3. Low-Level Image Feature

This chapter proposes a new type of features, called color-size feature, which contains the distribution information of both color and region-size together. We first describe watershed segmentation to partition images to regions. The information of region-size could be extracted from regions. Then we present the details of extracting color-size feature and provide several experiments to show the efficient of our work.

3.1. Image Segmentation

The goal of image segmentation is to partition an image into some different regions. Image segmentation is still an open problem in the area of computer vision. That is to say, it is difficult to look for a perfect approach for segmenting images. Thus, our idea is not to generate the best or perfect regions with segmentation, but rather to make useful ones. In this work, we adopt the well known watershed segmentation [Vincent and Soille 91][Wang 97], which is an efficient, automatic, and unsupervised segmentation method to partition an image into non-overlapping regions.

Because the basic watershed algorithm is highly sensitive to gradient noise, it usually results in over-segmentation. An example of over-segmentation in watershed regions is shown in Fgure 3-1. To overcome this problem, small local minima in the gradient image should be eliminated [Wang 97]. These minima are defined as local minima consisting of a small number of pixels or having low contrast with their neighbors, and are eliminated by assigned two s*caling parameters*: *r* and *h*. Parameter *r* is the size of the structuring element of dilation operators, whose application eliminates local minima of size less than r pixels, and parameter h is the height of elevation used to remove the local minima with low contrast. These two parameters can be used to control the coarseness of the segmentation results: as r and h increase, the number of regions generated decreases. Figure 3-2 illustrates how the number of regions changes for different scaling parameters r and h. In the evaluation of the proposed color-size feature, we set these parameters as r=3 and h=3, which results in 75,000 regions for the 1,600 images used in Section 3.4.

(a) number of regions: 1125. (b) number of regions: 1299.

Figure 3-1. Illustration of over-segmentation in watershed regions.

	r=1	r=3	r=5
H=1	 # of regions = 62	 # of regions = 20	 # of regions = 13
H=3	 # of regions = 44	 # of regions = 18	 # of regions = 12
h=5	 # of regions = 40	 # of regions = 17	 # of regions = 11

Figure 3-2. Watershed segmentation controlled by the scaling parameters r and h.

3.2. Region Size

The region size is the number of pixels in a region, or the size percentage of a region in an image when normalized. Figure 3-3 illustrates the distributions of the region size in two images of the same size (both 192x128 pixels), where each of the two examples contains the original image, the watershed results, and the distributions. The distributions of the region size shown in Figure 3-3(a) and (b) are significantly different. Hence, we expect that considering both the region size information and color features will yield more representative and discriminable features.

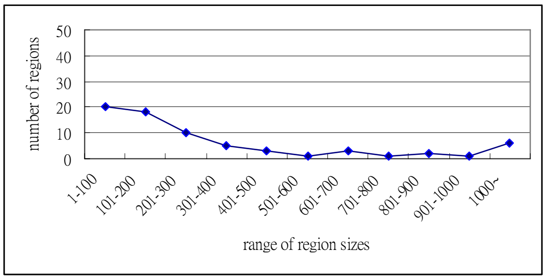
Given a pixel p in a region R of an image I, the region-size attribute for p equals the percentage size of I represented by R, and hence all pixels in the same region have the same region-size attribute. We describe the region-size feature on a region level rather than on a pixel level for simplicity.

Here we adopt the image data used in Section 3.4 to produce a region-size histogram. The data set contains 5,000 images and each image is divided by watershed segmentation with scaling parameters r=3 and h=3, as described in Section 3.1. Figure 3-4(a) plots the region-size histogram of all regions, where we quantize the region-size percentage into 100 levels, i.e. 0.01 in each level. Most regions are concentrated in the first two or three size levels, and the average region size is 0.0681. Hence, using equal quantization throughout the region-size histogram is inappropriate because the region-size histogram is not uniform. We also computed the cumulative distribution, which is shown in Figure 3-4(b). We set the number of quantized bins in the region-size attribute, S, to 4 in our implementation, and hence we defined the quantization boundaries of the region-size attribute at 0.001, 0.012, and 0.049 for 25%, 50%, and 75% of the regions, respectively.

source image

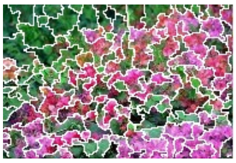
(a)

# of regions: 67



source image

(b)



# of regions: 131

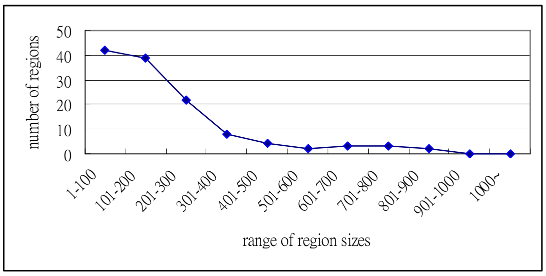
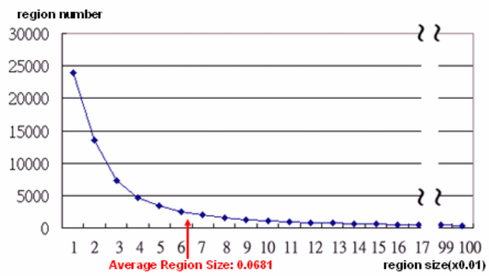
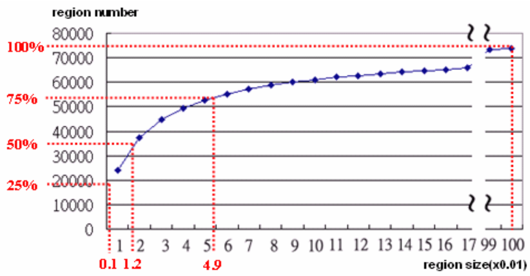


Figure 3-3. Distributions of region size information in two examples.



(a). Region-size histogram of all regions in about 75,000 regions.



(b). Cumulative histogram of region-size features in about 75,000 regions.

Figure 3-4. Extraction for the region-size feature.

Extracting the region-size feature is based on the results of image segmentation. Images with different structures will exhibit different segmentation results with the same scaling parameters, and hence the region-size distribution contains the structural information of an image. Therefore, below we introduce how to embed the region-size feature into the proposed color-size features.

3.3. Color-Size Histogram and Color-Size Moments

Embedding the region-size information results in each pixel of an image having four attributes: three color components and one region-size component. Let K_1, K_2, and K_3 be the number of bins used to quantize the three color attributes, and S be that to quantize the region-size attribute. Then, a *color-size histogram (CSH)* of a region is then a K_1 x K_2 x K_3 x S-dimensional feature set,

$$CSH = \{h_{ijkl} \mid 1 \le i \le K_1, 1 \le j \le K_2, 1 \le k \le K_3, 1 \le l \le S\}, \tag{3.1}$$

where each h_{ijkl} value in the histogram corresponds to the number of pixels having the values in color and region-size channels. For example, Figure 3-5 illustrates the voting process of extracting the color-size histogram. Pixel A of the image on the right hand side has a blue color, and is contained in an extra-large (XL) region. Then the bin corresponding to the blue color and the XL region-size will be incremented by one.

Let x_i, i=1, 2, 3, 4, be the value of pixel x in the i-th color component (i is 1, 2, or 3) or the region-size (i is 4), and N be the number of pixels in the image. The *color-size moments (CSM)*, with first- and second-order moments, of a region are defined as:

$$CSM = \{\mu_1, \mu_2, \mu_3, \mu_4, \sigma_1, \sigma_2, \sigma_3, \sigma_4\}, \tag{3.2}$$

where $\mu_i = \frac{1}{N}\sum_{x=1}^{N} x_i$, and $\sigma_i = \frac{1}{N}\sum_{x=1}^{N}(x_i - \mu_i)^2$, i = 1, 2, 3, or 4.

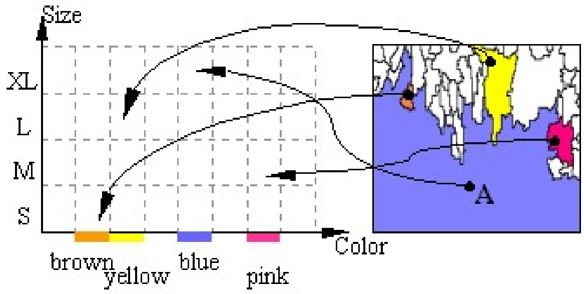
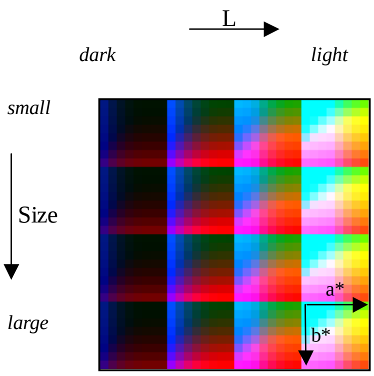
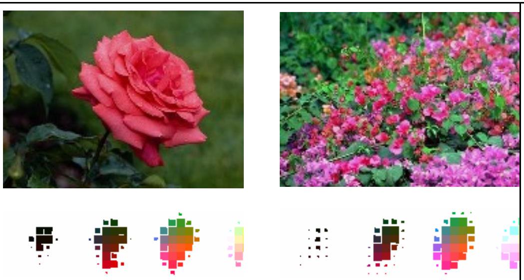


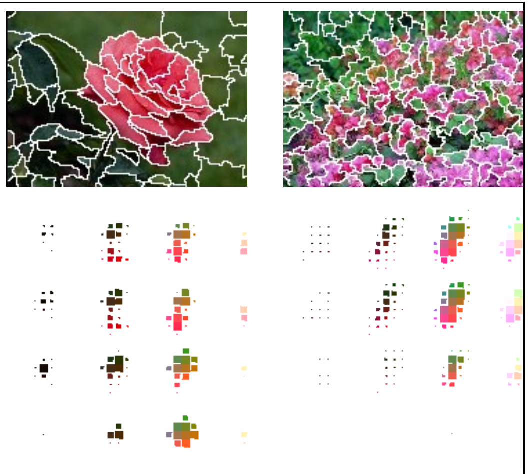
Figure 3-5. Illustration of the color-size histogram.



(a). The color pallet for visualizing color-size histogram where L, S, a, and b are quantized into 4, 4, 8, and 8 bins, respectively.



(b) the color histogram.



(c) the color-size histogram by setting *r*=1 and *h*=3

Figure 3-6. Illustration of color histogram and color-size histogram.

Figure 3-6 shows an example of the difference between the color histogram and the proposed color-size histogram. Figure 3-6(a) shows the color pallet for visualizing both the color in CIE-Lab color space and the region size. Figure 3-6(b) and (c) show two images and their corresponding color histograms, and Figure 3-6(d) and (e) show the segmentation results of the two images and their color-size histograms which are visualized based on the pallet of Figure 3-6(a). In this example, the two images have similar color histograms, but they are not actually similar if we consider the color-size histograms.

3.4. Evaluation

To precisely evaluate the efficacy of using color-size features, we need to design a compact experiment to avoid the influence of other factors. This is achieved by performing image classification (instead of image retrieval) using *k*-NN, which is one of the simplest classification methods. Note that we perform the leave-one-out strategy in the *k*-NN classifier [Duda et al. 01]. Here we compare the performances of using the size feature only, color histogram (*CH*) vs. color-size histogram (*CSH*), and color moments (*CM*) vs. color-size moments (*CSM*).

3.4.1. Data set

We arbitrarily chose 16 categories from Corel Photos, with each category consisting of 100 photo images in our image database, giving a total of 1,600 images in the data set. Table 3-1 lists the category IDs and semantic names of each category, which indicates the diverse content of the database. These images contain a wide range of content such as scenery, animal, plant, etc. Now we will perform some experiments to compare the performance using size feature, color histogram (CH) vs. color-size histogram (CSH), and color moments (CM) vs. color-size moments (CSM).

Table 3-1. The category ID and the semantic name of the data set.

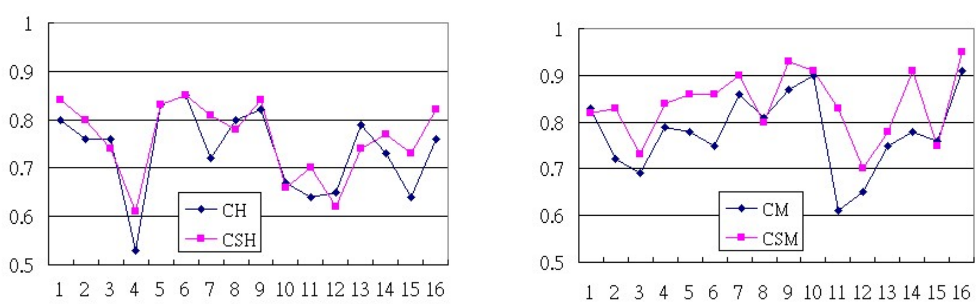
							
ID=1 Glaciers and Mountains	ID=2 Monument Valley	ID=3 Autumn	ID=4 Caverns	ID=5 Fireworks	ID=6 Doors of Paris	ID=7 Dolphins and Whales	ID=8 Owls
							
ID=9 Fitness	ID=10 Prehistoric World	ID=11 Bonsai and Penjing	ID=12 Tropical Plants	ID=13 Beautiful Roses	ID=14 Museum Duck Decoys	ID=15 Cuisine	ID=16 Museum Easter Eggs

Table 3-2. The recognition rates (%) using color-size moments with changing *r* and *k*.

	r=1	*r*=3	*r*=5
k=1	83.8	82.2	79.5
k=5	83.8	81.5	79.3
k=9	82.6	80.8	79.1

Table 3-3. The recognition rates (%) using region-size feature, CH: color histogram, CSH: color-size histogram, CM: color moments, and CSM: color-size moments.

k	Size	CH	CSH	CM	CSM
1	50	73.1	75.5	75.8	83.8
5	51.3	73.4	75.8	77.9	83.8
9	51.8	71.8	75.7	76.9	82.6



(a) color histogram vs. color-size histogram (b) color moments vs. color-size moments

Figure 3-7. The recognition rate of each category using different features with *k*=5 and r=1.

3.4.2. Results

The influence of the scaling parameters, r and h, in watershed segmentation is indicated in Figure 3-3 of Section 3.1. The segmentation results, i.e. the number of watershed regions, are more affected by r than by h, and hence we fix h at 3 in the subsequent experiments in this section.

Table 3-2 lists the classification rates using color-size moments with different scaling parameters r and k for the K-NN classifier. This table indicates that the classification rates are both good and stable using color-size moments with different r and k values. Therefore, in the subsequent experiments, we fix the parameter r at 1 for simplicity. Table 3-3 lists the recognition accuracies using five types of features with different values of k in the k-NN classifier. But using color-size features is better than using color features, when comparing either the color-size histogram vs. the color histogram or color-size moments vs. color moments. Moreover, color-size moments produce the best results for all values of k.

Figure 3-7 shows the detailed rates of each category for k=5 and r=1, which indicate that color-size moments are better than color moments, whereas there is no obvious different between the color-size histogram and the color histogram. Because the color histogram is in a high-dimensional space, the region-size feature cannot result in a significant improvement. On the other hand, since color moments are low-dimensional features, the size feature does improve the accuracy.

Table 3-4. The confusion matrix of each category using color-size moments with k=5 and r=1.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1	**82**	2	2	0	0	1	0	0	2	0	5	1	0	3	0	2
2	8	**83**	0	1	0	0	3	1	1	0	1	0	0	0	0	2
3	8	7	**73**	2	0	1	0	0	0	0	4	4	1	0	0	0
4	0	1	4	**84**	0	2	3	0	0	0	2	0	2	0	2	0
5	1	0	1	4	**86**	0	0	5	0	0	1	1	0	0	1	0
6	0	1	3	4	0	**86**	0	0	2	0	2	1	0	0	1	0
7	2	0	0	0	1	0	**90**	0	0	0	5	0	0	1	0	1
8	4	3	4	4	3	0	0	**80**	0	0	0	1	0	0	0	1
9	0	0	0	0	0	0	0	0	**93**	4	0	0	0	1	0	2
10	0	0	0	0	0	0	0	0	5	**91**	0	0	0	4	0	0
11	5	0	1	1	0	0	3	0	0	0	**83**	1	0	4	2	0
12	1	0	14	0	0	0	0	1	1	0	4	**70**	5	0	3	1
13	1	0	4	3	2	1	0	2	0	0	0	5	**78**	0	4	0
14	0	0	0	0	0	0	0	0	2	6	1	0	0	**91**	0	0
15	0	2	9	6	0	1	0	0	0	0	1	5	1	0	**75**	0
16	1	1	0	0	0	0	0	0	1	0	0	0	0	2	0	**95**

Table 3-4 is the classified confusion matrix of all categories using color-size moments with k=5 and r=1. The titles of each row and column are category id. Cells of this table are the number of testing results corresponding to the category id. The diagonal items with boldface in Table 3-4 are numbers of correct assignments, and the others are fault assignments. For each category, there are 100 testing samples totally of each category.