Cuckoo Optimization Algorithm based Image Enhancement

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Abstract—This paper proposes an extension to approach proposed in [13] for image enhancement using a combination of fuzzy logic technique and bio-inspired optimization algorithm. The transformation of the image data from RGB to HSV space has been done without altering HUE information. The image has been categorized into three regions with well tuned membership functions: underexposed, overexposed and mixed region on the basis of two threshold values. Gaussian membership function finds good suitability for fuzzification of overexposed and underexposed regions and mixed region is kept untouched which are further modified by a parametric sigmoid function. To get the quantitative analysis of the image; quality measures like fuzzy contrast, contrast and visual factors have been utilized. An objective function involves entropy and visual factor which is being optimized by bio-inspired optimization algorithm. Here, Cuckoo Optimization Algorithm (COA) has been used for parameter optimization and its results have been compared with the ACO based image enhancement on the scale of visual factor and execution time. COA based image enhancement found better than other approaches. The time taken to enhance the image has also been reduced as compared with latest approaches.

Index Terms—Spatial domain, Optimization, Image enhancement.

I. INTRODUCTION

The purpose of image enhancement is to improve the perceptibility of information contained in an image, or to increase the contrast in a low contrast image [1]. Image enhancement produces an output image that subjectively looks better than the original image. An approach of image enhancement based on human perception (retinex) and dynamic range compression was proposed by Rahman et al. in [2] which were further extended by Tao and Asari in [3] where more natural colors were produced by adjusting the saturation. On the other hand, Velde in [4] used the LUV color space to enhance an image, where each component was used to find the gradients which were being operated by conventional grey-level enhancement techniques.

Image processing has to deal with many ambiguous situations due to non-linearity in imaging system or improper lighting conditions. This vagueness in an image appears in the form of imprecise boundaries and color values. Fuzzy techniques offered a prospective to discern the imperfections of the image processing. Therefore, image processing and recognition, based on the theory of fuzzy sets, have attracted attention of many researchers. Since S. K. Pal et al. proposed the fuzzy enhancement method [5] in early 1980s but not
found to be fit for the images having less number of gray levels. This disadvantage was overcome by Peng et al. [6] where iterative fuzzy approach based on statistical feature of grey level was used. Hanmandlu et al. [7] proposed a Gaussian type of fuzzification function and a new intensification operator (NINT) which were tuned by finding the parameters on the basis of optimized fuzzy entropy and extension of this work has been discussed in [8, 9] which bestowed the histogram as a basis for fuzzy modeling of colored images and in [9] NINT operator was replaced by global contrast intensification operator (GINT).

Bio-inspired evolutionary algorithms have also been in the area of image enhancement. Kwok et al. presented an effective approach in [10], based on multi-objective PSO for contrast enhancement of gray-level digital images while keeping the mean intensity being preserved. Likewise, Hashmi et al. [11] introduced genetic algorithm to increase the visible details and contrast of low illumination. Hanmandlu et al. again extended the previous work in which they addressed the issues of underexposed and overexposed images in [12, 13]. BFO [18] and ACO [19] like evolutionary algorithm were used to minimize the objective function.

Now, this paper is an extended work of [13] for the enhancement of color images where fuzzy entropy has been considered as the landmark of the concept which is the measure of image quality in fuzzy domain and histogram as the basis for fuzzy modeling of color images. Here the results using COA have been compared with the ACO based image enhancement presented in [13]. This method has also been tested on many camera captured images.

Section 2 and Section 3 introduce partition of the image based on threshold and the fuzzification of the color image. Section 4 calculates the information present in a fuzzified image. The results are discussed in Section 5, and conclusions are drawn in Section 6.

II. IMAGE PARTITION BASED ON THRESHOLD VALUES

Categorization of the image into different regions has been carried out using “exposure” as a parameter for the division of an image into the under- and over-exposed regions is given by equation (1) as in [15].

\[
\text{Exposure} = \frac{1}{L} \left( \frac{\Sigma_{z=p}^{L-1} p(z) z}{\Sigma_{z=p}^{L-1} p(z)} \right)
\]

(1)

where \(z\), \(p(z)\) and \(L\) depicts the grey level of a pixel, the histogram and the number of grey levels in an image respectively. Two threshold parameters UT and LT have been considered for characterizing the image into under, mixed and over-exposed regions as mentioned in [13].

III. CONVERSION TO FUZZY DOMAIN

Depending on the values of UT and LT image is split into three regions which are fuzzified separately. A modified and tuned Gaussian Membership Function [10], has been used to fuzzify the underexposed region, and the overexposed region is given as:

\[
\mu_{z_u}(z) = \exp \left\{ - \frac{z_{\text{avg}} - z}{\sqrt{2} f_h} \right\}^{1.94}
\]

(2)

\[
\mu_{z_o}(z) = \exp \left\{ - \frac{z_{\text{max}} - z_{\text{avg}}(L-z)}{\sqrt{2} f_h} \right\}^{1.94}
\]

(3)

where \(z_{\text{max}}\) and \(z_{\text{avg}}\) represents the maximum intensity level in the image, the gray level of the underexposed region in the range \([0, UT - 1]\), and the average gray level value in the image respectively. \(f_h\) is called a tuned fuzzifier, and its initial value is found from equation (4),

\[
f_h = \frac{1}{\Sigma_{z=p}^{L-1} p(z) z^{1.95}}
\]

(4)

For enhancing the MF value of original gray level, a parametric sigmoid function for underexposed region [10] is given by

\[
\mu'_{z_u}(z) = \frac{1}{1 + e^{-t(\mu_{z_u}(z) - \mu_{u_0})}}
\]

and that for overexposed region is
\[
\mu^2_{z_0}(z) = \frac{1}{1 + e^{-h(\mu_{z_0}(z) - \mu_{e_0})}}
\]

where \(t\) and \(h\) are intensification parameters and \(\mu_{e_u}\) and \(\mu_{e_o}\) are the crossover points for under and overexposed regions respectively.

### IV. IMAGE INFORMATION

Image Information is required here for enhancement of image. Entropy has been used for getting the image information.

#### A. Definition of Entropy

One of the interesting points about transforming an image from the intensity domain into the fuzzy domain is how much information it can keep and this information is retrieved by entropy [14] which makes use of Shannon’s function, is given as:

\[
E = \frac{-1}{\ln(2)} \left( \sum_{z=0}^{L-1} \left( \mu^2_{z_0}(z) \ln \left( \mu^2_{z_0}(z) \right) + \left( 1 - \mu^2_{z_0}(z) \right) \ln \left( 1 - \mu^2_{z_0}(z) \right) \right) + \right)
\]

\[
\sum_{z=0}^{L-1} \left( \mu^2_{z_0}(z) \ln \left( \mu^2_{z_0}(z) \right) + \left( 1 - \mu^2_{z_0}(z) \right) \ln \left( 1 - \mu^2_{z_0}(z) \right) \right)
\]

\[
\sum_{z=0}^{L-1} \left( \mu^2_{z_0}(z) \ln \left( \mu^2_{z_0}(z) \right) + \left( 1 - \mu^2_{z_0}(z) \right) \ln \left( 1 - \mu^2_{z_0}(z) \right) \right)
\]

#### B. Objective Function for Optimization

If the desired visual factor \(V_t\) is known corresponding to \(V_f\) then the attainment of their equality is posed as a constraint, in the optimization of objective function [16]. This constrained optimization can be framed as:

\[
\text{Optimize the entropy function}
\]

Subject to the constraint \(V_t \approx V_f\)

For this, an objective function is set up as under

\[
J = E + \epsilon e^{-|V_t - V_f|}
\]

where \(\epsilon\) is a Lagrangian multiplier and \(\lambda\) is another constant. The optimization of the objective function has been done by considering parameters in the ranges \(1 < t < 10, 1 < h < 10\), and \(0 < \alpha < 255\). The values of \(\lambda = 0.6\) and \(\epsilon = 1.65\) have been considered to provide the better optimized value on the right hand side of (8).

### V. CUCKOO OPTIMIZATION ALGORITHM

In this paper, an evolutionary learning algorithm based on the egg laying behavior of cuckoo bird named as Cuckoo has been presented [17] that find the parameters by optimizing the objective function given in equation (8).

Birds (Cuckoo) search for the nearly desirable area to lay their eggs in order to maximize their eggs endurance rate. After stayed eggs grow and turn into a mature cuckoo, they make some societies. Each growing society has its home ground region to live in. The best habitat of all societies will be the destination for the cuckoos in other societies. Then, they introduce toward this best habitat. They will inhabit somewhere near the best habitat. Let the number of eggs each bird has and also the distance of cuckoo to the best habitat, some eggs placing radii is dedicated to it. Then, cuckoo starts to lay eggs in some random nests inside her egg placing radius. This process continues until the best position with maximum profit value is obtained and most of the cuckoo population is gathered around the same position.

### VI. RESULTS AND DISCUSSION

The proposed approach has been implemented on X2 Dual Core QL-60 at 1.69GHz using MATLAB version 7.6.0.324. Visual factor and entropy have been utilized as objective measures to evaluate the performance of proposed approach. A few of images from Figure 1 to Figure 3 have been considered and the results of their enhancement using COA have been compared with ACO based image enhancement [13]. It is found that COA
based image enhancement bestows more pleasing results and the enhancement of images is controlled by the optimizing the parameters $t, h, f_h$ and $\alpha_t$.

Fig. 1. (a) Original image of “Lena” (b) Enhanced image of “Lena” with the ACO algorithm (c) Enhanced image with COA

Fig. 2. (a) Original image of “Rose” (b) Enhanced image of “Rose” with the ACO algorithm (c) Enhanced image with COA

Fig. 3. (a) Original image of “Baby” (b) Enhanced image of “Baby” with the ACO algorithm (c) Enhanced image with COA

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<th>Table I. Initial Parameters Without Optimization</th>
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<th>Table II. Optimized Parameters After Applying COA</th>
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<th>Table III. Execution Time and Visual Factor</th>
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Table 2 presents the quantitative analysis of quality measure of all the images after enhancement which can be compared with the initial parameters of the images as shown in Table 1. But after applying the proposed technique some gray levels get shifted on the scale of histogram and the final value of visual factor shows that it is coming more closer to desired visual factor in case of proposed approach. Table 3 shows the comparison of their execution time and it has been observed COA speed up the operation.

VII. CONCLUSIONS

The results of COA based image enhancement have been compared with the existing method in [13] on the scale of visual quality and execution time. The results are found more appealing and faster than existing methods. This method has also been tested on many camera captured images. For the case of permanently degraded images, the technique can recover the lost details with saturation enhancement only up to some extent. The method which can map the nonlinear nature of the image in a better way than the proposed methodology can be considered as a future scope.

REFERENCES