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Analysis of the Effect of the Viewing Distance in Texture Perception using Morphological and Statistical Model

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***Abstract*—An analysis method of the effect of the viewing distance in texture perception using morphological and statistical model is proposed. Texture perception has been an area of interest for many researchers. However, the effect of the viewing distance which is an essential issue in texture discrimination is still an open problem. In this paper, we synthesized textures by controlling local and global textural features separately using a texture model based on mathematical morphology, namely the PGPC texture model. Visual sensory tests were carried out on thirty-two respondents in four experiments. The collected data was analyzed using the logistic regression model. The experimental results indicate that the viewing distance and the mutual interactions of local and global features of a texture have significant effects on human perception. Other factors such as prior knowledge and the order of the viewing positions influence human perception in texture discrimination. This study contributes to the construction of the numerical relation between the viewing distance and human texture perception.**

I. Introduction

Texture classification and discrimination are among the main topics of image analysis. Various methods of texture analysis, for example the co-occurrence matrix method and the spatial frequency method, have been proposed [1], [2]. Texture characteristics measurements, which are the main aims of the above popular methods, are often employed for texture classification and discrimination. Many psychologist and computer vision researchers have studied texture perception in order to find the most salient texture properties in texture discrimination [3], [4], [5]. Many textural features such as contrast, coarseness, regularity, directionality, etc. have been used to build texture models which mimic human visual system. However, the researchers do not have a common idea on which features should be adopted and how they should be defined and measured. Research in human perception has suggested that the viewing distance between some scenes and observers have some interesting effects on human visual impressions. Artists have created visual illusions such as picture mosaics and hybrid images. These images consist of two different interpretations that can be perceived by changing the viewing distance. A mosaic picture was achieved by using tiny pictures as mosaics to compose another global picture [6]. A hybrid image was generated by superimposing a low-pass filtered image and a high-pass filtered image [7]. However, the artists have mainly focused on the artistic effects and the techniques of creating the illusions rather than building computational models. Morioka *et al.* have constructed a mathematical model for geometrical characteristics from multiple images which were captured from various distances of a natural fabric texture [8]. Caputo *et al.* addressed the robustness of scale variations in material classification [9]. However,the numerical relation between the viewing distance and human perception is still an open problem.

In our previous research, we have proposed a model for texture description based on morphological operations [10], [11], [12], called "Primitive, Grain and Point Configuration (PGPC)" texture model [13]. The PGPC texture model regards a texture as an image composed by a regular or irregular arrangement of objects that are much smaller than the size of image and resemble each other. The objects arranged in a texture are called grains, and the grains are regarded to be derived from one or a few typical objects called primitives. The point configuration of the grains is expressed by a morphological skeleton [11]. The PGPC texture model has provided a method that local and global features can be modified separately. We applied binary texture manipulation based on the PGPC texture model to investigate human perception in binary textures [14]. It showed not only a respective influence of a local structure and the entire structure of the texture but also their mutual interactions are important for the identification of human visual impression. This conclusion also has been proved in the gray scale case [15].

In this paper, we synthesize textures by controlling local and global textural features separately using the PGPC texture model. This allows the synthesized textures to contain two interpretations. The visual perception may change by changing the viewing distance. We carry out visual sensory tests on four groups of respondents in two sets of experiments. In order to construct a statistical relationship between the viewing distance and human perception, we adopt the logistic regression

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to analyze the data obtained from human respondents.

The experimental results indicate that the viewing distance and the mutual interactions of local and global features of a texture have significant effects on human perception. Other factors such as prior knowledge and the order of the viewing positions influence human perception in texture discrimination. This study contributes to the construction of the numerical relation between the viewing distance and human texture perception.

II. Mathematical Morphology and Morphological Skeleton

In the context of mathematical morphology [10], [11], [12], an image object is defined by a set. In the case of binary images, this set refers to the pixel positions included in the object. In the case of gray scale images, an image object is defined by an umbra set. If the pixel value distribution of an image object is denoted as $f(x)$, where $x \in \mathbb{Z}^2$ is a pixel position, its umbra $U[f(x)]$ is defined as follows:

$$U[f(x)] = \{(x,t) \in \mathbb{Z}^3 | -\infty < t \leq f(x)\}. \tag{1}$$

Consequently, when we assume a "solid" whose support is the same as a gray scale image object and whose height at each pixel position is the same as the pixel value at this position, the umbra is equivalent to this solid and the whole volume below this solid within the support.

Another object, called structuring element, is defined in the same manner. The structuring element is equivalent to the window of an image processing filter, and supposed to have much smaller extent than the image object.

In mathematical morphology, opening is a fundamental operation. In the case of the binary image and structuring element, the opening of an image object X with respect to a structuring element B, denoted X_B, has the following property:

$$X_B = (X \ominus \check{B}) \oplus B, \tag{2}$$

where $\ominus$ denotes Minkowski set subtraction, $\oplus$ denotes Minkowski set addition, $\check{B}$ denotes the symmetrical set of B with respect to the origin.

The Minkowski set subtraction and the Minkowski set addition are defined as follows:

$$X \ominus B = \bigcap_{b \in B} X_b, \tag{3}$$

$$X \oplus B = \bigcup_{b \in B} X_b, \tag{4}$$

where X_b indicates the translation of X by b, defined as follows:

$$X_b = \{x + b, x \in X\}. \tag{5}$$

In the case of the gray scale image and structuring element, the opening is similarly defined by replacing the sets X and B with their umbra.

The skeleton $SK(X,B)$ is defined as follows:

$$SK(X,B) = \bigcup_{n=0}^{N} SK_n(X,B), \tag{6}$$

$$SK_n(X,B) = (X \ominus n\check{B}) - (X \ominus n\check{B})_B, \tag{7}$$

where nB is n-times homothetic magnification of B defined as follows:

$$nB = B \oplus C \oplus \ldots \oplus C \quad ((n-1) - times \;\; of \;\; \oplus), \tag{8}$$

$$0B = 0, \tag{9}$$

where C is another small structuring element. This definition is different from the usual one, however, we employ this definition to avoid the inconvenience that the difference between nB and $(n+1)B$ is too large for large B in the original definition.

The gray scale image composed by assigning a pixel value n to the pixels in $SK_n(X,B)$ is referred to as the medial axis transform. The original binary image is reconstructed by locating nB on every pixel of $SK_n(X,B)$ and calculating the union of all n. It indicates that $SK_n(X,B)$ is regarded as the grain location configurations of the texture X if we assume that B is the estimated primitive and nBs are the grains.

III. PGPC Texture Model

PGPC texture model [13] represents a texture image X as follows:

$$X = \bigcup_{n=0}^{N} B_n \oplus \Phi_n, \tag{10}$$

for nonempty Φ_n, where B_n denotes a grain, and Φ_n is point configuration, that is a set indicating pixel positions to locate the grain nB.

We assume here that $\{0B, 1B, \ldots, nB, \ldots\}$ are homothetic magnifications of a small object B as defined in (8) and (9), and that B_n in (10) is equivalent to nB for each n. In this case, B is regarded as the primitive and n is referred as the size of the magnification, X_{nB} is regarded as the texture image composed of the arrangement of nB only. Texture X can be synthesized by adopting the union of X_{nB}.

IV. Methods and Experiments

A. Texture synthesis

The textures used in our experiments were synthesized by controlling local and global parameters separately using the PGPC texture model. We have considered that the primitive or the grains of a texture show some local features, whereas the skeleton of a texture and the grain size distribution show some global features [16].

The synthesized textures and their skeletons and grains are shown in Fig. 1. The skeleton of texture 1 was created with horizontal directional strength, and the skeleton of texture 2 was created with diagonal directional strength. These skeletons have the same density and distributing properties. The grains

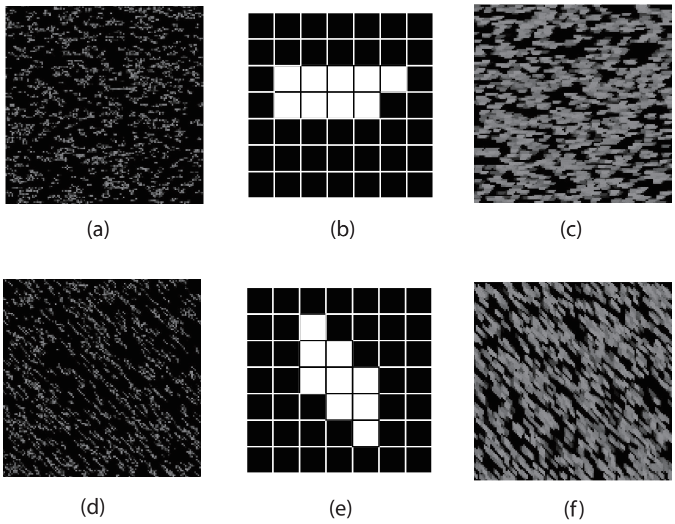

Fig. 1. Synthesized textures: (a) Skeleton of texture 1, (b) Grain of texture 1, (c) Synthesized texture 1, (d) Skeleton of texture 2 (e) Grain of texture 2, and (f) Synthesized texture 2.

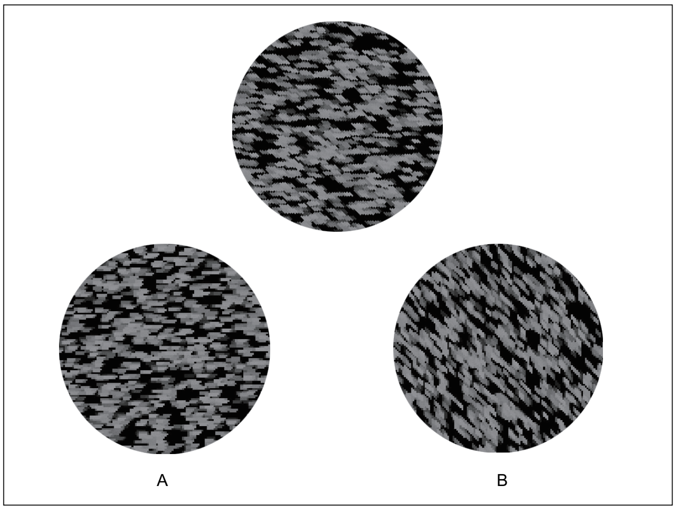

Fig. 2. The first scene used in the experiments.

of texture 1 and texture 2 enhanced the directionality in their respective synthesized textures. However, they represent different local features.

B. Visual sensory tests

The synthesized textures were cropped into discs in order to reduce the psychological effect of the horizontal and vertical borders of the texture frames.

Two groups of textures were used in the experiments. The textures in each group were presented in one scene. The two groups of textures were arranged in two scenes shown in Fig. 2 and Fig. 3. Three textures were included in each group: a standard texture, candidate texture A, and candidate texture B. The diameter of the textures is approximately two fifth of the scene height. In the first group, candidate texture A is the synthesized texture 1, candidate texture B is the synthesized texture 2, and the standard texture was derived from rotating the synthesized texture 2 forty-five degrees anticlockwise. The textures in the second group are twice the local magnifications of the respective textures in the first group.

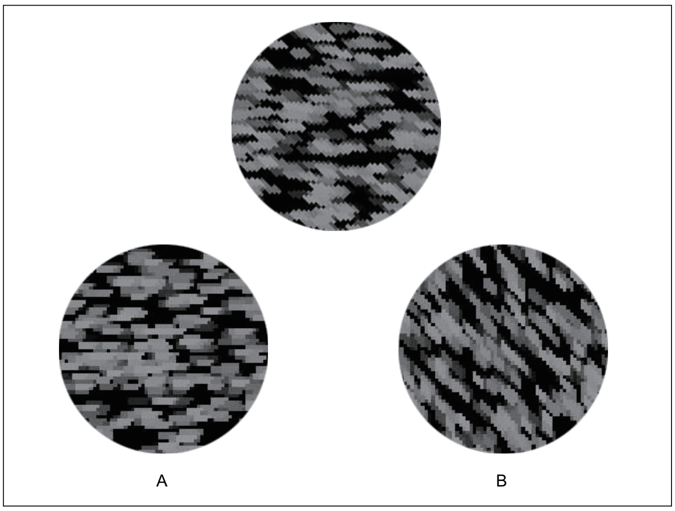

Fig. 3. The second scene used in the experiments.

Thirty-two respondents participated in two sets of experiments, sixteen in each set. All the respondents had normal or corrected-to-normal vision. The scenes were displayed on a 15-inch 4:3 LCD monitor.

In the first set of experiments, sixteen respondents were separated into two groups, eight in each group. The first group called *unsupervised-group* that the respondents in this group have not been informed with any prior information. The second group called *supervised-group* that in advance of the experiments, a brief explanation of global directionality and local grain feature was given to the respondents. The respondents in both groups were asked to sit and look at the monitor from the same distance as the height of the screen. The two scenes of textures were displayed respectively. Within each scene, the respondents were asked to select from candidate texture A and candidate texture B, which texture is more similar to the standard texture. After the respondents made their decisions of both scenes, they were asked to move back to the distance of twice, three times, and four times as the height of the screen in order. In each position, they were asked to do the same selecting task and give their decision respectively.

The procedure of the second set of experiments is similar to the first one. Sixteen respondents in this set were also separated into unsupervised and supervised groups. The difference is, in this set of experiments, the starting position is four times the distance from the screen and move closer to the screen successively.

The procedures of the two sets of experiments are shown in Fig. 4.

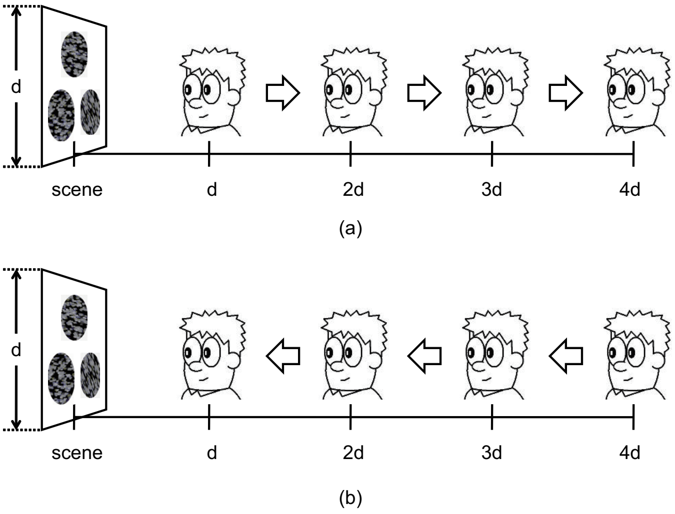

Fig. 4. The procedures of two sets of experiments

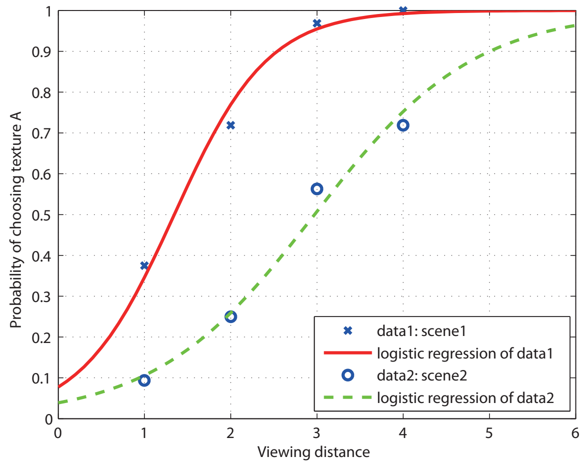

Fig. 5. Logistic regression: scene 1 versus scene 2.

C. Logistic regression

In order to construct a statistical relation between the viewing distance and human texture perception, we adopt logistic regression to analyze the binary data obtained from human respondents.

For a binominal variable Y, The probability p of $Y = 1$ can be defined by a function of a set of effect factors $x = (x_1, ..., x_r)$,

$$p = Pr\{Y = 1|x_1, x_2, ..., x_r\} = f(x_1, ..., x_r). \tag{11}$$

A logistic function can be defined by the formula:

$$f(Z) = \frac{1}{1 - e^{-Z}}, \tag{12}$$

where $f(Z)$ represents the probability of $Y = 1$, the variable Z represents the exposure to a set of effect factors which usually defined as:

$$Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_r x_r, \tag{13}$$

where β_0 is the intercept, and β_1, β_2, ..., β_r are the regression coefficients of x_1, x_2, ..., x_r respectively.

In this paper, a binominal variable $Y = 1$ if a respondent has chosen candidate texture A for the more similar texture to the standard texture and $Y = 0$ otherwise. The logistic regression model is applied to Y by introducing only one risk factor D which indicates the viewing distance:

$$p = \frac{1}{1 - e^{-\beta_0 - \beta_1 D}}, \tag{14}$$

where p represents the probability of choosing texture A, β_0 is the intercept, and β_1 is the regression coefficient of D.

V. Results and Discussions

We applied logistic regression to the data obtained from four groups of respondents in two sets of experiments. Figure 5 shows the logistic regression results of scene 1 and scene 2. The solid line represents the relation between the probability

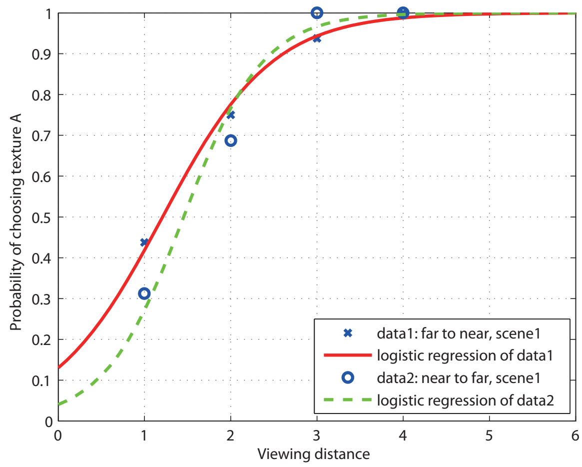

Fig. 6. Logistic regression: far to near versus near to far in scene 1.

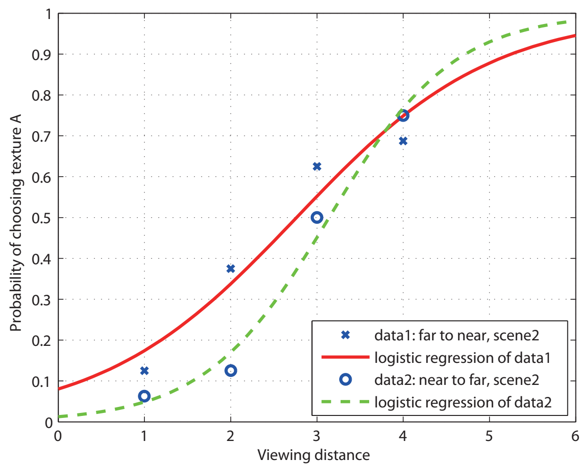

Fig. 7. Logistic regression: far to near versus near to far in scene 2.

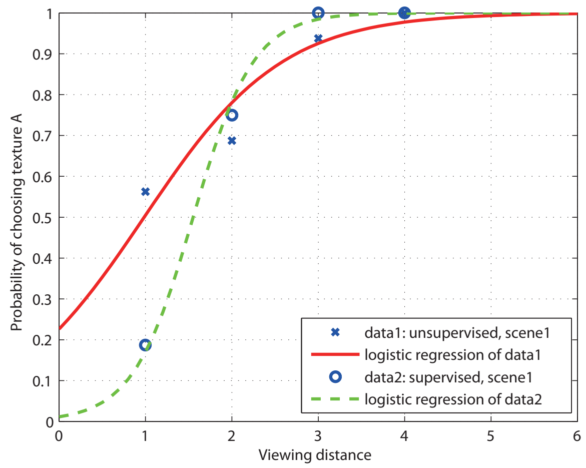

Fig. 8. Logistic regression: unsupervised versus supervised in scene 1.

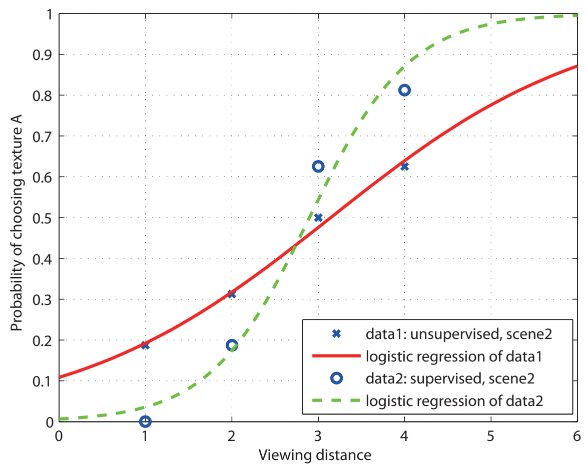

Fig. 9. Logistic regression: unsupervised versus supervised in scene 2.

for a respondent to select candidate texture A in scene 1 and their respective viewing distance. The dotted line represents the relation in scene 2. In both scenes, candidate texture A have similar global features with the standard texture, and candidate texture B have similar local features with the standard texture. That is, selecting texture A indicates global features dominated the perception of the respondent, selecting texture B indicates local features dominated the perception of the respondent. Both logistic curves in Fig. 5 show clear increasing domination of global features with the increasing of the viewing distance. Two parameters effect the shape of the logistic curve: β_0 and β_1 in (14). β_0 indicates the position of the curve, and β_1 indicates the changing rate of the curve. In this paper, we use $D_{p=0.5}$ instead of β_0 to evaluate the absolute position where local and global features have the same domination: $D_{p=0.5} = -\beta_0/\beta_1$. The results of $D_{p=0.5}$ and β_1 in various comparisons are shown in Tab. I and Tab. II.

In Fig. 5, the value of $D_{p=0.5}$ in scene 2 is almost twice larger than that in scene 1, due to the textures in scene 2 are twice the local magnifications of scene 1. However, the values of β_1 in scene 1 and scene 2 are also different. A larger β_1 value indicates a larger changing rate of the curve, that is the *confusing interval* where the respondents could not make unanimous decisions is larger. Because magnifications have changed the size and number of grains in the textural area, thus the balance of local and global features has been changed. This result indicates that the viewing distance and the mutual interaction of local and global features of a texture have significant effects on human texture perception.

In order to investigate the effect of the order of testing positions, we carried out two sets of experiments explained in the previous section. The logistic regression results are shown in Fig. 6 and Fig. 7 by comparing two different orders of the testing positions. Both the value of $D_{p=0.5}$ and the value of β_0 in *near-to-far* case are greater than those in *far-to-near* case. It indicates that, the respondents who participated in near-to-far experiments paid more attention to the local features of the textures. The respondents who participated in far-to-near experiments paid more attention to the global features of the textures. This result may dues to the prejudgment of the respondents. Although in the experiments the perceiving time of each scene was not limited, the respondents may more or less effected by the impressions of the scenes in the previous positions.

Comparison results between unsupervised and supervised groups are shown in Fig. 8 and Fig. 9. In both scenes, β_0 have greater values in supervised case than those in unsupervised case. That is, the confusing intervals in the supervised groups are smaller than those in the unsupervised groups. This result dues to the respondents in supervised groups paid more attention to the global directionality and the local grain shape that we explained before the experiments. The supervised respondents discriminated the textures mainly based on those two features. However, the respondents in the unsupervised groups had not have any prior information about the textures. They evaluated and discriminated the similarity of the textures according to various criteria which may include more textural features. The respondents in unsupervised groups were asked about their discriminating criteria after the experiments. Some unsupervised respondents were attracted by the distribution or density of the white grains and black blobs. The global directionality and the local grain shape are not the only attractive features. These results indicate that prior knowledge has significant effects in texture discrimination.

VI. Conclusions

We synthesized textures using the PGPC texture model based on mathematical morphology, and investigated the effect of the viewing distance in texture perception. Two groups of textures were synthesized by controlling local and global features separately using the PGPC texture model. Visual sensory tests were carried out on four groups of respondents in two sets of experiments. We adopted the logistic regression model to construct a statistical relationship between the

TABLE I
EXPERIMENTAL RESULTS

		far to near		near to far	
		unsupervised	supervised	unsupervised	supervised
scene1	$D_{P=0.5}$	-0.0784	1.6267	1.4249	1.4759
	β_1	0.7419	3.2831	1.8807	2.5697
scene2	$D_{P=0.5}$	2.2958	3.1068	3.9484	2.7570
	β_1	0.7070	1.1805	0.7513	3.0204

TABLE II
EXPERIMENTAL RESULTS2

		far to near	near to far	unsupervised	supervised	total
scene1	$D_{P=0.5}$	1.2096	1.4544	0.9847	1.5518	1.3458
	β_1	1.5696	2.1757	1.2478	2.8698	1.8418
scene2	$D_{P=0.5}$	2.7634	3.1407	3.1441	2.8982	2.9721
	β_1	0.8824	1.3891	0.6694	1.7331	1.0811

viewing distance and human perception. The experimental results indicate that the viewing distance and the mutual interactions of local and global features of a texture have significant effects on human perception. Other factors such as prior knowledge and the order of the viewing positions influence human perception in texture discrimination. This study contributes to the construction of the numerical relation between the viewing distance and human texture perception.

In further studies, we want to construct a general texture discrimination model considering the effect of the viewing distance. Further experiments on human perception in more textures and more viewing distances is also required.

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