IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 23 April 2023, accepted 21 May 2023, date of publication 24 May 2023, date of current version 7 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3279734

RESEARCH ARTICLE

Color to Grayscale Image Conversion Based on Singular Value Decomposition

ZAID NIDHAL KHUDHAIR[1,4], AHMED NIDHAL KHDIAR[2], NIDHAL K. EL ABBADI[3], FARHAN MOHAMED[4], (Senior Member, IEEE), TANZILA SABA[5], FATEN S. ALAMRI[6], AND AMJAD REHMAN[5], (Senior Member, IEEE)

[1]Faculty of Engineering, School of Computing, University of Technology Malaysia, Johor Bahru 81310, Malaysia
[2]Department of Electrical Engineering, Faculty of Engineering, University of Kufa, Najaf 54001, Iraq
[3]Computer Techniques Engineering Department, Al-Mustaqbal University, Babylon 51001, Iraq
[4]UTM-IRDA MaGICX, Institute of Human Centered Engineering, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia
[5]Artificial Intelligence and Data Analytics Laboratory, College of Computer and Information Sciences (CCIS), Prince Sultan University, Riyadh 11586, Saudi Arabia
[6]Department of Mathematical Sciences, College of Science, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia

Corresponding author: Tanzila Saba (tsaba@psu.edu.sa) and Faten S. Alamri (fsalamri@pnu.edu.sa)

This research was funded by Princess Nourah bint Abdulrahman University and Researchers Supporting Project number (PNURSP2023R346), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

ABSTRACT Color information is useless for distinguishing significant edges and features in numerous applications. In image processing, a gray image discards much-unrequired data in a color image. The primary drawback of colour-to-grey conversion is eliminating the visually significant image pixels. A current proposal is a novel approach for transforming an RGB image into a grayscale image based on singular value decomposition (SVD). A specific factor magnifies one of the color channels (Red, Green, and Blue). A vector of three values (Red, Green, Blue) of each pixel in an image is decomposed using SVD into three matrices. The norm of the diagonal matrix was determined and then divided by a specific factor to obtain the grey value of the corresponding pixel. The contribution of the proposed method gives the user high flexibility to produce many versions of gray images with varying contrasts, which is very helpful in many applications. Furthermore, SVD allows for image reconstruction by combining the weighting of each channel with the singular value matrix. This results in a grayscale image that more accurately captures the actual intensity values of the image and preserves more color information than traditional grayscale conversion methods, resulting in loss of color information. The proposed method was compared with a similar method (converting the color image into grayscale) and was found to be the most efficient.

INDEX TERMS Decolorization, grey image, image conversion, SVD, technological development.

I. INTRODUCTION

Currently, most of the captured images are color images. However, it is frequently necessary to convert a color image to grayscale images for printing, aesthetic intents, object detection, and publishing as less expensive, helping colorblind people preserve visual cues [1]. Color-to-grayscale conversion is the process of reducing the image dimensions by transforming the RGB tristimulus values (Red, Green, Blue) $\in R^3$ to the intensity value (I) R [2]. The lightness values ranged from zero (black) to 255 (white), as shown in Fig. 1. Generally, the conversion process produces an image with lower contrast than the original color image. The goal of each conversion algorithm is to preserve the local luminance consistency, global consistency, image contrast information, and hue order as much as possible [3]. Different processing methods are required for each pixel in various image-processing applications. Processing RGB pixels is not feasible due to high storage requirements and computation costs. The best solution to these issues is to convert an RGB image into a grayscale image [4]. Grayscale images are mainly used for shape characteristics, edge detection, circular objects, and

The associate editor coordinating the review of this manuscript and approving it for publication was Mingbo Zhao.

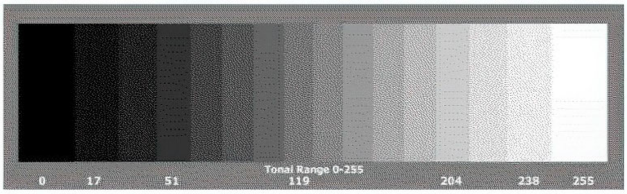


FIGURE 1. Sample of the grayscale image.

corners. Illumination and chrominance for matching and correlation had negative effects. Grey images are highly useful for further segmentation. The contrast and smoothness can be increased in grey images to obtain more image details. A grey image requires less memory space and is processed faster, which is common in image processing.

Suggesting a good algorithm that can transform an RGB image into a gray image while preserving salient features is a significant challenge and a complicated process. During the conversion process, numerous crucial image features, such as sharpness, shadows, contrast, and color structure, may need to be recovered. In addition, current methods consume large amounts of computational time and memory [5].

Algorithms for converting images into grayscale can be classified into two major groups. The first is based on color transformation. Usually, the color image (RGB) is transferred into other color spaces, separating the luminance from the chrominance channels. In the second group, the lightness channel can be extracted from the color space (L*a*b*) to build a grayscale image. The main problem with current color transform methods is that mapping the same gray value for various color values with the same luminance leads to the loss of edge and object boundaries [6].

Methods of converting color images to grayscale can be classified into three types: global method which has the power to produce a natural-looking gray image, in general, it is time-consuming. The second type is the local method, which has good local contrast preservation but may produce a local artifact. In addition, a poor property of the local mapping method is the possibility of mapping the same color value into various gray values. The third type is hybrid mapping, which combines the two previous mappings [7].

Using SVD to convert a color image to a grayscale enables the representation of the image as a collection of singular values that capture the intensity information of the image. This can be useful in image analysis and processing tasks performed on grayscale images. In addition, SVD is a robust technique for image processing, making it suitable for processing images that may be degraded or contaminated by noise.

The remaining paper is structured as follows: Section two described the main problems when converting color to a grayscale image. Whereas section three provides the main advantages of the current proposal. Section four provides a brief overview of prior research on converting color images to grayscale. In section five an idea about SVD and how it works is introduced. The methodology is presented in Section six. Section seven focuses on the results and validates the proposed algorithm. Finally, we conclude this reserach in section eight.

II. PROBLEM DESCRIPTION

Although many conversion techniques have been developed and reported in state of the art, they still pose several critical problems, such as [8] and [9]:

- Color distortion: Many grayscale conversion methods can result in color distortion. This is because these methods cannot accurately capture an image's true intensity values.
- Loss of color information: Many grayscale conversion methods result in the loss of color information, which can be significant in cases where the color information is important for interpreting the image.
- Reduced image quality: Conversion of color images into grayscale can reduce image quality, particularly in cases where the image contains subtle color variations that are important for interpretation.
- Inadequate representation: In some cases, grayscale images may not adequately represent the original color image because the information in the color channels may be lost during the conversion process.
- High computational complexity: Some grayscale conversion methods, such as those based on the color appearance model, can be computationally expensive, rendering them unsuitable for real-time application.

These problems have motivated researchers to develop new methods to convert color images into grayscale images that are more accurate, efficient, and robust. The SVD method aims to preserve important color information in an image, reduce color distortion, and enhance the image's visual quality.

III. ADVANTAGES OF THE PROPOSED METHOD

The proposed method for converting color images to grayscale is highly efficient and does not require specialized hardware, making it well suited for practical applications. It is designed to be easy to use and integrate into existing image processing pipelines.

In addition, the proposed method allows users to obtain high-quality grayscale images without sacrificing the critical details contained in color channels. This is achieved through a novel weighting scheme that effectively balances the contributions of different color channels to create a grayscale image that accurately reflects the underlying color content of the original image. As a result, this method can be used confidently in a wide range of applications in which color information is essential for accurate analysis and interpretation.

An important advantage of our grayscale conversion method is that it avoids color distortion, which can be a significant problem in many existing approaches.

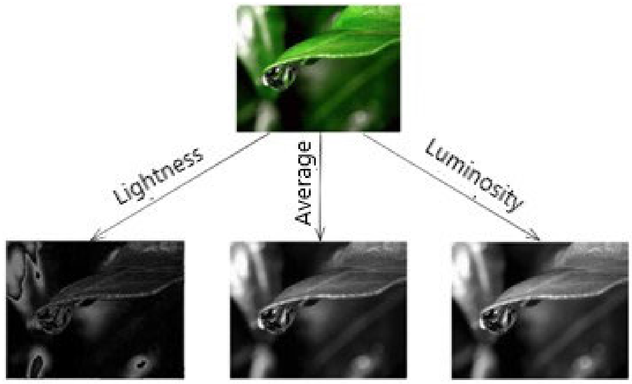


FIGURE 2. Conversion of a color image by three different methods.

One of the key advantages of the current method is its robustness to noise, which enables it to perform well even in noisy or low-quality images. In contrast, other methods may need help to produce high-quality grayscale results.

IV. BACKGROUND

Several methods have been proposed for converting color images into grayscale images. One of these methods is to use one of the (red, green, or blue) channels of the RGB image or one channel of another image color space, such as using channel V of the HSV color space. These methods may cause a loss of discriminative information [2].

A very simple method is based on the mean of the maximum and minimum values of three colors called (the lightness method) as in "equation (1)" [10]. The major weakness of this method is that it does not use three-color components.

$$Grayscale\ image = \frac{\min(R, G, B) + Max(R, G, B)}{2} \quad (1)$$

Another method obtained the grayscale value from the average value of the three colors as in "equation (2)" [11], [12]:

$$Grayscale\ image = \frac{R + G + B}{3} \quad (2)$$

This method assigns the same weight to each of the three-color components, which is a weakness because our eyes react differently to each color.

One of the best methods for converting color to gray is based on a weighted combination of RGB channels, called the luminosity method, as shown in "equation (3)" [13]:

$$Grayscale = 0.2989 \times R + 0.587 \times G + 0.114 \times B \quad (3)$$

However, this method has several areas for improvement, including a lack of color separation, insensitivity to saturation, poor handling of certain color combinations, and limited dynamic range. These weaknesses can result in a loss of contrast, detail, and color separation in the resulting grayscale image.

The differences between the two methods are shown in Fig. 2. Many conversion methods have recently been proposed, but their performances still need to be assessed. As a result, the benefits and drawbacks of color-to-grayscale conversion remain unknown, some of which are:

The authors in [8] presented a method that converts a color image into other color spaces (L*a*b*), where the luminance and chrominance components are separated and processed independently. The chrominance information is decomposed using singular value decomposition (SVD). The weight matrix was constructed by multiplying the eigenvalues and eigenvectors of the chrominance planes produced from the SVD analysis. To obtain low-contrast information, luminance information is combined with a weighted sum of chrominance data. This method has several advantages related to the preservation of color information, robustness, and flexibility, as well as potential disadvantages related to complexity, subjectivity, and loss of fine details.

In [14], a color-to-grayscale transformation employed three global linear weighting parameters derived directly from the correlations between the three-color channels (red, green, and blue) concerning a base image. The author considers the correlation values (magnitude and sign) to set the weighting parameters. This method has several advantages, including its efficiency, direct RGB channel processing, and comparability to state-of-the-art methods. However, it also has limitations, including limited applicability to other image processing tasks, limited accuracy due to reliance on correlations between channels and a contrast image, and limited flexibility due to fixed linear weighting parameters.

In [15], a method for converting a color image into a grayscale image was proposed based on extracting eigenvalues and eigenvectors from SVD. In this study, converting the input color image to the CIE L∗a∗b∗ space is beneficial for separately processing the luminance and chrominance information.

Multiplying the eigenvalues and eigenvectors resulting from the application of SVD to CIELab* produces chrominance matrices. The weighted sum of chrominance and luminance information obtained from the grayscale image. This method has several advantages related to the preservation of color information, robustness, and flexibility, it also has some potential disadvantages related to complexity, subjectivity, and loss of fine details.

In [16], a CNN incorporating a local feature network and coarse classifier was proposed to differentiate between different exposure conditions of color images. The network accomplishes this by learning local semantic features. The authors aimed to achieve optimal results in preserving the color contrast and exposure settings by training the model to map color and grayscale images. This method has some potential advantages in preserving color contrast and exposure settings as well as some potential weaknesses related to dependence on training data, complexity, loss of fine details, and difficulty in preserving color contrast.

In [17], the color image (RGB) is separated into three channels (red, green, and blue) based on the information-theoretic method, and two weight maps are defined. Using information maximization, the first weight map extracts the

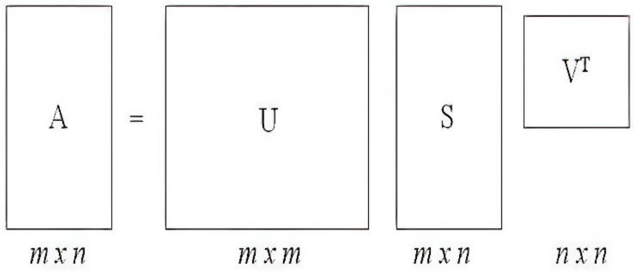


FIGURE 3. Schematic diagram of SVD [22].

visually salient regions. By contrast, the second weight map determines the local entropy per patch by filtering the local variation value for each image. This approach employs a multiscale fusion technique to alleviate the local distortions caused by weight map discontinuities. Information-theoretic methods have several advantages related to the preservation of visually salient regions, local contrast enhancement, and multi-scale fusion. However, the method may be computationally expensive and require additional optimization for certain image types or applications.

V. SINGULAR VALUE DECOMPOSITION (SVD)

In recent years, researchers in the field of image processing have focused on using one of the mathematical algorithms in the field of numerical linear algebra, which was applied in a small number of fields at the emerging time but has rapidly expanded to many other fields. This algorithm uses singular-value decomposition (SVD).

The SVD provides a capability for the researcher to use a lot of various dimension matrices by a generalization of the eigenvalue decomposition idea [18]. SVD transforms a matrix into three matrices $U\Sigma V^T$(U and V are rotation matrices and Σ is a scaling matrix) that carry some of the useful and unique properties of the original matrix. The SVD method in image processing regards algebraic features [19]. SVD decomposes any (m, n) matrix into three matrices as shown in Fig. 3, where *m* is the matrix rows, and n represents the matrix columns, where the rank r satisfies $r \le n \le m$, it can be decomposed into three matrices as follows:

$$A = USV^T \tag{4}$$

Recently SVD has gained popularity and become an attractive algebraic transform in image processing, owing to its stability and conceptual advantages. SVD is a reliable and robust orthogonal matrix factorization technique with prominent properties in imaging [20]. Recall that the Frobenius norm of an $n \times m$ matrix $A \in R^{n\times m}$ is defined.

However, this norm does not directly correspond to A as a representation of a linear map. Specifically, in many contexts, measuring the difference between two matrices is essential based on their effect on vectors. A norm on a vector space V is a function [21]:

$$\|.\| \, \mathcal{V} \, V \rightarrow \mathbb{R}$$

that satisfies the following three conditions:

- ☐ $\|v\| \ge 0$ **for all** $v \in V$ **and** $\|v\| = 0$ **if and only if** $v = 0$
- ☐ $\|kv\| = |k| \, \|v\|$ **for any scalar** $k \in \mathbb{R}$ **and vector** $v \in \mathbb{R}^d$
- ☐ $\|v + w\| \le \|v\| + \|w\|$ **for any two vectors** $v, w \in V$

The norm of a vector can be thought of as the length or magnitude of the vector.

VI. BLIND IMAGE QUALITY ASSESSMENT

Image quality assessment is a major challenge in digital image processing. It can be classified as subjective (based on the perceptual assessment of a human viewer) or objective (based on computational models and algorithms used to mimic the subjective assessment).

No-reference image quality is the main problem in measuring image quality, which is called blind image quality, which has no prior knowledge about the distortion type. Assessing the quality of an image without a reference has long been a challenging research problem, as the image may be subject to various types of distortion, which can cause highly varied image content. Additionally, the growing number and significance of digital images in our daily lives have resulted in significant interest within the research community in image quality assessment [23]. The Natural Image Quality Evaluator (NIQE) and Psychovisually-based image quality evaluator (PIQE) are prominent techniques in this category. The NIQE assesses deviations from statistical regularities in natural images without any exposure to distortion or training on human-rated distorted images. NIQE determines the perceptual quality of an image by comparing it to a default model derived from natural-scene images. A higher-quality image is indicated by a lower score [24].

The Psychovisually-based image quality evaluator (PIQE) demonstrated an inverse correlation with the perceptual quality of an image. A high score indicates low perceptual quality, whereas a low score indicates high quality [25]. In the current work, we used NIQE and PIQE to compare the quality of color image conversion methods; in general, the NIQE and PIQE values did not precisely reflect the quality of images, but they could be approximate values because we did not enhance the images before conversion (images may suffer from noise, blurring, etc.).

VII. PROPOSED METHODOLOGY

The color-to-grayscale conversion method proposed in this study is based on SVD, which is a mathematical technique that can be used to decompose a color image into its constituent color channels. By considering the relative importance of each channel, SVD can produce a grayscale image that more accurately captures the true intensity values of the image and reduces color distortion. The main steps of this proposal are summarized in Algorithm 1.

The goal of this algorithm is to convert a color image into a grayscale image. Grayscale images have only a single channel of information, where each pixel is represented by a single gray value instead of three-color values (red, green, and blue), as in a color image.

The algorithm takes a color image (X) as input and separates it into three color channels (red, green, and blue) using the RGB color model. The image size (the number of rows and columns) was determined.

A loop is then used to iterate through each pixel in the image, starting at the top-left corner (i = 1, j = 1) and progressing row-by-row.

For each pixel, the algorithm creates a vector (C) by reading one byte from each of the three color channels (red, green, and blue) at the current pixel location (i, j). Optionally, the algorithm can apply weight to one of the color channels to create three different vectors (C1, C2, and C3) that can be used to create three different grayscale images.

Singular Value Decomposition (SVD) was then applied to each vector (C, C1, C2, and C3) separately. SVD is a mathematical process that can decompose a matrix into three matrices (U, S, and V). These matrices represent the original matrix's rotation, scaling, and reflection. In this step, we focused on the diagonal matrix (S) and neglected the other two matrices. The norm value of the diagonal matrix is determined using "equation (5)."

$$\left\|\vec{S}\right\| = \sqrt{s1^2 \quad + s2^2 + \cdots + \quad sn^2} \tag{5}$$

where (s) is the value of elements in the diagonal of the (S) matrix and (n) is the number of elements in a diagonal matrix (rank).

The norm value (which may be larger than the image range values (255)) is normalized by dividing it by a specific value (k) to obtain the gray value corresponding to the color pixel. Parameter (k) controls the degree of contrast in the resulting grayscale image in addition to normalization.

The algorithm then calculates the gray value (G) for each pixel using the formula

$$G = \left\|\vec{S}\right\| / k \quad k = 2, 3 \ldots .N \tag{6}$$

where norm(S) is the Frobenius norm of matrix S. The Frobenius norm is a measure of the magnitude of the matrix S.

The gray value (G) was then saved in a grayscale image at the corresponding pixel location (i, j). This process continues until every pixel in the image has been processed.

Finally, the resulting grayscale image was displayed, showing the original image in a single-channel gray format.

Algorithm 1: Converting Color Image Into a Grayscale Image

Input: color image
Output: grayscale image (Gray Image)

Step 1: Input color image (X)
Step 2: Determine image size (number of rows (NR), number of columns (NC)).
Step 3: Input parameter (k)
Step 4: Loop i = 1: NR
Step 5: Loop j = 1: NC
Step 6: Read pixel (X (i, j))
Step 7: Separate (X(i, j)) into three channels (Red (xr), Green (xg), and Blue (xb))
Step 8: Create a vector for each pixel
C (i, j) = **[xr (i, j), xg (i, j), xb (i, j)]**
Step 9: Add weight to one of the three parameters in the vector
C (i, j) = [3 × xr (i, j), xg (i, j), xb (i, j)]
// Optional: you can create three vectors with different locations of weight to get three different gray images
C1 (i, j) = **[3 × xr (i, j), xg (i, j), xb (i, j)]**
C2 (i, j) = **[xr (i, j), 3 × xg (i, j), xb (i, j)]**
C3 (i, j) = **[xr (i, j), xg (i, j), 3 × xb (i, j)]**
Step 10: Find the SVD
$[U\ S\ V] = \text{SVD}\ (C\ (i, j))$
Step 11: Find the gray value
$G = \text{norm}\ (S)\ /\ k$
Step 12: Save the result in the gray image
Gray Image (i, j) = G
Step 13: End loop // (step 5)
Step 14: End loop // (step 4)
Step 15: Display the image.

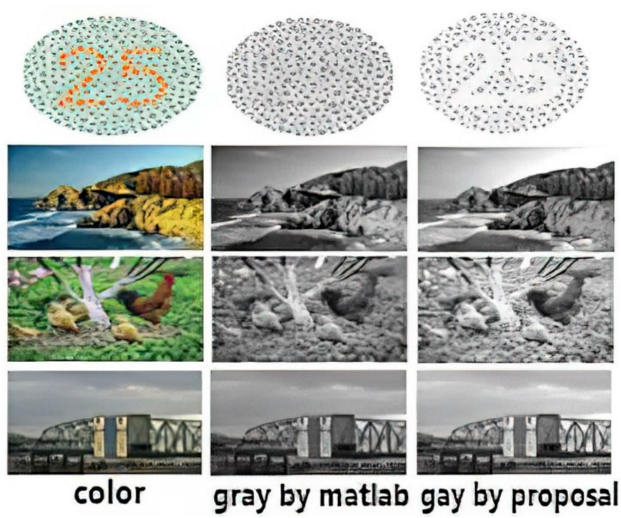


FIGURE 4. Comparing the converting color images into grayscale using the Matlab with the proposed method. (multiply the red channel by three, and divide the norm by two).

VIII. RESULTS ANALYSIS AND DISCUSSION

Initially, the proposed model was tested to convert color images into gray images. Accordingly, the results are shown in Fig. 4. We tested the effect of adding weight to one of the three channels (multiplying by three, while the other two channels did not change). In Fig. 5, the color image is converted into a gray image by multiplying the red channel by three, as shown in the second column. In contrast, the third column shows the result of multiplying the green channel

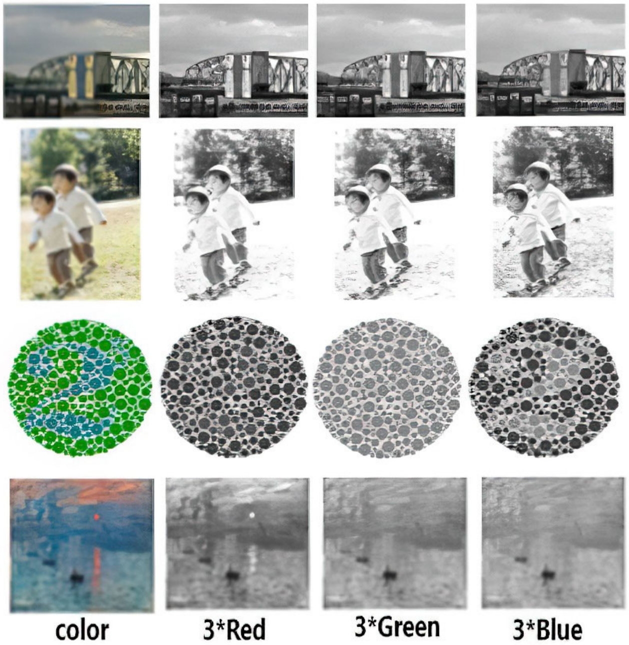


FIGURE 5. The difference between images when adding weight for each channel (multiply by three), and simple images (dividing parameter equal two).

by three, and finally, the blue channel is multiplied by three, as shown in the fourth column.

From Fig. 5, we argue that adding weight to one of the three channels may significantly affect the grayscale image resulting from this method. However, some of the images have a little effect depending on the image content. This will help produce a gray image suitable for some applications.

The other test examines the effect of multiplying the channels (red, green, or blue) by a specific factor. In this test, the color channel is multiplied by the factor (m), where (m = 1.. 8); the results are shown in Fig. 6.

We can conclude from Fig. 6 that factor three almost gives a reasonable gray image; therefore, factor three is a default color channel, and the user can change it according to his application and processing. Increasing the value of the multiplying factor can lead to the brightening of the image; this can be useful in some cases to extract the object in the image.

The other test was to test the effect of the divisor on the result, as shown in Fig. 7, for many images with different values of the divisor. This test was implemented on color images by changing the weight of the one-color channel. For example, in the first row, only the red channel was multiplied by five, whereas in the second row, the green channel was multiplied by five, and in the last row, only the blue channel was multiplied by five. Increasing the divisor parameters increases the brightness of the image.

Finally, the proposed method was compared with similar techniques for converting color images into grayscale images, as shown in Fig. 8.

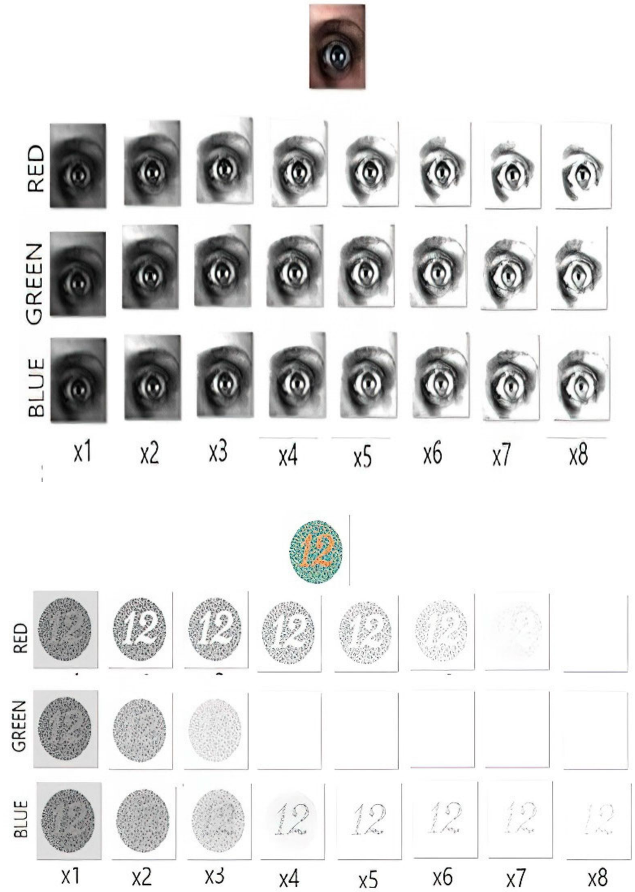


FIGURE 6. The result of color conversion is when multiplying each color channel by a specific weight (Dividing parameter equal to two.).

FIGURE 7. Effect of dividing image values by a specific number on the result of the gray image, where each channel multiplies by five.

Regarding visual quality, the results produced by the proposed method are significantly superior to those of other techniques.

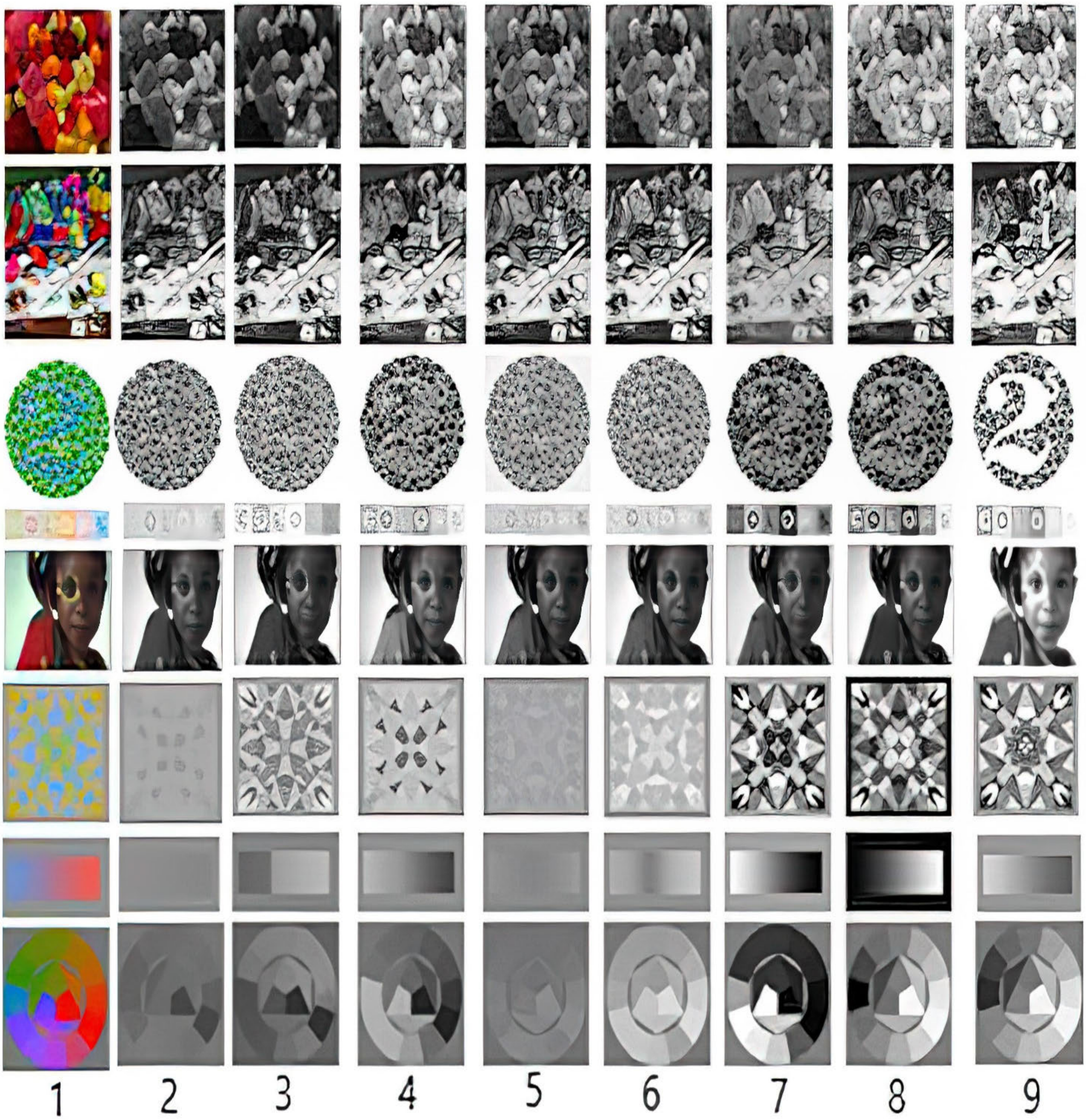


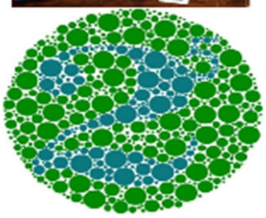
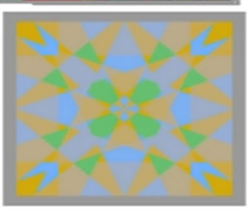
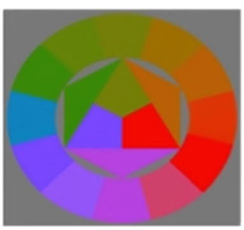
FIGURE 8. Comparing the proposed method with other methods. 1. Color image. 2. Matlab. 3. Reference [26]. 4. Reference [27]. 5. Reference [28]. 6. Reference [29]. 7. Reference [30]. 8. Reference [6]. 9. Proposed method.

Finally, the quality of the converted images for the different methods was compared and is listed in Table 1. It is clear from Table 1 that the proposed method provides a better image quality than the other methods. The SVD method produces grayscale images with a higher visual quality than traditional grayscale conversion methods. This is because SVD considers the relative importance of each channel in an image, resulting in a more accurate grayscale image.

IX. CONCLUSION

This paper presents a novel and innovative framework for grayscale image conversion from color images. It is a meaningful conversion that enhances the usual workflow for analyzing images that work on grayscale images. SVD is the best way to convert a vector into other vectors based on the relation between the input vector values. Furthermore, SVD can preserve more color information in an image than other gray-scale conversion methods. This is because SVD

TABLE 1. Compares the gray image quality of various methods.

Original image	Quality metric	Gooch	Grundland	Smith	Kim	Lu	T. Nguyen	proposed
	NIQE	5.68	7.50	7.09	6.51	6.20	6.75	4.29
	PIQE	28.21	29.05	27.41	43.16	24.41	28.61	31.01
	NIQE	3.58	3.30	3.40	3.61	3.27	3.42	3.07
	PIQE	43.62	42.30	43.10	52.75	44.40	43.88	41.93
	NIQE	10.77	10.69	8.13	7.58	10.41	10.82	7.13
	PIQE	63.16	64.88	46.05	52.72	65.21	64.24	42.41
	NIQE	24.89	26.08	19.77	23.85	40.16	24.39	11.47
	PIQE	81.22	81.83	84.50	80.32	77.60	80.80	66.08
	NIQE	5.90	5.30	5.65	5.62	5.70	5.98	4.57
	PIQE	50.07	54.11	55.44	72.46	52.73	55.25	48.57
	NIQE	11.20	10.25	7.46	6.82	11.21	11.73	4.60
	PIQE	79.74	79.53	70.60	66.29	79.57	80.84	46.48
	NIQE	10.07	11.04	9.76	9.82	12.06	10.64	7.45
	PIQE	92.14	100.0	90.50	100.0	100.0	100.0	79.95
	NIQE	9.15	9.01	7.50	7.58	9.23	8.81	5.76
	PIQE	81.46	83.78	79.56	79.76	82.66	81.56	57.39

considers the relative importance of each channel in the image and produces a grayscale image that more accurately captures the true intensity values of the image.

Unlike traditional methods, the proposed method has high flexibility for producing more than one version of a grayscale image. The parameters used in this method can help users produce appropriate images for processing and application. In addition, we resolved the problem of producing the same value for vectors of the same magnitude using the weight, which yields different values and grayscale images. This method's grayscale image result is highly promising and has very good quality. This method is more efficient than the other methods.

ACKNOWLEDGMENT

This research was funded by Princess Nourah bint Abdulrahman University and Researchers Supporting Project number (PNURSP2023R346), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. The authors would also like to thank Prince Sultan University, Riyadh Saudi Arabia for their support.

REFERENCES

[1] Y. Yang, M. Song, J. Bu, C. Chen, and C. Jin, ''Color to gray: Attention preservation,'' in *Proc. 4th Pacific-Rim Symp. Image Video Technol.*, Nov. 2010, pp. 337–342.
[2] A. Güneş, H. Kalkan, and E. Durmuş, ''Optimizing the color-to-grayscale conversion for image classification,'' *Signal, Image Video Process.*, vol. 10, no. 5, pp. 853–860, Jul. 2016.
[3] Y. Wan and Q. Xie, ''A novel framework for optimal RGB to grayscale image conversion,'' in *Proc. 8th Int. Conf. Intell. Hum.-Mach. Syst. Cybern. (IHMSC)*, vol. 2, Aug. 2016, pp. 345–348.
[4] K. Kumar, R. K. Mishra, and D. Nandan, ''Efficient hardware of RGB to gray conversion realized on FPGA and ASIC,'' *Procedia Comput. Sci.*, vol. 171, pp. 2008–2015, Dec. 2020.
[5] M. S. M. Rahim, A. Norouzi, A. Rehman, and T. Saba, ''3D bones segmentation based on CT images visualization,'' *Biomed. Res.*, vol. 28, no. 8, pp. 3641–3644, 2017.
[6] C. T. Nguyen and J. P. Havlicek, ''Color to grayscale image conversion using modulation domain quadratic programming,'' in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2015, pp. 4580–4584.
[7] X. Zhang and S. Liu, ''Contrast preserving image decolorization combining global features and local semantic features,'' *Vis. Comput.*, vol. 34, nos. 6–8, pp. 1099–1108, Jun. 2018.
[8] V. Sowmya, D. Govind, and K. P. Soman, ''Significance of incorporating chrominance information for effective color-to-grayscale image conversion,'' *Signal, Image Video Process.*, vol. 11, no. 1, pp. 129–136, Jan. 2017.
[9] T. Saba, S. U. Khan, N. Islam, N. Abbas, A. Rehman, N. Javaid, and A. Anjum, ''Cloud-based decision support system for the detection and classification of malignant cells in breast cancer using breast cytology images,'' *Microsc. Res. Technique*, vol. 82, no. 6, pp. 775–785, Jun. 2019.
[10] S. Liu, ''Two decades of colorization and decolorization for images and videos,'' 2022, *arXiv:2204.13322*.
[11] C. Kanan and G. W. Cottrell, ''Color-to-grayscale: Does the method matter in image recognition?'' *PLoS ONE*, vol. 7, no. 1, Jan. 2012, Art. no. e29740.
[12] W. H. Lim and N. A. M. Isa, ''Color to grayscale conversion based on neighborhood pixels effect approach for digital image,'' in *Proc. of 7th Int. Conf. Elect. Electron. Eng.*, Bursa, Turkey, 2011, pp. 1–4.
[13] K. Padmavathi and K. Thangadurai, ''Implementation of RGB and grayscale images in plant leaves disease detection–comparative study,'' *Indian J. Sci. Technol.*, vol. 9, no. 6, pp. 1–6, Feb. 2016.
[14] H. Z. Nafchi, A. Shahkolaei, R. Hedjam, and M. Cheriet, ''CorrC2G: Color to gray conversion by correlation,'' *IEEE Signal Process. Lett.*, vol. 24, no. 11, pp. 1651–1655, Nov. 2017.
[15] N. Damodaran, V. Sowmya, D. Govind, and K. P. Soman, ''Effect of decolorized images in scene classification using deep convolution features,'' *Procedia Comput. Sci.*, vol. 143, pp. 954–961, 2018.
[16] S. Liu and X. Zhang, ''Image decolorization combining local features and exposure features,'' *IEEE Trans. Multimedia*, vol. 21, no. 10, pp. 2461–2472, Oct. 2019.
[17] C. Ancuti, C. O. Ancuti, M. Feixas, and M. Sbert, ''Image decolorization based on information theory,'' in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2019, pp. 3242–3246.
[18] D. C. Lay, R. L. Steven, and J. McDonald, *Linear Algebra and Its Applications*, 5th ed. Boston, MA, USA: Pearson Education Press, 2016.
[19] H. Zhang, C. Wang, and X. Zhou, ''A robust image watermarking scheme based on SVD in the spatial domain,'' *Future Internet*, vol. 9, no. 3, p. 45, Aug. 2017.
[20] K. Santosh and B. Gawali, ''Recent trends in image processing and pattern recognition,'' in *Proc. 3rd Int. Conf. (RTIPR)*, Aurangabad, India, vol. 1380, 2020, pp. 1–213.
[21] B. Barnes, I. Adjei, C. Sebil, and E. Harris, ''Product-normed linear space,'' *Eur. J. Pure Appl. Math.*, vol. 11, pp. 740–750, Jul. 2018.
[22] K. J. Audu, ''Application of singular value decomposition technique for compressing images,'' *Gadau J. Pure Allied Sci.*, vol. 1, no. 2, pp. 82–94, Aug. 2022.
[23] D. Varga, ''No-reference image quality assessment with convolutional neural networks and decision fusion,'' *Appl. Sci.*, vol. 12, no. 101, pp. 1–17, 2022.
[24] A. Rubel, O. Ieremeiev, V. Lukin, J. Fastowicz, and K. Okarma, ''Combined no-reference image quality metrics for visual quality assessment optimized for remote sensing images,'' *Appl. Sci.*, vol. 12, no. 4, p. 1986, Feb. 2022.
[25] N. Venkatanath, D. Praneeth, M. Chandrasekhar, S. S. Channappayya, and S. S. Medasani, ''Blind image quality evaluation using perception based features,'' in *Proc. 21st Nat. Conf. Commun. (NCC)*, Feb. 2015, pp. 1–6.
[26] A. A. Gooch, S. C. Olsen, J. Tumblin, and B. Gooch, ''Color2Gray: Salience-preserving color removal,'' *ACM Trans. Graph.*, vol. 24, no. 3, pp. 634–639, 2005.
[27] M. Grundland and N. A. Dodgson, ''Decolorize: Fast, contrast enhancing, color to grayscale conversion,'' *Pattern Recognit.*, vol. 40, no. 11, pp. 2891–2896, Nov. 2007.
[28] K. Smith, P.-E. Landes, J. Thollot, and K. Myszkowski, ''Apparent greyscale: A simple and fast conversion to perceptually accurate images and video,'' *Comput. Graph. Forum*, vol. 27, no. 2, pp. 193–200, Apr. 2008.
[29] Y. Kim, C. Jang, J. Demouth, and S. Lee, ''Robust color-to-gray via nonlinear global mapping,'' *ACM Trans. Graph.*, vol. 28, no. 5, pp. 1–4, Dec. 2009.
[30] C. Lu, L. Xu, and J. Jia, ''Contrast preserving decolorization with perception-based quality metrics,'' *Int. J. Comput. Vis.*, vol. 110, no. 2, pp. 222–239, Nov. 2014.

ZAID NIDHAL KHUDHAIR received the B.Sc. degree in computer science from the University of Kufa, Iraq, in 2010, and the M.Sc. degree from the Faculty of Computing, University of Technology Malaysia, in 2013, where he is currently pursuing the Ph.D. degree. He is an Assistant Lecturer with the Department of Computer Engineering, Imam Ja'afar Al-Sadiq University. His research interests include computer vision, digital image processing, medical image processing, data and image security, computer networking, and real-time applications.

AHMED NIDHAL KHDIAR received the B.Sc. and M.Sc. degrees in electronic and communication engineering from Al-Nahrain University, Iraq, and the Ph.D. degree in electronic engineering/signal processing from USM University. He was an Academic Staff with Al-Sadiq University, Islamic University, Al-Nahrain University, and Kufa University, for more than 15 years. He is currently an Academic Lecturer and a Researcher. He published several articles in scientific journals and IEEE conferences.

NIDHAL K. EL ABBADI received the B.Sc. degree in chemical engineering from the University of Baghdad, in 1976, the B.Sc. degree (Hons.) in computer science from Al-Mustansiriya University, in 2000, and the M.Sc. and Ph.D. degrees in computer science from the Informatics Institute for Postgraduate Studies (IIPS), Iraq Commission for Computer and Informatics, in 2001 and 2006, respectively. He was an Engineer in many industrial plants. In 2006, he joined Al-Mustansiriya University, Iraq, as an Academic Staff. He is currently a Professor of computer techniques engineering with the Al-Mustaqbal University. He has successfully supervised many master's and Ph.D. students. He published more than 300 articles in various international journals and conference proceedings and eight books related to computer science. His research interests include image processing, computer vision, steganography, and the IoT [ACM Classification Codes (I3, I4, I5)]. He acts as a reviewer for various journals and conferences. He served as the conference chair and a technical committee member for numerous international conferences.

FARHAN MOHAMED (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees from Universiti Teknologi Malaysia (UTM) and the Ph.D. degree in computer science from Swansea University, in 2014. He is currently a Senior Lecturer with the School of Computing, Faculty of Engineering, UTM. He is also a Research Fellow with the Media and Games Innovation Centre of Excellence (MaGICX), Institute of Human Centred Engineering, UTM. He led a study with SME Corp-Huawei in analyzing SME digitalization, in 2018. His current works emphasize visual analytics, virtual environment, and procedural computer graphics. He received the Leaders in Innovation Fellowship from Newton Fund, Royal Academy of Engineering, U.K., in 2017. He is on the Executive Committee of the IEEE Computer Society Malaysia.

TANZILA SABA received the Ph.D. degree in document information security and management from the Faculty of Computing, Universiti Teknologi Malaysia (UTM), Malaysia, in 2012. She is currently the Associate Chair with the Artificial Intelligence and Data Analytics Laboratory (AIDA), Information Systems Department, College of Computer and Information Science, Prince Sultan University, Riyadh, Saudi Arabia. Her research interests include medical imaging, pattern recognition, data mining, MRI analysis, and soft computing.

FATEN S. ALAMRI received the Ph.D. degree in system modeling and analysis in statistics from Virginia Commonwealth University, USA, in 2020. Her Ph.D. research was in Bayesian dose response modeling, experimental design, and nonparametric modeling. She is currently an Assistant Professor with the Department of Mathematical Sciences, College of Science, Princess Nourah bint Abdulrahman University. Her research interests include spatial areas, environmental statistics, and brain imaging.

AMJAD REHMAN (Senior Member, IEEE) received the Ph.D. and Postdoctoral Research degrees (Hons.) from the Faculty of Computing, Universiti Teknologi Malaysia, Johor Bahru, Malaysia, with a focus on forensic documents analysis and security, in 2010 and 2011, respectively. He is currently a Senior Researcher with the Artificial Intelligence and Data Analytics Laboratory (AIDA), College of Computer and Information Science, Prince Sultan University, Riyadh, Saudi Arabia. He is a PI in several funded projects and also completed projects funded by MOHE Malaysia, Saudi Arabia. His research interests include data mining, health informatics, and pattern recognition.