# NOVEL PCA-BASED COLOR-TO-GRAY IMAGE CONVERSION

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## ABSTRACT

In this paper, we present a novel color-to-gray image conversion method which preserves both color and texture discriminabilities effectively. Unlike previous approaches, the proposed method does not require any user-specific parameters for conversion. Moreover, the computational complexity is low enough to be applied to real-time applications. These breakthroughs are achieved by applying the *ELSSP* (Eigenvalue-weighted Linear Sum of Subspace Projections) method, which is proposed in this paper for the color-to-gray image conversion. Experimental results demonstrate that the proposed method is superior to the state-of-the-art methods in terms of both conversion speed and image quality.

***Index Terms*—** Color-to-gray image conversion, PCA (Principal Component Analysis), subspace projection

## 1. INTRODUCTION

In spite of the prevalence of color image based applications, there are still needs for color-to-gray image conversion in widespread areas, e.g., black-and-white printers, feature extraction from gray images, artistic photography, etc. Since the color-to-gray image conversion is fundamentally a dimension reduction process, it entails an inevitable problem, i.e., loss of information. Therefore, we should concentrate on finding a *dense mapping* method during the conversion from three-dimensional color images into one-dimensional gray images. Many recent studies have aimed at producing perceptually discriminable gray images by using various mapping methods, which are grouped into three categories: global, local, and hybrid global-local mappings. As a global mapping instance, Grundland *et al.* [1] propose the *Decolorize* algorithm which intends contrast enhancement of a converted gray image by incorporating an image sampling and a dimensionality reduction process. Gooch *et al.* [2] present a local mapping algorithm called *Color2Gray*, which iteratively decides the gray levels that preserve color differences between all pairs of pixels. Smith *et al.* [3] present a mixture of global and local mapping methods whose goal is to raise the perceptual accuracy rather than exaggerate the discriminability. Lastly, Čadík [4] evaluates the performances of state-of-the-art algorithms by conducting comparative and subjective experiments, and then analyzes their strengths and weaknesses.

While many conversion techniques have been developed, they still pose the following critical problems: 1) formulaic expression adopted in many approaches [1], [3], [5], [6] such as $Y+\alpha C$, where $Y$: luminance, $C$: chrominance and $\alpha$: weighting factor, produces poor gray images when equiluminant color combinations are dominant in color images. 2) optimal user-specific parameter tuning is required for different color images. 3) computational complexity is too high to be applied to real-time applications, e.g., single channel image processing in vision technologies. In this paper, we show that these problems can be coped with by the proposed PCA-based algorithm.

As many studies have introduced, PCA [7] is a standard linear technique to reduce dimensions of data by projecting the data onto orthogonal subspaces which provide maximal data variations. Nevertheless, it is hard to separate samples in subspaces if the samples are clustered along projection directions in the original space. Therefore, we propose a new method, i.e., *ELSSP*, to solve this issue as well as the aforementioned conversion problems in previous approaches. The *ELSSP*-based color-to-gray image conversion method effectively preserves the discriminability in color images by simple linear computations in subspaces. As a result, we can retain the visual appearance with low computational complexity.

The rest of the paper is organized as follows. We describe details of the proposed method in Section II and show experimental results in Section III. Finally, we conclude with a summary of our work and future research in Section IV.

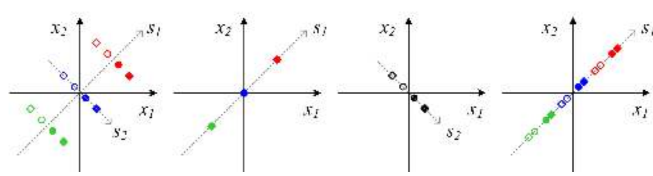



**Fig. 1**. (a) Data in sample space. (b) and (c) are projections onto the first and second principal subspaces. (d) Linear sum of the two subspace projections.

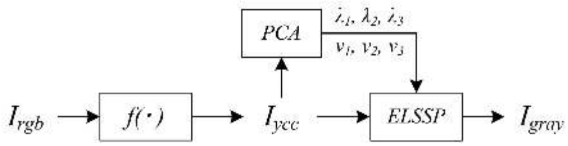



**Fig. 2**. Block diagram of the proposed *ELSSP*-based color-to-gray image conversion method.

## 2. PROPOSED METHOD

### 2.1. Subspace Projections

In order to discuss possible problems of the standard PCA-based color-to-gray image conversion, a simple exemplar case is illustrated in Fig. 1, which includes sample data in a two-dimensional sample space (i.e., $x_1$ vs. $x_2$), and the first and second principal subspaces (i.e., $s_1$ and $s_2$). Projection results of the sample data onto $s_1$ and $s_2$ are indicated in Fig. 1 (b) and (c) respectively. Although the projection result onto $s_1$ has the largest variation, the projected points are overlapped, so only three of twelve points are distinguishable. This implies the discriminability may not be guaranteed provided that the first principal subspace is only used for a dimension reduction process. However, we can observe that the discriminability of original samples can be effectively maintained if the projection results onto the first principal subspace are linearly combined with those onto the second principal subspace (See Fig. 1 (d)). We find that it is especially useful for color-to-gray image conversion and followings can be attained: 1) variation of the combined subspace projection results (i.e., gray image) is globally enhanced, 2) bins in gray scale histogram can be locally filled as a result of linear sum of subspace projections, 3) processing speed is very fast thanks to simple linear computations, and 4) robust operation is guaranteed regardless of color combinations (e.g., equi-luminance or -chrominance) of input images thanks to the eigen analysis.

### 2.2. ELSSP-based Color-to-Gray Image Conversion

Based on the aforementioned benefits from the combination of subspace projections, hereinafter, we introduce the proposed color-to-gray conversion method in detail using both a block diagram in Fig. 2 and an Algorithm 1.

First, we create a vectorized color image ($I_{rgb} \in \mathbb{R}^{3\times n}$, where $n$ is the number of pixels in an image) by stacking three color channels (i.e., red, green and blue). Then, a zero-mean YCbCr image ($I_{ycc} \in \mathbb{R}^{3\times n}$) is computed to separate luminance and chrominance channels using the conventional transfer function *f*(·) defined in [8]. Next, three eigenvalues ($\lambda_1 \geq \lambda_2 \geq \lambda_3 \in \mathbb{R}^1$) and corresponding normalized eigenvectors ($v_1, v_2, v_3 \in \mathbb{R}^3$) are obtained by PCA. To compute a gray image ($I_{gray} \in \mathbb{R}^n$), the proposed *ELSSP* is conducted, and then the output is scaled to [0, 255]. Note that we utilize the eigenvalues as weighting factors for projection results

**Algorithm 1** ELSSP-based Color-to-Gray Image Conversion

**procedure** COLOR-TO-GRAY($I_{rgb}$)
  $I_{ycc} \leftarrow f(I_{rgb})$ ▷ according to [8]
  $I_{ycc} \leftarrow I_{ycc} - I_{ycc,avg}$ ▷ $I_{ycc,avg} = mean(I_{ycc})$
  $\lambda_i, v_i \leftarrow PCA(I_{ycc})$ ▷ $i = 1, 2, 3$
  $\lambda_i \leftarrow \lambda_i / \|\boldsymbol{\lambda}\|, \quad v_i \leftarrow v_i / \|v_i\|$ ▷ $\boldsymbol{\lambda} = \{\lambda_1, \lambda_2, \lambda_3\}$
  $I_{gray} \leftarrow \sum_{i=1}^{3} \lambda_i \left(v_i^T I_{ycc}\right)$, then scaling to [0, 255]
  **if** $\|I_y - I_{gray}\| > \|I_y - (255 - I_{gray})\|$ **then**
    $I_{gray} \leftarrow 255 - I_{gray}$
  **end if**
**end procedure**

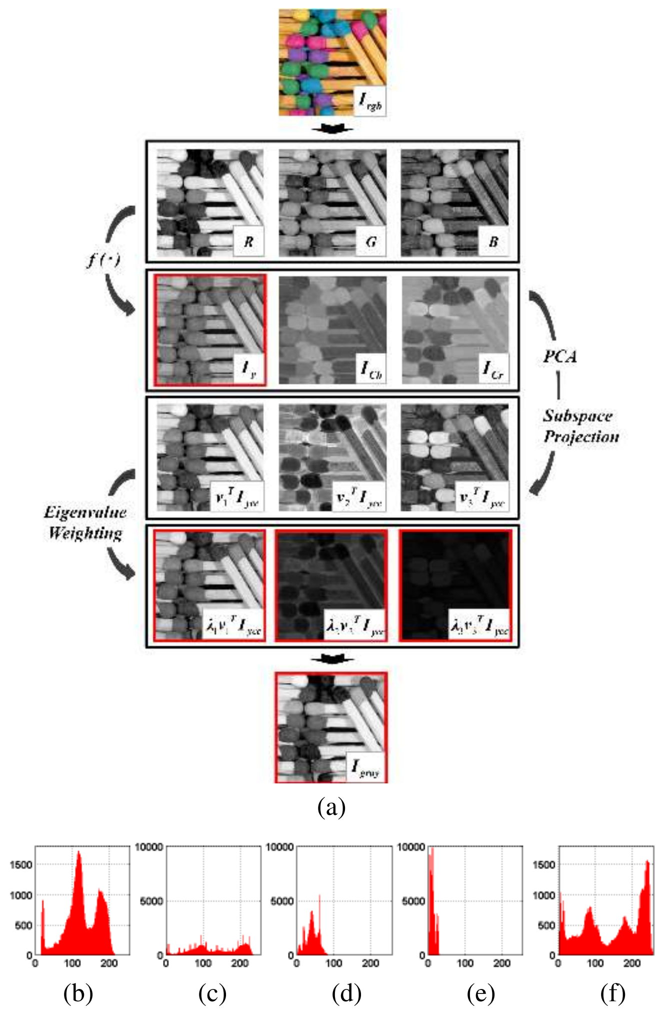



**Fig. 3**. Overall conversion process of the proposed method. (a) Resulting images at each processing block in Fig. 2. Histograms of (b) $I_y$ , (c) $\lambda_1 v_1^T I_{ycc}$ , (d) $\lambda_2 v_2^T I_{ycc}$ , (e) $\lambda_3 v_3^T I_{ycc}$ and (f) $I_{gray}$ images respectively.

on corresponding eigenvectors. As a result, the color-to-gray mapping is dominated by the first subspace projection, and the second and third subspace projections contribute to preserving details of a color image in a gray image (Refer to

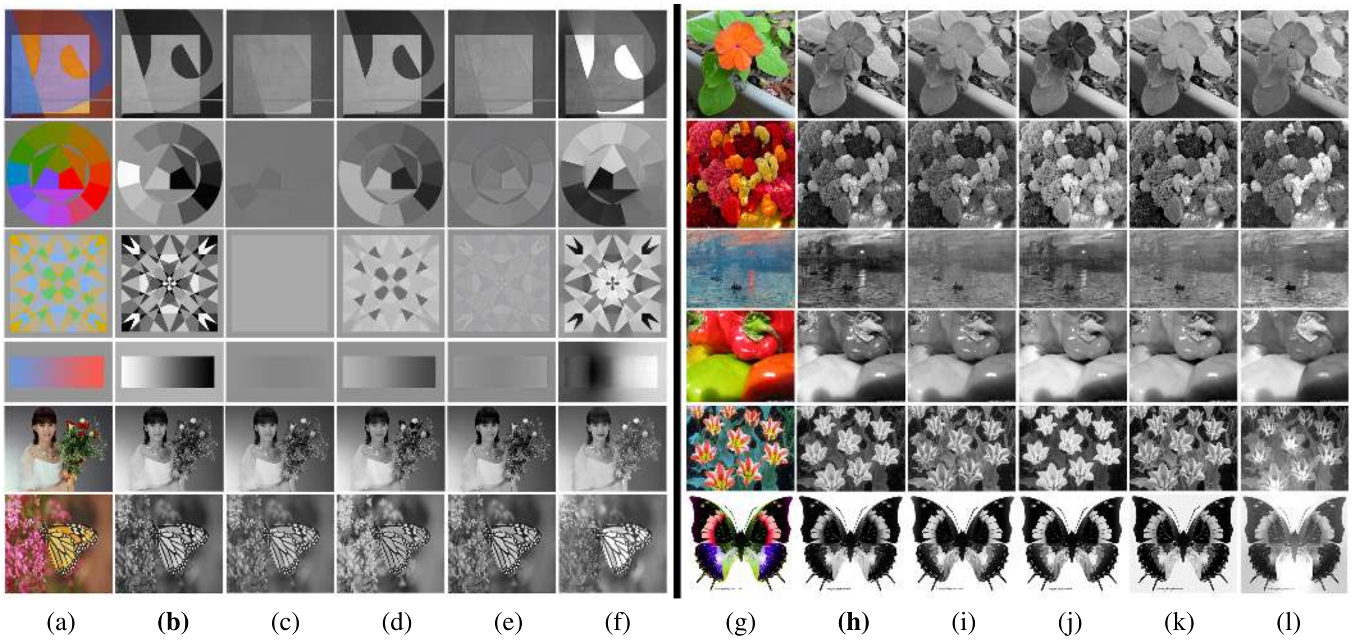



**Fig. 4**. Comparison of conversion results. (a),(g) Color images. (b),(h) Proposed method. (c),(i) CIE Y. (d),(j) Grundland *et al.* [1]. (e),(k) Smith *et al.* [3]. (f),(l) Gooch *et al.* [2]. Color images are courtesy of Čadík [4].

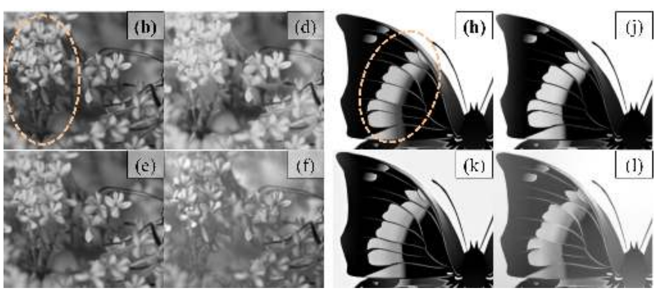



**Fig. 5**. Partially magnified images in the last row in Fig. 4.

Fig. 3 and 6 afterwards). Finally, we prevent $I_{gray}$ from being converted into a photographic negative image by comparing it with a luminance image ($I_y \in \mathbb{R}^n$) since the $I_{gray}$ consists of principal subspaces whose polarities depend on data distribution in sample space.

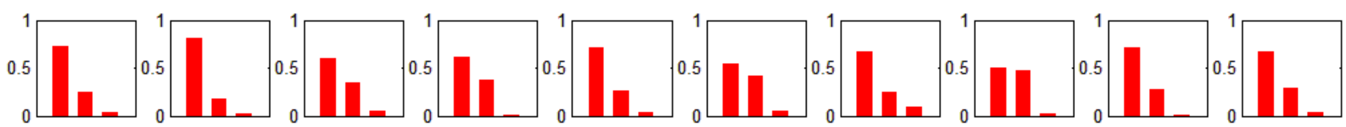
Figure 3 visualizes overall conversion process for an input color image by exemplifying resulting images and histograms at each processing block in Fig. 2. Note that the *ELSSP*-based method results in much more discriminable gray image than luminance image. Consequently, the histogram of $I_{gray}$ in Fig. 3 (f) is more spread out compared to that of $I_y$ in Fig. 3 (b) (Recall Fig. 1 (d)), which signifies an effective dense mapping capability of the proposed conversion method. An additional advantage of our method is that the overall conversion process does not require any user-specific parameters. Instead, we analyze color statistics as explained above, so the conversion process itself is adaptive to input color images.

## 3. EXPERIMENTAL RESULTS

To verify the performance of our method, we have conducted various experiments. First, for following comparisons, we selected three state-of-the-art methods (i.e., [1], [2] and [3]) which received favorable evaluations from subjective assessments in Čadík's work [4].

Figure 4 compares conversion results for selected color images from [4]. Remarkably, our results are more visually apparent than others, and the color mapping is consistent with visual perception as well. From partially magnified images in Fig. 5 (See the marked regions with care), we can also observe that the proposed method preserves both texture and color discriminabilities effectively. To support our assertion, we present the preference matrix in Table 1 which contains the averaged *paired comparisons* [9] from 15 subjects against all conversion results in Fig. 4. Figure 6 shows additional conversion results of the proposed method with sequential subspace projection results and corresponding eigenvalues. By examining the projection result onto each subspace, we can understand how the gray images are generated from the *ELSSP*-based method. Lastly, Table 2 compares color-to-gray conversion times for various input image sizes. We measured the average conversion time of 10 trials for each image size on a PC of 2.67 GHz CPU with 4.0 GB memory. Unlike other methods, the proposed method can operate in real-time under the QVGA (320×240) resolution. Also note that Gooch *et al.*'s work [2] is inappropriate to practical applications due to high conversion time [4].

(a)



(b)

**Fig. 6**. Additional conversion results of the proposed method with corresponding subspace projection results. (a) The $1^{st}$ row: color images. The $2^{nd}$, $3^{rd}$ and $4^{th}$ rows: projection results onto the first, second and third principal subspaces respectively. The $5^{th}$ row: output gray images. The $6^{th}$ row: CIE Y images. (b) Normalized eigenvalues for each principal subspace. Color images are courtesy of Grundland *et al.* [1] and from the Internet.

**Table 1**. Preference Matrix from the Paired Comparisons

| | **Ours** | CIE Y | [1] | [3] | [2] | Score |
|---|---|---|---|---|---|---|
| **Ours** | - | **13** | **9** | **11** | **12** | **45** |
| CIE Y | 2 | - | 5 | 6 | 8 | *21* |
| [1] | 6 | 10 | - | 9 | 10 | *35* |
| [3] | 4 | 9 | 6 | - | 9 | *28* |
| [2] | 3 | 7 | 5 | 6 | - | *21* |

**Table 2**. Color-to-Gray Conversion Time [$msec$]

| Size | 256×192 | 320×240 | 512×384 | 1024×768 |
|---|---|---|---|---|
| **Ours** | **27.6** | **42.5** | **105.4** | **405.3** |
| [1] | 84.9 | 135.5 | 290.4 | 1107.5 |
| [3] | 1296.2 | 1842.2 | 4130.3 | 15201.5 |

## 4. CONCLUSION

In this paper, we have presented a fast and robust PCA-based color-to-gray conversion method that does not require user-specific parameters. Experimental results demonstrate the effectiveness of the proposed method in terms of both speed and quality. In future work, we plan to verify the utility of the proposed method in machine learning or vision technologies. Since our method provides more informative gray images than luminance images, for instance, we can expect performance improvement in object detection [10] and tracking methods which operate based on the single channel image processing.

## 5. REFERENCES


[1] M. Grundland and N. A. Dodgson, "Decolorize: Fast, contrast enhancing, color to grayscale conversion," *Pattern Recognition*, vol. 40, no. 11, pp. 2891–2896, 2007.

[2] 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.

[3] K. Smith, P.-E. Landes, J. Thollot, and K. Myszkowski, "Apparent greyscale: A simple and fast conversion to perceptually accurate images and video," *Computer Graphics Forum*, vol. 27, no. 2, pp. 193–200, 2008.

[4] M. Čadík, "Perceptual evaluation of color-to-grayscale image conversions," *Computer Graphics Forum*, vol. 27, no. 7, pp. 1745–1754, 2008.

[5] C. Hsin, H.-N. Le, and S.-J. Shin, "Color to grayscale transform preserving natural order of hues," in *Proc. International Conference on Electrical Engineering and Informatics (ICEEI)*, 2011, pp. 1–6.

[6] R. Bala and R. Eschbach, "Spatial color-to-grayscale transform preserving chrominance edge information," in *Proc. Color Imaging Conference (CIC)*, 2004, pp. 82–86.

[7] I. T. Jolliffe, *Principal Component Analysis*, Springer, 2002.

[8] *Studio encoding parameters of digital television for standard 4:3 and wide screen 16:9 aspect ratios*, ITU-R BT.601.

[9] H. A. David, *The Method of Paired Comparisons*, Oxford Univ. Press, 1988.

[10] J. Lu and K.N. Plataniotis, "On conversion from color to gray-scale images for face detection," in *Proc. Computer Vision and Pattern Recognition (CVPR) Workshops*, 2009, pp. 114–119.