# Hue Preserving Color Image Enhancement using Multi-scale Morphology

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## Abstract

*A multi-scale morphological algorithm for local contrast enhancement of color images is presented in this paper. The three color components are used to construct the magnitude image and the direction cosines of the color vectors at each pixel location. The contrast of the magnitude image is enhanced using multi-scale morphological filters. The enhanced red, green and blue channel images are obtained by combining the enhanced magnitude image with the old direction cosines. This hue preserving algorithm is tested on several color images and the results are compared with those of two other standard techniques.*

**Keywords:** Multi-scale morphology, morphological towers, top-hat transformation, local contrast enhancement, color enhancement, performance analysis.

## 1. Introduction

With the rapid increase in the usage and applications of color images, it has become a necessity to develop tools and algorithms for color image processing. The commonly used hardware-oriented color models are (i) $RGB$, (ii) $CMY$ and (iii) $YIQ$. These models, in spite of being widely used in image processing algorithms, do not reflect intuitive color notions or perception of human vision. Because of this other models namely $HLS$, $HSV$ or $HVC$, for representing color are proposed [4].

Multi-scale or multi-resolution signal decomposition schemes, where objects or features are treated according to their scale or size, provide effective ways to process information. The concepts of mathematical morphology are also extended to multi-scale processing [9, 19]. The advantages of morphological operations of being sensitive to the shape of the features are combined with the concepts of multi-scale processing to realize a very powerful class of filters. The scale-space used by the authors in this work is represented as *morphological tower* [13, 11, 12].

Contrast enhancement of color images is an well studied problem. Boccignone and Picariello [1] have suggested a multi-scale approach to contrast enhancement using a non-linear scale-space representation of image generated by anisotropic diffusion. Another multi-scale contrast enhancement technique is developed by Toet [19] through non-linear pyramid recombination. A scheme for local contrast enhancement of gray-scale images using multi-scale morphology is also proposed in [11]. Strickland et. al. [17] have proposed a scheme for color enhancement based on saturation. A method for color equalization with its application to color images is developed by Bockstein [2]. A hue preserving enhancement scheme for a class of color images is proposed by Gupta and Chanda [5]. A scheme for color image enhancement employing genetic algorithm is proposed by Shyu et. al. [16]. Tang et. al. [18] have proposed a method of enhancing color images via Chromaticity diffusion. A multi-scale approach for color image enhancement has been proposed by Toet [20]. Oakley et. al. [14] has proposed an enhancement scheme for color images in poor visibility conditions.

In this paper we present a local contrast enhancement technique for color images using multi-scale morphology (MMS). We use usual notations of digital image processing [3] and mathematical morphology [6] in the following description. Section 2 presents the proposed method. Subsection 2.2 presents the theoretical formulation of the Section 3 presents the experimental results of the proposed scheme and comparison with other schemes. A quantitative performance analysis is also provided to evaluate these methods. Finally, concluding remarks are cited in section 4.

## 2. Proposed method

### 2.1. Multi-scale Morphology

FSP dilation and erosion [9] of a gray-level image $g(r,c)$ by a two dimensional point set $B$ is defined respectively, as

$$
\begin{aligned}
(g \oplus B)(r,c) &= max\{g(r-k, c-l) | (k,l) \in B\} \\
(g \ominus B)(r,c) &= min\{g(r+k, c+l) | (k,l) \in B\}
\end{aligned}
$$

The shape of the structuring element $B$ plays a crucial role in extracting features or objects of given shape from the im-

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age. However, for extraction of features or objects based on both shape and size we incorporate an additional attribute to the structuring element which is its *scale*. A morphological operation with a scalable structuring element is termed as *multi-scale morphology* [15, 9]. Multi-scale opening and closing [19, 15, 9] are defined, respectively, as

$$(g \circ nB)(r,c) = ((g \ominus nB) \oplus nB)(r,c) \quad (1)$$

$$(g \bullet nB)(r,c) = ((g \oplus nB) \ominus nB)(r,c) \quad (2)$$

where $n$ is an integer representing the scale factor of the structuring element. If $B$ is convex $nB$ is obtained by dilating $B$ recursively $n-1$ times with itself as [9].

The bright (dark) *top-hat transformation* [10] provides an excellent tool for extracting bright (respectively, dark) features smaller than a given size from an uneven background. as given by

$$g(r,c) = \underbrace{(g \circ B)(r,c)}_{\text{part 1}} + \underbrace{[g(r,c) - (g \circ B)(r,c)]}_{\text{part 2}} \quad (3)$$

Let us call part 1 of equation (3) the *base image* with respect to $B$ and part 2 the *feature image*.

In multi-scale techniques the scale-specific features need to satisfy the following criteria namely (i) causality, (ii) edge localization and (iii) scale calibration. The conventional opening and closing and hence the top-hat transformation do not satisfy these while those by reconstruction does. However, filtering by reconstruction incurs large computational cost. Since in the proposed method, the image is subjected to filtering for small number of low-valued scale factors the issues stated above are not so stringent and hence the conventional opening and closing may be used in stead of opening and closing by reconstruction respectively.

In the proposed work, we recombine the features extracted using multi-scale top-hat filters by assigning large weights to small features.

## 2.2. MMS Contrast Enhancement

In the RGB color representation the intensity at a pixel location is a 3-component vector which consists of red, green and blue intensity values. The magnitude of this vector at each pixel location $(r,c)$ give rise to a gray-scale image as given by the following equation.

$$g(r,c) = \sqrt{R^2(r,c) + G^2(r,c) + B^2(r,c)} \quad (4)$$

Now, in case of a gray-scale image a contrast stretching method using local statistics [7, 8] amplifies the difference between gray-level $g(r,c)$ and mean gray-level $\overline{g}(r,c)$ over a predefined neighborhood surrounding the pixel at location $(r,c)$ (same as location $x$) as given by

$$\tilde{g}(r,c) = \overline{g}(r,c) + k[g(r,c) - \overline{g}(r,c)] \quad (5)$$

where k is a global amplification factor and is greater than one. However, this kind of transformation using only local gray-level statistics and does not give any importance to shape of the features. Therefore we modify equation (5) from the perspective of mathematical morphological operators which preserve the shapes.

The feature image [i.e., part 2 of equation (3)] gives a measure of local contrast in the original image due to presence of bright features. Hence, combining equations (5) and (3) we suggest the following transformation for local contrast stretching

$$\tilde{g}(r,c) = (g \circ B)(r,c) + k[g(r,c) - (g \circ B)(r,c)] \quad (6)$$

where k is again a global amplification factor and is greater than one. So this transformation makes bright features brighter and, thus, improves the local contrast. With $k = 2$ the equation (6) becomes

$$\tilde{g}(r,c) = g(r,c) + [g(r,c) - (g \circ B)(r,c)] \quad (7)$$

Let us denote the top-hat image $[g(r,c) - (g \circ B)(r,c)]$ at scale 1 by $F_B^o(r,c)$, so that, we have equation (7) as

$$\tilde{g}(r,c) = g(r,c) + F_B^o(r,c) \quad (8)$$

Similarly we denote the bright-feature image at scale $n$ by $F_{nB}^o(r,c)$. Note that $F_{0B}^o(r,c)$ is an all-zero image. Let us define

$$\delta_n^o(r,c) = F_{nB}^o(r,c) - F_{(n-1)B}^o(r,c) \quad (9)$$

It is evident that $\delta_n^o(r,c)$ contains bright features that are larger than $(n-1)B$, but smaller than scale $nB$. Generalizing the equation for a number of scales, we have

$$\tilde{g}(r,c) = g(r,c) + k_1\delta_1^o(r,c) + k_2\delta_2^o(r,c) + \cdots \quad (10)$$

where $k_1 > k_2 > k_3 > \ldots$, since we know that smaller the size of a bright feature, more should be its intensity for detectability. Restricting the process up to the scale $m$ we get

$$\tilde{g}(r,c) = g(r,c) + \sum_{i=1}^{m} k_i\delta_i^o(r,c) \quad (11)$$

Theoretically, $m$ may correspond to SE as large as the entire image; however, for the present purpose $m$ need not be large. This is because large features, in general, contribute heavily to global histogram and thus can influence global contrast stretching in their favour. Secondly, the probability that $\delta_i^o(r,c)$ being null image is more as $i$ increases. Now taking $k_{i-1} = k_i + 1$ for all $i$ and choosing $k_m = 1$ we finally have local contrast stretching of bright features as

$$\tilde{g}(r,c) = g(r,c) + \sum_{i=1}^{m} F_{iB}^o(r,c) \quad (12)$$

Selecting $k_m = 1$ allows us to go for a straightforward combination of the feature images in the towers. Similarly for dark features, we have

$$\tilde{g}(r,c) = g(r,c) - \sum_{i=1}^{m} F_{iB}^{c}(r,c) \quad (13)$$

The enhanced gray-scale image is therefore obtained by assigning equal weights to both dark and bright features.

$$\tilde{g}(r,c) = g(r,c) + \frac{1}{2}\sum_{i=1}^{m} F_{iB}^{o}(r,c) - \frac{1}{2}\sum_{i=1}^{m} F_{iB}^{c}(r,c) \quad (14)$$

The enhancement of the magnitude image is basically either stretching or squeezing (depending on whether it is detected as a part of a bright or dark feature in the color image) the magnitude of the color vector at all pixel locations of the color image keeping its direction unchanged. Therefore, the final stretched color image is given by

$$\begin{pmatrix} \tilde{R}(r,c) \\ \tilde{G}(r,c) \\ \tilde{B}(r,c) \end{pmatrix} = \frac{\tilde{g}(r,c)}{g(r,c)} \begin{pmatrix} R(r,c) \\ G(r,c) \\ B(r,c) \end{pmatrix} \quad (15)$$

The proposed multi-scale enhancement scheme, presented above preserves the color properties like hue and saturation of the image. The color parameters hue, saturation and the lightness are defined as follows.

The hue $H$ is defined as

$$H(r,c) = \begin{cases} 60 \cdot h(r,c) & \text{if } h(r,c) \geq 0 \\ 60 \cdot h(r,c) + 360 & \text{if } h(r,c) < 0 \end{cases}$$

where

$$h(r,c) = \begin{cases} \{\frac{G(r,c)-B(r,c)}{R(r,c)-M_n}\} & \text{if } R(r,c) = M_x \\ \{2 + \frac{B(r,c)-R(r,c)}{G(r,c)-M_n}\} & \text{if } G(r,c) = M_x \\ \{4 + \frac{R(r,c)-G(r,c)}{B(r,c)-M_n}\} & \text{if } B(r,c) = M_x \end{cases}$$

where

$$M_n = min(R(r,c), G(r,c), B(r,c)) \quad (16)$$

$$M_x = max(R(r,c), G(r,c), B(r,c)) \quad (17)$$

The saturation and lightness are defined (respectively) as

$$S(r,c) = \frac{M_x - M_n}{M_x + M_n} \quad (18)$$

$$L(r,c) = M_x \quad (19)$$

Therefore the hue, saturation and the lightness of the enhanced image are given by

$$\tilde{h}(r,c) = h(r,c)$$

$$\tilde{S}(r,c) = S(r,c) \text{ and}$$

$$\tilde{L}(r,c) = \alpha L(r,c)$$

where $\alpha = \frac{\tilde{g}(r,c)}{g(r,c)}$.

# 3. Experimental results and discussion

The proposed algorithm has been tested on a set of color images and the results have been compared with that of other methods. Results on just two images are shown here only. Figs. 1(a) and (b) show the original color images. Let us call them 'garden' and 'flowers' images. Results of the proposed algorithm are shown in Figs. 2–3(i).

In our experiment, we have used $n = 1$, $m = 5$ and $B$ is a circular disk of radius 1. However, it should be noted that very large value of $m$ will not give noticeable improvement in the output since the feature images of progressively larger scales have gradually less influence in enhancing the image. The choice of $m$ may be done by the user such that the results should not look unrealistic due to over-enhancement in contrast. The resulting images are seen to have more contrast than the respective original versions without any effect on the color appearance. The results of the proposed scheme are compared with those of two other methods namely (i) the multi-scale pyramidal approach of Toet [20] [see Figs. 2–3(ii)] and (ii) the method employing genetic algorithm [see Figs. 2–3(iii)] due to Shyu et al. [16]. It may be interseting to see waht happens if the intensity component undergo global contrast enhancement scheme and then is combined with color information to produce the color image. We have run this experiment for both global linear stretching of histogram and global histogram equalization algorithm. The resultant images are shown in Figs. 2–3(iv) and Figs. 2–3(v) respectively. Visually (i.e., subjective quality of) the resulting images of our method have more contrast compared to that of other two methods. However, we suggest following objective criteria to eavluate the performance of various algorithms.

We consider a $3 \times 3$ mask, $A$, and compute the followings

$d\_red(i,j) = \sum_A [max\_red - min\_red]$
$avg\_red = \frac{1}{9}\sum_A d\_red(i,j)$
$d\_grn(i,j) = \sum_A [max\_grn - min\_grn]$
$avg\_grn = \frac{1}{9}\sum_A d\_grn(i,j)$
$d\_blu(i,j) = \sum_A [max\_blu - min\_blu]$
$avg\_blu = \frac{1}{9}\sum_A d\_blu(i,j)$

The overall contrast is defined as the minimum of the average contrasts of the three color components as given below.

$$Cont = min(avg\_red, avg\_grn, avg\_blu) \quad (20)$$

The overall contrast is computed for the original color image and the enhanced images resulting from all the enhancement schemes. From the table it is evident that the overall contrast is the best for the proposed method.

(a)

(b)

Figure 1: Original color images used in the experiment. (a) Garden and (b) Flowers

Table 1: Relative performance of the contrast enhancement schemes for color images

| Image | Enhancement scheme | | | | | |
|---|---|---|---|---|---|---|
| | Input | Toet [20] | Shyu [16] | Linear Str. | Hist. equa. | Pro-posed |
| Garden | 17.7 | 36.1 | 18.6 | 20.8 | 27.9 | 72.8 |
| Flower | 30.2 | 40.8 | 30.1 | 30.9 | 54.1 | 84.1 |

## 4. Conclusion

In this paper we have proposed a multi-scale scheme for contrast enhancement of color images. The magnitude image constructed from the red, green and blue color is enhanced using multi-scale morphological filters keeping the direction of the color vector unaltered. The enhanced color image is obtained by combining the enhanced magnitude image with the original direction cosine values. The algorithm is executed on a set of color images. The results have been compared with those of four other standard methods. The results due to the proposed method have been found to be reasonably satisfactory. The proposed method while performing enhancement preserves the color attributes namely hue and saturation.

(i)

(ii)

(iii)

(iv)

(v)

Figure 2: Results of (i) Proposed method, (ii) Method due to Toet's method, (iii) Method due to Shyu et al., (iv) Global contrast stretching, (v) Global histogram equalization.

(i)

(ii)

(iii)

(iv)

(v)

Figure 3: Results of (i) Proposed method, (ii) Method due to Toet's method, (iii) Method due to Shyu et al., (iv) Global contrast stretching, (v) Global histogram equalization.

# References


[1] G. Boccignone and A. Picariello. Multiscale contrast enhancement of medical images. *Proc. ICASSP'97, Munich, Germany, April 21-24*, 4:2789–, 1997.

[2] I. M. Bockstein. Color equalization method and its application to color image processing. *Journal of Opt. Soc. Am.*, A 3(5):735–737, 1986.

[3] B. Chanda and D. D. Majumder. *Digital Image Processing and Analysis*. Prentice-Hall of India Pvt. Ltd., New Delhi, 2000.

[4] J. D. Foley, A. V. Dam, S. K. Feiner, and J. F. Hughes. *Computer Graphics Priciples and Practice*. Addison-Wesley Publishing Company, second edition, Reading, MA, 1997.

[5] A. Gupta and B. Chanda. A hue preserving enhancement scheme for a class of color images. *Pattern Recognition Letters*, 17:109–114, 1996.

[6] R. M. Haralick and L. G. Shapiro. *Computer and Robot Vision, Vol. 1*. Addison-Wesley, Reading, MA, 1992.

[7] J. S. Lee. Digital image enhancement and noise filtering by use of local statistics. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, PAMI-2:165–, 1980.

[8] J. S. Lee. Refined filtering of image noise using local statistics. *Computer Graphics and Image Processing-4*, 15:380–389, 1981.

[9] P. Maragos. Pattern spectrum and multiscale shape representation. *IEEE Trans. on PAMI*, 11:701–716, 1989.

[10] F. Meyer. Contrast feature extraction. In J. L. Chermant, editor, *Quantitative Analysis of Microstructures in Material Sciences, Biology and Medicine*. Riederer Verlag, Stuttgart, Germany, 1978.

[11] S. Mukhopadhyay and B. Chanda. multiscale morphological approach to local contrast enhancement. *Signal Processing*, 80(4):685–696, 2000.

[12] S. Mukhopadhyay and B. Chanda. An edge preserving noise smoothing technique using multiscale morphology. *Signal Processing, In press*, -:–, 2001.

[13] S. Mukhopadhyay and B. Chanda. Fusion of 2d grays-cale images using multiscale morphology. *Pattern Recognition*, 34(10):–, 2001.

[14] J. P. Oakley and B. L. Satherley. Improving image quality in poor visibility conditions using a physical model for contrast degradation. *IEEE Transactions on Image Processing*, 7:167–179, 1998.

[15] J. Serra. *Image analysis using mathematical morphology*. Academic Press, London, 1982.

[16] M. Shyu and J. Leou. A geneticle algorithm approach to color image enhancement. *Pattern Recognition*, 31(7):871–880, 1998.

[17] R. N. Strickland, C. S. Kim, and W. F. McDonnell. Digital color image enhancement based on the saturation component. *Optical Engineering*, 26:609–616, 1987.

[18] B. Tang and G. Sapiro. Color image enhancement via chromaticity diffusion. *IEEE Transactions on Image Processing*, 10(5):701–707, 2001.

[19] A. Toet. A hierarchical morphological image decomposition. *Pattern Recognition Letters*, 11(4):267–274, 1990.

[20] A. Toet. Multi-scale color image enhancement. *Pattern Recognition Letters*, 13(3):167–174, 1992.

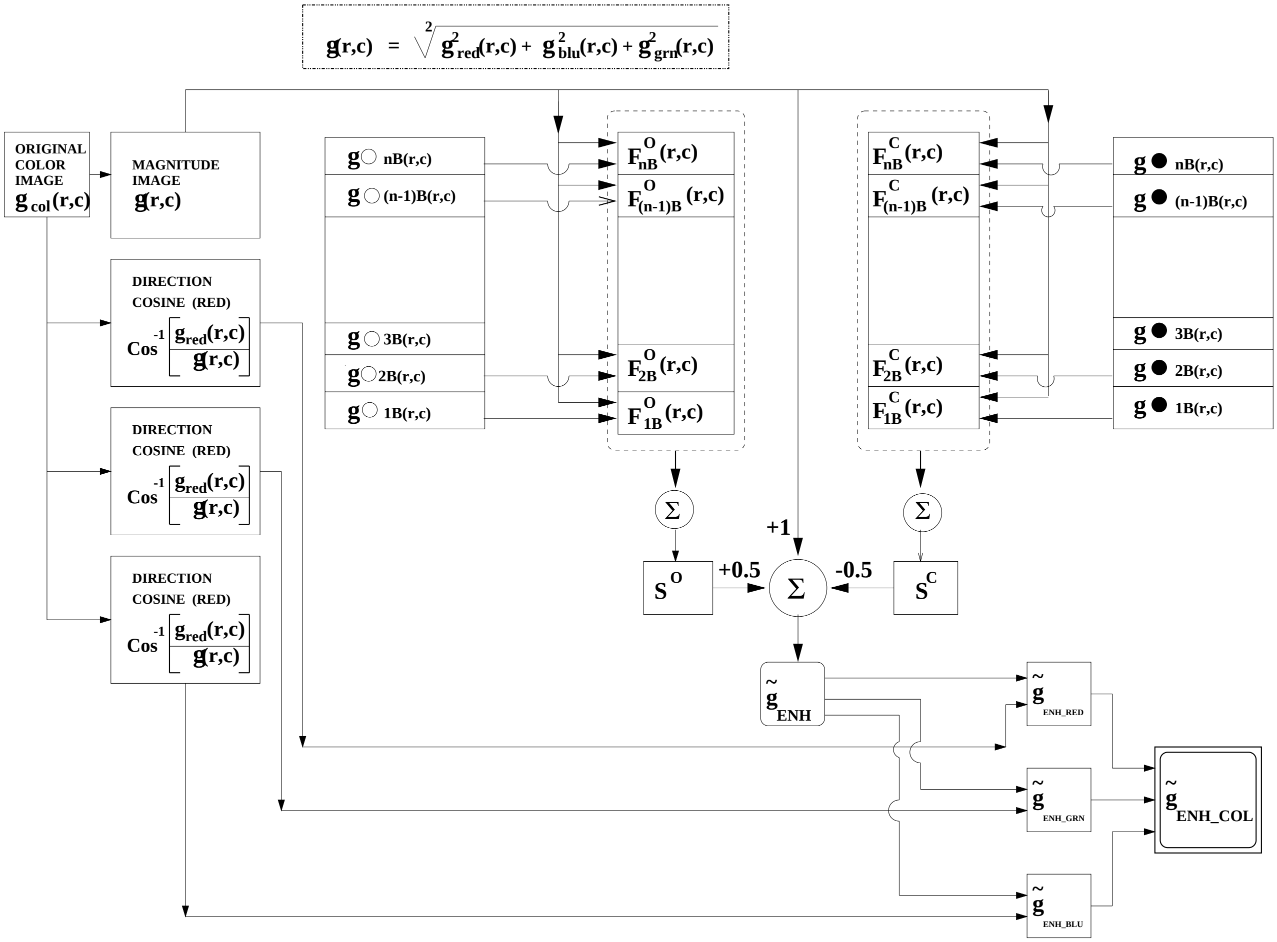


Figure 4: Scheme for color image enhancement using morphological towers