Image Texture Analysis Techniques- Survey

Anita Dixit,
Asst.Prof, Dept of ISE, SDMCET
Dharwad.
Research Scholar, JNIAS ,Hyderabad
anitadixitjoshi@gmail.com

Dr.Nagaratna. P Hegde,
Associate Prof., Dept of CSE
Vasavi College of Engineering, Hyderabad
nagaratnaph@gmail.com

Abstract

This paper discusses the various methods used to analyze the texture property of an image. Texture analysis is broadly classified into three categories: Pixel based, local feature based and Region based. Pixel based method uses grey level co occurrence matrices, difference histogram and energy measures and Local Binary Patterns(LBP) Local feature based method uses edges of local features and generalization of co occurrence matrices. Region based method uses region growing and topographic models.

Key Words: Co occurrence matrix, Local Binary Pattern, Histogram

Motivation

Texture analysis is one of the use full areas of study in machine vision. Human eyes are good judges of differentiating texture of natural surfaces. Successful vision system is the one which realizes this texture to the world surrounding it[2]. Major goals of texture research in computer vision are to understand, model and process texture, and ultimately to simulate human visual learning process using computer technologies.

Introduction

There are three fundamental features with which a human being used to interpret pictorial information; Spectral, Textural and Contextual. Spectral information is nothing but the average tonal variation in various bands. Textual information gives the spatial distribution of tonal variation with in a band. In contextual, information is derived from the blocks of pictorial data surrounds the area being analyzed. Spectral features describe the average tonal variation in various bands of visible and/or electromagnetic spectrum. Whereas Texture feature describe the spatial distribution of tonal variation with the band. Texture is concerned with the spatial distribution of grey tones. Texture can be classified into different types, such as Fine, coarse or smooth, rippled, irregular or lineated. Texture is innate property of virtually all surfaces-grain of wood, weave of a fabric, the pattern of crops in afield etc. it contains the important information about the structural arrangement of surfaces and their relationship with its surrounding environment. Since textural properties are contain important information in discrimination purpose. Hence it is important to build features for texture. [1]

One common approach used to characterize an image's spatial information is to extract features for classification which measure the spatial arrangement of gray tones within a neighborhood of a pixel. This feature extraction method is referred to as texture analysis and includes a multitude of possible features that have been developed to describe image texture.

Fig 1: Variety of textures (a) Tarmac (b) Brick (c) wood (d) carpet (e) water (f) cloth

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Fig 1 shows the different types of texture which are experienced my human vision system [4] in general. The components of a texture, the Texel(texture element), are notional uniform micro-objects which are placed in an appropriate way to form any particular texture. If an intensity variation appears to be perfectly periodic, it is called periodic pattern not texture. However, any completely random pattern would probably be called a ‘noise pattern’ rather than a texture. If a pattern has both regularity and randomness then probably it would be called *Texture.*

Texture Analysis :

One common approach used to characterize an image's spatial information is to extract features for classification which measure the spatial arrangement of gray tones within a neighborhood of a pixel. This feature extraction method is referred to as texture analysis[2] and includes a multitude of possible features that have been developed to describe image texture.

Texture analysis refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. Texture is an areal construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale. Thus, the perception of texture is a function of spatial and radiometric scales. Mathematical procedures to characterize texture fall into four general categories, statistical, geometrical, model-based methods and signal processing methods and include Fourier transforms, convolution filters, co-occurrence matrix, spatial autocorrelation, fractals, etc. [2]

Because texture has so many different dimensions, there is no single method of texture representation that is adequate for a variety of textures. Here, we provide a brief description of a number of texture analysis techniques and some examples

Statistical method

Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Depending on the number of pixels defining the local feature statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The basic difference is that first-order statistics estimate properties (e.g. average and variance) of individual pixel values, ignoring the spatial interaction between image pixels, whereas second- and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. The most widely used statistical methods are co occurrence features and gray level differences [1], which have inspired a variety of modifications later on. These include signed differences [7] and the LBP (Local Binary Pattern) operator [6], which incorporate occurrence statistics of simple local microstructures, thus combining statistical and structural approaches to texture analysis. Other statistical approaches include autocorrelation function, which has been used for analyzing the regularity and coarseness of texture and gray level run lengths but their performance has been found to be relatively poor

Model Based method

Model-based methods hypothesize the underlying texture process, constructing a parametric generative model, which could have created the observed intensity distribution. The intensity function is considered to be a combination of a function representing the known structural information on the image surface and an additive random noise sequence

Geometrical method

Geometrical methods consider texture to be composed of texture primitives, attempting to describe the primitives and the rules governing their spatial organization. The primitives may be extracted by edge detection with a Laplacian-of-Gaussian or difference-of-Gaussian filter Once the primitives have been identified, the analysis is completed either by computing statistics of the primitives (e.g. intensity, area, elongation, and orientation) or by deciphering the placement rule of the elements The structure and organization of the primitives can also be presented using Voronoi tessellations[2] Image edges are an often used primitive element. Harlick et al. [1] generalized cooccurrence matrices, which describe second-order statistics of edges. An alternative to generalized cooccurrence matrices is to look for pairs of edge pixels, which fulfill certain conditions regarding edge magnitude and direction. Properties of the primitives (e.g. area and average intensity) were used as texture features

Signal Processing Method

Signal processing methods analyze the frequency content of the image Spatial domain filters, such as Law's masks, local linear transforms proposed by Unser and Eden (1989), and various masks designed for edge detection are the most direct approach for capturing frequency information Rosenfeld and Thurston (1971) introduced the concept of edge density per unit area: fine textures tend to have a higher density of edges than coarse textures.

Texture Analysis methods:

Auto correlation and Fourier method.

As we know that the texture is property in which intensity of an image varies region to region. This prompts us to calculate the variance of intensity over the whole region of a texture. However most of the time this will not provide enough description which is most of time needed. Especially when texels are well defined or where there is high degree of periodicity in texture. Then it is natural to consider the use of Fourier analysis. Moreover Fourier method is difficult to apply to an image which is to be segmented for texture analysis

Autocorrelation shows the local intensity variation as well as repeatability of the texture. It is use full for distinguishing short range and long range order in the texture. Auto correlation is not a good discriminator. in natural textures. Hence Co occurrence matrix introduced by Harlick et al [1] became a large degree of standard.

Pixel Based Models

In pixel based models texture is described by statistics of distribution of grey levels or intensities in the texture. Most widely used pixel based model is Grey Level Co occurrence model (GLCM). This is first introduced by Harlick et.al [1].

Grey Level Occurrence matrix (GLCM)

The fundamental concept behind these matrices is spatial distribution of grey level elements. In this approach a set of matrices are created that show the probability that a pair of brightness values (i,j) will occur at a certain separation from each other ($\Delta x, \Delta y$). The assumption is that the textural dependence will be at angles of 0°, 45°, 90° or 135° (with 0° being to the right and 90° above) from the original pixel that means four GLCM matrices would have to be created. Consider an image to be analyzed has Nx resolution horizontally and Ny resolution vertically. Grey tone appearing in each resolution cell is quantized to Ng levels.

The set $L_x X L_y$ is the set of resolution of an image ordered in row and column. An image *I* can be represented as function which assigns some grey tone in G. we assume that texture-context information in an image *I* is contained in overall or average spatial relationship which the grey tones in image *I* have to one another. Texture-context information is more adequately specified by matrix relative frequencies Pij with which two neighboring pixels are separated by distance of *d* occur in an image such matrices of grey tone spatial dependency matrices are function of angular relationship between neighboring cells as well as the distance between them.

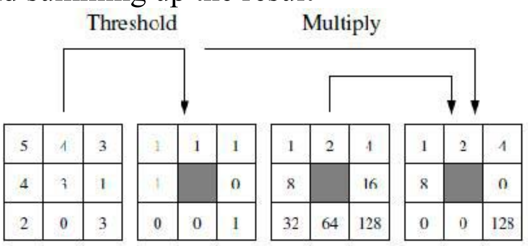
Since all texture information is present in grey tone spatial dependence matrices. Hence all texture features are extracted from these matrices. There are total 14 set of features of measures. But still it is difficult to say which measure describes which feature of texture.

Following are 3 features out of 14 which define the textural characteristics. They are Angular Second Moment(ASM), Contrast(CON) and Correlation(COR)

These metrics are calculated for each pixel for each using each of the four GCLMs and then a final texture value is usually calculated as an average of all four. It is obvious that these measurements can be computationally expensive especially as the quantization level becomes large. For many applications it may be beneficial to quantize the image into a smaller number of gray levels prior to creating the GLCMs

Local Binary Patterns

The local binary pattern (LBP) texture operator was first introduced as a complementary measure for local image contrast. 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 threshold values with weights given to the corresponding pixels, and summing up the result



$$LBP = 1+2+4+8+128 = 143$$
$$C = (5+4+3+4+3)/5 - (1+2+0)/3 = 2.8$$

Fig 2.Calculating the original LBP code and a contrast measure

Topi M¨aenp¨a¨a & Matti Pietik¨ainen[6] have explained LBP as follows, The LBP method can be regarded as a truly unifying approach. Instead of trying to explain texture formation on a pixel level, local patterns are formed. Each pixel is labeled with the code of the texture primitive that best matches the local neighborhood. Thus each LBP code can be regarded as a micro-texton. Local primitives detected by the LBP include spots, flat areas, edges, edge ends, curves and so on. Some examples are shown in Fig. 3 with the $LBP_{8,R}$ operator. In the figure, ones are represented as white circles, and zeros are black.

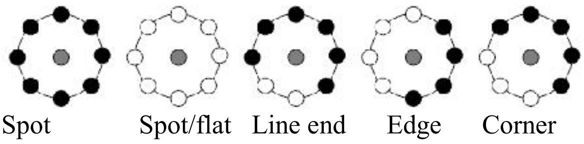


Fig 3. Different Texture Primitives detected by LBP

The LBP distribution has both of the properties of a structural analysis method: texture primitives and placement rules. On the other hand, the distribution is just a statistic of a non-linearly filtered image, clearly making the method a statistical one. For these reasons, it is to be assumed that the LBP distribution can be successfully used in recognizing a wide variety of texture types, to which statistical and structural methods have conventionally been applied separately. Ojala et.al [7]

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Texture Classification

Texture classification refers to assigning sample unknown 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 , texture synthesis, shape from texture. Fig4 shows the general fame work used for texture classification.

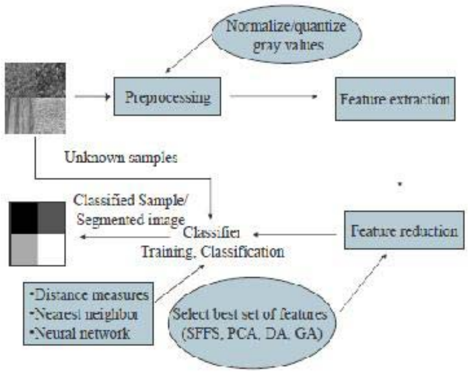

Fig-4. General frame work of texture classification

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.

Choosing an algorithm for Texture analysis

When choosing a texture analysis algorithm, a number of aspects should be considered [14] :

1. Illumination (gray scale) invariance; how sensitive the algorithm is to changes in gray scale.
2. Spatial scale invariance; can the algorithm cope, if the spatial scale of unknown samples to be classified is different from that of training data.
3. Rotation invariance; does the algorithm cope, if the rotation of the images changes with respect to the viewpoint.[14]
4. Projection invariance (3-D texture analysis); The algorithm may have to cope with changes in tilt and slant angles.
5. Robustness wrt. noise; how well the algorithm tolerates noise in the input images.
6. Robustness with respect to parameters; the algorithm may have several built-in parameters; is it difficult to find the right values for them, and does a given set of values apply for a large range of textures.
7. Computational complexity;
8. Generativity; regenerating the texture that was captured using the algorithm.
9. Window/sample size; how large sample the algorithm requires being able to produce a useful description of the texture content.

Given a texture description method, the performance of the method is often demonstrated using a texture classification experiment, which typically comprises of following steps

1. Selection of image data:
2. Partitioning of the image data into sub images:.
3. Preprocessing of the (sub)images:.
4. Partitioning of the (sub)images data into training and testing sets.
5. Selection of the classification algorithm.
6. Definition of the performance criterion: two basic alternatives are available, analysis of feature values and class assignments,

It is obvious that the final outcome of a texture classification experiment depends on numerous factors, both in terms of the possible built-in parameters in the texture description algorithm and the various choices in the experimental setup. Results of texture classification experiments have always been suspect to dependence on individual choices in image acquisition, preprocessing, sampling etc., since no performance characterization has been established in the texture analysis literature

Markov random field models of texture

Markov models have long been used for texture synthesis, to help with the generation of realistic images. However, they have also proved increasingly useful for texture analysis. In essence a Markov model is a 1D construct in which the intensity at any pixel depends only upon the intensity of the previous pixel in a chain and upon a transition probability matrix. Therefore, all experimental results should be considered to be applicable only to the reported setup. Fortunately, there is some recent work aimed at improving the situation with standardized test benches, for example the MeasTex framework for benchmarking texture classification algorithms. Additionally, an increasing number of researchers are making the imagery and algorithms used in their work publicly available in the web

Feature Extraction

Feature extraction (or detection) aims to locate significant feature regions on images depending on their intrinsic characteristics and applications. These regions can be defined in global or local neighborhood and distinguished by shapes, textures, sizes, intensities, statistical properties, and so on. Local feature extraction methods are divided into intensity based and structure based. Intensity-based methods analyze local intensity patterns to find regions that satisfy desired uniqueness or stability criteria. Structure-based methods detect image structures such as edges, lines, corners, circles, ellipses, and so on. Feature extraction tends to identify the characteristic features that can form a good representation of the object, so as to discriminate across the object category with tolerance of variations. [3] **.**

Feature Extraction Methods

Serkan Hutipoglu, and Sunjit K. Mitra[5] suggested two different methods for texture feature extraction, Quadratic teager filter and Singular value decomposition(SVD). Quadratic teager filter is used to find the local energy values. SVD values are used for feature extraction that represents the low frequency property of an image texture.

Applications

Four major application domains related to texture analysis are texture classification, texture segmentation, shape from texture, and texture synthesis

For texture analysis normally the image is converted to grey scale image. But the use of joint color texture method using color histogram was proposed in [10].

Using color and texture feature is an efficient combination for content based image retrieval [17]

Texture analysis is used majorly remote sensed images. Textural analysis techniques, namely fractals and spatial autocorrelation methods, were used to characterize these images in terms of image complexity and roughness associated with forests. The effects of spatial and spectral characteristics of the data on the estimates of the textural indices were also examined.

Fractals are measures of the self-similarity and thus ultimately measure the degree of complexity of the imaged land surface

Spatial autocorrelation is an assessment of the correlation of a variable in reference to spatial location of the variable. Spatial autocorrelation measures the level of interdependence between the variables, the nature and strength of the interdependence.

Conclusion

Texture is one of the important feature of recognizing an image. It is one such feature which cannot be defined properly in terms of computer vision.

Typically, a texture starts with a surface that exhibits local roughness or structure which is then projected to form a textured image. Such an image exhibits both regularity and randomness to varying degrees: directionality and orientation will also be relevant parameters in a good many cases. However, the essential feature of randomness means that textures have to be characterized by statistical techniques, and recognized using statistical classification procedures. Techniques that have been used for this purpose have been seen to include autocorrelation, co-occurrence matrices, texture energy measures, fractal-based measures, Markov random fields, and so on.

In this paper I have made an effort to present the various methods of texture analysis, texture classification and their applications.

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