Designing illuminant spectral power distributions for surface classification

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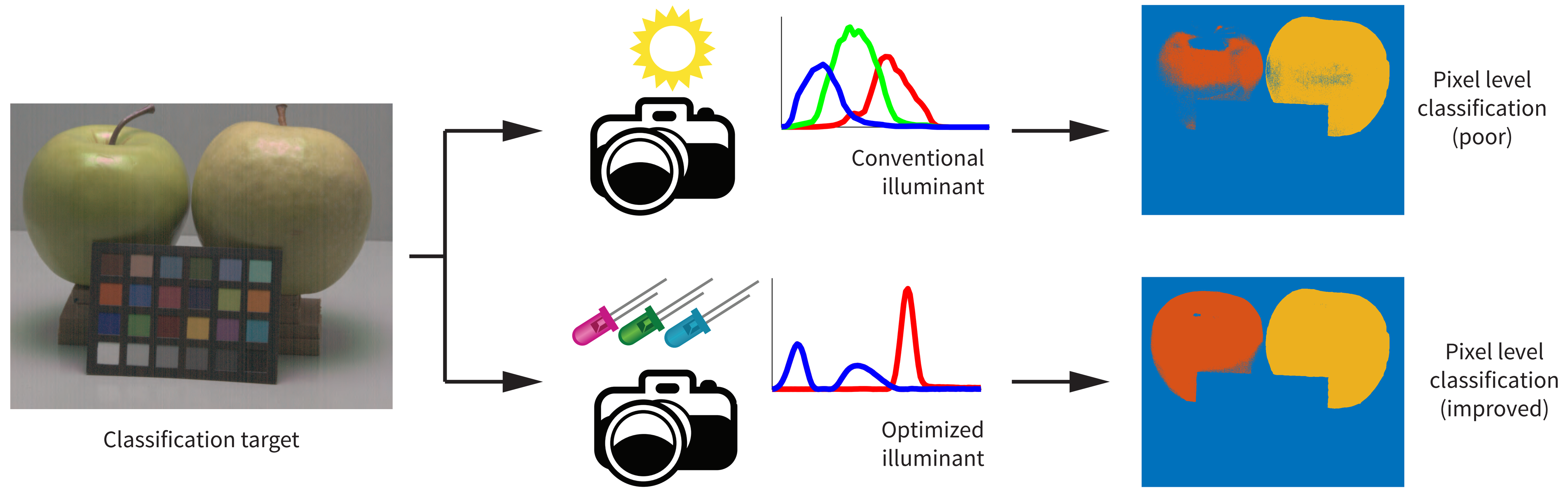
1. Introduction

Camera systems are often used for surface classification, rather than color reproduction (e.g., industrial inspection). In some of these conditions the illuminant spectral power distribution can be controlled. We describe two algorithms that select the illuminant spectral power distribution to optimize surface classification.



2. Camera as a projection operator

A pixel intensity m is a linear function of the surface reflectance r, illuminant x and pixel spectral responsivity function c

$$m_k = \int c(\lambda) r(\lambda) x_k(\lambda) d\lambda = \Delta\lambda c^T \mathbf{diag}(r) x_k = e^T x_k$$

The expected pixel response is computed by projecting the illuminant onto a reflectance-responsivity vector e. For a given camera, the pixel responsivity is fixed and known. Suppose we have a collection of surface reflectance spectra in the classification set, then the goal is to find an illuminant that maximizes the amount of information about r in m.

3. Unsupervised selection

Dimensionality reduction approach: find a set of projection directions (illuminants) that maximize the variance in the projected set of responsivity-reflectance vectors. Incorporate nonnegativity and spectral sparsity constraints to assure physical realizability of the computed directions.

Sparse Nonnegative Principal Component Analysis

1. Solve using ADMM

$$\begin{aligned} \text{maximize} \quad & \mathbf{tr}(\Sigma X) - \alpha \|X\|_1 \\ \text{subject to} \quad & 0 \preceq X \preceq I, \\ & \mathbf{tr}(X) = 1 \\ & X \geq 0 \end{aligned}$$

for optimal projection direction. The matrix Σ is the covariance of reflectance-responsivity vectors, and X is the outer product of the desired illuminant spectrum.

2. Deflate the covariance matrix.
3. Repeat 1 and 2 until the desired number of illuminants is found.

4. Supervised selection

Include camera image formation model directly into the pixel intensity based classifier training. Use alternating optimization over classifier weights and the desired illuminant spectra.

Classifier cost function; Decision boundary parameters; Class labels; Classifier and illuminant constraints; Illuminant spectra

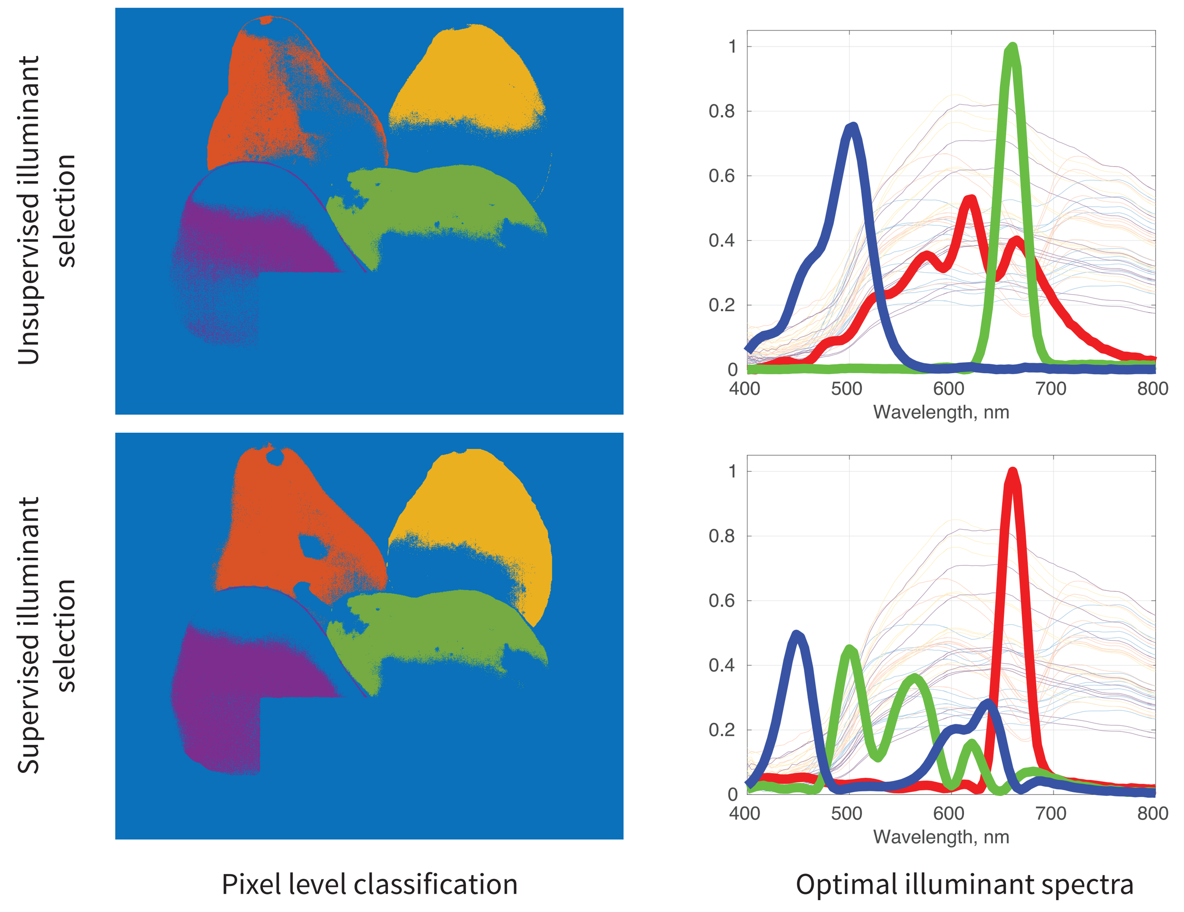
$$\begin{aligned} \underset{\theta, X}{\text{minimize}} \quad & f(\theta; X^T e, y) \\ \text{subject to} \quad & g(\theta, X^T e, y) \leq 0. \end{aligned}$$

5. Experiments

- Real vs. artificial fruit per-pixel classification experiments.
- Baseline: 34 RGB cameras and broadband illuminants.
- Proposed: Monochrome camera and optimal illuminants.
- Evaluation for different machine learning classifiers.

6. Results

The optimal illuminant spectra (thick lines) have energy concentrated at wavelengths with significant variability in the target reflectance spectra (thin lines).



The table provides quantifies pixel classification accuracy across different camera types and for different classification methods. Proposed methods outperform conventional approaches.

Camera	Classifier				
	SVM	KNN	DA	Tree	NB
RGB (worst)	75.2	78.4	74.9	73.6	66.0
RGB (avg.)	84.6	82.3	84.1	84.2	68.7
RGB (best)	85.6	83.3	85.3	85.8	72.7
Ours (Unsup.)	87.1	89.4	86.4	89.2	**83.7**
Ours (Sup.)	**91.5**	**92.6**	**91.2**	**91.2**	79.5

7. Conclusions

1. Conventional RGB cameras used with typical broadband illuminants are sub-optimal for surface classification tasks.
2. We describe two algorithms that optimize illuminant spectra for classification purposes. Imaging systems using these optimal lights outperform conventional RGB cameras and broadband illuminants in surface classification.
3. The methods we describe can also be used to analyze classification performance as a function of the number of illuminants and image acquisitions.