International Journal of Engineering &Technology, 8 (2) (2019) 63-71

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Automatic image colorization based on SVD and lab color space

Nidhal K. EL Abbadi [1] *, Eman Saleem [2]

[1] *Department of Computer Science, Education College, University of Kufa, Najaf, Iraq*
[2] *Department of Computer Science, Faculty of Computer Science and Mathematics, University of Kufa, Najaf, Iraq*
**Corresponding author E-mail: nidhal.elabbadi@uokufa.edu.iq*

Abstract

Images colorization is the operation of append colors to the grayscale image by using a reference color image. The main problem of coloring a grayscale image involves constructing three dimensional image from one dimensional array. The current paper developed a fully automatic image colorization system based on the singular value decomposition (SVD) transformation. SVD used to measuring the best pixel in the reference image proper to colorize the gray image, depending on comparing the pixel value and their neighbor values of the gray image with pixel value and their neighbors in the reference image. Using the color space is more suitable to many digital image processing than the RGB, for that the author suggested to convert reference image to the CIELab color space in this proposal. Gray image normalized according to the (L channel) of reference image. Ultimately, the intensity of the selected pixel in the gray image combine with (a, b channels) values of the best pixel from CIELab color space of reference image, which is finally converted to RGB color image. The suggested algorithm is the first algorithm utilized the SVD for image colorization which give good and promised results compared with other methods, and can be enhanced in the future.

Keywords: *Colorization; Gray Image; Image Processing; Lab Color Space; SVD.*

1. Introduction

The process of adding color to black and white still image and video is called colorization. In general, the term and process of colorization is an active area of many research, and challenging for many researchers.

Process of coloring grayscale images is a very difficult process due to blind work of adding colors to gray image without prior knowledge of true colors of objects included in the gray image. In other words, colorizing technique implies transferring colors between a source colored image to a destination grayscale image. There is no “accurate” solution for image colorization due to highly possible to get the same illuminance from different colors although there is difference in both the hue and saturation or one of them. Also some ambiguity may be arising when we colored objects has shapes related to the measuring the color of the entire object [1].

There are three classes of colorization technique: Hand coloring, Semi-automatic coloring and Automatic coloring. However, this classification has not been stated by any author. In hand coloring, most of work and effort required to colorization image done by human. Many software used for editing image such as paint or adobe Photoshop are used for adding color to gray image. The major drawback of this technique is time consuming, costly, and it is totally useless without human intervention. In semi-automatic coloring, user provides some colored scribbles and then the color is spilled over the image according to the indicated scribbles. In this method image may be segmented to many regions and the user suggest colors for each region. Though, this method is efficient but it is time consuming. It is more useful in medical image application like X-Ray, CT-Scan and MRI images. Unlike hand coloring and semi-automatic coloring, automatic coloring removes the user intervention to a large extent. A reference image is considered, which is chosen by the user, then pixels of gray image are matched with the pixels of target image and the most similar pixels are transferred using color transfer techniques. However, in this method it is recommend to convert RGB reference image to another color space to get color model should have separate luminance like HSB, HIS, YIQ and L*a*b* [2].

2. Related works

There are many ways utilized in this field, some of which we debate. Smriti and Ayush Proposed to uses a color image similar to a grayscale image. Both the gray image and the color image convert to the YCbCr color space. Then, the resulting images are divided into equal size windows and then calculate the mean and standard deviation depend on the brightness values of each window. For each window texture like energy, entropy, contrast, correlation and homogeneity depend on the correlation extracted for matching. Mean and standard deviation for each window determined. This method focuses on the finding the best matching to use for color transfer from colored image to gray image [3]. Wang and others suggested a method depend on correlation neighbourhood similarity pixels’ priori. This method looks for the group of pixels which have similarity with neighbourhood pixels. The computed weight of the pixels around the target pixel in lightness image transfer to the chrominance [4]. Devi and others introduced method based on dividing image to different size windows and convert each of them to YUV color space. The aim of this paper is to find the best window size and color space for image colorization [5]. Garg and others suggested method execute spontaneous colorization based on algorithm to create LBG codebook with different resemblance to determine the mapping of gray-scale image pixels with comparatively similar multicolour image pixels. The elaborate rendering assessment of the various similarity determine the fineness of colorization. trial is done with a test 28 images. Where they proved through of the analogous measures have shown that the Canberra distance and Manhattan distance performs other believe similarity measures for LBG based colorization method [6]. The Hu and others method based on seed pixel selected to support the users in deciding which pixels are highly desired to be colorized for an aloft fineness colorized image. They begin by dividing the grayscale image into non-overlapping windows, and then, for each window, two pixels that convergent the average luminance of window are chosen as the seeds. Then the seed is colored by the user, where they used optimization reduces the variation between the seeds and their neighbouring pixels that used to deploy the colors to the other pixels [7]. Deshpande and other proposed method based on colorize from examples. this way utilized a LEARCH frame work to practice a quadratic aim function in the colorized maps, so they can exercise a Gaussian random domain. The parameters of the objective function are dependent on image properties, utilizing a random forest. The objective function confesses liaisons on tall spatial measures, and can hegemony spatial wrong in the colorization of the image. Then they colorized the images by reduce this objective function [8]. Okura and other suggested another style of coloration based on unifies texture and color transfer. This method starts by analysing the source/exemplar pair to find the image regions where color transfer is insufficient. then the predicated error during the synthesis for enhancing the results will be updated by selecting the proper method for texture transfer [9]. Li and others proposed method for coloring gray images by using the automatic outcome-finding feature with outcomes combined through Markov Random Field (MRF) model to get better coloring. looking them symmetrical or asymmetrical image where vectors are used and then a determine for each local area of the gray image is selected in order to destination the coloring results. Therefore, use a descriptor depend on a luminance deviation to determine whether the area may be symmetrical or asymmetrical [10]. The rest of this paper include explanation in section II about the tools used in the paper and the suggested algorithm, while section III introduce the results, and finally conclude the proposed algorithm.

3. Material and methods

3.1. CIE L*a*b* (CIELAB)

Most of image processing applications convert the information of RGB color image to another mathematical color space that separate the color information from the brightness information. The image information will be transfer to three dimensions, one for brightness, or luminance space while the other two dimensional color space contains information about the relative amounts of the different colors. The advantage of transferring information of RGB image to another color space is that it creates a similar way of describing the colors by human. In this paper we suggested to use Lab color space.
Lab color space is the back-bone of all color management between devices in the color workflow. The Lab color space almost represented by 3- axis color system. Lab regards as absolute colors, that mean it is exact color. Lab color space can be use with different devices. An object’s color is measured in Lab color with a spectrophotometer.
Depended on the theory of the color of the antibody consist of the three main axes of the (L), which represent the color lightness and the two axes (a, b) for contrasting colors is the result of a non-linear conversion of color space coordinates CIE XYZ. Lab color model is a 3D actual number space, permitting an unlimited number of potential representations of colors. The space for digital representations is mapped onto a 3D integer space, so in general the value of L, a, and b are absolute. The values of lightness (L), ranging from the black (L = 0) to the white (L = 100). While the range of (a) values is between green (positive orientation) and red (negative orientation). The third component is (b) which represents the blue (negative orientation), and yellow, with blue in the negative orientation and yellow (positive orientation). The representation values for (a and b) will be in the domain of ±100 or −128 to +127 (signed 8-bit integer) [11] [12] [13]. Figure 1, display different color model according to the value of lightness.

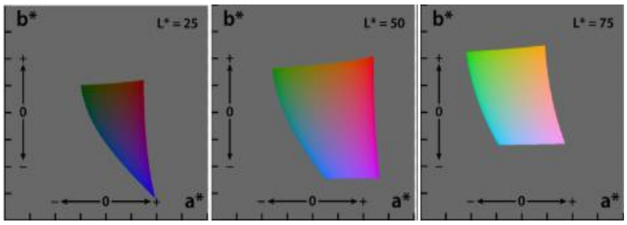


Fig. 1: CIE Lab Color Model with Different Lightness.

The process of converting RGB color space to Lab has no simple conversion formats, and it is suggested that converting RGB to a simpler color space CIEXYZ and then it is converted to Lab:

3.1.1. Convert from RGB to CIEXYZ

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{1}{0.176,97} \begin{bmatrix} 0.4900 & 0.31000 & 0.20000 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00000 & 0.01000 & 0.99000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

3.1.2. Convert XYZ to Lab

$$L = 116g\left(\frac{Y}{Y_n}\right) - 16 \tag{2}$$

$$a = 500\left(g\left(\frac{X1}{X1_n}\right) - g\left(\frac{Y1}{Y1_n}\right)\right) \tag{3}$$

$$b = 200\left(g\left(\frac{Y1}{Y1_n}\right) - g\left(\frac{Z1}{Z1_n}\right)\right) \tag{4}$$

$$G(t) = \begin{cases} \sqrt[3]{t} & if\ t > \sigma^3 \\ \frac{t}{3\sigma^2} + \frac{4}{29} & otherwise \end{cases} \tag{5}$$

The invers is represented as the following:

3.1.3. Convert Lab to XYZ

$$X_1 = X1_n\, g^{-1}\left(\frac{L^*+16}{116} + \frac{a^*}{500}\right) \tag{6}$$

$$Y_1 = Y1_n\, g^{-1}\left(\frac{L^*+16}{116}\right) \tag{7}$$

$$Z_1 = Z1_n\, g^{-1}\left(\frac{L^*+16}{116} + \frac{b}{200}\right) \tag{8}$$

$$G(t) = \begin{cases} t^3 & if\ t > \sigma \\ 3\sigma^2\left(t - \frac{4}{29}\right) & otherwise \end{cases} \tag{9}$$

where $\sigma = \frac{6}{29}$

3.1.4. Convert XYZ to RGB

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 0.41847 & -0.315866 & -0.082835 \\ -0.091169 & 0.25243 & 0.015708 \\ 0.00092090 & -0.0025498 & 0.17860 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{10}$$

3.2. Singular value decomposition (SVD) [14]

3.2.1. Definition of SVD

For any given matrix $A \in R^{m \times n}$ there exists decomposition A = USV^T such that

- The size of matrix U is an m × m and it is called the Left Singular Vectors of A
- Diagonal matrix S called Singular Matrix is an m × n matrix, where all the matrix elements except the diagonal elements should equal to zero.
- Finally the third matrix is V^T with n × n size called Right Singular Vectors of A, see Figure 2.

The singular value decomposition can be implemented on matrices $A \in R^{m \times n}$, where m ≥ n in general (It is possible for m < n, but it is not recommended of 3D Computer Vision). when m = n, all the diagonal values in the singular matrix will be non-zero. While the n diagonal values in the singular matrix will be non-zero values and the rest values will be equal to zero when m > n.
Note that the diagonal values of singular matrix are positive values, this because we determine these values by square roots of the eigenvalues of AA^T and A^TA.

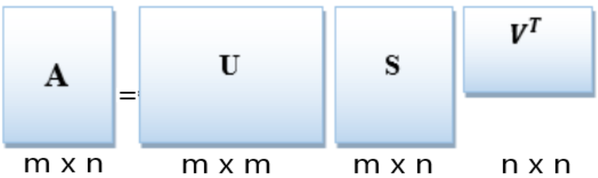


Fig. 2: Illustration of Factoring A to USV^T.

3.2.2. Properties of the SVD

There are many properties and attributes of SVD. Here we shortly introduce them.

- The SVD explicitly constructs orthonormal bases for the null-space and the range of a matrix.
- U, S, V provide matrix factorization of M with real-value, i.e., M = USVT.
- U is an m × n orthonormal columns matrix, UTU = Im, where Im is the m × m identity matrix.
- V is n × n orthonormal matrix, V T = V −1.
- S is m×n diagonal matrix, where s1, s2. . . sn, is non negative diagonal values.
- By convention the diagonal values in singular matrix are given in the sorted order s1 ≥ s2 ≥ . . . ≥ sn ≥ 0.
- The number of singular values sj that are non-zero represent the rank of M.
- The singular value s1, s2… sn are unique, while the matrix U and matrix V are not unique;

3.3. Proposed method

The current method proposed to combine the SVD with Lab color space to colorizing gray image. Up to our knowledge this is the first paper used the SVD for colorizing process. The proposed algorithm in Table 1 summarized the steps for colorization gray.

Table 1: The Proposed Algorithm

Algorithm 1: Colorization of Image
Input: Gray image, and RGB image (Reference image).
Output: Colorized image.
1. Select color reference image (I) (preferrred that has similar features to target grayscale image (G)).
2. Transform image (I) to CIELab color space.
3. Add one pixel padding to the image (G).
4. Normalize the intensity values of gray image (G) according to L channel of CIELab.
5. Transform color image (I) to gray-scale image.
6. Using sliding window 3x3 to scan the image (G) from left to right, and top to down (moving one pixel at each step).
7. Divide images (I) to (3*3) blocks.
8. Find the singular array (S) (using SVD transformation) for all blocks in image (I).
9. Compare each singular array (S) values of current block (window) for image (G) with all the singular array (S) values of blocks in image (I).
10. Find the Euclidean distance between singular arrays (S) values of blocks compared in step 9.
11. The minimum distance represents the more similar block from image (I) to the select block from gray image (G).
12. Combine the intensity value of pixel in the centre of current block in image (G), with the values of (a, b channels) of CIELab color space correspond to the pixel in the centre of block with min. distance in image (I), (this represent Lab pixel)
13. Store the results from 12 in image (T).
14. If the window did not reach the final block in right bottom corner of image (G), back to step 9.
15. Convert the CIELab color space image (T) to color model image (RGB).
16. Check performance

The first step in this proposal is to convert the color reference image to CIELab color space. We need to combine the gray value in the final step (which represent the brightness value in the target image) with (a, b) from CIELab (a, b represents the color information, described as two independent chromaticity layers "a" and "b"). Each layer can be "manipulated" individually, later these layers combined back together into a modified color image. It is recommended to add padding (one pixel around the gray image) to be sure that all pixels in gary image included in the colorizing process.

For accurate results it is very important to mapping the range of the gray image intensity values according to the range of L values. Normalize the gray intensity values to be similar to the range of lightness (L channel) in the CIELab according to the formulae 11.

$$Normalization = \frac{L_{max}}{f_{max} - f_{min}} * (f - f_{min}) \tag{11}$$

Where L_{max} is the maximum range of L in Lab color space, f_{max} is the maximum value in the gray image (f), f_{min} is the minimum value in gray image (f). The normalized gray image will be concatenate later with both (a, b channels of CIELab color space).

The gray-scale image is represented by only the luminance values that can be mapped between the two images, because a single luminance value could represent entirely different parts of an image. The remaining values within the pixel's neighbourhood are used to guide the mapping process, this is achieved by using the SVD transformation. Once a pixel is measured as best choose, the color information is transfer, but the original luminance value is retained.

The colored image selected by the user must be similar to the gray image in the structure, in order to obtain a natural coloration of the image, and the colors are realistic. The colored image is converted into a gray image and divided into (3x3) blocks, where each block transform by using SVD transformation. The result of transformation are three matrices U, S, and V. We will deal with the matrix S that contain the more information about the block values. The gray image scanned by using 3x3 sliding window which move one pixel at each step from left to right and top to down. At each step the block transform by using SVD transformation. Each (S) matrix values of each block in gray image compared with all (S) values for blocks in the reference image. The distance between any pair of blocks (S values) represents the similarities between them, less value regards as more similar.

The block ($B_{i, j}$) from color image which has minimum distance to the selected block from gray image ($K_{m, n}$) represent the best choose to color the pixel in the centre of gray image block ($K_{m, n}$). The value of (a, b) of Lab color space image correspond to the pixel at the centre of best block selected from color image ($B_{i, j}$) will be combine with normalized gray value correspond to the pixel at the centre of gray block ($K_{m, n}$) (it is regards as L channel), continue with this process will led us to get new CIELab image. Finally, the new CIELab image convert to RGB color image which is the colorized target image. Figure 5 show the flowchart for proposed algorithm.

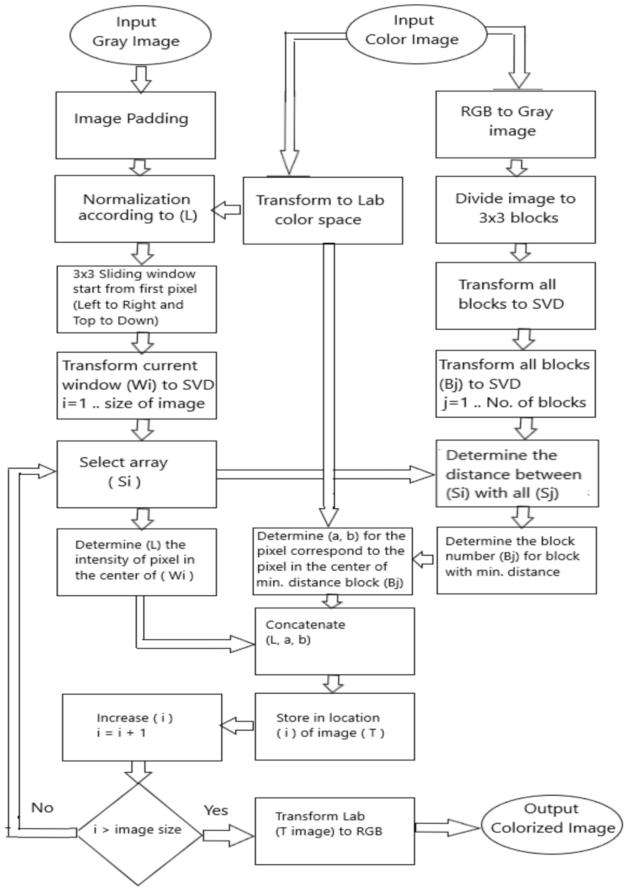


Fig. 5: Proposed Algorithm Flowchat.

4. Results and discussion

The proposed algorithm implemented with many gray scale image to test the algorithm performance, the performance measured by using PSNR and visual effect. For accurate measuring of colorization performance, we suggested to test gray image converted from known colored image, then compare the colorized image with ground truth image visually, and by determining the PSNR.

Selecting the reference image has highly impact on the colorization process. The color histogram of reference image has high effect on the colorization process and the color histogram for the colorized image. This show when colorizing gray image in Figure 6, with reference images that has different color histogram, the result show in Figure 7. It is clear the effect of colors in reference images on the colorized images, this obvious that we select the color from reference image according to the distance between (S) array in both image (gray, and reference image).

Fig. 6: Ground Truth Image on the Left and the Gray Image on the Right.

Image No.	Reference Image	Colorized Image
1		
2		
3		
4		

Fig. 7: Effect of Reference Image on Colorization Process.

At the same time when using reference image with different colors also have high effect on colorization process as show in Figure 7, image 1, and more effect in image 4.
Now, the same images in Figure 6 colorized by using reference image with desired colors needs to colorize gray image, the results show in Figure 8. It is very clear we get more pleasant image from colorization process, and visually very close to ground truth image.
Also when the reference image has the same categorize we get visually better results as show in Figure 9.

Reference Image	Colorized Image	PSNR
		28.1793
		28.0740
		27.3080
		27.2285

Fig. 8: Effect of Reference Image on Colorization Process.

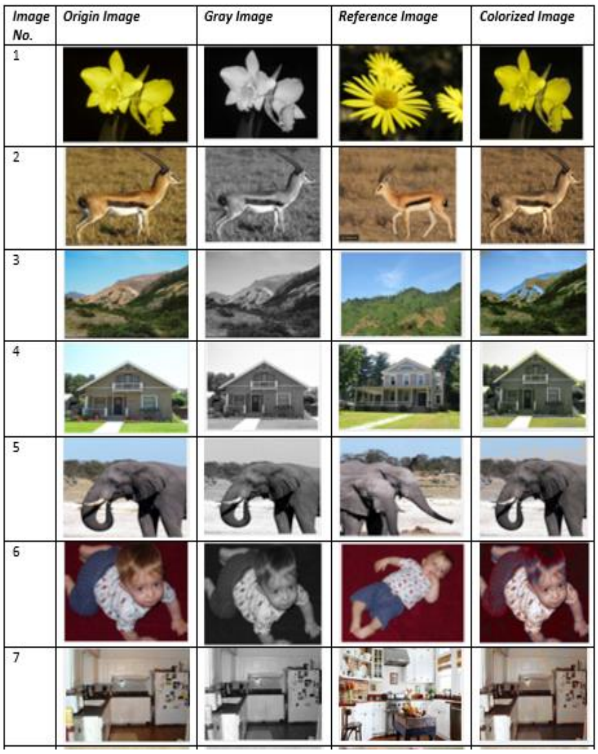


Fig. 9: Colorizing Images from Different Categorize.

4.1. Measuring PSNR

1) Mean Square Error (MSE): It is representing important parameter to measure the PSNR, and then the quality of the colorized image. Its equation:

$$MSE = \sum_{i=1}^{N} \sum_{j=1}^{M} (C(i,j) - I(i,j))^2 / M * N \tag{12}$$

Where C is colorization image, I is gray image, and (N x M) represent image size.

2) Peak Signal-to-Noise Ratio (PSNR): It is the ratio of the maximum signal to noise between two images as shown in Table 1. Its equation:

$$PSNR = 10\,log10\,(MAX^2 / MSE) \tag{13}$$

The PSNR indicate how the colorized image similar to the ground truth image. As show in Figure 8 and Figure 10.
At this point, according to the results from the previous works we conclude that the value of PSNR more than 20db regards as a good result, due to difficulties to get accurate colors. We have to know we select reference image without prior knowledge about the real colors of gray image, and we construct 3D image with three colors (Red, Green and Blue) from one-dimension image.
The final test is to test whether size of blocks and sliding widows effect on colorization process. It is clear from Figure 11, the colorization process did not affect with size of blocks this because we treat each pixel alone, and the neighbour pixels were just guide for colorization. So the block size has low effect when using SVD transformation for image colorization.

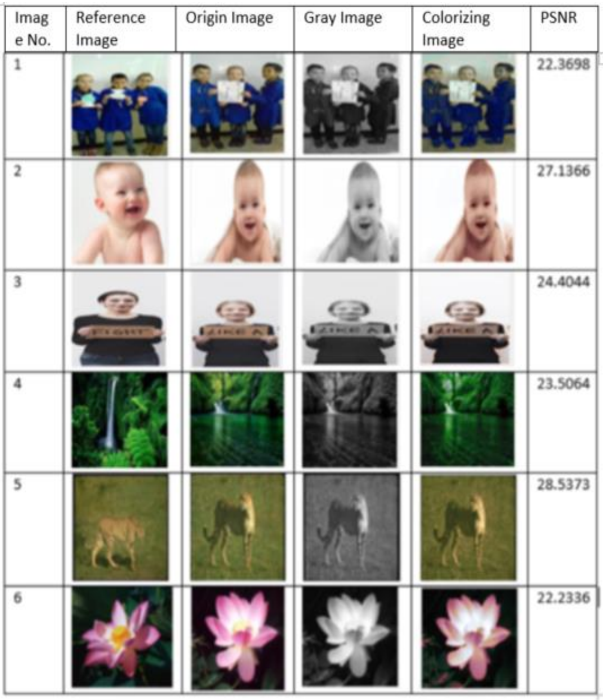
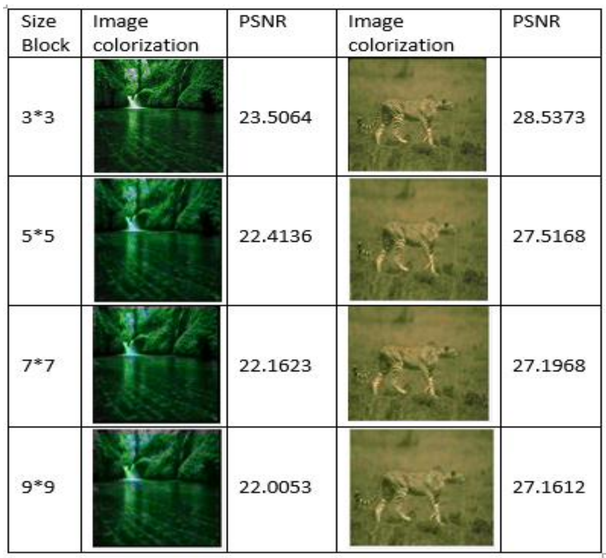


Image No.	Reference Image	Origin Image	Gray Image	Colorizing Image	PSNR
1					22.3698
2					27.1366
3					24.4044
4					23.5064
5					28.5373
6					22.2336

Fig. 10: The PSNR for Different Image Colorized by Proposed Method.



Size Block	Image colorization	PSNR	Image colorization	PSNR
3*3		23.5064		28.5373
5*5		22.4136		27.5168
7*7		22.1623		27.1968
9*9		22.0053		27.1612

Fig. 11: Colorize Images with Different Block Sizes.

We understand that the better source image is the image contains similar objects as the target gray-scale image.

5. Conclusions

In this paper, we introduced a new method to colorize grayscale images based on SVD algorithm, and Lab color space. This method gives very promised results. We conclude that the colorizing process will gives better results when choosing reference image with more suitable colors for coloring the gray image, and also when the reference image has the same category. Block size has no effect on colorizing process. The colorized image visually more close to ground truth image, and consistent with the human perception (the human perception high sensitive to any change in the color image).

The paper proved that using the SVD transformation was very useful to choose the best pixel information from reference image to colorize the selected pixel in gary image.

Measuring the PSNR proves the high quality of colorized image. From the experiment results we conclude that colorizing by using the Lab color space is more effective for improving colorization quality.

References

[1] Guillaume Charpiat, Matthias Hofmann, Bernhard Schölkopf, Automatic Image Colorization Via Multimodal Predictions, European Conference on Computer Vision (ECCV) (2008), pp 126-139. https://doi.org/10.1007/978-3-540-88690-7_10.

[2] Upasana Bisht, Tushar Patnaik, "Overview of Automatic Image Colorization Schemes", *International Journal of Advanced Engineering and Global Technology*, Vol-03, Issue-10, (2015) pp 1283-1287.

[3] Smriti Kumar, and Ayush Swarnkar. Gray image colorization in YCbCr color space, Emerging Technology Trends in Electronics, Communication and Networking (ET2ECN), 2012 1st International Conference on IEEE, (2012). https://doi.org/10.1109/ET2ECN.2012.6470101.

[4] Wang, Huanjuan, et al., Novel colorization method based on correlation neighbourhood similarity pixels' priori, Signal Processing (ICSP), 2012 IEEE 11th International Conference on. Vol. 2. IEEE, (2012). https://doi.org/10.1109/ICoSP.2012.6491722.

[5] Devi, Mandalapu Sarada, and Ankita Mandowara, Extended performance comparison of pixel window size for colorization of grayscale images using YUV color space, Engineering (NUiCONE), 2012 Nirma University International Conference on IEEE, (2012). https://doi.org/10.1109/NUICONE.2012.6493197.

[6] S. D., Garg, R. H., Ghewade, S. A., Jagdale, P. A., & Mahajan, Performance assessment of assorted similarity measures in gray image colorization using LBG vector quantization algorithm, International Conference on Industrial Instrumentation and Control (ICIC), IEEE, (2015).

[7] Hu, Min, Bo Ou, and Yi Xiao, "Efficient image colorization based on seed pixel selection", Multimedia Tools and Applications, vol 76, issue 22, pp 23567–23588 (2017). https://doi.org/10.1007/s11042-016-4112-9.

[8] Deshpande, Aditya, Jason Rock, and David Forsyth, Learning large-scale automatic image colorization, Proceedings of the IEEE International Conference on Computer Vision, (2015). https://doi.org/10.1109/ICCV.2015.72.

[9] Okura, Fumio, et al., Unifying color and texture transfer for predictive appearance manipulation, Computer Graphics Forum. Vol. 34. No. 4. 2015. https://doi.org/10.1111/cgf.12678.

[10] Li, Bo, Yu-Kun Lai, and Paul L. Rosin, "Example-based image colorization via automatic feature selection and fusion", Neurocomputing 266 (2017): 687-698. https://doi.org/10.1016/j.neucom.2017.05.083.

[11] Margulis, Dan, Photoshop Lab Color: The Canyon Conundrum and Other Adventures in the Most Powerful Color space.

[12] Kumar, Smriti, and Ayush Swarnkar, Colorization of gray scale images in lαβ color space using mean and standard deviation, Electrical, Electronics and Computer Science (SCEECS), 2012 IEEE Students' Conference on. IEEE, 2012. https://doi.org/10.1109/SCEECS.2012.6184773.

[13] Asmare, Melkamu Hunegnaw, Vijanth Sagayan Asirvadam, and Lila Iznita, Color space selection for color image enhancement applications, 2009 International Conference on Signal Acquisition and Processing. IEEE, 2009. https://doi.org/10.1109/ICSAP.2009.39.

[14] Nidhal Khdhair El Abbadi, *Data Hiding Schemes Based on Singular Value Decomposition: Handbook of Research on Threat Detection and Countermeasures in Network Security*, IGI Global, (2015), DOI: 10.4018/978-1-4666-6583-5.ch012. https://doi.org/10.4018/978-1-4666-6583-5.ch012.