IMAGE SEGMENTATION FROM TEXTURE MEASUREMENT

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ABSTRACT

It is known that the human visual system, unsurpassed in its ability to reconstruct surfaces, employs different cues to solve this difficult task. The prevailing method in digital photogrammetry is stereopsis. However, texture may provide valuable information about the shape of surfaces. In this paper we employ Laws' method of texture energy transforms to extract texture information from digital aerial imagery. The images are convolved with micro-texture filters to obtain local texture properties. Each micro-texture feature plane is transformed into an texture energy image by moving-window to render macro-texture features. Finally, the macro-texture feature planes are combined and then clustered into regions of similar texture pattern. The method is implemented in a scale-space approach, and the boundaries obtained from texture are compared with physical boundaries of the image.

KEY WORDS: Texture primitive, Micro-texture, Macro-texture, Texture energy, Image Analysis.

1. INTRODUCTION

The goal of digital photogrammetry is to reconstruct surfaces automatically. Surface reconstruction from raw imagery is known as an ill-posed problem. To solve this difficult task, different cues which contribute to object recognition and scene interpretation are employed. One of the important cues is texture. Texture may provide information to estimate shape, surface orientation, depth changes, material of objects. Texture information aids image analysis and interpretation.

Many texture analysis methods have been developed during the last two decades. Among the great variety of available methods, Laws' approach of texture energy measures appears to be a suitable method (Ballard and Brown, 1982; Gool *et al.*, 1985; Gong and Huang, 1988; Unser and Eden, 1990). Furthermore, this method resembles human visual processing of texture according to Laws' dissertation. One of the advantages of this method is to provide several texture feature planes from an original image. This is a great benefit especially if only monochrome imagery is available because to extract useful texture information from raw monochrome images is a difficult task even for the human vision system. More useful information and segmentation results could be obtained by integrating the additional texture feature planes.

2. CHARACTERISTICS OF TEXTURE

Texture is qualitatively described by its coarseness under the same viewing condition, and related to the repetition of the local spatial patterns. In addition to coarseness, other textural dimensions or parameters are commonly proposed, namely, contrast, density, roughness, directionality, frequency, regularity, uniformity, orientation, and so on (Tamura *et al.*, 1978).

Texture is a sophisticate visual primitive since texture element (texel) is determined by contextual process and a different level of hierarchy. Texture primitives consists 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 homogeneous aggregation of micro-texture. These two primitives cannot be confused with fine texture and coarse texture. The coarseness of texture is related to the spatial repetition period of the local structure. Therefore, micro-texture and macro-texture are not related the coarseness. However, in fact there are not clear criteria to differentiate micro-texture from macro-texture primitives, rather it is related to somewhat psychological effect as well as image scale and resolution. Since texture is hierarchical, texture within texture primitives themselves is visible (Gool *et al.*, 1985). It is important to understand how the human visual system works for texture discrimination and grouping. To develop a computational texture analysis system is not an easy task due to the great complicatedness of properties of texture.

Texture has following characteristics;

- Texture is shift, orientation, moment, contrast, and illumination invariant.

- Human texture perception tends to be sensitive first- and second-order statistics, and does not respond to higher than second-order. Discriminable textures can be generated having a common mean, variance, and auto-correlation function. Thus, second-order moments are sufficient measures of texture.

- Texture is hierarchical, i.e., it corresponds to different resolutions and then global unitary impression is offered to the observer. Global features characterize the whole texture rather than texels.

The above characteristics are helpful guidelines in designing texture analysis system. The other important characteristic is that texture is both stochastic and deterministic, therefore, texture analysis methods are categorized by two major approaches; statistical and structural approaches.

3. TEXTURE MEASUREMENT

Texture energy transform developed by Laws is a class of spatial-statistical approach. The characteristic of this method is more matched to intuition about texture features, i.e., similar to human visual processing (Laws, 1980; Ballard and Brown, 1982). This method was developed after he investigated and evaluated several existing methods including statistical, structural, co-occurrence, spatial frequency, and auto-correlation approaches.

3.1 Texture Energy

The original image or a patch of the original image (f) is convolved with micro-texture filters (h_k) to create micro-texture features (f'_k);

$$f'_k(i,j) = f(i,j) * h_k \tag{1}$$

where the micro-texture filters can be formed from following four one-dimensional vector masks;

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L5 = [ 1   4   6   4   1]
E5 = [-1  -2   0   2   1]
S5 = [-1   0   2   0  -1]
R5 = [ 1  -4   6  -4   1]
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A total of sixteen two-dimensional micro-texture filters can be created. These are L5L5, L5E5, L5S5, L5R5, E5L5, ..., R5R5. However, L5L5 is not used because the sum of the filter elements is not zero.

In order to obtain macro-texture features (f''_k), each of the micro-texture images (f'_k) is transformed into an texture energy image by moving macro-texture window;

$$f''_k(i,j) = \frac{1}{W^2} \sum_{n=-w/2}^{w/2} \sum_{m=-w/2}^{w/2} \left| f'_k(n,m) \right| \tag{2}$$

where w is size of a macro-window. The micro-texture feature values are replaced by average of absolute values in a macro-windows. The size of the optimal macro-window depends on texture coarseness or regularity, as well as the quality of the available micro-features.

Micro-texture filters are designed to measure local texture properties, while the macro-texture features measure properties of the texture field as a whole. The problem is there is no guarantee that any particular resolution or window size will be optimal for a given analysis (Laws, 1980).

3.2 Texture Classification

Texture segmentation can be performed by classification. Most of the classification algorithms are suitable for multispectral imagery. Since several different micro-texture filters provide many corresponding texture feature plates, to use a multispectral classification algorithm is a quite reasonable approach. Classification of imagery is one of the main tasks in remote sensing. However, the pure texture-based classification method does not seem to be successfully developed yet. The purpose of image segmentation, based on texture information, is to obtain useful surface information.

Unsupervised classification is more attractive than supervised classification methods, because sometimes *a priori* knowledge about the area of interest is not available. Furthermore, human operators' intervention will not be allowed in fully automatic mapping and surface reconstruction systems.

4. EXPERIMENTAL RESULTS

4.1 Selection of Imagery

Left image (photo scale: 1/3,800) of "Munich" model (Figure 1), which was digitized with an EIKONIX camera to a resolution of 4096 by 4096 pixels, was used to implement our task. The "Munich" image contains residential areas, major high-ways, small roads, different kinds of vegetation, and a water area (small pond). For the scale space approach, 512 by 512, 1024 by 1024, and 4096 by 4096 images were used.

4.2 Texture Energy Features

All fifteen micro-texture images were created in coarse level. Then, each image was evaluated to select suitable filters. In fact, computational methods were not involved to select filters. Based on visual evaluation of the micro- and macro-texture features, E5E5, E5S5, S5E5, and S5S5 filters were chosen. Any micro-filters which did not provide clear texture patterns were not used in further levels. Selected filters were used through the next two levels. Macro-texture features were obtained with different macro-window sizes for each level. Macro-filter sizes selected for each level were 5, 15, and 31 for 512 by 512, 1024 by 1024, and 4096 by 4096 images, respectively.

The micro-filters selected in this study provided a similar pattern of texture energy features. The filters seems to detect horizontal, vertical and diagonal patterns of texture. It is obvious that micro-texture patterns will disappear by use of larger macro-window size. However, more homogeneous macro-textures will appear. Grouping of the micro-textures provided macro-texture.

4.3 Integration of Texture Feature Plates and Classification

Each texture feature plate is regarded as a spectral band to apply multispectral analysis. The texture feature plates are combined to one image file with BIL (band interleaved by line) format. Iterative self-organizing data analysis technique (ISODATA) in ERDAS was used for classification. The advantage of ISODATA is that the algorithm represents a fairly comprehensive set of additional heuristic procedures which have been incorporated into an interactive scheme (Tou and Gonzalez, 1974). Classification was performed through all three resolution levels. Figures 3, 4, and 5 are the results of classification for each level. The boundaries of both original and classified texture images were detected by using a Sobel edge operator (Figure 2 and 6).

The classification results were improved from coarse level to fine level. Classification result of fine level renders original image. However, the feature boundaries were not preserved due to the relatively large macro-window size. More boundaries were obtained from texture classification by comparing to the boundaries of the original image, especially in residential and vegetation areas. This result is possible, because in those areas different texture patterns are mixed. The result still shows lots of micro-textures which are reasonable to be grouped into a homogeneous area.

Optimal size of macro-window depends on scale, resolution, and objects in the image. To find optimal size of the window size is not easy. In addition, other very crucial factor for texture analysis is the classification method.

5. CONCLUSIONS

Laws' texture energy transform provides information about texture patterns of the surface. His approach to detect micro-texture and then group into a macro-texture feature is very realistic and a proper approach. However, to determine the fixed macro-window size for entire image is a difficult task. It is not easy to develop the dynamic size of the window, i.e., the window size varies depending on the objects in the image.

So far, many of the texture analysis methods do not succeed for natural scene imagery. Most of authors have used synthetic image or geometrical composite (or mosaic) of natural texture image patches to develop and evaluate texture operators. However, these kinds of imagery do not provide enough texture properties of natural scene.

Since color imagery contains more information than a monochrome one, to use color image is one way to improve the texture analysis system.

Finally, the 3D object space approach of texture analysis is probably a more interesting and more powerful solution.

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Figure 2. Boundaries of original image.

Figure 1. Original image of Munich model.
(resolution : 512 x 512)

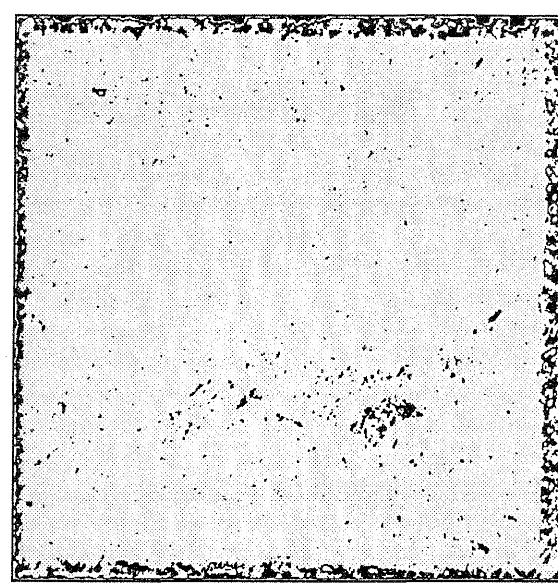

Figure 3. Texture classification of 512x512 image.
(macro-window size: 5)

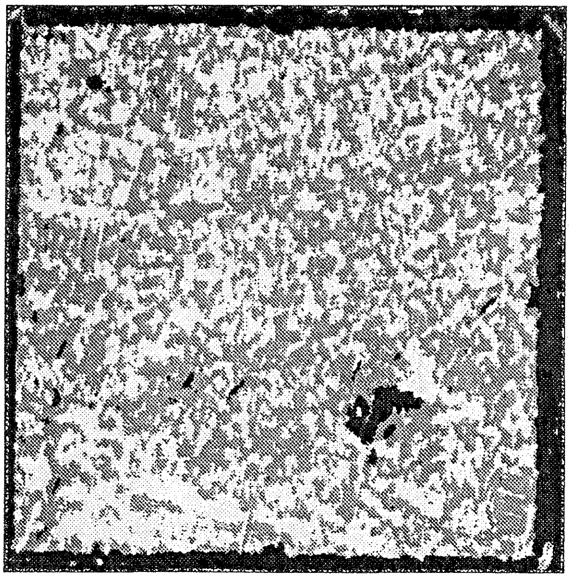

Figure 4. Texture classification of 1024x1024 image. (macro-window size: 15)

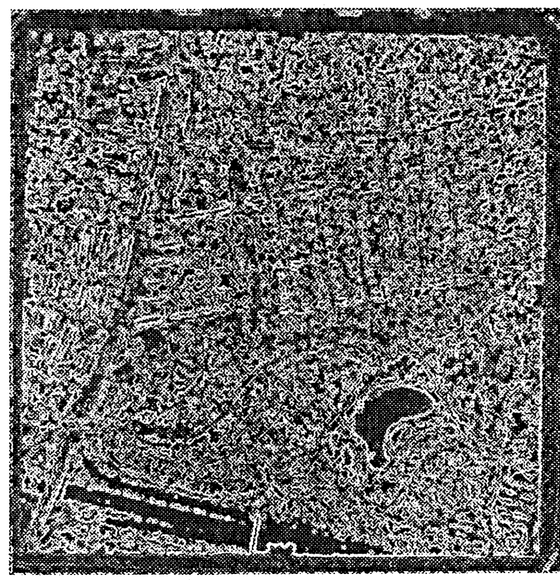

Figure 6. Boundaries of classified image (4096x4096)

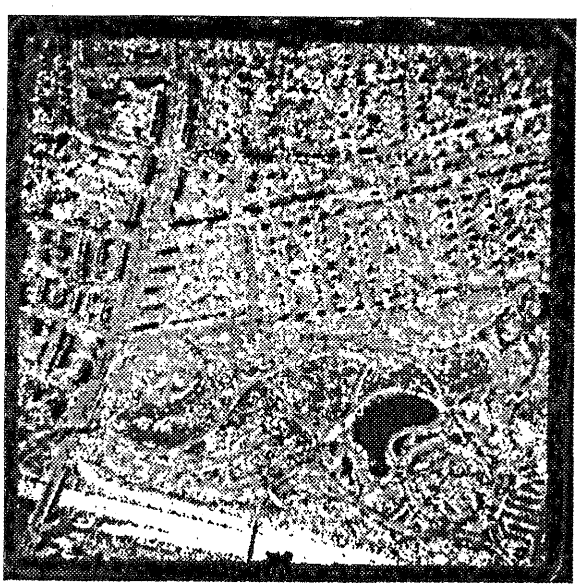

Figure 5. Texture classification of 4096x4096 image (macro-window size: 31)