LOCATION-ADAPTIVE TEXTURE: AN EXPERIMENT USING QUICKBIRD, ASTER AND LANDSAT ETM+ IMAGERY

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1. INTRODUCTION

One of the enduring problems in remote sensing analysis is how to exploit image texture [2]. A central question in texture analysis is the scale of the texture features analyzed, as determined by the size of the texture kernel (moving window). In a classic study, 90% of texture variability was found to be accounted for by the size of the kernel, compared to only 7% from the texture algorithm [3]. The major challenge in identifying an optimal kernel size is that *large* kernel sizes are required to produce relatively stable texture measures for characterizing spectral variability, but *small* kernel sizes are preferable to minimize the tendency of intra-class texture to overwhelm the inter-class texture that is usually of interest [2]. Thus the optimal texture scale is not just class dependent [1], but potentially also varies as function of location within an image class [2]. This paper is an investigation of how texture values vary with kernel size for different locations in an image, such as edges and interiors of classes, and whether such information can be used to develop a locally-adaptive texture measure. The approach is tested empirically with a case study utilizing images of three different spatial scales.

2. TEXTURE AND SCALE-BASED APPROACHES TO TEXTURE

Texture was calculated using the standard deviation of the image DN values in the kernel. The scale-dependent texture profile (termed "texture profile" for brevity) is a graph of texture values versus kernel size for a specific central pixel. Four broad classes of texture profiles were identified: flat and high, flat and low, rising, and falling (where these shape terms describe how texture changes from small to large kernel sizes). Within the rising and fall classes, eight sub-classes were defined to differentiate variations within the overall texture profile. Each texture profile was hypothesized to be associated with a specific image location. For example, flat and high texture profiles are associated with class edges, whereas flat and low profiles are typically found in the interior of relatively smooth classes. Rising profiles are found close to class edges or adjacent to small bright image objects. Optimal texture scales were then proposed for each image location. For example, falling texture, which is hypothesized to be associated with small image objects, was hypothesized to be represented best by the largest scale, so as to incorporate as many objects as possible. On the other hand, rising textures was hypothesized to be represented best by a scale where the profile is relatively flat.

3. CASE STUDY

The use of the texture profile in understanding and developing an optimal texture image was investigated with a case study of Morgantown, WV, USA. The city provides an ideal test site because of the sharp gradients in land use, and the wide range of urban and rural land cover-land uses. Three images at a range of spatial scales, but relatively similar dates or seasons, were selected: a multispectral QuickBird image with 2.8 m pixels acquired on 8/22/2002, an ASTER VNIR image with 15 m pixels acquired on 9/21/2001 and a Landsat ETM+ image with 30 m pixels, acquired on 9/17/2001. The Landsat and ASTER images were clipped to cover the same 19 x 14 km region, and the QuickBird image covered a 4.4 x 4.4 km subset of that region. Texture profiles were calculated for each image, using the red spectral band (Band 2 for ASTER, and 3 for Landsat and QuickBird). The red band was selected because it provided the best contrast between the urban land cover and the other classes. A set of rules using the Erdas Imagine Spatial Modeler (v 9.3) was constructed to identify each of the ten texture profiles, and to assign the texture from the hypothesized appropriate scale for that profile to the final adaptive texture image. Other than an additional median filter step applied to the texture generated for the coarser images, the processing procedures were exactly the same for the three images, despite the more than one order of magnitude difference in the pixel sizes.

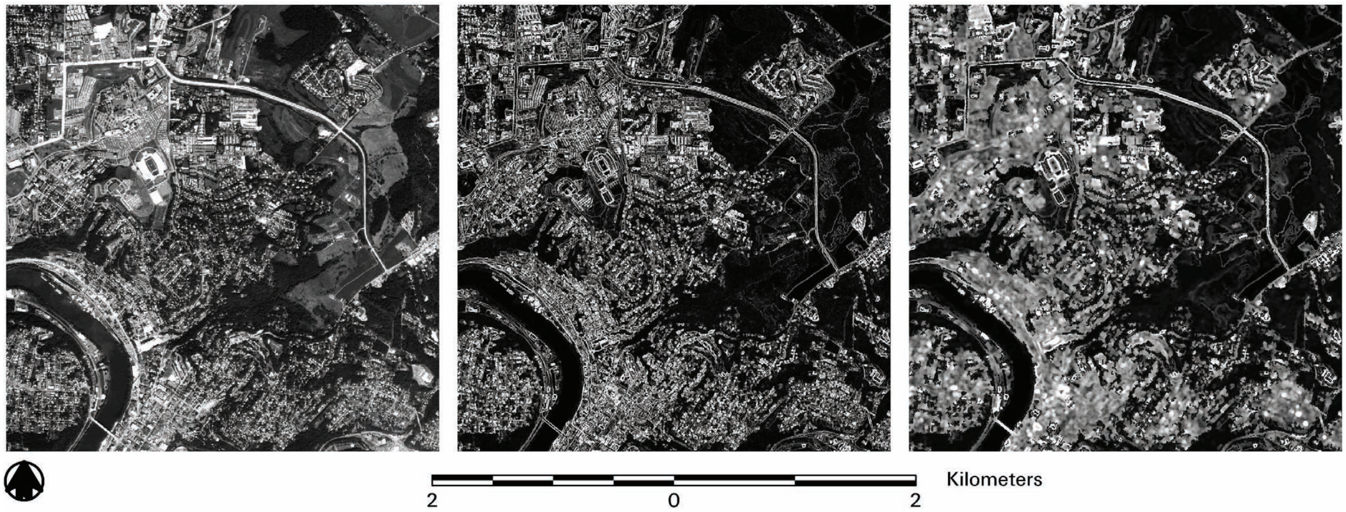

Figure 1. Left: QuickBird Band 3 (red) image of Morgantown, WV. Middle: 3x3 Texture image. Right: Adaptive texture image.

Each image was then classified using standard maximum likelihood classification, in order to test the empirical value of the adaptive texture measure in classification. A systematic series of classifications was conducted using the original multispectral data, and the multispectral data combined with texture computed from single kernel sizes as well as the adaptive texture measure. Classification accuracy was assessed using 600 randomly selected points across each of the three images that were verified based on 60 cm color DOQQ imagery acquired in April 2003.

4. RESULTS AND CONCLUSIONS

Figure 1 shows part of the QuickBird data. The original red band image (left image) shows a variety of textures, from the smooth texture of the river and agricultural areas, to the coarse texture of the urban development. The 3x3 texture (middle image) brings out the texture variation in the urban areas, but is highly varied, and tends to emphasize edges of image objects such as houses. The adaptive texture measure (right image) retains the crisp nature of the 3x3 texture at class edges, but results in notable smoothing of texture values across most of the urban area. For the ASTER and Landsat images (not shown) similar results were produced, with residential and commercial areas, as well as major highways generally associated with higher texture values. The maximum likelihood classifications of the various band combinations showed a consistent benefit of the adaptive texture, which overall gave the highest classification accuracy. As expected, texture data generated from single scales (whether one or multiples scales was included in the classification) generally increased the accuracy of classification of the urban classes, but tended to cause problems at the edges of classes.

These results suggest that the texture profile does provide a useful conceptual framework for approaching texture, and for understanding the limits to the incorporation of simple, first-order texture measures in a classification. The fact that the texture analysis method was essentially identical across an order of magnitude of scale difference in pixel size suggests that the texture rules developed here are generic, and not limited to one particular scale.

5. REFERENCES

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