Rebuttal: Multispectral Image Intrinsic Decomposition via Low Rank Constraint

Thank you for the insightful review. In this rebuttal, we claim some major comments as follows.

The contribution. (#R3) We'd like to clarify the contributions of the paper: 1. The low rank constraint is proposed for multispectral image intrinsic decomposition (MIID), which outperforms state-of-the-art algorithms in multispectral scenarios (as #R3 suggests, much more experimental validation is provided in the rebuttal material); 2. A MIID dataset with ground-truth is provided, which facilitates future researches on MIID problem.

Global constraint. (#R1, #R3) Thanks for the advise on building the algorithm on most recent techniques with global constraint. In fact, the high dimension of multispectral data would complicate the global constraint and bring tremendous computation cost than traditional RGB case. We will implement the global constraint with more computational efficiency (e.g. parallel design) in the near future.

Initial estimation. (#R1) Thanks for pointing out the importance of the initial estimation. The initial estimation is designed by assuming that the reflectance image has small deviation from the input image. We derive the bias distribution from MIT intrinsic dataset [3] and our MIID dataset, and the biases follow an heavy-tailed distribution with zero mean, and most biases are distributed near zero, which validate the assumption.

As to the illumination problem, there exist several promising methods to estimate illumination from a single multispectral image [4] and [2]. These methods could provide the prior knowledge of the illumination and facilitate the following estimation.

Also, thanks for pointing out our problem on parameter sensitivity. Fortunately, once the parameters are pre-optimized in a given data category, the estimation performance stays stable.

Low rank method. (#R2, #R3) We thank #R3 for suggesting to apply the algorithm in the logarithmic domain other than the image domain. We have compared with the baseline algorithm on both log-domain and image domain, the results show that image domain method achieves better results. We would like to explore low-rank property in log domain in the future.

Thanks for the advice of #R2 and we conducted an experiment to compare the performance of selecting 8 'best' bands with proposed PCA-based method. We compute structural similarity index (SSIM) distances between bands and select a least similar band with minimum average SSIM each time, until we get 8 'best' bands. The results show that the PCA-based methods achieves about 38% higher performance than selecting 8 'best' bands. We think this is because in the linear case, the PCA-based selection can also be regarded as the 'best' bands selection theoretically, which is a coincidence of the reviewer's suggestion.

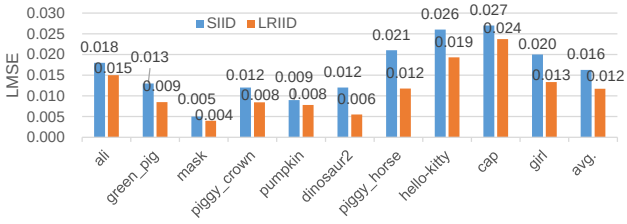

Figure 1. LMSE performance of SIID and our LRIID algorithm on our newly-captured dataset images.

Experiments. (#R3) In order to better illustrate the performance of the proposed method, both RGB counterpart on the MIT benchmark and more captured MIID dataset are provided. To enrich our dataset, we add 10 more groups of dataset in one week rebuttal. Furthermore, we also compare our algorithm with the latest SIID algorithm [1] on both their SIID dataset [1] and our newly-captured database (Fig. 1), the results demonstrate that our results are better both qualitatively and quantitatively on such extensive and more diverse datasets (MIT benchmark; 10 more MIID data; Comparison on SIID dataset).

Limiting by the page size, please find more dataset and results here: https://anonymouskids.github.io.

Typos. (#R2, #R3) Thanks for pointing out the typos and we already corrected them.

References

[1] X. Chen, W. Zhu, Y. Zhao, Y. Yu, Y. Zhou, T. Yue, S. Du, and X. Cao. Intrinsic decomposition from a single spectral image. *Applied Optics*, 56(20):5676–5684, 2017. 1

[2] M. S. Drew and G. D. Finlayson. Analytic solution for separating spectra into illumination and surface reflectance components. *JOSA A*, 24(2):294–303, 2007. 1

[3] R. Grosse, M. K. Johnson, E. H. Adelson, and W. T. Freeman. Ground truth dataset and baseline evaluations for intrinsic image algorithms. In *IEEE International Conference on Computer Vision*, pages 2335–2342, 2009. 1

[4] Y. Zheng, I. Sato, and Y. Sato. Illumination and reflectance spectra separation of a hyperspectral image meets low-rank matrix factorization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1779–1787, 2015. 1