Enhanced Content Based Image Retrieval Using Multiple Feature Fusion Algorithms

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ABSTRACT- Recently the usage of multimedia contents like images and videos has increased. This usage has created the problem of locating from a very large database. This paper presents Content Based Image Retrieval (CBIR) system that uses multiple feature fusion to retrieve images. The features like color, shape and texture are used. The color histogram is used to extract color feature and active contour model is used for shape extraction. K-means and SOM algorithms are used for clustering and dimensional reduction. The experimental results show that the proposed CBIR system is better in terms of precision, recall and speed of image retrieval.

Index Terms- Content Based Image Retrieval, color histogram, contour model, K-means, Self Organizing Map

1. INTRODUCTION

Content-Based Image Retrieval (CBIR) is a process that searches and retrieves images from a large database on the basis of automatically-derived features such as color, texture and shape. The techniques, tools and algorithms that are used in CBIR, originate from many fields such as statistics, pattern recognition, signal processing, and computer vision. This field of research is attracting professionals from different industries like crime prevention, medicine, architecture, fashion and publishing. For the past 10 decades the volume of digital images produced in these areas has increased dramatically and the World Wide Web plays a vital role in this upsurge. Several companies are maintaining large image databases, where the requirement is to have a technique that can search and retrieve images in a manner that is both time efficient and accurate (Xiaoling, 2009).

In order to perform the retrieval process two steps are involved. The first step is the 'feature extraction' step, which identifies unique signatures, termed as feature vector, for every image based on its pixel values. The feature vector is the characteristics that describe the contents of an image. Visual features such as color, texture and shape are used more commonly used in this step. The second step is the classification step which matches the features extracted from a query image with the features of the database images and group's images according to their matching.

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2. LITERATURE STUDY

Feature extraction mainly concentrates on color, texture and shape features. Out of these color feature is considered as the most dominant and distinguishing visual feature. A color histogram describes the global color distribution of an image and is more frequently used technique for content-based image retrieval (Wang and Qin, 2009) because of its efficiency and effectiveness.

Cinque et al. (1999) present a spatial-chromatic histogram considering the position and variances of color blocks in an image. Huang et al. (1997) proposes color correlogram for refining histogram which distills the spatial correlation of colors.

Xioling and Hongyan (2009) proposed a new method that combines color histogram and spatial information. The method was able to maintain the advantage of the robustness to image rotation and scaling of the traditional histogram, while incorporating the spatial information of pixels. This high dimensionality indicates that methods of feature reduction can be implemented to improve the performance. Another side effect of large dimensionality is that it also increases the complexity and computation of the distance function. It particularly complicates 'cross' distance functions that include the perceptual distance between histogram bins [2]. In my previous work, this method is enhanced to use a tree structured representation which combines color histogram and region features.

This method uses Self Organizing Map (SOM) to improve the accuracy, while simultaneously performs dimensionality reduction. The self-organizing Map (SOM), also known as a Kohonen map, is a technique which reduces the dimensions of data through the use of self-organizing neural networks. This approach uses the improved histograms as image feature vector. The feature vector, F(I), is generated for each image P in the collection. When a query is made, the feature vector for the query image is calculated and the similarity between any two images is calculated using the Euclidean distance between the feature vectors.

While combining the above procedure with SOM the following procedure is adhered. The SOM used consist of M x M units, where M x M >> N. This makes it possible to map distinct feature vectors to unique locations in the SOM, by allowing each image to occupy its own region of the map. The weight vectors of all units in the SOM are stored using a single color histogram. Since each pixel can keep 3 values in its HSV color space to handle weight vectors of k-dimensions, the pixels are grouped in K/3 tiles, with pixels from the same position of different tiles keeping the value of the same unit's weight vector. All values in the weight vectors are initialized using the weight factor calculated using Equation (5).

During training, the image blocks are given as input to the network. These input vectors are mapped with the network weight vectors to choose a neuron in the competitive layer as a winner. This winner is a neuron whose weight vector is much similar to the input vectors. In other words it is the neuron having the minimum Euclidean distance from the input vector. The input vector, say x is simultaneously applied to all nodes. The similarity between x and weight wi is measured in terms of spatial neighborhood Nm. The weights affecting the currently winning neighborhood undergo adoption at the correct learning step other weights remain unaffected. The neighborhood, Nm is found around the best matching node m such that

$$||x - w_m|| = \min [||x - w_i||] \quad (1)$$

The radius of Nm will be decreasing as the training progresses. Towards the end of training the neighborhood may involve no cells other than the central winning one. The weight-updating rule for Self Organizing Feature Map is defined as

$$\Delta w_i(t) = \alpha [x(t) - w_i(t)] \text{ for } i \in N_m(t) \quad (2)$$

Where Nm(t) denotes the current spatial neighborhood and α denotes the learning rate. After training the weight vectors of each neuron of the Kohonen layer acts as code vectors.

3. PROPOSED METHODOLOGY

Second work, that is, it combines SOM + Color features with shape feature. The three selected descriptors are color, texture and shape. Let C be the set of color features S be the set of shape features. Let R be the resultant feature vector after concatenating C and S. The average of all the respective features over the entire database is used to normalize the individual feature components. Let the normalized vectors be C' and S'. To avoid the curse of dimensionality, a k-means clustering algorithm is used. The k-means algorithm performs a two step procedure, where the first step removes redundant features and the second step retains points and removes points that are very near to the specific point. These points are removed because they may not provide additional information because of being in vicinity. The distance classifier used is Euclidean distance and the number of clusters is determined using the PBM cluster validity index (Pakhira *et al.*, 2004). To further select optimum feature vector, the SOM method proposed in Priya and Vasantha kalyani David (2010) is used.

If R' be the dimensionality reduced feature database and R" is the feature vector obtained from query image, then the retrieval system is based on a similarity measure defined between R' and R". Feature matching is performed using point pattern matching algorithm. This algorithm considers two points as matching if and only if, the spatial distance, directional distance and Euclidean distance between the corresponding features are within a threshold (Th) and each feature R'' and R' contain (c, s, θ, feature) (c, s features belonging to different feature vectors). This means that a point in R" is said to be a match with R', if the spatial distance (SD) between them is smaller than a given tolerance Th_1, the difference direction (DD) between them is smaller than an angular tolerance Th_2 and the Euclidean difference (ED) between them is between some threshold. To further improve the accuracy of the formulas, weights W_i is attached to each of the feature vectors. The weight is calculated as $W_i = \frac{1}{1+\sigma_i}$ where σ is the standard deviation of the ith feature of the image. The distance Equations (3) – (5) used for this purpose are given below.

$$SD(R', R'') = (W_c * |c''-c'|^2 + W_s * |s''-s'|^2)^{1/2} \le Th_1 \quad (3)$$

$$DD(R', R'') = \min(|\theta''-\theta'|, 360° - |\theta''-\theta'|) \le Th_2 \quad (4)$$

$$ED(R', R'') = \sqrt{\sum | f''-f'|} \le Th_3 \text{ where f is the feature} \quad (5)$$

The final matching score for the ED and point pattern matching technique is based on the number of matched pairs found in the two sets, and is computed using Equation 6.

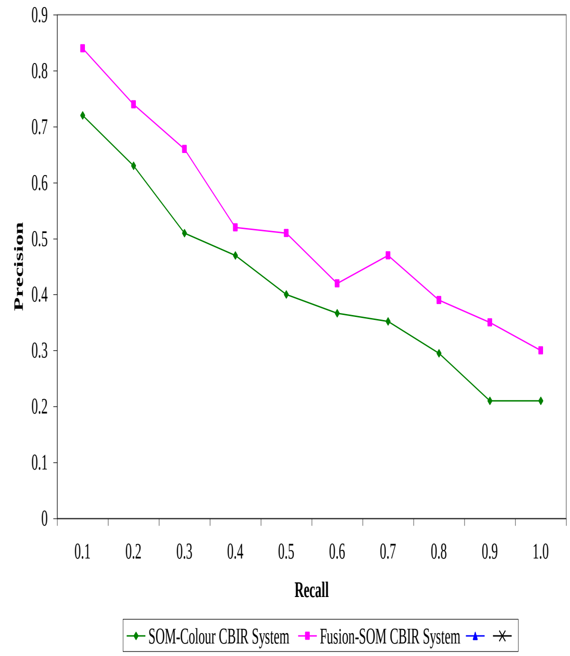
$$\text{Matching Score} = \frac{100xQ^2}{MxN} \quad (6)$$

where Q is the number of paired points between the database and the query concatenated point sets, while M and N are the number of points in R' and R'' respectively. The top 'n' closest images are taken as query result, excluding the query image present in the database.

4. EXPERIMENTAL RESULTS

The image database used during experimentation consists of 650 JPEG color images randomly selected from the World Wide Web. Figure depicts a sample of images in the database.

During testing, care was taken to choose a query image from different types of images like same scene, large change in appearance, etc. The performance metrics used during evaluation is the precision-recall measure and retrieval time. Precision is defined as the fraction of retrieved images that are truly relevant to the query image and recall is defined as the fraction of relevant images that are actually retrieved. Retrieval time is the time taken to retrieve images after giving the query image. The system was developed in MATLAB 7.3 and all the experiments were conducted in Pentium IV machine with 512 MB RAM. The histograms for all the images were constructed using 72 color bins after converting the RGB color space to HSV color spam.



From the figure, it could be seen that the fusion SOM CBIR method is an improved version of the base system using SOM and histogram. It also proves that combination of various features improves the image retrieval process. The image retrieval time of Fusion-SOM CBIR System was 1.43 seconds and that of SOM-color CBIR System was 1.67 seconds. Thus, the proposed method shows that a speed efficiency of 14.37%. This shows that the dimensionality reduction in both cases is excellent.

5. CONCLUSION

In this paper, SOM based color histogram method with multiple features for content based image retrieval is proposed. The proposed system used color features and shape features which were fused to obtain feature vector. A k-means clustering algorithm and SOM based dimensionality reduction techniques are used. A similarity measure that combines spatial distance, direction distance and Euclidean distance is used. Several experiments were performed to analyze the performance of the proposed system. The results proved that the combination method is efficient in terms of precision, recall and speed of image retrieval. The work can be extended with texture feature. Further, the present CBIR system can also be integrated with machine learning classifiers to further improve their performance.

References

[1] Xiaoling, W. (2009) A Novel Circular Ring Histogram for Content-Based Image Retrieval, First International Workshop on Education Technology and Computer Science, Vol. 2, Pp.785-788.

[2] Wang, S. and Qin, H. (2009) A Study of Order-Based Block Color Feature Image Retrieval Compared with Cumulative Color Histogram Method, Sixth International Conference on Fuzzy Systems and Knowledge Discovery, FSKD '09, IEEE Xplore, Vol. 1, Pp. 81 – 84.

[3] Pass, G. and Zabih, R, (1996) Histogram refinement for content-based image retrieval, Proc. WACV [C].Sarasoto, FL, Pp. 96-102.

[4] Banerjee, M., Kundu, M.K. and Das, P.K. (2004) Image Retrieval with Visually Prominent Features using Fuzzy set theoretic Evaluation, ICVGIP 2004, India.

[5] Chen, Y. and Wang, J. Z. (2002) A Region-Based Fuzzy Feature Matching Approach to Content-Based Image Retrieval, IEEE Trans. on PAMI, Vol. 24, No.9, Pp. 1252-1267.

[6] Deselaers, T., Keysers, D. and Ney, H. (2008) Features for image retrieval: An experimental comparison, Information Retrieval, Vol. 11, Pp. 77-107.

[7] Gevers, T. and Smeuiders, A.W.M. (1999) Combining color and shape invariant features for image retrieval, Image and Vision computing, Vol.17, No. 7, Pp. 475-488.

[8] Goh, S.T. and Tan, K.L. (2000) MOSAIC: A fast multi-feature image retrieval system, Data & Knowledge Engineering, Vol. 33, Pp.219-239

[9] Ha, J., Kim, G. and Choi, H. (2008) The Content-Based Image Retrieval Method Using Multiple Features, Fourth International Conference on Networked Computing and Advanced Information Management, 2008. NCM '08, Pp. 652 – 657.

[10] Harris, C. and Stephens, M. (1988) A combined corner and edge detectors", 4th Alvey Vision Conference, Pp. 147-151.

[11] Kokare, M. and Biswas, P.K. (2007) Texture image retrieval using rotated wavelet filters, Pattern Recognition Letters, Vol.28. Pp, 1240-1249.

[12] Li, J., Wang, J.Z. and Wiederhold, G. (2000) IRM: Integrated Region Matching for Image Retrieval, Proc. of the 8th ACM Int. Conf. on Multimedia, Pp. 147-156.

[13] Lin, H.J., Kao, Y.T., Yen, S.H. and Wang, C.J. (2004) A study of shape-based image retrieval, Proceedings of 24th International Conference on Distributed Computing Systems Workshops, Pp. 118 – 123.

[14] Manjunath, B.S. and Ma, W.Y (1996) Texture feature for browsing and retrieval of image data, IEEE Transaction on PAMI, Vol. 18, No. 8, Pp.837-842.

[15] Niblack, W. et al., "The QBIC Project: Querying Images by Content Using Color, Texture, and Shape, Proc. SPIE, vol. 1908, San Jose, CA, pp. 173–187, Feb. 1993.

[16] Pentland, A., Picard, R. and Sclaroff, S. (1994) Photobook: Content-based Manipulation of Image Databases," in Proc. SPIE Storage and Retrieval for Image and Video Databases II, San Jose, CA, Pp. 34–47.

[17] Sastry, C.S. and Ravindranath, M. (2007) A modified Gabor function for content based image retrieval, Pattern Recognition Letters, Pp, 293-300.

[18] Vadivel, A., Sural, S. and Majumdar, A.K. (2009) Image retrieval from the web using multiple features, Online Information Review, Vol. 33, Iss: 6, Pp.1169 - 1188

[19] Wu, J., Wei, Z. and Chang, Y. (2010) Color and Texture Feature For Content Based Image Retrieval, JDCTA: International Journal of Digital Content Technology and its Applications, Vol. 4, No. 3, Pp. 43-49

[20] R.Priya and Dr. Vasantha Kalyani David (2010) Improved Content Based Image Retrieval Using Color Histogram And Self Organizing Maps, IJCSIS: International Journal of Computer Science & Information Security Vol 8, No. 9, Pp243-248