# Vision Guided, Hyperspectral Imaging for Standoff Trace Chemical Detection

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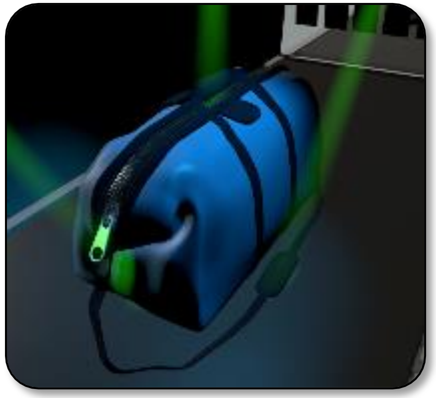
# So What, Who Cares

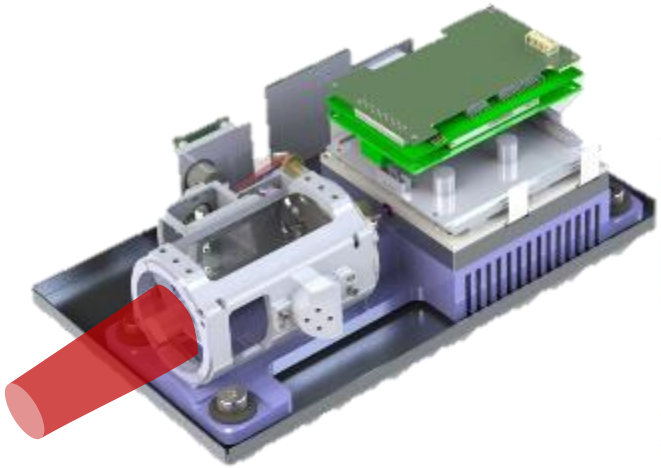
- What space/topic/area is being addressed?
  - Detection and identification of chemical residues on luggage at the checkpoint
  - As part of APEX Screening at Speed initiative
- What problem have you solved?
  - Identification of specific “target regions” on luggage; i.e., handles, zippers, etc.
  - Detection and classification of chemicals of interest from hyperspectral data cube
- How have you solved the problem?
  - Modern neural architectures for region identification from camera or video data
  - To date: classical statistical processing for identifying chemically anomalous regions
- So what? Who cares?
  - Promising approach to a very hard problem, real-time standoff trace chemical detection and mapping, combining singularly strong hardware with state-of-the-art processing
  - Strong example of academic/industrial collaboration to address significant problems

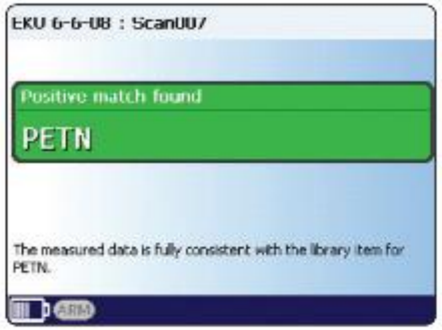
# The Problem and Approach

Problem: Detecting and identifying trace amounts of explosives on luggage contact points

Approach:



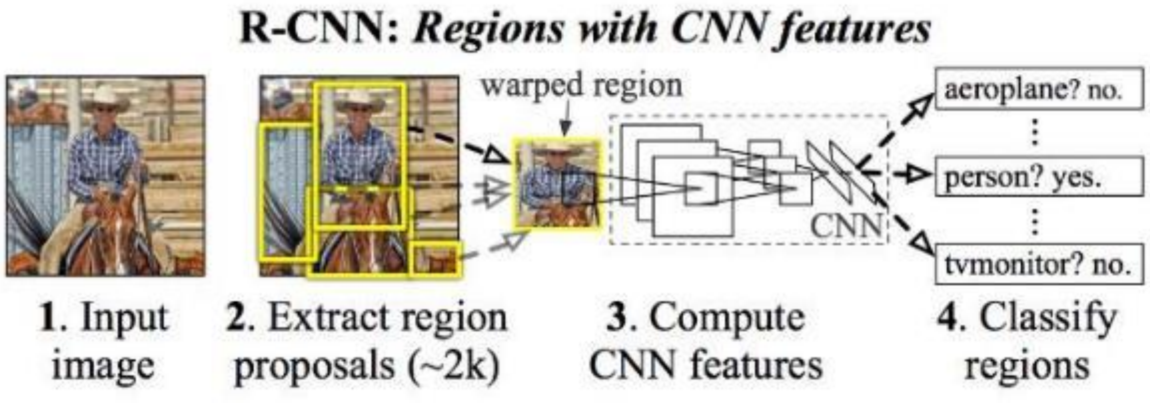



Locate Feature(s) of Interest → Direct the Analysis Beam → Chemical Examination of Feature(s) → Report Chemical ID & Confidence

# Target ID – A Deep Learning Approach

## Regional Convolutional Neural Net

1. A Convolutional Neural Network (CNN) is for image classification
2. An R-CNN is for object detection
3. A typical CNN can distinguish the class of an object, but not where it is located in an image
4. An R-CNN can take in an image, and correctly identify *where* the main objects (via a bounding boxes) are located




***R-CNN does what we do intuitively: it proposes boxes in the image (in this case about 2000 of them) and see if any of them actually correspond to an object***

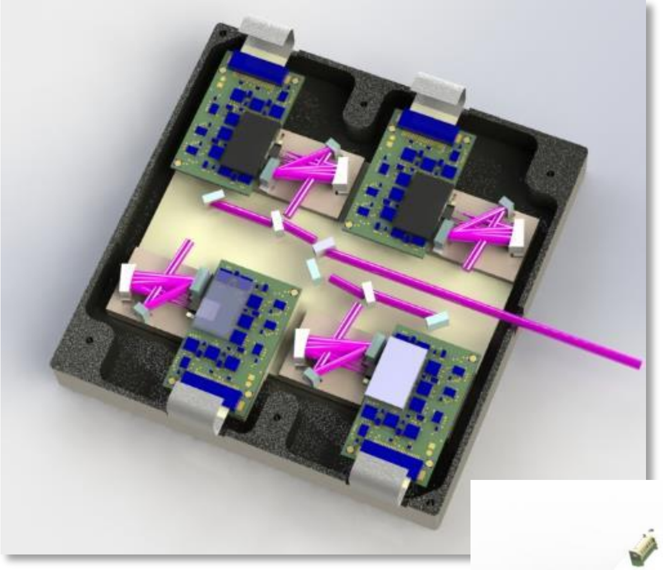
***→ Uses process called Selective Search***

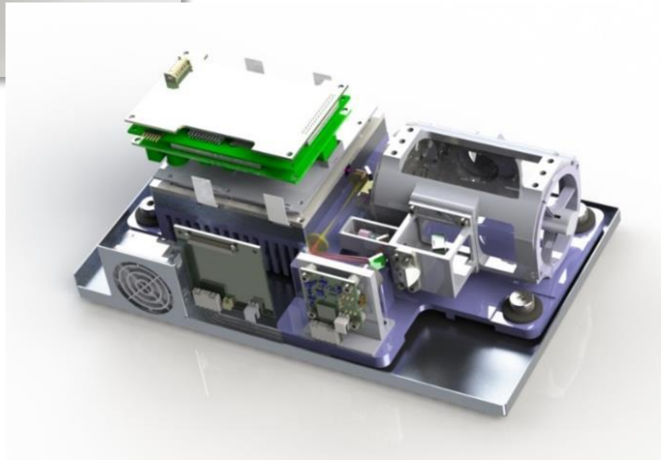
Image from: Girshick, Ross, et al. "Rich feature hierarchies for accurate object detection and semantic segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014.

# Implementing R-CNN

# Initial Processing Results

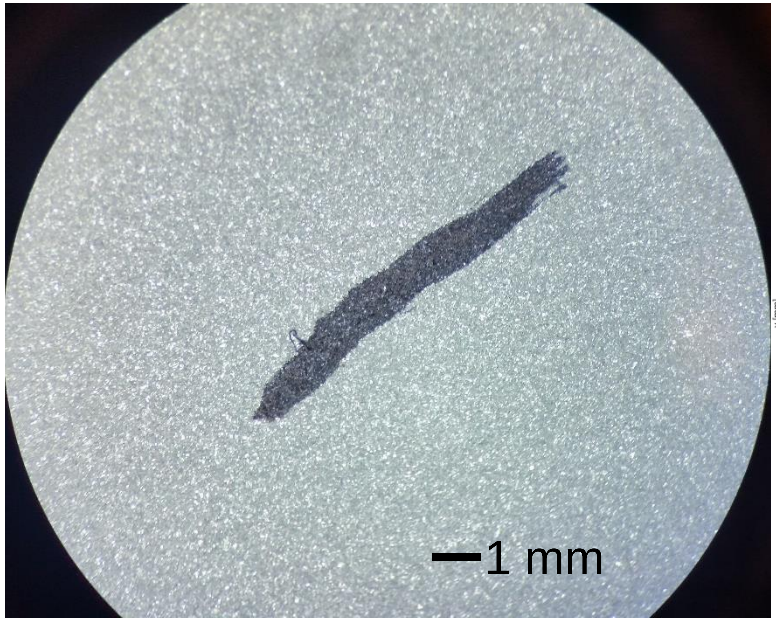
- Now that we have identified the region to probe, we need to identify possible chemical residues *quickly*
- Solution: Pendar's four array quantum cascade laser source covering the long wave IR (6.5-11$\mu$m) integrated into portable scanner
- Example: Sharpie on sandblasted aluminum
- Processing: statistical anomaly detection
  - Model background data cube as Gaussian random tensor
  - "Normalize" test data: subtract mean and divide by standard deviation in a multivariate sense
  - Large results = "not background"
- Continued work on more refined processing
  - If know "not background," can we say what it *is?*



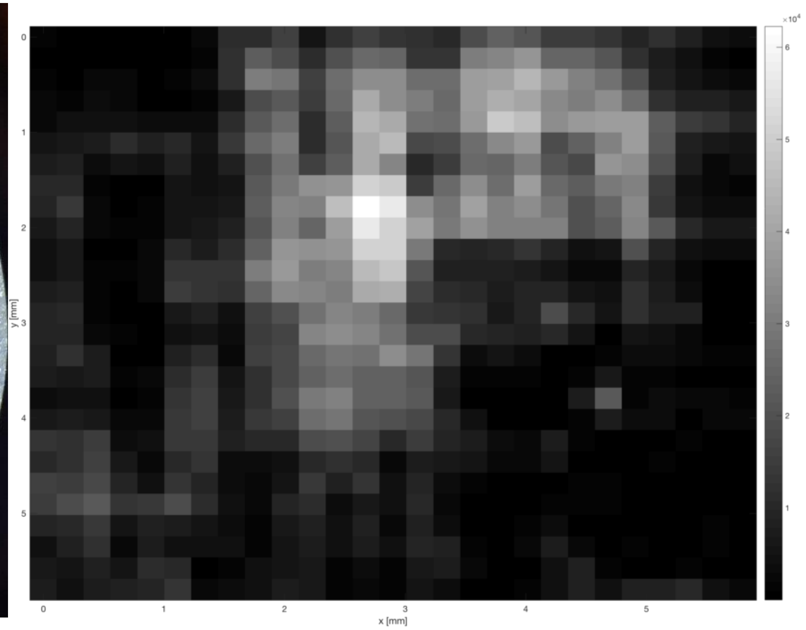


# Final processed results

Camera image



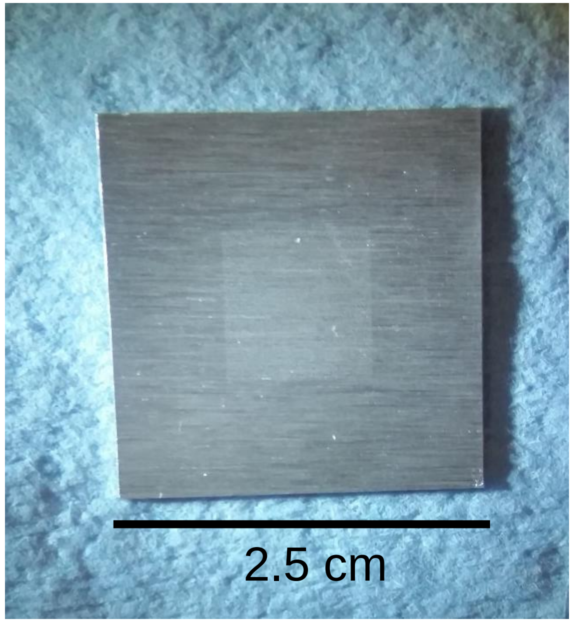

Processing output



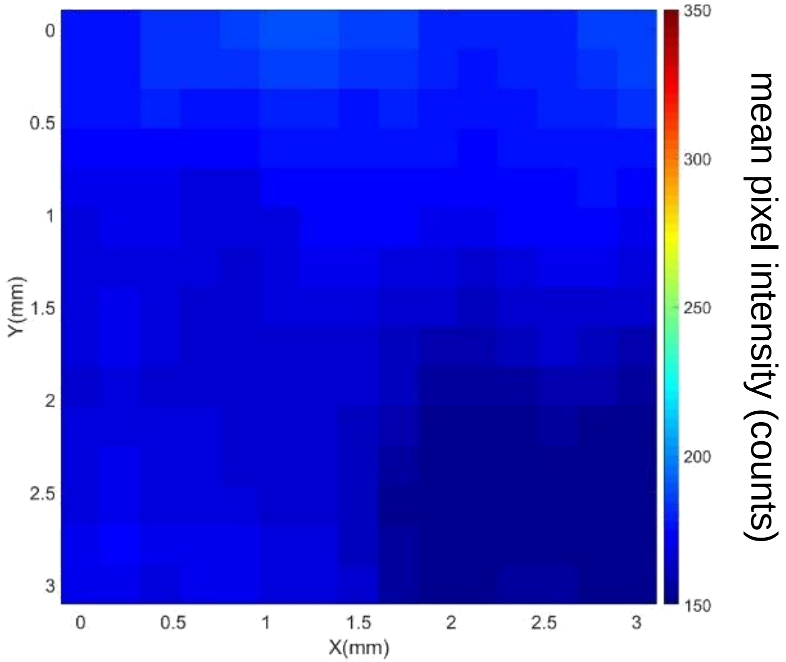

- Each pixel is a measure of the statistical deviation of the data at that location from the background
- Lighter shades indicate larger deviation and more anomalous behavior
- Calculation is a multivariate generalization of “subtracting the mean and dividing by the standard deviation”

# Toward Chemical Residue Identification: First Trace Sample: PETN on Aluminum ($53 \mu g / cm^2$)

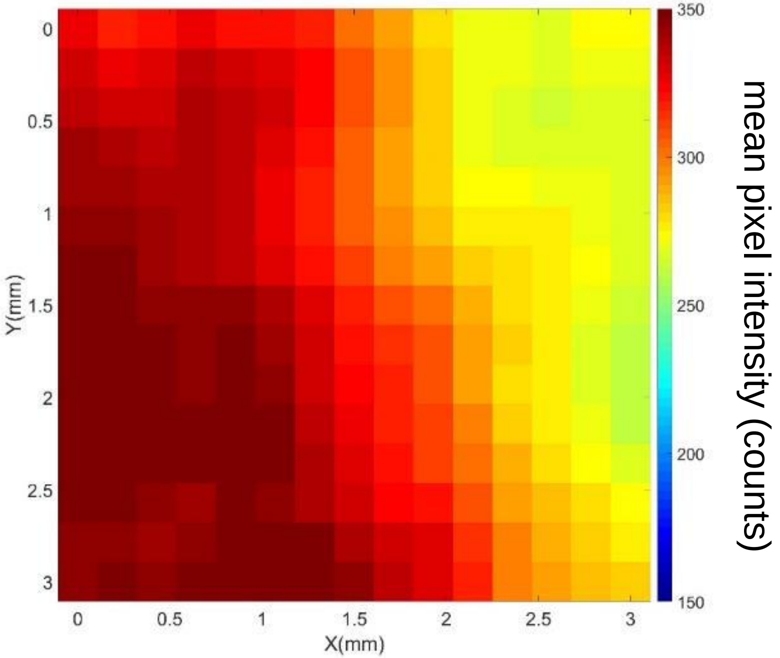
Sample




Data: Clean Al



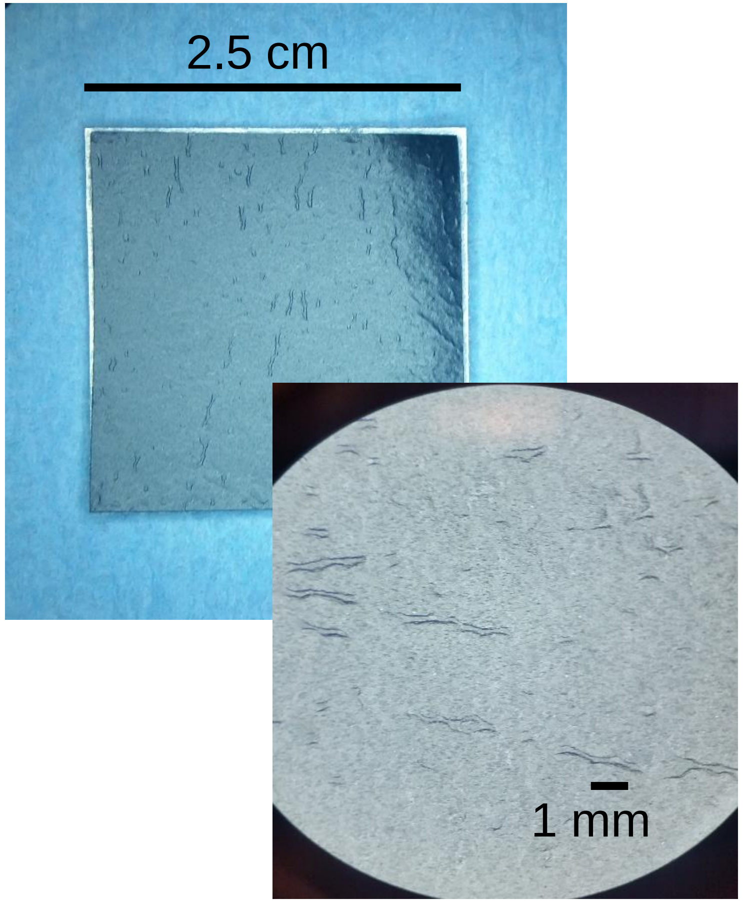

Data: PETN+Al

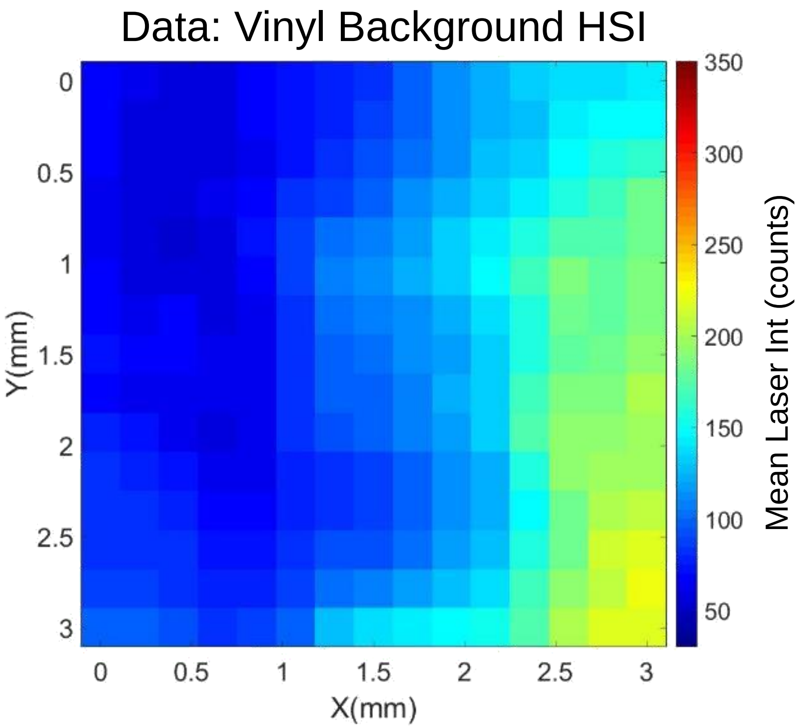


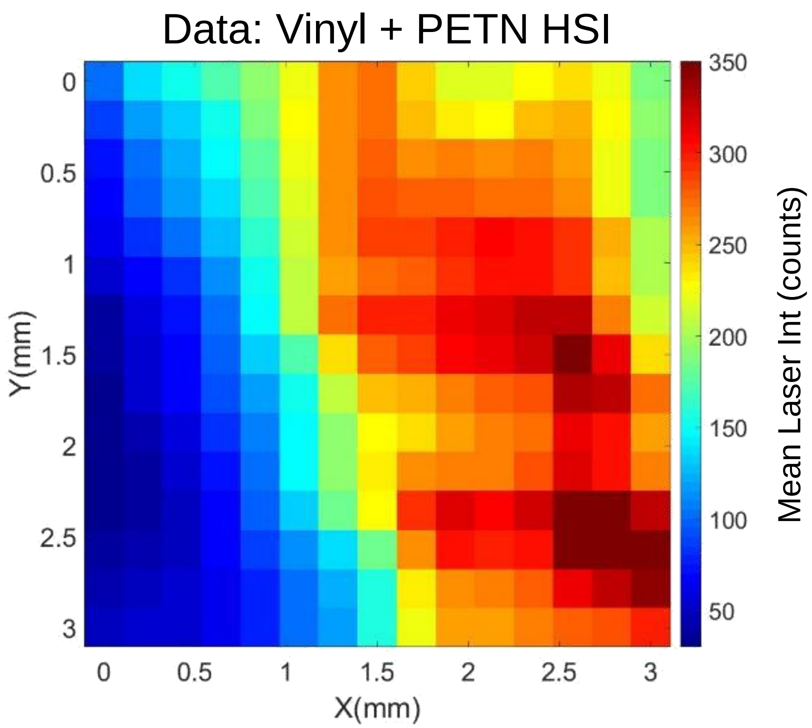

- Data = mean (over wavelength) photon counts
- Data collected at non-normal incidence to reduce speckle
- Clean Al: low returns as most incident photons forward scattered
- PETN+AL: less like a mirror and more photons scattered back to detector

# Toward Chemical Residue Identification: Second Trace Sample: PETN on Vinyl

Sample



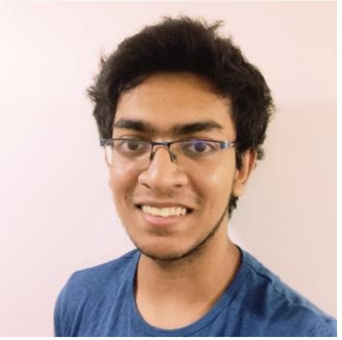
# Conclusion

- Problem of interest: standoff identification of trace chemicals at the checkpoint
- Challenges
  - Automated identification of regions of interest such as handles and zippers
  - Hyperspectral sensor meeting CONOP requirements
  - Signal variability caused by physics of light-substrate-target interactions
- Accomplishments
  - Neural approach to region identification
  - Quantum Cascade Laser technology, handheld-sized, battery-powered hyperspectral imager
  - Initial statistical approach to identification of chemical anomalies
  - Preliminary data suggesting sensitivity to chemicals of interest
- Ongoing effort
  - Refinement of algorithms
  - From anomalies to identification of specific compounds
  - Test, validation, and refinement

BACKUP

# The Team


Ashish Neupane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Romain Blanchard


Daryoosh Vakshoori

# Implementing R-CNN

**Create Database** → **Choose Architecture** → Train Network → Iterate/Test

## Database Creation

1. MATLAB script written to download ~10,000 images from Zappos.com
2. Database includes: carry-ons, backpacks, and suitcases

## Architecture

1. **Faster R-CNN** architecture was used
2. R-CNN uses **Selective Search** to propose possible regions of interest and a standard CNN to classify and adjust them
3. Faster R-CNN accelerates the search process by using a region proposal network in conjunction with the Fast R-CNN detector

# Implementing R-CNN

Create Database

Choose Architecture

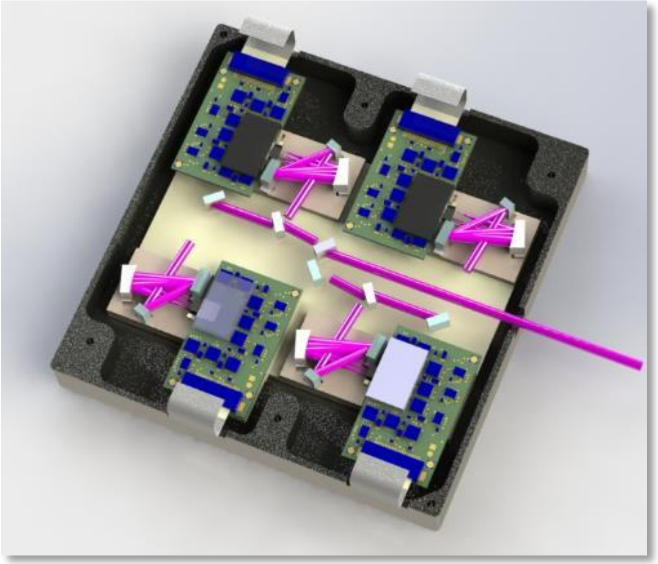
**Train Network**

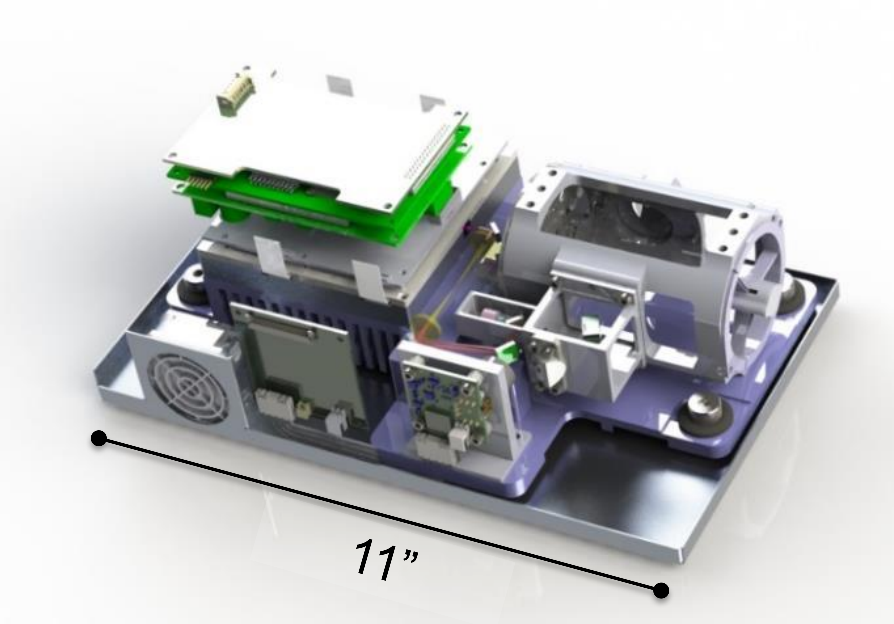
Iterate/Test


Training using Tensor Flow tools from Google

# The Pendar Hyperspectral System

- Now that we have identified the region to probe, we need to identify possible chemical residues *quickly*
- Solution: Pendar’s four array quantum cascade laser source covering the long wave IR (6.5-11$\mu$m) integrated into portable scanner






SOME SPECS:

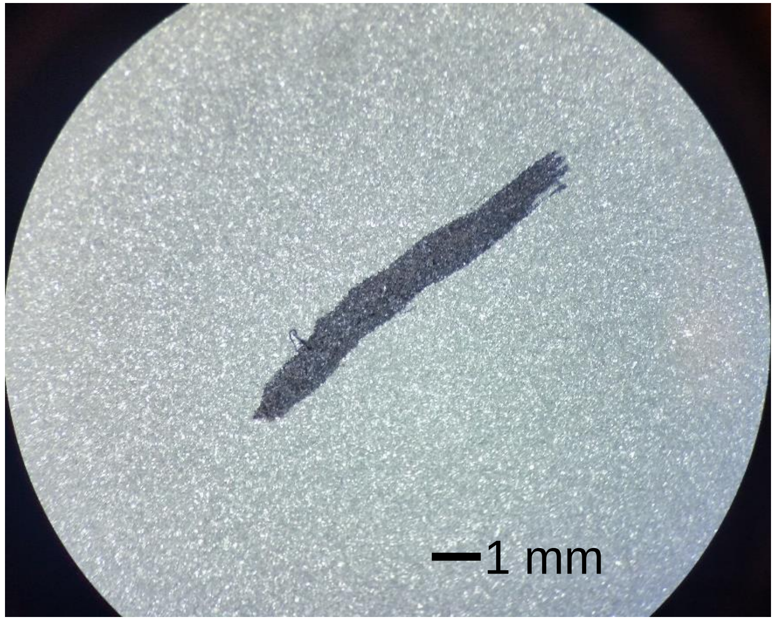
Volume = 0.08 cubic feet

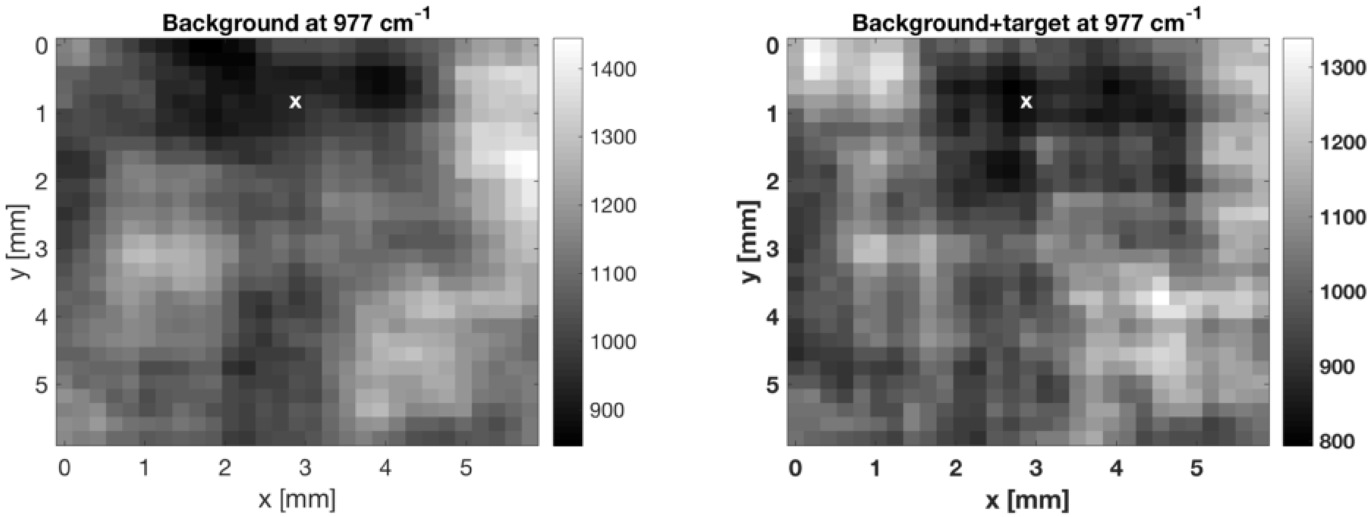
Weight = 4.5 Pounds

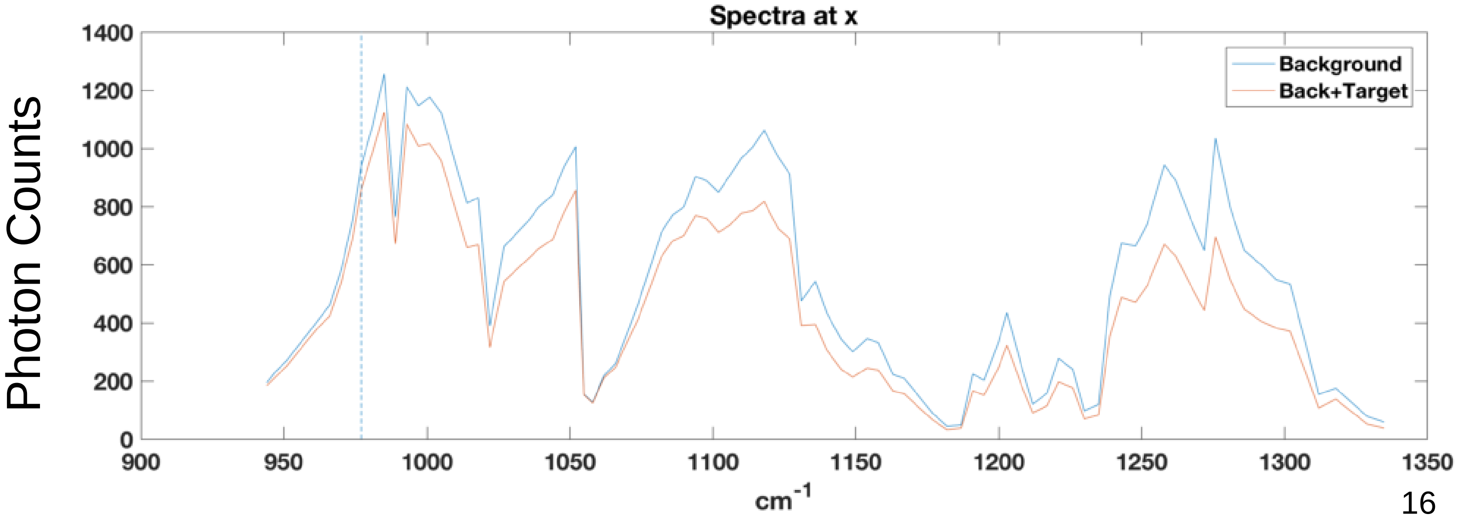
Handheld Compatible

One Moving Part

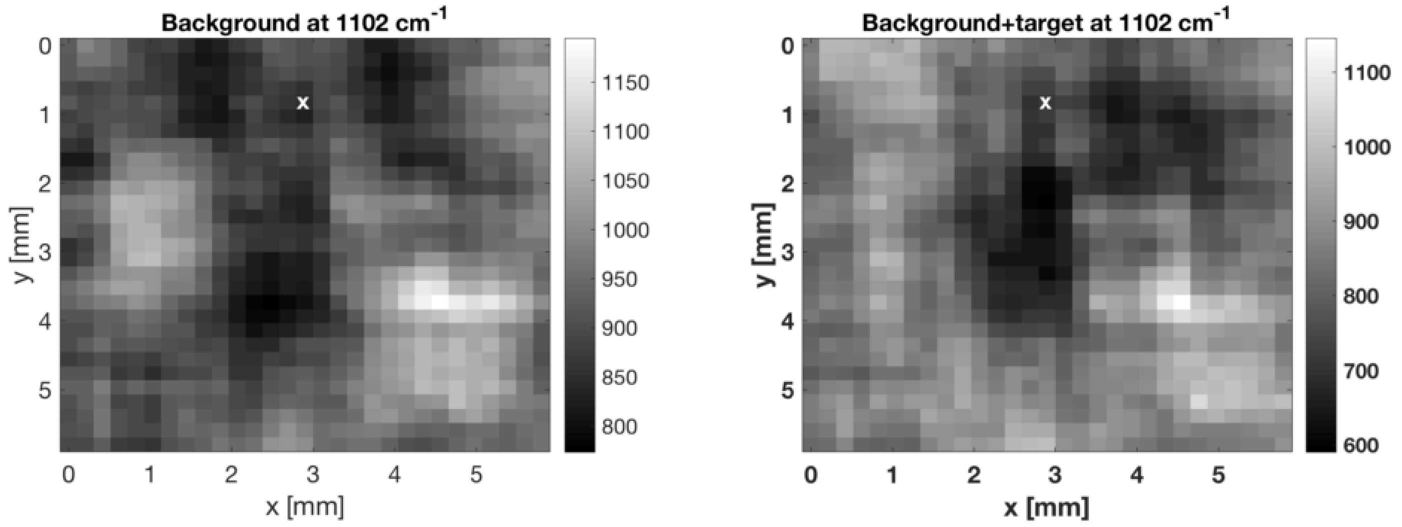
# Sharpy on Sandblasted Aluminum: 977 $cm^{-1}$

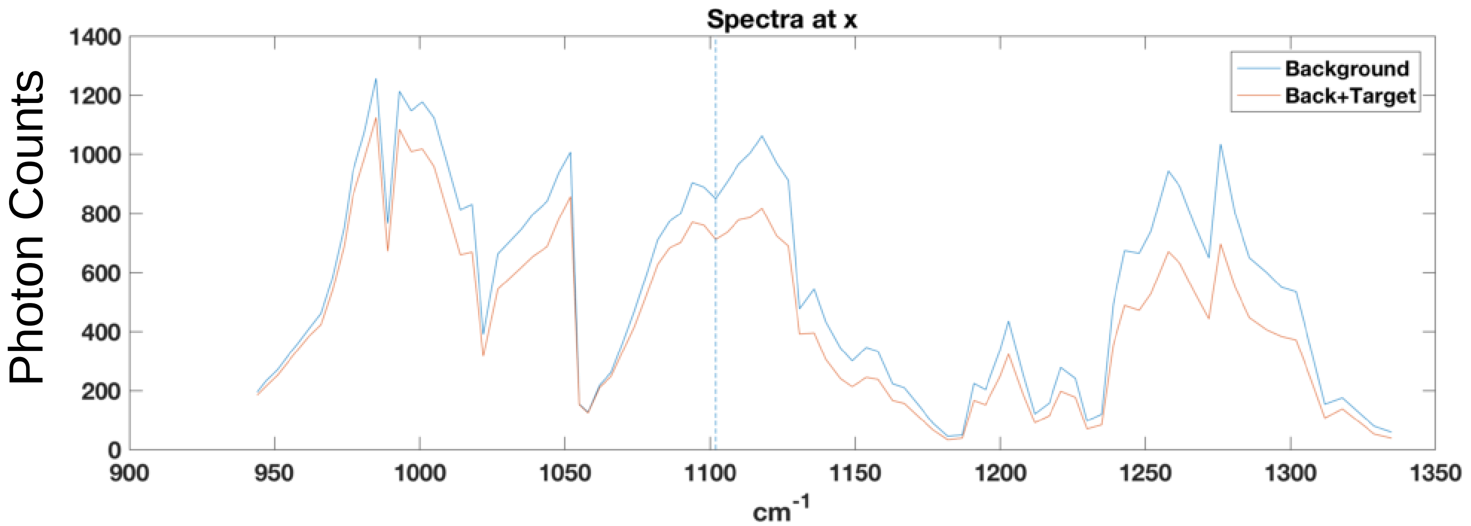


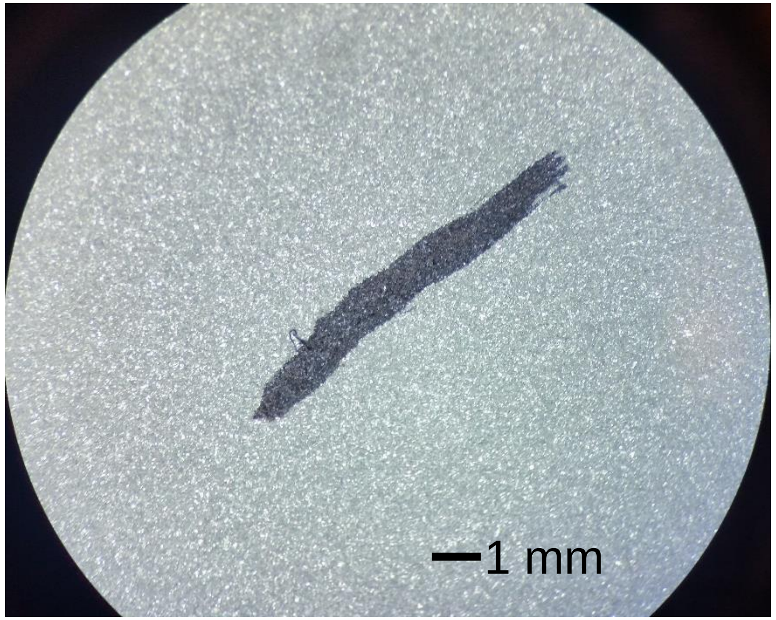



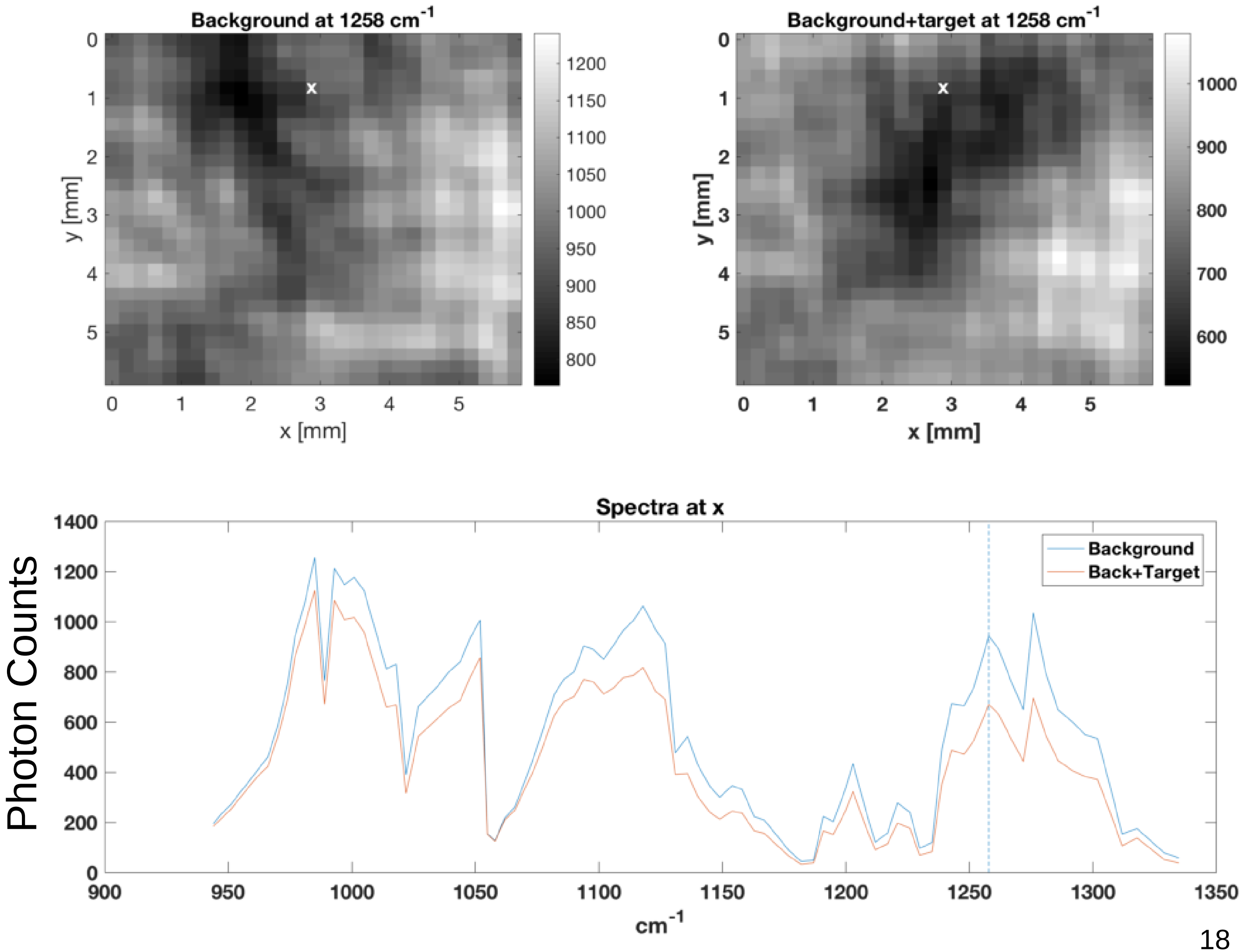
# Sharpy on Sandblasted Aluminum: 1102 $cm^{-1}$



# Sharpy on Sandblasted Aluminum: 1258 $cm^{-1}$

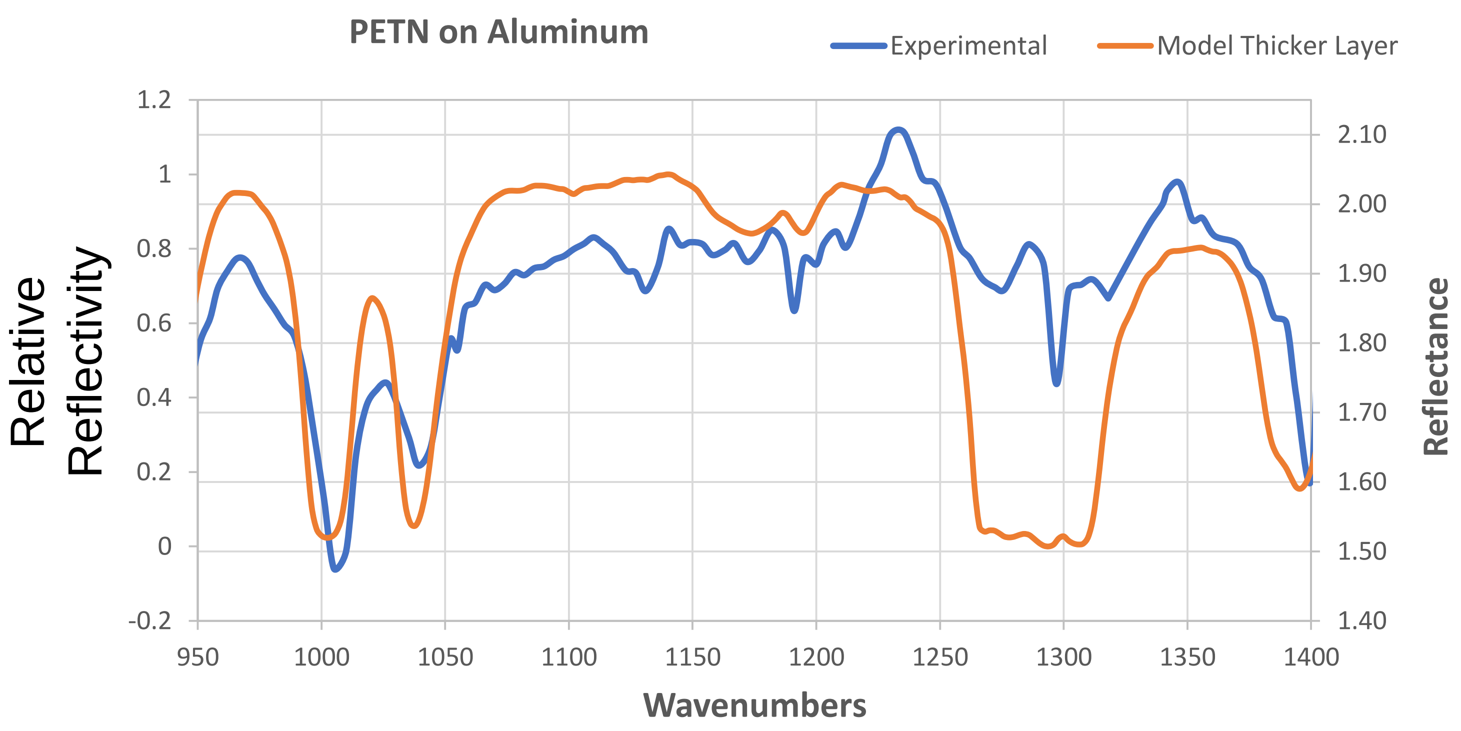


# Toward Chemical Residue Identification: First Trace Sample: PETN on Aluminum ($53 \mu g / cm^2$)

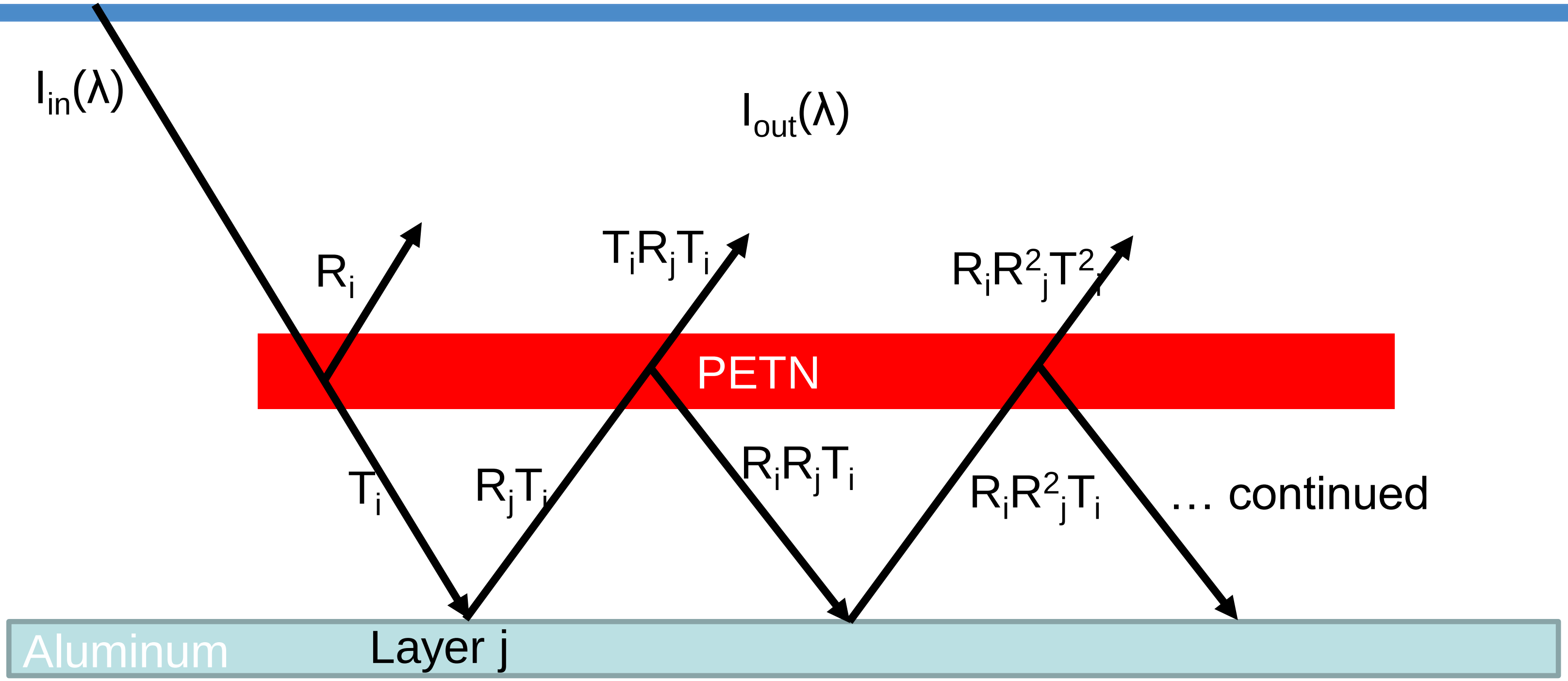
The experimental spectrum was obtained from averaged over the image coordinates

$$\frac{mean(I(x,y))}{mean(I_{bg}(x,y))} \quad \begin{matrix}\text{PETN+Al}\\ \text{Clean Al}\end{matrix}$$




- Plots demonstrate light attenuation due to PETN
- At photon energies corresponding to vibration transition frequencies of PETN molecules, less light returning because of PETN absorption
- Simple layered medium model model validates experimental results

# First Trace Sample: Interpreting the Results




Taking the total reflectivity for an infinite number of passes:

- A geometric series of R's and T's for layers i and j ($R_j$ is assumed to be constant across spectrum in the next slide)

$$R_{tot} = R_j + \frac{T_i^2 R_j}{1 - R_i R_j}$$