Dictionary-based BRDF Inference for Material Editing Network

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1. Summary

Editing materials of objects in image is an important yet challenging topic in computer vision and computer photography. Recently, There has been a rising interest in solving material editing problem by designing an end-to-end network architecture that first disentangles intrinsic properties from the given image, i.e. shape, illuminance, and material, and then feeds the predicted intrinsics to a physically rendering layer to accomplish the task. Different from previous works [2], which infer object material by exploiting a parametric BRDF model, I plan to pursue a dictionary-based approach, utilizing materials from MERL BRDF dataset [3] as the dictionary, combined with coefficients predicted by a deep neural network, as the material estimation of the given image.

Multiple BRDF models, as well as scattering, interreflection models will be learned. Differentiable physical rendering layer that replicates the image formation process will be learned. Deep learning tools such as Pytorch will be learned.

2. Background

Material editing has always been an interesting and important topic in computer vision and computational photography due to both its practical value. In the case of 2D design, many artists would like to effortlessly change the materials of objects. Even with a single 2D image of an object, material editing technique allows them to synthesize a new image that depicts the desired material.

However, material editing is an extremely challenging task as it requires to disentangle intrinsic physical properties from a single image. The intrinsic image decomposition itself has a large ambiguity since different combinations of shape, illumninance, and material can result in the same image. Early work mostly assumes at least one of these unknowns to be given. More recently, with the success of learning based methods, researchers turn their attention to more difficult settings, to assume no prior knowledge about any of the intrinsics properties to be given, and infer priors directly from data via a deep learning based approach. In this project, I will make the assumption that all intrinsic properties are unknown and predict shape, illuminance, and material simultaneously from the given single image.

3. Resources

- Dataset: (1) Training and testing dataa: Available dataset as described in [2] can be accessed through email. The available dataset is expected to have images of different combinations of 280 3D models, 80 different materials, and at least 10 HDR environment maps. (2) Dictionary: MERL BRDF dataset [3] which is public online will be used to form BRDF dictionary.

- Starter code: Currently, there's no public implementation of network architecture in [2]. I will try to contact the authors for starter code, if they are unable to provide the implementation, I will implement the network from scratch.

- Hardware: one available TITAN X GPU.

- Differentiable renderer in [1] might be needed if there's time for the extended goal. Would really appreciate it if the instructor could provide access to the renderer.

4. Goals and Deliveriables

- 50% Goal: implement the network architecture in [2] and reproduce their experimental results.

- 100% Goal: propose dictionary-based material prediction module, implement module, and explore different priors to optimize the results.

- 150% Goal: not only modeling BRDF, but also consider scattering. Possibly need the rendering engine.

5. Schedule

- <u>Nov. 2nd</u> Prepare training and testing datasets.

- <u>Nov. 9th</u> Implement network architecture in [2].

- Nov. 16th Reproduce experiment results mentioned in [1] as baseline to be compared to.
- Nov. 23rd Design and implement dictionary-based BRDF inference model. Explore effective priors.
- Nov. 30th Implement dictionary-based BRDF inference module and experiments.
- Dec. 7th Improve experiment results and possible extensions.
- Dec. 14th Prepare presentation slides and final reports.

References

[1] C. Che, F. Luan, S. Zhao, K. Bala, and I. Gkioulekas. Inverse transport networks. *arXiv preprint arXiv:1809.10820*, 2018.

[2] G. Liu, D. Ceylan, E. Yumer, J. Yang, and J.-M. Lien. Material editing using a physically based rendering network. In *Computer Vision (ICCV), 2017 IEEE International Conference on*, pages 2280–2288. IEEE, 2017.

[3] W. Matusik, H. Pfister, M. Brand, and L. McMillan. A data-driven reflectance model. *ACM Transactions on Graphics*, 22(3):759–769, July 2003.