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Article

A Cuckoo based Optimization Approach for Image Enhancement

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Abstract: The notion of enhancement of the image is to ameliorate the perceptibility of information contained in an image. In the present research, a novel technique for the enhancement of image quality is propounded using fuzzy logic technique with a cuckoo optimization algorithm. Generally, the image is transformed from RGB domain to HSV domain keeping the color information intact within the image. The image has been categorized into three regions: underexposed, overexposed and mixed region on the basis of two threshold values. For the fuzzification of under and overexposed area the degree of membership is defined by the Gaussian membership, while the mixed area is fuzzified by parametric sigmoid function. The key parameters like visual factors and fuzzy contrast provide the quantitative analysis of an image. An objective function is framed which involves entropy and visual factor has been optimized by a new evolutionary cuckoo optimization algorithm. The results procured after simulation by the cuckoo optimization algorithm are compared with Bacterial foraging algorithm and ant colony optimization based image enhancement and this approach is found to be improved.

1. Introduction

In digital image processing domain, Image enhancement gained impetus from last few decades and is of great significance. Image enhancement is the transformation of an image to amelioration for the machining investigation or ocular perceptiveness of human beings. To explore the hidden details or to make the significant enhancement to the contrast of an image amelioration is necessary and is the main purpose of enhancement of an image [1]. Enhancement of an image produces an improved output image that idiomatically looks improved than the original as propounded in [2]. Luminance maps of space variant [3], histogram modification for the contrast enhancement [4] and combined contrast enhancement and half-toning [5] had been incorporated partially and successfully, but none of these could generalize for all types of colored images. A Human perceptiveness based approach for the amelioration of image and dynamic compression range was proffered and incorporated by Rahman et al. in [6] which has been further extended and implemented by Tao and Asari in [7] where more congenital colors were generated by acclimating the saturation.

In [8], Velde implemented the LUV color space amelioration of an image, where all the components were used to ascertain the gradients and been operated by the conventional grey-level amelioration techniques. Eschbach and Webster in [9] propounded an approach for the improvement of appearance of digitally encrypted image having a pictorial scene and more specifically towards a technique for the enhancement of exposure based on preset threshold values T_{light} and T_{dark} . Eschbach and Kolpatzik in [10] also incorporated a method for the correction of color saturation in naturally scenic images, by iterative processing and juxtaposing the average saturation with the preset threshold T_{sat}.

To palliate the artifacts engendered by direct amelioration on R,G,B components of demeaned colored image, the chromatic information can be decoupled from the achromatic information there is a need of proper color space. Naik and Murthy [11] suggested and incorporated a novel approach to ameliorate the image in HSV color space with hue component maintained. This method was not so robust although the method was able to handle the gamut problem. To mitigate the weaknesses [12] in the exercise of image amelioration amalgamation of the images method [12] and the contrast enhancement based on the decision tree [13] was used.

Due to unsuitable lighting conditions or non-linearity behavior in imaging systems image processing may be having many ambiguous situations. These types of vagueness in an image appear in nebulous boundaries form and color values. Fuzzy logic techniques proffered a different and unique potential to perceive the imperfections of the image processing. Therefore, recognition and image processing, based on the fuzzy set theory, attracted the attention of many researchers since S. K. Pal et. al. proposed the fuzzy logic method for enhancement [14] in the early 1980s but did not find to be suitable for the images of a slight number of gray levels.

This drawback was overcome by Peng et. al. [15] where a frequentative fuzzy approach based on the statistical feature of the gray level was used. Hanmandlu et. al. [16-1997] propounded a Gaussian fuzzification function with a new escalation operator which were tuned and incorporated by calculating the parameters based on extremized fuzzy entropy and continued this work in [17-2003, 2006] to which he bestowed the histogram as a basis for colored images with fuzzy modeling and in [18] NINT operator had been replaced by global contrast intensification operator (GINT).

Kwok et. al. propounded an efficacious approach in [19], based on multi-objective PSO for contrast amelioration of gray-level digital images whereas the mean intensity has been preserved. Likewise, Hashmi et. al. [20] instigated genetic algorithm to enlarge the perceptible details and contrast of low-level illumination. Hanmandlu et. al. again extended the foregoing work in which they addressed the issues of underexposed and overexposed images [21, 22]. In that work BFO and ACO-like evolutionary optimization algorithm had been used to minimize the objective function. Contrast Enhancement is also used in forensics against the malicious persons who try to create a realistic composite image [25]. Histogram based image enhancement is very common and basic method which is still being used as presented in [26] for the remote sensing images since they suffer from low contrast. A new bio inspired Cuckoo Search Algorithm has recently been used by the Gang Cao et. al. [27] for the contrast enhancement of the satellite images where its efficiency is compared with the other meta-heuristic algorithms.

The present paper is the extension of the work propounded in [22] for the amelioration of colored images in which fuzzy entropy has been examined as the landmark of the concept which is the estimate of image standard in the fuzzy domain [22] and histogram as the basis for colored images fuzzy modeling. To disintegrate the chromatic and achromatic information HSV space had been used where V component is partitioned [22, 23] in agreement with the threshold values i.e. upper threshold (UT) and a lower threshold (LT) to differentiate the image into three category- underexposed, overexposed and mixed region. These regions are modified by GINT function as fuzzification function and sigmoid operator in the present work. Saturation component is also being varied according to intensity values in the image.

The visual factor and entropy have been used for defining the objective function which will be optimized by an evolutionary bio-inspired cuckoo optimization algorithm (COA) [24]. The egg laying behavior is the key motivation behind this optimization algorithm.

Next section will be dealing with Image partition based on threshold values; Section III is dealing with conversion to the fuzzy domain, Quality measures in the fuzzy domain will be discussed in section IV, results and discussion will be written in section V and finally, section VI is the conclusion.

2. Image partition based on Threshold values

Histogram of the image is not profitable to conquer the whole dynamic range which causes the exasperating artifacts and peculiar amelioration. The regions are defined on the basis of accumulation of grey levels in the histogram i.e. grey levels accumulated in the lower area defines the dark region, on the other hand grey levels accumulated in the upper area defines the bright region. These two regions are referred as underexposed and overexposed area respectively. In both the regions, one cannot willingly discern the image details. The intensity axis of HSV alone can be used for the partitioning the image into three parts as exemplified.

Categorization of the image into different regions had been carried out using “exposure” as a parameter as in [26]. All kind of image is having each type of region i.e. consider an image containing the defined percentage of all the three regions. These regions are quantitatively distinguished by defining a parameter called “exposure” which behaves like swivel is given by equation (1) as

$$Exposure = \left(\frac{1}{L}\right)\left(\frac{\sum_{z=1}^{L} p(z) \times z}{\sum_{z=1}^{L} p(z)}\right) \tag{1}$$

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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 have been considered for characterizing the image into under, mixed and over-exposed regions: Upper Verge (UV) and Lower Verge (LV) have been put in.

Grey levels below UV and above LV is presumed to represent the underexposed and overexposed regions respectively. The rest of the pixels represent the mixed region of the image. Hence, image has been divided into three parts as: $[0 : UV-1]$ for the underexposed region, $[UV : LV-1]$ for the mixed region and $[LV : L-1]$ for the over exposed region. The two thresholds UV and LV can be expressed in terms of the number of grey levels in an image and three parameters as:

$$\left.\begin{array}{l} \mathrm{UV} = \mathrm{L}(\alpha - \mathrm{m}) \\ \mathrm{LV} = \mathrm{L}(\alpha + \mathrm{s}) \end{array}\right\} \quad (2)$$

where, α represents the pivot, m and s lies in the range of 0 to α and 0 to (1 - α) respectively. These parameters are having the range [0,1].Values of m and s are close to 0 and α is close to 0.5, are able to produce the pleasing nature. For the mixed type images, the processing of under and overexposed regions is done at the same time to maintain the intuitive feel of the image intact. To do this the image is categorized into three regions which are separately processed by distinct operators. Initialization of algorithm has been carried out after considering the value of $exposure$ as value of pivot α and Further the optimum value has been computed by Cuckoo Optimization algorithm (COA). Both m and s are considered as 0.1 to simplify the computation.

3. Conversion to Fuzzy Domain

The original color (hue) information should be kept unaltered to enhance the color image. Thus, HSV color model [1] has been borrowed for enhancing the image in spatial domain. Here, the intensity component (V) and the saturation component (S) are independently processed. Ambiguity and uncertainty are the inherent characteristics associated with the image information. For instance, a pixel is wandering from darker to brighter and vice versa from its initial level is judged by the membership function or fuzzy approach. In the image enhancement process, goodness of results is ascertained by some defined objective quality criteria. The viewer, may judge the image quality in many different ways because his/her judgment is subjective. Therefore, fuzzy methodology has been proved very powerful and effective to encounter the problems of ambiguity and vagueness found in the images. Fuzzification, alteration of membership degree and defuzzification are the three basic steps to process the image in fuzzy domain. The suitability of membership function and defuzzification function is decided by the types of image.

The image of size $J \times K$ can be represented in fuzzy set notation as:

$$\mathrm{I} = \cup \left\{\mu(\mathrm{z_{jk}})\right\} = \left\{\frac{\mu_{\mathrm{jk}}}{\mathrm{z_{jk}}}\right\} \qquad \mathrm{j} = 1,2, \dots, \mathrm{J}; \mathrm{k} = 1,2, \dots, \mathrm{K} \quad (3)$$

where $\mu(z_{jk})$ or $\frac{\mu_{jk}}{z_{jk}}$ defines the membership function μ_{jk} of z_{jk}

Z_{jk}: intensity levels in the range $[0, L-1]$ at the the (j, k)th pixel.

Depending on the values of UV and LV image can be split into three regions which are fuzzified separately. For the fuzzification of the underexposed area a modified Gaussian Membership Function [19], has been used:

$$\mu_{\mathrm{Z_u}}(\mathrm{z}) = \exp\left\{-\left[\frac{\mathrm{z_{max}} - (\mathrm{z_{avg}} - \mathrm{z})}{\sqrt{2}\mathrm{f_h}}\right]^2\right\} \quad (4)$$

where, z_{max} , z and z_{avg} represents the maximum intensity level in the image, the gray level of the underexposed region in the range $[0, UV-1]$, and the average gray level value in the image respectively. f_h is called a fuzzifier, and its initial value is found from equation (5),

$$\mathrm{f_h^2} = \frac{1}{2}\frac{\sum_{\mathrm{z}=0}^{\mathrm{L}-1}(\mathrm{z_{max}} - \mathrm{z})^4 \mathrm{p(z)}}{\sum_{\mathrm{z}=0}^{\mathrm{L}-1}(\mathrm{z_{max}} - \mathrm{z})^2 \mathrm{p(z)}} \quad (5)$$

It has been noted here that instead of taking the intensity level at each pixel, only the histogram of luminance component $z \in (Z)$ is only considered for fuzzification to reduce the computational complexity.

Now, for the fuzzification of overexposed region of the image $z \geq LV$; a mirror function of above defined Gaussian MF is used which is defined as

$$\mu_{\mathrm{Z_o}}(\mathrm{z}) = \exp\left\{-\left[\frac{\mathrm{z_{max}} - (\mathrm{z_{avg}} - (\mathrm{L} - \mathrm{z}))}{\sqrt{2}\mathrm{f_h}}\right]^2\right\} \quad (6)$$

The mirror function has been chosen to eliminate the stacked upper levels. The MF defined above affects only their respective regions and do not alter another region as both are mutually exclusive. MFs in (4) and (6) become operational below the upper threshold and above lower threshold and the regions respectively between these two thresholds are not overlapped.

For enhancing the MF value of original gray level, a parametric sigmoid function for underexposed region (in [19]) is given by

$$\mu'_{Z_u}(z) = \frac{1}{1+e^{-t(\mu_{Z_u}(z)-\mu_{c_u})}} \tag{7}$$

and that for the overexposed region is

$$\mu'_{Z_u}(z) = \frac{1}{1+e^{-h(\mu_{Z_o}(z)-\mu_{c_o})}} \tag{8}$$

where t and h are intensification parameters and μ_{c_u} and μ_{c_o} are the crossover points for under and overexposed regions respectively. Aforementioned operators alter the MFs which are being converted back to spatial domain; that will be discussed in succeeding stages.

Intensity component alone does not guarantee to improve the information content perfectly sometimes. In such situations, saturation plays a significant role to restore the information thus attaining the pleasing nature of the image. And to know how much saturation should vary two power law operators have been introduced which alters the saturation component.

$$\left.\begin{aligned} I'_o(s) &= [I_o(s)]^{s_o}\ \forall \text{ pixels in the overexposed region} \\ I'_u(s) &= [I_u(s)]^{s_u}\forall \text{ pixels in the underexposed region} \end{aligned}\right\} \tag{9}$$

where, s_o and s_u are experimentally chosen saturation intensifier and de-intensifier respectively. I_u and I'_u represent the initial and moderated saturation values of HSV color image for the underexposed area; similarly I_o and I'_o are the respective saturation values for the overexposed area.

4. Quality Measures in Fuzzy Domain

4.1. Fuzzy contrast measures

The colored image quality can be analyzed by following two methods: 1) a logical and mathematical analysis of colored image and 2) a subjective visual inspection. Since the visual perception for the image may vary from person to person and therefore, is not helpful to give the precise performance measure of the system. The actual image quality will be approximated by employing the fuzzy performance measures that will match to the viewer perception also. For this, contrast, entropy and visual factor are defined as performance measures which are used to formulate the final objective function. The defined entropy and visual factors can be used as the quantitative measure of color image quality.

The measure of fuzzy contrast of an image is given by the deviation of the membership values of V component of the pixels from the crossover point. Fuzzy contrast has been defined separately for the underexposed region and for the overexposed region as well.

The fuzzy contrast for the underexposed region is given by:

$$FC_u = \left(\frac{1}{UV}\right)\left(\sum_{z=0}^{UV-1}\left(\mu'_u(z) - \mu_{c_u}\right)^2\right) \tag{10}$$

The average fuzzy contrast for the underexposed region is given as:

$$AFC_u = \left(\frac{1}{UV}\right)\left(\sum_{z=0}^{UV-1}\left(\mu'_u(z) - \mu_{c_u}\right)\ \right) \tag{11}$$

The fuzzy contrast for the overexposed region is given as:

$$FC_o = \left(\frac{1}{L-LV}\right)\left(\sum_{z=LV}^{L-1}\left(\mu'_o(z) - \mu_{c_o}\right)^2\right) \tag{12}$$

The average fuzzy contrast for the overexposed region is given as:

$$AFC_o = \left(\frac{1}{L-LV}\right)\left(\sum_{z=LV}^{L-1}\left(\mu'_o(z) - \mu_{c_o}\right)\ \right) \tag{13}$$

where all notations have their usual meanings. The same parameters (initial fuzzy value contrast and average fuzzy contrast) have been defined for the image before modifying their MFs as:

$$FC_{ui} = \left(\frac{1}{UV}\right)\left(\sum_{z=0}^{UV-1}\left(\mu_u(z) - \mu_{c_u}\right)^2\right) \tag{14}$$

$$AFC_{ui} = \left(\frac{1}{UV}\right)\left(\sum_{z=0}^{UV-1}\left(\mu_u(z) - \mu_{c_u}\right)\ \right) \tag{15}$$

$$FC_{oi} = \left(\frac{1}{L-LV}\right)\left(\sum_{z=LV}^{L-1}\left(\mu_o(z) - \mu_{c_o}\right)^2\right) \tag{16}$$

$$AFC_{oi} = \left(\frac{1}{L-LV}\right)\left(\sum_{z=LV}^{L-1}\left(\mu_o(z) - \mu_{c_o}\right)\ \right) \tag{17}$$

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In the above equation, the overall image intensity is defined by average fuzzy contrast, whereas the distribution of the gradient is given by fuzzy contrast. The ratio of average fuzzy contrast and fuzzy contrast is called as the quality factor which is a key parameter to define the visual factor and image quality subsequently. The quality or contrast factor for the underexposed region of modified image is:

$$\mathrm{FQ_u} = \left|\frac{\mathrm{AFC_u}}{\mathrm{FC_u}}\right| \tag{18}$$

Likewise, for the overexposed region:

$$\mathrm{FQ_o} = \left|\frac{\mathrm{AFC_o}}{\mathrm{FC_o}}\right| \tag{19}$$

The above-defined definitions in (18) and (19) bestow the measure of uncertainty available in the image and on the other hand the uncertainty in the V component values is depicted by a membership function.
Likewise, the quality/contrast factor of the original image for the underexposed area is

$$\mathrm{FQ_{ui}} = \left|\frac{\mathrm{AFC_{ui}}}{\mathrm{FC_{ui}}}\right| \tag{20}$$

and similarly for the overexposed area is:

$$\mathrm{FQ_{oi}} = \left|\frac{\mathrm{AFC_{oi}}}{\mathrm{FC_{oi}}}\right| \tag{21}$$

4.2. *Definition of Entropy*

The amount of information which remains intact within the image after being transformed from intensity domain to fuzzy domain is measured by Entropy which uses Shannon's function, is given as

$$\mathrm{E} = \left(-\frac{1}{\mathrm{L}\ln 2}\right)\left[\begin{array}{l}\left(\sum_{\mathrm{z}=0}^{\mathrm{UV}-1}\left\{\mu'_{\mathrm{Z_u}}(\mathrm{z})\ln\left(\mu'_{\mathrm{Z_u}}(\mathrm{z})\right)+\left(1-\mu'_{\mathrm{Z_u}}(\mathrm{z})\right)\ln\left(1-\mu'_{\mathrm{Z_u}}(\mathrm{z})\right)\right\}\right)+\\ \left(\sum_{\mathrm{z}=\mathrm{LV}}^{\mathrm{L}-1}\left\{\mu'_{\mathrm{Z_o}}(\mathrm{z})\ln\left(\mu'_{\mathrm{Z_o}}(\mathrm{z})\right)+\left(1-\mu'_{\mathrm{Z_o}}(\mathrm{z})\right)\ln\left(1-\mu'_{\mathrm{Z_o}}(\mathrm{z})\right)\right\}\right)\end{array}\right] \tag{22}$$

So, this function is optimized by determining the optimized values of four parameters t, h, f_h, and α.

4.3. *Visual Factor*

Visual factor bestows the amount of improvement in visual appearance after the enhancement of the colored image. The Visual factor is defined separately for the underexposed and overexposed areas. The visual factor for the underexposed area can be defined as:

$$\mathrm{VF_u} = \frac{\mathrm{FQ_u}}{\mathrm{FQ_{ui}}} \tag{23}$$

and likewise for the overexposed area is given as

$$\mathrm{VF_o} = \frac{\mathrm{FQ_{oi}}}{\mathrm{FQ_o}} \tag{24}$$

To yield the overall visual factor of the whole image it is required to combine the visual factor of both the areas which is given as:

$$\mathrm{VF} = \left(\frac{\mathrm{UV}}{\mathrm{L}}\right)\mathrm{VF_u} + \left(1-\frac{\mathrm{LV}}{\mathrm{L}}\right)\mathrm{VF_o} \tag{25}$$

The above definition limits the range of the contrast factor of the image to maintain the appealing view of the image. The Initial value of exposure affects the visual factor. Therefore, it can be empirically defined as:

$$\mathrm{V_{sf}} \rightarrow 1.5 - \left(\frac{0.9}{255}\right) * \alpha_\mathrm{i} \tag{26}$$

where, α_i is the initial value of exposure, and Vsf stands in the interval of [0.6 – 1.5].

4.4. *Formulation of Objective Function*

The objective function can be formulated by the parameters entropy function and the visual factor since they provides the measure of uncertainty associated with the image. Therefore, the objective function can be defined as
Extremize the function of entropy

$$\mathrm{J} = \mathrm{E} + \lambda \mathrm{e}^{|\mathrm{VF}-\mathrm{V_{sf}}|} \tag{27}$$

Subject to the constraint $V_{sf} \approx V_f$
where, V_{sf} is the desired visual factor and λ is a Lagrangian multiplier. The extremization of the J is done by considering the parameters in the ranges $1 < t < 10$, $1 < h < 10$, and $0 < \alpha < 255$. The value of $\lambda = 1$ has been considered to provide the equal weights to the two components on the right hand side of (27). In this paper, Cuckoo

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Optimization Algorithm (COA) has been presented which is also a bio-inspired algorithm and based on the egg lying behavior of the Cuckoo bird [24].

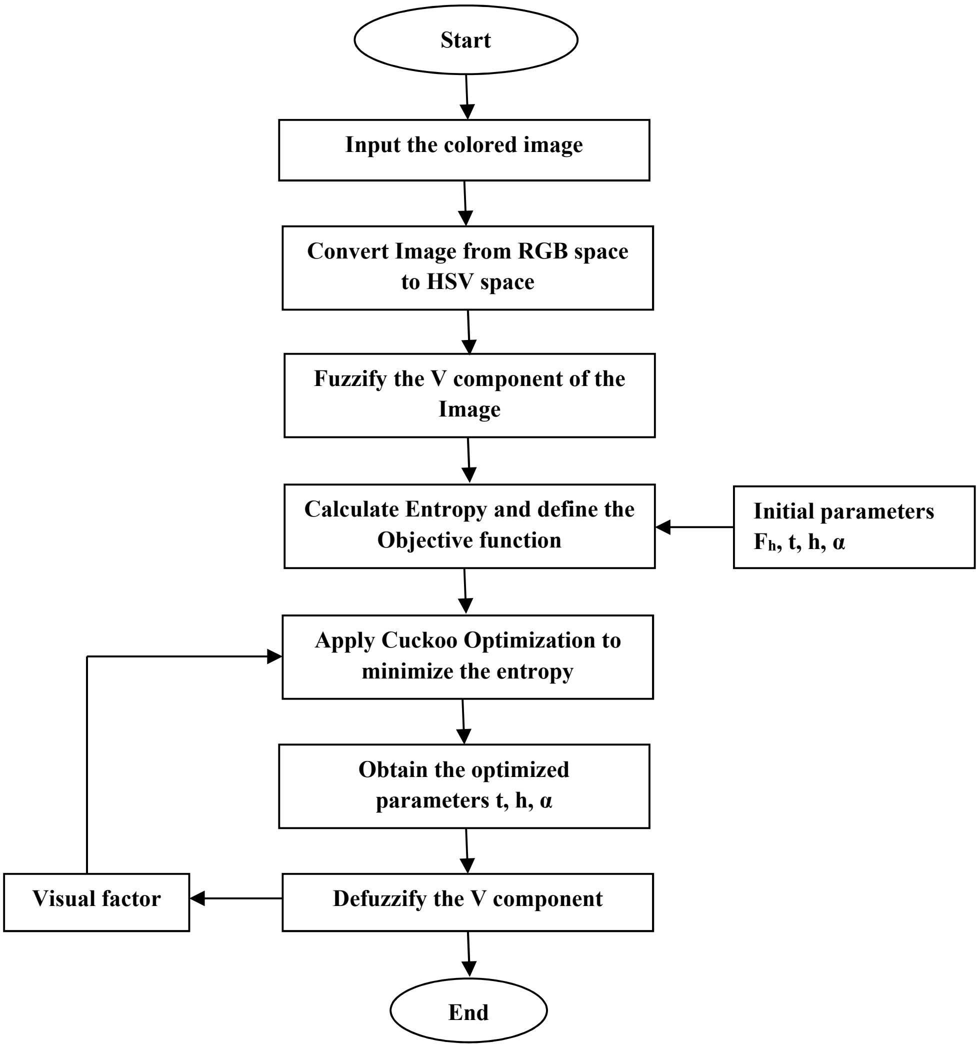

Fig. 1: Flowchart of enhancement technique

4.5. Cuckoo Optimization Algorithm

Optimization is simply the process of the betterment of something. In this paper, a novel bio-inspired algorithm has been presented which is influenced by the life style of a cuckoo bird. Cuckoo bird is famous for its unique egg laying and breeding characteristics. This property paves a way for optimizing the mathematical problems. Their best strategies are stealing the eggs, speed and surprise. The bird replaces the host bird egg with its own egg and tries to mimic the color of its own egg to match the host bird egg. The best mimicked egg survives and the weak eggs are thrown out by the host bird.

Therefore, the different stages to solve the objective function can be explained as; generating the habitat: Habitat basically represents an array of the order 1xNvar, which indicates the current position of the cuckoo.

Cuckoos panache for egg engendering: Cuckoo starts laying the eggs randomly in the host bird's nest within the range of "Egg laying radius (ELR)". Mathematically, ELR can be represented as:

$$\text{ELR} = \alpha \times \frac{Number\ of\ current\ cuckoo's\ eggs}{Total\ numbers\ of\ eggs} \times (var_{hi} - var_{low})$$

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The ELR is directly proportional to the total number of eggs, number of current cuckoo's eggs and also variable limits of var_{hi} and var_{low} and α is an integer, which is responsible for handling the optimum value of ELR. Some eggs are detected by the host bird and destroyed.

Immigration of cuckoos: The cuckoo grows, becomes adult and migrates to a new habitat and repeat the process. To evaluate this optimization problem, the group formation of cuckoos has been done with the help of K-means clustering technique (the value of K between 3 to 5 appears to be adequate in simulations).

Eliminating cuckoos in worst habitats: To maintain the balance, the number Nmax controls the upper limit of cuckoo because of limitations on food and inability to search proper nest.

4.5.1. Steps for image enhancement

1. Make the input of the given colored image and transform it from RGB color space to HSV space.
2. find the frequency distribution of the pixels $p(z)$ where $z \epsilon V$.
3. get the starting value of f_h, using (5).
4. find the values of exposure, α_i, UV and LV using equations (1), (2a) and (2b) and divide the V component of image into three regions: underexposed, mixed and overexposed.
5. Fuzzify V to get $\mu_u(v)$and $\mu_o(v)$ using equations (4) and (6) respectively.
6. Initialize both μ_{cu} and μ_{co} to 0.5 and t and h to random a variable and then calculate FC_{ui}, AFC_{ui}, FC_{oi}, AFC_{oi}, FQ_{ui}, $and\ FQ_{oi}$ as given in section A.
7. Modify the fuzzy MFs using the corresponding sigmoid functions for the underexposed and overexposed regions using (7) and (8) respectively keeping mixed region untouched.
8. Now calculate FC_u, AFC_u, FC_o, $AFC_o, FQ_u, and\ FQ_o$ from the modified membership values as given in section A.
9. Calculate the entropy E and visual factor VF using (22) and (25) by setting the soothing visual factor as
$$V_{sf} \rightarrow 1.5 - \left(\frac{0.9}{255}\right) * \alpha_i$$
$$V_{sf} \rightarrow 1.5 - \left(\frac{0.9}{255}\right) * \alpha_i$$
10. Optimize the objective function given by (27) and obtain the optimized parameters using the Cuckoo optimization algorithm.
11. Use the step 10 to modify the fuzzy membership values.
12. Apply the inverse functions on the respective modified membership degrees to defuzzify the values and normalize them in their respective under and overexposed area.
$$z = \begin{cases} \mu_u^{-1}(z) & \forall\ \ z < UV \\ z & \forall\ \ LV > z \geq UV \\ \mu_o^{-1}(z) & \forall\ \ L > z \geq UV \end{cases}$$
13. Set S_u to $\frac{3}{4}$ and S_o to $\frac{4}{3}$ to modify the saturation component in two regions.
14. Now transform back the HSV color space into corresponding RGB color space.

5. Results and Discussion

This work has been implemented on X2 Dual Core QL-60 at 1.69GHz using MATLAB version 7.6.0.324 and tested with all kind of images like underexposed, overexposed and mixed type of images. A few of tested images and camera captured images from fig (3) to fig (10) and fig (11) to fig(17) respectively containing (underexposed, overexposed and mixed type of images) have been considered and the results of their enhancement using COA have been compared with ACO and BFO algorithms. It is found that COA bestows more pleasing results and the enhancement of images is controlled by the optimizing the parameters $t, h, f_{h,} and\ \alpha_i$.

In fig (2) of the histogram for the image of "Face," it can be seen how the intensity distribution gets modified after the enhancement. This shape of transformation curve depends on upon the nature of image and type of operator used, therefore, found to be different for every image. The sigmoid operator may increase or decrease the intensity of the pixels depending on the region they operate on. Some nonlinear transformation curves of images such as "Baby", "Face" and "God" images appear in the Fig. 11(a), fig. 11(b) and fig. 11(c)after the application of operators and found to be different for different images.

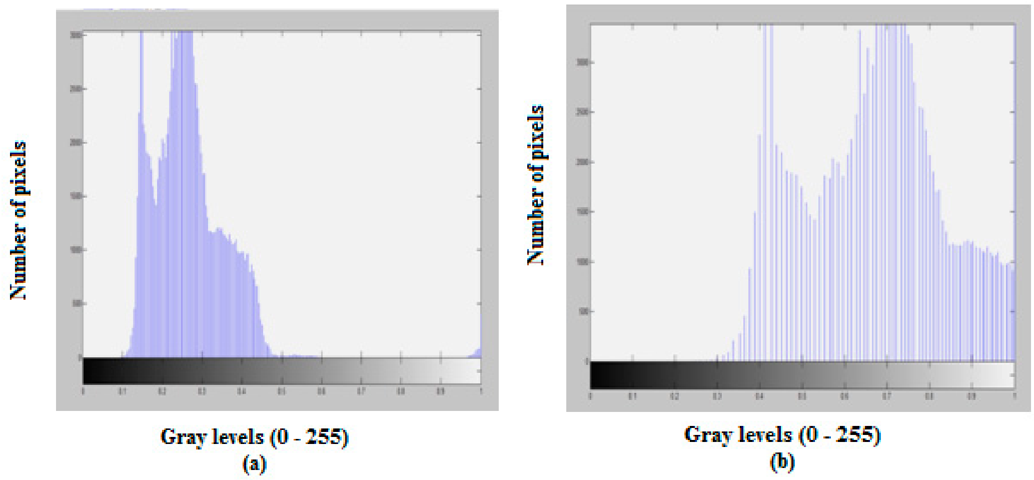
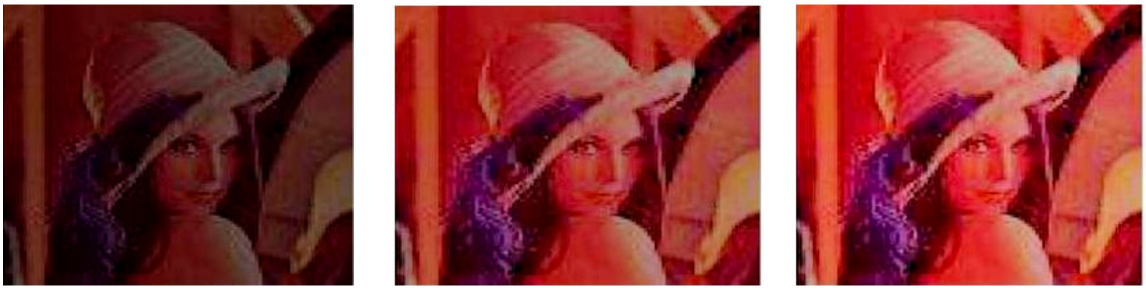


Figure. 2 Histogram for image "Face" (a) before and (b) after applying the proposed approach.



(a) (b) (c)

Figure. 3 (a) Original image of "Lena" (b) Enhanced image of "Lena" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 4 (a) Original image of "Man" (b) Enhanced image of "Man" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 5 (a) Original image of "Hills" (b) Enhanced image of "Hills" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 6 (a) Original image of "Face" (b) Enhanced image of "Face" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 7 (a) Original image of "Doctor" (b) Enhanced image of "Doctor" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

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(a) (b) (c)

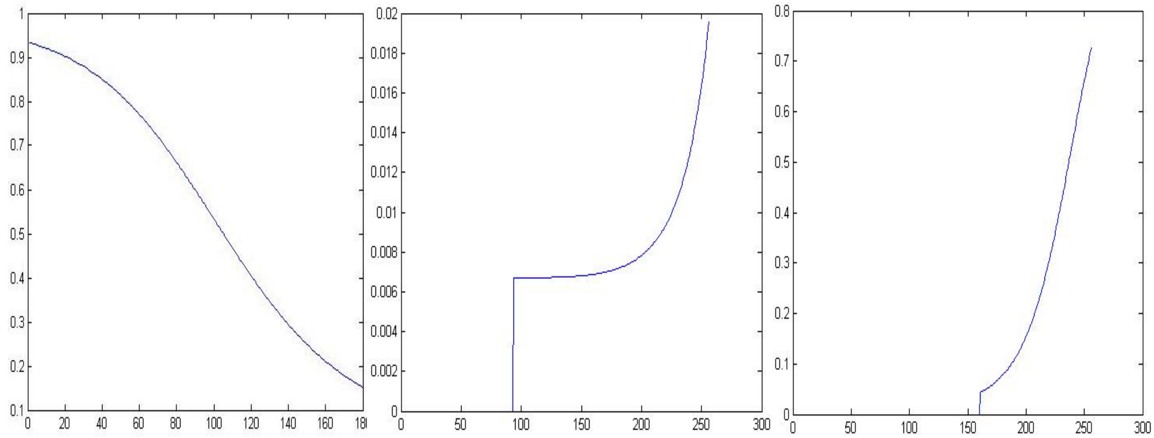
Figure. 8 (a) Original image of "Flower" (b) Enhanced image of "Flower" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 9 (a) Original image of "Scene" (b) Enhanced image of "Scene" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 10 (a) Original image of "Rose" (b) Enhanced image of "Rose" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.



(a) (b) (c)

Figure. 11 Transformation curve (a) "Baby" image (b) "Face" image and (c) "God" image.

Table [2] presents the quantitative analysis of a quality measure of all the images after enhancement which can be compared with the initial parameters of the images as shown in table [1]. The images like Parth, Rose which are having VF0 equals 1; indicates that image is over enhanced the image and the underexposed region operator does not work for thin kind of image. Likewise, the table [2] shows the zero value of VF0 for the images like a doctor, Parth 2, Lena indicating that image contains a high content of underexposed region. The visual factor after applying COA seems to serve as a good indicator of the effect of enhancement of the appearance of the image as compared to BFO and ACO algorithms.

Table 1. Initial parameters without optimization

s.no	image	t	g	Exposure	Image Size	E	V_u	V_o	V_{sf}	V_f
1	lena	5	5	0.24	269 x 235	0.419	0.78	0.11	0.19	0.77
2	doctor	5	5	0.26	329 x 447	0.497	1.03	0.157	1.45	0.27
3	face	5	5	0.27	341 x 455	0.342	1.04	0.48	1.19	0.48
4	rose	5	5	0.87	330 x 264	0.69	1.47	0.757	1.11	1.16
5	flower	5	5	0.35	323 x 323	0.728	1.41	0.031	0.41	0.37
6	hills	5	5	0.78	400 x 267	0.702	1.43	0.317	1.42	1.02
7	cougar	5	5	0.25	540 x 493	0.55	1.30	0.795	0.28	0.71
8	Man	5	5	0.91	428 x 600	0.47	1.152	1.158	0.45	1.42
9	scene	5	5	0.83	479 x 601	0.69	1.40	0.754	0.41	1.08
					Camera captured images					
10	deepak	5	5	0.76	2048 x 1536	0.70	2.90	0.585	0.33	2.03
11	God	5	5	0.53	1536 x 2048	0.69	1.33	0.255	0.75	0.66
12	Girl	5	5	0.41	2592 x 1944	0.701	1.22	0.24	1.39	0.52
13	Parth	5	5	0.32		0.49	0.34	1.75	1.12	1.74
14	Babyboy	5	5	0.23		0.34	1.41	0.00	1.12	1.35
15	Baby	5	5	0.32		0.51	1.51	0.11	1.14	1.27

Sometimes the modification in component alone does not produce fruitful results then saturation component has to play a vital role. This component is also modified in accordance with the equation (9) and the figure of girl and hills shows the effect of saturation component.

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Table2. Quality Measure of All the Images After Enhancement

s.no	image	t	g	y	F_{hold}	f_{hnew}	J	E	V_u	V_o	V_{sf}	V_f
1	Lena	9.6	1.5	247	74.9	112.1	1.21	0.665	0.94	0.56	0.33	1.50
2	doctor	13	3	370	84.6	133.1	0.33	0.54	1.91	0.019	0.17	1.09
3	Face	8.3	.97	231	137.2	97.8	.810	0.64	1.24	0.25	0.34	0.76
4	Rose	8.6	0.96	230	179.6	108.4	.611	0.63	0.0	0.97	0.39	1.46
5	flower	5.8	9.3	13	159.3	167.3	0.234	0.64	6.60	0.05	0.29	1.57
6	Hills	7.8	8.1	8	113.4	142.8	1.83	0.69	1.15	0.77	1.37	0.79
7	cougar	9.07	10	252	155.6	150	.834	0.63	1.91	0.78	0.18	1.21
8	Man	2.6	9.01	13	84.2	94.8	1.788	0.7417	1.01	0.76	1.45	0.80
9	scene	3.6	9.8	10	99.7	110.1	.323	0.71	1.09	0.15	0.29	0.83
Camera captured images												
10	deepak	0.97	9.08	9	107.9	161.2	1.56	0.73	3.99	0.89	0.17	2.19
11	god	3.6	9.8	10	99.7	123.2	1.34	0.65	2.22	0.94	0.85	1.23
12	girl	9.6	1.5	247	127.7	165.3	0.69	0.77	1.49	0.4	0.13	0.55
13	Parth	9	10	153	165.4	150	0.34	0.26	0.85	0.69	0.69	0.68
14	Baby boy	8.2	4.5	143	69.04	112	0.65	0.43	1.40	0.87	1.31	1.23
15	Baby	6	9	64	91.7	123	0.54	0.46	1.32	1.05	1.09	1.12

Table 3: Effectiveness of COA on the Time Scale

S. No	Image	BFO (time in sec.)	ACO (time in sec.)	COA (time in sec.)
1	Lena	7	1.56	1.05
2	Face	4.6	3.56	3.18
3	Doctor	4.9	2.54	2.1
4	Scene	11.3	4.11	3.5
5	Cricketer	7.05	1.92	1.3
6	Flower	6.84	1.99	1.4
7	Cougar	7.93	3.4	3.3
8	Man	6.50	3.7	3.4
9	Hills	7.43	3.3	3
10	Deepak	110	78	35
11	God	85	54	30
12	Girl	100	75	56
13	Parth	65	34	23
14	Babyboy	43	34	10
15	Baby	23	19	10

Table [3] shows the effectiveness of COA on the time scale also, i.e. its execution time is very less than the execution time of BFO and ACO algorithm. It means Cuckoo optimization algorithms speed up the process of enhancement. And table [4] shows the effect of no. of the nest on the value of optimization function and it is seen that the value of J decreases as no. of the nest increases. But after some time, even no. of the nest are increased the value of J remain same ,i.e, the same quality is achieved with the less no. of nests.

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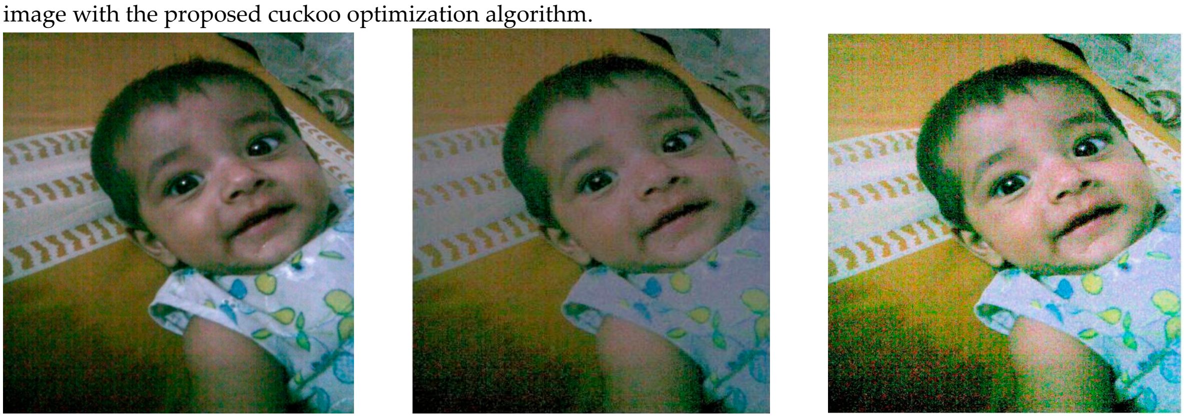
(a) (b) (c)

Figure.12 (a) Original image of "Baby" (b) Enhanced image of "Baby" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 13 (a) Original image of "Parth" (b) Enhanced image of "Parth" with the ACO algorithm (c) modified image with the proposed cuckoo optimization algorithm.



(a) (b) (c)

Figure. 14 (a) Original image of "BabyBoy" (b) Enhanced image of "BabyBoy" with ACO algorithm (c) the proposed cuckoo optimization algorithm.

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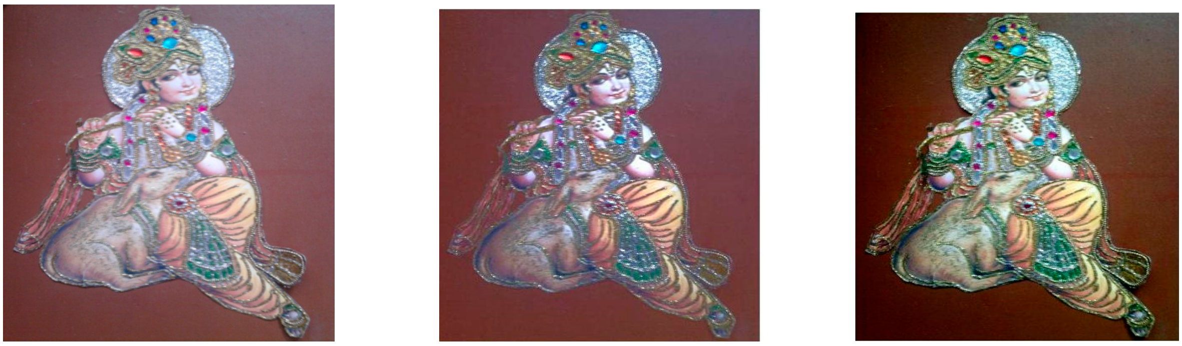
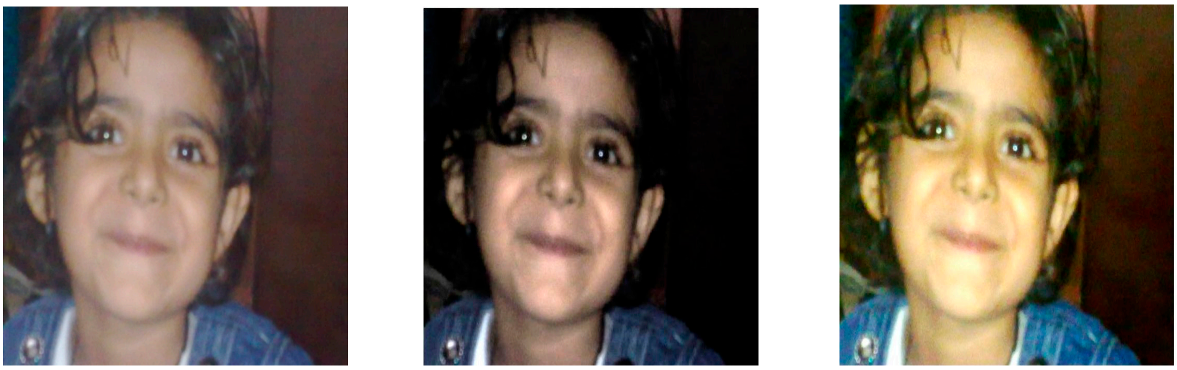


(a) (b) (c)

Figure. 15 (a) Original image of "God" (b) Enhanced image of "God" with ACO algorithm (c) modified image of "God" with the proposed cuckoo optimization algorithm.



(a) (b) (c)

Figure. 16 (a) Original image of "Girl" (b) Enhanced image of "Girl" with ACO algorithm (c) modified image of "Girl" with the proposed cuckoo optimization algorithm.

(a) (b) (c)

Figure. 17 (a) Original image of "Deepak" (b) Enhanced image of "Deepak" with ACO algorithm (c) modified image of "Deepak" with the proposed cuckoo optimization algorithm.

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Table 4. Effect of Number of Nests for Image of "God"

S. No	No. of nests	J	E	V_f
1	10	2.23	0.67	0.80
2	15	2.13	0.65	1.22
3	20	1.89	0.48	0.77
4	25	1.34	0.65	1.23
5	35	1.32	0.45	0.71

S. No.	Image	Camera type
1	Parth	Nokia 3110
2	Baby	Nokia 3110
3	Baby boy	Nokia 3110
4	Deepak	Samsung
5	Girl	Nokia N72
6	God	Samsung

Consent for Publication of Images:

"Image from fig.3 to 10 is standard test images as suggested by M. Krishna, Delhi College of Engineering"
"Images of fig. 12 to 14 is of same kid at different age and consent for publication of these images has been obtained from the parents"
"Images of fig. 15 is of the Hindu religion God"
"Images of fig. 16 is of sister of first author of this paper Deepak Narang and images from fig. 17 is of Deepak Narang itself"

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