Comparison of Wavelet Transform, Local Binary Pattern and dominant Local Binary Pattern for Texture Classification

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Abstract: This paper provides a comparative study between the three approaches namely Wavelet transform, Local Binary Pattern and Dominant Local Binary Pattern to extract image features for texture classification .The dominant local binary pattern method makes use of the frequently occurred patterns to capture descriptive textural information. This performance of this method is compared by using the classification rate by conducting experiments on the broadtz tests.

Keywords: Texture Classification; Wavelet Transform; Local Binary Pattern; dominant Local Binary pattern; Rate Recognition rate;

I. INTRODUCTION

Texture is the distribution of crystallographic orientations of a sample. A sample in which these orientations are fully random is said to have no texture. If the crystallographic orientations are not random, but have some preferred orientation, then the sample has a weak, strong, or moderate texture. The degree is dependent on the percentage of crystals that have the preferred orientation. Texture is seen in almost all engineered materials, and it can have a great influence on material properties. Also geologic rocks show texture due to their thermo-mechanic history due to formation processes. One extreme case is a complete lack of texture: a solid with perfectly random crystallite orientation, which will have properties at length, scales sufficiently larger than the size of the crystallites. The opposite extreme is a perfect single crystal, which has anisotropic properties by geometric necessity.

Texture analysis is important in many applications of computer image analysis for classification, detection or segmentation of images based on local spatial patterns of intensity or color. Textures are replications, symmetries and combinations of various basic patterns or local functions, usually with some random variation. Textures have the implicit strength [1] that they are based on intuitive notions of visual similarity. This means that they are particularly useful for searching visual databases and other human computer interaction applications. However, since the notion of texture is tied to the human semantic meaning, computational descriptions have been broad, vague and sometimes conflicting.

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The method of texture analysis [2] chosen for feature extraction is critical to the success of the texture classification. However, the metric used in comparing the feature vectors is also clearly critical. Many methods have been proposed to extract texture features either directly from the image statistics, e.g. Co-occurrence matrix, or from the spatial frequency domain.

Classification [3] refers to as assigning a physical object or incident into one of a set of predefined categories. In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is one of the four problem domains in the field of texture analysis. The other three are texture segmentation (partitioning of an image into regions which have homogeneous properties with respect to texture; supervised texture segmentation with a priori knowledge of textures to be separated simplifies to texture classification), texture synthesis (the goal is to build a model of image texture, which can then be used for generating the texture) and shape from texture (a 2D image is considered to be a projection of a 3D scene and apparent texture distortions in the 2D image are used to estimate surface orientations in the 3D scene).

Texture analysis [4] is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. A successful classification or segmentation requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection, for example for defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high.

Texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match. Optionally, if the best match is not sufficiently good according to some predefined criteria; the unknown sample can be rejected instead.

II. WAVELETS

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology. Interchanges between these fields during the last ten years have led to many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction. This paper introduces wavelets to the interested technical person outside of the digital signal processing field. I describe the history of wavelets beginning with Fourier, compare wavelet transforms with Fourier transforms, state properties and other special aspects of wavelets, and finish with some interesting applications such as image compression, musical tones, and de-noising noisy data.

The fundamental idea behind wavelets is to analyze according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mindset or perspective in processing data.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. This idea is not new. Approximation using superposition of functions has existed since the early 1800's, when Joseph Fourier discovered that he could superpose sines and cosines to represent other functions.

The wavelet analysis [7] procedure is to adopt a wavelet prototype function, called an "analyzing wavelet" or "mother wavelet." Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the prototype wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients. And if you further choose the best wavelets adapted to your data, or truncate the coefficients below a threshold, your data is sparsely represented. This "sparse coding" makes wavelets an excellent tool in the field of data compression.

Other applied fields that are making use of wavelets are: astronomy, acoustics, nuclear engineering, sub-band coding, signal and image processing, neurophysiology, music, magnetic resonance imaging, speech discrimination, optics, fractals, turbulence, earthquake-prediction, radar, human vision, and pure mathematics applications such as solving partial differential equations.

III. WAVELET TRANSFORM

By Wavelet transform[8],we mean the decomposition of a signal with a family of real orthonormal bases obtained through translation and dilation of a kernel function known as the mpther wavelet i.e.,

$$\psi_{m,n}(x) = 2^{-m/2}\psi(2^{-m}x - n) \text{ -------------- } (1)$$

where m and n are integers. Due to the orthonormal property, the wavelet coefficients of a signal f(x) can be

$$c_{m,n} = \int_{-\infty}^{+\infty} f(x)\psi_{m,n}(x)dx$$

and the synthesis formula

$$f(x) = \sum_{m,n} c_{m,n}\psi_{m,n}(x)$$

can be used to recover f(x) from its wavelet coefficients. To construct he mother wavelet $\psi(x)$,we may first determine a scaling function $\phi(x)$, which satisfies the two scale difference equation

$$\phi(x) = \sqrt{2}\sum_{k} h(k)\phi(2x-k) \text{ --------- } (2)$$

then the wavelet kernel $\psi(x)$ is related to the scaling function via

$$\psi(x) = \sqrt{2}\sum_{k} g(k)\phi(2x-k) \text{ ----------------- } (3)$$

Where $g(k)=-1^{k}h(1-k)$ ------------------------------------(4)

The coefficients h(k) in (2) have to meet several conditions for the set of basis wavelet functions to be unique, orthonormal, and have a certain degree of regularity. Several different sets of coefficients h(k) satisfying the above conditions can be found in the wavelet literature.

The coefficients h(k) and g(k) play a very crucial role in a given discrete wavelet transform. To perform the wavelet transform does not require the explicit forms of $\phi(x)$ and $\psi(x)$ but only depends on h(k) and g(k).Consider a J-level wavelet decomposition which cab be written as

$$f_0(x) = \sum_k c_{0,k} \phi_{0,k}(x)$$

$$= \sum_k c_{J+1,k} \phi_{J+1,k}(x) + \sum_{j=0}^{j} d_{j+1,k} \Psi_{j+1,k}(x)) \quad \text{-------} \quad (5)$$

where coefficients $c_{0,k}$ are given and coefficients $c_{j+1,n}$ and $d_{j+1,n}$ at scale j+1 are related to the coefficients $c_{j,k}$ at scale j via

$$c_{j+1,n} = \sum_k c_{j,k} h(k - 2n)$$

$$d_{j+1,n} = \sum_k c_{j,k} g(k - 2n) \quad \text{-----------}(6)$$

where $0 \leq j \leq J$.Thus (6) provides a recursive algorithm for wavelet decomposition through h(k) and g(k), and the final outputs include a set of J-level wavelet coefficients $d_{j,n,}$ $1 \leq j \leq J$,and the coefficient $c_{J,n}$ for a low-resolution component $\phi_{J,k}$ (x).By using a similar approach ,we can derive a recursive algorithm for function synthesis based on its wavelet coefficients $d_{j,n,}$ $1 \leq j \leq J$ and $c_{J,n}$

IV. LOCAL BINARY PATTERN

The LBP operator is a theoretically simple yet very powerful method of analyzing textures. Through its recent extensions, it has been made into a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Texture is described in terms of micro-primitives (textons) and their statistical placement rules. Optionally, the primitives may be coupled with a complementary measure of local image contrast, which measures the strength of the primitives.

The local binary pattern (LBP) texture operator was first introduced as a complementary measure for local image contrast1. The first incarnation of the operator worked with the eight-neighbors of a pixel, using the value of the center pixel as a threshold. An LBP code for a neighborhood was produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result. Since the LBP was, by definition, invariant to monotonic changes in gray scale, it was supplemented by an independent measure of local contrast.Fig.1 shows the operating pattern for local binary pattern.

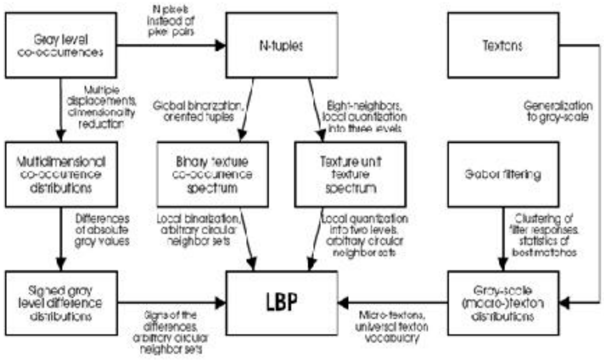

Fig.1 LOCAL BINARY PATTERN

V. DOMINANT LOCAL BINARY PATTERN

In the conventional LBP method proposed by Ojala et al. [19], only the uniform LBPs are considered. At a pixel, it gives a uniform LBP if the corresponding binary label sequence has no more than two transitions between "0" and "1" among all pairs of the adjacent binary labels. For example, the binary label sequences "10001111" and "00011000" are uniform LBPs. But the sequence "01001111" is not a uniform LBP because it has four transitions. In the textures which mostly consist of straight edges or low curvature edges, the uniform LBPs effectively capture the fundamental information of textures. However, in practice, there are some texture images having more complicated shapes. These shapes can contain high curvature edges, crossing boundaries or corners. Performing texture classification on these textures based on uniform LBPs is possibly problematic. The reason is that the uniform LBPs extracted from such images are not necessary to be the patterns having dominating proportions. Consequently, textural information cannot be effectively represented by solely considering the histogram of the uniform LBPs. Although utilizing the uniform LBPs is insufficient to capture textural information, we avoid considering all the possible patterns to perform classification. As pointed out by Ojala *et al.* [19], the occurrence frequencies of different patterns vary greatly and some of the patterns rarely occur in a texture image. The proportions of these patterns are too small and inadequate to provide a reliable estimation of the occurrence possibilities of these patterns. Therefore, we propose to use dominant local binary patterns (DLBPs) which consider the most frequently occurred patterns in a texture image. It avoids the aforementioned problems encountered by merely using the uniform LBPs or making use of all the possible patterns, as the DLBPs are defined to be the most frequently occurred patterns. In this paper, it will be demonstrated that a minimum set of pattern labels that represents around 80% of the total pattern occurrences in an image can effectively captures the image textural information for classification tasks. This required number of patterns remains the same as the DLBP features are subsequently extracted from the training image set or new testing images. Nonetheless, for two different texture images, the dominant patterns can be of different types. That is, the DLBP approach is not limited to consider only a fixed set of patterns (e.g., uniform patterns). This is distinct to the conventional LBP framework, in which the final feature vector representing an input image is the occurrence histogram of the fixed set of uniform patterns.

To retrieve the DLBP feature vectors from an input image, the pattern histogram which considers all the patterns in the input image is constructed and the histogram bins are sorted in no increasing order. Based on the previously computed number of patterns, the occurrence frequencies corresponding to the most frequently occurred patterns in the input image are served as the feature vectors. It is noted that the DLBP feature vectors do not bear information regarding the dominant pattern types, and they only contain the information about the pattern occurrence frequencies. According to the experimental results, omitting the dominant pattern type information in the DLBP feature vectors is not harmful. It is because the 80% dominant patterns of DLBP is a preponderance of the overall patterns, and the DLBP feature vectors are already very descriptive. It is practically improbable to have two distinct texture types which can resemble dominant pattern proportions of each other. Without encapsulating the pattern type information, the DLBP features also possess surpassing robustness against image noise, as compared to the conventional LBP features. Under the effect of image noise, the binary label of a neighboring pixel is possible to be flipped by the intensity distortion induced by noise. Flipped binary labels alter the extracted LBPs. As a result, even though some LBPs are computed on the same type of image structures, the extracted LBP type can vary significantly. Thus, the pattern type information is unreliable. In the conventional LBP framework, the pattern types are categorized as uniform patterns or non-uniform patterns. In which, under the effect of image noise, a large amount of useful patterns turns into non-uniform ones that are unconsidered in the conventional LBP method. On the contrary, the DLBP approach processes all 80% dominant patterns disregarding the pattern types.

VI. RESULTS

We use the peak Classification Rate (CR) to evaluate the quality of various face recognition algorithms. The CR formula is defined as follows:

$$CR = \frac{No\ of\ Correctly\ Classified\ Images}{Total\ no\ of\ Test\ Images} x\ 100$$

The CR values for the various face recognition method is given below in Fig.2.

METHOD	RECOGNITION RATE
Wavelet	87.25%
Gabor	90.34%
Novel Approach	98.63%

FIG.2.RATE RECOGNITION RATE

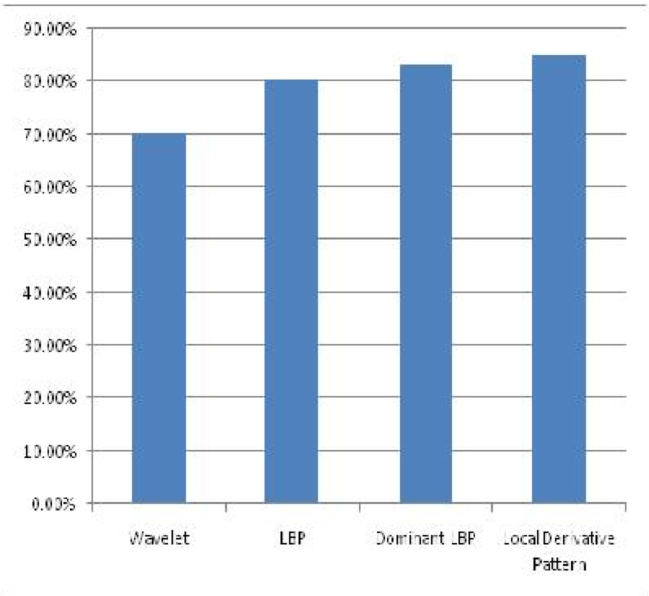

Fig.3 shows the bar graph of rate recognition rates.

VII. CONCLUSION

This application is proposes a comparative study on texture classification rate among three local texture features based algorithms. This system provides clear study on the area of texture classification. All the algorithms are properly implemented with the help of matlab features. This system properly maintains the data collection for the texture as different groups. This application takes groups of texture under grass, canvas, wood and water.

In classification experiments, the present generalized methods are analyzed according to its classification rate. The rotation invariant texture features of LBP method perform well on the gray scale textures. The bin size is properly reduced by the local texture pattern. For the color image the multivariate textural features are used for classification.

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