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 $\ell_2$-based alternatives using RX
  - Real Data results are presented

From Hyperspectral to Multispectral
- Given hyperspectral images, partition spectra into a number of bands $K$

Problem Statement
- Determine a vector of $K$ breakpoints $b_k = [b_1, \ldots, b_K]$
- Corresponding to $K - 1$ contiguous intervals $I_k = [b_k, b_{k+1}]$
- Producing a set of constants at $\mu_k = \frac{1}{|I_k|} \sum_{x \in I_k} x$
  - Each pixel $x$
- Such that a cost function $J(b_k, X)$ is minimized

Fast Hyperspectral Feature Reduction (FFR) [1]
- Error vector at interval $k$
  $e_k = (x_{k,j} - \mu_j) j \in I_k$
- Squared error at pixel $j$
  $\sum_{k=1}^K \sum_{j=1}^N |e_{k,j}|^2$
- Sum of squared error cost
  $J(b_k, X) = \sum_{j=1}^N \sum_{k=1}^K |e_{k,j}|^2$

The proposed Maximum of Mahalanobis Norms (MXMN)
- Error vector at interval $k$
  $e_k = (x_{k,j} - \mu_j) j \in I_k$
- Error covariance matrix in an interval $k$
  $\sum_{j=1}^N |e_{k,j}|^2$
- Mahalanobis norm of error $j$
  $\sqrt{\sum_{k=1}^K |e_{k,j}|^2}$
- Anomaly sensitive cost in an interval $k$
  $J(b_k, X) = \sum_{k=1}^K \sum_{j=1}^N |e_{k,j}|^2$
- Maximum of costs in all intervals
  $\max_{0 \leq k \leq K-1} J(b_k, X)$

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

RX – a benchmark Anomaly Detection Algorithm
- Background model pdf
  $p(x)$
- Hypotheses:
  $H_0 : x \sim p(x)$
  $H_1 : x \sim \eta$
- GLRT - Reed Xiaoli (RX)
  $I(x) = -\log p(x)$
  $\eta \sim \eta$
- Gaussian GLRT
  $p(x) = \mathcal{N}(\mu, \Sigma)$
  $I(x) = (x - \mu)\Sigma^{-1}(x - \mu) \sim \eta$

Example: HS channel image with anomalies

ROC curves by applying RX
- Number of hyperspectral channels 65
- Number of multispectral channels 16
- 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