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ELLIPSOID-SIMPLEX HYBRID FOR HYPERSPECTRAL ANOMALY DETECTION

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Abstract: The problem of anomaly detection in hyperspectral imagery is expressed in terms of a minimal volume set in a high-dimensional space that encloses the bulk of the data samples. The venerable RX algorithm employs an ellipsoid for this volume, but endmember methods can be used to create a simplex volume. This talk describes a hybrid ellipsoid-simplex volume and characterizes its performance on hyperspectral imagery by computing a plot of volume versus false alarm rate. This plot provides a generic measure of quality (smaller volumes are better) without requiring the identification of specific anomalies in the data.

ELLIPSOID-SIMPLEX HYBRID FOR HYPERSPECTRAL ANOMALY DETECTION

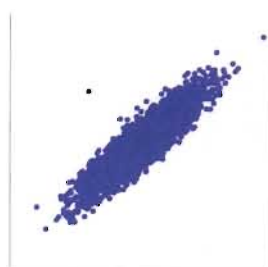
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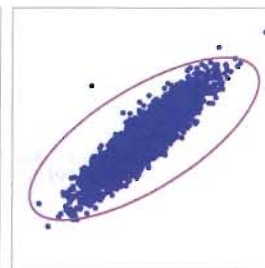
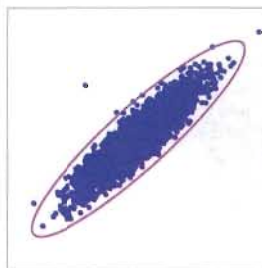
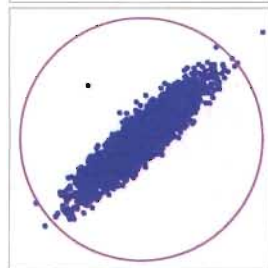
9 June 2011



Anomaly detection



- Anomalous points are unlike the others
- Anomalous points are far from others
- Mahalanobis depends on covariance
- Threshold: 99.9% are not anomalous
- Best detector has smallest volume



Family of concentric ellipsoids

- Gaussian distribution: $p(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d |W|}} \exp \left[-\frac{1}{2} r^2(\mathbf{x}) \right]$
- Mahalanobis distance: $r(\mathbf{x}) = [(\mathbf{x} - \mu)^T W^{-1} (\mathbf{x} - \mu)]^{1/2}$
- Covariance matrix: W
- Volume: $V(r) = \frac{\pi^{d/2} |W|^{1/2}}{\Gamma(1 + d/2)} r^d$
constant actually matters

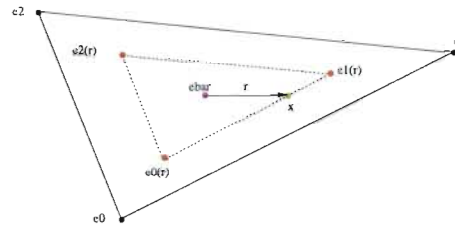
Endmember math

- Model data with a k -dimensional simplex
- There are $k + 1$ vertices: $\mathbf{e}_0, \mathbf{e}_1, \dots, \mathbf{e}_k$.
- Let $E = [\mathbf{e}_0 \mathbf{e}_1 \dots \mathbf{e}_k] \in \mathbb{R}^{d \times (k+1)}$
- Point \mathbf{x} is in *subspace* of simplex if $E\mathbf{a} = \mathbf{x}$
for some \mathbf{a} that satisfies sum-to-one constraint: $\mathbf{1}^T \mathbf{a} = 1$; i.e.,

$$\begin{bmatrix} \mathbf{1}^T \\ E \end{bmatrix} \mathbf{a} = \begin{bmatrix} 1 \\ \mathbf{x} \end{bmatrix}$$

- Point \mathbf{x} is in *interior* of simplex if $\mathbf{a} \succeq 0$
- Interpret \mathbf{a} as vector of *abundances*
of endmember materials in pixel \mathbf{x}

Family of concentric simplices



- Simplex delineated by endmembers: e_0 , e_1 , and e_2 .
- Centroid at \bar{e} .
- "Radius" r associated with point x in subspace of simplex
 - Defined so x is just inside the simplex of $e_0(r)$, $e_1(r)$, and $e_2(r)$,
 - where $e_i(r) = (1 - r)\bar{e} + re_i$.
- Radius given by formula $r(x) = 1 - (k + 1)\min[a(x)]$
 - note: $a(x) \geq 0$ implies $r(x) \leq 1$

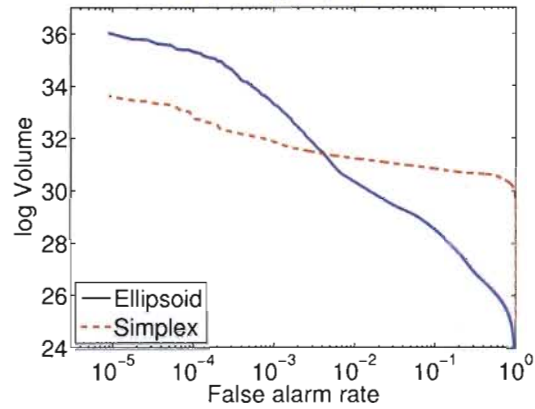
Volume of simplex

- Define $\hat{E} = [e_1 - e_0, e_2 - e_0, \dots, e_k - e_0] \in \mathbb{R}^{d \times k}$.
- Volume: $V = |\hat{E}^T \hat{E}|^{1/2} / k!$
- For simplex of "radius" r , volume is:

$$V(r) = \underbrace{\frac{|\hat{E}^T \hat{E}|^{1/2}}{k!}}_{\text{constant}} r^k$$

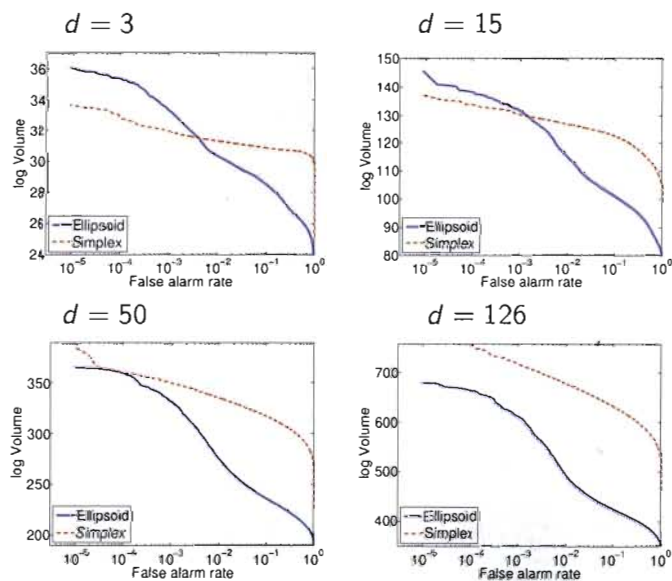
- Because we were careful about the constant pre-factors, we can compare ellipsoid-based anomaly detection to simplex-based anomaly detection: the smaller the volume, the better the detector.

Coverage plot



- To cover fraction $1 - \alpha$ of data requires volume V (i.e., to achieve a false alarm rate of α)
- Plot volume V versus false alarm rate α
- At very low false alarm rates, simplex is better (i.e., smaller) than ellipsoid

Coverage plot (cont'd)



Ellipsoid-simplex hybrid

While hyperspectral data is not typically Gaussian, there is a sense (e.g., see [Adler-Golden 2009, Bajorski 2008, Theiler et al 2005]) that it can be Gaussian in “some directions,” particularly the directions with lower variance. This intuition suggests a hybrid model for characterizing hyperspectral data: simplex-like in the large-variance directions and ellipsoid-like in the low-variance directions.

What does an ellipsoid-simplex hybrid look like?

- In 2-d
 - pure ellipse, pure triangle
 - hybrid: rectangle
- In 3-d
 - pure ellipsoid, pure tetrahedron
 - hybrid: cylindrical ellipse (elliptical cylinder?)
 - hybrid: triangular prism
- In d dimensions
 - First k dimensions are modeled as $k + 1$ endpoint simplex
 - Remaining $d - k$ dimensions are modelled with covariance matrix

Ellipsoid-simplex hybrid: how do you make one?

- Find $k + 1$ endmembers: $E = [\mathbf{e}_0 \mathbf{e}_1 \cdots \mathbf{e}_k]$
 - Some algorithms ask you to project to a k dimensional subspace; some do not.
- Let \mathbf{x}_s correspond to the projection of \mathbf{x} to the k dimensional simplex subspace:
 - $\mathbf{x}_s = \mathbf{e}_0 + \hat{E} \hat{E}^\# (\mathbf{x} - \mathbf{e}_0)$
- Let $\mathbf{x}_e = \mathbf{x} - \mathbf{x}_s$ be the (off-plane) residual
- Compute covariance $W = \langle \mathbf{x}_e \mathbf{x}_e^T \rangle$
- For \mathbf{x}_s and \mathbf{x}_e , can compute simplex radius r_s and Mahalanobis radius r_e .
 - r_s indicates in-plane anomalousness
 - r_e indicates off-plane anomalousness
- How to combine them into a single measure?

Ellipsoid-simplex hybrid (cont'd)

- r_s indicates in-plane anomalousness
- r_e indicates off-plane anomalousness
- How to combine them into a single measure?
- Detector fusion: $r = \max(r_s, r_e)$
 - Volume is product of simplex volume and ellipsoid volume

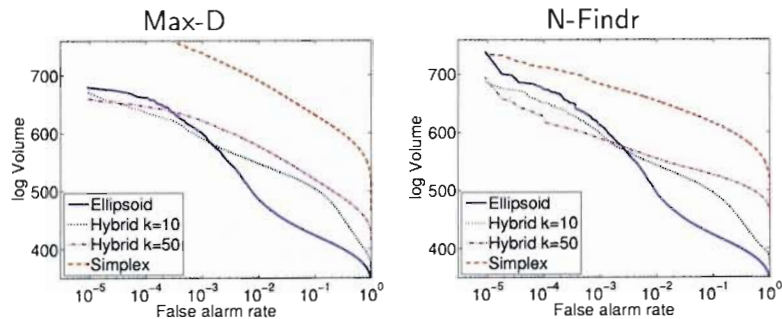
$$V(r) = \frac{\pi^{(d-k)/2} |W|^{1/2}}{\Gamma(1 + (d-k)/2)} \frac{|\hat{E}^T \hat{E}|^{1/2}}{k!} r^d$$

- Variant: $r = \max(\beta r_s, r_e)$
 - Accounts for different "scale" of r_s and r_e
 - Chose β so that $\text{median}(\beta r_s) = \text{median}(r_e)$
 - Volume formula is modified:

$$V(r) = \frac{\pi^{(d-k)/2} |W|^{1/2}}{\Gamma(1 + (d-k)/2)} \frac{|\hat{E}^T \hat{E}|^{1/2}}{k!} \beta^{-k} r^d$$

Volume
Ellipsoid
Simplex
Coverage
Hybrid

Coverage plots for Ellipsoid-Simplex hybrids



- Full $d = 126$ hyperspectral datacube
- Ellipsoids best characterize the “core” of the data ($\alpha > 0.01$)
- Hybrids are better at characterizing the “periphery”
- N-Findr is better than Max-D (by this metric)



Volume
Ellipsoid
Simplex
Coverage
Hybrid

Recap

- Simplex-based anomaly detection
 - Better coverage at smaller volume than ellipsoid-based (RX) anomaly detection
 - Better performance *only* at low dimensions
- Ellipsoid-simplex hybrid for anomaly detection
 - Simplex for k high-variance dimensions,
 - Ellipsoid for $d - k$ low-variance dimensions
- Emphasis on volume as a measure of anomaly detector performance
 - Do you have a better anomaly detector?
Volume versus false alarm rate provides a way to compare
 - And perhaps, a way to compare endmember algorithms



To Do

- Consider modified fusion of r_s and r_e ;
e.g., find better ways to choose β
- Use coverage plots to compare endmember finding algorithms
- Develop coverage plots as a metric for use in *local*
(segmented, or moving-window) anomaly detection schemes
- Characterize/visualize distinction between ellipsoid-dominated
(off-plane) and simplex-dominated (in-plane) anomalies.
- Develop simplex-based model for $p(\mathbf{x})$ for hyperspectral data
 - e.g., ellipsoid \rightarrow Gaussian; simplex \rightarrow ??
 - Use this $p(\mathbf{x})$ for target detection, change detection, etc.