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Color Image Fuzzy Classification Algorithm with Salient Regions

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Abstract: For the classical image segmentation algorithms, a larger number of implicit regions will be achieved, which leads to the lose of effectivity for these region-based image classification schemes. These individual regions are generally meaningful and unexpected results would be caused by these classification strategies, although some salient regions are extracted to reduce the complexity of region-based image classifications. Furthermore, these schemes are the arbitrary classification schemes and could not indicate the information about other implicit objects and the accurate semantic segmentation is still out of implicit semantic object regions in one image. In this study, we proposed one salient region based fuzzy classification (SrFC) method. Firstly, we give a salient region extraction algorithm based dominant colors and Gabor texture features. Then, according to the proposed classification scheme the salient regions from all the candidate images are clustered into disjoint categories. These categories are further used as for those for candidate images and for each candidate image its number of salient regions belonging to the same category would be used to evaluated the degree of the images belonging to the category. Experiments showed the propose SrFC scheme can achieve better performance than that of current common schemes. With comparison to the HCBA scheme for individual salient regions, the classification accuracy is improved about 16% by the proposed SrFC scheme.

Key words: Image classification, fuzzy classification, salient regions, unsupervised classification

INTRODUCTION

Image clustering or classification is one crucial step for image data mining (Yo-Ping and Tsun-Weim, 2004), which is a high-level operation for image analysis. However, by reason of gaps between low level image features and high level semantic objects (Pappas *et al*., 2007), the expected image classification results are still out of the human being's view. Here, this study is devoted to figure out a novel image classification method that could achieve feasible results consistent with human being perceptions under the current common non-semantic low-level image features. For most current common image classifications (Dong and Izquierdo, 2007; Selvan and Ramakrishnan, 2007; Badawy *et al*., 2001; Hurn *et al*., 1996; Hmida and Ben, 2006), they are dedicated to the analysis of special images with simple semantic objects other than complex objects, e.g., texture image classification (Selvan and Ramakrishnan, 2007), natural image classification (Dong and Izquierdo *et al*., 2007), financial documents clustering (Badawy *et al*., 2001), medical images (Hurn *et al*., 1996), face recognition and classification (Hmida and Ben, 2006), etc. For these specific images, image global features could present their implicit semantic objects and be used directly for image classification. But, this doesn't fit for the images with many semantic objects, as the corresponding global features could not describe any individual objects or their semantic combinations.

Thus, the local features of implicit regions are expected to denote correspond semantic objects. So, several region-based image classification schemes are given in recent literatures (Lezoray and Cardot, 2002; Zeljkovic *et al*., 2004; Sanghoon and Crawford, 2005; Singh and Markou, 2004; Fredembach *et al*., 2004), i.e., the hierarchical clustering based approach (HCBA) (Sanghoon and Crawford, 2005), the eigenregions based strategy (EBS) (Fredembach *et al*., 2004) and the novel region based methods (NRBM) (Singh and Markou, 2004). These methods are all the unsupervised approaches, as the implicit regions of all classification candidate images maybe present various features in terms of colors, textures and shapes. It's difficult to a limit number of regions for image classification. According to these region-based classification methods, one image is firstly segmented into different disjoint implicit regions and the local features for these regions are subsequently calculated. These regions are further classified into several semantic classes and the

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corresponding image features also calculated to classify the images into different semantic classes. However, the performance of these common region-based methods are badly effected by the limitation of current image segmentation algorithms, as accurate segmentations are still out of implicit semantic object regions in one image (Ling and Brady, 2006). For current most image segmentations based color or texture features, one semantic object with distinct regions would be segmented into several irrelevant regions. Meanwhile, this would also result in a larger number of implicit trivial regions, which greatly increases the complexity of these common region-based image classifications and the whole classification accuracy also is badly effected. Furthermore, one image generally contains multiple implicit semantic objects and it's unfavorable to classify the image into one unique category as these objects maybe present different categories.

In order to avoid to get rid of those trivial meaningful regions, we propose a novel unsupervised color image fuzzy classification scheme based salient regions. After the candidate images for classification were segmented into disjoint regions, one salient region extraction procedure is conducted to these regions and the salient regions larger than one given size are achieved. Thus, the corresponding classification algorithms could only deal with these salient regions. Salient regions of one image are those regions that present distinct characteristics in terms of their local features as such as colors, textures, shapes, etc. The salient regions of one images can generally reveal its main contents and they should take account of the implicit region sizes and their saliency relative to other regions. According to the proposed classification scheme, all the salient regions from all the classification candidate images are firstly put to together for salient region classification and the categories for salient regions are used for that of candidate images. Then, for one candidate image, its number of salient regions belonging to the same category would be used to evaluated the degree of the images belonging to the category. This classification strategy can overcome the robustness of the classical image classification schemes as showed above. With the novel fuzzy image classifications, one could achieve better classification results than the classical ones.

DEFINITION AND EXTRACTION OF SALIENT REGIONS

As pointed out in Kuan Yu-Hsin *et al*. (2006), one salient region should be compact, complete and significant enough and neither a small region nor a fragmentary region can be one meaningful region. Furthermore, in terms of colors and textures, the salient regions should also have distinguishing features from their neighbor regions or other regions. Provided that each region is characterized by its feature vectors, they are the syntheses of color and texture features and the new saliency metric could be outlined in the follows.

The color features consist of three main colors that can be achieved by color clusters of pixels in the region, while the texture features are described by the means and variances of Gabor filter bank at different frequencies and orientations. Thus, the color features of the i-th region are denoted as $Fc(i) = \{[r(k,i),g(k,i),b(k,i)] | k = 1,2,3\}$, $i = 1,2,\ldots, N$, where, N is the total number of region and (r_j,g_j,b_j) is the j-th main color in current regions, respectively. If P scales and Q orientations are considered in the Gabor bank, the textures of the i-th region are denoted as $F_t(i) = \{\mu_{m,n}(i), \sigma_{m,n}(i) | m = 1,2,\ldots,P; n = 1,2,\ldots,Q\}$, where, $\mu_{m,n}(i)$ and $\sigma_{m,n}(i)$ are the mean and variance of the Gabor filter coefficients for i-th region at m-th frequency and n-th orientation.

According to the feature vectors of all the regions, the saliency of one region is given as the sum of its Euclidean distance from all the other regions, i.e.,

$$s(i) = \sum_{j=1, j\neq i}^{N} \frac{1}{2}\left[\frac{d_c(i,j)}{\max\limits_{i,j}(d_c(i,j))} + \frac{d_t(i,j)}{\max\limits_{i,j}(d_t(i,j))}\right] \quad (1)$$

where, d_c (i, j) and d_t (i, j) are the Euclidean distances between the i-th and j-th region for color and texture features respectively and the two maximum terms are used to normalize the two distances into interval [0,1]. Meanwhile, they can be computed as:

$$d_c(i,j) = \sqrt{\sum_{k=1}^{3}\left[r_k(i) - r_k(j)\right]^2 + \left[g_k(i) - g_k(j)\right]^2 + \left[b_k(i) - b_k(j)\right]^2} \quad (2)$$

$$d_t(i,j) = \sqrt{\sum_{m=1}^{P}\sum_{n=1}^{Q}\left[\mu_{m,n}(i) - \mu_{m,n}(j)\right]^2 + \left[\sigma_{m,n}(i) - \sigma_{m,n}(j)\right]^2} \quad (3)$$

Then, the set of salient regions can be selected as:

$$i_{salient} = \{i \mid s(i) \geq s(j), j = 1,2,\ldots,N, i \neq j\} \quad (4)$$

In fact, more than one salient region should be found to meet for the requirements of image analysis, so the set of salient regions are selected as the first several regions according to their saliency values or those regions whose saliency values are greater than one given special threshold. Meanwhile, in order to reduce the computation complexity of saliency values, some small or fragmentary regions must be excluded from the candidate regions, as

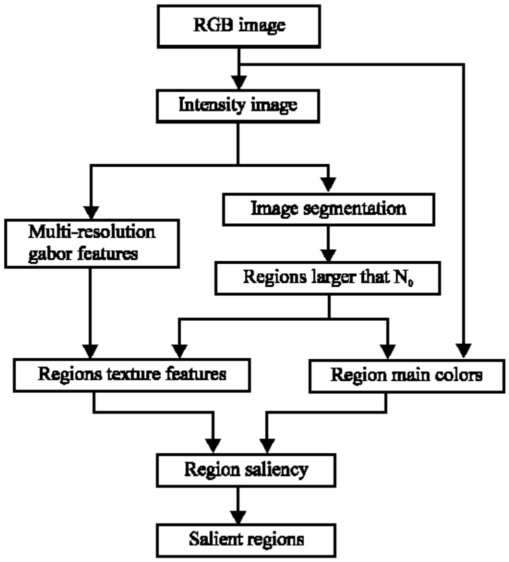

Fig. 1: The chart of salient region detection for the proposed saliency metric, where multiple salient regions could be generally extracted from one image and present its main contents

these regions are not considered as meaningful regions for incoming image processing. The chart of salient region detection is showed in Fig. 1, where No is the given minimum region size that one salient region should be.

LOCAL COLOR AND TEXTURE FEATURES

As target objects in implicit candidate images may present different scales and rotations, so the required features have to be invariant to translation, scaling and orientation. According to human being perception, the main or dominant colors, texture features, shapes have very important role to distinct different objects or regions from others. However, these features should be invariant to affine transformations. Here, we detail the extractions of dominant colors, invariant Gabor texture features (Arivazhagan *et al*., 2006) and generalized color moment invariants (Ling and Brady, 2006).

Dominant colors: Although people can distinct any acute differences in color spectrum, the human visual system cannot simultaneously perceive a large number of colors. Therefore, dominant colors can account for the spatially varying image characteristics in different implicit meaningful regions and are invariant to region scales. Inspired the results (Chen *et al*., 2005) about the perceptual color extraction, dominant colors for each segmented regions, can be extract according the following two steps.

For every salient region achieved, its color values in terms of red, green and blue color components are classified into K groups via the adaptive clustering algorithm (ACA) (Pappas, 1992). The ACA is an iterative algorithm that segments the image into K classes, where each class is characterized by a spatially varying characteristic function. The key to adapting to the local image values is that the ACA estimates the characteristic functions by averaging the image values correspond to each class over a sliding window whose size decreases as the algorithm converges. Then, the average values of each group are considered as the dominant colors and their corresponding percentage of occurrence in current regions are also further figured out according the region size and the current dominant color pixel number. Thus, the dominant colors Fc(i) of the i-th salient region is given as:

$$F_c(i) = \left\{\left(c_j^i, p_j^i\right) \middle| c_j^i = \left(r_j^i, g_j^i, b_j^i\right), j = 1, 2, \cdots, K\right\},\ i = 1, 2, \cdots, N \quad (5)$$

where, c_j^i is the j-th dominant color of i-th salient region, while p_j^i is its corresponding occurrence percentage. Furthermore, N and K is the total salient region number and the dominant color number respectively and a typical value for K is 4, i.e., K = 4. Note that this number can vary in different salient regions.

Mojsilovic *et al.* (2000) and Mikolajczyk and Schmid (2003) adopted this representation by using an (approximately) perceptually uniform color space (Lab). It has been shown that the quality of image retrieval algorithms can be substantially improved by using such color spaces (Gool and Moons, 1995) and dominant colors in one region can effectively describe the main color characteristics and texture features.

Generalized color moment invariants: A lot of work has been done on invariant descriptors around selected regions. The descriptors should be distinctive and robust to changes in viewing conditions, e.g., viewpoint, scaling and illumination. Mikolajczyk and Schmid (2003) presented a performance evaluation of different local descriptors including: shape context, steerable filters, differential invariants, spin images, SIFT, complex filters and moment invariants. The results show that the SIFT based descriptor performs the best and moment invariants and steerable filters show the best performance among the low dimensional descriptors. The above descriptors only use grey scale intensities inside the selected regions. Further, we will show that the performance of image retrieval is improved by using the colors information in the generalized color moment invariants.

In the following, two types of moment invariants, namely the traditional moment invariants and the generalized color moment invariants, will be introduced. The traditional moment invariants are computed for an image region based both on the pixels on the shape boundary and the interior. Given a function f(x, y), the traditional moments are defined as

$$F_m(pq) = \iint_R x^p y^q f(x,y)\,dxdy \tag{6}$$

where, R indicates the region on which the moments are calculated. The order of the moment is (p+q) where p and q are both natural numbers. In order to normalize the translation in the image plane, the central moments are derived based on the image centroid. Hu (1962) derived functions based on the scale normalized central moments and proposed seven RST (Rotation, Scaling and Translation) invariants of the second and third-order moments.

Since only seven invariants are too few for pattern recognition, more high order moment invariants are needed. Reddi (1981) showed that Hu's moments could be expressed in terms of radial and angular moments and subsequently, Li (1992) employed radial and angular moments in a general way to derive invariant functions. The five higher order invariants (Lezoray and Cardot, 2002) are added to Hu's moment invariants in our experiments. The order of moments used is less than or equal to 4.

Here, we describe geometric and photometric invariants based on the generalized color moments. The two sets of invariants discussed are invariant to affine geometric transformations and some photometric transformations. In Lezoray and Cardot (2002), the generalized color moments $F_m(pq, abc)$ are defined as follows:

$$F_m(pq, abc) = \iint x^p y^q \left[R(x,y)\right]^a \left[G(x,y)\right]^b \left[B(x,y)\right]^c dxdy \tag{7}$$

where, (R(x, y), G(x, y), B(x, y)) represents the RGB-values of the corresponding pixel and $F_m(pq, abc)$ is said to be a generalized color moment of order p + q and degree a + b + c. Hence, the generalized color moments cover the shape moments of binary images, the intensity moments of grey scale images and non-central moments of color images. Only small values of the order and the degree can generate a large number of generalized color moments.

Mindru *et al.* (2004) proposed several types of generalized color moment invariants based on the Lie group methods (Gool and Moons, 1995). These invariants are developed according to the combinations of geometric and photometric transformations. In our experiments, we adopt two types of these invariants, namely the GPD (Geometric and Diagonal Photometric transformations) invariants and the GPSO (Geometric and Scaling and Offset Photometric transformations) invariants. In total, 21 GPD invariants and 18 GPSO invariants are used and denoted as $F_{m\_gpd}(i)$ and $F_{m\_gpso}(i)$, respectively for the i-th salient region in current image segmentation results.

Texture representation: This part describes texture representation based on Gabor transform and texture classification with rotation normalization. A Gabor wavelet is also a complex planar wave restricted by 2-D Gaussian envelope. Aside from scale and orientation, the only thing that can make two Gabor wavelets differ is the ratio between wavelength and the width of the Gaussian envelope. Every Gabor wavelet has a certain wavelength and orientation and is then convolved with an image to estimate the magnitude of local frequencies of that approximate wavelength and orientation in the image. The Gabor wavelets can be considered as a class of self-similar functions.

For a given image f(x,y) of size N×Nc, its discrete Gabor wavelet transform is given by convolution Eq. 8.

$$G_{pq}(x,y) = \sum_s \sum_t f(x-s, y-t)\psi^*_{pq}(s,t) \tag{8}$$

where, s, t are the filter mask size variables; p, q are the scale and orientation values respectively and Ψ^*_{pq} is the complex conjugate of Ψ_{pq}, which is a self-similar function generated from the dilation and rotation of the mother wavelet Ψ and is defined as given in (9).

$$\psi(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right)\exp(2\pi jWx) \tag{9}$$

The Gabor wavelets are obtained through the generating function defined in (10), i.e.,

$$\psi_{pq}(x,y) = a^{-p}\psi(\bar{x},\bar{y}) \tag{10}$$

where, p = 0,1, . . ., P-1 and q = 0,1, . . ., Q-1; a, the scale factor; P, the total number of scales; Q, the total number of orientations; $\bar{x} = a^{-p}(x\cos\theta + y\sin\theta)$ and $\bar{y} = a^{-p}(-x\sin\theta + y\cos\theta)$; for a > 1 and $\theta = q\pi/Q$.

A set of Gabor wavelets of different scale and orientation is convolved with an image to estimate the magnitude of local frequencies of that approximate scale and orientation. After applying Gabor filters on the i-th region of one image with different orientation at different scale, the energy content is calculated by:

$$E_i(p,q) = \sum_x \sum_y \left|G_{pq}^i(x,y)\right|,\ i = 1,2,\cdots,N \qquad (11)$$

The mean μ_{pq} (i) and standard deviation σ_{pq} of all transformed coefficients for the i-th region are found using 12 and 13, respectively, that is

$$\mu_{pq}(i) = \frac{E_i(p,q)}{N_{reg}(i)},\ i = 1,2,\cdots,N \qquad (12)$$

$$\sigma_{pq}(i) = \sqrt{\frac{\sum_x \sum_y \left|G_{pq}^i(x,y)\right| - \mu_{pq}(i)}{N_{reg}(i)}},\ i = 1,2,\cdots,N \qquad (13)$$

where, $N_{reg}(i)$ is the size of the i-th region. These values represent the feature of the homogeneous texture image. A feature vector "Ft(i)" for texture representation of i-th region is created using the mean and standard deviation as feature components. If P scales and Q orientations are considered in the implementation, then the corresponding feature vector is given by

$$\mathbf{F}_t(i) = \left\{\mu_{pq}(i), \sigma_{pq}(i) \middle| p = 0,1,\cdots,P-1; q = 0,1,\cdots,Q-1\right\},\ i = 1,2,\cdots,N \qquad (14)$$

Similarity metric: Similarity metrics plays an important role for image classification. According to the results showed in literature by Kokare *et al*. (2003), the retrieval performance can be improved significantly by using the Canberra and Bray-Curtis distance metrics as compare to traditional Euclidean and Mahalanobis distance based approaches. Here, we use the Canberra distance as the metric of similarity for the proposed image retrieval.

If x and y are the feature vectors of database image and query image respectively of length d, then Canberra distance is given by

$$d(\mathbf{x},\mathbf{y}) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|} \qquad (15)$$

Thus, the similarity metric between the i-th salient region and the j-th region is given as their Canberra distance averages of dominant colors, geometric color invariants and texture Gabor features, which can be denoted as,

$$d(i,j) = \frac{1}{3}\left[d_c(i,j) + d_t(i,j) + d_m(i,j)\right] \qquad (16)$$

where, d_c (i, j), d_t (i, j), d_m (i, j) are their corresponding Canberra for dominant colors, geometric color invariants and texture Gabor features, which can be evaluated according to (15).

IMAGE FUZZY CLASSIFICATION BASED SALIENT REGIONS

Classification accuracy depends mainly on two factors: the accurate feature vectors that could uniquely denote the content of one image; the pretty image classification method with good results consistent to human being perceptions. The salient regions in one image could present its main contents and these contents should be also reflected in image classifications. Assume that there are N images in one image database and the i-th image has N_i salient regions. The proposed image fuzzy classification based salient regions (SrFC) can be formulated as following processes.

- The salient regions for all the images are extracted according to the procedure as showed in Fig. 1. Meanwhile, their corresponding features are also evaluated in terms of dominant colors, geometric color moment invariants and Gabor multi-resolution features.
- Then, these salient regions are put together for clustering according to their feature distances, where the hierarchical clustering method (Miyamoto and Nakayama, 1986) is used for salient region classification without predicted category numbers. Here, we assume that N_cat salient region categories are achieved and each salient region is exclusively subjected to one category.
- The categories for salient regions are further used for the categories of candidate classification images. For the i-th image, assume there are $N_{(i,j)}$ salient regions for the j-th image category and the fuzzy membership functions of the j-th category for the i-th image is given as

$$U(i,j) = \frac{N_{(i,j)}}{N_i},\ i = 1,2,\cdots,N,\ j = 1,2,\cdots,N_{cat} \qquad (17)$$

The membership value of each image is only one metric of degree for the image belonging to one category and it doesn't directly give the assured classification results. Thus, the classification could be consistent with human being perception in different views. Meanwhile, the fuzzy classification procedure based salient regions is further demonstrated by Fig. 2, which gives its details together other correlated disposing.

As showed in Fig. 2, the image segmentation, salient region extraction and clustering are the three fundamental steps, where the segmentation is conducted by the mean-shift algorithm given in literature (Comaniciu and Meer, 2002). Compared with the classic common region-based

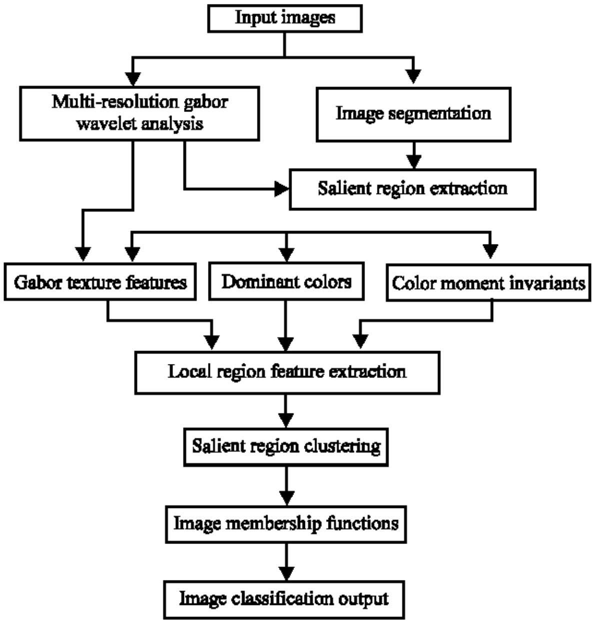

Fig. 2: The procedure of image fuzzy classification based salient regions, where the salient region clustering is conducted by the common hierarchical clustering

schemes (Lezoray and Cardot, 2002; Zeljkovic *et al*., 2004; Sanghoon and Crawford, 2005; Singh and Markou, 2004; Fredembach *et al*., 2004), the salient regions-based scheme takes account of the implicit salient objects as the corresponding semantic contents. This will lead to more accurate classification results. Furthermore, the geometric color moment invariants can improve the robustness of the proposed schemes under the cases with similar objects in different scales and orientations.

EXPERIMENTS

We applied the proposed classification strategy to several typical natural images and each of them has one or many salient objects. Firstly, as the images of (1-1), (2-1), …, (8-1) showed in Fig. 3, their corresponding salient regions were given by the image (1-i), (2-i), …, (8-i) for i>1, respectively, which were extracted according the salient region extraction algorithm as presented in section 2. Here the mean shift based image segmentation scheme (Lezoray and Cardot, 2002) was to used to conduct image segmentations. Clearly, as for the large number of implicit regions, it's convenient and efficacious to select those most representative or salient regions for the complexity reduction of image classification. Unlike the classical region-based classification schemes (Sanghoon and Craford, 2005; Signh and Markou, 2004; Fredembach *et al*., 2004), i.e., the hierarchical clustering based approach (HCBA) (Sanghoon and Crawford, 2005), the eigenregions based strategy (EBS) (Fredembach *et al*., 2004) and the novel region based methods (NRBM) (Singh and Markou, 2004), the proposed salient regions based fuzzy classification strategy achieved the classification results by clustering all the salient regions from these images into different disjoint salient region sets, as showed in Fig. 3. The salient region sets were achieved by clustering their feature vectors of dominant colors, simple Gabor multi-resolution features and geometric color moment invariants, where the hierarchical clustering algorithm (Miyamoto and Nakayama, 1986). For each salient region, its corresponding category flag is marked by the name at right of its number.

As indicated in Fig. 3, there are five categories according to the salient region clustering results, i.e., flower, grass, leaf, soil, butterfly, etc. These categories are further considered as the categories of the candidate classification images and the membership values of each image are evaluated by formula (17) and given in Table 1, respectively. The fuzzy classification results as showed in Table 1 could reflect the main contents in each images, while the classical HCBA, NRBM, EBS classify the candidate images into disjoint sets with the ignorance of other inferior contents.

In order to compare the performance different among different image classification schemes, we use the category with most largest membership values as the category of current considering images, i.e., the category "leaf" for iamge_1-1, "flower" for image_3-1, "grass" for image_5-1, "butterfly" for image_8-1, etc. Furthermore, we constructed one image database with about 200 images with categories such as the same that showed in Table 1. The classical HCBA, NRBM, EBS schemes and the proposed salient region-based fuzzy classification

Table 1: The membership values of the eight typical images under different image category

	Image							
Category	Image_1-1	Image_2-1	Image_3-1	Image_4-1	Image_5-1	Image_6-1	Image_7-1	Image_8-1
Grass	0.00	0.00	0.18	0.00	0.67	0.53	0.31	0.00
Flower	0.35	0.25	0.57	0.00	0.00	0.00	0.00	0.23
Leaf	0.40	0.65	0.25	0.65	0.33	0.47	0.69	0.36
Soil	0.25	0.10	0.00	0.35	0.00	0.00	0.00	0.00
Butterfly	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41

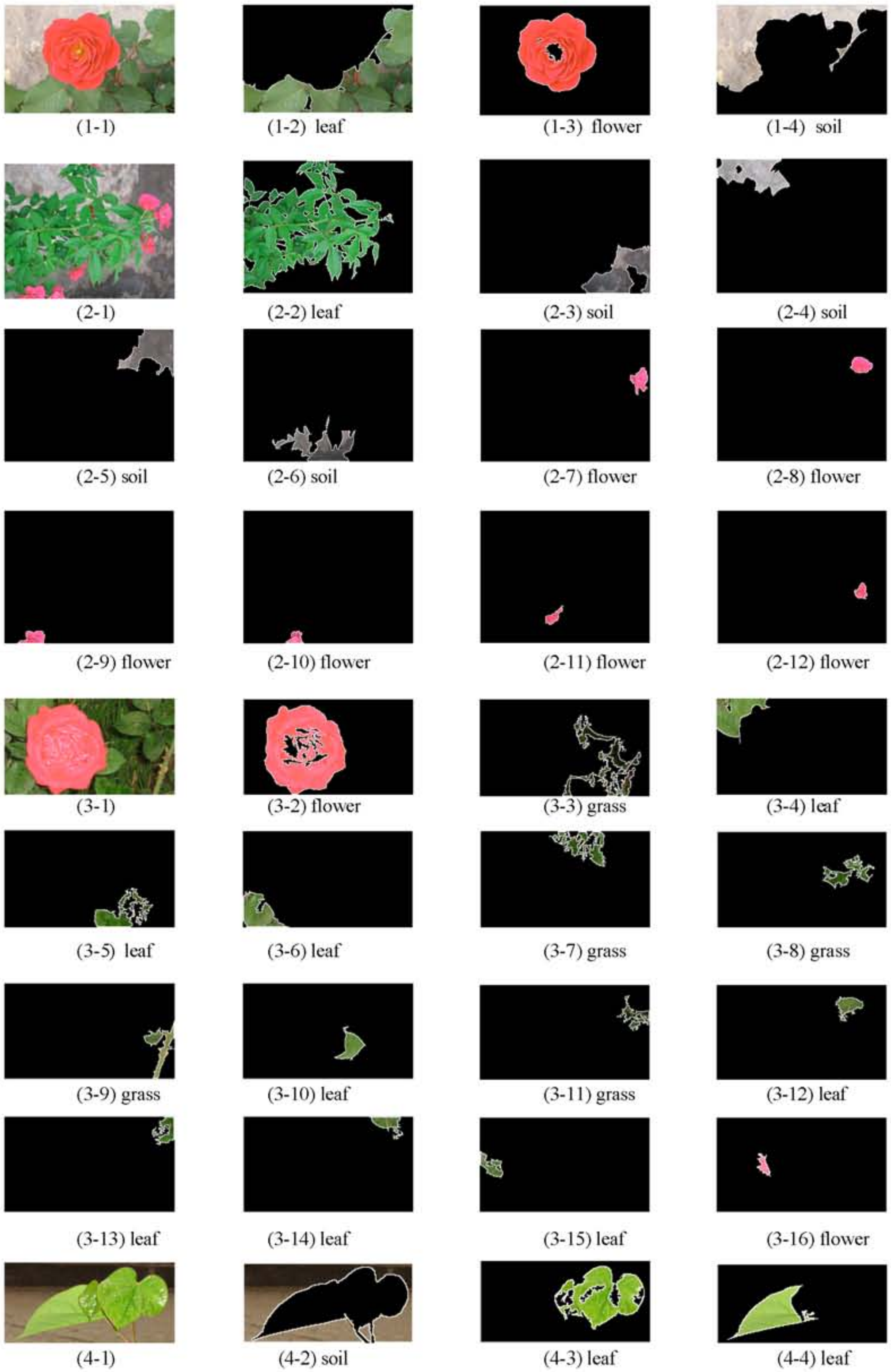

Fig. 3: Continued

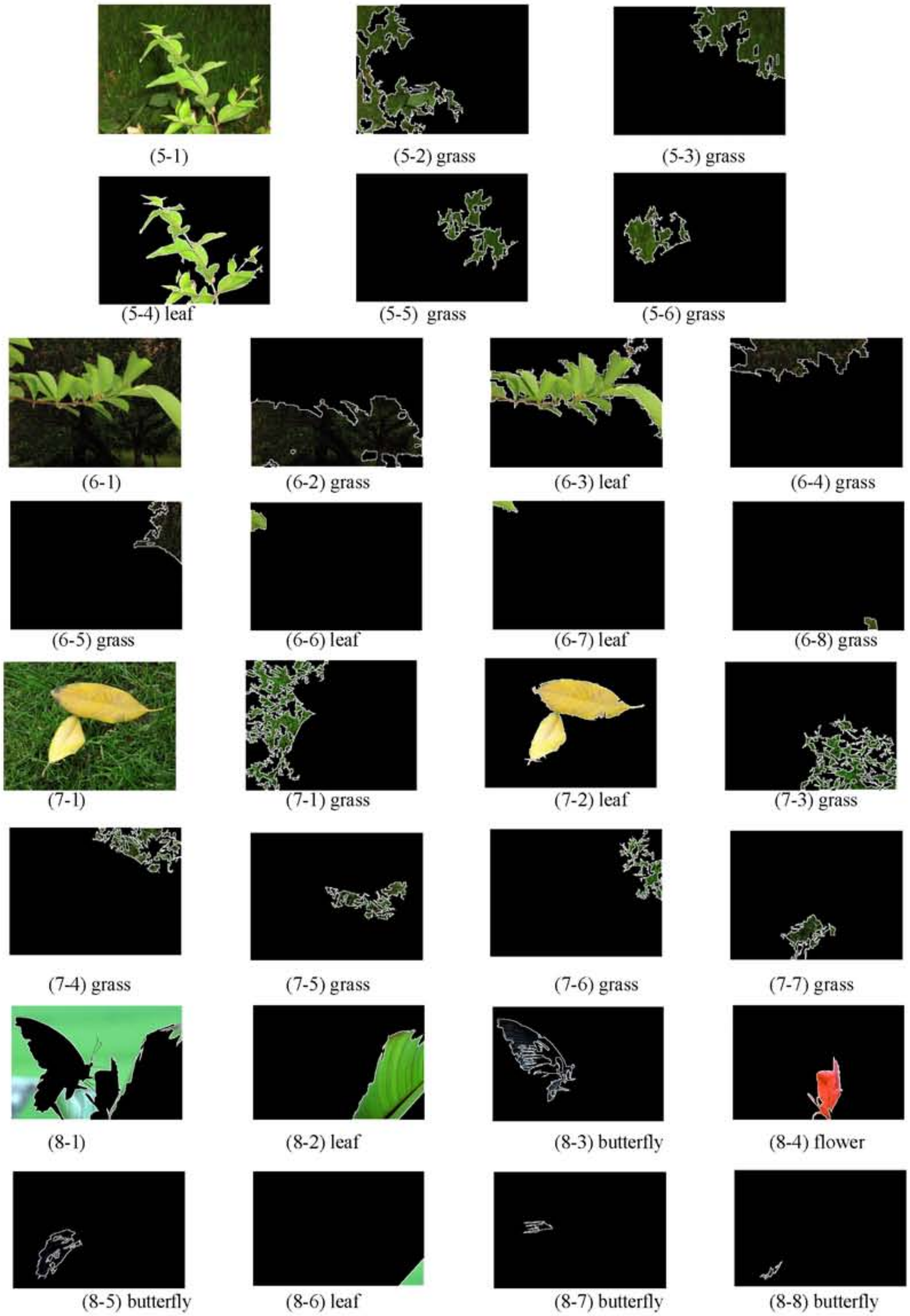

Fig. 3: Several typical images and their salient region classification results, where the salient regions of each image are obtained by the salient region extraction scheme

approach are considered for classification in the databases. The classification accuracies for these schemes are 73, 52, 61 and 89% fro the HCBA, NRBM, EBS and SrFC schemes respectively. As an alternative scheme for the HCBA, the proposed SrFC could obtain better performance by the combination of multiple salient regions. Furthermore, with comparison to the HCBA scheme for individual salient regions, the classification accuracy is improved about 16% by the proposed SrFC scheme, while the EBS scheme are effective for the images with single semantic objects.

CONCLUSIONS

In fact, the natural images are generally with several different semantic objects and we propose an novel multiple salient region based fuzzy classification scheme. This classification strategy could reflect the main contents in images, which are consistent with human being semantic perception. Compared with other classical common schemes, i.e., the HCBA, NRBM, EBS, the proposed SrFC scheme improved the classification accuracy by evaluating the membership values for all the categories, which are achieved by clustering all the salient region from all the images in databases. Meanwhile, we also propose one salient region extraction algorithm with consistency to human being distinct perception in terms of dominant colors, texture and geometric color moment invariants. The results of experiments with elaborately designed image databases, the proposes SrFC classification scheme could achieve the expected results.

REFERENCES

Arivazhagan, S., L. Ganesan and S.P. Priya, 2006. Texture classification using Gabor wavelets based rotation invariant features. Pattern Recog. Lett., 27 (16): 1976-1982.

Badawy El, O., M.R. Sakka, K. Hassanein and M.S. Kamel, 2001. Image data mining from financial documents based on wavelet features. Proceedings of International Conference on Image Processing. Thessaloniki, Greece.

Chen, J., T.N. Pappas, A. Mojsilovic and B.E. Rogowitz, 2005. Adaptive perceptual color-texture image segmentation. IEEE Trans. Image Process, 14 (10): 1524-1536.

Comaniciu, D. and P. Meer, 2002. Mean shift: A robust approach toward feature space analysis. IEEE Trans. Pattern Anal. Mach. Intel., 24 (5): 603-619.

Dong, L. and E. Izquierdo, 2007. A biologically inspired system for classification of natural images. IEEE Trans. Circuits Syst. Video Technol., 17 (5): 590-603.

Fredembach, C., M. Schroder and S. Susstrunk, 2004. Eigenregions for image classification. IEEE Trans. Pattern Anal. Mach. Intel., 26 (12): 1645-1649.

Gool, L.V. and T. Moons, 1995. Vision and Lie's approach to invariance. Image Vision Comput., 13 (4): 259-277.

Hmida, M.B. and J.Y. Ben, 2006. Fuzzy classification, image segmentation and shape analysis for Human face detection. Proceedings of 13th IEEE International Conference Elect., Circuits and Syst. Nice, France.

Hu, M., 1962. Visual pattern recognition by moment invariants. IEEE Trans. Inform. Theor., 8 (1): 179-187.

Hurn, M.A., K.V. Mardia, T.J. Hainsworth, J. Kirkbride and E. Berry, 1996. Bayesian fused classification of medical images. IEEE Trans. Med. Imag., 15 (6): 850-858.

Kokare, M., B.N. Chatterji and P.K. Biswas, 2003. Comparison of similarity metrics for texture image retrieval. Proceedings of TENCON 2003 Conference on Convergent Technologies for Asia-Pacific Region. Bangalore, India.

Kuan Yu-Hsin, Chen Shih-Ting, Kuo Chung Ming and Hsieh Chaur-Heh, 2006. A novel unsupervised salient region segmentation for color images. Proceedings of First International Conference on Innovative Computing, Information and Control. Beijing, China.

Lezoray, O. and H. Cardot, 2002. Cooperation of color pixel classification schemes and color watershed: A study for microscopic images. IEEE Trans. Image Process, 11 (7): 783-789.

Li, Y., 1992. Reforming the theory of invariant moments for pattern recognition. Pattern Recog., 25 (7): 723-730.

Ling, S. and M. Brady, 2006. Invariant salient regions based image retrieval under viewpoint and illumination variations. J. Visual Commun. Image Represent., 17 (6): 1256-1272.

Mikolajczyk, K. and C. Schmid, 2003. A performance evaluation of local descriptors. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition. Madison, USA.

Mindru, F., T. Tuytelaars and L.V. Gool, 2004. Moment invariants for recognition under changing viewpoint and illumination. Comput. Vision Image Understanding, 94 (1-3): 3-27.

Miyamoto, S. and K. Nakayama, 1986. Similarity measures based on a fuzzy set model and application to hierarchical clustering. IEEE Trans. Syst. Man Cybernetics, 16(3): 479-482.

Mojsilovic, A., J. Kovacevi, J. Hu, R.J. Safranek and S.K. Ganapathy, 2000. Matching and retrieval based on the vocabulary and grammar of color patterns. IEEE Trans. Image Process, 9 (1): 38-54.

Pappas, T.N., 1992. An adaptive clustering algorithm for image segmentation. IEEE Trans. Image Process, 40 (4): 901-914.

Pappas T.N., C. Junqing and D. Depalov, 2007. Perceptually based techniques for image segmentation and semantic classification. IEEE Commun. Mag., 45 (1): 44-51.

Reddi, S.S., 1981. Radial angular moment invariants for image identification. IEEE Trans. Patt. Anal. Mach. Intel., 3 (2): 240-242.

Sanghoon, L. and M.M. Crawford, 2005. Unsupervised multistage image classification using hierarchical clustering with a bayesian similarity measure. IEEE Trans. Image Process, 14 (3): 312-320.

Selvan, S. and S. Ramakrishnan, 2007. SVD-Based modeling for image texture classification using wavelet transformation. IEEE Trans. Image Process, 16 (11): 2688-2696.

Singh, S. and M. Markou, 2004. An approach to novelty detection applied to the classification of image regions. IEEE Trans. Knowledge Data Eng., 16 (4): 396-407.

Yo-Ping, H. and C. Tsun-Wei, 2004. Retrieving interesting images using fuzzy image segmentation and fuzzy data mining model. Proceedings of IEEE Annual Meeting of the Fuzzy Information Processing. Banff, Alberta, Canada.

Zeljkovic, V., A. Dorado, Z. Trpovski and E. Izquierdo, 2004. Classification of building images in video sequences. Elect. Lett., 40 (3): 169-171.