# Image Retrieval Using Space-Distributed Average Coordinates

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Abstract: In this paper, we present a content-based image retrieval method that is less sensitive to some rotations and translations of an image by using the fuzzy region segmentation. The algorithm retrieves similar images from a database using the two features of color and color spatial information. To index images, we use the average coordinates of color distribution to obtain the spatial information of each segmented region. Furthermore, we also propose the alternative to the ripple phenomenon, which is occurred in the conventional fuzzy region segmentation algorithm.

#### 1. Introduction

Due to the enormous increase of multimedia data, there is no doubt in that the image takes the most important part in multimedia. However, when handling the image, we need effective image processing, description, and management because the image has the distinctive characteristics that are different from the existing text. Active research is underway in image indexing and retrieval field by above demands. Therefore, the feature extraction of an image is an important task for image indexing and retrieval.

The most common method [1] for indexing color images is color histogram method that is insensitive to image rotation and object translation, because it uses the global information of image. However, the color histogram indexing has a disadvantage, which cannot distinguish an image from images with same color histogram but different content. To solve this disadvantage, more information has to be need. Texture, shape, sketch, and spatial relationship can help the indexing more powerful [2-4].

In [5], spatial information is incorporated. CCV's (color coherence vector) were indexed based on color coherence, which describe how much a certain bin is coherent. However, that is a simple description of how much, not where. Therefore, more precise information is needed.

In this paper, we review the conventional fuzzy region method [6-7] that is indexed by moments of each region. And we describe the proposed fuzzy region for region segmentation and average coordinates of color distribution as indices. We experiment the image retrieval simulation from a database using "query by example". Fig 1 shows the overall block diagram of the proposed image retrieval system.

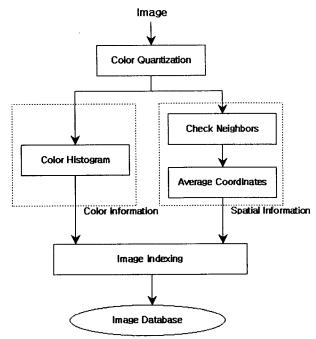


Fig. 1 Overall block diagram

# 2. Proposed Fuzzy Region Segmentation Algorithm

## 2.1 Conventional Fuzzy Region Segmentation

The fatal disadvantage of region segmentation is occurred by an object translation in an image. Thus, the fuzzy region is used to include more region boundary information that is less sensitive to small rotations and translations.

Fuzzy region is assumed that the main object of an image is located in the center. Region segmentation is performed based on this assumption. The conventional fuzzy region segmentation algorithm is defined by:

$$R_{o}(P) = \begin{cases} 1 & \text{for P inside } E_{a,b} \\ \frac{1}{2} \left( \cos \left( d_{ellipse} \left( P, E_{a,b} \right) \frac{\pi}{r} \right) + 1 \right) & \text{for P outside } E_{a,b} \end{cases}$$

$$\tag{1}$$

, where  $R_0$  means the center region, and  $E_{a,b}$  is the ellipse with long semi-axis a and short semi-axis b. r is the boundary width. Also,  $d_{ellipse}$  stands for the distance function, and  $P = (p_x, p_y)$ .

Above the region definitions have some drawbacks. That is, the ripple phenomenon is occurred in every corner of an image, because they use cosine function to include the region boundary information when they choose the small ellipse boundary width. It fluctuates and

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distorts the information of non-center regions. Therefore, more exact region segmentation should be established by solving this ripple phenomenon.

### 2.2 Proposed Fuzzy Region Segmentation

We exclude the ripple phenomenon of fuzzy region by adding some conditions, which insert '0' into the outside of ellipse boundary in the center region, that is, outside of a half period of cosine function. Therefore, we can exclude the ripple phenomenon of center region that can be occurred, and can avoid a loss of the information of non-center regions. We also apply the adaptive ellipse boundary width to region. The center region of the proposed fuzzy region is defined as follows.

$$R_{0}(P) = \begin{cases} 1 & \text{for P inside } E_{a,b} \\ \frac{1}{2} \left( \cos \left( d_{ellipse} \left( P, E_{a,b} \right) \frac{\pi}{r} \right) + 1 \right) \\ & \text{for P outside } E_{a,b} \text{ and inside } E_{a+r,b+r} \\ 0 & \text{for P outside } E_{a+r,b+r} \end{cases}$$

, where  $E_{a+r,b+r}$  is the ellipse with long semi-axis a+r and short semi-axis b+r. Therefore, image retrieval based on the proposed fuzzy region gives better results than the conventional one does.

# 3. Spatial Information Extraction of Proposed Fuzzy Region

In the conventional fuzzy region-based image retrieval, moments of each fuzzy region are used as image indices. However, moments are global information, and do not include local spatial information of an image. To include the local image features, in this paper the average coordinates of color distribution are used for extracting the spatial information.

The space-distributed average coordinates are local color spatial information and used as image indices of each region.

To compute the space-distributed average coordinates, the color quantization is first performed to reduce the color bins, and then pixel weights are calculated by comparing the adjacent pixel values. The average coordinates of color distribution are computed as follows.

#### 3.1 Space-Distributed Average Coordinates (SDAC)

Images are quantized into n levels. We need each color location feature to represent the spatial information. To obtain the color location feature, we calculate the representative coordinate by using each color distribution.

To measure the color coherence, we need to calculate the coordinate of each color bin. Thus, we take the weight, which is the number of neighborhoods with same color bin. Consequently, when same color bins are highly distributed in neighborhoods, that is, higher color coherence, the weights are increased. That means those weights highly affect computing the coordinate. While

same color bins are low distributed in neighborhoods, low coherence causes into small weight. That means pixels with small weight cannot affect obtaining the coordinate.

From this, SDAC can get better results to calculate the coordinate in large region than points and/or lines.

### 3.2 SDAC from Images

First the number of image color bins is reduced to extract the SDAC from the image. Then color distribution of each bins is checked, and algorithm takes the weights, which is more than the threshold value. It causes that SDAC is moved to the large region. The extraction algorithm is as follows.

STEP1: We perform color space quantization and compute histogram. Let an image is f(x, y) and the quantized image is  $\tilde{f}(x, y)$ .

$$f(x, y) \Rightarrow \tilde{f}(x, y)$$
: Color quantization  $h_k$ : Histogram of  $k^{th}$  bin

STEP2: We compare the 8-connected neighborhoods of each pixel, then count the number of neighbors that have the same bin. We use this number as weight. We also use threshold to reduce the influence of points and/or lines. So the pizel weight is defined as follows.

$$\alpha(x, y) = \begin{cases} Number \ of \ Neighborhoods \ with \ same \ value \\ if \ number \ge Threshold \\ 0 \\ if \ number < Threshold \end{cases}$$

STEP3: Given weights, we calculate the average coordinates of color distribution. We need some definitions.  $X_k(x, y)$  and  $Y_k(x, y)$  are x, y point in k<sup>th</sup> level, respectively.

$$X_{k}(x,y) = \begin{cases} x & \text{if } \widetilde{f}(x,y) = k \\ 0 & \text{otherwise} \end{cases}, \tag{4}$$

(3)

$$Y_k(x, y) = \begin{cases} y & \text{if } \tilde{f}(x, y) = k \\ 0 & \text{otherwise} \end{cases}, \tag{5}$$

In  $k^{\text{th}}$  level, representative points  $x_{k\_rep}$ ,  $y_{k\_rep}$  are

$$x_{k_{-}rep} = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \alpha(x, y) X_{k}(x, y)}{\beta h_{k}} , \qquad (6)$$

(2)

$$y_{k_{-}rep} = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \alpha(x, y) Y_{k}(x, y)}{\beta h_{k}} , \qquad (7)$$

where  $\beta$  is a scale factor.

Therefore, SDAC  $P_k$  in  $k^{th}$  level is

$$P_k = (x_{k rep}, y_{k rep}) , \qquad (8)$$

#### 3.3 Similarity

Thus, we can distinguish the local spatial colordistributed images from the same global colordistributed images by comparing the average coordinates of color distribution.

The measure of the similarity function is defined as follows.

$$d(Q,I) = \sum_{i=0}^{4} \sum_{j=0}^{n-1} \left\{ w_{1,i} \middle| h_{Q,i,j} - h_{I,i,j} \middle| + w_{2,i} D(p_{Q,i,j}, p_{I,i,j}) \right\}$$
(9)

where Q and I are the query image and an image in image database, respectively. i, j,  $w_{1,i}$ , and  $w_{2,i}$  indicate the region number, color bin, histogram weight of  $i^{th}$  region, and Euclidean distance weight of  $i^{th}$  region, respectively. And D means the Euclidean distance between  $p_{Q,i,k}$  and  $p_{I,i,k}$ .

# 4. Experimental Results

The proposed fuzzy region segmentation gives better results of the image indexing and retrieval, because they can solve some cases. For example, there are two or more same color regions on the opposite side of the image that can cause space-distributed average coordinates to index the wrong coordinates of the image.

To test the proposed method, we experiment the 500 outdoor color images for performing the retrieval. In our experiment, we set the *Threshold* value as '3'. Fig. 2 and Fig.3 depict the retrieval results using the conventional method and our proposed one, respectively. Fig. 3 also shows the retrieval list ordered by the similarity value. As the d(Q, I) goes lower, the similarity between two images increases.

In experiment to determine fuzzy region segmentation, factor a, b, and r are 50%, 30%, and 17% of an image, respectively. And both of histogram weight and space-distributed average point weight is same value to experiment both feature with same portion of similarity function.

In order to evaluate the performance of our proposed method, we use the precision, which is defined by [8]:

$$P_{\%} = \frac{P_r}{W_r} \times 100 \,(\%) \quad , \tag{10}$$

where  $P_r$  and  $W_r$  are the number of precisely retrieved images and the number of whole retrieved images in database, respectively. Our proposed method approximately performed 77.8% retrieval precision.

### 5. Conclusions

In this paper, we proposed the image retrieval method, which is robust in translation of an image by using the proposed fuzzy region and average coordinates of color distribution. Our method showed the better image retrieval performance than the conventional one did. The proposed method will give us more powerful image indexing and retrieval means if we use some other feature information such as texture.

#### References

- [1] M. J. Swain and D. H. Ballard, "Color indexing," *Int. J. Computer Vision*, vol. 7, no. 1, pp. 11-32, 1991.
- [2] F. Idris and S. Panchanathan, "Review of image and video indexing techniques," *Journal of Visual Communication and Image Representation*, vol 8, pp. 146-166, 1997.
- [3] John R. Smith and Shih-Fu Chang, "Integrated spatial and feature image query," *Multimedia System* 7, pp. 129-140, 1999.
- [4] Wynne Hsu, T. S. Chua, and H. K. Pung, "An integrated color-spatial approach to content-based image retrieval," In ACM Multimedia Conference, pp. 305-313, 1995.
- [5] G. Pass and R. Zabih, "Histogram Refinement for content-based image retrieval", 3<sup>rd</sup> IEEE Workshop on Applications of Computer Vision, December 2-4, pp. 96-102, 1996.
- [6] M. Stricker and A. Dimai, "Color indexing with weak spatial constraints," Proc. SPIE Storage and Retrieval for Image and Video Databases IV, vol. 2670, 1996.
- [7] M. Stricker and A. Dimai, "Spectral covariance and fuzzy regions for image indexing," *Machine Vision and Applications*, vol. 10, pp. 66-73, 1997.
- [8] B. Furht, S.W. Smoliar and H. J. Zhang, "Video and image processing in multimedia systems," kluwer Academic Publishers, 1995.

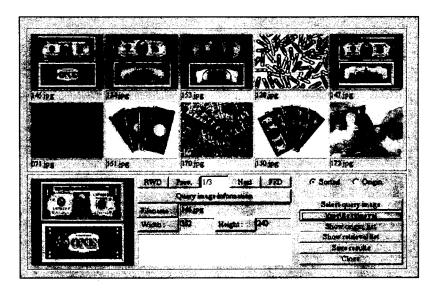


Fig. 2 Retrieval results by the conventional method. (High ranked order: from top left to bottom right)

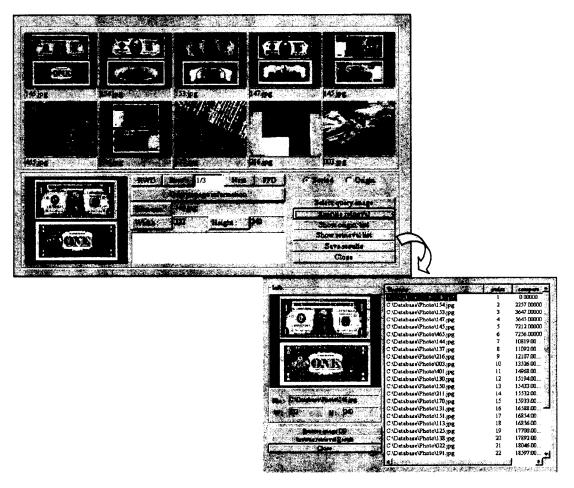


Fig. 3 Retrieval results and ranked order list by the proposed method.