Impression Estimation Model and Pattern Search System Based on Style Features and Kansei Metric

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ABSTRACT

In this study, we aimed to construct impression estimation models of clothing patterns based on style features and Kansei metric. We first conducted a subjective evaluation experiment and a factor analysis, and quantified visual impressions of flower patterns. Following that, we used style features using CNN as image features suitable for representing flower patterns. Then, with a Lasso regression, we reduced the dimension based on Kansei metric (impression evaluation) and modeled the relationship between visual impressions and image features. Furthermore, we implemented a pattern search system using the modeled relationship.

CCS CONCEPTS

• **Computing methodologies → Appearance and texture representations**; • **Human-centered computing → Interaction design process and methods**;

KEYWORDS

Fashion, CNN, Texture, Style Transfer, Lasso Regression

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1 INTRODUCTION

In recent years, societal demand is rising for technology that quantifies impressions and emotion aroused by the products in diverse fields, such as product design and the arts. These technologies make it possible to grasp people's preferring and levels of satisfaction and to develop them into specific designs.

In this study, we constructed impression estimation models of clothing patterns using CNN-style features and Kansei metric (impression evaluation). And we implemented a pattern search system based on the models. Regarding material patterns, a texture generation method, using image features extracted from deep neural network, was developed by Gatys et al., which demonstrated highly precise results [1]. However, the relationship between textures and impressions or feelings has still not been clarified. Therefore, we quantified visual impressions of clothing patterns by conducting a psychological experiment. Then, we extracted CNN-style features and reduced the dimension based on Kansei metric. Next, we constructed regression models that estimates impressions of clothing patterns from CNN-style features. Then, based on the obtained regression models, we estimated the impressions of clothing patterns that did not have impression labels. Finally, we created a data set consists of 1,158 clothing patterns and implemented a pattern search system using the data set (Fig.1).

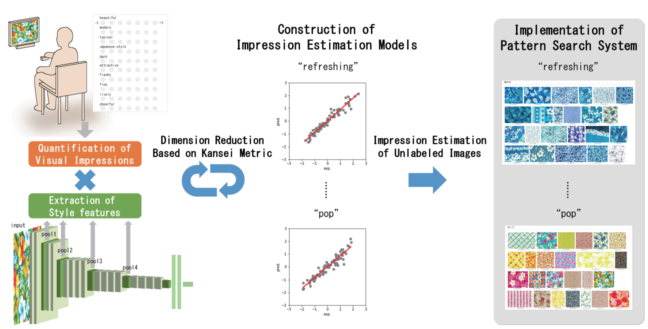

Figure 1: Flow Diagram

2 QUANTIFICATION OF VISUAL IMPRESSIONS OF CLOTHING PATTERNS

We conducted a subjective evaluation experiment to quantify visual impressions of clothing patterns. Experiment participants were 40 graduate and undergraduate students (18 male and 22 female). We used 75 flower pattern images as stimuli and 40 adjectives as evaluation terms. The participants observe the stimuli shown on an LCD monitor, and rate each image's degree of suitability for each evaluation term on a seven-point scale, from -3 to 3.

We then conducted a factor analysis (maximum likelihood method, Promax rotation) of the results obtained in the subjective evaluation experiment. The results are shown in Table 1. The factor analysis resulted in the extraction of six factors, which were interpreted as the following: Factor 1, the "pop" factor; Factor 2, the "elaborate" factor; Factor 3, the "refreshing" factor; Factor 4, the "novel" factor; Factor 5, the "tidy" factor; and Factor 6, the "stylish" factor.

We considered the raw scores and factor scores of adjectives obtained through this procedure to be the impression values of each stimulus.

Table 1: Factor Analysis Results

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
dark	−1.061	0.316	0.101	−0.256	−0.089	−0.023
bright	0.997	−0.228	0.081	0.109	−0.027	−0.007
cheerful	0.984	−0.182	−0.086	0.123	−0.089	0.054
gloomy	−0.863	0.120	−0.132	0.081	0.067	−0.165
colorful	0.753	0.299	−0.270	0.096	0.106	−0.232
vivid	0.748	0.343	−0.008	−0.111	0.002	0.076
lively	0.722	0.334	−0.039	0.013	−0.112	−0.051
luxuriant	0.691	0.473	−0.131	−0.178	0.495	0.057
plain	−0.684	−0.269	−0.101	0.041	0.150	−0.114
rustic	−0.673	0.171	−0.265	0.025	−0.303	−0.222
flashy	0.558	0.435	−0.155	−0.058	−0.159	0.072
stand-out	0.480	0.297	−0.029	−0.142	−0.435	0.093
glittering	0.457	0.363	0.015	−0.077	−0.333	−0.003
antique	−0.413	−0.001	−0.297	−0.125	0.214	−0.358
contemporary	0.378	−0.067	0.318	0.221	−0.106	0.361
complex	−0.135	1.035	0.095	0.190	0.238	−0.141
simple	0.029	−1.006	−0.041	−0.224	−0.276	0.098
multilayered	−0.074	0.996	0.247	−0.093	0.009	−0.133
rattling	−0.023	0.895	0.170	−0.170	−0.321	−0.182
extravagant	0.117	0.725	−0.274	−0.184	0.338	0.372
commonplace	0.000	−0.667	0.026	−0.324	0.026	−0.146
modest	−0.284	−0.600	−0.147	0.080	0.264	−0.120
unique	0.103	0.592	−0.067	0.585	0.020	−0.192
mysterioud	−0.483	0.554	−0.155	0.426	0.170	0.155
eccentric	0.118	0.368	−0.164	0.275	−0.335	0.221
cool-looking	0.034	0.037	1.008	−0.069	−0.087	−0.147
cool	−0.457	0.290	0.961	−0.038	−0.140	0.202
breezy	0.422	−0.087	0.721	0.002	0.253	−0.037
typical	−0.096	−0.022	0.093	−0.865	0.092	0.039
free	0.693	−0.019	0.018	0.695	−0.004	−0.146
futuristic	0.153	0.266	0.091	0.520	−0.132	0.245
elegant	−0.056	0.216	−0.076	−0.091	0.993	−0.045
mature	−0.542	0.126	0.048	0.012	0.725	0.274
beautiful	0.471	0.229	0.419	−0.130	0.623	0.064
calm	−0.378	−0.234	0.164	−0.010	0.465	−0.166
sophisticated	−0.046	−0.245	0.287	−0.094	0.374	0.573
Japanese-style	−0.387	0.206	0.040	0.060	0.284	−0.520
attractive	−0.134	0.275	0.325	0.184	0.099	0.487
Western-style	0.340	−0.190	−0.183	−0.431	0.242	0.459
modern	0.179	0.239	0.145	0.171	0.102	0.381

3 MODELING THE RELATIONSHIP BETWEEN VISUAL IMPRESSIONS AND IMAGE FEATURES

We used the style features of Gatys et al.'s style transfer [1] as image features to represent flower patterns. For style features, we made a Gram matrix of features map extracted from convolutional neural network VGG-19 used in general object recognition. The style features' ranks output by pooling layers of 1, 2, 3, 4 were 64 x 64, 128 x 128, 256 x 256, and 512 x 512, respectively.

Takemoto et al. used a Lasso regression to model the relationship between the quantified impressions of materials and the style features of textures [2]. Based on that method, we conducted a Lasso regression using the quantified impression values of flower patterns as objective variables and the style features obtained from each pooling layer as explanatory variables. With this, we obtained regression models for four types of dimensions for each evaluation term and factor, and used the regression model with the greatest coefficient of determination as the impression estimation model. The average coefficient of determination in all impression estimation models was 0.70 for the 40 evaluation terms, and 0.84 for the six factors.

By creating accurate regression models and calculating the regression coefficients, we modeled the relationship between visual impressions and image features for the flower patterns.

4 IMPLEMENTING A PATTERN SEARCH SYSTEM USING THE IMPRESSION ESTIMATION MODELS

Based on the impression estimation models mentioned in the previous section, we conducted an estimation of impressions for each evaluation term and factor for 1,083 flower pattern images that had not quantified impression values. Following this, we created a data set based on the estimated impression values and implemented a pattern search system. The method was set up to display images in order of highest impression value when one entered any of the 40 evaluation terms or six factors into the search screen. This shows the results of searching for "refreshing" factor and "pop" factor in the section for implementing the pattern search system in Figure 1. For "refreshing", many images were selected that were bluish and seemed summery. On the other hand, for "pop", images were selected that were vivid or had large patterns. For both, the obtained results did not feel subjectively out of place, suggesting the validity of this models.

5 CONCLUSION

In this study, we aimed to construct impression estimation models of clothing patterns based on CNN-style features and Kansei metric, and modeled the relationship between visual impressions and image features for the flower patterns. Furthermore, using the modeled relationship, we implemented a pattern search system.

As a future subject of this study, we will verify the validity of the estimation results and expand the image data with impression values.

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