Linear and kernel methods for multi- and hypervariate change detection

Allan A. Nielsen[a] and Morton J. Canty[b]

[a]Technical University of Denmark
DTU Space – National Space Institute
DK-2800 Kgs. Lyngby, Denmark

[b]Research Center Jülich
Institute of Chemistry and Dynamics of the Geosphere
D-52425 Jülich, Germany

ABSTRACT

The iteratively re-weighted multivariate alteration detection (IR-MAD) algorithm may be used both for unsupervised change detection in multi- and hyperspectral remote sensing imagery as well as for automatic radiometric normalization of multi- or hypervariate multitemporal image sequences. Principal component analysis (PCA) as well as maximum autocorrelation factor (MAF) and minimum noise fraction (MNF) analyses of IR-MAD images, both linear and kernel-based (which are nonlinear), may further enhance change signals relative to no-change background. The kernel versions are based on a dual formulation, also termed Q-mode analysis, in which the data enter into the analysis via inner products in the Gram matrix only. In the kernel version the inner products of the original data are replaced by inner products between nonlinear mappings into higher dimensional feature space. Via kernel substitution, also known as the kernel trick, these inner products between the mappings are in turn replaced by a kernel function and all quantities needed in the analysis are expressed in terms of the kernel function. This means that we need not know the nonlinear mappings explicitly. Kernel principal component analysis (PCA), kernel MAF and kernel MNF analyses handle nonlinearities by implicitly transforming data into high (even infinite) dimensional feature space via the kernel function and then performing a linear analysis in that space.

In image analysis the Gram matrix is often prohibitively large (its size is the number of pixels in the image squared). In this case we may sub-sample the image and carry out the kernel eigenvalue analysis on a set of training data samples only. To obtain a transformed version of the entire image we then project all pixels, which we call the test data, mapped nonlinearly onto the primal eigenvectors.

IDL (Interactive Data Language) implementations of IR-MAD, automatic radiometric normalization and kernel PCA/MAF/MNF transformations have been written which function as transparent and fully integrated extensions of the ENVI remote sensing image analysis environment. Also, Matlab code exists which allows for fast data exploration and experimentation with smaller datasets. Computationally demanding kernelization of test data with training data and kernel image projections have been programmed to run on massively parallel CUDA-enabled graphics processors, when available, giving a tenfold speed enhancement. The software will be available from the authors' websites in the near future.

A data example shows the application to bi-temporal RapidEye data covering the Garzweiler open pit mine in the Ruhr area in Germany.

Keywords: Orthogonal transformations, dual formulation, Q-mode analysis, kernel substitution, kernel trick, IR-MAD, kPCA, kMAF, kMNF, CUDA, ENVI, IDL, Matlab, radiometric normalization, remote sensing.

Further author information:
A.A.N.: Presently located at DTU Informatics – Department of Informatics and Mathematical Modelling, Richard Petersens Plads, Building 321, E-mail aa@space.dtu.dk, http://www.imm.dtu.dk/∼aa, Tel +45 4525 3425, Fax +45 4588 1397.
M.J.C.: E-mail m.canty@fz-juelich.de, http://mcanty.homepage.t-online.de/

1. METHODS

The presentation will give an overview of unsupervised, automatic change detection methods based on an iterated version of canonical correlation analysis with subsequent post-processing by means of linear and kernel versions of principal component analysis, maximum autocorrelation factor analysis, and minimum noise fraction analysis. These methods are described in detail in several of the publications in the literature list.

In the kernel MAF transformation the differencing to estimate the autocorrelation may be carried out in the original feature space followed by a kernelization of that difference. Alternatively, the differencing may take place in the enhanced feature space after the nonlinear mapping. The same applies to the noise modelling in the kernel MNF transformation.

The centering of the test data for kernelization with the training data may be carried out by means of the test data mean or by means of the training data mean. The latter seems more correct and it also saves a computationally costly run through the test data.

Below, results are shown for differencing in extended feature space and centering of the test data with the training data mean.

2. RAPIDEYE DATA EXAMPLE

The study site is located in the Ruhr area west of Köln/Cologne, Germany and comprises the Rhenish lignite district, the largest open-cast mining site in Germany. With an annual excavation of 300 million cubic meters (Hambach), 140 million (Garzweiler) and 80 million cubic meters (Inden), respectively, and a total lignite extraction of about 100 million metric tons per year, this area is highly dynamic and fast changing.

Two RapidEye images acquired on 24 May and 1 June 2009 were selected to illustrate the IR-MAD and subsequent kernel MAF analyses for change detection purposes. The subsets used here cover a region of 2,000 by 2,000 pixels centered on the Garzweiler site, where accurate GPS data were available for orthorectification, see Figures 1 and 2.

RapidEye is a constellation of five identical satellites operating in the same sun-synchronous orbit. Each of them has five spectral bands which cover the blue (440-510 nm), the green (520-590 nm), the red (630-685 nm), the red edge (690-730 nm), and the near infrared region (760-850 nm). Ground sampling distance is 6.5 m. Due to its off-nadir capabilities RapidEye is in principle able to achieve daily coverage.

3. CONCLUSIONS

In both change images (Figures 3 and 4) saturated colours (including black and white) indicate change, gray indicates no-change.

The IR-MAD variates corresponding to the highest canonical correlations, Figure 3, neatly pick up changes in the mine and in the agricultural regions surrounding it. Also, two clouds and their shadows (top-right in the image and in the bottom-left of the mine, 1 June 2009) are conspicuous. Even subtleties as cars present on the motor way in one time point only can be seen.

The kernel MAF transformation is based on a Gaussian kernel with a width equal to the mean value of all pairwise distances beetween observations in the original feature space. The first three kernel MAF variates shown in Figure 4 focus on the extreme changes (the clouds, the mine and a few of the agricultural fields surrounding it; the cars are even more conspicuous here than in Figure 3). The no-change background appears completely noise free.

This focus on extreme observations and adaption to the varying multi- or hypervariate background non-linearly mapped into high dimensional (in the case of the Gaussian kernel in principle infinite) feature space is characteristic for the kernel MAF/MNF transformations in other applications also including other change detection studies, food inspection, and irregularly spaced geochemical (geological) data.

Figure 1. Orthorectified RapidEye 2,0002,000 5 m pixels subsets, infrared/red edge/red as RGB, 24 May 2009. Includes material (2009) RapidEye AG, Germany. All rights reserved.

Figure 2. Orthorectified RapidEye 2,0002,000 5 m pixels subsets, infrared/red edge/red as RGB, 1 June 2009. Includes material (2009) RapidEye AG, Germany. All rights reserved.

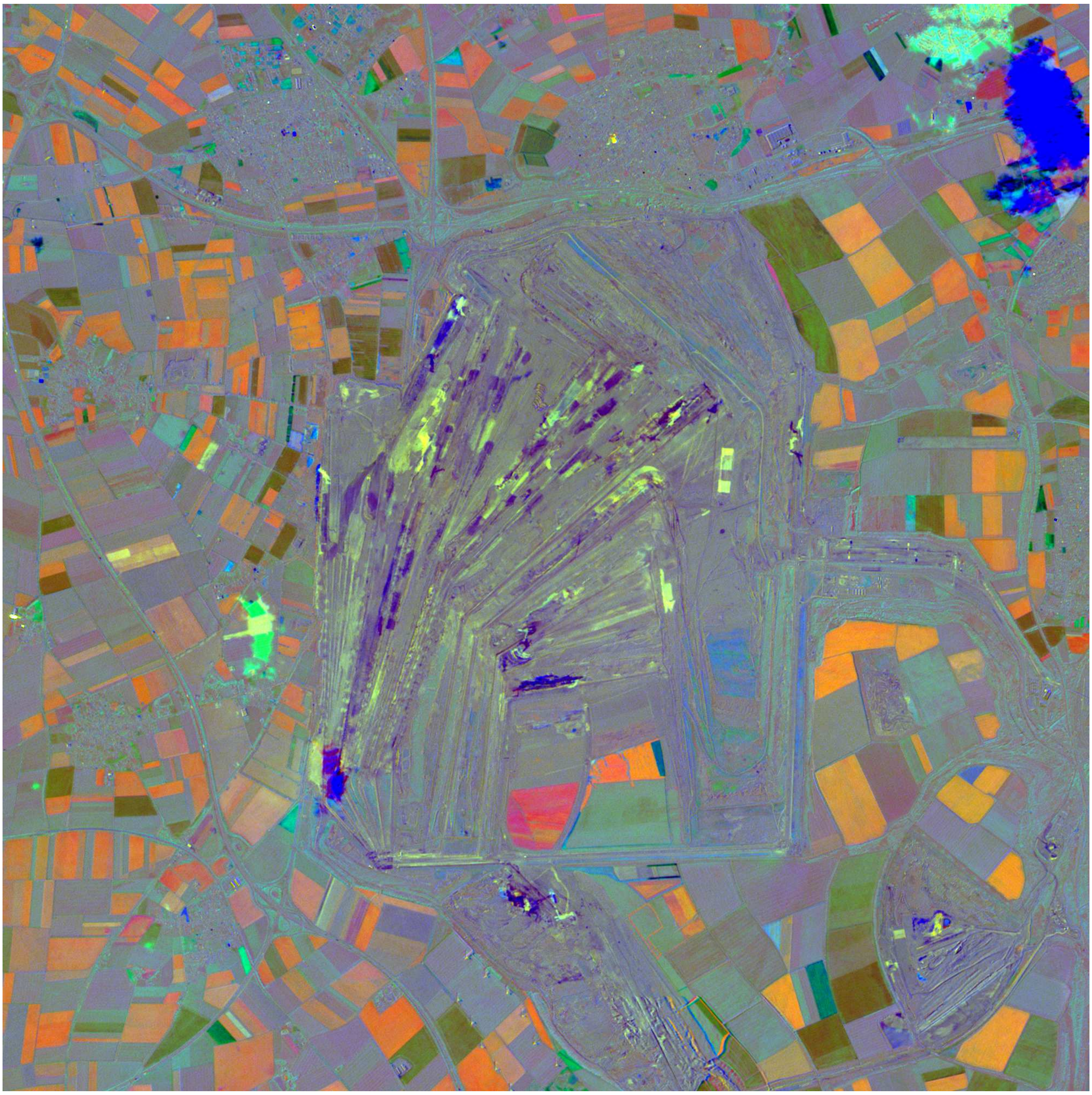

Figure 3. IR-MADs 5, 4 and 3 corresponding to the highest canonical correlations as RGB.

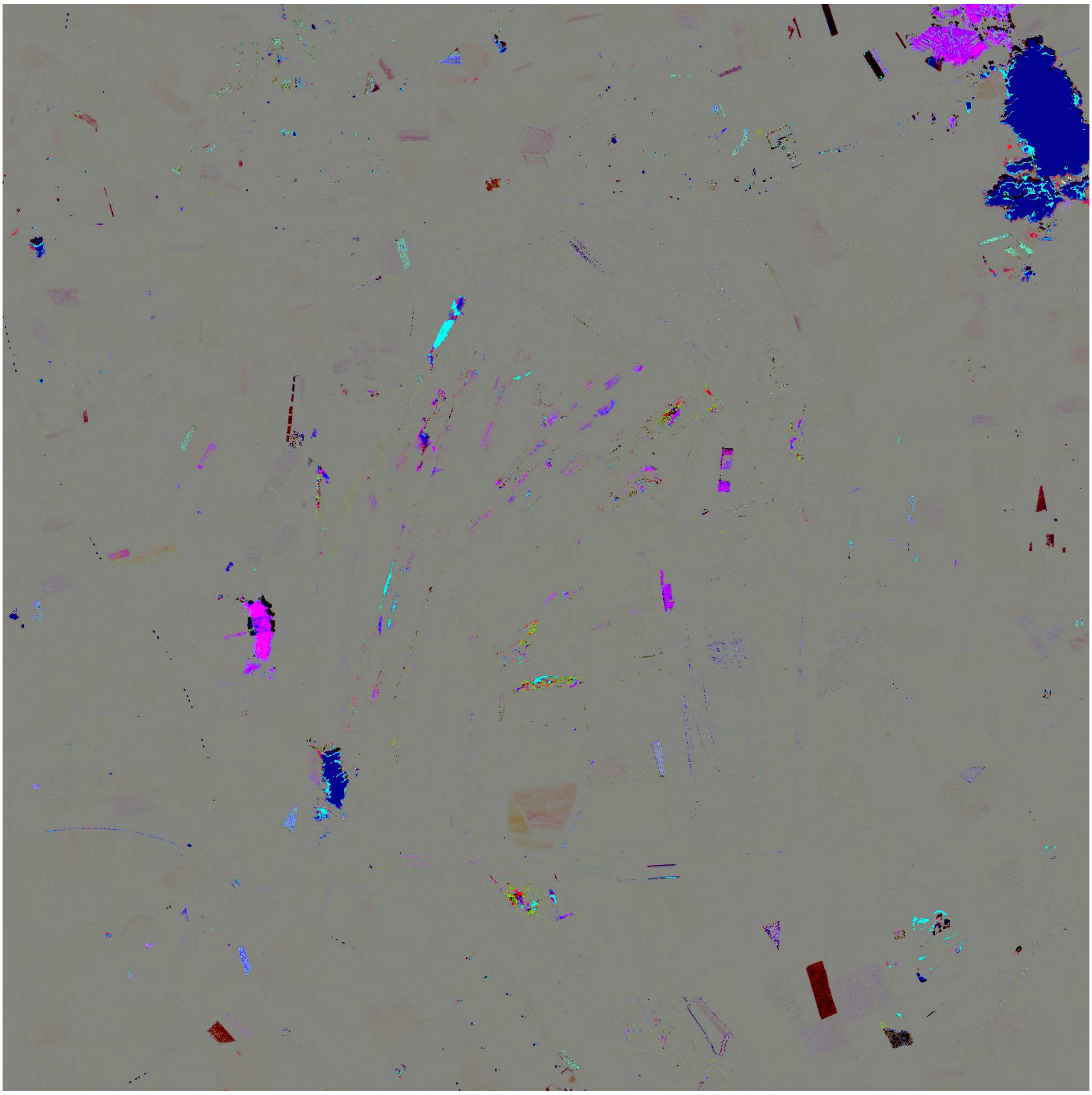

Figure 4. Kernel MAFs 1, 2 and 3 of all IR-MADs as RGB.

LITERATURE

[1] Bruzzone, L. and Prieto, D. F. (2000). Automatic analysis of the difference image for unsupervised change detection. *IEEE Transactions on Geoscience and Remote Sensing*, **38**(3), 1171–1182.

[2] Canty, M. J. and Nielsen, A. A. (2006). Visualization and unsupervised classification of changes in multispectral satellite imagery. *International Journal of Remote Sensing*, **27**(18), 3961–3975. Internet http://www.imm.dtu.dk/pubdb/p.php?3389.

[3] Canty, M. J. and Nielsen, A. A. (2007). Automatic radiometric normalization of multitemporal satellite imagery with the iteratively re-weighted MAD transformation. *Remote Sensing of Environment*, **112**(3), 1025–1036. Internet http://www.imm.dtu.dk/pubdb/p.php?5362.

[4] Canty, M. J., Nielsen, A. A., and Schmidt, M. (2004). Automatic radiometric normalization of multitemporal satellite imagery. *Remote Sensing of Environment*, **91**(3-4), 441–451. Internet http://www.imm.dtu.dk/pubdb/p.php?2815.

[5] Coppin, P., Jonckheere, I., Nackaerts, K., and Muys, B. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*, **25**(9), 1565–1596.

[6] Green, A. A., Berman, M., Switzer, P., and Craig, M. D. (1988). A transformation for ordering multispectral data in terms of image quality with implications for noise removal, *IEEE Transactions on Geoscience and Remote Sensing*, **26**(1), 65–74.

[7] Hotelling, H. (1936). Relations between two sets of variates, *Biometrika*, **XXVIII**, 321–377.

[8] Nielsen, A. A. (2007). The regularized iteratively reweighted MAD method for change detection in multi- and hyperspectral data. *IEEE Transactions on Image Processing*, **16**(2), 463–478. Internet http://www.imm.dtu.dk/pubdb/p.php?4695.

[9] Nielsen, A. A. (2010). Kernel maximum autocorrelation factor and minimum noise fraction transformations. Accepted for *IEEE Transactions on Image Processing*.

[10] Nielsen, A. A., Conradsen, K., and Simpson, J. J. (1998). Multivariate alteration detection (MAD) and MAF postprocessing in multispectral, bitemporal image data: New approaches to change detection studies. *Remote Sensing of Environment*, **64**, 1–19. Internet http://www.imm.dtu.dk/pubdb/p.php?1220.

[11] Nielsen, A. A., Hecheltjen, A., Thonfeld, F., and Canty, M. J. (2010). Automatic change detection in RapidEye data using the combined MAD and kernel MAF methods. IEEE IGARSS 2010 (invited contribution). Internet http://www.imm.dtu.dk/pubdb/p.php?5856.

[12] RapidEye AG. Internet http://www.rapideye.de.

[13] Schölkopf, B., Smola, A., and Müler, K.-R. (1998). Nonlinear component analysis as a kernel eigenvalue problem. *Neural Computation*, **10**(5), 1299–1319.

[14] Shawe-Taylor, J. and Cristianini, N. (2004). *Kernel Methods for Pattern Analysis*. Cambridge University Press.

[15] Singh, A. (1989). Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, **10**(6), 989–1002.