CBIR Based on Color and Texture Feature using DCT and DWT

Jayant Mankar[1], Kanchan harode[2], Megha pawase[3], Nisha titarmare[4]

Abstract—**In CBIR each image stored in the database, has its features extracted and compare to the features of the query image. In proposed work extraction of images are done by using DCT and DWT. It will extract the image feature to a distinguishable extend, GABOR and wavelet transform are used and extract their features from the images. In next process it involves the image matching their features that is visually similar. So this system improves the rate of retrieval from database.**

I. *INDEX TERMS*—**CONTENT-BASED IMAGE RETRIEVAL,** DCT, DWT**, COLOR, TEXTURE**

I. INTRODUCTION

A. CONTENT-BASED IMAGE RETRIEVAL

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. Content based image retrieval is a set of techniques for retrieving and visual semantics [1].

using the signature is to gain an improved correlation between image representation and visual semantics [1].

semantically-relevant images from an image database based on automatically-derived image features [1].

retrieval system is divided into off-line feature extraction and online image retrieval [1]. In off-line stage,the systemautomatically extracts visual attributes (color, shape, texture, and spatial information) of each image in the database based

on its pixel values and stores them in a different database within the system called a feature database. The feature data (also known as image signature) for each of the visual attributes of each image is very much smaller in size compared to the image data, thus the feature database contains an abstraction (compact form) of the images in the image database. One advantage of a signature over the original pixel values is the significant compression of image representation. However, a more important reason for using the signature is to gain an improved correlation between image representation

B. PRINCIPLE OF CBIR

Content-based retrieval uses the contents of images to represent and access the images. A typical content-based

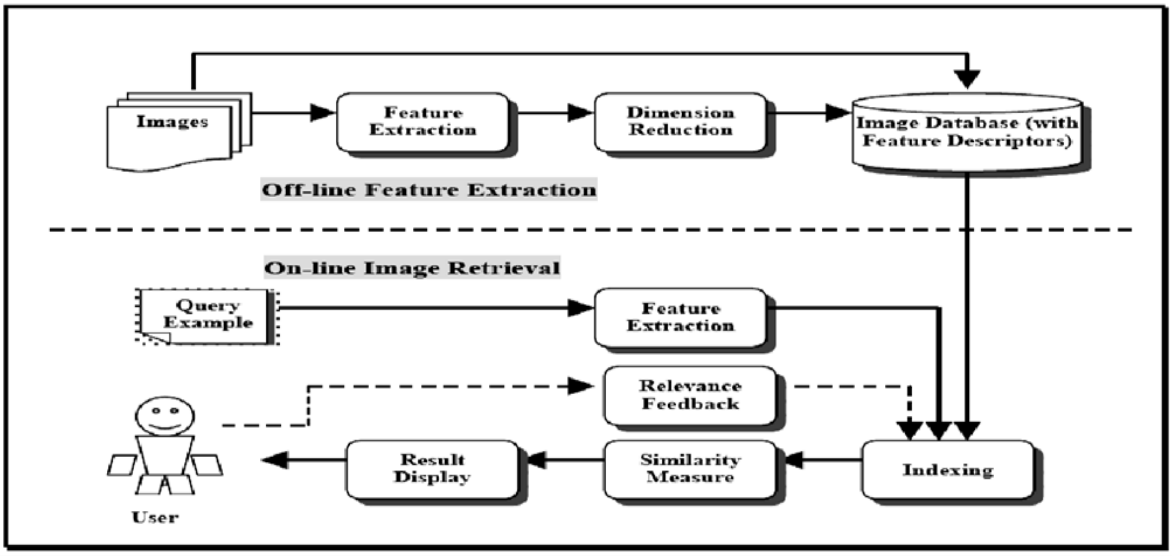

Fig 1.A Conceptual Framework for Content-Based Image Retrieval

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II. LITERATUERSURVEY

Content based image retrieval for general-purpose image databases is a highly challenging problem because of the large size of the database, the difficulty of understanding images, both by people and computers, the difficulty of formulating a query, and the issue of evaluating results properly. A number of general-purpose image search engines have been developed In the commercial domain, signature are called feature.

III. DISCRETEWAVELETTRANSFORM

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelet is discretely sampled. As with other wavelet transforms, a key advantage it has is temporal resolution, it captures both frequency and location information The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a lowpass filter with impulse response g resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k].$$

The signal is also decomposed simultaneously using a high-pass filter h. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter. However, since half the frequencies of the signalhave now been removed, half the samples can be

IV. DISCRETECOSINETRANSFORM

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient, whereas for differential equations the cosines express a particular choice of boundary conditions. Images are not in nite, and they are not periodic. The image has boundaries, and the left boundary seldom has anything to do with the right boundary. A periodic extension can be expected to have a discontinuity. That means a slow decay of Fourier coefficients and a Gibbs oscillation at the jump the one place where Fourier has serious trouble! In the image domain this oscillation is seen as ringing." The natural way to avoid this discontinuity is to *reect* the image across the boundary. With cosine transforms, a double-length periodic extension becomes continuous. A two-dimensional (2D) image may have (512)2 pixels. The gray level of the pixel at position (*i, j*) is given by an integer *x*(*i; j*) (between 0 and 255, thus 8 bits

QBIC [2] is one of the earliest systems. Recently, additional systems have been developed such as T.J. Watson [5], VIR [3], AMORE [6].

The common ground for CBIR systems is to extract a signature for every image based on its pixel values and to define a rule for comparing images. The signature serves as an image representation in the "view" of a CBIR system. The components of the

discarded according to Nyquist's rule. The filter outputs are then subsample by 2 (Mallat's and the common notation is the opposite, g- high pass and h- low pass):

$$y_{\mathrm{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

$$y_{\mathrm{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

This decomposition has halved the time resolution since only half of each filter output characterises the signal.

However, each output has half the frequency band of the input so the frequency resolution has been doubled.

per pixel). That long vector **x** can be altered by **x,h**, rest a row at a time (*j*, x) and then by columns (using the one-dimensional (1D) transforms of the rows). This is computationally and algebraically simplest: the 2D Toeplitz and circulate matrices are formed from 1D blocks.

V. FEATUREEXTRACTION

Feature extraction is a means of extracting compact but semantically valuable information from images. This information is used as a signature for the image. Similar images should have similar signatures. If we look at the image shown in Fig 2., the white color and the texture of the building are characteristic properties.

A. COLOR

One of the most important features visually recognized by humans in images is color. Humans tend to distinguish images based mostly on color features. Because of this, color features are the most widely used in CBIR systems and the most studied in literature.

B. COLOR HISTOGRAM

The most commonly used method to represent color feature of an image is the color histogram. A color histogram is atype of bar graph, where the height of each bar represents an amount of particular color of the color space being used

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in the image [7]. The bars in a color histogram are named as bins and they represent the x-axis. The number of bins depends on the number of colors there are in an image. The number of pixels in each bin denotes y-axis, which shows how many pixels in an image are of a particular color. The color histogram can not only easily characterize the global and regional distribution of colors in an image, but also be invariant to rotation about the view axis.

In color histograms, quantization is a process where number of bins is reduced by taking colors that are similar to each other and placing them in the same bin. Quantizing reduces the space required to store the histogram
information and time to compare the histograms. Obviously, quantization reduces the information regarding the content of images; this is the tradeoff between space, processing time, and accuracy in results [8].

C. TEXTURE

In the field of computer vision and image processing, there is no clear-cut definition of texture. This is because
available texture definitions are based on texture analysis methods and the features extracted from the image.

D. TEXTURE FEATURE EXTRACTION

Texture feature is computed using Gabor wavelets. Gabor function is chosen as a tool for texture feature extractionbecause of its widely acclaimed efficiency in texture feature extraction. Manjunath and Ma [4] recommended Gabortexture features for retrieval after showing that Gabor features performs better than that using pyramid-structured
wavelet transform features, tree-structured wavelet transform features and multi-resolution simultaneous autoregressive model. A total of twenty-four wavelets are generated from the "mother" Gabor function given in Equation using four scales of frequency and six orientations. Redundancy, which is the consequence of the non-orthogonality of Gabor wavelets, is addressed by choosing the parameters of the filter bank to be set of frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible in accordance with filter design in [4]. The lower and upper frequencies of the filters are set to 0.04 octaves and 0.5 octaves, respectively, the orientations are at intervals of 30 degrees, and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other [4]. Note that because of the symmetric property of the Gabor function, wavelets with center frequencies and orientation covering only half of the frequency spectrum are generated.

.Fig 2.Example of Image Properties.

VII. CONCLUSION

In this paper, content based image retrieval using DCT and DWT method is used for comparing the DCT retrieved images to the DWT retrieved images

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