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ESTIMATING TEXTURE INDEPENDENTLY OF TONE IN SIMULATED IMAGES OF FOREST CANOPIES

Tatiana Mora Kuplich[1]
Paul J. Curran[2]

[1]INPE - Instituto Nacional de Pesquisas Espaciais
Caixa Postal 515 - 12201-970 - São José dos Campos, Brasil
(tmk@ltid.inpe.br)

[2]Department of Geography - University of Southampton
Highfield – SO17 1BJ – Southampton, United Kingdom
(P.Curran@soton.ac.uk)

Abstract. Tone and texture are two fundamental characteristics of remotely sensed images. Current research on the remote sensing of tropical forest biomass uses the tone (i.e., backscatter) of Synthetic Aperture Radar (SAR) images as this is related directly to biomass (albeit up to the backscatter/biomass asymptote). As a tropical forest canopy ages so its unevenness increases, progressing from smooth to rough. Therefore a measure of SAR texture that is independent of SAR tone has the potential of increasing the biomass maxima that can be estimated with SAR data. This experiment used simulated SAR images designed to reproduce forest canopies and different patterns of tone (or contrast) and texture (or clumpiness). Twenty six texture measures (derived from local statistics, the grey-level co-occurrence matrix (GLCM) and variograms) were calculated for these simulated images. Measures sensitive to texture (clumpiness) and/or tone (contrast) were identified using Analysis of Variance (ANOVA). Seven texture measures were recommended for the estimation of tropical forest biomass with SAR images.

Keywords: SAR, texture, simulated images, forest canopies.

1. Introduction

Texture in remotely sensed imagery can be defined as variation in grey level tone within a neighbourhood. This variability reflects the spatial relations between pixels and is dependent upon (i) the spatial frequency of the neighbourhood and (ii) the spatial resolution of the remotely sensed data (Mather 1999).

Texture has proved to be a useful adjunct to tone for forest type discrimination with Synthetic Aperture Radar (SAR) data (Miranda et al. 1998, Kurvonen and Hallikainen 1999, Saatchi et al. 2000).

The three main approaches to the quantification of texture in remotely sensed images are first, *local statistics*, such as mean, skewness, kurtosis and coefficient of variation (cv) for an image window (Soares et al. 1997, Kurvonen and Hallikainen 1999). Second, *second-order statistics* (such as entropy, energy, contrast) which describe statistical dependence between pixels in a given distance and direction. These can be calculated from Haralick´s grey-level co-occurrence matrix (GLCM) (Haralick et al. 1973) or the Sum and Difference Histogram (SADH) (Unser 1986). Third, the *variogram* and its descriptors as a concise characterisation of the scale and pattern of spatial variability (Curran et al. 1998).

Microwave backscatter is recorded on SAR imagery as tone (Raney 1998) and is related positively to the biomass of forests up a wavelength-dependent asymptote (Imhoff 1995). For tropical forests the canopy becomes more uneven or "clumpy" with increasing biomass (Richards 1996). It has been hypothesised that texture (as a measure of both canopy biomass and unevenness) could be related positively to biomass up to and beyond the asymptote of the backscatter/biomass relationship.

This experiment used simulated images (Woodcock et al. 1988) and was part of a larger study concerned with the SAR backscatter/biomass relationship for tropical forest and pasture. The objective here was to identify texture measures that maximised the discrimination of textural information independently of tone (i.e., backscatter). Such measures would potentially increase the biomass range that could be estimated with SAR data.

2. Simulating images of forest canopies

Different levels of image contrast (tone) and "clumpiness" (texture) were created by means of nine matrices. These matrices were conceived as simulated digital images of forest, with DN varying from 1 to 9. The trees were disposed in big clumps, small clumps and randomly. Inside these three basic types of spatial arrangement (or texture) the contrast was simulated as high, medium and low. The mean ($\overline{X}$) DN was held constant in the images and the standard deviation (*S*) was adjusted to create the intended contrast (**Table 1)**.

Table 1. Simulated images, with different clumpiness and contrast. Standard deviations (*S*) defining contrast level (high, medium, low) are shown and *b* refers to big clumps, *s* refers to small clumps and *r* refers to random.

		CLUMPINESS		
		Big clumps	**Small clumps**	**Random**
CONTRAST	**High ($S \geq 2.5$)**	bhigh	shigh	rhigh
	Medium ($S \cong 1.5$)	bmed	smed	rmed
	Low ($S \leq 1$)	blow	slow	rlow

This small simulated data set was created in order to evaluate algorithm sensitivity to a wide range of textures (clumpiness) and tones (contrast). The simulation of real SAR images would include an even wider DN range and noise (to account for speckle). The nine matrices along with their representation as simulated digital images (in which minimum and maximum DNs were represented as black and white, respectively), are shown in **Figure 1**. Interestingly, the random arrangement (**Figure 1.g,h,i**) of the simulated images is visually similar to the real SAR images of tropical vegetation.

3. Texture measures

Twenty six texture measures were calculated for the simulated images:

* <u>Derived from local statistics</u>: mean absolute deviation (mad), median (med), entropy (ent), energy (ene), skewness (ske), kurtosis (kur) and coefficient of variation (cv).

*<u>Derived from the grey-level co-occurrence matrix (GLCM) and Sum and Difference Histogram (SADH)</u>: contrast (conh), entropy (enth), energy (eneh), homogeneity (hom), correlation (cor), chi-square (chi), mean of the sum vector (sme), variance of the sum vector (sva), entropy of the sum vector (sent), energy of the sum vector (sene), mean of the difference vector (dme), variance of the difference (dva), entropy of the difference vector (dent) and energy of the difference vector (dene) (Soares et al. 1997).

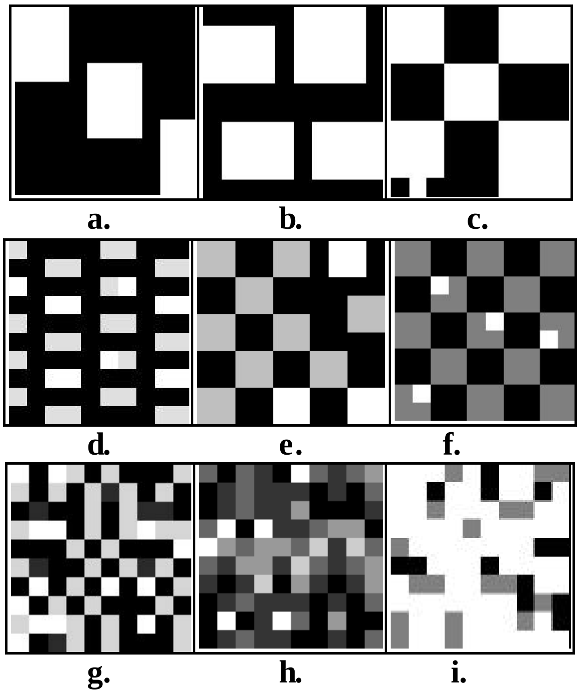

Figure 1. Simulated images with mean ($\overline{X}$ =3.56) and variable standard deviation (*S*). a. Big clumps, high contrast (*S*=3.75), b. Big clumps, medium contrast (*S*=1.51), c. Big clumps, low contrast (*S*=0.5), d. Small clumps, high contrast (*S*=3.52), e. Small clumps, medium contrast (*S*=1.66), f. Small clumps, low contrast (*S*=0.57), g. Random, high contrast (*S*=2.62), h. Random, medium contrast (*S*=1.4) and i. Random, low contrast (*S*=0.72).

* Derived from the variogram: semivariance at lags 1, 2 and 3 (lag1, lag2, lag3), sill and range.

Twenty one texture measures derived from the GLCM, SADH (using 3 x 3 pixel window) and local statistics were calculated for the simulated images. Variograms were computed, fitted with spherical models and used to calculate a further five texture measures. The local statistics, GLCM and SADH texture measures were calculated using a code written for IDL/ENVI (Rennó et al. 1998) and the variograms were calculated using the software GSTAT (Pebesma and Wesseling 1998).

The mean DN of texture bands created from simulated images and descriptors from the modeled variograms were input to an Analysis of Variance (ANOVA), with differences assessed at the 5% (á=0.05) level of significance. ANOVA highlighted the ability of any given texture measure to differentiate between levels of clumpiness (texture) regardless of contrast (tone).

4. Results and discussion

This section will review the ability of twenty six texture measures to differentiate between three levels of texture and three levels of tone.

4.1. Texture measures derived from local statistics

The local statistics mean absolute deviation, median, skewness and kurtosis, did not differentiate clumpiness (**Table 2**). Entropy was sensitive to clumpiness as it resulted in low values for *big* and *small clumps* images, and high values for *random* images (i.e., higher heterogeneity). Energy values, however, were less sensitive to clumpiness and contrast. The coefficient of variation decreased with image contrast for each clumpiness level making it unsuitable for quantifying texture in real data.

Table 2. Texture measures derived from local statistics for simulated images.

		mad	med	ent	ene	ske	kur	cv
Big clumps	High contrast	1.98	1.53	0.09	0.34	0.12	-0.51	0.34
	Medium contrast	1.83	1.79	0.11	0.31	0.03	-0.69	0.18
	Low contrast	1.72	1.72	0.11	0.30	0	-0.78	0.06
Small clumps	High contrast	1.83	1.79	0.11	0.31	0.03	-0.69	0.18
	Medium contrast	1.65	1.52	0.15	0.25	0.11	-0.91	0.23
	Low contrast	1.74	1.72	0.17	0.23	0.13	-0.82	0.08
Random	High contrast	1.68	1.31	0.22	0.20	0.10	-0.96	0.39
	Medium contrast	1.83	1.70	0.28	0.15	0.22	-0.50	0.18
	Low contrast	1.76	1.92	0.15	0.28	-0.56	-0.08	0.09

4.2. Texture measures derived from GLCM and SADH

The values of GLCM derived texture measures (x) were normalised $((x - x_{min}) / (x_{max} - x_{min}))$ for comparison here (**Figure 2)** and this produced values ranging between only 0 and 1.

Values of GLCM contrast and entropy were similar and increased with decreasing clumpiness (**Figure 2**). These measures contain information about DN disorder and scatter and are, therefore, more likely to differentiate clumpiness than contrast.

GLCM energy and homogeneity values were similar for *big clumps* and *small clumps* images (**Figure 2**). In addition, for both measures *random* images exhibited minimum and maximum values for medium and low contrast, respectively, indicating their sensitivity to contrast. The theory underlying these measures is related to uniformity and local similarity of pixel values and therefore these measures are unlikely to be suitable for differentiating between clumpiness.

GLCM correlation and chi-square values varied with clumpiness (**Figure 2**). Contrast levels were not distinct, as in *big clumps* images correlation mean values were similar. High correlation values corresponded to low chi-square values and *vice versa*, indicating the different information captured by these two measures.

The first two measures derived from sum of vector technique - mean and variance - varied according to clumpiness and to a lesser extent, contrast. Entropy of the sum vector values varied with contrast, especially for *small clumps* and *random* images. Energy of the sum vector values, however, did not differentiate either clumpiness or contrast. The measures derived from the difference vector – mean and variance - did discriminate clumpiness and contrast. For entropy and energy of the difference vector, the discrimination of clumpiness and contrast was less apparent. Values of entropy and energy of sum and difference vectors were similar with the same trends and magnitudes (**Figure 2**).

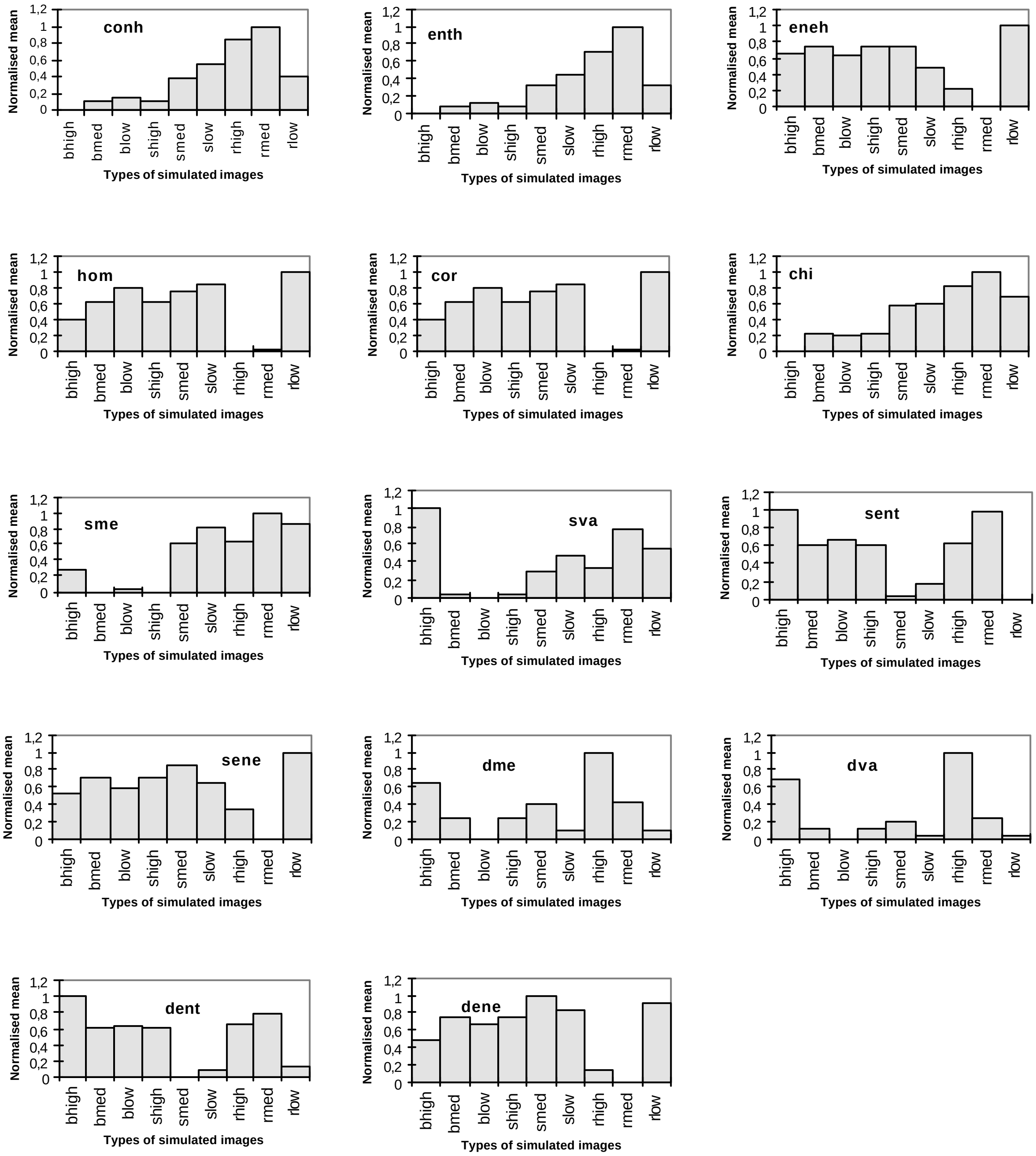

Figure 2. Normalised mean values of GLCM and SADH derived texture measures from simulated images. Codes for the simulated images are: b for big clumps, s for small clumps and r for random; high, med and low for high, medium and low contrast.

4.3. Texture measures derived from the variogram

A summary of the variogram descriptors is presented in **Table 3**. The modeled variograms contained no nugget variance as there was neither noise nor sub-pixel spatial variability.

Values of range tended to increase with clumpiness and indicated the size of elements within the images. In *big clumps* images, range corresponded roughly to the size of the clumps (three pixels). For *small clumps* images ranges were smaller than in *big clumps* images and were indicative of the average spacing of clumps (one pixel). Random images presented decreasing values of range for increasing contrast levels. Range was the only variogram-derived measure that was invariant with contrast (**Table 3**).

Table 3. Semivariance at lags 1, 2 and 3, sill and range of variograms produced from simulated images and fitted with spherical models.

		lag1	lag2	lag3	sill	range
Big clumps	High contrast	4.8	9.34	13.76	15.17	3.62
	Medium contrast	1.2	2.03	2.65	2.34	2.56
	Low contrast	0.12	0.21	0.3	0.26	2.57
Small clumps	High contrast	13.96	13.72	13.7	12.38	0.97
	Medium contrast	2.16	3.59	2.47	2.77	1.7
	Low contrast	0.31	0.48	0.29	0.33	1.26
Random	High contrast	9.14	5.27	7.55	6.87	0.97
	Medium contrast	1.89	2.02	1.94	2.02	1.27
	Low contrast	0.45	0.58	0.49	0.51	1.42

Semivariance values decreased with decreasing contrast and had increasing values with lag for *big clumps* images. For *small clumps* and *random* images there was no pattern and the semivariance either increased or decreased with lag. Sill values differentiated between contrast levels and indicated the total variance of the images; they were high for high contrast and decreased for medium and low contrast images.

4.4. Statistically significant differences in texture for different levels of clumpiness and contrast

Analysis of variance (ANOVA) was used to determine if differences in the values of texture measures were statistically significant for different levels of contrast and clumpiness (**Table 4**).

None of the texture measures were able to discriminate contrast and clumpiness concomitantly. Contrast (tone) was differentiated by five texture measures: coefficient of variation (cv), semivariance at lags 1, 2 and 3 and variogram sill. Cv has been shown to be a useful measure for discriminating between tropical forest regeneration stages (Luckman et al. 1997, Yanasse et al. 1997) and boreal forest types (Kurvonen and Hallikainen 1999). Semivariance estimates have been used for the successful classification of tropical vegetation (Miranda et al. 1998). Sill is a measure of image variance and was expected to vary according to contrast (Cohen et al. 1990).

Local statistics entropy (ent) and GLCM derived measures of contrast (conh), entropy (enth), correlation (cor), chi-square (chi) and mean of the sum vector (sme) differentiated clumpiness. Contrast, entropy and correlation are among the more common measures that can be derived from the GLCM (Baraldi and Parmigiani 1995) and have been used extensively for texture analysis in forest mapping (Ulaby et al. 1986, Kushwaha et al. 1994), land cover mapping (van der Sanden and Hoekman 1999) and crop discrimination (Soares et al. 1997). Clumpiness (texture) was also differentiated by range, a measure of image "coarseness" and also of the size of image elements (Treitz and Howarth 2000).

The remaining measures did not show any significant sensitivity either to clumpiness or contrast in the simulated images studied here.

Table 4. *P*-values for differences in contrast and clumpiness levels. The statistically significant values at á =0.05 are indicated in bold.

TEXTURE MEASURE	CONTRAST	CLUMPINESS	TEXTURE MEASURE	CONTRAST	CLUMPINESS
mad	0.595	0.462	**sme**	0.942	**0.029**
med	0.300	0.973	**sva**	0.546	0.524
ent	0.753	**0.044**	**sent**	0.083	0.314
ene	0.733	0.078	**sene**	0.248	0.759
ske	0.342	0.688	**dme**	0.070	0.612
kur	0.789	0.463	**dva**	0.082	0.617
cv	**0.020**	0.865	**dent**	0.269	0.196
conh	0.838	**0.031**	**dene**	0.519	0.198
enth	0.974	**0.049**	**lag1**	**0.013**	0.736
eneh	0.627	0.664	**lag2**	**0.011**	0.734
hom	0.105	0.485	**lag3**	**0.001**	0.886
cor	0.904	**0.006**	**sill**	**0.003**	0.855
chi	0.943	**0.012**	**range**	0.991	**0.005**

Summary

The experiment presented here highlighted the spatial variation content of imagery and therefore the need to consider texture as additional information when analysing the backscatter/biomass relationship in SAR images. Simulated images proved to be a useful tool for standardising the evaluation of twenty six texture measures.

The seven measures that were sensitive to clumpiness (texture) but not contrast (tone) were local statistics entropy (ent), GLCM contrast (conh), GLCM entropy (enth), GLCM correlation (cor), GLCM chi-square (chi), SADH mean of sum vector (sme) and variogram range (range). These measures have potential for strengthening the backscatter/biomass relationship at high levels of biomass.

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