# Chemical Plume Detection for Hyperspectral Imaging

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# Motivation

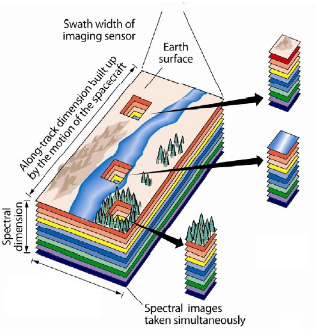
- Applications to defense and security
  - Provide warning of chemical weapon attacks
  - Chemical contamination: radiation leaks, toxic spills, etc.
- Project goals
  - Detect and identify gas plumes
  - Segment the image to obtain the location of the gas
  - Track the diffusion of the chemical plume in the atmosphere
- Challenges
  - LWIR data is not in the visible spectrum
  - High dimensional data makes computational analysis lengthy and difficult

# Hyperspectral Data Cube

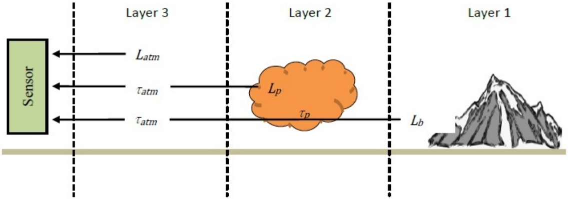
## Applied Physics Laboratory at Johns Hopkins University

Videotracking of
chemical plume release

- 3 LWIR sensors at different locations
- 129 channels in data cube
- frame rate: 0.2 Hz
- 30 minute video sequences



# Three-layer model for Hyperspectral Imaging




Linear mixing model[3]: $\epsilon(\nu) \approx \sum_{i=1}^{N} \alpha_i s_i(\nu) + n$

$s_i$ : spectral signature

$\alpha_i$ : abundance of $i$th signature

$\nu$ : wavenumber

$\epsilon$ : pixel emissivity

$n$ : noise

# Adaptive Matched Subspace Detector Algorithm[8]

Applied Physics Laboratory at Johns Hopkins University

# False Color RGB Representation

## The Plume of Doom

1. Load frames into a matrix
2. Perform Principle Component Analysis (find eigenvectors of $A^T A$)
3. Use the first 3 principle components to reduce dimension of each frame and label the projection on each component, red, green, and blue, respectively
4. Equalize the histogram of each frame with the Midway algorithm[4]

# False Color RGB Representation

The Plume of Doom

# Temperature Emissivity Separation[3]

## Data Conversion

$$\epsilon(\lambda) \approx \epsilon_p(\lambda) f(T_p - T_b) + \epsilon_b(\lambda)$$

$f$: Function of the temperature difference between the plume and the background
$\epsilon$: Emissivity
$\lambda$: Wavenumber
$T$: Temperature

- Calculation includes simplifying assumptions regarding temperature and atmospheric conditions
- Data processing results in NaNs in data set

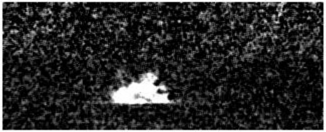
# Background Subtraction

## Computation of the disturbance field[6]

$$A_t = (1 - w)I_t + wA_{t-1}$$
$$\Delta_t = I_t - A_{t-1}$$

$A$: Temporal average image
$I$: Actual image after initial smoothing
$\Delta$: Disturbance field
$0 < w < 1$: History weight factor

- Real-time algorithm that employs temporal averaging
- Gives greater weight to last frames
- Running average decays exponentially relative to the frame number



Grayscale disturbance field of aa12 Victory chemical plume release

# Split Bregman Method for Unmixing[6]

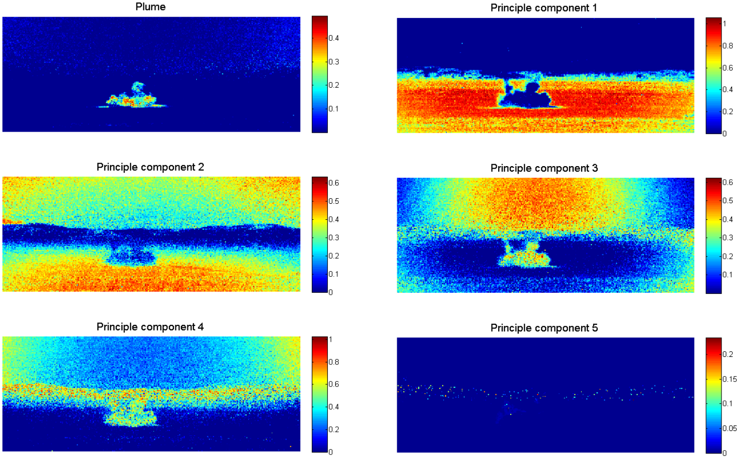
Outline

$$\min_{u} \|Au - f\|_2^2 + \eta|u|_1$$
$$\text{s.t. } u \geq 0,$$

where,
$A$: $m \times n$ matrix
$f$: Pixel in the image
$u$: Signature abundance
$\eta$: Sparsity constraint

This is solved for each pixel by a particular type of split Bregman iteration which is particularly suited for solving overdetermined systems (when $m > n$).

# Unmixing with $L_1$ Minimization[6]




Top left: Successful detection of the target chemical plume
Other frames: Identification of principle components in the image

# Automatic Target Generation Process[5]

## Method

We want to find pixels in the image that represent distinct signatures without prior knowledge of materials in the image.

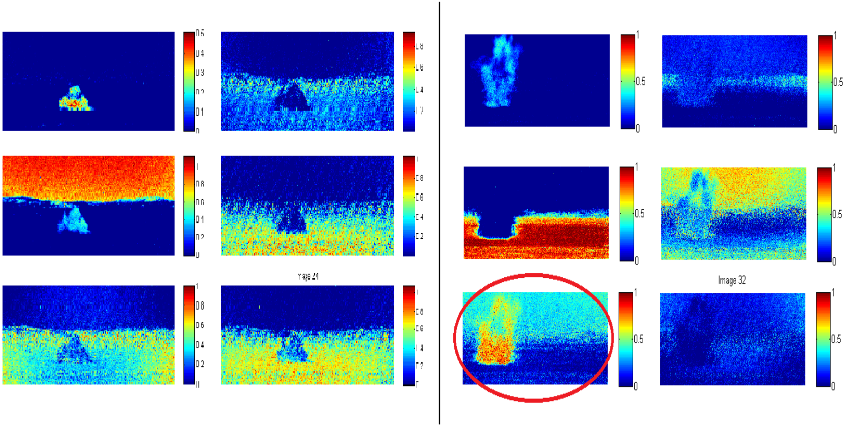
- Initialize with a random pixel, $\epsilon_0$
- Find pixels $\epsilon_i$, such that

$$\epsilon_i = \arg\max_x \|(I - U_{i-1}(U_{i-1}^T U_{i-1})^{-1} U_{i-1}^T)x\|_2$$

where $U_{i-1} = [\,\epsilon_1\ \epsilon_2\ \ldots\ \epsilon_{i-1}\,]$ is the subspace spanned by the previously found distinct pixels, and $x$ is a pixel in the image.

# Automatic Target Generation Process

## Results




Left: Good results using ATGP, Right: Incorrect endmember selection

# Spectral Clustering Algorithm[9]

- Construct a fully connected similarity matrix
  - Our similarity matrix is too large to make
  - There are a number of different similarity functions
  - Self similarity
- Formulate the graph Laplacian
- Normalize to get the symmetric graph Laplacian
- Compute smallest eigenvectors and eigenvalues
  - Algorithm to find smallest eigenvectors and values is not efficient

# Spectral Clustering

- Construct the $k$ nearest neighborhood
  - Allows for construction of sparse matrices
  - Can customize symmetry
- Normalize to get the symmetric similarity matrix
- Compute the largest eigenvectors and eigenvalues of the normalized similarity matrix

# Similarity Functions

- Gives a value for how "similar" a data point is to another data point
- 0 is for very dissimilar data and 1 is for very similar data
- An example is the Gaussian similarity function,

$$s(x_i, x_j) = e^{\frac{-\|x_i - x_j\|^2}{2\sigma^2}}$$

  - $\|x_i - x_j\|^2$ is a distance metric
  - The $\sigma$ constant is used for determining the Gaussian neighborhood
  - To illustrate the two extremes
    - A value of $\sigma = \infty$ yields a similarity matrix where all the points are connected with similarity of 1
    - A value of $\sigma = 0$ yields a similarity matrix where all the points are disconnected, similarity of 0

# Similarity Functions

## Continued

- Using different distance metrics

Euclidean

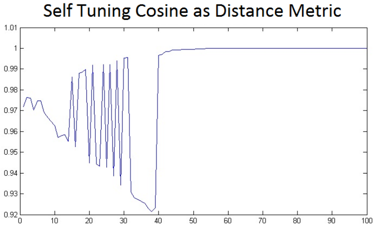
- $\|x_i - x_j\| = \sqrt{\sum_{k=1}^{n} (x_{i,k} - x_{j,k})^2}$
  where $n$ is the number of different wavelengths

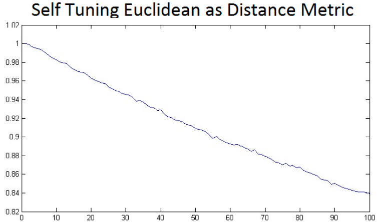
Cosine

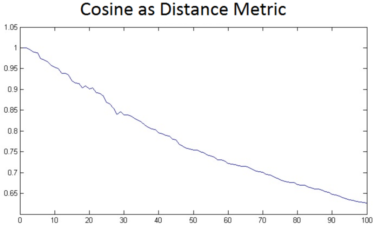
- $\|x_i - x_j\| = 1 - \frac{\langle x_i, x_j \rangle}{\|x_i\| \|x_j\|}$

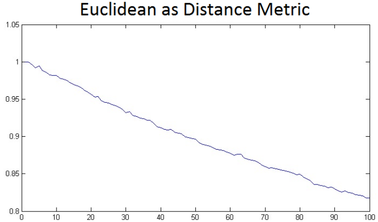
- Self tuning similarity function[10]
  - Instead of a constant sigma, across all values, self tuning tries to maintain local scaling
  - Uses a $k$ nearest neighbors similarity graph
  - $s(x_i, x_j) = e^{\frac{-\|x_i - x_j\|^2}{\sigma_i \sigma_j}}$ where $\sigma_i$ is the $k$'th nearest neighbor of $x_i$

# Results of Different Distance Metrics



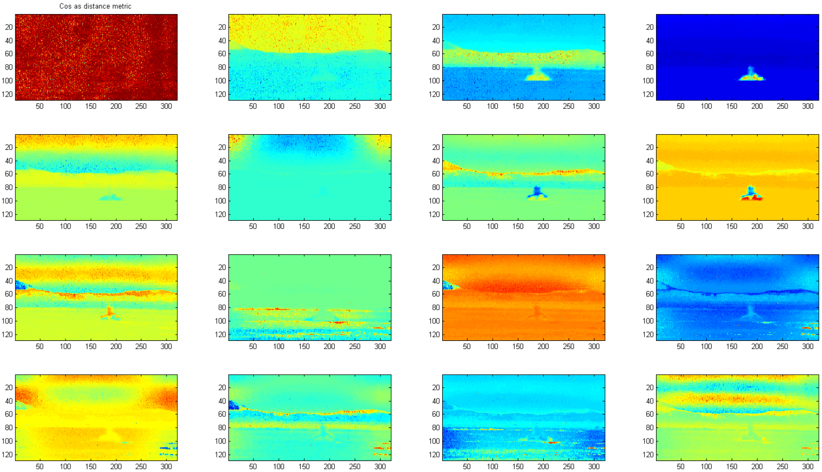



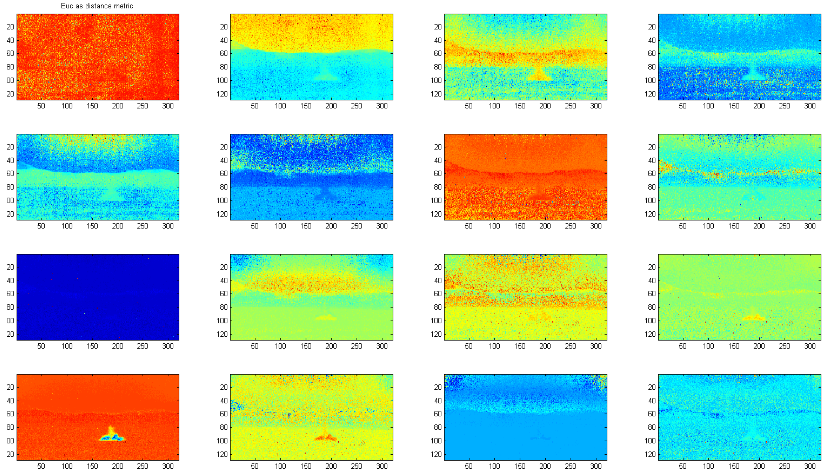

Resulting eigenvalues to show non-trivial clusters

# Results of Cosine Distance Metric



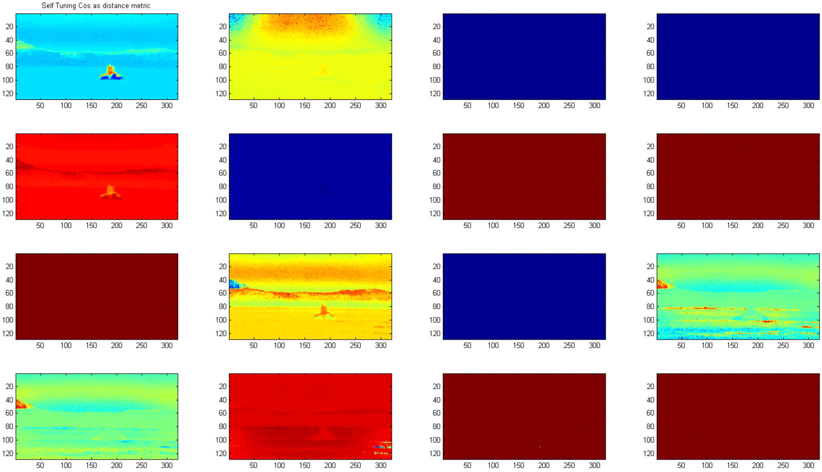

Plume identification in the fourth eigenvector

# Results of Euclidean Distance Metric



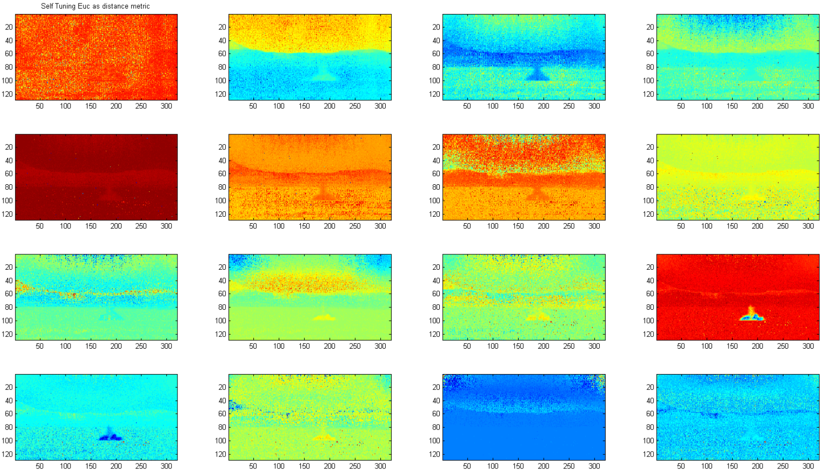

Plume identification in a later eigenvector than cosine

# Results of Self Tuning Cosine Distance Metric




Many trivial clusters shown by blank frames

# Results of Self Tuning Euclidean Distance Metric




Similarities with the Euclidean distance metric

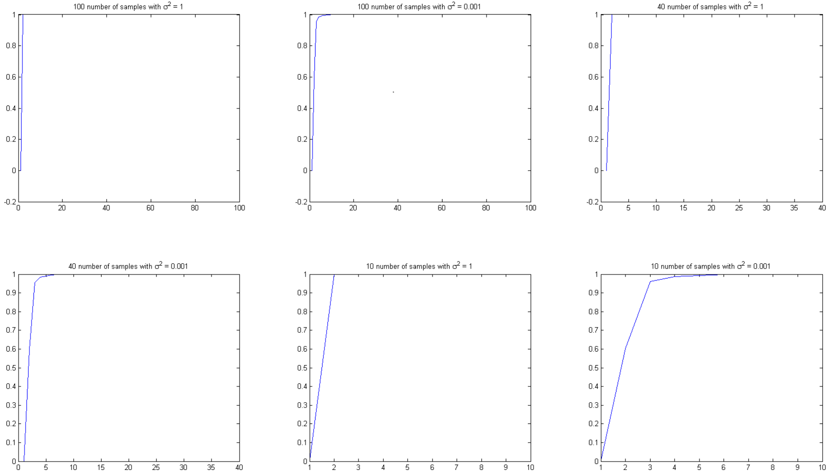
# Nyström Method[2]

## Eigenvalue and Eigenvector Approximation

- Alternative to full spectral clustering
- Many times faster, at the cost of precision
    - Nyström randomly selects a set of points, and utilizes these to approximate eigenvalues and eigenvectors
    - Due to the random selection, the resulting eigenvalues and eigenvectors can vary

# Nyström Method

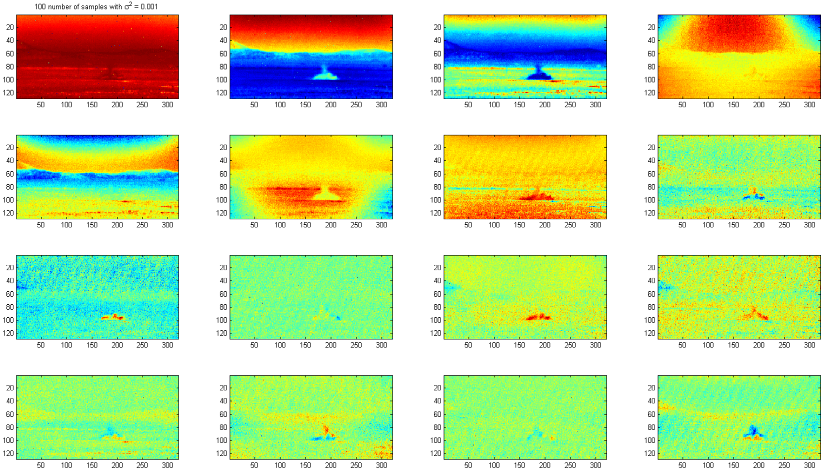
## Eigenvalue Results




Testing different parameters with the cosine distance metric

# Nyström Method

## Eigenvector Results




First few clusters are non-trivial but later eigenvectors degrade quickly

# Segmentation by minimizing the Ginzburg-Landau functional[2]

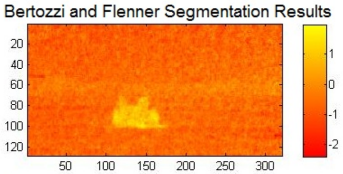
## Bertozzi and Flenner Method

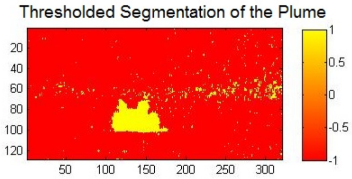
$$u = \arg\min_u \frac{\epsilon}{2}\int |\nabla u|^2 dx + \frac{1}{\epsilon}\int W(u)dx + F(u, u_0)$$

where $W(u)$ is a double-well potential, such as $W(u) = (u^2 - 1)^2$.

- By minimizing, $u$ will take on values of either -1, or 1 from the double well term
- The gradient term will stop sharp transitions from -1 to 1

# Segmentation by minimizing the Ginzburg-Landau functional


Testing parameters: c1 = 100, c = 5, epsilon = 1, dt = 0.001, 400 iterations, 100 eigenvectors

# Segmentation by minimizing the Ginzburg-Landau functional

## Merkurjev et. al Method

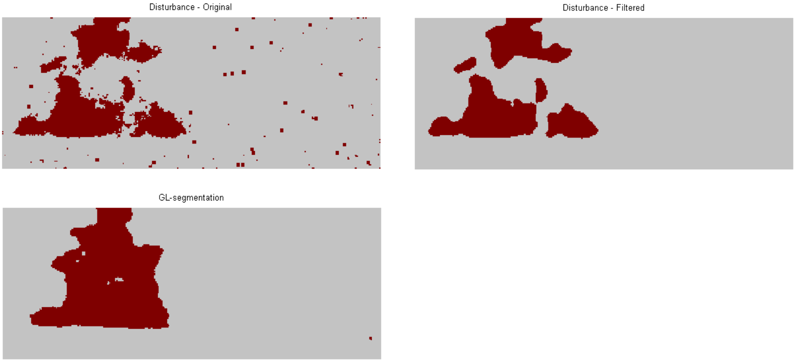
Numerically, solve a discretized heat equation plus a fidelity term and threshold per iteration.

1. Solve $\frac{dz}{dt} = -L_s z - C_1 \lambda(x)(z - z_0)$
2. Set $u_{n+1}(x) = \begin{cases} 1 & \text{if } y(x) \geq 0 \\ -1 & \text{if } y(x) < 0 \end{cases}$
   where $y(x) = S(\delta t) u_n(x)$, where $S(\delta t)$ is the evolution operator of the discretized heat equation.

This method requires an initialization "patch", and the Nyström extension to obtain eigenvectors.

# Segmentation by minimizing the Ginzburg-Landau functional

## Merkurjev et. al Method




Top left, Results of background subtraction. Top right, Initialization for the MBO Scheme. Bottom left, Results of segmentation

# Conclusions

- Filtering
  - Weighted average background subtraction outperformed subtraction of consecutive frames
- Classification
  - Unmixing techniques are a viable detection method
- Segmentation
  - Spectral Clustering is successful in its segmentation of the data
  - Nyström is able to segment the data, but it does not have the accuracy to be a standalone method
  - Ginzberg-Landau minimization results in better detection of thin gas than background subtraction alone

# Future Work

- Analyze false color RGB images of the plume
- Implement clustering with spatial information
- Minimize noise in the hyperspectral datacube

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# References


[1] Michael Borghese, Alex Honda, Samuel Lim, Daniel Waltrip, and Monica Yoo. Video tracking of airborne gases. Technical report, UCLA Department of Mathematics, 2010.

[2] Andrea L. Bertozzi and Arjuna Flenner. Diffuse interface models on graphs for classifcation of high dimensional data. To be published in a 2012 Multiscale Modeling and Simulation, 2012.

[3] J. B. Broadwater, D. Limsui, and A. K. Carr. A primer for chemical plume detection using lwir sensors. Technical report, National Security Technology Department, 2011.

[4] Julie Delon. Midway Image Equalization. Journal of Mathematical Imaging and Vision, 21: 119-134, 2004.

[5] Qian Du and Nareenart Raksuntorn and Nicolas H. Younan and Roger L. King. End-member extraction for hyperspectral image analysis. Applied Optics, 47:F77-F84 , 2008.

[6] Zhaohui Guo, Stanley Osher and Arthur Szlam. A split bregman method for non-negative sparsity penalized least squares with applications to hyperspectral demixing. ICIP, 1917-1920, 2010.

[7] Gilad Halevy and Daphna Weinshall. Motion of disturbances: detection and tracking of multi-body non-rigid motion. Machine Vision and Applications, 11: 122-137, 1999.

[8] Dimitris Manolakis, Christina Siracusa, and Gary Shaw. Adaptive matched subspace detectors for hyperspectral imaging applications. Technical report, MIT Lincoln Laboratory, 2001.

[9] Ulrike von Luxburg. A tutorial on spectral clustering. Statistics and Computing, 17:1-32, 2007.

[10] L. Zelnik-Manor and P. Perona. Self-Tuning Spectral Clustering. Advances in Neural Information Processing Systems, 17: 1601-1608, 2005.