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Research article

Does prior knowledge increase or decrease perceived visual complexity of texture images?

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A R T I C L E I N F O

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A B S T R A C T

Previous research has shown that the perceived visual complexity of an image is correlated with understandability of the image. It was considered that prior knowledge of the contents of an image makes images easier to understand, and thus reduces perceived visual complexity. In the present study, we examined the effect of prior knowledge on perceived visual complexity of texture images. We designed an experiment in which participants observed and rated four texture images with different levels of complexity and understandability; one group of participants received prior knowledge in the form of verbal cues about the names of the target stimuli while the other group did not receive any information regarding image content. We found that the effect of prior knowledge on visual complexity perception varied for the different images. For an image with low initial complexity, if cued information about the image is three-dimensional or dynamic, prior knowledge does not decrease but instead increases the perceived visual complexity. Moreover, cues that increase perceived visual complexity can be verbal rather than visual cues.

1. Introduction

When a human being observes an image, its visual complexity is an important perceptual feature for image recognition and identification. Studies have defined visual complexity as the amount of detail or intricacy of lines in an image [1], number of items in a pattern [2], and the degree of difficulty in providing a verbal description of an image [3,4]. Researchers have proposed many computational methods to measure and model image complexity based on image properties and features [5–16]. However, the perceived visual complexity of any image is difficult to quantify because it involves subjective human perception. In addition to image features, visual complexity perception is also influenced by the perceiver's knowledge, experience, and understanding of the visual object [17–19]. The perceived visual complexity is often measured through ratings provided by the participants based on their perceptions [19].

The human brain estimates the structures of the 3D world based on retinal images within several hundreds of milliseconds by the maximum a posteriori estimation based on a priori knowledge [20]. Prior knowledge and image features are both required to resolve the complexity and ambiguity of object perception [21]. Studies have suggested that prior knowledge influences our perception and decision-making [22–31].

For an image, understandability represents how easily an observer can comprehend the contents of the image. Research has shown that a strong correlation exists between understandability and the perceived visual complexity of an image, indicating that images with

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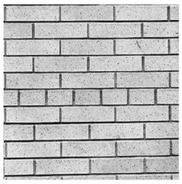
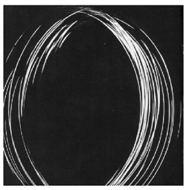
higher understandability have lower perceived visual complexity [32,33]. The rating which an individual gives based on the perceived understandability of an image, is related to their prior knowledge and experiences [34]. In a previous study, we assumed that more information about an image would help improve its understandability, and thus reduce perceived visual complexity. However, the results showed that providing three-dimensional information (i.e., depth information) for two-dimensional texture images did not reduce the visual complexity; in fact, the additional information increased perceived visual complexity [35]. Thus, we concluded that the effect of additional information on visual complexity is related to the type of information and the manner in which it is cued.

Naming a texture is a common way to reflect one's prior knowledge and experiences. The understandability of an image can be estimated based on the names given to it by the participants [34]. The influence of prior knowledge on visual perception can also be investigated using two-tone "Mooney" images [36]. In experiments which use Mooney images, with the help of prior knowledge, a set of meaningless 2D black-and-white patches can be coherently perceived as a well-constructed two-tone image [37,38]. Thus, providing additional perceptual information, such as the grayscale source image of a two-tone image, as prior knowledge may change the perceived visual complexity of the image.

Recent research suggests that verbal cues that offer no direct perceptual hints can also improve the visual recognition of ambiguous images and enhance objective visual discrimination performance. For example, participants who were verbally cued that there was a piece of furniture in the Mooney image performed significantly better in recognizing it as a desk than those who had not received any verbal cues [39].

In this study, we hypothesized that the verbally cued name of an image would increase its understandability, thus reducing the perceived visual complexity, meaning that a participant would rate an image as being less complex if he or she were told what the contents of the image were. We designed an experiment to compare the ratings of perceived image complexity between two groups of participants, with and without prior knowledge. We only provided verbal cues about the names of the target stimuli to provide prior knowledge, to avoid adding visual information or direct perceptual hints, such as showing another version of the image, or specifying the region of interest. We used texture images as visual stimuli because these can be represented in a lower-dimensional feature space, making their perceptual features easier to analyze and manipulate than natural images [40–42]. Aside from complexity and understandability, we also asked the participants to rate regularity, roughness, directionality, and density, which were considered as the other textural properties that affect perceived visual complexity [32].

Table 1
Target texture stimuli used in the experiment.

ID	Texture image	Name (as given by Brodatz [43])	Expected characteristics
D26 (*brick*)		Ceramic-coated brick wall	Expected to have low complexity and high understandability
D40 (*lace*)		Lace	Expected to have high complexity and high understandability
D44 (*light*)		Swing lights in a darkened room	Expected to have low complexity and low understandability
D107 (*paper*)		Japanese rice paper	Expected to have high complexity and low understandability

2. Materials and methods

2.1. Participants

The present study involved a sample of 50 college students who participated in the experiment. Of these, 49 were male and 1 was female, and they were randomly assigned to two groups. The age of the participants ranged from 15 to 22 years, with a mean of 17.6 years and a standard deviation of ±2.3 years. All participants had normal or corrected-to-normal vision and had not previously taken part in a similar study. Informed written consent was obtained from all participants, and they were provided with a comprehensive explanation of the experimental procedure. The study was conducted in accordance with the relevant ethical guidelines and regulations, including the Declaration of Helsinki. Furthermore, the study protocol received approval from the Ethics Committee of the National Institute of Technology, Gunma College, on April 13, 2021.

2.2. Stimuli

Eleven texture images from Brodatz's album [43] were selected as the experimental stimuli. The textures were grayscale images with a resolution of 640 × 640 pixels. Four of the eleven images were selected as the target images. These four textures were considered to present different levels of visual complexity and understandability. In this paper, we refer to *D26*, *D40*, *D44*, and *D107,* as *brick*, *lace*, *light*, and *paper*, respectively. Details of these four images are provided in Table 1. The other seven images were used as reference images to avoid biased target image scores due to insufficient references. Based on the complexity scores reported by Guo et al. [32], seven images with a large variation in the complexity score were selected; the reference images are shown in Fig. 1. The complexity scores reported by Guo et al. [32] for *D13*, *D47*, *D62*, *D64*, *D88*, and *D112* were 5.80, 2.47, 4.37, 3.03, 3.07, and 5.63, respectively, on a 7-point Likert scale, ranging from 1 (very low) to 7 (very high). *D97* was not included by Guo et al. [32]; however, we have included it in our paper, because we considered *D97* to be a typical image with high complexity and high understandability.

2.3. Apparatus

The texture stimuli were displayed on an LCD-MF223E monitor (IO DATA, Japan) (resolution:1920 × 1080 pixels; refresh rate: 60 Hz; 21.5 inch). Each texture stimulus was enlarged to cover the full screen. The participants were asked to sit with their eyes at a distance of approximately 1 m from the screen. Fig. 2 shows the experimental setup for this study.

2.4. Procedure

The participants were divided into two groups: those who possessed prior knowledge, and those who did not, with 25 individuals in each group. Participants in the group which possessed prior knowledge were provided information on the four target textures during the experiment, whereas, participants in the group which did not possess prior knowledge were not given any information about the

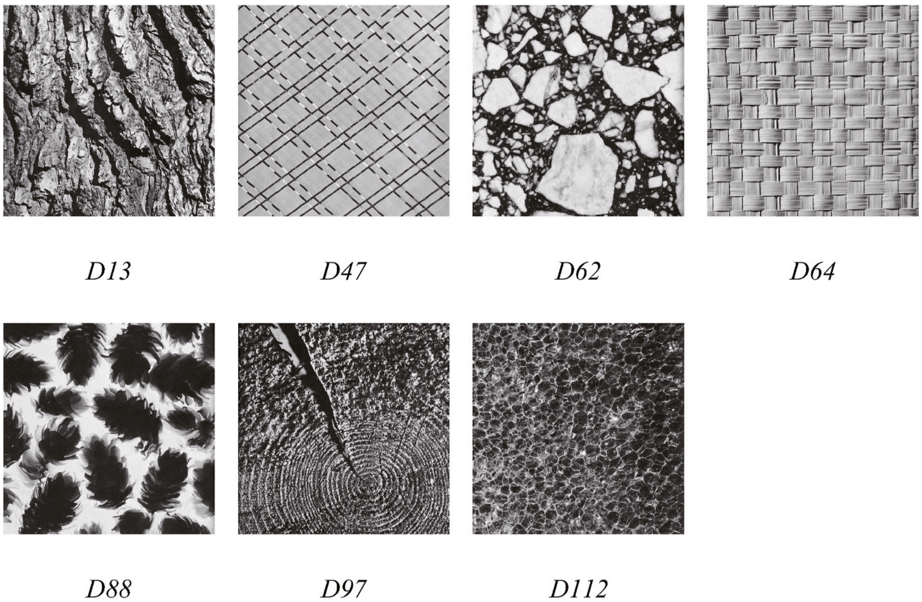


Fig. 1. Reference texture stimuli used in the experiment. *D13*: Bark of tree, *D47*: Woven brass mesh, *D62*: European marble, *D64*: Handwoven Oriental rattan, *D88*: Dried hop flowers, *D97*: Cross-section of a weathered tree stump, and *D112*: Plastic bubbles.

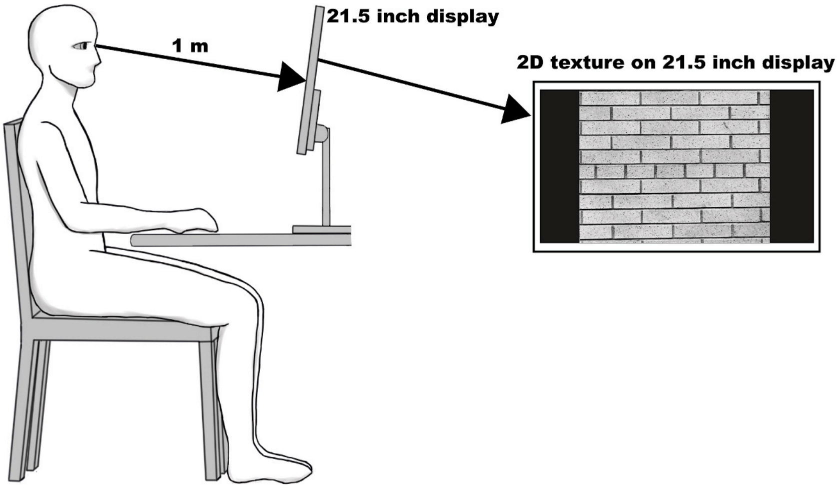


Fig. 2. Experimental setup for visual complexity.

textures. First, participants in both groups were asked to view all 11 textures once. The 11 textures were presented in random order, and 10 s were given for each texture. Subsequently, the participants were requested to re-examine each texture and assign a score on a 7-point Likert scale for its perceived complexity, regularity, density, directionality, roughness, and understandability. The scale ranged from −3 (indicating very low levels) to 3 (indicating very high levels). Both the exposure time for the stimuli and the participants' response time were unrestricted. The stimuli were presented in a random order, and a 10-s black screen was interposed between each stimulus presentation. Before a target texture stimulus (*brick*, *lace*, *light*, and *paper*) was displayed, the participants in the group possessing prior knowledge were verbally informed of the name of the image. The experimenter spoke the name of the texture once. The same information was displayed as text on the black screen before the corresponding target texture was presented. The names cued to the participants who were provided prior information were the Japanese translations (the participants' native language) of the names given by Brodatz [43] (See Table 1).

2.5. Statistical analysis

There were two independent variables: knowledge and texture. To statistically analyze the visual complexity of 2D textures, we adopted a two-way mixed ANOVA for knowledge (knowledge status: *prior knowledge*, *no prior knowledge*) and texture (texture level: *brick*, *lace*, *light, paper*) [44]. The main effect and interaction effect of each independent variable were calculated using a repeated-measure function of the general linear model in IBM SPSS Statistics (v.26). The post-hoc test was calculated using pairwise comparisons with Bonferroni corrections between each level. The effect sizes indicated in each table were estimated using partial η^2 and Cohen's *d* values. Descriptive statistics, including the mean (*M*) and standard deviation (*SD*), were calculated to quantify the perceived visual complexity of each image. The data used for correlation analysis had 100 (25 participants × 4 target textures) target textures for each parameter (complexity, regularity, density, directionality, roughness, and understandability). The correlation analysis was performed using a bivariate correlations function of Correlate in IBM SPSS Statistics software (v.26).

We conducted an a priori power analysis using the G*Power software [45] to determine the minimum required sample size for the

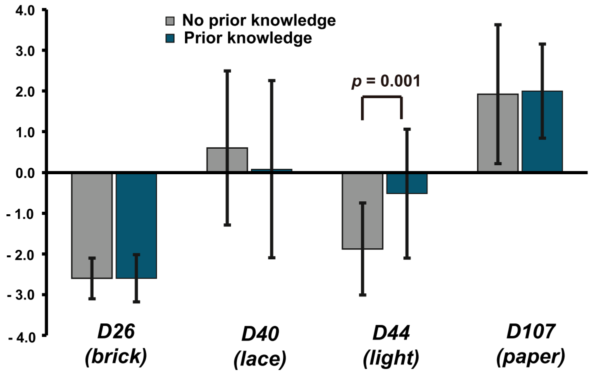


Fig. 3. Pairwise comparisons of the mean complexity scores between the prior knowledge and no prior knowledge conditions. Error bars indicate standard deviation (SD).

repeated measures and within-between interaction ANOVA. The numerical value of effect size was referred to as the effect size, f [46]. For an effect size of 0.15, alpha = 0.05, number of groups = 2, power = 0.80, number of measurements = 4, Corr among rep measures = 0.75, and non-sphericity correction = 1, the analysis revealed that a sample size of 16 participants in each group would be necessary to achieve an actual power of 0.8. To meet this requirement, we included 25 participants in each group.

3. Results

The effect of texture and prior knowledge in determining perceived visual complexity was analyzed using the two-way mixed ANOVA. The main effect of prior knowledge was not statistically discernible ($F(1,48) = 0.95$, $p = 0.334$, partial $\eta^2 = 0.019$), but the main effect of texture was discernible, indicating that the characteristics of the texture affected visual complexity perception ($F(3, 144) = 101.9$, $p < 0.0001$, partial $\eta^2 = 0.68$). Furthermore, there was a discernible interaction between prior knowledge and texture ($F(3, 144) = 4.21$, $p = 0.007$, partial $\eta^2 = 0.08$). We performed pairwise comparisons of the interaction between the factors of prior knowledge and texture, corrected using Bonferroni adjustment.

Fig. 3 shows the results of the pairwise comparison of the mean complexity between the no prior knowledge and prior knowledge conditions. For *light*, a discernible difference (CI: 0.58 to 2.14; $p = 0.001$ in Table 2) was observed between the complexity scores in the no prior knowledge ($M = -1.88$, $SD = 1.13$) and prior knowledge ($M = -0.52$, $SD = 1.58$) conditions. However, there were no discernible differences in *brick*, *lace*, and *paper* between the two conditions, as shown in Table 2.

The effect of texture and knowledge in determining perceived understandability was analyzed using the two-way mixed ANOVA as shown in S7 Table. Fig. 4 shows the results of the pairwise comparisons of the mean understandability between the prior knowledge and no prior knowledge conditions. For *light*, a discernible difference (CI: 0.311 to 2.25; $p = 0.011$) was observed between the understandability scores of the no prior knowledge ($M = -0.68$, $SD = 1.8$) and prior knowledge ($M = 0.6$, $SD = 1.61$) conditions. Furthermore, for *paper*, a discernible difference (CI: 0.27 to 1.81; $p = 0.009$) was observed between the understandability scores of the no prior knowledge ($M = -2.48$, $SD = 1.08$) and prior knowledge ($M = -1.44$, $SD = 1.58$) conditions; however, no discernible differences were observed between the two conditions for *brick* and *lace*.

Correlation analysis was performed to investigate the correlations between texture characteristics and visual complexity. The results for the prior knowledge and no prior knowledge conditions are presented in Tables 3 and 4, respectively. For both conditions, complexity was highly correlated with regularity (no prior knowledge: $r = -0.602$, $p < 0.0001$; prior knowledge: $r = -0.670$, $p < 0.0001$), directionality (no prior knowledge: $r = -0.58$, $p < 0.0001$; prior knowledge: $r = -0.59$, $p < 0.0001$), roughness (no prior knowledge: $r = 0.27$, $p = 0.008$; prior knowledge: $r = 0.36$, $p < 0.0001$), and understandability (no prior knowledge: $r = -0.49$, $p < 0.0001$; prior knowledge: $r = -0.71$, $p < 0.0001$). However, the correlation between complexity and density was relatively low (no prior knowledge: $r = 0.03$, $p = 0.767$; prior knowledge: $r = -0.25$, $p = 0.011$). In particular, for the no prior knowledge condition, there was no discernible relationship between complexity and density.

4. Discussion

4.1. Effect of prior knowledge on understandability and complexity

The results of the experiment show that for different texture images, prior knowledge had different effects on visual complexity perception. Among the four texture images in the experiment, except for *light*, prior knowledge had no statistically discernible effect on visual complexity perception.

As a strong correlation between understandability and visual complexity has been confirmed in previous studies [32,33], we assumed that prior knowledge would improve understandability and thus reduce visual complexity. However, the experimental results did not support this assumption. For *brick* and *lace*, the two textures with initially high understandability, there was no statistically apparent effect on either understandability (CI: −0.343 to 0.023; $p = 0.085$ and CI: −1.846 to 0.086; $p = 0.073$, respectively) or complexity (CI: −0.31 to 0.31; $p = 1.0$; CI: −0.68 0.64; $p = 0.37$, respectively). Whereas, for *light* and *paper*, the two textures with initially low understandability, prior knowledge significantly increased understandability (CI: 0.311 to 2.249, $p = 0.011$ and CI: 0.268 to 1.812, $p = 0.009$, respectively). However, perceived visual complexity did not decrease for *light* and *paper* (CI: 0.58 to 2.14; p = 0.001; CI: −0.75 to 0.91; $p = 0.85$, respectively); in fact, the perceived complexity significantly increased for *light*.

D44 (light) consists of abstract strokes of swinging lights in a darkened room. In the prior knowledge condition, possessing prior knowledge increased understandability of the image. However, the participants may have imagined more complex objects or actions in

Table 2
Pairwise comparisons of complexity between knowledge and texture.

Texture	Mean Difference	Std. Error	p	Cohen's d	95% Confidence Interval for Difference	
					Lower Bound	Upper Bound
D26 (*brick*)	0.0	0.15	1.0	0.0	−0.31	0.31
D40 (*lace*)	0.52	0.58	0.37	0.18	−0.68	0.64
D44 (*light*)	1.36	0.39	0.001	0.67	0.58	2.14
D107 (*paper*)	0.08	0.41	0.85	0.04	−0.75	0.91

Note: Std. Error: standard error; p: probability value; Cohen's d: effect size.

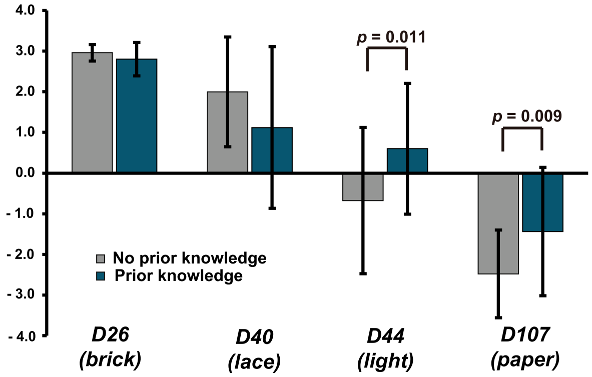


Fig. 4. Pairwise comparisons of the mean understandability scores between the prior knowledge and no prior knowledge conditions. Error bars indicate standard deviation (SD).

Table 3
Correlation between perceptual characteristics and perceived visual complexity in the No prior knowledge condition.

	Regularity	Density	Directionality	Roughness	Understandability
Complexity	−0.60**	0.03	−0.58**	0.27**	−0.49**
Understandability	0.71**	0.30**	0.52**	−0.35**	
Roughness	−0.26**	−0.02	−0.14		
Directionality	0.62**	0.22**			
Density	0.15				

*$p < 0.05$, **$p < 0.01$.

Table 4
Correlation between perceptual characteristics and perceived visual complexity in the prior knowledge condition.

	Regularity	Density	Directionality	Roughness	Understandability
Complexity	−0.67**	−0.25*	−0.59**	0.36**	−0.71**
Understandability	0.68**	0.26**	0.57**	−0.25*	
Roughness	−0.37**	−0.09	−0.26		
Directionality	0.80**	0.28**			
Density	0.36**				

*$p < 0.05$, **$p < 0.01$.

the background, such as 3D spatial information and dynamic movements of people, which were not captured in the image. Thus, prior knowledge led to increased complexity. The fact that 3D information, such as depth information, increases visual complexity was also confirmed in our previous study [35]. The current experimental results further indicate that 3D spatial information that can increase visual complexity may not necessarily be visual information.

D107 (paper) is an image of Japanese rice paper with an initially low understandability and high complexity. In the prior knowledge condition, possessing prior knowledge increased understandability, but the change in visual complexity was not statistically discernible. This may be because the texture is inherently complex, and the target is a stationary flat object; therefore, there was no significant change in complexity.

For *D26 (ceramic-coated brick wall)* and *D40 (lace)*, the understandability and complexity were not statistically different in the prior knowledge condition. It should be noted that prior knowledge even slightly reduced the understandability of the two textures, and the standard deviations increased (*SD*: increased from 0.20 to 0.41 and *SD*: increased from 1.35 to 1.99, respectively). This may be because of the already high understandability of the two textures. The additional information interfered with participants' judgments of understandability, thus increasing the variance of the results.

Only four target images were used in this study; however we aim to expand on the findings by adding more target images in future studies. Furthermore, most of the participants in the experiment were young males from engineering colleges. Age, gender, and professional background may also have an impact on visual complexity perceptions. Hence, in future studies, we will recruit a more diverse group of participants. We also plan to record the participants' response time and eye movements in our future work.

4.2. Relationship between texture characteristics and visual complexity

The results of the correlation analysis showed that complexity was highly correlated with image regularity, directionality, roughness, and understandability, whereas, complexity and density had relatively low correlations.

In the prior knowledge condition, understandability was the factor with the highest correlation with complexity, and the correlation coefficient was greater than that in the no prior knowledge condition (no prior knowledge: $r = -0.49$, $p < 0.0001$; prior knowledge: $r = -0.71$, $p < 0.0001$). This indicates that, after receiving prior knowledge, the participants tended to actively utilize this knowledge to comprehend the content of the texture when evaluating its visual complexity.

5. Conclusions

The aim of this study was to examine whether prior knowledge affected the perception of visual complexity by conducting an experiment that utilized texture images with varying levels of complexity and understandability. The results showed that the effect of prior knowledge on complexity perception varied for the different images. Furthermore, the effect of prior knowledge on complexity perception was not only related to the original understandability of the target image but also to the image content. With prior knowledge, an individual can comprehend 3D spatial information or dynamic movements from images. In the future, we plan to perform a quantitative analysis of images that contain dynamic content as well. We also aim to examine how prior knowledge affects visual complexity perception using more images, including RGB-depth images with depth information.

Author contribution statement

Liang Li; Woong Choi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e15559.

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