Discriminative Illumination:

Per-pixel Classification of Raw Materials based on Optimal Projections of Spectral BRDFs

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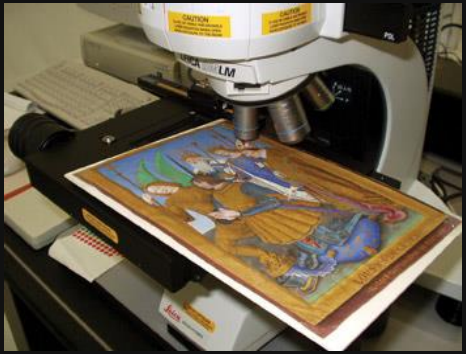
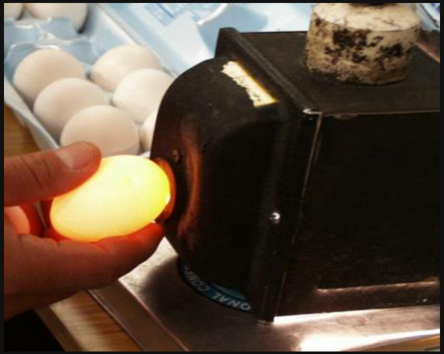
Raw Material Classification: What & Why?

- Classify unpainted/uncoated materials with appearance features (e.g., spectral reflectance, BRDF, translucency, polarization, texture, etc.)



Pigment Identification

Sorting Scraps for Recycling

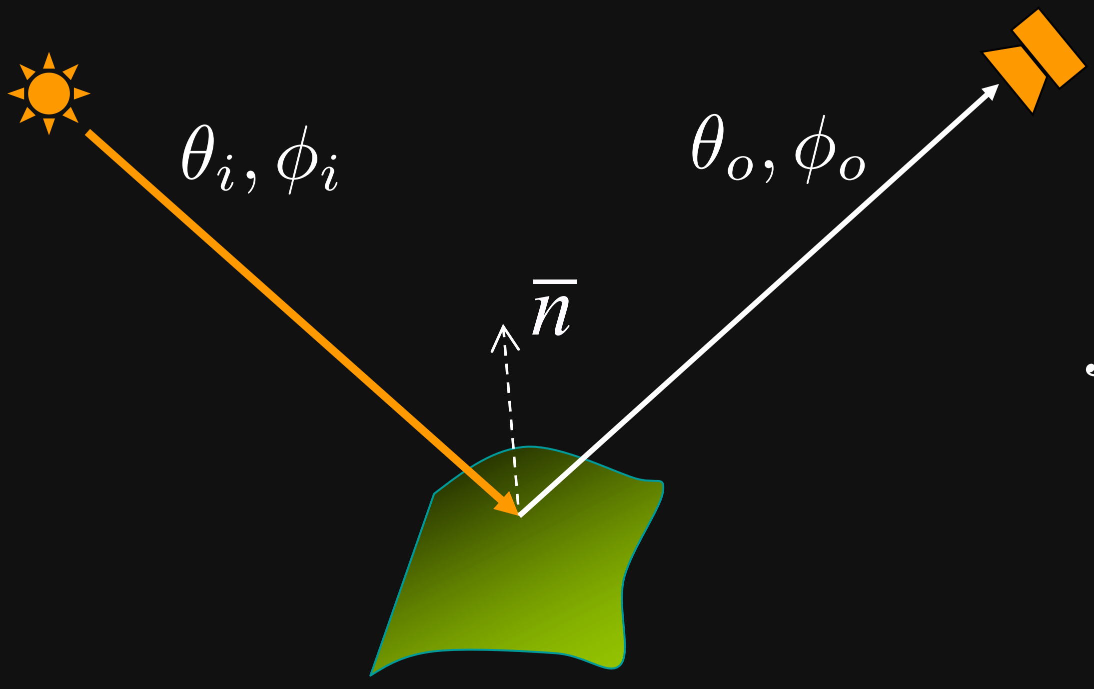


Egg Candling

Skin Monitoring for Smart Health

Classifying Materials with Spectral BRDF

- Define "materials" as Spectral Bidirectional Reflectance Distribution Function (BRDF)
- Suitable for some pure, raw materials (e.g., metal, ceramic, plastic, paint)



$$f(\theta_i, \phi_i, \theta_o, \phi_o, \lambda)$$

Spectral BRDF is more than Color + Gloss

Stainless Steel

Alloy Steel 4130

Carbon Steel A366

Alloy Steel 4130

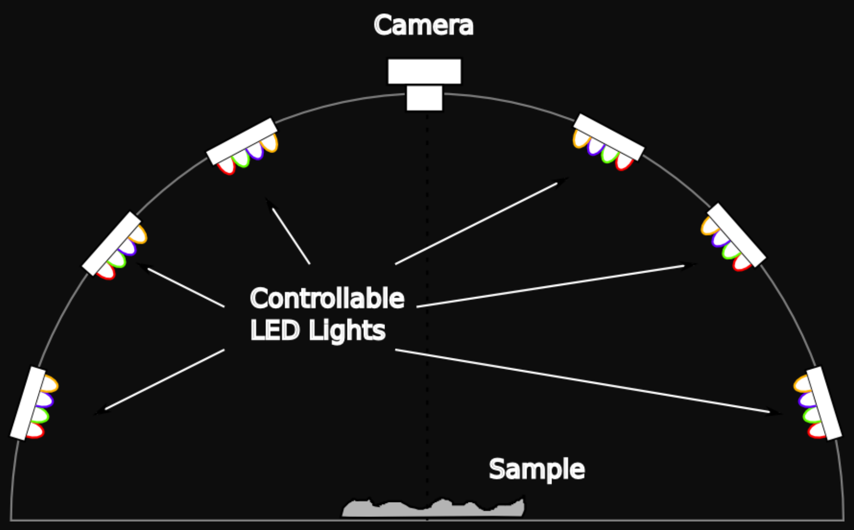
Related Work

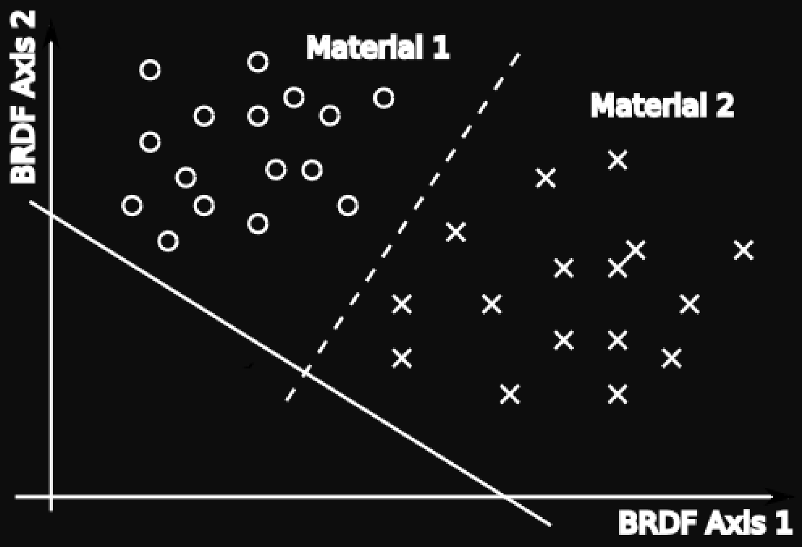
- Paint classification using BRDF slices
  [Wang et al. 2008]
- Optimal subset of illumination for steel classification
  [Jehle et al. 2010]
- Passive Approach: Material Recognition in Human Vision and Computer Vision
  [Adelson et al. 2001, 2003, 2007, 2008, 2010 etc.]

Challenge: High-Dimensionality

- Spectral BRDF (Slice) for Per-pixel Classification

$$f(\theta_i, \phi_i, \cancel{\theta_o, \phi_o}, \lambda)$$



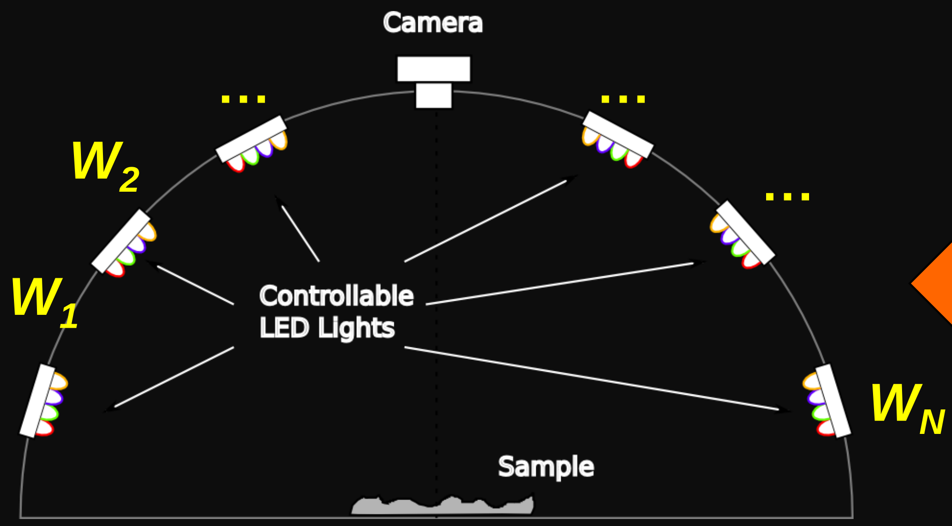


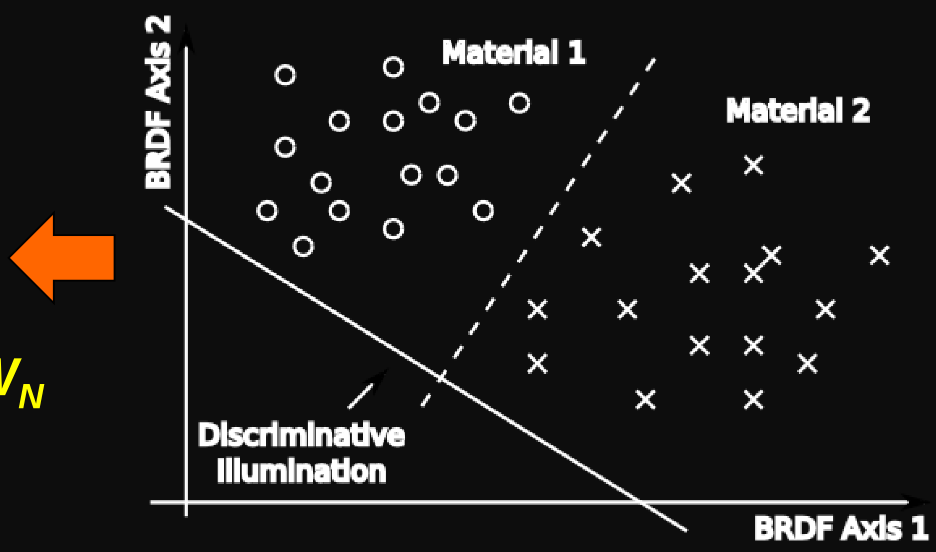
$$\mathbf{x} = [f_1, f_2, \cdots, f_N]^T$$

$$y = \mathbf{w}^T\mathbf{x} + b$$

Use Coded Illumination as a Classifier

- Directly measure "discriminative projections" of spectral BRDFs





$$I = \mathbf{w}^T \mathbf{x}$$

Measured Feature **Coded Illumination** **BRDF vector**

Learn Discriminative Illumination via Supervised Learning

- Take advantage of existing, labeled BRDF measurements

Fisher LDA:

$$\min \frac{\mathbf{w}^T \mathbf{S}_w \mathbf{w}}{\mathbf{w}^T \mathbf{S}_b \mathbf{w}} \qquad \text{s.t.} \qquad \mathbf{w}^T \mathbf{w} = 1$$

SVM:

$$\min \frac{1}{2} ||\mathbf{w}||^2 \qquad \text{s.t.} \quad y_i(\mathbf{w} \cdot \mathbf{x}_i - b) \geq 1$$

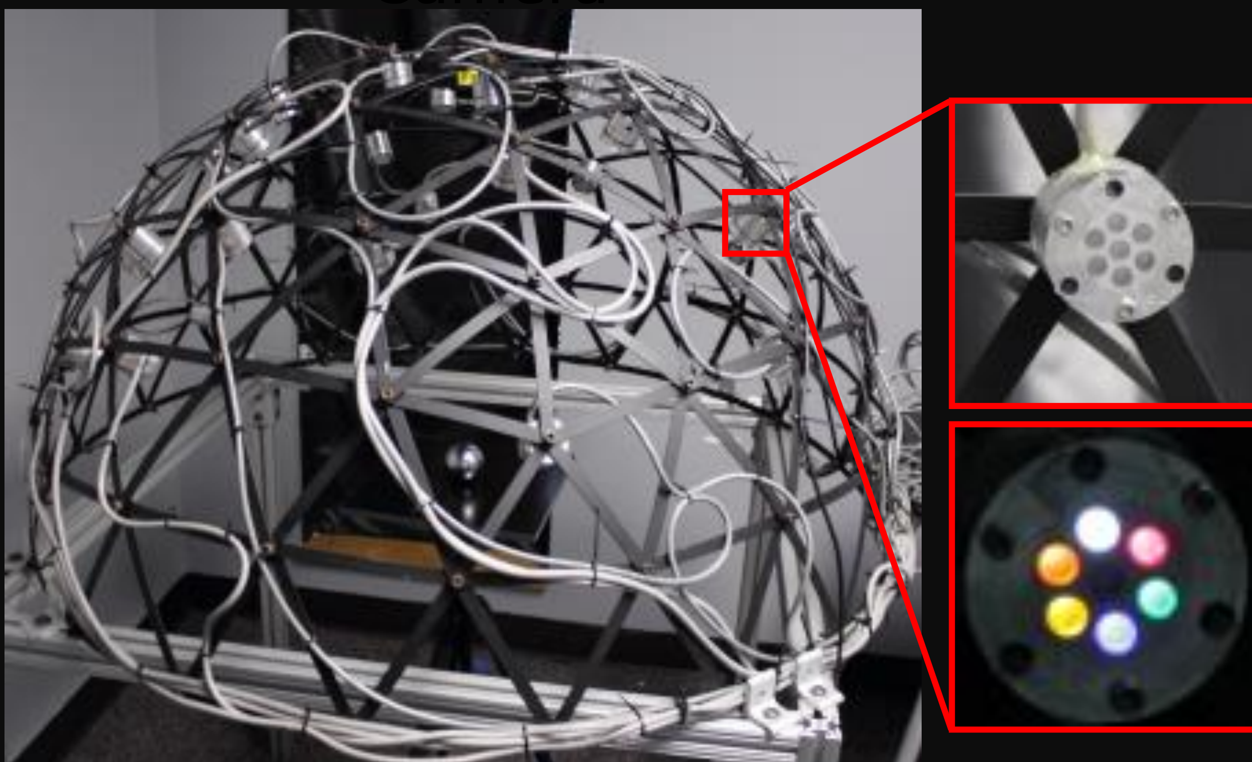
- Implement as the subtraction of two light patterns

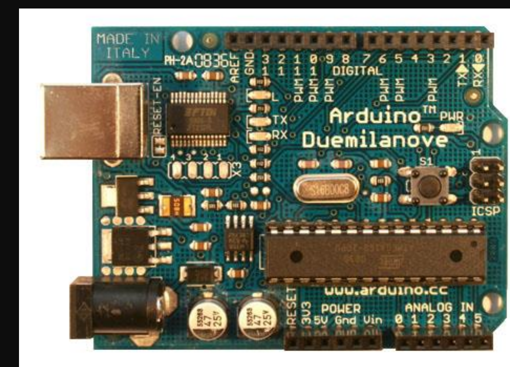
$$\mathbf{w} = \mathbf{w}^+ - \mathbf{w}^-$$

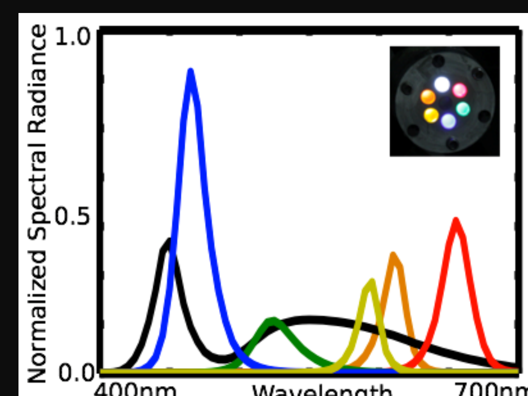
LED-based Multispectral Dome

- 25 LED clusters, 6 primaries, PWM control via Arduino boards

Camera

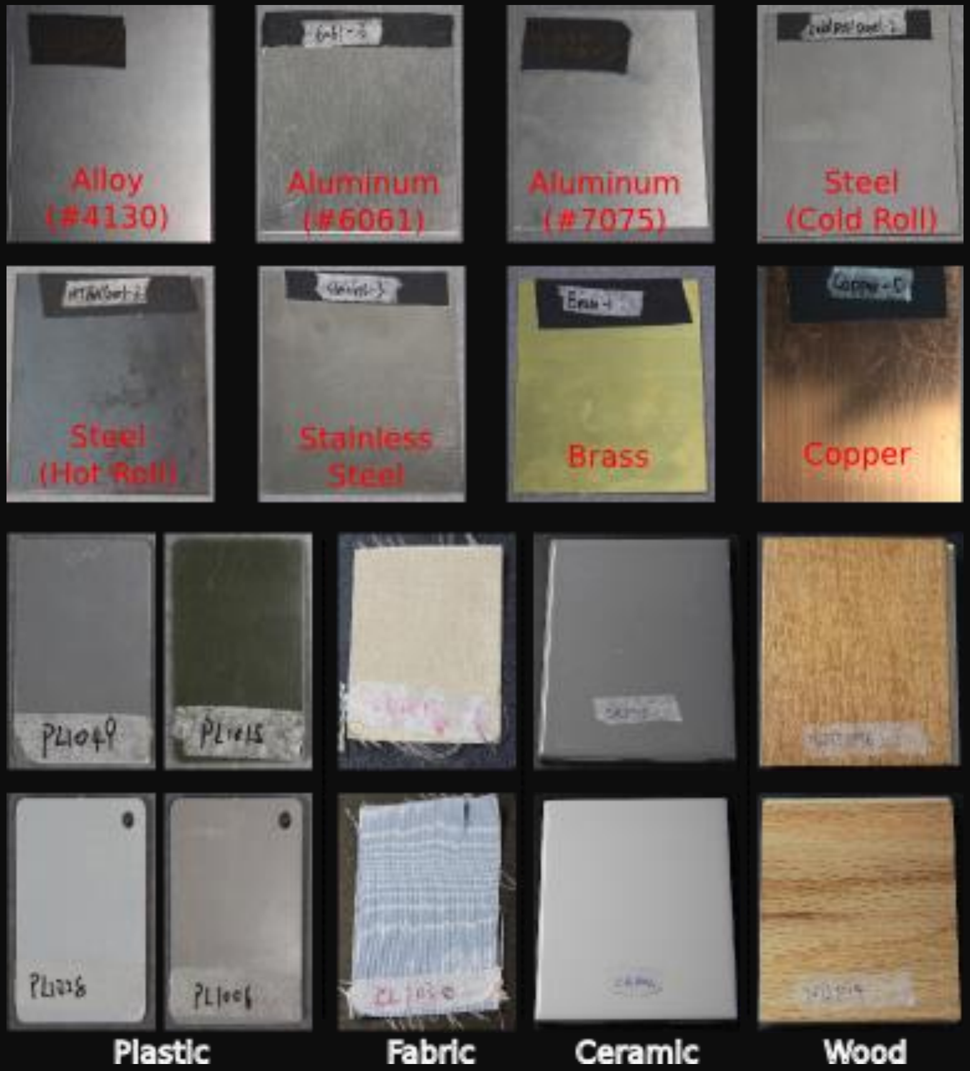






Raw Material Database

- 5 classes (metal, plastic, fabric, ceramic, wood)
- 7 subclasses in metal: alloy steel, carbon steel (cold/hot roll), stainless steel, aluminum, brass, copper.
- 100 samples in total
- 25*6=150 HDR images (1392x1040) per sample



Available online at www.cis.rit.edu/jwgu/research/fisherlight

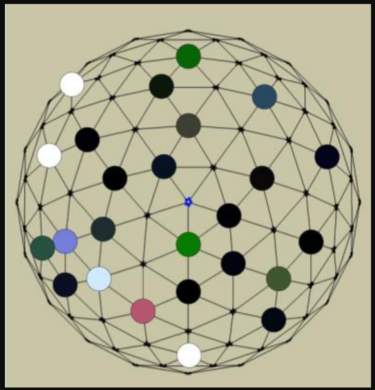
Example: Carbon Steel vs Alloy Steel

Alloy Steel (4130)

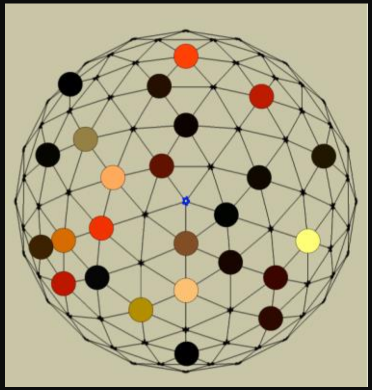
Carbon Steel (A366)

Results

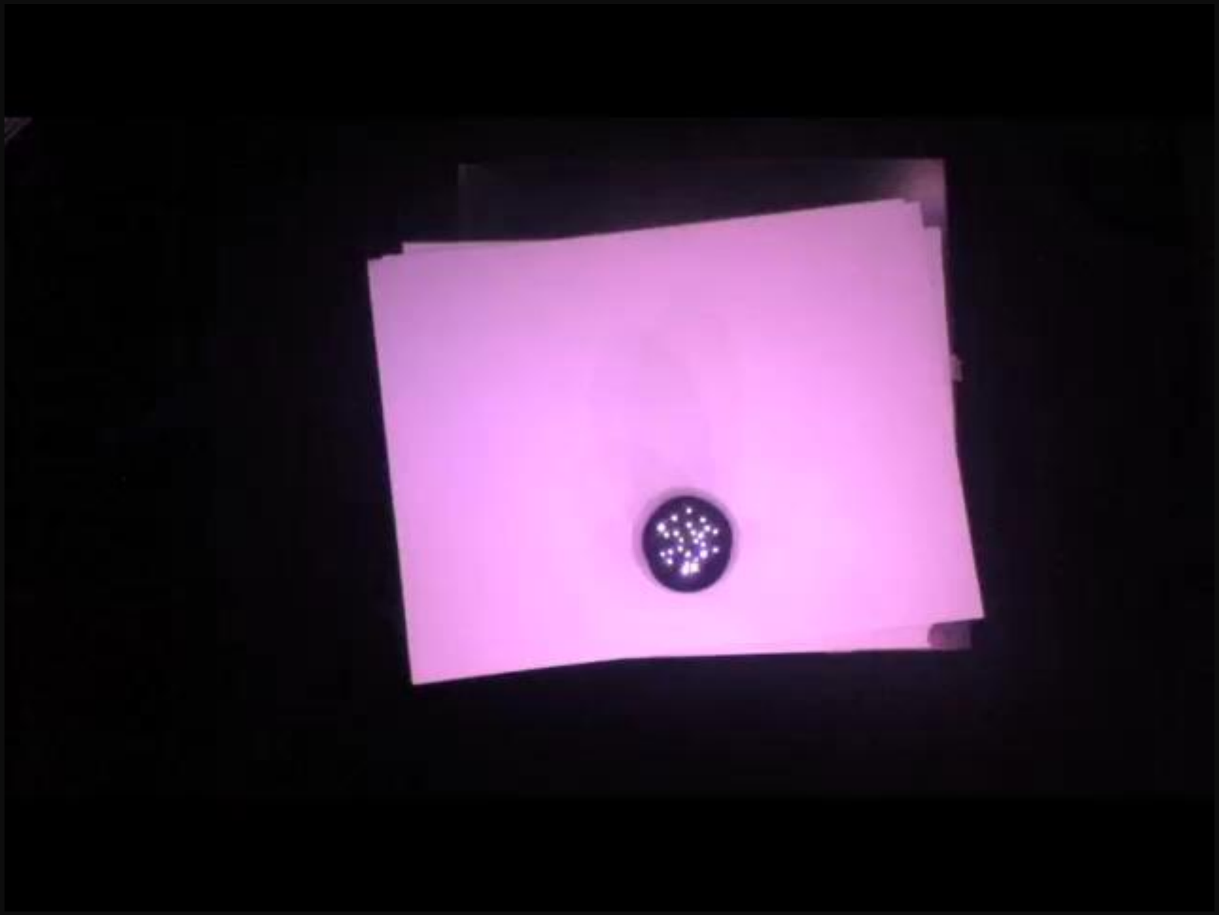
SVM Light



$\mathbf{w}^+$



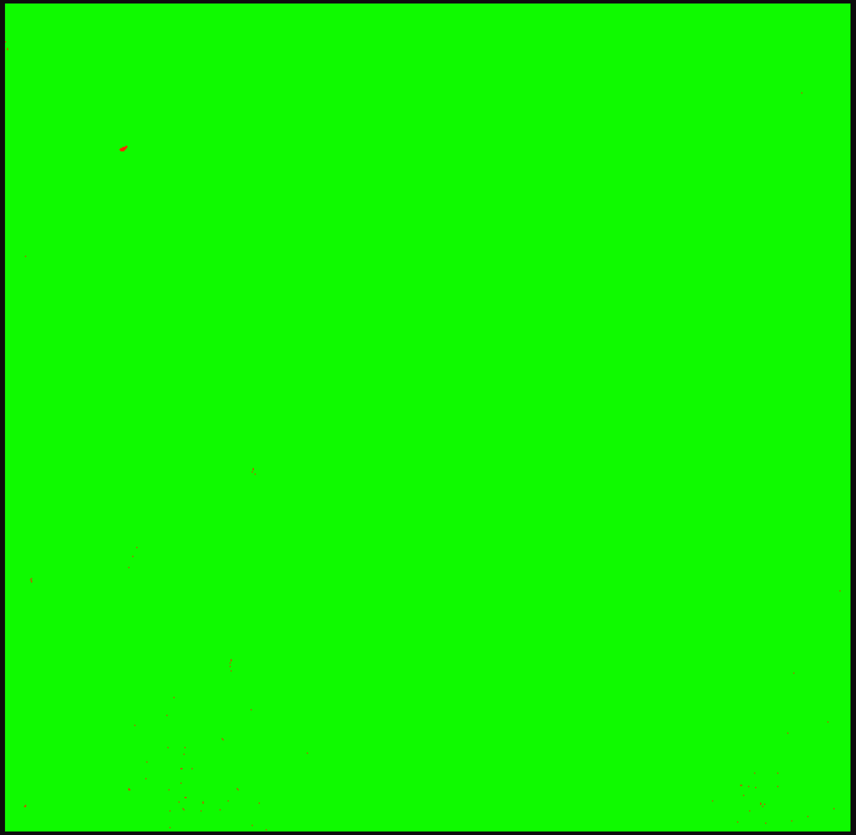
$\mathbf{w}^-$



- more videos at the project webpage

Classification Result (95% accuracy)

Alloy Steel (4130)



Carbon Steel (A366)

- In comparison, using the optimal 2 raw measurements (out of the 150) only results in 41% accuracy.

SNR Benefits Due to Light Multiplexing

- For read noise, the SNR gain is

$$\sqrt{M/2} \leq G_r \leq M/\sqrt{2}$$

- For photon noise, the SNR gain is

$$1 \leq G_p \leq \sqrt{M}$$

where *M* is the number of raw measurements.

(Please refer to the paper for detailed proof)

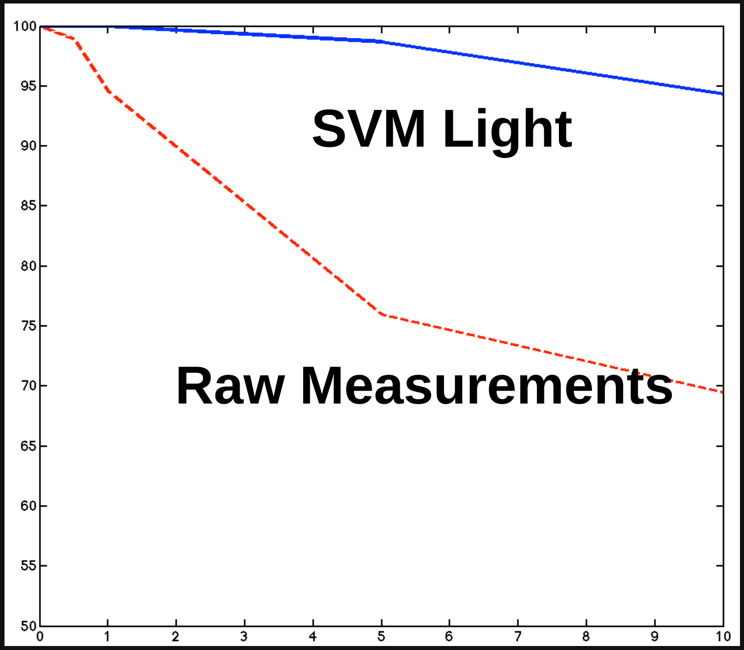
SNR Benefits: Simulation Results

- Based on the MERL BRDF database, with both photon noise and read noise.

[Matusik, et al., 2003]

paint vs plastic

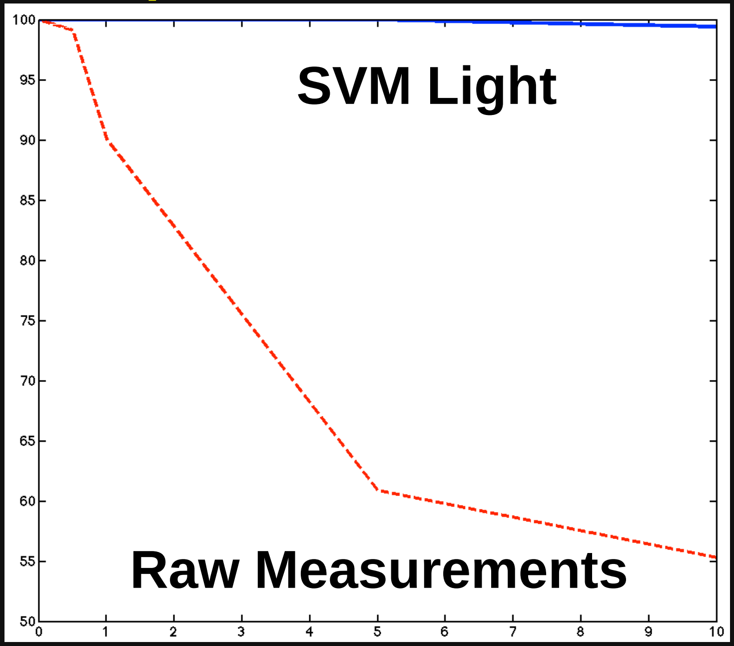
Accuracy (%)



Noise level (%)

phenolic vs metal

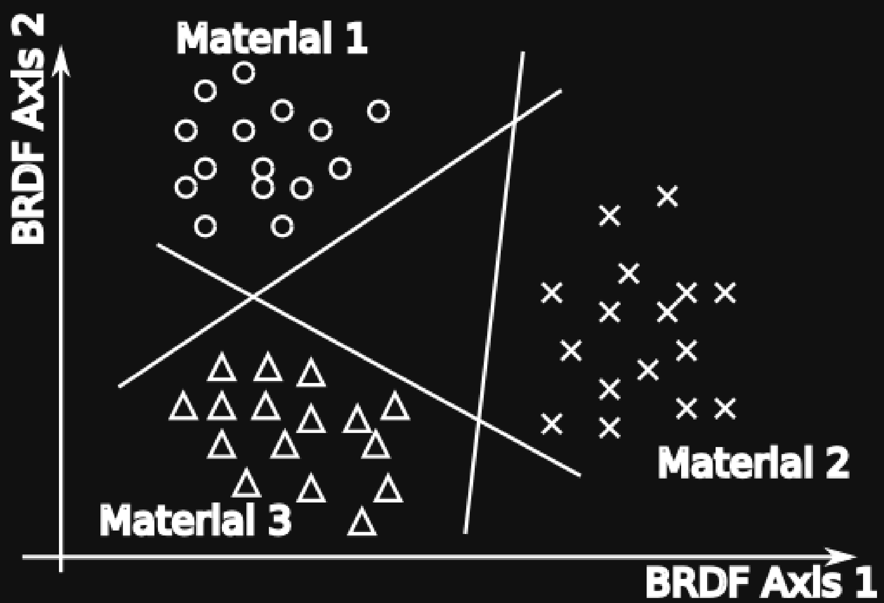
Accuracy (%)

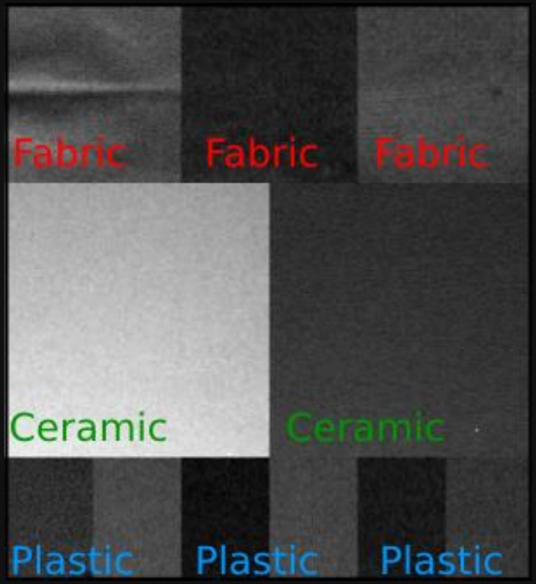


Noise level (%)

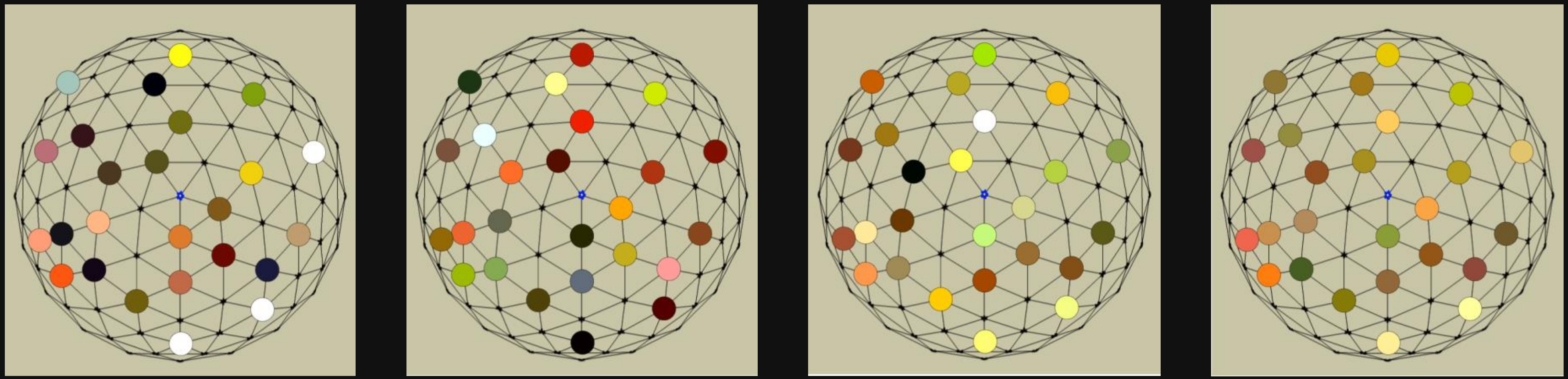
Extension 1: Multi-Class Classification

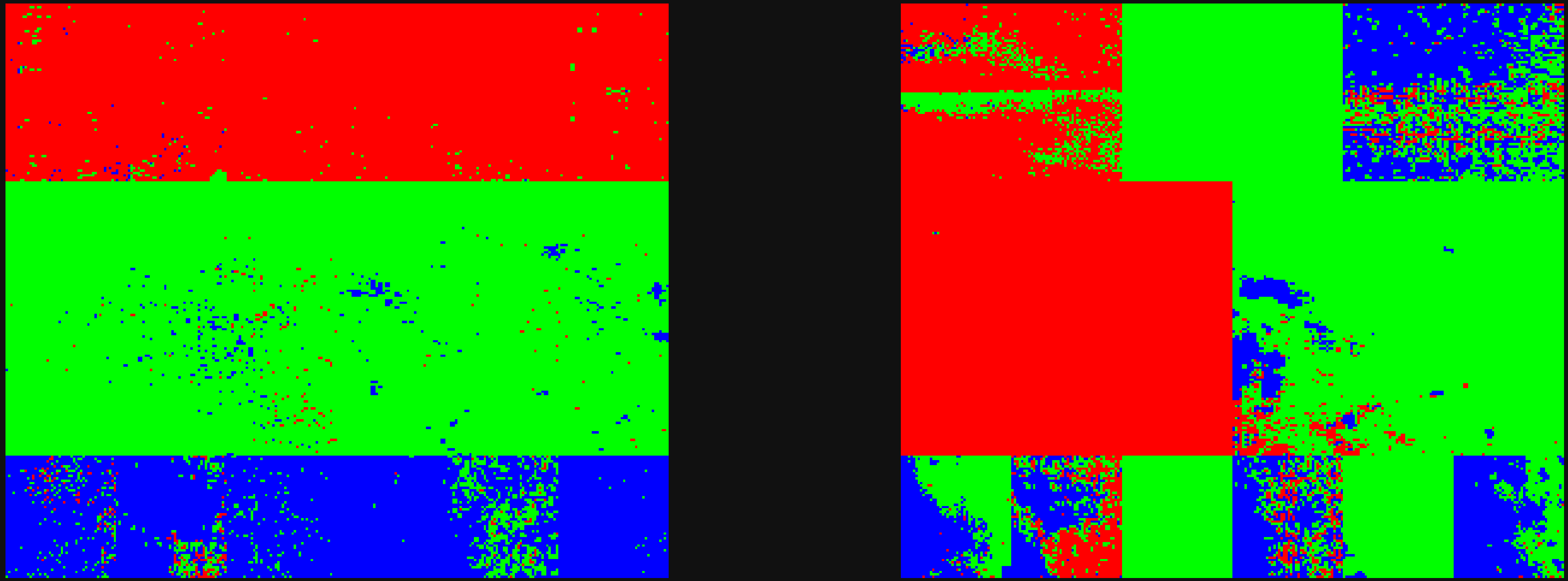
- Use multiple discriminative illuminations (e.g., one-vs-one, one-vs-many)





Results





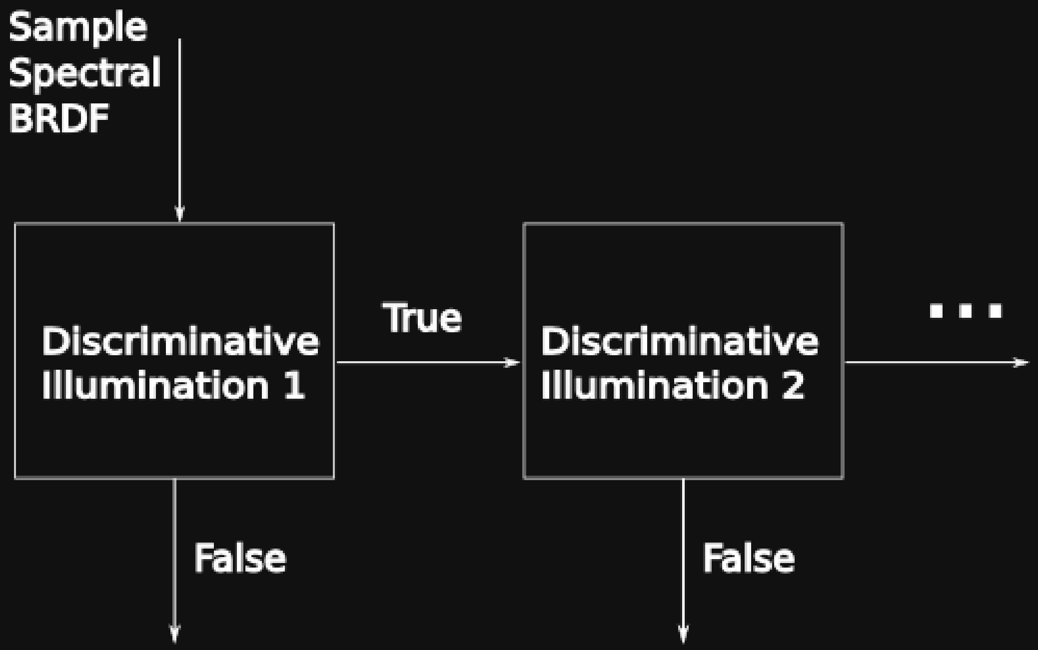
SVM Light (94%)

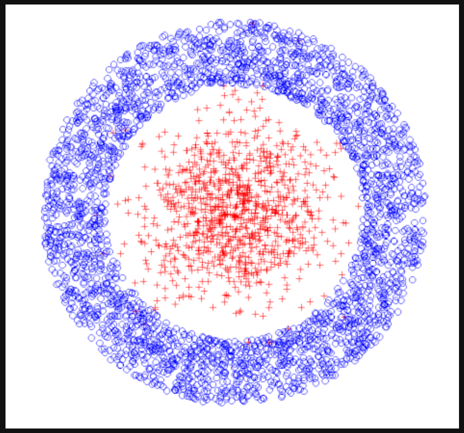
Optimal subset of
Raw Measurements (62%)

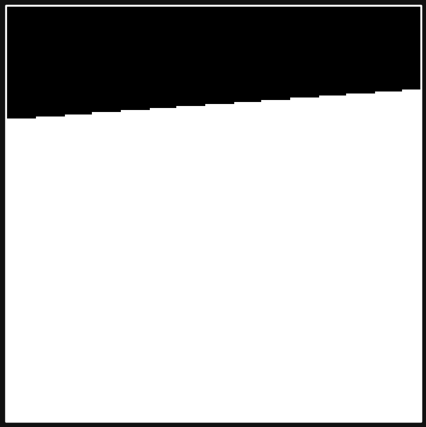
Extension 2: Nonlinear Classification

- Cascade structure: from linear to nonlinear

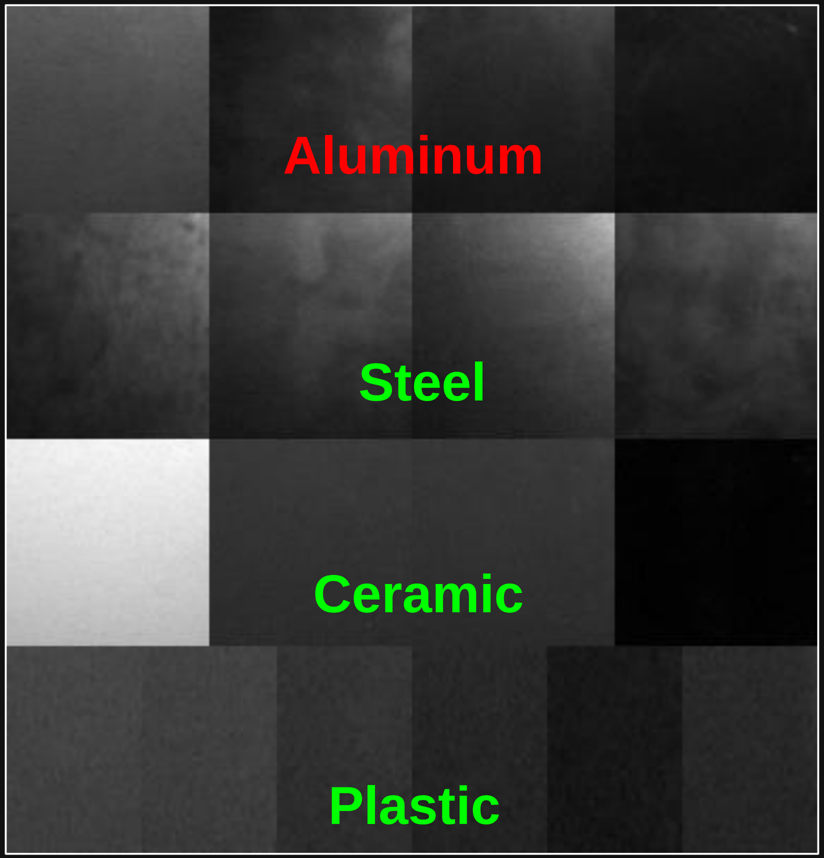
[Viola & Jones, 2001]

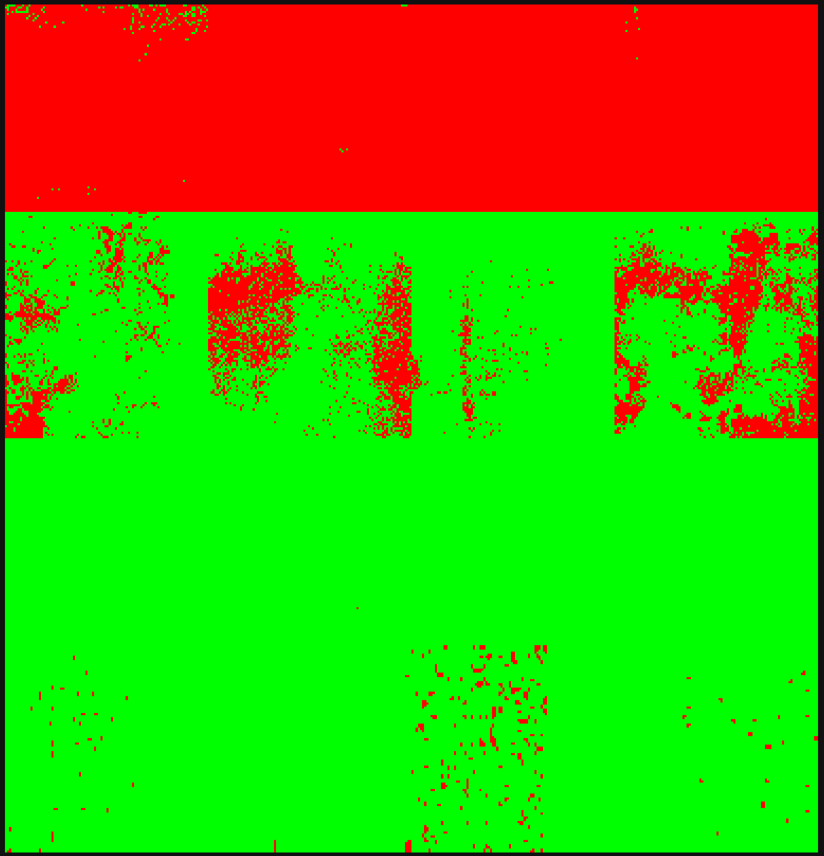






Aluminum Detection for Recycling

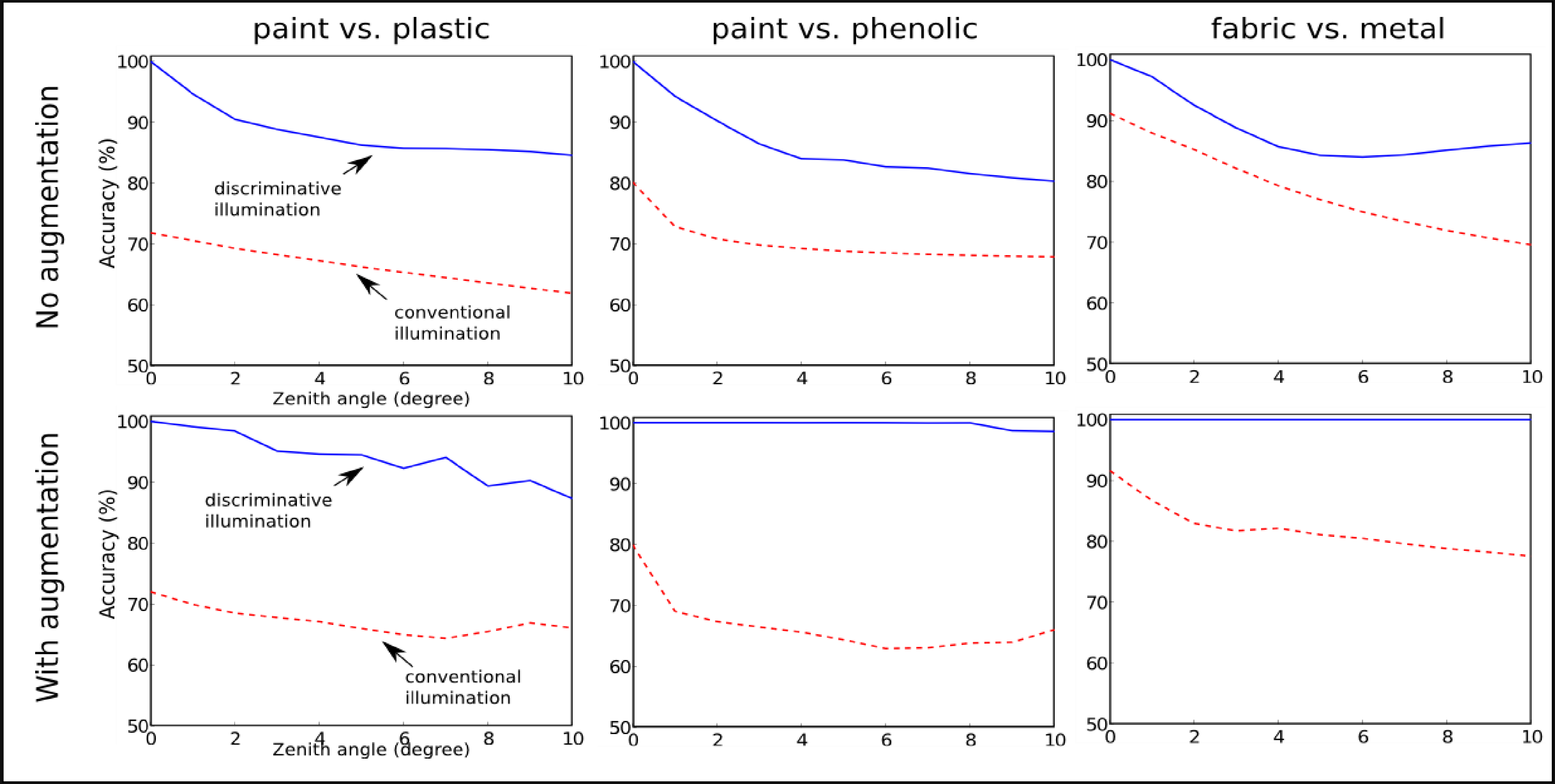




Four-stage Cascade Classifier

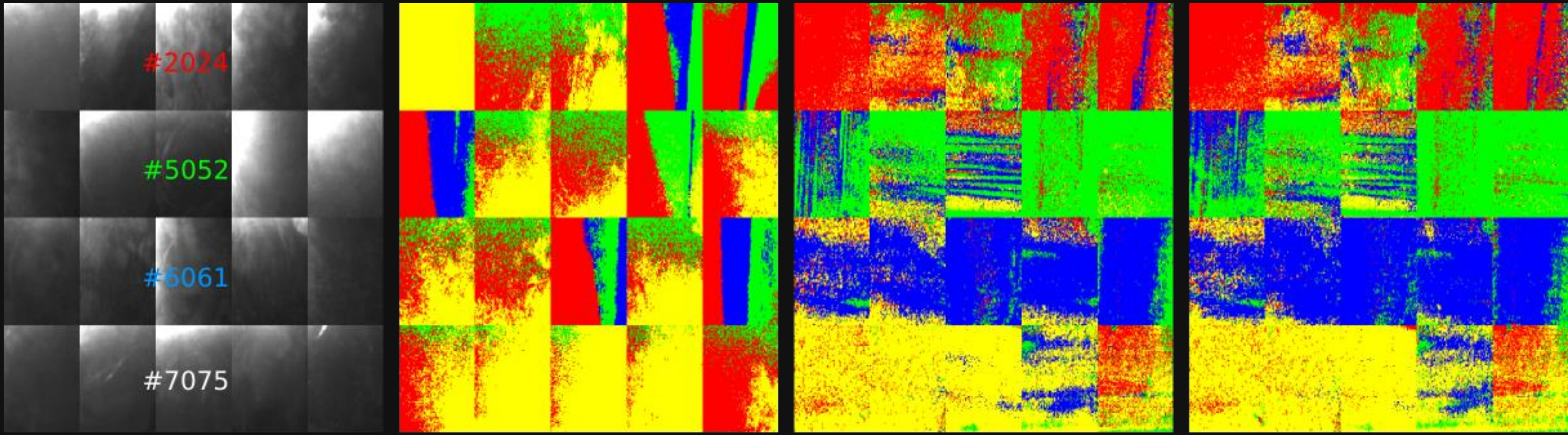
Extension 3: Surface Normal Variation

- Augment training data with rotational copies of BRDFs
- Limited to mild normal variation (+/- 10 degrees)



Sorting Aluminum by Alloy Family

- A challenging yet highly-demanded task in recycling



(a) Sample under LED#143 (b) Raw Measurement (37%) (c) Fisher Light (71%) (d) SVM Light (73%)

#2000 series – Alloyed with copper

#5000 series – Alloyed with magnesium

#6000 series – Alloyed with magnesium and silicon

#7000 series – Alloyed with zinc

Summary

- A first step of using computational illumination as "physics-based classifier" for raw material classification

- Ongoing & future work
  - Large surface normal variation
  - Other (more global) appearance features
  - Discriminative coding in cameras, sensors, displays, etc.

The Role of Computational Imaging

Controls	Signal Reconstruction	Detection/Recognition
Coded Aperture	Extended DOF	Optimal coded imaging systems for detection/recognition
Coded Exposure	High Speed Imaging	
Coded Light	Spectral Imaging	
Coded Sensor	Light Field Capture & Display	
…	Image Relighting	
	BRDF Acquisition	
	…	

Acknowledgements

- Gabrielle Gaustad from RIT Institute of Sustainability for discussion of recycling applications

- Oliver Cossairt, Mohit Gupta, and Shree Nayar from Columbia University and Toshihiro Kabayashi from Canon for discussion and comments

- Support from NYSP2I and RIT VPR

Thank You!

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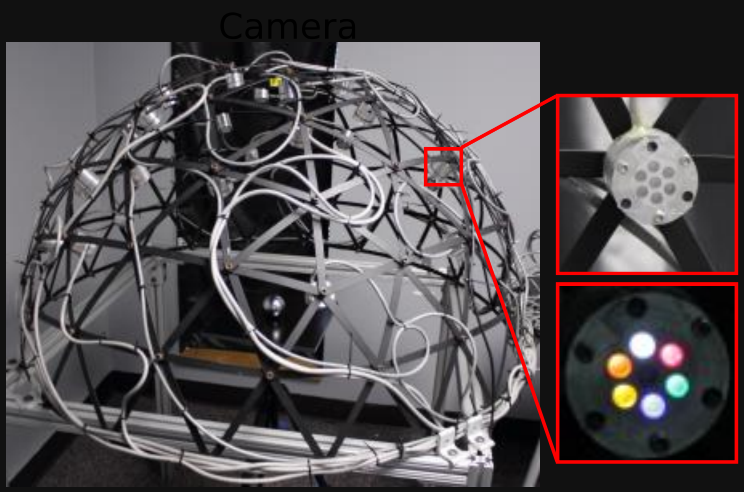
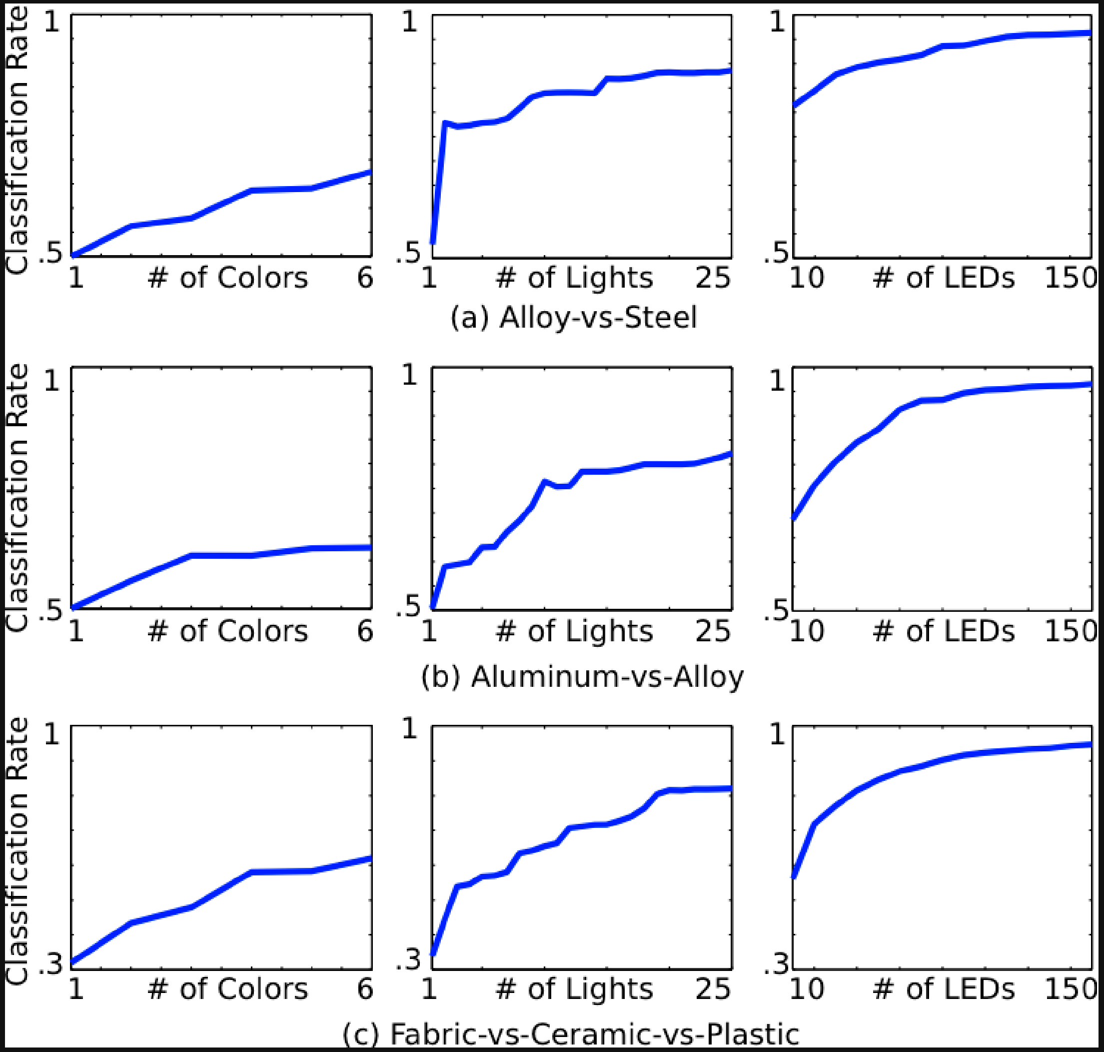
Both Color and BRDF are Useful





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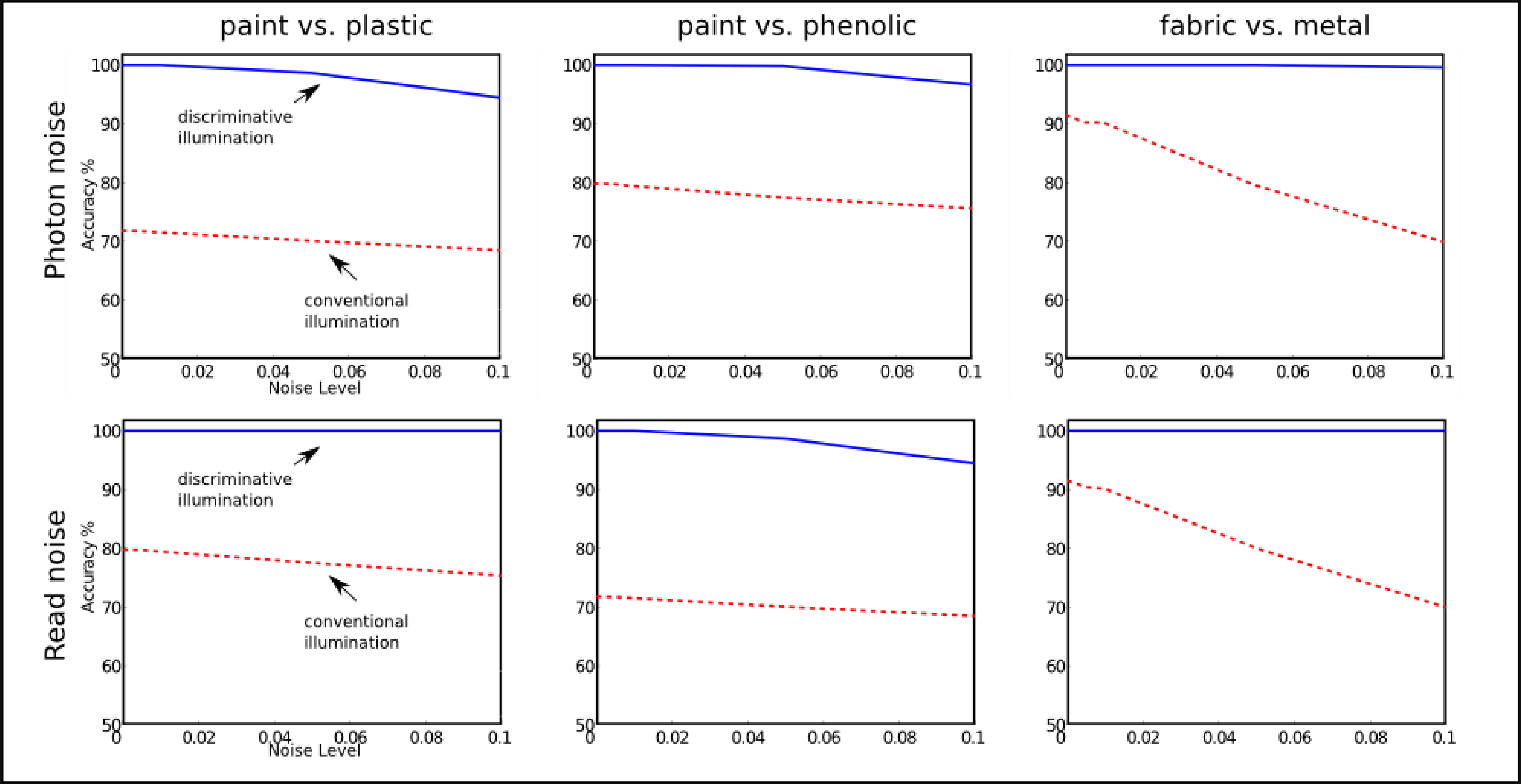

Related Work

- Paint classification using BRDF slices
  [Wang et al. 2008]
- Optimal subset of illumination for steel classification
  [Jehle et al. 2010]
- Feature-specific imaging and task-specific imaging
  [Neifeld et al. 2003, 2007, etc.]

- Passive Approach: Material Recognition in Human Vision and Computer Vision
  [E. Adelson et al. 2001, 2003, 2007, 2008, 2010 etc.]

Raw Material Classification: What & Why?

- Material recognition based on appearance features (e.g., spectral reflectance, BRDF, translucency, polarization, texture, etc.)

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Sorting Scraps for Recycling