IMAGE INDEXING BY MODIFIED COLOR CO-OCCURRENCE MATRIX

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ABSTRACT

Image indexing based on Modified Color Co-occurrence Matrix (MCCM) is proposed in this paper. First, CCM is simplified to represent the number of color (hue) pairs between adjacent pixels in the image. And then, CCM is split into diagonal and non-diagonal elements that constitute two elements of MCCM. Indexing the image by MCCM could exploit shape information in abstract level.

Proposed MCCM is accumulative feature. Experimental results show the superiority of the proposed MCCM based indexing in comparison to the indexing based on other accumulative features, color histogram and auto-correlogram with very competitive computational cost.

1. INTRODUCTION

The rapid growth of multimedia applications followed by the emergence of large-scale image collections has brought about the need for efficient methods for storage, browsing, indexing, and retrieval of images. In the early 1990s, the Content Based Image Retrieval (CBIR) was proposed to retrieve images based on visual features (contents) of images in substitute for the traditional annotation based retrieval, since the linguistic description of image by small number of key words is very limited in comparison to the richness of image contents. The visual contents, called as features, are numeric descriptors capturing specific visual characteristics. Most CBIR systems have two-step approach to retrieve images from the databases. First step is *indexing*: for each image in a database, feature vector is computed and stored in feature space. Second step is *searching*: given a query image by a user, its feature vector is computed and the system retrieves images having feature vectors that best match the query feature vector. In CBIR, image feature selection is most critical problem because it largely affects the remaining aspects of the system design and eventual capabilities of the system.

Generally the features in image databases are divided into color, local shape, and texture features. Features can be classified into three types based on the levels of semantics [1], namely object features with strong segmentation, salient features with weak segmentation, and accumulative features with no segmentation. The deeper semantic interpretation of image lies in the stronger segmentation of the scene. It is expected [1] that the salient features and accumulative features will receive more attention in the sense that automatic strong segmentation is hard to achieve and computationally expensive, and also complete feature descriptions may not be necessary at all to achieve similarity matching.

In this paper, Modified Color Co-occurrence Matrix (MCCM) was proposed as an image feature. First, CCM was simplified to account the number of certain colored pairs between all possible adjacent pixels in the image. For adjacency, four-connectedness was chosen. In this case, the diagonal matrix of CCM explains the color histogram of pixels that belong to the homogeneous regions. Experiment shows that this diagonal matrix follows the same trend as the color histogram of entire image. Non-diagonal elements contain the shape information because the color changes between adjacent pixels imply the possible existence of object edges. In matching stage, the similarity measure between the query image and database images was computed equally based on diagonal elements of CCM and non-diagonal elements of CCM that constitute two elements of MCCM. So the key contribution of proposed method is to exploit the shape information along with color information without big computation cost.

Therefore, the proposed MCCM is accumulative feature with exploited shape information, which is not taken into consideration in previous accumulative features ([6], [7]).

This paper is organized as follows. In section 2, the proposed MCCM based image indexing is studied. The matching scheme is given in section 3. Finally the performance of proposed method is compared with that of color histogram and color correlogram.

2. IMAGE INDEXING VIA MCCM

2.1. Color constancy

While the color has a significant attention in image retrieval because of its powerful discriminating power, it is complex to handle, for color is not invariant to the imaging conditions (orientation of the surface, position and spectrum of the illumination, viewpoint of the camera, and reflection characteristic of the surface). B.V. Funt and G.D. Finalayson [2] suggested color constant indexing that index the ratios of color RGB triples from neighboring pixels to achieve illumination independent retrieval. In [3], various color invariants under varying imaging conditions were derived from an analysis of the Shafer model of object reflection. But those methods could yield

color invariants with the cost of some loss in discriminating power among objects. So the balance between constancy of the measurement against unwanted disturbances, and retained discriminating power among objects is another critical issue in image retrieval. Invariance and discriminating power of the color invariants were experimentally investigated by J.M. Geusebroek et el [4] based on Kubelka Munk theory for the object reflectance properties.
In this paper, hue was adopted as a color invariants, for in [3] hue is proved to be invariant under the orientation of the object with respect to the illumination and camera direction.

2.2. Color Co-occurrence Matrix (CCM)

Conventional color co-occurrence matrix represents three-dimensional matrix where the colors of any pair are along the first and second dimension and the spatial distance between them along the third [5]. In this sense, conventional CCM is same as color correlogram [7]. In this paper, CCM is simplified to represent the number of color (hue) pairs between adjacent pixels in the image. For each pixels in the image, 4-neighbors (horizontal and vertical neighbors) are accounted.
Let I be an $N \times M$ image quantized to m colors, and $p(x,y)$ is the color of the image pixel (x,y). Then, the simplified CCM is given by

$$H^I(i,j) = \eta((p(x,y), p(\mathcal{N}_{(x,y)})) == (i,j))$$
$$= \alpha \sum_{x=1}^{N} \sum_{y=1}^{M} C_i(x,y) \sum_{(x',y') \in \mathcal{N}_{(x,y)}} C_j(x',y') \qquad (1)$$

where η indicates the number of times $(p(x,y), p(\mathcal{N}_{(x,y)}))$ equals the value of the color indices (i,j), and $\mathcal{N}_{(x,y)}$ indicates 4-neighbors of the pixel (x,y). $C_i(x,y)$ is given by

$$C_i(x,y) = \begin{cases} 1 & \text{if } p(x,y) = i \\ 0 & \text{o.w} \end{cases} \qquad (2)$$

And the normalization constant α is $1/4 \cdot N \cdot M$, for the total number of pixel pairs $(p(x,y), p(\mathcal{N}_{(x,y)}))$ is approximately $4 \cdot N \cdot M$ by discounting the difference of boundary pixels.
The simplified CCM is symmetric because the adjacent pixels pairs are neighbors of each other. In this paper, color was quantized to 16 colors, since empirically 16 colors (in hue model) are sufficient for proper color invariant object retrieval [3]. Therefore, the dimension of simplified CCM is 16×16.

2.3. Image indexing via Modified CCM (MCCM)

The homogeneous color region of the image contributes to the diagonal elements of CCM and non-homogeneous region to the non-diagonal elements of CCM.
Experiments showed that the histogram of diagonal elements of CCM follows a similar trend to the conventional color histogram. Example is given in Figure 1.
Edges are basic local shape features that carry useful information about object boundaries. Therefore, edges play an important role in image retrieval as a shape describing feature. Color edges are found at the pixels on which abrupt color changes occur. So the pixels pairs belonging to the color edges contribute to the non-diagonal elements of CCM.

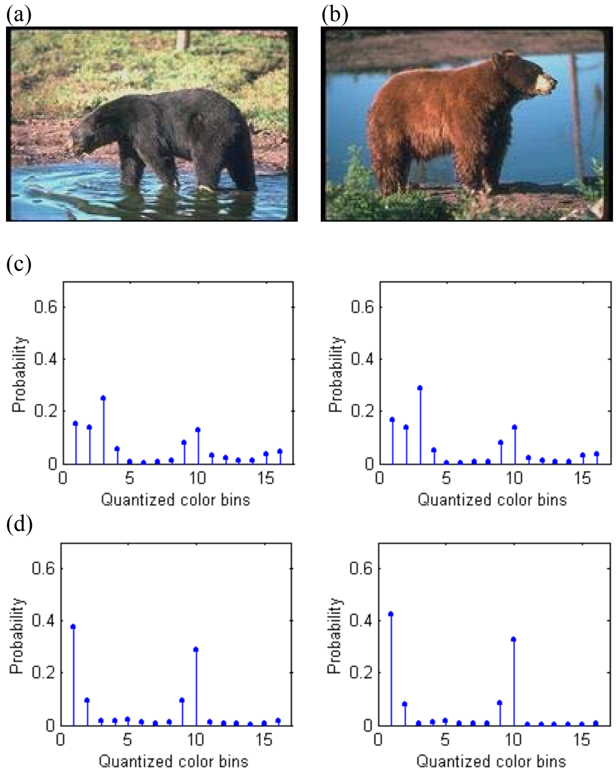

Figure 1. Comparison between the conventional color histogram (left) and the histogram of diagonal elements of CCM (right). ((c) is from image (a), and (d) is from image (b))

Experimentally, about 80 percent of pixels pairs belong to the diagonal elements of CCM in our database images. Experimental setup is described in detail in section 4.1. Therefore, if CCM is used as a feature vector of an image without modification, shape information is overwhelmed by color information. Problem is solved by indexing the image equally based on diagonal elements and non-diagonal elements of CCM. The feature vector of an image I is given by

$$F^I = \left(H_D^I, H_N^I\right) \qquad (3)$$

where, H_D^I and H_N^I are diagonal and non-diagonal elements of CCM each other. We call F^I as Modified CCM, MCCM.

3. IMAGE RETRIEVAL VIA MCCM

The images are preprocessed to extract their feature vectors F^I which are then stored along with the images in the database. Similarly, when the query image Q is given, its feature vector F^Q is computed and then matched with the feature vectors in the database. For comparison reasons in the literature, normalized histogram intersection proposed by Swain and Ballard [6] was used for the matching, since it is robust to substantial object occlusion and cluttering. The similarity

$S^{MCCM}(Q,I)$ between the query image Q and image I from the database is given by

$$S^{MCCM}(Q,I)=\frac{w_1 S_1(Q,I)+w_2 S_2(Q,I)}{w_1+w_2} \quad (4)$$

$$S_1(Q,I)=\frac{\sum_i \min\{H_D^Q(i),H_D^I(i)\}}{\sum_i H_D^Q(i)}$$

$$S_2(Q,I)=\frac{\sum_{(i,j),i\neq j}\min\{H_N^Q(i,j),H_N^I(i,j)\}}{\sum_{(i,j),i\neq j}H_N^Q(i,j)}$$

where w_1 and w_2 are the weights. In experiments, we assigned equal weights ($w_1=w_2=1$). To check the effect of separation of CCM by diagonal and non-diagonal elements, similarity $S^{CCM}(Q,I)$ based on CCM without separation is compared in experiments. $S^{CCM}(Q,I)$ is given by

$$S^{CCM}(Q,I)=\frac{\sum_{(i,j)}\min\{F^Q(i,j),F^I(i,j)\}}{\sum_{(i,j)}F^Q(i,j)} \quad (5)$$

4. EXPERIMENTS

In this section, the performance of the proposed MCCM based retrieval was compared with the performance of the other methods. Datasets are explained in section 4.1. In section 4.2, the previous methods to be compared with MCCM were reviewed. Complexity was investigated in section 4.3, and the results produced based on the performance criteria in section 4.4 were shown in section 4.5.

4.1. Datasets

The dataset consists of $N_1=6,550$ color images from UC Berkeley digital library project and various websites. The $N_2=80$ query images are made from the modification of 80 different images in the database. The queries are made to represent various situations like different views of the same scene, illumination changes, spatial translations, changes in appearance and size, etc.

4.2. Previous methods

The proposed image feature is accumulative feature. For comparison reason with other methods, the proposed method is compared with two commonly used accumulative features, color histogram [6] and color correlogram (auto-correlogram) [7]. Let the notation in section 2 holds for $N\times M$ image I . Color histogram is the histogram of quantized colors, given by

$$h^I(i)=N\cdot M\cdot \Pr_{(x,y)\in I}\left[(x,y)\in I_i\right] \quad (6)$$

where I_i is the set of pixels in image I that have the color index i as their value. Color correlogram is histogram of given color pairs of two pixels located at a given distance, expressed by

$$\gamma^I(i,j,k)=N\cdot M\cdot \Pr_{p_1\in I_i,p_2\in I}[p_2\in I_j \,||\, p_1-p_2|=k] \quad (7)$$

where $i\in[16]$, $j\in[16]$, and $k\in[d]$. Auto-correlogram captures the spatial correlation between identical colors only, defined by

$$\alpha^I(i,k)=\gamma^I(i,i,k) \quad (8)$$

The color correlogram technique is applied in object recognition in [8]. CCM in this paper can be considered as color correlogram with $k\in[1]$. The key contribution of the proposed technique lies in exploiting the data structure into homogeneous color regions and non-homogeneous color regions by dividing CCM into diagonal elements and non-diagonal elements.

The similarity measures between the query image and database images are computed based on histogram intersection for both the color histogram and auto-correlogram feature vectors.

$$S^{hist}(Q,I)=\frac{\sum_i \min\{h^Q(i),h^I(i)\}}{\sum_i h^Q(i)} \quad (9)$$

$$S^{auto}(Q,I)=\frac{\sum_{(i,k)}\min\{\alpha^Q(i,k),\alpha^I(i,k)\}}{\sum_{(i,k)}\alpha^Q(i,k)} \quad (10)$$

4.3. Complexity

Indexing complexity can be determined by the number of times the pixels (in color histogram) or the pixels pairs (in color correlogram and MCCM) appear in computation. Then, the indexing complexities of color histogram, color correlogram, and MCCM are $O(NM)$, $O(8\cdot(\sum_{k=1}^{d}k)\cdot NM)$, and $O(4\cdot NM)$ where, $8\cdot(\sum_{k=1}^{d}k)$ is due to the properties of L_∞ -norm and 4 is from 4-neighbors.

And, retrieval complexity can be determined by the dimension of the feature vector. Then, the retrieval complexities of color histogram, color correlogram, and MCCM are $O(m)$, $O(m^2 d)$, and $O(m^2)$, where m is color quantization level.

Therefore, computationally MCCM is very efficient in comparison to color correlogram.

4.4. Performance criteria

For performance criteria, the criteria in [3] were adopted. Let the rank r^{Q_i} denote the position of the correct answer for query image Q_i , $i=1,\cdots,N_2$, in the ordered list of N_1 match values. For the perfect match, $r=1$, and for worst match, $r=N_1$. The average ranking $\bar{r}$ and its percentile $\bar{r}\%$ are defined by

$$\bar{r}=\frac{1}{N_2}\sum_{i=1}^{N_2}r^{Q_i}\ ,\ \bar{r}\%=\left(\frac{1}{N_2}\sum_{i=1}^{N_2}\frac{N_1-r^{Q_i}}{N_1-1}\right)100\% \quad (11)$$

The cumulative percentile of query images producing a rank less than or equal to j is defined as

$$\chi(j)=\left(\frac{1}{N_2}\sum_{k=1}^{j}\eta(r^{Q_i}==k)\right)100\% \quad (12)$$

where η denotes the number of query images having rank k.

4.5. Results

In this section, the performance of proposed method was investigated for $N_2 = 80$ query images on the $N_1 = 6,550$ database images.

The retrievals based on S^{MCCM} along with S_1, S_2, and S^{CCM} in equations (4), (5) were compared with the retrievals based on previous methods S^{hist} and S^{auto} in equations (9), (10).

In Table 1, performances for different features were compared. The proposed MCCM based method outperforms the other methods. The notable thing is that S^{MCCM} yielded better result in comparison to S^{CCM}. It verifies the importance of the separation of CCM into diagonal elements and non-diagonal elements.

	$\bar{r}$ -measure	$\bar{r}\%$ -measure
S^{hist}	99.2	98.36
S^{auto}	96.6	98.41
S_1	102.9	98.29
S_2	94.5	98.46
S^{CCM}	82.8	98.65
S^{MCCM}	**61.1**	**99.00**

Table 1. Performance measure for different features.

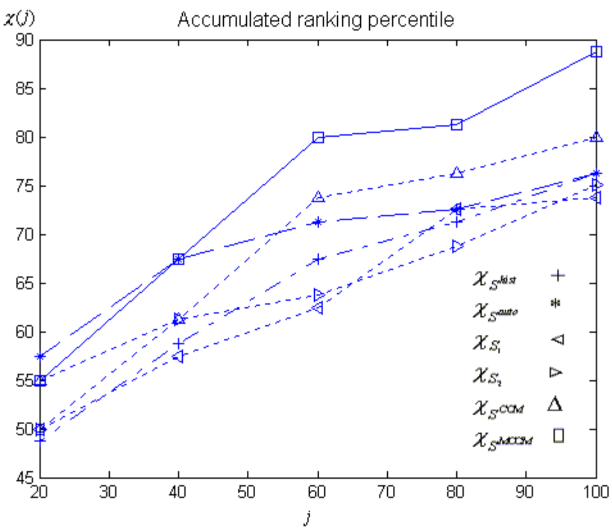

Figure 2. Accumulated ranking percentile χ plotted against ranking j for different features.

Figure 2 shows the accumulated ranking percentile χ plotted against ranking j for various features. Best performance is shown for $\chi_{S^{MCCM}}$. For small ranking j, auto-correlogram shows best result, but the queries that produce bad ranking (>100) degraded the average performance of auto-correlogram a lot.

5. CONCLUSIONS

In this paper, Modified Color Co-occurrence Matrix (MCCM) based image indexing was proposed. The homogeneous color region of the image contributes to the diagonal elements of CCM and non-homogeneous region to the non-diagonal elements of CCM. The diagonal elements of CCM have the color histogram information of entire image empirically, and the non-diagonal elements of CCM contain the shape information in abstract level theoretically. But indexing the images based on CCM without modification suppress the shape information (color edges), since the number of diagonal elements is far greater than that of non-diagonal elements of CCM. The key idea of our work lies in exploiting the shape information by indexing the images based on the diagonal elements and non-diagonal elements of CCM separately with equal weights.

Experimental results show the superiority of the proposed MCCM based indexing in comparison to the indexing based on other accumulative features, color histogram and auto-correlogram with very competitive computational cost.

6. REFERENCES

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