Relative Radiometric Normalization of Multitemporal images

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***Abstract* — A correct radiometric normalization between both images is fundamental for change detection. MAD method and its IR-MAD extension in an implementation on multisprectral aerial images is described in this paper.**

***Keywords* — Change detection, Iteratively reweighted multivariate alteration detection (IR-MAD), and Multispectral imagery.**

I. Introduction

This paper analyzes results of the application of an automatic method of radiometric normalization between two multitemporal images of the same zone. This radiometric adjustment is part of the preprocessing of image changes detection. Any surface in two images recorded with the same sensor should ideally appear with similar values in their digital levels, but in real practice it doesn't happen due to several reasons, among them different atmospheric conditions, and different lighting from different recorded dates. That is the reason why pixels from the same terrain can show different radiance values, and, therefore, different values in their digital levels. In satellite images radiometric normalization must determine ground absolute reflectivity through correction algorithms as well as atmospheric properties related to the moment of the acquisition of the image [1]. For aerial images (in which atmospheric effects are not as prominent as in satellite images), and for many applications of change detection lineal radiometric normalization of multitemporal is enough. To this end one of the images is taken as reference and the necessary radiometric correction is applied to the other in order to make the tone of its pixels with those of the reference image. The behaviour of the spectral signals of a reflective lambertian surface with times t_1 and t_2 can be accepted as a lineal function. This way the pixels of the image at time t_1 must be corrected to get radiometric normalization:

$$ND_k = a^k ND_k + b^k$$

where ND_k is the grey value in the k band of the image in row i and columns j at time t_1. ND_k normalizad pixel value in band k at time t_1 and a^k, b^k radiometric normalization constants for band k. According to the values taken by the coeficients, called gain and bias too[2], different normalization values will be obtained. Different methods have been analyzed in similar studies[3], which has been ordered in the following list from greater to less effectiveness:

- No-Change Regression Normalization.
- Dark Set-Bright Set Normalization.
- Simple Regression Normalization.
- Haze Correction Normalization.
- Mean-Standard Deviation Normalization.
- Minimum-Maximum Normalization.
- Pseudo-Invariant Normalization.

In aerial images can be difficult to get an absolute normalization due to the lack of atmospheric information associated to the image. Relative normalization based on the intrinsic radiometric information of the images is an alternative method, in which it is not necessary to know the absolute reflectivity of images[4]. In order to implement the relative radiometric normalization, it is assumed that the relationship between the radiance obtained by the sensors in two different instants from regions with constant reflectivity can be approximated by a linear function. The critical issue of the method is the determination of time invariant characteristics which can be the base of normalization

The MAD (Multivariate Alteration Detection) transformation applied to both images from different times is invariant to arbitrary linear transformations of the intensities of the pixels involved in the transformation. That is the reason why in the implementation of the change detection method (MAD) preprocessing with radiometric normalization is superfluous. This work proposes combined use of MAD transformation applied to not-normalized multitemporal images to select NOT-changed pixels and then their utilization for a relative radiometric normalization. This is a simple, quick and completely automatic procedure, compared with methods requiring manual selection of characteristics that do not change with time. Upon completion this method could be combined, if results are not satisfactory under visual exploration of radiometric changes in the normalized image, with a histogram based transformation that modify the digital level of one pixel of the image being corrected, taking one of the two images as reference, so the final histogram of the image is similar to the histogram chosen as base. El que los histogramas sean similares significa que el brillo medio,

DOI: 10.9781/ijimai.2010.139

contraste y distribución de niveles digitales sean también parecidos.

The IDL programming language has been used to implement this method in the ENVI software environment along with RADCAL-RUN extension. The method requires a previous transformation: IR-MAD (modification of MAD transformation [5]), which improves the location of no-change pixels. The quality of normalized images is evaluated in terms of the joint of t-test and F-test in order to compare the mean and the variance respectively. The MAD change detection procedure will be explained concisely in section II.

II. THE MAD AND IR-MAD TRANSFORMATIONS

The Multivariate Alteration Detection method (MAD) is a new change analysis method in multisprectal images originally proposed by [6]. The purpose of this method is that the data of two bitemporal multisprectal image Hill be transformed in such a way that the maximum variance in every band will be explained at the same time in the difference image. This transformation generates a set of mutually orthogonal difference images (MAD components), which have the same spectral dimension as the original multiespectral images that were transformed.

The method is based on correlation analysis. Linear correlation are obtained from two data sets, in such a way that the difference between the two first linear correlations correspond to the biggest correlation. This is called the first canonical correlation. The two corresponding linear combinations are the first canonical components.

The transformation is as follows [7]: first two N-dimensional multisprectal images are represented (where N means the number of bands) of a scene acquired in times t_1 and t_2 with two random vectors, called $\vec{X}$ and $\vec{Y}$, assuming a gaussian normal distribution:

$\vec{X} = \left(X_1,...,X_N\right)^T$, $\vec{Y} = \left(Y_1,...,Y_N\right)^T$. For the first image a lineal combination of the intensities can be established for every spectral band of the image, thus generating a scalar characterized by the random variable $\vec{U} = \vec{a}^T \cdot \vec{X}$. The same is done with the second image $\vec{V} = \vec{b}^T \cdot \vec{Y}$, and afterwards the scalar difference between both images is computed $\vec{U} - \vec{V}$. La información del cambio existente está ahora contenida en una sola imagen. Vectors $\vec{a}^T$ and $\vec{b}$ can be determined by using Principal Components (PC) analysis on $\vec{X}$ and $\vec{Y}$. Another procedure consists of defining simultaneously the set $\vec{a}^T$ and $\vec{b}$ through maximizing the variance of $\vec{U} - \vec{V}$ with the criterion $\mathrm{var}\left(\vec{U}\right) = \mathrm{var}\left(\vec{V}\right) = 1$. It is assumed that both $\vec{a}^T \cdot \vec{X}$ and $\vec{b} \cdot \vec{Y}$ have positive correlation. The determination of the difference between the linear combinations with maximum variance is the same as the determination of the linear combinations with minimal and positive correlation. This is implemented through the standard Canonical Correlation Analysis (CCA). Both $\vec{U}$ and $\vec{V}$ are called canonical variables.

A. *Canonical Correlation Analysis*

This analysis includes a linear transformation of each set of multiespectral images such as, instead of being ordered by its wavelength, transformed components are ordered according to their mutual correlation. The greatest mutual correlation between the images is called first canonical variable (CV) and so on orderly second, third, etc.

For the first image $\left(\vec{X}\right), \sum_{XX}$ is the variance-covariance matrix, and for the second image $\left(\vec{Y}\right), \sum_{YY}$, the covariance between them is $\sum_{XY}$ and the la correlation between $\vec{U}$ and $\vec{V}$ $\rho = corr\left(U, V\right)$:

$$\begin{aligned} \textstyle\sum_{XY} \sum_{YY}^{-1} \sum_{YX}^{T} \vec{a} &= \rho^2 \textstyle\sum_{XX} \vec{a} \\ \textstyle\sum_{YX}^{T} \sum_{XX}^{-1} \sum_{XY} \vec{b} &= \rho^2 \textstyle\sum_{YY} \vec{b} \end{aligned} \tag{1}$$

Thus the pair $\left(U_1, V_1\right)$ has the maximal correlation; the pair $\left(U_2, V_2\right)$ has the next maximal correlation subject to be orthogonal (uncorrelated) to $\left(U_1, V_1\right)$ and so on with the other pairs.

B. *MAD transformation*

Once the CCA has been exposed in the last paragraph, the MAD transformation defined as:

$$\begin{pmatrix} X \\ Y \end{pmatrix} \rightarrow \begin{pmatrix} a_N^T X - b_N^T Y \\ \vdots \\ a_1^T X - b_1^T Y \end{pmatrix} \tag{2}$$

The first MAD component has maximum variance in the intensity of its pixels. The absolute value of the last MAD component shows always the domain of the greatest undergone change. The correlation among the input bands and the MAD components make the interpretation of the mode of change easier. For 12 input bands (this is the case with two multitemporal images LANDSAT) the input is 6 MAD components, with which after the selection of a significant change threshold, the change-no change image can be represented. Depending on the type of present change, any of its components may exhibit significant change information. In fact one of the more interesting aspects of this method is that it orders different change categories in different uncorrelated components of the image.

MAD transformation is invariant to linear transformations applied to the original image (affine transformation type). This means too that it is invariant to radiometric and atmospheric corrections that could be applied. That is why it is considered a very robust method to detect changes. This invariance offers the possibility to use the MAD transformation to implement automatically a relative radiometric normalization onto multitemporal images, as it will be described subsequently.

C. Iteratively reweighted multivariate alteration detection (IR-MAD)

This transformation can be implemented in an iterative schema, in which, when means and covariance matrices are calculated for the next iteration of the MAD transformation, weights are applied to observations according to the probability of determining the NO-change in the preceding iteration. It all begins with the original MAD transformation by assigning, for example, the same weight =1 to every pixel. In order to choose the weight of pixel *j* in the next iteration w_j, the *Z* variable is used to represent the sum of the squares of the standard MAD components:

$$Z = \sum_{i=1}^{N} \left(\frac{MAD_i}{\sigma_{MAD_i}} \right)^2 \in \chi^2(N) \tag{3}$$

Where σ_{MAD_i} is given by equation:

$$\sigma^2_{MAD_i} = 2\left(1 - \rho_{N-i+1}\right) \tag{4}$$

NO-change observations are expected to distribute themselves normally and to be uncorrelated. The random variable *Z* should have a CHI-squared distribution with *N* degrees of freedom. For each iteration, weights determined by the CHI-squared distribution can be applied to observations, calling:

$$w_j = \Pr\left(No - change\right) = 1 - P_{\chi^2;N^{(Z)}} \tag{5}$$

Here $\Pr\left(No - change\right)$ is the likelihood that a pixel *Z* located in the CHI-squared distribution could be big or very big. A small value for *Z* implies a corresponding big probability. The iteration of the MAD transformation continues until it stops because it meets the criteria, such as the lack significant changes in the canonical correlation $\rho_i, 1 \ldots N$ [4].

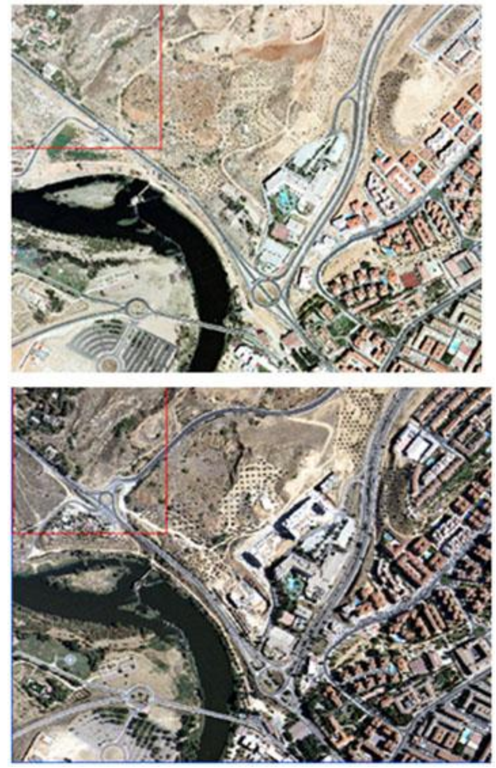

Fig. 1 Images from Toledo 1995 above, 2005 below

III. IMAGERY

RGB color images were employed that come from a photogrametric flight over the city of Toledo (Spain) in dates of 1995 and 2005. The sensor was that of an analogical aerophotogrametric camera WILD RC30, flight scale 1:20000. They are therefore multiespectral images with three bands corresponding to the visible part of the electromagnetic spectrum. The images were scanned by the Zeiss/Imaging photogrametric scanner with resolution of 21 microns. After the aerotriangulation of the set of images, orthopictures were taken with GSD value of 1 meter using DIGI3D software. Visually, in figure 1, the changes experimented in those years can be observed, also the difference in shades between the images.

IV. RADIOMETRIC NORMALIZATION

In order to implement the radiometric normalization the RADCAL_RUN extension [4] developed by Dr. M. J. Canty PhD and programmed in IDL language over the digital image processing software ENVI 4.7 is used. As reference image has been used that of the year 1995.

With the aim of carrying out a radiometric normalization tose pixels that satisfy $\Pr\left(No - change\right) \geq t$ are chosen, where *t* is a decision threshold, usually 95%. The steps involved in the radiometric normalization are the following: [7]

- Chose the values of weights equal to one for every pixel in the bitemporal scene.

- Repeat until the canonical correlations stop changing significantly:
  - Carry out a weighted sample of the bitemporal image so as to determine its mean vector and the covariance matrix.
  - Run CCA and build the MAD components M_i, $i=1,...,N$.
  - Recalculate the weights according to the equations (3) y (5).

The IR-MAD method is applied to the images. The development of the iterations of the canonical correlations is shown in figure 2. As it can be observed, the first iterations are the more important ones It stabilizes itself from the seventh one on.

In order to evaluate the process of normalization the program saves one in every three pixels of NO-change to carry out a reliability test. The mean and the variance are calculated before and after the normalization as well as the statistical hypothesis test of invariant pixels in both images.

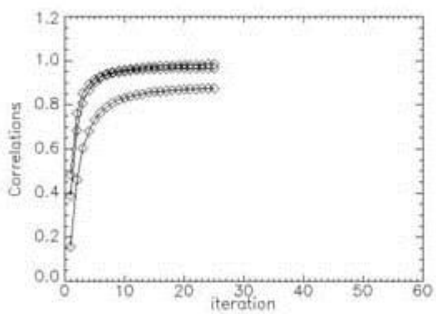

Fig. 2 Canonical correlations over 28 iterations

1794 pixels for the normalization and 898 pixels for the statistical tests were used. The results for the Student test for the mean in the red, green, and blue bands are -0.0077, -0.5409 and 0.1284 respectively. With these values the confidence interval has a p-value between 0.89 and 0.99 for red and blue bands and 0.58 for the green band. As it can be seen in figure 4 in red, the part of the reject of the test covers almost all the distribution. In this case we reject radiometric normalization. By jeans of a visual analysis the bad result is confirmed because it doesn't equal the radiometric values between the reference image, time 1 and the normalized one, time 2.

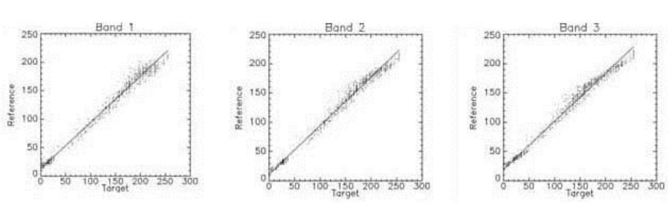

Fig. 3 Regressions on RGB spectral bands of the images.

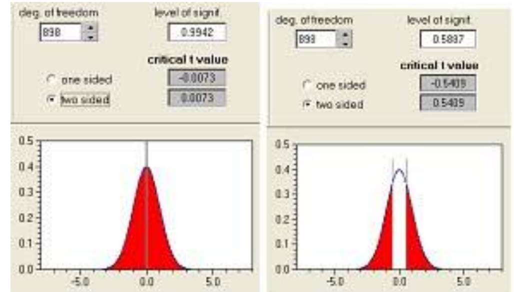

Fig. 4 T-Student results in standardization, left for the red band, green band right

The process is repeated but this time with the a priori condition of probability of belonging to NO-change pixels of 99%. With this premise the number of used pixels for the radiometric normalization has decreased considerably down to 368 and for the tests only 184 have been used. That means that the degrees of freedom have diminished for the calculation of confidence intervals. The results can be seen in table 2. They have clearly improved in respect with the previous test. The radiometric normalization can be accepted then.

Table 1
Comparison of means and variances for 898 test pixels, with paired t-test and F-test.

	Band 1	**Band 2**	**Band 3**
Target mean	108,28	109,87	103,46
Ref. mean	100,75	102,09	104,49
Norm. mean	100,75	102,20	104,46
t-stat	-0,0077	-0,5409	0,1284
p-value	0,9942	0,5887	0,8979
Target var.	7602,22	6630,20	5890,32
Ref. var.	4993,57	4506,05	3909,07
Norm. var	5016,76	4538,78	3937,31
F-stat	1,0046	1,0073	1,0072
p-value	0,9447	0,9137	0,9142

Table 2
New normalization, comparison of means and variances for 184 test pixels, with paired t-test and F-test.

	Band 1	**Band 2**	**Band 3**
Target mean	104,54	106,33	101,87
Ref. mean	97,43	99,05	103,53
Norm. mean	98,15	99,50	103,53
t-stat	-1,4692	-1,0096	-1,8733
p-value	0,1435	0,3140	0,0626
Target var.	7833,07	6823,08	6249,76
Ref. var.	5102,16	4634,28	4128,26
Norm. var	5270,16	4762,56	4293,28
F-stat	1,0329	1,0277	1,0400
p-value	0,8267	0,8537	0,7912

Fig. 5. Result of radiometric normalization. Reference image is on the left 1995, and normalized on the right 2005.

V.CHANGE DETECTION

One application among others of change detection is the updating of Geographic Databases. According to [8] the two main approaches to update a Database are: first to set up gradually a new Database that replaces the old one and the second approach is to detect, identify, and update only the changes. This option is faster and more convenient. That is the reason why automatic change detection is the first and most important step in the updating of Geographic Databases. The result of MAD transformation generates three components, see figure 6. Maximal change areas show white pixels (positive change) and black pixels (negative change). Through a colour combination of the three MAD components a new image is obtained where change is shown in magenta colour, the new road and the new buildings. A change classified image can be finally set up by establishing thresholds and postprocess filters. Correlation among components and original bands are shown in table 3. The greatest correlation corresponds to MAD 3, with negative correlation in the bands of the year 2005 and positive ones in the year 1995. MAD 1 component shows a noise image; in the MAD 2 one can be seen in black colour the negative change because of the new buildings and the new road. At last the MAD 3 component shows in white colour the positive change due mainly to the different orientation of the shadows of the buildings. This change will be eliminated later by means of the application of a shadows mask.

Table 3
Correlation matrix of the MAD components with the original bands.

		MAD 1	MAD 2	MAD 3
Toledo	R	0,079	0,084	0,465
1995	G	0,158	0,193	0,432
	B	0,052	0,279	0,413
Toledo	R	-0,303	-0,171	-0,397
2005	G	-0,385	-0,237	-0,333
	B	-0,242	-0,337	-0,343

In [9] and [10] MAD method is used as a technique of change detection between satellite multiespectral images.

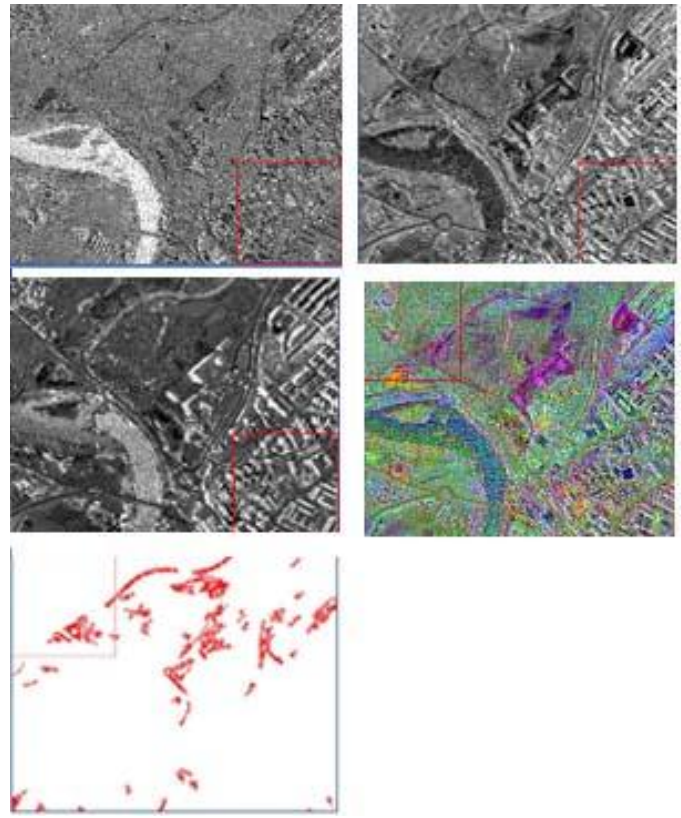

Fig. 6 MAD components and color composition where, in magenta, the detected change is observed. Exchange classified image below.

VI. CONCLUSIONS

Radiometric normalization among multitemporal multiespectral images using the IR-MAD transformation gives good results. This transformation selects invariant pixels in the presence of changed pixels. The associated statistics to the applied transformation with a *t* threshold, tables 1 and 2, has the utility of validate or reject the normalization. In the case of the aerial images in this work, a final threshold $t \geq 99\%$ was chosen to search for invariant pixels.

Finally, MAD transformation as method of change detection has highlighted existing changes. This technique depends on the chose threshold to highlight changes in each component. These thresholds have to be selected by means of an empiric method through observation by the image analyst.

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