Texture Analysis in Aerial Photography

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1 Abstract

Numerous practical applications of aerial photography require images to be interpreted in terms of their local texture. In order to faciliate the task of finding a texture of interest in an image or a set of images a system is developed which employs a spatial frequency characterisation of textures to detect a given texture in an image. The frequency content in different parts of the image is analyzed by an expansion into a set of *Gabor functions*. The coefficients in this expansion are used to characterize the texture in terms of different spatial scales and spatial frequencies. A patch-by-patch comparison of these parameters between a sample texture and the image can be used to highlight similar textures in an image.

The details of this approach are the topic of this project paper. In particular we discuss the idea of Gabor filtering in the fourier domain. An argument is made for the chosen set of Gabor functions (Gabor filters). Experiments are performed to assess the ability of the system to detect textures at different scales in real images. Also, we evaluate the possibility of detecting similar textures independent of their orientation in the image, which will be desirable in a number of possible applications.

2 Introduction

Aerial photography and other remote sensing image products have increasingly become an important means of aquiring information on a wide range of structures and parameters on the earths surface. The vast amount of data aquired by different imaging systems is leading to difficulties in the time-intensive task of interpreting the resulting images. It is therefor of interest to find means of analysing the images more efficiently and in a more objective way.

A lot of the information in an image is contained in its local texture and a number of applications are concerned with the detection of areas within a set of images that match a given texture pattern. Examples of this are land-use analysis or studies of urban development. Suburban development or agricultural monocultures as well as certain agricultural techniques appear as a characteristic texture in an aerial photo.

The perception of texture is a fundamentally neuro-psychological problem. The question arises, how the textures that appear similar to the human eye can be classified and parameterized more objectively. Gabor filters have been used in the past to classify textures. Experiments with the perception of textures by humans have led to a set of parameter values for the Gabor filter wavelets, which seems to parallel the human perception closely (**??**).

We used this set of parameters in our texture analysis system.

3 Gabor filters

A Gabor function is a two-dimensional Gaussian, modulated with a complex exponential. It's frequency domain representation is also Gaussian, convolved with a δ-function.

$$g(x,y) = (\frac{1}{2\pi\sigma_x\sigma_y})e^{-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2})}e^{i2\pi Wx} \tag{1}$$

$$G(u,v) = e^{-2\pi^2(\sigma_x^2u^2+\sigma_y^2v^2)} * *\delta(u-W) \tag{2}$$

$$= e^{-2\pi^2(\sigma_x^2(u-W)^2+\sigma_y^2v^2)} \tag{3}$$

where the fourier transform convolution theorem was employed. The shape of the function $g(x,y)$ is shown in figure (**??**). The parameters σ_x and σ_y have the effect of generalizing the shape of the Gaussian hump in two dimensions, so that the

contour lines can now be chosen to be elliptical rather than circular. We have tried to choose the shape of these ellipses in a way that most closely mimics the human perception, as will be discussed further below.

Applying the function $g(x, y)$ as a filter to an image amounts to a convolution of the image with this function. In the frequency domain, the fourier transform of the input image is multiplied with the transfer function, i.e. G(u,v). Again, the choice of σ_x and σ_y controls the shape of the contour lines of the transfer function while W can be chosen to place the Gaussian hump in the (u,v)-plane. These properties make Gabor functions suitable for the analysis of images with respect to their local frequency content.

We now want to construct a set of Gabor functions which are chosen to be sensitive to different orientations and spatial frequencies in an image. To understand this idea, a pictorial viewpoint in terms of corrogations and the respective filter responses will be given later. For now, we define a filter bank as

$$g_{mn}(x, y) = a^{-m} g(x', y'), \text{ where a¿1; m,n integer} \tag{4}$$

$$x' = a^{-m}(x \cos\Theta + y \sin\Theta) \tag{5}$$

$$y' = a^{-m}(-x \sin\Theta + y \cos\Theta) \tag{6}$$

$$\tag{7}$$

The angle $\Theta = n\pi/k$ determines the orientation of the function. Here, the parameter k is the number of orientations. a is the scale factor which can be used as a parameter to change the width of the function. The factor a^{-m} in equation (7) ensures that all filters in the filter bank have the same energy:

$$E_{mn} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |g_{mn}(x, y)|^2 dx dy \tag{8}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |a^{-m} g(x', y')|^2 dx dy \tag{9}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |g(x', y')|^2 dx' dy' \tag{10}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |G(u, v)|^2 du dv \tag{11}$$

$$= (2\pi\sigma_x\sigma_y)^{-1} \tag{12}$$

which is obviously independent of the choice of m and n. In equation (12) we made use of Parcevals theorem.

The rotation theorem of two dimensional fourier transforms states that a rotation in either domain corresponds to a rotation by the same amount in the other domain. Making use of this property we can place a number of these filter wavelets in the (u,v)-plane, eventually covering most of it. This is shown in figure (**??**), where the half-width contours of a set of wavelets are plotted. As can be seen from the plot, they are arranged such that the half-width contours of two neighboring filters touch. Adding all the contribution of these filters together will *not* give a constant response for all frequencies. But as the transfer function is known, the original image can be reconstructed from the filtered results.

4 The filter parameters

5 Sample responses

6 Texture classification

7 Application to a real image

8 Making the filter orientation independent

9 Further improvement and Conclusion

10 References