CHANGE DETECTION IN INDUSTRIAL AND URBAN SCENES USING VNIR AND TIR HYPERSPECTRAL IMAGERY

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ABSTRACT:

Detecting changes rapidly and automatically in multi-temporal remotely sensed imagery of urban and industrial scenes, is of widespread interest in several applications as security and civil infrastructures mapping. Hyperspectral change detection has been shown to be a promising technique for detecting imperceptible targets in convolution background. However, the complexity of the terrain and the multi-temporal images, which include positional deviation, radiant variation, shadows and spatial structure alteration, severely affects the automation of the change detection.
For the detection of small changes in industrial area, AHS-160 flight campaign acquired VIS to LWIR data in two operational periods during the same day over the port of Antwerp, Belgium. The Covariance-Equalisation (CE) multivariate statistical techniques, which detects differences between linear combinations of the spectral bands from the two acquisitions, where applied for change detection. The change detection using the CE technique resulted in false-alarm rates that were higher than desired. It seems that the misdetections of this method are originating from the basic assumption that non-target changes (i.e. illumination and other background changes) are space invariant. This assumption seems not valid in the case of the investigated data sets and one way to solve such space varying changes is to search for differences between spectral clusters.

Therefore, this paper also develops and enlarges three clustering based methods to detect man-made changes in VNIR and TIR hyperspectral scenes. The methods perform clustering of a reference image and then detect changes in a target image using a class-conditional distance detector. Three iterative clustering methods are employed: (a) class-conditional CE (QCE), (b) bi-temporal QCE and (c) Wavelength Dependent Segmentation (WDS). 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 VNIR and TIR data sets with respect to the VNIR data set alone.

1. INTRODUCTION

Detecting changes in images of the same scene taken at different times is of widespread interest due to a large number of applications in diverse disciplines including remote sensing, surveillance, medical diagnosis and treatment, civil infrastructure, and underwater sensing (Radke et al., 2005). In the last years, there has been a substantial research in detecting land cover changes in hyperspectral imagery. Many of those techniques are multivariate statistical based methods, which detect

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differences between linear combinations of the spectral bands from the two acquisitions, as the Cross-Covariance (CC) (Schaum and Stocker, 1997), the Multivariate Alteration Detection (MAD) (Nielsen, 2007) and the Temporal PCA (TPCA) (Vongsy, 2007). However, although hyperspectral change detection has been shown to be a promising approach for detecting subtle targets in complex backgrounds (Eismann, 2008), the complexity of the urban terrain and the multi-temporal images, which include positional deviation, radiant variation, shadows and spatial structure alteration, severely affects the automation of the change detection. Eismann et al. explored the space-varying nature of those effects on changes and investigated spectrally segmented linear predictors to accommodate these effects, through empirical measurements (2008a) and using urban hyperspectral temporal scenes (2008b).

This paper assesses and compares the performance of the Covariance-Equalisation (CE) (Schaum, 2004), which is a multivariate statistical based method, using temporal VNIR and thermal hyperspectral data sets. Later it investigates the class-conditional change detector QCE developed by Eismann et al., (2008a; 2008b) using those data sets. And finally it enlarges the class-conditional method by applying bi-temporal QCE and by using a Wavelength Dependent Segmentation (WDS).

1.1 Data collection

On the 16th of June 2005, the Airborne Hyperspectral Scanner (AHS-160) flight campaign acquired VIS to LWIR data over the petrochemical port of Antwerp, Belgium. The image data were collected in two operational periods during the same day: morning from 9h30 till 10h (Figure 1a) and afternoon from 15h30 till 16h00 (Figure 1b). The AHS data spatial resolution is 2.5 m at nadir and the complete image covers an area of 50 km^2. The raw hyperspectral data sets were radiometrical, geometrical and atmospherical corrected. The data calibrations were produced using ground truth spectra that were collected using ASD spectrometer (0.4-2.5 μm) and field thermal imaging reflectometer (SOC 400T) (2.0-14.0 μm). The different temporal scenes were registered using a two stages registration process. The first stage consists of image co-registration, which orthorectifies the image and the second which achieved spectra change analysis at pixel-level using nearest neighbour algorithms (Eismann et al., 2008b).

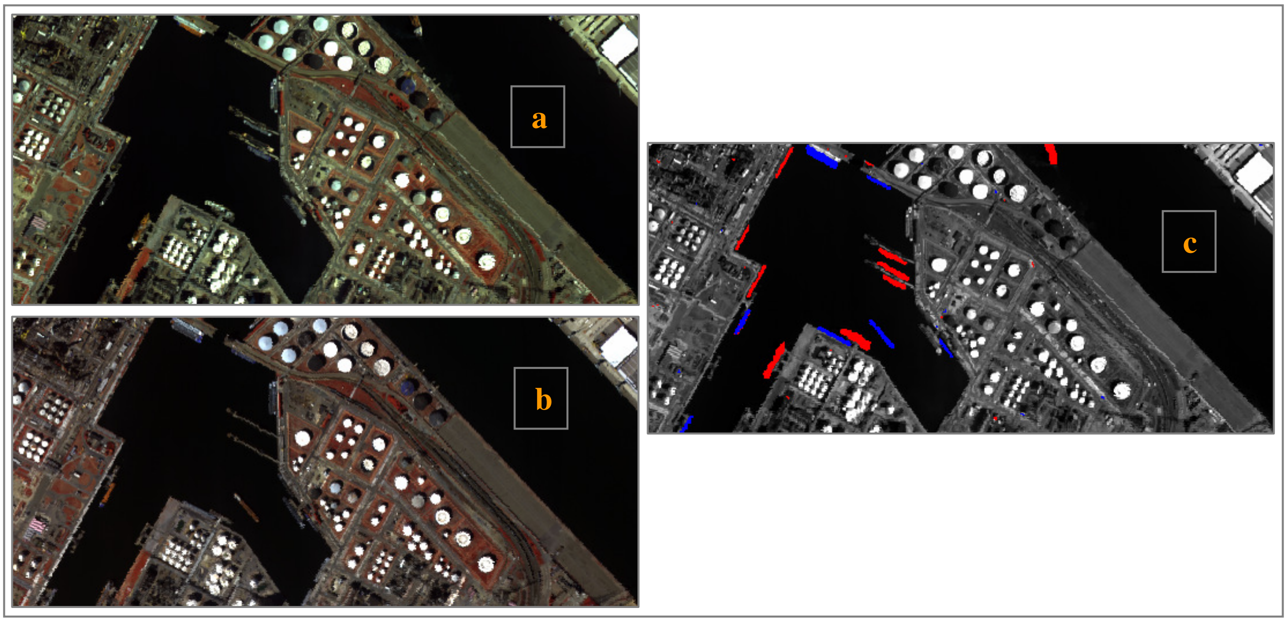

Figure 1: AHS-160 Port of Antwerp scenes; (a) morning, (b) afternoon, (c) validation data set with changes appeared in the morning and are not in the afternoon scene (red) and changes appeared in the afternoon and are not in the morning scene (blue).

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 (Schaum and Stocker, 2004):

$$\begin{aligned} x_i &= T_x \rho_i + d_x \\ y_i &= T_y \rho_i + d_y \end{aligned} \quad (1)$$

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:

$$x = T_{xy} y + d_{xy} \quad (2)$$

where

$$\begin{aligned} T_{xy} &= T_x T_y^{-1} \\ d_{xy} &= d_x - T_{xy} d_y \\ \hat{x} &= \hat{T}_{xy} y + \hat{d}_{xy}. \end{aligned}$$

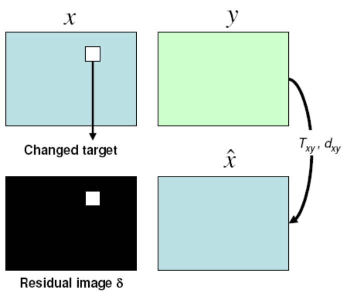

Figure 2: CE method

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

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

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:

$$\begin{aligned} C_x &= V_x D_x V_x^T \\ C_y &= V_y D_y V_y^T \end{aligned} \quad (4)$$

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:

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

2.2 Class-conditional CE (QCE)

Eismann et al. (2008a, 2008b), represents the image with a normal mixture model and allow the transformation parameters $\hat{T}_{xy}$ and $\hat{d}_{xy}$ to differ between spectral classes. In this way, each spectrum $\boldsymbol{x}$ is defined by class index $\boldsymbol{q}$ (where $q = 1,2,\ldots..Q$) 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:

$$\hat{x}|q = \hat{T}_{xy}|q\ y + \hat{d}_{xy}|q \quad (6)$$

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

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

For the QCE method (Figure 3), after applying PCA on the reference Image x, two iterative clustering methods are employed: The vector quantization (Linde et al., 1980) and the stochastic expectation maximization (SEM) (Masson Pieczynski, 1993). The minimum size of the classes is restricted to 6 to be sufficiently large to avoid any rank deficiency or matrix singularities in computing the transformation. We were testing the QCE with Q=6, 9, 11, 21, Q_{SEM} is the max Q obtained using the SEM method)

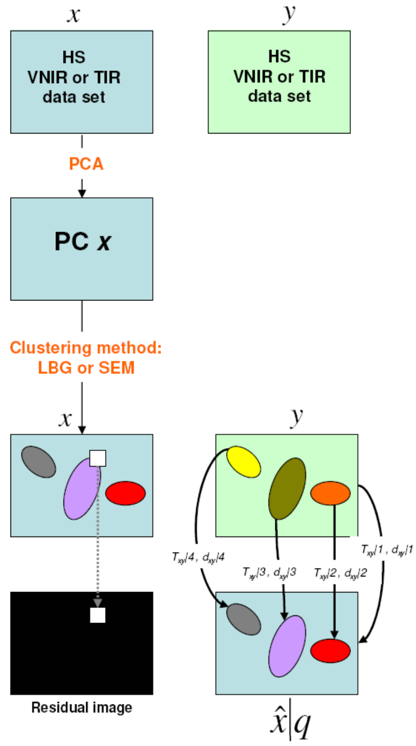

Figure 3: QCE method

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:

$$\hat{y}|q = \hat{T}_{yx}|q\, x + \hat{d}_{yx}|q) \qquad (8)$$

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

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

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

$$\delta_{bi-direction} = \delta_1 + \delta_2 \qquad (10)$$

2.4 Wavelength Dependent Segmentation (WDS)

In case where VNIR and TIR hyperspectral data sets (as of the AHS) 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 our data sets, we were segmenting the VNIR images (W_{VNIR}) and applying the transformation on the TIR data sets (Figure 4):

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

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

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

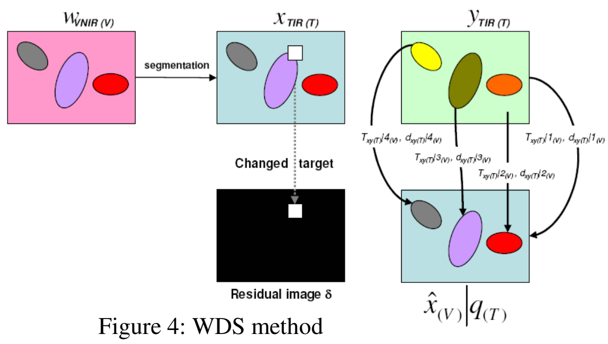

Figure 4: WDS method

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

3. RESULTS

Based on the CE results presented in Figure 5, one can see that change detection using the CE technique resulted in low detection rate (VNIR 'Area Under Curve' AUC=66% and TIR AUC=54%). The false-alarm rates are higher than desired and are originating mainly from shadows and water-level changes.

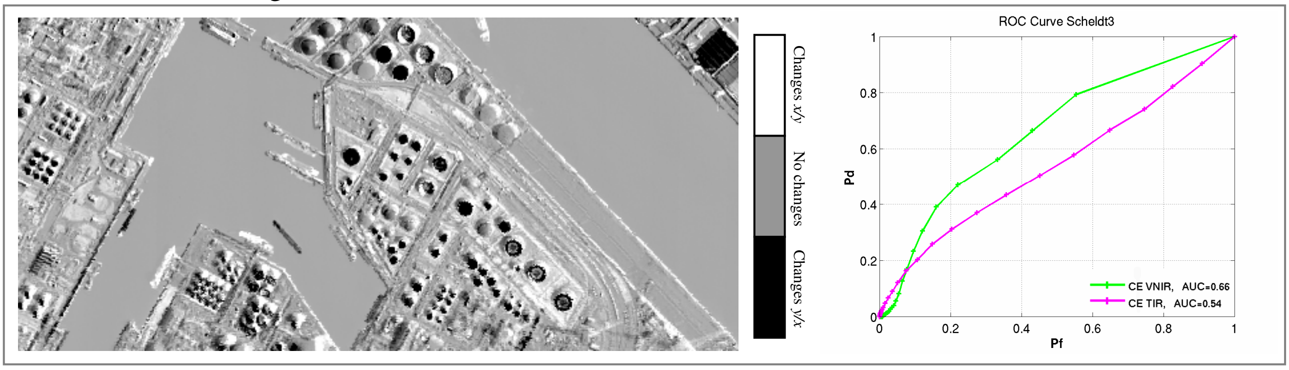

Figure 5: CE change detection of the VNIR scenes (left) and AUC results for the VNIR and the TIR data sets (right))

Figure 6 shows that the results of the QCE change detection method are not dependent on the number of classes (Q) and that QCE outperforms CE. The best results of the QCE changed detection acquired using the VNIR Q=6 classes (AUC=81%) and the TIR Q=11 (AUC=77%). The QCE results were significantly improved in relation to the results were obtained using the CE method, which originated from the basic assumption that non-target changes (i.e. shadows and other illumination changes) are space invariant. The lower false alarm detection obtained using the QCE in general and specifically QCE using the TIR data sets, proved that one way to solve such space varying changes is to search for differences between spectral clusters.

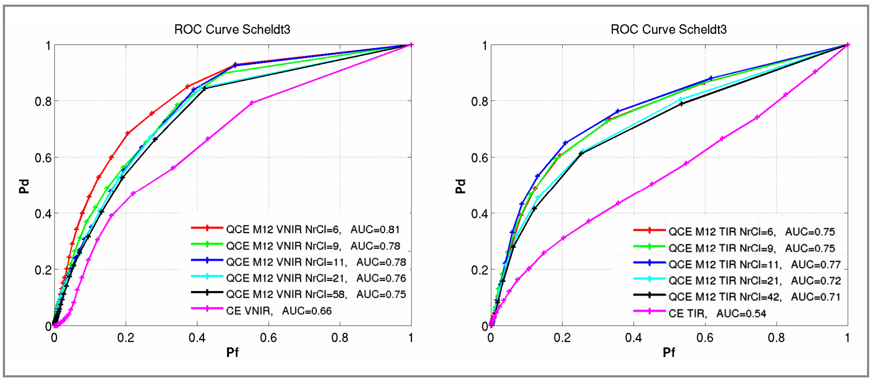

Figure 6: QCE and CE change detection in the VNIR scenes (left) and TIR scenes

The bi-temporal QCE results presented in Figure 7 show no improvement in change detection using the VNIR data sets. However, using the TIR data sets there is improvement in 2%-4% in the detection (with AUC=79% using TIR and Q=9, 11).

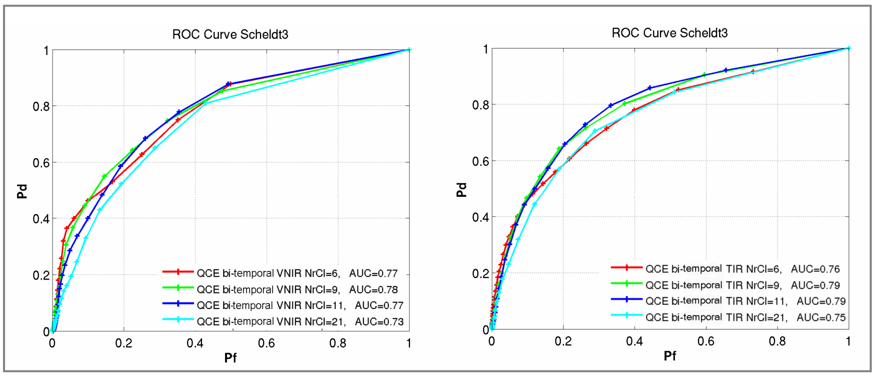

Figure 7: QCE bi-temporal change detection in the VNIR scenes (left) and TIR scenes

The WDS results presented in Figure 8 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%).

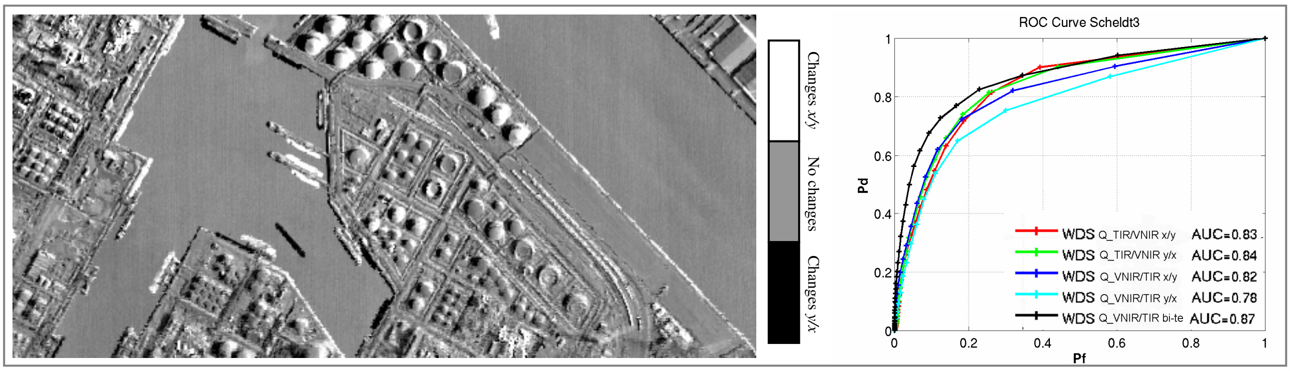

Figure 7: WDS bi-temporal change detection in the TIR scenes (left) and AUC results for the VNIR and the TIR data sets (right))

4. 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 VNIR and TIR data sets with respect to the VNIR or the TIR data set separately.

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