

# Colorization Of Gray Image In $La\beta$ Color Space Using Texture Mapping And Luminance Mapping

<sup>1</sup>Mrs. Smriti Kumar' <sup>2</sup>Mr. Deepak Singh

<sup>1,2</sup>,Department of Electronics and Telecommunication Engineering, CSIT Durg, India.

## Abstract:

Gray Scale image colorization is an appealing area in the world of image processing. This work presents a simple process for colorizing gray image, using a colored image which is similar to this gray scale image but not the colorized version of the gray image. Here we convert both these images to a decorrelated color space  $la\beta$  and then divide these images into small windows of equal size, then we calculate mean and standard deviation for data points based on luminance values in each of these windows to compute a luminance measure and we also extract texture features like energy, entropy, contrast, correlation and homogeneity based on correlation matrix for each of these windows. We apply proper weights to these texture features to calculate a texture similarity measure and then calculate a similarity measure based on the texture similarity measure and luminance measure for each of these windows in both the images. Then we compare each window in gray scale image with every other window in colored image using this similarity measure and find the best matching window. Then the chromatic properties of some randomly selected data points of this colored window are transferred to the gray window pixel by pixel, based on the luminance mapping and thus colorization of gray scale image is achieved, which produces believable results.

**Keywords:** Colorization, Contrast, Correlation, Energy, Entropy, Gray Scale Images, Homogeneity,  $la\beta$  Color Space, Luminance Measure, Mean And Standard Deviation, Similarity Measure, Texture Feature, Texture Similarity Measure.

## 1. Introduction

Color can increase the visual appeal of grayscale images such as the black and white photos, old movies or scientific data. In medicine, image modalities which only acquire grayscale images such as Computerized Tomography (CT), X-ray images and Magnetic Resonance Imaging (MRI) can be enhanced when colorized for demonstrations and presentations. Even for some scientific images information content can be enhanced with color when variations in chromaticity as well as luminance are exploited. The task of adding colors to a grayscale image involves assigning three-dimensional (RGB) pixel values to a gray scale image but it is also a fact that gray scale images vary along only one dimension (luminance or intensity). This fact is also well known that a variety of colors may have the same luminance value although hue or saturation variation is possible, the problem of colorizing grayscale images has no inherently "correct" solution. Due to these uncertainties, in the colorization process there is a large role of human interaction. Colorization is a term introduced in 1970 and was later patented by Wilson Markle. Colorization trends have been classified into three categories - Hand coloring is the first one, Semi automatic coloring stands next, and automatic coloring is the third one. Semary N. A. [1]. Hand coloring has been a way of showing talent in art. Usually image editing software's like Adobe Photoshop or Paint shop Pro are used similarly to convert gray images to color images. Semiautomatic coloring refers to mapping luminance values to color values, which is done by converting a gray image in to an indexed image. Pseudo coloring is a common example [2][3]. Automatic coloring can be classified into three categories [1], which are transformational coloring, Image Matching and User Selection, this classification is made according to the source of colors to be transferred to the gray image pixels. Technique of our interest here is Image Matching/ Coloring by Reference. This technique is based on the fact that for each gray pixel  $I_g(x, y)$  in target gray scale image there exists a colored pixel  $I_s(x_2, y_2)$  in reference or source image such that the distance  $E$  (which is some similarity measure) between them exhibits the minimum value. The chromatic properties in " $I_s$ " are transferred to " $I_g$ " and the achromatic value of " $I_g$ " are retained. When one represents any typical three channel image in any of the well-known color spaces, the different channels' values will be correlated. For instance, in RGB color space, most pixels for the red and green channel will have large values if the blue channel is large. This implies that if we want to alter the chromatic properties of a pixel in a coherent way, we must modify all color channels in tandem. Thus any type of color modification process gets complicated. So we require an orthogonal color space without correlations between the axes. Ruderman et al [4] developed a color space, called  $la\beta$ , which minimizes correlation between channels for many natural scenes, since it is based on data-driven human perception research that assumes that the human visual system is ideal for processing natural scenes. There's little correlation between the axes in  $la\beta$  space, which allows the application of different operations in different color channels without the troubles, due to undesirable cross-channel artifacts. Apart from this,  $la\beta$  color space is logarithmic, which means that to a first approximation the uniform changes in channel intensity are equally detectable [5]. This makes  $la\beta$  space, a very popular choice where colorization is concerned. The complete coding of this work has been done in MATLAB 10.

## 2. Methodology

For colorization purpose we convert our source (i.e. Color Image) and target (i.e. Gray Scale Image) images into decorrelated color space  $l\alpha\beta$  and then divide these images into small windows, whose size may vary according to the type of image (We tried various images and found that, a window size of '5 X 5' suffices for most of the images but some challenging images require larger window size). After this we extract texture features like energy, entropy, homogeneity, contrast and correlation based on correlation matrix for the purpose of texture matching, for each window. We also calculate mean and standard deviation for each pixel in this window and find out an average value of these. Then we compare each target (gray scale) image's window with all the windows of source (colored) image and find out the best matching window in source image based on a similarity measure which gives equal weight to both texture feature matching as well as mean and standard deviation matching (luminance matching). Then the chromatic values of some randomly selected data points from the source image window are transferred to the target image window, based on luminance mapping. The resulting image of this process is colorized version of target gray scale image. The basic method here matches the three-dimensional distribution of texture features and luminosity values between the images and then transforms the color distribution of the source (colored) image to match the distribution of the target (grayscale) image. A grayscale image is represented by a one dimensional distribution, hence between the two images one can match only the luminance channels. Apart from this we also match texture features like energy, entropy, homogeneity, contrast and correlation based on correlation matrix. Once a target image window matches a source image window, the color information is transferred between pixels but the original luminance value is retained. The  $l$  channel in  $l\alpha\beta$  color space determines the luminance value. For colorization purpose, mean and standard deviations along each of the three axes are required. Hence, we compute these measures for the windows in both the source and target images, for each pixel in each of the windows. We calculate the mean and standard deviation [9][10] for each axis separately in  $l\alpha\beta$  space. For this first, we subtract the mean from the data points:

$$l^* = l - \langle l \rangle, \quad (1.1)$$

$$\alpha^* = \alpha - \langle \alpha \rangle, \quad (1.2)$$

$$\beta^* = \beta - \langle \beta \rangle, \quad (1.3)$$

Then, we scale the data points by factors determined by the respective standard deviations:

$$l' = (\sigma_\tau^l / \sigma_\sigma^l) l^*, \quad (2.1)$$

$$\alpha' = (\sigma_\tau^\alpha / \sigma_\sigma^\alpha) \alpha^*, \quad (2.2)$$

$$\beta' = (\sigma_\tau^\beta / \sigma_\sigma^\beta) \beta^*, \quad (2.3)$$

Using above formulae is luminosity match measure 'LM' is calculated for each window in both the images. 'LM' is average of luminosity scale calculated by (1) and (2) in a window, for all the pixels.

Then we calculate texture features like energy, entropy, homogeneity, contrast and correlation based on correlation matrix for each of the windows in both images based on following formulae [6]:

$$S = -c \sum_j P[i,j] \log P[i,j], \quad (3.1)$$

$$J = -\sum_i \sum_j P^2[i,j], \quad (3.2)$$

$$\text{Con} = -\sum_i \sum_j (i-j)^2 P[i,j], \quad (3.3)$$

$$H = -\sum_i \sum_j P[i,j] / (1+|i-j|), \quad (3.4)$$

$$\text{Cor} = -[\sum_i \sum_j ij P[i,j] - \mu_i \mu_j] / \sigma_i \sigma_j, \quad (3.5)$$

Where  $S$  is entropy,  $J$  is energy,  $\text{Con}$  is contrast,  $H$  is homogeneity,  $\text{Cor}$  is correlation.  $P[i,j]$  is the value of element in co-occurrence matrix and  $[i,j]$  is the coordinate,  $\mu_i$  and  $\mu_j$  are mean of  $p_i$  and  $p_j$  respectively, where [6] :

$$p_i = -\sum_j P[i,j], \quad (4.1)$$

$$p_j = -\sum_i P[i,j], \quad (4.2)$$

Now, these texture features are weighted appropriately, weights are calculated for each of these features based on the formula [7]:

$$W(i, j) = e^{-d(x_i, x_j)/2} \quad (5.1)$$

Where  $\omega$  is the parameter under consideration and

$$d(x_i, x_j) = \|x_i - x_j\|^2, \quad (5.2)$$

Then a texture similarity measure 'TM' based on Euclidean distance is calculated for each window in both source and target images. Now, a similarity measure 'E' is computed for each of these windows which give equal weight to 'TM' and 'LM'. Based on 'E' each window in target gray scale image is compared to every window of source colored image and the best match is found out.

Now we select some data points randomly from the source image window using jitter sampling and the chromatic values of these pixels in source image window are transferred to the pixels of target image window, based on the mean and standard deviation calculations for luminance mapping, but their luminosity values are retained.

We intend here to transfer one image's appearance to another; hence it's possible to select source and target images that may not work well together, but the result's quality depends on the images' similarity in composition. We have also used the conventional method for colorization in  $l\alpha\beta$  space and compared the resulting images obtained with those obtained in  $L\alpha\beta$  method based on time required for processing, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross correlation (NK), Structural Content (SC), Maximum Difference (MD), Normalized Absolute Error (NAE), Visual Quality with respect to the target gray scale image. This calculation is based on following formulae [8]:

$$MSE = [\sum_{j=1}^M \sum_{k=1}^N (x_{j,k} - x'_{j,k})^2] / MN, \quad (6.1)$$

$$PSNR = 10 \log[(2^n - 1)^2 / MSE], \quad (6.2)$$

$$NK = \sum_{j=1}^M \sum_{k=1}^N (x_{j,k} \cdot x'_{j,k}) / \sum_{j=1}^M \sum_{k=1}^N (x_{j,k})^2, \quad (6.3)$$

$$SC = \sum_{j=1}^M \sum_{k=1}^N (x_{j,k})^2 / \sum_{j=1}^M \sum_{k=1}^N (x'_{j,k})^2, \quad (6.4)$$

$$MD = \text{Max}(|x_{j,k} - x'_{j,k}|), \quad (6.5)$$

$$NAE = \sum_{j=1}^M \sum_{k=1}^N |x_{j,k} - x'_{j,k}| / \sum_{j=1}^M \sum_{k=1}^N |x_{j,k}|, \quad (6.6)$$

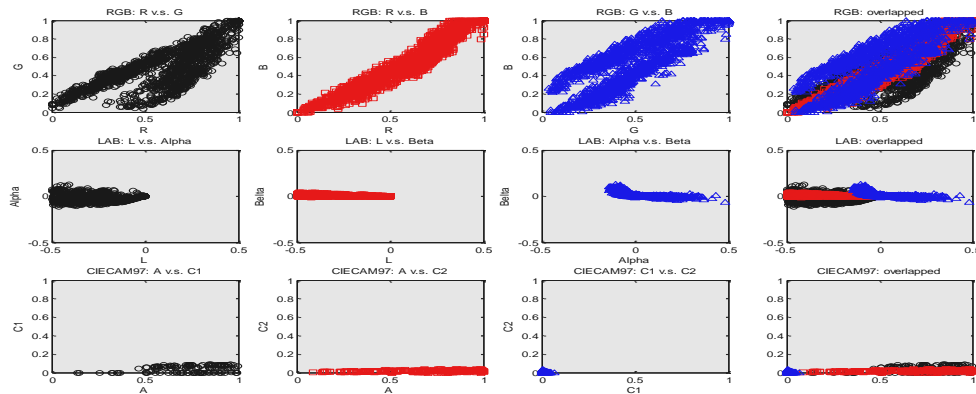
The results are tabulated in Table 1 and 2. Apart from this to show the significance of choosing the right color space, we compared four different color spaces. These color spaces are RGB as used by most graphics algorithms, CIECAM97s, and  $l\alpha\beta$  which is very popular decorrelated color space and which we have used in our method. The reason behind choosing the CIECAM97s color space is that it closely relates to  $l\alpha\beta$  color space. It has three channels A, C1 and C2 [9][10]. Its chromatic channels C1 and C2 resemble the chromatic channels in  $l\alpha\beta$  space; accept a scaling of the axes. The achromatic channel A is different). It is also important to note here that the CIECAM97s operates in linear space, and  $l\alpha\beta$  are defined in log space. Using image in Figure 1, we have produced scattered plots of 2,000 data points, which were chosen randomly [9][10] in  $l\alpha\beta$ , RGB, and CIECAM97s. Figure 2 depicts these scatter plots that show the pairs of axes (any two axes out of three axes) plotted against each other. The data points in sample image are decorrelated if the data are aligned to the axis, as can be seen for all three pairs of axes in  $l\alpha\beta$  and CIECAM97s spaces where as RGB color space exhibits correlation to a large extent between all pairs of axes as the data cluster around a 45-degree slope line, between the two axes. This validates for  $l\alpha\beta$  color space because different input data (randomly selected), has been used.

### 3. Result

Our colorization method produces believable colorized output images, as is obvious from the results in Figure (3-5). We have presented a comparison between results obtained by colorization in  $l\alpha\beta$  color space using our method and by conventional colorization technique in  $l\alpha\beta$  color space in Table (1-2). The results are compared with the original target image based on various parameters like Time Taken, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Correlation (NK), Maximum Difference (MD), Normalized Absolute Error (NAE) and Visual Quality Obtained. As is apparent from this comparison our proposed colorization method in  $l\alpha\beta$  color space produces much better results. Images of various dimensions ranging from 256x256 to 1024x1024 were tested and the method proved successful, the time taken for colorization ranges from 25 seconds to 275 seconds.



**Figure. 1 Image Analyzed**



**Figure. 2 Comparison between various color spaces**



**Figure. 3(a) Gray Scale Target Image**



**Figure. 3(b) Colored Source Image**



**Figure. 3(c) Target Image Colored by Conventional Method**



**Figure. 3(d) Target Image Colored by Proposed Method**



**Figure. 4(a) Gray Scale Target Image**



**Figure. 4(b) Colored Source Image**



**Figure. 4(c) Target Image Colored by Conventional Method**



**Figure. 4(d) Target Image Colored by Proposed Method**

**Table 1. Comparison between results of Figure 3.**

<b>DIFFERENT METHODS</b> ▶	<b>PROPOSED TECHNIQUE</b>	<b>CONVENTIONAL TECHNIQUE</b>
<b>PARAMETERS</b> ▼		
Time taken (sec)	11.5790	68.3276
Mean square error	309.7544	1315.7
Peak signal to noise ratio	23.2206	15.2509
Normalized cross correlation	1.2155	0.8782
Structural content	1.2927	0.6498
Maximum difference	19	101
Normalized absolute error	0.1466	0.3362
Visual quality	Good	Average

**Table 2. Comparisons between results of Figure 4.**

DIFFERENT METHODS ▶	PROPOSED TECHNIQUE	CONVENTIONAL TECHNIQUE
PARAMETERS ▼		
Time taken (sec)	12.25	94.49
Mean square error	348.8706	3079.8
Peak signal to noise ratio	22.7042	13.2455
Normalized cross correlation	1.4651	0.8380
Structural content	1.4215	0.4603
Maximum difference	19	68
Normalized absolute error	0.1693	0.4966
Visual quality	Good	Average



**Figure. 5(a) Gray Scale Target Image**



**Figure. 5(b) Colored Source Image**



**Figure. 5(c) Target Image Colored by Proposed Method**

## Conclusion

In this work we have successfully colorized gray scale images of various sizes in  $la\beta$  color space. Here we take a reference colored image or source image which is similar in texture to the target gray scale image, it is not necessary that this image is colored version of the target gray scale image, it can be any similar colored image. The quality of output depends on the choice of this reference or source image. We convert both the target and source images in  $la\beta$  decorrelated color space, to avoid cross channel artifacts, and divide these images in windows of equal size. Then for each of these windows a luminosity measure based on mean and standard deviation is calculated. Again texture features like energy, entropy, contrast, homogeneity and correlation based on correlation matrix are extracted for each of these features are weighted properly and then for each window a texture similarity measure is calculated. After this we have calculated a similarity measure that gives equal weight to both luminosity measure as well as texture similarity measure for each window. After this each window in target image is compare with every window in source image and the best matching window is found out. Then we select some data points randomly from the source image window using jitter sampling and the chromatic values of these pixels in source image window are transferred to the pixels of target image window, based on the mean and standard deviation calculations for luminance mapping, but their luminosity values are retained and colorized version of target image is obtained. We compare our results with the output obtained by colorization in  $la\beta$  color space and come to the conclusion that the results obtained by colorization in  $la\beta$  color space using our proposed technique are of better quality visually as well as on the basis of image quality parameters like Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Correlation (NK), Maximum Difference (MD), Normalized Absolute Error (NAE) etc.

## References

- [1] Semary N. A., "Texture recognition techniques for natural gray images", Radio Science Conférence, 2007. NRSC April, 2007.
- [2] Gonzalez R. C., Woods R. E., and Eddins, S. L., "Digital Image Processing Using Matlab." Pearson Education New Delhi (India), Edition No. 1 (Reprint), 2004.
- [3] Solomon C., Breckon T., "Fundamentals of Digital Image Processing.", Wiley – Blackwel , UK, Edition No. 1, 2011.
- [4] Daniel L. Ruderman, Thomas W. Cronin and Chuan-Chin Chiao, "Statistics of cone responses to natural images: implications for visual coding", J. Opt. Soc. Am. A/ Vol. 15, pp. 8, August, 1998.
- [5] D.R.J. Laming, Sensory Analysis, Academic Press, London, 1986.
- [6] Shaoyuan Sun, Jing Z., Liu G., Li Z., "Transfer Color to Night Vision Images.", Chinese Optics Letters, Vol.3(8), August, 2005.
- [7] Weiss, Y., "Segmentation using eigenvectors: A unifying view", In Proc. IEEE Intl. Conf. Computer Vision, Vol. 2, Corfu, Greece, pp. 975–982, 1999
- [8] <http://www.mathworks.fr/matlabcentral/Image Quality>
- [9] Smriti Kumar, Ayush Swarnkar, "Colorization of Gray Scale Images in  $la\beta$  Color Space using Mean and Standard Deviation" IEEE SCEECs 2012, MANIT, Bhopal (India), IEEE Conference Publications, March 2012.
- [10] Welsh, T., Ashikhmin, M. and Mueller, K., "Transferring color to grey scale images", In: Proceedings of 29th Annual Conference on Computer Graphics and Interactive Techniques, ACM-SIGGRAPH2002, pp. 277- 280, ACM Press, New York, USA, 2002.