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An Efficient Color Clustered Image Regions Based Retrieval Approach For Image Database Repository

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Abstract— In recent years, technological achievements pave a wide range for the development of images in various aspects and it is essential to have an effective technique for retrieving images from large domains. Content Based Image Retrieval (CBIR) method provides an efficient image retrieval of relevant images from large image databases that can fill the semantic gap between the adopted method and the user. The images are predominated with various low level features like color, texture, shape etc., are used to calculate the similarity and dissimilarity among the images. The features of the query image not only a sufficient factor for retrieving images but also applying eminent technique will be made in reality. In CBIR, various methods are involved in retrieving images, but there remains a lack in efficiency or in effectiveness. To promote, a new technique called Color Image Segmented Clustering has been proposed for improving the efficiency in retrieving images by fully exploiting the similarity information among the images.

Keywords— Content Based Image Retrieval, Segmentation, Cluster groups, similarity measurement, image retrieval.

I. INTRODUCTION

The massive growth in digital imaging during the last decade caused the huge collection of images to be created in many areas. It is a difficult task to search images from those large data repository. In CBIR, it is given with a query image that obtains the images of the same object or scene from an image database. Due to huge collections of images in the image database, efficiency is a vital factor for content-based image retrieval. Therefore, developing an efficient retrieval method for content-based image retrieval is of great significance. The remainder of this paper is organized as follows. Section 2 briefly describes content based image retrieval. Section 3 describes the various methods in the development of content based image retrieval system. Image Splitting techniques have been discussed in section 4. Section 5 describes the techniques involved in extracting the color feature of the images and section 6 describes the standard clustering techniques involved in creating cluster groups with color as key and predominant factor. Section 7 and section 8 describe the general methodology in the case of image indexing and the parameters used for the comparison of similarity of images. Section 9 puts forth the proposed system that minimizes the effort in image retrieval without much human intervention and section 10 finally concludes this study over the content based image retrieval.

II. CONTENT BASED IMAGE RETRIEVAL

In Content Based Image Retrieval (CBIR), retrieval of image is based on similarities between the contents, i.e., textures, colors, shapes etc., which are measured as the lower level features of an image. In CBIR each image stored in the database, has its features extracted and compared to the features of the query image. Thus, broadly, it involves two processes, viz, feature extraction and feature matching [1].

The CBIR system is divided into following stages: Preprocessing, Feature Extraction and Feature Matching.

A. *Preprocessing*

The image is first processed in order to extract the features, which describe its contents. The processing involves filtering, normalization, segmentation, and object identification. The output of this stage is a set of significant regions and objects.

B. *Feature Extraction*

Features such as shape, texture, color, etc. are used to describe the content of the image. Image features can be classified into primitives.

C. *Feature Matching*

Feature vectors were identified and stored in a feature vector table and matched with that of the query image feature vectors.

III. VARIOUS METHODS IN CBIR

There exist a variety of methods in different periods for retrieving images in Content based images retrieval including Querying by Image Content (QBIC) was developed by IBM to retrieve images without any verbal description, but by sorting the image database and querying it by shape, color, texture and spatial location. Virage Video Engine [2] was developed for multimodal indexing and retrieval of videos.

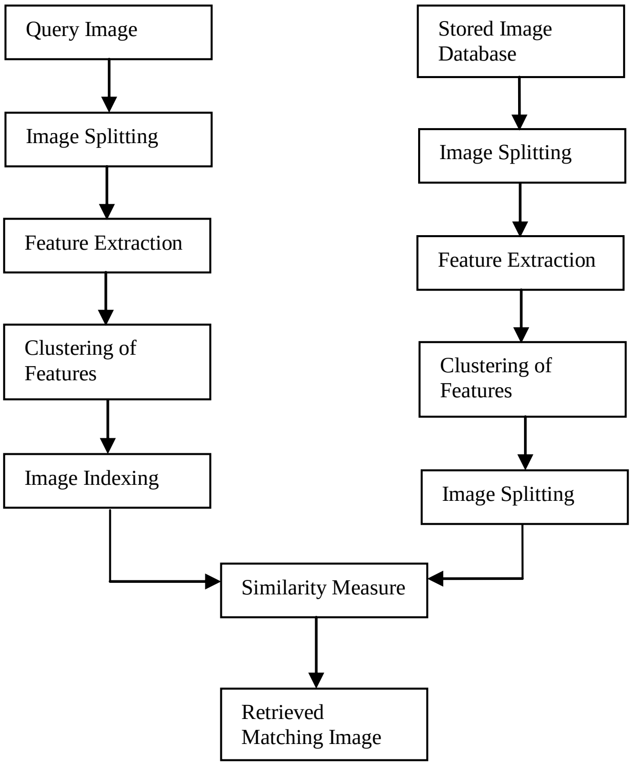


Fig.1 Content Based Image Retrieval Architecture

Library-based coding [3] is a way of representing images and uses retrieval-enabled MPEG for efficient querying and retrieval. A stochastic model like Photo book and blob world system, analyses images in both time and frequency domain using 2D discrete wavelet transform and does regular fragmentation of images into homogeneous regions.

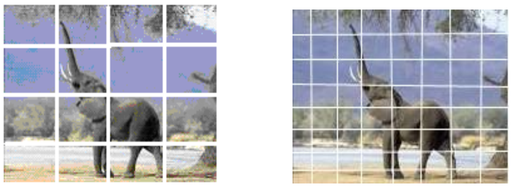
Semantics-sensitive integrated matching is a wavelet-based approach like the WBIIS system [4], but uses better strategies to capture image semantics, better integrated region matching (IRM) metrics and image segmentation algorithms. FACERET [5] is an interactive face retrieval system which uses self-organizing maps and relevance feedback to solve the complexity with non-trivial high level human description. It uses Principal Component Analysis (PCA) projections to project face images to a dimensionally reduced space. Another approach is the linguistic indexing of pictures [6] using a 2-D multi-resolution hidden Markov model (2DMHMM) for the statistical modeling process and statistical linguistic indexing.

Personalizable Image Browsing Engine (PIBE) uses browsing tree, a hierarchical browsing structure for quick search and visualization of large image collections and Costume enabled automatic video indexing. Evolutionary searching, feature dependency measure, boosting and Bayes' error were proposed for generic feature selection. Support Vector Machine (SVM), a swiftly growing field within pattern recognition-based feature detection, is used for facial recognition system. Over the years, several efficient algorithms in CBIR shed light on new interesting facts on multimedia, computer vision, information retrieval and human-computer interaction. It has resultant in a high resolution, high-dimension and maximum throughput of images searchable by the content. Due to its high resolution and quality of the image retrieved, its application is expanded in the field of biomedical imaging, astronomy and various other scientific fields.

IV. IMAGE SPLITTING

Image segmentation can be seen as the process of dividing an image into disjoint homogeneous regions. These homogeneous regions usually contain similar objects of interest or part of them. The extent of homogeneity of the segmented regions can be measured using some image property (e.g. pixel intensity). The image splitting is the method of dividing the image into non overlapping parts.

a. Full Image (1 Part) b. Four Parts



a. Sixteen Parts b. Sixty Four Parts

Fig.2 Splitting of an image into regions

In the process of image segmentation, the system first segments every image into regions, and then extracts features of each region.

V. COLOR FEATURE EXTRACTION

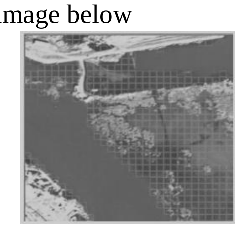
Color is the most popularly used features in image retrieval and indexing. On the other hand, due to its inherent nature of inaccuracy in description of the same semantic content by different color quantization and /or by the uncertainty of human perception, it is important to capture this inaccuracy when defining the features. It is applied with fuzzy logic to the traditional color histogram to help capture this uncertainty in color indexing [7] [8]. In image retrieval systems color histogram is the most commonly used feature. The main reason is that it is independent of image size and orientation. Also it is one of the most straight-forward features utilized by humans for visual recognition and discrimination. Statistically, it denotes the joint probability of the intensities of the three color channels. Once the image is segmented, from each region the color histogram is extracted. The major statistical data that are extracted are histogram mean, standard deviation, and median for each color channel i.e. Red, Green, and Blue. So totally $3 \times 3 = 9$ features per segment are obtained. All the segments need not be considered, but only segments that are dominant may be considered, because this would speed up the calculation and may not significantly affect the end result.

A. Conventional Color Histogram

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in the image. From a probabilistic perspective, it refers to the probability mass function of the image intensities.

Some of the techniques tried were – Average color in Gray scale, Average color in RGB format and Average color in YCBCR (Y is the luminance and CB, CR are the chrominance components). The objective to use this feature is to filter out images with larger distance at first stage when multiple feature queries are involved. Another reason of choosing this feature is the fact that it uses a small number of data to represent the feature vector and it also uses less computation as compared to others. However, the accuracies of query result could be significantly impact if this feature is not combined with other features.

We evaluated the various methods using Precision and Recall (introduced in the next section which compares the Precision and Recall values of the methods), and found that YCBCR performs better than the other two. Hence we used it as the basis of color extraction as shown in the image below



$$\text{Average color} = \frac{\sum (\text{intensity of all pixels in the current block})}{(\text{total pixels in the block})}$$

The output of this procedure would be a region matrix, of 30X30 (for 10X10 block or 37X37 for 8X8) size, with ‘1’ in the areas corresponding to the presence of color match and ‘0’ in the areas without color match.

VI. IMAGE CLUSTERING

Image clustering is usually performed in the early stages of the mining process. Feature attributes that have received most attention for clustering are color, texture and shape. Generally, any of the three, individually or in combination, could be used. There is a wealth of clustering techniques available: hierarchical clustering algorithms, partition-based algorithms, mixture-resolving and mode-seeking algorithms, nearest neighbor clustering, fuzzy clustering and evolutionary clustering approaches. Once the images have been clustered, a domain expert is needed to examine the images of each cluster to label the abstract concepts denoted by the cluster. The partition- based clustering algorithm and manual labeling technique is used to identify material classes of a human head obtained at five different image channels (a five-dimensional feature vector) [9].

A. Color Clustering

The unsupervised segmentation is achieved by a two-level approach, i.e., color reduction and color clustering. In color reduction, image colors are projected into a small set of prototypes using self-organizing map (SOM) learning. In color clustering, simulated annealing (SA) seeks the optimal clusters from SOM prototypes. This two-level approach takes the advantages of SOM and SA, which can achieve the near-optimal segmentation with a low computational cost.

The color reduction transforms into based on SOM learning, where M is a set of 2-D vectors. Given the number of color clusters , color clustering attempts to organize the data set into a set of clusters , such that the vectors in a cluster are 'more similar' than the vectors belonging to other clusters. The SA mimics the principle of annealing in the physical domain. The optimal solution is obtained by consisting in randomly perturbing the system, and gradually decreasing the randomness to a low final level. It provides a good solution for the color clustering

The supervised segmentation involves color learning and pixel classification. In color learning, color prototype is defined to represent a spherical region in color space. A procedure of hierarchical prototype learning (HPL) is used to generate the different sizes of color prototypes from the sample of object colors. These color prototypes provide a good estimate for object colors. The image pixels are classified by the matching of color prototypes. In supervised segmentation, the pixel classifier is trained for the best partition of color space using the sample of object colors. The image is segmented by assigning the pixel to one of the predefined classes. The common techniques of supervised segmentation are discussed, including maximum likelihood, decision tree, nearest neighbor and neural networks [9].

The segmentation of image frames is hierarchized by three classifiers, i.e., k nearest neighbor, näive bayes, and support vector machine. Image segmentation is performed by a procedure of supervised pixel classification [10]. The rule of minimum distance decision is used to assign each pixel to a specific class in a color texture space.

VII. IMAGE INDEXING

Image mining systems require a fast and efficient mechanism for the retrieval of image data. Conventional database systems such as relational databases facilitate indexing on primary or secondary key(s). Currently, the retrieval of most image retrieval system is, by nature, similarity-based retrieval. In this case, indexing has to be carried out in the similarity space. One promising approach is to first perform dimension reduction and then use appropriate multi-dimensional indexing techniques that support Non-Euclidean similarity measures [11]. Indexing techniques used range from standard methods such as signature file access method and inverted file access method, to multi-dimensional methods such as K-D-B tree [12], R-tree [13], R*-tree [14] and R+-tree [16], to high-dimensional indexes such as SR-tree [15], TV-tree [17], X-tree [18] and MinMax [20].

Other proposed indexing schemes focus on specific image features. An efficient color indexing scheme for similarity-based retrieval which has a search time that increases logarithmically with the database size [20]. A multi-level R-tree index, called the nested R-trees method has been proposed for retrieving shapes efficiently and effectively [19]. With the proliferation of image retrieval mechanisms, a performance evaluation of color-spatial retrieval techniques which serves as guidelines to select a suitable technique and design a new technique is discussed [21].

VIII. SIMILARITY COMPARISON

The retrieval process starts with feature extraction for a query image. The features for target images (images in the database) are usually precomputed and stored as feature files with the above said techniques applied over the images. Using these features together with an image, similarity measure, the resemblance between the query image and target images are evaluated and sorted. Similarity measure quantifies the resemblance in contents between a pair of images. Depending on the type of features, the formulation of the similarity measure varies greatly. The Mahalanobis distance and intersection distance are commonly used to compute the difference between two histograms with the same number of bins. When the number of bins is different, the Earthmover's distance (EMD) is applied. Euclidean distance is used for similarity comparison.

R= (C1-Ci) 2+(D1-Di) 2+(H1-Hi) 2+(E1-Ei) 2+(µ1-µi) 2 [22]

where, R= the resultant distance.

IX. PROPOSED SYSTEM

The main objective of the proposed system is to provide a tool for efficient image retrieval from a huge content of image database using features based on Color and retrieve the images to identify the most similar images to the query image. During retrieval, the proposed system allows users to specify a region of interest from the query image. For query by specified region, the user selects a region of interest from the query image as the query region. The system calculates the low-level features of the query region. Then, a subset of N images is retrieved from the database. This set consists of those images which contain region(s) of same concept as that of the query region. Based on their low-level features, these N images are ranked according to their Earth Mover's Distance (EMD) [23] to the query image. All together, these N images consist of N_0 regions. In calculating EMD distance, color feature of the region feature is normalized to the range [0,1], in order to prevent a dimension with large value from dominating the others. The selected images can be ranked based on the ratio of the size of the selected region(s) in an image to the size of the image.

A. Binary Tree Structure

Binary partition tree is a structure used to represent the regions of an image. A binary tree is used as a base for each region of each image in the database. In the binary partitioning tree leaves represents regions belonging to the initial partition. The root node corresponds to the entire image. To construct a binary tree, the algorithm starts from an arbitrary region which considered as the first node and then selecting a neighbor region as its sibling, these nodes are added as children of their parent. This process is repeated until all regions have been added to the binary partitioning tree.

TABLE I: COMPARISON OF EXISTING CBIR METHODS VERSUS THE PROPOSED METHOD

Method	No. of Categories of Images	No. of Images per Category	Approx Precision	Performance Evaluation
SIMPLIcity	10	100	0.8227	Better than CH2
WBIIS (Wavelet-Based Image Indexing and Searching)	9	100	0.6	Better than SIMPLIcity
Color Histogram 1	13.1 filled color bins	100	-	Good
Color Histogram 2	42.6 filled color bins	100	-	Better than CH1
IRM (Integrated Region Matching)	3	20	0.61	Good
MiCRoM (Minimum Cost Region Matching)	3	20	0.76	Better than IRM
OCRM (Optimal Cost Region Matching)	3	20	0.76	Better than MiCRoM
Proposed Method	10	500	around 0.9	Better than the existing methods

To have more precise measure, each image in the database is divided into equal fixed-sized squared blocks. A distinct tree should be created for each block. For each node of the constructed binary partitioning tree, calculate the mean color and area of its corresponding region. These values i.e. mean color and mean area for all nodes are concatenated to construct a feature vector representing one block. The process of concatenating feature vectors of a block is repeated for all blocks to construct a feature vector for entire image. With the support of the feature vector of the blocks in the binary tree hierarchy a similarity comparison has been made with the query image such that it makes the identification process with the image database repository.

X. CONCLUSION

A new technique is named Color Image Segmented Clustering for improving the efficiency in retrieving images by fully exploiting the similarity information among the images that copes with the recent issues in the research. The system tries to get better in the retrieval process of an image with efficiency and also tries to reduce human intervention. The adaptability can be enhanced by reducing the number of iterations by using the navigation patterns. It can be incorporated with the powerful Relevance Feedback technique to improve the performance over a period of time.

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