Change Detection in Multispectral Imagery from Multisensor

Lu ZHANG
Joint Laboratory for Geoinformation Science, Chinese University of Hong Kong
Room 615, Esther Lee Building, Chung Chi College, CUHK, Shatin, N.T., Hong Kong
zhanglu@cuhk.edu.hk

Mingsheng LIAO
State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University
129 Luoyu Road, Wuhan, P.R.China
liao@lmars.whu.edu.cn

Abstract: In this paper a method based on canonical correlation analysis, called MNF/MAD is proposed for change detection in multispectral imagery from multisensor. This method is able to concentrate change information in all spectral bands, and it has the merit of insensitive to linear transformations such as gain settings of measuring devices and linear radiometric correction schemes. A case study using Landsat7 ETM+ and SPOT5 HRG images is conducted to validate the feasibility and effectiveness of this method.
Keywords: Change Detection, Multisensor, CCA, MAD, MNF.

1. Introduction

Change detection is one of the major applications of remotely sensed data obtained from earth-orbiting satellites because of repetitive coverage at short intervals and consistent image quality [1]. This depends on the fact that the knowledge of the dynamics of either natural resources or man-made structures on the earth surface is a valuable information source for decision-making in a variety of applications [2].

In general change detection is carried out in images acquired by the same sensor to ensure comparability in various aspects over the time span of interest. However, in some cases it is unavoidable to work with multitemporal images from different sensors. For example, in long time series analysis, one of the sensors may not have existed at the earlier dates, or it stopped collecting image for technical or other reason. In other cases, we do not have image data available from a certain sensor at specified date due to reasons such as fixed revisiting cycle or bad weather condition, so that we have no alternative but use image available from other sensors instead.

Usually properties of image data acquired by different sensors are distinct from each other in various aspects, including spatial resolution, number of spectral bands, spectral resolution, and radiometric resolution, etc. When change detection methods based on Post-Classification Comparison are employed, this is not a big problem, and the change detection result is produced by just comparing classification maps of multisensor images, where the key technique is to ensure high accuracy of classification result. However, if those methods based on direct comparison of pixel values are adopted, differences between multisensor images may render their analysis more difficult than that for images from the same sensor. For example, Change Vector Analysis (CVA), a classical change detection method, requires bi-temporal images to have equal number of spectral bands corresponding to each other one by one. In the case of TM and SPOT images are used, which have six and four bands respectively, CVA could not be applied on all bands simultaneously. Moreover, since none of TM and SPOT band pair does not exactly coincide with each other, even simple differencing method could not work.

To overcome above problem in multisensor change detection based on direct comparison, we propose to apply the Minimum Noise Fraction/Multivariate Alteration Detection (MNF/MAD) method to change detection in multispectral imagery from multisensor. The critical idea of MNF/MAD method is to construct a few variates containing most change information by exploring the intrinsic correlation structures between the two temporal images. Such a method consists of three major steps: 1) performing the Canonical Correlation Analysis (CCA) on multitemporal images to construct canonical variates; 2) using the so-called MAD transformation to produce the MAD variates containing uncorrelated information pertinent to temporal differences; 3) applying the Minimum Noise Fraction (MNF) transformation to the MAD variates to concentrate change information and separate them from noises. By employing this method, bi-temporal change information can be concentrated as much as possible into relatively a few resultant variates facilitating following interpretations such as extraction of change areas and identification of change types. In addition, exploring the statistical correlations between these resultant variates and those original spectral bands, we may find out the nature of changes to a certain extent. Another advantage of this method over those traditional methods is its invariant to linear scaling, which means it is insensitive to adjust of measuring unit, gain and offset settings of measuring devices, and linear radiometric and atmospheric corrections

2. Methodology

According to basic theories of remote sensing, owing to complications and uncertainties during imaging processes, multispectral imagery in general can be taken as a group of random variables, often called multivariate, and each pixel value vector could be regarded as a certain realization of this multivariate. In this way, multisensor change detection could be considered as a problem of finding out differences between two groups of random variables corresponding respectively to two multispectral images of the same area acquired at different times. This problem could be solved by employing the MNF/MAD method described in following sections.

2.1 Canonical Correlation Analysis

The Canonical Correlation Analysis (CCA) is a statistical analysis method in classical multivariate statistics. This method investigates the relationship between two groups of random variables. To give an explicit mathematic formulation, let us consider two column vectors *X* and *Y* composed of p and q dimensional random variables:

$$\begin{cases} X = [x_1, x_2, \cdots, x_p]^T \\ Y = [y_1, y_2, \cdots, y_q]^T \end{cases} \tag{1}$$

For multisensor change detection, above *X* and *Y* represent multispectral images of different times, correspondingly *p* and *q* are the numbers of spectral bands. Without loss of generality, we assume that $p \leq q$.

Define linear transformation as below:

$$\begin{cases} U = a^T X = a_1 x_1 + a_2 x_2 + \cdots + a_p x_p \\ V = b^T Y = b_1 y_1 + b_2 y_2 + \cdots + b_q y_q \end{cases} \tag{2}$$

Where $a = [a_1, a_2, \cdots, a_p]^T \in R^p$ and $b = [b_1, b_2, \cdots, b_q]^T \in R^q$ are coefficient vectors. Different values of *a* and *b* produce different combinations *U* and *V*. The objective of CCA is to maximize the correlation between *U* and *V*, i.e.

$$Corr\{U, V\} = \frac{Cov\{U, V\}}{\sqrt{Var\{U\}Var\{V\}}} = \max \tag{3}$$

Without loss of generality, *U* and *V* are assumed to comply with distributions of standard deviation, shown as below:

$$\begin{cases} Var\{U\} = a^T Cov\{X\} a = 1 \\ Var\{V\} = b^T Cov\{Y\} b = 1 \end{cases} \tag{4}$$

Where $Cov\{X\}$ and $Cov\{Y\}$ are covariance matrices of *X* and *Y* respectively. Now, to maximize $Corr\{U,V\}$, $Cov\{U,V\}$ must be maximized. For simplicity, we assume *U* and *V* are positively correlated. According to statistics, $Cov\{U,V\}$ can be calculated as:

$$Cov\{U, V\} = a^T Cov\{X, Y\} b \tag{5}$$

Where $Cov\{X,Y\}$ is covariance matrix between *X* and *Y*. In this way, CCA comes down to searching for coefficient vectors *a* and *b* which meet equations.

$$\begin{cases} a^T Cov\{X\} a = 1 \\ b^T Cov\{Y\} b = 1 \\ Corr\{U,V\} = a^T Cov\{X,Y\} b = \max \end{cases} \tag{6}$$

Obviously it is a problem of conditional extreme value. Making use of Lagrange multiplier, we can get the result as following style:

$$\begin{cases} Aa = \lambda^2 a \\ Bb = \lambda^2 b \end{cases} \tag{7}$$

Therefore, CCA is converted into computing eigenvalues and eigenvectors of square matrices A and B. It can be solved easily in linear algebra. The calculated p eigenvalues λ^2 can be sorted by value as $\lambda_1^2 \ge \lambda_2^2 \ge \cdots \ge \lambda_p^2 > 0$, each λ_i corresponds to a pair of U_i and V_i, called the ith canonical variables. In fact, λ_i (i=1,2,…,p) is the correlation coefficient between U_i and V_i, i.e. $\lambda_i = Corr\{U_i, V_i\}$. An interesting and important property of canonical variables is:

$$\begin{cases} Corr\{U_i, U_j\} = 0 \\ Corr\{V_i, V_j\} = 0 \qquad i \ne j, i, j = 1, 2, \cdots, p \\ Corr\{U_i, V_j\} = 0 \end{cases} \tag{8}$$

Eq. (8) means: 1) each pair of canonical variables of X are uncorrelated; 2) each pair of canonical variables of Y are uncorrelated; 3) each pair of canonical variables of X and Y with different sequence numbers are uncorrelated. This implies when we analyze correlativity of X and Y, we need only to analyze correlativity of U_i and V_i. The correlation coefficient of two variables reveals their affinity, the bigger the correlation coefficient is, the more the affinity is.

2.2 Multivariate Alteration Detection

For change detection using remotely sensed imagery, if there are strong correlations between multitemporal images, then methods like simple subtraction are prone to being unable to reveal change information to the full extent. So temporal correlations must be removed as much as possible before change analysis. The Multivariate Alteration Detection (MAD) based on CCA provides a promising approach for this objective.

As seen in previous section, for two multivariate X and Y, their canonical variable pairs U_i and V_i can be sorted by their correlations. When we get the difference variable D_i of one pair U_i and V_i, we can derive variance of D_i as

$$\begin{aligned} Cov\{D_i\} &= Cov\{U_i - V_i\} \\ &= Var\{U_i\} + Var\{V_i\} - 2Corr\{U_i, V_i\} \end{aligned} \tag{9}$$

With Eq. (4), (9) can be simplified as

$$Cov\{D_i\} = 2(1 - Corr\{U_i, V_i\}) \tag{10}$$

It can be seen clearly that in order to maximize $Cov\{D_i\}$, $Corr\{U_i,V_i\}$ should be minimized. Thus the component D_i with maximal variance corresponds to the canonical variable pair U_i and V_i with minimum correlation.

Now, MAD transformation can be formulated as following [3]:

$$\begin{cases} \begin{bmatrix} X \\ Y \end{bmatrix} \mapsto M \\ M = \tilde{\alpha}^T X - \tilde{\beta}^T Y \end{cases} \tag{11}$$

Which makes $Cov\{M\}$=max, subject to constraint of unit variances: $Var\{\tilde{\alpha}^T X\} = Var\{\tilde{\beta}^T Y\} = 1$. And M is called MAD variate of state change.

The problem is to find out coefficient vectors $\tilde{\alpha}$ and $\tilde{\beta}$ which meet such condition. As the same as CCA, it can be solved using Lagrange multiplier, moreover, the solution resembles that of CCA except for reverse order.

Inferred from that of canonical variables, MAD variates have important properties as below:

1) $Var\{M_i\} \geq Var\{M_j\}$, if $i \leq j$. That means MAD variate components are arranged in order of decreasing variance.

2) $Cov\{M_i, M_j\} = 0$, if $i \neq j$, i.e. each pair of MAD variate components are uncorrelated or called orthogonal.

3) As opposed to the principle components in PCA, the MAD variates are invariant to linear scaling, which means that they are insensitive to linear transformations such as gain and offset settings of measuring devices, and linear radiometric and atmospheric correction schemes.

2.3 Minimum Noise Fraction Transformation

Theoretically, among components of the MAD variate, the first one M_1 ought to contain most change information, while other components contain decreasing change information. However, this is not the case in practice due to noises in remotely sensed images. Noises may often be modeled as random variables uncorrelated with signals. During MAD transformation, these noises will be concentrated into those MAD components with low correlations, which will result in deviation of change information distribution from theoretical model, so as to hinder following interpretations of change detection result [4].

To solve such a problem, another orthogonal multivariate linear transformation called Minimum Noise Fraction (MNF) is introduced into change detection as a post-processing step for MAD transformation. MNF transformation is firstly proposed by Green et al [5]. It is analogous to PCA except that MNF produces uncorrelated components with decreasing Signal-to-Noise Ratios (SNR) instead of variances. Here SNR is defined as the ratio of signal variance to noise variance, i.e.

$$SNR_i = \frac{Var\{S_i(x)\}}{Var\{N_i(x)\}} \tag{12}$$

In above definition, $S_i(x)$ and $N_i(x)$ are uncorrelated components of signal and noise in the ith channel of p-dimension image $Z(x)$, where x is the variable of observation location, and $Var\{\}$ means calculating variance. Please note that we assume additive noise $N(x)$ in image $Z(x)$, i.e.

$$Z(x) = S(x) + N(x) \tag{13}$$

MNF transformation is to find out coefficient vector a_i that makes linear combination $a_i^T Z(x)$ satisfy:

$$\begin{cases} Var\left\{a_i^T Z(x)\right\} = 1 & i = 1, \cdots, p \\ Cov(a_i^T Z(x), a_j^T Z(x)) = 0 & i \neq j \\ SNR_1 \geq SNR_2 \geq \cdots \geq SNR_p & SNR_i = \dfrac{Var(a_i^T S(x))}{Var(a_i^T N(x))} \end{cases} \tag{14}$$

By applying Lagrange multiplier, above problem comes down to solving a generalized eigen-equation:

$$\Sigma a = \lambda \Sigma_N a \tag{15}$$

Where Σ and Σ_N are covariance matrices of $Z(x)$ and $N(x)$ respectively. Eigenvalue λ_i satisfies $\lambda_i = SNR_i + 1$, i=1,…, p.

MNF is invariant to linear transformations as well as MAD, so that it is also insensitive to linear transformations such as gain settings and linear radiometric correction schemes, which is helpful to interpretation of change detection results.

The objective of MNF transformation is to separate signal from noise as much as possible. By MNF, change information in MAD variate could be concentrated as much as possible to facilitate interpretation and analysis. The first result component, called MNF/MAD1 of highest SNR ought to contain most change information in theory, with all components in order of decreasing SNR containing decreasing change information.

The proposed MNF/MAD method is applicable to change detection in multispectral imagery from multisensor due to several reasons. Firstly, in the mathematical model of CCA, as shown in Eq. (1), it is not a necessary condition that the numbers of random variables in two groups are the same. This means significantly that the two images at different times used in MAD method are allowed to have unequal numbers of spectral bands, i.e. $p \neq q$, which in theory makes it suitable to be applied to multisensor change detection. Secondly, MNF/MAD method is invariant to linear transformations, which implies that the requirements on radiometric normalization and rectification will be lowered and costs in this aspect will be reduced significantly. On the contrary, it is a difficult but important work for traditional change detection methods to perform radiometric normalization between multisensor images.

3. Experimental Results

A case study of multisensor change detection using MNF/ MAD method is carried out on a Landsat7 ETM+ image and a SPOT5 HRG image. These two kinds of data are well known to be suitable for land use/land cover investigation due to their preferable spatial resolution and spectral characteristics. Both of them cover visible and infrared spectrum, but they do not have the same bands. ETM+ has 7 multispectral bands, called TM1~7, while HRG has 4, called XS1~4. Moreover, they have different spatial resolutions, 30m for ETM+ bands (except 60m for TM6) and 10m for HRG bands.

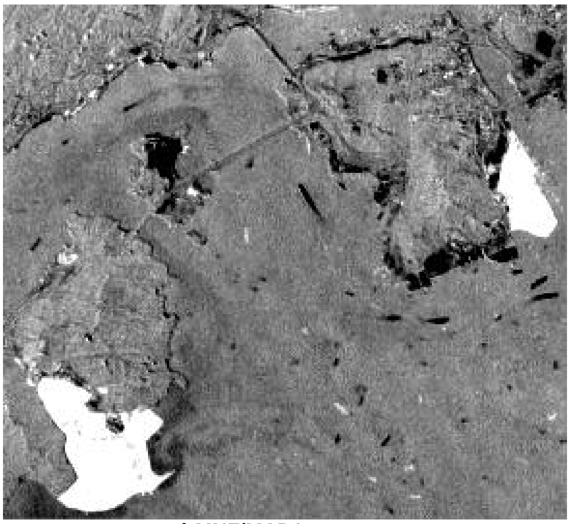
An ETM+ image and a HRG image covering western Hong Kong area are selected for our experiment. Acquisition times of the two images are Nov 1, 2000 (time t_1) and Nov 8, 2002 (time t_2) respectively. All spectral bands except thermal infrared one TM6 are included in study. At first the ETM+ image is resampled to 10m resolution as the same as HRG image. Then the two images are co-registered to each other with precision of ±0.5 pixels, and subsets of size 875×797 pixels are extracted as experimental data from both images, shown in Fig.1. The band combinations in Fig.1 are TM543 for ETM+ and XS432 for HRG respectively.

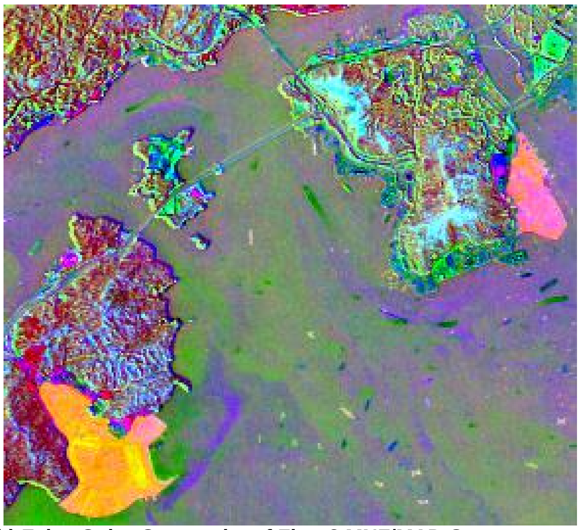
a) Landsat7 ETM+ b) SPOT5 HRG

Fig.1 Original Images

Main procedure of our experiments is as following: Firstly perform CCA on original images to derive 4 pairs of canonical variables arranged in the order of decreasing correlation; then rearrange canonical variable pairs in reverse order; next by subtracting the rearranged canonical variables of time t_1 from that of time t_2, we can get the MAD variate image; finally apply MNF to the MAD variate image to separate change information from noises and produce MNF/MAD result image.

The experimental results are shown in Fig.2, in which a) is the component MNF/MAD1 image, and b) shows the false color composite of first 3 result components. In a), those portions of very bright or very dark tone should have pixel values far away from zero, and could be identified as changed areas with high probability, for example the two areas of very bright tone in the lower left part and upper right part reveal changes caused by reclamation activities at the Penny's Bay and Southeast Tsing Yi respectively. Whereas other areas showing middle gray tone should have pixel values close to zero, which could be identified as unchanged in all probability.





a) MNF/MAD1 **b) False Color Composite of First 3 MNF/MAD Components**

Fig.2 Experimental Result Images

Correlations between MNF/MAD components and original image bands are listed in Table 1. From this table, one can find out certain natures of these result components. Component MNF/MAD1 is negatively correlated with all TM bands while positively correlated with all XS bands, thereby it should reveal the overall changes from time t1 to time t2. Moreover, it shows lower correlations with two near-infrared bands, i.e. TM4 and XS3 than other bands, which implies that the largest change occurred in artificial features rather than vegetations, mainly caused by reclamation activities. The component MNF/MAD2 shows positive correlations with TM1, 2, 3 and XS3, and shows negative correlations with TM4 and XS1,2. This correlation structure resembles greatly to that of vegetation indices, thus MNF/MAD2 may be considered as a certain kind of index for vegetation changes during the period.

Table1. Correlations between Result Components and Original Image Bands

Correlation Coefficients		MNF/MAD components			
		1	2	3	4
Original image bands	TM1	-0.2225	0.1294	-0.0970	-0.1628
	TM2	-0.3195	0.1159	-0.0970	-0.1688
	TM3	-0.4263	0.1300	-0.0408	-0.0395
	TM4	-0.1799	-0.1170	0.0013	0.0006
	TM5	-0.2894	-0.0331	0.1405	-0.0043
	TM7	-0.3428	0.0376	0.1510	0.0209
	XS1	0.3595	-0.1109	0.1927	0.1080
	XS2	0.4100	-0.1081	0.1697	0.0024
	XS3	0.2786	0.0782	0.0911	0.0015
	XS4	0.3881	-0.0121	-0.0036	0.0015

4. Conclusions

MNF/MAD method based on CCA is introduced into change detection in remotely sensed multispectral imageries from multisensor. It is capable of concentrating most change information into a few result components and has the merit of insensitive to linear transformations such as gain settings of measuring devices and linear radiometric correction schemes. A case study on Landsat7 ETM+ and SPOT5 HRG images in western Hong Kong area is carried out. The experimental results justified the feasibility and effectiveness of applying MNF/MAD method to multisensor change detection.

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