“Cross-material” Texture Perception: An Exploratory Analysis of Woven Fabrics and Tree Barks

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Abstract

The visual impression of fabric is important in determining and communicating its quality. Many researchers have studied the visual texture and aesthetics of fabrics, naturally by using fabric materials. However, textile designers often draw inspiration from other materials, then design fabrics by unveiling the nature of the materials’ rich texture from the view of general design elements and principles. This study aimed to provide empirical support for the validity of such a cross-material design strategy. The visual textural impression was compared between 17 woven fabrics and 10 tree barks in two psychological experiments. Participants were asked to sort the fabrics based on their visual textural resemblance and match them to images of barks. The participants were then asked to rank the fabrics and barks separately according to seven bipolar adjective pairs related to design principles. Results from visual matching showed that the 17 fabrics and 10 bark images formed three distinct groups. The second experiment showed that the groupings predicted from the ranking data were consistent with those found by the visual matching. This study demonstrates that the design elements and principles used underlie the perception of visual texture commonly across different materials, strengthening the effectiveness of cross-material design.

Key Words: Visual impression, Visual texture, Natural texture, Design strategy, Design principles

1. Introduction

More than being merely functional, fabrics can be designed to have an added aesthetic value. No less than tactile perception, visual impression is important in determining and communicating the quality of a product. Many researchers have studied the visual texture and aesthetics of fabrics. Brand \cite{1} defined fabric aesthetics using six aesthetic concepts (style, body, cover, surface texture, drape, and resilience), each of which was associated with a pair of physical properties and common words. Hoffman \cite{2} proposed bipolar word to measure the aesthetic appeal of a fabric in terms of good or bad. Mori and Endou \cite{3} studied lace patterns and examined the relationships between parameters related to textural features (e.g., uniformity and contrast) and sensory evaluation (beauty, comfort, transparency, light sensation, and lacunarity). They found that the beauty of lace was related to its entropy and fractal dimension. Lee and Sato \cite{4} investigated the relationship between the physical properties of fabrics and psychological factors related to the perception of visual texture. They used textiles samples as well as corresponding images rendered on photographic paper. Factor analysis revealed that voluminous and warm, glossy, and fine feelings were the three felt most often by subjects when they viewed both real textiles and printed samples, but the contributions of these three emotional factors differed between real textiles and printed samples.

Naturally, as described above, most studies that have investigated the visual impression of fabrics have done so by using fabric materials. However, in the field of textile design, it is not unusual for designers to determine fabric designs from non-fabric materials. They often strive for design hints from other materials that have rich textures, such as stone, leather, and bark. Usually, designers devise the required visual characteristics of fabrics from non-fabric materials in two steps. First, they extract design elements such as point, line, shape, form, space, texture, and color from pictures of the non-fabric materials. They then integrate the design elements by employing design principles such as unity, balance, proportion,

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rhythm, emphasis, and contrast [5]. Because the design elements do not come from existing and common fabrics, the final design can achieve a novel and original fabric aesthetic. Although this strategy is believed to work in practice, it is an open issue whether this cross-material design paradigm gives the consumer the visual impression that the designer intended.

The purpose of this study was to provide empirical support for the validity of the aforementioned cross-material design strategy. To this end, we compared the visual textural impressions of woven fabrics with those of tree barks. We conducted two psychological experiments. In the first experiment, 17 fabrics were grouped in several sets based on textural resemblance, and then each set was matched visually to one of 10 bark images. In the second experiment, a ranking method was used to investigate the visual textures of the fabrics and barks in relation to design principles. Subjects were asked to rank the fabrics/images according to seven bipolar adjective pairs related to design principles. We discuss the results with a view to providing informative guidelines for the design of fabrics or indeed other products.

2. Materials and methods

2.1 Bark images

We are interested in designing a fabric to express a natural texture, specifically that of tree bark. We chose 10 bark images (labeled B1–B10) taken of trees of various textures and adjusted to grayscale (Fig. 1). As shown in Fig. 1, points and horizontal lines are clearly observed as design elements from which to produce fabrics. The size of the bark images shown to subjects was 10 × 15 cm.

2.2 Fabric samples

Inspired by the bark images, we designed 17 cotton fabrics. To reflect the differences among the horizontal lines seen in Fig. 1, we used three types of weft yarn, namely, hand-spun, machine-spun and slub yarn. We showed previously that using hand-spun yarns influences surface texture and mechanical properties, as do the yarn count and weave density [6]. In this previous study, the surface

| Sample no. | Type of weft yarn | Yarn count (tex) | Yarn diameter (mm) | Yarn density (cm) | Weight (g/m²) | Thickness (mm) |
|------------|------------------|----------------|-------------------|------------------|--------------|--------------|
|            |                  | Weft Average CV (%) | Ends Picks |              |              |              |
| F01        | Hand-spun        | 57.7 0.52 52.55   | 18.7 17.1 | 178.3 1.37   |
| F02        | Hand-spun        | 86.5 0.72 44.86   | 18.8 14.4 | 214.5 1.42   |
| F03        | Hand-spun        | 115.2 0.82 52.69  | 18.5 13.6 | 237.0 1.68   |
| F04        | Hand-spun        | 235.8 1.43 42.84  | 18.2 9.9  | 329.3 1.80   |
| F05        | Hand-spun        | 244.2 1.51 37.52  | 18.2 6.6  | 242.8 1.76   |
| F06        | Hand-spun        | 270.4 2.22 71.52  | 18.1 6.4  | 244.0 1.84   |
| F07        | Machine-spun     | 60.9 0.39 18.73   | 18.9 18.8 | 187.5 1.09   |
| F08        | Machine-spun     | 174.9 0.77 19.21  | 18.5 12.8 | 145.0 0.97   |
| F09        | Slub yarn        | 55.8 0.46 62.04   | 18.8 18.5 | 180.3 1.15   |
| F10        | Hand-spun        | 87.0 0.53 18.51   | 18.5 14.7 | 145.3 1.17   |
| F11        | Machine-spun     | 235.8 1.43 42.84  | 18.3 9.8  | 236.5 1.69   |

CV: coefficient of variation = (standard deviation / mean) × 100

Table 1 Sample specifications.
irregularity was affected by using hand-spun yarn, which has a large variation in thickness in the weft direction of the woven fabric. Therefore, in the present study, we use yarn of the same warp (machine-spun yarn, 14.76 × 2 tex) to emphasize the weft yarn in a plain weave structure using a handloom. The specifications of the samples and scanned images are given in Table 1 and Fig. 2, respectively. The weft yarns of fabric samples F01–F10 were Thailand-made hand-spun yarns. The sample pairs F01/F02, F03/F04, F05/F06, and F07/F08 were woven with the same yarn count but with different yarn densities. Samples F11–F14 contained machine-spun yarns. The sample pair F11/F12 was woven with the same yarn but different yarn densities. The weft yarn counts of F11 and F12 were smaller than those of F13 and F14. Samples F15 and F16 contained the same slub yarn but at different densities. Sample F17 was woven by two-shuttle alternation using hand-spun yarn (235.8 tex) and machine-spun yarn (87 tex).

The samples were neither dyed nor bleached and were yellow-gray. The chromaticity was measured by a spectrophotometer (CM-3600d; Konica Minolta) and expressed by CIELAB [7]; the average chromaticity was \( L^*, a^*, b^* \) = (85, 0.42, 12.14) and the average color distance range was 1.07 (standard deviation = 0.57). The color of a sample made little difference to how it was perceived visually. Each fabric sample (15 × 15 cm) was mounted in a gray cardboard frame (2.5 cm wide) before being presented to the participants.

2.3 Participants

The 40 participants (mean age 26.7 years; range 22–39 years) were students at the Kyoto Institute of Technology and neophytes to psychological experiments on fabrics. The 20 participants were women and 20 were men. The nationalities of the participants were Thai (20), Japanese (12), Chinese (4), Mongolian (1), Vietnamese (1), South African (1), and Nicaraguan (1).

2.4 Procedure

2.4.1 Experiment 1: association between fabrics and barks according to visual appearance

The 40 participants performed a free-sorting task on the fabrics. The 17 fabric samples were presented on a table simultaneously and randomly. The participants were asked to group the fabrics according to resemblance, but no other criteria were specified. The participants were free to make any number of groups and to assign any number of fabrics to each group. Once the grouping task had been completed, the 10 bark images were displayed on the table, again simultaneously and randomly. For each fabric group that they had created, the participants were asked to match it with what they deemed to be the most representative bark image. The experiment is shown schematically in Fig. 3. The illuminance at the center of each sample as measured perpendicular to the sample surface on the table was 977 ± 70 lx. The room was maintained at a temperature of 22 ± 3°C and a relative humidity of 35 ± 5%.

To study the association between the fabrics and barks, we subjected the cross-material matching data first to correspondence analysis (CA) [8] and then to seriation [9], a sequencing technique for reordering distance matrices. We used the numbers of matches between fabrics and barks to build a contingency table with barks as columns and fabrics as rows. We then used the CA package [10] in R (hereinafter version 3.3.2) to perform CA on the contingency table. We used the seriation package [11] in R to reveal any regularity or patterning among the correspondences.
2.4.2 Experiment 2: association between fabrics and barks according to design principles

We conducted this experiment to investigate further the perception of visual texture in relation to the principles that underlie cross-material design. Independent of each other, the participants performed a ranking task on the 17 fabrics and 10 barks. The samples were again displayed on a table simultaneously and randomly. The participants were asked to rank the samples according to seven given bipolar adjective pairs, namely harmonious/inharmonious, regular/irregular, static/dynamic, repetitive/random, mechanical/hand-drawn, two-dimensional/three-dimensional, and filled/empty. These adjective pairs were integrated by the design elements to construct design principles.

We analyzed the ranking data of both the fabrics and bark images using the normalized rank method [12,13] to obtain ranking scales. We then used the rankings of each fabric/image for each adjective pair to build a contingency table that we subjected to seriation using the seriation package [11] in R based on principal component analysis (PCA).

We conducted multidimensional scaling (MDS) analysis [14] to visualize the perceptual distance between the fabrics and bark images. We used the dendextend package [15] in R to transfer the ranking scales of the fabrics and bark images from the contingency table to a distance matrix, and we using the smacof package [16] in R to perform MDS on this distance matrix. On the MDS map, the smaller the distance between fabrics or bark images, the more similar they are to each other. Finally, we used the stats package in R to perform cluster analysis [17] on the distance matrix to visualize the cluster hierarchy.

3. Results

3.1 Experiment 1: association between fabrics and barks according to visual appearance

We formed the frequency data from the cross-material matching performed by the 40 participants on the fabrics and bark images into a contingency table. Figure 4(a) show the table as a balloon plot of fabrics (rows) versus bark images (columns) in which the larger the balloon, the higher the association between the two corresponding materials. We found relatively high associations between fabrics F11 and F12 (woven by machine-spun yarn) and bark image B01, between F10 (large yarn count of hand-spun yarn) and B10, between F17 (hand-spun yarn alternated with machine-spun yarn) and B09, and between F15 and F16 (slub yarn) and B07. A consistent pattern along a column or row in the plot indicates that those fabrics or barks are more similar to each other than to another material. In this respect, we found several highly similar fabric pairs, namely, F03/F04, F11/F12, and F15/F16. By contrast, the barks showed relatively unique patterns except for B02 and B03.

To visualize the pattern similarity more clearly, we subjected the contingency table to seriation analysis, in which both rows and columns were reordered to place similar fabrics and barks closer
together; the result is the grayscale heat map in Fig. 4(b). A careful observation of the global pattern in this map reveals three groups of fabrics based on their visual resemblances to the bark images. The first group comprises F11 and F12 and is associated with B01. The second group comprises F08–F10 and F17 and is associated with B09 and B10. The third group comprises F01–F07 and F13–F16 and is associated with B02–B08.

As shown in Fig. 5, CA also revealed three cross-material groups. According to the inset in Fig. 5(a), three dimensions account for 87.6% of the variance and so are sufficient for representing the data. The CA map with dimensions 1 and 2 (Fig. 5(a)) shows three material clusters. The first cluster (comprising F11 and F12 and associated with B01) is in the upper-left quadrant far from the origin, indicating distinctness from the others. The second cluster (comprising F08–F10 and F17 associated with B09 and B10) is in the upper-right quadrant, and the third cluster (comprising F01–F07 and F13–F16 associated with B02–B08) is in the lower-left quadrant.

Fig. 4 (a) Balloon plot of contingency table relating fabrics and barks. Columns represent bark images, rows represent fabrics. The size of a circle represents the number of participants who matched that bark and fabric. (b) Seriation of contingency table. The gray level indicates the number of subjects who matched a bark and fabric. The symbols indicate the types of yarn; ⬤ indicates hand-spun yarn fabrics, ▲ indicates machine-spun yarn fabrics, ■ indicates slub yarn fabrics, ○ indicates hand-spun yarn alternated with machine-spun yarn fabric.

Fig. 5 Correspondence analysis (CA) of fabric/bark contingency table. (a) Correspondence map of dimension 1 vs. dimension 2. Fabrics and barks are plotted simultaneously. The inset is a scree plot of eigenvalue against dimensionality. (b) Correspondence map of dimension 1 vs. dimension 3. The symbols indicate the types of yarn; ⬤ indicates hand-spun yarn fabrics, ▲ indicates machine-spun yarn fabrics, ■ indicates slub yarn fabrics, ○ indicates hand-spun yarn alternated with machine-spun yarn fabric.
F08–F10 and F17 and associated with B09 and B10) is in the upper-right quadrant. The remaining fabrics and barks comprise a large group near the origin, indicating average visual texture. Within this group, there is a subgroup (comprising F15 and F16 and associated with B07) as suggested by the CA map with dimensions 1 and 3 (Fig. 5(b)) and the seriation grayscale heat map (Fig. 4(b)).

3.2 Experiment 2: association between fabrics and barks according to design principles

What kind of visual texture perception underlies the cross-material correspondence revealed by the fabric/bark visual matching? To answer this, in experiment 2, we collected ranking data independently for the fabrics and bark images in relation to seven visual properties related to design principles, namely, harmonious, three-dimensional, dynamic, irregular, random, hand-drawn, and empty. If any of these visual properties underlie the cross-material matching, we expect that the cross-material correspondence predicted from the ranking data would also show a similar grouping in the data for direct visual matching. Simultaneously, the prediction would reveal which of the seven properties is or are important for visual matching. To assess the cross-material correspondence, we used the normalized rank method to convert the fabric and bark ranking data to psychological factors that we then subjected to seriation analysis.

The results of the above process are shown in Fig. 6 in the form of a grayscale heat map in which the fabrics and barks are reordered according to the seven psychological factors represented by their corresponding adjective pairs. Notably, the fabrics are arranged sometimes intermittently with the barks, indicating that some fabrics are more similar to some barks than to the other fabrics with respect to some of the psychological factors. This intermittent pattern suggests three groups similar to those found in the visual-matching task (Fig. 4(a)), supporting the above prediction. The first group (F11, F12, and B01) is characterized by a low "filled" value but high values for the other scales. The second group (F01–F04, F13–F16, and B02–B04) is characterized by a low “filled” value and medium values for the other scales. The third group (F05–F10, F17, and B05–B10) is characterized by a relatively high “filled” value but low values for the other scales.

To compare the groups more clearly, we subjected the matrix data to MDS analysis to visualize the cross-material correspondence geometrically. The results shown in Fig. 7(a) again reveal the groups found by visual matching (Fig. 5(a)). Because the scree plot of the stress values (see inset in Fig. 7(a)) shows an inflection point at the second dimension, we accepted a two-dimensional solution for the MDS map. Although the MDS map does not show clearly separated groups, the fabric and bark groupings found by visual matching (enclosed by dotted lines) are generally close together, suggesting that the cross-material correspondence predicted from the ranking data is consistent with that found by visual matching, at least to a first approximation. We confirmed this by hierarchical clustering analysis. The cluster tree shown in Fig. 7(b) again reveals three groups at height 6 (dotted line), the members of which are quite consistent with those from visual matching. Importantly, some differences from the visual matching are also evident.

![Fig. 6 Seriation of ranking-value contingency table. The rows contain both 17 fabrics and 10 barks, while the columns represent seven adjective pairs. The gray level indicates the scale value. The symbols indicate the types of yarn; □ indicates hand-spun yarn fabrics, ▲ indicates machine-spun yarn fabrics, ■ indicates slub yarn fabrics, ◆ indicates hand-spun yarn alternated with machine-spun yarn fabric.](image-url)
Globally, the fabrics and barks are distributed more evenly over the perceptual space than are those found by visual matching. Locally, the association between fabrics and barks becomes weak in several regions, for example, F11 and F12 with B01, F10 with B10, and F15 and F16 with B07 (Fig. 5(a) and (b)).

The question arises as to how the design principles help group the fabrics and barks. We explored this question by applying clustering analysis to the seven properties related to design principles. The results are shown in Fig. 8. The tree structure clearly demonstrates the hierarchical nature of the design principles governing the fabrics and barks. At the first level, filled/empty separates from the other properties. At the second level, the remaining six properties divide into two groups. The first group comprises two-dimensional/three-dimensional and static/dynamic, and the second and larger group comprises harmonious/inharmonious, mechanical/hand-drawn, repetitive/random, and regular/irregular.

4. Discussion

In summary, the cross-material visual texture matching in experiment 1 showed that the 17 fabrics and 10 bark images formed three distinct groups. Experiment 2 showed that those three cross-material groups were consistent with the cross-material correspondence predicted from the ranking data with respect to seven properties related to design principles, namely harmonious/inharmonious, regular/irregular, static/dynamic, repetitive/random, mechanical/hand-drawn, two-dimensional/three-dimensional, and filled/empty.

To our knowledge, the present study is the first to have demonstrated consistency between cross-material matching and design elements and principles. This gives empirical support for the cross-material design strategy, encouraging designers who want to use other materials with appealing textures to generate new ideas for the
visual characteristics of a target product. Because our non-specialist participants judged the material textural characteristics to be shared across different materials based on design elements and principles, designers can use this design strategy confidently to transfer impressions from the design elements and principles underlying the reference materials to the design of the target material. For this transfer, the hierarchical nature found for the design principles may be useful. For example, if designers want to create a new appealing textured fabric, they may design fabrics with particular emphasis on the filled/empty principle because the hierarchical tree suggests that filled/empty is a more special property than the others. However, in the design process, it difficult to make a design appealing based on only one principle. Thus, a good solution would be to combine filled/empty with other principles; examples might be designing a fabric that looks empty but dynamic, or designing a fabric that looks filled but harmonious. For such endeavors, a subtree structure other than filled/empty would also be helpful.

The present cross-material grouping based on design principles also showed an intriguing difference from simple cross-material visual matching. The fabrics and barks were distributed more evenly over the space spanned by the design principles than were those found by simple matching. There are at least two reasons for this difference. The first lies in the difference between the tasks. In the visual-matching task, we required the participants to match the samples, leading to a focus on the perceived similarities between fabric and bark. By contrast, in the ranking task, we required the participants to rank the materials, leading to a focus on the dissimilarities between fabric and bark. Therefore, the perceptual distance between fabric and bark as measured by ranking tended to be larger than that measured by matching, leading to a relatively uniform distribution over perceptual space. The second reason lies in the differing natures of the perceptual spaces, wherein that defined by design principles is much richer than that defined by visual matching. In other words, visual matching reflects only visual appearance, whereas the design principles reflect not only appearance but also higher-order cognition such as preference, beauty, liveliness, and uniqueness. Some fabrics and barks that are quite alike in textural appearance are nevertheless distinguished by higher-order cognition, leading to a more-uniformly distributed pattern in the design space.

5. Conclusions

This study has provided empirical support for a cross-material strategy for fabric design. Non-specialists performed cross-material visual matching easily, revealing three fabric/bark cross-material groups that were consistent with the different fabric yarn types. Furthermore, the non-specialists’ psychological perceptions of the fabrics with respect to general design elements and principles were quite similar to those of the barks, consistent with the fabric/bark visual texture matching. Overall, this study has demonstrated that the general design elements and principles used by designers underlie the visual perception of texture commonly across different materials, strengthening the effectiveness of cross-material design. Our results on fabrics and barks can apply to other materials.

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