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13—31 A Competitive Learning Algorithm for Color-Based Image Retrieval

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Abstract

The paper aims to build up a common color codebook, which represents well the database color information under consideration, to improve the performance of the image retrieval problem. The frequency sensitive competitive learning neural network algorithm is used for this task, in order to form the set of prototypes that represents well the environment. The similarity measure is a performed aid of a suitable distance measure. An image database of 250 images is used to test the performance of the algorithm.

Keywords : Content-based image retrieval, Competitive learning, Color matching.

1 Introduction

Image retrieval based on image content has received considerable attention within the image database community [1][2][3]. The basic idea of this promoter approach is to reduce the space of all possible colors such that new extracted features can be organized for future search. Traditional textual features such as filenames, captions, and keywords usually used to retrieve images suffer from several problems. First of all, human intervention, inherently subjective and not unique, is required to describe and tag the contents of images in term of a selected set of captions and keywords. As the size of the database grow, the use of keywords becomes inadequate to represent the image content.

Generally, content based image retrieval need to automatically extract primitive visual features from images and to retrieve them on the basis of these features. Humans use color, shape, and texture to understand and recollect image contents. Therefore, it's natural to use these features for the automatic image retrieval application.

Image retrieval, with color as feature for image matching [4], tries to obtain a list of images from the database which are similar in color to a given query image. The measure of similarity between feature values of two images is based on all most case on color histogram matching technique. So we suggest in this paper to use a common color codebook, that contains prominent and distinctive colors, for the interpretation of the color information of the entire database. This suggestion is motivated by several obvious and objective remarks. First, the human eyes can not distinguish close colors very well, and the database contains a large set of similar colors. Second, The storage and the computational time required for the retrieval process can be reduced. Third, the database can consist of certain kind of images, for example rural or urban images, where certain colors are dominant. So, it's very useful to use a learning algorithm that can extract pertinent color information. In this paper, we use a data reduction technique, based on a competitive learning neural network algorithm to build up the color codebook. Figure 1 shows the image retrieval model.

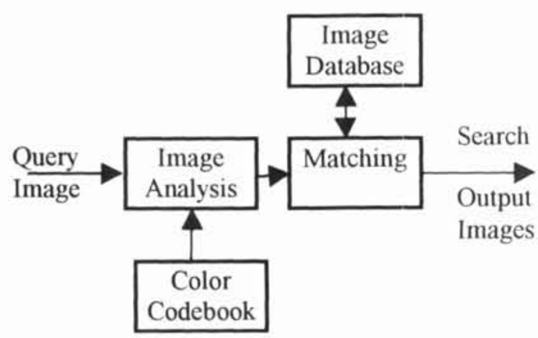

Figure 1 : The image retrieval model

In fact, the algorithm is used for mapping the 3-D color space involved by the image database to a set of colors that represents well the population. The color codebook represents the original color content in terms of minimizing the mean square error using a small number of colors. The frequency sensitive variant of the competitive learning algorithm, used here, has the advantage of using more prototypes for representing regions with large concentration in the color space, and less prototypes for modeling regions with low concentration.

The rest of the paper is organized as follows : Section 2 is concerned with the past works based color matching for image retrieval. Section 3 describes the competitive learning algorithm, while section 4 represents the similarity mesure used. Results and discussions are provided in section 5, which is followed by the conclusions reached and references used.

2 General survey over recent works in image retrieval based on color

Color histogram is a popular color representation scheme that has been used in many image retrieval application [5][6]. It works quite well in quantifying global content in images. Regardless of the color space, color information in an image can be represented either by a single 3-D histogram or three separate 1-D histograms. These schemes are essentially invariant under rotation and translation of the input image. Let $H = \{H(i), i = 1,2,\dots,n\}$ be the histogram of an image, where n is the number of bins of H . A suitable normalization of H also provides scale invariance. The normalized histogram I is defined as follows :

$$I(j) = \frac{H(j)}{\sum_{i=1}^{n} H(i)}$$

Several algorithms have been developed for matching color histograms efficiently. Swain and Ballard [5] have proposed a color matching method known as histogram intersection. The core idea in their technique is to compute the match value as follows :

$$D(Q,I) = \frac{\sum_{j=1}^{n} min(Q_j, I_j)}{\sum_{j=1}^{n} I_j}$$

where Q and I are respectively the query and the model (an image from the database) 3-D image histograms. It's obvious that the match value is closer to unity if the model image is similar to the query image. The method can also be used with three 1-D histograms.
The distance method is based on Euclidean or Manhattan distance to compute similarity between histograms, or feature vectors extracted from these histograms.
In the reference color table method [4], a set of reference colors is defined. This set of colors is selected such that all colors in the application are approximately covered perceptually. The similarity mesure is based on histograms of the pixels with newly assigned colors.
If we have a prior knowledge of the colors in the database, then one can use a suitable reference table to obtain good retrieval efficiency. However, in the case, where such information is not available, it's not feasible to pickup manually a set of colors from the database to form the reference color table. So, it's very useful to use a clustering algorithm that can do this task automatically, by mapping the 3-D color space constituted by the database colors into a finite subset of prototype colors such that the average distance between database colors and their respective closest colors is minimized.
It's obvious that the use of a common color codebook reduce the storage required for histograms, since one 3-D histogram is used to represent the color information of the database images, the computational time is also decreased. In addition the total number of histogram bins can be fixed depending on applications.

3 Building the common color codebook

Competitive learning is an effective data compression technique, it has been used for vector quantization using neural networks since the algorithm is of low computational complexity [9][10]. The adaptive process involved by the algorithm tun the neural network units to a specific features of inputs. The network topology consists of two layers, Input and output layer. The input layer is feedforward connected to the output layer. The input layer receives the input signals $X=\{x_R, x_G, x_B\}$, RGB color components, while the output layer elaborates prototype colors of inputs. Each interconnection from an input unit j to an output unit i has a weight w_{ij}. So for each output unit corresponds a weight vector $W_i = \{w_{iR}, w_{iG}, w_{iB}\}$, i=1,2,...,M, with M design the number of prototypes to be formed. The number of output units is determined by the dispersion of classes presented in the input patterns. In the training phase, the training base is formed of all the database image colors. Synaptic vectors W_i evolve from an initial random position to the centroïdes of clusters in the input data. A competition is held among neurons of the output layer, the winner is the one whose weight vector is closest to the presented input vector, in technical term terms the winner neuron, at time t, is one with minimum Euclidean distance from the current input vector $X(t)$.

$$d(X(t), W_i(t)) = \|X(t) - W_i(t)\|$$

One typical competitive learning algorithm can be described as follows :

$$W_k(t+1) = \begin{cases} W_k(t) + C(t)[X(t) - W_k(t)] & if\ k\ wins \\ W_k(t) & if\ k\ loses \end{cases}$$

$$where \quad k = \{1,2,\dots,M\}$$

$W_k(t+1)$ and $W_k(t)$ are respectively the k^{th} synaptic vector after and before adjustment. $C(t)$ is the scalar learning rate value at time t, often given by an hyperbolically decreasing function.

$$C(t) = \frac{c_1}{t + c_2}$$

where t is time iteration, c_1 and c_2 are constants. Since $C(t)$ is between 0 and 1, c_2 must be greater than c_1.
The algorithm described above is very sensitive to initial synaptic vectors. Synaptic vectors near a cluster of observations win the competition during the learning procedure and the others remain unchanged and don't contribute to building the codebook.
The frequency sensitive competitive learning algorithm [11][12] try to overcome this drawback by using the following modified Euclidean distance :

$$d(X(t),W_i(t)) = g_i(t).\|X((t)-W_i(t)\|$$

where $g_i(t)$ is an increasing function, usually the number of time the i^{th} synaptic vector wins the competition during the learning stage. This reduce the likelihood that the unit will be the winner next steps. Then the other units with low count have more chance to win the competition. So all the output units will contributes to form the codebook. The algorithm has also the advantage of generating prototypes that follow inputs distribution as possible.

4 Color histogram matching

After performing the training phase, the common color codebook is constructed. For each database image, each pixel color is assigned to the closest prototype color in the codebook. Histogram of pixels with newly assigned colors is computed. Thus :

$$\bar{f} = (\lambda_1, \lambda_2, .. \lambda_M)$$

Where λ_i, $i = \{1,2,..., M\}$, is the relative pixel frequency for the i^{th} prototype color in the image. The similarity measure is performed by a weighted Euclidean distance :

$$D(Q,I) = \sum_{i=1}^{M} w_i \sqrt{(\lambda_i^Q - \lambda_i^I)^2}$$

$$w_i = \begin{cases} \lambda_i^Q \ \ if \ \lambda_i^Q, \lambda_i^I > 0 \\ 1 \quad if \ \lambda_i^Q \ or \ \lambda_i^I = 0 \end{cases}$$

where λ_i^Q and λ_i^I represent respectively the i^{th} relative pixel frequency of the query and the model image.

5. Experimental results

The database used for evaluating the approach is of 250 images, with 128x128 pixels and 256 colors. Color maps of images are piled up in a single matrix to form the data in which the competitive learning will be performed. Histograms with respect to the constructed color codebook are computed for all the database images.
In this section, we evaluate the performance of the proposed technique. We have used the performance criterion [7]. This is defined as follows : 10 images which represents the population well are picked as query images, and we manually list corresponding similar images found in all the database. Similarity measure is performed over all the database images against each query image, to obtain short lists of similar images. We define the efficiency of retrieval η_t for a given short list of size T as follows :

$$\eta_t = \begin{cases} n/N & if \ N \le T \\ n/T & if \ N > T \end{cases}$$

Where n is the number of similar images retrieved in the short list and N is the total number of similar images in the database. Table 1 represents the retrieval efficiency of different methods. It's obvious that the common color codebook method is superior to that of histogram intersection and statique moments method [8]. The database contain a large variety of images, so the efficiency of retrieval η_t increase as the codebook is large.
Time used in the search process by the reference color table and our aproach is the same, since for the two methods a fixed number of prototype colors is used for computing histograms.

6 Conclusion

The reference color table is a good image retrieval method when we have a priori knowledge of colors in the database, and when there are no on-going additions/deletions to the database. But in this method the reference color table is built perceptually. So we suggest in this work to construct a common color codebook aid of a suitable competitive learning neural networks algorithm. According to the database analyzed a large or a small number of colors can be used. The results provided by the approach are very satisfactory.

References

[1] C. Faloutos, M. Flickner, W. Niblack, D. Provic, W. Equitz, R. Barber, << Efficient and Effective Query by Image content >>. Research report, IBM Alameda Reseach Center, 1993.

[2] V.N. Gudivada and V. Raghavan, << Content-based image retrieval system, In IEEE Computer, pages 18-22 September 1995.

[3] W. Niblack, R. Barber, W. Equitz, M. Flickner, and others, << The QBIC project : querying images by content using color, texture, and shape, >> In Proc. of SPIE, Storage and retrieval for image and video data bases, vol. 1908, San Jose, CA, pp. 173-187, February 1993.

[4] B. M. Mehtre, M.S. Kankanhalli, A. D. Narsimhalu, and G. S. Man., << Color matching for image retrieval, >> Pattern Recognition Letters, vol. 16, pp. 325-331, March 1995.

[5] M. J. Swain, and D. H. Ballard, << Color indexing,>> International Journal of Computer Vision, 7(1) 11-32, 1991.

[6] J. Hafner, al.<< Efficient color histogram indexing for quadratic distance functions >>, In IEEE Transaction on Pattern Analysis and Machine Intelligence, July 1995.

[7] M. S. Kankanhalli, and others << Cluster-based color matching for image retrieval.>> Pattern Recognition, vol. 29, pp. 701-708, 1996.

[8] M.A.Stricker et M.Orengo.<<Similarity of color images>>. Dans SPIE Conference on Storage and Retrieval for Image and Video Databases V, volume SPIE-2420, pages 381-392,1995.

[9] T. Kohonnen, << An introduction to neural computing, >>, Neural Networks, vol. 1, pp. 3-16, 1988.

[10] C. W. Kim, S. Cho, C.W. Lee, << Fast competitive learning with classified learning rates for vector quantization >>, Signal Processing (Image Communication) ,vol. 6, pp 499-505, 1995.

[11] S. C. Ahalt, A. K. Krishnamurthy, P. Chen and D. E. Melton, << Competitive learning algorithms for vector quatization >>, Neural Networks, Vol. 3, pp. 277-290, 1990.

[12] W. C. fang, B. J. Sheu, O. T. –C. Chen, and J. Choi, << A VLSI processor for image data compression using self-organisation Networks >>, IEEE Trans. on Neural Networks, vol. 3, n° 3, pp. 506-518, May 1992.

Table 1 : Average efficiency of different methods.

Matching method	T=5	T=9
Hist. intersection	0,533	0,463
Statique moments	0,666	0,629
Com. color codebook of size		
64	0,900	0,833
128	0,933	0,907
256	0.980	0,944