Analysis of the Cultural Elements of Perceptual Information for Multi Feature Fusion of Clothing

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Abstract **—To improve the rationality for composition analysis of clothing sensibility data, a fast density peak clustering (FDPC)-based composition analysis method for clothing sensibility data of is proposed. Firstly, clothing sensibility information model is introduced and acquisition mode of sensibility information is given to realize effective splitting of information; secondly, density peak clustering is introduced to analyze composition of clothing sensibility data. At the same time, to improve cluster analysis effect, dynamic cutoff distance is used to realize improve convergence performance of cluster analysis algorithm; finally, the validity of proposed method is verified through simulation experiment.**

Keywords- fast peak; density peak clustering; clothing sensibility data; composition analysis

I. INTRODUCTION

The sensibility information of clothing includes 2 categories of information, external design (external form, color of clothing, texture and falling feeling of fabric, details and other aspects) and internal design (hand feeling, performance, comfort and structure division of clothing material, etc.). External design information acts on consumers the most directly and rapidly and may produce effect independently prior to internal information to a great degree before internal and external information jointly have effect on consumers' consumption judgment. Modern society is more and more significantly characterized with fast rhythm and high information capacity and consumers face many opportunities and selections. They often need to make consumption judgment within a short time. Hence, external information may play a role of front-end smoothing in consumption behavior and it is of great importance to research the impact of external information on consumers.

As for traditional acquisition of consumers' emotional information, the subjects' attitude towards measurement object is often investigated in form of qualitative research (such as interview) and quantitative research (such as questionnaire). The general practice is: to describe clothing to be evaluated with several pairs of bipolar adjectives (such as magnificent/simple, modern/classic, professional/casual, elegant/brisk, smooth/coarse, etc.) through designing semantic difference scale and Likert scale and other forms, rate adjectives with figures or adverb of degree, conduct statistical analysis for rated data with SAS, SPSS and other software, obtain inter-adjective relevance or principal component, acquire fuzzy set of clothing sensibility evaluation, conduct cluster analysis and obtain classification result of all samples and each type of representative samples.

To improve composition analysis precision for clothing sensibility data, a fast density peak clustering-based composition analysis method for clothing sensibility data of is proposed in the Thesis and the validity of proposed method is verified through simulation experiment.

II. ACQUISITION OF CLOTHING SENSIBILITY DATA

A. Model Description

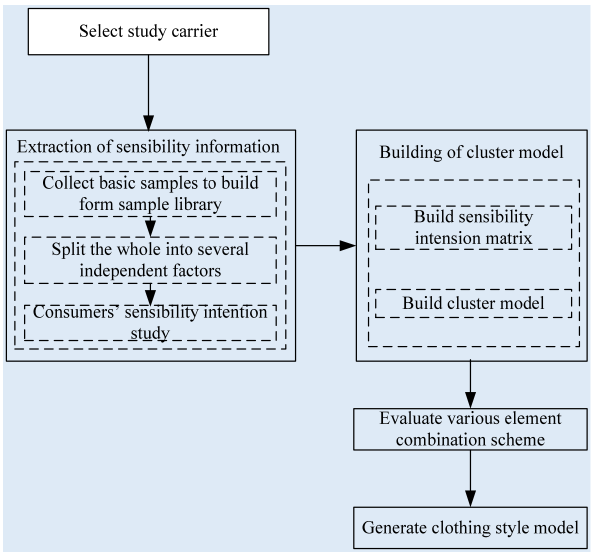

Figure 1. Modeling steps

Sensibility data mining of clothing includes two parts, sensibility data extraction and cluster modeling. Fig. 1 shows modeling steps. As for sensibility information, basic form sample library is built through widely collecting information extraction of related samples to a certain degree and combined quantity will increase exponentially. The more design elements, the more sensibility information of corresponding product and the closer relevancy with consumers' emotion preference. To truly reflect consumers'

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sensibility intension, split sensibility factors are provided with consumers' sensibility intention of design elements. Consumers' sensibility information is acquired through questionnaire to provide basis for sensibility cluster modeling.

B. Acquisition of Sensibility Information

302 pictures of related samples were collected from Internet, magazine and various channels to screen and exclude with the same or similar samples and preliminarily obtain 260 basic samples to build form sample library based on this. It can be seen from basic sample that the overall style of men's jackets can be deemed as the combination of several design factors (such as style, color, fabric, etc.) and can be decomposed to many components, such as silhouette, color, fabric, pocket, collar, etc. It can be divided into many components which can be subdivided again based on these several components. There are many optional catalogues under each component. As there is repeated or meaningless catalogue, catalogues shall be pre-screened to reserve necessary catalogue.

Sensibility intention study: (1) questionnaire design. The questionnaire form shall be designed to conform to principles of psychology and ergonomics. There is a large quantity of external design information evaluated in the experiment of the Thesis after subdivision. The form of questionnaire has been optimized according to experience of prior pre-experiment, specifically as follows: subdivide split element catalogue to 19 components and build a visual plane altas for design elements of men's jackets to make subjects find their favorite sensibility feature among several types of optional catalogues and accurately select design element combination which most conforms to their own "beautiful" sensibility intension. (2) Subject selection. Healthy male and female college students were selected as experiment subject, including 60 students from costume design major (almost half male and female college students respectively) and 60 students from other majors (accounting, Chinese, law, advertising, electronics, music, etc.). They are aged between 20-24 and the average age is 21.2 years old.

III. FDPC-BASED CLOTHING SENSIBILITY INFORMATION ANALYSIS

A. Fast Density Peak Clustering

n groups of clothing sensibility information data are used to conduct similar matrix $s_{n\times n}$ and $s_{n\times n}$ is taken as input of retrieval algorithm of proposed clothing sensibility information. It is assumed that the distance cutoff parameter is dc and sub-block density value ρ_i corresponding to each data point of clothing sensibility information i is calculated. Sub-block density value can be calculated with $cut-off$ function, with form as follows:

$$\rho_i = \sum \chi\left(d_{ij} - d_c\right) \tag{1}$$

In Equation (4), Function $\chi(x)$ can be defined as:

$$\chi(x) = \begin{cases} 1, x < 0 \\ 0, x \geq 0 \end{cases} \tag{2}$$

After obtaining density value ρ_i by use of Equation (4), clothing sensibility information data point i and the point larger than density value shall be provided with minimum distance value δ_i calculation, with form as follows:

$$\delta_i = \min_{j:\rho_j > \rho_i}\left(d_{ij}\right) \tag{3}$$

As for clothing sensibility information point with maximum ρ_i value, the point shall be provided with corresponding δ_i treatment, with form as follows:

$$\delta_i = \min_{j:\rho_i = \max\{\rho_j\}}\left(d_{ij}\right) \tag{4}$$

Each point i of clothing sensibility information can obtain corresponding ρ_i and δ_i values. If ρ_i and δ_i of the clothing sensibility information point are large, the point shall be taken as cluster center of clothing sensibility information. During judgment of cluster analysis, each clothing sensibility information point shall be provided with corresponding ρ_i and δ_i calculation to obtain density peak corresponding to each clothing sensibility information point i:

$$\gamma_i = \rho_i \times \delta_i \tag{5}$$

After obtaining density peak γ_i corresponding to each clothing sensibility information point i, ρ_i can be taken as horizontal coordinate and δ_i can be taken as vertical coordinate to draw decision-making diagram of clothing sensibility information. Users shall select cluster center point according to value γ_i and other clothing sensibility information points shall be incorporated to recent clothing sensibility information point cluster with higher density.

Clothing sensibility information point in the cluster can be divided to inter-cluster and outer-cluster. Inter-cluster node has large local density value and it is core cluster area and it has relative value of local density in outer-cluster category. It is cluster edge area. Correspondingly, if $h_i = 1$, it indicates that x_i is outer-cluster clothing sensibility information point. If $h_i = 0$, it indicates that x_i is inter-cluster clothing sensibility information point.

B. DPC Improvement Based on Cutoff Distance

Cutoff distance dc during traditional DPC process is constant. Selection of cutoff distance parameter dc has serious influence on effect of cluster process. Too small or large value is not favorable for improvement of algorithm performance: if the value of dc is too large, the sub-block density corresponding to clothing sensibility information point i will present large value, causing clothing sensibility information hard to be differentiated; if the value of dc is too small, clothing sensibility information point i will cause meaningless split of the same cluster. Hence, reasonable selection of cutoff distance parameter dc can realize improvement of effective performance during DPC process.

Dynamic adjustment parameter is designed as per distance cutoff parameter dc, which can ensure more rapid convergence speed under the condition of improving convergence precision condition. The improvement made is to design outer-cluster point rejection process in final process and execute step shown in Equation (4) to conduct DPC re-iteration. As for n clothing sensibility information points, similar matrix between all clothing sensibility information points $S_{n\times n}$ can be calculated. As DPC algorithm generally takes diagonal value $S(k,k)$ on $S_{n\times n}$ as inter-cluster regional division basis of clothing sensibility information point k. To improve the convergence speed of algorithm division, distance cutoff parameter dc is selected based on matrix $S(k,k)$ value and variance. Self-adaptive selection process is as follows:

$$dc_i = dc_0 + \alpha(e^{-(d\max_i - d\min_j)2} - \beta) \tag{6}$$

In Equation (9), dc_0 is the initial value of set distance cutoff parameter dc and it is assumed that $dc_0 = 0.02$. α and β are the scope parameter of area, which can realize setup of variation amplitude and speed of cutoff parameter. The larger α is, it indicates that the larger interference of iteration process with distance cutoff parameter dc is. The role of parameter β is to play an auxiliary role for parameter α, thus limiting distance cutoff parameter dc in the set section. Here, $\alpha = 0.4$ and $\beta = 0.5$.

C. Similar Matrix

Reasonable acquisition of similar matrix can realize effective improvement of cluster precision and construction mode of similar matrix for regional relevance fusion is designed accordingly. Significance is divided based on relevance of different areas of clothing sensibility information to realize automatic adjustment of weight.

Suppose that accumulative HSV histogram form corresponding to sub-block area i of clothing sensibility information is $G_k(i)$ and the corresponding weight vector can be expressed as W_k, with D as quantity of divided area corresponding to clothing sensibility information, then the calculation process of similarity weight $W_{p,q}$ existing between clothing sensibility information p and q is as follows:

$$W_{p.q}(m) = \frac{W_p(m)W_q(m)}{\sum_{i=1}^{D} W_p(i)W_q(i)} \tag{7}$$

Hence, the value $S'(p,q)$ of distance between clothing sensibility information p and q can be calculated as:

$$S'(p,q) = \sum_{i=1}^{D} W_{p.q}(i) dis(G_p(i), C_q(i)) \tag{8}$$

In Equation (11), $dis(G_p(i), C_q(i))$ is the Euclidean distance of area i between clothing sensibility information p and q. Then $S'(p,q)$ is normalized and negation operation is conducted to obtain the similarity between clothing sensibility information p and q. The calculation form is:

$$S(p,q) = -\frac{S'(p,q) - \min(S')}{\max(S') - \min(S')} \tag{9}$$

In Equation (12), $S(p,q) = S(q,p)$ and $S(k,k) = 0$, $k = 1,2,\cdots,N$.

As shown in Equation (11), the regional weight calculation process of the clothing sensibility information is related to important vector existing between pictures and the similarity of clothing sensibility information sub-block in the subject area can be effectively reduced with Equation (11) and (12) to realize similarity of subjects between clothing sensibility information.

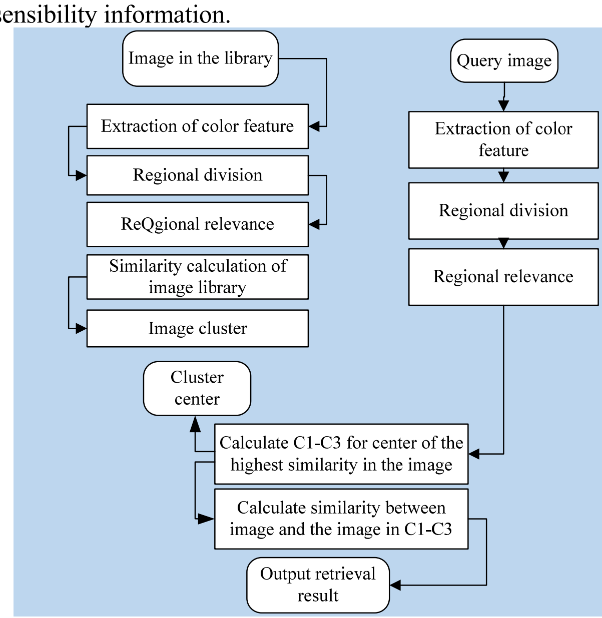

Figure 2. Cluster process for clothing sensibility information retrieval

To realize cluster of clothing sensibility information retrieval, assuming that the clothing sensibility information of sample is I and feature extraction process is conducted for clothing sensibility information I before judging the cluster center of clothing sensibility information I with the distance between clothing sensibility information I and center area. However, as the cluster center obtained during DPC process is based on similar matrix, the center quantity is more than true category quantity, which will cause wrong accumulation in clothing sensibility information retrieval. Firstly, 3 groups of clothing sensibility information cluster centers with the highest similarity to clothing sensibility information I should be found: C_1, C_2, C_3 . Then, after similarity comparison between clothing sensibility information I and clothing sensibility information in cluster centers C_1, C_2, C_3 , it can be back to retrieval to output clothing sensibility information. The retrieval process of clothing sensibility information is shown in Fig. 2.

During cluster process of above clothing sensibility information, the calculation complexity of algorithm is: $O(tKmn)$. Where, t is number of iterations, K is number of clusters, with m number of records and n number of dimensions.

IV. EXPERIMENT ANALYSIS

arff format document obtained through conversion as per input matrix is input to WEKA for preprocessing (including algorithm selection and parameter setup) before operating simpleKMeans algorithm. Cluster output data are rearranged and representative design model of the cluster is obtained according feature of each cluster, as shown in Table 1. Figures in the bracket in the table indicate selection of each attribute design element by representative design model of different clusters. Specific selection method of design element is to evaluate selection average value (characteristic value) of all subjects of certain cluster for all design elements of certain attribute. Design elements are selected according to the principle of maximum characteristic value as the constituent part of representative design model of the cluster. Table 1 lists the characteristic value and standard deviation of selected design elements. It can be seen from the distribution proportion of 110 samples (subjects) in 4 clusters that the result of cluster output is relatively ideal and number of examples in all clusters is relatively balanced to reach expected effect.

TABLE 1. CLUSTER MODELING

Attributes	Cluster 0			Cluster 1			Cluster 2			Cluster 3		
	19%			21%			25%			35%		
	No.	Average value	Deviation	No.	Average value	Deviation	No.	Average value	Deviation	No.	Average value	Deviation
shape	4	0.65	0.48	1	0.56	0.5	2	0.47	0.44	1	0.61	0.48
length	3	0.37	0.49	2	0.55	0.5	2	0.69	0.5	2	0.62	0.47
decoration	2	0.38	0.49	1	0.48	0.46	1	0.68	0.51	1	0.61	0.45
Internal cutoff line	6	0.7	0.47	3,4	0.47	0.45	6	0.35	0.48	2	0.66	0.42
Collar style	3	0.48	0.5	7	0.42	0.41	6	0.28	0.39	2	0.65	0.38
Pocket style	2	0.26	0.45	5	0.42	0.41	2	0.28	0.46	1	0.50	0.39
Pocket position		0.88	0.39	2	0.45	0.49	3	0.8	0.44	3	0.56	0.45
Pocket quantity	2	0.67	0.46	1	0.51	0.49	2	0.8	0.45	7	0.48	0.42
Sleeve style	2	0.66	0.48	2	0.50	0.48	2	0.82	0.48	2	0.49	0.5
Cuff style	2	0.62	0.5	4	0.44	0.45	2	0.67	0.48	2	0.55	0.51
Lower hem style	3	0.44	0.51	1	0.46	0.5	2	0.7	0.47	3	0.51	0.49
Button	2	0.95	0.49	2	0.48	0.44	1	0.68	0.46	4	0.48	0.48
Zipper	1	0.66	0.44	1	0.46	0.5	1	0.69	0.47	1	0.48	0.41

The distance from representative design model of the cluster can be calculated in each example of cluster and the distance can indicate the coincidence degree between the example and the cluster feature. The less the distance is, the more the example can reflect the cluster feature. Hence, as for multiple samples, at the time of selecting multiple representative examples of certain type of design styles, the example with small distance from representative design model shall be preferably followed. The representative design model built under most conditions in the experiment will not completely coincide or conform to certain example in the cluster. Therefore, the example with the least distance from representative design model of the cluster can be selected as representative example of the cluster and data sample to subsequent research works. Hence, certain error will be brought theoretically. However, as true example data come from truly existing subjects, many related research works under many conditions are strongly related to the subject. For example, subjects' physiological and psychological indicator data are required as research object and content. At this time, it more conforms to the physical significance of experiment research to select representative example instead of representative design model.

V. CONCLUSIONS

A fast density peak clustering-based composition analysis method for clothing sensibility data of is proposed in the Thesis. On the basis of giving clothing sensibility information model and introducing acquisition method of sensibility information, density peak clustering is introduced for composition analysis of clothing sensibility data and dynamic cutoff distance is used to improve density peak clustering algorithm. Simulation experiment verifies the advantage of the proposed method in improving rationality of composition analysis of clothing sensibility data.

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