6U-1

Features for Recognizing Good Continuity Parts in Trademark Images

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1. Introduction

The similarity inspection between a new trademark and numbers of registered ones needs hard labor, where there is ambiguity in grouping of multi-element pattern on human perception depending on the image type such as abstract images. By regarding grouping areas as a query for similarity retrieval[1], researches on recognizing grouping areas in images would be used for bringing out higher performance on CBIR (Content-Based Image Retrieval). However, continuity in grouping recognition has been avoided in all the existing systems[1][2] for the reason good continuity should be treated as multi-factor which cannot be briefly designed.

In order to enhance performance of CBIR systems for trademarks, this paper proposes a method for recognizing good continuity parts using features for grouping components according to Gestalt Psychology.

2. Good Continuity in Gestalt Psychology

Gestalt principle shows there are several factors in grouping perception. In this research, a method for recognizing grouping patterns on good continuity among the factors is investigated. Fig. 1 shows an example of images where good continuity is appeared. Although Fig. 1 is a set of small components, humans perceive the image that two broken curves cross each other. However, it is a difficult problem for CBIR systems to recognize patterns such as this.

Fig. 1 A grouping pattern on good continuity.

When humans perceive grouping patterns on good continuity, there is possibility that humans could focus on the two factors of proximity and shape similarity to sets of linear and dotted components. In one image, when distances between the components are large, humans perceive them individual objects; however, if they are close, humans perceive them as a family. On the other hand, when their shapes are very similar, they are perceived as a family such a linear object; however, if not, humans do not perceive them a family. Hence, to recognize the grouping patterns, the proposed method should be designed considering the two factors.

3. Recognition of Grouping Areas on Continuity

The proposed method is designed assuming bi-level images whose size is 256×256. In the proposed method, the first families on only proximity are found by extracting a feature between components, and the grouping pattern on good continuity is finally fixed by examining shape similarity between neighbor components in each of the families, i.e., the proposed method is composed with the two steps.

3.1 Recognition on Proximity

Families according to proximity are recognized by measuring the shortest distance P_i between a couple of components C_i and C_{i+1} (Fig.2). Then, the absolute value of the difference d_i of 2 distances P_i and P_{i+1} between 2 couples composed with a series of 3 components C_i, C_{i+1}, and C_{i+2} is calculated. This calculation is conducted to every combination in the whole image. Regarding d_i as a valuable, whether the series of three components is a grouping part on proximity is judged by threshold T_1. If $d_i < T_1$, the series of components is regarded as a grouping part. T_1 can be obtained by a discriminant machine. The learning data was obtained from patterns selected by results of a questionnaire (for 10 participants and 75 sample images). Using the results of the questionnaire, we made two classes of G1 and G2 by hand. G1 is the group of families which got votes of 80% or more and G2 is the group of families which got only 20% or less. From the results, 87 and 42 patterns were selected in each group for G1 and G2, respectively. Then, T_1 was obtained by linear SVM (Support Vector Machine).

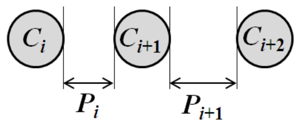

Fig.2 P_i and P_{i+1} for the components C_i, C_{i+1}, and C_{i+2}.

3.2 Recognition on Shape Similarity

Among features for extracting characteristics of image shape, circularity $C_r(i)$ and equivalent diameter $D_m(i)$ are extracted in this research. $C_r(i)$ is given by

$$C_r(i) = \frac{4\pi S_i}{l_i^2},$$

where S_i is the area and l_i the perimeter of C_i. And, equivalent diameter $D_m(i)$ is given by

$$D_m(i) = \frac{2\sqrt{S_i}}{\pi}.$$

Here, difference of the circularity F_1 and difference of the equivalent diameter F_2 between 2 neighbor components C_i and C_j is respectively given by

$$F_1 = |C_r(i) - C_r(j)| \quad \text{and} \quad F_2 = |D_m(i) - D_m(j)|,$$

respectively. As well as the proximity's case, 2 classes of G3 for images showing shape similarity and G4 for images not showing the similarity were made from the results of the questionnaire. By using F_1 and F_2 as valuables of a discriminant machine, recognition of shape similarity is conducted to every family obtained in Sect. **3.1** and the final grouping pattern on good continuity for an image is fixed as the final output. To obtain the decision function for judging that components are grouped on shape similarity, the learning data were obtained by the same way of the proximity's case. In the selection, 27 and 22 patterns were selected for G3 and G4, respectively. The discriminant score Z was obtained from the decision function determined by the linear SVM as follows:

$$Z = (-1.65\times10^{-3})F_1 - (2.42\times10^{-5})F_2 + 1.65\times10^{-4}.$$

4. Experimental Results

To examine performance of the proposed method, we compared grouping results by the proposal with human perception. 75 test trademarks were used as queries in the experiments and 10 participants answered the questionnaire. The 75 images differ from the images used in Sect. **3**. According to the decision ways for T_1 and Z shown above, we made G1, G2, G3, and G4 by hand from results of the questionnaire for the test images. The numbers of patterns in G1 and G2 were 44 and 19, respectively. And, in G3 and G4, the numbers were 44 and 38, respectively. Regarding the handmade classes G1–G4 as correct answers, correspondence ratios between the correct answers and final outputs of the proposed method have been examined by the ratios of precision, recall and F-value.

Table 1 shows experimental results of just recognition on proximity, i.e., correspondence ratios for G1 and G2, in which we show results by linear discriminant analysis (LDA) for a reference. And, Table 2 shows experimental results for final outputs, i.e., correspondence ratios for G3 and G4. Similarly, we show results by LDA as a reference. From Table 2, we can see all of the ratios (in SVM) except Recall for G4 have been more than 80%.

Next, reversing the order that the first step is proximity and the second is shape similarity, the recognition has been conducted. In this experiment, G5 and G6 were prepared to step 1 on behalf of G1 and G2, and G7 and G8 to step 2 on behalf of G3 and G4. Table 3 shows experimental results of just recognition on shape similarity as step 1, and Table 4 shows results of final outputs via the reversible steps, where we can see there would be no significant difference between the ratios for G3 and G7.

Table 1 Results of the discriminations (G1 – G2)

	tool	Recall	Precision	F-value
G1	SVM	100%	100%	100%
	LDA	100%	86.27%	92.62%
G2	SVM	100%	100%	100%
	LDA	63.15%	100%	77.41%

Table 2 Results of the discriminations (G3 – G4)

	tool	Recall	Precision	F-value
G3	**SVM**	**91.11%**	**80.39%**	**85.41%**
	LDA	95.55%	71.66%	81.89%
G4	SVM	72.97%	87.09%	79.40%
	LDA	54.04%	90.90%	67.79%

Table 3 Results of the discriminations (G5 – G6)

	tool	Recall	Precision	F-value
G5	SVM	91.11%	80.39%	85.41%
	LDA	95.55%	71.66%	81.89%
G6	SVM	72.97%	87.09%	79.40%
	LDA	54.04%	90.90%	67.79%

Table 4 Results of the discriminations (G7 – G8)

	tool	Recall	Precision	F-value
G7	**SVM**	**83.78%**	**86.11%**	**84.93%**
	LDA	83.78%	81.11%	82.42%
G8	SVM	54.54%	50.00%	52.17%
	LDA	54.54%	50.00%	52.17%

5. Discussions

Table 2 shows the proposal outputs a different pattern from human perception in some cases. In fact, all the failure cases were happened in which the size of neighbor components is much different each other. When neighbor component's sizes gradually vary, difference between the components is perceived at the location where the size is changed remarkably. In addition, the aspect of smoothness as linear objects was not considered in the proposal. Fig. 4 shows components whose shape is different draw a curve. We need to consider this problem more deeply.

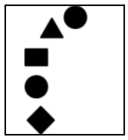

Fig. 4 A linear arrangement by components whose shape is different each other.

6. Conclusions

This paper presented a method for recognizing grouping patterns on good continuity in abstract images. Experimental results to examine performance of the proposal showed correspondence ratios between grouping patterns by the proposed method and results of the questionnaire were more than 85.41%. As future works, we need to investigate on grouping objects which have linear arrangement.

References

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