Precise Detection in Densely Packed Scenes — Supplementary material —

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1. Qualitative Monkey detection results on our SKU-110K benchmark

Our SKU-110K images contain tightly packed items, covering much of the image plane. It is therefore instructional to examine a naive baseline which places detection bounding boxes at random locations in the image. As the paper reports, although some detections are inevitably correct, most detections are not and the overall accuracy is very low. Some qualitative examples are provided here. See Sec. 5.2 in the submission for more details.



Table 1. Qualitative Monkey baseline detection results on SKU-110K. See Sec. 5.2 in the paper for more details.

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2. Qualitative detection results on our SKU-110K benchmark



Table 2. **Qualitative results on SKU-110K.** Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 3. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 4. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 5. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 6. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 7. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

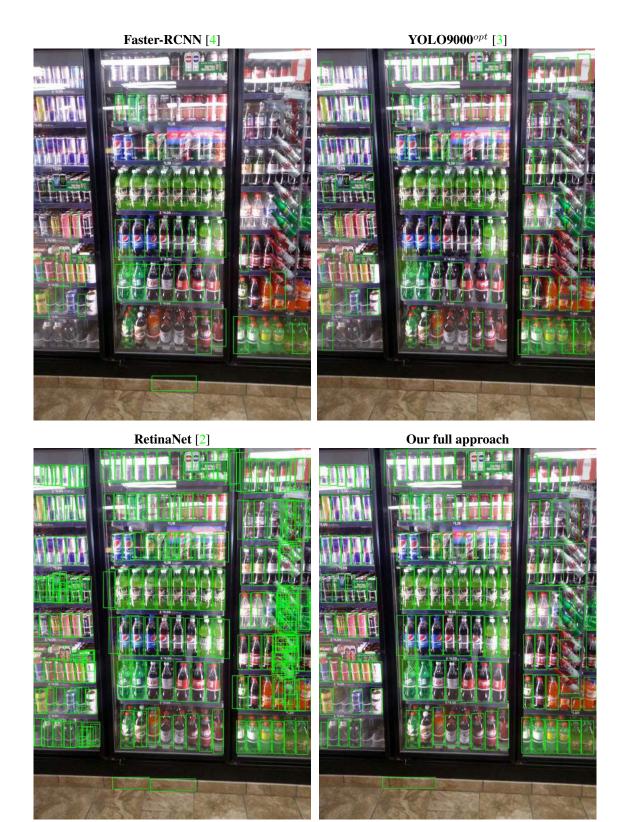


Table 8. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

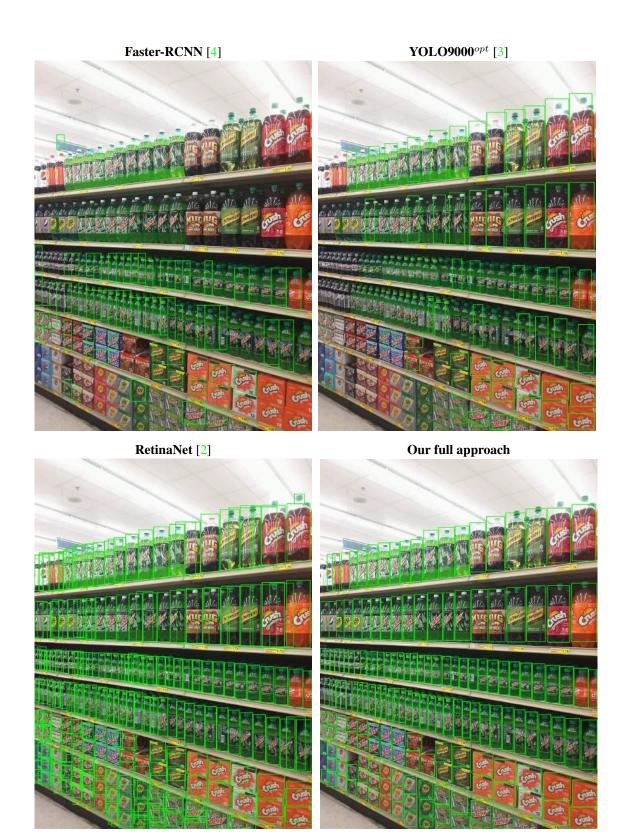


Table 9. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

Faster-RCNN [4]

YOLO9000^{opt} [3]



RetinaNet [2]



Our full approach



Table 10. **Qualitative results on SKU-110K (cont.).** Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

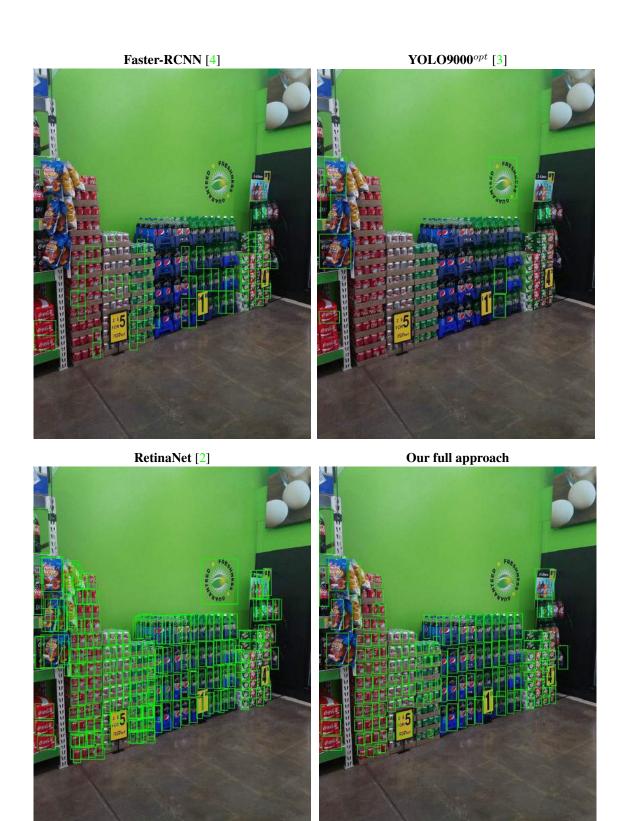


Table 11. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 12. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.



Table 13. **Qualitative results on SKU-110K (cont.).** Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

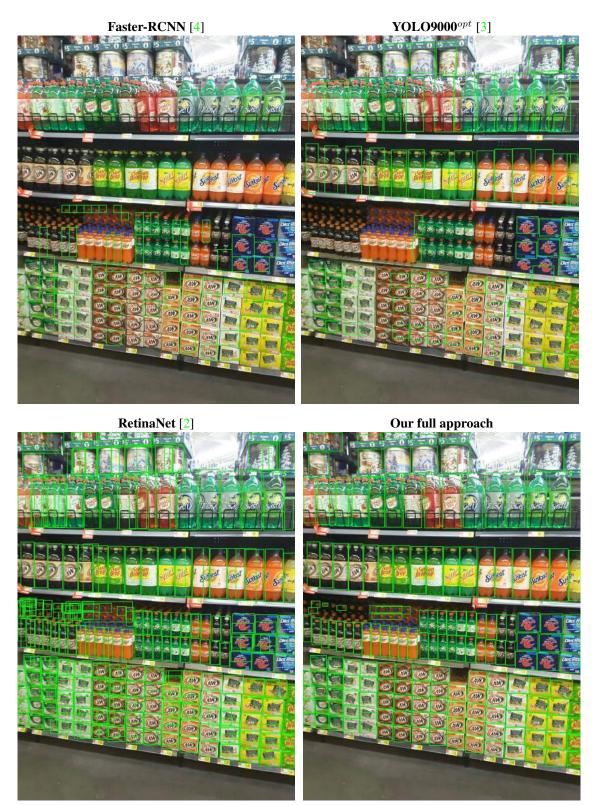


Table 14. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

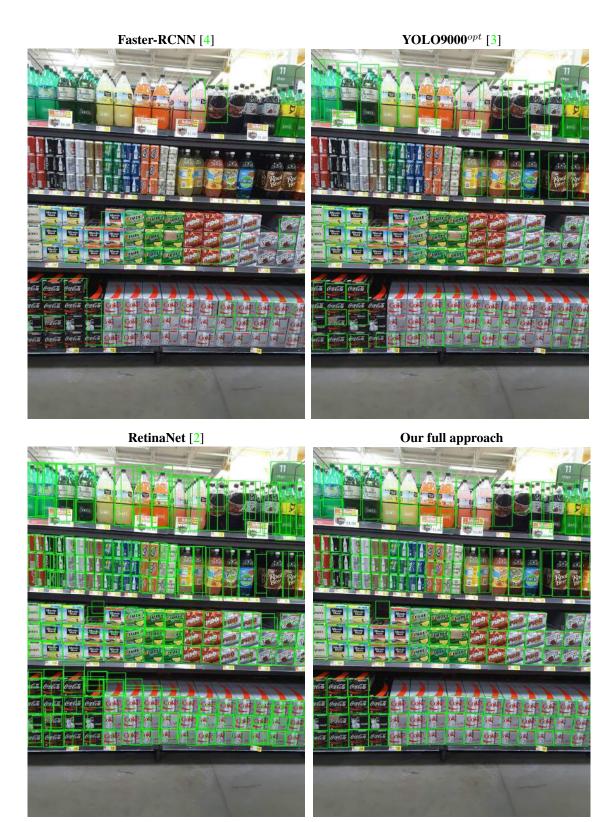


Table 15. Qualitative results on SKU-110K (cont.). Extending Fig. 5 in the submission. See Sec. 5.2 in the paper for more details.

3. Qualitative detection results on CARPK benchmark



Table 16. Qualitative detection results on CARPK [1]. Results provided only for our full method. See Sec. 5.3 in the paper for details.

4. Qualitative detection results on PUCPR+ benchmark



Table 17. Qualitative detection results on PUCPR+ [1]. Results provided only for our full method. See Sec. 5.3 in the paper for details.

References

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