CORRELATION OF OBJECT-BASED TEXTURE MEASURES AT MULTIPLE SCALES IN SUB-DECIMETER RESOLUTION AERIAL PHOTOGRAPHY

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ABSTRACT:

Texture measures are commonly used to increase the number of input bands in order to improve classification accuracy, especially for panchromatic or true colour imagery. While the use of texture measures in pixel-based analysis has been well documented, this is not the case for texture measures calculated in an object-based environment. Because texture calculations are computer intensive, fewer variables are preferred and knowledge of correlation and how it changes across segmentation scales is required. The objectives of this study were to assess correlations between texture measures as a function of segmentation scale while mapping rangeland vegetation structure groups using 5-cm resolution true-color aerial photography. Entropy, mean and correlation were least correlated with other texture measures at all scales. The highest correlation that remained stable across all segmentation scales was found for contrast and dissimilarity. We observed both increasing and decreasing correlation coefficients for texture pairs as segmentation scale increased, and there was larger variability from one scale to the next at finer segmentations and more consistency in correlation at medium to coarse scales. This was attributed to the fact that at finer segmentation scales, smaller objects were more numerous, and the ratio of edge to interior pixels for an image object was higher than at coarser scales. This approach allowed for determining the most suitable and uncorrelated texture measures at the optimal image analysis scale, was less computer intensive than a series of test classifications, and shows promise for incorporation into rangeland monitoring protocols with very high resolution imagery.

1. INTRODUCTION

Texture measures are commonly used in remote sensing in an attempt to increase classification accuracy and/or compensate for a low number of input bands, such as in panchromatic or true colour imagery. The additional information that can be exploited by using texture can be especially useful with high resolution satellite imagery and/or aerial photography (Ryherd and Woodcock, 1996; Wulder et al., 1998; Franklin et al., 2000; Coburn and Roberts, 2004). While the use of texture measures in pixel-based analysis for vegetation classification has been well documented (Gong et al., 2003; Tuominen and Pekkarinen, 2004; Pouliot et al., 2006), this is not the case for texture measures calculated in an object-based environment, with few exceptions ((Herold et al., 2003; Carleer and Wolff, 2006). Even when object-based image analysis (OBIA) is used, texture may be calculated in a pixel-based environment, and then imported as an additional band for further OBIA (Moskal and Franklin, 2002; Ivits et al., 2005). One of the reasons is that texture calculations can be very time consuming in OBIA, especially if multiple segmentation scales are analyzed and the imagery has high to very high resolution.

In OBIA, the analyst is usually faced with two main challenges: determination of the optimal segmentation scale, and selection of the most suitable features for classification. Due to the sensitivity of texture to scale (Ferro and Warner, 2002), an optimal segmentation scale is especially important when texture features are included. With multiple texture features, it is prohibitive to use trial and error, visual analysis, or test classifications to assess appropriate texture features or analysis scales due to computation times. Knowledge of correlation between texture features, and how correlation changes with segmentation scale is useful for selection of the least correlated texture features.

In this study, we used sub-decimeter resolution aerial photography acquired with an unmanned aerial vehicle (UAV), using an off-the shelf digital camera due to its light weight. Texture added an additional band to the highly correlated red, green, and blue (RGB) bands. The imagery was acquired for the purpose of mapping rangeland vegetation as part of on ongoing research project at the USDA Agricultural Research Service (ARS) Jornada Experimental Range in southern New Mexico. This research is aimed at determining the utility of UAVs for rangeland mapping and monitoring and developing a workflow for processing and analyzing UAV imagery in a production environment (Rango et al, 2006; Laliberte et al., 2007b).

Texture had proven to be a useful parameter for mapping rangeland vegetation, and had improved classification accuracy over only using RGB bands in a related study (Laliberte and Rango, in review). However, because a decision tree was used for feature selection, correlated features can be included and may be selected by the decision tree. Other feature selection tools, such as Feature Space Optimization in the OBIA software Definiens (Definiens, 2006) may also select correlated features. In the case of texture, use of unnecessary and correlated features can slow down classification times dramatically.

The objectives of this study were to assess correlations between texture measures as a function of segmentation scale, using as an example the mapping of rangeland vegetation structure groups (Bare Ground, Grasses, Shrubs) with 5-cm resolution true-colour aerial photography, acquired with an unmanned aerial vehicle (UAV).

2. METHODS

2.1 Study area and Imagery

The imagery was acquired in October 2006 at the Jornada Experimental Range in southern New Mexico over arid rangeland with a mixture of shrubs, grasses, and bare soils common to the northern part of the Chihuahuan desert. We used a small UAV (MLB BAT 3) with a weight of 10 kg and a wingspan of 1.8 m, equipped with a Canon SD 550 seven-megapixel digital camera. Imagery was acquired with 60% forward and 30% side lap for photogrammetric processing. Eight images were orthorectified and mosaicked into an image with a 5 cm ground resolution and covering an area of 490 m x 188 m.

2.2 Image Processing

Image analysis was performed using the object-based image analysis software Definiens Professional 5 (Definiens, 2006). The segmentation approach is a bottom-up region merging process based on heterogeneity of image objects, and controlled by three segmentation parameters: color/shape, compactness/smoothness, and a scale parameter (Benz et al., 2004). Color/shape and compactness/smoothness were set to 0.9/0.1 and 0.5/0.5 respectively, using as a guideline previous research with UAV imagery in this area (Laliberte et al., 2007b). We chose 15 segmentation scales (scale parameters) from 10 to 80 in increments of 5. At scales coarser than 80, individual shrubs were being merged together, therefore 80 became the cut-off for the coarsest scale.

The classes of interest were Bare Ground, Grass, and Shrub, and ground truth data consisted of 300 samples (100 per class) of polygons mapped in the field with differentially corrected GPS. Half of those samples were set aside for accuracy assessment. Classification was performed using a nearest neighbour classification, and accuracy was assessed by evaluating overall, producers, and users accuracies as well as the Kappa Index of Agreement (Congalton, 1991).

The texture measures used in this study were second order statistics derived from the grey-level co-occurrence matrix (GLCM), and describe changes in grey level values of pixels and relationships between pixel pairs in a given pair (Haralick et al., 1973). The 10 texture measures were derived after segmentation and represent texture features calculated on image objects (Table 1). In this software, pixels that border the image object directly are taken into account in order to reduce border effects (Definiens, 2006). Texture was calculated on RGB bands and on the average of all directions, because the vegetation classes of interest were not directionally biased.

We used a decision tree (CART®, Salford Systems) to determine the optimal texture measures for each segmentation scale based on the 150 input samples for the three classes. A decision tree is a non-parametric tool, and as such is not sensitive to outliers and correlated variables (Breiman et al., 1984). Decision trees are an excellent data reduction tool, especially when many features are available (Chubey et al., 2006; Laliberte et al., 2007a). However, a decision tree may select correlated variables; therefore an additional correlation analysis can further reduce data dimensionality. Spearman's rank correlation analysis was used to determine correlations, because this approach does not require assumptions of normality and linearity (Sokal and Rohlf, 1995).

Texture Measure	**Abbreviation**	**Formula**
GLCM Homogeneity	MHOM	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
GLCM Contrast	MCON	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
GLCM Dissimilarity	MDIS	$\sum_{i,j=0}^{N-1} P_{i,j}\lvert i-j\rvert$
GLCM Entropy	MENT	$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$
GLCM Angular 2nd moment	MASM	$\sum_{i,j=0}^{N-1} P_{i,j}^2$
GLCM Mean	MMEAN	$\frac{\sum_{i,j=0}^{N-1} P_{i,j}}{N^2}$
GLCM Standard Deviation	MSTD	$\sum_{i,j=0}^{N-1} P_{i,j}(i,j-\mu_{i,j})$
GLCM Correlation	MCOR	$\sum_{i,j=0}^{N-1} P_{i,j} \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i\,\sigma_j}$
GLDV Angular 2nd moment	VASM	$\sum_{k=0}^{N-1} V_k^2$
GLDV Entropy	VENT	$\sum_{k=0}^{N-1} V_k(-\ln V_k)$
$P_{i,j}$ is the normalized co-occurrence matrix, N is the number of rows or columns, σ_i and σ_j are the standard deviation of row i and column j, μ_i and μ_j are the mean of row i and column j, V_k is the normalized grey level difference vector, and k = |i-j|		

Table 1. Texture measures used in the analysis.

3. RESULTS AND DISCUSSION

3.1 Texture Features and Scale

The texture measures chosen by the decision tree at each segmentation scale are shown in Table 2. For each scale parameter, the order of texture features is displayed based on variable importance scores from the decision tree. For example, at scale 60, the order of texture features was MENT first, and MDIS second. The first variable represents the first splitter in the decision tree. As the scale increased, fewer variables were chosen by the tree, and MENT, MCON, and MSTD were

SP	MENT	MEAN	MCOR	MCON	MHOM	MDIS	MSTD	VENT
10	3	4	5	6	7		1	2
15	2		4		5	1		3
20	2			1				
25	2	3	5	1			4	6
30	2	5	6			1	4	3
35	2	4		5		3	1	
40	2			3			1	
45	1	4	5	2	6	7	3	
50	2					1		
55	1					2		
60	1					2		
65	1	4		2			3	
70	1			2		4	3	
75	1			2			3	
80	1			2			3	

Table 2. Order of texture features chosen by a decision tree for each scale parameter (SP).

selected in the same order from scale 65 to 80. The cross-validated relative cost (CVRC) of the decision tree, a measure of misclassification, representing the error rate of the tree, showed that the error rate decreased from 60% at scale 10 to 20%, the lowest value, at scale 60 (Figure 1). Those results were mirrored by the overall accuracies and the KIA values, which increased with increasing segmentation scales, reaching the highest values of 98% and 0.97 KIA at scale 65.

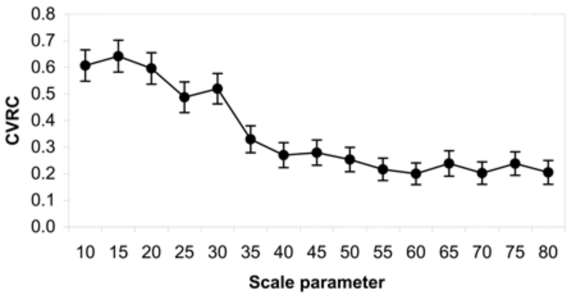

Figure 1. Cross-validated relative cost (CVRC) or error rate of decision trees for 15 segmentation scales.

3.2 Correlation of Texture Features

The highest correlation coefficients that remained stable across all scale parameters were found for MCON-MDIS and VASM-VENT (Figure 2), which was expected based on the equation structure (Hall-Beyer 2007) (see Table 1). For that reason, a graph of correlation coefficients for MDIS was omitted from Figure 2, because it was very similar to MCON. The values exported from Definiens for MASM for segmentation scales greater than 35 were all 0, therefore only coefficients up to that scale are shown in the graph.

MCOR, MMEAN, and MENT had the least correlation with other texture measures, although individual responses varied for some segmentation scales. We observed a definite change in correlation coefficients with scale parameter for several texture measure pairs. Some displayed decreasing correlation with increasing segmentation scale (MCON-MSTD, MHOM-MMEAN), others showed increasing correlation with increasing segmentation scale (MCON-VENT, MSTD-VENT).

Comparisons with other studies using texture at multiple scales can only be made with pixel-based studies, because to our best knowledge, there have been no studies of the use of various texture measures and their correlations in OBIA across multiple scales. While we saw several similarities with the choice of texture measures across multiple image types from other studies, our results with regard to correlation of texture measures are quite variable compared to other studies. This is understandable, because pixel-derived texture measures are compared with object-derived texture measures. In the following comparison, we are describing texture measures from our study using the abbreviation (i.E. MCON), and texture measures from other studies spelled out (i.E. contrast).

Clausi (2002), and Barber and LeDrew (1991) both reported that contrast and dissimilarity were strongly correlated, similar to our findings. Clausi (2002) noted that correlation was not correlated with any other texture measure and that there were high correlations between entropy and angular second moment. In our study, MENT and MASM had a high correlation only at the 2 finest scales, then decreased to correlations near 0 at scale 25. Although MCOR was one of the texture measures least correlated to all others, it still displayed considerable ranges in correlation for different scales. For example, after scale 30, correlation coefficients between MCOR and MCON increased to 0.6 and up to 0.7 for the coarsest scale. Generally speaking, Baraldi and Parmiggiani (1995) and Barber and LeDrew (1991) found higher correlation coefficients than we did. Baraldi and Parmiggiani (1995) determined that contrast and homogeneity were strongly and inversely correlated, while we observed an inverse, but weak correlation, with the highest correlation coefficient in our study at 0.5.

At scales 65-80, the decision tree selected MENT, MCON, and MSTD. Hall-Beyer (2007) placed these three texture measures in separate groups, whereby MENT is in the Orderliness group, MCON in the Contrast group, and MSTD in the Statistics group. In terms of choosing uncorrelated variables, Hall-Beyer (2007) advised to pick texture variables from separate groups, which our analysis appeared to corroborate. Our correlation analysis showed that, although MENT and MCON were closely correlated at scales smaller than 40, the two variables were not correlated at the coarser scales, where the accuracy was highest. The same held true for MCON and MSTD, and for MENT and MSTD. At finer segmentation scales, correlated variables were selected by the decision tree, and this knowledge is especially useful at fine scales, because classification times increase dramatically at finer scales and with multiple texture features.

At finer segmentation scales (below 20-25), correlation coefficients often changed at a greater rate from one scale to the next, while at coarser segmentation scales, the rate of change in correlation coefficient from one scale to the next was smaller (Figure 2a). Because image objects are very small at fine scales, the ratio of edge to interior pixels is greater at fine scales than at coarser scales, possibly resulting in more accurate representation of texture at coarser scales. In other words, if the image object is too small, texture may not be an appropriate feature to use, and correlations between texture pairs can vary greatly. For example, for MCONT-VENT, correlations changed from a strong negative correlation at fine scales to no correlation at scale 20, and then to correlations of 0.7.

In our study, observations with regard to the stability of correlations from one scale to the next mirrored the error rate of the decision tree (Figure 1.) as well as overall accuracy. At smaller scales, overall accuracy using texture measures was around 90% at scales up to 25, then increased to accuracies in the high 90% range at scales greater than 45. While those accuracy values are relatively high for all segmentation scales, we observed a marked increase in accuracy after scale 40.

In pixel-based texture calculations, the boundary problem increases with texture window size (Coburn and Roberts, 2004), as windows can straddle the boundary between ecotones or different landscape features. As the segmentation scale increases in OBIA, adjacent image objects differ more with regard to their homogeneity than adjacent image objects at very fine scales, and the boundary problem actually decreases with segmentation scale. For that reason, texture from pixel-based analysis calculated with different window sizes has very different results than texture from OBIA calculated at different segmentation scales.

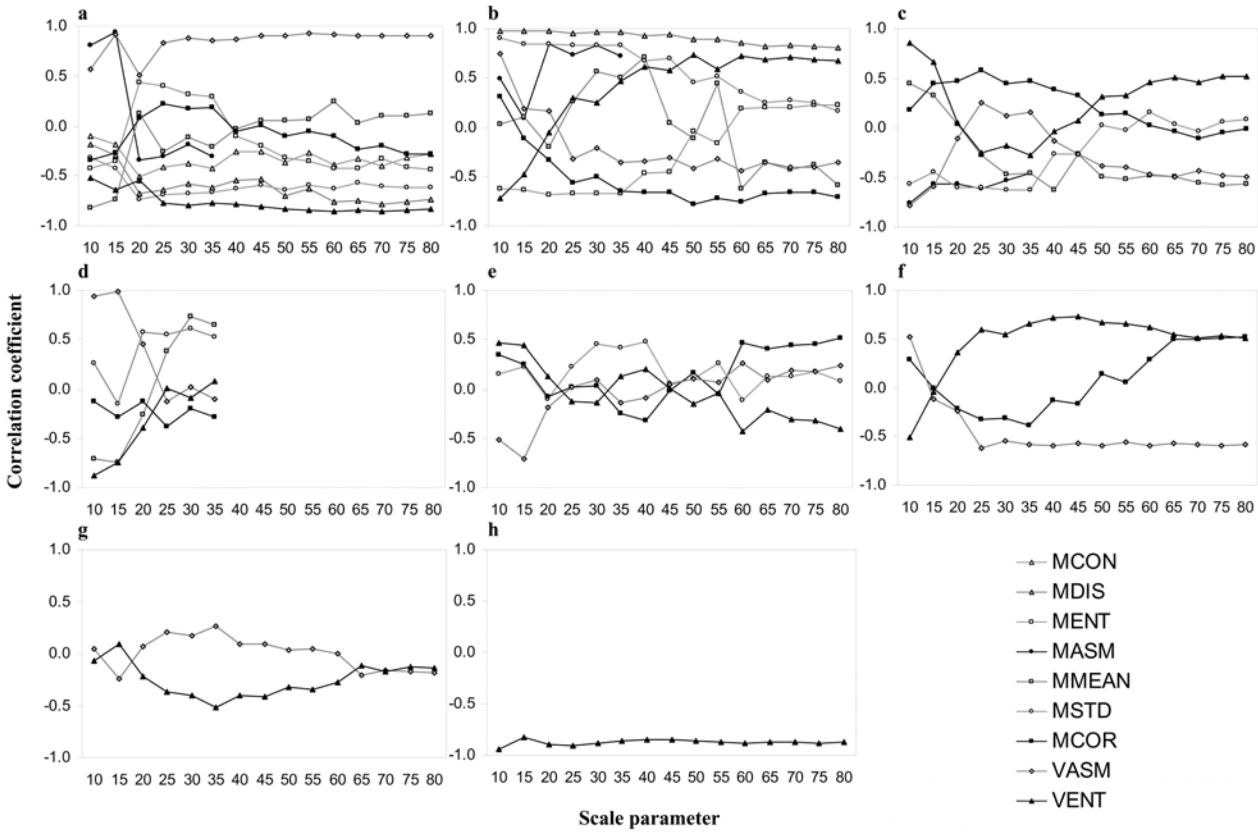

Figure 2. Correlation coefficients of texture measures for 15 segmentation scales. Shown are correlations of a) MHOM, b) MCON, c) MENT, d) MASM, e) MMEAN, f) MSTD, g) MCOR, and h) VASM. Texture measures for comparison are shown in the legend.

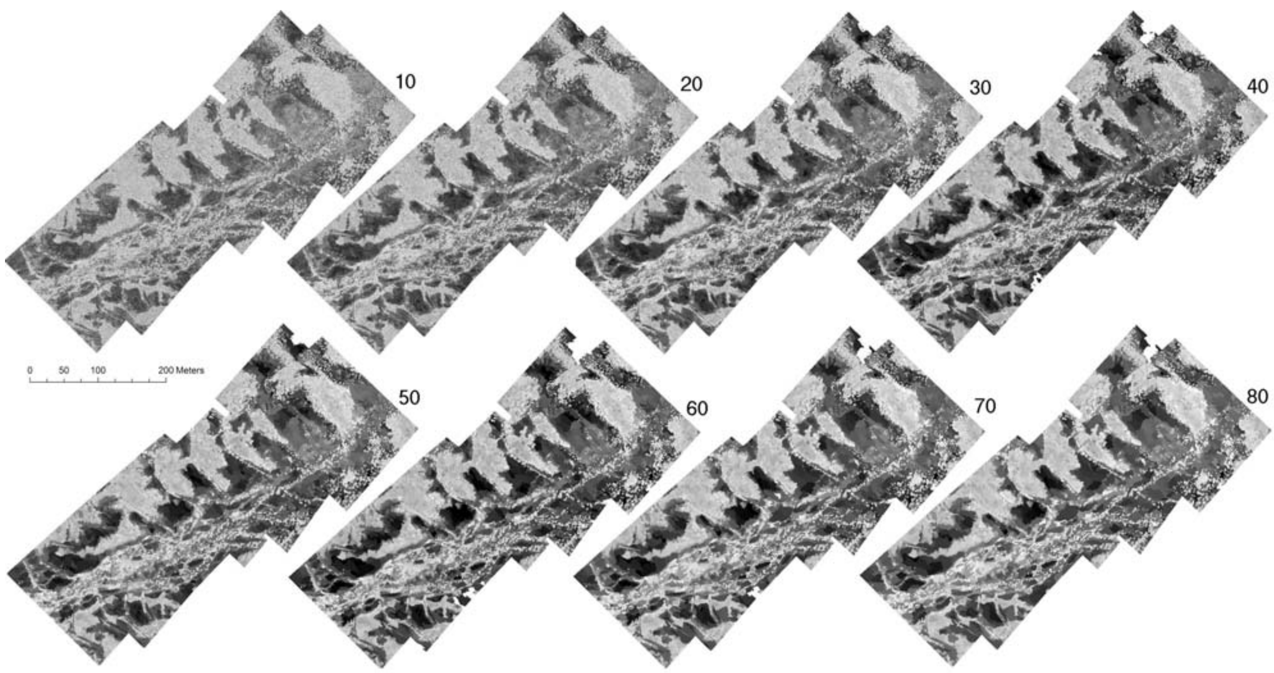

Figure 3. The texture measure entropy at eight segmentation scales from 10 to 80.

What remains the same in pixel- or object-based analysis, however, is the fact that texture is highly sensitive to scale, and an appropriate scale has to be chosen for an effective and meaningful analysis. Fewer variables are preferred, especially if calculations are computer intensive, as they are for texture. In this study, MENT was the texture measure ranking either first or second from scale 15 to 80 and was chosen in every decision tree. It also had the least correlation with other texture measures, and if only one variable were chosen for analysis, it would be MENT. Figure 3 shows the texture measure MENT at all segmentation scales. Gray values describing Bare Ground, Grass, and Shrub show more differentiation at coarser than at finer scales.

4. CONCLUSIONS AND FUTURE WORK

Using a decision tree allowed for reducing the number of input texture variables and assisted with the selection of the image analysis scale, which was confirmed based on overall accuracy and KIA values. Correlation analysis for texture pairs was used to further reduce the number of input variables. In our study, correlated variables were selected by the decision tree at finer scales, but less so at the coarser scales. Reducing data dimensionality is especially important when texture is used at fine analysis scales due to computation times.

We observed both increasing and decreasing correlation coefficients for texture pairs with increasing segmentation scales, with larger variability from one scale to the next at finer segmentations and more consistency in correlation at medium to coarse scales. This study suggests that the boundary problem common to texture analysis in pixel-based approaches appears to decrease in object-based image analysis with segmentation scale.

In this study, the highest overall accuracy, the CVRC of the decision trees, and the stability of correlation for variable pairs from one segmentation scale to the next all pointed to an optimal segmentation scale at or around 60. Additional studies in other vegetation communities and/or the use of more classes are needed to confirm if CVRC of decision trees coupled with correlation analysis can be used to determine not only the most suitable variables, but also the analysis scale. This would reduce computation times significantly, because calculating overall accuracies at multiple scales is computer intensive, while decision tree analysis can be performed more rapidly. Tools that allow for the determination of the optimal segmentation scale as well as feature selection are crucial in OBIA using Definiens, because much time is spent on those two aspects of image processing.

This approach allowed for determining the most suitable and uncorrelated texture measures at the optimal image analysis scale for mapping vegetation structure groups with sub-decimeter resolution imagery. In future studies, we plan to map individual species with this approach and incorporate these techniques into rangeland monitoring protocols with very high resolution imagery acquired either with piloted or unmanned aircraft.

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