# DETECTION OF OCCLUDED TARGETS USING THERMAL IMAGING SPECTROSCOPY

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## ABSTRACT

Automatic detection of occluded targets from a sequence of images is an interesting area of research for defense related application. In this paper, change detection methods are investigated for the detection of buried improvised explosive devices (IED) using temporal thermal hyperspectral scenes. Specifically, the paper assesses the detection of buried small aluminium plates using the TELOPS Hyper-Cam sensor and by applying two change detection algorithms: multivariate statistical based method (Cross-Covariance (CC)) and class-conditional change detector (QCC).
It was found that spectral based change detection is a good method for the detection of buried IED under disturbed soil. Moreover, the Cross-Covariance (CC)) and the class-conditional (QCC) change detector were able to detect changes using short temporal sequences as long temporal sequences pairs.

***Index Terms***— Thermal hyperspectral, Change detection, improvised explosive devices (IED), buried object.

## 1. INTRODUCTION

Over the past several years, different remote sensing techniques applied for the detection of buried and occluded improvised explosive devices (IED). This includes ground penetrating radar, laser and optical remote means. Spectral IED detection either examines the apparent temperature difference in more detail (because multiple bands are used instead of one) or detects the spectral difference of their covering material with respect to their backgrounds. Spectral based detection of occluded target detects the disturbed soil or vegetation as a result of occluding or burying the device, not the device itself. Upon burying the IED in bare soil, the placement or presence of the IED will change the particle size, texture, or the moisture of a small region around it [1].The use of thermal hyperspectral images for IED detection was also investigated in the last few years [2-3].

However, thermal spectral limitations of a single scene is required the use of higher-order decision fusion to achieve target/clutter discrimination (fusion of thermal, textural and spectral information) [1-2]. In this paper, change detection methods are investigated for the detection of buried IED using temporal thermal hyperspectral scenes. Specifically, the paper assesses the detection of buried small aluminum plates using the TELOPS Hyper-Cam sensor and by applying two change detection algorithms: multivariate statistical based method (Cross-Covariance (CC)) and class-conditional change detector (QCC).

## 2. DATA SET

The ‘buried objects’ experiment took place by TELOPS during October 21$^{st}$ 2009 inside unexploited a rock and sand quarry in the periphery of Quebec City (Canada).

The TELOPS Hyper-Cam sensor was setup a distance of 250cm away from the target site looking downwards at it at an angle of 26 degree (Figure 1). The spectra were collected using 660 spectral bands in the wavelengths 800-1350 cm$^{-1}$. The camera equipped with a magnifying telescope resulting in an instantaneous field of view of 1.4 μrad. The detector area was set to 220 pixels by 200 pixels resulting in a FOV of 17.6° by 16°.

Four buried targets consisted of 6.5x8x0.25 inches aluminum plates (Figures 1 and 2) were buried in the sandy experiment site and bordered with several rocks (10-25cm in diameter). The targets were buried at depths of 2, 5 10 and 15 cm as indicated on Figures 1 and 2. All targets were buried in the ground on October 20$^{th}$ 2009 between 12:00 and 13:00, the day prior to the experiment. Special care was taken during the burial of the targets on October 20$^{th}$ 2009 not to disturbed the soil in the region indicated “undisturbed area” on the upper part of Figure 2.

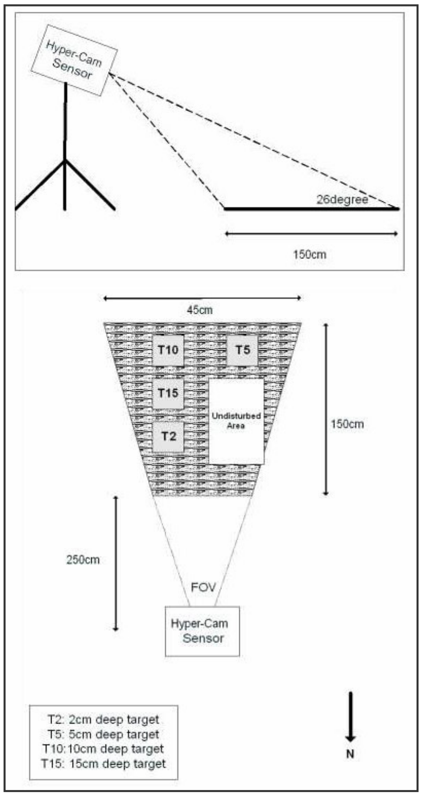


Figure 1: view of the experimental layout showing the Hyper-Cam field of view, buried targets and undisturbed area.

The data collection started at 6:40 am on October 21st 2009 in 9 different time sequences and consisted of the following:

- 50 acquisitions of a blackbody scene at a given temperature;
- 100 acquisitions of the target site;
- 50 acquisitions of a blackbody scene at a second given temperature.

Table 1 details the environmental conditions for the each of the nine IED sequences.

| Sequence | Start time | Ambient Temp C° | Humidity % | Ground Temp (E=0.98) |
|---|---|---|---|---|
| IED#1 | 06:40 | 1.3 | 80 | -7.3 |
| IED#2 | 07:55 | 1.8 | 79 | -2.5 |
| IED#3 | 09:10 | 3.1 | 78 | 7 |
| IED#4 | 10:50 | 6.5 | 57 | 1.5 |
| IED#5 | 00:00 | 9.9 | 45 | 16 |
| IED#6 | 13:16 | 9.1 | 45 | 12-14 |
| IED#7 | 14:24 | 9.3 | 44 | 9.5-11 |
| IED#8 | 15:34 | 7.9 | 44 | 3.5-4.5 |
| IED#9 | 17:24 | 4.4 | 54 | -1.3 |

Table 1: Experiment log.

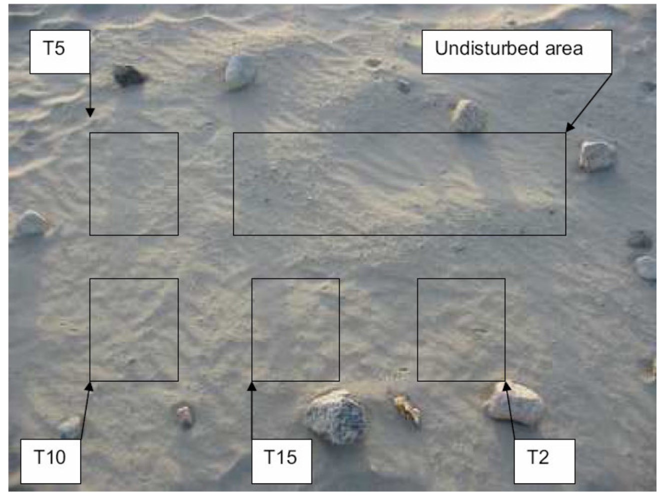


Figure 2: Target site showing the location of the buried targets.

## 3. CHANGE DETECTION METHODS

For automatic target detection of the buried objects, two change detection methods were utilised: cross covariance (CC) and class conditional CE (QCE).

### 3.1 Cross-Covariance (CC)

For the two hyperspectral matrices x and y, the diagonal matrices *Tx* and *Ty* are written as follow [4]:

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

where $\rho i$ 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:

$$\begin{aligned} x &= T_{xy} y + d_{xy} \\ T_{xy} &= T_x T_y^{-1} \\ d_{xy} &= d_x - T_{xy} d_y \\ \hat{x} &= \hat{T}_{xy} y + \hat{d}_{xy.} \end{aligned} \tag{2}$$

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:

$$C_x = V_x D_x V_x^T$$
$$C_y = V_y D_y V_y^T \qquad (4)$$

where *Vx* and *Vy* are the eigenvector matrices, and *Dx* and *Dy* are the diagonalised covariance matrices; then, the Cross-Covariance (CC) change detection method uses:

$$\hat{T}_{xy}^{(CC)} = C_{xy} C_{yy}^{-1}$$
$$\hat{d}_{xy}^{(CC)} = m_x - \hat{T}_{xy}^{(CC)} m_y . \qquad (5)$$

### 3.2 Class-conditional CC (QCC)

QCC [5-6] 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 QCC method we are assigning a class-conditional probability function $p(x|q)$ to the transformation parameters in (2) as follows:

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

And the change residual image ($\delta_1$) is defined as follows:

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

For the QCC method, after applying PCA on the reference Image *x*, the stochastic expectation maximization (SEM) [7] was employed. The SEM is a quadratic clustering algorithm that addresses the bias against overlapping class-conditional probability density functions by employing a Monte-Carlo class assignment. Stochastic modeling was selected rather than linear mixing modeling for the following reasons; in thermal imagery the temperature variations will cause a nonlinear large radiance offset due to changes in the upwelling radiance spectra and in the down-welling illumination that is influenced by local component as emission from nearby objects [8].

## 4. RESULTS

The CC change detection processing was applied to 72 pairs of the 9 sequences images. One can learn from the several results are presented in Figure 3, that the changes obtained are spectra based changes and not thermal based. Apart of illumination and shadow effects, the obtained changes were not varied along the day. However, due to the fact that the thermal spectra are influenced by the down-welling illumination, clear changes between the obtained spectra were recorded only from sequence #3 (09h10 am). In the afternoon, when the influences of up-welling spectra increase, the spectra increase, the spectra changes between the disturbed soil and its surrounding were reduced.

In the left column of Figure 3, the disturbed soil is clearly detected using the sequence image #3 (i.e. image x = #3). It is also clearly detected using short temporal sequences (i.e. x=3; y=4) as long temporal sequences (i.e. x=3; y=8).

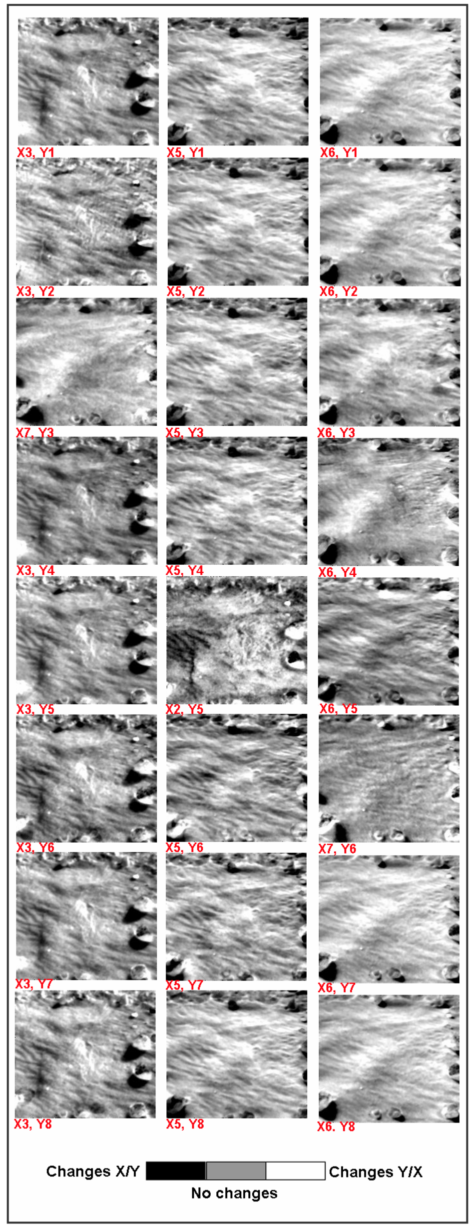


Figure 3: Several CC change detection results.

Further, the detection of the buried objects was applied using the QCC method. Following the results acquired using the CC method, the transformation parameters based spectral classes were obtained only using the hyperspectral matrices x=#3; #4;

x=#3; #4; #5. We tested the QCC with $Q=Q_{SEM}$ (which is the max Q obtained using the SEM method). For the three images the $Q_{SEM}$ identified five classes: three soils (included the disturbed soil), stone and shadow (Figure 5). The quartz doublet feature centered at 1176 and 1123 $cm^{-1}$ (8.5 µm and 8.9 µm) is clearly identified in the spectra of the undisturbed soils in Figure 4. One can see clearly that the fine particles of recently disturbed soil were suppressed the quartz spectral features.

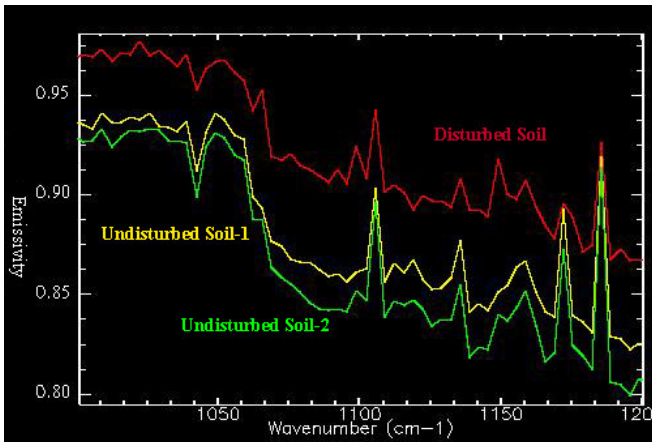


Figure 4: Spectra of the three detected soils using SEM.

Figure 5 presents the results of the QCE detection. One can identify clearly in the different sequences images the disturbed soil. As for the CC method, the changes clearly detected using the short temporal sequences as in the long temporal sequences.

## 5. CONCLUSIONS

Spectral based change detection found to be a good method for the detection of buried IED under disturbed soil. The TELOPS Hyper-Cam sensor founds to be sensitive enough to detect buried small aluminium plates using temporal hyperspectral scenes. The Cross-Covariance (CC)) and the class-conditional change detector (QCC) were able to detect changes using short temporal sequences as long temporal sequences pairs.

## 6. REFERENCES

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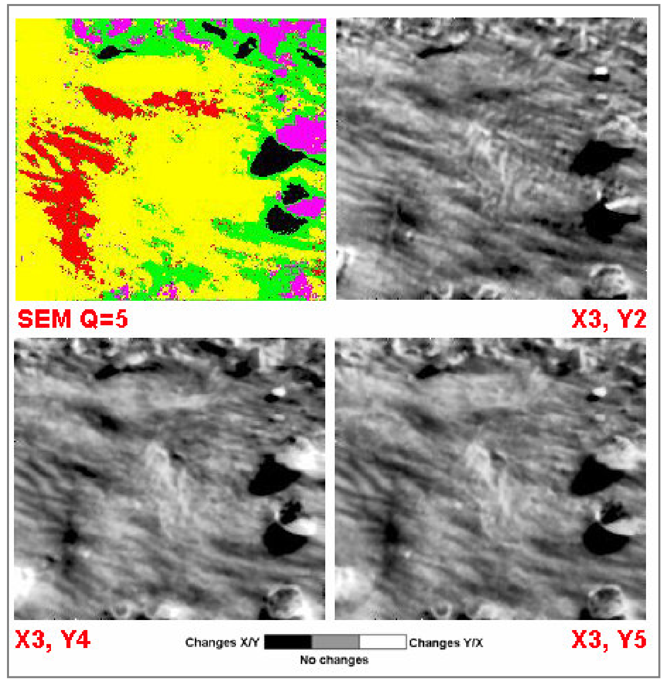


Figure 5: QCC results; SEM Q=5 and three QCC detection.

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