

Performance Analysis of Type-2 Fuzzy System for Image Enhancement using Optimization

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Abstract: This study performed the enhanced performance analysis of type-2 using cuckoo optimization algorithm. Two thresholds the lower and the upper are defined to provide an estimate of the under exposed, mixed-exposed and over-exposed regions in the image. The red, green and blue (RGB) color space is converted into Hue, Saturation and value (HSV) color space so as to preserve the chromatic information. Gaussian membership functions suitable for the underexposed and overexposed regions of the image are used for the type-2 fuzzification. Parametric sigmoid functions are used for enhancing the luminance components of under and over-exposed regions, Mixed-exposed regions are left untouched throughout the process. An objective function comprising of Shannon entropy function as the information factor and visual appeal indicator is optimized using Cuckoo algorithm to ascertain the parameters needed for the enhancement of a particular image visual appeal is preferred over the consideration in entropy so as to make the image human-eye-friendly. On comparison, this approach is found to be better than the artificial ant colony system optimization (ACO)-based approach.

I. INTRODUCTION

One of the most common defects found in a recorded image is its poor contrast. This degradation may be caused by inadequate lighting, the aperture size, the shutter speed, and the nonlinear mapping of the image intensity. The effect of such defects is reflected on the range and shape of the gray level histogram of the recorded image. Image enhancement techniques achieve improvement in the quality of the original image or provide additional information that was not apparent in the original image. It improves the appearance of an image by increasing the dominance of some features or by decreasing the ambiguity between different regions of the image. The main objective of image enhancement is to process the image so that the result is more suitable than the original image for a specific application. Image enhancement methods may be categorized into two broad classes: Spatial domain methods, Transform domain

In [1] authors proposed an extended form of bi-histogram equalization called bi-histogram equalization with neighborhood metric (BHENM). In an experimental trial, BHENM simultaneously preserved the brightness and enhanced the local contrast of the original image. But the execution time of this method was three times higher than that of GHE. In this area, M. A.-A.-Wadud et al. [2] proposed a modified method for histogram equalization which was named as dynamic histogram equalization which partitioned the image histogram based on local minima and assigned specific gray level ranges for each partition before equalizing them separately. This work was further modified by Chen and Nor Ashidi in [3] where quadrants dynamic histogram equalization (QDHE) algorithm separated the histogram into four (quadrant) sub-histograms based on the median of the input image. Finally, each sub-histogram was equalized. Authors in [4] proposed a method for altering the exposure in an image, by iteratively comparing the intensity with a pair of preset thresholds T_{light} and T_{dark} , which indicated the satisfactory brightness and darkness, respectively, while processing the image until the threshold conditions were satisfied.

In [5] authors suggested a method for correcting the color saturation in natural scene images, by iteratively processing and comparing the average saturation with the preset threshold T_{sat} . Hue, saturation and intensity are the attributes of color. Hue is that attribute of a color which decides what kind of color it is, i.e., a red or an orange. If hue is changed then the color gets changed, thereby distorting the image. One needs to improve the visual quality of an image without distorting it for image enhancement. In [6] authors suggested a novel and effective way of tackling the gamut problem during the preprocessing itself. In this way they used the HSV space for enhancement while hue was kept preserved. The proposed technique for noisy color images indeed enhanced the image but the clarity of the enhanced image was still poor. In [7] authors proposed a similar approach by working only on the luminance component of HSV color space where the V component is divided into smaller blocks and then uses multiple steps to preserve the details. Conventional contrast

enhancement methods are application oriented and they need transformation functions and parameters which had to specify manually. In [8] authors proposed a decision tree based contrast enhancement algorithm to enhance the color images like dark, low contrast, bright, mostly dark simultaneously. These image categories were handled by piecewise linear based experimental method. This enhancement method was automatic and parametric free.

In [9] authors presented rule-based fuzzy operators in order to apply the principles of approximate reasoning to digital image processing. This work showed how a fuzzy operator, which was able to perform detail sharpening, could be designed. The results showed that the proposed technique was insensitive to noise. The gray level maximum had not been changed in the classical fuzzy enhancement method proposed in [10], so this method was not fit for the enhancement problem of degraded images with less gray levels and low contrasts; the fact that the range of membership function of gray levels was not normalization form, i.e. [0,1], is another disadvantage of the traditional fuzzy enhancement approach. To deal with the problems mentioned above, a generalized iterative fuzzy enhancement algorithm was proposed in [11]. A new image quality assessment criterion was suggested on the basis of the statistical features of the gray-level histogram of images to control the iterative procedure of the proposed image enhancement algorithm. Computer simulation results showed that this new enhancement method was more suitable than fuzzy enhancement and gray-level transformation for handling the enhancement problems of images with less gray levels and low contrasts.

Authors in [12] proposed a Gaussian type of fuzzification function that was containing a single fuzzifier and a new intensification operator called NINT that contained an intensification parameter. Fuzzifier had been obtained by maximizing the fuzzy contrast and the parameter was obtained by minimizing the entropy. This work was confined to the enhancement of gray images only. In [13] authors extended the approach in [12] for the enhancement of color images. In that work histogram was used as the basis for fuzzy modeling of color images. The main emphasis had been laid on the fuzzy entropy measure. The ‘index of fuzziness’ and ‘entropy’ [10] were used to represent the quantitative measures of image quality in the fuzzy domain, though the image quality remains subjective in nature.

Authors in [14] introduced a global contrast intensification operator (GINT), which contains three parameters, viz., intensification parameter, fuzzifier, and the crossover point. Gaussian membership function had been used to fuzzify the image information in spatial domain. Fuzzy contrast-based quality factor and entropy-based quality factor and the corresponding visual factors were defined to get desired appearance of images. By minimizing the fuzzy entropy of the image information with respect to these quality factors, the intensification parameters were calculated globally. By using the proposed technique, a visible improvement in the image quality was observed only for under exposed images. And authors in [15] extended the work of [14] for the overexposed images also. In [14] histogram was divided into two regions on the basis of value of exposure which were fuzzified separately. Bacterial foraging optimization algorithm [16] was used to find the parameters of membership function. Further extension of this work was presented in [17]. In this authors partitioned the image into three regions which were named as underexposed, overexposed and mixed region. In this Ant colony optimization [18] was introduced to tune the membership function.

II. PROPOSED METHODOLOGY

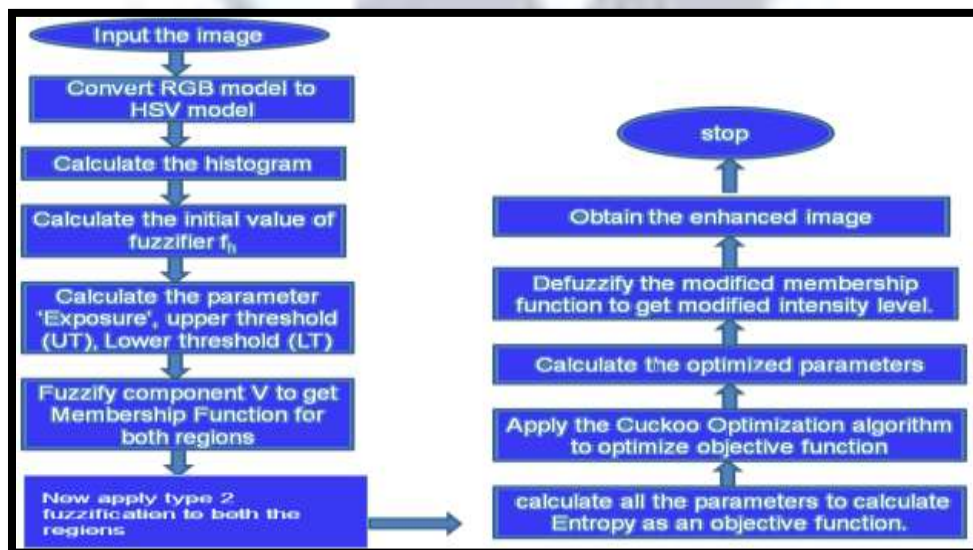


Fig. 1: Flowchart of proposed methodology

The complete work has been framed in to a flowchart as shown below in Fig. 3.1. Direct enhancement of the RGB color space is inappropriate for the human visual system, since it may produce color artifacts and distort the original color (hue) of the image. Hence, the chromatic and achromatic information should be decoupled, which is the reason for using HSV color space in this work.

In this approach, luminance component of HSV color space has been used, where the V component is divided into smaller blocks and then uses multiple steps to preserve the details. A method for the automatic enhancement of all types of degraded images has been proposed in this work. The saturation is varied depending upon the region and luminance, while keeping the hue of the image fixed. The exposure [16] is used for the division of the histogram into two parts underexposed and overexposed. The value of exposure is taken as the initial value for another variable pivot, which is further used for calculating the lower threshold [LT] and upper threshold [UT] to categorize the image into under, mixed and over-exposed regions. Type 2 fuzzification function and sigmoid operator are for the enhancement. The parameters of the operators are varied to a particular type of degradation. The minimization of the proposed objective function which is a function of Shannon entropy and visual appeal leads to enhancement of the image by stretching intensity (V) component of pixels about the crossover point. The entropy and visual factor involved in the objective function are optimized using the evolutionary algorithm [19]. Afterwards, accordingly image is defuzzified and brought back to RGB model. The detailed discussion on the proposed methodology has been discussed in coming sections.

A. Image Partition Based on Exposure

Images of scenes seldom appear natural in comparison to their visual perception; hence histogram of image fails to occupy the whole dynamic range. It is known that when intensity distribution is skewed towards the lower part of the histogram then the region appears darker whereas when it is skewed towards the upper part of the histogram then the image appears brighter. In both the cases, the image is perceived as blurred. The images, in these situations are known to possess a high dynamic range; in that they have regions of underexposed, overexposed and mixed region. By underexposed or overexposed regions in an image, it is meant that the region where a group of neighborhood pixels have grey levels very close to either the least or the highest respectively of the available dynamic range. It may be noted that when dealing with color images, only the V component of HSV is utilized for the purpose of delineation of an image histogram into underexposed, mixed-exposed and overexposed regions.

The parameter — “exposure” which is a measure of intensity exposition in an image is used to categorize the image into different regions. Every image is now considered as a mixed image containing a certain percentage of each type of regions. The parameter “exposure” which acts as an initial pivot for the division of an image into the under- and over-exposed regions is given by,

$$\text{Exposure} = \left(\frac{1}{L}\right) \left(\frac{\sum_{z=1}^L p(z)*z}{\sum_{z=1}^L p(z)}\right) \quad (3.5)$$

wherez indicates the grey-level of a pixel, p(z) denotes the histogram and represents the number of grey levels in an image. Since a single parameter cannot characterize the under, mixed and over-exposed regions of an image, two threshold parameters: Upper Threshold (UT) and Lower Threshold (LT) are introduced. All grey levels below UT are assumed to lie in the underexposed region and all grey levels above LT lie in the overexposed region. The remaining pixels lie in the mixed region. Thus it has been divided the grey levels into three parts: for the [0 : UT – 1] underexposed region, [UT : LT – 1] for the mixed region and [LT : L – 1] for the over exposed region. The two thresholds and can be expressed in terms of L and three parameters as

$$UT = L(\alpha - u) \quad (3.6)$$

$$LT = L(\alpha + l) \quad (3.7)$$

where α is the pivot, u lies in the range of 0 to α and l lies in the range to $(1 - \alpha)$. These parameters are assumed to lie in the range [0,1]. If the values of u and l are close to 0 and α is close to 0.5, then the image is found to be of pleasing nature. Different operators are defined for the enhancement of the underexposed and overexposed regions.

For the mixed type images, processing should be done simultaneously to obtain an image of pleasing nature. Before the start of enhancement, an image is classified into three regions and then each region is processed separately. Initially the value of pivot α is set to exposure and its optimum value is found by Cuckoo optimization Algorithm (COA). In order to simplify the computations, both u and l are set to 0.1.

B. Fuzzification of the image through Type-2

In many image processing applications, the image information to be processed is uncertain and ambiguous. For example, the question of whether a pixel should be turned darker or brighter from its original gray level comes under the realm of the fuzzy approach. In image processing, some objective quality criteria are usually defined to ascertain the goodness of the results, e.g., the image is good if it possesses a low amount of fuzziness indicating high contrast. The human observer, however, does not perceive these results as good because his/her judgment is subjective and different people differently judge the image quality. Fuzzy type-2 techniques offer powerful tools that efficiently deal with the vagueness and ambiguity of images by associating a degree of belongingness to a particular property.

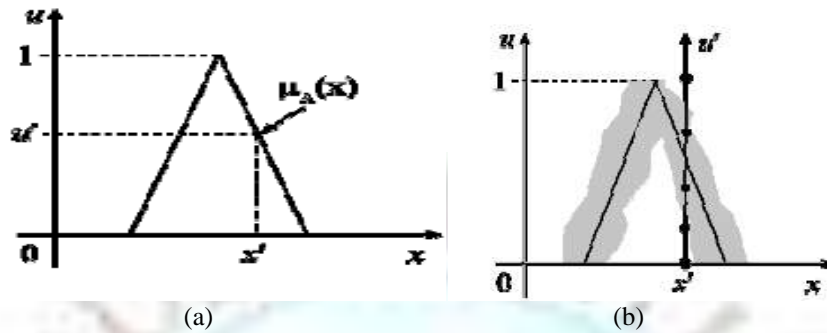


Fig. 2: Membership function (a) Type-1 and (b) Type-2

Fuzzy type-2 set theory was introduced by L. A. Zadeh. Type-2 set are the improvements or an extension to the type-1 sets. Type-2 play an important role in finding the exact membership function where there is uncertainty in its shape, its location or in its other parameter. Thus the clear difference comes between Type-1 and Type-2 is that Type-2 fuzzy logic systems gives more degree of freedom for better representation of uncertainty as compared with type-1 fuzzy sets.

The four source of uncertainty have been identified for type-1 fuzzy logic system are as Uncertain meaning of the words, Consequences associated with a histogram of values, Uncertain measurements, noisy data. These uncertainties in fuzzy sets have crisp membership functions makes them unable to model such uncertainty. Fig. 3.5 (a,b) shows that by blurring the membership function of type-1 we can obtain type-2 fuzzy set. And the value of x' , instead of a single value membership function u' , the membership function takes on value wherever the vertical line intersects the blur as shown in fig. 3.5(b). This due to because there is no need to weight those value the same, we can assign an amplitude distribution to all of them. To perform all these thing, we create three-dimensional membership function, which is a type-2 membership function that characterizes a type-2 fuzzy set.

We can characterize a type-2 fuzzy set \tilde{A} as [34]

$$\tilde{A} = \{ (x, u, \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1] \} \tag{3.8}$$

Where J_x is the primary membership of x and $\mu_{\tilde{A}}(x,u)$ is a type-2 membership function and $0 < \mu_{\tilde{A}}(x,u) \leq 1$. The footprint of uncertainty (FOU) which represents the uncertainty in the primary membership of the type-2 fuzzy set \tilde{A} is expressed as

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x \tag{3.9}$$

he shaded region in fig. 3.5 (b) indicates FOU. In [20] the author indicates that in order to develop a fuzzy type-2 logic system. We need to be able to perform set theoretic operations on type-2 fuzzy sets know properties of membership grades of type-2 sets deal with type-2 fuzzy relations and their compositions perform type reduction and defuzzification to obtain a crisp output from the fuzzy logic system. The technique that describe above is used to enhancement the image

C. Objective Function for Optimization

Since the difference in visual factor provides the measure of uncertainty associated with the change in image perception as a result of enhancement and the entropy function, constructed from the MFs, also represents the uncertainty associated with

the image information. Therefore, combination of both factors is treated as an objective function. Therefore, if the desired visual factor V_{sf} is known corresponding to the VF, then the attainment of their equality is posed as a constraint, in the optimization of objective function. This constrained optimization can be framed as

Optimize the entropy function
 Subject to the constraint $V_{sf} \approx VF$

For this, an objective function is set up as

$$J = E + \epsilon e^{\lambda |VF - V_{sf}|} \quad (3.33)$$

where, ϵ is a Lagrangian multiplier and λ is a constant. The optimization of the objective function is done by taking parameters in the ranges $1 < t < 10, 1 < h < 10, \text{ and } 0 < \alpha < 255$. For the sake of simplicity, the value $\epsilon = 1.65$ is considered and $\lambda = 0.6$ to achieve the better optimization of Eq. (3.33). In this paper, an evolutionary learning technique, viz., Cuckoo Optimization Algorithm (COA) [33] has been presented, that finds the parameters by optimizing the objective function given in Eq. (3.33).

Optimization is the process of making something better. In other words, optimization is the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or result. The input consists of variables: the process or function is known as the cost function, objective function, or fitness function; and the output is the cost or fitness. There are different methods for solving an optimization problem. Some of these methods are inspired from natural processes. These methods usually start with an initial set of variables and then evolve to obtain the global minimum or maximum of the objective function. Genetic Algorithm (GA) has been the most popular technique in evolutionary computation research. Genetic Algorithm uses operators inspired by natural genetic variation and natural selection. Another example is Particle Swarm Optimization (PSO) which was developed by Eberhart and Kennedy in 1995. In this work, introduction of a new evolutionary optimization algorithm which is inspired by lifestyle of a bird family called cuckoo. Specific egg laying and breeding of cuckoos is the basis of this novel optimization algorithm. Cuckoos used in this modeling exist in two forms: mature cuckoos and eggs. Mature cuckoos lay eggs in some other bird's nest and if these eggs are not recognized and not killed by host birds, they grow and become a mature cuckoo. Environmental features and the immigration of societies (groups) of cuckoos hopefully lead them to converge and find the best environment for breeding and reproduction. This best environment is the global maximum of objective functions.

III. RESULTS AND DISCUSSION

This work has been implemented on Intel(R) Core (TM) 2 Duo E8400 at 3.00GHz 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 test images and camera captured images from Fig. 4.1 to Fig. 4.8 and Fig. 4.9 to 4.17 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 based approach [29]. It is found that COA based proposed approach bestows more pleasing results and the enhancement of images is controlled by the optimizing the parameterst, h, f_h , and α_i .

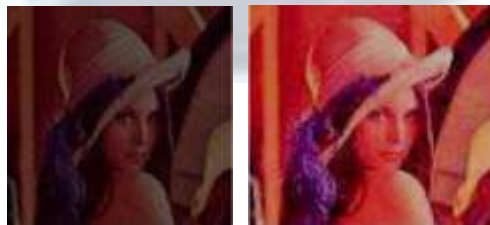


Fig. 3.1 (a) Original image of “Lena” and Enhanced image of “Lena” with the (b) .



Fig. 3.2 (a) Original image of “Man” and Enhanced image of “Man” with the (b) modified image with the proposed COA.

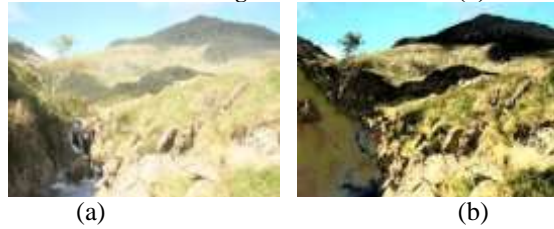


Fig. 3.3 (a) Original image of “Hills” and Enhanced image of “Hills” with the (b) modified image with the proposed COA.



Fig. 3.4 (a) Original image of “Face” and Enhanced image of “Face” the (b) modified image with the proposed COA.



Fig. 3.5 (a) Original image of “Doctor” and Enhanced image of “Doctor” with the (b) modified image with the proposed COA.



Fig. 3.6 (a) Original image of “Flower” and Enhanced image of “Flower” with the (b) modified image with the proposed COA.

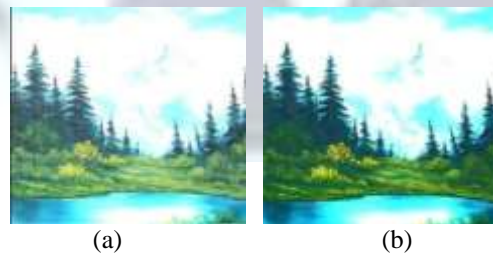


Fig. 3.7 (a) Original image of “Scene” and Enhanced image of “Scene” with the (b) modified image with the proposed COA.



Fig. 3.8 (a) Original image of “Rose” and Enhanced image of “Rose” with the (b) modified image with the proposed COA.

Fig. 3.8(a) shows the histogram for the image of “Face”, it can be seen how the intensity distribution gets modified after the enhancement as shown in Fig. 3.8(b). The shape of transformation curve depends 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 upon the region they operate on.

Table 4.1 presents the quantitative analysis of quality measure of all the images after enhancement which can be compared with the initial parameters of the images .. The images like Rose which are having V_0 approximately equals 1; indicates that image is overenhanced and the underexposed region operator does not work for this kind of image. But after applying the proposed technique some gray levels get shifted towards left on the scale of histogram and the final result shows some value of visual factor for under exposed region as well. It has been observed that proposed based approach with tuned membership function enhances the image with good color perception.

Initially zero value of V_0 for the images like Doctor, Lena etc. indicating the more content of dark region. Now, ACO based approach changes the overall visual factor by 45.53% and COA based technique changes visual factor by 33.92% showing that COA is computing the VFs more close to soothing factor as demonstrated by Table 4.2. Table 4.2 demonstrates the comparison of visual factors of all the images and the corresponding variations depending upon the density of gray levels of that image.

After applying the above mentioned techniques the visual factor changes respectively, gradually drawing closer towards soothing factor, hence the visual appearance of the images gets enhanced. The visual factor after applying COA seems to serve as good indicator of effect of enhancement of appearance of image as compared to ACO.

Table 4.2 also shows the comparison of their execution time. It has been observed that the execution time of ACO is quite more than COA. ACO takes an average of 100 seconds to run an image while COA reduces this time by 96% and 97.3% respectively for the image like Lena and likewise for the camera image like God this reduction is 41.6%, and 60% respectively. Likewise the COA give the fast results for other images like Lilly, Cricketer, where ACO execution was 83.53, 93.7, 113.2, 182.07, respectively. Therefore, the crux of this discussion is that the enhancement occurs quite faster by using COA. It means that COA speeds up the process of enhancement.

Enhancement of saturation is necessitated in restoring the lost details of an image. As the value of saturation is reduced, the image regains its pleasing nature in the underexposed region whereas increasing the saturation helps the overexposed region. Fuzzy logic-based image enhancement has been undertaken by fuzzifying the color intensity property of an image. An image may be categorized into underexposed and overexposed and mixed regions with the amount of threshold values indicated by a parameter.

IV. CONCLUSION

A well tuned Gaussian MF suitable for underexposed and overexposed regions of the image has been used for the fuzzification. Enhancement of the fuzzified image has been carried out using a generalized intensification operator, i.e., GINT, of sigmoid type, which depends on the crossover point and the intensification parameter. The optimum values of these parameters have been obtained by the constrained fuzzy optimization.

Table 4.1 Optimized Parameters of Images after Enhancement

S. No.	Image	t	g	f_{hne}	J	E	ex ne w	V_{sf}	V_f
1	Lena	13.75	13.08	74.93	4.343	.7292	.2492	.2152	.1764
2	Man	8.292	9.611	80.60	1.571	.5457	.9245	1.404	.4546
3	Hills	6.540	10.40	113.4	1.846	.7105	.9567	.4310	.7357

4	Face	10.64	11.84	13.72	10.64	.7532	.168	.7963	.4472
5	Doctor	7.32	5.52	84.6	4.326	.6196	.9214	.1903	.5129
6	Flower	11.13	14.89	15.93	3.201	.7287	.5500	.9652	.5845
7	Scene	10.86	7.279	99.76	2.166	.7663	.8044	1.163	.3757
8	Rose	11.86	5.569	17.96	2.299	.5855	.5962	.9611	.1620

Table 4.2 Comparison of Visual Factors and Time Taken of Proposed Approach fuzzy type-2 Approach

S. No	Image	Type 1 (Time in sec.)	Type 2 (Time in sec.)	V _f (Type 1)	V _f (Type 2)
1	Lena	5.213	1.085	1.23	.1764
2	Face	33.52	1.252	.9734	.4472
3	Doctor	16.55	1.258	1.024	.5129
4	Scene	7.657	1.514	.9120	.3757
5	Hill	18.67	1.402	1.232	.7357
6	Flower	24.87	1.404	1.342	.5845
7	Rose	39.43	1.263	.8567	.1620
8	Man	13.90	.9831	.9893	.4546

Uncertainties may arise in different guises which sometimes are difficult to model or an image of non-linear nature shows difficulty during enhancement. So, any technique which can model the uncertainties in better way or can encounter the non-linearities may be targeted as future scope.

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