Supplementary Figures for Unmixing-Based Soft Color Segmentation for Image Manipulation

YAĞIZ AKSOY
ETH Zürich and Disney Research Zürich
TUNÇ OZAN AYDIN and ALJOŠA SMOLIĆ
Disney Research Zürich
and
MARC POLLEFEYS
ETH Zürich

In this document, we present several extra figures and extensions of figures in the main document in Figures 1-5. In addition, we present additional results of our method in comparison with KNN [Chen et al. 2013], CU [Aksoy et al. 2016], ML [Singaraju and Vidal 2011], AO [Tai et al. 2007], and SM [Levin et al. 2008] methods, in the same format as in Figure 12 in the main publication in Figures 6-9.

As we discuss in detail in Sections 4 and 6 of the main publication, various deficiencies of the methods we compare ourselves against tend to produce certain types of visual artifacts consistently over many images. As such, the comparisons we present here do not reveal additional problems or visual artifacts, but rather support our point that current methods have fundamental shortcomings, which consistently manifest themselves as characteristic visual artifacts.

We strongly advise to read Section 7, as well as the theoretical analysis in Section 4, before analysing Figures 6-10 in this document. Here, we assume that the reader has already a good understanding of the competing methods and the various problems associated with them. For brevity, we list a number of points below that are valid for Figures 6-10. In the caption of each figure, we highlight certain interesting cases for individual images.

—ML and SM put too much emphasis on spatial connectedness, and hence produce worse soft *color* segmentation results.

—AO suffers from color homogeneity issues, as well as producing hard edges at layer transitions.

—CU similarly encounters spatial coherency problems, which result in hard edges in regions where layers overlap. Also, the lack of matte sparsity results in the emergence of spurious small alpha values where the alpha values should be zero.

—KNN fails to satisfy the color constraint (Equation 1 in the paper).

—Especially AO and KNN suffer from prohibitively long runtimes, as analyzed in Figures 10 and 11 of the main publication.

—All competing methods require the size of their color-model (and thus the number of layers) as an a priori user defined parameter. Our method on the other hand operates fully automatically.

—Color models estimated by AO or GMM tend to have very high color variance.

—K-means and GMM color models often miss distinct colors especially if they only cover small areas in the image.

Note that a total of 100 comparisons are provided as supplementary material.

REFERENCES

AKSOY, Y., AYDIN, T. O., POLLEFEYS, M., AND SMOLIĆ, A. 2016. Interactive high-quality green-screen keying via color unmixing. *ACM Trans. Graph. 35,* 5, 152:1–152:12.

CHANG, H., FRIED, O., LIU, Y., DIVERDI, S., AND FINKELSTEIN, A. 2015. Palette-based photo recoloring. *ACM Trans. Graph. 34,* 4, 139:1–139:11.

CHEN, Q., LI, D., AND TANG, C.-K. 2013. KNN matting. *IEEE Trans. Pattern Anal. Mach. Intell. 35,* 9, 2175–2188.

LEVIN, A., RAV-ACHA, A., AND LISCHINSKI, D. 2008. Spectral matting. *IEEE Trans. Pattern Anal. Mach. Intell. 30,* 10, 1699–1712.

SINGARAJU, D. AND VIDAL, R. 2011. Estimation of alpha mattes for multiple image layers. *IEEE Trans. Pattern Anal. Mach. Intell. 33,* 7, 1295–1309.

TAI, Y.-W., JIA, J., AND TANG, C.-K. 2007. Soft color segmentation and its applications. *IEEE Trans. Pattern Anal. Mach. Intell. 29,* 9, 1520–1537.

TAN, J., LIEN, J.-M., AND GINGOLD, Y. 2016. Decomposing images into layers via rgb-space geometry. *ACM Trans. Graph. 36,* 1, 7:1–7:14.

Fig. 1. The layers extracted by the proposed algorithm together with the seed points and the color models. Original images by Flickr user Mike Kniec (left) and Death to the Stock Photo.

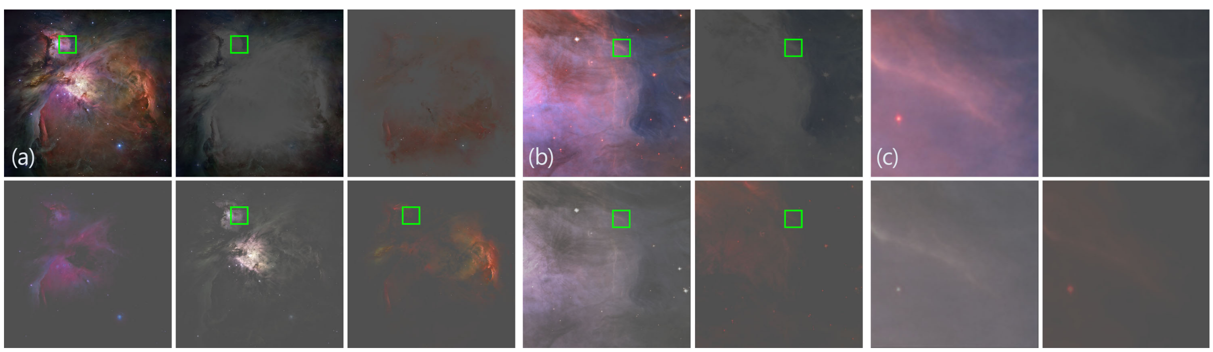

Fig. 2. Our algorithm is able to process a 100MP image to get corresponding soft layers (a) thanks to our per-pixel formulation and matte regularization by guided filtering. (b) and (c) show insets from the input layer and three of the layers at 10x and 100x magnification. This image was processed in 4 hours using up to 25 GB of memory. Note that KNN and AO can only process a 2.5MP image within the same time budget, and SM requires more than 25 GB of memory for a 5MP image.

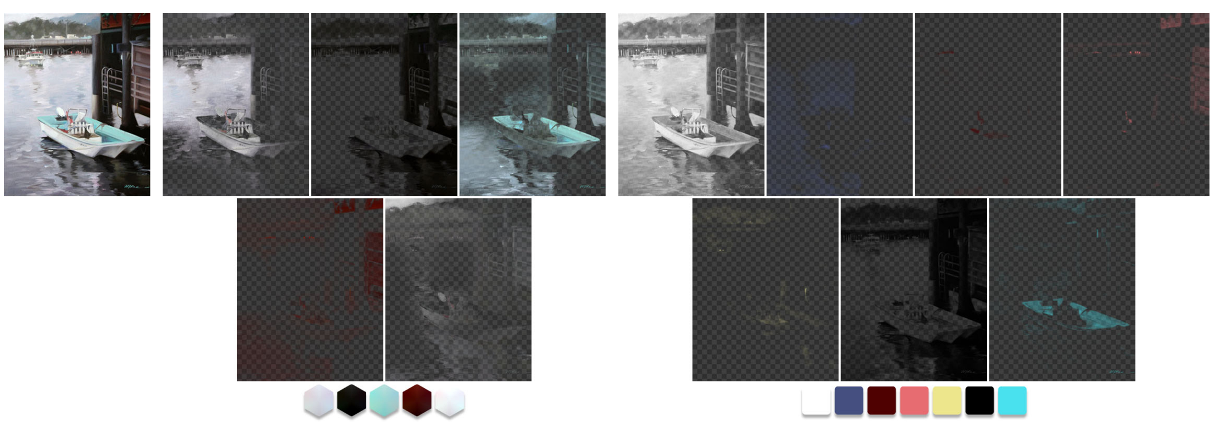

Fig. 3. The soft color segments produced by the proposed algorithm (left) and by the method by Tan et al. [2016] (right). The layers by Tan et al. [2016] have been converted to alpha-add representation from overlay representation (see the appendix) for a more meaningful comparison. This figure is an extension of Figure 13 in the main document.

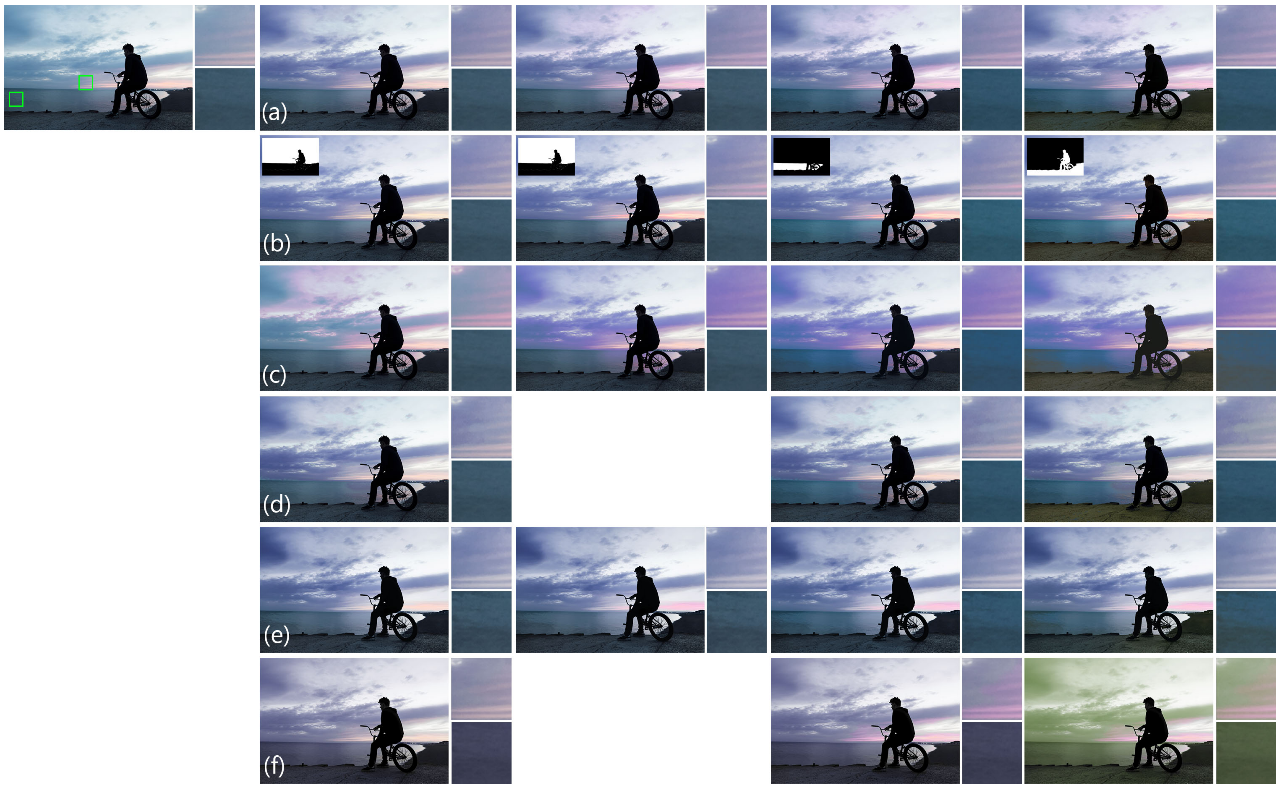

Fig. 4. Step-by-step editing of the image on the left in Adobe Photoshop using our layers (a), by a professional artist using only Adobe Photoshop (b), using the palete-based image editing tool by Chang et al. [2015] (c), and the layers computed by AO [Tai et al. 2007] (d), KNN [Chen et al. 2013] (e), and RGBSG [Tan et al. 2016] (f). AO and RGBSG rows lack one step each (the color of the sunset for AO and the color of the sea for RGBSG) because the layers corresponding to the intended edits did not exist in their color model. This figure is an extension of Figure 17 in the main document. Original image by Death to the Stock Photo.

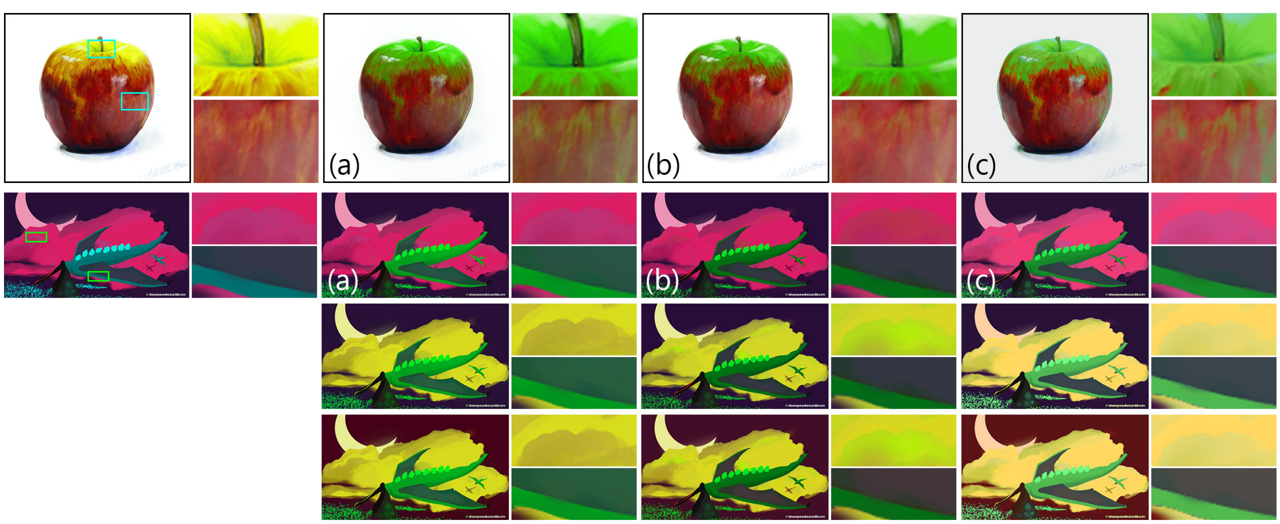

Fig. 5. Color editing results using our layers (a), layers by Tan et al. [2016] (b) and using the recoloring application by Chang et al. [2015] (c) on images used by Tan et al. [2016] and Chang et al. [2015] in their papers. This figure is an extension of Figure 18 in the main document.

Fig. 6. Note that KNN does not retain the actresses lips in the magenta layer (5). This results in violating the color constraint, see Figure 5 in the main paper. The orange layer (4) of CU vs. ours clearly shows the effect of matte sparsity. Also note how the K-means color model completely misses the magenta color in the image. Original image by Flickr user Jason Bolonski.

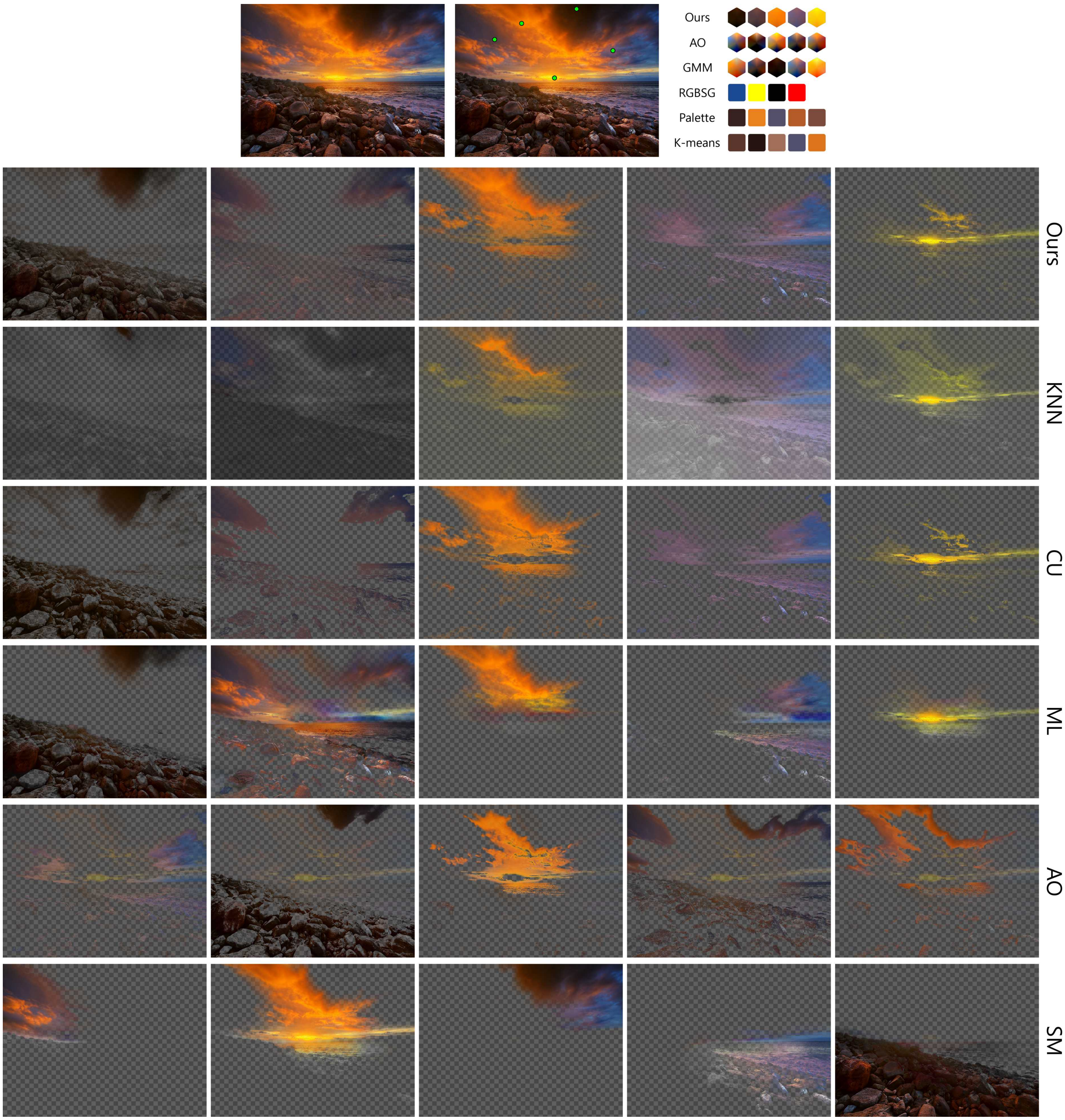

Fig. 7. Note how KNN produces layers with lower color homogeneity in comparison to our method. Original image by Flickr user Paul Bica.

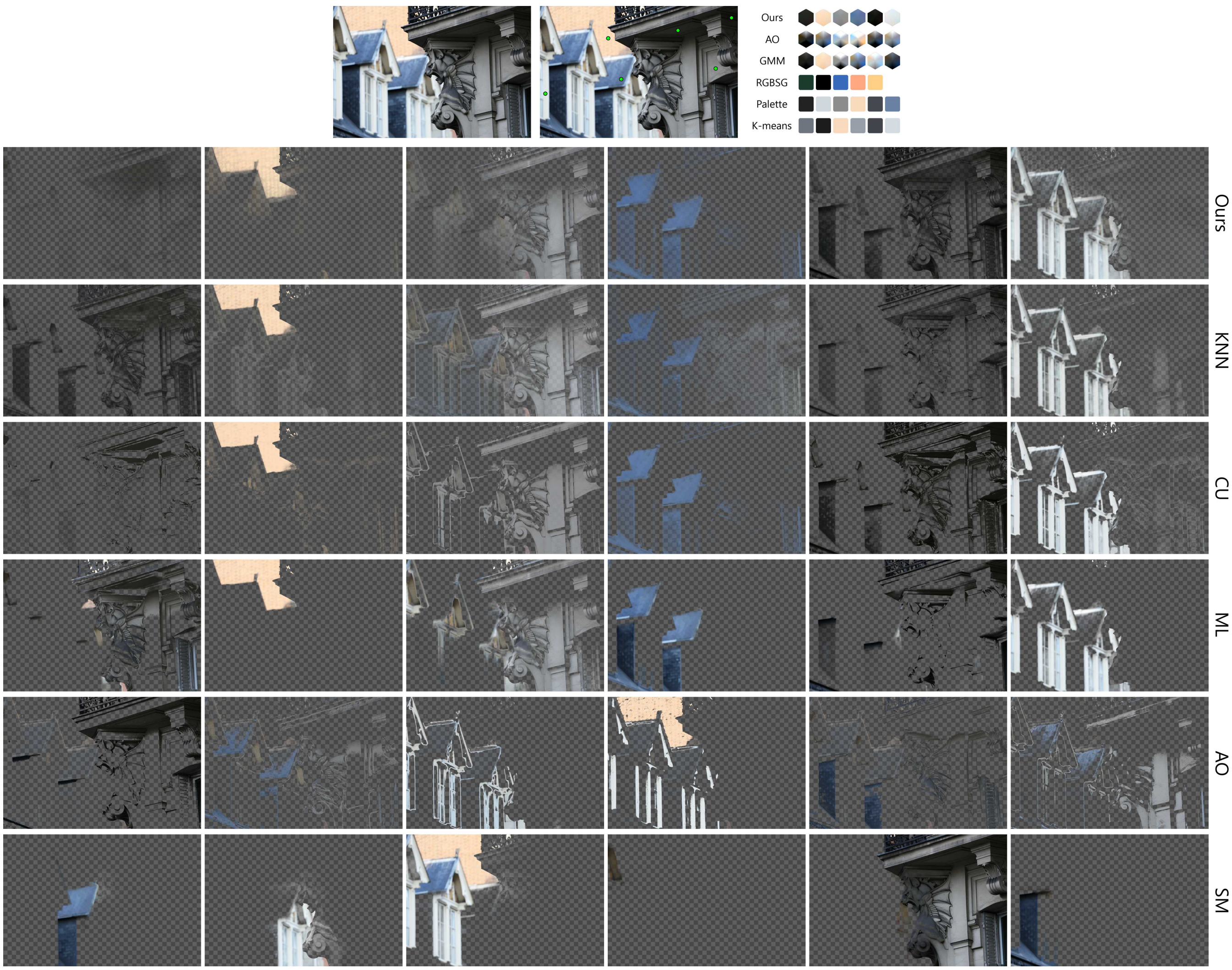

Fig. 8. Note that CU's white layer (6) has erroneous small alpha values distributed on the right hand side, where the layer should have been fully transparent. KNN has issues with color homogeneity in layers (3) and (4). Original image by Flickr user taymtaym.

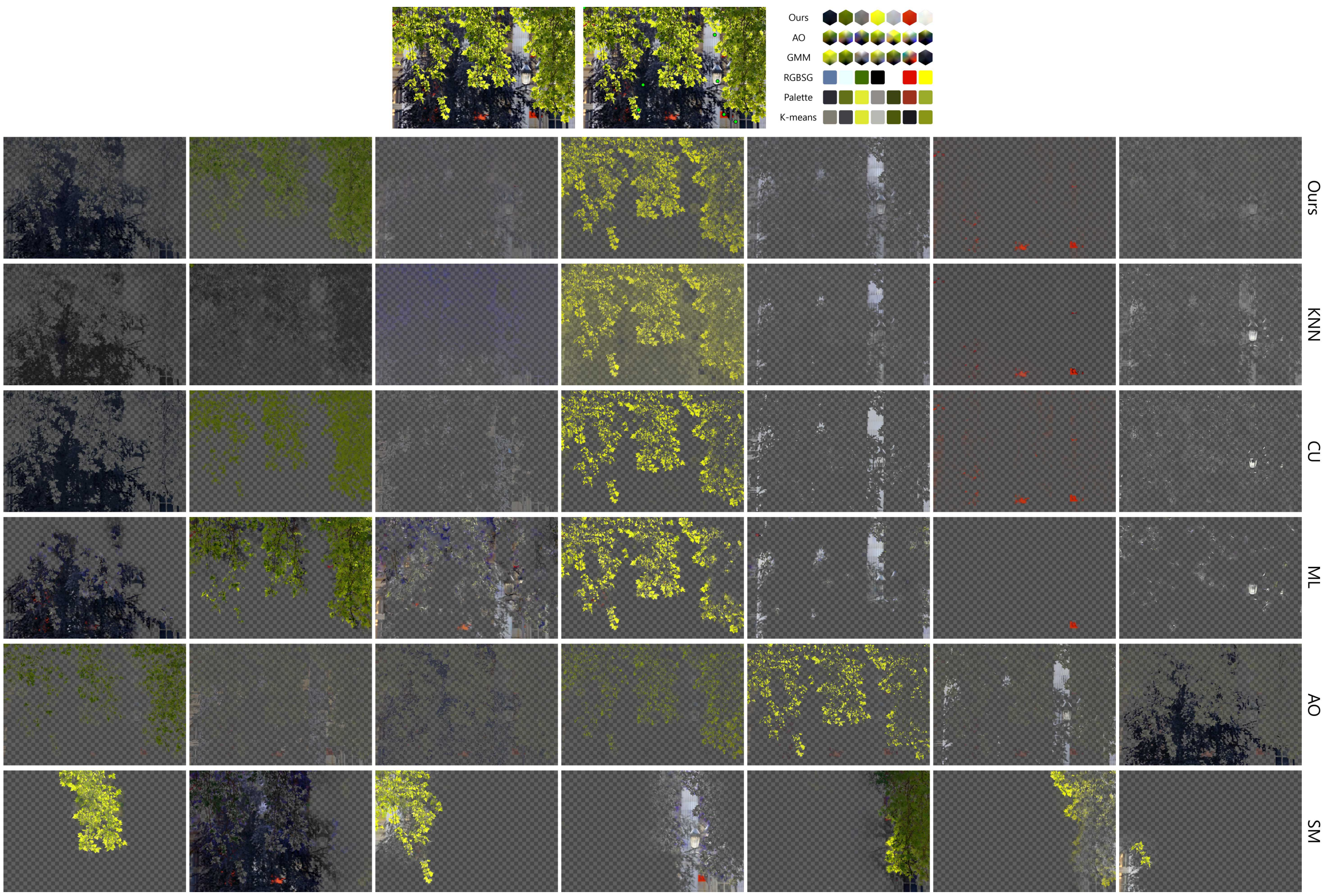

Fig. 9. Note the color homogeneity issues of KNN, especially in layers (3) and (4). Original image by Flickr user taymtaym.

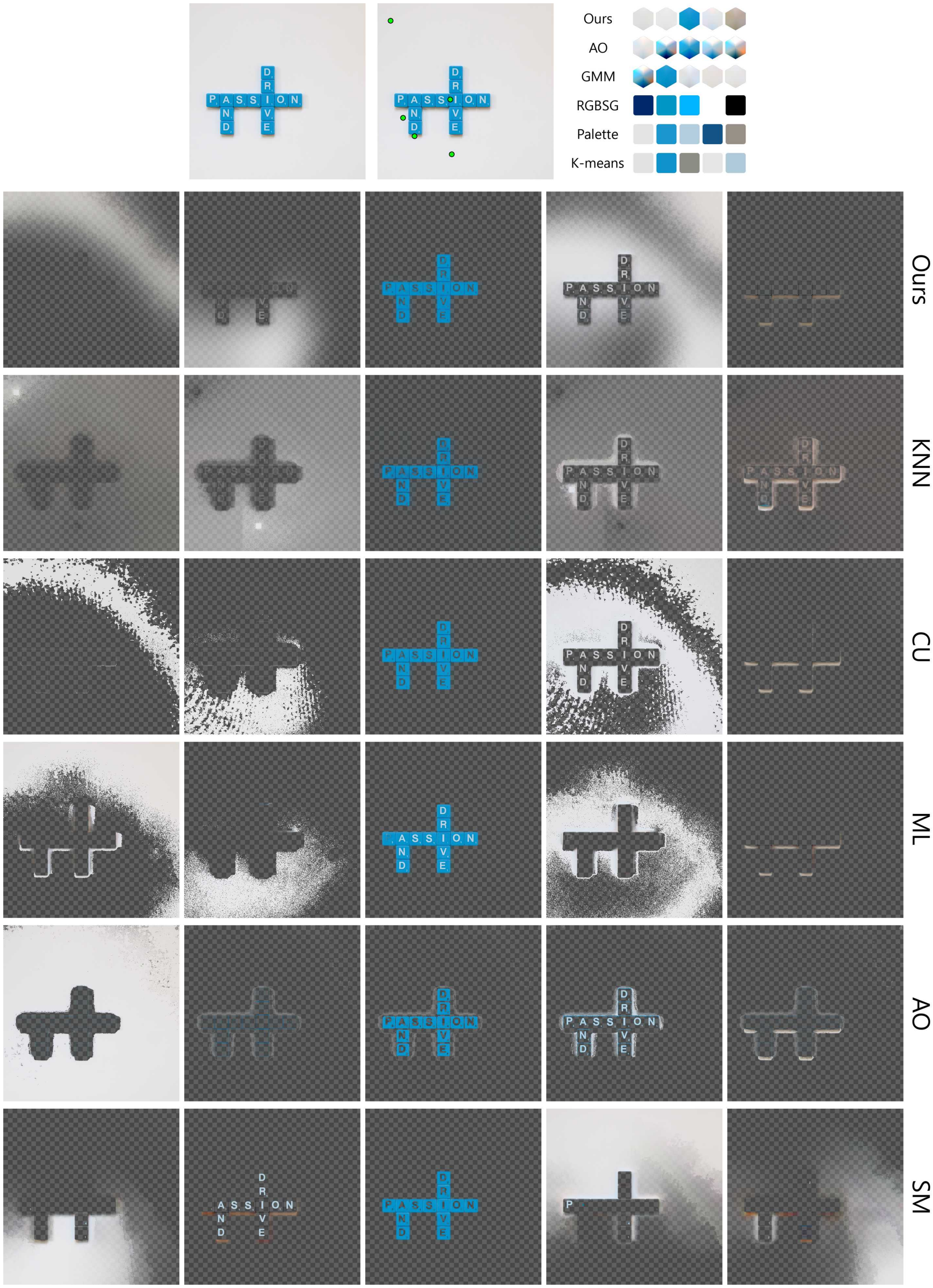

Fig. 10. Note the absence of spatial smoothness in results by CU and ML. Also, as we discuss in the main paper, KNN enforces hard constraints, which result in disturbing box shaped artifacts (see KNN layers (1,2,4)).