Research on blur discrimination thresholds of three-Channel for color image

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Abstract. On the basis of modern theory of color vision, the blur discrimination threshold of color image with three channels (luminance, red-green and the yellow-blue channel) in the opponent color space (DKL space) is studied through visual experiments in this paper. The visual evaluation experiment is designed by the psychophysical method based on Quest algorithm. Finding the blur discrimination threshold of color image according to the DKL space is of great significance for helping us understand color perception of image. It also has a wide range of applications in areas such as color image compression during color image transmission. Two (flowers and artificial object) typical images in the McGill standard color image database were chosen as the experimental images. After converting the color space of the image from RGB to DKL space, Gaussian low-pass filtering is used to establish the fuzzy image database. Quest algorithm which is a psychological physical method is used to design the visual evaluation experiment. Eleven volunteers with normal color vision were invited to participate in the visual evaluation experiment for each of the three channels of the two images. Our main conclusions are: (1) Human eyes are more sensitive to luminance information than color information. (2) The larger the contrast of the image and the smaller the uniformity of the image, the more sensitive the human eye is to changes in image blur.

1. Introduction
Visual information is an indispensable part of the information composition for humans. The study of blur discrimination threshold of the color image in the opponent color space (DKL-Derrington-Krauskopf-Lennie) provides important application value for digital image compression, transmission and display, and provides a research basis for human eye vision resolution threshold.

Huw C. Owens[1] discussed the blur discrimination thresholds of red-green, blue-yellow and luminance channels according to the modulated square wave. For all observers, the blur discrimination thresholds for red-green, and luminance channels are similar, and the threshold for yellow-blue channel is higher. Ferzli et al. proposed a “just noticeable difference” model[2] to establish the relations between image data and human perception; they also presented a perceptual no-reference image sharpness metric by measuring the spread of edges[3][4].

This paper studies the blur discrimination thresholds of the color image based on DKL color space. We investigated the observers’ focus points on selected images and when the selected images were divided into three channels. Eleven observers were invited to participate in a visual evaluation experiment to determine the three-channel blur discrimination thresholds of the color image. Through analysing experimental results, the relationship between blur discrimination threshold and texture of any particular image is discussed.
2. Method
After completing the space conversion from RGB to the opponent color space, the typical images in McGill image database were selected for Gaussian filtering processing, and the experimental fuzzy image database was established. The DKL color space was employed to define the chromatic and luminance properties of the image stimuli in these experiments. Based on the activations of the L (long-wavelength-sensitive), M (medium-wavelength-sensitive), and S (short-wavelength-sensitive) cones, the two chromatic and one luminance channels of the DKL space are defined by combinations of cone activations. On this basis, the visual evaluation experiment was designed by using the principle of Quest algorithm. Finally, the observers were invited to complete the experiment and a series of experimental data was obtained.

2.1. Blurred images for experiment

2.1.1. Conversion of color space for the image.
A lookup table was created to firstly convert RGB space to CIEXYZ space, then to LMS space and to DKL space subsequently. The image was divided into luminance, red-green, and yellow-blue channels in the DKL space.

The formula for converting LMS space to DKL space[5] is shown below (equation (1)):

$$
\begin{bmatrix}
D \\
K \\
L
\end{bmatrix} =
\begin{bmatrix}
22.0454 & 22.0454 & 0.0 \\
13.8336 & -32.4902 & 0.0 \\
-12.7279 & -12.7279 & 9.6048
\end{bmatrix}
\begin{bmatrix}
L \\
M \\
S
\end{bmatrix}
$$

(1)

2.1.2. Typical image selection.
The images used in these experiments are from a standard color image database provided by Olmos & Kingdom of McGill University. The McGill image database is widely used in computer vision and biological research, with 9 types of natural images: animals, flowers, leaves, fruits, land surface, artificial objects, Shadows, snow and textures. The images of flowers and artificial objects were selected as research objects in this study.

The more obvious the texture feature, the more information that can be observed. Contrast and uniformity of image were used to measure the texture information of the image in this study. Based on the gray level co-occurrence matrix, the contrast and uniformity of the image in McGill database were calculated. The functions of contrast of image and uniformity of image are given below:

$$
\text{Contrast} = \sum \sum (a - b)^2 p(a, b, d, \theta)
$$

(2)

$$
\text{Uniformity} = \sum \sum \frac{1}{1+(a-b)^2} p(a, b, d, \theta)
$$

(3)

Where N is the number of gray levels of the image. Assuming that the gray value of one certain pixel is a, along the $\theta$ direction, the corresponding gray value of one pixel with the distance of d from this pixel is b. The number of times the two points appear in the image is called the frequency $[p(a, b, d, \theta)] N*N$.

Two images (numbered 43 in flowers and numbered 135 in artificial object) with the largest contrast which means they have the most obvious texture feature were selected for experiment in this study. After this, the experimental images were converted from RGB space to DKL space with luminance, red-green, and yellow-blue channels, as shown in figure 1:
2.1.3. Image blurring processing.

The Gaussian low-pass filter (equation (4)) was used to filter the image to obtain the required experimental image database.

\[ H(u, v) = e^{-\frac{1}{2\pi^2 D_0}} \]

where \( D_0 \) is a proper range of required by the Quest algorithm in visual experiments. We used parameter \( B(B=500-D_0) \) to describe the degree of blur, and \( B_0 \) was used to represent blur discrimination thresholds of color image.

2.2. Design of visual evaluation experiment

Quest algorithm is a Bayesian adaptive psychometric method[6] and it is widely used for its effectiveness in threshold estimation. Therefore, Quest was used for visual experiment programming in this study.

The basic idea of Quest algorithm is to place each determination at the current most probable Bayesian estimate of threshold. The procedure was conducted in three steps:

- Initial probability density function (equation (5)):

\[ q_0(T) = \frac{A}{[B e^{-C(T-t)} + C e^{B(T-t)}]} \]

Where \( T \) is the threshold of log units, \( A \) determines the magnitude of the fitted curve, \( B \) and \( C \) determine the slopes of the fall-off at low and high thresholds, \( t \) is to the most probable log value of threshold. In this paper, \( A, B, C \) are 6.29, 1.22, 5.07 respectively.

- The method of choosing the stimulus intensity for any determination.

The psychometric function describes the relations between some physical measures of a stimulus and the probability of the particular psychophysical response. “2 alternative force choice” is used in our experiment, the psychometric function is expressed by \( p(r, x, T)[6] \) (equation (6)), which represents the probability of a response. \( r \) (0 or 1), \( T \) is the subject with log threshold, \( x \) is a stimulus of log intensity.

\[ p(r, x, T) = \Psi(x - T) = 1 - \delta - (1 - \gamma - \delta) \exp[-10\beta(x - T + \epsilon)] \]

Where \( \delta \) is the false negative rate, \( \gamma \) is the false positive rate, \( \beta \) determines the slope of the psychometric function and \( \epsilon \) determines the threshold criterion, they are 0.5, 0.01, 3.5 and 1.5 in this paper respectively. Then the probability density function (equation (7)) after nth response was given below:

\[ q_n(T) = p(r_n, x_n, T) \cdot q_{n-1}(T) \]
The next log stimulus intensity $x_{n+1}$ was chosen as the one corresponding to the maximum probability.

- The method for choosing a final threshold estimate.

The standard deviation of the nth response (equation (8)) was:

$$V_n = \sqrt{\int (T - m_n)^2 q_n(T) dT / \int q_n(T) dT}$$

(8)

Where $m$ is the mean of the probability density function. If $V_n$ reaches the termination condition, corresponding $T$ is the final thresholds result.

2.3. Experiment

2.3.1. Experimental condition

Eleven observers with normal visual were invited to participate in these experiments. All experiments were conducted in an indoor lighting room in the National Laboratory of Color Science and Engineering of Beijing Institute of Technology. The experimental environment is shown in figure 2:

2.3.2. Experimental steps

Before the experiment, the experimental software was initiated and the observer’s viewing distance was adjusted. During the experiment, several determinations of whether there is a difference between the two images were made by the observer until the end of the program. After the experiment, the original data of experiment were saved and the observer was invited to fill out the observer information record form.

The program interface is shown in figure 3. There are two images in the program interface, one is clear and the other is blurry, and they are randomly positioned either on the left or right side. The observer needs to determine whether there is a difference between the two images then click ‘Yes’ or ‘No’ button.

Figure 2. Experimental environment

Figure 3. Program interface
2.3.3. Experimental data

Eleven observers with normal visual were invited to participate in these experiments, and each of them completed six procedures on the three channels of the two images. For each procedure, we have saved a set of experimental data including: (1) Number of clicks and the corresponding B. (2) The result of blur discrimination threshold \( \text{B}_0 \) of each procedure. (3) The left or right position of the clear image on the screen.

3. Result

3.1. Data analysis

3.1.1. The experiment data analysis for one experiment

During the experiment, we recorded the B value of the observer each number they click. As shown in the figure 4, we can see the experimental data of the three-channel of the two images of the observer No. 3. The x axis of the figure is the number of clicks, and the y axis is the corresponding blur value. The B corresponding to the last number of clicks on each curve is the blur discrimination threshold \( \text{B}_0 \) of each procedure.

![Figure 4. B changes of an experiment for one observer](image)

3.1.2. Statistical results of all observers

As shown in table 1, the statistical results of three channels (luminance, red-green and yellow-blue) of the two images were calculated. We calculated the standard deviation of the results of eleven observers for each image. Comparing with our blur range (0-500), the standard deviation is an acceptable value, which indicates the stability of our experimental results.

| Blur discrimination thresholds | Flower image | Artificial image |
|-------------------------------|--------------|-----------------|
|                               | L            | R-G             | Y-B            | L            | R-G             | Y-B            |
| Average \( \text{B}_0 \)      | 255.1        | 378.0           | 368.6          | 322.8        | 393.1           | 416.4          |
| Max \( \text{B}_0 \)          | 293          | 407             | 386            | 392          | 415             | 432            |
| Min \( \text{B}_0 \)          | 218          | 362             | 337            | 296          | 359             | 400            |
| Standard deviation            | 31.3         | 15.0            | 15.6           | 30.6         | 17.0            | 9.7            |
3.2 Blur threshold results

Figure 5 shows the average $B_0$ in three channels (luminance red-green and yellow-blue channel) of the two images. We can see from the final results that: (1) The blur discrimination threshold of three-channel of the flower image is smaller than that of the artificial object image. (2) The blur discrimination of luminance channel is smaller than the thresholds of red-green channel and yellow-blue channel in both of the two images; Comparing with the luminance channel, the blur discrimination thresholds of color channel are closer.

4. Discussion

This paper analyses the influence of the image texture information on the blur discrimination threshold of color image. Two indicators (contrast of image and uniformity of image) were used to represent the image texture information in these experiments.

| Image texture information | Flower image | Artificial image |
|---------------------------|--------------|------------------|
|                           | L    | R-G | Y-B | L    | R-G | Y-B |
| Contrast                  | 0.95 | 0.12| 0.17| 0.42 | 0.08| 0.04|
| Uniformity                | 0.81 | 0.96| 0.95| 0.86 | 0.97| 0.99|

The blur discrimination threshold represents the ability of the human eye to distinguish image blur, the higher the threshold, the weaker the human eye's ability to distinguish changes in blur. Image contrast represents the image color and luminance information richness, the higher the contrast, the more image information; Image uniformity represents the changing trend of the image information, the greater the uniformity, the more regular the change of the image information.
Figure 6 shows the relationship between $B_0$ and the corresponding image texture information. The x axis of the figure is the image texture information (contrast and uniformity of image) of three channels of the two images, and the y axis is the corresponding $B_0$. From the approximate linear relationship between them, we come to the following possible explanations that: (1) When the image luminance and color information are very rich, the human eye is more sensitive to distinguish image blur changes; (2) When the image texture information changes rapidly, it is easier for the human eye to distinguish the change in image blur.

5. Conclusion

Three-channel blur discrimination threshold results for two types of the typical images were obtained in this study.

| Average blur discrimination thresholds | Luminance | Channels | Red-Green | Yellow-Blue |
|--------------------------------------|-----------|----------|-----------|-------------|
| Flower image                         | 255.1     | 378.0    | 368.6     |
| Artificial image                     | 322.8     | 393.1    | 416.4     |

Through the analysis of the experimental results and the characteristics of the images itself, we get the following summary:

- Comparing with the color channel, the blur discrimination threshold of luminance channel is lower, which indicates that the human eye is more sensitive to luminance information.
- The larger the contrast of the image, the smaller the uniformity of the image, and the smaller the corresponding blur threshold of the color image, which means that the human eye is easier to distinguish the blur change of the image with rich content and sharp changes.

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