Sparse-sampling strategies in beam-scanning imaging

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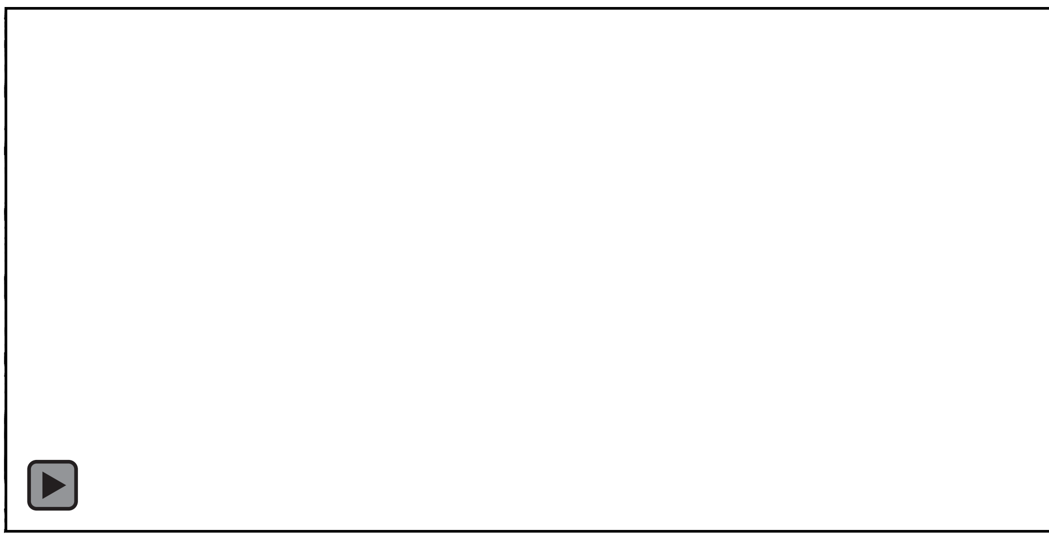
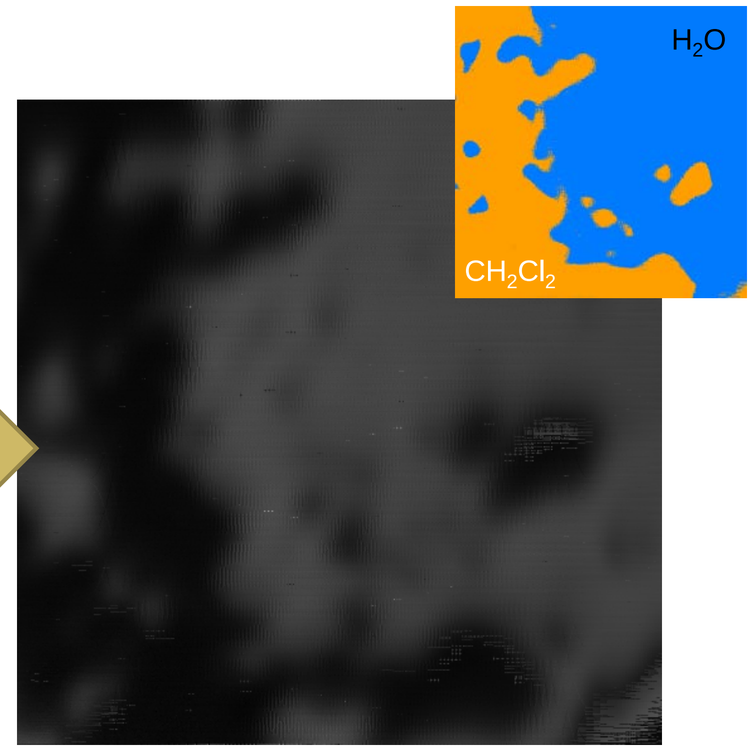
The Goal: Stand-off detection of energetic materials through beam-scanning MIR spectroscopic imaging of objects in motion.

The Technology: Hardware and software for image reconstruction through sparse sampling in space, time, and wavelength.



Sparse sampling in space and time

Bright field images of an Air-Force test pattern



Sparse sampling in space and wavelength

Mid-infrared images obtained using a QCL array

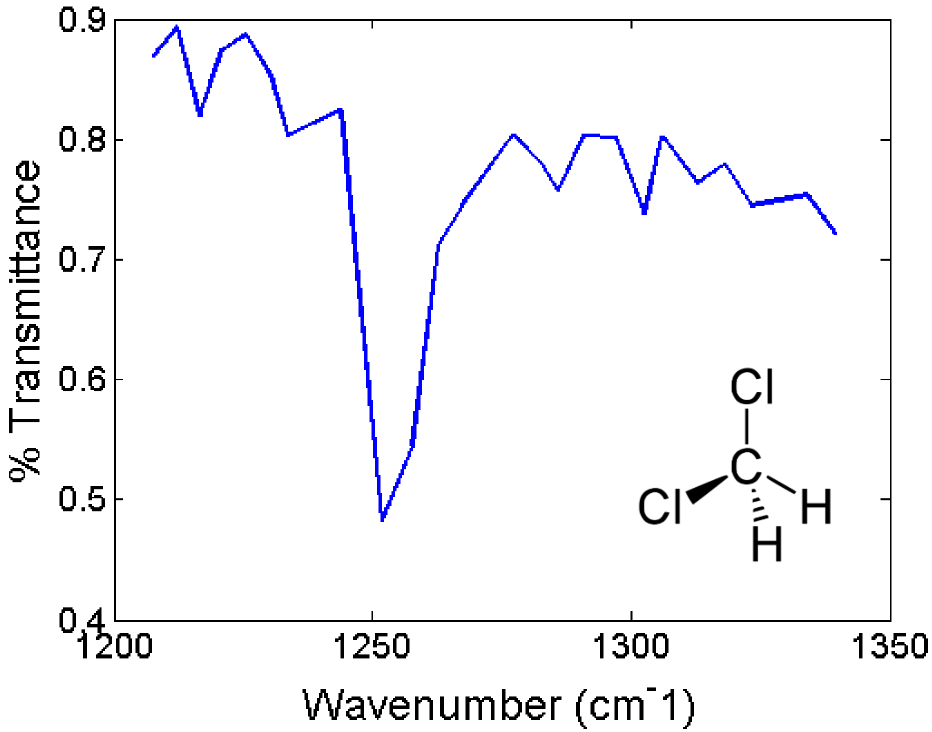
Proposed Action Plan

- Proposed activities will integrate spectral acquisition with spatio-temporal sparse sampling. Key components include:
  - Software for spectral acquisition with arbitrary scan patterns (e.g., Lissajous).
  - Extension of reconstruction software for problems of arbitrary dimensionality.
  - Characterization of the instrument using model compounds.
  - Assess compatibility with back-scattered light detection.
  - Integration of multiple co-propagating QCL arrays for improved duty cycle and spectral coverage.
  - Redesign the instrument for implementation in a portable platform.

Note: Beam-scanning mid-infrared light presents no significant health risks from laser exposure (well below the OSHA recommended MPE for far-infrared).

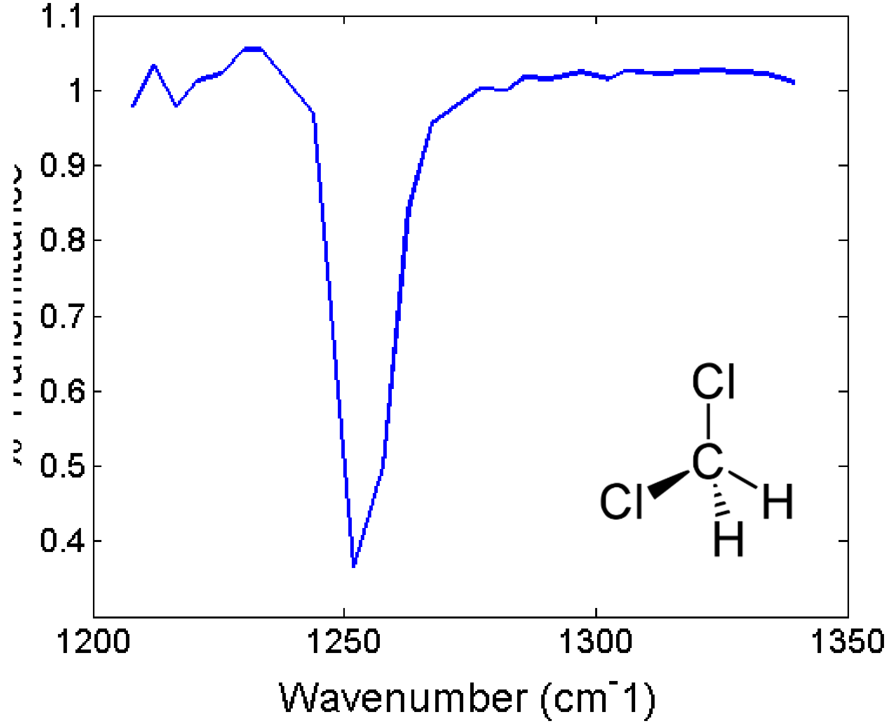
The “fingerprint” region of the spectrum

Single Spectrum - 9.6 μs



1250 cm^{-1}: H-C-H wag

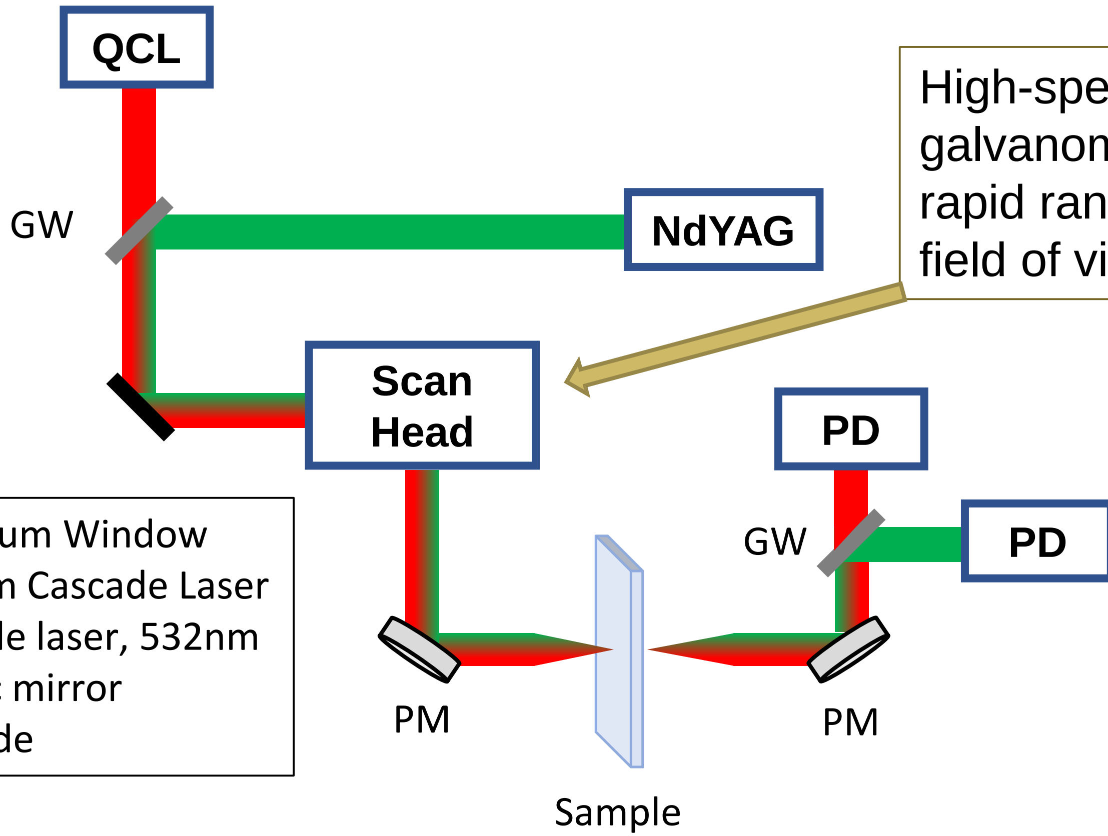
Averaged Spectrum – 1.6 ms



1250 cm^{-1}: H-C-H wag

Raster scan: "optimally bad"

Chemical Imaging: Hardware



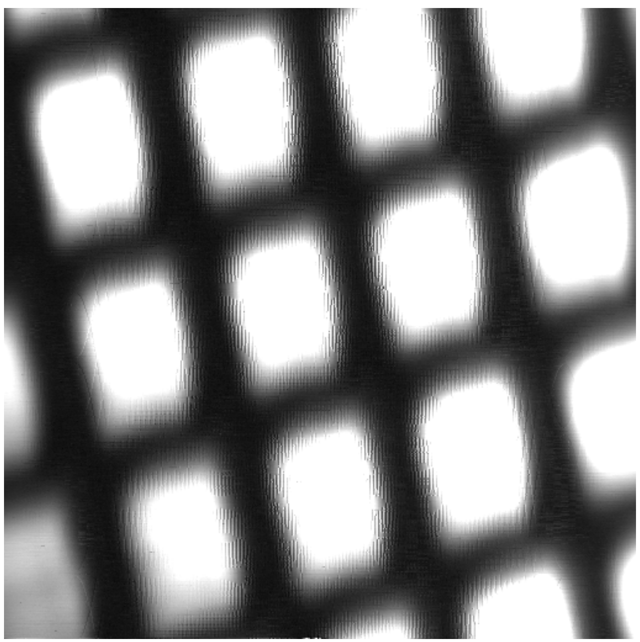
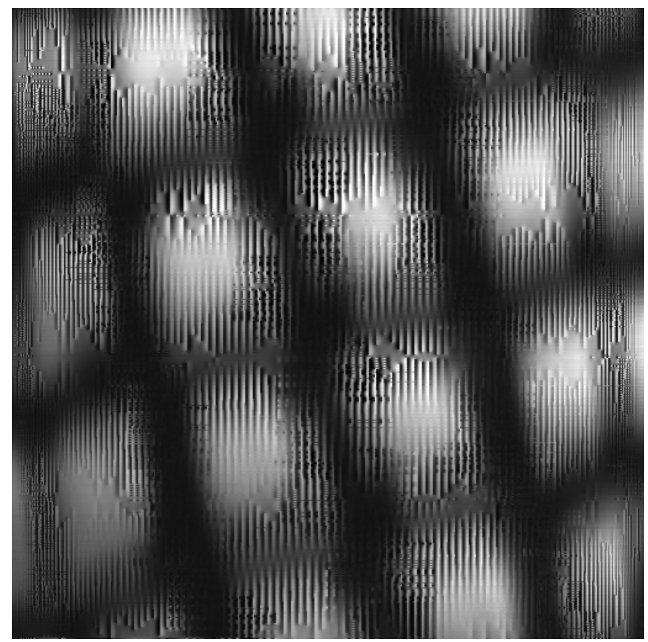
High-speed (5 kHz bandwidth) galvanometer mirrors enable rapid random access within the field of view.

GM = Germanium Window
QCL = Quantum Cascade Laser
Nd:YAG = visible laser, 532nm
PM = Parabolic mirror
PD = photodiode

Chemical Imaging: Software

In-Painting: Sparse sampling enables recovery of a multi-dimensional image using knowledge from data acquired at other positions/times/wavelengths.

Model-based iterative reconstruction (MBIR): Will enable recovery of high-quality images across multiple dimensions from sparsely sampled data.

	20 µs / pixel MIR spectroscopy (5.2s)	5 µs / pixel MIR spectroscopy (1.2s)
Wire mesh		

100mm

Inpainting Image Interpolation Algorithms

Multidimensional Discrete Cosine Transform (DCT) Reconstruction

Damien Garcia
University of Montréal

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right]$$

$$k = 0, \ldots, N-1$$

- Fully automated smoothing procedure for uniformly sampled datasets
- Allows fast reconstruction of data by means of the discrete cosine transform
- Estimates pixel value based on values of surrounding pixels in arbitrary dimensions (e.g. X, Y, time, wavelength, etc.)

Garcia, D. *Computational Statistics & Data Analysis* 54 (2010), p. 1167-1178.

Model Based Image Reconstruction (MBIR)

- Maximum a posteriori (MAP) estimation with a generalized Gaussian Markov random field (GGMRF) prior model
  - Adapted for 3D space-time
- Iterative model-based image reconstruction algorithm
- Estimates pixel value based on values of surrounding pixels in X, Y, and time.

Estimate $\hat{x}$ from $y = Ax + W$ using $\hat{x} = \min(c(x))$

Charlie Bouman
Suhas Sreehari

$$c(x) = \frac{\|y - Ax\|^2}{2\sigma_W^2} + \frac{\sum_{\{i,i\}\in C} q_{i,j}\left|x_i - x_j\right|^p}{p\sigma_x^p} + \frac{\sum_{t\in T} r_t\left|x - x^{(t)}\right|^p}{p\sigma_t^p}$$

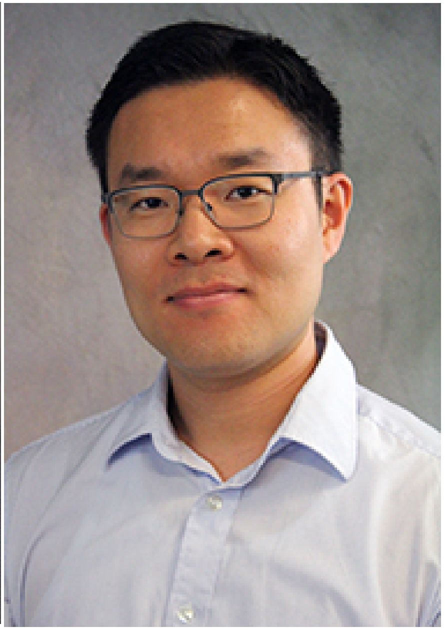
Regularizing function for X and Y

Regularizing function for time

Sullivan, S.Z.; Muir, R.D.; Newman, J.A.; Carlsen, M.A.; Sreehari, S.; Doerge, C.; Begue, N.J.; Everly, R.M.; Bouman, C.A.; Simpson, G.J. *Opt. Express.* **2014**, *22*, 24224.

Supervised Learning Approach for Dynamic Sampling (SLADS): Raman

The Team

Yours Truly
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(Head, Department of Mathematics)

Mark Witinski!
(Pendar)

Spectral Classification

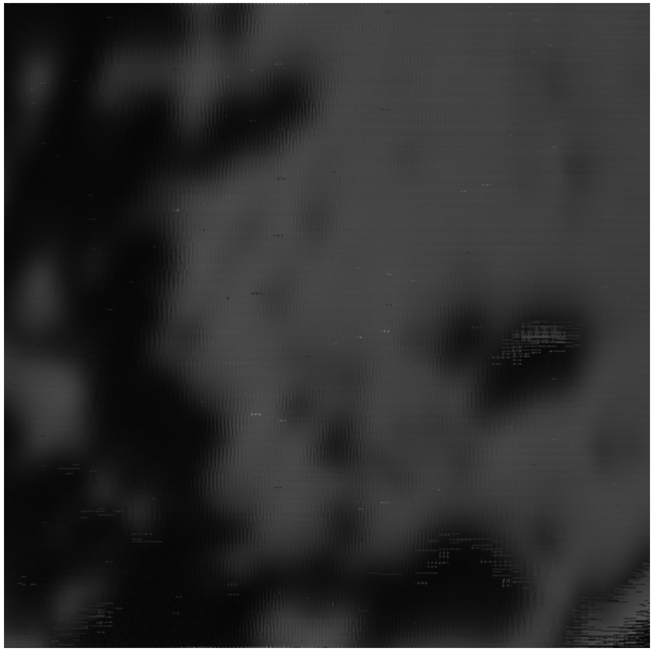
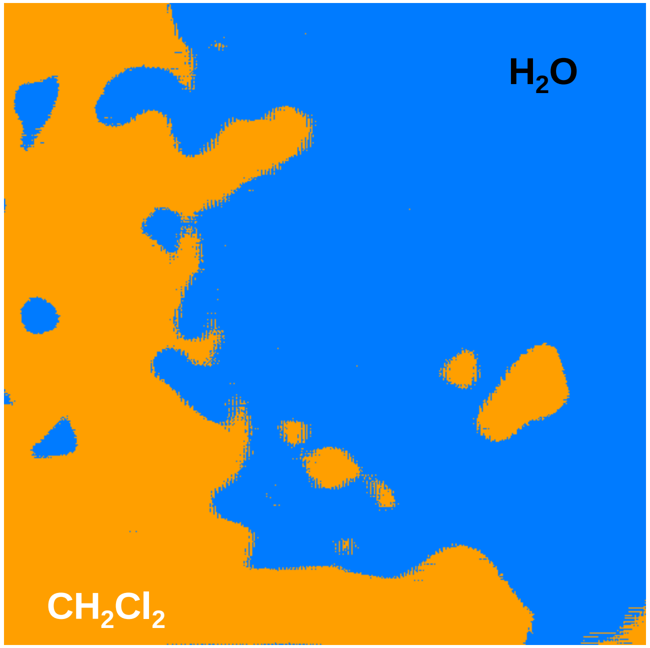


Image stack of laser transmittance as a function of mid-infrared wavelength.

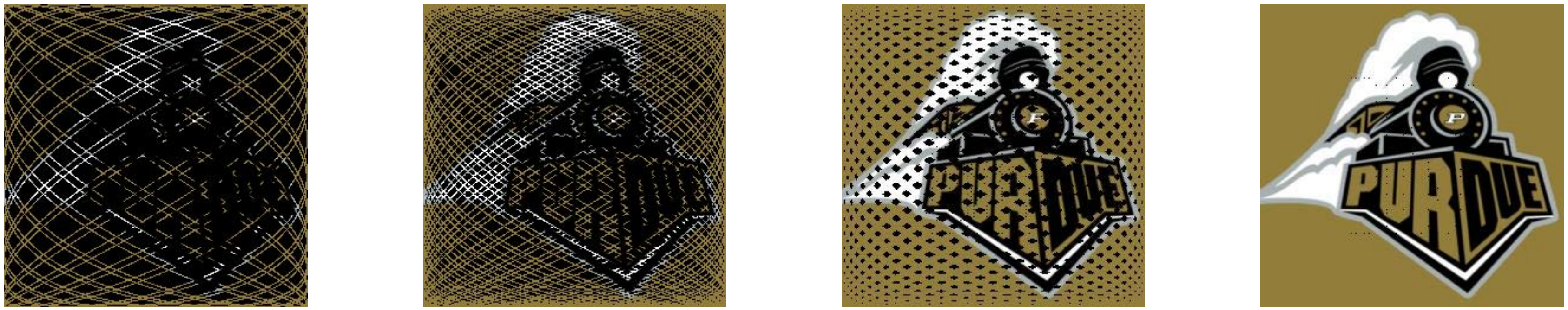


Classification was performed by PCA followed by k-means clustering (2 clusters).

Acquisition settings: 20 μs integration time, 512×512 images, ~5s imaging time

Lissajous vs. Raster Scanning

Lissajous Trajectory
Imaging



1 ms | 2 ms | 10 ms | 20 ms

Raster Scan Imaging