Technion – IIT Dept. of Electrical Engineering

Signal and Image Processing lab

Hyperspectral Channel Reduction For Local Anomaly Detection

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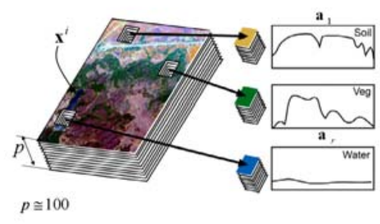
Outline

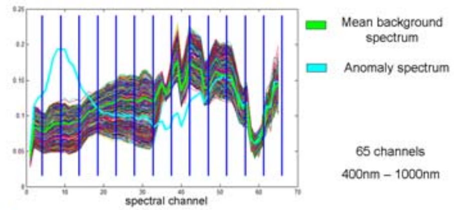
- Designing *Multispectral Filters* (MF) for *Anomaly Detection* algorithms
- Filter design is based on processing *Hyperspectral Images*
- MF are obtained by replacing subsets of adjacent spectral bands by their means
- Partition is optimal in terms of minimizing the *Maximum of Mahalanobis Norms (MXMN)*
- Improved ROC compared to ℓ_2 -based alternatives using RX
- Real Data results are presented

Hyperspectral Imaging



From Hyperspectral to Multispectral

- Given hyperspectral images, partition spectra into a number of bands K



- Which partition is best for detecting anomalies for a given K?

Problem Statement

- Determine a vector of K breakpoints $\mathbf{b}_K = \{b_1, \dots, b_K\}$
- Corresponding to $K-1$ contiguous intervals $I_k = [b_k, b_{k+1})$
- Producing a set of constants at each pixel j $\mu_{k,j} = \frac{1}{|I_k|}\sum_{i \in I_k} x_{i,j}$
- Such that a cost function $J(\mathbf{b}_K, \mathbf{X})$ is minimized

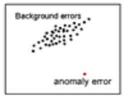
Fast Hyperspectral Feature Reduction (FFR) [1]

- Error vector at interval k in pixel j $\mathbf{e}_{k,j} \triangleq \{(x_{i,j} - \mu_{k,j}) : i \in I_k\}$
- Squared error at pixel j $e_j^2 \triangleq \sum_{k=1}^{K-1} \|\mathbf{e}_{k,j}\|^2$
- Sum of squared error cost $J(\mathbf{b}_K, \mathbf{X}) \triangleq \sum_{j=1}^{N} e_j^2$
  - *Is not sensitive enough to anomaly contributions*
  - *Partition is governed by the background process*
  - *Anomalies are misrepresented*

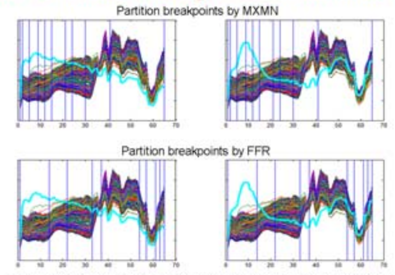
[1] *A. C. Jensen and A. S. Solberg, "Fast Hyperspectral Feature Reduction Using Piecewise Constant Function Approximations," IEEE Geoscience and Remote Sensing Letters, vol. 4, no. 4, Oct. 2007.*

The proposed Maximum of Mahalanobis Norms (MXMN)

- Error vector at interval k in pixel j $\mathbf{e}_{k,j} \triangleq \{(x_{i,j} - \mu_{k,j}) : i \in I_k\}$
- Error covariance matrix in an interval k Σ_k
- Mahalanobis norm of error j in an interval k $G(\mathbf{e}_{k,j}) = \sqrt{\mathbf{e}_{k,j}^T \Sigma_k^{-1} \mathbf{e}_{k,j}}$
- Anomaly sensitive cost in an interval k $D_k = \max_{j=1}^{N} G(\mathbf{e}_{j,k})$
- Maximum of costs in all intervals $J(\mathbf{b}_K, \mathbf{X}) = \max_{k=1}^{K} D_k$
  - *Allows capturing misrepresented anomaly contributions*
  - *Eliminates heavy tails of errors pdf*
  - *The more "Gaussian" interval is, the coarser is the partition in it*

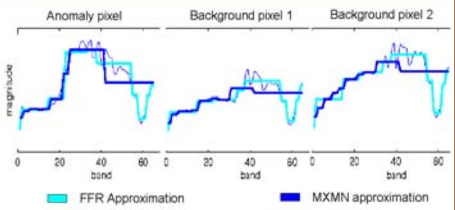


Partition breakpoints: MXMN vs. FFR MXMN trained on image without anomalies



Number of Multispectral Filters 10 | Number of Hyperspectral Channels 65

Partition Examples: MXMN vs. FFR MXMN trained on image without anomalies



Number of Multispectral Filters 10 | Number of Hyperspectral Channels 65

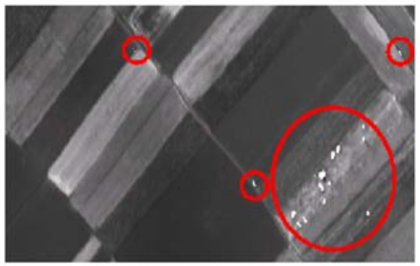
RX – a benchamark Anomaly Detection Algorithm

- Background model pdf $p(\mathbf{x})$
- Hypotheses: $H_0 \;:\; \mathbf{x} \sim p(\mathbf{x})$, $H_1 \;:\; \mathbf{x} - \mathbf{a} \sim p(\mathbf{x})$
- GLRT - Reed Xiaoli (RX) $L(\mathbf{x}) = -\log p(\mathbf{x}) \underset{H_0}{\overset{H_1}{\gtrless}} \eta$
- Gaussian GLRT $p(\mathbf{x}) = N(\mathbf{x}|\mu, \Gamma)$

$$L(\mathbf{x}) = (\mathbf{x} - \mu)^\top \Gamma^{-1} (\mathbf{x} - \mu) \underset{H_0}{\overset{H_1}{\gtrless}} \eta$$

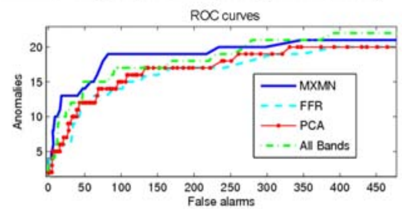
Mahalanobis distance

Example: HS channel image with anomalies



ROC curves by applying RX

- Number of hyperspectral channels 65
- Number of multispectral channels 10
- Number of hyperspectral images 6 (300 x 400 x 65)



Conclusion

- A new criterion (MXMN) was proposed for Multispectral filter design
- MXMN allows capturing anomalies well
  - In terms of hyperspectral partition granularity
  - In terms of Rx performance (ROC curves)
- In the presented example, the anomaly representation performance was good even after training on data without anomalies
- MXMN was evaluated on real data images