On the use of synthetic images for change detection accuracy assessment

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Abstract

Land cover change detection is the major goal in multitemporal remote sensing studies. It is well known that remotely-sensed images of the same area acquired on different dates tend to be affected by radiometric differences and registration problems. These influences are considered as noise in the process and may induce the user to both: signalling false changes and masking real surface changes. The difference image produced by subtracting two co-registered images is a standard initial step in change detection algorithms. This image naturally appears to be noisier than the original ones and has at least two populations: i) the noise-like and ii) the real changes. The problem that arises is how to discriminate them. There are several approaches to perform change detection reported in the literature and some studies have employed synthetic images. By using synthetic images, the accuracy assessment of specific algorithm can be done more accurately. The question at this point is: what is the acceptable noise level to be added on the synthetic images to simulate a real problem? This paper attempts to answer this question by suggesting values of SNR (signal-to-noise ratio) obtained from experiments performed on TM-Landsat-5 and CCD-CBERS-2B images.

Keywords: Change detection, accuracy assessment, signal-to-noise ratio, SNR.

1. Introduction

The development of new techniques and algorithms to perform change detection has attracted attention in several fields of study, including the monitoring by security video cameras, medical diagnostics, civil infrastructure and remote sensing. Researchers tend to use similar methodologies and algorithms in common, in despite of the differences among the areas of application (Radke *et al.*, 2005). Applications for remote-sensing data include the monitoring of areas cleared and burned, the assessment of natural disasters, the analysis of urban expansion, and the monitoring of cultivated areas (Bazi *et al.*, 2005).

Most change detection methods proposed in the remote sensing literature are based on image differencing (Bruzzone and Prieto, 2000; Celik, 2009; Teng *et al.*, 2008): that is, on the subtraction between two registered images acquired for the same area at two different times (t_1 and t_2). The differences are usually calculated pixel by pixel and separately for each spectral band. Under the hypothesis of limited changes from t_1 to t_2, changes can be detected in the tails of the probability density function of the pixel values in the difference image (Bruzzone and Serpico, 1997).

Remotely-sensed images of the same area acquired on different dates tend to be highly affected by radiometric differences and registration problems. These influences are considered as noise in the process. As the variance of the difference image is statistically computed by the sum of each image individual variance (minus two times the covariance), the difference image presents more noisy than the original ones. This fact causes in the difference image the appearance of at least two populations: *i*) the noise-like and *ii*) the real changes.

The problem that arises in the solution of change detection approaches is how to discriminate real changes from noise. There are several approaches to perform change detection reported in the literature. In general, kappa coefficient, detection rate, false-alarm rate, ROC (Receiver Operating Characteristic) curve and the simple overall accuracy value are the measures chosen to evaluate change detection results. Some studies have employed synthetic images to perform accuracy assessment. By using synthetic images, the accuracy assessment of specific algorithm can be done more accurately. The question at this point is: what is the noise level to be added on the synthetic images to simulate a real problem? This paper attempts to answer this question by suggesting values of SNR (signal-to-noise ratio) to be used when assessing the accuracy of new algorithms for change detection. The results obtained on TM-Landsat-5 and CCD-CBERS-2B images are presented and discussed.

2. Methods

According (Teng *et al.*, 2008), the premise of using remotely sensed images for change detection is that changes in objects of interest will result in changes in radiance values. Consequently, the digital numbers are expected to record these changes. The problem, however, is that the aforementioned noise should mask real changes or generates false-alarms.

Despite the consensus about the pervasive presence of noise, there is a lack of studies about the acceptable level to be added on images to simulate real situations. This step is required for generating synthetic pairs of images to be used for accuracy assessment in change detection studies.

It is not easy to separate the noise from the signal because it is impossible to determine where the noise ends and the signal begins. The methodology proposed here is very simple and just attempts to suggest reference values. Four steps were conduced:

1st Obtaining a pair of images with close acquisition dates;
2nd Computing the image difference;
3rd Exclusion of outliers and changed areas;
4th Noise modeling and computation of SNR.

Let $\mathbf{X}_1$ and $\mathbf{X}_2$ be two images of the same scene recorded at two different – but close – dates (t_1, t_2). Assume that the difference $\mathbf{X}_2 - \mathbf{X}_1$ is denoted by $\mathbf{D}$. In the raster format, $\mathbf{D}$ is a matrix $rc \times p$, where r and c are the number of rows and columns of image. The dimensionality is given by p: the number of spectral bands.

The exclusion of outliers was based on Mahalanobis distance, following the Equation (1), based on the chi-square distribution:

$$(\mathbf{d}-\boldsymbol{\mu}_\mathbf{d})'\Sigma^{-1}(\mathbf{d}-\boldsymbol{\mu}_\mathbf{d}) > \chi^2_{p,\alpha} \tag{1}$$

where $\mathbf{d}$ is a difference vector (one row of $\mathbf{D}$), $\boldsymbol{\mu}_\mathbf{d}$ is the mean vector and $\boldsymbol{\Sigma}$ the covariance matrix of $\mathbf{D}$. This expression requires the components of $\mathbf{D}$ to be Gaussian. According to (Bruzzone and Prieto, 2000), the assumption of normality is reasonable for many applications involving images acquired by passive sensors. A high level of confidence (e.g. 1-α=99.73%) must be used to remove only the extreme discrepancies between $\mathbf{X}_1$ and $\mathbf{X}_2$. Thus, the called *noise* (or *pseudo*-noise) is obtained from the difference between images excluding the outliers.

In general, SNR is defined as the power ratio between a signal (X) and the noise (e). There are different ways to access the SNR, but the most common definition uses the logarithmic decibel scale, as presented in the Equation (2):

$$SNR = 10\log_{10}\left(\frac{Var(X)}{Var(e)}\right). \tag{2}$$

Images with SNR≤10dB are noisy, while SNR>30dB ensure very sharp images. SNR can be calculated separately for each spectral band, but it is possible to obtain a multivariate measure of SNR. The Equation 3 suggests an expression based on the trace of the covariance matrices of $\mathbf{X}$ and $\mathbf{D}$. The image $\mathbf{X}$ is the mean between $\mathbf{X}_1$ and $\mathbf{X}_2$, excluding the pixels classified as *changed* by the Equation (1).

$$\mathrm{SNR} = 10\log_{10}\left(\frac{tr(\Sigma_\mathbf{X})}{tr(\Sigma_\mathbf{D})}\right) \tag{3}$$

The Equation 3 should be used with caution because it is influenced by the scale.

3. Experiments and Results

Two pairs of images were analyzed in order to model the noise and estimate SNR reference values. The study area covers a region in the northern of Rio Grande do Sul state, Brazil. The area comprises two distinct sub-areas of 222-079 orbit-point Landsat-TM images and 159-131 orbit-point CBERS2B-CCD images. All four images that were used have acquisition date in October 2009. The geometric correction of Landsat-TM and CBERS2B-CCD images was registered with the use of Landsat 5 and 7 GLS-2005 (Global Land Survey) images. Both pairs of images were co-registered and the accuracy (RMS) at the control points was estimated as 0.4 pixels. Table 1 shows a brief description of the images that were used.

Table 1: Description of the two pairs of images used in the experiments.

Satellite	*Sensor*	*Number of spectral bands used*	*Images size* ($R \times C$)	*Acquisition dates* (t_1 / t_2)	*Registration error*
CBERS 2B	CCD	4	3901 × 2902	05Oct2009 13Oct2009	0.4
Landsat 5	TM	6	2602 × 1936	13Oct20009 29Oct2009	0.4

The color composite images and the difference image histograms for both sensors – CBERS and Landsat – are showed in Figures 1 and 2. Visually, the histograms suggest the Gaussian model. Normality tests were not performed because the very large number of pixels (5×10^6) always leads to reject the null hypothesis.

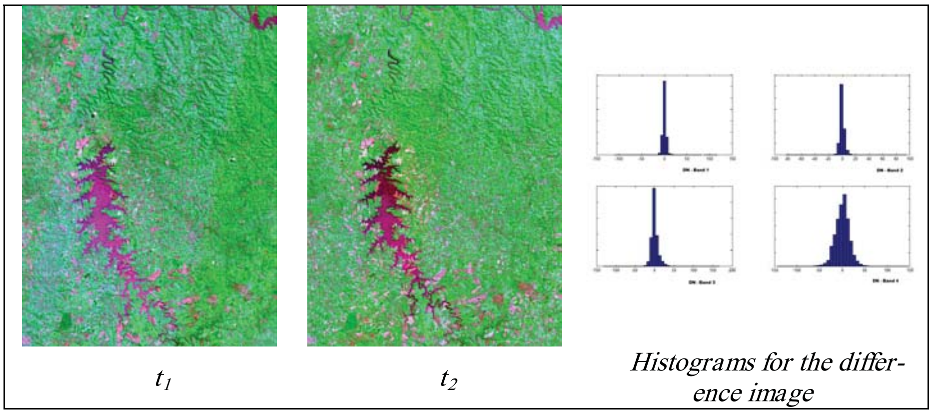

Figure 1: CBERS color composite images (R-G-B, 2-3-4) in t_1 and t_2 and four univariate histograms for difference image

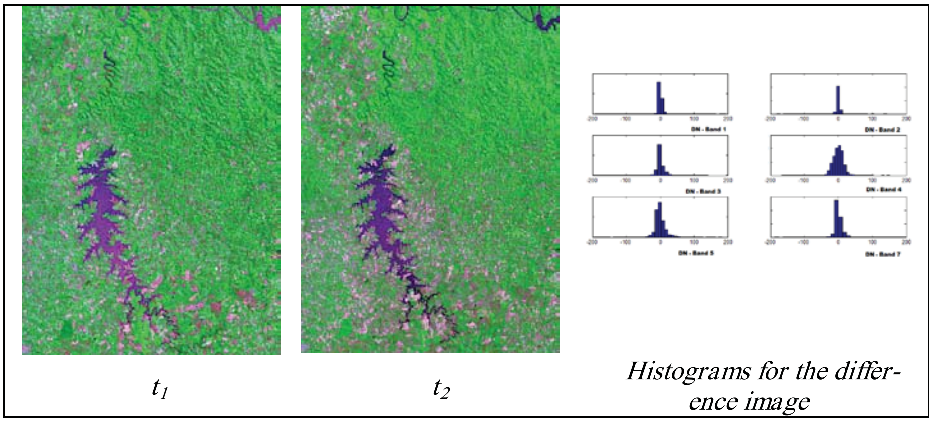

Figure 2: Landsat color composite images (R-G-B, 2-3-4) in t_1 and t_2 and six univariate histograms for difference image

The Table 2 shows the descriptive statistics and SNR values estimated from the data after removing the outliers at 99.73% confidence level.

Table 2: Descriptive Statistics for signal and noise. Estimated values for SNR.

Satellite / Sensor	*Spectral band*	*Signal*		*Noise*	*Univariate SNR*	*Multivariate SNR*
		Mean	*Variance*	*Variance*		
CBERS 2B CCD	B1	48.79	16.85	12.89	1.16dB	4.02dB
	B2	42.80	14.00	9.72	1.58dB	
	B3	42.52	140.59	67.89	3.16dB	
	B4	120.08	665.55	240.94	4.41dB	
Landsat–5 TM	B1	64.22	41.24	24.28	2.30dB	3.52dB
	B2	31.30	26.36	13.33	2.96dB	
	B3	31.97	115.56	83.59	1.41dB	
	B4	82.62	420.98	190.88	3.44dB	
	B5	81.42	555.41	198.92	4.46dB	
	B7	33.90	181.27	84.77	3.30dB	

Assuming that the noise is well represented by the difference image with no outliers, the experimental results suggest SNR values less than 5dB to simulate real situations. Regarding the coefficient of variation (CV) – i.e. the ratio between the noise standard deviation and the mean of signal – the results range from 7 to 29%. It means that the standard deviation to be introduced for generation of synthetic images must be 7 to 29% of the mean.

4. Final Remarks

This paper attempted to suggest reference values for SNR to be used in the generation of synthetic images for change detection accuracy assessment. The experimental results showed SNR values lower than 5dB as more realistic. In the literature, there are studies as (Bruzzone and Prieto, 2000) that presents accuracy results based on synthetic images with SNR≤10dB. On the other hand, there are studies where SNR values are very high, not representing a real situation.

The analyst can be also use the CV values as a reference to contaminate the original image with noise.

Finally, the authors encourage the use of synthetic images for assessing the accuracy of new algorithms to perform change detection. By using this kind of images, the analyst can introduce your own *change map*, with total control over the level noise. Thus, the conventional accuracy measures can be easily calculated.

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