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Texture Classification with Feature Analysis Using Wavelet Approach: A Review

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Abstract: ***Textures play important roles in many image processing applications, since images of real objects often do not exhibit regions of uniform and smooth intensities, but variations of intensities with certain repeated structures or patterns, referred to as visual texture. The textural patterns or structures mainly result from the physical surface properties, such as roughness or oriented structured of a tactile quality. It is widely recognized that a visual texture, which can easily perceive, is very difficult to define. The difficulty results mainly from the fact that different people can define textures in applications dependent ways or with different perceptual motivations, and they are not generally agreed upon single definition of texture. The development in multi-resolution analysis such as Local Binary Pattern and wavelet transform help to overcome this difficulty.***

Keywords: Wavelet Transform, Fourier transform, Fast Fourier transformation, Gray level co occurrence matrix, Feature Extraction.

1. Introduction

Wavelet Transform is used to analyze textures in order to sort out their different types. The goal of such analysis is to get the features that will allow us to distinguish the types of textures. In general the transformation process performed by Convoluting of the given signal with their basis function which are usually orthogonal, which make the transformation revertible, this means that the original function in the original domain can be extracted without losing information [1].

The Fourier transform is a convolution transformation which transforms the signal from its time domain to the frequency domain. A wide area of application is found with the use of the Fast Fourier transformation algorithm (FFT) which extends two-dimension field. [2].

The lack of localization (i.e., not knowing when in times the frequencies occur) with Fourier and other related transforms is a major drawback, and is partly what led the Mathematician to explore Wavelet Theory. The Wavelet Transform (WT) is found to be more efficient than Fourier transform (WT). The Discrete Wavelet Transform (DWT) is as fast as the Fast Fourier Transform (FFT) in which the linear operation that operates on data vector whose length is an integer power of two, transforming it into numerically different vectors of the same length [3].

The Wavelet Transform plays substantial role in multi-resolution technique, particularly in image processing. Wavelet Transform is very powerful model for texture discrimination [4].

2. Literature Survey

Signals generated from natural sources such as digital images are often non-stationary in nature i.e. their content varies in time or space. Frequency analysis of such signals should therefore include spatial information resulting in so called spatial-frequency representations. Although the classic frequency analysis tool, the Fourier transform, inherently assumes stationary signals, there have been many attempts throughout the last century to integrate spatial information into a frequency representation. These have included the Gabor, Haar, Walsh-Hadarmard and other expansions, sub band filtering, scale space decompositions etc. In order to extract the most important features of textures, we use the DWT and this gives us more accurate results. Wavelet transforms are widely applied in many fields for solving various problems. The continuous wavelet transform (CWT) of a signal, x (t), is the integral of the signal multiplied by scaled and shifted versions of a wavelet function and is defined by [05].

$$CWT(a, b) = \int_{-\infty}^{\infty} x(t)\, 1/\sqrt{|a|}\,(t-b/a)\, dt \qquad (1)$$

Where, a and b are so called the scaling (reciprocal of frequency) and time localization or Shifting parameters, respectively. Calculating wavelet coefficients at every possible scale is computationally a very expensive task. Instead, if the scales and shifts are selected based on powers of two, so-called dyadic scales and positions, then the wavelet analysis will be much more efficient. Such analysis is obtained from the DWT which is defined as,

$$DWT(j, k) =)\, 1/\sqrt{|2^j|} \int_{-\infty}^{\infty} x(t)\psi(t-2^{jk}/2^j)\, dt \qquad (2)$$

Where, a and b are replaced by 2j and k2j, respectively.

Jean Morlet in 1982 introduced the idea of the wavelet transform. Any function can be considered as a wavelet function, as long as it satisfies the following conditions [06]

- A wavelet function's square integral is finite. This defines a wavelet must have a finite (small) energy. i.e.:

$$\int_{-\infty}^{\infty} |\psi(t)dt|^2 < \infty \qquad (3)$$

- The integral of wavelet function, equals to zero. This defines that the function must be oscillatory (a wave). i.e.:

$$\int_{-\infty}^{\infty} |\psi(t)dt|^2=0 \quad (4)$$

- A single wavelet function is known to be a mother wavelet. The equation of a mother wavelet is

$$W(a,b)=1/\sqrt{a}\int x(t)\Psi^*(t-b/a)dt \quad (5)$$

Where x (t) is signal function in time domain;* is a convolution operator; parameter 'a' is the scaling parameter or scale; that measures the degree of compression. The parameter b is the translation parameter that decides the time location of the wavelet.

3. Texture and Features

Feature extraction is the first stage of image texture analysis. Results obtained from this stage are used for texture discrimination, texture classification or object shape determination.

Haralick in 1973 has defined texture as a wide variation of features of discrete gray tone. For texture classification, a set of meaningful features is to be defined. For this fundamental patterns are categorized into three groups; viz. Spectral, textural and contextual. Spectral features represent the average tonal variations in various bands in visible spectrum. Textural features have information about the spatial distribution of tonal variations within a band. Contextual features have the information, derived from of surrounding area in image. While dealing with computerized process of image processing, textural features are important. Tone depends on varying shades of gray of resolution cell. Texture concerns with the spatial distribution of gray tones. He prepared co-occurrence matrix i.e. gray tone spatial-dependence probability distribution matrix. Different textural properties- features- like homogeneity, contrast, energy, entropy etc. are extracted from co-occurrence matrix. [7]

There are four major issues in texture analysis:

- Shape from texture: to reconstruct 3D surface geometry from texture information.
- Texture discrimination: to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation).
- Feature extraction: to compute a characteristic of a digital image able to numerically describe its texture properties.
- Texture classification: to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs.

4. Review of Texture Classification

Texture analysis is usually categorized into following methods:

- **Fractal Methods** [8, 9] exploit the fact that textures are often very self similar. This can be best exemplified by the fact that textures often look similar at different scales. Methods have been proposed that extract the fractal dimension of a texture image and use this to characterize the texture.

- **Spatial-frequency Techniques** [10] have found large numbers of successful applications to texture characterization recently. They currently are favored within many content based retrieval applications.

- **Structural Methods:** Structural approaches represent texture by well defined primitives (micro-texture) and a hierarchy of spatial arrangements (macro-texture) of those primitives. A set of primitives is organized according to a certain placement rule. The placement rule defines the spatial relationship among primitives and may be expressed in terms of adjacencies .The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. The abstract descriptions can be well defined for natural textures because of the variability of both micro- and macrostructure and no clear distinction between them. [11]

- **Stochastic Methods:** This is model based approach. These methods assume that textures are the realization of stochastic processes and estimate the associated parameters. In geometrical methods textures are considered to be composed of texture primitives and are extracted and analyzed. Several stochastic models have been proposed for texture modeling and classification such as Gaussian Markov random fields and spatial autocorrelation function model. The parameters of the model are estimated and then used for image analysis. In practice, the computational complexity arising in the estimation of stochastic model parameters is the primary problem. The fractal model has been shown to be useful for modeling some natural textures. It can be used also for texture analysis and discrimination; however, it lacks orientation selectivity and is not suitable for describing local image structures.

- **Spectral Methods:** In Spectral approach, the methods collect a distribution of filter responses for a further classification. The signal processing techniques are mainly based on texture filtering for analyzing the frequency contents either in spatial domain or in frequency domain. Filter bank instead of a single filter has been used, giving rise to several multi-channel texture analysis systems such as Gabor filters and wavelet transforms. The signal processing techniques are mainly based on texture filtering for analyzing the frequency contents either in spatial domain or in frequency domain. Filter bank instead of a single filter has been used for several multi-channel texture analysis systems such as Gabor filters and wavelet transforms. Gabor filters is powerful and precise for describing texture patterns. Wavelet transform can provides a precise and unifying frame work for the analysis and characterization of a signal at different scales i. e. multi resolution. The efficient and leading method used for texture classification here is Wavelet Transform. [11]

- **Statistical methods:** Statistical methods analyze spatial distribution of pixels using features taken from the first and second-order histograms based on the assumption that the intensity variations are more or less constants within a region and take greater values outside their boundary. They represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. The most popular second-order statistical features for texture analysis are derived from the so-called co-occurrence matrix (Haralick 1979). They were demonstrated to feature a potential for effective texture discrimination in biomedical-images. Inside of this group one can highlight the features extracted from the co-occurrence matrix. Another statistical method used is autocorrelation function. [11]

5. Texture Feature Analysis Methods

The main purpose of texture feature extraction is to obtain relationships among the pixels that belong to a similar texture, such as spatial gray level dependence. These relationships allow distinguishing every distinctive texture from the others. Texture feature extraction methods are locally applied to every pixel of the input image by evaluating some type of difference among neighboring pixels through small square windows that overlap over the entire image. The result obtained for each window is assigned as a feature value to the center pixel of that window. In order to obtain a good texture characterization, it is desirable to work with large windows, since they obviously contain more information than small ones.

There are several texture feature extraction methods namely:

- GLCM method
- Statistical method
- Run Length method
- Texture Spectrum method
- Tamura's method
- Wavelet based method
- Gabor filters method
- Law's method

5.1. Gray level co-occurrence matrix

Gray Level Co-occurrence Matrices (GLCM) is an old feature extraction for texture classification that was proposed by Haralick back in 1973 .It has been widely used on many texture classification applications and remained to be an important feature extraction method in the domain of texture classification. It is a statistical method that computes the relationship between pixel pairs in the image. Robert M. Haralick suggested the use of gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features among those we have considered:

- Angular second moment
- Contrast
- Entropy
- Homogeneity
- Maximum Probability
- Variance

The GXG gray level co-occurrence matrix Pd for a displacement vector d= (dx, dy) is defined as follows. The entry (i,j) of Pd is the number of occurrences of the pair of gray levels i and j which are a distance d apart. Formally, it is given as

$$Pd(i,j)=\{((r,s),(t,v)):I(r,s)=i,I(t,v)=j\} \qquad (6)$$

Where (r, s), (t, v) Є N X N, (t, v) = (r + dx, s + dy) and |.| is the cardinality of a set.

GLCM texture considers the relation between two pixels at a time, called the reference and the neighbor pixel.

5.2. Run Length Texture Feature Extraction

The gray level run length approach characterizes coarse textures as having many pixels in a constant gray tone run and fine textures as having few pixels in a constant gray tone run.

The autoregressive model is a way to use linear estimates of a pixel's gray tone given the gray tones in a neighborhood containing it in order to characterize texture. For coarse textures, the coefficients will all be similar. Coarse textures are represented by a large number of neighboring pixels with the same gray level, whereas a small number represents fine texture. A primitive is a continuous set of maximum number of pixels in the same direction that have the same gray level. Each primitive is defined by its gray level, length and direction.

- Large number of neighboring pixels o the same gray level - coarse texture
- Small number ... Fine texture
- Lengths of texture primitives in different directions can be used for texture description
- Primitives - length, direction, gray level

$$K = \sum_{a=1}^{L} \sum_{r=1}^{N_r} B(a, r)$$

Based on the definition of the run length matrix, the following features are defined.

- Short Run Emphasis
- Long run Emphasis:
- Gray Level Non-Uniformity
- Run Length Non-Uniformity
- Run Percentage

Texture features are extracted using respective methods for different types of textures such as large, fine, coarse to find out optimal window size to capture texture pattern [12]

5.3. Gabor filters

Gabor filters is a popular signal processing method, which is also known as the Gabor wavelets. The Gabor filters are defined by a few parameters, including the radial center frequency, orientation and standard deviation. The Gabor filters can be used by defining a set of radial center frequencies and orientations which may vary but usually cover 180° in terms of direction to cover all possible orientations. Due to the large feature size produced by signal processing methods, the Gabor filters requires to be downsized to prevent the "curse of dimensionality".

Principal Component Analysis (PCA) is one of the popular methods to downsize the feature space [13]. Gabor filter is still often used in texture classification but sometimes combined with other methods.

6. Choice of Wavelet Filter

Villasenor et al. [14] produced a definitive guide for wavelet basis selection for wavelet image compression. Less attention has been paid to filter choice for texture classification and analysis. When using the DWT for texture analysis and classification, the filters should be chosen to ensure an effective characterization of the spatial-frequency content. Many different filter characteristics can be considered important to the choice of filter. These characteristics include:

a) Regularity: This can be defined as the number of times the wavelet basis is continuously differentiable. This reflects the bases' "smoothness" and usually reflects the frequency Localization of the basis.

b) Compact Support: Spatial localization of wavelet filters is important in texture characterization.

c) Shift Invariance: The sub sampling necessary for the critical decimation of the DWT results in shift variance. However, the amount of shift variance can vary from filter to filter. Shift invariance is important for properly characterizing textures as a representation should not be dependent on the position of the input signal.

7. Extension to Two Dimensions

To extend the wavelet transform to two dimensions it is just necessary to separately filter and down sample in the horizontal and vertical directions. This produces four sub bands at each scale. Denoting the horizontal frequency first and then the vertical frequency second, this produces high-high (HH), high-low (HL), low-high (LH) and low-low (LL) image sub bands. By recursively applying the same scheme to the low-low sub band multi resolution decomposition can be achieved. Figure 7.1. Shows the normal layout of such decomposition at each scale the sub bands are sensitive to frequencies at that scale and the LH, HL and HH sub bands are sensitive to vertical, horizontal and diagonal frequencies respectively. In this, the known texture images are decomposed using DWT-discrete wavelet transform. The mean and standard deviation of approximation and detail sub-bands of three level decomposed images (i.e., LLk, LHk, HLk and HHk; for k = 1; 2; 3) are calculated as features and stored in feature library [15].

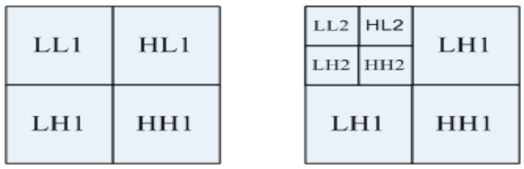

Figure 7.1: Block Diagram of Decomposition Using DWT

8. Texture Classification

Texture Classification: In this classification the unknown texture is decomposed using DWT and a similar set of wavelet statistical and co-occurrence matrix features are extracted and compared with the corresponding feature values stored in the Features library**.** [15]

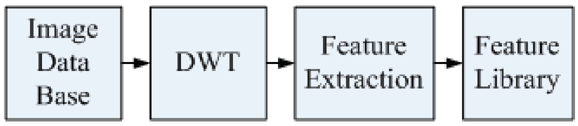

Figure 8.1: Texture Classification

9. Conclusion

Texture is an important cue which is used in many applications such as satellite imagery, printed documents, medical image analysis such as tumor identification and target identification. Texture has a variety of applications in the diverse fields. Texture analysis is a major step in texture classification, image segmentation and image shape identification. Wavelet Transform is one of the efficient and popular tools. and is much better than Gabor Filters or Fourier Transform The advantage of using wavelet-based coding in image compression is that it provides significant improvements in picture quality at higher compression ratios over conventional techniques. Since wavelet transform has the ability to decompose complex information and patterns into elementary forms, it is commonly used in acoustics processing and pattern recognition. Moreover, wavelet transforms can be applied to the following scientific research areas: edge and corner detection, partial differential equation solving, transient detection, filter design, electrocardiogram (ECG) analysis, texture analysis, business information analysis.

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