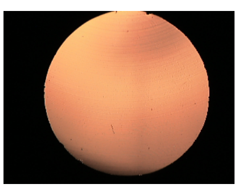
# Reflectance Hashing for Material Recognition

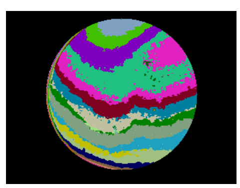
Hang Zhang[1] Kristin Dana[1] Ko Nishino[2]
[1]Department of Electrical and Computer Engineering, Rutgers University. [2]Department of Computer Science, Drexel University.

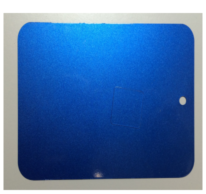
Prior methods for material recognition use two distinct approaches. One approach assesses material identity using reflectance as an intrinsic property of the surface [2, 5, 8]. Another main approach identifies material labels using the appearance of the surface within the real world scene [6, 7, 9]. Using reflectance instead of scene appearance has the advantage that reflectance is a direct measurement of the material characteristics, instead of its phenomenological appearance [1]. Reflectance is mostly unique to the material, whereas the appearance is the convoluted end result of the interaction of all the intrinsic and extrinsic factors and thus more difficult to decipher.

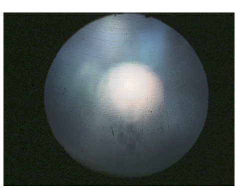
Our approach uses reflectance for material recognition. However, we bypass the use of a gonioreflectometer by using a novel one-shot reflectance camera based on a parabolic mirror design [3]. The output of this camera is a *reflectance disk*, a dense sampling of the surface reflectance of the material projected into a single image as shown for two example surfaces in Figure 1. The pixel coordinates of these reflectance disks correspond to the surface viewing angles. The reflectance has class-specific stucture and angular gradients computed in this reflectance space reveal the material class. We encode the discriminative optical characteristics of materials captured in the reflectance disks with a texton-based representation to achieve gradient in angular space. We incorporate the utility of boosting to identify a discriminitive and compact representation. We address the issue of high dimensionality using a novel application of binary hash codes to encode reflectance information in an efficient yet discriminative representation. The key idea is to obtain sufficient sampling of the reflectance with enough discriminative power and reduce its representation size so that it can be effectively used for probing the material.


(a) Leather Surface


(b) Reflectance Disk


(c) Texton Map


(d) Auto Paint Surface


(e) Reflectance Disk

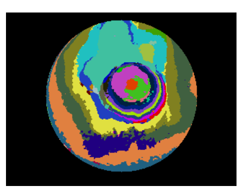

(f) Texton Map

Figure 1: Reflectance disks provide a quick snapshot of the intrinsic reflectance of a surface point. Gradients of the reflectance space are captured with textons and provide a signature for material recognition.

We present a database of reflectance disks comprised of twenty different diverse material classes including wood, velvet, ceramic and automotive paint with 10 spot measurements per surface and with three different surface instances per class. Measurements include three on-axis illumination angles and ten random spot measurements over the surface. Each spot measurement is a reflectance disk composed of a dense sampling of viewing angles totaling thousands of reflectance angles per disk. The database of 3600 images or reflectance disks is made publicly available.

We introduce *reflectance hashing*, a new method that combines binary hash coding and texton boosting, for efficient and accurate recognition of materials. Reflectance hashing is based on features selected in many iterations (700) and uses iterative quantization [4] as the binary embedding method. The overall recognition rate is 92.3%, and several individual class recognition rates are significantly higher than the traditional boosting method. From the empirical results shown in Figure 2, we see that reflectance hashing recognition rate reaches around 90% when using 128 or 256 bit codes. The method of ITQ gives the best results for this material recognition task. These results demonstrate the effectiveness of using reflectance for fast sensing and recognition of real-world materials.

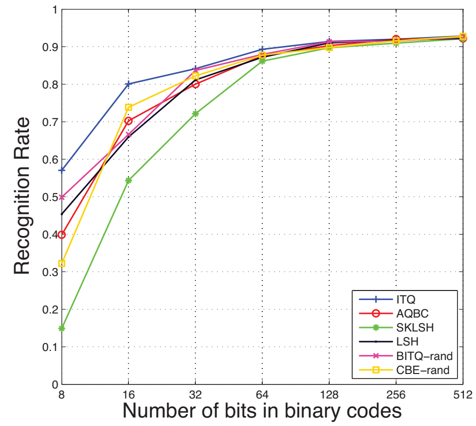



Figure 2: Accuracy of nearest neighbor search and recognition rate as a function of the number of code bits for the binary embedding with 10 nearest neighbors. Several binary embedding methods have been evaluated.

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This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.