Classification of Texture with Features Extraction using Wavelet Approach

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Abstract—**Texture is an important aspect in image processing. Texture is repetition of patterns. Texture has a wide range of application; so it is very important to achieve correct texture classification. Texture classification is done by different methods and approaches on the basis of different features. Wavelet Transform is one of the popular and efficient ways of texture classification. Wavelet Transform employs multi resolution technique with less no. of coefficients which helps in fast and accurate texture classification. This paper elaborates the texture classification method with the help of wavelet for extracting the features. The system is trained for known textures and when unknown texture appears, its extracted features are compared with stored known features to classify it correctly.**

Keywords- feature, Texture, Texture classification, texture training ,Wavelet transform.

1. INTRODUCTION

Textures are visual patterns with characteristics of shape, size, brightness etc. Texture can be defined as a regular repetition of a pattern on a surface. Texture is a property that represents the surface and structure of an image. Textures can be fine, coarse, rippled, irregular, lineated, Texture analysis is the major step in image segmentation and texture classification. Texture analysis is a no. of mathematical models and procedures to identify the variations. A region in an image is said to have a constant texture if its characteristics are same or slowly changing. Properties like contrast, uniformity and regularity play important role to define, analyze and classify a texture. The first step of texture analysis is mainly to segment an image into some homogeneous sub-images. Many properties can be used to determine the region homogeneity such as the texture, the color of a region and the gray-level intensity. When there are many texture images in practice, texture is the main information that can describe the texture images exactly. Most natural surfaces exhibit texture. Texture analysis offers interesting possibilities to characterize the structural heterogeneity of classes. The texture of an image is related to the spatial distribution of the intensity values in the image, and as such contains information regarding contrast, uniformity, regularity etc. A considerable number of quantitative texture features can be extracted from images using different methodologies in order to characterize these properties, and then can be used to classify pixels following analogous processes as with spectral classifications. Texture analysis plays an important role in many biomedical images, satellite images, remote sensing, DNA analysis, protein analysis, Signal processing, image smoothing, image de-noising, speech recognition, heart rate and ECG analysis etc. Its tasks are mainly to cover these fields such as classification, segmentation, and synthesis. Texture is characterized by the spatial distribution of gray levels in a neighborhood. Although the texture has been widely applied to image analysis, no specific and universe definition is proposed for texture.

Although textures are widely used as descriptors, it has been difficult to establish an appropriate definition. Many vision researchers have given definitions frequently in the context of different applications areas.

The organization of the paper is as follows: second section explains about features of the texture; whereas third section elaborates different approaches of texture classification. The fourth section compares Wavelet Transform with Gabor Filters and Fourier Transform; whereas fifth section elaborates method of texture classification.

2. TEXTURE AND FEATURES

There are four major issues in texture analysis:

1) Feature extraction: to compute a characteristic of a digital image able to numerically describe its texture properties;

2) Texture discrimination: to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation);

3) 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) Shape from texture: to reconstruct 3D surface geometry from texture information.

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

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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.[1]

3. DIFFERENT APPROACHES OF TEXTURE CLASSIFICATION

Approaches to texture analysis are usually categorized into following methods:

i)*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.[2]

ii) *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 ill defined for natural textures because of the variability of both micro- and macrostructure and no clear distinction between them.[2]

iii) *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 modelling 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.

iv)*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.[2]

4. WAVELET TRANSFORM

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 [3]

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

$$\int_{-\infty}^{\infty} \left| \Psi(t)\, dt \right|^2 < \infty$$

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

$$\int_{-\infty}^{\infty} \left| \Psi(t)\, dt \right| = 0$$

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

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

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. Scaling is a property to create different lengths of wavelet functions by compressing or dilating the mother wavelet, in order to capture different frequency resolutions in the entire data. However, translation is a property to translate or move every generated wavelet function over the entire data, in order to capture the spatial localization information. These two important properties have actually explained the capability of multi-resolution analysis in wavelet transform [4]. If value of $|a| < 1$, then the wavelet is the compressed version (smaller support in time- domain) of the mother wavelet and corresponds mainly to higher frequencies. On the other hand, when $|a| > 1$, then $\psi[a\ ,b(t)]$ has a larger time-width than $\psi\ (t)$ and corresponds to lower frequencies. Thus, wavelets have time-widths adapted to their frequencies. Morlet first considered wavelets as a family of functions constructed from translations and dilations the "mother wavelet" $\psi(t)$. The basic idea of the wavelet transform is to represent any function as a superposition of wavelets. Any such superposition decomposes the given function into

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different scale levels where each level is further decomposed with a resolution adapted to that level. Typically, the wavelet transform maps an image on a low resolution image and a series of detail images. The low resolution image is obtained by iteratively blurring the image, and detail images contain the information lost during this operation.[3]

4. COMPARISON OF WT WITH GF AND FT

Gabor filters have proven to be powerful and precise for describing texture patterns. Wavelet transform is better than Gabor Filter. Gabor filter requires proper tuning of the filter parameters at different scale; whereas in low pass filter and high pass filters used in Wavelet Transform remains the same between two consecutive scales.

Output of Gabor filter bank are not mutually orthogonal, resulting in significant correlation between texture features; whereas wavelet transform provides precise and unifying framework for analysis and characterization of the signal at different scales. This means Gabor filter requires proper adjustment in filter parameters for different scale whereas Wavelet transform uses fixed parameters for analyzing image in different scales.

Fourier transform is a powerful mathematical tool commonly used, but Wavelet transform superseded it in many ways. Fourier Transform is a powerful tool for analysis of components of stationary signals. Stationary signals are those signals that there is no change in their properties. They are composed of some combinations of sine and cosine signals. Wavelet transform allows filters to be constructed for stationary as well as for non-stationary signals.

Fourier Transform is mainly used in signal processing and filtering applications; whereas Wavelet Transform is though used for signal processing and filtering, it is also used for nonlinear regression and compression.

Wavelet is a small wave i.e. an oscillation that decays quickly; whereas sinusoids used in Fourier transform are big waves. It is often possible to obtain a good approximation of the given function by using only a few coefficients with wavelet transform as compared to Fourier transform.

The main difference is that wavelets are well localized in both time and frequency domain whereas the standard Fourier transform is only localized in frequency domain. The Short-time Fourier transform (STFT) is also time localized and frequency localized but there are issues with the frequency time resolution and wavelets often give a better signal representation using Multi-resolution analysis

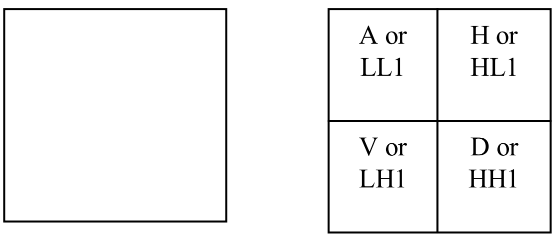

Fig. 1 discrete wavelet decomposition [one level]

5. METHOD FOR TEXTURE CLASSIFICATION

Texture classification employs two steps, (a) texture training and (b) texture classification. The features are extracted by decomposition of Discrete Wavelet Transform. Wavelet Statistical Features are mean and standard deviation of approximation [A] and detail sub-bands [V, H and D] of image. Wavelet Co-occurrence Features are contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence and max probability; derived from co-occurrence matrix [6].

5.1 DECOMPOSITION OF IMAGE USING DWT

The signals are of two types so are the wavelet transforms,
1] CWT – Continuous Wavelet transform

CWT is applied to the signals that are described by continuous function like recording of a speech signal or a music signal.

2] DWT – Discrete Wavelet transform

DWT on the other hand is applied to signals that are described by a sequence of numbers. It is derived from CWT. It is suitable for image analysis. The discrete sets of scaling parameter and translation parameter are used to provide sufficient information. This reduces complexity of calculations and saves time too. This is hugely advantageous in signal processing and image analysis.[7]

The DWT decomposes a signal $x[n]$ into an approximation (low-frequency) components and detail (high frequency) components using wavelet function and scaling functions to perform multi-resolution analysis. It decomposes into four sub-bands which are created from separate application of vertical and horizontal filters. Fig. 1 shows this. These sub-bands represent the finest wavelet coefficients named as LH1, HL1 and HH1 or V, H and D whereas approximation image, LL1 or A represents coarse level wavelet coefficients. This A or LL1 can be further decomposed. These values of coefficients in approximation and detail images are essential features and are used for texture identification and thus classification. [7]

5.2 TEXTURE TRAINING

Fig. 2 illustrates texture training. In texture training, the known texture images are decomposed using DWT-discrete wavelet transform as explained in previous section. Wavelet Statistical Features of approximation [A] and detail sub-bands [V, H and D] of image are calculated and stored in features library for further reference and utilization.[6]

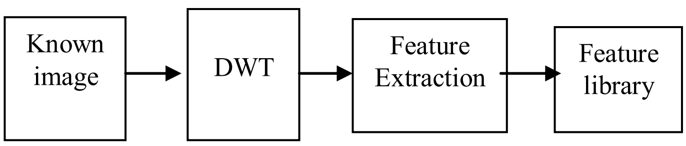

Fig. 2 block diagram of texture training

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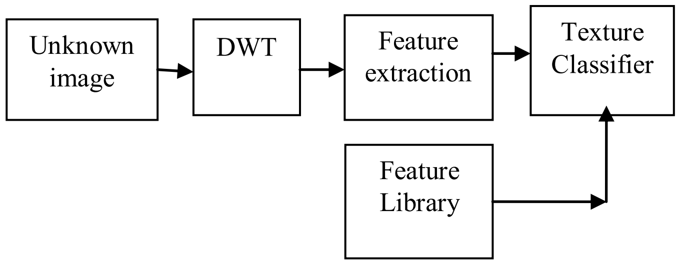


Fig. 3 block diagram of texture classification

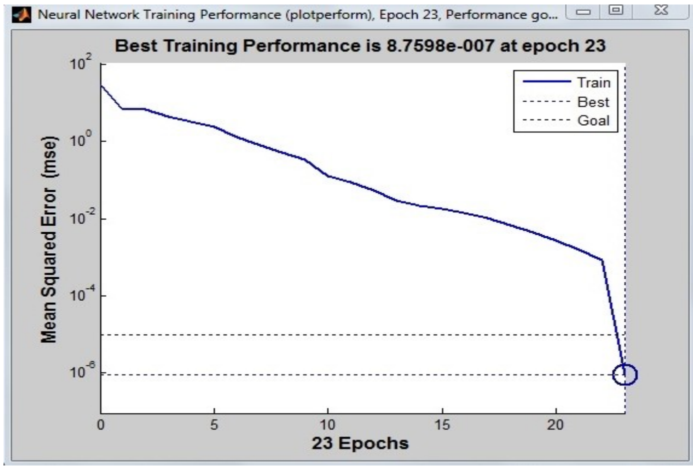
5.3 TEXTURE CLASSIFICATION

Fig.3 elaborates texture classification. In texture classification, an unknown image, whose texture to be classified is decomposed by Discrete Wavelet Composition- DWT and the features are extracted similar to texture training. This extracted set of wavelet feature are then compared stored set of features. The classifier used can be an Artificial Neural Network or a k-N classifier. As the feature extraction leads to a large dataset, it is preferred to use an Artificial Neural Network as a classifier, which facilitates easy and fast computation and clustering.

As artificial Neural Network is used, the performance is improved with iterations. The target set as expected output. The input fed to ANN is the extracted features; which is multiplied by the weights to give the output. This is actual output. The difference between Expected and actual output is error. The mean square of error is one of the parameter to check the performance of the system.MSE should be minimum. To achieve this, MSE is reduced iteratively. The graph 1 depicts this. The gradient controls the slope of the graph. If gradient is small, it takes a long time to achieve whereas if gradient is high, output may shoot to give undesired values. The gradient in turn can be controlled by mu; which decides how the weights to be adjusted during iterations; as the weights are random. [5]

6. CONCLUSION

Texture is an integral part of image processing. 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. It is used for Feature extraction, image analysis, texture identification and classification, image segmentation and image synthesis. This scheme of texture classification using wavelet transform can be implemented efficiently. It can be used for different sets of textures.



Graph1: Performance plot for ANN

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