Effects of wood texture and color on aesthetic pleasure: two experimental studies

Zetian Dai[1,2], Juan Xue[2], Shoushan Wang[3]
[1]Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur, Malaysia
[2]Collage of art, Suzhou University of Science and Technology, Suzhou, China
[3]School of Art, Jinan Preschool Education College, Jinan, China

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ABSTRACT

The texture and color on wood are key factors that influence an individual's perception of it. However, little research has been done to confirm what kind of pattern in textures and colors are more likely to evoke individual aesthetic pleasure. Therefore, twenty-four decorative wood from northern China were selected, identified, and quantified in their colors with a CR-5 Colorimeter. We picked out eight kinds of wood with optimal texture characteristics through feature-fusion wood grain recognition (FWGR) and enhanced the texture features with photoshop in VR space. The result show that, in the color dimension, woods in the hue range of 20-25 and saturation of 65-75 were considered beautiful for individual perception of aesthetic. In the texture dimension, the size of the space affects the individual's preference for texture. When the pattern of the wood ray is continuous and clear, the individual's perception of its fluidity is enhanced; while for the fuzzy and interrupted pattern of the wood ray, the individual does not follow the fluidity of the line but focuses on the overall uniformity.

Corresponding Author:

Shoushan Wang
School of Art, Jinan Preschool Education College
Dangui Road 2011, Changqing District, Jinan City, Shandong Province, China
Email: shoushanwang@126.com

1. INTRODUCTION

Wood, an ecological decorative material, has a unique natural texture and color, giving people a feeling of intimacy, comfort and warmth [1]. For architecture and interior design easily, Wood brings occupants close to nature, and the aura it exudes is one of the manifestations of the rustic life loved by people living in the city [2], [3]. It also has moisture-regulating properties, sound-insulating and sound-absorbing properties, and thermal and electrical insulation properties, which make wood widely used in interior design, architecture, and furniture. In addition, wooden artifacts and products, with specific textures and color combinations, have a large degree of positive impact on consumer desire to purchase [4].

Much of the above phenomenon stems from pre-constructed impressions of wood and aesthetic tendencies, which relate to the tactile texture, price, and cultural meanings behind different types of wood [5]. It has been shown that knowledge frameworks about wood, especially cultural meanings, subliminally influence consumers' purchase intentions over time [6]. And inherent impressions about the price of wood can influence consumers' aesthetic preferences in the short term, even if they cannot accurately identify the species [7]. Several studies have shown that individuals' aesthetic preferences for wood are based on two main visual dimensions: texture and color, where the frequency of knots on the surface also influences to some extent individuals' aesthetic preferences for wood.

In previous studies, the aesthetic feedback for wood is mainly reflected in the visual sparsity and uniformity of the wood texture, involving straight, chaotic, curved and knotty figures. It has been suggested that a uniform surface texture (with light colors) is easily preferred. Ilce *et al*. [8] found that wood texture with U-shaped and V-shaped curves in the surface grain of wooden furniture was more preferred by college graduates, while high school students preferred the knotty figure. In empirical aesthetics, Nyrud *et al*. [9] presented that the harmony of wood texture is strongly related to the degree of homogeneity, while Høibø and Nyrud [4] found through semantic analysis that the harmony of wood surface is related to stains, surplus color, knot shape, dry knots, spike knots, and knot checks. However, the logic underlying the aesthetic impact of wood in interior spaces has not been clearly explained, and few studies have explored whether there is a fixed pattern and law in the texture and color of wood favored. That is, the majority of researchers did not elaborate on what specific wood grain patterns and color ranges are more likely to evoke Individual aesthetic pleasure. Therefore, in this study, we selected 24 decorative woods commonly used in northern China (Shandong Province), scanned them with CR-5 colorimeter, and then identified and quantified their colors by Munsell color model. In addition, eight woods with the most representative texture feature were selected and categorized by feature-fusion wood grain recognition (FWGR) [10]. By collecting participants' feedback on aesthetic pleasure across a range of texture patterns and colors, it was determined in which patterns of it appeared to be more favored by individuals.

2. KEY TERMS

2.1. Aesthetic

By reviewing the collected literature, we found that the concept of aesthetics is broad. Different studies have interpreted aesthetics in different ways. Although the term Aesthetic is mentioned in the literature, the confusion of multiple related terms (e.g. beautiful, hedonistic, appreciative, pleasurable, happy, fond) and concepts does not contribute to the rigour and generality of aesthetic research. Perhaps it is due to the diversity in people' perceptions of beauty in art, design and nature, as different cultural backgrounds, personalities and upbringings have led to different views on aesthetics. Therefore, even if pleasure is related to the concept of beauty, it is not the whole content of aesthetics. In this study, we used the term "aesthetic pleasure" to qualify the meaning of aesthetics, i.e., the beauty-ugliness dimension in aesthetics. Specifically, we quantified participants' aesthetic feelings on a 7-point likert scale (5-7: beautiful; 4: indifferent; 1-3: ugly).

2.2. Wood texture

The texture of wood is mainly a linear pattern formed by fusiform cells in the cambium in trees [11]. Different cutting methods result in different wood textures, with four types of sawing methods: plain/flat sawn, quarter sawn, rift sawn, and live sawn [12]. Macroscopically, wood texture is mainly in the form of wood rays [13]. When the ray width is below 0.05 mm, it cannot be distinguished by the naked eye, which is called fine wood ray; when 0.05~0.2 mm, it can be observed by the naked eye, which is called medium wood ray; when the width is above 0.4 mm, it is called the broad wood ray.

In this study, wood texture refers to the linear pattern formed by rays on the surface of wood. Generally speaking, they are subdivided into: straight grain, interleaved grain, spiral grain, wave grain [14]. In order to better quantify the wood grain, according to the overall trend of the linear pattern, we can summarize it as star (straight wood grain/interlaced grain)-curve (spiral pattern, wave pattern); according to the density of the linear pattern, it is summarized as dense-spare; classified as clear-vague according to the coherence and clarity of the pith rays.

3. THE MEATHOD FOR WOOD IDENTIFICATION

3.1. Texture recognition and classification

The methods of wood texture analysis can be generally classified as statistical, model, and spectral methods. Among them, gray-level co-occurrence matrix (GLCM) is the most commonly used analysis method in the statistical method [15]. In GLCM, the elements that need to be identified which mainly consist of the number of pairs of pixels with a certain distance and a certain angle on the gray level [16]. When the image gray level is generated with a step size of, the feature parameters that are applicable to describe the wood texture are derived as the correlation contrast, angular second order moments, variance, and mean. [17]. The fractal and Markov random field methods, which are commonly used in model methods, are also able to identify well the distribution density, uniformity, width, and other characteristics of wood texture [18], [19]. In the analysis of spectral methods, wavelet transform (WT) is widely used in the analysis of textures. This is a good representation of the regularity and directionality of the texture by extracting the WT energy distribution ratio and EHL/ELH values in the frequency domain as feature parameters [20].

Several studies have found that curvilinear and chaotic patterns, which are characteristic of wood surface grain, are not better recognized [21]. To address this problem, Ilce *et al*. [8] improved the traditional spectral method by fusing WT and curvelet transform (CT), which is called FWGR (see Figure 1). Ilce *et al*. [8] took symlets4 wavelet basis to sample images of wood, performed second level wavelet decomposition, and further processed the wavelet coefficient of subgraphs. The results show that this method can efficiently analyze wood texture and quickly identify and classify wood ray characteristics such as straight, curved, messy, parabolic, and knotty figure.

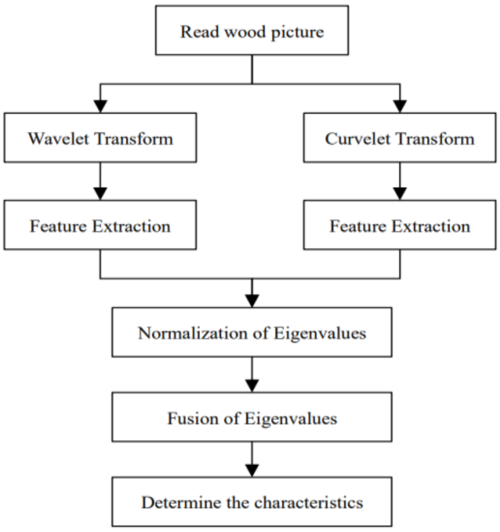


Figure 1. Feature-fusion wood grain recognition

3.2. Color recognition and classification

Compared with texture, color information is more intuitive, which also allows the identification of wood color features to be realized by extracting the low-order moment (LOM) of the image [22], where the color moments are The basic method for identifying wood color features includes the first-order moment represented by mean, the second-order moment represented by variance, and the third-order moment represented by skewness [23]. The following is the mathematical formula of color moments, where $p_{i,j}$ are the pixel values at the image (i and j are the two dimensions of the orthogonal basis); μ_i, σ_i and s_i, respectively, are the first, second and third order moments of image processing.

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} p_{i,j} \tag{1}$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{i,j} - \mu_i\right)^2\right)^{\frac{1}{2}} \tag{2}$$

$$s_i = \left(\frac{1}{N}\sum_{j-1}^{N}\left(p_{i,j} - \mu_i\right)^3\right)^{\frac{1}{3}} \tag{3}$$

CIELab, a color model based on the physiological characteristics of the human eye, is the main model presented by most color recognition instruments, especially for the study of color classification by the human eye [24]. However, the internal dimensions of CIElab are highly correlated, which is not conducive to the disassembly analysis of color in experimental studies, and does not meet the premise of most statistical methods, such as Multicollinearity and homogeneity of variance. Therefore, the Munsell color model, a color system with three independent dimensions, hue (H), saturation (S), value (V), is widely used in cognitive psychology experiments. The following is the conversion formula between CIElab and Munsell Color model:

$$H = -0.03636L^* + 0.02663r - 14.3\theta + 0.09131r\theta + 14.826 \tag{4}$$

$$V = 0.1002L^* - 1.16 \tag{5}$$

$$C = 0.1439r + 1.054\theta - 1.022\theta^2 + 0.0497r\theta - 0.167 \tag{6}$$

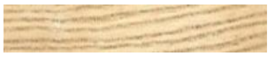
$$\theta = actan\left(\frac{a^*}{b^*}\right) \tag{7}$$

$$r = (a^{*2} + b^{*2})^{\frac{1}{2}} \tag{8}$$

among them, V is the lightness value (value), H is the hue label value (hue), and C is the purity/color degree (saturation), r and θ are intermediate variables used in the transformation.

4. STUDY 1
4.1. Research design
As Table 1 show that the researchers selected the top 24 most common decorative woods in the Shandong decoration market as samples. The size of these wood samples is 200×90×12 mm^3 (L×W×H), and the three sides have been identified and measured many times, which have made 2K high-definition maps. We used the CR-5 Colorimeter to identify and classify the colors of 24 wood, and converted the CIElab to the HSV (Munsell color model). The experiment mainly uses the Munsell color model for quantification, the three dimensions are highly correlated and have poor uniformity, which cannot meet the premise of the linear regression model calculation.

Table 1. Color characteristics and aesthetic pleasure for wood

No	Name	Latin name	Aesthetic pleasure	HSV	Sample map
1	Poplar	Populus alba	2.40(0.54)	H:36-39, S:26-30, V:80-83	
2	White oak	Quercus alba	3.72(1.13)	H:39-40, S:50-54, V:80-84	
3	Indian rosewood	Dalbergia latifolia Roxb.	6.43(0.63)	H:23-26, S:73-78, V:59-64	
4	Black walnut	Juglans spp	5.10(1.23)	H:26-28, S:73-80, V:18-23	
5	Red walnut	Aucoumeaklaineana	6.05(0.75)	H:18-23, S:66-70, V:32-38	
6	Belize rosewood	Dalbergia Stevenson Standl	6.35(0.46)	H:23-25, S:70-74, V:42-49	
7	Anigre	Aningeriarobusta	4.70(0.79)	H:31-33, S:54-63, V:89-91	
8	European Ash	Fraxinus spp	2.73(0.84)	H:34-41, S:27-34, V:72-76	
9	Jatoba	Hymenaeacunrbaril L	4.33(1.23)	H:30-32, S:50-54, V:53-54	
10	Boxwood	Euonvmusjaponlcus	3.35(1.36)	H:34-36, S:39-43, V:46-52	
11	Golden teak	Tectona grandis	5.37(0.49)	H:24-27, S:57-60, V:60-65	
12	Burma teak	Tectona grandis L.F.	3.88(0.38)	H:36-41, S:76-80, V:65-67	
13	Cherry wood	Prunus serrulata	5.18 (0.63)	H:28-31, S:66-68, V:64-71	
14	Sandal	Dalbergia bariensis	4.86(0.67)	H:31-34, S:89-93, V:82-94	
15	Cypress	Juniperus formoseensis Hayata	4.05(1.23)	H:32-35, S:53-58, V:87-89	
16	Dahurian larch	Larix gmeliniiRupr.	3.70(0.76)	H:32-35, S:57-61, V:89-93	
17	Tauari	Couratarispp	3.58(0.89)	H:26-29, S:37-40, V:84-88	
18	Amur Linden	Tilia amurensisRupr.	4.23(1.23)	H:37-41, S:40-43, V:86-87	
19	Beeh	Fagussylvatica	2.53(0.38)	H:43-46, S:47-48, V:83-84	
20	Northeast China ash	Fraxinus mandschuricaRupr	4.10(0.65)	H:34-37, S:33-38, V:87-90	
21	China-fir	Pseudotsuga Gaussenii Flous	4.13(0.45)	H:37-42, S:53-57, V:92-96	
22	Rattan	Calamus tetradactylus	2.82(1.12)	H:35-40, S:24-29, V:91-95	
23	Rubber wood	Hevea brasHiensis	2.37(1.6)	H:32-36, S:16-19, V:91-96	
24	Ayus	Triplochitonscleroxylon	2.78(1.05)	H: 40-45, S:16-19, V:96-97	

Although some studies have shown that individuals can process the two dimensions of wood (color and texture) independently [25], In order to avoid confounding interference as much as possible, we still use Photoshop to weaken the wood texture and knotty. The processed 24 kinds of wood textures were displayed to the participants in random order through a 4K computer display screen, and the participants were instructed to follow the 7-point likert scale (5-7: beautiful; 4: indifferent; 1-3: ugly) to rate each wood. Finally, bring the HSV coefficient of wood into the multiple regression equation, and use SPSS to calculate the influence of hue, saturation, and value on aesthetic pleasure.

4.2. Participants

We recruited 60 participants (aged 18-27 years; 33 males and 27 females) as subjects for this wood color experiment. The visually impaired participants took the vision and color vision tests with their corrective devices (contact lenses or glasses) and the results showed no individuals with color weakness or color blindness among them.

4.3. Result

Twenty-four wood colors were analyzed and categorized by Munsell colour to obtain quantified hue (H), saturation (S), and value (V). A regression analysis was performed with HSV as the predictor variable and aesthetic pleasure as the dependent variable. From Table 2, we found that after weakening texture and knotty, the whole Munsell colour model could explain 62.1% of individuals' aesthetic pleasure in wood, and the whole regression model was highly significant, R^2=0.621, F=75.112, p<0.001. Hue as a predictor was highly significant (β=0.429, p<0.001), and similarly saturation as a predictor of aesthetic pleasure was statistically significant (β=0.455, p<0.001). However, value as a predictor of aesthetic pleasure was not significant (β=-0.021, p=0.327) (detail in Table 3).

Table 2. Analysis of variance (ANOVA) of Munsell colour system

Model	Sum of squares	df	Mean square	F	R^2	Sig.
Regression	1611.235	3	537.078	754.112	0.621	0.000
Residual	1022.718	1436	0.712			
Total	2633.953	1439				

Table 3. Analysis of regression coefficient

Munsell colour	B	β	t	Sig	Collinearity statistics	
					tolerance	VIF
H	-0.095	-0.429	-19.542	0.000	0.562	1.778
S	0.031	0.455	22.898	0.000	0.686	1.458
V	-0.001	-0.021	-0.980	0.327	0.578	1.731

We integrated the hue range (H:15-45) of the 24 woods and their corresponding mean scores for aesthetic pleasure. According to Figure 2, the hue of woods between 15-20 and 20-25 were very popular and were judged to be beautiful in this range, with asiatic rosewood, belize rosewood, and red walnut being representative. 25-30 were judged to be mainly beautiful (anigre and sandal), but indifferent is beginning to appear (e.g., Jatoba); the richest aesthetic feedback on wood is between 30 and 35, which contains beautiful, indifferent, and beautiful grades. Finally, hue is mainly judged as ugly in the range of 35-40 and 40-45.

According to munsell colour model we found that the hue range of 15-45 is a color area that transitions from red to yellow. Between 15-25, the color tends to be red or red-orange, while between 25-35 it gradually shifts to orange, and between 35-45 it transitions to yellow. It is worth noting that aesthetic pleasure is usually given higher feedback when hue is around 24. According to Figure 2, the aesthetic pleasure is usually higher when hue is around 24, while the aesthetic evaluation is lower when hue is around 40.

Unlike hue, the saturation of the 24 woods spanned a larger range (S:18-92). According to Figure 3, all the woods with saturation in the range of 15,035 were judged as ugly; woods with saturation in the range of 35-45 and 45-55 were both indifferent and beautiful. Interestingly, woods in the saturation range of 55-65 are found to be beautiful (e.g., golden teak and red walnut), but some are still considered indifferent (e.g., China-fir and cypress), as well as ugly (e.g., dahurian larch). The woods in the range 65-75 are all above 5; H in the range 75-85, there are both ugly and beautiful woods, while in the darkest color range 85-95, there is only one type of black walnut and he is judged as indifferent.

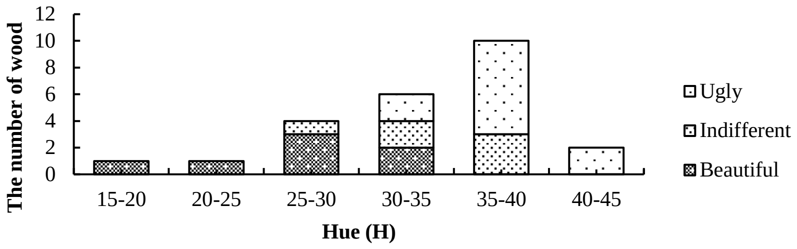


Figure 2. Aesthetic pleasure on the hue range of 15 to 45

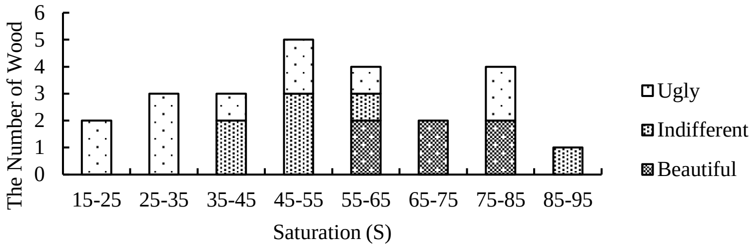


Figure 3. Aesthetic pleasure on the saturation range of 15-95

4.4. Discussion

Based on the above results, we checked the visualization model in the Munsell colour system and found that the colors preferred by the participants were mainly in the range of orange-red color. Also, combining the highest frequency of saturation (55-85) of the beautiful level, we found that those popular colors were close to red sandal wood (Pterocarpus santalinus L.f.) and Huanghua pear (Dalbergia odorifera T. Chen). For the Huanghua pear, its warm color and flowing texture have made it one of the symbols of nobility since the Tang Dynasty. Similarly, red sandal wood represents the via media of confucian culture, and it was also the raw material for ornaments, crafts, and furniture of the ancient royal family (Lyu red sandal wood represents the via media of Confucian culture, and it was also the raw material for ancient royal ornaments, crafts, and furniture. Perhaps it was the Chinese wood cultural environment, and the collective perception of the value of wood, that influenced their aesthetics of wood color, even they were not involved in related fields such as wooden artifacts or furniture.

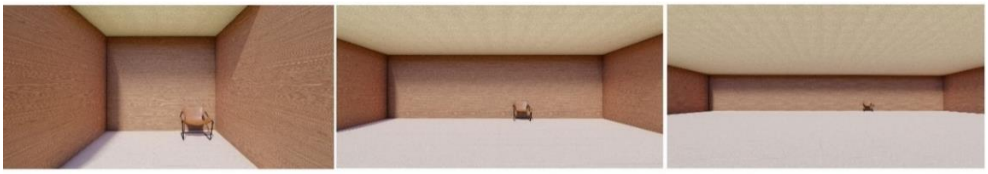
5. STUDY 2

5.1. Research design

Through FWGR, the texture features of 24 common decorative woods in Shandong are simplified into three dimensions: density (Dense/Spare), resolution (Clear/Vague), and curvature (staright/curve). Finally, the most representative 8 kinds of wood are determined under the combination of three dimensions: northeast, China ash, China-fir, tauari, sandal, dahurian larch, beeh, rubber wood, ayus (detial in Table 4). The wood was photographed and mapped in 2K HD to better highlight the characteristics of the texture, and the researchers used photoshop to emphasize the characteristics of the original texture, which made the three original dimensions of the wood more visible. In addition, the knotty figure pattern and frequency of occurrence are not stable, so the knotty was not taken into account (detail in Table 1). The color of all eight types of wood was unified to a dark log color (H:30, S:88, V:86) while retaining the original wood texture conditions. The treated wood maps were given to the walls of the virtual reality (VR) space, and participants who assembled the VR equipment rated their aesthetic pleasure.

5.2. Virtual reality space

The experimental equipment used was HTC Vive Cosmos, with a Bluetooth grip and a head-mounted display (HMD). Subjects can move freely in the space, and the Bluetooth handle will have vibration feedback when touching the walls of the virtual space. According to the international golden ratio of residential openings and depths (6:4), and the standard residential floor height (3 m), three scales of VR spaces were constructed, and their length-width-height data were Room A: 4×3×3 m; Room B: 9×6×3 m; Room C: 18×12×3 m on the walls of the three spaces (see Figure 4). Finally, the three dimensions of wood texture and the three types of VR spaces were combined to form a 3×3 multi-factor ANOVA. This was used to determine, which factors play a major role and whether there is an interaction between the dimensions.



Room-A (4m×3m×3m) Room-B (9m×6m×3m) Room-C (18m×12m×3m)

Figure 4. Three ample of VR space

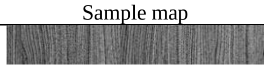
5.3. Participants

The researchers distributed questionnaires to recruit subjects at three universities in Shandong. The 120 participants were recruited, including 67 males and 53 females of Chinese han ethnicity, aged 18-29 years, with an average age of 24.8. Twenty-five of the students recruited were freshmen, twenty-six were sophomores, thirty-eight were juniors, and thirty-one were graduate students. All participants were given a little gift at the end of the data collection.

5.4. Wood texture identification and classification

We identified the textures of 24 common decorative woods in Shandong by GLCM. Then, the texture features were categorized into three dimensions using FWGR: density (Dense/Spare), resolution (clear/vague), and curvature (staright/curve). We finally identified the eight most representative woods in the three dimensions with each other: Northeast China ash, China-fir, tauari, sandal, dahurian larch, beeh, rubber wood, ayus (detial in Table 4). The eight woods were photographed and mapped in 2K HD, and their textures were highlighted in Photoshop to make the intersection of the three dimensions more visible.

Table 4. Texture features of the wood

No	Name	Latin name	Feature	Sample map
1	Northeast China ash	Fraxinus mandschuricaRupr	Dense×Clear×Staright	
2	China-fir	Pseudotsuga Gaussenii Flous	Dense×Clear×Curve	
3	Tauari	Courataríspp	Dense×Vague×Staright	
4	Sandal	Dalbergia bariensis	Dense×Vague×Curve	
5	Dahurian larch	Larix gmelinii (Rupr.) Rupr.	Spare×Clear×Curve	
6	Beeh	Fagussylvatica	Spare×Vague× Curve	
7	Rubber wood	Hevea brasHiensis	Spare×Clear×Staright	
8	Ayus	Triplochitonscleroxylon	Spare×Vague×Staright	

5.5. Result

Through the result of one-way ANOVA analysis (see Table 5), we found that among the 8 kinds of wood, NorthChina ash, sandal, and ayus have very significant aesthetic pleasure affected by the size of space, F=10.126/12.119, P_s<0.001. China-fir, beeh, more significant F=5.581/6.847, P_s<0.05, while the aesthetic pleasure of tauari is not affected by the size of the space, F=2.086, P=0.126. Similarly, the aesthetic pleasure of rubber wood was not significant, F=2.626, P=0.074.

Based on the results in Table 6, we performed pairwise comparsion (LSD) on 5 woods affected by spatial scale. The results showed that the participants' feedback on NorthChina ash's aesthetic pleasure was significantly different in Room-A (4×3×3 m) and Room-C (18×12×3 m) ($M_{Room\text{-}A}$=4.30, SD=1.20; $M_{room\text{-}C}$=3.83, SD=0.89), P＜0.001; There is also a significant difference between Room-B (9×6×3 m) and Room-C (18×12×3 m) ($M_{Room\text{-}B}$=4.450, SD=1.208; $M_{Room\text{-}C}$=3.83, SD=0.88), P<0.001.

Table 5. One way ANOVA analysis

Wood	Mean (SD) Room-A	Room-B	Room-C	F	Sig
NorthChina Ash	4.300(0.599)	4.450(1.208)	3.833(0.882)	10.126	0.000**
China-fir	4.525(0.458)	4.597(1.317)	4.091(1.522)	5.581	0.003*
Tauari	3.141(0.734)	3.150(0.785)	3.400(1.266)	2.086	0.126
Sandal	2.683(0.979)	2.725(1.122)	3.192(1.031)	8.739	0.000**
Dahurian larch	3.266(0.843)	3.142(1.042)	3.166(0.863)	0.439	0.645
Beeh	4.425(0.886)	4.908(1.359)	4.492(0.987)	6.847	0.001*
Rubber wood	2.975(0.983)	3.316(1.270)	3.200(1.313)	2.626	0.074
Ayus	5.125(0.352)	4.808(1.258)	4.375(1.115)	12.119	0.000**

Table 6. Results of pairwise comparsion

Wood	(I) Space	(J) Space	Mean difference (I-J)	Std. Error	Sig
NorthChina Ash	Room-A	Room-B	-0.150	0.14293	0.295
	Room-A	Room-C	0.467	0.14293	0.001*
	Room-B	Room-C	0.617	0.14293	0.000**
China-fir	Room-A	Room-B	-0.667	0.5832	0.647
	Room-A	Room-C	0.433	0.5832	0.007*
	Room-B	Room-C	0.500	0.5832	0.002*
Sandal	Room-A	Room-B	-0.042	0.1350	0.758
	Room-A	Room-C	-0.508	0.1350	0.000*
	Room-B	Room-C	-0.467	0.1350	0.001*
Beeh	Room-A	Room-B	-0.483	0.1416	0.001*
	Room-A	Room-C	0.667	0.1416	0.638
	Room-B	Room-C	0.467	0.1416	0.003*
Ayus	Room-A	Room-B	0.367	0.1526	0.039
	Room-A	Room-C	0.750	0.1526	0.000*
	Room-B	Room-C	0.433	0.1526	0.005*

Similarly, in the aesthetic pleasure of China-fir, Sandal, and Ayus, there were significant differences between Room-A and Room-B, P_s< 0.001; and Room-B and Room-C, P_s< 0.001. Only in the aesthetic pleasure of Beeh, the differences between Room-A and Room-B the differences were statistically significant between ($M_{Room\text{-}A}$=4.425, *SD*=0.886; $M_{Room\text{-}B}$=4.908, *SD*=1.359), P<0.001, and also between Room-B and Room-C ($M_{Room\text{-}C}$=4.492, *SD*=1.359), P<0.05.

Collectively, among the three types of spaces, Beech (Spare×Vague×Curve) has a relatively high aesthetic pleasure, M=4.425/4.908/4.492, SD=0.886/1.359/0.987; Ayus (Spare×Vague×Staright) also has an aesthetic rating close to Beautiful, M=5.125/4.808/4.375, SD=0.352/1.258/1.115. The aesthetic pleasure of North-China ash (Dense×Clear×Staright) and China-fir (Dense×Clear×Curve) is between indifference and beautiful (see Table 6). Compared with the wood whose average score belongs to ugly, the above woods have a fixed combination, that is, when the aesthetic pleasure of Spare×Vague is very likely to be defined as beautiful. Similarly, when the wood texture is Dense×Clear, it is judged as between Beautiful and Indifference. However, when the texture was Spare×Clear or Dense×Vague, the vast majority of participants gave an aesthetic rating of 3 or less.

We chose Room-B as the base line (detail in Table 7), and quantified the 8 types of wood into three dimensions: density (Dense/Spare), resolution (Clear/Vague), curvature (Staright/Curve), which were brought into more than 3×3 factor analysis of variance. The results in Table 7 showed that only Dense had a significant effect on the evaluation of aesthetic pleasure, F=16.54, p<0.001, η^2=0.017; the effect of resolution on aesthetic pleasure was not statistically significant, F=0.088, p=0.776, η^2=0.001; Similarly, the effect of curvature on aesthetic pleasure is not statistically significant, F=1.341, p=2.471, η^2=0.001.

Table 7. Tests of between-subjects effects

Source	Type III sum of squares	Df	Mean square	F	Sig	η^2
Corrected model	657.566a	7	93.938	65.417	.000**	.325
Intercept	14500.376	1	14500.376	10097.856	.000**	.914
Density	23.751	1	23.751	16.540	.000**	.017
Resolution	.126	1	.126	.088	.767	.001
Curvature	1.926	1	1.926	1.341	.247	.001
Density * Resolution	619.209	1	619.209	431.209	.000**	.312
Density * Curvature	.651	1	.651	.453	.501	.000
Resolution * Curvature	1.276	1	1.276	.889	.346	.001
Density * Resolution * Curvature	10.626	1	10.626	7.400	.067	.008

5.6. Discussion

Researchers constructed three types of virtual spaces and determined differences in the aesthetic pleasure of wood textures within them. We found that the effect of wood texture on aesthetic feedback decreases as the space becomes larger. In small spaces (Room-A: 4×3×3 m), participants were more consistent in their aesthetic scores. While in medium space (Room-B: 9×6×3 m) and large space (Room-C: 18×12×3 m), the difference is relatively large. It is worth noting that the differences in the scores of the same wood texture among the three types of spaces are mainly concentrated between small spaces and other medium and large spaces, while the difference between large spaces and medium spaces is not statistically significant.

In the multivariate ANOVA we found that only dense have a statistically significant effect on aesthetic pleasure among the three dimensions of texture, in which there was an interaction between Dense and Resolution. Specifically, spare×vague is the most preferred mode by participants, and most individuals rated between beauty and indifference when dense×clear was present. However, when the combination of spare×clear or dense×vague occurred, the participants' aesthetic evaluation of such woods was generally relatively low. We argue that the individual's sense of pleasure for wood textures, more inclined to the continuity of the fluidity, which enhances the perception of grouped information, creates order and guides the individual through different content subdivisions. When tight wood ray is too vague, it will make the whole texture look messy and irregular (e.g. Tauari). However, a tight but clear line will make the material appear more fluid and neater. Likewise, when wood ray appears heavily curved (e.g. parabolic, spiral, wave pattern), soothing spaces and proper spacing will not allow individuals to fall into particular shapes.

6. CONCLUSION

In order to explore the factors that affect the aesthetics of wood, we designed two experimental studies. One is a multivariate ANOVA of wood color and aesthetic composition, and the other is a regression analysis of wood texture on aesthetic composition. In terms of colour, lightness of wood is not the key to aesthetic pleasure. However, unlike in Alaska, Madagascar and Norway, the participants' underlying logic for wood color seems to be similar to the color of Huanghua pear and red sandal wood, that is, the closer the color is to these two woods, the higher the aesthetic pleasure. Certainly, this does not prevent some participants from preferring the heavy brown of black walnut and the tawny of Cherry wood. In light of this, from the perspective of interior space, this research result supports

This phenomenon at least shows that for young people (18-27 years old) in Shandong, the influence of regional culture still takes priority in the relationship between wood color and aesthetic pleasure. Therefore, the researcher speculated that perhaps the cultural symbols represented by wood color occupy the main logic for aesthetic pleasure, which is an important factor not taken into account in the previous related studies.

In terms of texture, we found that the size of the space can influence the individual's preference for texture. Within the minor space (4×3×3 m), individuals were more conscious of the details in the texture. Whereas within medium spaces (9×6×3 m) and large spaces (18×12×3 m), individuals are influenced by the spatial scale, allowing them to focus on the overall movement of the texture. When the wood ray pattern is continuous and clear, individuals' perception of its smoothness is reinforced; whereas, when a fuzzy and intermittent pattern appears, individuals do not pursue linear smoothness, but instead focus on overall uniformity. Thus, the aesthetic preference for wood texture in this study follows the continuity and balance of previous studies of gestalt.

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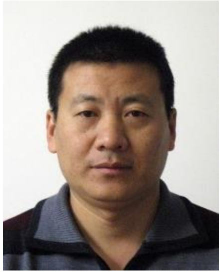
BIOGRAPHIES OF AUTHORS

Zetian Dai presently pursuing Ph.D from UCSI University in Faculty of Social Sciences and Liberal Arts. His research focuses on creativity and aesthetics in the pedagogy, which mainly quantifies creative development for students through the algorithm. He can be contacted at e-mail: daydzt@163.com.

Juan Xue graduated from Soochow University with a PhD in Design Art. Currently she is a professor at the School of Art, Soochow University of Science and Technology. She was formerly the Dean in the School of Art at Shandong Jianzhu University. In recent years she has engaged in interdisciplinary research between software engineering and art-and-design. She can be contacted at e-mail: 15806639626@163.com.



Shoushan Wang received M.S. in Software Engineering from the Sichuan University in 2010. Currently, he workingasan Associate Professor in Jinan Preschool Education College, and engaged in art design and image processing teaching. He can be contacted at e-mail: shoushanwang@126.com.