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A Study on the Emotional Evaluation of Fabric Color Patterns

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Abstract : There are two new models developed for objective evaluation of fabric color patterns by applying a multiple regression analysis and an adaptive fuzzy-rule-based system. The physical features of fabric color patterns are extracted through digital image processing and the emotional features are collected based on the psychological experiments of Soen[3, 4]. The principle physical features are hue, saturation, intensity and the texture of color patterns. The emotional features are represented thirteen pairs of adverse adjectives. The multiple regression analyses and the adaptive fuzzy system are used as a tool to analyze the relations between physical and emotional features. As a result, both of the proposed models show competent performance for the approximation and the similar linguistic interpretation to the Soen's psychological experiments.

Key words : objective evaluation, fabric color patterns, multiful regression analysis, adaptive fuzzy-rule-based system, digital image processing, hue, saturation texture, emotional evaluation

1. Introduction

Studies[1, 2] have shown that the color arrangement corresponds to human feelings and can be used for color planning. Soen[3, 4] has tried to analyze the human feeling objectively when those see color patterns. Soen has constructed 30 random color patterns in order to test the human response. There are two different types of color patterns: the first one is 18 patterns with various hue, the equal average brightness and dot sizes(4×4) and the second one is 12 patterns with various brightness, dot sizes(2×2, 4×4, 8×8) and the equal average hue. Therefore, the 18 patterns are distributed on the hue hexagonal plane with middle brightness and the other 12 patterns are on the line of black and white in RGB color space in order to test the human response against the hue distribution and degree of brightness.

He performed the psychological experiments with 31 competent persons in order to evaluate color effects to human feelings. The 13 emotional features to express human feelings include 'like-dislike', 'beautiful-ugly', 'natural-unnatural', 'dynamic-static', 'warm-cold', 'gay-sober', 'cheerful-dismal', 'unstable-stable', 'light-dark', 'strong-weak', 'gaudy-plain', 'hard-soft', and 'heavy-light'. He summarized the results from psychological experiments that the emotional features of human might be expressed by the average hue, average brightness and the dot size of color patterns. The results of psychological experiments are shown in Figure 1. The diameters of the circles in this figure are proportional to the numbers obtained by subtracting 2 from the psychological evaluation values.

In order to quantify the results shown in Figure1, Soen has also constructed a model using the multiple regression analysis. The model takes the physical features extracted from fabric color

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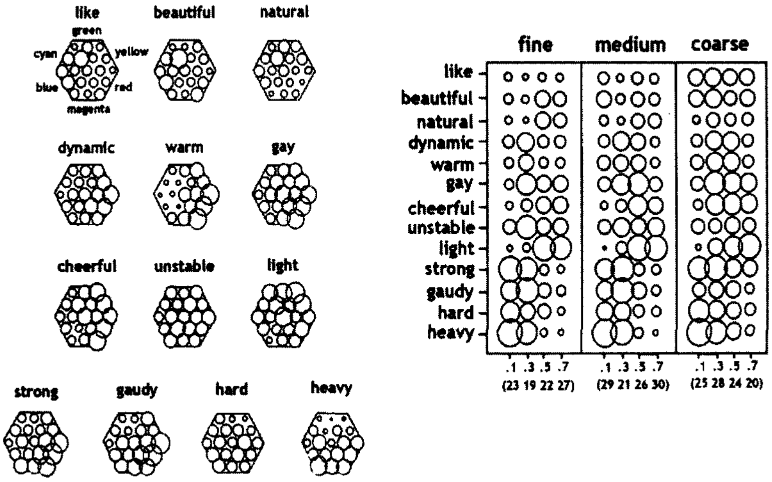

Fig. 1. The Effects of Color, Dot Size and Intensity on the Psychological Evaluation

patterns as input variables and provides output grades on 13 emotional features. The model uses the CIE-LUV color space[5]. The physical features include the average color components $\overline{L^*}, \overline{u^*}, \overline{v^*}$ and the energies D_L, D_M, D_H in the low, medium, and high frequency bands of the Fourier domain. The model converts them into 13 emotional features. There are, however, several problems in the model since he included all six physical features and 2^{nd} and 3^{rd} order of those for predicting the 13 emotional features without variable selecting process [6]. Therefore, the model can not single out the significant variables for predicting the 13 emotional features. In this study, we describe the physical features of the fabric color patters based on different color spaces and convert into emotional features using different modeling approaches to overcome these shortcomings.

2. Physical Features of Fabric Color Patterns

We can assume that the relationships among the average hue, the dot size and emotional features follow the linguistic rules. Based on Soen's work[3, 4], humans feel "warm", as the average hue becomes close to red while those feel "like" as the average hue become close to blue. Similarly, the relationships between average brightness and emotional features follow the linguistic rules. The humans feel "light," as the average brightness becomes higher. According to these rules, the input variables can be average hue, brightness and the dot size in the model which can evaluate the human emotional features. We have used HSI color space[5] in which each of red, blue and green can be transformed into hue(H), intensity(I) and saturation(S) since HSI works better for human eyes system than the RGB system. Hue is an attribute associated with the dominant wavelength in a mixture of lightwaves. So actually the dominant color that human observe is the hue. Saturation tells the amount of white light mixed with a hue. The brightness of an object is its intensity. High intensity means that it is very bright, while a darker image has lower intensity. HSI color space is very useful because human vision system looks at the objects in this way, i.e., it recognizes the hue and saturation. On the other hand, I is decoupled from the other two parameters in an image. The RGB

Table 1. 100% HSI Color Values, V_a and V_b

	White	Yellow	Cyan	Green	Magenta	Red	Blue	Black
H	-	60°	180°	120°	300°	0°	240°	-
S	0	1	1	1	1	1	1	0
Va	0	0.5	-0.5	-1	-0.5	1	-0.5	0
Vb	0	0.866	0.866	0	-0.866	0	-0.866	0

color space is transformed into HSI color space[5] as follows.

$$\frac{1}{3}(R+G+B) \quad (1)$$

$$\frac{3}{(R+G+B)}[\min(R,G,B)] \quad (2)$$

$$\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)^{\frac{1}{2}}\right]}\right\} \quad (3)$$

Accordingly, HS plane corresponds to hue hexagonal plane in HSI color space in Figure 2. A certain point inside the HS plane, P, represents color. We define a vector p that starts from origin to P. H, the hue of the color point P is given by angle between the vector p and the red axis. S, the saturation of the color point P is proportional to the distance from the point P to the center of the HS plane. If we draw a line perpendicular to the surface of the HS plane and going through the

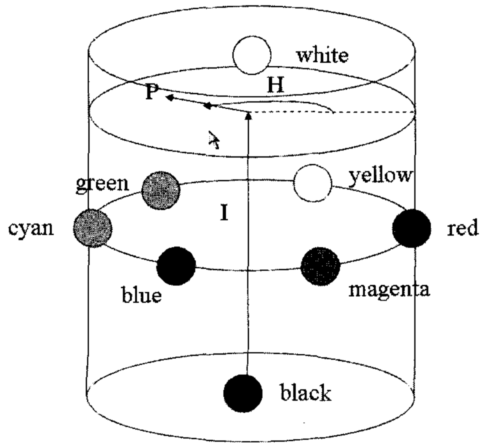

Fig. 2. HIS Color Space

center, this line represent I, the intensity of the color point P. For convenient modeling, we transformed HS plane into polar coordinate system represented by V_a and V_b,

$$V_a = S \cdot \cos H \quad (4)$$

$$V_b = S \cdot \sin H \quad (5)$$

where, $0° \leq H \leq 360°$, $0 \leq S \leq 1$, $0 \leq \sqrt{V_a^2 + V_b^2} \leq 1$.

In Table 1, the V_a is the biggest around red and smallest around green while V_b is the biggest around yellow and cyan and smallest around magenta and blue.

For the effects of texture, we can also assume that the relationships between the texture and human emotional features follow the linguistic rules. For example, humans feel "like" as the dot size become coarser. In other word, humans feel "like" as the fabric color pattern looks sparser. Accordingly, we quantified the texture, degree of coarse or sparse, for fabric color patterns using GLRLM(Gray Level Run Length Matrix)[7]. Let the GLRLM be

$$\text{GLRLM}(m,n) = \text{Card}[\{(i,j) \in \wedge_{MN} \mid I(i,j) = m, \tau(M,\theta) = n\}] \quad (6)$$

where $\wedge_{MN}$ is $M \times N$ matrix, $I(i, j)$ is the value of pixel placed in i, j of matrix, $\tau(M, \theta)$ is the run-length of pixel, m, in the direction of θ, and card is the cardinality of the set. In order to remove the directional properties, the GLRLMs were averaged in the direction of 0°, 45°, 90°, 135° and the run-lengths were normalized such that the sum of the run-lengths become 1. In this matrix, the fabric patterns look brighter where the GLRLM

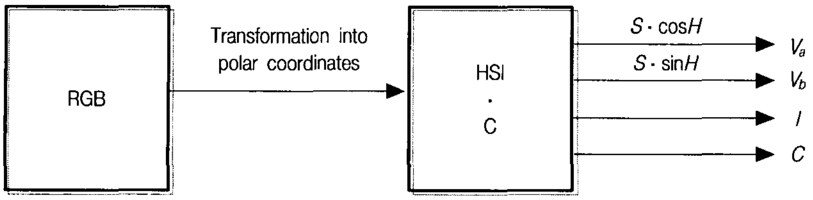

Fig. 3. Extraction of Physical Features in HSI Color Space

value is large for the large *m*. And the fabric patterns look sparser where the GLRLM value is large for the large *n*. Finally, the texture value *C* is defined as a scalar, SRE(Short Run Emphasis). Let SRE be

$$\text{SRE} = \sum_m \sum_n GLRLM(m, n)/n^2 \tag{7}$$

From the equation 7, the SRE of patterns becomes smaller as the run-length becomes larger. Therefore, the SRE is smaller with sparser patterns and vice versa. Figure 3 shows the procedure of extracting physical features from RGB color patterns. For this study, four different physical features from Soen's work[3, 4] are used for evaluating emotional features.

3. Conversion of the physical Features to Emotional Features

In evaluating the relationships between physical features and emotional features, we proposed two different prediction models, a multiple regression analysis and an adaptive fuzzy system.

The newly defined physical features, V_a, V_b, I, C, were used as predictor variables and 13 emotional features as response variables for the multiple regression analyses. We ran stepwise multiple regression analyses using the SAS® system.

$$\begin{aligned} Y_i = {} & C_{i1} + C_{i2}V_a + C_{i3}V_b + C_{i4}V_{a2} + C_{i5}V_{b2} \\ & + C_{i6}V_{a2}V_b + C_{i7}V_aV_{b2} + C_{i8}V_a^3 + C_{i9}V_b^3 \\ & + C_{i10}I + C_{i11}C + C_{i12}I_2 + C_{i13}C_2 \end{aligned} \tag{8}$$

where Y_i represents a regression equation of the ith emotional feature of 13 descriptive scales based on "hue" and "saturation," and Y_i represents a regression equation based on "intensity" and "texture." The equation 8 includes the second- and third-order terms of the variables V_a and V_b, because the effects of hue and saturation were more sensitive than the other variables.

Figure 4 shows the block diagram for the conversion of the physical features to the emotional features using adaptive fuzzy system. For the conversion of the physical features to the emotional features, two control rules are applied. Each control rule Ri is of the form:

$$R_i : \text{If } V_a \text{ is } \begin{bmatrix} positive \\ zero \\ negative \end{bmatrix} \text{ and } V_b \text{ is } \begin{bmatrix} positive \\ zero \\ negative \end{bmatrix},$$

$$\text{then } EV_1^i \text{ is } \begin{bmatrix} High \\ Middle \\ Low \end{bmatrix} \tag{9}$$

$$R_i : \text{If } I \text{ is } \begin{bmatrix} positive \\ zero \\ negative \end{bmatrix} \text{ and C is } \begin{bmatrix} positive \\ zero \\ negative \end{bmatrix},$$

$$\text{then } EV_2^i \text{ is } \begin{bmatrix} High \\ Middle \\ Low \end{bmatrix} \tag{10}$$

where EV_1^i and EV_2^i are i^{th} control outputs for the i^{th} emotional feature. In order to merge the two control outputs, we have used the γ model and a fuzzy set operator.

Table 2. Multiple Regression Analyses Results

Emotional Features	Regression Model	R^2
Like-Dislike	$Y_1 = 4.20 - 2.61\ C$	0.2300
Natural-Unnatural	$Y_3 = 3.09 - 1.75\ V_a - 2.42\ V_a\ 3 + 1.01\ V_b^3 + 2.80\ V_a V_b^2 + 1.01\ I$	0.5920
Dynamic-Static	$Y_4 = 3.94 + 0.709\ V_a + 1.67\ V_a^2\ V_b$	0.4480
Warm-Cold	$Y_5 = 3.85 + 1.63\ V_a$	0.6150
Gay-Sober	$Y_6 = 4.30 + 0.896\ V_a$	0.3690
Cheerful-Dismal	$Y_7 = 2.76 + 0.673\ V_a + 1.43\ V_b^3 + 5.12\ I - 4.48\ I^2$	0.6370
Unstable-Stable	$Y_8 = 3.89 + 0.294\ V_a + 1.28\ C$	0.2910
Light-Dark	$Y_9 = 2.40 + 0.998\ V_b + 3.88\ I$	0.7710
Strong-Weak	$Y_{10} = 5.20 + 1.10\ V_a - 1.92\ I^2 - 4.84\ IC$	0.7370
Gaudy-Plain	$Y_{11} = 4.69 + 1.25\ V_a - 2.14\ I^2$	0.5960
Hard-Soft	$Y_{12} = 4.93 - 1.14\ V_b^3 - 2.17\ I$	0.6880
Heavy-Light	$Y_{13} = 6.11 + 0.899\ V_a - 1.14\ V_b - 4.49\ I$	0.8150

3.1 Evaluation Based on Multiple Regression Analyses

Table 2 shows the results of stepwise regression analyses. We included input variables only which have statistical significance (p-value $\leq$ 0.05). The p-value means that the smaller p-value, the stronger sample evidence that the alternative hypotheses ($C_{ij} \neq 0$) are true.

It is interesting that "warm," "natural," and "dynamic" are affected by hue more than intensity and texture. The effects of intensity are great on "cheerful," "light," "hard," and "heavy." For "like" and "unstable," texture shows significant effects.

It is apparently shown that sparse texture enhances "like" while dense texture enhances "unstable." As the hue approaches around red, "dynamic," "warm," "gay," "cheerful," "strong," "gaudy," and "heavy" are enhanced. The "unstable" is also enhanced slightly since the correlation coefficient is small. Only "natural" is enhanced around blue and cyan and "light" is enhanced around yellow or cyan. Therefore, the V_a is the most significant contributing factor for emotional features. The brighter intensity enhances "natural," "cheerful," and "light" while shows negative effects on "hard," "heavy," and "strong," and "gaudy." Accordingly, "heavy," "strong," and "gaudy" enhances around dark red. The results from the multiple regression analyses are in consistency with Soen's results [3] given in Figure 1.

Soen has used 13 predictor variables for multiple regression analyses regardless of p-value. Therefore, R^2s for his model show higher than those of the proposed model. The R^2s for proposed model are reasonable considering the number of predictor variables since the R^2 becomes higher as the number of predictor variables increases.

3.2 Evaluation Based on an Adaptive Fuzzy System

Adaptive Fuzzy System

In this study, the fuzzy rule-based system consists of two control rules, membership function, and inference procedure as shown in Figure 4. The first control rule was designed from the 6 hues in hexagonal plane in Figure 2 and grey and the second control rule was designed from the distribution in I, C plane. The output of the adaptive fuzzy system used for product inference, fuzzifier, center average defuzzifier [8] is as follows,

$$f(x)=\frac{\sum_{i=1}^{n} \bar{y}^{l}\left(\prod_{i=1}^{n}\mu_{F_i^l}(x_i)\right)}{\sum_{i=1}^{n}\left(\prod_{i=1}^{n}\mu_{F_i^l}(x_i)\right)} \tag{11}$$

where $\bar{y}^{l}$ is the maximum of $\mu_{F_i^l}$, $\mu_{F_i^l}(\bar{y}^{l})=1$.

The membership function is defined as a Gaussian function,

$$\mu_{F_i^l}(x_i)=a_i^l\exp\left[-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)^2\right] \tag{12}$$

where a_i^l, $\bar{x}_i^l$, σ_i^l are the adjustable parameter. The equation 11 is replaced by equation 12,

$$f(x)=\frac{\sum_{i=1}^{M}\bar{y}^{l}\left[\prod_{i=1}^{n}a_i^l\exp\left[-\left(\frac{x_i-\bar{x}_i^l}{\sigma_i^l}\right)^2\right]\right]}{\sum_{i=1}^{M}\left[\prod_{i=1}^{n}a_i^l\exp\left[-\left(\frac{x_i-\bar{x}_i}{\sigma_i^l}\right)^2\right]\right]} \tag{13}$$

Therefore, the fuzzy system is useful for modeling nonlinear system in the point of approximation. As mentioned above, EV_1 and EV_2 are fuzzy outputs through Equation 13 for evaluating emotional features ranging from 7 to 1. Therefore, these are not appropriate for inputs of the γ-model. Accordingly, these were normalized by subtracting 1 from each data point and then dividing the differences by 6. The normalized EV_i is denoted by x_i and used for input for γ-model.

γ-model

The γ-model developed by Zimmermann and Zysno is a fuzzy set operator consisting of intersection and union,

$$y=\left(\prod_{i=1}^{n}x_i^{\delta_i}\right)^{1-\gamma}\left(1-\prod_{i=1}^{n}(1-x_i)^{\delta_i}\right)^{\gamma}$$

$$\begin{cases}\sum_{i=1}^{M}\delta_i=n,\\ 0\le\gamma\le1\\ \prod_{i=1}^{n}x_i^{\delta_i}:\cap\,operator\\ 1-\prod_{i=1}^{n}(1-x_i)^{\delta_i}:\cup\,operator\end{cases} \tag{14}$$

where x_i is an input value for decision making, δ_i is a weight for x_i, $0\le x_i\le 1$, and γ is a parameter representing the degree of compensation between union and intersection operation.

The γ-model is a monotonically increasing function for γ, $(x_{\min})^n\le\gamma\le 1-(1-x_{\min})^n$. Here, $x_{\min}$ is $\min(x_1, \cdots, x_n)$ and $x_{\max}$ is $\max(x_1, \cdots, x_n)$ [8]. Accordingly, γ-model works as union operator, intersection operator or compensation operator according to γ, and has similar feature to human's decision making process.

In this study, the γ-model has used for deciding the weight δ_i and the type of operator, γ for fusing the EV_1 and EV_2.

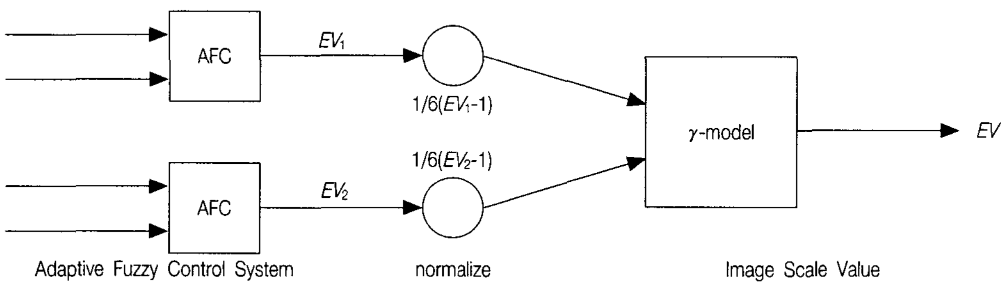

Fig. 4. Transform of Physical Features into Emotional Features Using the Adaptive Fuzzy System and γ-Model

Fuzzy Training Algorithm

For the proposed fuzzy model, we determined the parameters, a_i^l, $\overline{x_i^l}$, σ_i^l, $\overline{y^l}$, δ_j, and γ through training based on the Soen's psychological experimental data[3, 4]. The performance of the model was evaluated by the square sum error of the differences between the emotional features from Soen's psychological experiment and the predicted values, EV, from the model,

$$\sum_{k=1}^{N}\left(f_k - Y_k\right)^2 \begin{cases} k: \text{input pattern number} \\ N: \text{total pattern number} \\ f_k: \text{aggregation function} \\ Y_k: \text{desired output} \end{cases} \tag{15}$$

The parameters were determined using gradient descent methods[9, 10] to minimize the square sum error given in the above equation. Let, the a_i^l in the fuzzy membership function from Equation 12 be 1. Also, the number of rules for each fuzzy system is 7, let the initial values of the γ-model be δ_j = 1.0 and γ = 0.5, and trained until the square sum error becomes within the range from 0.00001 to 0.1. The parameters for γ-model are shown in Table 3. The γ values range from 0.334 to 0.807 which means that the compensation operator used for fusing EV_1 and EV_2. For "beautiful," "dynamic," "warm," and "cheerful," the effects of hue and saturation are greater than those of intensity and texture. The intensity and texture affect "heavy" and "light" more than hue and saturation. These results agree well with those of regression analyses partially.

3.3 Multiple Regressions Vs. Adaptive Fuzzy System Approach

The results from multiple regression analyses were compared with those from adaptive fuzzy system. The performances of two approaches were evaluated by two ways: one is to compare the approximation capability using the 30 random color patterns and the other is to compare the practical applicability using 5 real fabric color patterns.

The performance of the models for random color pattern was evaluated using correlation coefficients (r) given in Table 4. The adaptive fuzzy system shows better performance than multiple regression analyses with respect to correlation coefficients. However, the multiple regression analyses models explain the Soen's psychological experimental results given in Figure 1 better than the adaptive fuzzy approach. The multiple regression models show the good capabilities to single out the significant variables for predicting the 13 emotional features.

A brief experiment was performed by using 5 real color patterns to examine the practical applicability of the above models. Five patterns shown in Figure 5 were used for this experiment. The r, g, b intensities of each pixel were transformed into H, S, and I parameters, and the texture value C were calculated from GLRLM. The

Table 3. Parameters for γ-model

parameter	like-dislike	beautiful-ugly	natural-unnatural	dynamic-static	warm-cold	gay-sober	cheerful-dismal
γ	0.64	0.62	0.54	0.48	0.64	0.37	0.50
δ_{VaVb}	1.03	1.31	1.13	1.16	1.11	1.04	1.15
δ_{IC}	0.97	0.69	0.87	0.84	0.89	0.96	0.85
parameter	unstable-stable	light-dark	strong-weak	gaudy-plain	hard-soft	heavy-light	-
γ	0.54	0.33	0.81	0.46	0.79	0.74	-
δ_{VaVb}	0.98	0.92	0.94	0.96	0.94	0.86	-
δ_{IC}	1.02	1.08	1.08	1.04	1.06	1.14	-

Table 4. Correlation Coefficients for two models

Emotional Features	Multiple Regression Analyses	Adaptive Fuzzy System
Like-Dislike	0.480	0.985
Beautiful-Ugly	-	0.980
Natural-Unnatural	0.769	0.998
Dynamic-Static	0.669	0.999
Warm-Cold	0.807	0.998
Gay-Sober	0.607	0.999
Cheerful-Dismal	0.798	0.985
Unstable-Stable	0.539	0.967
Light-Dark	0.878	0.999
Strong-Weak	0.858	0.981
Gaudy-Plain	0.772	0.996
Hard-Soft	0.829	0.998
Heavy-Light	0.902	0.996

four values were substituted in equations given in Table 1 for multiple regression models and into input values in Figure 3 for the adaptive fuzzy system trained using random color patterns. The predicted emotional features were calculated using the two models.

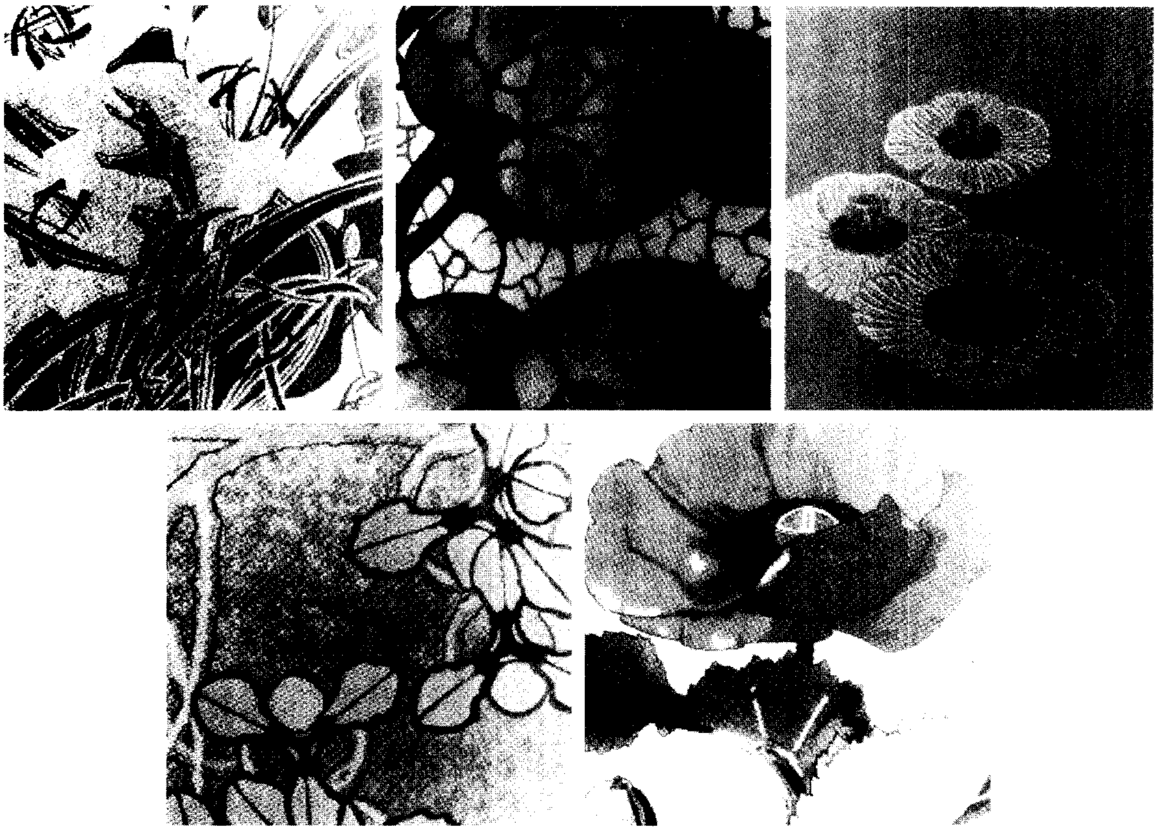

Fig. 5. Real Fabric Color Patterns

Table 5. The number of patterns within the 1σ of Actual Evaluated Values

Emotional Features	Multiple Regression				Adaptive Fuzzy System			
	0.3σ	0.5σ	0.7σ	1σ	0.3σ	0.5σ	0.7σ	1σ
Like-Dislike	0	0	2	3	1	2	4	5
Beautiful-Ugly	-	-	-	-	2	2	3	3
Natural-Unnatural	1	1	2	4	1	2	3	4
Dynamic-Static	3	3	3	4	1	2	3	3
Warm-Cold	1	1	2	2	0	0	0	1
Gay-Sober	0	1	3	4	0	0	3	3
Cheerful-Dismal	0	0	1	2	0	1	1	2
Unstable-Stable	2	2	3	5	2	2	5	5
Light-Dark	2	2	2	3	0	0	0	1
Strong-Weak	1	2	3	4	4	4	4	4
Gaudy-Plain	2	3	4	5	1	3	4	5
Hard-Soft	1	2	3	5	1	1	4	5
Heavy-Light	2	2	4	4	0	0	2	4

On the other hand, the emotional features for these patterns were evaluated by six examinees. The averages and standard deviations were calculated for each emotional feature. In order to compare the actual evaluated emotional features with the calculated values, the number of patterns was counted within 0.3, 0.5, 0.7 and 1 standard deviations. The results are shown in Table 5.

For "like," "unstable," "gaudy," and "hard," both models show remarkable predictabilities. The results using multiple regression models for "Dynamic," "Warm," "Gay," and "Light" show better practical applicability than those using fuzzy system. For "Like" and "Beautiful," the fuzzy system show better performance.

4. Conclusion

In this paper, we proposed the two objective evaluation approaches using hue(H), saturation(S), intensity(I) and the texture(C) based on the multiple regression analyses and adaptive fuzzy system, which can transform the physical features of a fabric color pattern to the emotional features. The Adaptive fuzzy system was compared to the multiple regression analyses. The performance of the models was evaluated with respect to approximation capability using random color patterns and practical applicability using real fabric color patterns.

The adaptive fuzzy system show better approximation capability than the multiple regression analyses. There are, however, advantages in the multiple regression analyses which can single out the significant physical features for each of 13 emotional features. The results from the multiple regression analyses show better agreement with those from Soen's psychological experiments.

Considering practical applicability, multiple regression models show better predictabilities for "dynamic," "warm," "gay," and "light" than the adaptive fuzzy system even though the correlation coefficients of multiple regression models were lower than those of the fuzzy models for these emotional features. This means that the correlation coefficients may not be the most significant factor to determine the predictability of the model. For "Like" and "Beautiful," the fuzzy system show better performance. In both approaches, it is important to single out the significant physical features using HSI color space and develop prediction models for emotional features. These models might be useful for emotion-based retrieving and designing fabric color patterns.

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