RESEARCH ARTICLE OPEN ACCESS

Implementation of Threshold Entropy Filter for Segmentation of Different Textures Using MATLAB

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ABSTRACT
The area of texture segmentation has undergone tremendous growth in recent years. There has been a great deal of activity both in the refinement of previously known approaches and in the development of completely new techniques. Although a wide variety of methodologies have been applied to this problem, there is a particularly strong concentration in the development of feature-based approaches and on the search for appropriate texture features. Texture classification is used in various pattern recognition applications that possess feature-liked Appearance. This paper aims to compile the recent trends on the usage of feature extraction and classification methods used in the research of texture classification as well as the texture datasets used for the experiments. In this paper, we present a survey of current texture segmentation methods.
Keywords:-Texture, Pixel, Segmentation, Filter.

I. INTRODUCTION

Texture [3] 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.

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 REVIEW

Vaijinath V. Bhosle and Vrushsen P. Pawar[4] in the paper “Texture Segmentation: Different Methods” discussed that Image Segmentation is an important pixel base measurement of image processing, which often has a large impact on quantitative image analysis results. The texture is most important attribute in many image analysis or computer vision applications. The procedures developed for texture problem can be subdivided into four categories: structural approach, statistical approach, model based approach and filter based approach. Different definitions of texture are described, but more importance is given to filter based methods. Such as Fourier transform, Gabor, Thresholding, Histogram and wavelet transforms. These filters are used to VisTex images and Brodatz Textures Database. The main objective of this paper is to study different methods for texture segmentation.

J. Yuan, D. Wang and A. M. Cheriyadat[5] in the paper “Factorization-Based Texture Segmentation” introduced a factorization-based approach that efficiently segments textured images. They used local spectral histograms as features, and construct an M × N feature matrix using M-dimensional feature vectors in an N-pixel image. Based on the observation that each feature can be approximated by a linear combination of several representative features, they factor the feature matrix into two matrices-one consisting of the representative features and the other containing the weights of representative features at each pixel used for linear combination. The factorization method is based on singular value decomposition and nonnegative matrix factorization. The method uses local spectral histograms to discriminate region appearances in a computationally efficient way and at the same time accurately localizes region boundaries. The experiments conducted on public segmentation data sets show the promise of this simple yet powerful approach.

Michal Haindl and Stanislav Mikes [1]in the paper "Unsupervised Texture Segmentation" discussed three efficient and robust methods for unsupervised texture segmentation with unknown number of classes based on the underlying Markovian and GM texture models and their modifications for medical mammographics and remote sensing applications, respectively. Although these algorithm use the random field type models they are fast because they use efficient recursive or pseudo-likelihood parameter estimation of the underlying texture models and therefore they are much faster than the usual Markov unsupervised segmentation.

Nawal Houhou, Jean-Philippe Thiran and Xavier Bresson[6] in the paper "Fast Texture Segmentation Based on Semi-Local Region Descriptor and Active Contour" presented an efficient approach for unsupervised segmentation of natural and textural images based on the extraction of image features and a fast active contour segmentation model. We address the problem of textures where neither the gray-level information nor the boundary information is adequate for object extraction. This is often the case of natural images composed of both homogeneous and textured regions. Because these images cannot be in general directly processed by the gray-level information, they propose a new texture descriptor which intrinsically defines the geometry of textures using semi-local image information and tools from differential geometry. Then, they use the popular Kullback-Leibler distance to design an active contour model which distinguishes the background and textures of interest. The existence of a minimizing solution to the proposed segmentation model is proven. Finally, a texture segmentation algorithm based on the Split-Bregman method is introduced to extract meaningful objects in a fast way. Promising synthetic and real-world results for gray-scale and color images are presented.

Kyong I. Chang, Kevin W. Bowyer and Munish Sivagurunath [7] in the paper "Evaluation of Texture Segmentation Algorithms" presented a method of evaluating unsupervised texture segmentation algorithms. The control scheme of texture segmentation has been conceptualized as two modular processes: (l) feature computation and (2) segmentation of homogeneous regions based on the feature values. Three feature extraction methods are considered: gray level co-occurrence matrax, Laws' texture energy and Gabor multi-channel filtering. Three segmentation algorithms are considered: fuzzy c-means clustering, square-error clustering and split-and-merge. A set of 35 real scene images with manually-specified ground truth was compiled. Performance is measured against ground truth on real images using region-based and pixel-based performance metrics.

Taramati S Taji and Deipali V Gore[3] in the paper "Overview of Texture Image Segmentation Techniques" discussed that 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. 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.

Ani1 K. Jain and Farshid Farrokhnia [2] in the paper "Unsupervised Texture Segmentation Using Gabor Filters" presented a texture segmentation algorithm inspired by the multi-channel filtering theory for visual information processing in the early stages of human visual system. The channels are characterized by a bank of Gabor filters that nearly uniformly covers the spatial-frequency domain. They propose a systematic filter selection scheme which is based on reconstruction of the input image from the filtered images. Texture features are obtained by subjecting each (selected) filtered image to a nonlinear transformation and computing a measure of “energy” in a window around each pixel. An unsupervised square-emr clustering algorithm is then used to integrate the feature images and produce segmentation. A simple procedure to incorporate spatial adjacency information in the clustering process is also proposed. They report experiments on images with natural textures as well as artificial textures with identical 2nd- and 3rd-order statistics.

Jitendra Malik, Serge Belongie, Thomas Leung and Jianbo Shi [8] in the paper “Contour and Texture Analysis for Image Segmentation” provided an algorithm for partitioning grayscale images into disjoint regions of coherent brightness and texture. Natural images contain both textured and untextured regions, so the cues of contour and texture differences are exploited simultaneously. Contours are treated in the intervening contour framework, while texture is analyzed using textons. Each of these cues has a domain of applicability, so to facilitate cue combination we introduce a gating operator based on the texturedness of the neighborhood at a pixel. Having obtained a local measure of how likely two nearby pixels are to belong to the same region, we use the spectral graph theoretic framework of normalized cuts to find partitions of the image into regions of coherent texture and brightness.

III. CONCLUSION

Texture segmentation has come a long way from manual segmentation to reasonable automated segmentation. Using just a few simple grouping cues, one can now produce rather impressive segmentation on a large set of Textures. In some cases from texture, meaningful objects have been identified based on variations of color depth beyond a threshold value. In some case boundary between two regions are measured by comparing intensity differences across the boundary and intensity differences between neighboring pixels within each region. But the works done so far will not be able to get meaningful texture segmentation in all cases, particularly when the threshold values change drastically within the same object or the object is a combination of various different parts with different features and colors. Although it is safe to draw the conclusion that very thorough, accurate and meaningful texture segmentation would be extremely difficult to achieve, the past and present directions and efforts of research on this problem seem to be appropriate and as such should be continued to achieve more accuracy as far as possible.

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