DETECTION OF SMALL CHANGES IN COMPLEX URBAN AND INDUSTRIAL SCENES USING IMAGING SPECTROSCOPY

M. Shimoni, R. Heremans* and C. Perneel***

* Signal and Image Centre, Dept. of Electrical Engineering (SIC-RMA), 1000 Brussels, Belgium – mshimoni@elec.rma.ac.be; rhereman@elec.rma.ac.be
** Dept. of Mathematics, Royal Military Academy, 1000 Brussels, Belgium – christiaan.perneel@rma.ac.be

1. INTRODUCTION

Hyperspectral change detection has been proved to be a promising technique for detecting indiscernible targets in different background. However, in the case of dense industrial and urban areas the complexity of the terrain and the multi-temporal images, which include positional deviation, radiant and atmospheric variation, shadows and spatial structure alteration, severely affects the automation of the change detection.

This paper develops and enlarges four clustering based methods to detect man-made changes in VNIR and TIR hyperspectral scenes. The first applied method is Covariance-Equalisation (CE) multivariate statistical techniques, which detects differences between linear combinations of the spectral bands from the two acquisitions. The other three methods perform clustering of a reference image and then detect changes in a target image using a class-conditional distance detector: (a) class-conditional CE (QCE), (b) bi-temporal QCE and (c) Wavelength Dependent Segmentation (WDS). For the detection of small changes in industrial and urban areas, data from two flight campaigns were used: AHS-160 over the port of Antwerp and over the city of Kalmthout (Belgium).

It was found that the use of a spatially adaptive detector greatly increases change-detection performance for both target detection and false alarm reduction. Moreover, WDS clustering based methods demonstrated a substantial improvement in change detection when applied on combined-wavelengths (as MWIR and LWIR or VNIR and TIR) hyperspectral data sets with respect to a single-wavelength data set.

2. CHANGE DETECTION METHODS

This paper investigates four different change detection methods: covariance equalisation (CE), class conditional CE (QCE), bi-temporal QCE and wavelength dependent segmentation (WDS).

2.1 Covariance Equalisation (CE)

For the two hyperspectral matrices x and y, the diagonal matrices *Tx* and *Ty* are written as follow [1]:

$$x_i = T_x \rho_i + d_x \quad ; \quad y_i = T_y \rho_i + d_y \tag{1}$$

where ρi is the spectral reflectance, and the offset vectors dx and dy are changes between the observations. For notation convenience, we will drop the spatial position index on the vector:

$$\hat{x} = \hat{T}_{xy}\, y + \hat{d}_{xy}. \tag{2}$$

And the change residual image (δ) is defined as follows:

$$\delta = x - \hat{x} = x - (\hat{T}_{xy}\, y + \hat{d}_{xy}) \tag{3}$$

Based on the second order statistics, the transformation parameters $\hat{T}_{xy}$ and $\hat{d}_{xy}$ can be estimated using the mean vectors m_x and m_y and the covariance matrices C_x and C_y. If the covariance matrices are diagonalised in the form:

$$C_x = V_x D_x V_x^T \quad ; \quad C_y = V_y D_y V_y^T \tag{4}$$

where Vx and Vy are the eigenvector matrices, and Dx and Dy are the diagonalised covariance matrices. Then, the Covariance Equalisation (CE) change detection method uses:

$$\hat{T}_{xy}^{(CE)} = C_{xx}^{1/2} C_{yy}^{-1/2} \quad ; \quad \hat{d}_{xy}^{(CE)} = m_x - \hat{T}_{xy}^{(CE)} m_y. \tag{5}$$

2.2 Class-conditional CE (QCE)

Eismann et al. [2-3], represents the image with a normal mixture model and allow the transformation parameters to differ between spectral classes. In this way, each spectrum $\boldsymbol{x}$ is defined by class index $\boldsymbol{q}$ (where $q = 1,2,.....Q$) and has a prior probability $P(q)$ to belong to each respective class. In the QCE method we are assigning a class-conditional probability function $p(x|q)$ to the transformation parameters in (2) as follows:

$$\hat{x}|q = \hat{T}_{xy}|q\; y + \hat{d}_{xy}|q \tag{6}$$

And the change residual image (δ_1) is defined as follows:

$$\delta_1 = x - \hat{x}|q = x - (\hat{T}_{xy}|q\; y + \hat{d}_{xy}|q) \tag{7}$$

For the QCE method, after applying PCA on the reference image x, the stochastic expectation maximization (SEM) [4] clustering method is employed.

2.3 Bi-temporal QCE

In (6) the transformation parameters $\hat{T}_{xy}$ and $\hat{d}_{xy}$ the class-conditional is based on the segmentation of x. However, in the case where the materials and the objects distribution in y were different, the segmentation of y and the transformation parameters will differ as:

$$\hat{y}|q = \hat{T}_{yx}|q\; x + \hat{d}_{yx}|q) \tag{8}$$

Therefore, the residual image δ_2 which is based on the segmentation of y will be defined as follows:

$$\delta_2 = y - \hat{y}|q = y - (\hat{T}_{yx}|q\; x + \hat{d}_{yx}|q) \tag{9}$$

Moreover, one might expect that by merging δ_1 (7) and δ_2 (9) the change detection will be improved:

$$\delta_{bi-direction} = \delta_1 + \delta_2 \tag{10}$$

2.4 Wavelength Dependent Segmentation (WDS)

In case where VNIR and TIR hyperspectral (as of the AHS) or MWIR and LWIR hyperspectral (as of the FIRST) data sets are used, one might expect that merging the complementarity of the spectra information in the different wavelength regions, will improve the change detection performance. Based on the QCE method, we were developing the Wavelength Dependent Segmentation (WDS) method, which is segmenting the hyperspectral data of one wavelength region and applying the class-conditional transformation on the other wavelength region. Using the AHS data sets for example, we were segmenting the VNIR images (W_{VNIR}) and applying the transformation on the TIR data sets:

$$\hat{x}_{(T)}\big|q_{(V)} = \hat{T}_{xy_{(T)}}\big|q_{(V)}\ y_{(T)} + \hat{d}_{xy_{(T)}}\big|q_{(V)} \qquad (11)$$

And the residual image δ_{WDS} is defined as follows:

$$\delta_{wds} = x_{(V)} - \hat{x}_{(V)}\big|q_{(T)} \qquad (12)$$

Based on the same principle, we were also segmenting the TIR images and applying the transformation on the VNIR data sets.

RESULTS

Based on the CE results presented in Figure 1a, one can observe that change detection using the CE technique were resulted in low detection rate; VNIR 'Area Under Curve' AUC=66% (Figure 1a) and TIR AUC=54% (Figure 1b). Figures 1a and 1b also shows that the results of the QCE change detection method are not dependent on the number of classes (Q) and that QCE outperforms the CE method. The bi-temporal QCE results presented in Figures 1c and 1d show no improvement in change detection using the VNIR data sets in comparison to the QCE. However, using the TIR data sets there is improvement in 2%-4% in the detection (with AUC=79% using TIR and Q=9 or Q=11).

The WDS results presented in Figure 2 shows significant improvement in change detection in the VNIR and the TIR data sets. The results are supporting the assumption that the spectral information in the different wavelengths regions is complementary. The detection results were improved in relation to the QCE method in 3%-5% using the VNIR data sets and in 3%-8% using the TIR data sets. The WDS method is found to be more sensitive while obtaining the transform parameters using the *x* (moment 1 scene) or the *y* (moment 2 scene). Moreover, by combining the residual images obtained using the two moments scene (bi-temporal), the WDS obtained the highest change detection results (AUC=87%).

CONCLUSIONS

Based on the results presented in this paper, the following conclusions can be drawn:

- QCE Change detection based clustering method improves the detection with respect to the CE method;
- Bi-direction clustering method was found to be a good change detection method for TIR hyperspectral;

▪ Clustering based methods demonstrated an improvement in change detection when applied using the WDS method on combined wavelengths data sets with respect to the single-wavelength hyperspectral data set.

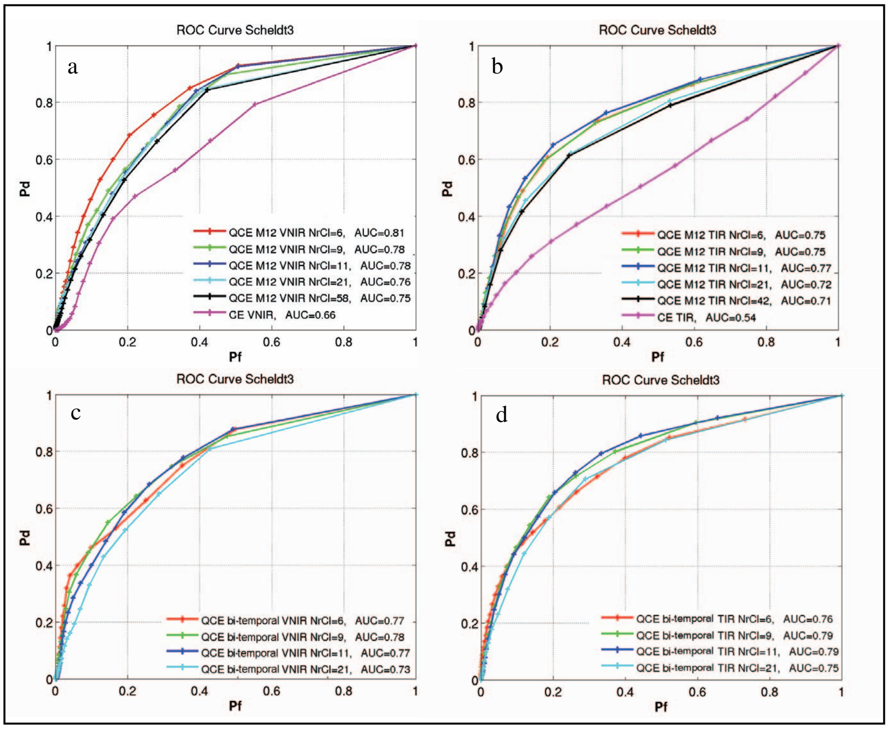

Figure 1: AUC results: (a) QCE and CE change detection in the VNIR scenes; (b) QCE and CE change detection in the TIR scenes; (c) QCE bi-temporal change detection in the VNIR scenes; (d) QCE bi-temporal change detection in the TIR scenes

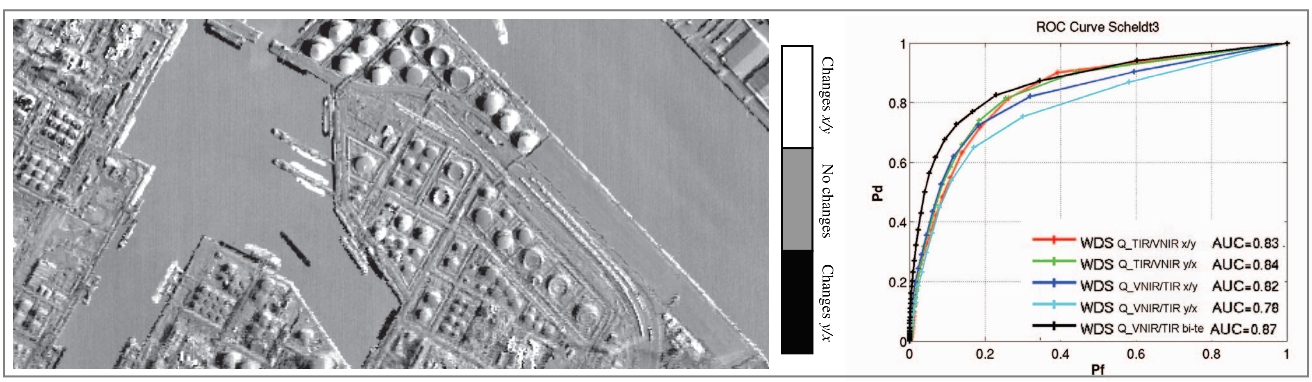

Figure 2: WDS bi-temporal change detection in the AHS TIR scenes (left) and AUC results for the VNIR and the TIR data sets (right) – Port of Antwerp

REFERENCES

[1] Schaum, A. and Stocker, A., Hyperspectral change detection and supervised matched filtering based on covariance equalization, In Proc. SPIE, 5425, 77–90, 2004.

[2] Eismann, M. T., Meola, J. and Hardie, R. C., Hyperspectral change detection in the presence of diurnal and seasonal variations, IEEE Trans. Geosc. And Rem. Sens., 46 (1), 237–249, 2008.

[3] Eismann, M. T., Meola, J., Stocker, A. D., Beaven, S. G. and Schaum, A. P., Airborne hyperspectral detection of small changes, Appl. Opt., 47, 27-45, 2008.

[4] Masson, P. and Pieczynski, W. SEM algorithm and unsupervised statistical segmentation of satellite images, IEEE Trans. Geosci. Remote Sens., 31 (3), 618–633, 1993.