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Visual Perception Preserving Decolorization Method

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Abstract

This paper presents a decolorization method using gradient and saliency as the maintained features in the conversion to preserve the local and global visual perception. First, we construct a linear parametric mapping function of RGB color channels. Then, we calculate the feature value of each pixel in the color image and the parameterized grayscale image, the feature value integrates the pixel gradient and region saliency. Finally, we search for the parameters which can get the minimum of the total differences between the feature values of color and grayscale images, and substitute into the linear parametric function to get the decolorization result. To enhance the efficiency of getting the best parameters, we properly relax the strict computation formulas of the gradient and saliency to construct a linear least square problem, and obtain the optimal parameters by solving optimization. Experimental results show that our method using the discrete searching strategy can maintain the contrasts meanwhile avoid the excessive enlargement of the contrasts during the color-to-gray conversion, this property guarantees the preserving of the visual perception. Our method using the linear least square strategy can reduce the computation time and frequently get the similar results with our discrete searching method.

Keywords*: decolorization, color-to-gray conversion, pixel gradient, region saliency, discrete searching, linear least square*

1. Introduction

Image decolorization is the process of converting a color image which has three channels to a single channel grayscale image. With the development of the imaging and display devices, color images are easily to get, but in order to save resource and cost, color images are often converted to grayscale form to store, transmit or process. The instinctive way of decolorization is converting the image from the RGB color space to a color space which can separate the luminance and chrominance information, and picking the luminance information as the decolorization result. Taking the YUV color space which is usually adopted for example, this simple decolorization way will lose the contrast in the isoluminance areas [1] as shown in the middle column of Figure 1, and bring obstacles to the applications, such as the region recognition in the black-and-white e-book and printing, or the feature extraction in the image retrieval and object tracking. The left and right column of Figure 1 respectively shows two color images and the decolorization results of our method, it can be seen that our decolorization research is necessary and effective.

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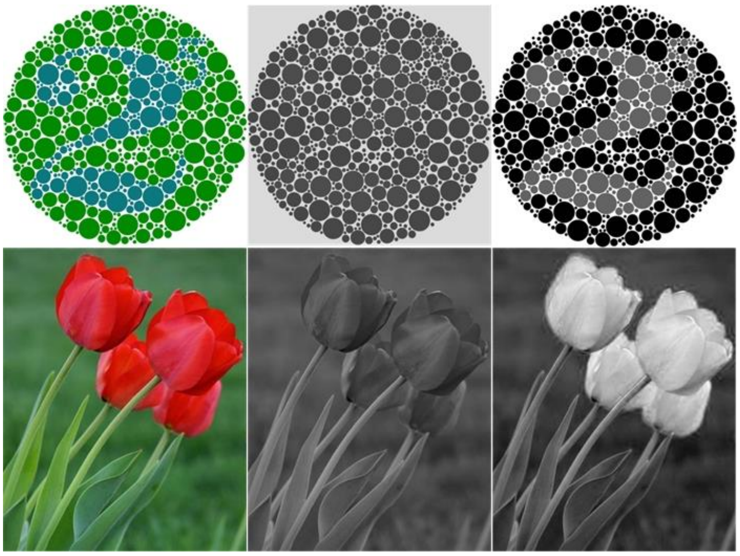

(a)Color image (b)CIE Y image (c)Our result

Figure 1. A Demonstration of Color Image Decolorization

As a channel number reduced procedure, the information loss is unavoidable. The purpose of decolorization is to preserve as much visually meaningful information about the color image as possible, meanwhile produce perceptually natural and pleasing grayscale image [2]. The existing algorithms can be roughly categorized into local and global methods.

Local methods employ different mapping functions to different local regions to conduct the color-to-gray conversion. In the work of [3], it utilized an iterative searching optimization method to get a grayscale image which can represent all the differences between the adjacent color pairs. [4] proposed a two-step method, it used the Helmholtz-Kohlrausch(H-K) color appearance operator to get a preliminary grayscale image, constructed the Laplacian pyramid and used the adaptively-weighted multi-scale unsharp mask technology to enhance the local contrast. [5] proposed a method which converted the color image with three channels to a feature space with more than three dimensions and utilized the sparse linear model to complete the conversion. In the work of [1], it constructed a parametric mapping function in the CIELab color space, and utilized the discrete searching strategy to select the best parameters according to the local region saliency. Although these methods can preserve local details, they may convert the same color pixels in different locations of the image to different gray values because of the different mapping functions and bring abrupt change or edge distortion to the continuous areas.

Global methods employ a single mapping function to the whole color image to conduct the color-to-gray conversion [6]. In the work of [7], it proposed a decolorization method using the wavelet transform to add the high frequent details to the grayscale image. [8] proposed a method which first constructed a nonlinear mapping function about the three color channels(lightness, chroma and hue), then optimized the parameters in the approximated function to obtain the satisfied grayscale image. [9] proposed method first constructed a finite multivariate polynomial mapping function using R,G,B values and their combinations as the monomials, then presented a bimodal contrast preserving objective function according to the color distance calculated in CIELab color space and got the optimization solution of the objective function through iteration. This method cannot maintain the color order and is time-consuming. To enhance the efficiency, the work of [10] further proposed a method which constructed a linear parametric mapping function using R,G,B values and set constraints for the parameters to conduct a discrete searching process. [11] proposed a linear weighted mapping method in the RGB color space, utilized the different combinations of the two scale parameters in the bilateral filter to measure the contrast difference and voted in a few better gray images, then selected the best one according to the user's preference. This method demonstrated the effectiveness of the linear mapping of R,G,B values in the decolorization research, but it calculated the bilateral filter output for every combination of the scale parameters to search for the better ones, the procedure was time-consuming, and it needed the user participation to get the final result.

In this paper, we propose decolorization methods without the requirement of user participation. We convert the color image in RGB color space by using the linear parametric mapping function. Because the human visual system is more sensitive to the contrast of the adjacent pixels and regions than to their absolute values [12], we use the pixel gradient and region saliency which can reflect the local and global contrast as the maintained features to preserve the visual perception, and get the best parameters which makes the grayscale image has the minimum feature difference with the initial color image by using the discrete searching strategy. To further enhance the efficiency of getting the best parameters and to improve the parameters' numerical precision, we properly relax the strict formulas of computing the pixel gradient and region saliency values, in order to construct an objective function which can be solved by the linear least square optimization method. Experimental results show that our method using the discrete searching strategy can preserve the visual perception during the color-to-gray conversion by maintaining the local and global contrasts simultaneously. The method solving the linear least square problem can enhance the efficiency of getting the best parameters, although the relax of the equations will influence the performance of the method to some extent, it frequently gets the similar results with our discrete searching method in the experiment, this property could be used to integrate the two methods to enhance both the performance and efficiency.

2. The Visual Perception Preserving Decolorization Method

2.1. Linear Parametric Mapping Functions

For a color image has $M \times N$ pixels, its Y image in the YUV color space is a linear combination of the R,G,B channel images with the fixed parameters, which is

$$Y = 0.2989R + 0.5870G + 0.1140B \tag{1}$$

In fact, using the Y image to represent the grayscale form of the color image, is not only because it's easy to implement and compatibility with the display equipments, but also because it's perform well in most practices except for those isoluminance areas [11]. To avoid the contrast loss in these areas, we use the unfixed parameters which are adaptive to each color image to get the satisfied grayscale image. The linear parametric mapping function is as follows:

$$g = w_r R + w_g G + w_b B \tag{2}$$

Where, g is the vector which represents the values of the parameterized grayscale image, R, G, B are the vectors which respectively represent the normalized values of the R, G and B image. w_r, w_g, w_b are the channel parameters to be calculated according to the features of the color and grayscale images, we represent the three parameters using a vector w,that is $w = (w_r, w_g, w_b)$.

2.2. Computation of the Maintained Features

To preserve the visual perception in the color-to-gray conversion, we construct a feature covers both the local and global contrasts of the image. Specifically, the local contrast is reflected by the gradient of pixel and global contrast is reflected by the saliency of region.

We follow the Sobel operator gradient computation framework to quantify the local contrast of the image. Sobel operator uses two 3×3 templates to filter the image and measure the horizontal and vertical contrasts of the local neighborhood of a pixel. The two templates are shown in Figure 2.

-1	-2	-1
0	0	0
1	2	1

(a)Horizontal template

-1	0	1
-2	0	2
-1	0	1

(b)Vertical template

Figure 2. The two templates of the Sobel Operator

For a pixel p in the location (i, j) of the parameterized grayscale image, its value is denoted as $g_{i,j}$, its horizontal gradient is computed as following:

$$\begin{aligned} D_h(g_{i,j}) &= (g_{i+1,j-1} + 2g_{i+1,j} + g_{i+1,j+1}) - (g_{i-1,j-1} + 2g_{i-1,j} + g_{i-1,j+1}) \\ &= w_r D_h(R_{i,j}) + w_g D_h(G_{i,j}) + w_b D_h(B_{i,j}), \end{aligned} \tag{3}$$

Where, $D_h(R_{i,j}) = (R_{i+1,j-1} + 2R_{i+1,j} + R_{i+1,j+1}) - (R_{i-1,j-1} + 2R_{i-1,j} + R_{i-1,j+1})$, and $D_h(G_{i,j})$, $D_h(B_{i,j})$ can be calculated in the same way .

Similarly, the vertical gradient is computed as following:

$$\begin{aligned} D_v(g_{i,j}) &= (g_{i-1,j+1} + 2g_{i,j+1} + g_{i+1,j+1}) - (g_{i-1,j-1} + 2g_{i,j-1} + g_{i+1,j-1}) \\ &= w_r D_v(R_{i,j}) + w_g D_v(G_{i,j}) + w_b D_v(B_{i,j}), \end{aligned} \tag{4}$$

where, $D_v(R_{i,j}) = (R_{i-1,j+1} + 2R_{i,j+1} + R_{i+1,j+1}) - (R_{i-1,j-1} + 2R_{i,j-1} + R_{i+1,j-1})$, and $D_v(G_{i,j})$, $D_v(B_{i,j})$ can be calculated in the same way.

Then, we compute the total gradient of the grayscale image using the absolute values instead of the square values to simplify the computation and approximate the linear relationship, that is

$$\begin{aligned} D_g(i,j) &= \left|D_h(g_{i,j})\right| + \left|D_v(g_{i,j})\right| \\ &= \left|w_r D_h(R_{i,j}) + w_g D_h(G_{i,j}) + w_b D_h(B_{i,j})\right| + \left|w_r D_v(R_{i,j}) + w_g D_v(G_{i,j}) + w_b D_v(B_{i,j})\right|. \end{aligned} \tag{5}$$

For the computation of the color pixel's gradient value $D_c(i, j)$, we use the vector space method which explores both the single color channel's own information and the three channels' joint information[13], and adopt the absolute operation instead of the square operation to consistent with that of the grayscale image.

We use the region saliency to quantify the global contrast of the image. For the initial color image, our method utilizes the K-means clustering algorithm to separate the image to n regions. The number n is defined equal to the number of distinct colors, and is obtained as following:

1. Uniform quantizing the R,G,B channel images to 12 different values, and the number of colors will be reduced from 256^3 to 12^3=1728. This process is because the human visual system cannot distinguish the color difference in magnitude of 1/(256^3), properly enlarge the interval of the quantization will not bring obvious influence to the perception of region saliency [14];
2. Sorting the quantized colors in their frequency descending order and calculating the summation of the sorted colors' frequencies, when the summation is just over 0.9, the number of the involved more frequently occurring colors is taken as the number n. This process is because the color in a natural image typically covers only a small portion of the full color space, using the more frequently occurring colors to replace those less frequently occurring colors will not bring obvious influence to the global saliency of the distinct colors.

Through these procedures, the number n is less than 30 for most of the test images in our experiment. And through image segmentation, the image can be separated to n regions. Then, the saliency of region s in the color image is calculated as,

$$S_c(\Re_s) = N(\Re_s)\sum N(\Re_t)d(c_s, c_t) \tag{6}$$

Where, $\Re_s, \Re_t$ represent different regions, $N(\Re_s)$ is number of the pixels in region $\Re_s$, $d_c(c_s, c_t)$ is the color difference between the center pixels of the two regions and calculated in the CIELab color space as,

$$d_c(c_s, c_t) = |L_s - L_t| + |a_s - a_t| + |b_s - b_t| \tag{7}$$

Where, L, a, b represent the three components of a color in the CIELab color space respectively.

Substituting the region saliency to the corresponding pixels, for a pixel p in the location (i, j) and region s, its saliency value in the initial color image is available as,

$$S_c(i, j) = S_c(\Re_s) \tag{8}$$

For the region saliency of the grayscale image, in order to maintain the global perception, the segmentation of the obtained grayscale image should be as similar as possible to the initial color image, we use the same region segmentation to measure the preserving of the region saliency in the conversion, and the saliency of region s in the parameterized grayscale image is calculated as,

$$S_g(\Re_s) = N(\Re_s)\sum N(\Re_t)d_g(\bar{g}_s, \bar{g}_t) \tag{9}$$

Where, $\bar{g}_s$ and $\bar{g}_t$ are the mean values of the gray pixels in region $\Re_s$ and $\Re_t$, they are calculated as,

$$\bar{g}_s = \frac{1}{N(\Re_s)} \sum_{p \in \Re_s} (w_r R_p + w_g G_p + w_b B_p) = w_r \bar{R}_s + w_g \bar{G}_s + w_b \bar{B}_s \tag{10}$$

Where, R_p, G_p, B_p respectively are the R,G,B value of the pixel p, and $\bar{R}_s = \frac{1}{N(\Re_s)} \sum_{p \in \Re_s} R_p$, the same as $\bar{G}_s$ and $\bar{B}_s$. $d_g(\bar{g}_s, \bar{g}_t)$ is the difference between the mean values of the two regions as,

$$\begin{aligned} d_g(\bar{g}_s,\bar{g}_t) &= \left|\bar{g}_s-\bar{g}_t\right| \\ &= \left|(w_r\bar{R}_s+w_g\bar{G}_s+w_b\bar{B}_s)-(w_r\bar{R}_t+w_g\bar{G}_t+w_b\bar{B}_t)\right| \\ &= \left|w_r(\bar{R}_s-\bar{R}_t)+w_g(\bar{G}_s-\bar{G}_t)+w_b(\bar{B}_s-\bar{B}_t)\right|. \end{aligned} \tag{11}$$

Then, equation(8) can be transformed to

$$\begin{aligned} S_g(\Re_s) &= N(\Re_s)\sum N(\Re_t)\left|w_r(\bar{R}_s-\bar{R}_t)+w_g(\bar{G}_s-\bar{G}_t)+w_b(\bar{B}_s-\bar{B}_t)\right| \\ &= \left|w_rN(\Re_s)\sum N(\Re_t)(\bar{R}_s-\bar{R}_t)+w_gN(\Re_s)\sum N(\Re_t)(\bar{G}_s-\bar{G}_t)+w_bN(\Re_s)\sum N(\Re_t)(\bar{B}_s-\bar{B}_t)\right| \\ &= \left|w_rS_R(\Re_s)+w_gS_G(\Re_s)+w_bS_B(\Re_s)\right|. \end{aligned} \tag{12}$$

Substituting the region saliency to the corresponding pixels, a pixel p in the location (i,j) and region s, its saliency value in the parameterized grayscale image can be represent as,

$$S_g(i,j)=S_g(\Re_s) \tag{13}$$

We combine the local and global contrast of the image to construct the feature to be preserved in the color-to-gray conversion, the feature value is defined as

$$F_c=\alpha D_c+(1-\alpha)S_c \tag{14}$$

$$F_g=\alpha D_g+(1-\alpha)S_g \tag{15}$$

Where, D_c is a vector composed by $D_c(i,j)(i=1,...,M;j=1,...,N)$, S_c, D_g, S_g are also vectors composed by their corresponding values. F_c is the vector composed by the feature values of the pixels in the initial color image, F_g is the vector composed by the feature values of the pixels in the grayscale image, α is the factor to manipulate the importance of the local and global contrast which is a constant in the process(we set $\alpha=0.3$ to stress the global contrast which is conform to the human visual perception).

2.3. Computation of the Decolorization Result

The purpose of our method is to get the grayscale image which can best preserve the perception of the initial color image, the feature difference is computed as follows:

$$J(w)=\left\|F_g-F_c\right\|_2^2 \tag{16}$$

For a color image which is intended to be converted to grayscale image, its feature vector F_c needs to be computed only once and will keep unchanged during the process. The feature vector F_g is changed with the different parameter vector w. The works of [10],[11] have proven that slightly varying the parameters will not change the appearance of the grayscale image too much, we discretize the parameters w_r, w_g, w_b in the range of [0,1] with interval 0.1. In order to avoid overflow of the gray values, we set constraint to the parameters as $w_r+w_g+w_b=1$, then, the number of the parameter vector w is $N_p=\frac{11\times(11+1)}{2}=66$. For every w, we compute the corresponding F_g and $J(w)$. The parameters which can get the minimum $J(w)$ is selected as the best parameters, the corresponding grayscale image is the output of this method.

Through the discrete searching strategy, we get the grayscale image which best preserves the pixel gradient and region saliency of the initial color image. But it needs to repeatedly calculate the feature values and feature difference of the different parameterized grayscale images for 66 times, which is time consuming. Because of the nonnegative of the parameters and the relative independence of the R,G,B channels, we relax the strict computation of the absolute values in equation(5) and equation(12) to get the approximated local and global contrasts as follows:

$$\begin{aligned}\hat{D}_g(i,j) &= w_r(|D_h(R_{i,j})|+|D_v(R_{i,j})|)+w_g(|D_h(G_{i,j})|+|D_v(G_{i,j})|)+w_b(|D_h(B_{i,j})|+|D_v(B_{i,j})|) \\ &= w_r D_R(i,j)+w_g D_G(i,j)+w_b D_B(i,j)\end{aligned} \tag{17}$$

$$\hat{S}_g(\Re_s) = w_r\,|S_R(\Re_s)| + w_g\,|S_G(\Re_s)| + w_b\,|S_B(\Re_s)| \tag{18}$$

For a given color image, all the values in right-hand size of equation(17) and equation(18) are available except for the three parameters w_r, w_g, w_b. Substituting the region saliency to the corresponding pixels, the representation of $\hat{S}_g(i,j)$ is got. Through combination of the two contrasts, we get the new feature of grayscale image and represent it in the row vector form as

$$\hat{F}_g = \alpha\hat{D}_g + (1-\alpha)\hat{S}_g = w_r V_R + w_g V_G + w_b V_B \tag{19}$$

where, $V_R = \alpha D_R + (1-\alpha)|S_R|$, and V_G , V_B can be calculated in the same way. To calculate the best parameters, we construct the objective function as

$$f(w) = \min\|wV - F_c\|_2^2 \tag{20}$$

Where, V is a matrix composed by the row vectors V_R, V_G and V_B , as $V = \begin{bmatrix} V_R \\ V_G \\ V_B \end{bmatrix}$, F_c is a row vector.

In the objective function of equation(20), the parameter vector $w=(w_r, w_g, w_b)$ is the unknown term. The function conforms to the linear least square(LLS) problem[15], the optimal value of the vector combined by the linear parameters($w=(w_r, w_g, w_b)$) can be efficiently worked out by solving the LLS optimization problem. Substituting the optimal solver into the linear mapping function of equation(2), the color-to-gray conversion result is obtained.

3. Experimental Results

In the experiment, we denote our method using the discrete searching strategy to get the best grayscale image as DSSD method, and denote our method using the linear least square optimization to get the result as LLSD method. We compare our results with CIE Y, Lu12 [9] and Du15 [1] results and use Cadik's decolorization dataset[16] which is the publicly available decolorization benchmark dataset to conduct the process. To evaluate the quality of the compared methods, subjective assessment is the most intuitive manner, which mainly depends on the human observation. We set out the initial 24 color images of the Cadik's dataset and the result images of the compared methods in Figure 3 and Figure 4.

It can be seen that our two methods can get satisfied decolorization results for the 24 color images in Cadik's dataset, especially the DSSD method. For example, observing the results of the synthetic images with no.2,6,7,8,11,17, our two methods all can keep the color and region contrasts in the images, the general validity of our methods in processing the synthetic images is superior to the other compared methods. Observing the results of the nature images with no.10,13,14,15,22, our methods preserve the visual perception during the conversion by combining the local and global contrasts, taking the DSSD result of the image no.10 for example, it emphasizes the contrasts between the apple and grapes, grapes and plums which are both the visual attention focus regions, meanwhile keeps the distinguishable between the shaddock and avocado in the right size of the image without enhancing the contrast in order to preserve the visual perception consistency with the color image.

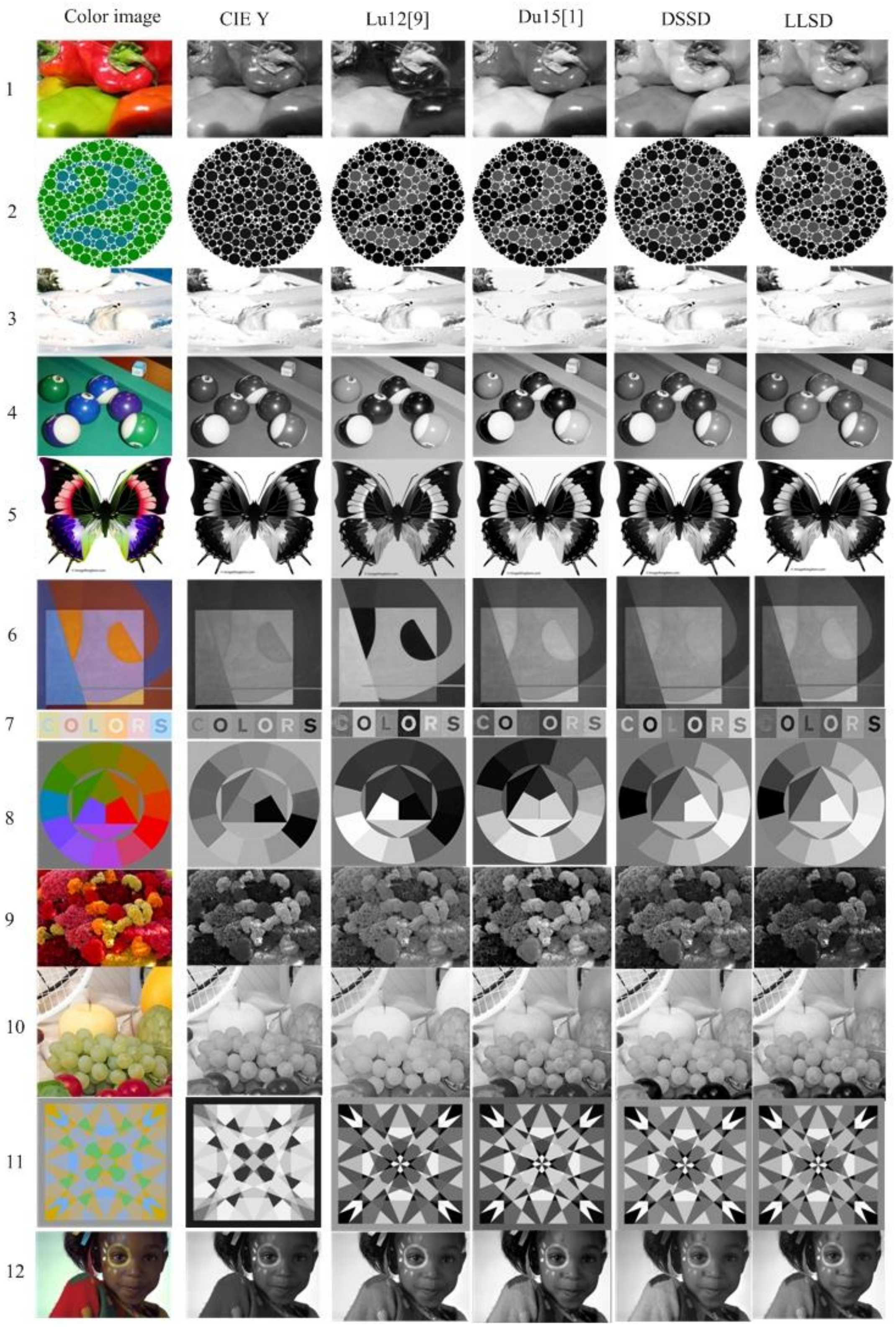

Figure 3. Comparison of the Initial Color Image, Results of CIE Y, Lu12[9], Du15[1] and our Two Methods

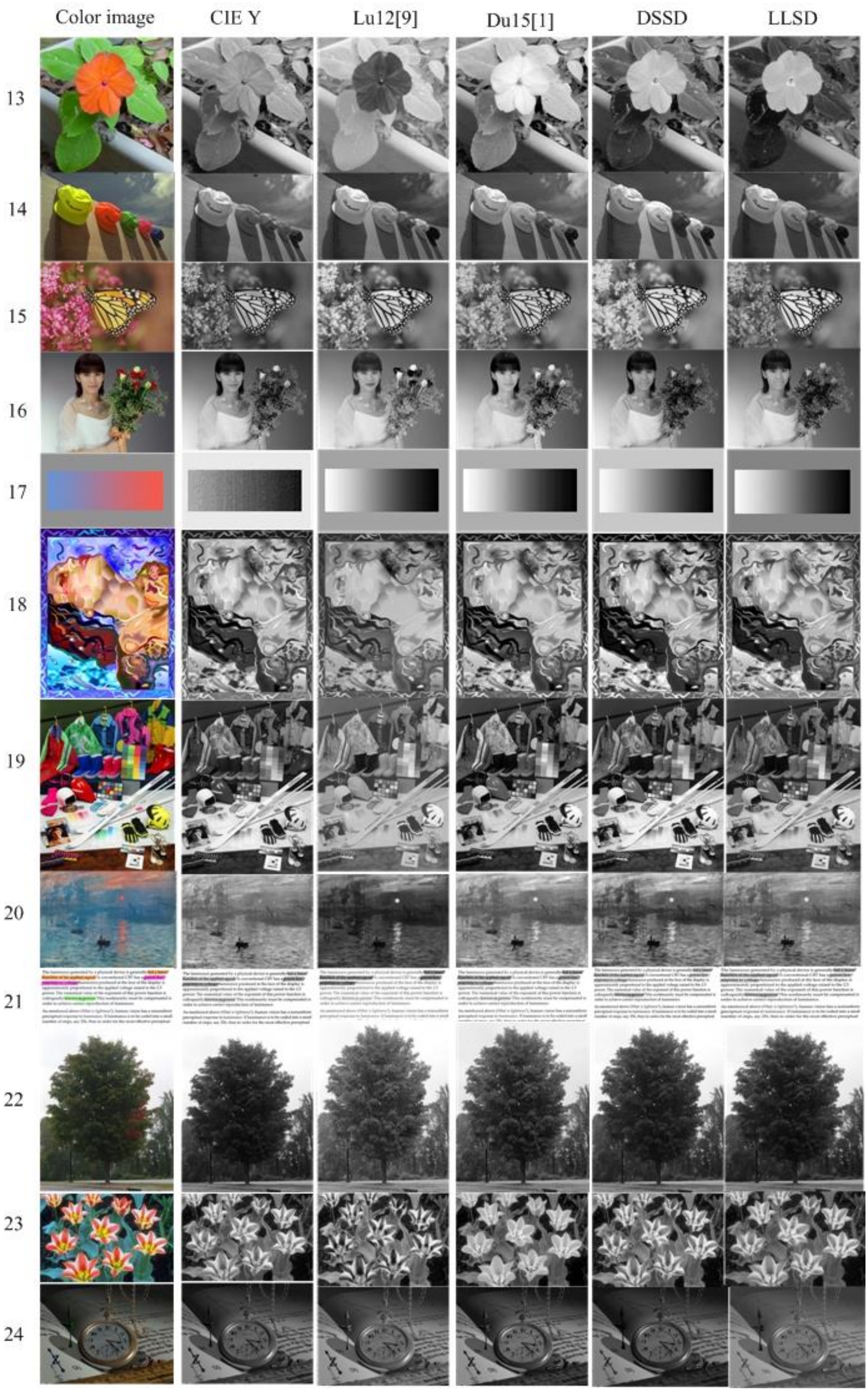

Figure 4. Comparison of the Initial Color Image, Results of CIE Y, Lu12[9], Du15 [1] and Our Two Methods

To objective evaluate the qualities of the decolorization methods, we employ the E-score metric which is a harmonic mean of the color contrast preserving ratio (CCPR) metric and the color content fidelity ratio(CCFR) metric[17].

$$CCPR = \frac{\#\left\{(x,y)\middle|(x,y)\in\Omega,\left|g_x - g_y\right|\geq\tau\right\}}{\|\Omega\|} \tag{21}$$

Where, Ω is the set containing all the pixel pairs (x, y) of the initial color image with difference $\delta_{(x,y)} \geq \tau$, τ is a set threshold, $\|\Omega\|$ is the number of pixel pairs in Ω . $\#\left\{(x,y)\middle|(x,y)\in\Omega,\left|g_x - g_y\right|\geq\tau\right\}$ is the number of pixel pairs in Ω which have difference $\left|g_x - g_y\right| \geq \tau$ after decolorizaton.

$$CCFR = 1 - \frac{\#\{(x,y)\,|\,(x,y)\in\Theta,\delta_{x,y}\leq\tau\}}{\|\Theta\|} \tag{22}$$

Where, Θ is the set containing all the pixel pairs (x, y) of the grayscale image with difference $\left|g_x - g_y\right| > \tau$, $\|\Theta\|$ is the number of pixel pairs in Θ . $\#\{(x,y)\,|\,(x,y)\in\Theta,\delta_{x,y}\leq\tau\}$ is the number of pixel pairs in Θ which have difference $\delta_{(x,y)} \leq \tau$ in the initial color image.

$$E - score = \frac{2\cdot CCPR\cdot CCFR}{CCPR + CCFR} \tag{23}$$

We compute E-score values of the different methods' results of the 24 color images in Cadik's dataset, vary τ from 1 to 40, and get the average E-scores for the whole dataset as shown in Figure 5.

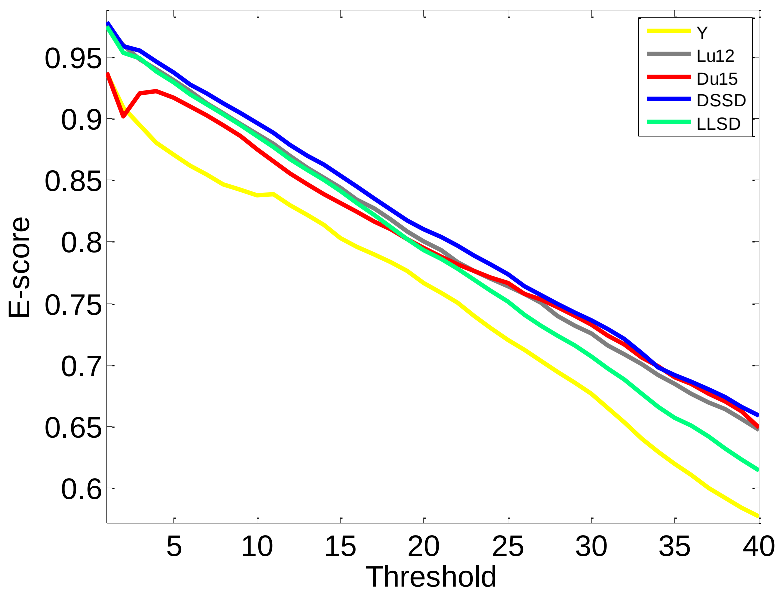

Figure 5. E-Scores Plot on Cadik's Dataset

Our DSSD method can get higher average E-scores than the other compared methods, which certifies the performance of this method in both preserving the contrasts and avoiding exaggeration of the contrasts during the color-to-gray conversion. The average E-scores of our LLSD method are unsatisfactory, the advantage of this method is the high efficiency. For a 390×390 image, it takes only 0.59 seconds on a computer with a 2.4GHz Intel Core i5 CPU and is just about 1/3 of the time taken by the DSSD method. Observing the results of our two methods in Figure 3 and Figure 4, more than half of the 24 images get similar results (image no.2,3,5,6,8,11,13,17,18,20,21,22,23). We take the images in the color250 dataset which is proposed in paper [17] to further demonstrate the relationship of our two methods. Compared with the Cadik's dataset, images in the color250 dataset cover more image categories, such as nature picture, data graph, planar map, satellite map and so on. Two examples are shown in Figure 6 and Figure 7.

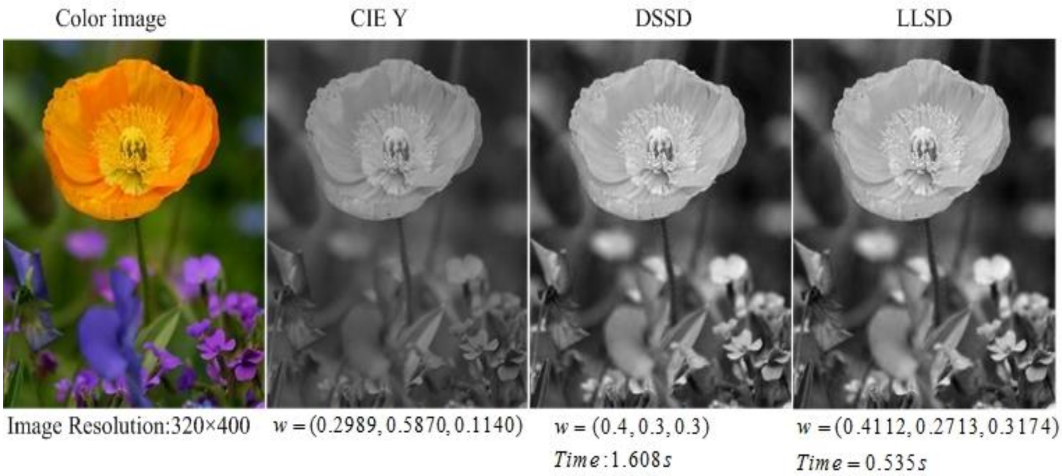

Figure 6. The Example to Demonstrate the Similar Results and Computation Time Relationship of our Two Methods

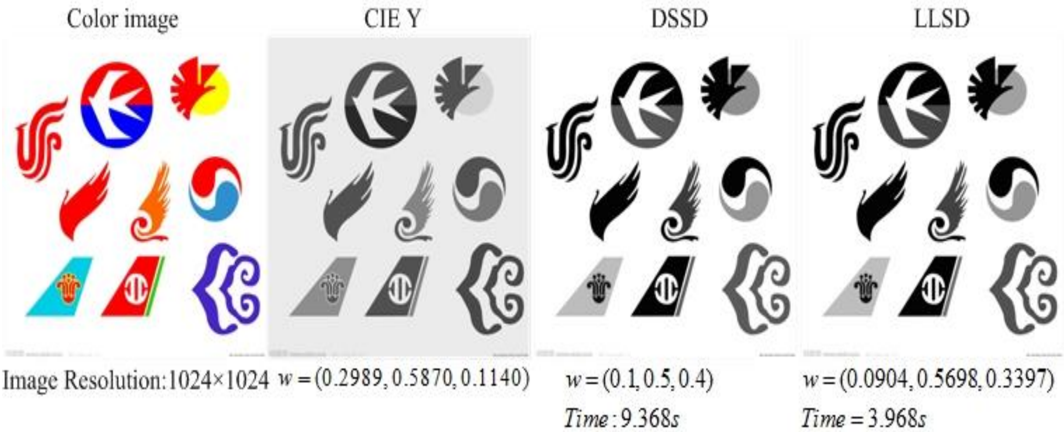

Figure 7. The Example to Demonstrate the Similar Results and Computation Time Relationship of our Two Methods

For all the 250 images in color250 dataset, we compare the parameters computed by our two methods, and label the results with each of the three parameters' differences less than 0.1 to be the similar results. The number of the images with similar results is 139. This demonstrates the LLSD method can frequently get similar results with the DSSD method, and considering the high efficiency of LLSD method, it's promising to design a strategy combining the two methods to consider both the performance and efficiency.

4. Conclusions

In this paper, we propose a visual perception preserving decolorization method. We use the pixel gradient and region saliency to reflect the local and global contrasts of the image, because the human visual perception is more sensitive to the contrast of the adjacent pixels and regions than to their absolute values, our method can preserve the visual perception. We use two strategies to get the best parameters of the linear mapping function which are discrete searching strategy and linear least square optimization strategy. The result quality of the discrete searching strategy is better while the efficiency of the linear least square optimization strategy is higher, how to design a method combining the advantages of the two strategies is the problem to be researched in our future work.

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