Visual perception of textiles using surface and display samples

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In this study, 15 parameters representing textile properties are evaluated by the psychophysical method of categorical judgment with samples presented either in a light booth or on a display to investigate human visual perception based on the textural features of textiles. Visual perceptions of textiles can be expressed by the properties of regularity, smoothness, and warmth, which respectively explain the geometric placement rules of primitive elements, depth information, and emotion of textiles. Textiles with large primitive elements have high regularity and coarseness, whereas textiles with subtle primitive elements exhibit randomness and smoothness. Texture analysis results of the surface samples coincide well with those of display samples.

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Texture is one of the key factors in textile apparel design. The textural features of textiles can express the unique style and character of modern fashion. Although the tactile perception of textiles has been widely studied[1] and compared with visual experiments[2], more studies are required to analyze the visual perceptual effect of textile properties, which is presented as a combination of color and texture according to evaluations obtained using the psychophysical method of categorical judgment[3] and pair comparison[4].

A texture is arranged and combined with elements of diverse properties, causing perceptual disparities in uniformity, coarseness, regularity, line-like, directionality, randomness, and so on[5]. Properties that consumers use to discriminate between different textural patterns include coarseness, contrast, complexity, busyness, directionality, and texture strength. In general applications, the results of texture measurements represent part of the aforementioned textural properties[6]. Based on an analysis of psychophysical assessments, the perceptual dimensions of textiles can be employed to develop a perceptual model that corresponds to human visual perceptions. Collecting various kinds of textile samples is relatively difficult; thus, determination of whether or not surface samples can be substituted by display samples in visual experiments for texture and color evaluation is meaningful. In this letter, the perceptual properties of surface and display textile samples are evaluated, and results of texture analysis for surface samples are discussed. Comparisons between surface and display samples are also implemented to build a perceptual model and clarify whether or not display samples can be used as alternatives to surface samples for future research.

Fifty-seven textile samples from 15 color centers were selected for this study. Each color center presented 2 to 5 textures, some of which are illustrated in Fig. 1. According to the results of a pilot experiment, the samples were classified into five categories based on the size of the texture elements. The spectral reflectance of all of the samples was measured using a spectrophotometer (Color Eye 7000A, GretagMacbeth, USA), and CIELAB colorimetric data for each color center were calculated using the CIE D65 and 1964 standard colorimetric observer, as listed in Table 1. To classify the textures adopted in this study for further analysis, each textile sample was given a unique name combining its color and texture, as shown in Fig. 1; in Fig. 1, letters stand for colors whereas numbers refer to levels of texture. For example, O1 indicates a sample with orange color and the lowest texture level of 1, as presented by BR1 in Fig. 1.

A panel of 10 observers (5 females and 5 males) from Zhejiang University participated in the psychophysical evaluations. All of the observers were 23–35 years of age and had normal color vision according to the Ishihara test. The experiment was divided into two sessions. In the first session, textile surface samples were visually estimated. In the second session, simulated versions of the textile samples presented on a display were assessed.

In the surface sample experiments, an illuminating and viewing geometry of 45/0 as well as a viewing distance of 50 cm are adopted; these details correspond to a viewing angle of 6° when the observer is positioned on a chin-rest. The test sample was placed at the center of the bottom panel in the light booth of a GretagMacbeth SpectraLight III instrument to ensure uniform illumination by the D65 simulator with a white point luminance of 318 cd/m^2. At the beginning of the visual experiment, every observer was subjected to 2 min of dark adaption and followed by 1 min of light adaption[7].

For the display sample experiments, textile surface samples were photographed by a digital camera (D3X, Nikon, Japan) in a light booth with a setup identical to that used for the surface sample session. Camera characterization based on the polynomial regression model[8] was performed to convert the RGB digits of the captured images to their corresponding CIEXYZ values, followed by transformation of the CIEXYZ data to RGB values in a professional liquid crystal display (ColorEdge CG241W, Eizo, Japan) through colorimetric characterization of the gain–offset–gamma model[9]. The mean accuracy of camera characterization for all 57 samples is 1.72 ΔE^*_{ab} units, whereas the mean accuracy of display

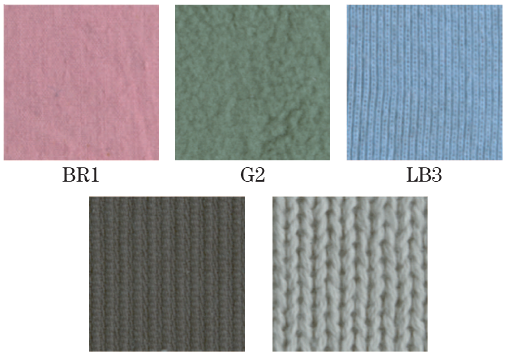

Fig. 1. (Color online) Textile samples with different colors and textures.

Table 1. CIELAB Values at the Color Centers of the Textile Samples

Color Centers	L^*	a^*	b^*
White (W)	99.16	0.12	4.59
Light-Blue (LB)	92.24	−3.97	−6.28
Bright-Red (BR)	89.31	17.34	1.11
Red (R)	45.87	62.78	34.38
Orange (O)	58.10	43.12	28.12
Green (G)	55.89	−20.75	21.63
Yellow (Y)	83.04	16.46	66.60
Blue (B)	61.26	−15.05	−27.92
Purple (P)	68.74	10.07	−27.85
Bright-Yellow (BY)	80.19	4.37	13.72
Grey (Gr)	45.26	−0.03	−2.42
Light-Purple (LP)	23.83	16.91	1.05
Dark-Blue (DB)	23.62	0.72	−11.69
Dark-Orange (DO)	36.23	6.98	7.59
Black (K)	21.82	0.25	−0.60

characterization is 0.93 ΔE^*_{ab} units; these values are comparable those reported by other studies[10]. The average color difference between the surface samples in the light booth and the display is 3.58 ΔE^*_{ab}; in the case of samples out of the color gamut of the display, a maximum color difference of 7.52 ΔE^*_{ab} is observed. During the experiment, the viewing distance was fixed at 100 cm with the observer positioned on a chin-rest; thus, a viewing angle of about 7° is obtained. The test sample was presented in the central region against a background of neutral gray with 20% of the peak white luminance of the display.

Fifteen very frequently used visual perceptual properties that could exactly represent human perception for textures were estimated in a dark room for textiles, including contrast, repetitiveness, busyness, randomness, smoothness, strength, directionality, complexity, fineness, regularity, linelikeness, uniformity, warmth, activeness, and relaxation[2,4,6,11]. These properties were assessed using a 5-point numerical category scale, ranging from 1 (lowest attribute) to 5 (highest attribute), to describe perceptual feelings; the description for contrast is listed in Table 2 as an example. In total, 17,100 judgments were collected throughout the entire visual experiment, i.e., 2 sample modes (surface and display) × 15 properties × 57 samples × 10 observers.

To evaluate inter-observer accuracy, the coefficient of variation (CV) was employed as a statistical measure to represent the discrepancy between two datasets, as shown in the following equation:

$$\mathrm{CV} = \frac{100}{\overline{y}} \sqrt{\frac{\sum (x_i - y_i)^2}{n}}, \tag{1}$$

where x_i indicates the individual observer data for the ith sample, y_i indicates the average data for all observers of the ith sample, $\overline{y}$ indicates the average data for y_i, and n indicates the number of judgments. The mean observer accuracy is 24 CV units, ranging from 18 to 30, for the surface sample session and 26 CV units, ranging from 20 to 33, for the display sample session. Compared with published studies[12,13], the observer variation obtained in this work is acceptable for representing the credibility of the experimental data. The observer accuracy for the visual assessment of surface samples is better than that for display samples. However, the inter-observer accuracy for assessments of relaxation, complexity, and strength properties is very poor, which indicates that these three properties are difficult to visually estimate.

The raw data of the experimental results assigned by the observers are categorical grades, not interval-scaled values. Thus, the equal interval scaled values for each property were obtained by applying Case V of Thurstone's law of comparative judgment[14]. Firstly, the raw data were converted to a frequency matrix denoting the numbers of individual categorical grades from which the cumulative frequency matrix can be obtained by calculating the cumulative sum of the frequency values. A cumulative probability matrix was then deduced and further converted to the z-score matrix according to the inverse of the standard normal cumulative distribution. Finally, the scale values of the categorical judgments were computed from the difference matrix and categorical boundary estimations of the z-score values.

To discuss the relationships among different properties evaluated in this study, the scale values were processed by factor analysis based on the principal components analysis method together with an orthogonal rotation technique. Three components are extracted from the experimental data of the surface and display samples, as summarized in Table 3. The results marked in bold font indicate that the properties can be categorized to the corresponding component; here, the absolute values stand for the relevant contributions. Three factors accounting for 83.07% and 82.74%, among which component 1 contributes 44% and 38% of the total variance, are extracted for the surface and display samples. In both cases, the properties of repetitiveness, regularity, linelikeness, directionality, randomness, busyness, and strength are related to component 1. Component 2 comprises

Table 2. Description of Numerical Category for Contrast

Category	Definition
1	Strongly Low Contrast
2	Low Contrast
3	Moderately
4	High Contrast
5	Strongly High Contrast

uniformity, smoothness, fineness, contrast, and complexity; warmth, activeness, and relaxation make up component 3. Surface and display samples feature the same underlying dimensions for these 15 visual properties.

Given that most of the crucial textile properties are categorized as components 1 and 2, two-dimensional factor plots of these two components are drawn by the factor loadings listed in Table 3 to further investigate the discrepancies among the 12 properties involved; plots for surface and display samples are shown in Figs. 2(a) and (b), respectively. Most of the properties may be found at similar locations in these two plots. Component 1 represents regularity in texture, which appears to be the most important feature used by observers in distinguishing textures. Regularity is significantly correlated (p <0.005) with the properties of repetitiveness, directionality, linelikeness, and randomness. The Pearson correlation coefficient between the scale values of the regularity property and the combination of other properties in component 1 is 0.998; thus, component 1 can be interpreted by the regularity property and modeled by the combination of a primitive element and the placement rules that specify how this element can be replicated. The smoothness property also has obvious correlations (p <0.005) with the properties of uniformity, contrast, fineness, and complexity. Component 2 can be explained by the smoothness property with a Pearson correlation coefficient of 0.997 between the smoothness property and component 2, whereas the warmth property can stand for component 3 with a Pearson correlation coefficient of 0.812 between the warmth property and the properties of activeness and relaxation. In total, the components extracted from the display samples are very similar to those extracted from the surface samples. Completely non-repetitive textures can be adequately described through fractal dimensions corresponding to the orthogonal regularity and smoothness properties, which are a measure of surface coarseness[15].

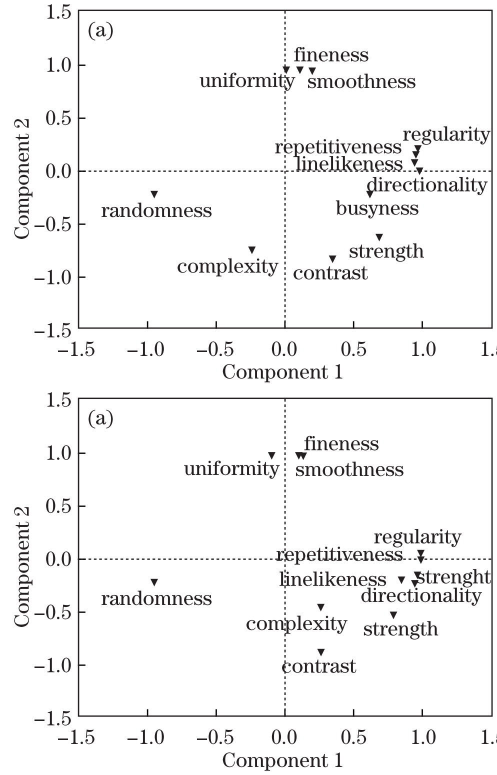

Fig. 2. Factor plots of the 12 properties involved in components 1 and 2 for surface and display samples: (a) surface samples; (b) display samples.

Table 3. Factor Matrix of 15 Properties of Surface and Display Samples

	Surface Samples			Display Samples		
	Component 1	Component 2	Component 3	Component 1	Component 2	Component 3
Directionality	0.970	−0.010	−0.089	0.982	−0.055	−0.055
Regularity	0.965	0.204	−0.029	0.982	0.018	−0.043
Repetitiveness	0.956	0.147	0.068	0.956	0.152	−0.052
Randomness	−0.947	−0.225	0.080	−0.949	0.221	0.071
Linelikeness	0.935	0.065	−0.176	0.942	0.228	−0.012
Busyness	0.617	−0.220	0.067	0.792	0.543	0.008
Strength	0.686	−0.623	0.147	0.854	0.203	−0.003
Smoothness	0.009	0.951	0.014	−0.110	−0.960	−0.114
Uniformity	0.112	0.947	−0.013	0.089	−0.958	−0.145
Fineness	0.195	0.932	−0.098	0.111	−0.947	−0.174
Contrast	0.342	−0.835	0.011	0.279	0.873	0.216
Complexity	−0.245	−0.759	−0.094	0.238	0.516	−0.249
Warmth	0.016	−0.126	0.912	0.060	0.147	0.931
Activeness	0.132	−0.005	0.902	0.096	0.143	0.930
Relaxation	−0.269	0.109	0.686	0.136	−0.013	−0.231

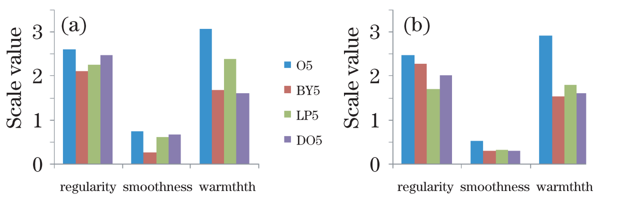

Fig. 3. (Color online) Scale values for textiles with large primitive elements but different colors: (a) surface samples; (b) display samples.

Strength, which is highly related to other properties highlighted in recent published research[6], contributes nearly equally to components 1 and 2 for surface samples, as shown in Fig. 2; thus, strength is difficult to classify into any principal component. A strong correlation with a Pearson correlation coefficient of 0.949 is found between strength and the combination of contrast, regularity, and repetitiveness. As the impact of strength is related to those of contrast, regularity, and repetitiveness, strength is designated a high-level property rather than a basic independent property.

All of the textile samples with similar textural features but different colors or with the same color but different textural features may be assigned to one of the following groups. One group of 4 samples with the same texture level of 5 but different color centers, including O5, BY5, LP5, and DO5, are compared. The scale values of regularity, smoothness, and warmth are plotted for the surface and display samples in Figs. 3(a) and (b), respectively, to reveal similar trends. The regularity property has high scale values, which indicates that all of the samples in this group are highly repetitive and directional. Comparatively low scale values for the smoothness property suggest that samples with large texture elements are relatively rough. The scale values of the smoothness property for the display samples are lower than those for the surface samples because the high luminance in the light booth diminishes the contrast in surface samples, and textiles with low contrast show obscure texture depths that appear smoother. This finding verifies that evaluations for contrast are significantly correlated with those for smoothness. Warmth mainly depends on colors because its scale values are considerably different among textiles with different colors.

Another group of textiles with the same texture level of 2 but different color centers includes samples LB2, R2, G2, B2, P2, LP2, and DB2. Figures 4(a) and (b) demonstrate the scale values of regularity, smoothness, and warmth for surface and display samples, respectively. Evident differences in characteristics between these textile samples and those with large primitive elements are observed. The textiles in this group have low scale values for regularity but high scale values for smoothness; thus, the primitive elements of these samples are obscure and the contrast is low. Warmth, which is dependent on the colors of the textile samples, shows features similar to those described in the first group.

The scale values of regularity, smoothness, and warmth for the surface and display samples DO1, DO2, DO3, DO4, and DO5 are plotted in Figs. 5(a) and (b) respectively; in these plots, variation trends are similar for different sample modes. These samples have the same color but different texture levels. Apparent variations are found in the scale values for the properties of regularity and smoothness, whereas the scale values for warmth are relatively consistent. This result again confirms that evaluations of warmth are dependent upon color.

The regularity property demonstrates the geometric placement rules[13] of primitive elements; the smoothness property explains the depth information of textiles; the warmth property represents emotions for textiles that vary with colors. Compared with published studies[4,6,13], the evaluated perceptions of regularity, smoothness, strength, complexity, and warmth properties in the present work are similar, but different perceptual assessments for contrast and busyness are observed because of differences in the textile samples adopted among studies.

To determine correlations between assessments from the surface and display samples precisely, the scale values of the perceptual properties of surface and display samples are compared with each other, and their corresponding Pearson correlation coefficients are listed in Table 4. All of the properties are significantly related (p <0.005) and, except for the complexity and relaxation properties, show good consistency. Almost all of the scale values of complexity for display samples are higher than those for surface samples. This finding may be likely attributed to differences in the luminance used in viewing conditions because high luminance in the light booth decreases contrast and degrades details. Obvious discrepancies also occur in evaluations of the relaxation property, which may be explained by inherent difficulties in assessing relaxation and complexity, as demonstrated by the corresponding large CV values of observer accuracy. Despite these minor differences, however, overall consistency is found between scale values for the surface and display samples.

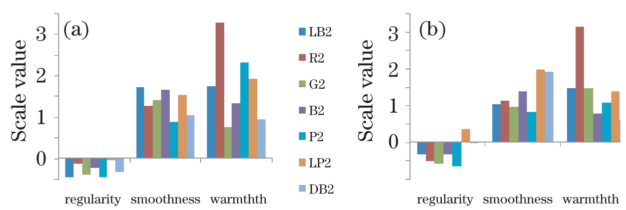

Fig. 4. (Color online) Scale values for textiles with subtle texture elements but different colors: (a) surface samples; (b) display samples.

Table 4. Pearson Correlation Coefficients of Perceptual Properties between the Surface and Display Samples

Contrast	Repetitiveness	Busyness	Randomness	Smooth	Strength	Directionality	Complexity
0.821	0.891	0.743	0.903	0.781	0.847	0.942	0.295
Fineness	Regularity	Linelikeness	Uniformity	Warmth	Activeness	Relaxation	Overall
0.867	0.896	0.903	0.809	0.900	0.892	0.279	0.863

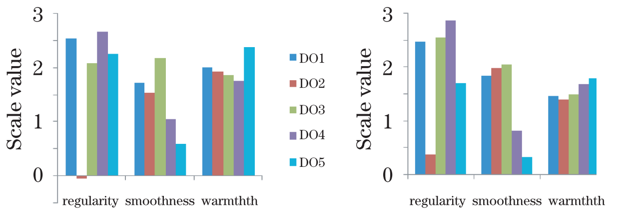

Fig. 5. (Color online) Scale values for textiles with the same color but different textures: (a) surface samples; (b) display samples.

Table 5. Pearson Correlation Coefficients of Components of Surface and Display Samples

Surface/s Display Sample	Component 1	Component 2	Component 3
r	0.951	0.935	0.758
p	0.000	0.000	0.001

As mentioned above, three principal components are extracted from the scale values of both surface and display samples, and similarities and differences in these components may be observed. For further discussion, Table 5 summarizes the correlations of the three principal components of the surface and display samples. Pearson coefficients indicate significantly high correlations (p <0.005) between individual components, which indicates that assessment of the visual perceptual properties of textiles via a display yields reliable results. Thus, designing complex samples as a more convenient and efficient alternative when surface samples are not readily available is feasible.

In conclusion, three principal components are extracted to explain the visual perceptions of textiles. These components are described by regularity, smoothness, and warmth and account for the placement rules of texture elements, depth, and emotion of textile samples. The strength property could not be classified into any component; thus, it is considered a high-level property. Textiles with large texture elements exhibit properties of regularity and coarseness, whereas textiles with subtle texture elements are considered random and smooth. Surface and display samples yield highly similar results. The findings in this study contribute to the perceptual model required in the description of texture correlated with visual perception. The consistency between perceptual assessments of surface and display samples implies that display samples may be adopted in future research as a valid alternative to traditional surface samples. Virtual samples will be generated in the future for further experimentation to expand the scope of this study.

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