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Unsupervised clustering methods for content based image retrieval

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***Abstract*— In this paper, we proposed the unsupervised clustering methods for content based image retrieval. Content based image retrieval method (CBIR) is widely used in searching the data (image) from the large database. Collect the images from ORL database. All the images are portioned into different sub patterns like clusters using unsupervised methods such as k-mean algorithm, k-medoids algorithm. In this paper we extract the features from the all database images by using these methods. These are considered as local features to recognize the corresponding images from the database. We used ORL and COREL databases. As compared to existing techniques this proposed method gives better experimental results.**

***Index Terms*—** K-mean algorithm, K-medoids algorithm and classifier.

I. INTRODUCTION

The evolution of the World Wide Web (WWW), the advances in computer technologies, and the recent information explosion in multimedia content have produced an enormous number of digital data archives in a variety of application domains such as entertainment, commerce, education, biomedicine, military, and web image classification and searching. Correspondingly, many techniques have been developed for fast indexing, retrieval, and manipulation of the digital images. However, traditional text-based (keyword-based) image retrieval methods do not work well as the image contents cannot be accurately described by human language and different persons may perceive the same image differently. In addition, it is time-consuming to manually annotate each image due to the enormous size of image databases. As a result, content-based image retrieval (CBIR) has been brought to the forefront since the early 1990s. In this paper, we present a novel fusion framework for general-purpose image retrieval based on both regional color and texture features and the global and semi-global edge histogram descriptors (EHDs) expanded from the normative EHD for MPEG-7 [3,4].We have developed a fast and automatic statistical-clustering-based segmentation method that provides reasonable segmentation results where each segmented region generally Corresponds to an object or parts of an object. Each region-based feature is then individually fuzzified to incorporate the segmentation-related uncertainties into the retrieval algorithm. The global and semi-global EHDs, which do not depend on segmentation, have been further utilized to decrease the impact of inaccurate region segmentation and reduce the possible retrieval accuracy degradation for the accurate segmentation cases. The resemblance of two images is then defined as the overall similarity between two families of region-based fuzzy color and texture features, global and semi-global EHDs. This overall similarity is quantified by a computationally efficient distance metric which integrates properties of all fuzzy regions in the images, the normalized area percentage difference between matched regions, the normalized distance from the region center to the image center, different contributions from color and texture features, and different contributions from regional, global, and semi-global features. It is noteworthy that the objective of the proposed method is to match entire images, including backgrounds and main objects. It may not perform very well for situations where the goal is to find images containing a specific object where the background is not important. Consequently, some approaches such as color coherence vector, color correlogram, spatial color histogram, and spatial chromatic histogram [26] have been proposed to overcome the spatial limitation by incorporating spatial information in the descriptor. However, most approaches have been proposed to focus on the local features to extend the capability of CBIR so users can retrieve images based on potential interest regions. These local-feature based approaches are likely to provide a big step towards the semantics based retrieval since human perceptions of certain visual contents could potentially be associated with interesting classes of objects/regions or semantic meanings of objects/regions in the image. Among various local-feature based approaches, the region-based image retrieval methods have been widely studied since they have a strong correlation with real-world objects. In region-based image retrieval, each image is first segmented into homogenous regions and features for each region are extracted. The overall similarity between two images is calculated based on all the corresponding region-based features. Several important region based retrieval systems are briefly reviewed here.

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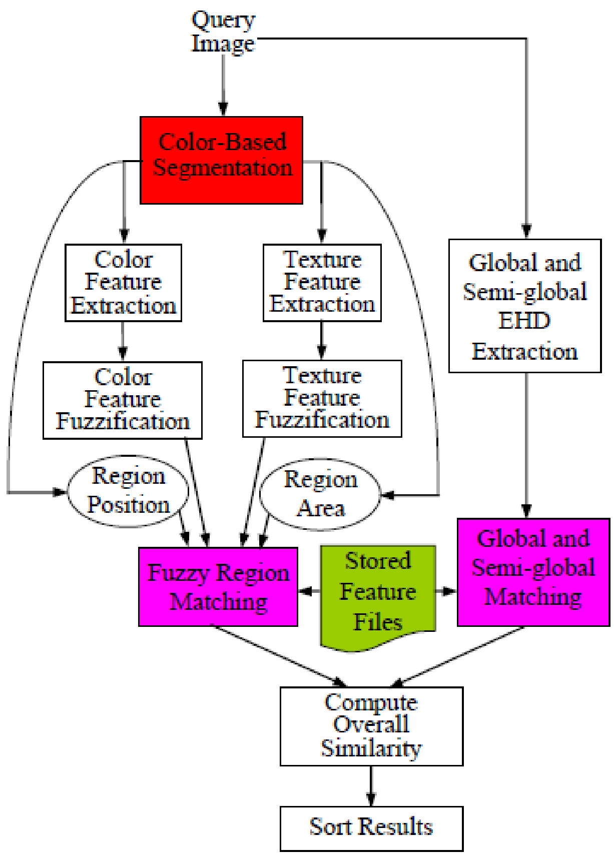
Basics concepts of k-mean algorithm and k-medoids are discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

II. CONTENT BASED IMAGE RETRIEVAL (CBIR) APPROACH

Block diagram



III. PROPOSED METHOD

Proposed Algorithm

Proposed method is presented below:

1. It dramatically reduces the computational cost since texture features are excluded, where the complicated statistical computation is usually involved.
2. It is fully automatic due to the adaptive learning nature of the clustering method.
3. It is robust in the sense that each segmented region generally corresponds to an object or parts of an object.
4. To segment an image into coherent regions, the image is first divided into non-overlapping square image-blocks and a color feature vector is extracted for each image-block.
5. The size of the image-block is chosen to be 2 × 2 because fine details can be preserved. The LUV color space is used to extract color features for each image-block since the perceptual color abilities of the human visual system are proportional to the numerical difference in the LUV color space.
6. The image-block-based color features are the means of each color component in the corresponding image-block.
7. After obtaining the color features for all 2 × 2 image blocks, a statistical-clustering method, an unsupervised K-Means algorithm [35], is used to cluster these color features into several groups, where each group in the color feature space corresponds to one spatial region in the image space.
8. The learning nature of this K-Means algorithm enables an automatic and iterative segmentation process, which accommodates the fact that the number of regions in an image is unknown before segmentation.
9. Suppose there are *M* blocks {*xi*= 1, . . . , *M*} for each image.
10. The goal of the K-Means algorithm is to group each of *M* blocks into one ofthe *K*clusters, whose cluster centers are ˆ *x*1, ˆ *x*2, . . . , ˆ *xK*.

IV. EXPERIMENTAL RESULTS

a) Feature extraction process

In the experiments, two quantitative measurements, the pre cision rate and there call rate, are employed to perform the quality assessment for the above-mentioned various methods. They are defined in Eqs. (24) and (25) (He etal.,2010). The precision rate is defined as the ratio of retrieved images similar to the query image among the total number of retrieved images. The recall rate can be defined as the percentage of retrieved images similar to the query image among the total number of images similar to the query image in the database. Precision rate ¼ no: of relevant images retrieved total no: of images retrieved where p indicates the number of relevant images retrieved, q denotes the number of relevant images in the data base which are not retrieved ,and represents the number of non-relevant images in the database which are retrieved. Two image databases are employed for performance evaluation in this paper. One is the clothing image database collected from the Internet, partially shown in Fig. 3 (⟨http://www.tobby.com.tw⟩). It contains seven categories and each category has 160 images, that is, there are totally1120 images. The other one is the Corel image database, partially shown It contains ten categories and each category has100 images, that is, there are totally 1000 images.

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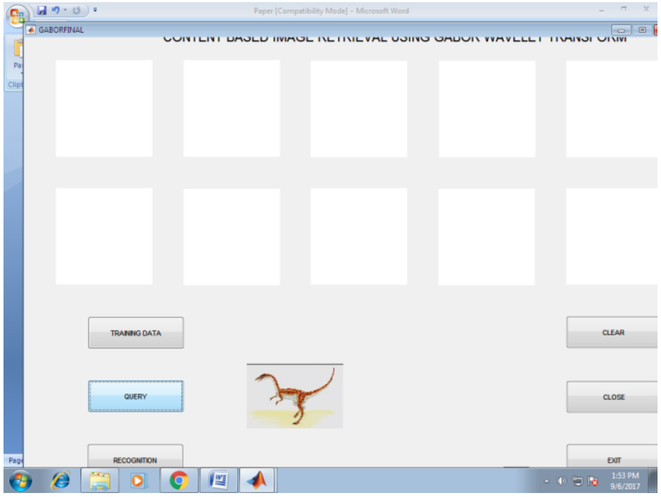


Figure2: Query image

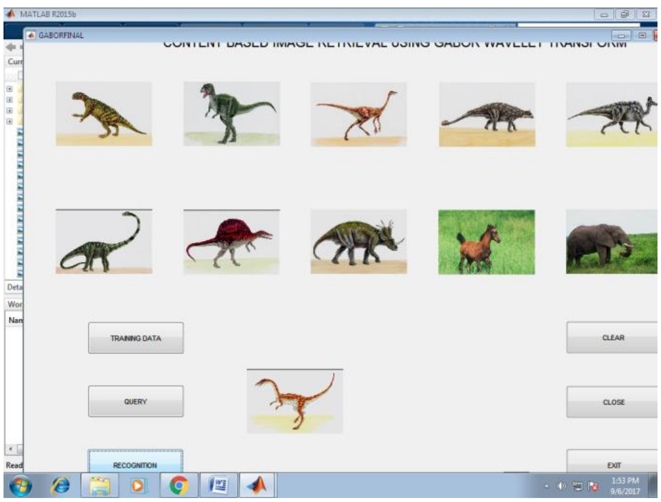


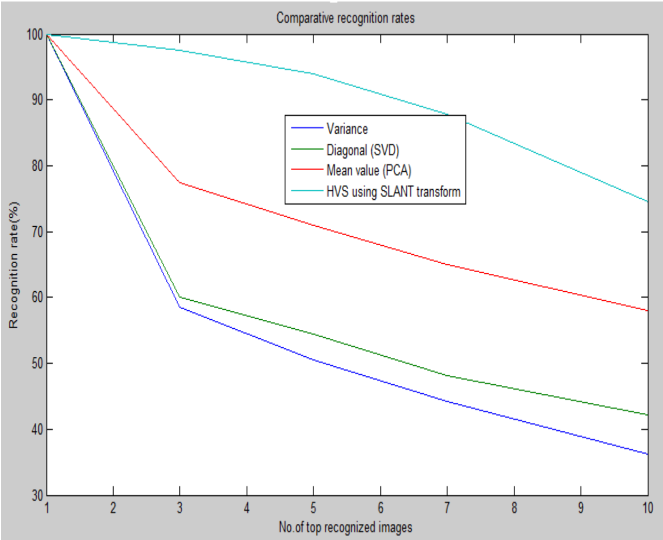
Figure3: Retrieval result

To verify the effectiveness of the proposed approach, the overall average retrieval accuracy obtained by assigning different weights to the global-based and regional-based similarity scores is shown in Fig. 9, where G and R, respectively, represent global and regional weights. It also clearly shows the effectiveness of our fusion approach (G:R = 3: 7) as it achieves the best accuracy. Additional experiments using the same test bed, the same 150 query images, and the 20 returned images are performed on several variants of our proposed method to experimentally illustrate the validity of our method. These variants include: The experimental results on 5000 images from the COREL database demonstrate that the proposed algorithm achieves good retrieval accuracy with fast speed due to the small feature vector size (i.e., 3 elements for color, 6 elements for texture, 5 elements for global EHDs, and 25 elements for semi-global EHDs). 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 with a compromised efficiency. Other fuzzy membership functions and other global feature representations may be further studied to improve the retrieval accuracy. Instead of searching the image database sequentially as currently implemented in our system, some tree-structure-based indexing methods may be explored to further speedup the retrieval. To further analyze the number of ordered visual words, we compare the retrieval accuracy of our indexing method under different numbers of ordered visual words, as shown in Fig. 4. The retrieval accuracy is evaluated by the accuracy value of magazine dataset and the MAP value of UK bench dataset. As the number of visual words increases from 1 to 2, both the accuracy value and the MAP value are improved, because two ordered visual words increase the distinction among the quantized feature descriptors and remove the false feature point correspondences. However, when the number of ordered visual words increases from 3 to 4, the accuracy value and MAP value are smaller than those when the number of ordered visual words is 2. This is because the distinction among the quantized feature descriptors is excessively increased and the similarity between two similar images is reduced. To ensure the retrieval accuracy, the number of ordered visual words is set as 2, which is the best choice for the ordered quantization. In the subsequent experiments, our indexing method employs two ordered visual words.

Table 1: Recognized efficiency on face database

	No. of top recognized matches				
	1	***3***	***5***	***7***	***10***
Mean	*100*	*58.5*	*50.5*	*44.2*	*36.25*
Variance	*100*	*60*	*54.5*	*48.2*	*42.25*
LPP	*100*	*77.5*	*71*	*65*	*58*
Unsupervised method (Proposed)	***100***	***94***	***90***	***87***	***65.5***

b) Comparative recognition rates:



V. CONCLUSIONS

In this paper, we have been successfully implemented the unsupervised clustering methods for content based image retrieval. Content based image retrieval method (CBIR) is widely used in searching the data (image) from the large database. Collect the images from ORL database. All the images are portioned into different sub patterns like clusters using unsupervised methods such as k-mean algorithm, k-medoids algorithm. In this paper we extract the features from the all database images by using these methods. These are considered as local features to recognize the corresponding images from the database. We used ORL and COREL databases. As compared to existing techniques this proposed method gives better experimental results.

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