# Supplementary Materials

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## 1. Derivation of SNR Gain of the Proposed Discriminative Illumination Method

For the simplicity of derivation, let us assume a two-class linear classification task. If we use raw measurements of spectral BRDF for classification, we need to first sequentially acquire the $M \times 1$ measurements $\mathbf{x}$, and then perform linear classification based on a discriminative function $y = \mathbf{w}^T\mathbf{x} + b$. Assuming there is additive noise in the imaging system, the noise $\mathbf{n}$ is added to the measurement $\mathbf{x}$, *i.e.*, $y = \mathbf{w}^T(\mathbf{x} + \mathbf{n}) + b$. Assuming the variance of noise is $\sigma$, the SNR of using raw measurement is $\mathbf{w}^T\mathbf{x}/|\mathbf{w}|_2\sigma$.

For the discriminative illumination method, instead of $M$ measurements, we at most capture two images, *i.e.*, the images under $\mathbf{w}^+$ and $\mathbf{w}^-$. For fair comparison, we need to make sure that the total amount of incident light used is the same as the method of using raw measurements. Since when using raw measurements the total incident light energy is $M$, for discriminative illumination, the incident light should be scaled from $\mathbf{w}$ to $M\mathbf{w}/|\mathbf{w}|_1$. Therefore, the measured signal is $M\mathbf{w}^T\mathbf{x}/|\mathbf{w}|_1$. The additive noise is added to the measured signal.

- If read noise dominates, the SNR of the proposed method is $M\mathbf{w}^T\mathbf{x}/(\sqrt{2}\sigma|\mathbf{w}|_1)$ since there are two captured images. The SNR gain compared to the method of using raw measurements is $G_r = M|\mathbf{w}|_2/(\sqrt{2}|\mathbf{w}|_1)$.
- If photon noise dominates, the variance of the photon noise is $\sqrt{M}\sigma$, and thus the SNR is $M\mathbf{w}^T\mathbf{x}/(\sqrt{M}\sigma|\mathbf{w}|_1)$ The SNR gain compared to the method of using raw measurements is $G_p = \sqrt{M}|\mathbf{w}|_2/|\mathbf{w}|_1$.

Since $|\mathbf{w}|_1/M \leq |\mathbf{w}|_2/\sqrt{M} \leq |\mathbf{w}|_1/\sqrt{M}$, we have

$$\sqrt{M/2} \leq G_r \leq M/\sqrt{2}, \quad \text{and} \quad 1 \leq G_p \leq \sqrt{M}. \tag{1}$$

In the presence of both read noise and photon noise, the SNR gain is a combination of $G_r$ and $G_p$.

## 2. Discriminative Abilities of Spectral BRDF

Before we perform material classification with the multi-spectral dome, we want to understand how discriminative

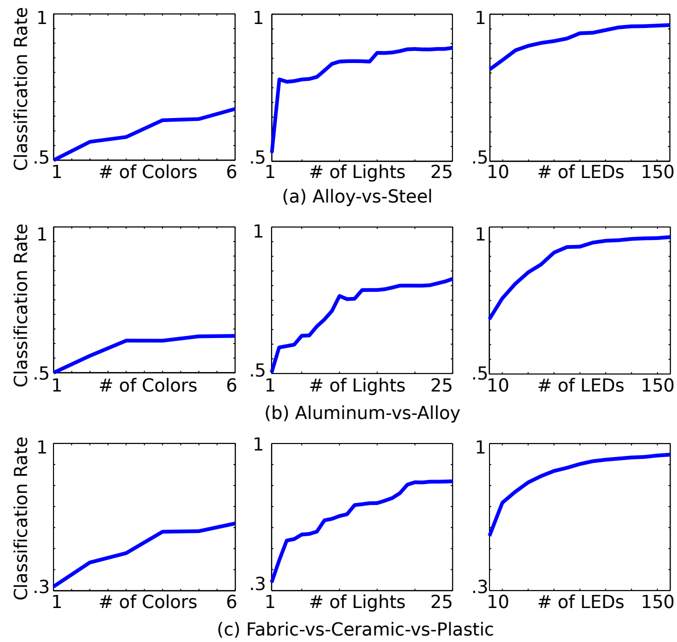


Figure 1. Discriminative ability of spectral BRDF for material classification. We evaluate the contribution of color and BRDF for material classification using three classification tasks, *i.e.*, (a) alloy-vs-steel, (b) aluminum-vs-alloy, and (c) fabric-vs-ceramic-vs-plastic. In each row, the left is the classification rate versus the number of colors used, which shows the performance based only on color. The middle shows the classification rate versus the number of incident light directions (*i.e.*, the number of LED clusters in which we use only the white LED in each cluster). This plot shows the performance based only on BRDF. The right shows the classification performance when we use both color and BRDF. As shown, color and BRDF are complimentary to each other for material classification. These plots also show that 6 colors, 25 LED clusters and 150 LEDs are necessary and sufficient, since the performance improvement (versus the number of colors, LED clusters and LEDs) saturates around these values.

the six color bands and the 25 incident light directions are for material classification. Thus, as shown in Figure 1, we perform simulations for three classification tasks, alloy-vs-steel, aluminum-vs-alloy, and fabric-vs-ceramic-vs-plastic. For each sample, we measure $25 \times 6 = 150$ images corresponding to the 150 LEDs in the dome. Thus each point on a sample plate has a $150 \times 1$ feature vector for classification. The left column of Fig. 1 shows the classification rates if we only use the color features for classification, *i.e.*, we turn on the LED of the same color in all the LED clusters. The curves show that as the number of color bands increase, the performance increases but soon reaches the limit. The middle column of Fig. 1 shows the classification rates if we only use the angular distribution of reflectance (*i.e.*, BRDF) for classification, *i.e.*, we use only white LEDs and disable all other color LEDs. Similarly, as the number of LED clusters increases, the performance increases white it saturates around 25. Finally, if we use both color and BRDF information, as shown in the right column of Fig. 1, the classification performance will further improve. These plots show that (1) color and BRDF are complimentary to each other for material classification, and (2) 6 colors, 25 LED clusters and 150 LEDs are necessary and sufficient, since the performance improvement (versus the number of colors, LED clusters and LEDs) saturates around these values.

## 3. Dealing with Surface Normals

As shown in [1, 2], the local coordinates and the global coordinates are related by a rotation corresponding to the surface normal. Thus, by tilting a flat sample plate at multiple angles, we augment the training data set with variants of the spectral BRDF feature vector. The learned discriminative illumination can then tolerate some normal variation for material classification.

Figure 2 shows a toy example which demonstrates the feasibility of the proposed idea in Section 6 to deal with surface normal variation for material classification. We create a sample with random surface normals (with $\pm 10$ degree variation in its tilt angle), as shown in Fig. 2(c). The sample consists of two BRDFs. Figures 2(a)(b) show the renderings of the two BRDFs, and Fig. 2(d) shows the distribution of the two BRDFs on the sample. With a conventional point light source, the appearance of the sample is shown in Fig. 2(e). Because of the random surface normal, it is difficult to separate the two BRDFs. Under the learned discriminative illumination, as shown in Fig. 2(f), the two BRDFs can be separated more accurately. Certainly, this approach will work within some range of surface normal variation, depending on the complexity of the BRDFs and classifiers.

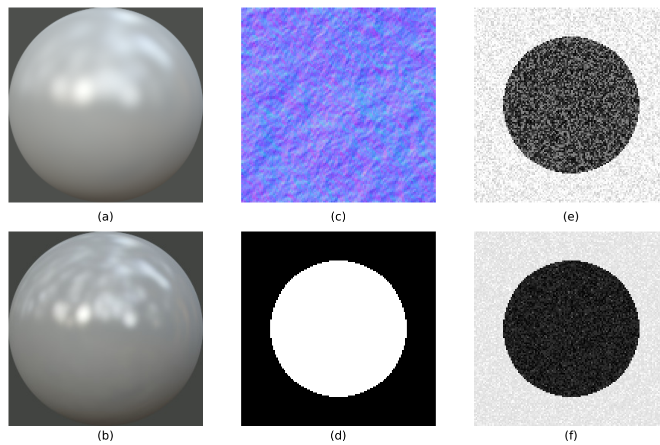


Figure 2. Preliminary simulation results of extending discriminative illumination for material classification with unknown surface normals. (a)(b) Renderings of two BRDFs under natural lighting. (c) A sample with random surface normal ($\pm 10$ degrees variation in the tilt angle, color coded). (d) The distribution of the two BRDFs on the sample. (e) Measured image under a point light, with which it is difficult to separate the two BRDFs. (f) Measured image under a discriminative illumination, with which we can separate the two BRDFs more accurately.

## References

[1] R. Ramamoorthi and P. Hanrahan. A signal-processing framework for inverse rendering. In *Proceedings of SIGGRAPH*, 2001. 2

[2] O. Wang, P. Gunawardane, S. Scher, and J. Davis. Material classification using BRDF slices. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2805–2811, 2009. 2