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Content Based Image Retrieval Using Dominant Color and Texture Features

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ABSTRACT

The purpose of this Paper is to describe our research on different feature extraction and matching techniques in designing a Content Based Image Retrieval (CBIR) system. Due to the enormous increase in image database sizes, as well as its vast deployment in various applications, the need for CBIR development arose. Content Based Image Retrieval (CBIR) is the retrieval of images based on features such as color and texture. Image retrieval using color feature cannot provide good solution for accuracy and efficiency. The most important features are Color and texture. In this paper technique used for retrieving the images based on their content namely dominant color, texture and combination of both color and texture. The technique verifies the superiority of image retrieval using multi feature than the single feature.

KEYWORDS : *Content Based Image retrieval (CBIR), Co-occurrence matrix, Euclidian distance.*

I. INTRODUCTION

Due to the proliferation of video and image data in digital form, Content Based Image Retrieval (CBIR) has become a prominent research topic. This motivates the extensive research into image retrieval systems. In the earlier image retrieval systems are rather text-based search since the images are required to be indexed. However, with the substantial increase of the size of images as well as the size of image database, the task of user-based annotation becomes very cumbersome, and, at some extent, subjective and thereby, incomplete as the text often fails to convey the rich structure of the images.

This motivates the research into what is referred to as CBIR. Therefore an important problem that needs to be addressed is fast retrieval of images from large databases. To find images that are perceptually similar to a query image, image retrieval systems attempt to search through a database. CBIR can greatly enhance the accuracy of the information being returned and is an important alternative and complement to traditional text-based image searching. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results. Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

For describing image content, color and texture features have been used. Color is one of the most widely used low level visual features and is invariant to image size and orientation.. For representing color in terms of intensity values, a color space is defined as a model. A color component or a color channel is one of the dimensions.

The RGB model uses three primary colors, red, green and blue, in an additive fashion to be able to reproduce other colors. As this is the basis of most computer displays today, this model has the advantage of being easy to extract. In a true-color image each pixel will have a red, green and blue value ranging from 0 to 255.

Without any other information, many objects in an image can be distinguished solely by their textures. Texture may describe the structural arrangement of a region and the relationship of the surrounding regions and may also consist of some

basic primitives. Texture is a very general notion that can be attributed to almost everything in nature. For a human, the texture relates mostly to a specific, spatially repetitive (micro) structure of surfaces formed by repeating a particular element or several elements in different relative spatial positions. Generally, the repetition involves local variations of scale, orientation, or other geometric and optical features of the elements.

Texture is a key component of human visual perception. Like color, when querying image databases, this makes it an essential feature to consider. Everyone can recognize texture, but it is more difficult to define. Unlike color, texture occurs over a region rather than at a point. It is normally perceived by intensity levels and as such is orthogonal to color. Texture can be described in terms of direction, coarseness, contrast and so on. It has qualities such as periodicity and scale.

Image textures are defined as images of natural textured surfaces and artificially created visual patterns, which approach, within certain limits, these natural objects. Image sensors yield additional geometric and optical transformations of the perceived surfaces, and these transformations should not affect a particular class of textures the surface belongs. It is almost impossible to describe textures in words, although each human definition involves various informal qualitative structural features, such as fineness, coarseness, smoothness, granularity, lineation, directionality, roughness, regularity, randomness, and so on.

These features, which define a spatial arrangement of texture constituents, help to single out the desired texture types, e.g. fine or coarse, close or loose, plain or twilled or ribbed textile fabrics. It is difficult to use human classifications as a basis for formal definitions of image textures, because there is no obvious ways of associating these features, easily perceived by human vision, with computational models that have the goal to describe the textures.

Nonetheless, after several decades of research and development of texture analysis and synthesis, a variety of computational characteristics and properties for indexing and retrieving textures have been found. In many cases, the textural features follow from a particular random field model of textured images.

II. Literature Review

In [1], an efficient image retrieval technique which uses dominant color and texture features of an image is proposed. The proposed method yielded higher average precision and average recall with reduced feature vector dimension.

A new and effective color image retrieval scheme for combining all the three i.e. color, texture and shape information, which achieved higher retrieval efficiency is presented in [2]. By using fast color quantization algorithm with clusters merging, the image is predetermined, and then a small number of dominant colors and their percentages can be obtained. Then using a steerable filter decomposition which offers an efficient and flexible approximation of early processing in the human visual system, the spatial texture features are extracted. After that the pseudo-Zernike moments of an image are used for shape descriptor, which have better features representation capabilities and are more robust to noise than other moment representations. Finally, the combination of the color, texture and shape features provide a robust feature set for image retrieval.

Trademark image retrieval (TIR) system is proposed in [3] to deal with the vast number of trademark images in the trademark registration system. The proposed approach commences with the extraction of edges using the canny edge detector, performs a shape normalization procedure, and then extracts the global and local features. The local features describe the interior details of the trademarks, while the global features capture the gross essence of the shapes. To measure the similarity between the query and database images, a two-component feature matching strategy is used.

In [4], a further exploration and study of visual feature extraction is done. According to the HSV (Hue, Saturation, and Value) color space, the work of color feature extraction is finished, the process is as follows:

In non-equal intervals, the color space is quantified, one dimension feature vector is constructed and by cumulative histogram color feature is represented. Similarly, by using gray-level co-occurrence matrix (GLCM) or color co-occurrence matrix (CCM), the work of texture feature extraction is obtained.

An image retrieval system is presented in [5], which used HSV color space and wavelet transform approach for feature extraction. Firstly, the color space is quantified in non-equal intervals, then one dimension feature vector is constructed and the color feature is represented. Similarly, by using wavelet, the work of texture feature extraction is obtained. Finally, based on wavelet transform, color feature and texture feature are combined. A

method of multi features retrieval is provided. The image retrieval experiments indicated that visual features were sensitive for different type images. With simple variety, the color features opted to the rich color image. Texture feature opted to the complex images.

A comprehensive survey, highlighting current progress, emerging directions, the spawning of new fields, and methods for evaluation relevant to the field of image retrieval is presented in [6]. It consider that the field will experience a paradigm shift in the foreseeable future, with the focus being more on application-oriented, domain specific work, generating considerable impact in day-today life.

Dominant color descriptor (DCD) is one of the color descriptors proposed by MPEG-7 in [7] that has been extensively used for image retrieval. Among the color descriptors, the salient color distributions in an image or a region of interest are described by DCD. DCD provides an intuitive, effective and compact representation of colors presented in an image. The efficiency of computation for dominant color extraction is significantly improved by this approach.

A content-based image retrieval method based on an efficient combination of multi resolution color and texture features is proposed in [8]. Color auto correlograms of the hue and saturation component images in HSV color space are used as its color features. BDIP (Block Difference of Inverse Probabilities) and BVLC (Block Variation of Local Correlation coefficients) moments of the value component image are adopted as its texture features. In multiresolution wavelet domain, the color and texture features are extracted and combined. At a point where the retrieval accuracy becomes saturated, the dimension of the combined feature vector is determined. Experimental results show that the proposed method yields higher retrieval accuracy than some conventional methods even though its feature vector dimension is not higher than those of the latter for six test DBs. Especially, for queries and target images of various resolutions, it demonstrates more excellent retrieval accuracy.

In [9], a detailed evaluation of the use of texture features in a query-by-example approach to image retrieval is presented. Three radically different texture feature types motivated by statistical, psychological and signal processing points of view are used. The features were evaluated and tuned on retrieval tasks from the Corel collection and then evaluated and tested on the TRECVID 2003 and Image CLEF 2004 collections. For the latter two the effects of combining texture features with a color feature were studied. Texture features that perform particularly well are identified, demonstrating that they provide robust performance across a range of datasets. Image retrieval mechanism is explored in [10], based on combination of color and texture features. Using the discrete wavelet frame analysis, which is an over complete decomposition in scale and orientation, texture features are extracted.

In [11], a survey of how the user can formulate a query, whether and how relevance feedback is possible, what kind of features are used, how features from query image and data base image are matched, how the retrieval results are presented to the user, and what indexing data structures are used is described.

The aim of [12] is to clarify some of the issues raised by this new technology, by reviewing its current capabilities and limitations, and its potential usefulness to users in higher education and elsewhere. It is based both on a review of the research and professional literature, and on discussions with users and managers of large collections of image data, multimedia authors, researchers, software developers, and representatives of standards bodies.

III. Proposed Methodology

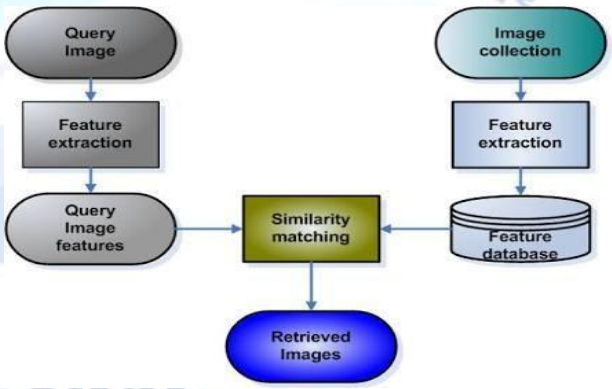


Fig 1. CBIR flow chart

A. *Feature Extraction*

Feature extraction is one of the most important step in developing a classification system. This step describes the various features selected by us for classification of the selected image.

There are many features extracted for the query image for that we consider features as follows:

i. Histogram of individual image
ii.GLCM (Gray level co-occurrence matrix)
iii. Color Dominant

i. Histogram of image

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance. A normalized histogram gives the relative proportions of each pixel in the image and hence approximates to the probability distribution of pixel intensities. A normalized histogram is one in which the sum of the frequencies is exactly 1. The histogram's *x*-axis reflects the range of values in Y. The histogram's *y*-axis shows the number of elements that fall within the groups; therefore, the *y*-axis ranges from 0 to the greatest number of elements deposited in any bin.

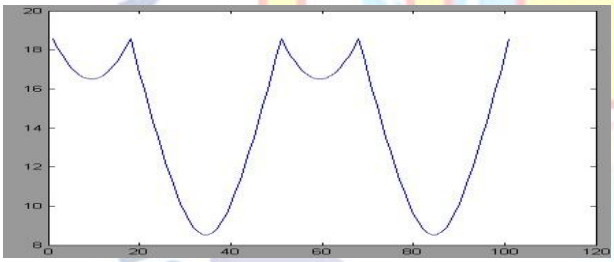


Fig 2. Histogram Plot

ii.GLCM (Gray level co-occurrence matrix)

A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures.Based on the GLCM four statistical parameters energy, contrast, correlation and homogeneity are computed.

iii. Color Dominant

Dominant color region in an image can be represented as a connected fragment of homogeneous color pixels which is perceived by human vision. Image Indexing can be based on this concept of dominant color regions present in the image. The segmented out dominant regions along with their features can be used as an aid in the retrieval of similar images from the image database.

B. Similarity Matching

The similarity matching stage is the main decision making stage of CBIR system and uses the features extracted in the previous stage to identify the image. It uses two algorithms Euclidean Distance Algorithm, K-Means Clustering Algorithm

C. Euclidean Distance Algorithm

It is necessary to have a certain measure to tell the quality of the system and to compare several images or words and establish which is the most similar image or word given a query. As it will be shown, distance methods play an important role in classification since some may be more suitable for certain features than others.

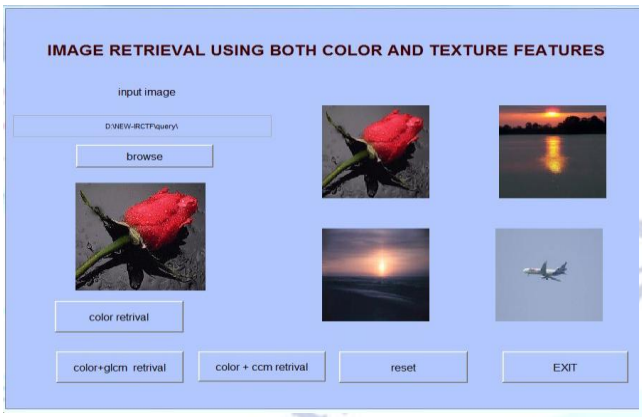
D. K-Means Clustering Algorithm

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters fixed a priori. The main idea is to define k centroids for k clusters, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done.

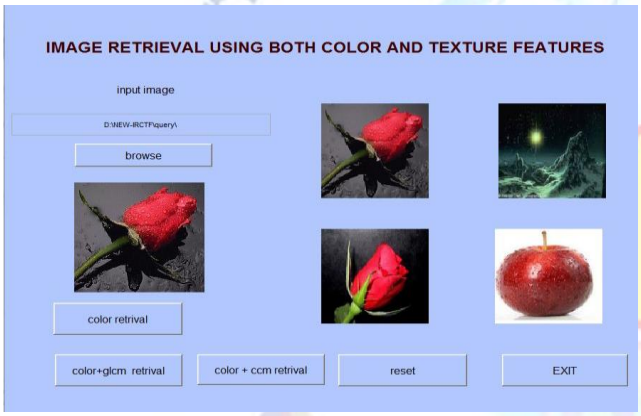
III. Proposed Methodology

The results provided by search engines will already be quite good, especially since the queries chosen are most popular product queries for which large number of relevant web pages and images exists. The results for query is observed and shown in Fig.3 for the query image “Bat” using Euclidean distancemethod and in Fig.4 the

result for the same query image is shown using k means clustering method. In both results time required by each method is noted and that time is recorded.



The fig 3 is the result of Euclidean distance method by colour retrieval method.



The fig 4 is the result of the COLOR+GLCM method of color retrieval.

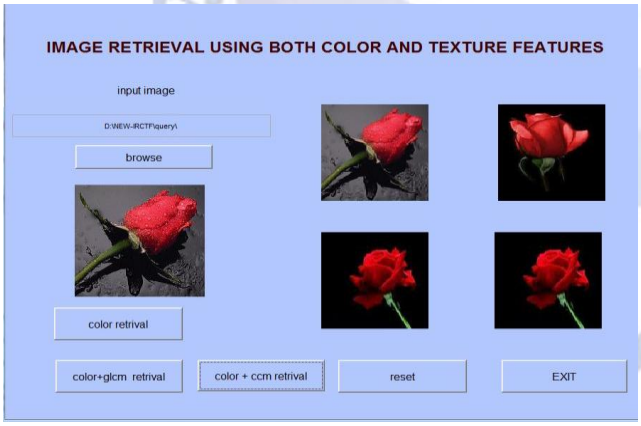


Fig 5 Image retrieval results for query image "rose" using COLOR+CCM method.

IV. CONCLUSION AND FUTURE SCOPE

In this paper, we have focused on recently developed image mining techniques. The purpose of image mining techniques is discovering meaningful correlations and formulations from previously collected image data. Many different application areas utilize image mining as a means to achieve effective usage of semantic information about images. Image mining is becoming progressively more widespread in both the private and public sectors. Sector such as biomedical, space research organization, remote sensing, fashion, crime prevention, publishing, medicine, architecture, commonly use image mining to reduce costs, enhance research, and increase sales. As image mining is still not fully focused, there is a huge scope for its development. Future research should highlight on development of powerful query language, devise automated image mining techniques based on image retrieval techniques based on its content. The CBIR provide simple mechanism for image retrieval by measuring minimum distances among the images. The similarity measurement of images is based on the common visual feature between the images. Image clustering and finding the minimum distance among the images provides better image retrieval results.

Future Scope

In our Content Based Image Retrieval system, we have extracted dominant color and texture features. Suggestions for future enhancement of our system will be as follows

- We can provide compact storage for large image databases.
- In addition, we can incorporate user-feedback into the system.
- We can explore methods for combining color and texture features. This will help in increasing efficiency of retrieval system.

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