COMPARISON OF RADIOMETRIC NORMALIZATION METHODS ON LANDSAT ETM+ AND ASTER DATA

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ABSTRACT
Change detection techniques are widely diffused to derive basic information in the analysis of land cover transformations. Some difficulties in multi-date imagery treatment persist in remote sensing applications because of errors due to noise, to environmental conditions and to geometric and radiometric distortions introduced during the acquisition or transmission phases of satellite systems. Such assumptions may have impact on the accuracy of subsequent human or machine-assisted multi-temporal image analysis. Preliminary geometric and radiometric processing of remotely sensed data are consequently necessary in order to correct degradations and noises introduced during the imaging process.

The methods of radiometric correction for multi-temporal analysis of satellite imagery can be absolute and relative. The absolute methods are not always feasible because they need to measure the optical properties of the atmosphere acquired “in situ” and simultaneously with the moment of scene recording. The relative methods proceed under the assumption that the relationship between the at-sensor radiances recorded at two different times from regions of constant reflectance is spatially homogeneous and can be approximated by linear functions.

The most difficult time-consuming aspect of all these methods is the determination of suitable time invariant features upon which the normalisation is based (PIF - Pseudo Invariant Features) with the scarce possibility to homogenise data in accurate way.

The research proposes the investigation of normalization methods in order to prepare next Change detection techniques for land cover transformations, executable on satellite data that are heterogeneous for spatial and spectral resolution.

To that end, the most suitable radiometric correction techniques and the development of innovative algorithms and automatic methodology were conducted in order to improve the accuracy level of results. With this aim, the relative radiometric normalization scene-to-scene with ELC (Empirical Line Calibration) and MAD (Multivariate Alteration Detection) techniques on LANDSAT ETM+ and ASTER data were investigated. In the ELC technique Pseudo-Invariant Features (PIFs) were manually selected, whereas the Features to derive the normalization coefficients were automatically identified with the aid of an algorithm based on MAD transformation.

Finally, an empirical test by analysing the Gain and Offset results was proposed in order to allow the selection of bands with optimal behaviour within MAD transformation, usable for next multi-temporal analysis (classifications, vegetation index analysis, etc.).
1. INTRODUCTION

The high technologic content of satellite sensors offers an excellent opportunity to monitor regularly large surfaces, with comparatively reasonable times and costs. Moreover, such systems become an indispensable tool in territories with lack of data for environmental control or inaccessible and unlikely known.

According to Jungho and Jensen (2005) the goal of remote sensing Change detection is (a) to detect the geographic location of change found when comparing two (or more) dates of imagery, (b) to identify the type of change if possible, and (c) to quantify the amount of change.

In literature there are many techniques for multi-temporal analysis and Image differencing is the most direct method. The simple difference between two co-registered satellite data, acquired in different times, offers a quantitative assessment of change percentage “point to point” (Nielsen et al., 1998). The limits of this technique are connected to the difficulty to achieve absolute accuracy (Meyer et al., 1993), to the temporal stability of sensor calibration, to the level of correlation of bands, and to the geometry of sun-earth-sensor. Such elements do not enable an effective comparison among images because such data have not a common radiometric reference.

The radiometric calibration makes this technique particularly advantageous and can be absolute or relative. Such pre-processing method is important in land cover classifications and for many other applications, such as image mosaicking or tracking vegetation indices over time etc. (Yang and Lo, 2000). Furthermore, if change detection procedures - such as image differencing or change vector analysis - are preferred, it must generally be preceded by radiometric calibration (either absolute or relative) in order to quantify temporal phenomena from multi-date imagery (Coppin et al., 2004).

Absolute radiometric correction of multi-temporal satellite imagery requires atmospheric corrections associated with the atmospheric properties at the time of the image acquisition. The digital number of a pixel is converted to a percent reflectance value using established transformation equations or atmospheric models (Song et al., 2001). Data for the characterisation of the relevant atmospheric processes modulating the incoming radiation at the satellite sensor require auxiliary data of parameters, such as the content of aerosols, ozone or water vapour in different atmospheric layers (Mitchell et al., 1993; Vermote et al., 1995).

Whenever atmospheric parameters for historical dates of imagery are not available or absolute surface radiances are not necessary, a relative calibration (named by many authors as normalisation) of the satellite images to a master
scene, based on the radiometric information intrinsic to the images, is an alternative (Hall et al., 1991; Furby et al., 2001; Du et al., 2002).

One advantage of this procedure is that the original radiometric condition of the reference image is retained, obviating the computational effort required to convert each image to units of radiance or reflectance (Yuan and Elvidge, 1996). With this aim, Jensen (1996) suggested the Multiple-date Empirical Radiometric Normalization. This method involves the selection of ground targets whose reflectance values are considered constant over time, otherwise named by Schott et al. (1988) as Pseudo-Invariant Features (PIFs). Selection of such ground targets results in radiometric normalization that is entirely dependent on the abilities and local knowledge of the analyst (Janzen et al., 2006) and, consequently, it is subjected to unavoidable errors in the procedure accuracy.

In this study the radiometric normalization scene-to-scene with ELC (Empirical Line Calibration) and MAD (Multivariate Alteration Detection) techniques (Canty et al., 2004) on LANDSAT ETM+ and ASTER data were analysed by executing a quantitative and qualitative comparison.

With the ELC technique Pseudo-Invariant Features (PIFs) were manually selected, whereas the Features to derive the normalization coefficients were automatically identified with the aid of an algorithm based on MAD transformation. Homogenization and registration in an unique digital information environment, with the identification and quantification of variation occurred in a chosen test area, will permit the rapid evaluation of risk level and the consequent planning of prevention and intervention works. With this aim, a further empirical test by analysing the Gain and Offset results was proposed in order to allow the selection of bands with optimal behaviour within MAD transformation.

2. METHODOLOGY

2.1-MULTIPLE-DATE EMPIRICAL RADIOMETRIC NORMALIZATION

Relative normalization techniques are not “corrections” in the sense that they use actual atmospheric measurements from the time of image acquisition, but rather attempt to uniformly minimize effects of changing atmospheric and solar conditions relative to a standard image selected by the user (Callahan, 2003). There are several methods (Hall et al., 1991; Du et al., 2002) proposed for the relative radiometric normalisation of multispectral images taken under different conditions at different times. They all proceed under the assumption that the relationship between the at-sensor radiances recorded at two different times from
regions of constant surface reflection can be approximated by linear functions (Jensen, 1996). Such required relations are commonly named *Scene-to-Scene* techniques and are funded on a linear relation between resampled pixels of ‘reference’ or ‘master’ image (Y) and pixels of image to be normalized, denoted as ‘target’ or ‘subject’ (X) (Casselles et al., 1989). The selection of the targets is manually executed. The common form for linear radiometric normalization is

\[ N_k = g_k X_k + o_k \]  

where \( X_k \) is the digital value (DN) of band \( k \) in image \( X \) and \( N_k \) is the normalized DN of band \( k \) on date 1 and \( g_k \) and \( o_k \) are normalization constants for band \( k \). Some authors calculated the \( g_k \) and \( o_k \) basing the empirical analysis on statistical parameters of the entire \( X \) and \( Y \) images (Yuan and Elvidge, 1996).

Schott et al. (1988) proposed that in the case of the availability of a large amount of homogeneously distributed invariant pixels, a regression of the same pixels would produce the best results, but assumed that these pixels are not identifiable. This would be satisfied if ground truth data of the true invariant pixel were available, which is rarely the case. Thus, their idea was to introduce the term pseudo-invariant feature (PIF). Pseudo-invariant features are used for a stochastic estimation of coefficients for an image to image radiometric normalisation.

In our work the ELC (*Empirical Line Calibration*) was applied as first method of investigation. This method uses PIFs of master and target images (ROI *Regions Of Interest*) and allows to calculate *Gains* and *Offsets* by means of the ordinary least square regression analysis.

The most difficult and time-consuming aspect of the above methods is the determination of suitable time invariant features upon which the normalisation is based. Besides the loss of accuracy in manual identification of invariant targets, a further limit is the case in which satellite data are afflicted by intrinsic radiometric problems with different climatic conditions related to acquisition phase, as cloud or snow covers (Moran et al., 1992; Caprioli at al., 2006).

Moreover, the regression procedure would need of targets selected on the whole range of values (*bright - midrange - dark*) with the same dimension and the same number. Every target should contain only minimal amounts of vegetation and would be localized in a flat area with regular characteristics (Hong et al., 2005), far from borders of the acquired scene, in order to minimize errors due to co-registration (Furby et.al., 2001).

In order to remedy to such inconveniences by identifying potential no-change pixels a priori, Schott et al. (1988) proposed the usage of band ratios and Hall et
al. (1991) the Tasseled cap transformation. Du et al. (2002) applied PCA (Principal Components Analysis) to assist user in the selection of invariant features or \textit{no-change} pixels.

As in our study, this last is of limited effectiveness in presence of data with a high level of temporal and intrinsic change, and with invariant pixels in lower number in comparison with the remainder pixels of the whole image.

\section*{2.2 - MULTIVARIATE ALTERATION DETECTION TECHNIQUE}

The MAD procedure is based on a classical statistical transformation referred to as correlation analysis to enhance the change information in the difference images and briefly described as follows.

Invariant pixels are selected by means of the simple image difference $D$ (with $F$ and $G$ matrixes or random vector) acquired in two different dates ($t_1$, $t_2$):

\begin{equation}
D = F - G = \begin{bmatrix} F_1 - G_1 & \ldots & F_k - G_k \end{bmatrix}^T = a^T F - b^T G
\end{equation}

with

\begin{equation}
F = \begin{bmatrix} F_1 \ldots F_k \end{bmatrix}^T \quad \text{and} \quad G = \begin{bmatrix} G_1 \ldots G_k \end{bmatrix}^T
\end{equation}

$k =$ band number.

Analogously to the principal component transformation, the vectors $a$ and $b$ are sought subject to the condition that the variance of $D$ is maximized and subject to the constraints that:

\begin{equation}
\text{var} (a^TF) = \text{var} (b^TG) = 1
\end{equation}

As a consequence, the difference image $D$ contains the maximum spread in its pixel intensities and - provided that this spread is due to real changes between $t_1$ and $t_2$ - therefore $D$ corresponds to maximum change information.

Determining the vectors $a$ and $b$ in that way is a standard statistical procedure which amounts the so-called generalised eigenvalue problem. For a given number of bands $N$, the procedure returns $N$ eigenvalues, $N$ pairs of eigenvectors and $N$ orthogonal (uncorrelated) difference images, referred to as to the MAD variants (Nussbaum et al., 2007).

Since relevant changes of man-made structures will generally be uncorrelated with seasonal vegetation changes or statistic image noise, they expectedly
concentrate in the higher order components (if sorted according to the increasing variance). Furthermore, the calculations involved are invariant under affine transformation of the original image data. Assuming that changes in the overall atmospheric conditions or in sensor calibrations (Nielsen et al., 1998) are approximately equivalent to affine transformations of the pixel intensities, the method is insensitive to both of these effects.

Areas with a light rate of change will have a very low DN value. The limit of this procedure consists in lack of simultaneous comparison of all changes for all bands.

Although the principle is similar to ELC (invariant pixels are used in an regression approach), MAD transformation is fully automatic, overcoming the above-mentioned problems with the concentration of information on the global change rate (Canty, 2005).

The main progress is the automatic identification of “no change” pixels, that are homogeneously distributed over the entire image and different surface types.

3. - DATA AND RESULTS

In this study two kinds of satellite images on two Italian test areas (Fig. 1) were used: LANDSAT 7 ETM+ and ASTER.

Fig. 1. Location of satellite data acquisitions on the test areas of Lazio and Apulia regions (Italy)
The three LANDSAT ETM+ data were acquired over Aurunci chain, in southern Apennine of Lazio (Italy), on September 24, 1999 (Fig. 2A – reference image A), April 6, 2001 (Fig. 2B – target image B) and February 2, 2002 (Fig. 2C – target image C). Every image was a subset of the whole scene with the dimensions of 650 × 650 pixels. This territory was chosen because it presents a diversified morphology with active anthropic dynamics and permits to test the effectiveness of normalization algorithms, both the consolidated (ELC) and the innovative (MAD) ones, even in unfavourable climatic and territorial situations. With this aim, LANDSAT ETM+ satellite data - acquired in different periods of the year were analysed, with various atmospheric and illuminated conditions.


In order to validate both the procedures, further investigations were conducted on ASTER data with different intrinsic image characteristics and a subset area test.
of the dimensions of 700 × 700 pixels (Fig. 3A – reference image A and Fig. 3B – target image B). The acquisitions were made on June 24, 2003 and September 14, 2004, that is with similar atmospheric conditions, on a flat coastal territory of Apulia (Italy).

The above-mentioned intrinsic characteristics of such data permitted the better evaluation of results, by executing a quantitative and qualitative comparison of Gains and Offset values obtained on diversified territorial and atmospheric contexts.

Figs. 3A, 3B - RGB 321 colour composite of ASTER data over Apulia (Italy): June 2003, September 2004

Before the execution of radiometric correction procedures, the images were co-registered by means of Image-to-Image technique provided by ENVI image processing software. 30 GCPs (Ground Control Points) on the LANDSAT ETM+ 1999 data and 28 GCPs on the ASTER 2003 data, as reference images, were identified. With this aim, a not parametric model, based on the 3° order polynomial function, was used and a value lower than 0.5 pixel for RMS was obtained. Next, the whole set of images were resampled with Nearest Neighbour method (30 m for the LANDSAT ETM+ data and 15m for the ASTER data) in order to not alter heavily the radiometric content of images.

As discussed in the previous chapter, both the next normalization procedures were conducted without executing any radiance/reflectance calibration, by choosing to work on row data (DN) and without considering the influences derived from different morphologic contexts, with the aim to homogenize multi-date imagery. Such decision was matured by considering the lack of onerous
historic at-sensor and atmospheric data or with the aid of ground spectrometer data contemporaneous to the acquisition date of the analyzed images (absolute calibration).

In the first phase of this study, related to ELC processing (ENVI User’s Guide, 2003), the pixel indispensable to calculate the calibration parameters (*Gain* and *Offset* expressed in Digital Numbers) were manually selected from the ground truth data. With this aim, 10 targets or pseudo-invariant features (PIFs) (Sand, Buildings, Water, Bare soil, Rock) from the positional point of view and with similar radiometric characteristics were selected. The dimension of every target was of 5 x 5 pixels, making the selection with the help of Band Ratio and Principal Component analysis. Such dimension was due to the medium geometric resolution of data and realizing the impossibility to distinguish on video smaller indubitable pseudo-invariant regions. The Fig. 4 shows an example of PIFs individuation on a subset area of the LANDSAT reference data (September, 1999).

In a comparative way MAD technique was next implemented by using CDSAT-ENVI plug-in. Such procedure permitted the automatic identification of invariant pixels, while the calibration parameters were determined with orthogonal regression. As Canty et al. (2004) pointed out, while in the model for least squares regression the $x$ is considered as an independent predictor and is assumed to be error-free, the orthogonal regression allows for error in both $x$ and $y$ spaces, because in the calibration case both the reference and the target variable are considered arbitrary.

The exactness of both the procedures was evaluated by means of the comparison of *Gain* and *Offset* values (Table 1 and Table 2) obtained on both the two different sensors data. Such values must be near respectively to one and zero (Du et al., 2002) in order to not loose the radiometric resolution in comparison to the initial data.

A further empirical analysis was proposed in order to verify the possibility to use MAD procedure choosing bands with optimal behaviour as regards *Gain* and *Offset* results. In the column named *Test* of the Table 1 and Table 2 the values considered positive of $g_k < 0.75$ and $o_k < \sigma_{offset}$ in absolute terms were pointed out, in order to allow an easy selection of best bands for next multi-temporal analysis. For the entire image of every band was imposed that:

$$ Test = 1 \text{ if both the conditions } |g_k| < 0.75 \text{ and } |o_k| < \sigma_{offset} \text{ were verified.} $$

The decision thresholds (0.75 and $\sigma_{offset}$) were chosen on the base of the experiences conducted with empirical procedures made in precedent works (Caprioli et al., 2006; Hong and Zang, 2005). The term $g_k < 0.75$ was to make
independent the single band from the behaviour of the whole set of bands (Jensen, 1996), while the second condition $|\alpha| < \sigma_{\text{offset}}$ was to consider the errors that were common to all the bands (sensor noises, terrain effects, etc.).

For both the procedures (ELC and MAD) the *Gains* and *Offsets* values of TIR bands of LANDSAT ETM+ (Band 6) and ASTER (Bands 10-14) sensors were
widely higher than the values of the remaining bands (Figs. 5A, 5B, 5C and 5D). This was due to the alterations induced by the resampling of the lower geometric resolution data (from 60 m for LANDSAT ETM+ to 30 m and from 90 m for ASTER to 15 m) and by the intrinsic characteristics of bands that works in thermal range and with electromagnetic radiation emitted rather than reflected.

![Figs. 5A, 5B - Comparison between the results of Gain and Offset calculated for LANDSAT ETM+ bands](image)

Table 1 - Results of Gains and Offsets obtained with ELC and MAD methods on LANDSAT ETM+ data

<table>
<thead>
<tr>
<th></th>
<th>ELC - Empirical Line Calibration</th>
<th>Radiometrical Normalization with MAD</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>A → C</td>
<td>B → C</td>
</tr>
<tr>
<td>Gain</td>
<td>Offset</td>
<td>Gain</td>
</tr>
<tr>
<td>Band 1</td>
<td>1,65</td>
<td>-21,41</td>
</tr>
<tr>
<td>Band 2</td>
<td>1,50</td>
<td>-6,54</td>
</tr>
<tr>
<td>Band 3</td>
<td>1,43</td>
<td>-4,46</td>
</tr>
<tr>
<td>Band 4</td>
<td>1,41</td>
<td>6,28</td>
</tr>
<tr>
<td>Band 5</td>
<td>1,12</td>
<td>15,15</td>
</tr>
<tr>
<td>Band 6</td>
<td>2,76</td>
<td>-166,37</td>
</tr>
<tr>
<td>Band 7</td>
<td>1,21</td>
<td>3,99</td>
</tr>
<tr>
<td>Mean</td>
<td>1,58</td>
<td>-24,77</td>
</tr>
<tr>
<td>St. dev. (\sigma)</td>
<td>(58,79)</td>
<td>(0,22)</td>
</tr>
</tbody>
</table>

The values of the ELC Gains column on Table 1 were quite low while the ELC Offsets column pointed out an high variability within all the bands, with \(St. \, dev. \, \sigma\) of 58,79 for \(A \rightarrow C\) and 15,23 for \(B \rightarrow C\), considering \(C\) as reference image and \(A\) and \(B\) as target images. The MAD Gains and Offsets columns showed a lower global \(St. \, dev. \, \sigma\), with similar values for \(A \rightarrow C\) and \(B \rightarrow C\) normalizations.
Figs. 5C, 5D - Comparison between the results of Gain and Offset calculated for ASTER bands

Table 3. Results of Gains and Offsets obtained with ELC and MAD methods on ASTER data

<table>
<thead>
<tr>
<th>Band</th>
<th>ELC-Empirical Line Calibration</th>
<th>Radiometrical Normalization with MAD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A → B Gain</td>
<td>Offset</td>
</tr>
<tr>
<td>Band 1</td>
<td>1,13</td>
<td>15,87</td>
</tr>
<tr>
<td>Band 2</td>
<td>1,08</td>
<td>19,44</td>
</tr>
<tr>
<td>Band 3</td>
<td>0,99</td>
<td>21,77</td>
</tr>
<tr>
<td>Band 4</td>
<td>1,05</td>
<td>4,36</td>
</tr>
<tr>
<td>Band 5</td>
<td>1,11</td>
<td>1,23</td>
</tr>
<tr>
<td>Band 6</td>
<td>1,10</td>
<td>1,16</td>
</tr>
<tr>
<td>Band 7</td>
<td>1,06</td>
<td>1,21</td>
</tr>
<tr>
<td>Band 8</td>
<td>1,03</td>
<td>0,81</td>
</tr>
<tr>
<td>Band 9</td>
<td>1,31</td>
<td>0,39</td>
</tr>
<tr>
<td>Band 10</td>
<td>2,41</td>
<td>-9,87</td>
</tr>
<tr>
<td>Band 11</td>
<td>2,11</td>
<td>-8,21</td>
</tr>
<tr>
<td>Band 12</td>
<td>2,22</td>
<td>-9,66</td>
</tr>
<tr>
<td>Band 13</td>
<td>2,46</td>
<td>-12,22</td>
</tr>
<tr>
<td>Band 14</td>
<td>2,41</td>
<td>-11,47</td>
</tr>
<tr>
<td>Mean</td>
<td>1,53</td>
<td>1,06</td>
</tr>
<tr>
<td>St. dev. σ</td>
<td>0,62</td>
<td>11,27</td>
</tr>
</tbody>
</table>
Fig. 6A. RGB 321 natural colour of a subset area of LANDSAT raw data (April 2001) and the related histogram
Fig. 6B. RGB 321 natural colour of a subset area of LANDSAT – ELC processed data (April 2001) and the related histogram
This was validated in the MAD Test column, where the homogeneous behaviours of the LANDSAT bands were derived, except for the Bands 3 and 5.

In Table 2 the behaviour of ASTER data with both the methods leaded to similar results, particularly in the SWIR bands, with the only difference emerged in the Test column with the Band 1. This similarity was due to the intrinsic characteristic of imagery. Besides the augmented spatial resolution, the ASTER data presented the absence of clouds, the different sun angle and the temporal range with acquisition date of similar climatic conditions.
All these aspects carried out positive results on both LANDSAT and ASTER data with comparable imagery homogenised with normalization, helpful to a next coherent multi-temporal analysis.

This was also confirmed from a visual/qualitative point of view by comparing the raw data with the corrected or normalized images. The Figs. 6A, 6B and 6C were chosen as an example to show one of such comparisons on LANDSAT data (April 2001) in which the qualitative enhancements of the normalized imagery were proved by means of the shifts resulted from histograms analysis.

4. - CONCLUSION

The analysis of the results demonstrates the advantages in using the automatic MAD technique for radiometric normalization of multi-temporal satellite data in terms of saving processing time. Moreover, MAD technique identifies several PIFs in comparison with the ELC method, with a consequent better accurate analysis. The procedure requires only a subjective parameter such as chi square percentile, without any other adjustable criteria for defining PIF features.

On the whole, the MAD and the ELC based normalisation techniques generally produce comparable results, especially for images with lower level of noise. A certain amount of problems were proved on image with intrinsic radiometric problems, such as haze phenomenon and cloud covers. As aid to such inconveniences, the empirical test proposed in this study, by analysing the Gain and Offset results, could be helpful for the selection of bands with optimal behaviour within MAD transformation, usable for next change detection analysis.

Generally, the mean values after the image normalisation in both approaches are well represented. The variances of “no change” pixels in both normalisation approaches are slightly underestimated. The regression parameters on “no change” pixels are better represented in the MAD based approach.

Due to its completely automatic operation, and as parameters are free and fast, the MAD based normalisation technique was favoured in comparison with the definition of decision thresholds or individuation of PIF (Pseudo Invariant Features) with subjective criterions by using ELC techniques. In fact, with MAD transformation the basic data come completely from the same image, without interference of unfavourable climatic conditions or every type of noise/variation in terms of reflectance.
REFERENCE