AN INTEGRATED GLOBAL AND FUZZY REGIONAL APPROACH TO CONTENT-BASED IMAGE RETRIEVAL

Xiaojun Qi, Yutao Han
Computer Science Department, Utah State University, Logan, UT 84322-4205

Keywords: Content-based image retrieval, image segmentation, similarity measure, fuzzified region features, fuzzy region matching

Abstract: This paper proposes an effective and efficient approach to content-based image retrieval by integrating global visual features and fuzzy region-based color and texture features. The Cauchy function is utilized to fuzzify each independent regional color and texture feature for addressing the issues associated with the color/texture inaccuracies and segmentation uncertainties. The overall similarity measure is computed as a weighted combination between global and regional similarity measures incorporating all features. Our proposed approach demonstrates a promising performance on an image database of 1000 general-purpose images from COREL, as compared with some variants of the proposed method and some peer systems in the literature.

1 INTRODUCTION

Content-Based Image Retrieval (CBIR) has become an active research area since the early 1990s. Most CBIR techniques automatically extract low-level features (e.g., color, texture, and shapes) to measure the similarities among images by comparing the feature differences.

Non-spatial color methods (e.g., color histogram, color moments, and color sets (Long *et al.*, 2002) and spatial color methods (e.g., color coherence vector, color correlogram (Long *et al.*, 2002), spatial color histogram (Rao *et al.*, 1999), and spatial chromatic histogram (Cinque *et al.*, 2001) are commonly used in image retrieval. The spatial color methods outperform the non-spatial ones with the sacrifice of more computational costs. Statistics-based texture features, including Tamura features, Wold features, Gabor filter features, and wavelet features (Long *et al.*, 2002), are other important visual features used in image retrieval. Many current systems (Shih *et al.*, 2001); (Liang and Kuo, 1999) combine some low-level features to get better retrieval results. Since these features are extracted from the whole image and do not have explicit semantic meanings, segmentation-based image retrieval has gained more attention.

In segmentation-based image retrieval, each image is first segmented into homogenous regions and features for each region are extracted and similarities are calculated based on these region-based features. A few related works are reviewed below. In (Deng *et al.*, 2001), dominant colors for each segmented image are obtained and a dominant-color-based similarity score is computed to measure the difference between two regions. (Suematsu *et al.*1999) propose a region-based method which performs image segmentation and retrieval by using the texture features computed from wavelet coefficients. (Carson *et al,*1997) use expectation-maximization on color and texture features to segment the image into coherent regions and the region-based color, texture, and spatial features are further utilized for retrieval. (Ardizzoni *et al,*1999) use color and texture features captured from wavelet coefficients for both segmentation and retrieval. (Li *et al,*.2001) and (Chen and Wang 2002) use color features and texture features for each 4×4 block to segment the image. The region-based color, texture, and shape features are utilized for retrieval. In (Li *et al.*, 2001), an Integrated Region Matching (IRM) scheme is proposed to decrease the impact of inaccurate region segmentation. In (Chen and Wang, 2002), a Unified Feature Matching (UFM) scheme is proposed, where region-based multiple fuzzy feature representations and fuzzy similarity measures are used to improve the retrieval accuracy.

In this paper, we propose an efficient CBIR system by combining fuzzy region-based color and

Qi X. and Han Y. (2004).
AN INTEGRATED GLOBAL AND FUZZY REGIONAL APPROACH TO CONTENT-BASED IMAGE RETRIEVAL.
In *Proceedings of the First International Conference on E-Business and Telecommunication Networks*, pages 339-344
DOI: 10.5220/0001390003390344
Copyright © SciTePress

texture features and global features. The overall similarity score is calculated by assigning different weights to the fuzzy local features and global features for accurate retrieval. The remainder of the paper is organized as follows. Section 2 describes the general framework of our proposed system. Section 3 illustrates the experimental results. Section 4 draws conclusions.

2 PROPOSED APPROACH

The block diagram of our proposed CBIR approach is shown in Fig. 1. The first step of our algorithm is to calculate the global visual features. It then segments an image into coherent regions based on the color features. Image indexing and retrieval is finally taken based on global features and weighted independent fuzzy color and texture features incorporating the segmented region area and region position relative to the image boundary.

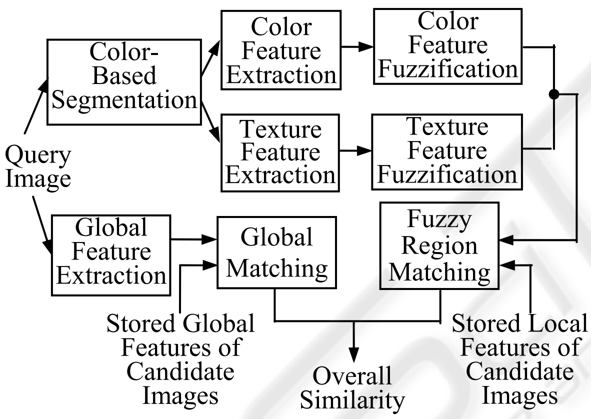


Figure 1: Block diagram of our CBIR system.

2.1 Global Feature Extraction

The global features include color-texture features, color moments and color histogram. The global color-texture feature is derived from a chromatic representation computed from a family of reduced dimensionality color spaces (Vertan and Boujemaa, 2000). Since the overall color-texture features are limited by the initial luminance normalization, we add RGB moments (i.e., mean and variance) and normalized 32-bin RGB histogram to compensate for the lack of such luminance information.

2.2 Color-Based Image Segmentation

In the proposed approach, we exclusively use color features for efficient image segmentation. To segment an image into coherent regions, the image is first divided into 2×2 non-overlapping blocks and a color feature vector (i.e., the mean color of the block) is extracted for each block. The Luv color space is used because the perceptual color difference of the human visual system is proportional to the numerical difference in this space.

After obtaining the color features for all blocks, an unsupervised K-Means algorithm (Hartigan *et al.*, 1979) is used to cluster these color features. This segmentation process adaptively increases the number of regions C (initially set as 2) until a termination criterion is satisfied (i.e., the average distance between all pairs of cluster centers is less than a predetermined threshold value). This predetermined threshold is empirically chosen so a reasonable segmentation can be achieved. Fig. 2 shows the intermediate segmentation results of one sample image from our test database by adaptively and gradually increasing the number of regions C.

Figure 2: Segmentation results by the unsupervised K-Means clustering algorithm.

2.3 Fuzzy Feature Representation and Fuzzy Region Matching

2.3.1 Fuzzy Feature and Region Matching

Based on the segmentation results, the representative color feature $\vec{f}_j^c$ for each region j is calculated by the mean of color features of all the blocks in region j. The representative texture feature $\vec{f}_j^t$ for each region j is computed by the average energy in each high frequency band of the level one wavelet decomposition. The wavelet transformation is applied to a "texture template" image obtained by keeping all the pixels in region j intact and setting all the pixels outside region j as white. The computational cost of deriving this representative texture feature is minimal compared to most methods (Li *et al.*, 2001; Chen and Wang, 2002) which average the texture features of all the blocks in the region. Furthermore, this representative texture feature captures more accurate regional edge distribution since averaging the block-based texture features will generate a small value due to the block homogeneity.

To fuzzify each feature, the Cauchy function (Hoppner *et al.*, 1999), defined as:

$$C(\vec{x}) = \frac{1}{1+\left(\frac{\|\vec{x}-\vec{f}\|}{d}\right)^{\partial}} \qquad (1)$$

is utilized, where d represents the width of the function, $\vec{f}$ represents the center location of the fuzzy set, and ∂ represents the shape (or smoothness) of the function. One example of the Cauchy function is illustrated in Fig. 3 with ∂ being 0.01, 0.1, 0.2, 0.5, 1, 1.5, 3, 5, 10, and 100.

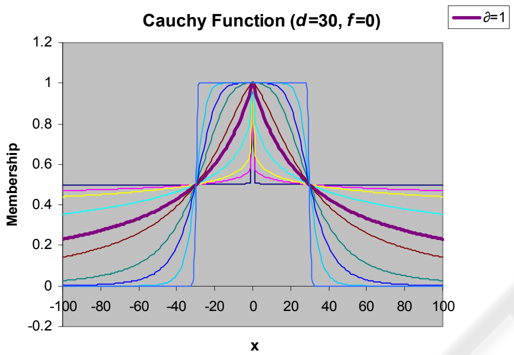


Figure 3: One example of the Cauchy function with fixed d and f.

Because of the property of the Cauchy function, the similarity between the fuzzified color or texture features for any region u and v in two images A and B can be computed:

$$S^{c|t}(u,v) = \frac{\left(d_A^{c|t}+d_B^{c|t}\right)^{\partial}}{\left(d_A^{c|t}+d_B^{c|t}\right)^{\partial}+\left\|\vec{f}_u^{\,c|t}-\vec{f}_v^{\,c|t}\right\|^{\partial}} \qquad (2)$$

where: ∂ represents the shape of the Cauchy function and is set to be 1; $\vec{f}_u^{\,c|t}$ and $\vec{f}_v^{\,c|t}$ are the representative color or texture features of regions u and v in images A and B; $d_A^{c|t}$ and $d_B^{c|t}$ are calculated as:

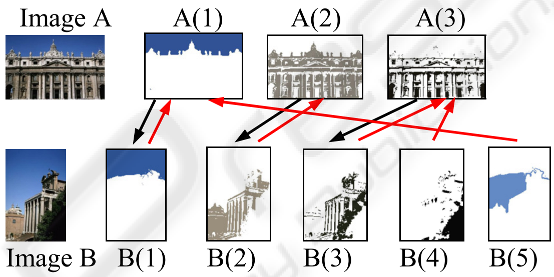
$$d^{c|t} = \frac{2}{C(C-1)}\sum_{i=1}^{C-1}\sum_{k=i+1}^{C}\left\|\vec{f}_i^{\,c|t}-\vec{f}_k^{\,c|t}\right\| \qquad (3)$$

2.3.2 Fuzzy Region Matching

A fuzzy region matching scheme is further used in our approach since a region in one image could correspond to several regions in another image due to the imperfect segmentation. That is, a region u in image A will be compared with every region v in image B by computing the overall region similarity:

$$S(u,v) = \lambda_1 S^c(u,v) + (1-\lambda_1)S^t(u,v) \qquad (4)$$

where $S^c(u,v)$ and $S^t(u,v)$ are calculated by using (2) and λ_1 determines the contribution of color features in measuring the similarity and is set to be 0.9. The region in image B, which yields the largest overall region similarity in (4), is considered to be the best matched region for region u in image A. Its color-based similarity S^c and texture-based similarity S^t are saved in vectors $\boldsymbol{L}^c$ and $\boldsymbol{L}^t$ for calculating the image similarity. This fuzzy region matching scheme is illustrated in Fig. 4.



Matched Region Pairs		L^c	L^t
A→B	A.(1)→ B (1)	0.97414	0.94468
	A (2)→ B (2)	0.94438	0.92848
	A (3)→ B (3)	0.89681	0.87261
B→A	B (1)→ A (1)	0.97414	0.94468
	B (2)→ A (2)	0.94438	0.92848
	B (3)→ A (3)	0.89681	0.87261
	B (4)→ A (3)	0.81972	0.7239
	B (5)→ A (1)	0.83261	0.96419

Figure 4: Fuzzy region matching scheme.

2.4 Similarity Measure

Global features are involved in the calculation of the global similarity S_g. The simple Euclidean distance is used to measure the global similarity.

A weighted similarity scheme is used in calculating the region-based similarity score $S_l^{c|t}$:

$$S_l^{c|t} = ((1-\lambda_2)\vec{w}_a + \lambda_2\vec{w}_p)^T L^{c|t} \qquad (5)$$

where $\vec{w}a$ contains the normalized area percentages, $\vec{w}p$ contains the normalized weights for the region positions, and λ_2 adjusts the significance of $\vec{w}a$ and $\vec{w}p$ and is set as 0.1. The overall region-based similarity score S_l is calculated as the weighted sum of S_l^c (color-based similarity score) and S_l^t (texture-based similarity score):

$$S_l = \lambda_1 S_l^c + (1-\lambda_1)S_l^t \qquad (6)$$

where λ_1 is the same as in (4).

The overall image similarity is computed as:

$$S = (1 - \lambda_3)S_g + \lambda_3 S_l \qquad (7)$$

where λ_3 adjusts the significance of the regional and global similarity measure in the overall similarity and is set to be 0.8.

3 EXPERIMENTAL RESULTS

To date, we have tested our CBIR algorithm on a general-purpose image database with 1000 images from COREL. These images have 10 categories with 100 images in each category. The categories contain different semantics. To evaluate the retrieval effectiveness of our algorithm, we randomly select three query images with different semantics (i.e. Africa, Beach, and Building). The top 11 returned results and the similarity scores are shown in Fig. 5. A retrieved image is considered as a correct match if and only if it is in the same category as the query image.

To perform a more quantitative evaluation, we randomly choose 15 images from each category (i.e., 150 images in total) as query images and the precision is calculated by evaluating the top 20 returned results. Several peer retrieval methods are also used to compare the retrieval performance. These methods include our proposed method (Prop.), global color histogram method with 32 color bins (HisC), and Non-Fuzzified Efficient Color Representation (ECR) method (Deng *et al.*, 2001) applied to our segmentation results. In order to ensure fair comparison, we used the same 1000 images from COREL as a test bed, the same 150 images as queries, and top 20 returned images. Fig.6 illustrates the average precision for each category by applying all these methods on the same query images.

It is clear that our proposed method performs much better than both approaches in almost all image categories. In particular, our method outperforms the HisC method in all image categories and improves the overall average retrieval accuracy by 78.51%. Our method yields much better retrieval accuracy than the ECR method in all image categories except for the Mountain (category 9). The overall average retrieval accuracy is improved by 46.95%.

Figure 5: Retrieval results of 3 queries. The query and the most similar images are the same and at the upper left corner. The segmentation of the query is shown at the right side of the query with the number of regions indicated below. Other numbers are the similarity scores.

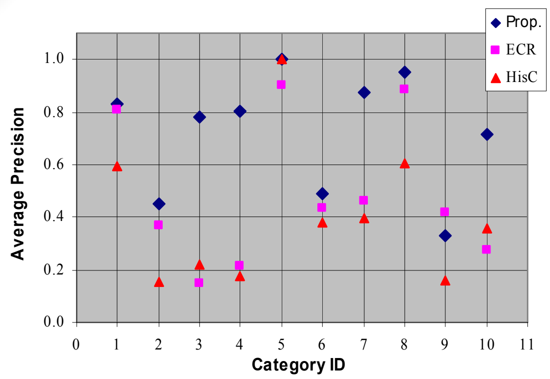


Figure 6: Comparison of the average retrieval precision of three different methods.

Our method is also compared with the UFM method (Chen and Wang, 2002) using the same test bed, the same query images, and same number of returned images. Experimental results summarized in Table 1 show that our method has better retrieval accuracy in 6 categories and worse accuracy in 3 categories. It improves the UFM method, which uses additional regional shape for retrieval, by 3.88% in the overall retrieval accuracy. The improvement over IRM (Li *et al.*, 2001) is around 10.28%.

More returned images are used to further test the retrieval accuracy of our method. Fig. 7 illustrates the average precision for each category by evaluating the top 20 and top 50 returned results. It shows that the average precision drops as more results are returned. However, there are only a little precision decrease in categories 2, 4, 5, 8, and 9, which is very promising.

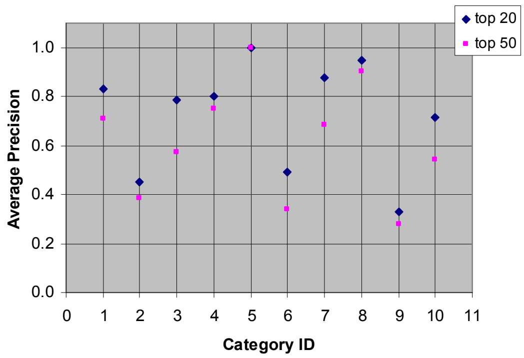


Figure 7: Comparison of the average retrieval precision for different number of returned images.

Fig. 8 compares the average retrieval precision from top 20, 30, **…**, 100 returned images when four methods are applied to the same 1000 images from COREL by using the same 150 query images. It clearly shows that our proposed method ranks the best in all cases.

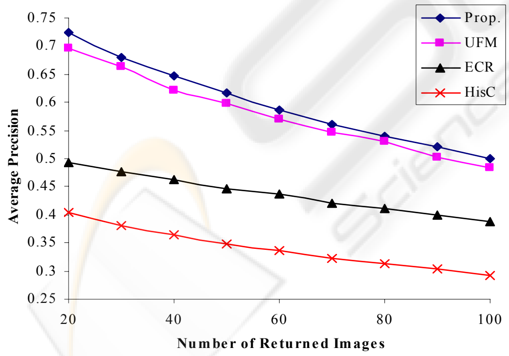


Figure 8: Comparison of the average retrieval precision with different number of returned images.

Additional experiments using the same test bed, the same 150 query images, and top 20 returned images are performed on several variants of our proposed method to illustrate the validity of our method. Table 1 numerically lists the average precision for each category by applying our proposed method, our global method without using any local features (PrGl), our fuzzy region-based method without using any global features (PrRe1), our fuzzy region-based method using only color and no global features (PrRe2), HisC, ECR, and UFM methods.

Several comparisons are made from Table 1:

1) Our PrG1 method vs. the HisC method: Our global method performs much better in all image categories. The overall average retrieval accuracy is improved by 40.74%. This result indicates that our global features are more effective than color histogram.
2) Our PrRe1 method vs. our PrRe2 method: The former has better retrieval performance in all image categories except for the Dinosaur and Mountain, which have the same retrieval accuracy (i.e., 99.3%) for Dinosaur and a little worse accuracy for Mountain. The overall average retrieval accuracy is improved by 7.87%. This result indicates that the integration of local textures does improve the retrieval accuracy.
3) Our PrRe2 method vs. the ECR method: The fuzzy measure improves the overall accuracy by 31.71% even though it does not perform better in all categories.
4) Our method vs. our PrG1 method: Our method yields much better retrieval accuracy in all categories except for the Dinosaur with the same retrieval. The 26.84% improvement in the overall accuracy shows that the integration of the local features dramatically increases the retrieval accuracy.
5) Our method vs. our PrRe1 method: Our method yields better retrieval accuracy in 7 categories and a little bit worse performance in 2 categories. Our method outperforms our PrRe1 method by 3.43% improvement in the overall accuracy. It is clear that the integration of the global features does improve the retrieval performance.

Table 1: Comparison of the average retrieval precision of seven different methods

Category	Prop.	PrGl	PrRe1	PrRe2	HisC	ECR	UFM
Africa	0.830	0.697	0.740	0.620	0.597	0.810	0.697
Beach	0.453	0.343	0.463	0.413	0.157	0.367	0.527
Building	0.783	0.410	0.780	0.710	0.220	0.150	0.710
Vehicle	0.803	0.587	0.750	0.633	0.173	0.217	0.773
Dinosaur	1.000	1.000	0.993	0.993	1.000	0.900	1.000
Elephant	0.490	0.437	0.390	0.333	0.380	0.437	0.423
Flower	0.877	0.637	0.927	0.863	0.397	0.463	0.947
Horse	0.950	0.863	0.933	0.920	0.607	0.887	0.897
Mountain	0.330	0.293	0.300	0.303	0.160	0.417	0.333
Food	0.717	0.433	0.717	0.687	0.357	0.277	0.650
Ave.	**0.723**	**0.570**	**0.699**	**0.648**	**0.405**	**0.492**	**0.696**

4 CONCLUSIONS

A novel CBIR approach is proposed in this paper. This approach combines weighted fuzzy region-based color and texture features and global features for effective and efficient image retrieval. The region-based color and texture features are independently obtained from the unsupervised segmentation. The Cauchy fuzzification is further applied to fuzzify each feature for fuzzy region matching. The global features are also included to improve the retrieval accuracy. The proposed approach is efficient, effective, and unique because:

- The unsupervised K-Means algorithm is exclusively performed on the 2×2 block-based color features to quickly and efficiently segment an image into coherent region.
- The color and texture are treated as two separate features to represent each region from different perspectives. Such a separation achieves better retrieval performance than the other schemes combining the color and texture as one comprehensive feature (e.g., UFM method).
- Each independent color and texture feature is fuzzified for fuzzy region matching by assigning different weights to the respective features. Such fuzzification addresses the issues related to imperfect segmentation and inaccurate color/texture.
- The use of Cauchy function greatly reduces the computational cost for the fuzzy region matching as illustrated in (2).
- The region area and region position are incorporated into the regional features based on the general observations in terms of semantics.
- The global color-texture features are extracted from the reduced dimensionality color space.

The experimental results on 1000 images from COREL database demonstrate that the proposed algorithm achieves good retrieval accuracy with fast speed due to the small size of the feature vector (less than 200 elements).

Shape or spatial information is not considered in our implementation for the efficiency consideration. It may be further integrated into the retrieval system to improve the accuracy. Other global feature representations may be further studied.

REFERENCES

Ardizzoni, S., Bartolini, I., and Patella, M., 1999. Windsurf: Region-based image retrieval using wavelets. *DEXA workshop,* pp. 167-173, Florence, Italy.

Carson, C., Belongie, S., Greenspan, H., and Malik, J., 1997. Region-based image querying. In *CVPR'97 Workshop on Content-Based Access of Image and Video Libraries*, pp. 42-49, San Juan, Puerto Rico.

Chen, Y. and Wang, J., 2002. A region-based fuzzy feature matching approach to content-based image retrieval. *IEEE Trans on PAMI* 24(9), pp. 1252-1267.

Cinque, L., Ciocca, G., Levialdi, S., Pellicano, A., and Schettini, R., 2001. Color-based image retrieval using spatial-chormatic histogram. *Image and Vision Computing* 19, pp. 979-986.

Deng, Y., Manjunath, B. S., and Kenney, C., 2001. An efficient color representation for image retrieval. *IEEE Trans on Image Processing* 10(1), pp. 140-147.

Hartigan, J. A, and Wong, M. A., 1979. Algorithm AS136: A K-Means Clustering Algorithm. *Applied Statistics* 28, pp. 100-108.

Hoppner, F., Klawonn, F., Kruse, R., and Runkler, T., 1999. *Fuzzy Cluster Analysis: Methods for Classification, Data Analysis, and Image Recognition*, John Wiley & Sons.

Li, J., Wang, J, and Wiederhold G., 2001. Simplicity: semantics-sensitive integrated matching for picture libraries. *IEEE Trans on PAMI* 23(9), pp. 947-963.

Liang, K. and Kuo, C.-C.J., 1999. WaveGuide: a joint wavelet-based image representation and description system. *IEEE Trans on Image Processing,* 8(11), pp. 1619-1629.

Long, F., Zhang, H., and Feng, D., 2002. Fundamentals of content-based image retrieval. In Feng, D., Siu, W. C., and Zhang, H. J., (eds.), *Multimedia Information Retrieval and Management – Technological Fundamentals and Applications*. Springer.

Rao, A., Srihari, R. K., and Zhang, H., 1999. Spatial color histograms for content-based image retrieval. In *IEEE Int. Conf. on Tools with Artificial Intelligence*, pp. 183-186, Chicago, Illinois, USA.

Shih, T., Huang, J., Wang, C., Hung, J., and Kao, C., 2001. An intelligent content-based image retrieval system based on color, shape and spatial relations. In *Proceedings of Natl. Sci. Counc. ROC(A)*, 25(4), pp. 232-243.

Suematsu, N., Ishida, Y., Hayashi, A., and Kanbara, T., 1999. Region-based image retrieval using wavelet transform. In *10th International Workshop on Database and Expert Systems Applications*, pp. 167-173.

Vertan, C., and Boujemaa, N., 2000. Color Texture Classification by Normalized Color Space Representation. In *Int. Conf. on Pattern Recognition (ICPR'00)*, Vol. 3, pp. 3584-3587, Barcelona, Spain.