,

$$P_P(A_i) = \sum_{\mu_A(x) \in A_i} P(x) \tag{14}$$

In these two formulas, A is the fuzzy set, N is the number of the subset $A_1, \ldots, A_N$ of fuzzy set A. M is the partition method of fuzzy domain and uniform partition or non-uniform partition can be chosen according to different images. $\mu_A(x)$ is the membership of image grayscale value and $P(x)$ is the frequency of image grayscale value. $P_P(A_i)$ is the sum of the frequencies of the spatial-domain grayscale values when the spatial-domain pixel point x is mapped onto the fuzzy subset A_i throughthe membership function $\mu_A(\ )$. It can show that when $P_P(A_i) = 0.5$, the fuzzy entropy can amount to the maximum value; therefore, in the partition methods of fuzzy domain, $P_P(A_i) = 0.5$ should be made in M.

Based on the above research, the self-adaptive image enhancement of ABC algorithm can be realized through the following steps.

(a) Transform the image from the grayscale domain to the fuzzy domain within the value range of the parameters; compute the fuzzy entropies of different parameters respectively to make the parameter selection method to maximize fuzzy entropy is the optimal parameter selection method and record the parameter and fuzzy entropy.
(b) Use the determined parameters to transform the image from the grayscale domain to the fuzzy domain and conduct fuzzy enhancement.
(c) Transform the data from the fuzzy domain to the spatial domain of the image so as to realize the selection of self-adaptive parameters, namely the self-adaptive fuzzy enhancement.

5. Simulation Experiment and Result Analysis

The self-adaptive fuzzy enhancement algorithm proposed in this paper is realized under the maximum fuzzy entropy criterion; therefore, the selection of optimal fuzzy parameters is the parameter optimization under the maximum fuzzy entropy in essence and it can directly use fuzzy entropy as fitness function and it adopts the new definition of fuzzy entropy proposed in this paper, as demonstrated in Formula (12) and (13). In order to reduce as much program running time as possible, it stabilizes when the population size is 30 and the termination algebra is 100. The initial value of fuzzy parameter F_d in bee colony algorithm is generated randomly. Therefore, we choose the termination algebraof 100.

Figure 3 is the contrast chart between the original image and the algorithm of this paper. Table 1 is the average value, standard deviation and entropy of original image, PSO and algorithm of this paper. Fig.4 is the histogram of the average value, standard deviation and entropy of original image and algorithm of this paper.

Figure 3. Original image and result of algorithm of this paper

Table 1 Average Value, Standard Deviation and Entropy of Original Image, PSO and Algorithm of This Paper

	Average Value	Standard Deviation	Entropy
Original Image	50.2849	43.7312	7.3471
PSO	151.4758	82.8231	6.8263
Algorithm of This Algorithm	121.2631	51.8472	8.3489

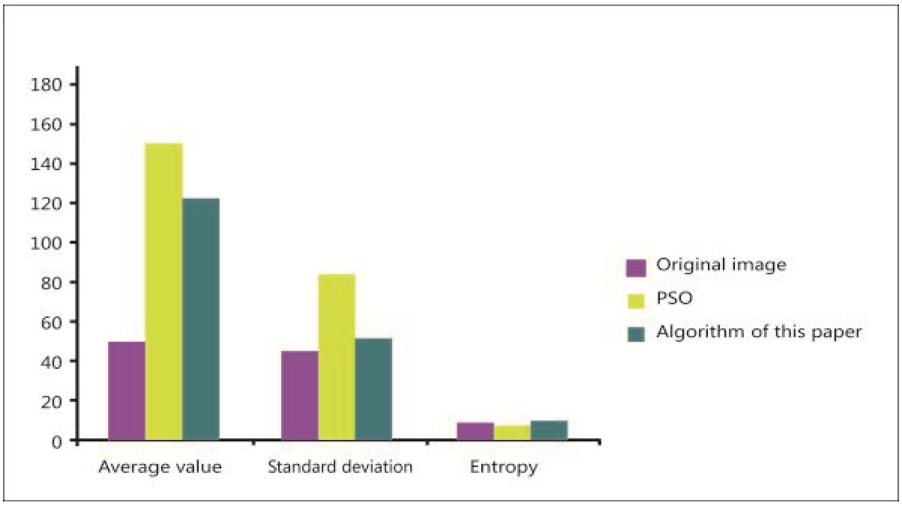

Figure 4. Histogram of average, standard deviation and entropy

The average value increases after histogram equalization, demonstrating that the brightness is high and the standard deviation is small and reflecting that the equalization effect is not good enough. It can be seen from the experimental data that average value and mean square deviation increase after being processed by PSO algorithm; however, the entropy decreases; the brightness increases and the definition becomes bad. It can be seen that after

PSO process, obvious color distortion appears and definition decreases. The artificial bee colony algorithm has better dynamic range compression and definition enhancement as well as color fidelity ability. And we can find that it can enhance the dynamic range compression of the image, the visual effects of the image and the image details and has certain color fidelity capacity.

6. Conclusion

Image enhancement is the basic technique of digital image processing and it can effectively improve the global or local characteristics of the image.By using the global optimization capacity and parallelism of ABC algorithm, this paper proposes a new definition of fuzzy entropy as the fitness function of bee colony algorithm, which can automatically search the optimal fuzzy parameters, improve the stability of the algorithm and the ability to maintain details, realize the self-adaptive fuzzy enhancement of the image, have better color fidelity capacity and improve the image quality for approximate real-time applications.

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