

Image Robber Using Wavelet Transformation and Hue Histogram

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ABSTRACT: An image retrieval system is used for browsing, searching and retrieving images from a large database of digital image. Image retrieval is the basic principle task in the present scenario. Content Based Image Retrieval is the popular image retrieval system by which the target image to be retrieved based on the useful features of the given image. CBIR (Content Based Image Retrieval) scheme searches the most similar images of a query image using Color Histogram. It compare the feature vector of all the images in the database with that the query image using some preselected similarity measures, and then sorting of the results. In this paper, we present CBIR system based on color, shapes and texture using DWT (Discrete Wavelet Transformation) Technique for image retrieval. DWT represent the some of wavelet functions. In this paper DWT consist dubacheise transformation method. It improves the accuracy of image and fast retrieval into image retrieval techniques. Experimental result show confirms that the proposed method is most effective.

KEYWORDS: CBIR, DWT Techniques, Dubacheise transformation, RGB Color, HSV Color.

I. INTRODUCTION

Research on content-based image retrieval has gained maximum momentum during the last decade. CBIR is the process of retrieving images from a database digital images according to the visual content of the images. It means that it is the retrieval of images that have similar content of colors, textures or shapes. Images have always been an inevitable part of human communication and its roots millennia ago. Images make the communication process more interesting, illustrative, elaborate, understandable and transparent.

A lot of research work has been carried out on Image Retrieval by many researchers, expanding in both depth and breadth [1]-[5]. In CBIR system, it is usual to group the image features in three main classes: color, texture and shape [6]-[7]. Ideally, these features should be integrated to provide better discrimination in the comparison process. Color is the most common visual feature used in CBIR, primarily because of the simplicity of extracting color information from images [8-9]. To extract information about shape and texture [10] feature are much more complex and costly tasks, usually performed after the initial filtering provided by color features. The most basic step in designing a CBIR system is to select the most effective image features to represent image contents [11]. Global features related to color or texture are commonly used to describe the image content in image retrieval. The main drawback using global features is this method cannot capture all parts of the image having different characteristics [12]. Since simply color, texture and shape features cannot sufficiently represent image semantics, semantic-based image retrieval is still an open problem. CBIR is one of the fabulous and effective image retrieval method and is widely studied in both academic and industrial arena. In this paper we propose an image retrieval system, called Discrete Wavelet Transformation (DWT). This reduces the processing time for retrieval of an image with more promising representatives. The extraction of color features from digital images depends on an understanding of the theory of color and the representation of color in digital images. Color spaces are an important component for relating color to its representation in digital form. The transformations between different color spaces and the quantization of color information are primary determinants of a given feature extraction method. Color representations-color histogram, color correlogram, color coherence vector and color moment, under certain a color space [13-16].

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(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

The rest of the paper is organized as follows: In section 2, a brief review of the related work is presented. The section 3 describes the color feature extraction. The section 4, presents the texture feature extraction and the section 5, presents the similarity matching. The proposed method is given in section 6 and section 7 describes the performance evaluation of the proposed method. Finally the experimental work and the conclusions are presented in section 8 and section 9 respectively.

II. RELATED WORK

CBIR has become an active and fast-advancing research area in image retrieval in the last decade. The difference between the user's information need and the image representation is called the semantic gap in CBIR systems. The limited retrieval accuracy of image centric retrieval systems is essentially due to the inherent semantic gap between users.

A.W.M. Smeulders, M. Worring, and R. Jain [1] describe "Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself.

Gulfishan Firdose Ahmed, Raju Barskar [2] in this paper, the basic components of content-based image retrieval system is introduced. The semantic-based image retrieval is a better way to solve the "semantic gap" problem, so the semantic-based image retrieval method is stressed in this paper. Other related techniques such as relevance feedback and performance evaluation also discussed. In many areas of commerce, government, academia, and hospitals, large collections of digital images are being created. Many of these collections are the product of digitizing existing collections of analogue photographs, diagrams, drawings, paintings, and prints. Usually, they are searched by using keyword indexing, or simply by browsing. Digital images databases however, open the way to content-based searching. In this paper the survey is done on some technical aspects of current content-based image retrieval systems.

X. Zhou and T. Huang [3] in this paper analyze the nature of the relevance feedback problem in a continuous representation space in the context of multimedia information retrieval. Emphasis is put on exploring the uniqueness of the problem and comparing the assumptions, implementations, and merits of various solutions in the literature. An attempt is made to compile a list of critical issues to consider when designing a relevance feedback algorithm. With a comprehensive review as the main portion, this paper also offers some novel solutions and perspectives. Relevance feedback is a feature of some information retrieval systems. The idea behind relevance feedback is to take the results that are initially returned from a given query and to use information about whether or not those results are relevant to perform a new query.

Chun et al. [12] proposed a CBIR method based on an efficient combination of multi resolution color and texture features based CBIR. Their colors, auto correlograms features of the hue and saturation component images in HSV color space are used. As its texture features, block difference of inverse probabilities and block variation of local correlation coefficient moments of the value component image are adopted. The color and texture features are extracted in multi resolution wavelet domain and then combined.

S. Tong and E. Chang [13] this paper describes that Support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

D. Tao, X. Tang, and X. Li [14] in this paper, authors make theoretical and practical comparisons between principal and complement components of image features in CBIR RF. Most of the previous RF approaches treat the positive and

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negative feedbacks equivalently although this assumption is not appropriate since the two groups of training feedbacks have very different properties. It means that all positive feedbacks share a homogeneous concept while negative feedbacks do not. Authors explore solutions to this important problem by proposing an orthogonal complement component analysis. Experimental results are reported on a real-world image collection to demonstrate that the proposed complement components method consistently outperforms the conventional principal components method in both linear and kernel spaces when users want to retrieve images with a homogeneous concept.

III. COLOR AND TEXTURE FEATURES

A. COLOR SPACES

Color spaces are important component in representing images in digital form. Color representations: color histogram, color coherence vector which are together called as color space. The color histogram feature is the most important in image retrieval. Here color histogram is a vector which is collection of element where each element stands for the no of pixels in a bin of image.

(i) Color feature extraction

A color image can be represented using three primaries of a color space. Since the RGB color space does not correspond to the human way of perceiving the colors, so the HSV color space in this approach is used. HSV is an intuitive color space in the sense that each component contributes directly to visual perception, and it is common for image retrieval systems. Hue is used to distinguish colors or represents a pure color, where as saturation gives a measure of the percentage or amount of white light added to a pure color. Value refers to the perceived light intensity or measures brightness. Advantages of HSV color space are: good compatibility with human intuition and there is a separability of chromatic and achromatic components. The color distribution of pixels in an image contains sufficient information. There are Global color properties and Local color properties for an image. The following two features to represent the global properties of an image can be used. The mean of pixel colors states the principal color of the image, and the standard deviation of pixel colors represents the variation of pixel colors in an image. The variation degree of pixel colors in an image is called the color complexity of the image. Global Color Properties:

The mean (μ) and the standard deviation (σ) of a color image are defined as follows:

$$\mu = \frac{1}{N} \sum_{i=1}^N p_i \dots \dots \dots (1)$$

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (P_i - \mu)^2} \dots \dots (2)$$

Where $\mu = [\mu H, \mu S, \mu V]^T$ and $\sigma = [\sigma H, \sigma S, \sigma V]^T$, each component of μ and σ indicates the HSV information, and P_i indicates the i th pixel of an image. Local Color Properties: The local color properties in an image play also an important role to improve the retrieval performance. Hence, a feature called binary bitmap can be used to capture the local color information of an image.

B. TEXTURE

This feature is generally used in similarity matching of images. Texture means smoothness, coarseness and regularity. The texture features are analyzed using statistical approach. The content based image retrieval system is implemented with determining support. Here we are using K-means clustering technique of data mining to create index of images in database once index is created we implement retrieval and search process using index. Commonly in traditional image search and retrieval process every time when a query image is done against database then the query image is verified with every image in database. During this process feature extraction is performed for query images and database images in every search process. Also similarity matching is performed in every search process. As the search process is costly and time consuming every time. In case of proposed system, first K-means clustering creates index and images are organized in clusters in memory. Every cluster is collection of similar images based on content. Now every time search process is implemented the feature extraction and similarity matching are performed on clusters rather than individual images. This shows that the process is improved and is of less cost than the traditional one.

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(i)Texture properties

Texture is an important attribute that refers to innate surface properties of an object and their relationship to the surrounding environment. The gray level co-occurrence matrix (GLCM) is a simple and effective method for representing texture. GLCM creates a matrix with the directions and distances between pixels, and then extracts meaningful statistics from the matrix as texture features. The GLCM represents the probability $p(i, j, d, \theta)$ that two pixels in an image, which are located with distance d and angle θ , have gray levels i and j .

IV. PROPOSED METHOD

DISCRETE WAVELET TRANSFORMATION

(i)Dubacheise transformation method

The wavelet representation gives information about the variations in the image at different scales. Discrete Wavelet Transform (DWT) represents an image as a sum of wavelet functions with different locations (shift) and scales [5]. Wavelet is the multi-resolution analysis of an image and it is proved that having the signal of both space and frequency domain [6]. Any decomposition of an 2D image into wavelet involves a pair of waveforms: the high frequency components are corresponding to the detailed parts of an image while the low frequency components are corresponding to the smooth parts of an image. DWT for an image as a 3D signal can be derived from a 2D DWT, implement 2D DWT to every rows then implement 2D DWT to every column. Any decomposition of a 3D image into wavelet involves four sub-band elements representing LL (Approximation), HL (Vertical Detail), LH (Horizontal Detail), and HH (Detail), respectively. The wavelet transform may be seen as a filter bank and illustrated as follow, on a one dimensional signal $x[n]$. $x[n]$ is input signal

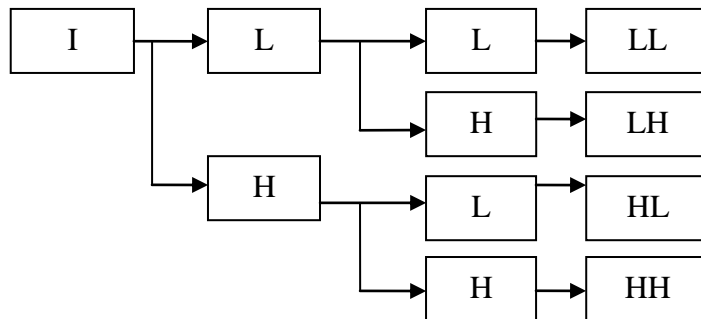


Figure 1. Level 1 of 3D DWT

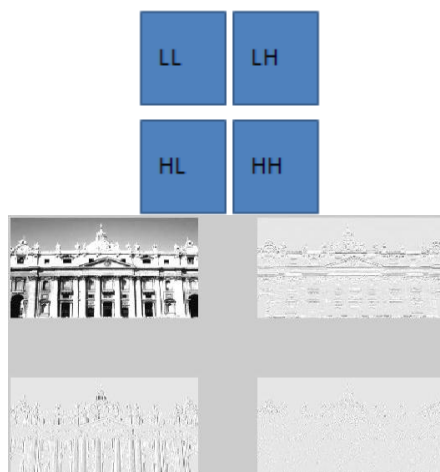


Figure 2.Example of DWT

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that contains high frequencies and low frequencies. $h[k]$ and $g[k]$ is channel filter bank involving sub sampling. $c[n]$ is called averages contains low frequencies signal. $d[n]$ is called wavelet coefficients contain high frequencies signal. $c[n]$ and $d[n]$ be sub sampled (decimated by 2:) the next process for further decomposition is iterated on the low signal $c[n]$.

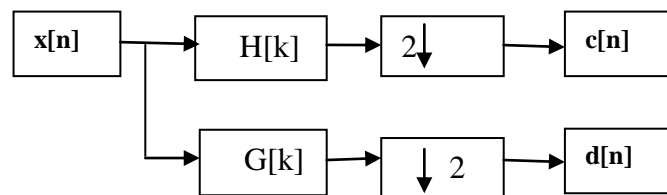


Figure 3. Two channel filter bank

For example, 2D Haar wavelet decomposition is expressed as follows, let $x[n]$ be an input, $x[n]= X_0,X_1,X_2,\dots X_{N-1}$ which contains N elements. Then output will consist of $N/2$ elements of averages over the input and is stored in $c[n]$. Also the other output contains $N/2$ elements wavelet coefficients values and is stored in $d[n]$. The Haar equation to calculate an average AV_i (See Eq.1) and a wavelet coefficient WC_i (See Eq.2) from pair data odd and even element in the input data are:

$$AV_i = \frac{X_i + X_{i+1}}{2} \quad (1)$$

$$WC_i = \frac{X_i - X_{i+1}}{2} \quad (2)$$

Where:

AV = Average

WC =Wavelet coefficient

C. Image Retrieval Algorithm

The proposed image retrieval algorithm is as follows,

Step1: First Read Query image and Convert from RGB image to gray image and HSV image then Decomposition using wavelet transformation.

Step2: Make every Wavelet coefficients, $WC_{new} = |WC_{old}|$.

Step3: Combination of horizontal details and vertical details, $CVdHd(i,j) = \text{Max}(Vd(i,j), Hd(i,j))$.

Step4: Choose significant points on $CVdHd(i,j)$ by threshold the high value.

Step5: Choose points on HSV image and it neighbor (3x3 pixel) base on coordinate significant points on $CVdHd(i,j)$ then Forming color feature vector by using The first order statistical moment and the second order statistical moment.

Step6: Forming texture feature vector by using Gabor transform on 7x7 pixel neighbor of significant points and Implement min/max normalization on all feature vector with range [0 1].

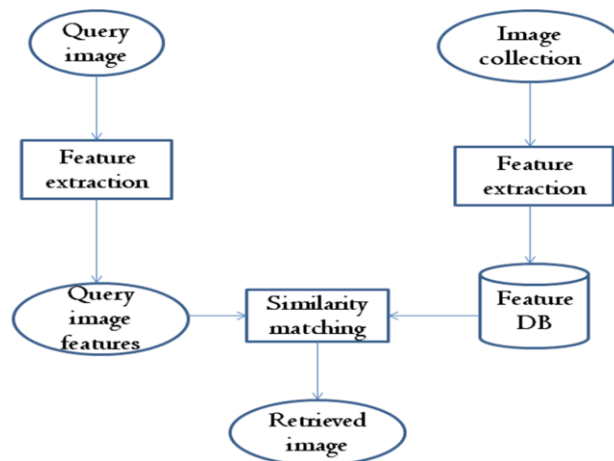
Step7: Measure the distance between feature vector image query and feature vector image in the dataset by using Euclidean distance then display image results with X top ranking from the dataset.

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D.SYSTEM DESIGN



V. PERFORMANCE EVALUATION

The performance of retrieval of the system can be measured in terms of its recall and precision. Recall measures the ability of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only the models that are relevant. It has been reported that the histogram gives the best performance through recall and precision value [35, 44]. They are defined as:

$$\text{Precision} = \frac{\text{Number of relevant image retrieved}}{\text{Total number of images retrieved}} \tag{5}$$

$$\text{Recall} = \frac{\text{Number of relevant image retrieved}}{\text{Total number of relevant image}} \tag{6}$$

Where A represent the number of relevant images that are retrieved, B, the number of irrelevant items and the C, number of relevant items those were not retrieved. The number of relevant items retrieved is the number of the returned images that are similar to the query image in this case. The total number of items retrieved is the number of images that are returned by the search engine.

VI. EXPERIMENT RESULT

Category	Shape		Color	
	Precision	Recall	Precision	Recall
Elephant	0.51	0.06	0.65	0.15
Bike	0.74	0.09	0.7	0.17
Dinosaur	0.83	0.2	0.75	0.18
AVG	0.69	0.03	0.23	0.05

Table 1 color and shape based precision and recall analysis

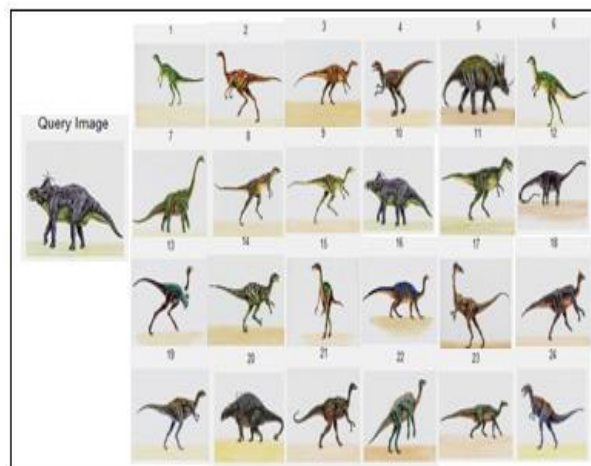
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Category	Color & Shape (CCV)		Color & Shape (Histogram)	
	Precision	Recall	Precision	Recall
Elephant	0.76	0.04	0.45	0.1
Bike	0.59	0.08	0.38	0.08
Dinosaur	0.69	0.15	0.44	0.1
AVG	0.22	0.03	0.14	0.03

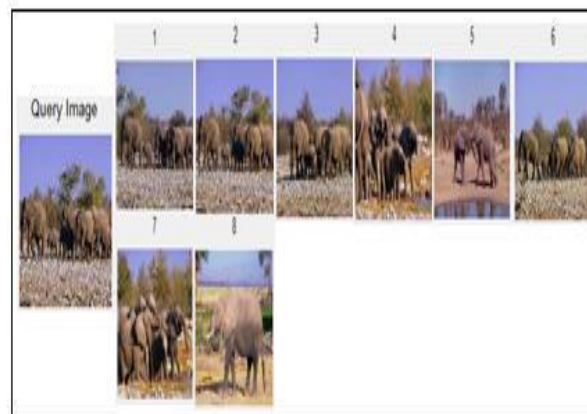
Table 2 combination of color and shape precision and recall analysis



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VII. CONCLUSION

In this paper, we presented a novel approach for Content Based Image Retrieval by combining the color and texture features called Discrete Wavelet Transformation (DWT). The experimental result shows that the proposed method outperforms the other retrieval methods in terms of Average Precision. Moreover, the computational steps are effectively reduced with the use of Wavelet transformation. As a result, there is a substantial increase in the retrieval speed and accuracy.

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