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A Novel Texture Based Automated Histogram Specification for Color Image Enhancement Using Image Fusion

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Abstract

A novel texture based color image enhancement methodology that focuses on an automated way of target image generation is proposed here. The images in the database with highest histogram correlation with input image are identified for extracting different features. Target image is obtained by fusing images selected based on minimum Euclidean distance between extracted features. The proposed method is a simple color image enhancement methodology where the range (the gamut) of the R, G, and B channels is optimally preserved. We derive a new quantitative validation approach to identify visibility loss problem that may occur during enhancement. The maximum possible contrast enhancement is achieved by stretching the intervals of the color levels to the maximum possible extent using a sigmoid function. The proposed method has been compared with other state-of-the-art algorithms reported in the literature

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Keywords: Color Image Enhancement;Texture;Image Fusion;Color Images;Sigmoid Function.

1. Introduction

Because all images contain features that are hardly detectable by eye, we often transform images to reveal those features. Contrast generally refers to the difference in luminance or gray level values in an image. It is the property which enables us to differentiate between the varying details in an image. Contrast enhancement[9] is an

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image processing technique that is used to increase the contrast of an image, thereby preserving the natural look of the images.

Numerous contrast enhancement techniques exist in literature, such as gray-level transformation techniques (e.g., logarithm transformation, power-law transformation, piecewise-linear transformation, etc.) and histogram processing techniques (e.g., Histogram Equalization (HE), Histogram Specification etc)[9]. Histogram Equalization (HE) is one of the most well-known methods for contrast enhancement. It is useful for images with poor intensity distribution. Moreover, it cannot be applied directly to color images, because HE applied to each color channel independently disturbs perceived colorfulness of the obtained image.

The existing state-of-the-art methods includes Naik & Murthy[3], Exact Histogram based method[12], Histogram Warping[7], method proposed by Ancuti et.al[13] etc. The main feature of work presented by Naik & Murthy lies in the way of extending any gray scale image enhancement method to color images without encountering gamut problem. The overall enhancement obtained by this method depends on the already existing different contrast enhancement functions for gray scale images. In Exact Histogram based methods, the input histogram is mapped to target image histogram. The enhancement depends on the method used to generate target histogram. Histogram Warping is an algorithm for global contrast enhancement of images with multimodal histograms. To locate modes and valleys, histogram analysis is performed by kernel density estimation. This enhancement technique cannot be applied to different category of images. The method proposed by Ancuti et.al is generally indented for enhancing those images that are degraded by fog, haze etc.

In conventional as well as state-of-the-art algorithms, enhanced output image depends on target image which in turn depends on the method used to generate it. The existing traditional approaches are time consuming and do not achieve enhancement up to the expected level of human vision. They lack the ability to provide discriminate way of enhancement to various categories of input images based on their statistical features. Most of the existing techniques are intended only for certain category of images. These are all well known algorithms that independently handle gamut problem effectively[3], but lack capability to handle loss of visibility problem. Visibility [10] is a measure of how clearly an image can be viewed and it is an essential property which has to be improved after enhancement.

Each image is unique in its statistical parameters. If the selection of target image could be automated based on these statistical parameters, different level of enhancement can be achieved for various categories of images. This approach can make enhancement task more effective. But no such research work has yet been reported in the area of image enhancement.

When an input image is given, it can be compared against images in database to retrieve highly correlated set of images. Some of the well known statistical parameters can be computed from input[5] as well as from correlated set of images. Each computed parameter of input image is compared against stored vector by computing Euclidean distance[11]. The statistical parameter which results in minimum Euclidean distance is taken as the criteria for selecting images for fusion. The selected images are fused hierarchically to obtain fused images. Among the obtained set of fused images, one with highest entropy is selected as target image. EME[2] is defined as the measure of enhancement, or measure of improvement. The EME of target image is compared with EME of input image to ensure success of enhancement. It was observed that, if the EME of target image is lower compared to EME of input image, histogram specification can lead to loss of visibility. In such cases, the number of images in the database is increased so that the algorithm can find most suitable target image for enhancement.

In this paper, we propose a novel texture based automated histogram specification for color image enhancement. The proposed method is capable of enhancing distinct categories of images like low contrast image, image with non-uniform illumination, fog image etc. The entire process is divided into four phases: (i) Target Image Generation phase (ii) Quantitative Validation phase (iii) Histogram Specification phase (iv) Post Processing phase.

The rest of the paper is organized as follows: Sections 2 sketches our texture based color image enhancement methodology. Section 3, evaluates our algorithm analytically by computing Contrast Improvement Index (CII) [4], Absolute Mean Brightness Error (AMBE) [8], and EME. The obtained results are compared with state-of-the-art techniques such as Naik & Murthy and method proposed by Ancuti et.al. We conclude our work with a brief discussion in Section 4.

2. Proposed Method.

A novel color image enhancement technique that adaptively generates the good quality target image for different categories of input image is proposed. The image database that we used in our work contains randomly selected set of images of distinct categories. This enables the algorithm in finding most similar images for image fusion such that, it would lead to generation of a good target image. Better the target image selected better would be the level of enhancement achieved. Fig. 1 shows the sample set of images stored in the image database. The proposed algorithm automatically finds a suitable target image from image database for input image using texture extraction[6], matching and image fusion. Fig. 2 shows the general framework consisting of different phases involved in the proposed image enhancement method.

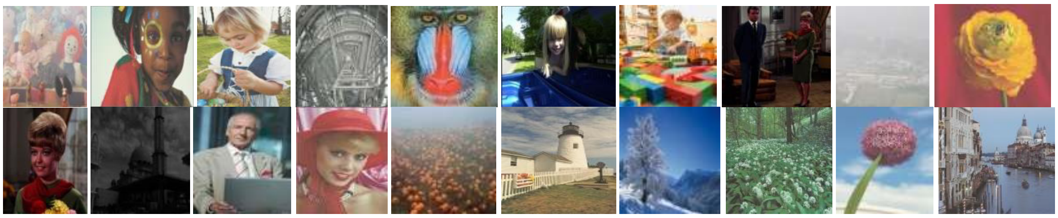


Fig.1 Sample set of images in the database.

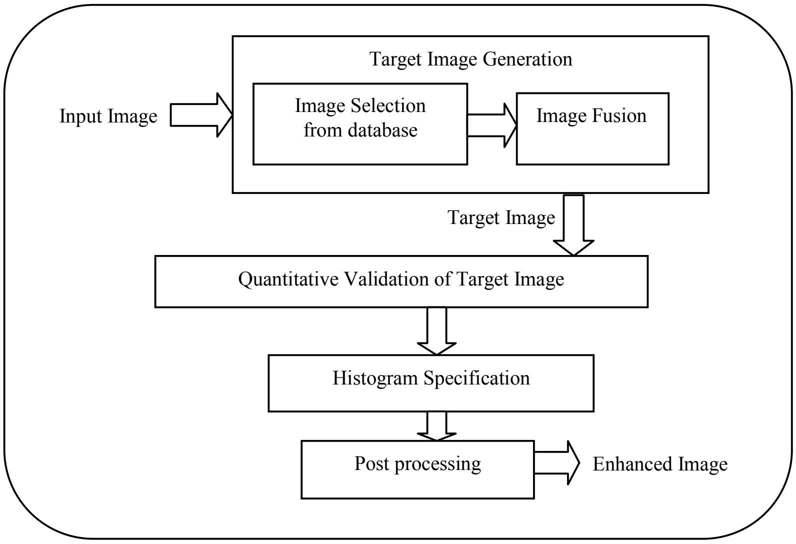


Fig. 2 General framework showing different phases in the proposed Image Enhancement Method.

2.1 Target Image Generation Phase:

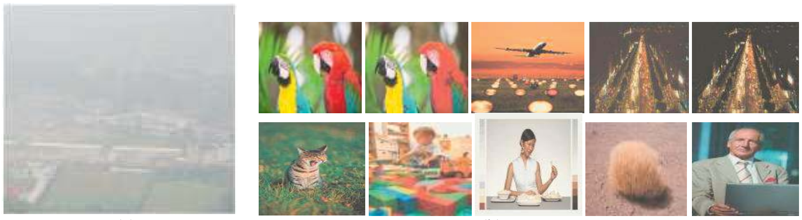
This phase deals with an automated way of generating a target histogram. It consists of following stages: (i) Image selection from database for fusion and (ii) Image fusion to obtain the target image.

2.1.1 Image selection from database for fusion

Let $f = (f_r, f_g, f_b)$ be the input RGB image to be enhanced, where f_r, f_g, f_b are its red, green and blue channels, respectively of size $M \times N$. Similarly, let f_d be the RGB image in the database. Let H_1 and H_2 represent the histogram of the grayscale versions of f and f_d, respectively, of same size. The correlation between the histograms H_1 and H_2 can be obtained as follows:

$$d(H_1, H_2) = \frac{\sum_i (H_1(i) - \bar{H}_1)(H_2(i) - \bar{H}_2)}{\sqrt{(\sum_i (H_1(i) - \bar{H}_1))^2 (\sum_i (H_2(i) - \bar{H}_2))^2}} \qquad \forall\, i \in \{1, 2, \ldots\ldots, 255\} \tag{1}$$

where $\bar{H}_k = \frac{1}{N}\sum_i H_k(i)$ and N is the total number of histogram bins. The histogram correlation is used to identify set of images in the database that are having highest histogram correlation with that of input image histogram because higher the correlation, higher would be the similarity between the features.



(a) (b)

Fig. 3 (a) Query image to be enhanced (b) Retrieved set of highly correlated images from the database.

Let $I = \{I_1, I_2, \ldots, I_n\}$ represent the retrieved set of highly correlated images from the database (as shown in Fig. 3). Different statistical parameters such as mean[9], entropy[10], and visibility[10] are extracted from f and I. Mean (μ) represents the average intensity value of an image, Entropy (q) measures the information content in an image and Visibility (V) can be defined as a measure of how clearly an image can be seen or viewed. Mathematically, these parameters can be represented as:

$$\mu = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} f_{m,n} \tag{2}$$

where $f_{m,n}$ represent image pixel value and MN represent the total number of pixels in the image.

$$\text{Entropy (q)} = -\sum_{i=0}^{255} p(i) \log_2 p(i) \tag{3}$$

where $p(i)$ is the Probability Density Function (PDF) defined over the image.

$$V = \sum_{m=1}^{M} \sum_{n=1}^{N} \left| f_{m,n} - \left(\frac{\mu}{\mu^{\alpha+1}}\right) \right| \tag{4}$$

where $f_{m,n}$ represent image pixel value, μ represent mean intensity value of the image and α is a visual constant which typically holds value from 0.6 to 0.7.

Euclidean distance[11] between the vectors containing the above mentioned set of extracted features of input image f and database image in I can be computed as:

$$\text{Euclidean distance, } d\,(x_f, x_d) = \left\| x_f - x_d \right\|^2 \tag{5}$$

where $x_f = [\mu_f, E_f, V_f]$ and $x_d = [\mu_d, E_d, V_d]$ represent computed mean, entropy and visibility of input image f and database image in I, respectively. A set of five images among I having the minimum distance value are selected for image fusion [as shown in Fig. 4].

Fig. 4 Image set selected for fusion

2.1.2 Image Fusion to Obtain a Target Image.

The set of five images selected for fusion will be most similar with input image in their features. To obtain the target image, image fusion technique is used. Image fusion[10] is the process of combining two or more images such that the resultant image will be having information from the entire source images selected for fusion. In this method, image fusion is done based on entropy. Other features like visibility, histogram similarity can also be used, but empirically it was found that reference image selected based on entropy contributed much in achieving maximum enhancement.

Image fusion principle: While fusing two images, one is selected as foreground image and other as background image. The parameter β defines the rate of mixing of these images, where β∈ (0,1). Let $I' = \{I_{1,} I_{2,}, \dots \dots \dots, I_5\}$ represent the set of selected images for fusion such that $I' \subset I$ and $E = \{e_1, e_2 \dots \dots, e_5\}$ represent the entropy of all images in I'. A new set of images can be obtained by fusing all combinations of images in I'. Let X, Y represent two of the images selected from I' to be fused and e_1, e_2 represent their entropy, respectively. Value of parameter β can be set based on the following conditions:

$$\beta = \begin{cases} 0.25, & e_1 < e_2 \\ 0.75, & e_1 > e_2 \\ 0.5, & e_1 = e_2 \end{cases} \tag{6}$$

Let $X_{m,n}$, $Y_{m,n}$ represent pixel values of images to be fused, and $Z_{m,n}$ represent pixel values of the fused image. Then, $Z_{m,n}$ can be computed as:

$$Z_{m,n} = \beta\,(X_{m,n}) + (1 - \beta)\,(Y_{m,n}) \tag{7}$$

Let $Z = \{Z_{1,} Z_{2,}, \dots \dots \dots, Z_{10}\}$ be the set of fused images obtained. From this set, one with highest entropy is selected as target image (f'). Fig. 5 shows the set of fused images obtained by fusing all combinations of two images from I'.

Fig. 5 Generated set of fused images.

2.2 Quantitative validation.

This phase deals with quantitative validation of target image selected to ensure success of enhancement. This is done prior to histogram specification[9]. It is necessary because we empirically found that if the selected target histogram is unsuitable for the input image, histogram specification of input image with respect to target image histogram would result in loss of visibility rather than enhancement. We refer to this problem as Visibility Loss problem.

Visibility Loss problem: Visibility loss problem generally occur due to failure in identifying a suitable target image from database corresponding to the input image for histogram specification. The significance of the target image selected is identified by measuring the EME of input image and target image. Empirically it was found that, for successful enhancement EME of target image selected must be greater than EME of input image so that histogram specification would ultimately result in effective enhancement. If the specified condition is not satisfied, histogram specification would lead to visibility loss problem.

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

Fig.6 (a) Input image (EME = 7.6019) (b) Target image (EME = 2.6838) (c) Enhaned image with visibility loss (EME = 5.4843) (d) New target image (EME = 9.112) (e) Enhnced image without visibility loss (EME = 10.3699).

Fig. 6 illustrates handling of visibility loss problem that may occur during enhancement. Fig. 6(a) shows the input image to be enhanced with EME= 7.6019, 6(b) shows the selected target image with EME= 2.6838 and 6(c) shows the enhanced image which contains the visibility loss problem with EME= 5.4843. This problem can be solved by increasing the number of images in the database so that the algorithm can successfully identify a target image by fusing images more closer to the input image. Initially, in our experiment the database consisted of around 200 images of different categories. By extending the number of database images to 350, we could identify appropriate target images for more category of input images, which made enhancement task more efficient. Fig. 6(d) shows new target image selected with EME= 9.112 and 6(e) shows the enhanced result obtained with EME = 10.3699. But increasing the number of images in database, may increase the computational time required for database search. Such problem can be solved to a great extent by using an efficient clustering algorithm like BIRCH[1] which can deal with large data sets.

2.3 Histogram Specification.

The objective of Histogram Specification (HS) [9] is to generate an output image that has a specified desirable histogram. Let $h_{f_c}, h_{f_c'}$ represent the histograms of f_c and f_c' respectively, for a particular color channel c. The cumulative distribution functions F_{f_c} and $F_{f_c'}$ for h_{f_c} and $h_{f_c'}$ can be obtained, respectively as:

$$F_{f_c} = \sum_{i=o}^{j} h_{f_c}(\mathrm{i}) \qquad j \in \{0, 1 \dots \dots, L-1\} \qquad (8)$$
$$F_{f_c'} = \sum_{i=o}^{j} h_{f_c'}(i)$$

A look-up table can be designed by looking for gray level match. For each gray level $h_{f_c}(l) \in \{0, 1 \dots, L-1\}$ find corresponding $h_{f_c'}(j)$ such that $F_{f_c'}(j)$ best matches $F_{f_c}(l)$. This value can be maintained in the look-up table as $lookup_c(l) = j$. Finally, the enhanced image $\hat{f}_c$ is obtained by replacing each pixel in f_c with the corresponding value j obtained from the look-up table as follows:

$$\hat{f}_{c(m,n)} = lookup_c(f_{c(m,n)}) \qquad (9)$$

After histogram specification, it is possible that the range of r, g and b channels in $\hat{f}$ may not be optimally preserved resulting in gamut problem.

Gamut problem: We know that for the input color image $f_c \in \{0, 1, \dots \dots, L-1\}$ $\forall c \in \{r, g, b\}$, where L represent the maximum number of possible gray level value. The enhanced image $\hat{f}$ of f can be correctly displayed or visualized only if

$$\hat{f}_c \in \{0, 1..., \mathrm{L}-1\} \qquad \forall c \in \{r, g, b\} \qquad (10)$$

To detect whether the enhanced image $\hat{f}$ has gamut problem or not, we adopted the following procedure. Find the maximum and minimum value in the enhanced image $\hat{f}$ for a particular color channel c as follows:

$$mx_c = \max\{\hat{f}_c\}, \qquad mn_c = min\{\hat{f}_c\} \tag{11}$$

Then the gamut problem is identified for the enhanced image $\hat{f}$, if $mx > L-1$ or if $mn < 0$. In such a situation, the pixel values of $\hat{f}$ can be redefined as follows:

$$\hat{f}_c = (\hat{f}_c - mn_c)/(mx_c - mn_c) \qquad \forall c \in \{r, g, b\} \tag{12}$$

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

Fig.7 (a) Input image (b) Target image (c) Enhanced output image with gamut problem and (d) Enhanced image preserving the color gamut.

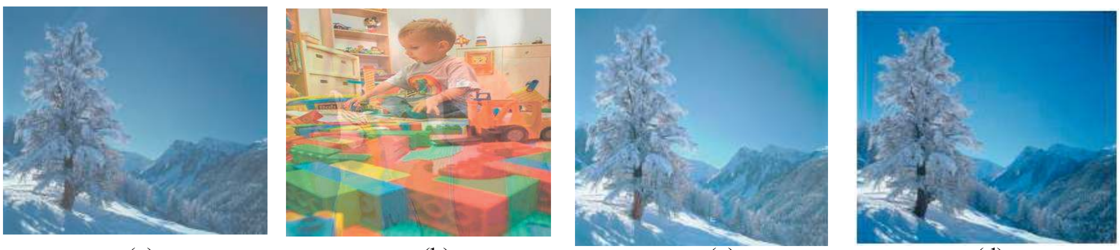
Fig.7 illustrates handling of gamut problem by proposed method. Fig. 7(a) shows the input image to be enhanced with EME= 1.2913, 7(b) shows the selected target image with EME=2.6838, 7(c) shows the enhanced image which contains the gamut problem with EME=4.8609 and 7(d) shows enhanced image obtained preserving the gamut by normalization with EME= 5.6573.

2.4. Post Processing

Post processing enhances the quality of a finished image by making them visually clearer as well as by retaining the look and feel of the image. Here, post processing is done using sigmoid function. Sigmoid functions[5] are continuous non-linear functions that maps entire range of x to the domain [0, 1] of y. The sigmoid function is applied on each independent channel of $\hat{f}$ as follows:

$$\hat{f}_{c(m,n)} = \hat{f}_{c(m,n)} + k_1\left(\frac{\hat{f}_{c(m,n)}}{1-e^{\left(k_1\left(k_1+\hat{f}_{c(m,n)}\right)\right)}}\right) \qquad \forall\, c \in \{r, g, b\} \tag{13}$$

where $\hat{f}_{c(m,n)}$ represent image pixel value of a particular color channel c of $\hat{f}_c$ and k_1 is empirically taken as 0.75. This function further enhances the image by stretching the intervals of the color levels to the maximum possible extent. Fig. 8 shows the image enhancement results obtained after applying the post processing method.



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

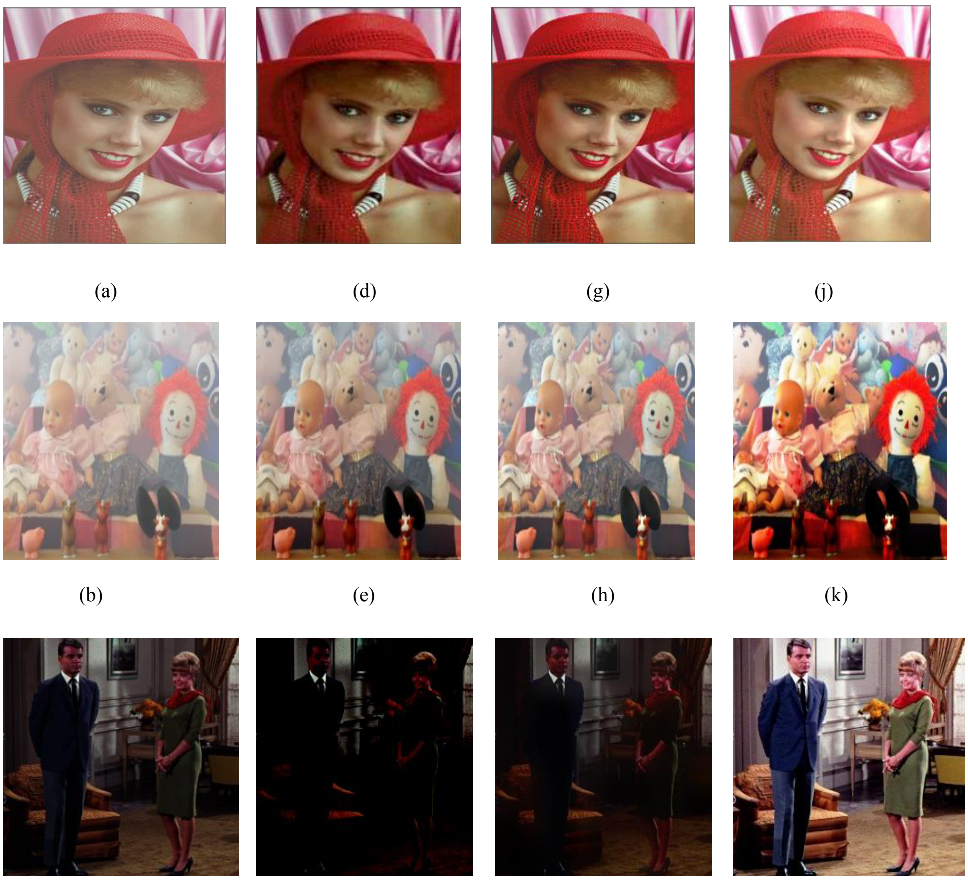
Fig.8 (a) Input image (EME= 5.4644) (b) Selected target image (EME=5.653) (c) Enhanced image before post processing (EME= 6.3160) (d) Enhanced image after post processing (EME=7.321).

3. Experimental Results:

In this section, we evaluate the performance of the proposed algorithm and compare it with two state-of-the-art methods Naik & Murthy[3] and Ancuti et.al's method[13]. The database used in the experiment consists of 400 images taken from the standard image data set. The samples in the database include low contrast images, fog images, etc. We have used three evaluation metrics; EME[2], AMBE[8] and CII[4] to prove the superiority of the proposed method over Naik's method and Ancuti et.al's method.

Fig. 9 shows the experimental result obtained for three images belonging to the categories of image with color gamut problem, fog image and low contrast image, respectively. Result analysis shows that the state-of-the-art methods are capable of enhancing certain category of images and fails when a distinct category of input image is given. This is because either they are meant for enhancing a particular type of images or the enhancement depends upon method used to obtain target image. From the results obtained, we can see that proposed method is capable of enhancing different categories of images since it is using automatic generation of target image based on the texture of the input image to be enhanced.

The quantitative values obtained for the various evaluation metrics are shown in Table 1. EME values obtained for the proposed method show that they are comparable with the state-of-the-art methods used. AMBE values are lower in the proposed method which indicates that brightness of the original image is preserved in the enhanced image. The values obtained for CII in proposed method shows that there is significant improvement in contrast of the enhanced image. Subjective analysis of results in Fig. 9 shows that the proposed method outperforms the state-of-the-art methods.



(c) (f) (i) (l)

Fig. 9 (a) Input image $Lady$ (b) Input image $Doll$ (c) Input image $Couple$ (d)-(f) Enhancement resluts of Naik & Murthy's method (g)-(i) Enhancement results of Ancuti et.al's method (j)-(l) Enhancement results of the proposed method.

Table 1: Quantitative Evaluation of the proposed method.

Image	Original Image			Naik & Murthy			Ancuti et al			Proposed method		
	EME	AMBE	CII	EME	AMBE	CII	EME	AMBE	CII	EME	AMBE	CII
Lady	4.5189	-	-	8.9303	0.1708	1.2327	7.9303	0.1098	1.2325	7.5678	0.0046	1.2435
Doll	3.4669	-	-	6.7063	0.1908	1.3327	8.9303	0.1497	1.8287	8.9303	0.1703	2.2586
Couple	20.247	-	-	14.9303	0.498	0.8657	18.9304	0.413	0.8732	38.9303	0.1708	1.2327

4. Conclusions.

This paper presents a novel texture based, automated way of generating target image for color image enhancement. The proposed method uses an adaptive target image generation based on the statistical parameters of input image to be enhanced. Performance of the proposed method depends on the features of images selected for fusion and the quality of target image generated. The proposed algorithm contains a new quantitative validation approach to detect Visibility Loss problem and its solution. The proposed method also efficiently handles the gamut problem. Here, post processing is done using sigmoid function to achieve the maximum image enhancement. As shown in experimental analysis, the proposed method has been proved to be a successful approach to deal with various categories of images.

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