An Efficient Region-Based Image Representation Using Legendre Color Distribution Moments

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ABSTRACT
By exploiting region Legendre color distribution moments, a region-based image representation in terms of storage and complexity is proposed. The representation consists of three steps: First, an image is segmented regions by a classical algorithm. Second, a compact, fixed-number and computation effective representaton is designed for the color contents of each region of an image, which takes not only the local color feature of a region into consideration, but also the correlation of the color distribution of the region. Third, we use Legendre color distribution moments as feature vector of the regions to match images. With the robustness to rotation and translation, the representation avoids shortcoming of losing the correlation of the color distribution and the spatial color distribution information in color histogram. experimental results on a database of 1000 general-purposed images demonstrate the efficiency and effectiveness of the proposed representation for image retrieval.

Categories and Subject Descriptors
H.3.3 [**Information Search and Retrieval**]: – Retrieval Model; Search Process

General Terms
Algorithm, Performance, Design, Experimentations

Keywords
region-based image retrieval; region Legendre color distribution; color histogam; color moments

1. INTRODUCTION
With the rapid growth of large image and video database, it becomes more and more important to efficiently manage, organise and navigate multimedia databases. content-based image retrieval (CBIR) has become a hot issue in recent decades. early CBIR systems exploit low level image feature such as color, texture and shape as key to retrieve images [1].

However, low level image feature can not reflect image semantic, there exists great gap between low level feature and semantic concepts embedded in the image contents. Although many efforts have been carried out to bridge the semantic gap[2-11], the improvement gained is unsatisfactory. Researchers argue that the key to effectively improve CBIR performance lies in the ability to access the image at the level of objects, the reason why the users retrieve image is to search for images containing particular objects of interest, so the ability to represent, index and query images at the level of objects is critical, this method is called region-based image retrieval (RBIR).

The color content of an image is an important element in CBIR, and several CBIR systems which utilized color content have been developed in recent years [1,12-16]. However, most of them is impratical for huge multimedia database. The reason for which follows, if the number of histogram bins is small, the performance of image retrieval is poor, but if the number of histogram bins is large enough, the storage space and computation time is high. In addition, color feature vector of an image is extracted globally in above those methods, spatial color distribution information and the correlation of the color distribution are not considered. Legendre color distribution moments are a compact, fixed-number and computation effectively image representation[17], but this method can not reflect the spatial color distribution of an image, and this color feature representation will lead to the limited color discriminating capabilities in image retrieval.

In this paper, we present an efficient region-based image representation using region Legendre color distribution moments. This paper is organized as follows: Section 2 describes the representation of images based on image segmentation, opponent color space, Legendre moments and the extraction of region Legendre color distribution moments. Region-based image similarity measurement is presented in Section 3. We provide experimental results that compare the proposed algorithms in this paper with other methods in Section 4. And last section is conclusion.

2. IMAGE SEGMENTATION AND IMAGE CONTENT REPRESENTATION

2.1 Image Segmentation

The segmentation method we use is described in [18]. Firstly, colors in the image are quantized to several representing classes that can be used to differentiate regions in the image. Secondly, image pixel colors are replaced by their corresponding color class labels, thus forming a class-map of the image. Thirdly, a criterion for homogeneity of a certain pattern using this class-map is proposed. Applying the criterion to local windows in the class-map results in the J-image, in which high and low values correspond to possible region boundaries and region centers, respectively. Fourthly, a region growing method is then used to segment the image based on the multi-scale J-images. Finally, visually similar regions are merged together to avoid over-segmentation. In this way, we keep the natural boundary of an object; meanwhile, we can define compact feature representation of a region.

2.2 Opponent color space

Although (R,G,B) color space is the most useful representation for a digital image, owing to the susceptibility to the change of brightness, the direct exploitness of (R,G,B) triplet for image indexing is unreliable [17]. Therefore, we have to map the (R,G,B) triplet to the brightness independent color space prior to indexing.

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \quad (1)$$

Since b=1-r-g, two dimensional color components (r,g) are sufficient to describe the color content of an image. In order to avoid R=G=B=0, which will cause an undefined devision, we use a transformation $R \to R+\tau, \quad G \to G+\tau, B \to B+\tau$ and modify the equation to

$$\begin{aligned} r &= \frac{R+\tau}{R+G+B+3\tau} \\ g &= \frac{G+\tau}{R+G+B+3\tau} \\ b &= \frac{B+\tau}{R+G+B+3\tau} \end{aligned} \quad (2)$$

Here τ is an arbitrary small number, the brightness independent is not affected since $R,G,B \gg \tau$. In experiment, we set $\tau = 0.001$

It is well known that original encoding of color in RGB color space is less uniform than an oppnenent encoding, there is three axes in the oppenent color space: white-black, yellow-blue and red-green axes. Each axis is mutually uncorrelated and expresses independent information. The opponent color space

$$(rg, yb) = \left(r - g, \frac{r}{2} + \frac{g}{2} - b \right) \quad (3)$$

is more uniform and can be more effectively characterized by color distribution feature. Note that the white-black axis is not used since it encodes brightness information and will not be included in the color histogram. It is directly to show that $-1 \le rg \le 1$ and $-1 \le yb \le 1$.

2.3 Legendre moments

The Legendre moments of order (m + n) are defined as

$$\lambda_{mn} = \frac{(2m+1)(2n+1)}{4} \int_{-1}^{1}\int_{-1}^{1} P_m(x)P_n(y)f(x,y)dxdy \quad (4)$$

where m, n = 1, 2, 3, . . . , ∞. The nth-order Legendre polynomials is defined as

$$P_n(x) = \sum_{j=0}^{n} a_{nj}x^j = \frac{1}{2^n n!}\frac{d^n}{dx^n}\left(x^2-1\right)^n \quad (5)$$

Legendre polynomials up to the sixth order are as follows:

$$\begin{aligned} P_0(x) &= 1 \\ P_1(x) &= \frac{1}{2}x \\ P_2(x) &= \frac{1}{2}(3x^2-1) \\ P_3(x) &= \frac{1}{2}(5x^3-3x) \\ P_4(x) &= \frac{1}{8}(35x^4-30x^2+3) \\ P_5(x) &= \frac{1}{8}(63x^5-70x^3+15x) \\ P_6(x) &= \frac{1}{16}(231x^6-315x^4+105x^2-5) \end{aligned}$$

The set of Legendre polynomials $\{P_n(x)\}$ form a complete orthogonal basis set on the interval [-1, 1]

$$\int_{-1}^{1} P_n(x)P_m(x)dx = \frac{2}{2n+1}\delta_{nm} \quad (6)$$

This property of Legendre polynomials is important to ensure information compactness and minimal information redundancy of the Legendre moments. The orthogonality, and hence uncorrelatedness, of Legendre polynomials is the primary reason we choose Legendre moments in place of regular moments for the characterisation of the color space. By the orthogonality principle, the image function *f (x, y)* can be written as an infinite series of expansion in terms of Legendre polynomials over the square [-1 ≤ x, y ≤ 1].

$$f(x,y) = \sum_{m=0}^{\infty}\sum_{n=0}^{\infty} \lambda_{mn} P_m(x) P_n(y) \qquad (7)$$

where the Legendre moments $\{\lambda_{mn}\}$ are computed over the same square. If only Legendre moments of order m + n ≤ D are given, the function *f(x,y)* can be approximated by a continuous function which is a truncated series.

$$\hat{f}(x,y) = \sum_{m=0}^{D}\sum_{n=0}^{m} \lambda_{m-n,n} P_{m-n}(x) P_n(y) \qquad (8)$$

If only Legendre moments of order $m \le m_{max}$ and $n \le n_{max}$ are given, then we have

$$\hat{f}(x,y) = \sum_{m=0}^{m_{max}}\sum_{n=0}^{n_{max}} \lambda_{mn} P_m(x) P_n(y) \qquad (9)$$

very often, depending on the nature of the application, finite orders of Legendre moments are sufficient to characterise the *f(x, y)*.

2.4 Legendre color distribution moments representation of the region

For one region R_p in an image, Let $I(i,j)_{R_p} = [R(i,j), G(i,j), B(i,j)]_{R_p}$ is represented the region R_p where $I(i,j)$ is the color of the pixel points (i,j) in the region R_p. Let $W^p = \{(i,j) \mid (i,j)$ are the pixel points of region $R_p\}$, $|W^p|$ is the number of pixel in the region R_p, if we map the RGB triplet to the opponent color space, we have $I(i,j)_{R_p} = [rg(i,j), yb(i,j)]$ or more concisely $I(k) = [rg(k), yb(k)]$, where $k = 0, 1, \ldots, |W^p| - 1$, then we can define the number of pixels with color value (x,y) in the region R_p as follows

$$M(x,y)_{R_p} = \sum_{k=0}^{|W^p|-1} \delta(x, rg(k))\delta(y, yb(k)) \qquad (10)$$

where $\delta(u,v)$ is the Kronecker delta

$$\delta(u,v) = \begin{cases} 1 & u = v \\ 0 & otherwise \end{cases} \qquad (11)$$

We define the Region Legendre color distribution moments (RLCDM) $\lambda^c_{m,n}$ as the Legendre moments of $M(x,y)_{R_p}$ with (m + n) being the order, using the equation (4), substituting the *f(x,y)* with $M(x,y)_{R_p}$, and letting $(x_k, y_k) \in \{(x,y) \mid M(x,y)_{R_p} \neq 0\}$, we have

$$\begin{aligned}\lambda^c_{mn} &= A_{mn} \sum_k P_m(x_k) P_n(y_k) M(x,y)_{R_p} \\ &= A_{mn} \sum_k \sum_{l=0}^{|W^p|-1} P_m(x_k) P_n(y_k) \delta(x_k, rg(l)) \delta(y_k, yb(l)) \qquad (12) \\ &= A_{mn} \sum_{l=0}^{|W^p|-1} P_m(rg(l)) P_n(yb(l))\end{aligned}$$

where $A_{mn} = (2m+1)(2n+1)/|W^p|$. The RLCDM is calculated directly using the last equation of (12) and there is no histogram construction process. Generally, the lower order and RLCDM represents slow-changing components in the color space, while the higher order represents the fast changing components. In our experiment, λ_{00} is left out because its value is a constant regardless of the image.

3. SIMILARITY MEASUREMENT

Assume that one query image Q and one image T in the database are denoted as $Q = \{q_1, \ldots, q_i, \ldots, q_m\}$ and $T = \{t_1, \ldots, t_j, \ldots, t_n\}$ respectively, here q_i and t_j are represented one region in the query image Q and one image T in the database respectively. Let $V \in R^L$, where *L* is the lenghth of the feature vector, V^k_{qi} and V^k_{tj} represent the feature vector of one region in the query image *Q* and one image *T* in the database respectively. The distance function between two regions q_i and t_j is defined as

$$Dis(q_i, t_j) = \sum_{k=1}^{L} \left| V^k_{qi} - V^k_{tj} \right|, 1 \le i \le m, 1 \le j \le n \qquad (13)$$

The overall image similarity between one query image Q with regions $\{q_1, \ldots, q_i, \ldots, q_m\}$ and one image T with regions $\{t_1, \ldots, t_j, \ldots, t_n\}$ in the database is measured as a weighted sum of the similarity between region pairs, which is defined as

$$Dis(Q,T) = \sum_{i=1}^{M} \gamma_i \times Dis(q_i, T) \qquad (14)$$

$$Dis(q_i, T) = \sum_{j=1}^{N} \lambda_{i,j} \times e^{-Dis(q_i, t_j)} \qquad (15)$$

M and N are the number of segmented regions in the query image Q and the image T in the database, respectively. γ_i is the importance weight for the region q_i in the query image Q, it is initialized to $\frac{1}{M}$ and will be updated according to user's feedback. $\lambda_{i,j} \in (0,1]$ is used to adjust the effect of region q_i and t_j on the similarity measure. The effect of region size is taken into account now, $\lambda_{i,j}$ is defined as

$$\lambda_{i,j} = \frac{size(q_i)+size(t_j)}{size(Q)+size(T)} \times \frac{size(q_i)/size(Q)}{size(t_j)/size(T)} \qquad (16)$$

Here size is defined as the number of pixel in a region, the first term of equation (16) take into account the relative size of the regions with respect to images they belong to, which is based on the consideration that larger regions are more likely to attract human attention than smaller ones. The second term of equation (16) takes into account the similarity of size ratio of regions, which is derived from the fact that similar objects may have similar size ratio in compared images.

4. EXPERIMENTAL RESULTS

The system is implemented on PC with Core(TM) Duo 1.8 GHz CPU and memory 1.00 G/Windows XP and using Matlab 7.0 integrated environment. We evaluated our prototype system using a general-purpose image database containing 1000 JPEG images with size of 384×256 or 256×384 pixels from COREL photo gallery. These images are divided into 10 semantic categories including Africa, buildings, horses, elephants, dinosaurs, flowers, buses, beach, mountains, and food, there are 100 images in each semantic category.

As an evaluation method, image retrieval precision and recall are most frequently used in the current image retrieval systems. For a query image, a retrieval image is considered relevant one if and only if it belongs to the same category as the query image. Based on this, image retrieval precision and recall are defined as

$$precision = \frac{number\ of\ \ relevant\ images\ retrieved}{number\ of\ \ \ images\ retrieved} \qquad (17)$$

$$recall = \frac{number\ of\ \ relevant\ images\ retrieved}{number\ of\ \ relevant\ images\ in\ database} \qquad (18)$$

The effectiveness of the algorithm proposed in this paper is compared with color histogram(HIST), color moments(CM) and Legendre color distribution moments(LCDM)[1,12,17], all these methods are modified to work in opponent color space. Above these methods are selected for comparison because image's content is globally characterized by color, which cannot reflect color spatial distributed information of regions and regions importance in an image.

The first method is color histogram(HIST), which is one of the most commonly used method to capture the color content of an image. L_1 distance is employed to measure the similarity between histograms. To make comparision between two methods fisible, the length of the feature vector of the two methods is almost same when the histogram quantization levels are Q=1,2,…,8 and the order of RLCDM are D=1,2,…,10

The second one is the color moments(CM), which is represented by obtaining the regular moments of both the trace and the distribution of the color space. The quantization level of the CM method which we used in the experiment is Q=128, which is much better pricision than other small Q.

The third retrieval method is designed to prove that our region Legendre color distribution moments has better discriminating power than a global Legendre color distribution moments. The length of the feature vector of these two methods is the same since the order of RLCDM(or LCDM) are D=1,2,…,10.
In total, four image retrieval methods are implemented in this experiment, the results of retrieval precision of the four methods are summarized in Fig.1 the numbers in x-axis corresponds to the length of the feature vector.

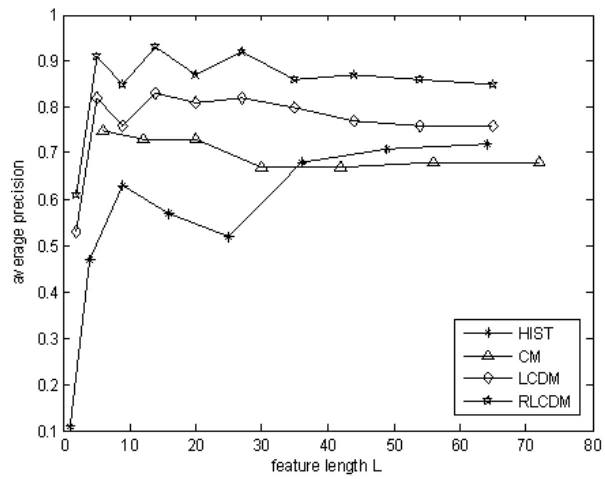

Fig. 1 The Comparision Of Retrieval Precision Of The Four Methods

As shown in Fig. 1, on the one hand, RLCDM algorithm shows the best performance at all the same length of feature vector in the four retrieval methods, LCDM and CM provide better retrieval precision than HIST. on the other hand, when the length of the feature vector of the RLCDM is L=5 corresponding D=2, the retrieval results of RLCDM is almost the highest. The length of the feature vector for HIST, CM, LCDM and RLCDM are Q2, (D + 1) (D + 2) and D(D + 3)/2, respectively. The length of the feature vector for each image is crucial, it directly determines the retrieval time needed for each query and the storage space needed for each image in the image database. It is obvious that just a small number of RLCDM are needed to characterise the color content of an image, by using RLCDM as feature vectors, a significant amount of storage space can be saved, especially when compared with HIST. In addition, smaller length of feature vector also means that the time needed for similarity comparison is less

5. CONCLUSION

A efficient image representation using region Legendre color distribution moments is proposed in this paper. The main feature of this method is

1. The method not only utilizes local information of the region, but also color distribution information of the region

2. We obtain RLCDM directly from the color space without first constructing the color histogram.

3. RLCDM is compact in the sense since only a few terms of RLCDM are needed to obtain retrieval accuracy comparable to that of a full color histogram. The short feature length of RLCDM also means that shorter retrieval time are needed to retrieve images from the database. This is especially important when considering the fact that image databases nowadays are growing rapidly in size.

Experiment results verify the effectiveness and efficientness of the proposed method. In the future, we will consider other feature information of image such as shape and texture, and the relevance feedback mechanism will be considered, in which the weigths of feature vector and region will be tuned on-line to capture user's intention better.

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7. REFERENCES

[1] G. Paschos, I. Radev, and N. Prabakar, "Image content-based retrieval using chromaticity moments", IEEE Trans. Knowl. Data Eng., 2003, 15, (5), pp. 1069–1072.

[2] Z. Su, H.-J. Zhang, and S. Li, "Relevance Feedback in Content-Based Image Retrieval: Bayesian Framework, Feature Subspaces and Progressive Learning," *IEEE Trans. on Image Processing*, vol.12, no.3, 2003.8.

[3] J. He, M. Li, H.-J. Zhang, Hanghang Tong, Changshui Zhang, "Mean Version Space: A New Active Learning Method for Content-Based Image Retrieval," *ACM SIG MM Workshop on Multimedia Information Retrieval*, pp.15-23, 2004.

[4] G. Aggarwal, A. T. V., and S. Ghosal, "An Image Retrieval System With Automatic Query Modification," *IEEE Trans. on Multimedia*, Vol.4, No.2, June 2002, pp. 201-214.

[5] K.-M. Lee, and W. N. Street, "Cluster-Driven Refinement for Content-Based Digital Image Retrieval," *IEEE Trans. On Multimedia*, Vol.6, No.6, December 2004, pp.817-827.

[6] B.C. Ko, H. Byun, "FRIP: A Region-Based Image Retrieval Tool Using Automatic Image Segmentation and Stepwise Boolean AND Matching," *IEEE Trans. on Multimedia*, Vol.7, No.1, February 2005, pp.105-113.

[7] D. Tao, X. Tang, X. Li, and Y. Rui, "Direct Kernel Biased Discriminant Analysis: A New Content-Based Image Retrieval Relevance Feedback Algorithm," *IEEE Trans. on Multimedia*, Vol.8, No. 4, August 2004, pp.716-727.

[8] Y. Lu, H.-J. Zhang, L. Wenyin, and C. Hu, "Joint Semantic and Feature Based Image Retrieval Using Relevance Feedback," *IEEE Trans. on Multimedia*, Vol.5, No.3, September 2003, pp.339-347.

[9] X. S. Zhou, T. S. Huang, "Relevance Feedback in Image Retrieval: A Comprehensive Review," *International Journal of Multimedia Systems*, Vol.8, pp 536-544, 2003.

[10] J. Aamores, N. Sebe, P. Radeva, T. Gevers, A. Smeulders, "Boosting Contextual Information in Content-Based Image Retrieval," *ACM SIG MM Workshop on Multimedia Information Retrieval*, pp.31-39, 2004.

[11] H. Xie and A. Ortega, "An User Preference Information Based Kernel for SVM Active Learning in Content-based Image Retrieval," *ACM SIG MM Workshop on Multimedia Information Retrieval*, pp.1-6, 2005.

[12] M. Swain, and D. Ballard, "Color indexing", Int. J. Comput. Vision, 1991, 7, (1), pp. 11–32.

[13] G. Pass, R. Zabih, and J. Miller, "Comparing images using colour coherence vectors". Proc. 4th ACM Int. Conf. Multimedia, pp. 65–73, February 1996.

[14] J. Huang, S. Kumar, M. Mitra, W. Zhu, and R. Zabih, "Image indexing using color correlograms", Proc. IEEE Computer Society Conf. on Computer Vision, 1997, pp. 762–768.

[15] J. Han, and K. K. Ma, "Fuzzy colour histogram and its use in color image retrieval", IEEE Trans. Image Process., 2002, 11, (8), pp. 944–952.

[16] G. Qiu, and K. Lam, "Frequency layered color indexing for contentbased image retrieval", IEEE Trans. Image Process., 2003, 12, (1), pp. 102–113.

[17] P.-T. Yap, R. Paramesran, "content-based image retrieval using legendre chromaticity distribution moments." . Vision, Image and Signal Processing, IEE Proceedings, Vol. 153, Issue 1, 9 Feb. 2006, 17 – 24.

[18] Y. Deng, B. S. Manjunath, and H. Shin, "Color image segmentation," in *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition, CVPR'99*, vol. 2, Fort Collins, CO, June 1999, 446–451.