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ORIGINAL ARTICLE

Interactive two-scale color-to-gray

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Abstract Current color-to-gray methods compute the grayscale results by preserving the discriminability among individual pixels. However, human perception tends to firstly group the perceptually similar elements while looking at an image, according to the Gestalt principles. In this paper, we propose a novel two-scale approach for converting color images to grayscale. First, we decompose the input image into multiple soft segments where each segment represents a perceptual group of content. Second, we determine the grayscale of each perceptual group via a global mapping by solving a quadratic optimization. Last, the local details are added into the final result. Our approach is efficient and provides users quick feedback on adjusting the prominent gray tones of the results. As an important aspect of algorithm, our approach offers users an easy, intuitive interactive tool for creating art-like black-and-white images from input color images. Experimental results show that our approach better preserves the overall perception and local details. User studies have been conducted to show the applicability of our approach.

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1 Introduction

Nowadays, with the rapid development of digital camera, color photography has become much more common. But grayscale images did not die off. A grayscale image is simply one in which the value of each pixel is a single sample representing only intensity information. The popularity of grayscale images has many reasons. On one hand, due to economic reasons, grayscale printing is still widely used and appears in newspapers, magazines, and books. On the other hand, since the stark contrasts can enhance the subject matter, grayscale images have been a favorite artistic choice among many photographers around the globe.

Color-to-gray conversion algorithm remains widely used to make grayscale images from color ones. The conversion is a dimensionality reduction problem which converts three-dimensional color data into a single dimension and inevitably leads to the loss of information. One simple approach is to directly use the intensity channel (CIE L) as the grayscale result. However, this approach may lose feature discriminability in isoluminant regions. To retain the original discriminability of color images, many color-to-gray conversion algorithms [1, 3, 6–8, 14] have been proposed.

Up to now, most of the algorithms for color-to-gray conversion compute the grayscale results by preserving the discriminability between individual pixels. According to the characteristics of human visual system (HVS), these methods are not very reasonable. Human visual system does not perceive the world as a collection of individual "pixels". It tends to group together the similar elements instead of

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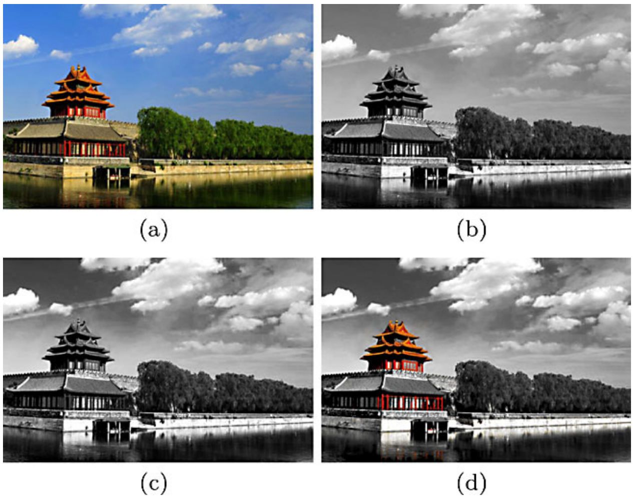


Fig. 1 Given an input color image (**a**) our approach generates its grayscale version (**b**) by preserving its perceptual properties. Our approach allows the user to create an art-like black-and-white image (**c**) interactively. The user can also easily generate a black-and-white image by preserving the color of the salient region while removing the colors of the other regions

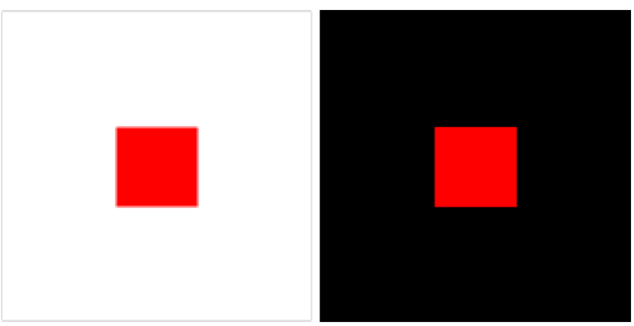


Fig. 2 The human perception in one region of the image is affected by its surroundings [5]. The *red patch* looks brighter against the white surrounding (*left*) than against the *black* surrounding (*right*)

processing a large number of smaller stimuli. The Gestalt school of psychology [10] proposed many theories to explain how humans naturally perceive the world. The essence of Gestaltism is that "the whole is greater than the sum of its parts". The Gestaltists describe a number of "principles" that appear to guide the organization of elements into perceptual groups. According to the Gestalt principles [10], for an image, human perception tends to group pixels with similar color or texture while looking at it. For example, when looking at Fig. 1(a), we are inclined to combine all the green tree elements as a group and the building and the cloud respectively as other groups.

Furthermore, psychological studies have shown that the perception of one region in the image is affected by its surroundings [5]. For instance, in Fig. 2, the two small patches have exactly the same red. However, for our perception system, we will not believe that they are the same due to their different surroundings. The patch looks brighter against the white surrounding (left) than against the black surrounding (right). One perceptual group with its surrounding perceptual groups are defined as a framework in [5]. Experiments showed that the perceptual results highly depend on the frameworks.

In this paper, we propose a novel two-scale approach for converting color images into grayscale ones. The image is represented as perceptual groups according to Gestalt principles. The global gray tone of the resulting grayscale image is determined by the averaged color of each group as well as its surrounding. It is performed by solving a quadratic programming problem. For each group, its local details are computed by a local contrast enhancement processing. The final gray image is obtained by combining the global gray and local details.

In order to meet the needs of the user's creativity, our approach offers a simple and intuitive interactive tool for color-to-gray conversion. It is very useful to assist users to create art-like black-and-white images from color images. Users can adjust the global appearance of the resulting grayscale image in real time. They can manually adjust the brightness of selected groups. Black-and-white images with one color can also be easily generated using our interactive tool.

A number of experimental results have shown the applicability and flexibility of our approach. Three user studies were conducted to evaluate our approach. The results have shown that our approach performs much better than the previous color-to-gray methods and our approach generates similar black-and-white images as artists did. The key contributions of our approach are summarized as follows:

– A two-scale approach for color-to-gray is proposed. It preserves the perception between perceptual groups and their local details in the resulting grayscale.
– Our approach allows users to adjust the global gray tone of the resulting grayscale in real time and obtain various grayscale versions of the given color image.
– Our approach provides an easy, intuitive interactive tool for generating the art-like black-and-white images. This is a creative tool for everyday users to meet their different needs.

2 Related work

2.1 Color-to-gray algorithms

Current color-to-gray methods can be classified into two main categories: local mapping and global mapping.

In local mapping methods, the color-to-gray mapping of pixel values is dependent on the local distributions of colors, which is varying spatially. Bala and Eschbach [1] presented an approach which adds high-frequency chromatic components to luminance. They preserve chrominance edges locally by introducing high-frequency chrominance information into the luminance channel. Neumann et al. [11] reconstructed the grayscale image from the gradients of a color image. Smith et al. [14] decomposed the image into several frequency components and adjusted combination weights using chromatic channels. These local mapping algorithms effectively preserve local features but may distort appearances of constant color regions.

In global mapping methods, the same color-to-gray mapping is used for all pixels in the input. Gooch et al. [7] introduced the Color2gray algorithm for finding gray values that best match the original color difference through an objective function minimization process. Rasche et al. [13] tried to preserve contrast while maintaining consistent luminance. Rasche et al. [12] projected colors onto a linear axis in a 3D color space, where a linear mapping was optimized for local feature preservation. Grundland and Dodgson [6] proposed a fast linear mapping algorithm that adds lost chromatic information to the luminance channel. They projected the color differences onto the two predominant chromatic contrast axes and then added to the luminance image. Kuhn et al. [9] proposed a mass-spring-based approach for enhancing contrast during color-to-grayscale conversion. Kim et al. [8] proposed a nonlinear global mapping method for color-to-gray conversion. This method formulates a nonlinear global mapping by an optimization which preserves feature discriminability and reasonable color ordering.

Čadík [3] proposed an evaluation on various color-to-gray conversions. Nearly 20,000 human responses were surveyed and used to evaluate the accuracy and preference of the conversions. The result showed that the Decolorize [6] and Smith et al. [14] conversions were overall the best ranked approaches.

2.2 Human perception on images

Gestalt principles [10] are rules of the organization of perceptual scenes. These theories attempt to describe how people organize visual elements into groups or unified wholes when certain principles are applied. These principles include similarity, continuation, closure, proximity, and figure, etc.

Psychological studies have shown that the lightness perception of an image is not only affected by the luminance but also by the surroundings. Gilchrist et al. [5] presented an anchoring theory of how the visual system perceive lightness values. The theory offers an explanation of both illumination-independent and background-independent constancy. Lightness values cannot be tied to absolute luminance values for there is no systematic relationship between absolute luminance and perception lightness. Anchoring theory tries to find the relationship between them. It is very complex but can be formulated by highest luminance rule and area rule[5] roughly. The highest luminance rule shows that the perception lightness affected by the highest luminance instead of the average luminance. And the area rule describes how relative area and relative luminance combine to anchor lightness perception. It can be formulated by a quantitative formulae as shown in [5].

3 Algorithm

In this paper, we choose the CIELAB color space as the foundation of the conversion. Compared with the RGB color space, the CIELAB color space is relatively perceptually uniform. Its Euclidean distances closely correspond to the perceptual dissimilarity [15]. Figure 3 shows the overview of our color-to-gray method.

3.1 Perceptual groups

When looking at an image, our visual system tends to group things in some principles, such as proximity or similarity [10]. According to [5], the perceptual appearance of one group is affected by its framework which consists of its neighborhood groups and itself. We adopt segmentation technique to approximate the goal of perceptual grouping. Instead of using the traditional segmentation approaches which lead to hard boundaries between adjacent groups, we use the soft segmentation technique proposed in [2] except that we rely on the real time edit propagation method in [18] to extract soft segments. Other methods for soft segmentation, such as diffusion map [16] and AppProp [17], can also be used here.

For a given input color image I, we derive a soft segmentation of the image pixels. Using the approach of [2], we associate each pixel $i \in I$ with K probabilities. Denote $P_i = (p_i^1, \dots, p_i^K)$ as its probability vector where p_i^t is its probability belonging to segment t $(t = 1, 2, \dots, K)$ and $\sum_{t=1}^K p_i^t = 1$. Then I is decomposed into K segments, i.e., $I = \bigcup_{t=1}^K S_t$, where each segment consists of the pixels whose probability for that segment is the largest, as shown in Fig. 3(b). In our implementation, we set $K = 4\sim12$.

3.2 Global gray tone

For each segment S_t $(t \in [1, K])$, we compute its average color $c_t = (L_t^c, a_t^c, b_t^c)$ by averaging the colors of all its pixels, which is regarded as its global color tone (see Fig. 3(c)). We expect that the resulting grayscale g_t of S_t preserves the perceptual appearance in its corresponding framework. Therefore, we minimize the total difference of distances between the averaged color and the resulting gray value within

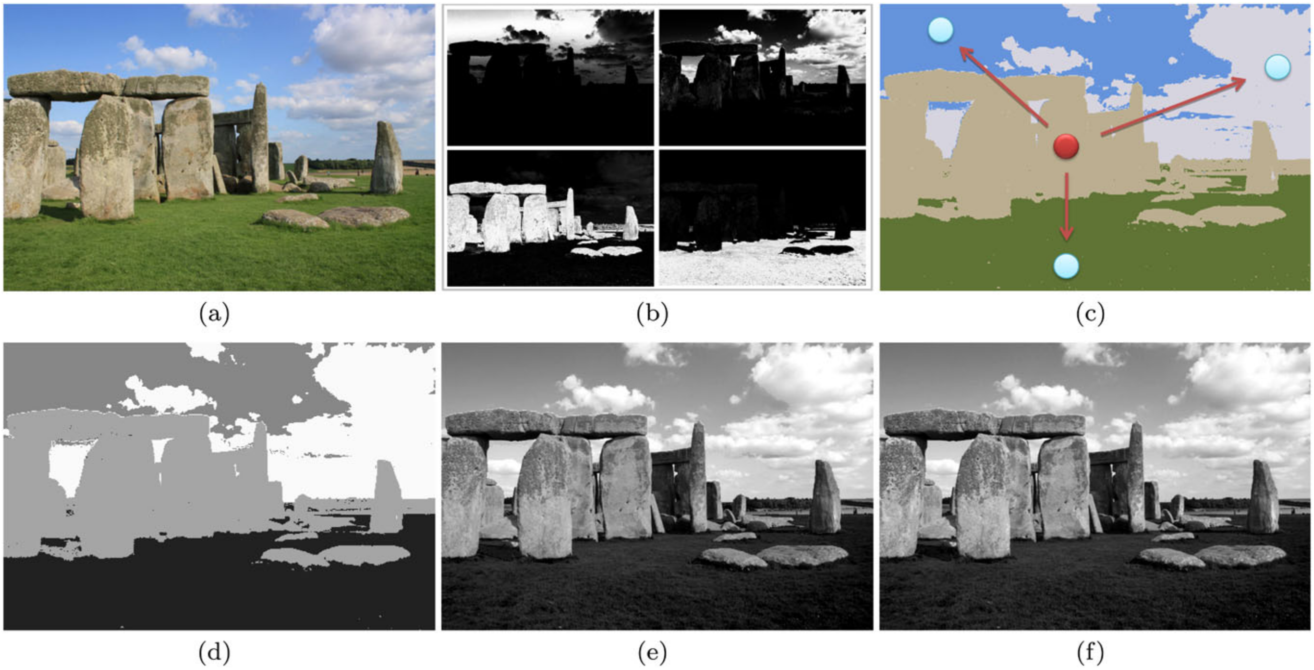


Fig. 3 Overview of our color-to-gray algorithm. Given an input color image (**a**), we decompose it into a few perceptual groups (**b**) by soft segmentation algorithm. Based on the averaged colors of the perceptual groups (**c**), the global gray tones of the groups are computed (**d**). Then the local contrast is enhanced within each of the group (**e**). The final grayscale result (**f**) is obtained by a fusion process

its framework:

$$E_g(t) = \sum_{s \in N_t} w_{ts} \times (g_t - g_s - \gamma \times \delta_{ts})^2 \tag{1}$$

where N_t is the index set of segments of the framework of S_t and γ is a parameter which is used to adjust the strength of contrast between segments in the resulting grayscale image. We set $\gamma = 1.15$ by default.

δ_{ts} is the distance between the averaged colors of S_t and S_s, which is defined as $\delta_{ts} = \text{sign}(t,s) D_{ts}$, $D_{ts} = \sqrt{(L_t^c - L_s^c)^2 + (a_t^c - a_s^c)^2 + (b_t^c - b_s^c)^2}$. The sign function sign$(t,s)$ determines the relative ordering of two colors, which is calculated by the prioritized sign decision scheme [8]. The highest priority is given to the sign of the H–K effect predictor difference ΔL^{HK}. If ΔL^{HK} is zero, we use the sign of ΔL. If ΔL is zero, we use the sign of $\Delta L^3 + \Delta a^3 + \Delta b^3$.

w_{ts} is the weight of difference between S_t and S_s. According to [5], we define $w_{ts} = (r_t + r_s) \times (D_{ts}/D_{\max})$, where r_t and r_s are respectively the area ratios of S_t and S_s relative to the whole image I and $D_{\max}$ is the maximum color distances between any two segments.

Combining all frameworks, the global gray tones can be obtained by minimizing the following function:

$$E_g = \sum_{t=1}^{K} E_g(t) + \left(\sum_{t=1}^{K} r_t \times g_t - L^c \right)^2 \tag{2}$$

where L^c is the averaged luminance of I. The second term of (2) is added to reduce the degrees of freedom in the optimization system.

Equation (2) is a quadratic function of the gray values. Its minimization can be obtained by solving a sparse linear system. The size of linear system is the number of segments, generally 4∼12, and independent on the image resolution. Therefore, the linear system can be solved in real time. This enables real-time adjustment of the global tone in the resulting grayscale image. This is very helpful for users to adjust the results according to their preferences in real time. After the optimization, we get the global gray tone values for all segments, as shown in Fig. 3(d).

3.3 Local contrast enhancement

After we obtain the global gray values for all segments, we need to retain visually important image features in each segment. Like [6], we compute a direction that minimizes the loss of local contrast when the luminance channel is used as the result for grayscale in this segment.

For each segment S_t, we compute its own optimal direction (a, b) to minimize the contrast loss. Like previous methods, we can estimate the local contrast loss of each pixel against all pixels in this segment. However, this will require a significant amount of computation due to the large number of pixels. The soft segmentation provides an effective way to reduce the computational cost. As the result of soft segmentation, each pixel in the segment S_t has the probability p_i^t indicating the degree belonging to the current segment. These probabilities give a sort criteria to pixels in this segment. The difference of probabilities generally reflects the difference of colors. We divide S_t into m subgroups with equal numbers according to the corresponding segmentation probability. For each pixel in each subgroup, we randomly choose one pixel from every other subgroup. Therefore, each pixel in S_t is paired with a group R_i with $m-1$ pixels in S_t respectively. We set $m=3$ in our implementation. For each segment S_t, we compute (a,b) by minimizing the contrast loss for all defined pairs. The energy function is defined by

$$E_l(t) = \sum_{i\in S_t}\sum_{j\in R_i}[\Delta L_{ij} + \Delta a_{ij}\times a + \Delta b_{ij}\times b - \delta_{ij}]^2 \quad (3)$$

where $\Delta L_{ij} = L_i - L_j$, $\Delta a_{ij} = a_i - a_j$ and $\Delta b_{ij} = b_i - b_j$.

Minimization of $E_l(t)$ can be obtained by solving a linear system which has only two variables. Then we add a amount of chrominance to the luminance to better preserve detail feature in every soft segment:

$$L_i = L_i + a_i \times a + b_i \times b \quad (4)$$

as shown in Fig. 3(e).

It is worthwhile to mention that our method is different from Grundland and Dogdson [6]. First, in our algorithm, each segment has its own optimal direction (a,b). Grundland and Dogdson computed only one direction in the whole image. For complex data, only one direction is not sufficient to cover all the contrast loss. Our method that computes one optimal direction in each segment is more robust. Second, Grundland and Dogdson determined the direction of minimizing contrast loss directly through a weighted sum of the oriented chromatic contrasts. The direction calculated by our optimization algorithms is more reasonable. Third, we propose an effective and reasonable grouping method, based on the result of soft segmentation, to reduce the computational cost. Last, Grundland and Dogdson computed contrast loss in RGB color space while ours is in the CIELAB color space. The CIELAB color space is relatively perceptually uniform. The Euclidean distance between two colors in CIELAB color space approximates their relative perceptual difference.

3.4 Fusion process

Thanks to the probabilities of pixels in the soft segmentation, we can compute the final grayscale of pixel $i \in I$ by linearly combining information of all segments as follows (see Fig. 3(f)):

$$G_i = \sum_{t=1}^{K} P_i^t G_i^t \quad (5)$$

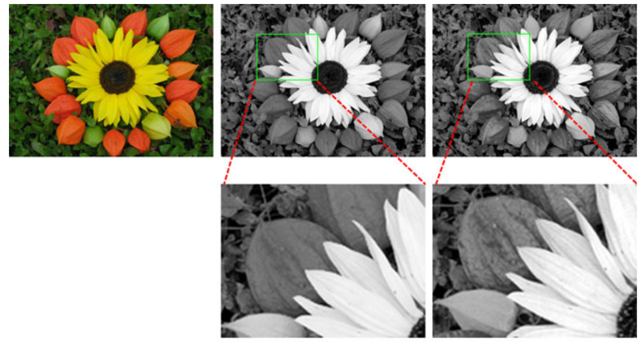


Fig. 4 Illustration of the local contrast enhancement. (**a**) Input color image; (**b**) the global gray tone; (**c**) the result after the local contrast enhancement

Fig. 5 The gray results of our method with different numbers of soft segments. (**a**) Original color image; (**b–d**) the gray results produced by our method using 6, 5, 4 soft segments, respectively. The produced results are all acceptable

where the grayscale value G_i^t of S_t is

$$G_i^t = L_i + a_i \times a^t + b_i \times b^t + \left(g_t - g_t^c\right) \quad (6)$$

where g_t^c is the average luminance of S_t.

4 Results and applications

We implemented our algorithms in C++ using OpenCV 2.1 and tested on a large number of images (Figs. 1, 3, 4, 7, 11, and the supplementary materials). If the image size is 1024×768, and there are up to 10 soft segments, global gray tone in Sect. 3.2 is obtained by solving a linear system whose size is 10, and local contrast enhancement in Sect. 3.3 only needs to solve linear systems that have two variables. It allows real-time interactions. All experiments were performed on a PC with a 2.93 GHz Intel Core i3 CPU and 4 GB memory. The current implementation runs on a single core.

Different images have different number of perceptual groups. For different number of segments, our algorithm can always produce acceptable results, as shown in Fig. 5. This is because the local contrast processing enhances the strength of contrast for pixels in each segment.

Fig. 6 The global gray tone results with different parameters: (**a**) $\gamma = 1.0$; (**b**) $\gamma = 1.1$; (**c**) $\gamma = 1.2$. The input color image can be seen in Fig. 3(a)

The user is allowed to adjust the parameter γ in the equation (2) to enhance (weaken) the strength of contrast between segments by increasing (reducing) the value of γ. Note that the objective function in Eq. (2) is quadratic, resulting in a sparse linear system. The size of linear system is the number of segments, generally 4∼12, It can be solved in real time. This enables real-time adjustment of the global tone in the resulting grayscale image. Figure 6 shows some results generated by adjusting the parameter γ. See the accompanying video for more results.

Figure 11 shows some gray results generated by our approach as well as the comparisons with the previous methods. From the results and comparisons, we can see that our technique well preserves the overall visual appearance and local detail feature and performs better than the other methods in most test images. Thanks to the global mapping used in every segmentation and the coarse soft segmentation, our algorithm avoids contouring and halo artifacts that can occasionally afflict the previous approaches. See the accompanying supplementary file for more results.

4.1 Applications

Interactive black-and-white image creation As Ansel Adams once said, "You don't take a photograph, you make it." It seems especially true for black-and-white images. Nowadays, creating an amazing black-and-white image takes the form of converting a color photo to grayscale. The black-and-white interpretation of color photo is rather subjective. User interaction becomes very necessary to enable users to create some results they are satisfied with.

Our approach offers an intuitive and handful interactive tool for users to meet this creative need. Users can adjust the lightness of every perceptual segment easily. Users directly paint on the region using a brush in the image. We first identify which of segments "responds" most strongly to this painting by measuring the probability of each segment in the pixels covered by the painting. Then users can increase (decrease) its brightness by intuitively increasing (decreasing) its average grayscale value. The use of a coarse soft segmentation avoids the appearance of artifacts. Figure 7 shows two examples of black-and-white images created using our interactive tool.

Fig. 7 Our method can easily help users to generate black-and-white images (*middle row* and *lower row*) from input color images (*upper row*)

Black-and-white image with one color Black-and-white image with one color is another form of art which attracts much attention of artists during recent years. Our method is very suitable for creating this kind of images. To provide more flexibility to users, we propose an interactive implementation of our method. The user labels the perceptual group in the image as initial seed area for soft segmentation. By this, the user only needs to label the object he wants to keep the color in the resulting grayscale image. After converting a color image to grayscale, our method will automatically add the chrominance components to the labeled object, as shown in Fig. 8. The artifact which may appears at the border of object is avoided due to the use of soft segmentation.

4.2 User studies

The results of color-to-gray image conversion are relatively subjective. To further evaluate the performance of our method, we have conducted three user studies. We adopt the paired comparison technique [4] used by Čadík [3] to evaluate color-to-gray image conversions. It is the two-alternatives forced choice (2AFC) experiment paradigm. We compared the performance of five state-of-the-art color-to-gray methods, i.e., [6–8, 14], and our method.

User study I In the first user study, the subjects were asked to select one image they preferred from two grayscale images shown side by side. The two gray images were converted from a color image. One of them is the result pro-

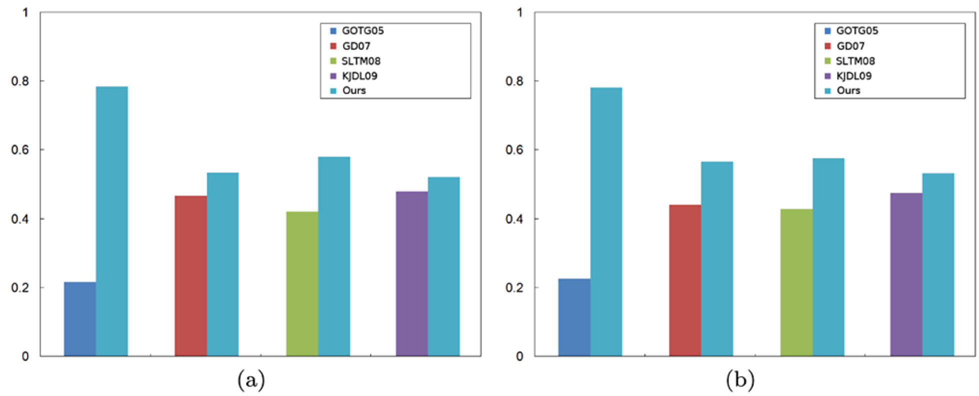


Fig. 9 Results of user study I (**a**) and II (**b**). The bars in the histogram show the number of subjects' choices in the user studies

Fig. 8 Black-and-white images with one color produced by our method. *Upper row*: input color images; *Lower row*: the results

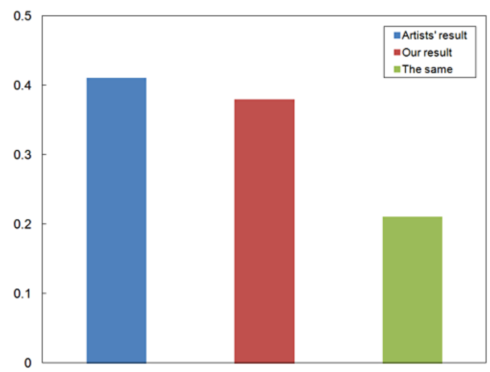


Fig. 10 Result of user study III. The bars in the histogram show the numbers of subjects' choices

duced by our method and the other is produced by a method which is randomly selected from the four previous methods. For each pair, the images are put in a random order.

User study II The second user study is similar to the first one. The difference is that the original color image was shown to the subjects for each gray image pair.

User study III In the third user study, the subjects were shown three images, one of which is the original image. The other two are black-and-white images, one of which is the result produced by our method and the other is produced by artists using Photoshop. The two gray images are put in a random order.

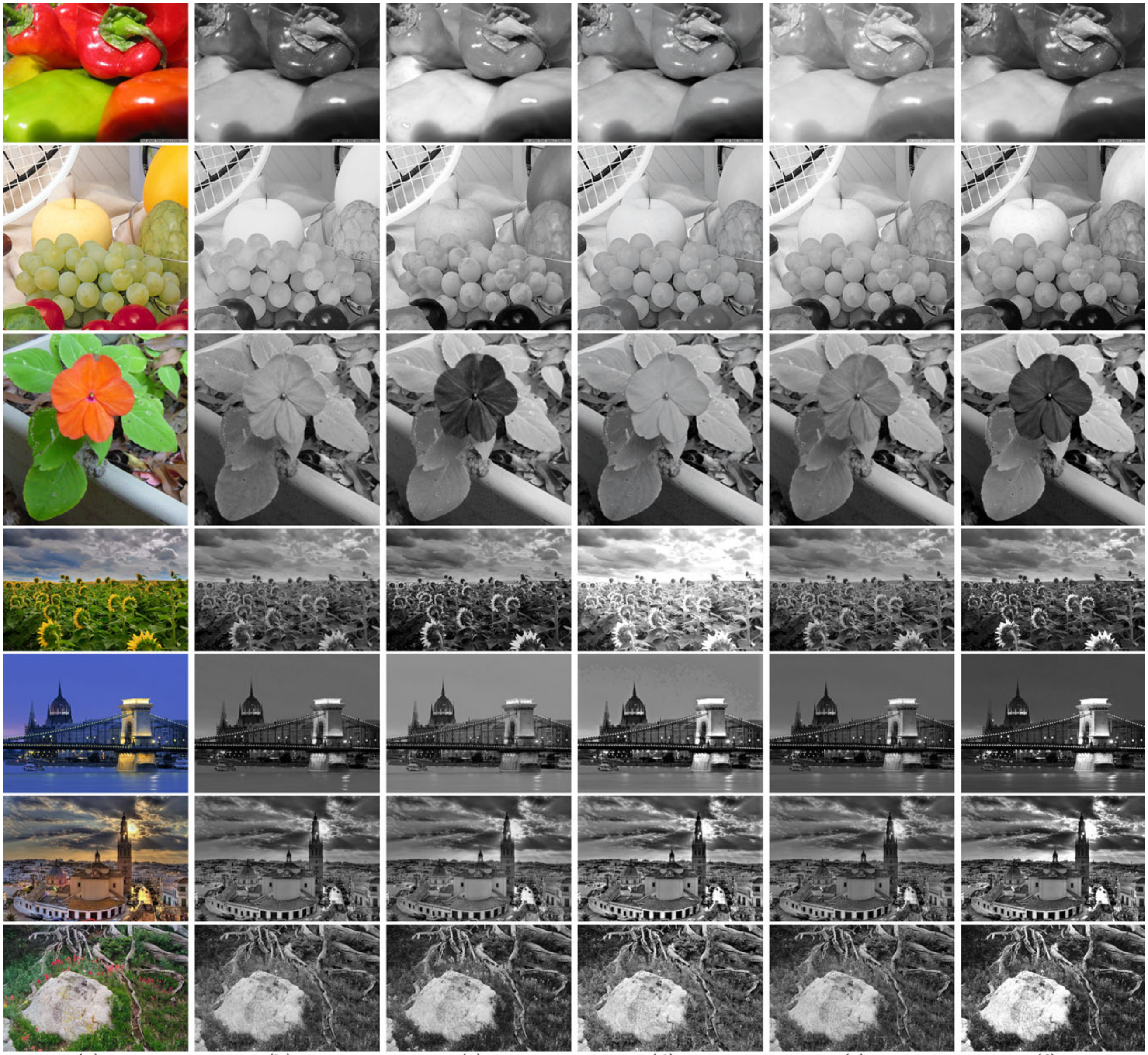
Analysis A total of 96 subjects (66 males and 30 females), whose ages range from 20 to 37, participated in the studies. We chose two groups of images. One group contains 19 images. The other group contains 7 images. In the first user study, we randomly select 10 images from the first group. In the second user study, we randomly select 15 images from the first group. In the third user study, we randomly select 5 images from the second group. The gray image results used in the first and second user study are generated by our method with default parameters. In the third user study, the gray image results are generated by our interactive tool.

Figure 9 shows the results of user study I and II. From the results, we see that the subjects preferred the results produced by our method than all the previous methods. This is promising. The reason might be that our method keeps the perceptual consistency between the color images and the gray images well.

Figure 10 shows the result of user study III. Although more subjects thought the black-and-white images produced by artists are better than those produced by our method, many of them thought that they look quite similar for many images. Therefore, our method really provides a high performance tool to create art-like black-and-white images.

5 Conclusions

An interactive two-scale approach for converting color images into grayscale ones is presented in this paper. Instead of considering the individual pixels in the images, our approach



(a) (b) (c) (d) (e) (f)

Fig. 11 Comparison results between our method and previous methods: (**a**) original color images; (**b**) the results of [7]; (**c**) the results of [6]; (**d**) the results of [14]; (**e**) the results of [8]; (**f**) our results

decomposes the image into perceptual groups according to Gestalt principles. The global gray tones are determined based on the anchoring theory in color perception. This is formulated as a quadratic optimization problems. Then local details are added by a local contrast enhancement processing respectively for each perceptual group. Thanks to the soft segmentation scheme used in our approach, the results produced by our approach are free of artifacts caused by hard segmentation. Our approach gains much better results than current color-to-gray approaches. Furthermore, our approach proposes an interactive editing tool for color-to-gray conversion . It is intuitive and flexible to create art-like black-and-white images from color images. The results are comparable to those made by the artists using Photoshop. User studies have been conducted to validate the applicability of our proposed approach. Future works include extending our approach for color image editing and image colorization. This is possible but needs further investigation and extra effort.

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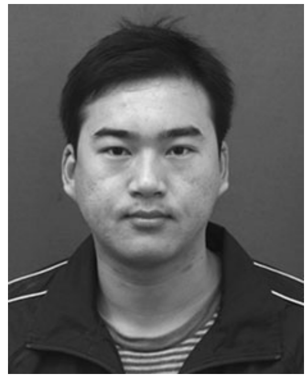

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