

# Color Image Enhancement by Fuzzy Intensification

M.Hanmandlu  
Dept. of Elect. Engg.  
I.I.T., Delhi  
New Delhi-110016  
[mhmandlu@hotmail.com](mailto:mhmandlu@hotmail.com)

Devendra Jha  
Dept. of Elect. Engg.  
I.I.T., Delhi  
New Delhi-110016  
[devendrajha@hotmail.com](mailto:devendrajha@hotmail.com)

Rochak Sharma  
Dept. of Elect. Engg.  
Delhi College of Engg.  
Delhi -110042  
[rochak@mailandnews.com](mailto:rochak@mailandnews.com)

## Abstract

A Gaussian membership function to model image information in spatial domain has been proposed in this paper. We introduce a new contrast intensification operator, which involves a parameter  $t$  for enhancement of color images. By minimizing the fuzzy entropy of the image information, the parameter  $t$  is calculated globally. A visible improvement in the image quality for human contrast perception is observed, also demonstrated here by the reduction in 'index of fuzziness' and 'entropy' of the output image.

## 1. Introduction

Fuzzy sets [1] offer a problem-solving tool between the precision of classical mathematics and the inherent imprecision of the real world. The imprecision in an image is contained within gray or color value to be handled using fuzzy sets [2]. An image can be considered as an array of fuzzy singletons having a membership value that denotes the degree of some image property.

Fuzzy logic was used in [3] for improving contrast in an image. Fuzzy rule based image enhancement and noise smoothing are discussed in [4]. Choi and Krishnapuram [5] have suggested a robust fuzzy filtering technique for noise removal and edge enhancement. Hanmandlu et al. [6] have attempted contrast stretching by fuzzy modeling of image information. However, these works have been confined to the enhancement of gray images only. In this paper, we use histogram as the basis for fuzzy modeling of color images. The main emphasis has been laid on the entropy based fuzzy modeling for contrast intensification of color images. Though the image quality is subjective in nature, yet we attempt to use the quantitative measures such as 'Index of fuzziness' and 'entropy' [3] to represent the image quality in the fuzzy domain.

## 2. Fuzzification and Intensification

An image  $I$  of size  $M \times N$  and intensity level in the range  $(0, L-1)$  can be considered as collection of fuzzy singletons in the fuzzy set notation,

$$I = \cup \{ \mu_X(x_{mn}) \} = \{ \mu_{mn}/x_{mn} \} ; m=1,2,\dots,M; n=1,2,\dots,N \quad (1)$$

where  $\mu_X(x_{mn})$  or  $\mu_{mn}/x_{mn}$  represents the membership or grade of some property  $\mu_{mn}$  of  $x_{mn}$ .  $x_{mn}=0,1,\dots,L-1$  is the color intensity at  $(m,n)^{th}$  pixel. For a color image, the membership functions are taken for the unions of all colors  $X$ ,  $X \in \{R, G, B\}$  or  $X \in \{H, S, V\}$ . For the transformation of the color  $X$  in the range  $(0, 255)$  to the fuzzy property plane in the interval  $(0,1)$ , a membership function of the Gaussian type :

$$\mu_X(x_{mn}) = \exp(- (x_{max} - x_{mn})^2 / 2f_h^2) \quad (2)$$

is often selected, as it involves a single fuzzifier,  $f_h$ .

Here,  $x_{max} \leq L-1$ , is the maximum color value present in the image. The membership values are restricted to the range  $[\alpha, 1]$ , with  $\alpha = \exp(-x_{max}^2/2f_h^2)$ . For computational efficiency, histogram of color  $X$  is considered for fuzzification. So,  $\mu_X(k)$  represents the membership function of color  $X$  for a value  $k$ ,  $k=0,1,2,\dots,L-1$ ,

$$\mu_X(k) = \exp[-(x_{max}-k)^2/2f_h^2] \quad (3)$$

This function is the same as in (2), with  $x_{mn}$  replaced by an index  $k$ , the intensity at the  $(m, n)$  th spatial location. Fig. 4.a shows the Gaussian membership function of color intensity with typical  $f_h = 135, 112$  and  $95$ . It is observed that at higher values of  $f_h$  the image will be brighter.

The membership values are transformed back to the spatial domain after the desired operator is applied in the fuzzy domain. The corresponding inverse operator from fuzzy domain to spatial domain is given as:

$$k' = x_{max} - (-2 \ln [\mu'_X(k)] f_h^2)^{1/2} \quad (4)$$

where,  $\mu'_X(k)$  and  $k'$  are the modified membership function and intensity value respectively.

We are confined to image enhancement using fuzzy contrast intensification operator. The original contrast intensification operator, INT[1] depends on the membership function only. It needs to be applied successively on an image for obtaining the desired

enhancement. This limitation is removed in the proposed new intensification (NINT) operator using a sigmoid function given by:

$$\mu'(k) = \frac{1}{1 + e^{-t(\mu_X(k) - 0.5)}} \quad (5)$$

A plot of  $\mu_X(k)$  Vs  $\mu'_X(k)$  for different values of parameter  $t$  is shown in Fig.4. It is observed that except for values of  $t > 5$ , the NINT operator, shown in Fig.4(d), has a similar response as that of INT operator, shown in Fig. 4(c). If the parameter  $t$  were incremented by 1 in the NINT operator, the gap between successive curves would be much less than that due to INT operator applied repetitively. Thus minute changes in the level of enhancement are possible with the new operator. The changes in the membership function using the NINT operator are shown in Fig. 4(b) and 4(d). Unlike INT operator, NINT operator does not change uniformly. At the extremes, the change in the membership function is marginal and is faster as well as linear in the middle range.

### 3. Determination of Fuzzifier

We introduce the concept of fuzzy contrast that depends on how far the membership functions are stretched by an operator with respect to the crossover point, i.e., 0.5. We take it as the cumulative variance of difference between the membership function and 0.5 over all pixels. Then the fuzzy contrast is written as:

$$C = \sum_{k=0}^{L-1} [\mu'_X(k) - 0.5]^2 p(k) \quad (6)$$

$$\sum_{k=0}^{L-1} p(k) = 1 \quad (7)$$

where  $p(k)$  stands for the frequency of occurrence of intensity  $k$ . After substituting for the membership function in (6) from (3) and (5) and maximizing  $C$  with respect to  $f_h$ , we can derive an approximate formula by taking the first two terms in the expansion of (6) as follows:

$$f_h^2 = \frac{1}{2} \frac{\sum_{k=0}^{L-1} (x_{\max} - k)^4 p(k)}{\sum_{k=0}^{L-1} (x_{\max} - k)^2 p(k)} \quad (8)$$

It may be noted that the intensification operator does not change the frequency of occurrence of a membership function. However, after transforming back to the spatial plane, the distribution might change due to enhancement.

### 4. Derivation for Intensification Parameter

The 'index of fuzziness'  $\gamma(X)$  that gives the amount of fuzziness present in an image determines the amount of vagueness by measuring the distance between its fuzzy property plane and the nearest ordinary plane. Accordingly, entropy,  $H(X)$  which makes use of Shannon's function, is regarded as a measure of quality of information in an image in the fuzzy domain. It gives the value of indefiniteness of an image. These quantities [3] are defined by the following equations:

$$H(X) = -\frac{1}{\ln 2} \sum_{k=0}^{L-1} [\mu_X(k) \ln(\mu_X(k)) + (1 - \mu_X(k)) \ln(1 - \mu_X(k))] p(k) \quad (9)$$

$$\gamma(X) = \min_{k=0}^{L-1} [\mu_X(k), 1 - \mu_X(k)] p(k) \quad (10)$$

Since  $H(X)$  provides useful information about the extent to which the information can be retrieved from the image, this should serve as a guide for finding a suitable value for  $t$ . As  $H(X)$  is a function of  $\mu'_X(k)$  which in turn is a function of  $t$ ,  $\mu_X(k)$  and  $f_h$ , so the derivative of  $H(X)$  with respect to  $t$  is obtained as,

$$\frac{\partial H(X)}{\partial t} = \frac{1}{\ln 2} \sum_{k=0}^{L-1} \left[ \frac{-t(\mu_X(k) - 0.5)^2 e^{-t(\mu_X(k) - 0.5)}}{(1 + e^{-t(\mu_X(k) - 0.5)})^2} \right] p(k) \quad (11)$$

This equation indicates that 't' needs to be computed numerically.

### 5. Results

The color image is first converted from RGB to HSV domain to preserve the hue of the image. HSV consists of Hue, Saturation and Value, i. e., the intensity of a pixel in a colored image. The fuzzifier,  $f_h$  and intensification parameter,  $t$  for both S and V components are calculated separately. After intensification, V and S are added with weights 0.35 and 0.65 respectively. The values of weights are decided by visual assessment of image. Throughout the intensification process the hue is kept constant, however, this can also be intensified and added to the final result with a weight less than 0.15, in case hue correction is needed. Index of fuzziness and entropy of V and S for the original and enhanced images are also calculated. These quantities decrease as the enhancement proceeds.

We have considered five images, viz., Human face, Trees, Timber yard, a Meeting in progress and a Lab for the demonstration. These images and their enhanced versions are shown in Figs.1 (a-e) and Fig. 2(a-e) respectively. The original images have poor brightness

and the details are not discernable. Also colors are not perceivable to the eye. A clear improvement is seen as far as the details and restoration of colors are concerned. Representative Histograms to validate the proposed method, for both the original and enhanced 'Timber' image, are also shown in Fig. 3. Different parameters for the original and enhanced images are listed in the Table1.

## 6. Conclusions

We present a Gaussian membership function that transforms the saturation and intensity histograms of HSV color model to those in the fuzzy domain. A new intensification operator named NINT is proposed for global contrast enhancement. The fuzzifier and intensification parameters are evaluated automatically for the input color image, by optimizing the contrast and entropy in the fuzzy domain. The method has been applied to various test images and found suitable for enhancement of low contrast and low intensity color images. It is observed that the 'index of fuzziness' and the 'entropy' decrease with enhancement.

## 7. References

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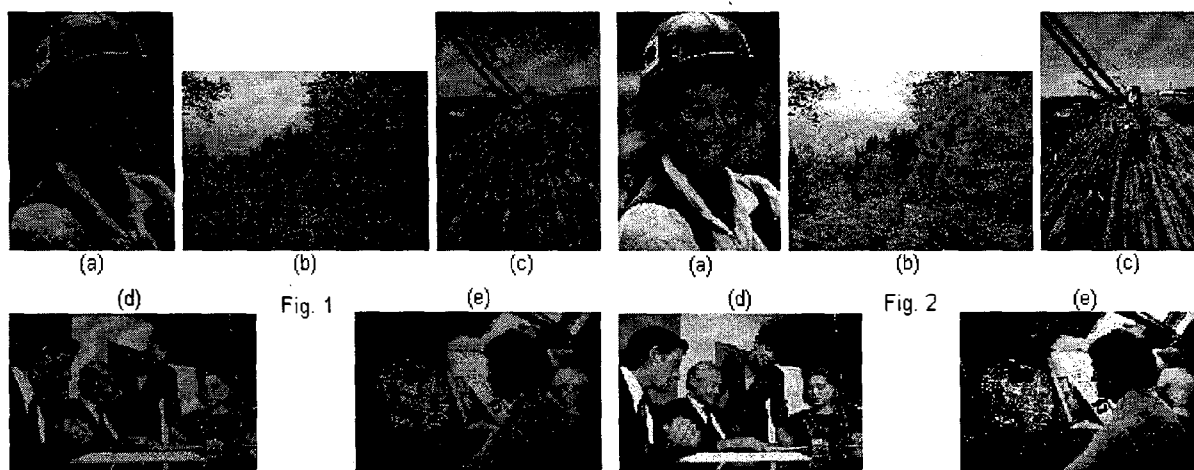


Figure 1: Set of Original Images

Figure 2: Set of Enhanced Images



Figure 3(a): Histograms for Original Image of Fig.1 (c) Timber

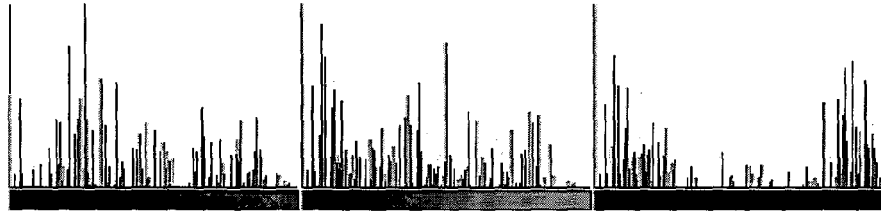


Figure 3(b): Histograms for Enhanced Image of Fig.2 (c) Timber

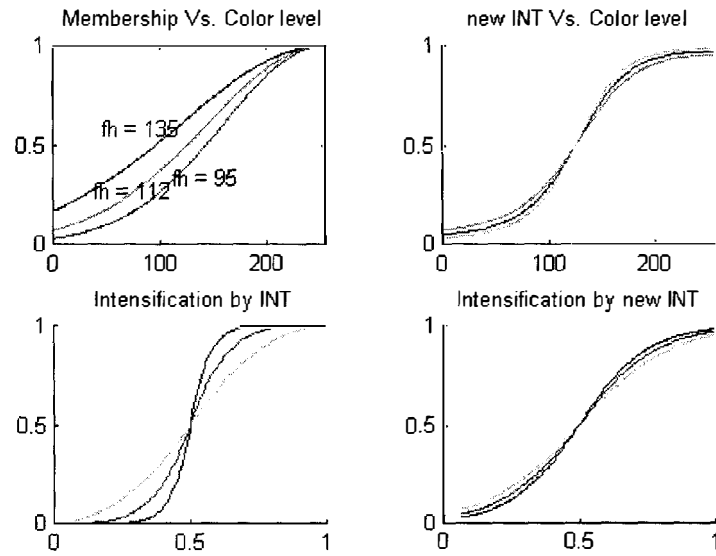


Figure 4: Membership function and Intensification operators (a),(b),(c),(d) clockwise from top left

Table1

Images		Saturation			Intensity			t
		$H$	$\gamma$	$f_h$	$H$	$\gamma$	$f_h$	
Face	Original	0.8952	0.9324	156	0.8732	0.9311	143	17
	Enhanced	0.7320	0.8451		0.7531	0.8322		
Trees	Original	0.8104	0.9692	78	0.8360	0.9545	77	15
	Enhanced	0.7521	0.8819		0.7503	0.8952		
Timber	Original	0.8853	0.8995	163	0.9012	0.8825	138	16
	Enhanced	0.6983	0.8563		0.7489	0.8698		
Meeting	Original	0.7985	0.9357	159	0.7752	0.9448	166	16
	Enhanced	0.7545	0.8778		0.7332	0.9190		
Lab	Original	0.8195	0.9331	161	0.7929	0.9417	168	17
	Enhanced	0.7675	0.8786		0.7218	0.8867		