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Texture image segmentation using combined features from spatial and spectral distribution

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Abstract

Texture discrimination is playing a vital role in a real world image classification and object identification in a content based image retrieval (CBIR) system. For discriminating the textures, exact features have to be extracted. Although there are many techniques available they are not capable of classifying the universal textures because of their inherent limitations. In this paper, a novel method is introduced to extract the features by combining the texture discriminating features of spatial and spectral distribution of image attributes, and a comparison is made with the popular Gaussian and Gabor wavelets based methods for segmenting the image. The segmented outputs and the classification efficiency of the proposed method are found to be better and the time taken is reasonable.

Keywords: Gaussian wavelets; Gabor wavelets; Texture segmentation; Spatial; Spectral histogram

1. Introduction

Digital image libraries are becoming widely used, as more visual information is presented in digital form and are made available via Internet. To improve the digital access of visual objects, however, there must be an effective and precise method for users to search, browse, and interact with these collections and to do so in a timely manner. As a result, content-based image retrieval from large image database has been a fast growing research area. An extensive review on this subject is found in (Smeulders et al., 2000).

There are two types of retrieving the images in a CBIR system. They are global image retrieval and object/region based retrieval. In the first case the query image is matched with the database images by considering the entire image as a single feature set. In the second case the objects in the images are segmented and these objects, being the sub set of the images are matched with the objects stored in the image dataset. Though segmenting the objects at semantic level from the images is impractical with many real world images it is possible to separate them into its constituent regions characterized by the homogeneous properties. In practice the regional properties are defined in terms of the low level features such as color, shape and texture, out of which the texture plays a vital role in discriminating the regions. There are two phases in the segmentation process. The first one is feature extraction (FE) phase, where a set of feature descriptors is generated uniquely to represent the characteristics of each pixel in association with its

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neighbors to represent the texture characteristics. The second phase is clustering, where the pixels with the homogeneous attributes are clustered and labeled. The color features can be directly represented by their color attributes and can be clustered using the methods like simple color value threshold techniques (Cheriet et al., 1998), fuzzy C-means, K-means, SOM clustering. There are also block-based methods in CBIR, in which the images are not segmented but divided into several blocks from which features are extracted.

In this paper, the main focus is on the textured images as most of the real world images are textured. Texture image analysis is a topic investigated by researchers in the last few decades. Texture is a surface property of an object that is reflected in a digital image as a local pattern of intensity variation. When a digital image contains regions of distinctly different textures, it is possible to segment the image into its constituent parts based on them.

A good texture feature must allow us to determine both similarities and dissimilarities in intensity variation patterns present in different regions. It is well known that texture of regions cannot be characterized by intensity statistics alone (Julesz et al., 1978). The features have to represent statistical as well as structural characteristics of the texture using any mathematical measure or rule. Some of the most popular texture feature extraction methods are based on the gray level co-occurrence statistics (Gotlieb and Kreysig, 1990; Haralick, 1979), texton gradients, edge gradients (Marr and Hildreth, 1980), filtering methods like morphological filters, Fourier filters, random field models (Chellappa and Chatterjee, 1985), Gabor filters (Fogel and Sagi, 1989), wavelet packet approaches (Chang and Kuo, 1993; Laine and Fan, 1993), wavelet frames (Unser, 1995), wavelets like Gaussian (Cheriet et al., 1998; Charalampidis and Kasparis, 2002), fractal dimension (Kapalan, 1999), and local binary patterns (Ojala et al., 2002). Each method is superior in discriminating its texture characteristics and there is no universal method available for all textures. Randen and Husoy (1999) observed that the particular texture classification technique is restricted to a limited real texture. Every texture has a band of frequency components in it, where the selection of filter banks for extracting the features becomes a non-trivial task.

In this paper, different set of features is obtained by combining the spatial and spectral distribution of the image attributes to discriminate the texture for image segmentation. The novelty of this work is demonstrated by comparing the output with the segmented images obtained by Gaussian and Gabor wavelets.

The contents of the paper are organized as follows. In Section 2 the feature extraction techniques for discriminating the texture using Gaussian wavelets, and Gabor wavelets are presented. Section 3 describes the feature construction procedure by combining the spatial and spectral intensity distribution. In Section 4 the texture images obtained from the various benchmark image database are presented along with the segmented output images. Section 5 concludes the paper with some closing remarks.

2. Wavelet based feature description for texture segmentation

Image segmentation is the process in which the objects are separated from the image background and each other. There are two types of segmentation. They are total and partial segmentation. Total segmentation is possible only when tasks are simple. The segmentation of dark non-touching objects from a light background is an example of total segmentation. In more complicated problems, low-level image processing techniques handle the partial segmentation tasks, in which only the cues, which aid further high-level processing, are extracted. Often, finding the parts of object boundaries is an example of low-level partial segmentation.

The goal of texture segmentation is to partition an image into homogeneous regions and identify the boundaries, which separate regions of different textures. Segmentation is obtained by considering a gradient in the texture feature space, by unsupervised clustering, or by texture classification followed by labeling. Segmentation by labeling often suffers from a poor localization performance because of the conflicting requirements of region labeling and boundary localization in terms of the neighborhood observation (window size). Wavelet analysis has practically become ubiquitous tool in image and signal processing. Two basic properties, phase and frequency localization and multi-resolution analysis, make this a very attractive tool in image analysis. Wavelets, such as Gaussian and Gabor due to their multi-resolution capability have emerged as effective tools for analyzing textural information.

2.1. Gaussian wavelet features

The 1-D Gaussian smoothing function at scale 's' is

$$\psi(x,s) = \exp(-x^2/2s^2) \tag{1}$$

It can be expanded to 2-D Gaussian smoothing function at scale 's' which is defined as

$$\psi(x,y,s) = \exp(-(x^2+y^2)/2s^2) \tag{2}$$

Using this Gaussian function, computation of the filtered signal in an arbitrary direction θ requires

$$\Re^{\theta}(x,y,s) = \Re^{0}(x,y,s)\cos\theta + \Re^{90}(x,y,s)\sin\theta \tag{3}$$

It is computed as a linear combination of the two directions 0° and 90°, defined by the partial derivative of the smoothing function $\Psi(x,y,s)$ along x- and y-directions, respectively. $\Re^0$ is the first-order partial derivative of the function in Eq. (2) with respect to 0° or in x-direction and is represented by

$$\Re^{0}(x,y,s) = (-x/s^2)\exp(-(x^2+y^2)/2s^2) \tag{4}$$