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Content based Image Retrieval Using Clustering Method

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Abstract

Content-based image retrieval (CBIR) is the deployment of computer vision methods to the information retrieval challenge, that is, the subject of seeking out digital images in vast databases. Techniques based on automated feature extraction methods for obtaining similar images from image databases are under the purview of CBIR. Traditional content based image retrieval (CBIR) systems extract a single feature at a time and use it to categorize and group images in response to a query. To bridge the gap between high-level concepts and low-level features, our innovative method integrates many feature extraction algorithms. In color-based retrieval, we use quadratic distance formulas to calculate the HSV affinity matrix for photos in the query and the database. Wavelet decomposition at six stages is used in texture-based retrieval. Finding the similarity measures between the query image and the images in the database is done with the help of the Euclidean distance classifier. The integrated method used to decrease the file sizes of the retrieved photographs keeps the user from having to pay as much attention to the process.

Keywords: Content based Image Retrieval, Wavelet Decomposition, Texture Features, Nearest-Neighbors Method.

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Introduction

As technology improves, more and more picture databases are being built by a wide variety of tools for use in areas as diverse as law, medical, publishing, advertising, architecture, engineering, and fashion. It is necessary to use image processing techniques to deal with these photos. Image retrieval [1-3] is the process of obtaining an image from a specified database. As a result, a plethora of methods have arisen to provide the need. There are three main types of image retrieval methods, and they are: text-based image retrieval (TBIR), content-based image retrieval (CBIR), and semantic-based image retrieval (SBIR) The advancement of humanity in a variety of different topic areas is dependent on the accumulation of information in the form of images. The retrieval of digital images presents a number of difficult research questions. There have been a lot of ideas for Content-Based Image Retrieval (CBIR) system prototypes, but very few of them have been implemented into commercial systems. The comparison of the query to the image is what drives the search in content-based image retrieval systems, which work with the entire image. Color, texture, and shape are three primary methods that are utilized in picture retrieval. The procedures outlined here are utilized in order to retrieve an image from the image database. They do not care about the different resolutions of the photos, their size, or the spatial color distribution. Because of this, none of these techniques are suitable for the retrieval of artistic images. As a result, we put forward an innovative concept for a color and texture-based picture retrieval system that makes use of clustering.

A. Previous Work

The query image and the images in the database, which are referred to as target images, are seen by a typical CBIR system as collections of features. This type of system then ranks the relevance between the query image and any target image in proportion to a similarity measure that is calculated from the features. To put it another way, these characteristics, also known as the signatures of images, are what define the content of images. The scope of representation can be broken down into essentially two different categories for features, which are global features and local features. A probability-based similarity measure was presented by Barnard et al. [4-5], which integrates the information that is provided by text with the visual information that is provided by image characteristics.

These aspects of an image's content are referred to as the similarity- induced semantics, and they can be captured by the aforementioned similarity measures in one way or another. Nevertheless, the significance of an image is often never immediately clear. In most cases, the similarity-induced semantics do not agree with the high-level concept that is being communicated by the image (semantics of the image). The difference between the comparatively limited descriptive ability of low-level visual features and high-level concepts is referred to as the semantic gap [6-9], and it indicates the discrepancy between the two levels of information. There have been a lot of different ideas put out for how to close the semantic gap. According to the level of involvement of the user in the retrieval process, they can be divided into two categories: relevance feedback and picture database preprocessing utilizing statistical categorization.

Even while these categorization algorithms are effective in their respective application areas, the simplistic ontologies that were built atop them are unable to include the rich semantics of a large image collection.

B. Proposed Approach

In the method that we have proposed, color and texture features are first extracted, and then the results of those analyses are integrated. Because of this, the sizes of the clusters are drastically cut down, and the semantic gap also shrinks. In the new updated methodology, the clustering is performed with a modified K means algorithm. This ensures that photos that are extremely similar are grouped together, in contrast to the traditional CLUE method.

The remaining parts of the paper are structured as described below. In Section II, the Color and Texture Based integrated Approach's general methodology is outlined and discussed. In Section III, an overview of the algorithm and a discussion of the computational challenges are presented. The findings of the simulation, as well as the analysis, are covered in Section IV. Our conclusion can be found in Section V, along with a description of the work that remains to be done.

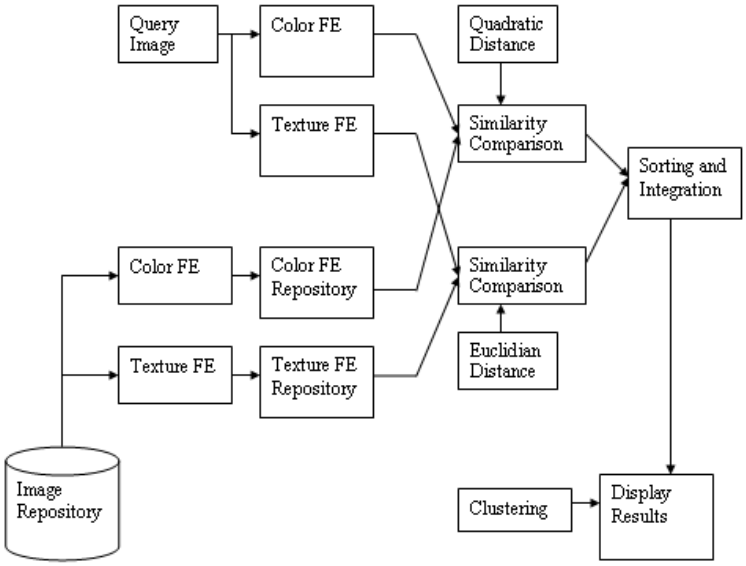

Fig. 1: Proposed System Block Diagram

Color and Texture based Integrated Approach

In this section, we create a new retrieval technique for color and texture information [9] and combine them to reduce cluster size and semantic gap.

A. System Overview

Figure 1 depicts the global block diagram. Our CBIR system is composed of three modules: the feature extraction (FE) module, the respiration module, the feature comparison module, the Integration module, and the clustering section.

B. Database Images Preprocessing and Feature Extraction

The color and texture properties of each image stored in the database are extracted and saved in the feature respiratory that correlate to those attributes. After that, those are examined in light of the features of the image that have been required. After that, the findings from the comparisons of each feature are combined and ranked in order to reduce the overall size of the cluster.

Algorithmic View

This part begins with the extraction of picture features based on texture and color, and then proceeds to explain the integration and clustering of those features in the sections that follow.

A. Texture Feature Based CBIR

2D Texture Characteristics Utilizing Wavelets: The wavelet transform[10] allows for the depiction of a picture at multiple scales, each one corresponding to a distinct level of detail within the original image. The aim behind wavelets is to take advantage of the characteristics of the wavelet coefficients at the coarser scales. The 2Dfiltering process separates a picture into its constituent signals, three of which are detail signals that are sensitive to direction: the LH signal highlights horizontal features, the HL signal highlights vertical ones, and the HH signal highlights diagonal ones. High-band energy (where texture is) can be expressed as the square root of the second-order moment of the wavelet coefficients. These moments are obtained by subjecting each patch to a Daubechies wavelet transform on a single level.

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \quad (1)$$

B. Color Feature Based Retrieval

The construction of the color histogram for an image involves counting the number of pixels that are of each color. It has been looked into in [tools, totally, and automated] how color histograms can be used to retrieve information from image databases. The retrieval method based on histograms is fraught with a number of challenges. The high dimensionality of the color histograms is the first of these factors to consider. Even with a severe quantization of the color space, the feature spaces of the picture histogram can occupy more than 100 dimensions in the real valued space. Due to the large dimensionality of the problem, it is necessary to employ techniques such as feature reduction, pre-filtering, and hierarchical indexing. The computation of the distance function likewise becomes more difficult as the number of dimensions in the problem rises. It makes the 'cross' distance functions, which include the perceptual distance across histogram bins, extremely difficult to understand.

Histogram Quadratic Distance

Let's say that h and g stand for two different color histograms. The formula for computing the Euclidean distance between two color histograms, h and g, is as follows:

$$d^2(h,g) = \sum_A \sum_B \sum_C (h(a,b,c) - g(a,b,c))^2 \quad (2)$$

In this formula for determining distance, the only comparison that is made is between the identical bins in the two different histograms. In spite of the fact that two distinct bins may represent visually comparable colors, cross-wise comparisons are not performed. Every single bin adds exactly the same amount to the total distance.

Histogram Intersection Distance

In [11], a method for the retrieval of color images using the color histogram intersection was suggested. The following equation describes the point where histograms h and g intersect:

$$d(h,g) = \frac{\sum_A \sum_B \sum_C \min(h(a,b,c), g(a,b,c))}{\min(|h|,|g|)} \quad (3)$$

Where "h" and "g" represent the magnitude of each histogram, which corresponds to the total number of samples. There is no consideration given to the intersection distance for colors that are absent from the user's query image. The contribution of the backdrop colors is less as a result. A histogram with the fewest possible samples is used to standardize the sum. The QBIC system, which was first described in [1, 6], made use of the color histogram quadratic distance. The formula for the cross distance is as follows:

$$d(h,g) = (h-g)^t A (h-g) \quad (4)$$

The formula for cross distance takes into account the cross-correlation between histogram bins by basing it on the perceptual similarity of the colors that are represented by the bins. A matrix denoted by the letter A is referred to as a similarity matrix, and it serves as a representation for the entire collection of cross-correlation values. And the answer to the question of how to find the $(i,j)^{th}$ member of the similarity matrix A is as follows: for the RGB space.

$$a_{ij} = 1 - d_{ij} / \max(d_{ij}) \quad (5)$$

Where d_{ij} is the L_2 distance in the RGB space between the colors I and j. The cross term contributes to the perceived distance between color bins when the quantization of the color space is not perceptually uniform. It can be expressed as an equation for the HSV space as follows:

$$a_{ij} = 1 - \frac{1}{\sqrt{5}} [(v_i - v_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2]^{\frac{1}{2}} \quad (6)$$

Where the value refers to the proximity in the HSV color space.

C. Integrated Approach

In our proposed new method, we combine the results from the color feature and the results from the texture feature. In this way, the images with high probabilities are sorted and shown as the results of the integrated approach.

The results of combining the features are then put into groups using the Nearest Neighbor Method (NNM), which is described in [12].

By using our integrated approach, the gap between low-level features and high-level ideas is greatly reduced.

D. Clustering

We use the CLUE clustering algorithm to put together groups of images.

Closest Image Clusters

The CBIR output images are put into groups by our proposed system. The images in each cluster are more alike than those in other clusters.

Nearest-Neighbors Method (NNM)

To begin, it selects NN to serve as seeds. The next thing that you need to do is locate the NN for each seed. In the end, the nearby target images are selected to be all of the unique target photos among the seeds and their NN, that is, unique target images within the target images. Therefore, there is a cap on the number of target photos that are located in close proximity to one another. If the distance is measured in meters, then both approaches, if they are performed with the appropriate settings, will produce the same results. However, when dealing with non-metric distances, and particularly when the triangle inequality condition is satisfied, the collection of target images selected by two distinct approaches may be significantly different from one another regardless of the parameters that are utilized. This is due to the fact that an inequality involving triangles has been violated: Even though both photographs are very close to the query image, there is still a possibility that the gap between them is quite great. When compared to the FRM, our empirical findings reveal that the NNM has a tendency to develop a more structured group of target images when the distance is not a metric one. This occurs when the proper decisions are made regarding and. Because the experimental retrieval system we are using does not use metric measurements to determine how similar two photos are to one another, we are using NNM in this work.

Simulation Results and Analysis

The system is built on a platform with Pentium processor CPU. Matlab software is used to run the system. Two general-purpose image databases are used to test the system. The first database (DB1) has 500 pictures of animals, people, roses, landscapes, leaves, trees, and cars. These pictures come from the COREL photo gallery and other places on the web. The second database (DB2) has a thousand pictures of things like animals, flowers, and waterfalls. In the image databases, there are no rules about what kinds of cameras or lighting conditions can be used. A search in the first database takes about 76 seconds on average, while a search in the second database takes about 2 minutes on average. To figure out how well our system works at retrieving information, we pick 8 different queries with different meanings at random. We do an experiment with different ways to measure distance. To compare, you can use the inverse cosine distance, the Euclidean distance, and the different rankings CR, TR, and SR. This means that there are 48 different retrieval results for each of the eight queries. For each result of a query retrieval, we look at the precision of the retrieval based on how well the image fits the meaning of the query. Precision is the number of images that are relevant to the query out of all the images that were found. In this case, the recall values are not calculated because they are the same as the precision values. The results for the first I1 images that were retrieved are shown.

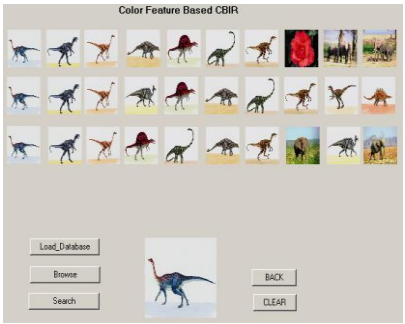

Fig 2.a: Color Feature based CBIR

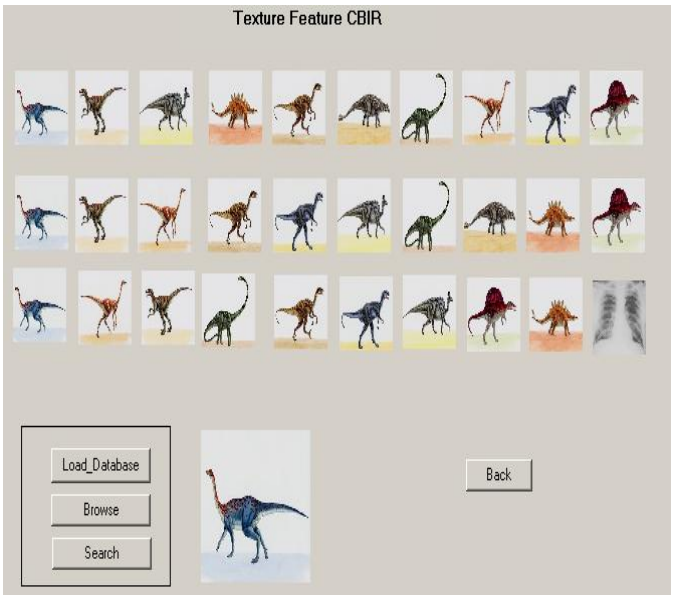

Fig. 2b: Texture Feature based CBIR

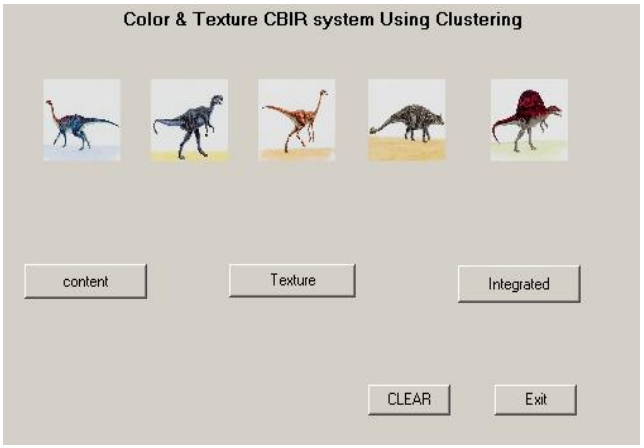

Fig. 2c: Integrated CBIR Using Clustering

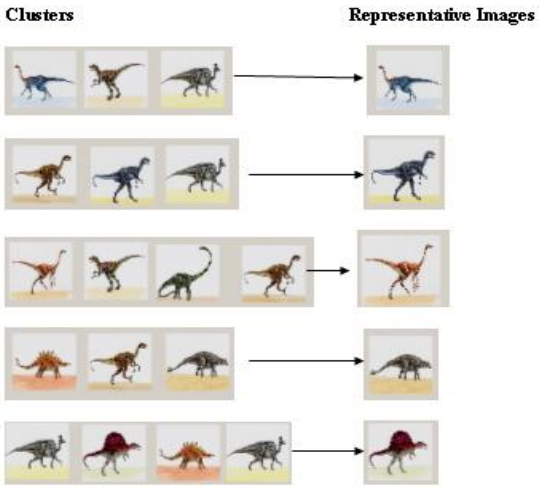

Fig. 2d: Cluster and Representative Images

From the simulation results our proposed integrated approach shows that the clustering of similar images are high and the size of clusters are reduced compared with the conventional clustering retrieval methods.

Conclusion and Future Work

We presented a novel framework for a content-based image retrieval system that provides cluster-based searching. This searching method introduces a number of different ways for users to locate their target by making use of feature weights and reducing the size of clusters while maintaining good similarity features. Additionally, less attention is needed to maintain the system. In our next updates, we will broaden the feature selections available to the user and provide additional distance measurement options in an effort to produce better results.

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