QUANTITATIVE COMPARISON OF SEGMENTATION RESULTS FROM IKONOS IMAGES SHARPENED BY DIFFERENT FUSION AND INTERPOLATION TECHNIQUES

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ABSTRACT

The image sharpening and segmentation procedures have great importance on the classification success. For this reason this work proposes to evaluate segmentation results obtained from IKONOS images sharpened by different image fusion methods and interpolation techniques. The images were processed by different image fusion methods based on Principal Components, Grand-Schmidt and Wavelet transform. The resulting images are evaluated in terms of spectral information preservation. All hybrid images were segmented using algorithms based on region growing implemented in the SPRING 4.3 and eCognition 5.0 systems. The same segmentation parameters were used in all experiments. Segments obtained from thirty-two test-areas on an urban landscape were quantitatively compared by statistic t-tests. The results showed that the standardization of segmentation parameters and classification methodologies are not possible without taking into account the fusion and interpolation techniques used in the sharpening process.

1. INTRODUCTION

Image sharpening and segmentation procedures are methodological steps carried out in most of urban studies that utilize high resolution remote sensing imagery (< 1m). A very common purpose to sharp (or fusion) an image is to combine the multiespectral information with the spatial information from a panchromatic band with higher resolution, obtaining a product with enhanced and richer spectral and spatial resolution (Wald et al., 1997). The region-based approach analysis of high resolution imagery is much more suitable than a pixel-based approach, especially on urban areas in which targets have high spectral heterogeneity and complex spatial disposal. Recent investigations have shown that a pixel-based high resolution imagery analyses produce the salt-and-pepper effect and thematic maps with limited accuracies (Franklin *et al.* 2000, Zhu *et al*. 2000). Although the region-based analysis overcomes the mentioned problems (Meinel et al., 2001), a segmentation process is necessary to generate the regions before classifying them. Image segmentation is the process in which an image is partitioned into meaningful regions (objects) based on homogeneity or heterogeneity criteria (Haralick and Shapiro 1992). It represents the interface between image pre-processing and image understanding (object recognition) procedures. Hence, the quality of classification is directly affected by the segmentation quality.

In a context where the standardization of segmentation parameters or even classification methodologies are been persuaded topics the implications on the segmentation fusion products generated by different methods are yet to be further analyzed. The ultimate aim of this paper is to evaluate the segmentation results when the images are sharpened by different fusion and interpolation techniques. An IKONOS image of a residential area of the city of São José dos Campos (Brazil) was processed by eight different image fusion methods and interpolation techniques. The sharpened images were segmented using the same segmentation parameters and the segments geometric attributes of thirty-two test areas were statistically analyzed.

2. SEGMENTATION AND SHARPENING METHODS SELECTED FOR EVALUATION

The choice of image fusion methods to be analyzed was based on the possibility to process the four IKONOS multispectral bands at once and the availability of these methods in widely used image processing softwares. The following eight image fusion and interpolation methods were selected for evaluation:

- Principal Component with nearest neighbor interpolation technique (PC_NN);
- Principal Component with cubic convolution technique (PC_CC);
- Principal Component with bilinear interpolation technique (PC_B);
- Gran-Schmidt with nearest neighbor interpolation technique (GS_NN);
- Gran-Schmidt with cubic convolution technique (GS_CC);
- Gran-Schmidt with bilinear interpolation technique (GS_B);
- Wavelet proposed by Guarguet (1996) (WG);
- Wavelet proposed by Ventura (2002) (WV);

The Principal Components and the Gran-Schmidt methods along with the nearest-neighbor, bilinear and cubic convolution techniques are available in the ENVI 4.3 software. The fusion methods based on wavelets developed by Ventura (2002) and Guarguet (1996) are available in the open source library TerraLib. This library has been developed in the Division of Image Processing at National Institute for Space Research (INPE) and it can be downloaded at http://www.dpi.inpe.br/terralib/.

Two image segmentation algorithms were selected for evaluation: (1) the region growing algorithm available in the SPRING 4.3 software that is free downloaded in (www.dpi.inpe.br/spring/), and (2) the region growing algorithm available in the eCognition 5.0 system (Baatz and Schape, 2000) that has been used widely by the urban remote sensing researchers community. These two segmentation algorithms were well evaluated by Meinel and Neubert (2004) and were considered the best ones.

3. STUDY AREA

The study area is delimited by coordinates 407395W, 7433715S and 408329W, 7434623S at spatial reference UTM/WGS84, zone 23 at southern hemisphere. This is mainly a high standard residential area of São José dos Campos city (Figure 1). Most of the houses in this area have ceramic tile roofs, swimming pools and grass gardens.

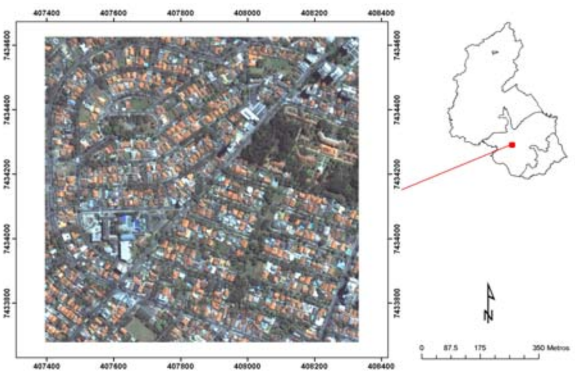

Figure 1. Study area and its location on the municipality of São José dos Campos

4. METHODOLOGY

To evaluate the influence of different image sharpening methods on the segmentation results the following processing steps were preceded: (1) processing IKONOS images by different methods and interpolation techniques; (2) evaluating the hybrid images in terms of spectral information preservation; (3) selecting the best fusion method as the reference method; (4) normalizing the mean and standard deviation values of the sharpened images conform to the reference one; (5) segmenting the images using the same segmentation parameters using both segmentation algorithms mentioned before; (6) calculating the objects geometric measurements for thirty-two test areas, and (7) evaluating the segmentation results.

4.1. Measures for evaluating the sharpened images

The purpose of this step is to find out the best fusion method in terms of spectral information preservation. This method is taken as the reference method. Two measures to evaluate the spectral information preservation were used: BIAS and Correlation Index.

BIAS value calculates the difference between the mean values of the original and sharpened images (ideal case equals zero) :

$$\mu_{ORIGINAL} - \mu_{SHARPENED} \tag{1}$$

where $\mu_{ORIGINAL}$ and $\mu_{SHARPENED}$ are the mean values of the original and sharpened images, respectively.

The Correlation Index between the original and sharpened images (ideal case equals one) is given by:

$$\alpha_{original,sharpened} = \frac{\Lambda_{original,sharpened}}{\sqrt{\sigma^2_{original}\sigma^2_{sharpened}}} \tag{2}$$

where $\Lambda_{original,sharpened}$ = the covariance among the original and the sharpened image of a given band

σ^2 = the standard deviation of the image of a given band.

The best fusion method was the Principal Components with the nearest-neighbor interpolation technique (PC NN), which showed the correlation index closer to one and the Bias closest to zero (Table 1). The segments obtained using the sharpened image processed by PC NN method were compared with the segments obtained by the other fusion methods.

Band	BIAS	Corr. Index
	PC NN	
B1	-9.143972	0.676965
B2	-6.674768	0.65278
B3	-4.355432	0.675711
B4	1.425276	0.648594
	PC CC	
B1	-9.689009	0.657142
B2	-6.676587	0.646359
B3	-3.985717	0.665506
B4	1.57718	0.597472
	PC B	
B1	-10.528807	0.664186
B2	-6.933944	0.64926
B3	-4.133351	0.667237
B4	1.699402	0.608837
	GS NN	
B1	-10.114095	0.669505
B2	-7.177298	0.652454
B3	-3.396238	0.6801
B4	0.685108	0.628953
	GS CC	
B1	-10.732204	0.653719
B2	-7.880836	0.645531
B3	-3.701562	0.667523
B4	0.841488	0.60058
	GS B	
B1	-12.5835	0.654083
B2	-8.755472	0.643645
B3	-4.407556	0.664676
B4	0.964452	0.614272
	WV	
B1	-10.229806	0.433221
B2	8.703358	0.482646
B3	25.062016	0.555849
B4	37.785912	0.432773
	WG	
B1	-10.280569	0.389587

B2	8.605182	0.444547
B3	24.831315	0.515722
B4	37.720533	0.415833

Table 1. Quantitative evaluation of the image sharpening methods by the measures Bias and Correlation Index

4.2. Measures for evaluating the segmented images

There is a large variety of quantitative segmentation evaluation approaches proposed in the literature (Estrada and Jepson, 2005; Hirschmugl, 2002; Schukraft and Lenz, 2003; Zhang et al., 2004). In this study, geometric attributes such as area (A_i), perimeter (P_i) and Shape Index (SH_i) were used in the segmentation evaluation similar to the procedure proposed by Neubert and Meinel (2003; 2004). The Shape Index (3) comes from landscape ecology and addresses the polygon form.

$$SH_i = \frac{P_i}{4\sqrt{A_i}} \quad . \tag{3}$$

4.3. Measures for evaluating the segmented images

After calculating the geometric attributes for thirty-two test areas, statistical tests were conducted to evaluate whether or not segments generated from sharpened images were significantly different in relation to the reference segments (those obtained from image sharpened by reference fusion method).

Simple linear regressions were applied, considering as dependent variable (Y) the geometric attributes of the reference segments. On the other hand, geometric attributes of the segments generated from images sharpened by the other seven methods were taken as independent variable (X). This procedure was performed for both segmentation algorithms (SPRING 4.3 and eCognition 5.0). If the segments of the images processed by different fusion methods were equal, then the linear regression coefficients would assume the following values: $\beta_0 = 0$, $\beta_1 = 1$ and $\beta_1 \neq 0$. Tests concerning coefficients β_0 and β_1 can be set up in ordinary fashion using the *t* distribution. To test whether $\beta_0 = 0$ the statistics

$$t^* = \frac{b_0}{s\{b_0\}} \tag{4}$$

were calculated and to test whether $\beta_1 \neq 0$ the statistics

$$t^* = \frac{b_1}{s\{b_1\}} \tag{5}$$

were calculated. To test whether $\beta_1 = 1$ the statistics

$$t^* = \frac{b_1 - 1}{s\{b_1\}} \tag{6}$$

were calculated. Where b_1 is the inclination coefficient of the fitted regression line and $s\{b_1\}$ is an unbiased estimator of the standard error of b_1.

For the three tests the two alternative hypotheses are:

$$H_0 : \beta n = X$$
$$H\alpha : \beta n \neq X$$

The decision rule for these statistic tests when controlling the level of significance at α is:

If $|t^*| \leq t(1-\alpha/2; n-2)$, conclude H_0

If $|t^*| > t(1-\alpha/2; n-2)$, conclude $H\alpha$.

5. RESULTS

The *t* statistics were calculated for three measures for each of the seven segmentations obtained from images sharpened by seven different methods. This was performed for segmentations obtained using SPRING 4.3 (Table 2) and eCognition 5.0 softwares (Table 3). Three levels of confidence were considered: 99%, 95% and 90%. The lower the level of confidence the more robust the test is.

*Mt	*Ms	Test	Stat t	1 - α		
				99%	95%	90%
PC		$\beta_0 = 0$	0.44	H0	H0	H0
CC	A_i	$\beta_1 \neq 0$	7.67	Ha	Ha	Ha
		$\beta_1 = 1$	0.69	H0	H0	H0
PC		$\beta_0 = 0$	2.03	H0	H0	H0
B	A_i	$\beta_1 \neq 0$	12.5	Ha	Ha	Ha
		$\beta_1 = 1$	1.84	H0	Ha	Ha
GS		$\beta_0 = 0$	0.79	H0	H0	H0
NN	A_i	$\beta_1 \neq 0$	5.54	Ha	Ha	Ha
		$\beta_1 = 1$	1.58	H0	H0	Ha
GS		$\beta_0 = 0$	0.20	H0	H0	H0
B	A_i	$\beta_1 \neq 0$	4.91	Ha	Ha	Ha
		$\beta_1 = 1$	1.63	H0	H0	Ha
GS		$\beta_0 = 0$	0.95	H0	H0	H0
CC	A_i	$\beta_1 \neq 0$	8.22	Ha	Ha	Ha
		$\beta_1 = 1$	0.13	H0	H0	H0
		$\beta_0 = 0$	1.68	H0	H0	Ha
WV	A_i	$\beta_1 \neq 0$	2.05	H0	Ha	Ha
		$\beta_1 = 1$	3.26	Ha	Ha	Ha
		$\beta_0 = 0$	0.63	H0	H0	H0
WG	A_i	$\beta_1 \neq 0$	4.81	Ha	Ha	Ha
		$\beta_1 = 1$	0.33	H0	H0	H0
PC		$\beta_0 = 0$	0.01	H0	H0	H0
CC	P_i	$\beta_1 \neq 0$	6.98	Ha	Ha	Ha
		$\beta_1 = 1$	0.58	H0	H0	H0
		$\beta_0 = 0$	1.36	H0	H0	Ha
PC	P_i					

B		$\beta_1 \neq 0$	8.92	Ha	Ha	Ha
		$\beta_1 = 1$	1.13	H0	H0	H0
GS		$\beta_0 = 0$	0.60	H0	H0	H0
NN	P_i	$\beta_1 \neq 0$	3.07	Ha	Ha	Ha
		$\beta_1 = 1$	0.34	H0	H0	H0
GS		$\beta_0 = 0$	0.88	H0	H0	H0
B	P_i	$\beta_1 \neq 0$	4.45	Ha	Ha	Ha
		$\beta_1 = 1$	2.61	Ha	Ha	Ha
GS		$\beta_0 = 0$	0.00	H0	H0	H0
CC	P_i	$\beta_1 \neq 0$	6.34	Ha	Ha	Ha
		$\beta_1 = 1$	1.43	H0	H0	Ha
		$\beta_0 = 0$	2.47	Ha	Ha	Ha
WV	P_i	$\beta_1 \neq 0$	1.39	H0	H0	Ha
		$\beta_1 = 1$	3.86	Ha	Ha	Ha
		$\beta_0 = 0$	1.94	H0	Ha	Ha
WG	P_i	$\beta_1 \neq 0$	2.50	Ha	Ha	Ha
		$\beta_1 = 1$	2.98	Ha	Ha	Ha
PC		$\beta_0 = 0$	1.54	H0	H0	Ha
CC	SH_i	$\beta_1 \neq 0$	6.46	Ha	Ha	Ha
		$\beta_1 = 1$	2.39	H0	Ha	Ha
PC		$\beta_0 = 0$	0.86	H0	H0	H0
B	SH_i	$\beta_1 \neq 0$	5.38	Ha	Ha	Ha
		$\beta_1 = 1$	1.30	H0	H0	H0
GS		$\beta_0 = 0$	1.70	H0	Ha	Ha
NN	SH_i	$\beta_1 \neq 0$	3.48	Ha	Ha	Ha
		$\beta_1 = 1$	1.66	H0	H0	Ha
GS		$\beta_0 = 0$	2.34	H0	Ha	Ha
B	SH_i	$\beta_1 \neq 0$	4.52	Ha	Ha	Ha
		$\beta_1 = 1$	3.22	Ha	Ha	Ha
GS		$\beta_0 = 0$	1.89	H0	Ha	Ha
CC	SH_i	$\beta_1 \neq 0$	5.59	Ha	Ha	Ha
		$\beta_1 = 1$	2.96	Ha	Ha	Ha
		$\beta_0 = 0$	2.90	Ha	Ha	Ha
WV	SH_i	$\beta_1 \neq 0$	1.91	H0	Ha	Ha
		$\beta_1 = 1$	3.10	Ha	Ha	Ha
		$\beta_0 = 0$	12.4	Ha	Ha	Ha
WG	SH_i	$\beta_1 \neq 0$	0.19	H0	H0	H0
		$\beta_1 = 1$	198	Ha	Ha	Ha

Table 2. T-tests performed for segmentations in the SPRING 4.3 system. *Mt and Ms stand for method and measure, respectively

In the case that segmentation results are equal, we would expect conclusion H_0 for the tests $\beta_0 = 0$, $\beta_1 = 1$ and $H\alpha$ for the test $\beta_1 \neq 0$. This means that the regression line passes through the origin with an angle of 45°. For the confidence level of 99%, the fusion methods whose segments were equal to those obtained from images sharpened by PC_NN method were PC_CC, PC_B and GS_NN. In these cases, the images were segmented using the segmentation algorithm implemented in the SPRING system. In relation to the geometric attribute A_i only the method WV did not present segments equal to those of the reference segments. For the geometric attribute P_i, methods GS_B, WG and WV are statistically different from the reference segments. For the geometric attribute SH_i only PC_CC, PC_B and GS_NN are equal to the reference segments. At the confidence level of 95% none of the segmentation results generated using SPRING system obtained segments equal to the reference segments for the three attributes. Segments obtained from images sharpened by methods PC_B and WV were only those whose attributes A_i are statistically different from the reference segments. As for attribute P_i, methods GS_B, WG and WV are statistically different from the reference segments just as like at confidence level of 99%. For attribute SH_i, segments obtained from image sharpened by PC_B are statistically equal to the reference segments at confidence levels of 95% and 90%. Segments obtained from images sharpened by methods PC_CC, GS_CC and WG have values of A_i equal to those of the reference segments at confidence level of 90%. As for attribute P_i, methods PC_CC and GS_NN are only ones whose segments are statistically equal to the reference segments.

Surprising is the fact that none of the segments generated by eCognition system are statistically equal to the reference segments at all of the confidence levels. In lots of cases not even a linear statistical association between the measures calculated for the reference segments and the others could be assumed. In the linear regression tests $\beta_0 = 0$ and $\beta_1 = 1$ the majority of the cases assumed $H\alpha$ for segmentations generated in the eCognition system. The only exception is for segments obtained from images sharpened by method GS_B at confidence level of 99% (Table 3).

*Mt	*Ms	Test	Stat t	1 - α		
				99%	95%	90%
PC		$\beta_0 = 0$	2.72	Ha	Ha	Ha
CC	A_i	$\beta_1 \neq 0$	1.95	H0	Ha	Ha
		$\beta_1 = 1$	3.30	Ha	Ha	Ha
PC		$\beta_0 = 0$	3.90	Ha	Ha	Ha
B	A_i	$\beta_1 \neq 0$	3.69	Ha	Ha	Ha
		$\beta_1 = 1$	5.32	Ha	Ha	Ha
GS		$\beta_0 = 0$	3.70	Ha	Ha	Ha
NN	A_i	$\beta_1 \neq 0$	2.41	H0	Ha	Ha
		$\beta_1 = 1$	3.85	Ha	Ha	Ha
GS		$\beta_0 = 0$	2.52	Ha	Ha	Ha
CC	A_i	$\beta_1 \neq 0$	3.20	Ha	Ha	Ha
		$\beta_1 = 1$	2.62	Ha	Ha	Ha
GS	A_i	$\beta_0 = 0$	4.58	Ha	Ha	Ha

B		$\beta_1 \neq 0$	0.31	H0	H0	H0
		$\beta_1 = 1$	5.46	Ha	Ha	Ha
		$\beta_0 = 0$	5.38	Ha	Ha	Ha
WG	A_i	$\beta_1 \neq 0$	4.68	Ha	Ha	Ha
		$\beta_1 = 1$	5.52	Ha	Ha	Ha
		$\beta_0 = 0$	5.31	Ha	Ha	Ha
WV	A_i	$\beta_1 \neq 0$	4.95	Ha	Ha	Ha
		$\beta_1 = 1$	5.48	Ha	Ha	Ha
		$\beta_0 = 0$	3.64	Ha	Ha	Ha
PC CC	P_i	$\beta_1 \neq 0$	1.37	H0	H0	Ha
		$\beta_1 = 1$	4.30	Ha	Ha	Ha
		$\beta_0 = 0$	5.04	Ha	Ha	Ha
PC B	P_i	$\beta_1 \neq 0$	3.96	Ha	Ha	Ha
		$\beta_1 = 1$	6.40	Ha	Ha	Ha
		$\beta_0 = 0$	4.94	Ha	Ha	Ha
GS NN	P_i	$\beta_1 \neq 0$	2.12	H0	Ha	Ha
		$\beta_1 = 1$	4.83	Ha	Ha	Ha
		$\beta_0 = 0$	3.26	Ha	Ha	Ha
GS CC	P_i	$\beta_1 \neq 0$	2.78	Ha	Ha	Ha
		$\beta_1 = 1$	3.61	Ha	Ha	Ha
		$\beta_0 = 0$	4.71	Ha	Ha	Ha
GS B	P_i	$\beta_1 \neq 0$	-0.41	H0	H0	H0
		$\beta_1 = 1$	5.33	Ha	Ha	Ha
		$\beta_0 = 0$	10.3	Ha	Ha	Ha
WG	P_i	$\beta_1 \neq 0$	3.74	Ha	Ha	Ha
		$\beta_1 = 1$	17.0	Ha	Ha	Ha
		$\beta_0 = 0$	10.2	Ha	Ha	Ha
WV	P_i	$\beta_1 \neq 0$	4.01	Ha	Ha	Ha
		$\beta_1 = 1$	17.1	Ha	Ha	Ha
		$\beta_0 = 0$	4.27	Ha	Ha	Ha
PC CC	SH_i	$\beta_1 \neq 0$	0.49	H0	H0	H0
		$\beta_1 = 1$	4.59	Ha	Ha	Ha
		$\beta_0 = 0$	4.90	Ha	Ha	Ha
PC B	SH_i	$\beta_1 \neq 0$	0.64	H0	H0	H0
		$\beta_1 = 1$	5.32	Ha	Ha	Ha
		$\beta_0 = 0$	4.10	Ha	Ha	Ha
GS NN	SH_i	$\beta_1 \neq 0$	2.32	H0	Ha	Ha
		$\beta_1 = 1$	3.97	Ha	Ha	Ha
		$\beta_0 = 0$	2.57	Ha	Ha	Ha
GS CC	SH_i	$\beta_1 \neq 0$	1.13	H0	H0	H0
		$\beta_1 = 1$	2.76	Ha	Ha	Ha
		$\beta_0 = 0$	1.89	H0	Ha	Ha
GS B	SH_i	$\beta_1 \neq 0$	1.63	H0	H0	Ha
		$\beta_1 = 1$	2.10	H0	Ha	Ha
		$\beta_0 = 0$	15.1	Ha	Ha	Ha
WG	SH_i	$\beta_1 \neq 0$	1.04	H0	H0	H0
		$\beta_1 = 1$	21.4	Ha	Ha	Ha
		$\beta_0 = 0$	14.9	Ha	Ha	Ha
WV	SH_i	$\beta_1 \neq 0$	1.00	H0	H0	H0
		$\beta_1 = 1$	21.5	Ha	Ha	Ha

Table 3. T-tests made for the eConition 5.0 segmentations. *Mt and Ms stand for method and measure respectively

6. CONCLUSION

This work evaluated the differences among segmentation results obtained from IKONOS images sharpened by different image fusion and interpolation techniques. The segments obtained from images sharpened by method based on Principal Components and interpolated byNearest Neighbor technique were taken as reference segments in the evaluation process. The experiments showed that none of the segmentation results obtained from sharpened images were statistically equal to the reference segmentation at any level of confidence for segmentations generated with eCognition 5.0 systems. As for the segmentations generated with SPRING 4.3 system, the results showed that using different interpolation techniques but same sharpening methods can produce segments statistically equal to the reference segments at high levels of confidence (99, 95%).

Therefore, the results presented in this paper showed statistical evidences that the standardization of segmentation parameters or classification methods should take into account the image sharpening and interpolation techniques when analyzing images.

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