
Exploitation of Sparsity for Hyperspectral Target Detection
CentraleSupélec
Ahmad W. BITAR
06 June 2018
Reason one : The targets occupy a very small part of the entire image scene
The targets are spatially sparse (few pixels in a million pisel image). The background has a low rank property. Based on these two assumptions, we propose a novel target detector for hyperspectral imagery.
Reason two: A hyperspectral test pixel lies in a low dimensional subspace
A hyperspectral test pixel lies in a low dimensional subspace of the p-dimensional spectral-measurement space. The background dictionary is usually constructed via a dual sliding concentric window.
We aim to alleviate the serious challenge on building the dictionary of the background. Following which various detectors can be used to carry out a more elaborate binary hypothesis test.
Reason three: The covariance estmation is challenging in large dimensions
The traditional covariance estimators (e.g. the Sample Covariance, Tyler estimator) behave very poorly in large dimensions. We propose new estimators by assuming the covariance matrix is sparse, namely, many entries are zero.
Some concluding remarks and directions for future work
The direct use of RPCA is inadequate to distinguishing the true targets from the background. A modification of it is necessary.
Several proposed methods have been proposed and tested on both synthetic and real datasets for an automatic target detection.
The end
Thank you ...

Ahmad BITAR

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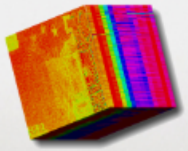

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Thank you ...

Sparsity

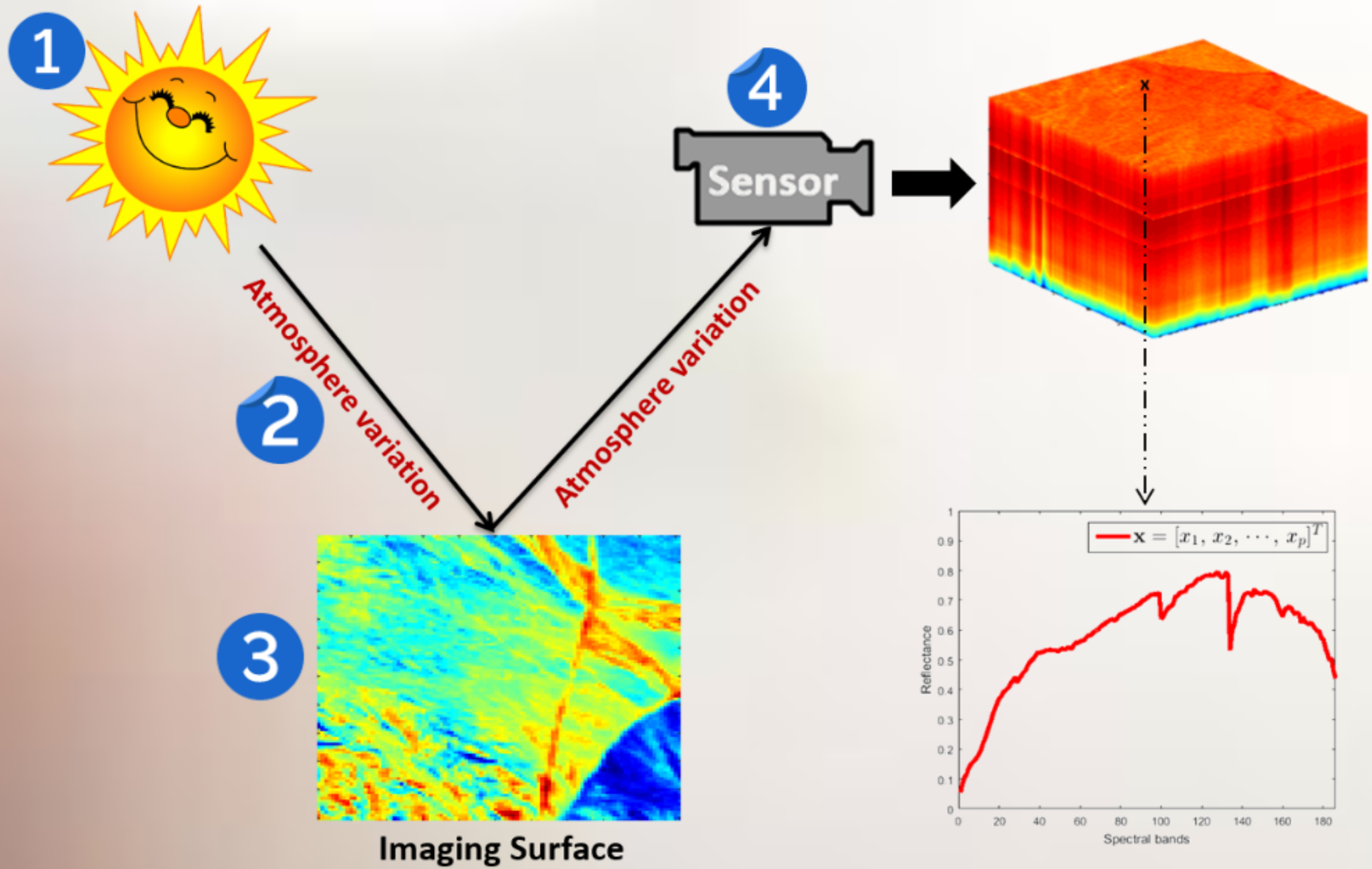
" Small in number or amount, often spread over a large area "

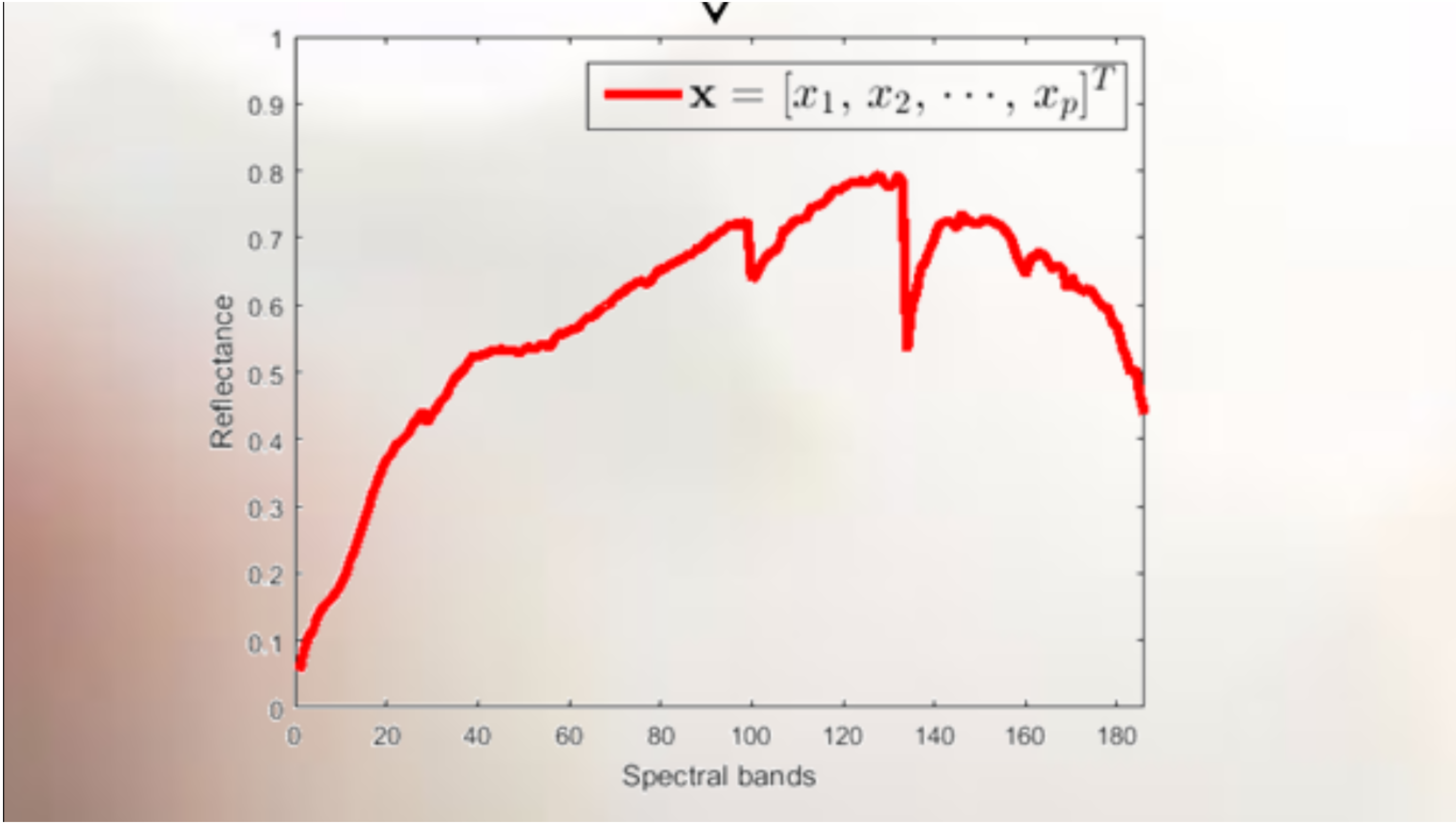

Sparse traffic

How and Why can Sparsity be exploited for Hyperspectral Target Detection

Introduction to Hyperspectral Target Detection

Hyperspectral (passive) Remote Sensing System :





$\mathbf{x} = [x_1, x_2, \cdots, x_p]^T$
Reflectance
Spectral bands
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
20
40
60
80
100
120
140
160
180

Hyperspectral Target Detection: concept and applications (1/3)

Target detection is one of the most important applications in hyperspectral imagery

$$\begin{cases} H_0 : \boldsymbol{x} = \text{background} & \Rightarrow \text{Target absent} \\ H_1 : \boldsymbol{x} = \text{Target + background} & \Rightarrow \text{Target present} \end{cases}$$

Hyperspectral Target Detection: concept and applications (2/3)

Replacement signal model :

$$\boldsymbol{x} = \alpha\, \mathbf{t} + (1 - \alpha)\, \mathbf{b}$$

$$0 \leq \alpha \leq 1$$

t : target spectrum

b : background spectrum

Hyperspectral Target Detection: concept and applications (3/3)

Applications to target detection :

- Application to target detection when the target t is known
  for example: Matched Filter, Normalized Matched Filter, Kelly detector.

- Application to target detection when the target t is not known (anomaly detection)
  for example: Reed and Xiaoli Detector, Kelly anomaly detector.

a ship at sea

Serious challenges in hyperspectral target detection (1/2)

- [**Challenge one**] The dependency on the unknown covariance matrix Σ (of the background surrounding the test pixel), and the estimation challenges of Σ in large dimensions and to ensure success under different environment.

Behave poorly in large dimensions

*The Sample covariance

*Robust estimators (i.e. The Tyler estimator)

Serious challenges in hyperspectral target detection (2/2)

- [**Challenge two**] The sensor noise, atmospheric conditions, material composition, etc.

This is inadequate

The classical target detectors that depend on the target to detect **t**, use only a single reference spectrum for the target of interest.

How and Why can Sparsity be exploited for Hyperspectral Target Detection

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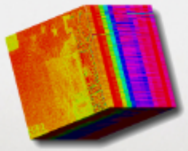

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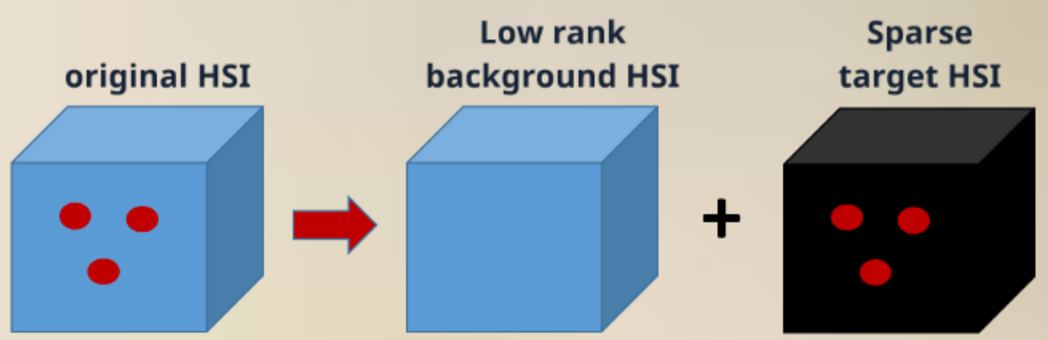
Reason one: The targets occupy a very small part of the entire image scene

- The targets are randomly distributed in the image.
- The targets have low probability to appear in each pixel in the entire image scene.

So how to exploit sparsity ?

1. The targets are spatially sparse (few pixels in a million pixel image).

2. The background has a low rank property.



our novelty against state of the art

[Shih-Yu Chen] [Yubin Niu] [Yuxiang Zhang]

- The objects to separate from the background are proven to be the true targets!
- The sparse target HSI is directly used for detection.

General Background (1/4)

Suppose a data matrix **D** can be decomposed as:

$$\mathbf{D} = \underbrace{\mathbf{L}_0}_{\text{low rank}} + \underbrace{\mathbf{E}_0}_{\text{sparse}}$$

How can both the low rank and sparse components be recovered accurately ??

General Background (2/4)

The Robust Principal Component Analysis (RPCA) :

$$\min_{\mathbf{L},\mathbf{E}} \left\{ \mathrm{rank}(\mathbf{L}) + \lambda \left\| \mathbf{E} \right\|_l \right\} \quad s.t. \quad \mathbf{D} = \mathbf{L} + \mathbf{E}\,,$$

NP-HARD to solve

$\lambda > 0$ is a regularization parameter

$\|\mathbf{E}\|_l$ indicates certain sparse regularization strategy: $\{\|.\|_0\,,\ \|.\|_{0,2}\,,\ \|.\|_{2,0}\}$

convex surrogation

$$\mathrm{rank}(.) \rightarrow \|.\|_*$$

$$\{\|.\|_0\,,\ \|.\|_{0,2}\,,\ \|.\|_{2,0}\} \rightarrow \{\|.\|_1\,,\ \|.\|_{1,2}\,,\ \|.\|_{2,1}\}$$

General Background (3/4)

Success of RPCA in some applications: Face recognition and video surveillance

- **RPCA for face recognition** **(the matrix L is the object of interest)**

$D = L + E$

Removing shadows, specularities, and saturations from a face

This example is taken from **[Candes et al.]**

Removing shadows, specularities, and saturations from a face

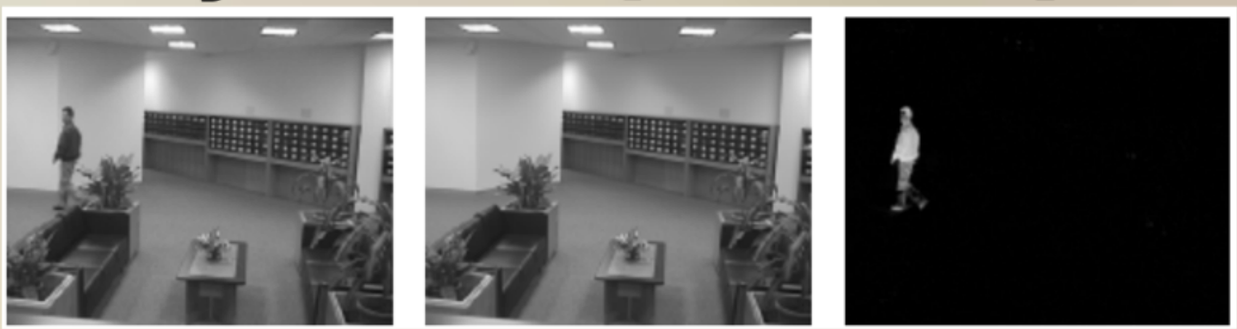
This example is taken from **[Candes et al.]**

General Background (4/4)

Success of RPCA in some applications: Face recognition and video surveillance

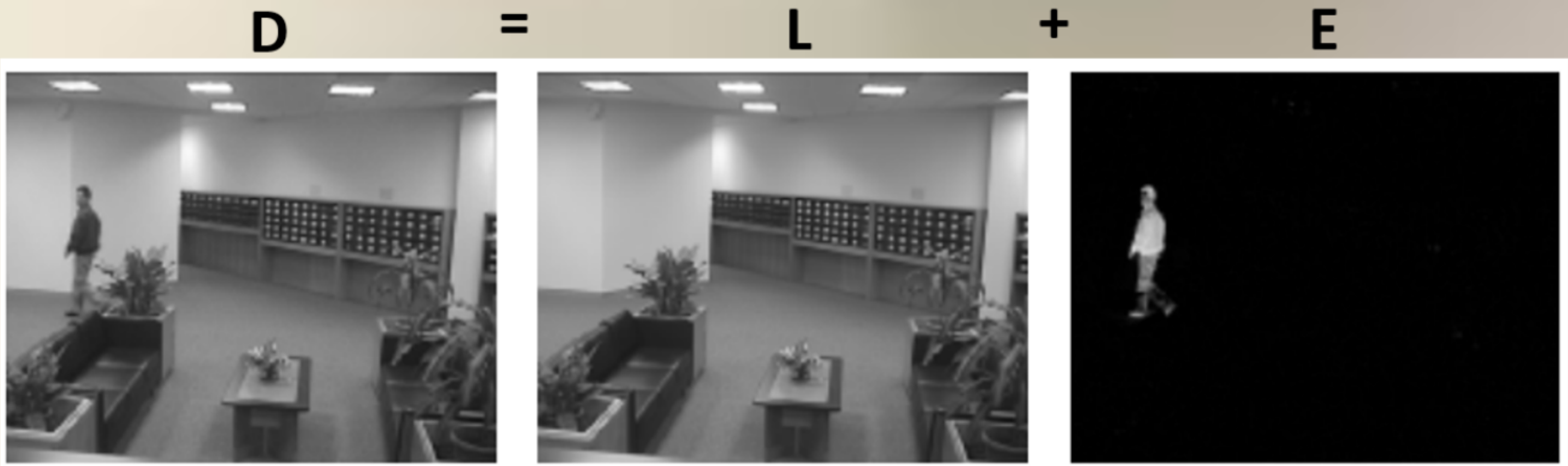
- **RPCA for video surveillance** (the matrix E is the object of interest)

D = L + E



Detecting the moving objects from a static background

This example is taken from [Candes et al.]



Detecting the moving objects from a static background

This example is taken from **[Candes et al.]**

Our study on testing the RPCA for Hyperspectral Target Detection (1/5)

How is RPCA exploited for Hyperspectral imagery?

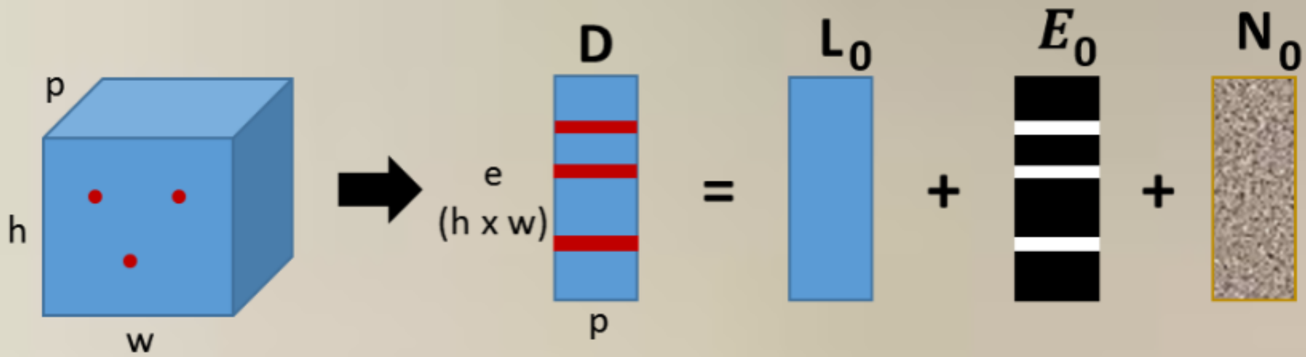
So how to define both $\mathbf{L}_0$ and $\mathbf{E}_0$?

- The total image area of all the target(s) should be small relative to the whole image (spatially sparse). $\rightarrow$ $\mathbf{E}_0$

- The background is not too heavily cluttered with many different materials with multiple spectra: The background has a low rank property . $\rightarrow$ $\mathbf{L}_0$

Our study on testing the RPCA for Hyperspectral Target Detection (2/5)

How is RPCA exploited for Hyperspectral imagery?



We aim to minimize the following problem:

$$\min_{\mathbf{L},\mathbf{E}} \left\{ \tau \, \mathrm{rank}(\mathbf{L}) + \lambda \, \|\mathbf{E}\|_{0,2} + \|\mathbf{D} - \mathbf{L} - \mathbf{E}\|_F^2 \right\}, \quad \textbf{NP-HARD}$$

$$\downarrow$$

$$\min_{\mathbf{L},\mathbf{E}} \left\{ \tau \, \|\mathbf{L}\|_* + \lambda \, \|\mathbf{E}\|_{1,2} + \|\mathbf{D} - \mathbf{L} - \mathbf{E}\|_F^2 \right\}, \quad \textbf{CONVEX}$$

Our study on testing the RPCA for Hyperspectral Target Detection (3/5)

Is the direct use of RPCA adequate to distinguishing the targets?

NO

In contrast to what have been proved in state of the art

[Yuxiang Zhang, Shih-Yu Chen]

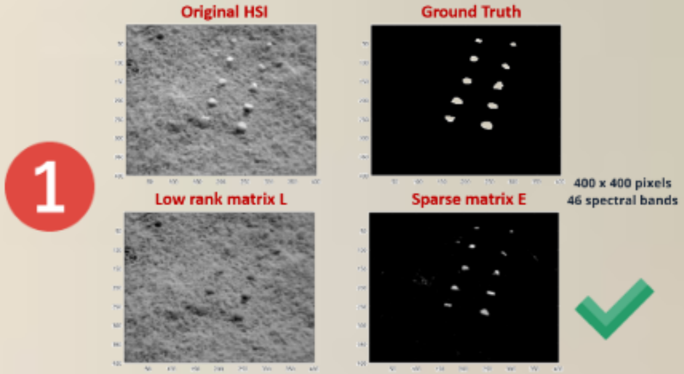
Our findings:

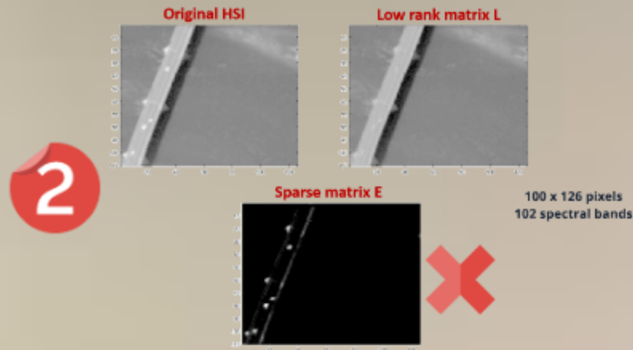
The RPCA only searches for small heterogeneous and high contrast objects. RPCA is not adequate to distinguishing the targets ...

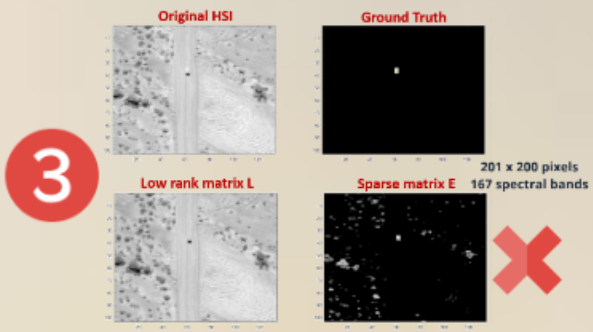
Our study on testing the RPCA for Hyperspectral Target Detection (4/5)

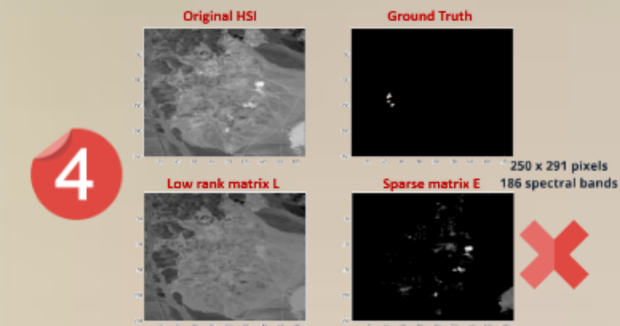
Let us prove what we have found

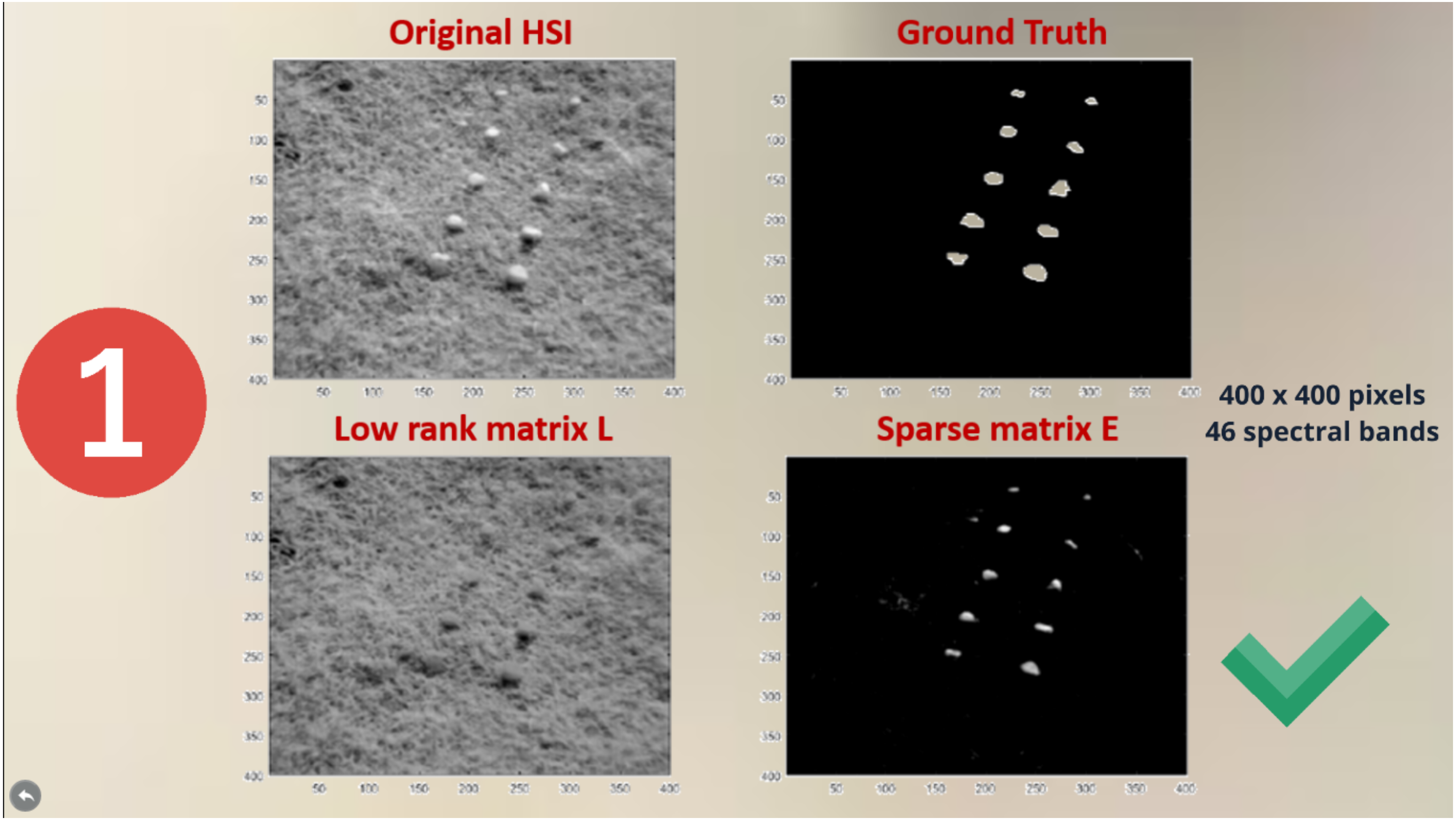
Our study on testing the RPCA for Hyperspectral Target Detection (5/5)



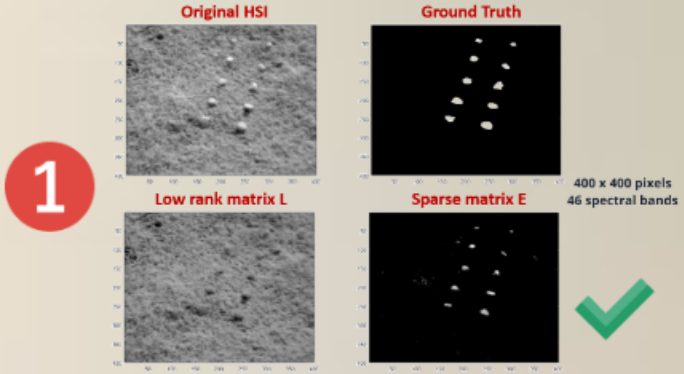


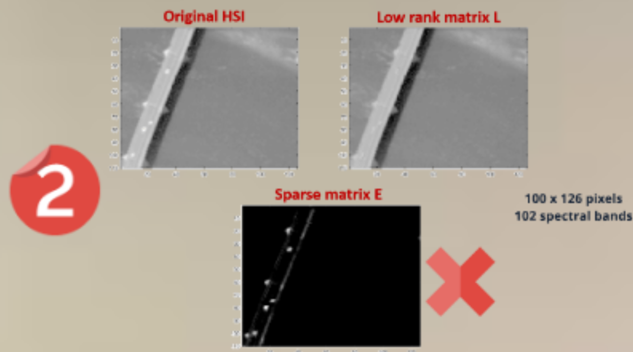


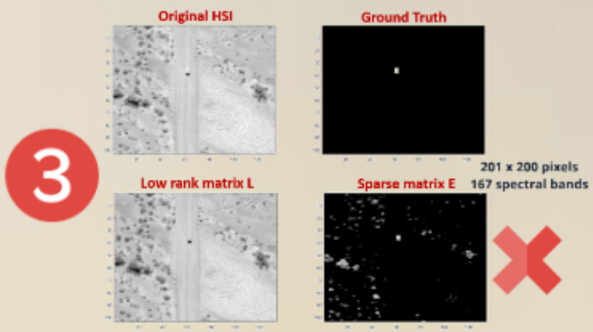


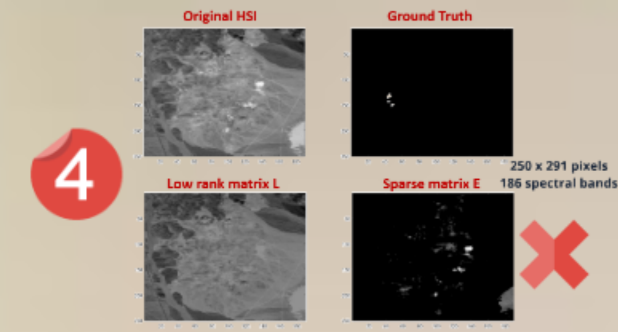

1
Original HSI
Ground Truth
Low rank matrix L
Sparse matrix E
400 x 400 pixels
46 spectral bands

Our study on testing the RPCA for Hyperspectral Target Detection (5/5)



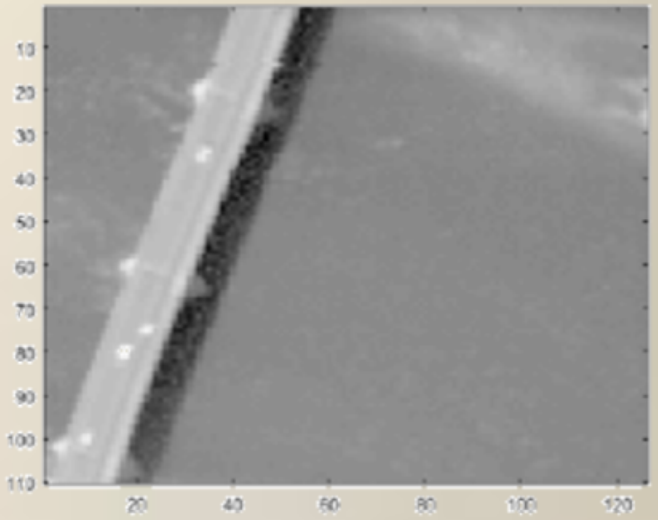




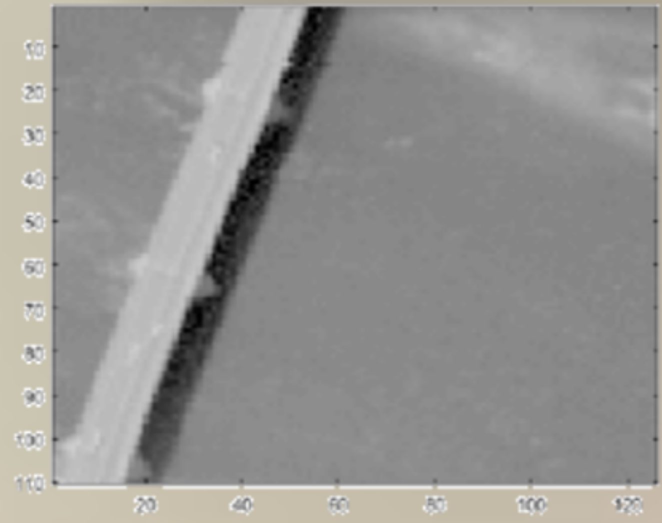


2

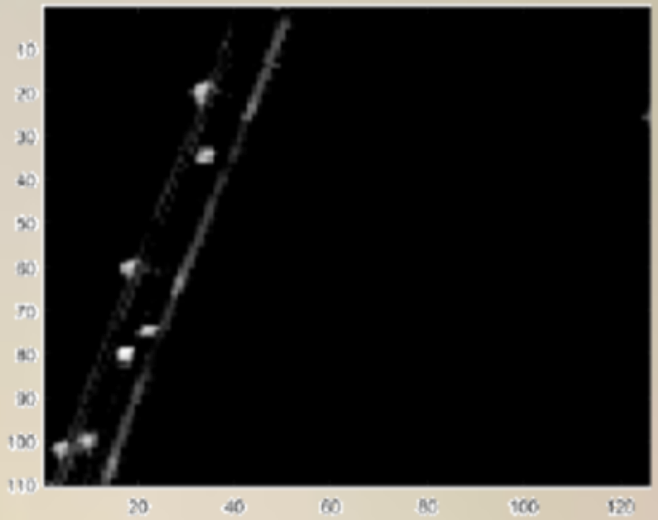
Original HSI



Low rank matrix L

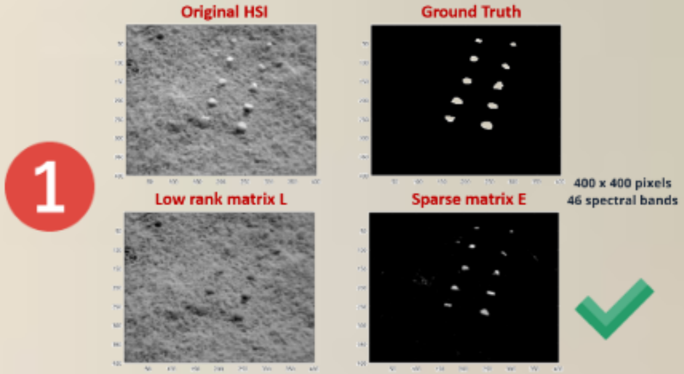


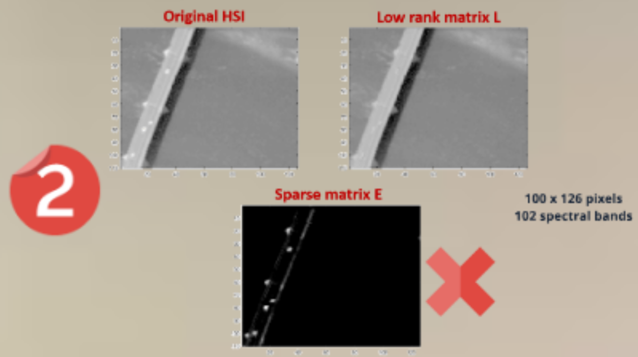
Sparse matrix E

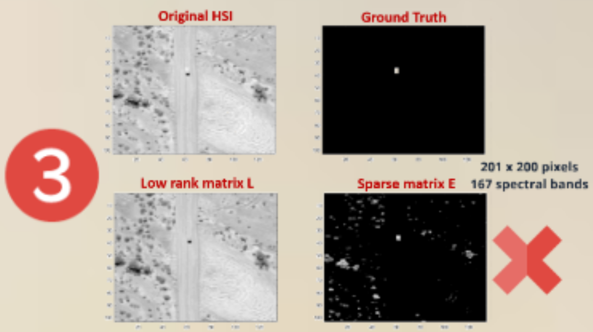


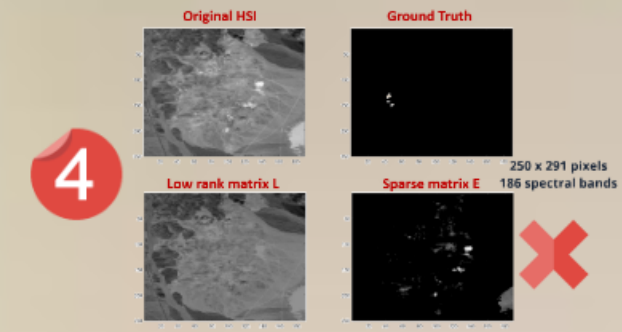
100 x 126 pixels
102 spectral bands

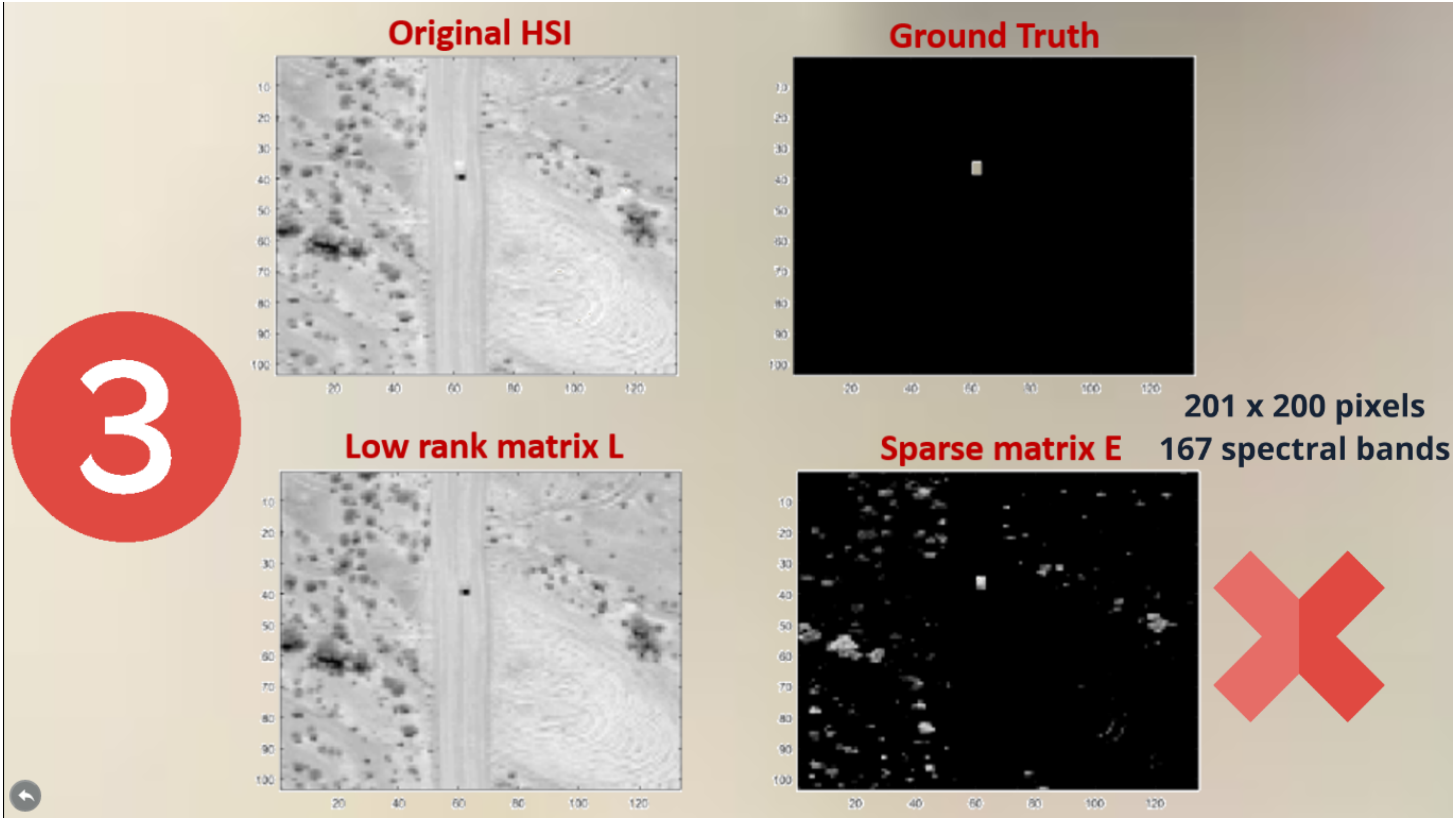
Our study on testing the RPCA for Hyperspectral Target Detection (5/5)



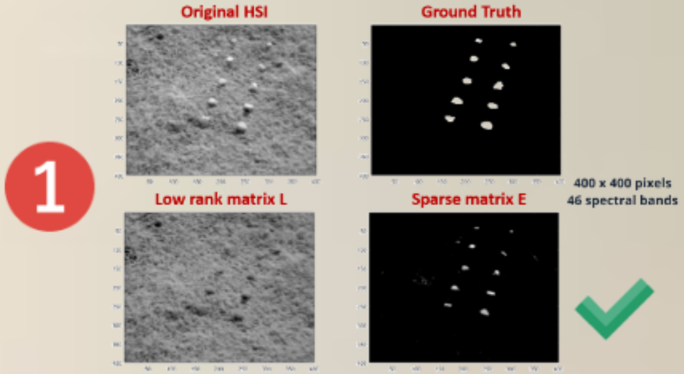


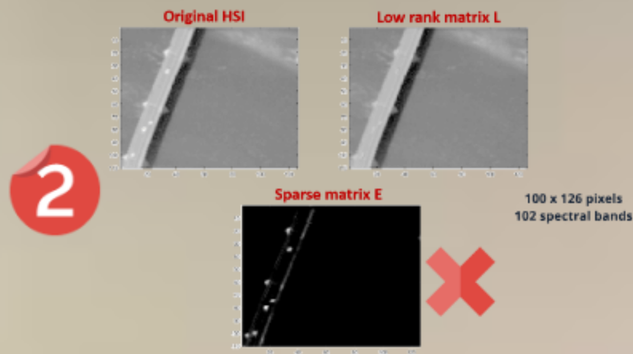


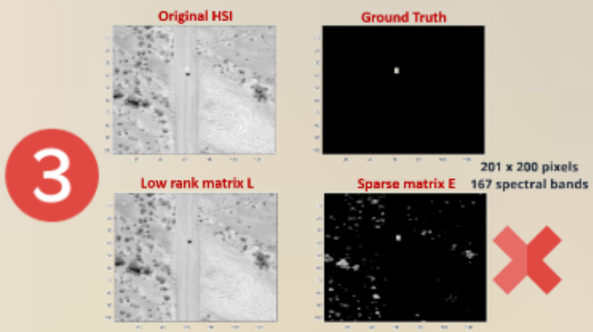


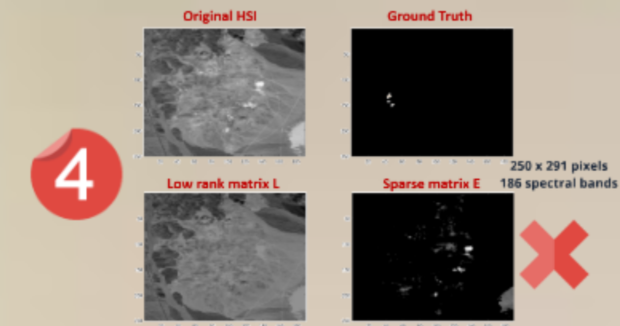

3
Original HSI
Ground Truth
Low rank matrix L
Sparse matrix E
201 x 200 pixels
167 spectral bands

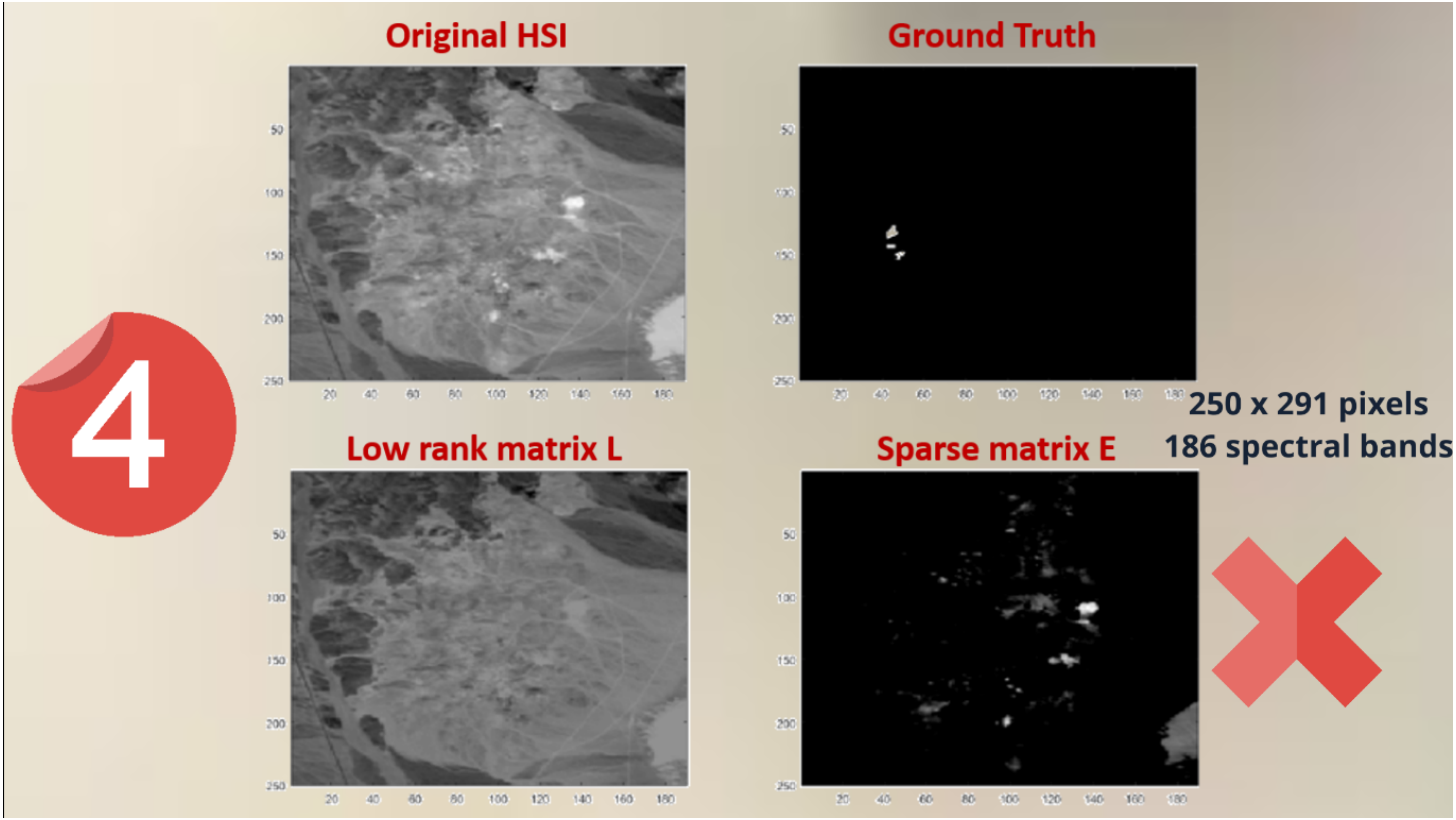
Our study on testing the RPCA for Hyperspectral Target Detection (5/5)










4
Original HSI
Ground Truth
Low rank matrix L
Sparse matrix E
250 x 291 pixels
186 spectral bands

Let us modify the RPCA (1/3)

We suppose that a target prior information is provided to the user:

The target spectra is known

Our problem formulation:

1. Let us consider that the given HSI contains q pixels of the form:

$$\mathbf{x}_i = \alpha_i \, \mathbf{t}_i + (1 - \alpha_i) \, \mathbf{b}_i, \quad 0 < \alpha_i \leq 1 \quad i \in [1, q]$$

2. Assume that all $\{\mathbf{t}_i\}_{i \in [1,q]}$ consist of similar materials:

$$\mathbf{x}_i = \alpha_i \sum_{j=1}^{N_t} \left(\beta_{i,j} \, \mathbf{a}_j^t \right) + (1 - \alpha_i) \, \mathbf{b}_i \quad i \in [1, q] \, .$$

Let us modify the RPCA (2/3)

$$\mathbf{D} = \mathbf{L}_0 + (\mathbf{A}_t\, \mathbf{C}_0)^T + \mathbf{N}_0$$

Let us modify the RPCA (3/3)

In order to recover the low rank and sparse components:

$$\boxed{\min_{\mathbf{L},\mathbf{C}} \left\{ \tau \, \mathrm{rank}(\mathbf{L}) + \lambda \left\| \mathbf{C} \right\|_{2,0} + \left\| \mathbf{D} - \mathbf{L} - (\mathbf{A}_t \mathbf{C})^T \right\|_F^2 \right\}}$$

NP-HARD

Convex surrogation

$$\boxed{\min_{\mathbf{L},\mathbf{C}} \left\{ \tau \, \left\| \mathbf{L} \right\|_* + \lambda \left\| \mathbf{C} \right\|_{2,1} + \left\| \mathbf{D} - \mathbf{L} - (\mathbf{A}_t \mathbf{C})^T \right\|_F^2 \right\}}$$

Our novel target detector

We use $(\mathbf{A}_t\mathbf{C})^T$ directly as a detector !!

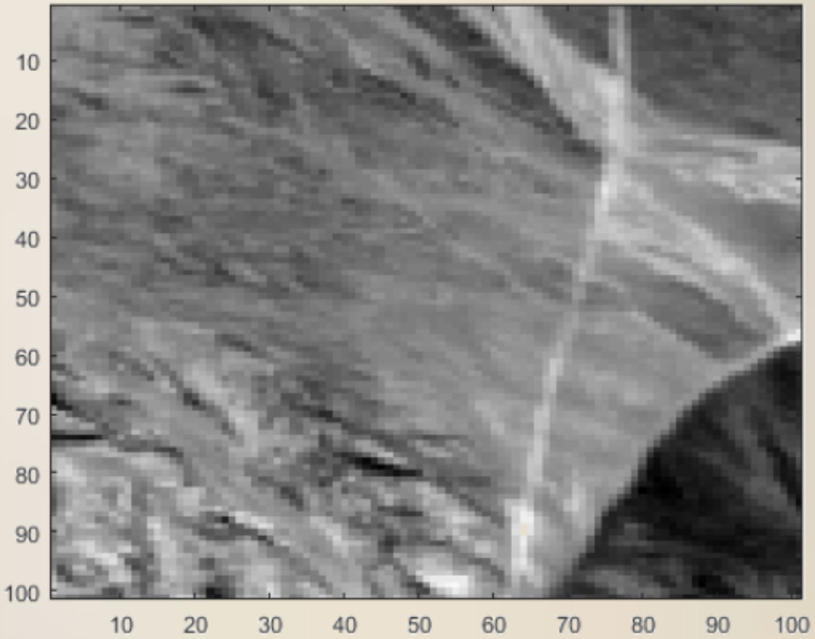
The sparse target image should be very sparse with very little false alarms

We do not need the the target fraction to be entirely removed and deposited in the sparse image

The choice of λ should be high enough !!

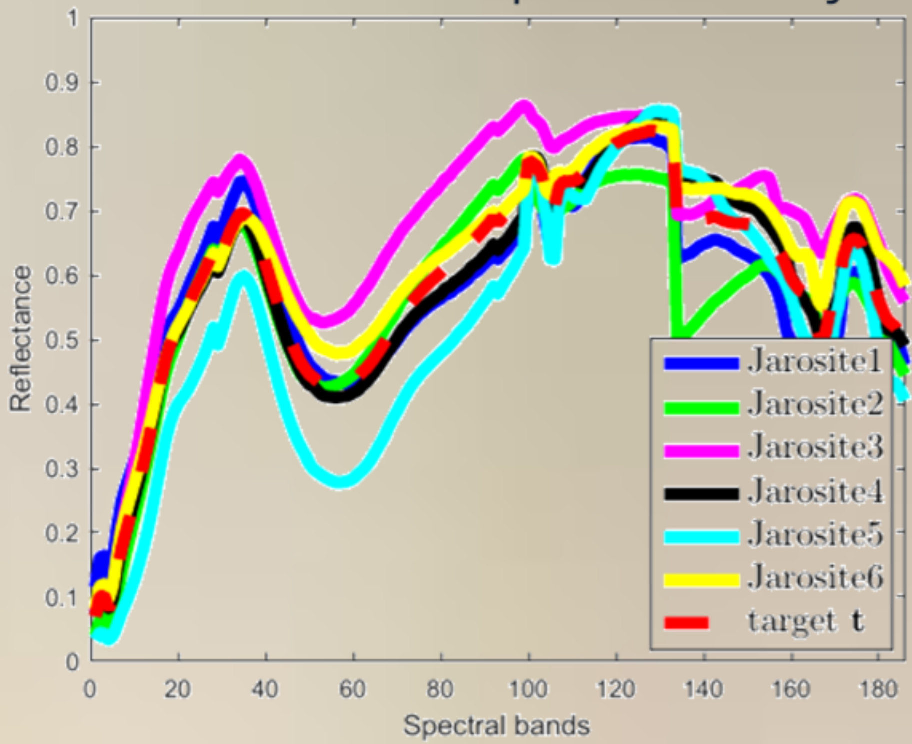
Synthetic Application to target detection (1/10)

101 x 101 x 186 zone



7 target blocks are incorporated in the image for 7 target blocks are incorporated in the image for $\alpha \in [0.01, 1]$

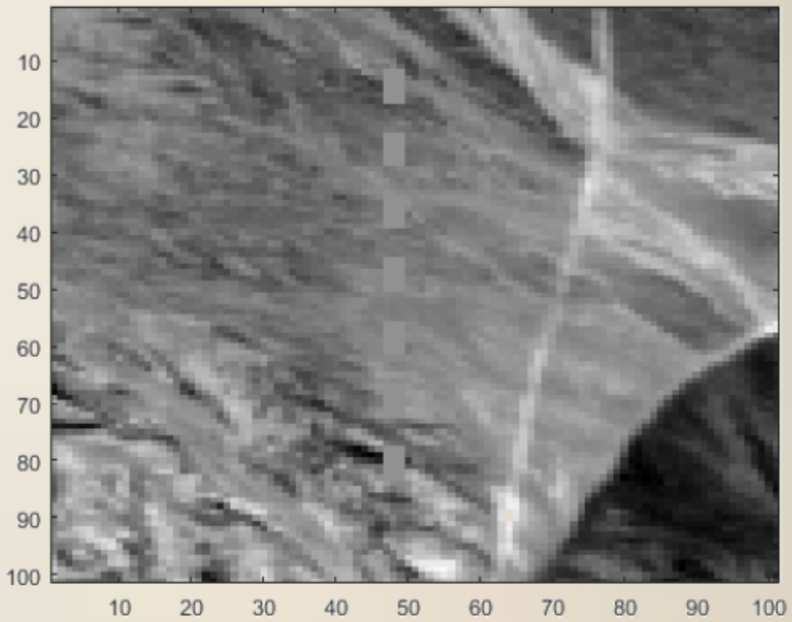
Jarosite target samples taken from the USGS spectral library



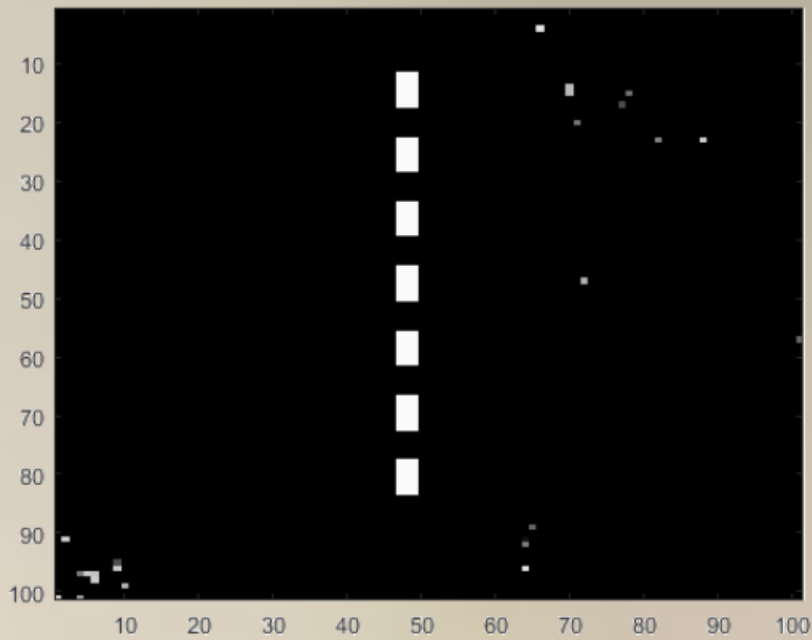
$\mathbf{A}_t$

Synthetic Application to target detection (2/10)

$\alpha = 1$

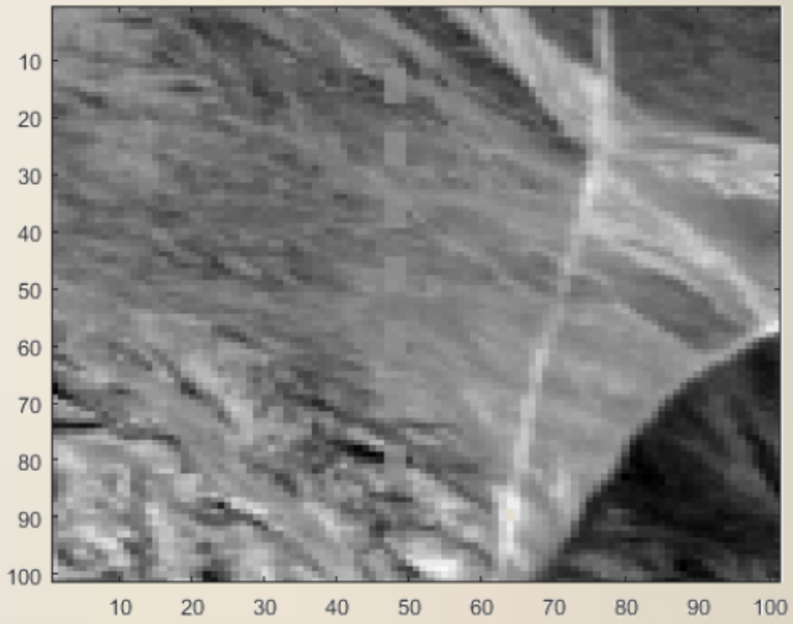


$(\mathbf{A}_t\mathbf{C})^T$

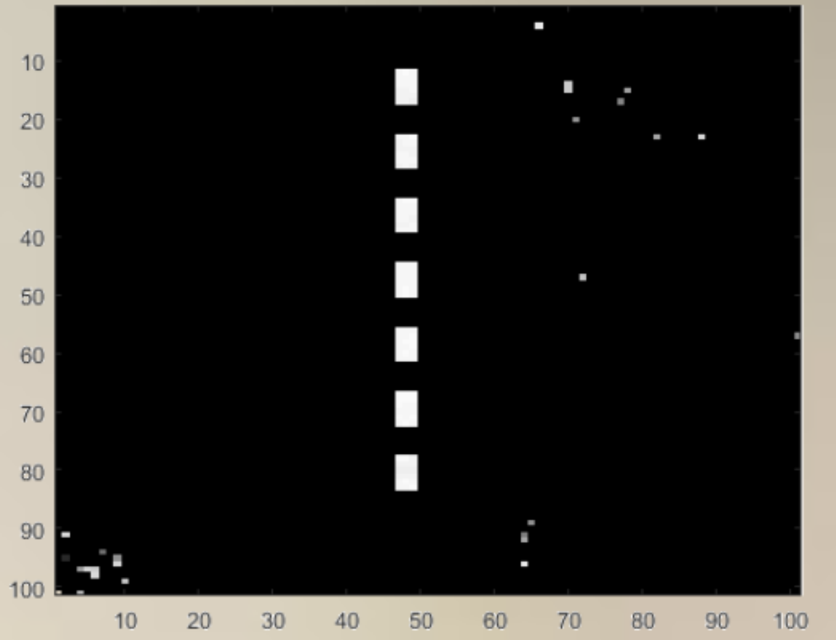


Synthetic Application to target detection (3/10)

α =0.8

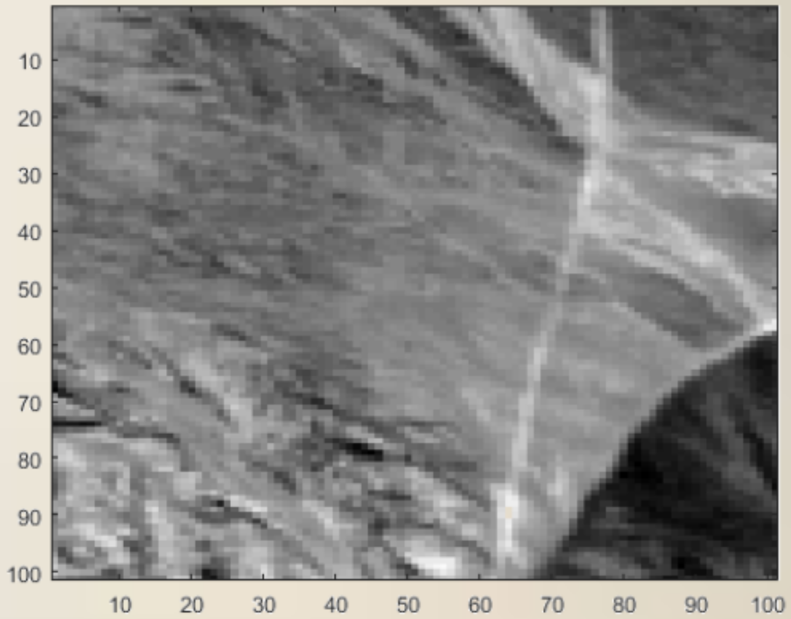


$(\mathbf{A}_t\mathbf{C})^T$

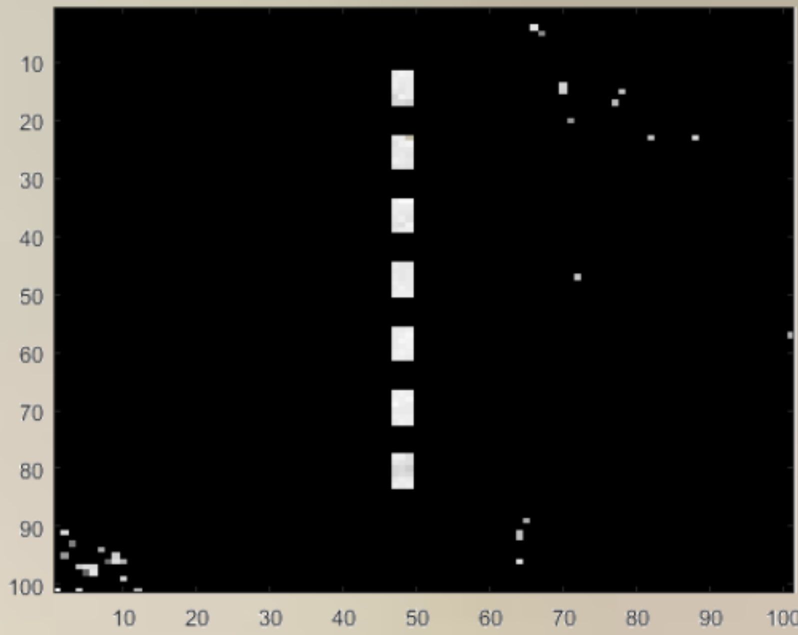


Synthetic Application to target detection (4/10)

α =0.5

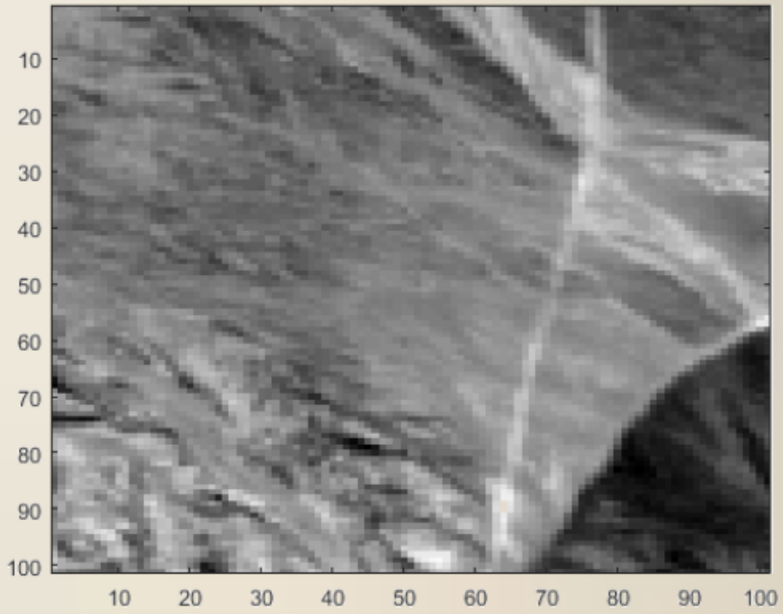


$(\mathbf{A}_t\mathbf{C})^T$

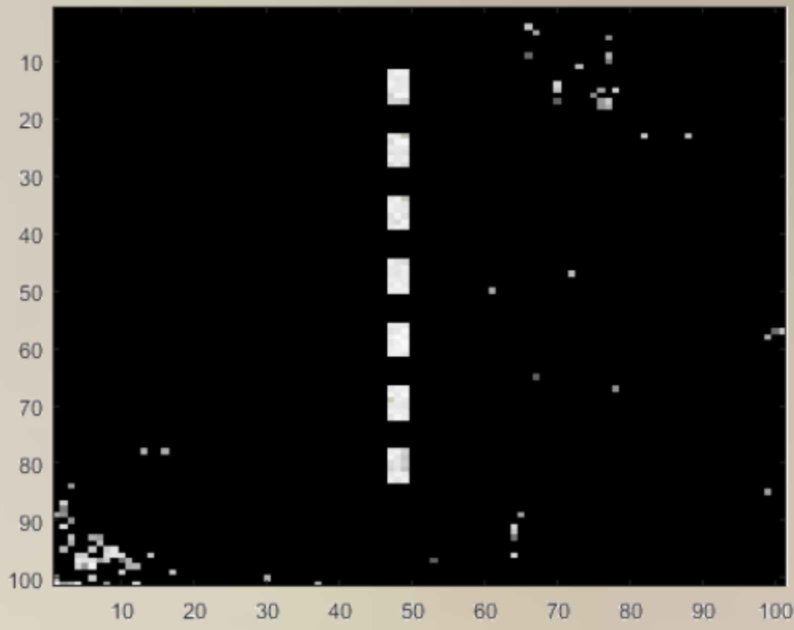


Synthetic Application to target detection (5/10)

α =0.3

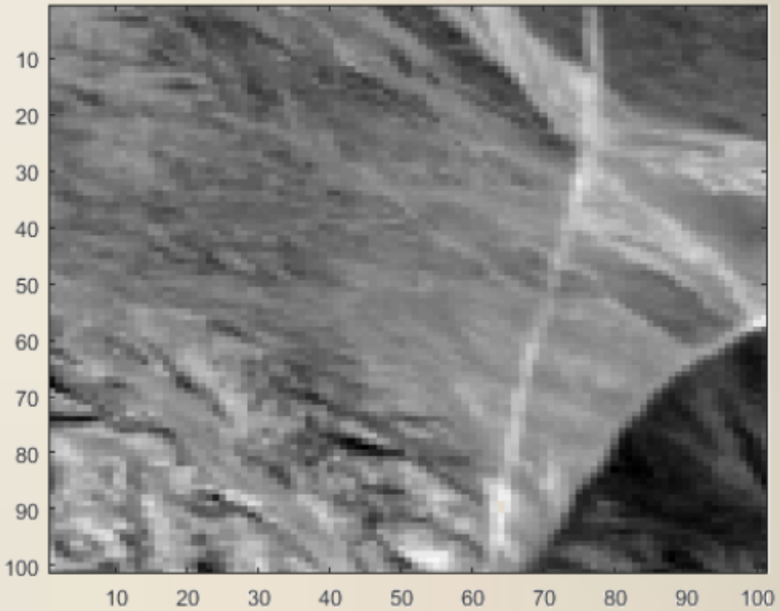


$(\mathbf{A}_t\mathbf{C})^T$

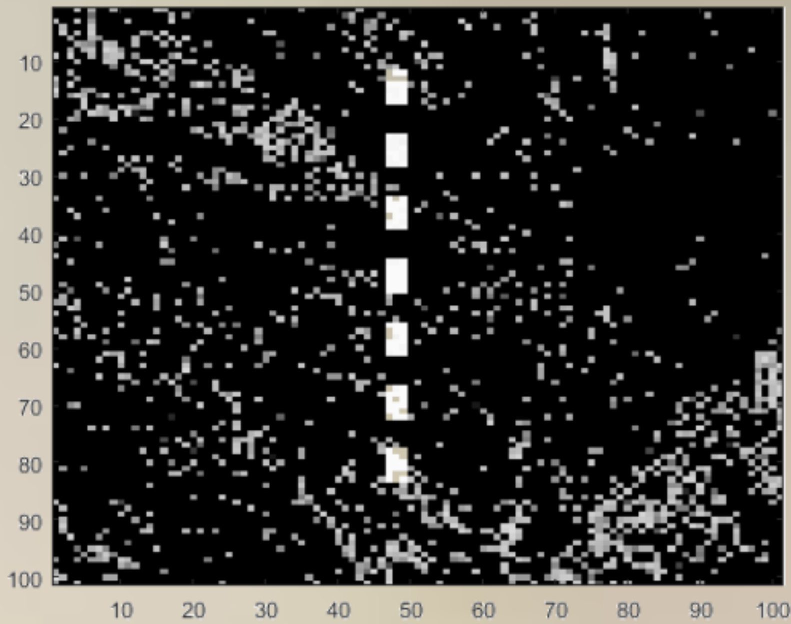


Synthetic Application to target detection (6/10)

$\alpha = 0.1$

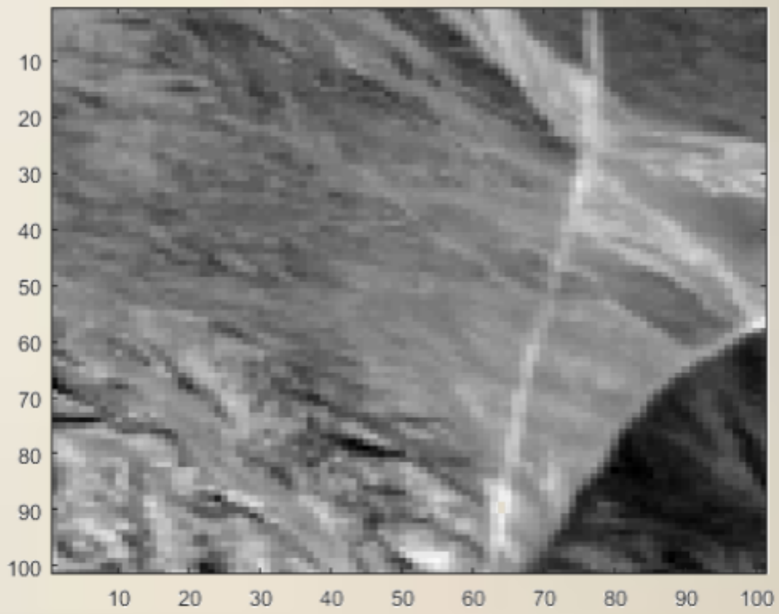


$(\mathbf{A}_t\mathbf{C})^T$

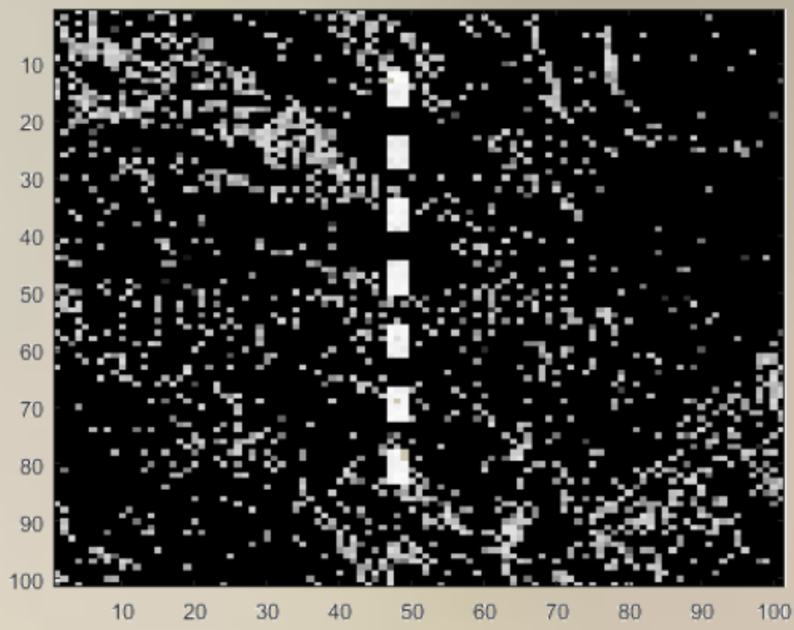


Synthetic Application to target detection (7/10)

α =0.05

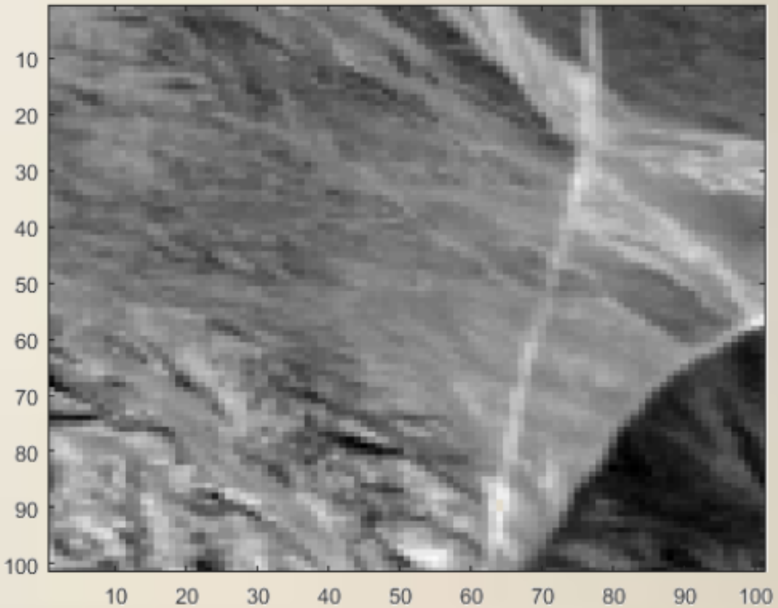


$(\mathbf{A}_t\mathbf{C})^T$

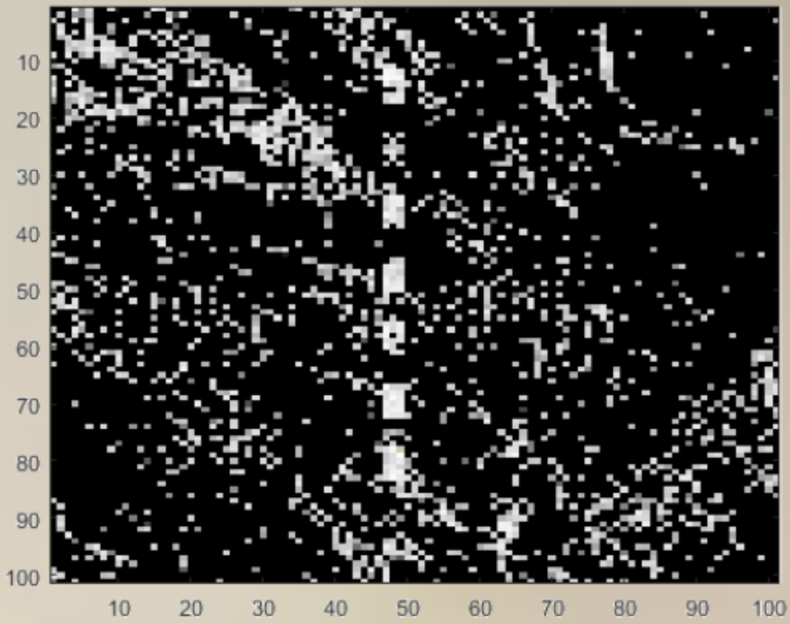


Synthetic Application to target detection (8/10)

α =0.02

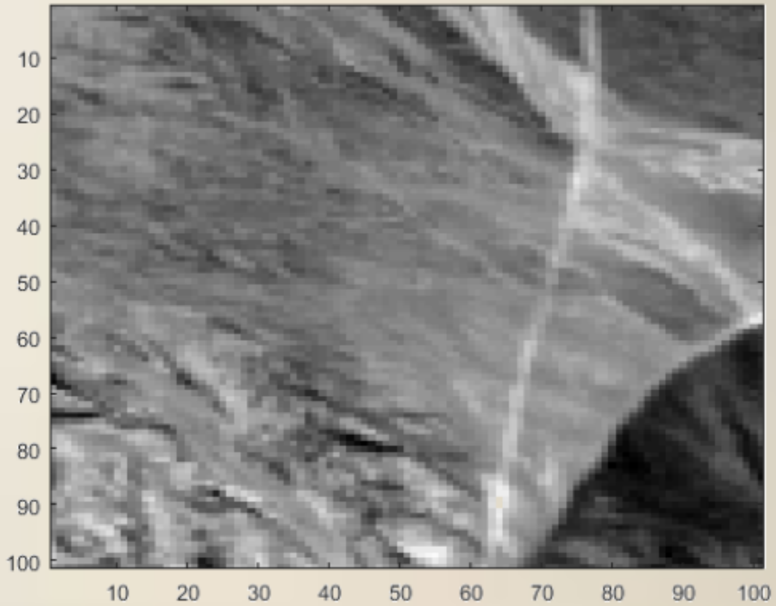


$(\mathbf{A}_t\mathbf{C})^T$

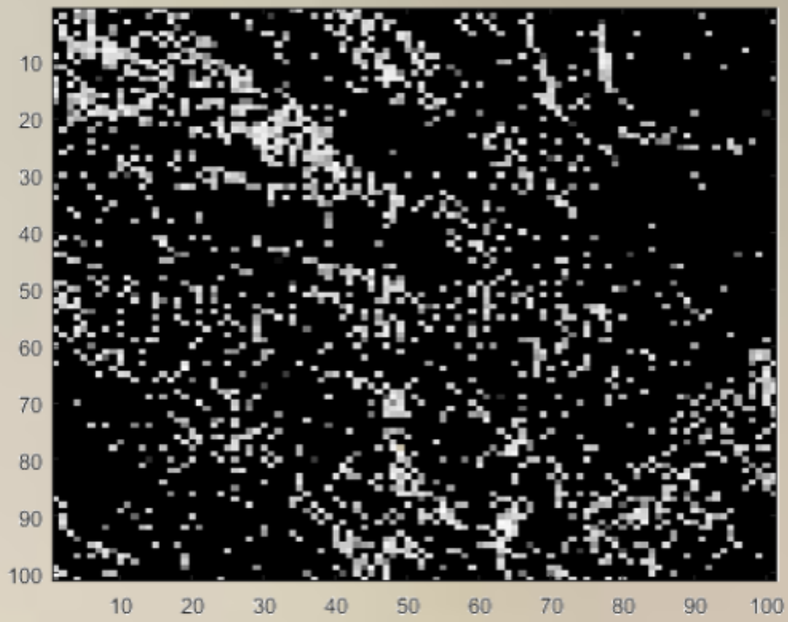


Synthetic Application to target detection (9/10)

α =0.01



$(\mathbf{A}_t\mathbf{C})^T$



Synthetic Application to target detection (10/10)

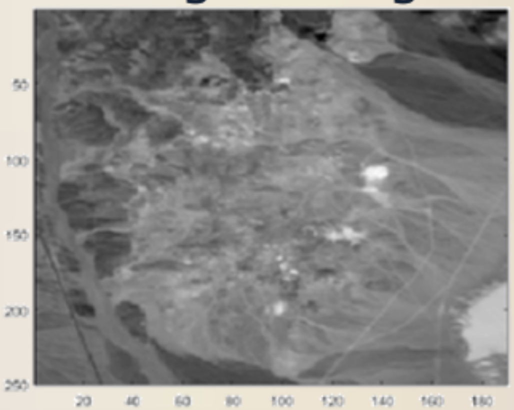
Some concluding remarks about the obtained results

- The target fill fraction affects the detection performance !!
- The results strongly depend on the relaxation norm used from the sparse matrix $(\mathbf{A}_t\mathbf{C})^T$
- There is a room for non target signals to appear in the sparse image $(\mathbf{A}_t\mathbf{C})^T$

High false alarms !!

Real experiments for target detection

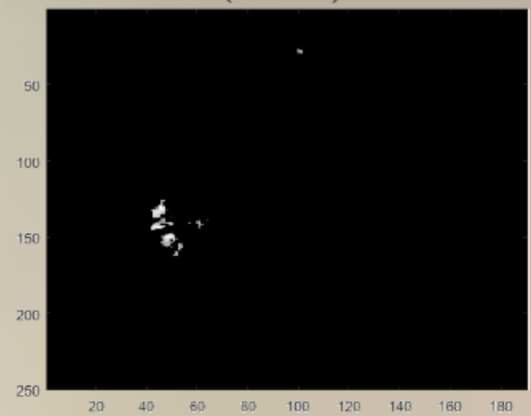
original image

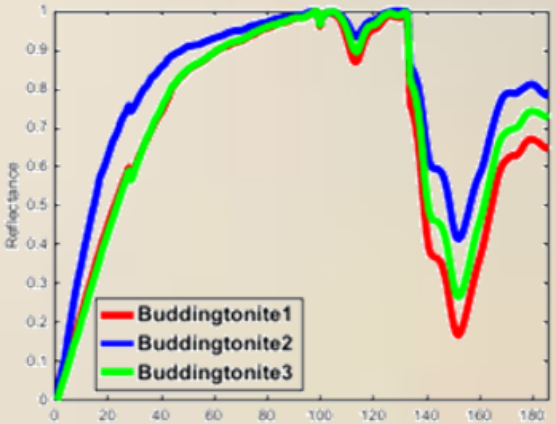


250 x 291 x 186

Ground Truth

$(\mathbf{A}_t\mathbf{C})^T$





$= \mathbf{A}_t$

Buddingtonite target samples from the ASTER spectral library

Exploitation of Sparsity for Hyperspectral Target Detection

CentraleSupélec | **Ahmad W. BITAR** | **06 June 2018**

Reason one : The targets occupy a very small part of the entire image scene

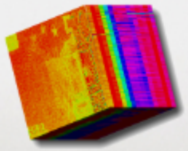
The targets are spatially sparse (few pixels in a million pixel image). The background has a low rank property. Based on these two assumptions, we propose a novel target detector for hyperspectral imagery.

Reason two: A hyperspectral test pixel lies in a low dimensional subspace

A hyperspectral test pixel lies in a low dimensional subspace of the p-dimensional spectral-measurement space. The background dictionary is usually constructed via a dual sliding concentric window.

We aim to alleviate the serious challenge on building the dictionary of the background. Following which various detectors can be used to carry out a more elaborate binary hypothesis test.

Reason three: The covariance estmation is challenging in large dimensions



The traditional covariance estimators (e.g. the Sample Covariance, Tyler estimator) behave very poorly in large dimensions. We propose new estimators by assuming the covariance matrix is sparse, namely, many entries are zero.

Some concluding remarks and directions for future work

The direct use of RPCA is inadequate to distinguishing the true targets from the background. A modification of it is necessary.

Several proposed methods have been proposed and tested on both synthetic and real datasets for an automatic target detection.

The end

Thank you ...

***Reason two**: for any test pixel* $\mathrm{x} \in \mathbb{R}^p$*, it lies approximately in a low-dimensional subspace of the p-dimensional spectral measurement space*

So how to exploit sparsity?

The work of [Chen et al. 2011]

If x is pure background → x can be represented by few atoms taken from the *background dictionary*

If x is pure target → x can be represented by few atoms taken from the *target dictionary*

The work of [Zhang et al. 2015]

If $\mathbf{x} \in H_0$ → x can be represented by few atoms taken from the *background dictionary*

If $\mathbf{x} \in H_1$ → x can be represented by few atoms taken from the union of the background and *target dictionaries*

General background (1/3)

- If $\mathbf{x} \in H_0$:

$$\begin{aligned} \mathbf{x} &= \varrho_1\, \mathbf{a}_1^b + \varrho_2\, \mathbf{a}_2^b + \cdots + \varrho_{N_b}\, \mathbf{a}_{N_b}^b \,, \\ &= \left[\mathbf{a}_1^b,\ \mathbf{a}_2^b,\ \cdots,\ \mathbf{a}_{N_b}^b\right] \left[\varrho_1,\ \varrho_2,\ \cdots,\ \varrho_{N_b}\right]^T \,, \\ &= \mathbf{A}_b\, \boldsymbol{\varrho} \end{aligned}$$

sparse vector

[Zhang et al. 2015]

- If $\mathbf{x} \in H_1$:

$$\begin{aligned} \mathbf{x} &= \beta_1\, \mathbf{a}_1^b + \beta_2\, \mathbf{a}_2^b + \cdots + \beta_{N_b}\, \mathbf{a}_{N_b}^b + \theta_1\, \mathbf{a}_1^t + \theta_2\, \mathbf{a}_2^t + \cdots + \theta_{N_t}\, \mathbf{a}_{N_t}^t \,, \\ &= \left[\mathbf{A}_\mathbf{b}\ \mathbf{A}_t\right] \left[\boldsymbol{\beta}^T\ \boldsymbol{\theta}^T\right]^T \,, \\ &= \mathbf{A}\, \boldsymbol{\gamma} \end{aligned}$$

sparse vector

$$\hat{\boldsymbol{\varrho}} = \arg\min_{\boldsymbol{\varrho}} \|\mathbf{x} - \mathbf{A}_b \boldsymbol{\varrho}\|_2 \quad \text{s.t.} \quad \|\boldsymbol{\varrho}\|_0 \leq k_0 \,,$$

$$\hat{\boldsymbol{\gamma}} = \arg\min_{\boldsymbol{\gamma}} \|\mathbf{x} - \mathbf{A}\boldsymbol{\gamma}\|_2 \quad \text{s.t.} \quad \|\boldsymbol{\gamma}\|_0 \leq k_0'$$

$$\hat{\boldsymbol{\varrho}} = \underset{\boldsymbol{\varrho}}{\operatorname{argmin}} \|\mathbf{x} - \mathbf{A}_b \boldsymbol{\varrho}\|_2 \quad \text{s.t.} \quad \|\boldsymbol{\varrho}\|_0 \leq k_0 \,,$$

$$\hat{\boldsymbol{\gamma}} = \underset{\boldsymbol{\gamma}}{\operatorname{argmin}} \|\mathbf{x} - \mathbf{A} \boldsymbol{\gamma}\|_2 \quad \text{s.t.} \quad \|\boldsymbol{\gamma}\|_0 \leq k'_0$$

Orthogonal Matching Pursuit algorithm (OMP)

General background (1/3)

The SRBBH target detector :

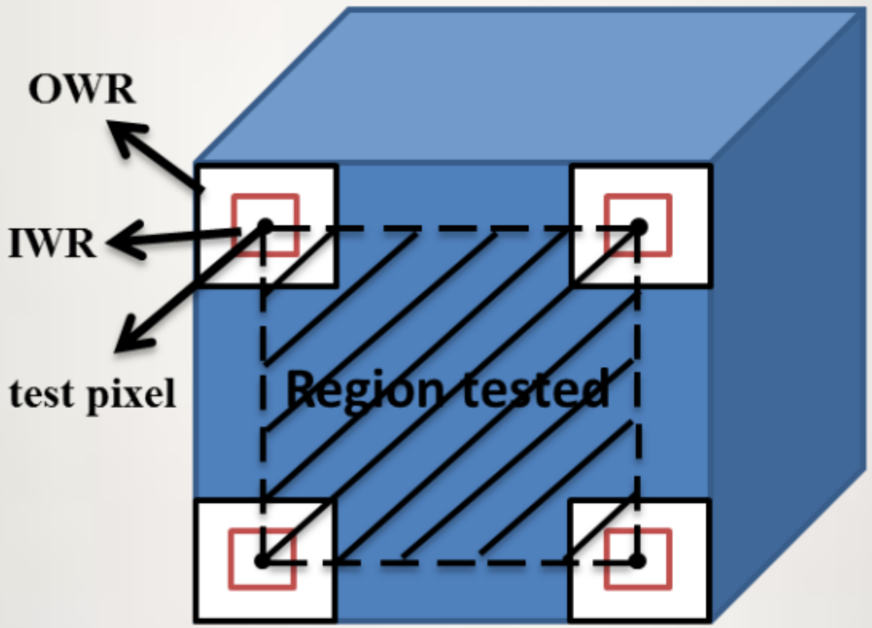
$$D_{SRBBH}(\mathbf{x}) = \left\|\mathbf{x} - \mathbf{A}_b\, \hat{\boldsymbol{\varrho}}\right\|_2 - \left\|\mathbf{x} - \mathbf{A}\, \hat{\boldsymbol{\gamma}}\right\|_2$$ [Yuxiang Zhang]

If $D_{SRBBH}(\mathbf{x}) > \eta$ ➡ target present

If $D_{SRBBH}(\mathbf{x}) \leq \eta$ ➡ target absent

General background (1/3)

The usual estimation of $\mathbf{A}_b$



The dual concentric window

The problem to solve

Is the dual concentric window good idea?

NO

- **Information about the target size is not available !**
- **The target could be of irregular shape !**

STOP USING IWR

The problem to solve

Is the dual concentric window good idea?

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STOP USING IWR

The problem to solve

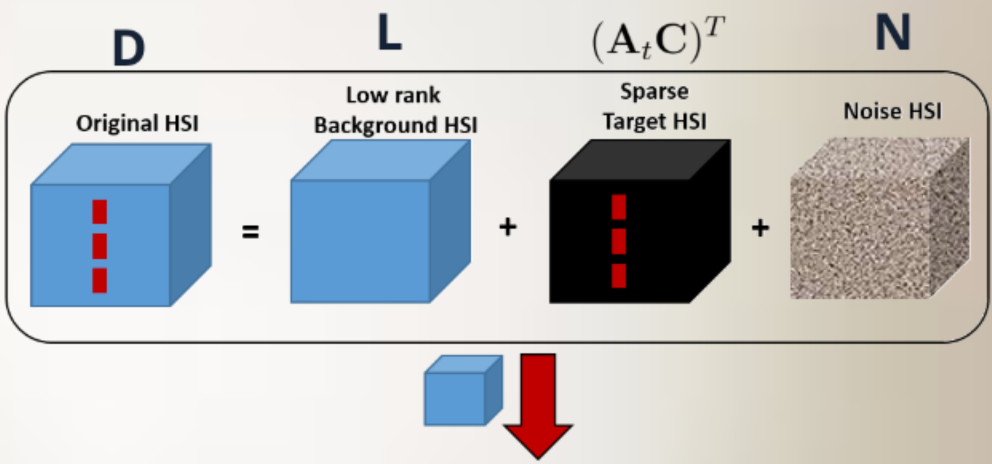
Is the dual concentric window good idea?

NO

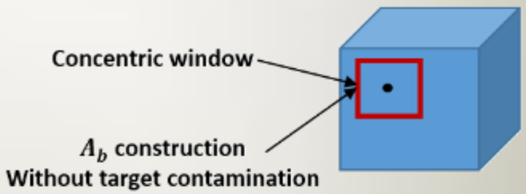
- **Information about the target size is not available !**
- **The target could be of irregular shape !**

STOP USING IWR

Let us improve the usual $\mathbf{A}_b$ *construction*



Improving the target detection performance by constructing the background dictionary A_b from the low rank background HSI L



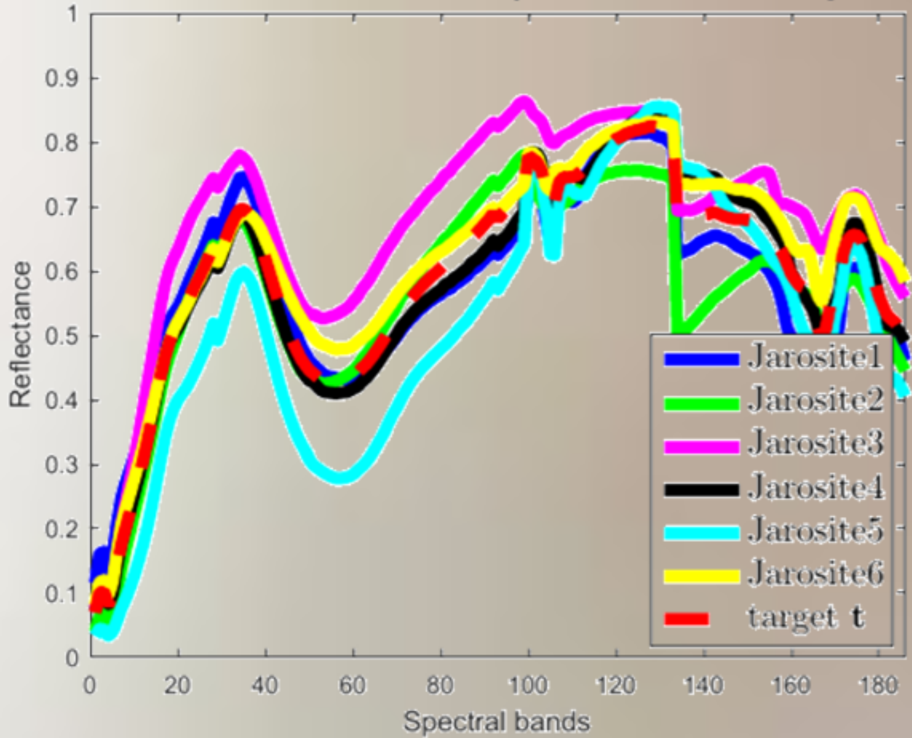
Synthetic Application to target detection (1/11)

Same application as before

101 x 101 x 186 zone

7 target blocks are incorporated in the image for 7 target blocks are incorporated in the image for $\alpha \in [0.01, 1]$

Jarosite target samples taken from the USGS spectral library



$\mathbf{A}_t$

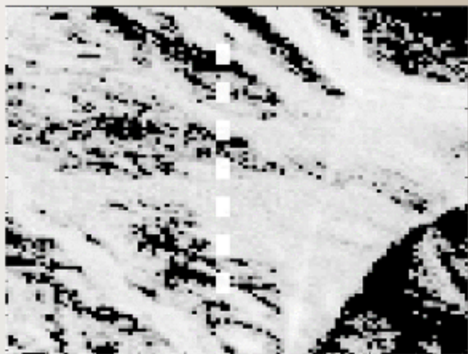
Synthetic Application to target detection (2/11)

Separation evaluation our target and background separation model

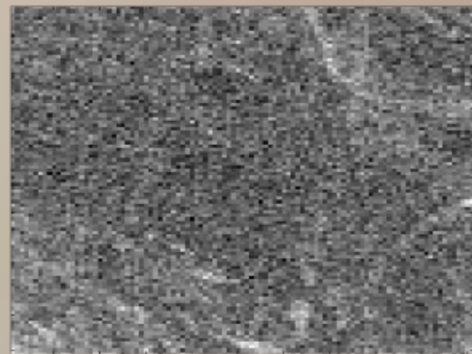
D

L

$(\mathbf{A}_t\mathbf{C})^T$



N



$$\alpha = 0.1$$

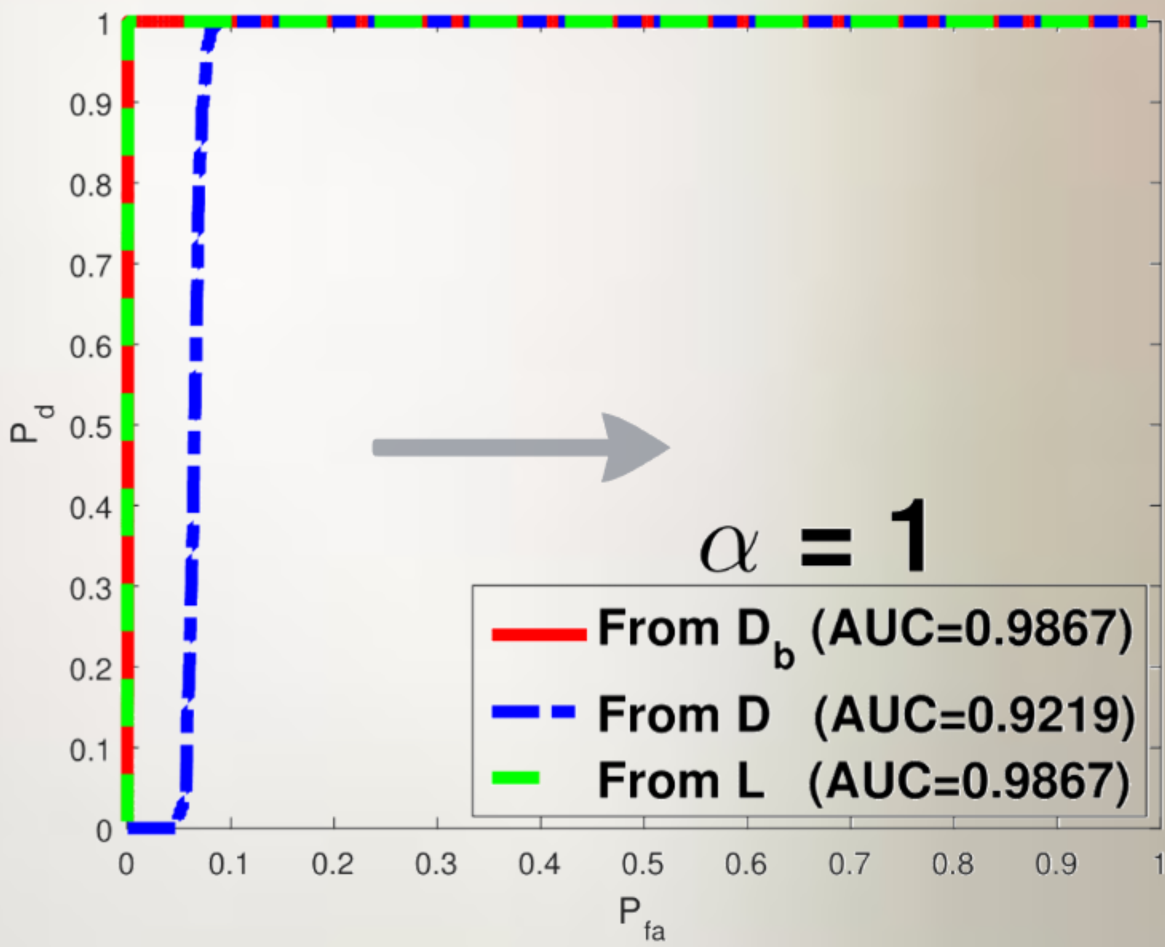
Synthetic Application to target detection (3/11)

Concentric window of size : 5 x 5

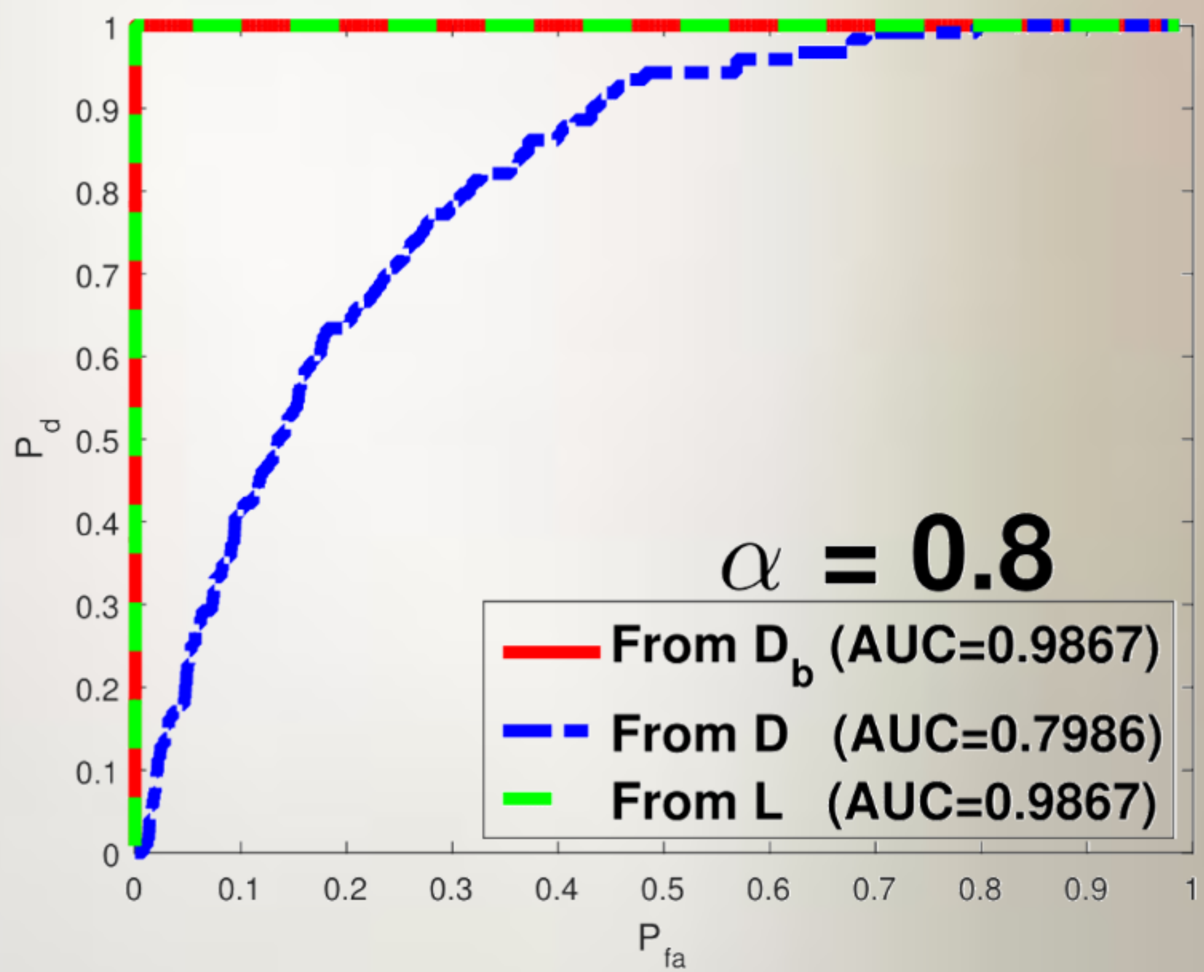
We shall use $\mathbf{D}_b$ $\longrightarrow$ Pure background HSI (without the targets)

We shall use $\mathbf{D}$ $\longrightarrow$ HSI after incorporating the targets

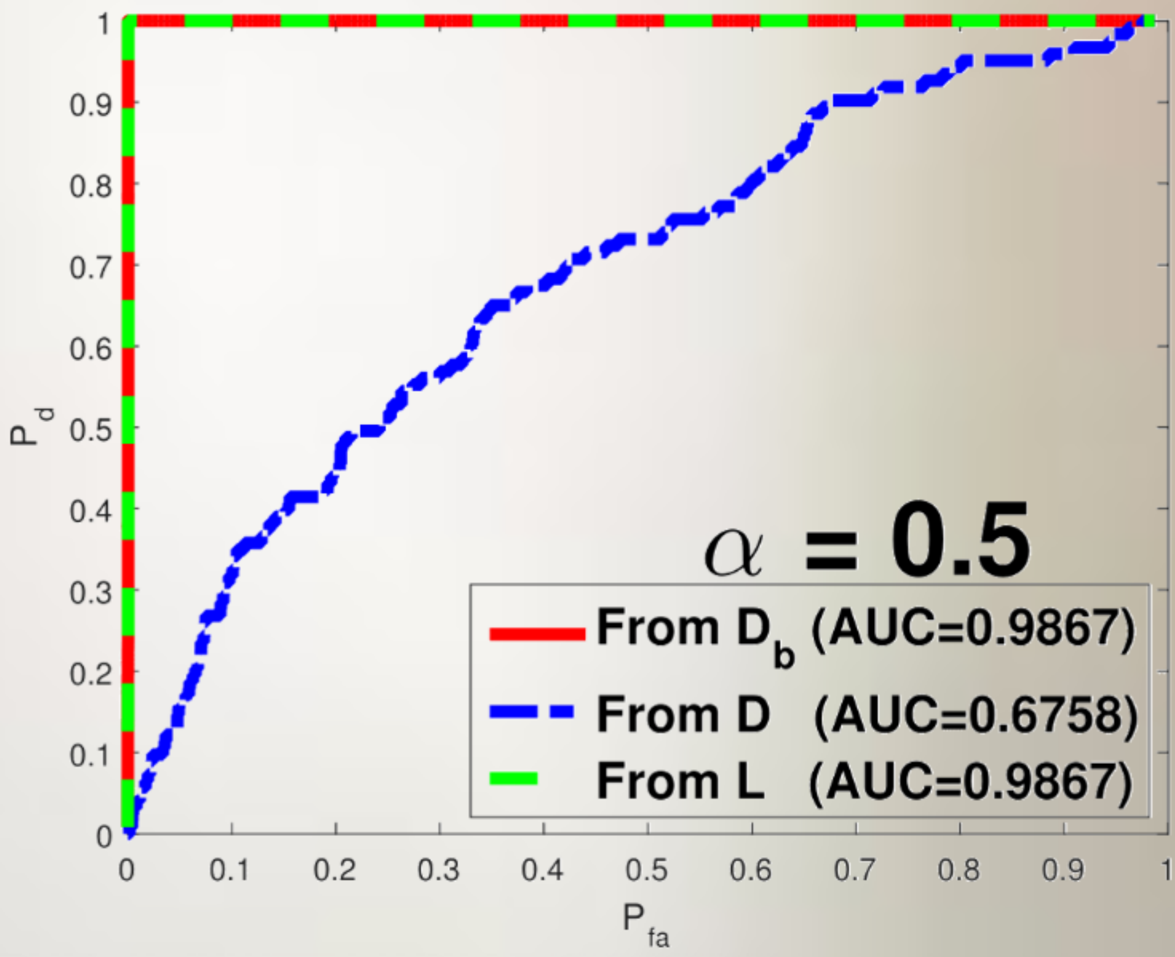
Synthetic Application to target detection (4/11)



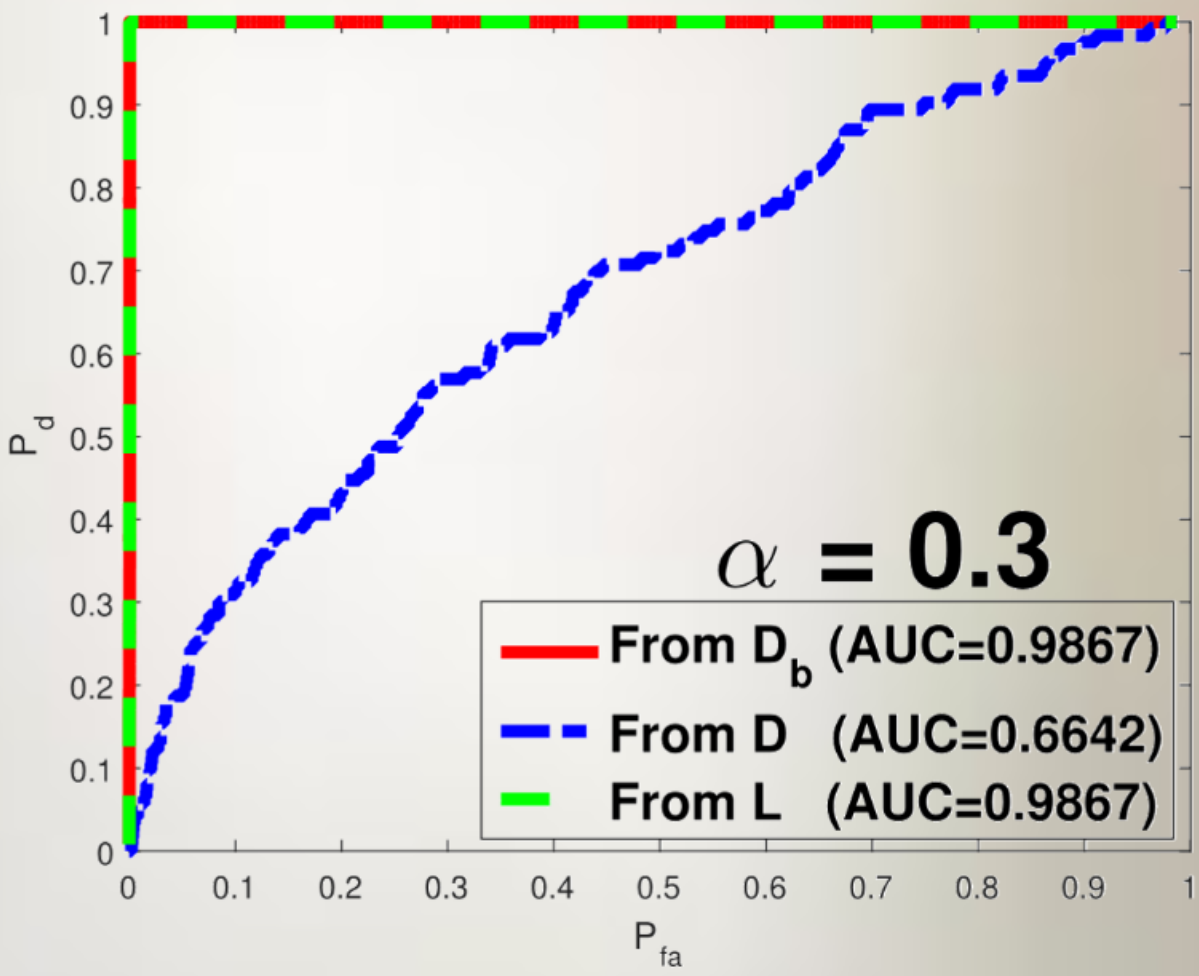
Synthetic Application to target detection (5/11)



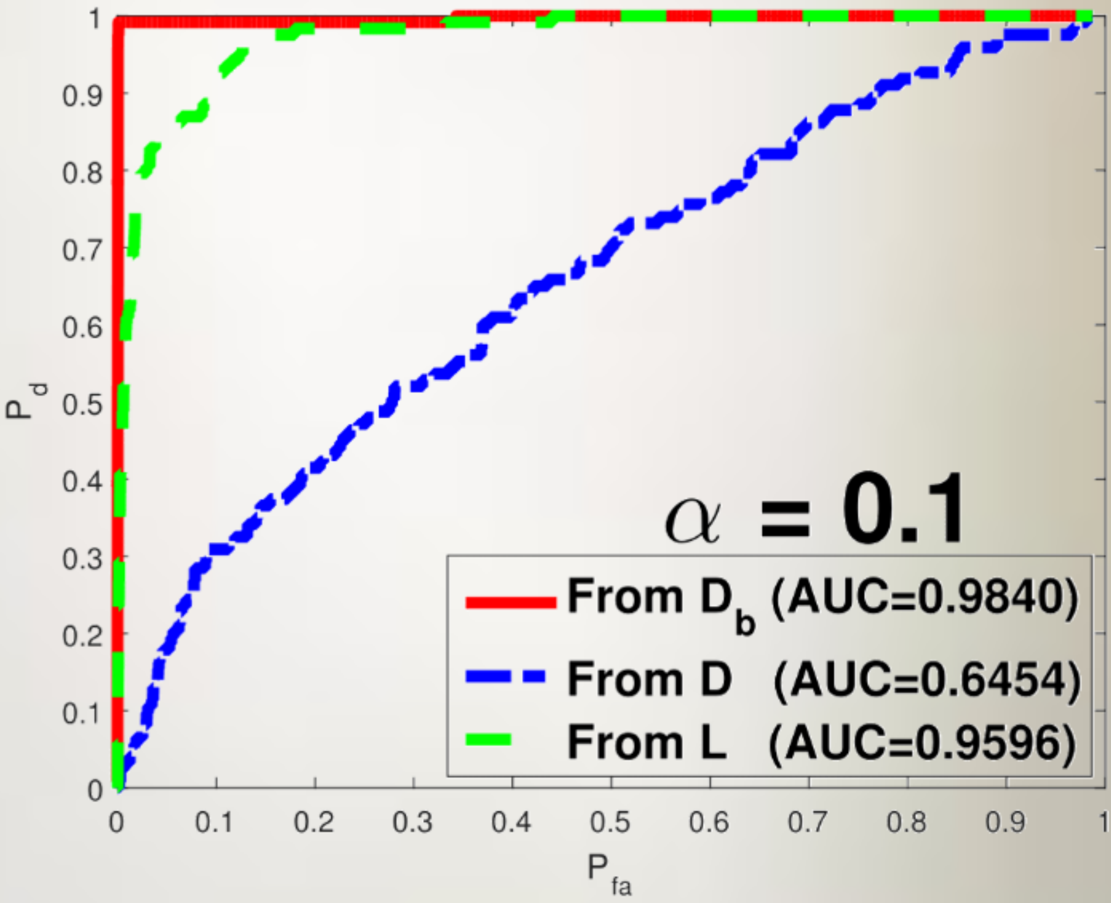
Synthetic Application to target detection (6/11)



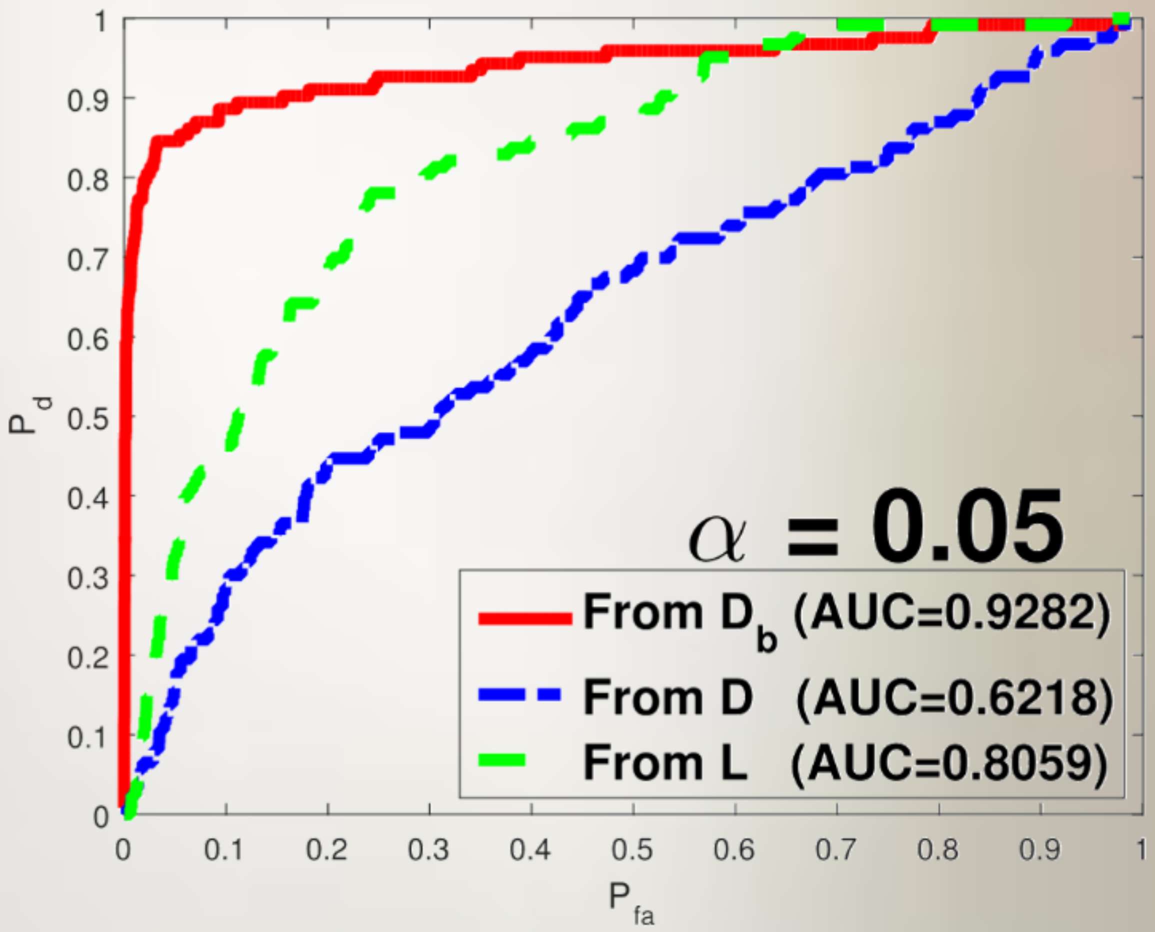
Synthetic Application to target detection (7/11)



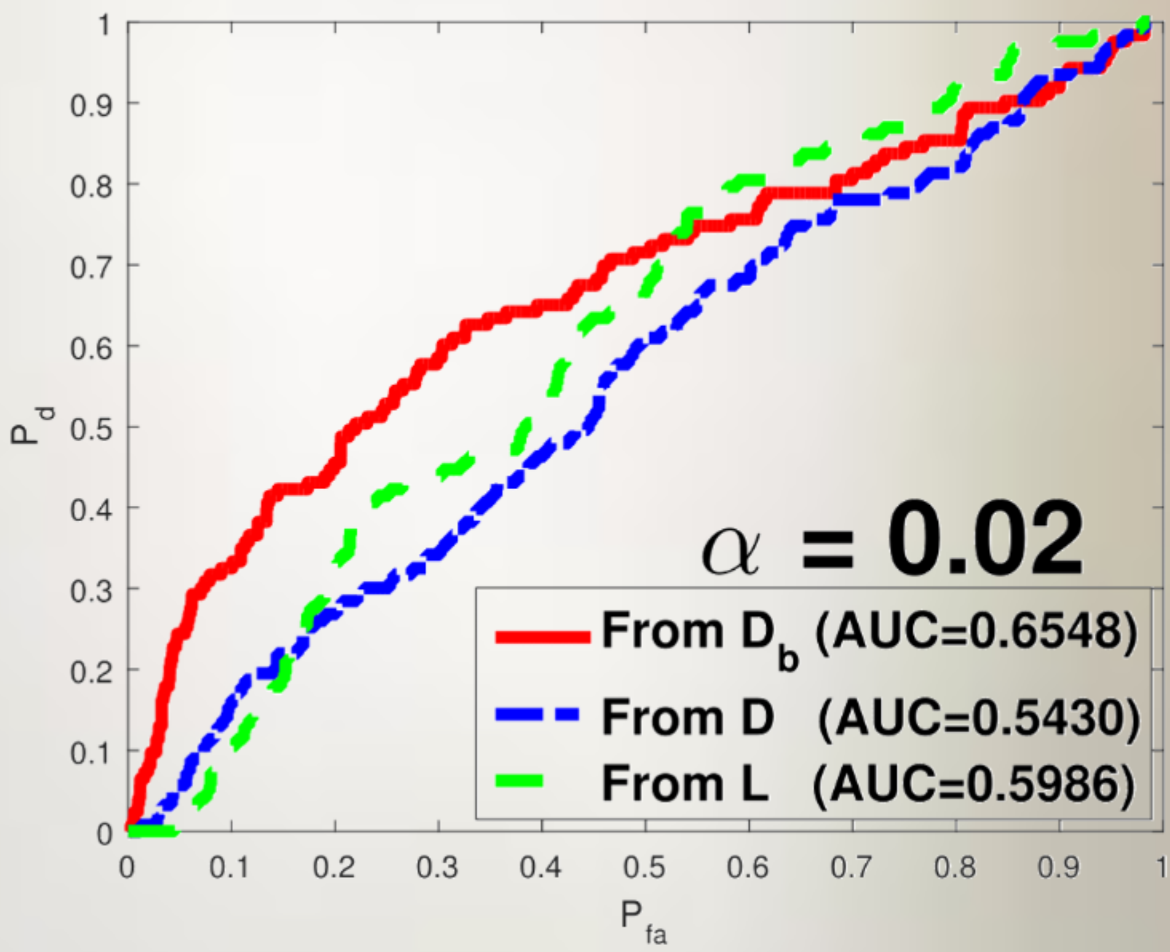
Synthetic Application to target detection (8/11)



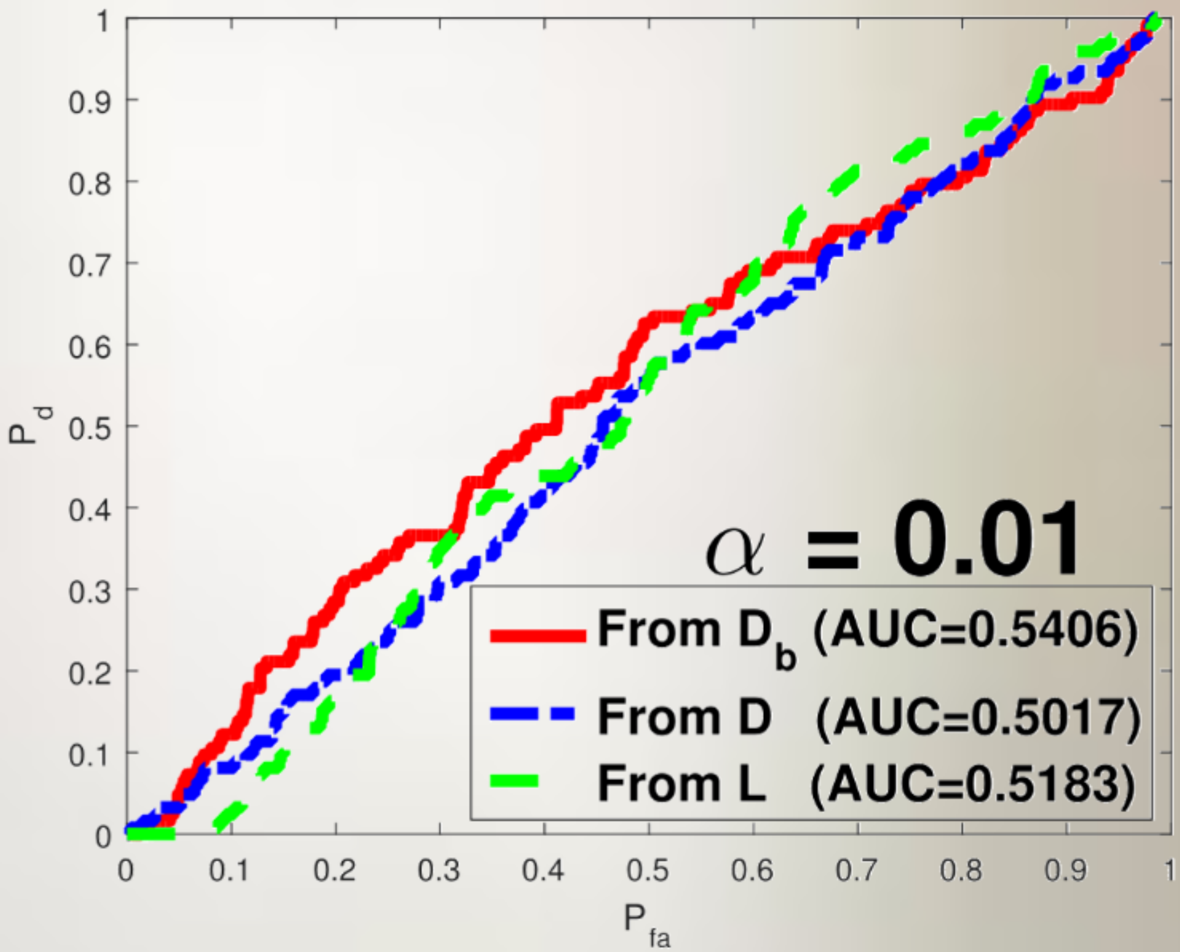
Synthetic Application to target detection (9/11)



Synthetic Application to target detection (10/11)



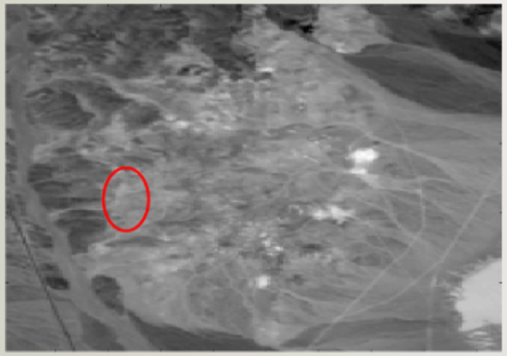
Synthetic Application to target detection (11/11)



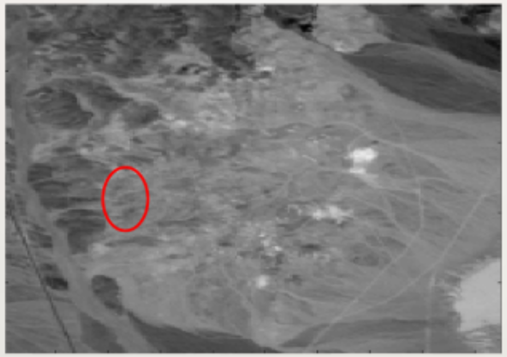
Real experiments for target detection (1/2)

Separation evaluation our target and background separation model

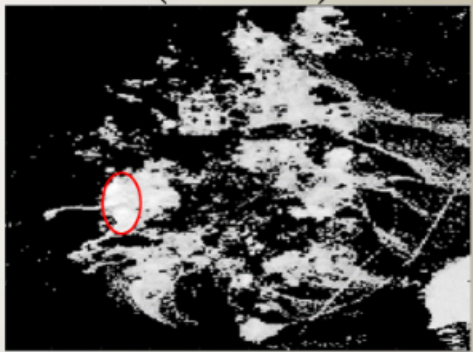
$\mathbf{D}$



$\mathbf{L}$



$(\mathbf{A}_t\mathbf{C})^T$

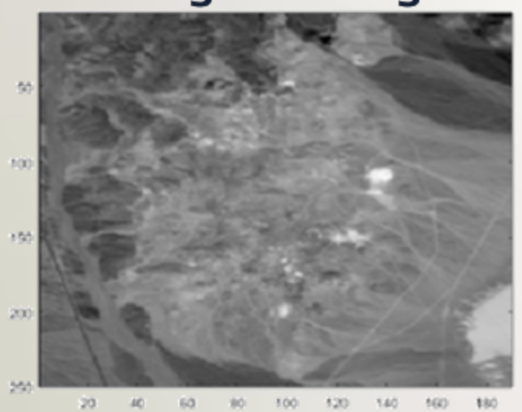


$(\mathbf{A}_t\mathbf{C})^T$

after some thresholding

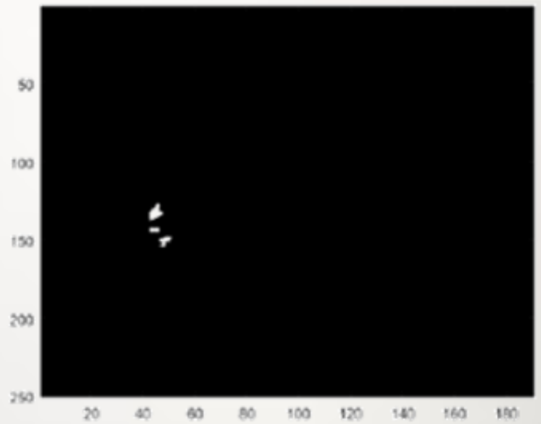
Real experiments for target detection (2/2)

original image

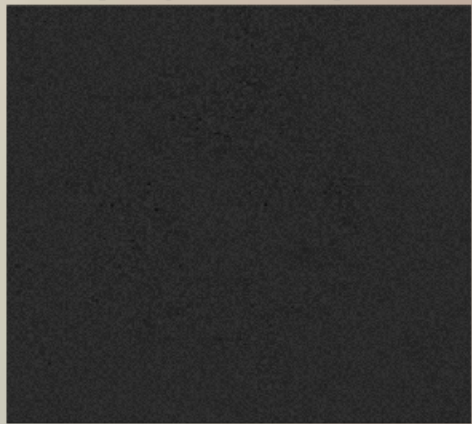


250 x 291 x 186

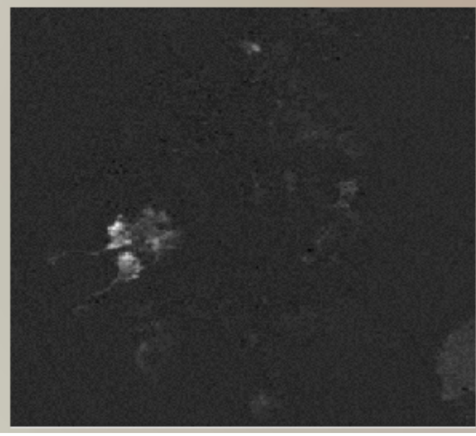
Ground Truth

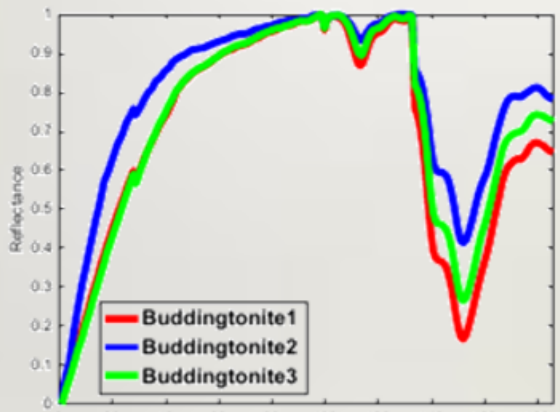


without our proposed separation method



With our proposed separation method





$$= \mathbf{A}_t$$

Exploitation of Sparsity for Hyperspectral Target Detection

CentraleSupélec | **Ahmad W. BITAR** | **06 June 2018**

Reason one : The targets occupy a very small part of the entire image scene

The targets are spatially sparse (few pixels in a million pisel image). The background has a low rank property. Based on these two assumptions, we propose a novel target detector for hyperspectral imagery.

Reason two: A hyperspectral test pixel lies in a low dimensional subspace

A hyperspectral test pixel lies in a low dimensional subspace of the p-dimensional spectral-measurement space. The background dictionary is usually constructed via a dual sliding concentric window.

We aim to alleviate the serious challenge on building the dictionary of the background. Following which various detectors can be used to carry out a more elaborate binary hypothesis test.

Reason three: The covariance estmation is challenging in large dimensions

The traditional covariance estimators (e.g. the Sample Covariance, Tyler estimator) behave very poorly in large dimensions. We propose new estimators by assuming the covariance matrix is sparse, namely, many entries are zero.

Some concluding remarks and directions for future work

The direct use of RPCA is inadequate to distinguishing the true targets from the background. A modification of it is necessary.

Several proposed methods have been proposed and tested on both synthetic and real datasets for an automatic target detection.

The end

Thank you ...

Reason three: *the covariance estimation is very challenging in large dimensions*

- In large dimensions, it is impractical to use traditional covariance estimators

- Sparsity assumption to alleviate the large covariance dimensionality

many entries are zero !

So how to exploit sparsity ?

Our main contributions and results can be found in the thesis report!

Assuming the unknown covariance matrix (of the background surrounding the test pixel) Σ is sparse

Many entries are zero in Σ

$\Sigma = T^{-1} D T^{-T}$

T: Cholesky factor

D: diagonal matrix

Developing new covariance estimators by imposing sparsity on Σ via its Cholesky factor T

☆ The proposed estimators are plugged-in into classical target detectors

If Σ is really sparse

Potentially improving the target detection

If Σ is not sparse

Not obtain worse detection results than to those of the traditional covariance estimators

Some of the obtained results

Models	Σ	$\hat{\Sigma}_{SCM}$	$\hat{\Sigma}_{OLS}$	$\hat{\Sigma}_{OLS}^{Soft}$	$\hat{\Sigma}_{OLS}^{SCAD}$	$\hat{\Sigma}_{L_1}$	$\hat{\Sigma}_{SCAD}$	$\hat{\Sigma}_{SMT}$	$B_k(\hat{\Sigma}_{SCM})$	$\hat{\Sigma}_{SCM}^{Soft}$	$\hat{\Sigma}_{SCM}^{SCAD}$
Model 1	0.9541	0.7976	0.8331	0.9480	0.9480	**0.9509**	**0.9509**	0.9503	**0.9509**	**0.9509**	**0.9509**
Model 2	0.9540	0.7977	0.8361	0.9124	0.9124	0.9264	0.9264	0.9184	**0.9478**	0.9274	0.9270
Model 3	0.9541	0.7978	0.8259	0.8169	0.8257	0.8236	**0.8261**	0.7798	0.5321	0.5969	0.5781
MUSE	Not known	0.6277	0.6575	0.9620	**0.9643**	0.8844	0.8844	0.7879	0.9277	0.7180	0.7180

Traditional estimators **Our proposed estimators** **State of the art**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06 June 2018
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The direct use of RPCA is inadequate to distinguishing the true targets from the background. A modification of it is necessary.
Several proposed methods have been proposed and tested on both synthetic and real datasets for an automatic target detection.
The end
Thank you ...

Conclusion

Three reasons of sparsity have been presented :

The first reason

- The RPCA is inadequate to distinguishing the true targets from the background.
- The RPCA is modified for automatic target detection : **D**= **L** + $(\mathbf{A}_t\mathbf{C})^T$ +**N**
- The object of interest is : $(\mathbf{A}_t\mathbf{C})^T$ it is directly used for the detection

The second reason

- The background dictionary construction has been improved by exploiting the sparse and target separation model proposed in the reason one

Directions for future work

- Evaluate the proposed methods on more real datasets.
- The use of other proxies than the $l_{2,1}$ (closer to the $l_{2,0}$) which can help to alleviate the $l_{2,1}$ artifact and probably facilitate manual selection problem of the tuning parameters τ and λ.


The end
Thank you ...