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)
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
Challenge: High-Dimensionality

- Spectral BRDF (Slice) for Per-pixel Classification

\[ f(\theta_i, \phi_i, \theta_o, \phi_o, \lambda) \]

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

\[ y = \mathbf{w}^T \mathbf{x} + b \]
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:

\[
\min \frac{w^T S_w w}{w^T S_b w} \quad \text{s.t.} \quad w^T w = 1
\]

SVM:

\[
\min \frac{1}{2} \|w\|^2 \quad \text{s.t.} \quad y_i (w \cdot x_i - b) \geq 1
\]

• Implement as the subtraction of two light patterns

\[ w = w^+ - w^- \]
LED-based Multispectral Dome

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

- more videos at the project webpage
Classification Result (95% accuracy)

- 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

\[ \sqrt{\frac{M}{2}} \leq G_r \leq \frac{M}{\sqrt{2}} \]

• 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**

噪声级别（%）

准确性（%）

SVM Light

Raw Measurements

**phenolic vs metal**

噪声级别（%）

准确性（%）

SVM Light

Raw Measurements
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

#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

<table>
<thead>
<tr>
<th>Controls</th>
<th>Signal Reconstruction</th>
<th>Detection/Recognition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coded Aperture</td>
<td>Extended DOF</td>
<td>Optimal coded imaging systems for detection/recognition</td>
</tr>
<tr>
<td>Coded Exposure</td>
<td>High Speed Imaging</td>
<td></td>
</tr>
<tr>
<td>Coded Light</td>
<td>Spectral Imaging</td>
<td></td>
</tr>
<tr>
<td>Coded Sensor</td>
<td>Light Field Capture &amp; Display</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>Image Relighting</td>
<td></td>
</tr>
<tr>
<td></td>
<td>BRDF Acquisition</td>
<td></td>
</tr>
<tr>
<td></td>
<td>...</td>
<td></td>
</tr>
</tbody>
</table>
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Both Color and BRDF are Useful
SNR Benefits: Simulation Results

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

![Graphs showing the effects of SNR benefits with different materials and noise levels.](Image)
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.]

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