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Gray Image Colorization Based on General Singular Value Decomposition and YCbCr Color Space

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Abstract

Colorization the gray image is the process of adding colors to the gray image without prior knowledge about the real colors of image. In general, the term and process of colorization is an active area of many researches, and challenging for many researchers. In this paper, we suggested new method for automatic colorizing gray image depending on general singular value decomposition (GSVD) algorithm with YCbCr color space. Up to our knowledge, this is the first work uses the GSVD algorithm in this field. We suggested using reference color image. Both reference image and gray image transformed to YCbCr color space (gray image converted to 3D image by redundant the gray image three times). GSVD is applied for each block from gray image with all blocks from reference image (converted to gray image) to find the best blocks can be combined together from both reference image and gray image. The (Y, Cb, Cr) from YCbCr color space of gray and reference images combines (Y channel corresponding to block of gray image combine with (Cb and Cr) channels from block corresponding to reference image). This process continues for all blocks of gray image. Finally, the resulted image (YCbCr image) is transformed to RGB image (colorized image). Results are promising and dependable.

Keywords: Colorization; Gray image; GSVD; Image processing; YCbCr color space

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 researches, 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. The main problem of coloring a grayscale image involves constructing three dimensional image (three arrays for red, green, and blue) from one dimensional array (gray image). In other words, colorizing technique implies transferring colors between a sources colored image to a destination grayscale image.

There is no "accurate" solution for image colorization due to highly possible to get the same luminance from different colors although there is difference in both the hue and saturation or one of them. In addition, some ambiguity may be arising when we colored objects having shapes related to the measuring the color of the entire object (Charpiat, Hofmann, & Scholkopf, 2008). There are three classes of colorization technique: Hand coloring, Semi-automatic coloring and automatic coloring. However, no author has stated this classification. 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 useless without human intervention. In semi-automatic coloring, user provides some colored scribbles and then the color is spill over the image according to the indicated scribbles. In this method image may be segment to many regions and the user suggests colors for each region. However, 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 largely. A reference image is considering, which the user chooses, 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 recommending to convert RGB reference image to another color space to get color model which should have separate luminance like HSB, HIS, YIQ and La*b*. (Bisht, & Patnaik, 2015). There are many ways utilized in this field, some of which we debate.

Kumar, & Swarnkar, 2012 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 depending 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 of the best matching to use for color transfer from colored image to gray image.

Wang *et al*., 2012 suggested a method depend on correlation neighborhood similarity pixels' priori. This method looks for the group of pixels, which have similarity with neighborhood pixels. The computed weight of the pixels around the target pixel in lightness image transfer to the chrominance.

Devi, & Mandowara, 2012 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.

Thepade *et al*., 2015 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 multicolor image pixels. The elaborate rendering assessment of the various similarity determine the fineness of colorization. Trial is doing with a test 28 images. They are proved through of the analogous measures, having shown that the Canberra distance and Manhattan distance performs while other believe similarity measures for LBG based colorization method.

Hu, Ou, & Xiao, 2017 method based on seed pixel selected to support the users in deciding which pixels is 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 neighboring pixels that are used to deploy the colors to the other pixels.

Deshpande, Rock, & Forsyth, 2015 proposed method based on colorization from examples. This way utilized a LEARCH framework 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 reducing this objective function.

Okura, Vanhoey, & Bousseau, 2015 suggested another style of coloration based on unifies texture and color transfer. This method starts by analyzing 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.

Li, Lai, & Rosin, 2017 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, using a descriptor depends on a luminance deviation to determine whether the area may be symmetrical or asymmetrical.

The rest of this paper includes explanation in section II about the tools used in the paper and the suggested algorithm, while section III introduces the results, and finally concludes the proposed algorithm.

2. Methods

2.1 YCbCr Color Space

YCbCr color space is one of the types of color spaces used in the transformation of images color, which consists of three channels, Y which represents the light or the equivalent of the gray image, while the other two channels represent the color levels of this space. This color space is used to obtain a representation that is more efficient for images. It works by separating the luminance and coloring components in a particular scene and using fewer parts to color the luminance (Kerr, 2012).

The following equations are used for conversion from RGB to YCbCr:

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$

$$Cb = 128 - 0.168736R - 0.331264G + 0.5B \tag{2}$$

$$Cr = 128 + 0.5R - 0.418688G - 0.081312B \tag{3}$$

Where $R^{`}, G^{`}$ *and* $B^{`}$ Represent pixels in color image.

Convert from YCbCr to RGB:

$$R = Y + 1.402\,(Cr - 128) \tag{4}$$

$$G = Y - 0.34414\,(Cb - 128) - 0.71414\,(Cr - 128) \tag{5}$$

$$B = Y + 1.772\,(Cb - 128) \tag{6}$$

2.2. General Singular Value Decomposition Algorithm (GSVD)

GSVD is a matrix decomposition, which is more general than the SVD.

For a given I × J matrix A, in order to generalize the singular value decomposition, it involves using two positive definite square matrices with size I × J and J × J individually. These two matrices express constraints imposed individually on the columns and the rows of A. Formally, if M is the I × J matrix expresses the constraints for the rows of A and W the J × J matrix of the constraints for the columns of A. Matrix A is now decomposed into (El Abbadi, 2007):

$$A = \widetilde{U}\widetilde{\Delta}\widetilde{V}^T \quad \text{with}: \ \widetilde{U}^T M \widetilde{U} = \widetilde{V}^T W = I \tag{7}$$

In other words, the generalized singular vectors represent orthogonal under the constraints that is imposed by M and W. This decomposition can be reached because of the standard singular value decomposition. We start by defining the matrix $\widetilde{A}$ as:

$$\widetilde{A} = M^{\frac{1}{2}} A W^{\frac{1}{2}} \quad \Leftrightarrow A = M^{-\frac{1}{2}} \widetilde{A} W^{-\frac{1}{2}} \tag{8}$$

The standard singular value decomposition is computed as follows:

$$\widetilde{A} = P\Delta Q^T \quad \text{with}: \ P^T P = Q^T Q = I \tag{9}$$

The matrices of the generalized eigenvectors are reached as follows:

$$\widetilde{U} = M^{-\frac{1}{2}} P \quad \text{and} \quad \widetilde{V} = W^{-\frac{1}{2}} Q \tag{10}$$

The diagonal matrix of singular values is simply equal to the matrix of singular values of $\widetilde{A}$:

$$\widetilde{\Delta} = \Delta \tag{11}$$

We verify that:

$$A = \widetilde{U}\widetilde{\Delta}\widetilde{V}^T \tag{12}$$

By substituting:

$$A = M^{-\frac{1}{2}} \widetilde{A} W^{-\frac{1}{2}} \tag{13}$$

$$A = M^{-\frac{1}{2}} P\Delta Q^T W^{-\frac{1}{2}} \tag{14}$$

$$A = \widetilde{U}\Delta\widetilde{V}^T (\text{ from equation 8}) \tag{15}$$

Suffices to show that:

$$\widetilde{U}^T M \widetilde{U} = P^T M^{\frac{1}{2}} M M^{-\frac{1}{2}} P = P^T P = I \tag{16}$$

And

$$\widetilde{V}^T W \widetilde{V} = Q^T W^{-\frac{1}{2}} W W^{-\frac{1}{2}} Q = Q^T Q = I \tag{17}$$

It is in several types, it enters into a lot of applications, within the matrices algebra field in particular, and in general applied mathematics (Wei, Xie, & Liping, 2016).

General Singular Value Decomposition (GSVD).

$[U.V.X.C.S] = GSVD(A, B)$ Returns unitary matrices U and V, square matrix X, and diagonal matrices nonnegative C and S so that

$$A = U * C * X^T$$

$$B = V * S * X^T$$

$$C^T * C + S^T * S = I$$

The columns A and B must be equal, but can have different numbers of rows. If $A_{m\times p}$ and $B_{n\times p}$ then $U_{m\times m}$, $V_{n\times n}$ and $X_{p\times q}$ where $q = \min(m + n, p)$.

2.3. Proposed Method

Colorization process needs human intervention in determining the color image by which the gray image is colored, whether symmetrical or otherwise. The proposed algorithm 1 summarized the steps for colorization gray image relying on YCbCr color space.

Algorithm 1: Colorization of Image

Input: Gray image and RGB image as reference image.

Output: Colorization of gray image.

1. Select color reference image (I) (preferred that has similar features to target grayscale image (G)).
2. Transform image (I) to YCbCr color space (image IC).
3. Convert the gray image into three layers by repeating the gray image for each layer (image T).
4. Transform image (T) to the YCbCr color space (image TC).
5. Transform color image (I) to gray-scale image (K).
6. Divide image (G) to non-overlap blocks.
7. Select block (i) from image (G), the blocks selected sequentially from left to right, and top to down.
8. Determine the five arrays (U, S, V, X, C) (using GSVD transformation) for the selected block from step 7 with all blocks in image (K) (image K divided to blocks with same size of blocks of step 6 by using sliding window (window can be moving N pixels at each time (1<= N <=block size). from left to right and top to down).
9. Determine the distance between array (X) and array (C) for all blocks of (K) in step 8.
10. Find the location of the pixel in the center of block from image (K) with minimum distance results from step 9.
11. Combine the (Y channel) of block from image (TC) correspond to the selected block (i) in image (G) at step 7 with (Cb and Cr channels) of block from image (IC) corresponding to the block with minimum distance from step 10.
12. If there is more block/s in image G, go to step 7.
13. Convert YCbCr image result from step 11 to (RGB) color model image.
14. Check performance

The first step in this proposal is to convert the gray image to three 2D arrays (image T), which is like the color image, this is achieved by repeating gray image for each layer of 3D image (three layers can be imagine them as Red, Green and Blue layers). Image (T) is transformed to YCbCr color space (image TC). In addition, the reference image (color image) is transformed to YCbCr color space (image IC). Our goal is to create YCbCr image, by combining (Y) channel from image TC, with chromatics channels (Cb and Cr) from image IC, then transforming image to RGB image as shown in Figure 1:

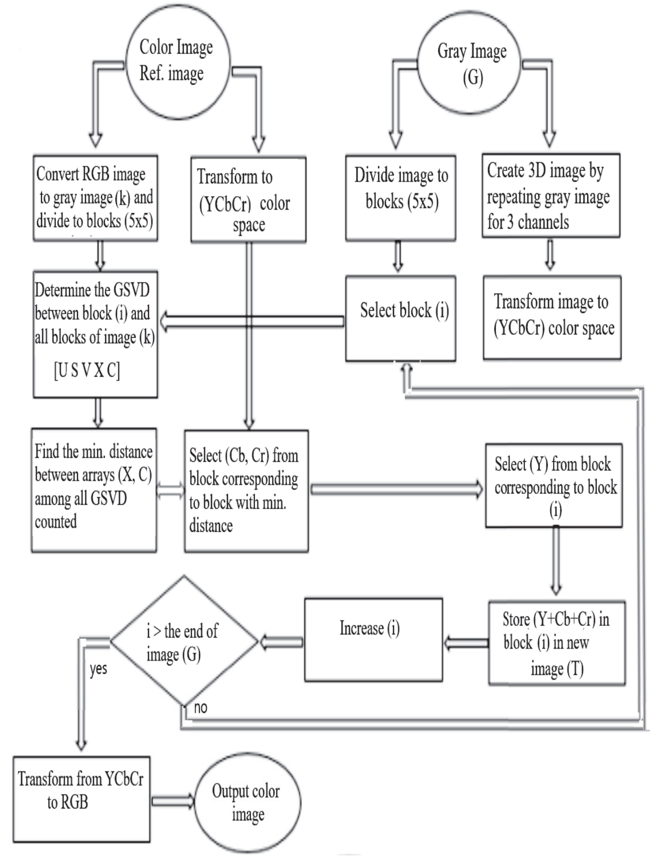


Fig. 1. Proposed algorithm flowchart.

Now we divide the gray image G to non-overlap blocks (5x5 or 7x7). We need to find the best matching blocks from image (IC) (Cb, Cr channels) which can be combined with each block from image (TC) (Y channel). The suggested algorithm in this paper determines the best matching block from image (IC) by using new method to determine the distance between any two blocks based on the GSVD transformation. The target image (image G) is divided into non-overlapping blocks. The color image (I) is converted into a gray image (K) and then divided into overlapping blocks with the same size of gray image blocks. GSVD algorithm is applied between each block of the target image with all blocks of the reference image, five matrices will be produced (U, S, V, X, C), the two arrays (X, C) contains the special information related to the two images.

The best (Cb, Cr from image IC) to be combined with (Y from image TC corresponding to block (i)) is in the block with minimum distance between matrix (C) and matrix

(X). After we check all the blocks from target image, we have to transform YCbCr image to RGB image.

2.4. Image Quality Metrics (Memon, Unar, & Memo, 2015)

In the development of image processing algorithms, Image Quality Measurement (IQM) plays an important role. To evaluate the performance of processed image, IQM can be utilized. Image Quality is defined as a characteristic of an image that measures the processed image degradation by comparing to an ideal image.

1. Peak Signal-to-Noise Ratio (PSNR)*:* it is used to measure the proportion of the similarity or extent of the difference between two images of the same structure. It is determined by:

$$\mathrm{PSNR} = 10 \log_{10} (R^2 / \mathrm{MSE}) \quad (18)$$

The value of R is decided by the format of the image. If the image is an 8-bit image, R = 255.

A higher value of PSNR specifies the reconstruction of higher quality.

2. Average Difference (AD): provides the average of change concerning the colored image and reference image. AD can be expressed as follows:

$$\mathrm{AD} = \frac{1}{\mathrm{NM}} \sum_{i=1}^{N} \sum_{j=1}^{M} [A(i,j) - B(i,j)] \quad (19)$$

Zero is the perfect value of AD.

3. Root Mean Square Error (RMSE)*:* Similar to MSE, but its root is found.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{NM}} \sum_{i=1}^{N} \sum_{j=1}^{M} (C(i,j) - I(i,j))^2} \quad (20)$$

Smaller value of the RMSE represents the better result.

4. Maximum Difference (MD): Represents the maximum error between the reference image and the image after coloring.

$$\mathrm{MD} = \max|A(i,j) - B(i,j)| \quad (21)$$

The higher the value of MD the poorer the quality of the image.

5. Structural Content (SC): It is measures the similarity between two images.

$$\mathrm{SC} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (y(i,j))^2}{\sum_{i=1}^{N} \sum_{j=1}^{M} (x(i,j))^2} \quad (22)$$

A higher value of SC (Structural Content) shows that image is of poor quality

6. Normalized Absolute Error (NAE): It also measures the similarity between the two images.

$$\mathrm{NAE} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (|A(i,j) - B(i,j)|)}{\sum_{i=1}^{N} \sum_{j=1}^{M} A(i,j)} \quad (23)$$

The best result (image quality) when the NAE approaches to zero.

7. Normalized Cross Correlation (NCC): measure shows the comparison of the processed image and reference image; it is expressed by as follows:

$$\mathrm{NCC} = \sum_{i=1}^{N} \sum_{j=1}^{M} \frac{(A_{ij} * B_{ij})}{{A_{ij}}^2} \quad (24)$$

8. Structure Similarity Index (SSIM): The SSIM index evaluates a test image X with respect to a reference image Y to quantify their visual similarity. The general formula is (Renieblas, Nogués, González, Gómez-Leon, Del, 2017):

$$\mathrm{SSIM}(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[r(x,y)]^{\gamma} \quad (25)$$

Where α, β, and γ are parameters that define the relative importance of each component, and:

$$l(x,y) = (2\mu_x\mu_y + C1)/(\mu_x^2 + \mu_y^2 + C1) \quad (26)$$

$$C(x,y) = (2\sigma_x\sigma_y + C2)/(\sigma_x^2 + \sigma_y^2 + C2) \quad (27)$$

$$r(x,y) = (\sigma_{xy} + C3)/(\sigma_x\sigma_y + C3) \quad (28)$$

Where C1, C2, and C3 are constants introduced to avoid instabilities when average pixel value $(\mu_x^2 + \mu_y^2)$, standard deviation $(\sigma_x^2 + \sigma_y^2)$, or $\sigma_x\sigma_y$ is close to zero. SSIM (x, y) ranges from 0 (completely different) to 1 (identical patches).

9. Pearson Correlation Coefficient (PCC): is a very helpful statistical formula uses to determine just how strong that relationship is between those two variables, the formula is:

$$\mathrm{PCC} = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (29)$$

The value PCC range between [1 and -1]. If the value is in the positive range, then that means the relationship between the variables is positively correlated, while bad correlated when the value is in the negative range.

3. Results and Discussion

There are many tests we did to test the performance of proposed algorithm:

1. Histogram of (RGB) color reference image, has high effect on the colorization process, and the color histogram for the colorized image. Figure 2 Shows the result of colorizing number of gray images and the PSNR when they are compared them with ground truth images. The PSNR is with accepted range for colorizing process, and visually there is high similarity between the ground truth and colorized image. For blind colorization, these results are very good.

2. The proposed algorithm implemented with many gray scale images to test the algorithm performance, the first 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, which help to 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. Fig. 2 show the result of colorization process for many different images and what is the PSNR for each one. Visually the colorized image have good similarity with ground truth image, also the PSNR results are very reasonable for full automatic colorization.

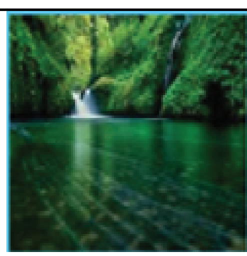
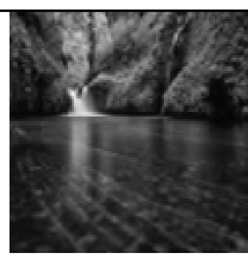
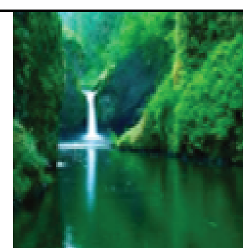
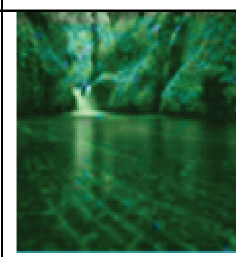
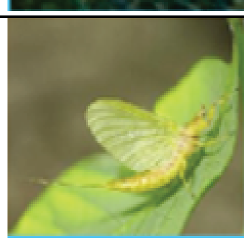
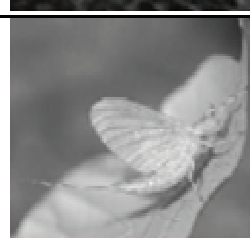
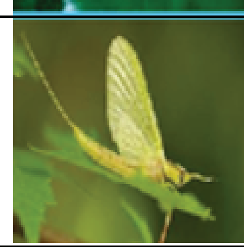
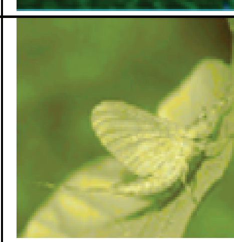
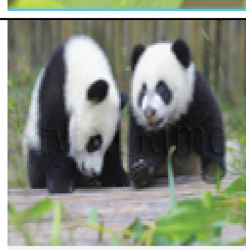
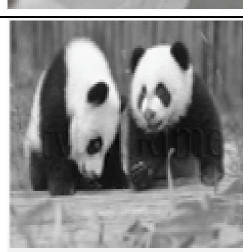
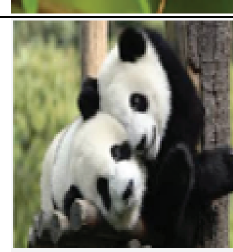
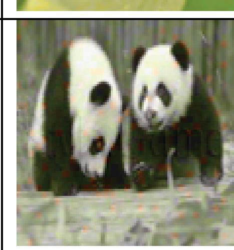
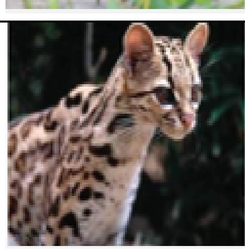
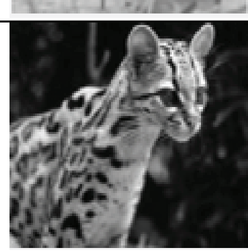
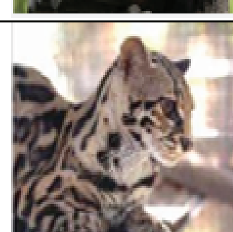
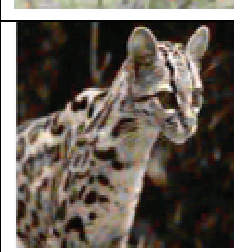
Image No.	Origin Image	Gray Image	Reference Image	Colorized Image	PSNR
1					23.5091
2					22.0515
3					21.1255
4					23.5359

Fig. 2. the PSNR for different image colorized by proposed method.

3. The other test was test the quality of the colorized images by using the measurements listed in section 2.4. We used the same tested image from Figure 2 and implemented the performance measurements on them, the results show in Table 1. The results are in generally good, where most of the measures were prove good ratio of similarity between the colorized image and ground truth image. But there is a deviation in some metrics, for example RMSE, this due to very high challenge to reconstruct 3D image from one-dimension image, nowadays may be it is impossible to get real colors. Although it is very difficult to colored gray image with the real color of original image in blind coloring process (full automatic process), but the results in Table 1 are very promised and dependable. Also we note that the runtime is relatively high due to searching process, this time depend on image size, block size, step for window sliding, and on the computer specification.

Table 1. measuring image quality after colorization process.

Measures	Ideal value	Image 1	Image 2	Image 3	Image 4
AD	0	-1.5	0.28	0.99	0.006
MD	0	116.3	152	187	185.3
RMSE	0	15.21	16.00	16.58	12.37
NAE	0	0.48	0.17	0.13	0.16
NC	1	0.98	0.98	0.96	0.98
SC	1	1.23	1.05	0.98	1.03
PCC	1	0.77	0.76	0.90	0.93
SIMM	1	0.56	0.76	0.78	0.83
TIME (sec)		2.96	1.68	1.22	1.97

4. In addition, we test the effect of block size on colorization process, the result of using the images from Figure 3 listed in Figure 4. It is clear that the size of blocks (5x5 and 7x7) have approximately the same effect and regards as the best choice. It is clear when the bock size increase this will led to reduce runtime, but at the same time this will effects slightly on the image coloring quality. We recommend using the (7x7) block size to reduce the time and keep the quality in reasonable state.

5. We compared the result visually with other works as shown in Figure 5. The results were promised and they are better than the other works. The images in Figure 5 are tested with other algorithms published in references cited in the figure.

6. Also we test colorization gray image by using different reference image some of them not have the same sense as shown in Figure 6, it is clear no significant difference between colored images.

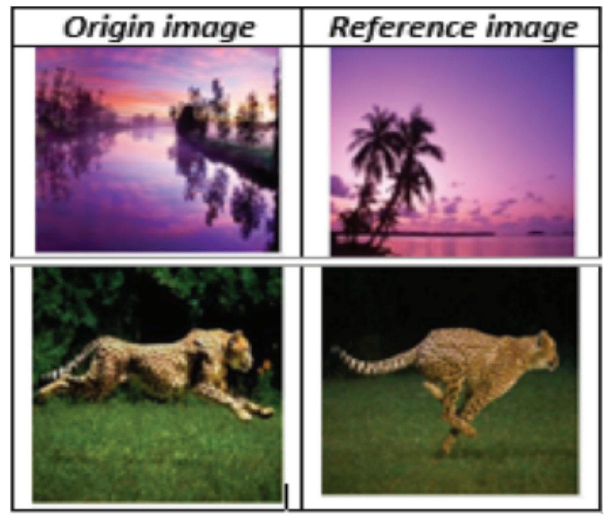


Fig. 3. The origin image and reference image

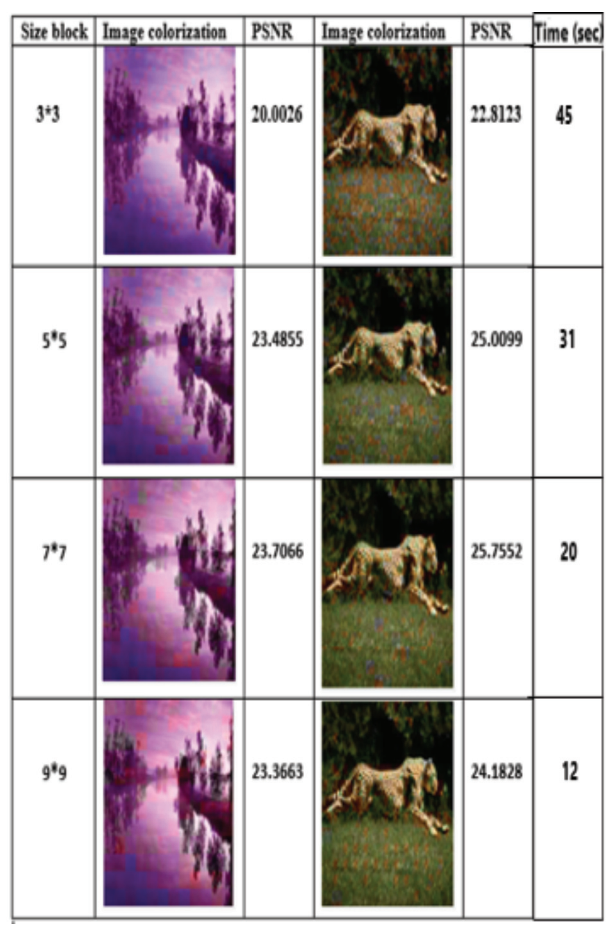
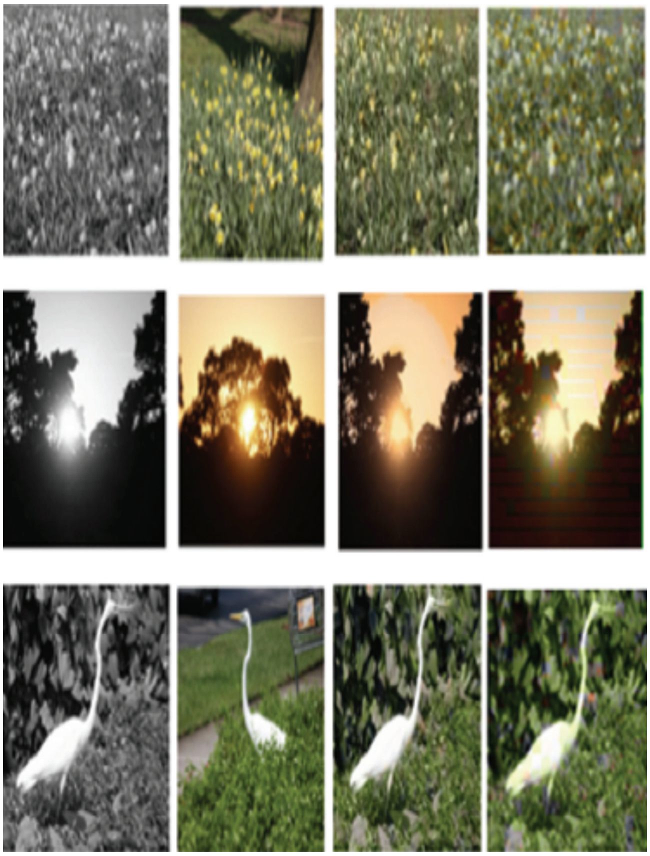


Fig. 4: Colorize images with different block size.



Input image Ref. image Hu M. 2017 proposed

Fig. 5(a).

Input image Ref. image Kumar S. 2012 proposed

Fig. 5(b).

Input image Ref. image LiB. 2017 proposed

Fig. 5(c).

Fig. 5. Comparison of proposed colorization process with **A.** algorithm from (Hu M. 2017). **B**. algorithm from (Kumar S. 2012). **C**. algorithm from (Li B. 2017)

Ref. image	Gray image	Colorized image	PSNR
			20.03
			20.97
			20.03

Fig. 6. Colorized image by using different image references.

4. Conclusion

In this paper, we suggested a new way to colorize grayscale images depending on GSVD algorithm. Up to our knowledge, this is the first work in this field using the GSVD algorithm as a distance measures. The algorithm depends on dividing the images into many blocks, the best size of block is (7x7). The suggested algorithm used the YCbCr color space, the Y channel from gray image combines with best values for (Cb, and Cr) from reference image, this process is highly enhancing the colorization process. Using reference image with similar structure and color histogram to the gray image will enhance the quality of colored image. The results depend on the selected reference image, which will affect the color transfer to gray image. Image quality measured by using many performance measurements and the result was good as in Table 1. We obtained pleasant image and good results according to PSNR. The drawback of this algorithm is more time consuming compared with other works. The advantage of this algorithm is its ability to find the best color that can transfer from block in reference image to block in gray image based on measuring the distance between blocks by using the GSVD. Also the color space YCbCr can increase the quality of colored image. from other side the drawback of this algorithm is the trade of between increasing the block size (which reduce time) and the quality of image which decrease with increasing block size.

5. Author's contribution

Most of colorization algorithms of target images is crucially dependent on correct segmentation of reference image. Also most of them significantly rely on the texture based features for matching of objects in reference and target image. Since segmentation process and texture matching are not perfect, assignment of colors is not proper and leakage of colors takes place, even if reference and target images are almost similar. To recover these problem, we suggested to use GSVD as a distance measure to find the best block from reference image can barrow the color from it to colorized the selected block of gray image. Up to our knowledge this the first work used the GSVD as a distance measure, and this the first work combine the YCbCr and GSVD to colored the gray image. Using the GSVD improve the results.

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تلوين الصور الرمادية بالإعتماد على تعميم تحليل القيمة المفردة وفضاء الألوان YCbCr

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الملخص

يشير مصطلح تلوين الصور الرمادية إلى عملية إضافة ألوان إلى الصور الرمادية بدون معرفة مُسبقة بحقيقة ألوان الصورة الأصلية. وبشكل عام فإن مصطلح وعملية التلوين تعتبر مساحة بحث علمي فعالة وتحدي كبير لكثير من الباحثين. في هذا البحث، تم اقتراح طريقة جديدة لتلوين الصور الرمادية آلياً بالاعتماد على تعميم تحليل القيمة المفردة (GSVD) وفضاء الألوان (YCbCr). وحسب علمنا، فإن هذه الطريقة هي الأولى التي تستخدم GSVD في هذا المجال. تستند عملية التلوين إلى اختيار صورة ملونه عشوائياً لتكون مصدر للألوان تسمى الصورة المصدر. كلا الصورتين الرمادية والصورة المصدر يتم تحويلهما إلى فضاء الألوان YCbCr (الصورة الرمادية يتم تحويلها إلى صورة ثلاثية الأبعاد وذلك بتكرار الصورة الرمادية ثلاث مرات). يتم إيجاد أقرب مسافة (أقرب تشابه أو تفاضل) بين كل بلوك من الصورة الرمادية مع جميع بلوكات الصورة المصدر وذلك باستخدام خوارزمية GSVD (الصورة المصدر يتم تحويلها إلى صورة رمادية في هذه المرحلة). تُدمج قيم كل من (Y, Cb, Cr) لكل من الصور الرمادية والمصدر معاً (حيث يتم اختيار قيمة Y التي تقابل بلوك الصورة الرمادية لتدمج مع كل من (Cb, Cr) اللاتي تقابلان البلوك المناسب في الصورة المصدر). هذه العلمية تستمر لحين أن يتم معالجة جميع بلوكات الصورة الرمادية. الصورة الناتجة هي بفضاء الألوان (YCbCr) والتي يتم تحويلها إلى صورة بفضاء لوني RGB. كانت النتائج من هذه الطريقة مشجعة وواعدة ومن الممكن الاعتماد عليها.