

# Material-Specific Chromaticity Priors

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## 1 Introduction

Recent advances in machine learning have enabled the recognition of high-level categories of materials with an accuracy of up to 80% [1]. With these techniques, we can construct a per-pixel material labeling from a single image. We observe that groups of materials have distinct chromaticity footprints (see Figure 1). We propose a novel combination of techniques, where we use a material classifier to predict the dominant material category of objects, which in turn is useful to constrain reflectances in the context of the intrinsic images problem [2]. Preliminary evaluation indicates our method has promise. In Figure 1, the chromaticities in YUV color space plotted in heatmap colors, from random samples of different material categories. Blue represents UV values that are the least frequent, red those that are the most frequent. The plots show that various subgroups of materials have different characteristics. Plastic has a much wider range of chromaticity values than sky. Wood spans a limited range of unsaturated colors, while metal has quite a few outliers due to strong specular reflections. This suggests we can use knowledge of the material in a scene to predict the chromaticities and thereby improve estimation of the underlying reflectance.

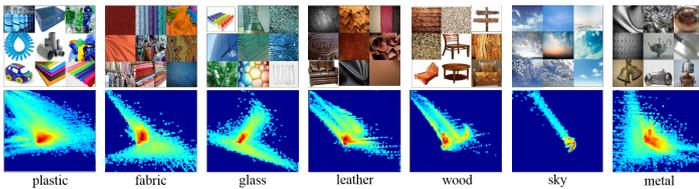


Figure 1: Chromaticity plots in heatmap colors.

## 2 Our approach

Figure 2 gives an overview of our method. Using recent deep learning techniques, we segment objects in areas of homogeneous materials. We assign a material label to each pixel in these regions. Areas with different materials form islands within the space of chromaticity distributions. If the category is known, it makes sense to use this knowledge to properly constrain the chromaticity values and place more stringent priors on the reflectance of segmented objects parts.

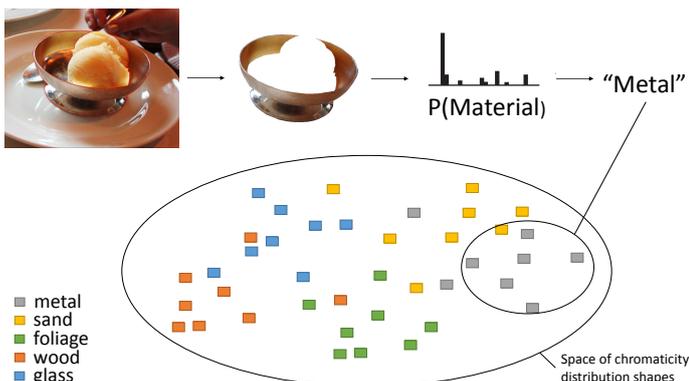


Figure 2: Birds-eye overview of our approach: using material classification to predict the chromaticity distribution, which in turn constrains reflectance for intrinsic image decomposition.

Preliminary evaluation of our method on the MIT dataset is shown in Table 1 and Figure 3. It shows the MSE error metric of the estimation and the ground truth data. The normal prior trains chromaticity on 10 other images from the MIT dataset. Our method trains the chromaticity prior on images from specific material categories in OpenSurfaces and consistently performs better.

Table 1: Preliminary evaluation of our method on the MIT dataset, showing the MSE error metric of the estimation and the ground truth data. The best scores are in bold. Less error is better.

	normal prior MSE	material-specific prior MSE	Difference
cup2	25.8316	<b>22.4774</b>	14.92%
frog2	35.4718	<b>29.8646</b>	18.77%
paper2	33.3270	<b>30.0913</b>	10.75%
pear	31.8777	<b>27.6916</b>	15.11%
potato	29.2384	<b>26.2526</b>	11.37%
raccoon	27.5501	<b>24.2536</b>	13.59%
sun	36.1633	<b>32.7922</b>	10.28%
teabag1	43.5110	<b>37.6781</b>	15.48%
squirrel	40.1366	<b>35.4141</b>	13.34%

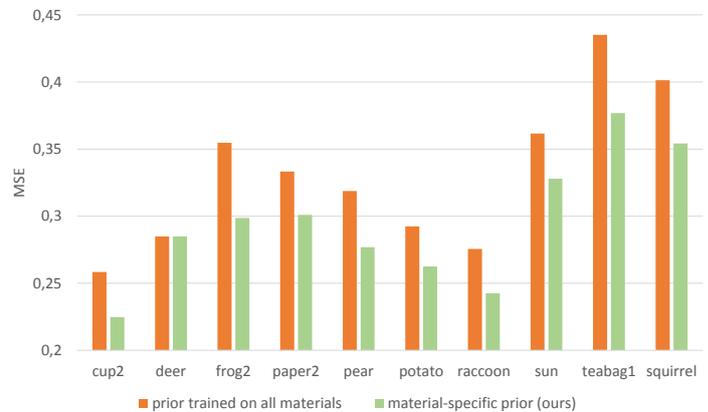


Figure 3: Graph of the error left after optimization. Less is better. Our method of training on specific materials consistently outperforms training on all materials.

This prior is useful in the context of intrinsic image decomposition, where it can be used to constrain reflectance estimation. Table 1 contains preliminary evaluation results on the MIT intrinsic images dataset [2].

[1] Sean Bell, Paul Upchurch, Noah Snavely, and Kavita Bala. Material recognition in the wild with the materials in context database. *Computer Vision and Pattern Recognition (CVPR)*, 2015.

[2] Roger Grosse, Micah K. Johnson, Edward H. Adelson, and William T. Freeman. Ground-truth dataset and baseline evaluations for intrinsic image algorithms. In *International Conference on Computer Vision*, pages 2335–2342, 2009. doi: <http://dx.doi.org/10.1109/ICCV.2009.5459428>.