Multiple Classifier Based on Fuzzy C-Means for a Flower Image Retrieval

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Abstract

In this paper, we propose a flower image retrieval system with multiple classifier based on fuzzy c-means that uses different important features depending on the flower structure. Flowers may be classified into three types according to their structure: Rounded flowers, Flowers with many petals and Flowers with clear one petal. However, it is difficult to uniquely decide the types of flower because flower structure may be ambiguous. Therefore, we construct three classifiers based on the fuzzy c-means algorithm in order to deal with the ambiguous shape of flowers. Its effectiveness is confirmed by flower image retrieval experiments, where the target flower is retrieved by the proposed multiple classifier at 71.9% up to the third rank, at 82.1% up to the fifth rank, and at 93.3% up to the tenth rank.

1. Introduction

When we want to know the information of wild flowers seen in the mountain path, roadside and garden, an electronic flower encyclopedia is useful. However, it is difficult to use it then and there because it requires keywords typed in from the keyboards. Hence it is desired to just taken a flower picture and then transmit it to a system and immediately receive the detailed information from the system.

Several flower recognition systems have been developed. Saitoh, et al.[1] worked on Automatic Recognition of Wild Flowers using frontal flower images and leaf images. Tabata, et.al [2] developed Convenient Image Retrieval System of Flowers for Mobile Computing Situations (COSMOS). Jie Zou, et al.[3] studied Model Based Interactive Flower Recognition.

Flowers have various kinds and shapes. For example, the number of petals is an important feature for flowers such as lily, but it is not important for flowers such as morning glory with one piece of petal. The whole shape is an important feature for morning glory. Therefore, it is required to select important features according to the flower type among all features obtained from an input flower. From this viewpoint, in this study, we propose a contents based flower image retrieval system with multiple classifiers which select important features for each classifier and weight the importance on each classifier according to the membership in the fuzzy c-means method.

2. Flower image retrieval system

In this section, we describe a processing flow in the flower image retrieval system along with the extraction method of flower regions and features.

2.1. A flow in the system

A flow in the system is shown in Fig.1. First, a flower region is extracted from a frontal flower image. Secondly, the color and shape features of the flower region are computed. Finally, similarity matching is performed based on multiple classifier between query image and database images. The detail of this multiple classifier will be described in section 3. If a user send a flower image taken by his mobile phone to this system, he receives the thumbnail images the similar of flowers up to the fifth rank as the result with the detailed information such as features, flower name, family name, genus name and so on from flower database.

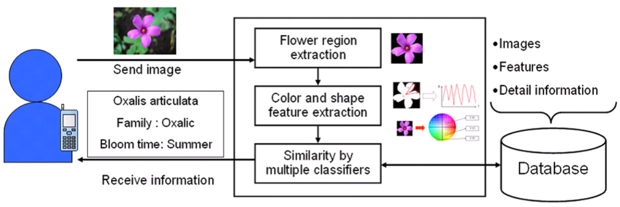

Figure 1: Flow in a flower image retrieval system

2.2. Flower region extraction

In this study, Flower regions are extracted using k-means algorithm. We show below a condition in photography.

- Take a flower picture from the front position.
- Without overlapping with other flowers.
- As big as possible in the central area.

Flower region extraction is shown in Fig.2. First, the RGB components of an image are extracted and converted from RGB color space to HSV color space. Hue, Saturation and

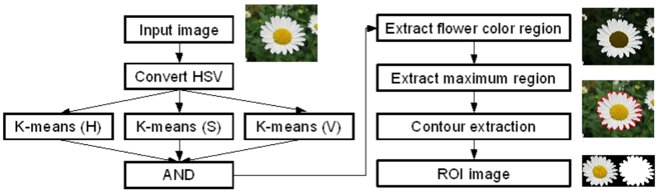

Figure 2: Flow of flower region extraction

Value are clustered using k-means algorithm respectively. Six centroids are computed for each H, S and V. Consequently, he number of centroids is 18 in total. After all centroids are fixed by k-means algorithm, 6 color regions are selected as flower region candidates (red, yellow, cyan, blue, magenta and white). A large color region locating at near center is selected as flower region among the candidates. For this purpose, new measure E is computed for each candidate region as follows:

$$E = \frac{\rho}{\sigma} \tag{1}$$

where ρ is the number of pixels in the candidate region and σ is the pixel distribution from center of the image defined as follows:

$$\sigma = \frac{1}{\rho} \sum_{s \in S} d(s) \tag{2}$$

where S is the pixels in the candidate region and $d(s)$ is Euclidean distance from the center of the image to the pixel s. The larger and the closer to the center the candidate region is, the larger the value E is. Among candidate regions, the flower region is decided as a region with maximum values of E, indicating the big and central region.The flower region and its binarized images are output. Then the color and shape features are computed on them.

2.3. Features extraction

2.3.1. *Color features*

The color values of the flower image are given in the RGB color space. They are converted into the HSV space. Then the HS space is divided into 100 segments, where the distribution is computed using the pixel values on the flower region as shown in Fig.3. The distribution is used as the color features $C_n(i)$, where i is flower image number and n is dimension.

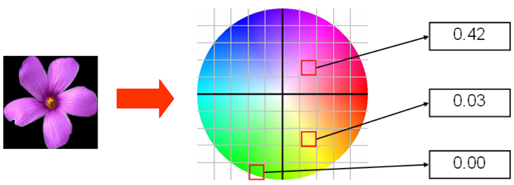

Figure 3: HS color space

2.3.2. *Shape features*

Shape features are defined on the contour of the flower region. Euclide distance d_k is computed from the center of gravity G of the flower region to the contour pixel $cont_k$. A waveform shown in Fig.4 is obtained, where the x-axis is the accumulated perimeter length and the y-axis is the distance to the center. The waveform is transformed into frequency domain by Fourier transform as follows:

$$d_k = f(cont_k), (k = 1, 2, ...N) \tag{3}$$

$$F_n = \sum_{k=1}^{N} d_k \exp\left(\frac{-2\pi ikn}{N}\right) \tag{4}$$

Then, the shape feature $S_l(i)$ is defined as 30 dimensional power spectrum in low-frequency range. Fig. 5 shows an example of shape feature which is different depending on the each classifier. It is described in section 3.3

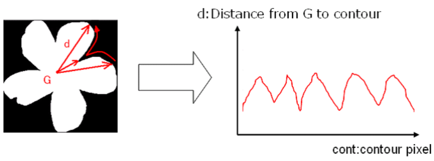

Figure 4: One dimension contour graph

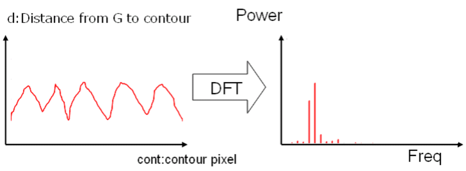

Figure 5: Power spectrum graph

2.4. Recognition

Similarity matching is performed based on the multiple classifier described below.

3. Multiple classifier

Flowers are classified into three types according to their structure: "gamopetalous", "many petaled" and "a single petaled". For each types, a related classifier is constructed based on the difference of flower structure. The method we employed to classify the database images as well as query image into three types is Fuzzy C-means clustering, because flowers have various structures and it is difficult to decide one structure clearly. We allow them to belong to many classes (i.e. membership). The degree of membership of the query image to each defined structure in Fuzzy C-means clustering is used to weight the similarity computed at each classifier. Linearly-coupled similarity matching of 3 classifiers is finally the similarity for the query image.

3.1. Classification based on structure

Average and entropy of power spectrum are computed from shape feature $S_l(i)$. Compactness $= 4\pi S/L^2$ is computed from the binary image of the flower regions. Here S is the flower region area and L is the contour length. Three flower structure types are defined using these flower features as shown in Table 1.

Table 1: Features of three structure types

Compactness	Entropy	Average	Type
High	Medium	Low	gamopetalous
Low	High	High	many petaled
Low	Low	Medium	a single petaled

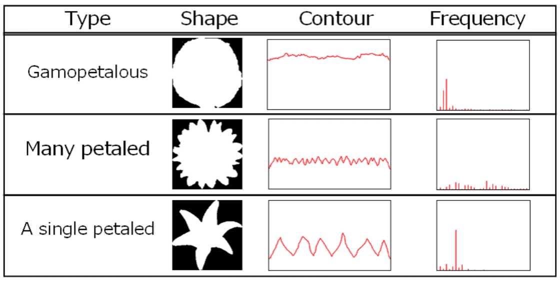

Figure 6: Samples of three structure types

Examples of 3 structures are shown in Fig.6. Flowers having rounded shape such as glory morning are within "gamopetalous" class. They are comparatively high compactness. Since their characteristics appear at low-frequency range, average is low and entropy is medium due to the ambiguity of the contour. Flowers having many petals and complex shape such as sunflower are within "many petaled" class. They have comparatively low compactness because of the complex shape. Since their characteristics appear from low-frequency range to high-frequency range, the average and entropy are high. Flowers such as lily are within "a single petaled" class. They have comparatively low compactness. Since their characteristics appear at peak-frequency and usually it indicates the number of petals, the average is lower than "many petaled" and higher than "gamopetalous" and the entropy is low. It is difficult that all flowers are classified into one of three structures clearly. Therefore, we allow them to belong to many classes with Fuzzy C-means clustering.

3.2. Fuzzy C-means clustering

It is Fuzzy C-means clustering [4] that the database images and query image are classified into 3 classes defined in section 3.1. u_{ij} is the degree of membership of the image i to the cluster j in image i. It is shown as follows:

$$\{u_{ij} \in [0,1]\,,\ \sum_{j=1}^{C} u_{ij} = 1 \ for\ all\ i\} \tag{5}$$

Fuzzy C-means clustering is based on the minimization of the following objective function:

$$J_m = \sum_{i=0}^{N_d} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \tag{6}$$

In this study, the number of cluster C, and the number of data (i.e. database images and query image) are set to 3 and N respectively. A fuzziness coefficient m is any real number greater than 1. In particular, when $m \approx 1$, it is crisp c-means clustering. The larger m is, the fuzzier u_{ij} is. Measured data x_i is composed of compactness, average and entropy. Center of the cluster C_j is initialized. Membership matrix U and C_j is updated for database images and query image in the iteration process. This iteration will stop when $\left\| U^{k+1} - U^k \right\| < \epsilon$ at k-step, where ϵ is a termination criterion between 0 and 1. If this iteration stops, u_{ij} is given for all images. Membership of query image $\boldsymbol{U_0}$ (i.e. query image is $i = 0$) is the weights to each classifier. We describe it in section 3.4.

3.3. Classifier

The classifier F_1, F_2 *and* F_3 are described in detail. F_1 is classifier for "gamopetalous", F_2 is classifier for "many petaled" and F_3 is classifier for "a single petaled". Different shape features used in each classifier as well as similarity V_{ij} are described here. V_{ij} is the similarity between database image i and query image in classifier F_j. In section 2, we defined $C_n(i)$ and $S_l(i)$. On the other hand, in this section, different shape feature $H_j(i)$ used in each classifier is defined based on the fact that each class has its own characteristics.

(1) Classifier F_1 "gamopetalous"
Compactness $H_1(i) = 4\pi S/L^2$ is employed because it is difficult to describe respective petal, and the compactness describes the whole shape.

(2) Classifier F_2 "many petaled"
Complexity $H_2(i) = L^2/S$ is employed. Complexity has characteristic of the whole shape as well. The more complex the shape is, the larger $H_2(i)$ is.

(3) Classifier F_3 "a single petaled"
$H_3(i)$ = (moving radius minimum)/(moving radius maximum) is employed. Moving radius is distance from the gravity to the contour. It has characteristic of the one petal. The longer one petal is, the larger $H_3(i)$ is.

Similarity V_{ij} in each classifier is calculated based on three types of similarities $D_c(i, j)$, $D_s(i, j)$ and $D_h(i, j)$ using features $C_n(i)$, $S_l(i)$ *and* $H_j(i)$. Color similarity $D_c(i, j)$ is calculated using histogram intersection for $C_n(i)$ as follows:

$$D_c(i, j) = \sum_{n=1}^{100} min(C_n(0), C_n(i)) \tag{7}$$

Shape similarity $D_s(i, j)$ is calculated using histogram intersection of $S_l(i)$ with gauss weight as follows:

$$D_s(i, j) = \sum_{n=1}^{30} (min(S_l(0), S_l(i)) * Gauss) \quad (8)$$

where $Gauss$ is weight of band frequency range because the important frequency range differs from class to class as described in section 3.1. We define $Gauss$ low-frequency range $2*N(0, 5^2)$ in F_1, high-frequency range $2*N(15, 5^2)$ in F_2 and band -frequency range $N(peak, 3^2)$ in F_3 (shown in Fig.7).

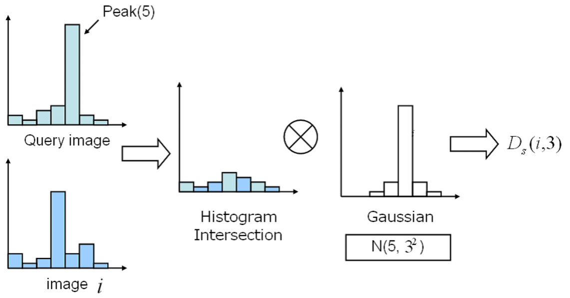

Figure 7: Histogram intersection by Gauss function in F_3

Another shape similarity $D_h(i, j)$ for $H_j(i)$ is calculated as follows:

$$D_h(i, j) = 1 - \left|H_j(0) - H_j(i)\right| \quad (9)$$

Each similarity is normalized to [0,1]. Similarity V_{ij} is calculated as follows:

$$V_{ij} = D_c(i, j) + D_s(i, j) + D_h(i, j) \quad (10)$$

3.4. Multiple classifier

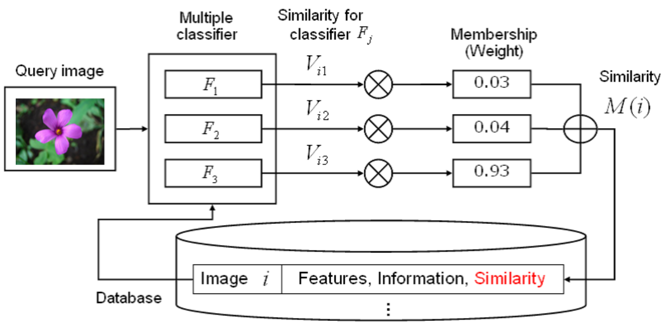

Figure 8: Recognition using multiple classifier

Flow of recognition using multiple classifier is shown in Fig. 8. Similarity between database image i and query image is calculated in classifier F_1, F_2 *and* F_3. Similarity vector is $\boldsymbol{V_i} = (V_{i1}, V_{i2}, V_{i3})^t$ and final similarity $M(i)$ is calculated as follows:

$$M(i) = \boldsymbol{U_0} \cdot \boldsymbol{V_i} \quad (11)$$

where $\boldsymbol{U_0}$ is the weight of similarity to V_{ij}. In Fig. 8 similarity $M(i)$ between database image i and query image is shown as:

$$M(i) = 0.03 \times V_{i1} + 0.04 \times V_{i2} + 0.93 \times V_{i3} \quad (12)$$

Finally, results are shown to the user within the fifth rank in $M(i)$.

4. Recognition experiment

Images of 21 flower families, 112 species with 4 samples (i.e. 448 images) were used for recognition experiment. One among four samples is used as a query image (112 images in total) and the others (336 images) are used as the database images. We evaluated cumulative recognition rate with 4 cross validation.

Table2 shows the recognition accuracy by the single classifier and the multiple classifier at cumulative recognition rates with four-cross validation, where the single classifier uses only the common feature vector ($C_n(i)$ and $S_l(i)$) to all classes. From the table, multiple classifier shows the better result than no fuzzy and the single classifier.

Table 2: Recognition rates [%] for each classifier

-		1st	3rd	5th	10th
Single classifier		33.7%	65.4%	77.0%	90.2%
Multiple classifier	No fuzzy	40.0%	68.3%	79.7%	90.4%
	Fuzzy	42.2%	71.9%	82.1%	93.3%

5. Conclusion

We proposed the flower image retrieval system as a flower encyclopedia using multiple classifier. The experimental results showed the effectiveness of the retrieval system. Remaining problems are about classification more than three classes and feature analysis optimized for individual class. At present, it is a difficult problem to retrieve the same flower with different colors. In the future, we will add information about flower blooming time and habitat which plays an important role for recognition accuracy improvement.

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