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# Overview of Texture Image Segmentation Techniques

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***Abstract—Texture is pervasive in natural images and is a powerful cue for a variety of image analysis and computer vision applications like image segmentation, shape recovery from texture, and image retrieval [1]. Texture analysis has wide range of applications like medical diagnosis, content-based-image retrieval, satellite imaging and many others. Since texture is not a local phenomenon, one must take into account a neighbourhood of each pixel in order to classify that pixel exactly. The problem of segmenting an image based on texture basis is referred to as texture segmentation problem. Textures may be regular or randomly structured and various structural, statistical, and spectral approaches have been proposed towards segmenting them. The advancement in the last two decades in image analysis and computer vision has deepened the understanding of this field, yet it remains an open and challenging problem. Many recent techniques of texture representation and texture feature extraction are discussed here.***

***Keywords— Texture image segmentation, feature extraction techniques, Gabor transforms, Wavelet transform***

## I. Introduction

Texture can be termed as a measure of the variation in the intensity of a surface, quantifying properties such as smoothness, coarseness and regularity. It is widely used as a region descriptor in image analysis and computer vision. Texture is characterized by the spatial distribution of gray levels in the neighbourhood of pixels. Resolution at which image is observed determines how texture is perceived. An effective and efficient texture segmentation method is very useful in applications like analysis of aerial images, biomedical images and seismic images as well as automation of industrial applications, surface inspection. Texture is qualitatively described as the repetition of the local spatial patterns. Many textural dimensions or parameters are commonly proposed, namely, coarseness, contrast, density, roughness, directionality, frequency, regularity, uniformity, orientation, and so on (Tamura et al., 1978).
Texture primitives consist of micro-texture and macro-texture. Micro-texture is the smallest primitive while macro-texture is referred to larger primitive, i.e., macro-texture is composed of homogeneous aggregation of micro-texture. There is no clear criterion to differentiate micro-texture from macro-texture primitives. Texture plays an important role in many machine vision tasks such as surface inspection, scene classification, surface orientation and shape determination. For example, surface texture features are used in the inspection of semiconductor wafers, gray-level distribution features of homogeneous textured regions are used in the classification of aerial imagery, and variations in texture patterns due to perspective projection are used to determine three- dimensional shapes of objects.

## II. Literature Survey

### 1. Texture Representation Methods:

Texture is widely used in many fields such as video compression, video registration, and image segmentation. Texture segmentation involves accurately segmenting an image into differently textured regions ("textures"). Alternatively, texture segmentation can be viewed as the problem of accurately delineating the borders between different textures in an image. Texture segmentation is usually finished within two steps: the extraction of texture features and the image segmentation. There are a number of methods for texture representation, among which are structural, statistical, signal processing, and model-based methods.

***(A) Structural approaches*** (Haralick 1979, Levine 1985): These represent texture as composed of texture elements (textons). Here texture is defined by means of well-defined primitives called micro texture and a hierarchy of spatial arrangements of those primitives called as macro texture. To describe the texture, one must define the primitives and the placement rules. 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. A powerful tool for structural texture analysis is provided by mathematical morphology (Serra 1982, Chen 1994). It may prove to be useful for bone image analysis, e.g. for the detection of changes in bone microstructure. The method was successfully applied in medicine, especially for detection of changes in bone micro-structure.

***(B) Statistical approaches:*** In contrast to structural methods, statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Here the texture is represented indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. The main quality of these methods is the spatial distribution of grey values. These are the earliest methods of texture analysis in computer vision. Texture is described as a collection of statistics and selected features like mean, variance, etc. These features can also be classified as first-order statistics by applying operators directly on grey pixel values, second-order statistics by calculating the illumination difference for pixels fixed at a distance *d* from each other. Methods based on second-order statistics have been shown to achieve higher discrimination rates than the power spectrum (transform-based) and structural methods (Weszka 1976). Accordingly, the textures in grey-level images are discriminated spontaneously only if they differ in second order moments. Same second- order moments, but different third-order moments require deliberate cognitive effort. This may be an indication that also for automatic processing, statistics up to the second order may be most important (Niemann 1981). The most popular second-order statistical features for texture analysis are derived from the co-occurrence matrix (Haralick 1979). They were demonstrated to feature a potential for effective texture discrimination in biomedical-images (Lerski 1993, Strzelecki 1995). Probably the most important second-order statistical features for texture analysing are co-occurrence matrices. The co-occurrence matrix method named GLCM has become one of the most important and widely used statistical derivation approach in texture analysis.

***(C) Texture analysis based on model*** (Cross 1983, Pentland 1984, Chellappa 1985, Derin 1987, Manjunath 1991, Strzelecki 1997): These use fractal and stochastic models and attempt to interpret an image texture by use of generative image model and stochastic model. Estimated model parameters are used for image analysis. In practice, the computational complexity in the estimation of stochastic model parameters is the main problem. The fractal model has been known to be useful for modelling some natural textures. It can also be used for texture analysis and discrimination (Pentland 1984, Chaudhari 1995, Kaplan 1995, Cichy 1997); however, it lacks orientation selectivity and is not suitable for describing local image structures. These methods are usually used for specific textures analysis tasks like using fractals to adjust the textural properties of images. This model has proved good results especially in synthesize of images. A very popular approach for modelling images is the Markov random fields approach. They are able to capture the local (spatial) contextual information in an image. These models assume that the intensity at each pixel in the image depends on the intensities of only the neighbouring pixels.

***(D) Transform methods:*** These techniques of texture analysis, such as Fourier (Rosenfeld 1980), Gabor (Daugman 1985, Bovik 1990) and wavelet transforms (Mallat 1989, Laine 1993, Lu 1997) represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). Both spatial and frequency domain approaches can be used for filtering images and capturing relevant information. Due to lack of spatial localisation methods, which are based on the Fourier transform perform poorly in practice. Gabor filters provide good spatial localization; however, their usefulness is limited in practice because there is usually no single filter resolution at which one can localize a spatial structure in natural textures. Compared with the Gabor transform, the wavelet transform features several advantages:
i) Variation in the spatial resolution allows it to represent textures at the most suitable scale,
ii) Wide range of choices is available for the wavelet function, so one is able to choose wavelets best suited for texture analysis in a specific application which make the wavelet transform attractive for texture segmentation. The drawback of wavelet transform is that it is not translation-invariant (Brady 1996, Li 1997).
Multi-channel filtering [2]-[4] has been one of the most successful deterministic methods for texture analysis. While some of these are based on Gaussian–Markov random field texture models [5], others employ multi resolution autoregressive models [6] or hybrid approaches that combine statistical and structural techniques [7].
The multi-channel filtering approach to texture analysis is intuitively appealing because the dominant spatial-frequency components of different textures are different. An important advantage of the multi-channel filtering approach to texture analysis is that one can use simple statistics of gray values in the filtered images as texture features. This simplicity is the direct result of decomposing the original image into several filtered images with limited spectral information. The main issues involved in the multi-channel filtering approach to texture analysis are: 1) functional characterization of the channels and the number of channels, 2) extraction of appropriate texture features from the filtered images. 3) The relationship between channels (dependent vs. independent), and 4) integration of texture features from different channels to produce a segmentation.

## 2. Feature Extraction Techniques

For the purpose of feature extraction, two-dimensional (2-D) Gabor filters seem to be good candidates because of some outstanding properties like an optimum joint resolution in the space/spatial-frequency domain [8] as well as orientation and frequency selectivity. Since Gabor filtering requires excessive computational effort, it is necessary to make efficient selection of the proper number of filters and their parameters so that the computation time is minimized while obtaining the best segmentation quality. Representations based on multiresolution are very effective for analysing the information content of images. In computer vision, it is tedious to analyse the information content of an image directly from the gray-level intensity of the image pixels.

*1)* ***Feature-based methods*** characterize a texture as a homogeneous distribution of feature values such as gray level co-occurrence matrix (GLCM) and Laws' texture energy (LAWS). Even though both GLCM and LAWS were originally proposed in the context of texture classification, many researchers have applied them to texture segmentation [10, 11, 12, 13, 14, 15]. Spatial/spatial-frequency methods use a technique to generate a group of features from filtered images computed from frequency information at localized regions, such as Gabor functions or wavelet model.

***a) Gray level co-occurrence matrix (GLCM)*** was introduced by Haralick [16]. A co-occurrence matrix describes how often one gray level appears in a specified spatial relationship to another gray level. The entry at ***(i, j)*** of the GLCM indicates the number of occurrences of the pair of gray levels ***i*** and ***j*** which are a distance ***d*** apart along a given direction $\theta$. The values of ***d*** and $\theta$ are parameters for constructing the GLCM.

***b) Laws' texture energy (LAWS)*** combines predetermined one-dimensional kernels into various convolution masks [17]. The output image of the convolution process is considered as an "energy image", followed by a texture energy transformation in which each pixel at the centre of a local window ***(l (i, j))*** is replaced by the mean of absolute value in the filter window ***(f (i, j))*** as follows:

$$s(i,j) = 1/(2 \times n+1)^2 \sum_{k=i-n}^{i+n} \sum_{l=j-n}^{j+n} | f(k,l) - l(i,j) |$$

Where ***n*** is size of the mask.

***c) Gabor multi-channel filtering*** with Gabor functions (GABOR) was proposed by Jain and Farrokhnia [18]. Many texture-segmentation techniques are based on a filter-bank model, where the filters, called Gabor filters, are derived from Gabor elementary functions. The goal is to represent texture differences into detectable filter-output discontinuities at texture boundaries. By finding these discontinuities, one can segment the image into differently textured regions. However if the Gabor filter parameters are suitably chosen distinct discontinuities occur. Feature images are obtained by submitting each selected filtered image to a nonlinear transformation and computing a measure of energy around each pixel. Then, the average absolute deviation from the mean in small overlapping windows is computed.

According to Mallat [25], multiresolution representation provides a simple hierarchical framework for interpreting the image information. At different resolutions, the details of an image generally characterize different physical structures of the scene. At a coarse resolution, these details relate to the larger structures which provide the image "context". It is therefore obvious to analyse first the image details at a coarse resolution and then gradually increase the resolution. Such a coarse-to-fine technique is useful for pattern recognition algorithms. It has already been widely studied for low-level image processing such as stereo matching and template matching.

Multichannel filtering approach for texture analysis is intuitively appealing because it allows us to exploit differences in dominant sizes and orientations of different textures. In several papers the successful applications of multichannel filtering for texture segmentation were reported [19, 20, 21] using various filtering techniques, such as isotropic filters [22] discrete cosine transform (DCT) [23] and Gabor filters. The reason for the popularity of Gabor filters is due to their joint optimum resolution in time and frequency. Randen and Husoy [24] have examined the performance of multichannel segmentation schemes based on a more general class of filters including Gabor filters. However a large combination of parameters makes texture discrimination using Gabor filters computationally expensive. Recent development in wavelet theory has provided a promising alternative through multichannel filter banks that have several potential advantages over Gabor filters namely,

(i) Wavelet filters cover exactly the complete frequency domain.

(ii) Fast algorithms are readily available to facilitate computation.

***2) Wavelet transform:*** More recently, studies on successful application of wavelet theory on texture analysis have been reported using the multiresolution signal decomposition developed by Mallat [25]. He used quadrature mirror filters to relate information at different scales of decomposition of the embedded subspace representation. Unser [26] used over complete wavelet decomposition of the standard wavelet and characterized the texture by a set of channel variances estimated at the output of the filter bank. The standard or the octave band wavelet decomposition imply finer frequency resolution in the low-frequency region than in the high-frequency region. The work of Chang and Kuo [27] indicates that the texture features are more prevalent in the intermediate frequency band. Laine and Fan [28] carried out studies on texture analysis based on this indication. They used multi-channel wavelet frames for feature extraction. One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high- frequency signals with relatively narrow band-width. So the main motivation of using the decomposition scheme based on M- band wavelets is to yield improved segmentation accuracies. The standard wavelet decomposition which gives a logarithmic frequency resolution whereas the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Further as an additional advantage, M-band wavelet decompositions yield a large number of sub bands which is required for good quality segmentation. In the filter-bank paradigm, if an input image contains two differently textured regions, then local spatial-frequency differences between the regions will (hopefully) produce differences in one or more filter-output sub images. Thus, textural differences are transformed into discontinuities in sub image output, where the discontinuities signify transitions between differently textured regions. These discontinuities can then be used, through further processing, to partition the image into different regions.

## 3. Feature Extraction Operators

Several feature extraction operators are discussed in this section.

### *A. Grey Level Difference Operators*

The first order statistical methods provide no information about the repeating nature of the texture. The GLCM method is a way of extracting second order statistical texture feature and contains information about the position of pixels having similar grey values. The co-occurrence matrix is a complex but relatively compact descriptor of the contents of the image.

 

Let's consider the following matrix $P_{ij}(x, y)$. Each element ***(x, y)*** in this matrix tells us how many pixels with intensity ***x*** have a pixel at intensity ***y*** that is ***i*** columns to the right and ***j*** rows below. So basically, ***(i,j)*** tells us how the two pixels are positioned one relative to the other and the ***(x, y)*** pair tells us how different their intensities are. All we have to do is to decide which of these points are we interested in and we can use a set of these as a descriptor very rich in information for the image patch. Actually this is one of the first descriptors that were proposed for texture analysing. Several features can be extracted and further analysed:

a) The ***energy*** or homogeneity sums up all the codes of the matrix and this gives us details on the dispersion of appearance. See figure 1 for description. The homogeneity is also known as Angular Second Moment (ASM).

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) * p(i,j)$$

b) If we have a regular texture that keeps getting repeated in exactly the same way over and over again, it means that one of the elements in the co-occurrence matrix will have a huge size and most of the other elements will be close to 0. In this case the entropy is going to be relatively low, because low entropy suggests a spiked aspect. The ***entropy*** formula is displayed below

$$Entropy = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) * \log(p(i,j))$$

c) The ***contrast*** is also defined as the local variation of the intensity

$$Contrast = \sum_{i=0}^{G-1} n2 \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) \right\},$$

d) The ***variance*** operator puts very high weights on the elements that differ from the average value in the matrix

$$Variance = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (1-\mu)^2 * p(i,j)$$

### *B. Edge Detection Operators*

The edges of objects in an image hold much of the information like location of objects, their size, shape, and something about their texture. An edge represents the transition of gray level of an image from an area of low values to high values or vice versa. The edge itself is at the centre of this transition. Edge detectors can be used as texture operators. This is because a textured area has many edges compared with a smooth area. Applying an edge detector to a texture produces many strong, bright edges while edge detector in a smooth area yields nothing. Smoothing the edge detector result gives a bright area that can be separated from the dark area that lacked edges.

The range operator is an edge detector that does work well on some textures. It takes the pixels in an ***n x n*** area, sorts them by value, and replaces the centre pixel with the range (the largest pixel value minus the smallest). Other edge operators that have provided good results in texture analysis are the variance, sigma and skewness.

### *C. Local Binary Pattern*

The Local Binary Pattern (LBP) operator is a simple and powerful gray-scale invariant texture primitive, derived from a general definition of texture in a local neighbourhood. The LBP method can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. The most important property of the LBP operator in real-world applications is its invariance against monotonic gray level changes caused, for example, by illumination variations. Another very important is its computational simplicity, which makes it possible to analyse images in challenging real-time settings. LBP is also very flexible: it can be easily adapted to different types of problems and used together with other image descriptors.

One of the several extensions that were added to the initial LBP operator is the use of circular neighbourhood and bilinear interpolation of values at non-integer pixel coordinates which allow any radius and number of pixels in the neighbourhood [29]. The variance in the gray scale of the local neighbourhood can be used as the complementary contrast measure.

## III. Conclusion

Segmentation of an image into differently textured regions is a difficult problem. Usually, one does not know a priori what type of textures exist in an image, how many textures there are, and what regions have which textures [30]. The segmentation can be supervised or unsupervised. In unsupervised segmentation no a priori information about the textures present in the image is available. This makes it a very challenging research problem in which only limited success has been achieved so far. The task of texture segmentation has been conceptualized as two modular processes: (l) feature extraction and computation and (2) segmentation of homogeneous textured regions based on the feature values. Texture Segmentation is often obtained by adopting independent sub processes of texture feature extraction, feature selection or reduction if number of features is very large followed by a segmentation algorithm. Texture analysis can be classified broadly into following categories namely, structural, statistical based, model based and transform based.

Usually, texture feature extraction methods are locally applied to every pixel of the input image by evaluating some type of difference among neighbouring 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 centre 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. On the other hand, goal of texture segmentation is separating the different uniform regions that constitute an input image by taking texture similarity into account. Finding precise localizations of boundary edges between adjacent regions is a fundamental goal for the segmentation task, and can only be ensured with relatively small windows. Therefore, good texture feature extraction requires large windows, while precise boundary localization demands small ones. Since both tasks must be applied in order to segment textured images, a certain trade-off regarding window size must be made.

Structural texture is the one in which original texture appears repeatedly in the space, and stochastic decomposition is designed for analysing the periodic macro texture. In the statistical method, local texture feature values such as the gray level co-occurrence matrix (GLCM) or the geometric characteristic values such as the border can be chosen to characterize the texture features; In model-based analysis method, the texture feature can be described by the random model, the parameters of which can also be utilized to segment the texture image. In signal processing-based method, wavelet decomposition is usually used.

One of the main drawbacks of using standard wavelets is that they are not suitable for the analysis of high- frequency signals with relatively narrow band-width. So the main motivation of using the decomposition scheme based on M-band wavelets is to yield improved segmentation accuracies. The standard wavelet decomposition gives a logarithmic frequency resolution, whereas the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Further as an additional advantage, M-band wavelet decompositions yield a large number of sub bands which is required for good quality segmentation.

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