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Research Article

Lighting Transfer across Multiple Views through Local Color Transforms - Supplementary Document

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1 Description of this document

Color spaces. We learn the color transforms in the RGB space. Learning and propagating color transforms in different color spaces yields a different result. We show the influence of color space choices in Fig. 1, the output of RGB space has the fewer color artifacts compared to other color spaces.

Local linear model and affine model. We show a comparison between the locally linear model [2] and affine model [4] with results of two datasets. The case of real scene (Fig. 2) shows that the image generated by affine model appears a bit blurry, whereas the result of linear model looks visually sharper. On the other hand, the quantitative analysis on the synthetic scene (Fig. 3) shows there is no significant difference between the accuracy of both models. Therefore, we choose the linear transforms for better visual appearances.

Compare to Shih et al. In Fig. 4, we compare our result to Shih et al. [4], which uses a database of 495 time-lapses videos for time hallucination. Their result image is a synthesis of the "blue hour", we obtained it directly from their supplementary document.To match their comparison, we generate a result with the same target image of Laffont et al. [1]. All results are plausible, but Laffont et al. and our results have the lighting transfered from a specific target. In addition, our method do not require image decomposition, which is a time-consuming part in Laffont et al's work.

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Compare to deep learning style transfer. In Fig. 5, we compare our result to deep photo style transfer [3], which uses deep-learning approach for photographic style transfer. We run the code on author's github and generate images of 230px width due to limited GPU resources. The segmentation masks are produced manually by us. All the images are 230 pixel wide for fair comparison. While their method transfers the source images to a style close to the targets, our results have fewer color artifacts.

2 Accompanying video

We show photo collections of harmonized lighting and synthetic time-lapses generated by our method in the video (Section 4 Applications). Results of two scenes are shown in the video, i.e. Manarola and FluorenceDuomo. For each scene, we generate harmonized images of two different lighting, and one time-lapse video made from linearly interpolated result images. We also include a side-by-side comparison with Laffont et al. [1].

References

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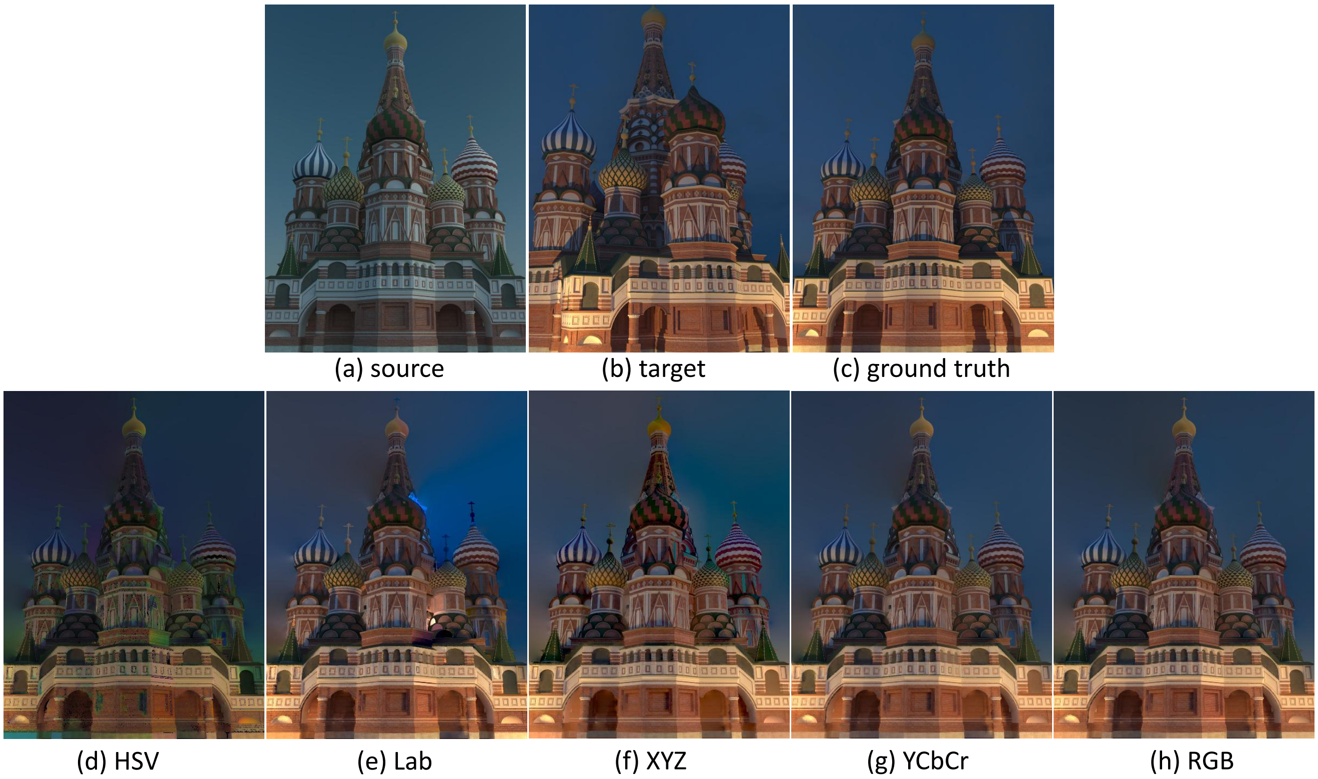

Fig. 1 We show RGB color space is a better choice for learning local transforms among other spaces, e.g., HSV, Lab, xyz, and YCbCr. The result of RGB space has fewer color artifacts compared to others.

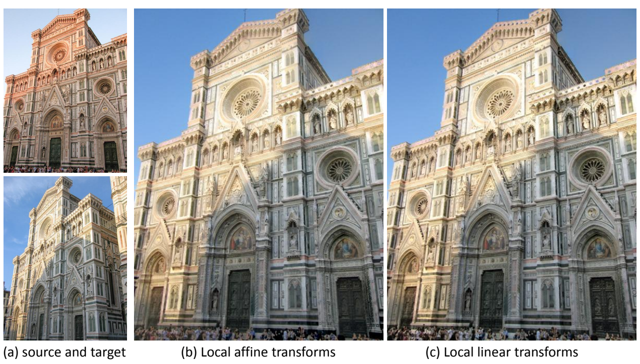

Fig. 2 Results of linear model and affine model on real scene. We show that the image generated by affine model appears a bit blurry, whereas the result of linear model looks visually sharper.

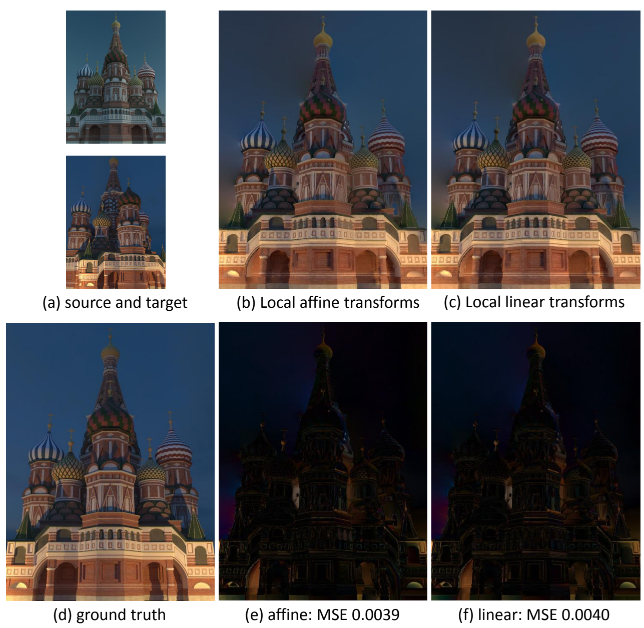

Fig. 3 Results of linear model and affine model on synthetic scene. Quantitative analysis shows there is no significant difference between the accuracy of both models.

Fig. 4 Comparison to Shih et al. We obtained the synthetic ”blue hour” image (c) directly from their supplementary document. To match their result, we generate an output with the same target image of Laffont et al (b). All results are plausible, but ours (d) and Laffont et al's have the specific lighting transfered from a target. In addition, our method do not require image decomposition, which is a time-consuming part in Laffont et al's work.

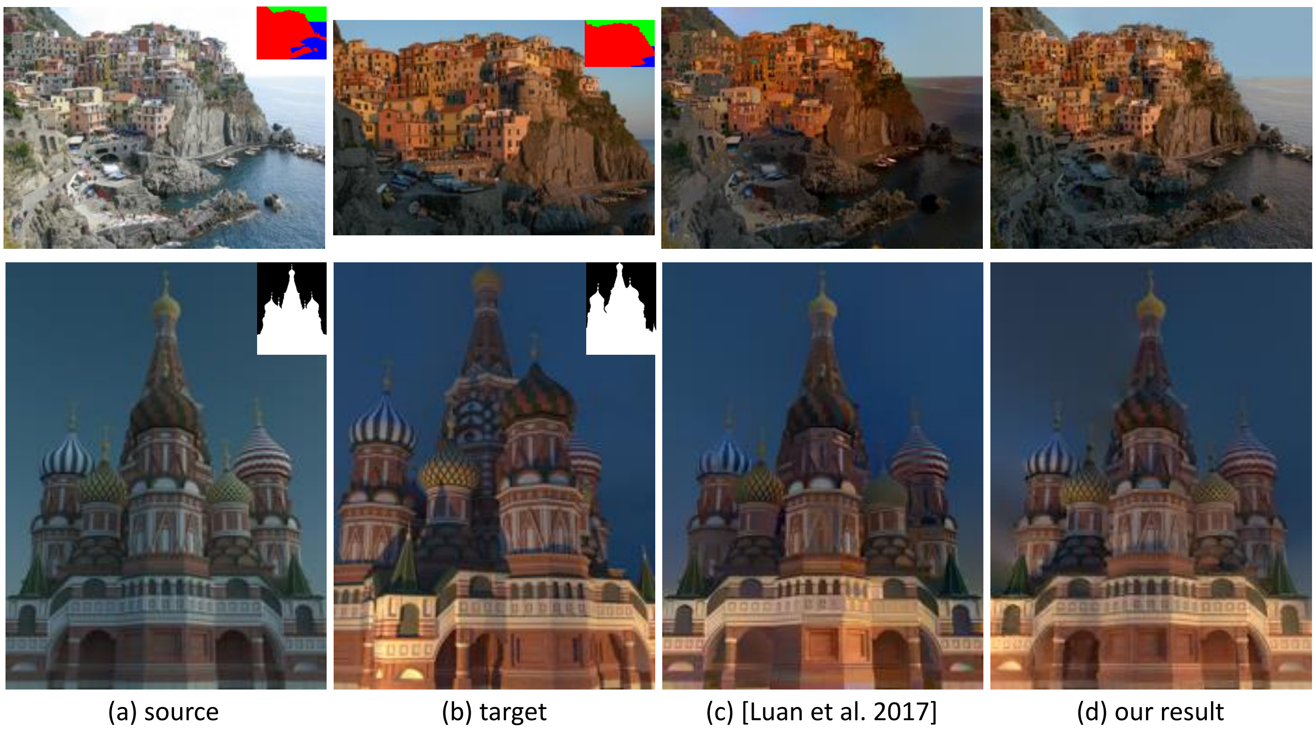

Fig. 5 Comparison to the work of Luan et al, which uses deep-learning approach for photographic style transfer. While their method transfers the source images to a style close to the targets, our results have fewer color artifacts.