CrossNet: Latent Cross-Consistency for Unpaired Image Translation

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Figure 1: Given two unpaired sets of images, we train a model to perform translation between the two sets. Here we show, from left to right, our results on changing a specular material to diffuse, enhancing a mobile phone image to look like one taken by a Digital SLR camera and foreground extraction.

1. Supplementary Material



Figure 2: A variety of image-to-image translation results of our method (CrossNet), applied on style transfer tasks.



Figure 3: Results of our Specular to Diffuse: The odd colums show the inputs while the even ones show our output. The four left most columns depict a translation form a specular input to a diffuse output, while the four right rows show the opposite direction of translation.



Figure 4: Results of employing CrossNet for enhancing a mobile phone photo to DSLR quality. We show the input, our result, Cycle GAN's, MUNIT's and DPED's results, from left to right. The odd rows show the full images, while the even rows show a zoom-in.



Figure 5: Results of employing CrossNet for enhancing a mobile phone photo to DSLR quality. We show the input, our result, Cycle GAN's, MUNIT's and DPED's results, from left to right. The odd rows show the full images, while the even rows show a zoom-in.



Figure 6: Results of employing CrossNet for foreground extraction applied on elephant photos. From left to right, we show the input image, CrossNet, CycleGAN and GrabCut.



Figure 7: Results of employing CrossNet for foreground extraction applied on the UT Zappos50K dataset. From left to right, we show the input image, CrossNet, CycleGAN and AGGAN.



Figure 8: Results of employing CrossNet for foreground extraction applied on horse photos from the HDSeg dataset. From left to right, we show the input image, the ground truth and CrossNet's results.