Content-Based Image Retrieval Using Texture Wavelet

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Abstract

Multimedia content analysis is applied in different real-world computer vision applications, and digital images constitute a major part of multimedia data. In last few years, the complexity of multimedia contents, especially the images, has grown exponentially, and on daily basis, more than millions of images are uploaded at different archives such as Twitter, Facebook, and Instagram. To search for a relevant image from an archive is a challenging research problem for computer vision research community. Most of the search engines retrieve images on the basis of traditional text-based approaches that rely on captions and metadata. In the last two decades, extensive research is reported for content-based image retrieval (CBIR), image classification, and analysis. In CBIR and image classification-based models, high-level image visuals are represented in the form of feature vectors that consists of numerical values. The research shows that there is a significant gap between image feature representation and human visual understanding. Texture is an important cue for the analysis of many types of images. The term is used to point to intrinsic properties of surfaces, especially those that don't have a smoothly varying intensity. It includes intuitive properties like roughness, granulation and regularity. Texture can be defined as the set of local neighborhood properties of the gray levels of an image region. Texture analysis is considered a challenging task. The ability to effectively classify and segment images based on textural features is of key importance in scene analysis, medical image analysis, remote sensing and many other application areas. A wide variety of texture analysis methods has been proposed in the past.

I. Introduction

Images are widely used nowadays. It has the advantage of visual representation and it is usually adopted to express other mediums. With the rapid development of computers and networks, the storage and transmission of a large number of images become possible. Instead of text retrieval, image retrieval is wildly required in recent decades. Content-based image retrieval (CBIR) is regarded as one of the most effective ways of accessing visual data [1]. It deals with the image content itself such as color, shape and image structure instead of annotated text. Huge amounts of data retrieval challenge the traditional database technology, but the traditional text-object database cannot satisfy the requirements of an image database. The traditional way of an annotated image using text, lacks the automatic and effective description of the image. In order to implement CBIR, the system need to understand and interpret the content of managed images. The retrieval index should be produced automatically, which provides more a visual retrieval interface to users.

CBIR refers to image content that is retrieved directly, by which the images with certain features or containing certain content will be searched in an image database. The main idea of CBIR is to analyze image information by low level features of an image [2], which include color, texture, shape and space relationship of objects etc., and to set up feature vectors of an image as its index. Retrieval methods focus on similar retrieval and are mainly carried out according to the multi-dimensional features of an image.

The progress of CBIR research was lucidly summarized at a high level in [2], [3]. Features are the basis for CBIR, which are certain visual properties of an image. The features are either global for the entire image or local for a small group of pixels. According to the methods used for CBIR, features can be classified into low-level features and high-level features. The low-level features are used to eliminate the sensory gap between the object in the world and the information in a description derived from a recording of that scene. The high-level features are used to eliminate the semantic gap between the information that one can extract from the visual data and the interpretation that the same data has for a user in a given situation.

Texture plays an important role in many machine visions tasks such as surface inspection, scene classification, surface orientation and shape determination. Texture is characterized by the spatial distribution of gray levels in a neighborhood. Though texture is widely used and intuitively obvious, it has no precise definition due to its wide variability. According to Sklansky, ‘‘an image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic’’. This definition explains many of the textures found in natural images. The local image region, statistics or property that is repeated over the textured region, is called a texture element or texel. It must be noted that the texture has both local and global meaning, i.e., it is characterized by invariance of certain local attributes that are distributed over a region of an image.

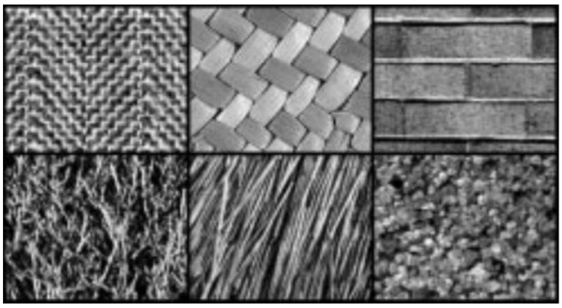


Figure 1: Some examples of Brodatz textures regular ones

II. Texture’s descriptors

Like color, texture is a fundamental characteristic of images because it concerns an important part of human vision. Much research has been carried out in both the fields of texture analysis and synthesis.

The study of the texture of the objects of an image can have very different objectives: to obtain information on the nature of an object, to segment the image into homogeneous regions, to identify the texture in order to reduce it to a whole parameter (image compression), image search by content, etc.

According to [4], a formal definition of texture is almost impossible.

Generally speaking, texture results in a spatial arrangement of pixels that intensity or color alone is not sufficient to describe. They can consist of a structured placement of elements but can also have no repeating elements.

Many definitions have been proposed, but none is perfectly suited to the different types of textures encountered. In a definition commonly cited [5], texture is presented as a structure having certain spatial properties that are homogeneous and invariant by translation. This definition states that the texture gives the same impression to the observer regardless of the spatial position of the window through which he observes this texture.

There are a large number of textures. They can be separated into two classes: structured textures (macro textures) and random textures (micro textures).

A structured texture is formed by the repetition of a primitive at regular intervals. We can differentiate in this class perfectly periodic textures (tiling, checkerboard, etc.), textures whose primitives undergo deformations or changes in orientation (brick wall, coffee beans, etc.).

Random textures are generally distinguished by a finer appearance (sand, grass, etc.). Unlike structural type textures, random textures do not have an isolable primitive or repetition frequency. We cannot therefore extract from these textures a primitive that is repeated in the image but rather a vector of statistical parameters that are homogeneous at each texture.

In all cases, these objectives require the extraction of one or more characteristic parameters of this texture.

III. General application of texture wavelet

Apart from methodological work, which uses well controlled experiments, important experimental knowledge is coming from the application to real world problems. In a growing number of areas, wavelet-based texture methods are being investigated. An online collection of ongoing work is being maintained by Livens [6]. The most widely use is found in the analysis of medical images. Texture analysis of images can contribute to a better interpretation of medical images. This type of analysis provides not only qualitative but also quantitative information about tissue affection degree. In this work an algorithm is developed which uses the wavelet transform to carry out the supervised segmentation of echo graphic images corresponding to injured Achilles tendon of athletes. To construct the pattern, the image corresponding to healthy tendon tissue of the athlete, is taken as a reference based upon the duplicity of this structure. Texture features are calculated on the expansion wavelet coefficients of the images. The Mahala Nobis distance between texture samples of the injured tissue and pattern texture is computed and used as the discriminating function. It is concluded that this distance, after appropriate medical calibrations, can offer quantitative information about the injury degree in every point along the damaged tissue. Further, its behavior along the segmented image can serve as a measure of the degree of change in tissue properties. The parameter, similarity degree, is defined and obtained by taking into account the correlation between distance histograms for the healthy tissue and the damaged one. It is also shown that this parameter, when properly calibrated, can offer a quantitative global evaluation of the state of the injured tissue.

Other application includes tissue characterization [7]. An application of texture features for content-based searches in large image databases is shown by in [8]. Combined color and texture descriptions are expected to become very important for this area. Another successful area is remote sensing, where promising work was reported [9] [10]. Other applications are found in material science, where characterization of corrosion is reported [11]. An application of the segmentation of marble images has been carried out [11]. Although the amount of work on applications is growing fast, it is still relatively small and many opportunities for new research remain in this area.

IV. mathematical aspect of wavelet transformation

a. Fourier transformation.

At the core of signal processing is the Fourier Transform (FT). The FT decomposes a function into sines and cosines. In theory, any function can be represented in this way, that is, as a sum of (possibly infinite) sine and cosine functions of different amplitudes and frequencies.

We have two forms of Fourier transformations:

For CTS	$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}\,dt$
For DTS	$F(\omega) = \sum_{-\infty}^{+\infty} f(n)e^{-j\omega n}$

Figure 2 : CFT : Continuos Fourier Transformation, DFT : Discret Fourier Transformation.

b. Limitations of Fourier Transformation.

The major disadvantage of the Fourier transformation is the inherent compromise that exists between frequency and time resolution. The length of Fourier transformation used can be critical in ensuring that subtle changes in frequency over time.

In Fourier transformation:

- ➢ No means of identifying exactly where an event occurs.
- ➢ Does not cope well with discontinuous, bursts of signals (video, music...).

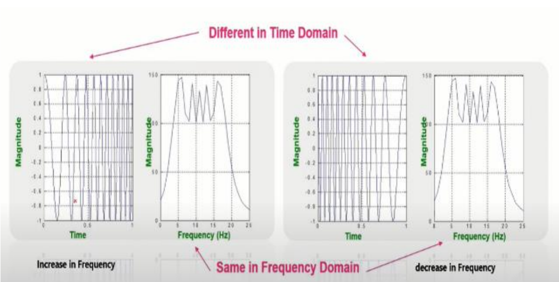


Figure 3 : Example of Fourier Transformation : The increase and decrease in frequency

as this figure show, if we increase or decrease the frequency, we always get the same Magnitude, also the spectrum cannot tell us what happened in the time domain, the frequency and time information are not available in the forest spectrum.

c. Wavelet Transformation

A Wavelet is a wave-like oscillation that is localized in time, an example is given below.

Wavelets have two basic properties: scale and location. Scale (or dilation) defines how “stretched” or “squished” a wavelet is. This property is related to frequency as defined for waves.

Location defines where the wavelet is positioned in time (or space).

The Wavelet defined as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathbb{R}$$

Figure 4 : Wavelet Formula

Here a and b are called Dilatation (Scale) and Translation (Position) parameters respectively.

$$\psi(t) = e^{j\omega_0 t}e^{-\frac{t^2}{2}}$$

Figure 5 : Formula of wavelet example

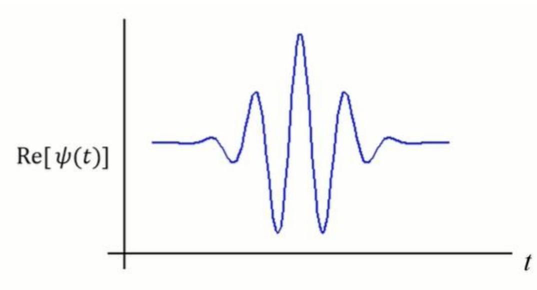


Figure 6 : Wavelet example

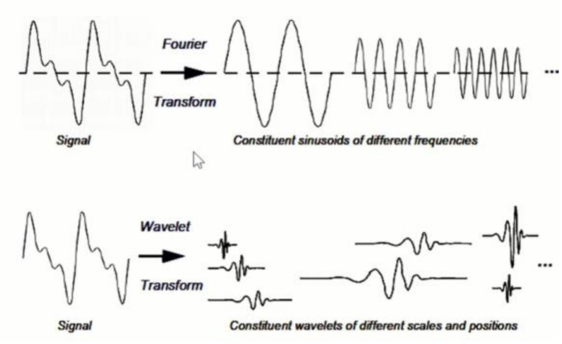


Figure 7 : Wavelet Transformation vs Fourier Transformation

Continuous and Discontinuous Wavelet Transformation:

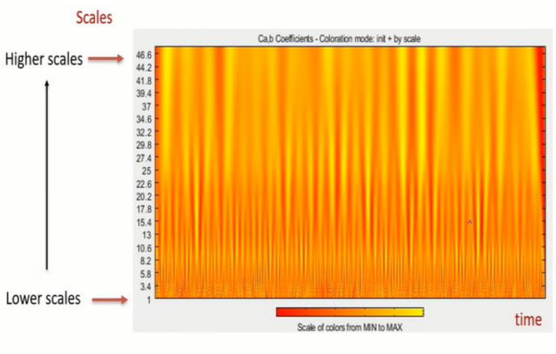


Figure 8 : Continuous wavelet transformation scaled by time

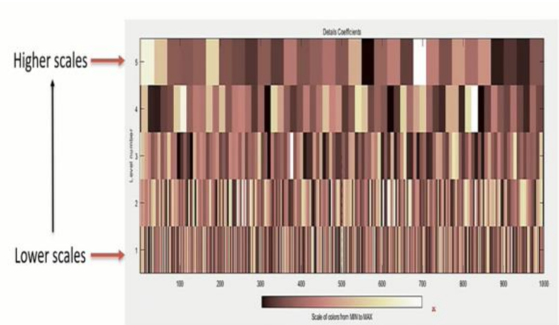


Figure 9: Discontinuous wavelet transformation scaled by time

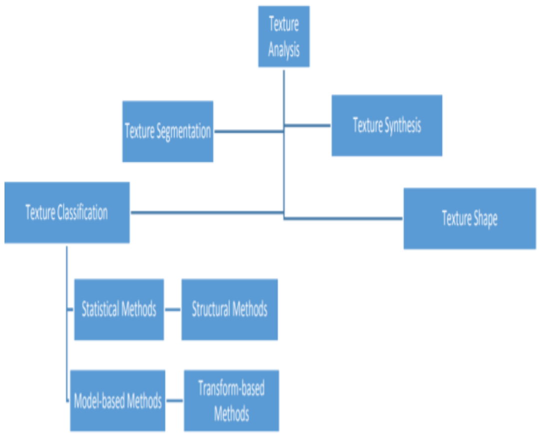
V. Other descriptors using the same technique

Statistical texture processing methods that make up most of the methods presented in the field of machine vision, spot localization of pixel values. These bundles of image texture analysis methods perform a series of statistical analyzes calculated on the brightness intensity distribution functions of the pixels.

Functionally used for different edge, line and orientation detection, however Wavelet Effective for image recovery with a salient point characteristic.

for another side at the physical level, the difference is in the discrete and continuous transforms.

The Gabor transform is generally implemented continuously using a Fourier transform. The wavelet transform has one implementation, called the continuous wavelet transform.



One of the most important methods in texture analysis is the transformation method. The Gabor transform is similar to the wavelet transform, in which the functions have the basis of Gaussian nature and therefore this transformation is optimal in the frequency domain arrangement. The Gabor transform is an optimal transformation to minimize the two-dimensional uncertainty associated with location and frequency domains. This wavelet can be used as directional and comparable scale detectors to reveal lines and edges in images [12].

Additionally, the statistical properties of this transformation can be used to determine the structure and visual content of the other image. The characteristics of the Gabor transformation are used in several image analysis applications, including texture categorization and segmentation, image recognition, alphabet recognition, image recording, routing, and motion. Gabor filters are defined in the spatial and frequency domains.

VI. Example of application

Wavelet transform could be applied to images as 2-dimensional signals. To refract an image into k level, first the transform is applied on all rows up to k level while columns of the image are kept unchanged. Then this task is applied on columns while keeping rows unchanged. In this manner frequency components of the image are obtained up to k level. These components are LL that is approximation of image and HL, LH and HH that are horizontal, vertical and diagonal frequency details [13].

These frequency components in various levels let us to better analyze original image or signal. Wavelet Transform in 2-D can be defined as following:

$CWT\ (s, a, b) = 1\ \sqrt{s} \iint f\ (x, y)\ \Psi\ (x{-}a\ s, y{-}b\ s)\ dxdy$

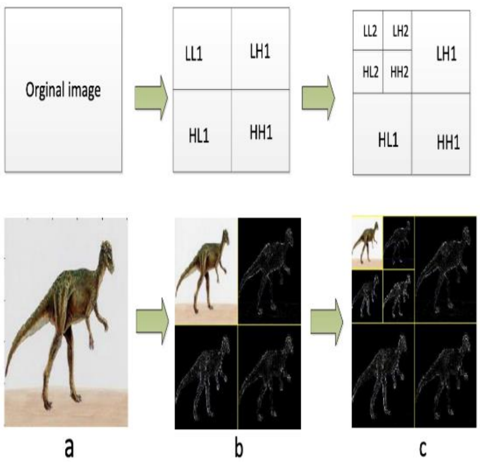
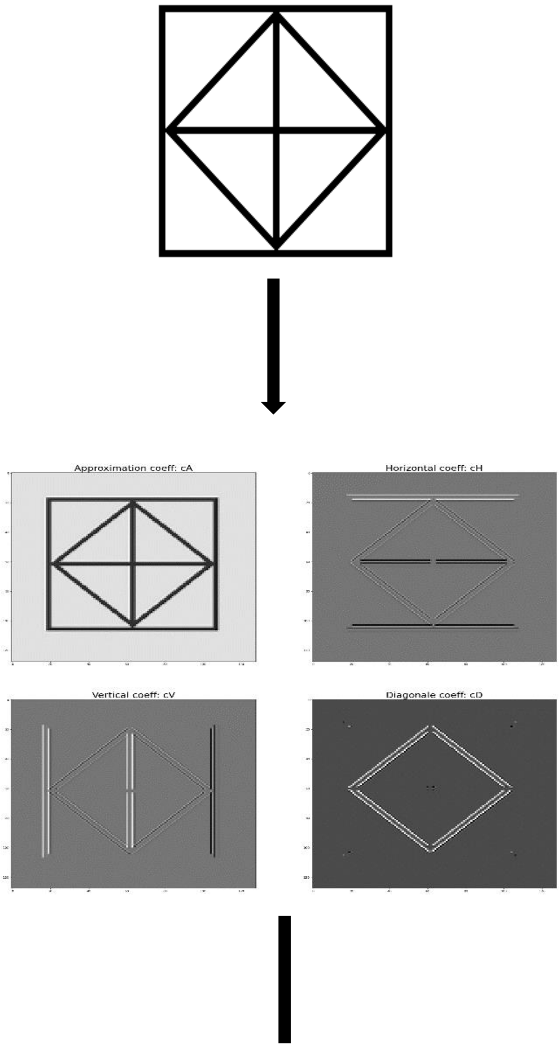


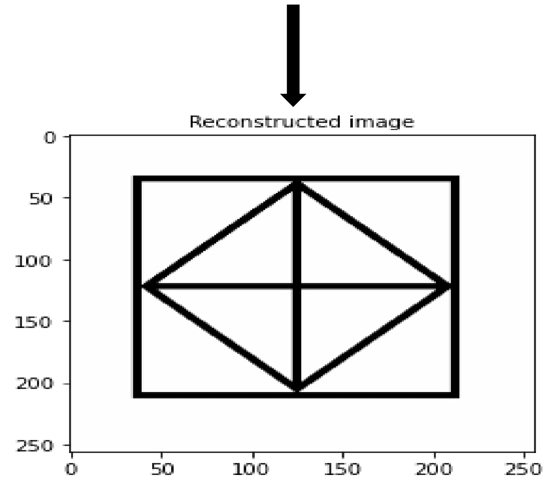
Figure 10 : For a sample image, the wavelet decomposition for 2 levels

Wavelet features are extracted based on the wavelet transformation which is described in the previous section. Here we extract features using approximation, vertical and horizontal frequency components of the image. The decomposed image consists of LL, LH, HL and HH components in each level. LL includes low frequency factors and HL, LH and HH include factors of high frequencies in horizontal, vertical and diagonal directions respectively. These frequency components are equal-sized matrices. The Frobenius norm of the rows of LL and LH matrices and also the Frobenius norm of the columns of HL matrix are proposed to be used in feature extraction phase.

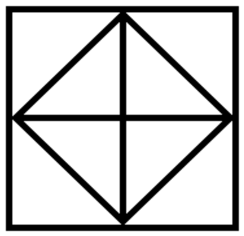
Explication:

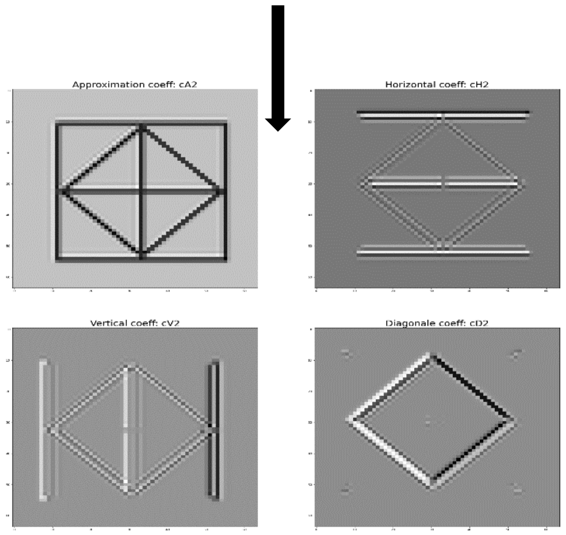
- One level decomposition

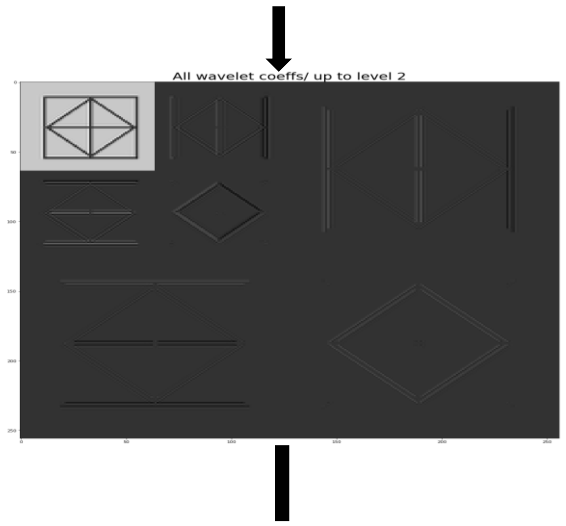


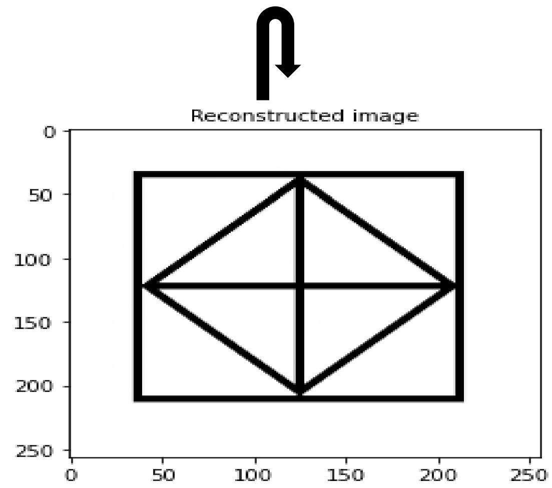


➢ Two level decomposition:









We can also have an efficient algorithm for Content Based Image Retrieval (CBIR) based on Decomposition Wavelet Transform (DWT) and Edge Histogram Descriptor (EHD) feature of MPEG-7. The proposed algorithm is explained for image retrieval based on shape and texture features only not on the basis of color information. Here input image is first decomposed into wavelet coefficients. These wavelet coefficients give mainly horizontal, vertical and diagonal features in the image. After wavelet transform, Edge Histogram Descriptor is then used on selected wavelet coefficients to gather the information of dominant edge orientations. The combination of DWT and EHD techniques increases the performance of image retrieval system for shape and texture-based search. The performance of various wavelets is also compared to find the suitability of particular wavelet function for image retrieval. The proposed algorithm is trained and tested for Wang image database. The results of retrieval are expressed in terms of Precision and Recall and compared with various other proposed schemes to show the superiority of our scheme.

VII. Conclusion

After a survey the previous CBIR works, the paper explored the low-level features of texture extraction for CBIR. After comparing the two-level decomposition as well as using wavelet coefficient, the paper implemented a CBIR system using texture fused features. Similar images can be retrieved quickly and accurately by inputting an image. More low-level features such as shape and spatial location features etc. will be fused to make the system more robust in the future. The image feature matching method and semantic based image retrieval are the other two important aspects for the CBIR system.

CBIR is a fast-developing technology with considerable potential in digital libraries, architectural and engineering design, crime prevention, historical research and medicine. Nevertheless, the effectiveness of current CBIR systems is inherently limited because they only operate at the primitive feature level. Furthermore, the technology still lacks maturity, and is not widely used on a significant scale. CBIR is a fast-developing technology with considerable potential in digital libraries, architectural and engineering design, crime prevention, historical research and medicine. Nevertheless, the effectiveness of current CBIR systems is inherently limited because they only operate at the primitive feature level. Furthermore, the technology still lacks maturity, and is not widely used on a significant scale.

In recent times, there is no general breakthrough in CBIR in spite of the diverse methods and tools developed to formulate and execute queries in large databases based on their visual contents. Hence, future works should be tailored towards the development of CBIR systems that will resolve the problem of semantic gap in CBIR.

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IX. figure list