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「人工感性」システムの実現を指向した多色配色の美的感性をもつ計算モデルの構築

Construction of an Artificial KANSEI System Simulating the Mental Function of Multi-Color Aesthetic Evaluation

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In this research, we constructed an artificial KANSEI system simulating the mental function of multi-color aesthetic evaluation through back-propagation neural network. Helmut Leder's psychological model served as the theoretical framework. We determined the macro-structure of the system via two psychological experiments using Semantic Differential method. The aesthetic score of a multi-color stimulus was defined as its factor score on "Pleasure" factor extracted in the first experiment, and the three factors extracted in the second experiment, i.e. "Staticness", "Turbidity" and "Heaviness", were regarded as simple physical visual features. Then, the number of hidden-layer nodes, the learning rate and the momentum constant of each neural network were optimized by genetic algorithm. Finally, the satisfactory performance of the system in two simulation tests suggests that the system possesses a high predicting power to the aesthetic score of any 4*4 grid multi-color stimulus.

1. Introduction

This research aims to construct an artificial KANSEI system simulating the sense of beauty to multi-color objects by approximating the mapping relationships between the primary color information of multi-color objects and the aesthetic evaluation. Being a hybrid of a psychological approach and a computational approach to the topic of multi-color aesthetics, this research can be expected to shed new light on the study of the enigmatic psychological mechanism of multi-color aesthetic evaluation and at the same time make a contribution to the field of KANSEI (affective) engineering by offering a computing tool of automatic aesthetic evaluation to multi-color objects.

The theoretical framework of this research is Helmut Leder[Leder 04]'s psychological model. According to this model, during the psychological process of multi-color aesthetic evaluation, the primary color information of a multi-color stimulus is firstly transformed into several simple physical visual features in the Perceptual Analyses Stage of the visual information processing module, and then, the results of the information processing in this module serve as the inputs into the affective evaluation module. The output of the affective evaluation module is the aesthetic evaluation to this stimulus. Figure 1 is a scheme of Leder's psychological model.

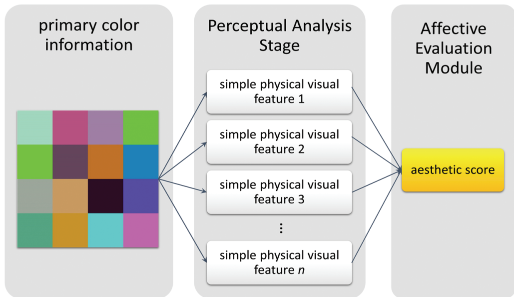

Figure 1: A scheme of Leder's psychological model

The whole research is composed of three stages: The first stage is the conduction of two psychological experiments using Semantic Differential (SD) method. The second stage is the building of the artificial KANSEI system using back-propagation neural network based on the empirical data obtained from the two experiments. The third stage is two simulation tests of the predicting power of the system. (The construction and the simulations of the system were implemented on MATLAB.)

2. Research Background

Multi-color aesthetics has been a topic in computer science for several decades, especially in the areas of artificial intelligence, KANSEI engineering (affective computing) and digital image processing. We define the concept "computational multi-color aesthetics (CMCA)" as the research field which employs modern computational technology to study and (or) apply the psychological principles concerning multi-color aesthetics. Generally speaking, there are two main approaches in CMCA:

The first approach is an exploratory one, trying to extract the psychological rules regarding multi-color aesthetics by machine learning techniques, e.g. artificial neural network, support vector machine or boost algorithms. Its typical pro-

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cedure is like this: Firstly, a set of primary color features of multi-color images are determined. Then, the mapping relationships between these features and the aesthetic score are extracted through a certain machine learning technique on the basis of a training set of multi-color images with their aesthetic scores labelled by human subjects. Most of the studies taking this approach are targeted to construct an automatic aesthetic evaluation system or an image classifier system. The researches [Gedeon 08], [Matsuura 08] and [Ogawa 11] exemplify this approach.

The second approach is an implementary one which quantifies or directly practices some existing theory on multi-color aesthetics such as Moon & Spencer's theory and Ou & Luo's theory. Oftentimes, in the studies taking this approach, the application of a certain theory on multi-color aesthetics functions as an auxiliary module working to automatically assess the aesthetic scores of multi-color images in integrated systems whose aims, in most cases, are to promote the automation in industry design, software (or website) user-interface design or color education. The typical examples of this approach are [Meier 88], [Cohen-Or 06] and [Hsiao 08].

The present research is intended to construct a computing system simulating the unknown mental mechanism of multi-color aesthetics through the extraction of the regulations hidden in experimental data by artificial neural network, rather than using an existing theory. Therefore, this research can be categorized to the first approach, i.e. the exploratory approach, in CMCA.

3. Experiment I

The first experiment aims to quantify the concept "aesthetic evaluation" in Leder's model. 35 computer-generated 4*4 grid multi-color squares (400*400 pixels) were employed as the experimental stimuli. The component colors of every stimulus were randomly determined in RGB color space. The multi-color square in the leftmost block in Figure 1 is one example of them.

In order to avoid the fatigue effect, this experiment was divided into two sessions carried out independently. 8 subjects (6 males & 2 females, aged from 20 to 22) participated in the first session where 20 stimuli were used. 12 subjects (8 males & 4 females, aged from 20 to 24) took part in the second session where the rest 15 stimuli were used. The subjects were asked to evaluate the stimuli on 24 adjective pairs selected from a number of past researches on affective effects of color. (To see a detailed description of the experimental procedures, please refer to our previous paper[Fang 15].)

The evaluation data on these adjective pairs with regard to each stimulus were averaged across the subjects, and then imported into the factor analysis package of IBM SPSS Statistics (version 19). Three main factors "Activity", "Pleasure" and "Potency" were extracted. Based on Osgood[Osgood 62][Osgood 69]'s interpretation of Pleasure factor, namely the factor conventionally named as "Evaluation", we define the aesthetic score of a multi-color stimulus as the inverse of its factor score on Pleasure factor.

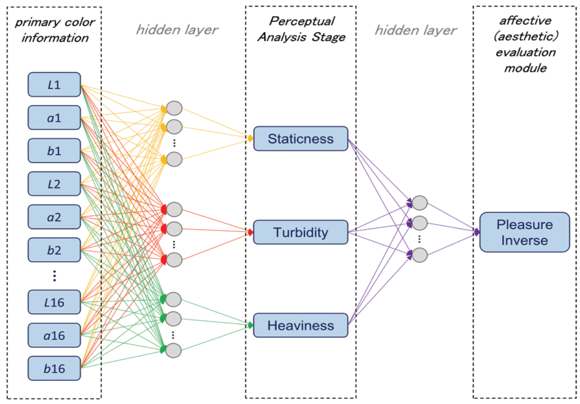

Figure 2: Macro-structure of the artificial KANSEI system

4. Experiment II

The second experiment is devised to specify and quantify the simple physical visual features into which the primary color information of multi-color stimuli is transformed.

The same multi-color stimuli employed in Experiment I were used in this experiment. Like Experiment I, this experiment was also divided into two sessions conducted independently. 15 subjects (11 males & 4 females, aged from 20 to 24) took part in the first session where 20 stimuli were used. 12 subjects (8 males & 4 females, aged from 20 to 24) participated in the second session where the rest 15 stimuli were used. An adjective pair list we created in a previous pilot study[Fang 15] was used in this experiment. This list contained 45 adjective pairs all concerning physical visual aspects of color image. After the completion of the experiment, the Cronbach's α coefficient of every adjective pair, averaged across the two sessions, was calculated. The evaluation data on those adjective pairs with this coefficient higher than 0.60 (which means relatively high subject-wise consistency) were imported into the factor analysis package.

Three main factors "Staticness", "Turbidity" and "Heaviness" were extracted. Each of them is regarded as representing a simple physical visual feature, and the corresponding feature values of a multi-color stimulus are defined as its factor scores on the three factors.

5. System Structure

As shown in Figure 1, this psychological model is composed of three levels: primary color information as the first level, simple physical visual features as the second level, and aesthetic evaluation as the third level. We chose to use 3-layer back-propagation neural network (BPNN) to undertake the inter-level connections. Thus, the artificial KANSEI system built in this research is a hierarchical BPNN system the macro-structure of which is shown in Figure 2.

As demonstrated in Figure 2, the system takes a 2-level structure. The first level consists of three parallel BPNNs.

The first BPNN (called "BPNN 1" for short) works to transform the primary color information of a multi-color stimulus, defined as the *Lab* values (CIE 1976 L*a*b* Color Space) of the component colors of the stimulus, into the visual feature "Staticness". BPNN 1 has 48 input nodes corresponding to the *Lab* values of every component color of the stimulus, and its sole output node simulates its factor score on Staticness factor. The second BPNN (called "BPNN 2" for short) serves to map the primary color information of a multi-color stimulus to the visual feature "Turbidity". The input nodes of BPNN 2 are the same as those of BPNN 1, and the sole output node of BPNN 2 simulates the factor score of the stimulus on Turbidity factor. The function of the third BPNN (called "BPNN 3" for short) is to transform the primary color information of a multi-color stimulus to the visual feature "Heaviness". BPNN 3 shares the same input nodes with BPNN 1 and BPNN 2, but its sole output node simulates the factor score of the stimulus on Heaviness factor. A fourth BPNN (called "BPNN 4" for short) forms the second level of the system. BPNN 4 operates to map the three visual features "Staticness", "Turbidity" and "Heaviness" of a multi-color stimulus to the variable "Pleasure Inverse" representing the inverse of the aesthetic score of the stimulus. The output nodes of BPNN 1, BPNN 2 and BPNN 3 serve as the input nodes of BPNN 4, and its sole output node simulates the factor score of the stimulus on Pleasure factor. Besides, the activation function of every node in the system was set as *tansig* function: $f(x) = \frac{2}{1+exp(-2x)} - 1$.

6. System Parameter Optimization

Having determined the macro-structure of the system, the next work was to find, for every constituent BPNN, the set of system parameter values producing the best performance by genetic algorithm (GA). The system parameters to be optimized were the hidden-layer node number, the learning rate and the momentum constant. Figure 3 is the flowchart of the GA program (coding operation parameters: Table 1; Gray code; Ranking Method; Stochastic Universal Sampling; crossover rate=0.7; mutation rate=0.7/string length; population size=40; maximum generation=100th).

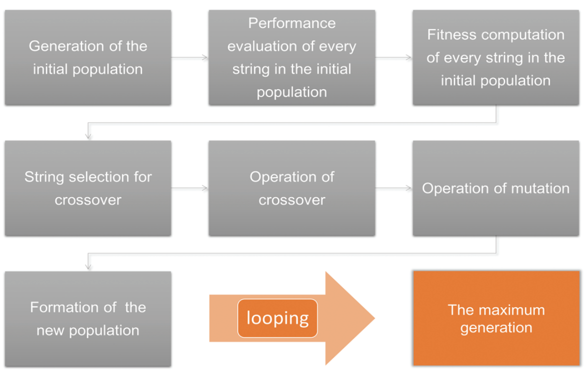

Figure 3: Procedure of the genetic algorithm program

Table 1: Coding operation parameters in the GA program

Parameter	Length	Range	Step Size	BPNN No.
Number of Hidden-Layer Nodes	3 bits	{4, 8,16, 24, 32, 48, 64, 72}	unequal	1, 2, 3
	2 bits	{1, 2, 3, 4}	1	4
Learning Rate	3 bits	[1/9, 8/9]	1/9	1, 2, 3, 4
Momentum Constant	2 bits	[0.2, 0.8]	0.2	1, 2, 3, 4

With the optimization results displayed in Table 2, both the network structures and the learning algorithms of the BPNNs were determined. Next, we conducted two simulations to test the predicting capacity of the system.

7. Simulation I

In the first simulation, the 35 stimuli used in Experiment I&II were divided into two groups: The training set contained 30 stimuli which had been used during the process of system parameter optimization, and the validation set contained the rest five stimuli. The validation-set stimuli could be deemed as qualified test targets due to the fact that they had not been involved in the construction process of the system.

The whole simulation consisted of 50 iterations each of which is composed of two phases: the training phase and then the prediction phase. In the training phase, the training set was employed to train the four BPNNs with their associated input-end information and output-end information (termination criteria of the training processes: maximum number of iterations=1000, mean square error=1.00E-05). Next, in the prediction phase, the primary color information of each validation-set stimulus was imported into the input layers of the first-level BPNNs, producing the prediction for the values of three visual feature "Staticness", "Turbidity" and "Heaviness". Then, these three predictions were further transformed by BPNN 4 into the prediction (in the fashion of inverse) for the aesthetic score.

The simulation result demonstrates that the prediction

Table 2: Optimum parameter value sets

BPNN No.	Number of Hidden-Layer Nodes	Learning Rate	Momentum Constant
1	4	1/3	0.2
2	24	5/9	0.2
3	8	7/9	0.2
4	1	1/9	0.4

errors regarding four of the five validation-set stimuli are remarkably low, and the overall average error is 0.3453, accounting for merely 17.65% of the largest possible error 2.0, implying that the system may possess a remarkable predicting power. In addition, Shapiro-Wilk Test shows that the predictions to the five validation-set stimuli can all be regarded as normally distributed (Ps: 0.183, 0.676, 0.266, 0.475 and 0.627), implying the robustness of the prediction calculation by the system.

8. Simulation II

In order to check out the possibility that the predicting ability of the system is limited within the multi-color stimuli used in Experiment I&II, we carried out the second simulation. In this simulation, all the stimuli employed in the two experiments were used as the training set, and 25 newly generated multi-color stimuli formed the validation set. The aesthetic scores of these validation-set stimuli were obtained through a third psychological experiment which shared the same procedure with Experiment I.

The simulation result exhibits that the average of the absolute value of prediction error is 0.2959, which accounts for only 14.8% of the largest possible error (2.0), and the distribution of error across the 50 iterations can be regarded as following a normal distribution (Shapiro-Wilk Test: P=0.432) with an average value (0.016) fairly close to zero and a small standard deviation (0.382). Therefore it is cogent to believe that the system possesses a high ability to generalize to any 4*4 grid multi-color stimuli the knowledge it has learnt from the associated information of the training-set stimuli gained in Experiment I&II.

9. Conclusion and Future Works

This research constructed, on the basis of Leder's psychological model, an artificial KANSEI system which simulated the mental function of multi-color aesthetic evaluation. Firstly, we quantified Leder's originally qualitative model by defining the concept "aesthetic evaluation" as Pleasure factor in Experiment I and specifying the simple physical visual features as the three factors "Staticness", "Turbidity" and "Heaviness" in Experiment II. Then, the macro-structure of the system was built through BPNN. The hidden-layer node number, the learning rate and the momentum constant of each BPNN were optimized by genetic algorithm. Finally, we carried out two simulation tests to estimate the predicting capacity of the system to the aesthetic scores of the multi-color samples which the system had never met before. Its performance in both simulations turned out to be satisfactory, indicating that the trained systems, especially the one in Simulation II, were able to predict with considerably high precision the aesthetic score of any 4*4 grid multi-color objects. Furthermore, from a psychological perspective, it is reasonable to regard the macro-structure of the system as a remarkably accurate approximation to the cognitive structure behind the sense of beauty to multi-color objects.

In regard to future application, this artificial KANSEI system can be used in the development of automatic multi-color aesthetic evaluation systems, which can be integrated in pattern recognition modules in affective-content-based image search engines, and even systems generating color images with high aesthetic scores. On the academic plane, our future researches will continue the exploration of the converging points of psychology and artificial intelligence, and delve into the cognitive-psychology and cognitive-neuroscience underpinnings of the sense of beauty to multi-color stimuli.

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