HYPERSPECTRAL DATA, CHANGE DETECTION AND THE MAD TRANSFORMATION

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Abstract

This paper deals with the application of the MAD transformation to change detection in bi-tempotal hyperspectral data. Several processing schemes are proposed in order to facilitate both the actual change detection, the many variables involved and the spatial nature of the data.

The MAD Transformation Applied to Hyperspectral Data

The multivariate alteration detection (MAD) transformation (Nielsen et al., 1998) is based on the established technique of canonical correlation analysis (CCA). The MAD variates are calculated as the differences between the canonical variates from an ordinary CCA (in reverse order). The canonical variates are found by solving two coupled generalised eigenvalue problems. The MAD change variables are invariant to linear (affine) transformations in the original variables such as 1) an additive shift in mean level (offset) or a multiplicative shift in calibration of a measuring device (gain), and 2) data normalisation or calibration schemes that are linear (affine) in the gray values of the original variables. Changes of such nature are not detected which is an enormous advantage over most other multivariate change detection schemes published.

The sum of the squared MAD variates standardised to unit variance ideally follow a χ^2 distribution with as many degrees of freedom as there are terms in the sum. This can be exploited to identify both change and no-change observations by means of percentiles in the χ^2 distribution. The no-change observations (the ones with very low χ^2 values, say, below the 1% fractile) can be used in an automated procedure to normalise data between the two points in time, Canty et al (2004).

The invariance of the MAD variates to linear (affine) transformations of the original variables can be exploited when we work with hypervariate data. If we have very many variables the solutions to the coupled generalised eigenvalue problems involved may become unstable due to ill-conditioned variance-covariance matrices. A possible solution to (near) singularity problems in hyperspectral data transformations may be regularisation as hinted in Nielsen and Müller (2003). Possible (near) singularities may also be remedied by means of for instance singular value decomposition, principal component analysis (PCA) or maximum autocorrelation factor (MAF) analysis applied to the variables at the two points in time separately before doing canonical correlation and MAD analysis. This approach is used here.

Hyperspectral Data and Processing Scheme

Two geometrically and atmospherically corrected HyMap scenes with 126 spectral bands acquired on 30 June 2003 at 8:43 UTC and 4 August 2003 at 10:23 UTC covering a small area near Lake Waging-Taching in Southeast Germany near the city of Salzburg (in Austria) are used to illustrate the method. The image size is 400 by 379 5 m by 5 m pixels. The 30 June data are shown in Figure 1 and the 4 August data are shown in Figure 2.

Figure 1: HyMap data from 30 June 2003 at 8:43 UTC
798 nm (red), 677 nm (green), 570 nm (blue)

The processing scheme presented here consists of four steps. The originally measured 126 spectral bands at the two points in time are subjected to 1) CCA and MAD transformation; 2) PCA with 100 components retained at each point in time; and alternatively to 3) MAF analysis with 40 components retained at each point in time (processing step 4 follows below). For the PCA the number of components retained corresponds to a span in eigenvalues of about 10^8. For the MAF analysis the number of components retained was determined based on visual inspection; the cut-off occurs at an autocorrelation of 0.10-0.20. For both steps 2 and 3 the retained components from the two points in time are used as input to the MAD transformation to detect change. Without PCA or MAF pre-processing the CCA and MAD processing in step 1 gives negative estimates of the lower order squared canonical correlations which are clear signs of singularity problems.

Figure 2: HyMap data from 4 August 2003 at 10:23 UTC
798 nm (red), 677 nm (green), 570 nm (blue)

The change detected in steps 2 and 3 are shown in Figure 3 (left and middle subfigures). Using the 40 MAF components rather than the 100 principal components clearly cleans up noise in the change image. The change detected in the 40 retained MAF components is associated with the infrastructure such as built-up areas in the villages and field boundaries. These changes, however, constitute artefacts and can be attributed to the following main causes: a) the time of acquisition for the second image is about two hours later than for the first acquisition; consequently, near sharp edges such as buildings and forest stands there is a shift in shadow which causes the large changes between the two images, and besides, in the villages a change in the direction of specular reflectance of roof tops can play a prominent role; b) small anomalies in the geometric correction and divergences that result from resampling procedures during data processing can attribute to high differences along field boundaries, lake shore and infrastructure. To remedy this we 4) leave out observations with high change (above the 95% fractile) due to these effects from the statistics calculations in a second MAD transformation of the 40 retained MAF components. The resulting change image is shown in Figure 3 (right subfigure).

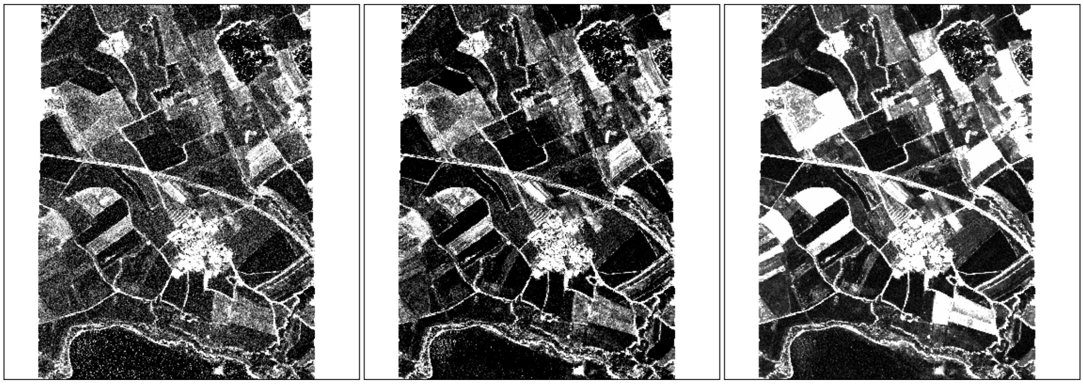

Figure 3: The approximate χ^2 value stretched linearly between the 1% and 99% fractiles of the relevant χ^2 distributions for the left and middle images. The right image is stretched linearly between ad hoc limits 20 and 200. Bright regions are areas of high change, dark regions are areas of no change.

More specifically Figure 3 shows the approximate χ^2 values for the MAD transformation based on the 100 PCs (left), the 40 MAFs (middle), and the 40 MAFs after removing observations with high change in the situation depicted in the middle subfigure from the statistics calculations (right). The approach illustrated in the right subfigure highlights change in areas outside the high change areas in the middle subfigure such as the fields.

Figure 4 shows the first three MAD variates of the first 40 MAFs after removing observations with high change in the situation depicted in the middle subfigure of Figure 3 from the statistics calculations. Saturated colours give a more subtle indication of change areas as depicted in the first three change variables than does the right subfigure in Figure 3. Correlations between the MAD variates and the originally measured spectral bands facilitate interpretation of the types of change indicated in Figure 4.

Figure 5 shows the first three MAF variates of the MAD variates of the first 40 MAFs after removing observations with high change in the situation depicted in the middle subfigure of Figure 3 from the statistics calculations. Here, saturated colours simultaneously indicate high change areas as depicted in all change variables and high autocorrelation, and again correlations between the new variates (here the MAFs of the MADs) and the originally measured spectral bands facilitate interpretation of the types of change indicated. These correlations are not shown here.

Change Detected

The change detected over the five weeks by the method in step 4 is due to growth of the main crop types such as maize, barley and wheat. Furthermore, change can be detected that results from cutting and regrowth of meadows, i.e., from both decrease and increase of plant organic matter. Meadows in the area are cut approximately five times during the growing season, independently from each other as regards the point of time. As one would expect, on pastures, which are constantly being grazed, on forest stands and on the lake in the south, almost no change can be observed.

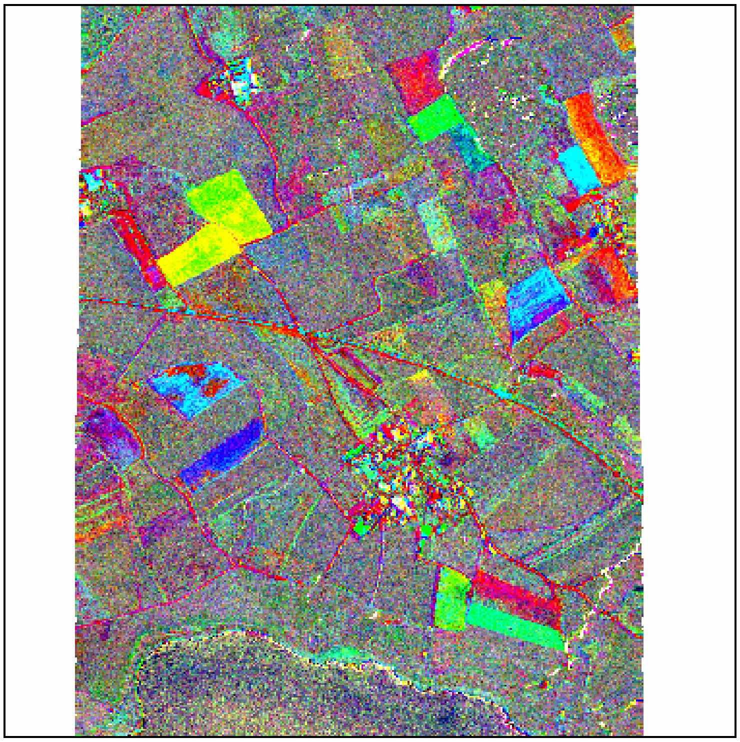

Figure 4: MAD variates 1 (red), 2 (green) and 3 (blue) of the 40 MAFs after removing observations with high change in the situation depicted in the middle subfigure of Figure 3 from the statistics calculations.

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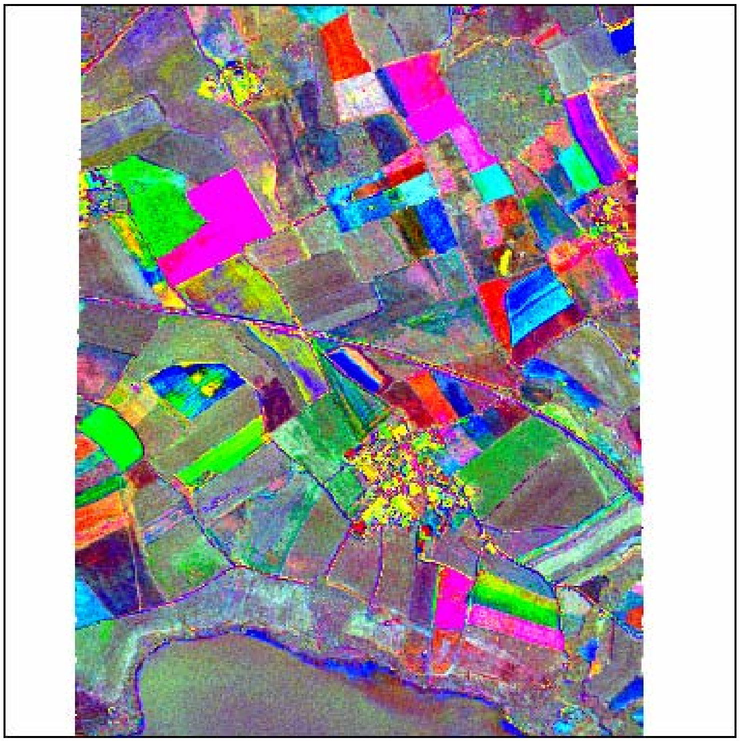

Figure 5: MAF variates 1 (red), 2 (green) and 3 (blue) of the MAD variates of the 40 MAFs after removing observations with high change in the situation depicted in the middle subfigure of Figure 3 from the statistics calculations.