Supplemental materials for "ImageSpirit: Verbal Guided Image Parsing"

Ming-Ming Cheng¹ Shuai Zheng^{1*} Wen-Yan Lin² Vibhav Vineet² Paul Sturgess² Nigel Crook² Niloy J. Mitra³ Philip Torr¹ ¹University of Oxford ²Oxford Brookes University ³University College London

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1 Image parsing results

To evaluate per-pixel object class prediction results, we compared our scene parsing results [Cheng et al. 2014] with H-CRF [Ladicky et al. 2009] and DenseCRF [Krähenbühl and Koltun 2011] on aNYU dataset. The statistics in the main paper show that our method produces more accurate object class prediction results. Visual comparisons for all results of 725 testing images in aNYU dataset are show in Fig. 6-36. Besides more accurate object class prediction, our method also produces attribute predictions which are important for using verbal commands to improve scene parsing. Verbal guided image parsing results are shown for both aNUY dataset (Fig. 1-3) as well as Google images (Fig. 4-5).

References

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* joint first author.



Figure 1: Compared with state of art methods, our approach gives more accurate per-pixel object classification. More over, even if our automatic attribute prediction results are of low quality, they can still be effectively used to verbally control the image parsing process.



Figure 2: Compared with state of art methods, our approach gives more accurate per-pixel object classification. More over, even if our automatic attribute prediction results are of low quality, they can still be effectively used to verbally control the image parsing process.



Figure 3: Compared with state of art methods, our approach gives more accurate per-pixel object classification. More over, even if our automatic attribute prediction results are of low quality, they can still be effectively used to verbally control the image parsing process.



Figure 4: Our system that is trained on the aNYU indoor dataset, generalizes to images of similar scene types obtained from Google. Our system allows users to refine this initial results verbally (see V-Guided for results).



Figure 5: Google images where verbal parsing is difficult: when there is no suitable configuration of attributes (predicted attributes, color attributes, position attributes, or their combinations) related to the desired object region, verbal interaction does not help.



Figure 6: Comparision of automatic per-pixel object class prediction. Our results generally have higher quality than DenseCRF. Moreover, the additional attribute prediction allow users of our system to verbally refine the results, enabling an intuitive editing mode.



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