Reducing Boundary Effects in Image Texture Segmentation Using Weighted Semivariogram

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1. Introduction

Texture, characterized by the spatial distribution of gray levels in a neighbourhood, is an important feature for many types of images including remotely sensed data, natural scenes and biomedical modalities and plays an important role in machine vision tasks such as surface inspection and scene classification. So texture analysis has been widely applied to many fields such as industrial automation, bio-medical image processing and remote sensing (Arivazhagan S. and Ganesan L., 2003).

Three primary issues are usually focused in texture analysis, texture classification, texture segmentation and shape recovery from shape. And a set of methods were proposed for texture analysis, which have been categorized into four groups: statistical, geometrical, model-based and signal processing-based (Tuceryan M. and Jain A.K., 1993).

As a statistical method, geostatistical technique has been popularly used in many texture anlaysis. It has been shown that range is directly related to the texture and/or objects size while sill is proportional to global object (class) variance; although it is effected by external factors i.e. image noise. Geostatistical method is based on the theory of regionalised variable, which can explore the spatial autocorrelation between pixels in the neighbourhood using variogram functions. A set of univariate and multivariate texture measures of spatial variability based on variogram estimators are available, such as variogram, madogram (mean absolute difference), rodogram (root pair difference), which show good performances in the classification and segmentation of remotely sensed images (Lark R M, 1996; Carr J.R. and Miranda F.P., 1998; Chica-Olmo M. and Abarca-HernaÂndez F., 2000).

In the process of texture calculation, moving window is used and features extracted are assigned to the center pixel of the window. So some problems arise in the process of texture computation and segmentation. One crucial issue, which is focused on in this paper, is the boundary blurring problem. Boundary regions tend to form new classes and go misclassified when using move-window in image classification, image segmentation and feature extraction. Many texture categories together with the boundary classed may overlap in the feature space. Boundary misclassification becomes especially problematic when using larger window sizes and for images with irregularly shaped boundaries (D.A. Clausi, 2004). The situation is that the larger the window size is, the more obvious the boundary effect is. But it's also suggested that the homogenous regions of different texture within the image must be sufficiently large to allow computation of the variogram up to a reasonable number of lags, and automatic fitting of (non-linear) models to variograms is unreliable (Atkinson P.M., 2000). So it has been in a dilemma to choose parameter for texture analysis. This paper will present an innovation to variogram-based texture derivation, which will improve boundary accuracy for image segmentation application.

2. Methods

In traditional variogram functions, features extracted are assigned to the center pixel of the window and pixel pairs in the image window are given a uniform weighting, which means that pixel pairs far from the center have the same impact with the ones close to the center. Thus boundary-blurring problems happen as pixels in the window across boundaries show higher contrasts than the ones in the window in the same class. By weighting pixel pairs in the center of the window higher than pixel pairs at the window boundary, boundary classes will be better classified.

For continuous variables, such as reflectance in a given waveband, the experimental semivariance is defined as half the average squared difference between values separated by a given lag h, where h is a vector in both distance and direction. Thus, the experimental variogram (or semivariogram, SV) $\gamma(h)$ may be obtained from $i=1,2...,N(h)$ pairs of observations $\{Z(x_i), Z(x_i+h)\}$ defined on a support $N(h)$ at locations $\{x, x+h\}$ separated by a fixed lag h :

$$\gamma(h) = \frac{1}{2}E(Z(x)-Z(x+h))^2 = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[z(x_i)-z(x_i+h)]^2$$

$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}|z(x_i)-z(x_i+h)|^m, (m \in [0,2])$ is used as the extension of the above formula.

An inverse distance weighting scheme is proposed based on the pixel pair's distance from the center of the window. This technique will be referred as weighted semivariogram (WSV) method. As shown in Fig.1, the distance between the pixel pairs and the center determines the impact on feature value of the center pixel. The greater the distance AB ($AA_1 + AA_2$ is also tried as a substitute) is, the lower impact is. So the function can be written as:

$$\gamma(h)=\frac{\sum_{i=1}^{N(h)} W_i[z(x_i)-z(x_i+h)]^2}{2\sum_{i=1}^{N(h)} W_i},$$

where W_i is equal to $\exp\left[-\frac{1}{2}\left(\frac{AB}{\sigma}\right)^2\right]$ (σ is taken to be $\frac{1}{4}$ of the window size) or $1/(AA_1+AA_2)$ in Fig.1.

Also, $\gamma(h)=\frac{\sum_{i=1}^{N(h)} W_i\,|\,z(x_i)-z(x_i+h)\,|^m}{2\sum_{i=1}^{N(h)} W_i}, m\in[0,2]$ is tested.

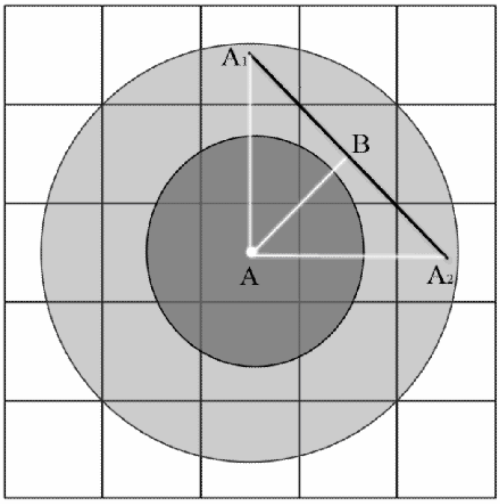
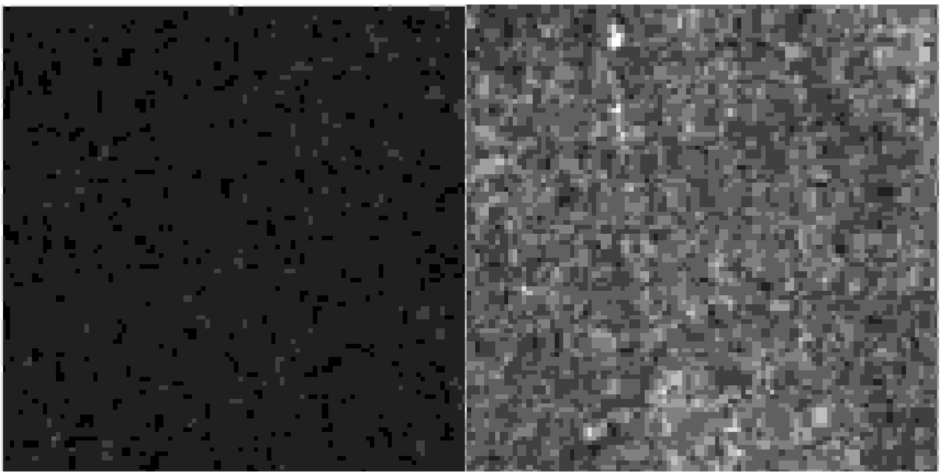


Figure1 Measuring the distance between the pixel pairs to the center, B is the midpoint of A_1A_2 .

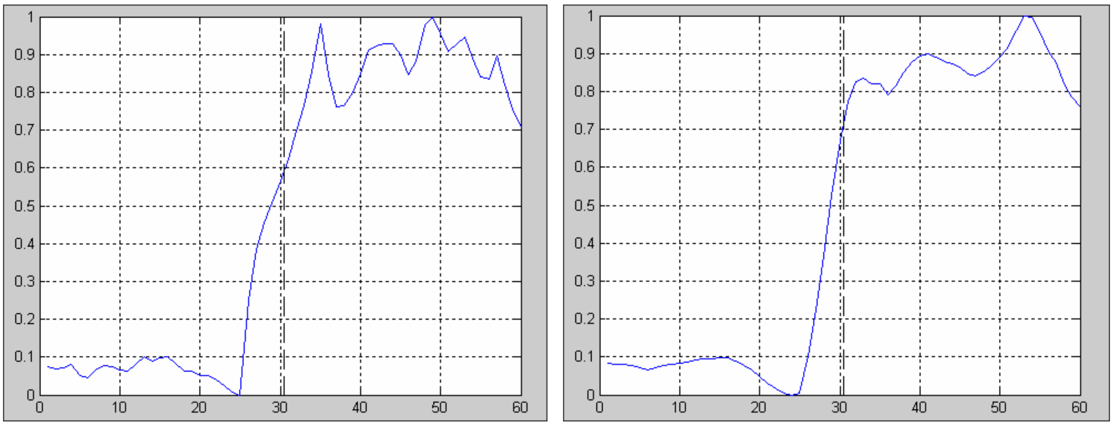
3. Experiments and Results

To compare which method can give better performance in boundary preservation, one test image (Fig 2(a)) is selected to generate textures. Sub images are cut from wetland area SAR image acquired from ENVISAT ASAR, including water (left-side) and land (right-side). Window size of 11×11 is selected and lag of 1 is used to compute texture. Then a boundary transect picture is got (Fig 2b, Fig 2c), which is the profile view of the texture value of as the image moves across the texture boundary. We can see that the boundary gets sharper and thinner when WSV is used, which means that boundary effect is reduced in some degrees.

Another sub image (Fig.3a) of Wetland area acquired from ENVISAT ASAR sensor is selected to test the segmentation performance. Two methods are used to generate textures and derive water from the image (Fig.3c, Fig.3d), in which the same window size of 7×7 and lag of 1 are selected. The true boundary is given to compare the segmentation performance. The segmentation accuracies of the two methods are 76.13% and 83.13% separately, which means 7 percent improvement for accuracy is got by using the WSV method.



(a)



(b) (c)

Figure 2 Edge transects across boundary of water and land texture images acquired from ENVISAT ASAR sensor. Broken lines represent the boundary. (a) Original image, consisting of water (left-side) and land (right-side), (b) texture transect got by SV, (c) texture transect got by WSV.

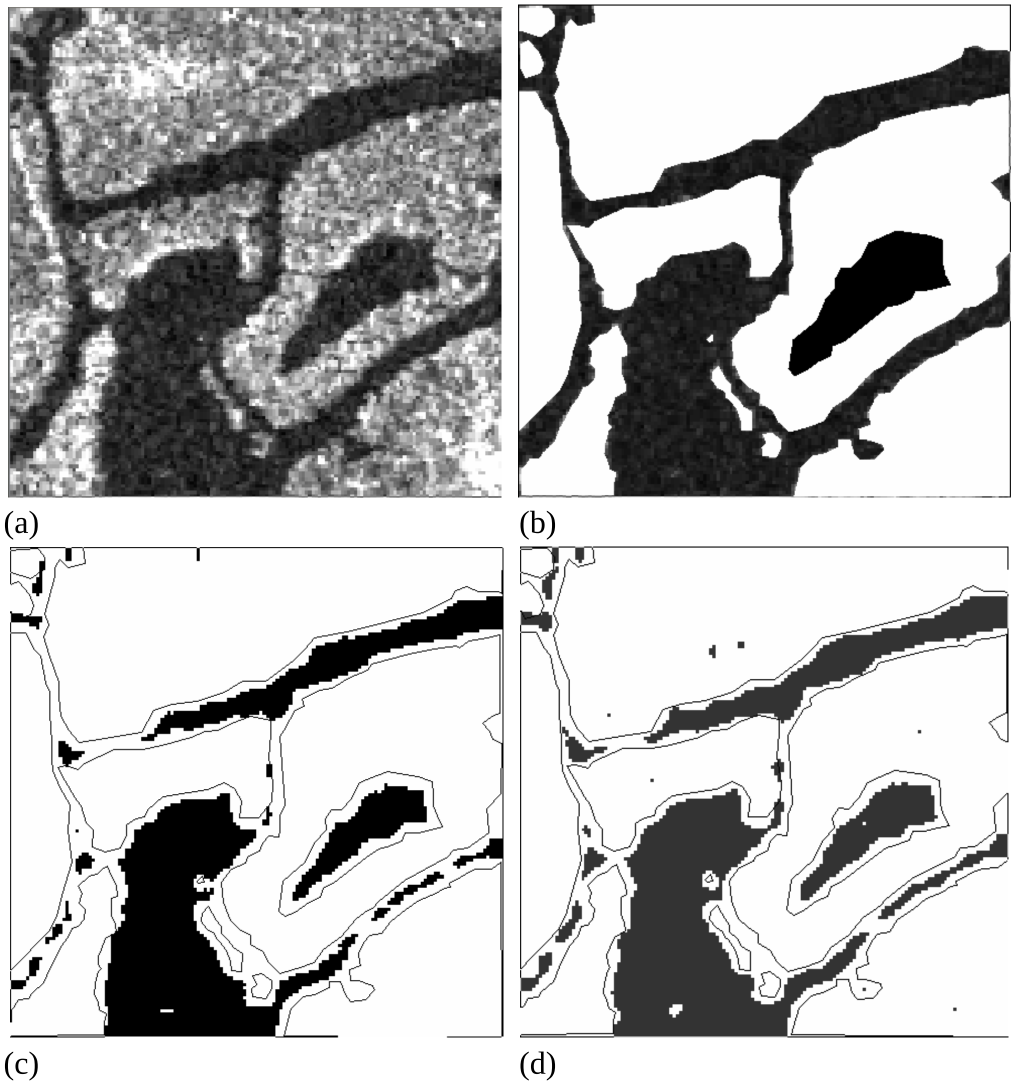


Figure 3 ENVISAT ASAR image of Wetland. Grey lines are the true boundaries. (a) Original, (b) Manual segmentation, (c) SV segmentation, (d) WSV segmentation.

4. Conclusions

This paper focuses on reducing the boundary effects for texture segmentation. From the tests some conclusions are reached: The WSV is a novel method for texture segmentation and should be better than the traditional semivariogram method. Better features are derived by weighting pixel pairs in the center of the window higher than the boundary ones, and class boundaries can be better identified. Before carrying out texture segmentation, transects across class boundaries are derived to analyze the performance of the feature separability, which is used to choose optimal window size and lag for texture computation. It’s believed that, with the aid of precise texture information, better classification performance should be achieved for high resolution remotely sensed images and the combination with spectral information is suggested.

5. Acknowledgements

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