Supplementary Material of AttentionNet: Aggregating Weak Directions for Accurate Object Detection

Donggeun Yoo	Sunggyun Park	Joon-Young Lee*	Anthony S. Paek	In So Kweon
dgyoo@rcv.kaist.ac.kr	sunggyun@kaist.ac.kr	jylee@rcv.kaist.ac.kr	apaek@lunit.io	iskweon@kaist.ac.kr
KAIST	KAIST	KAIST	Lunit Inc.	KAIST

This supplementary material contains extra experiments, example images, and details of AttentionNet [2].

1. Effectiveness of the Second Augmentation Rule

The second rule in the augmentation for training regions is as follows.

> A positive region can include multiple instances, but a target instance must occupy the biggest area.
> Within a cropped region, an area of the target instance is at least 1.5-times larger than that of the other instances.

This rule is important to separate multiple instances that are overlapped. Table 1 and Fig. 1 show the impact of this rule.

Table 1: Average precisions (%) with/without the second augmentation rule on PASCAL VOC 2007 "person".

Method	The second rule	AP(%)
AttentionNet	No.	51.3
AttentionNet	Yes.	**61.7**
AttentionNet + Refine	No.	52.7
AttentionNet + Refine	Yes.	**65.0**

*This work was done when he was in KAIST. He is currently working in Adobe Research.

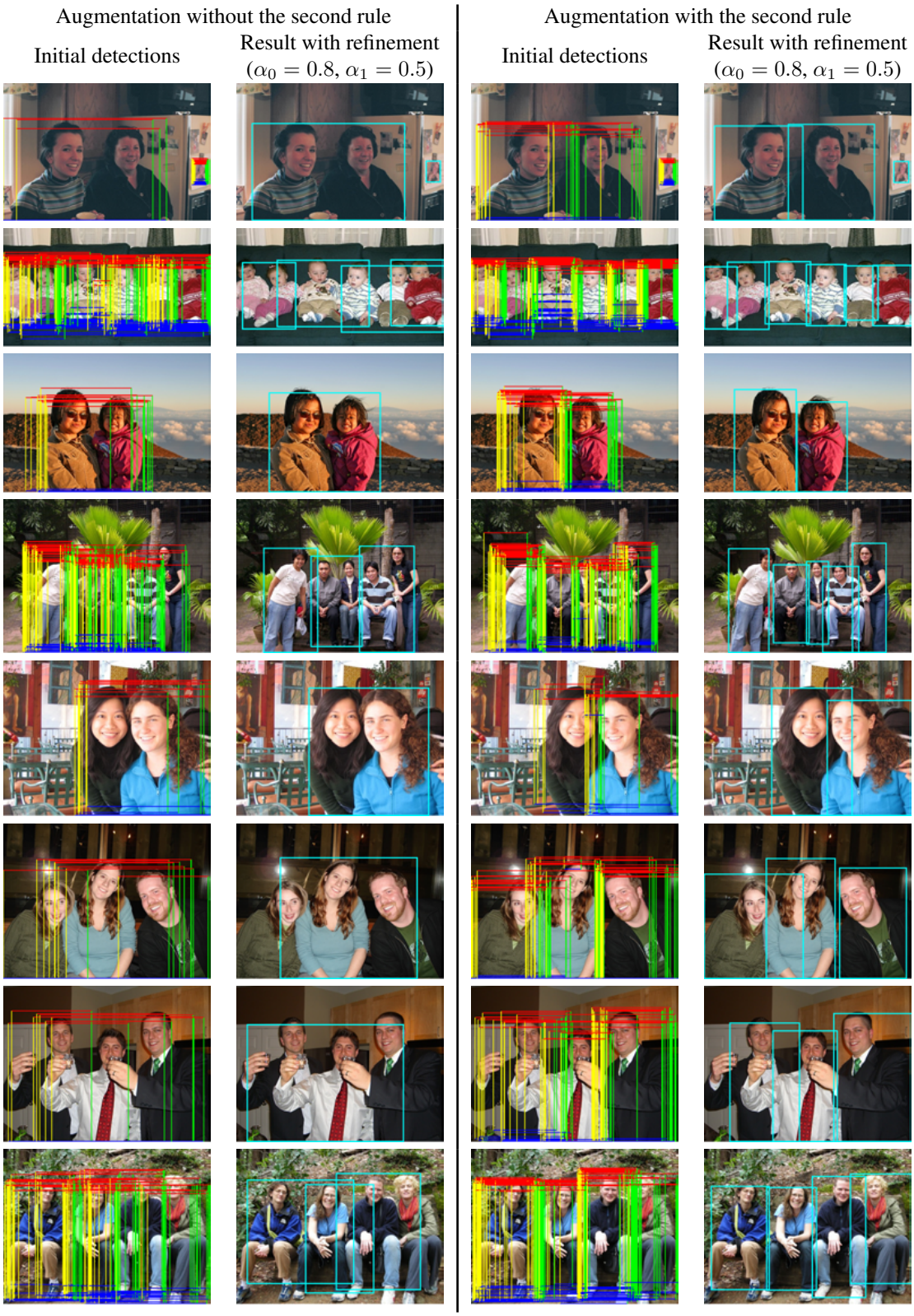


Figure 1: Detection examples with/without the second augmentation rule on PASCAL VOC 2007 “person”.

2. Performance to Number of Scales

Fig. 2 shows the performance to the number of scales. An image of a scale (e.g. 2) has two times larger resolution than that of the previous scale (e.g. 1). As shown in this figure, more than 6 scales are enough to achieve the best performance.

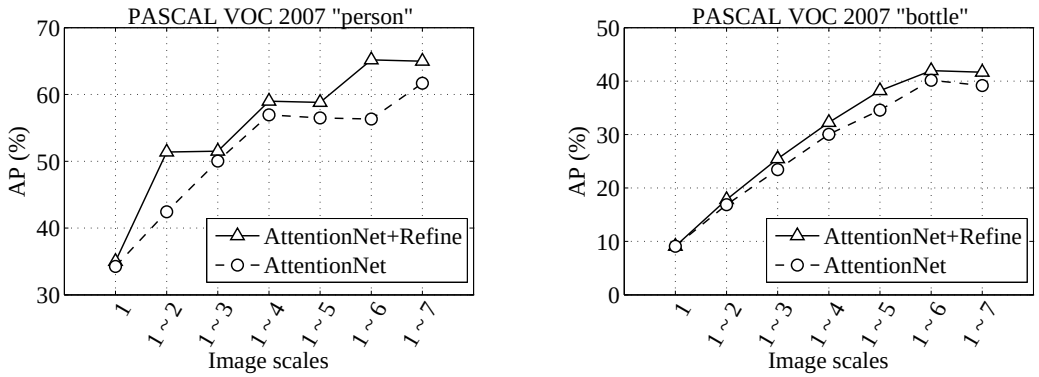
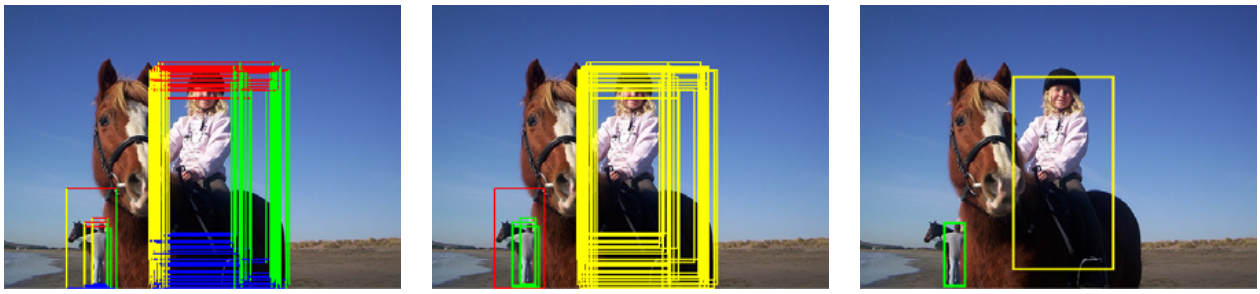


Figure 2: Performance to the number of scales on PASCAL VOC 2007 “person” (left) and “bottle” (right). The tick label of the horizontal axis is the combination of scales.

3. Details of Merging Initial Detections.

When we merge the initially detected bounding boxes as drawn in Fig. 3-(a), we reject the isolated bounding boxes which are not merged with other bounding boxes, because they are prone to be outliers from our multi-scale sliding window scheme.



(a) Initial detections

(b) Grouped bounding boxes ($\alpha_0 = 0.6$)

(c) Merged bounding boxes

Figure 3: A real example of the initial merge procedure. A red bounding box in (b) is an outlier to be rejected, because it is not grouped with other bounding boxes. α_0 is a value of intersection over union (IoU) for the initial merge.

4. Qualitative Comparison

We show our detection examples and comparisons. We compare our detection results with Region-CNN (R-CNN) results, obtained from the source code[1] provided by Girshick *et al*. [1]. *We draw all bounding boxes detected by AttentionNet without any score threshold*, while only those that achieved greater than 30% AP in R-CNN are drawn. Through Fig. 4 to Fig. 12, we show both cases when our results are either superior or inferior to R-CNN.

[1] https://github.com/rbgirshick/rcnn

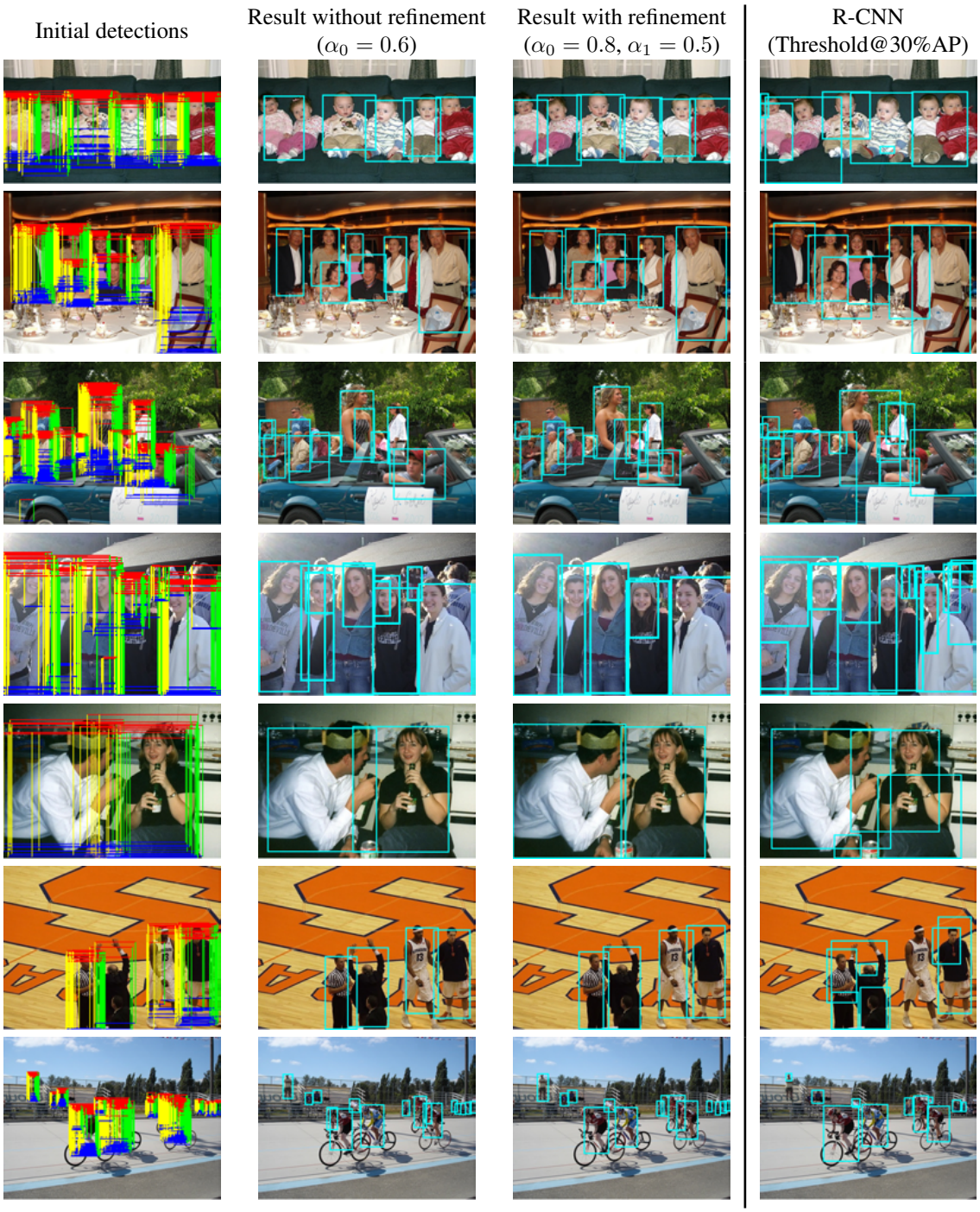


Figure 4: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "person".

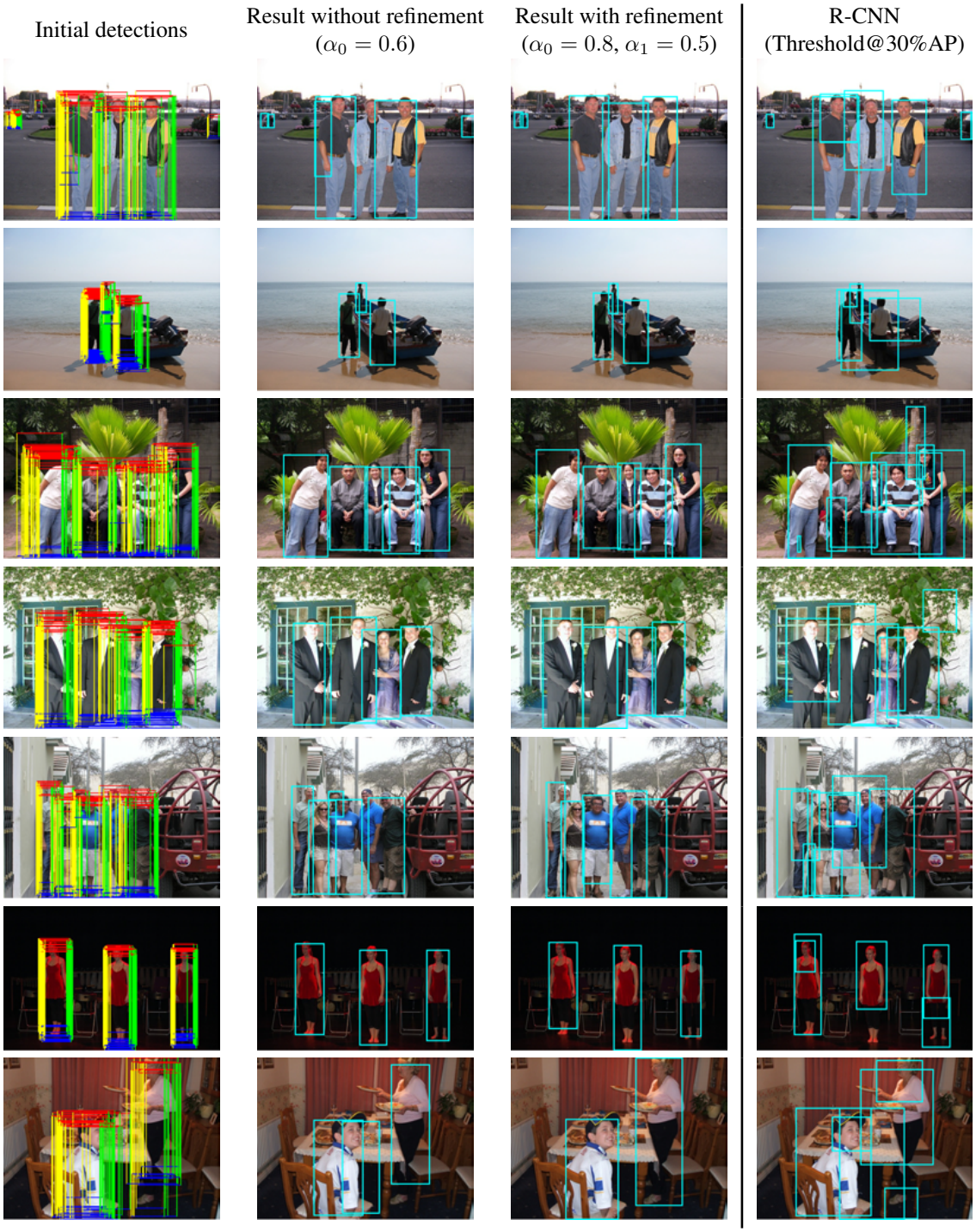


Figure 5: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "person".

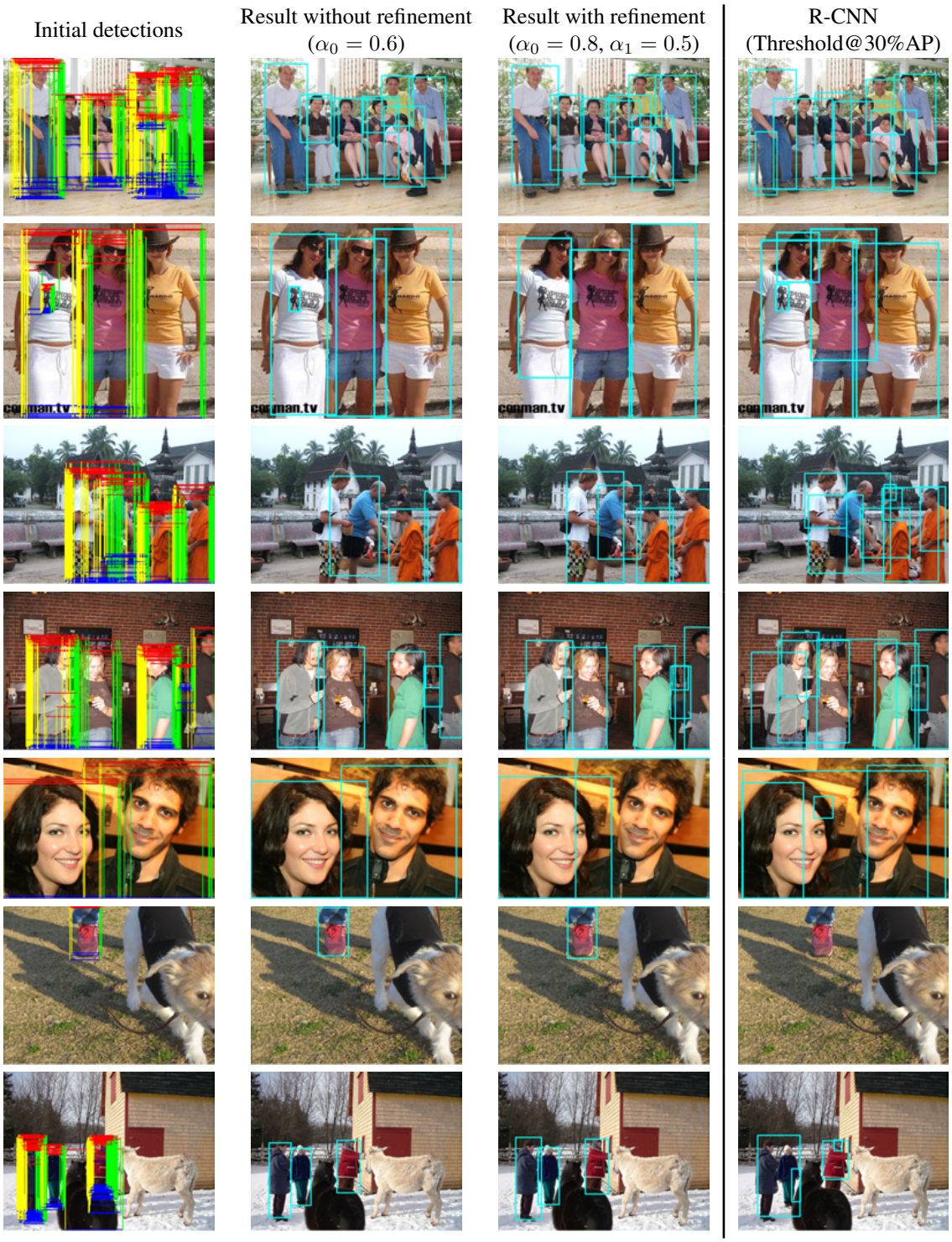


Figure 6: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "person".

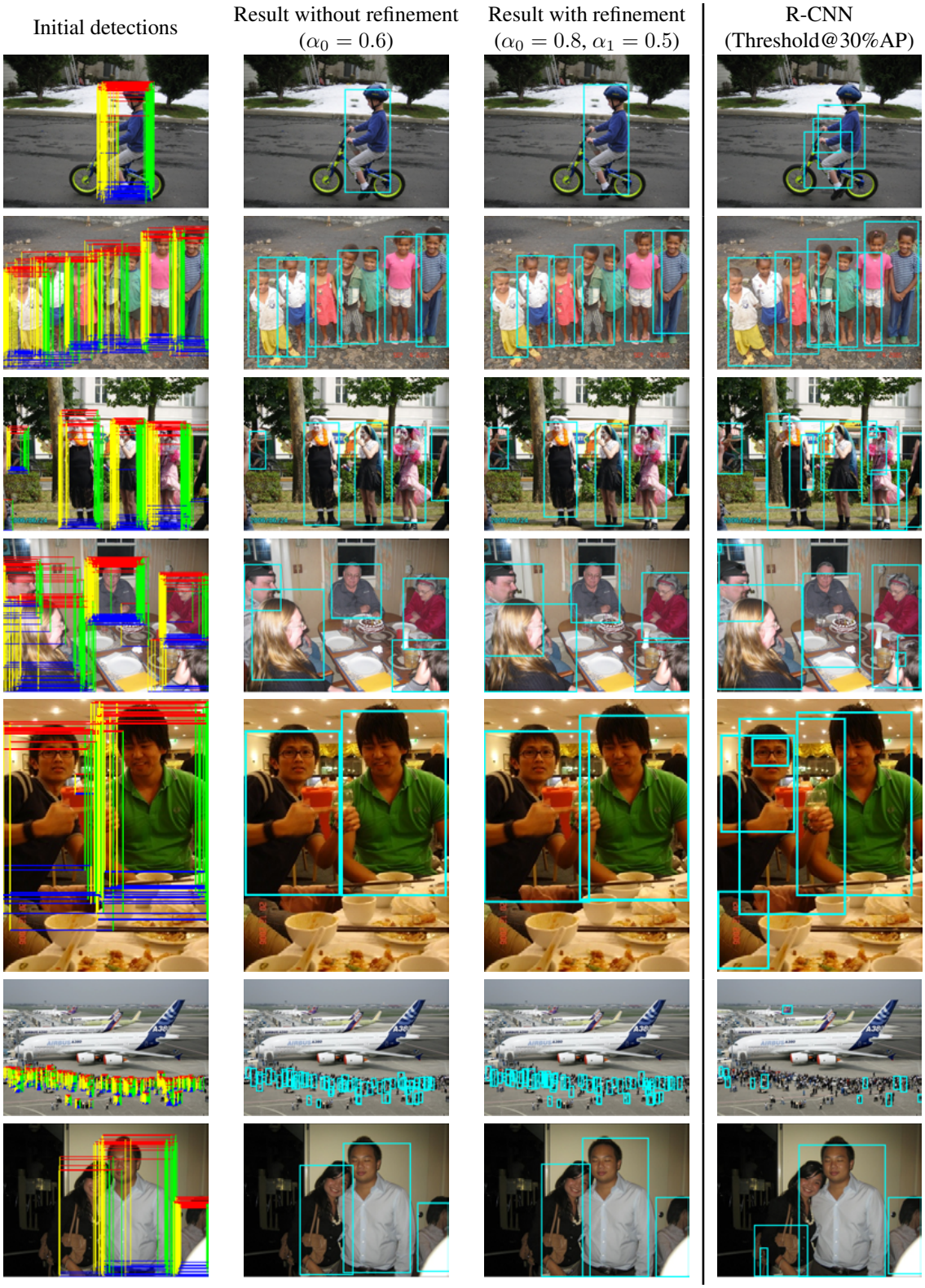


Figure 7: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "person".

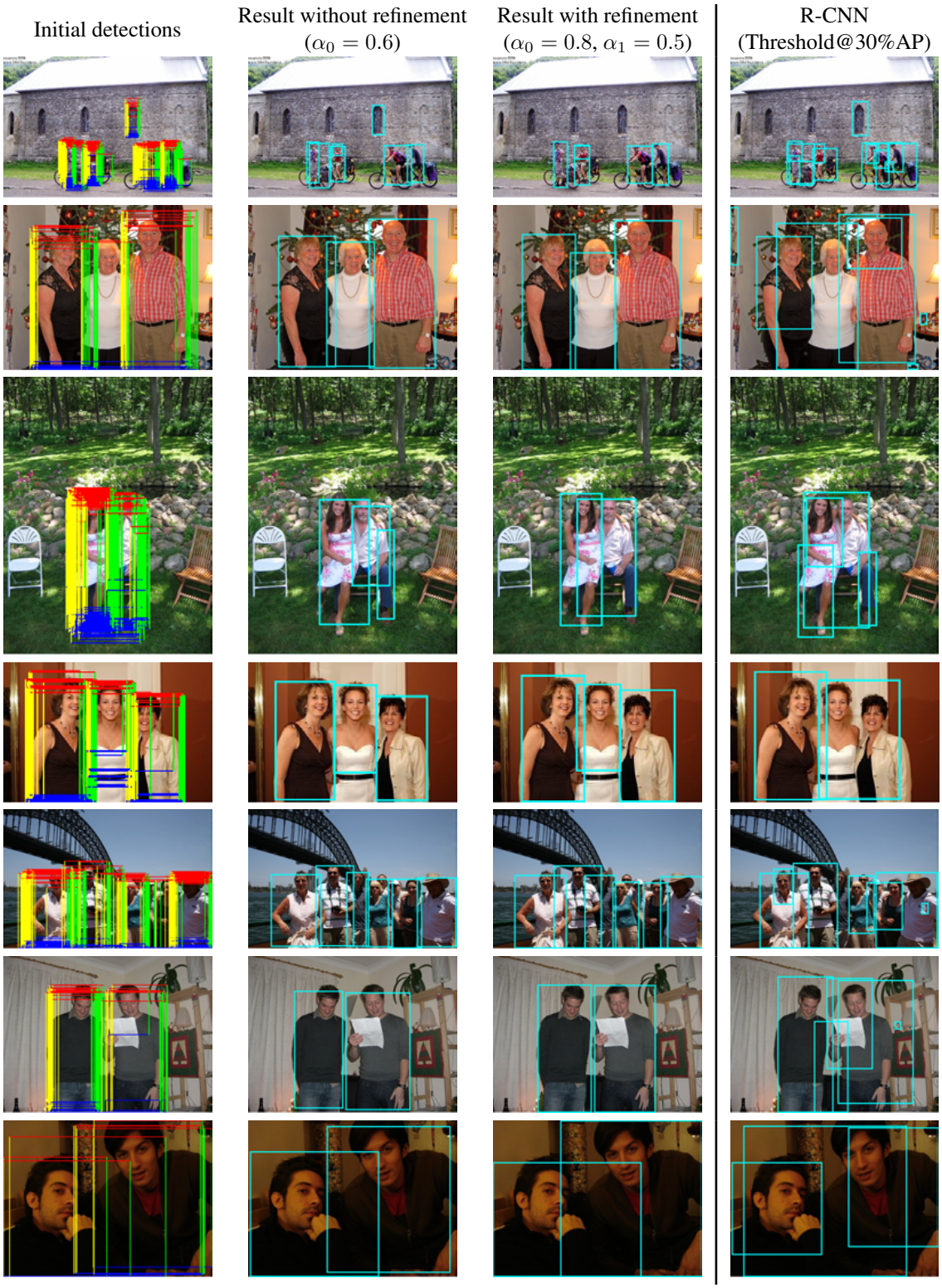


Figure 8: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "person".

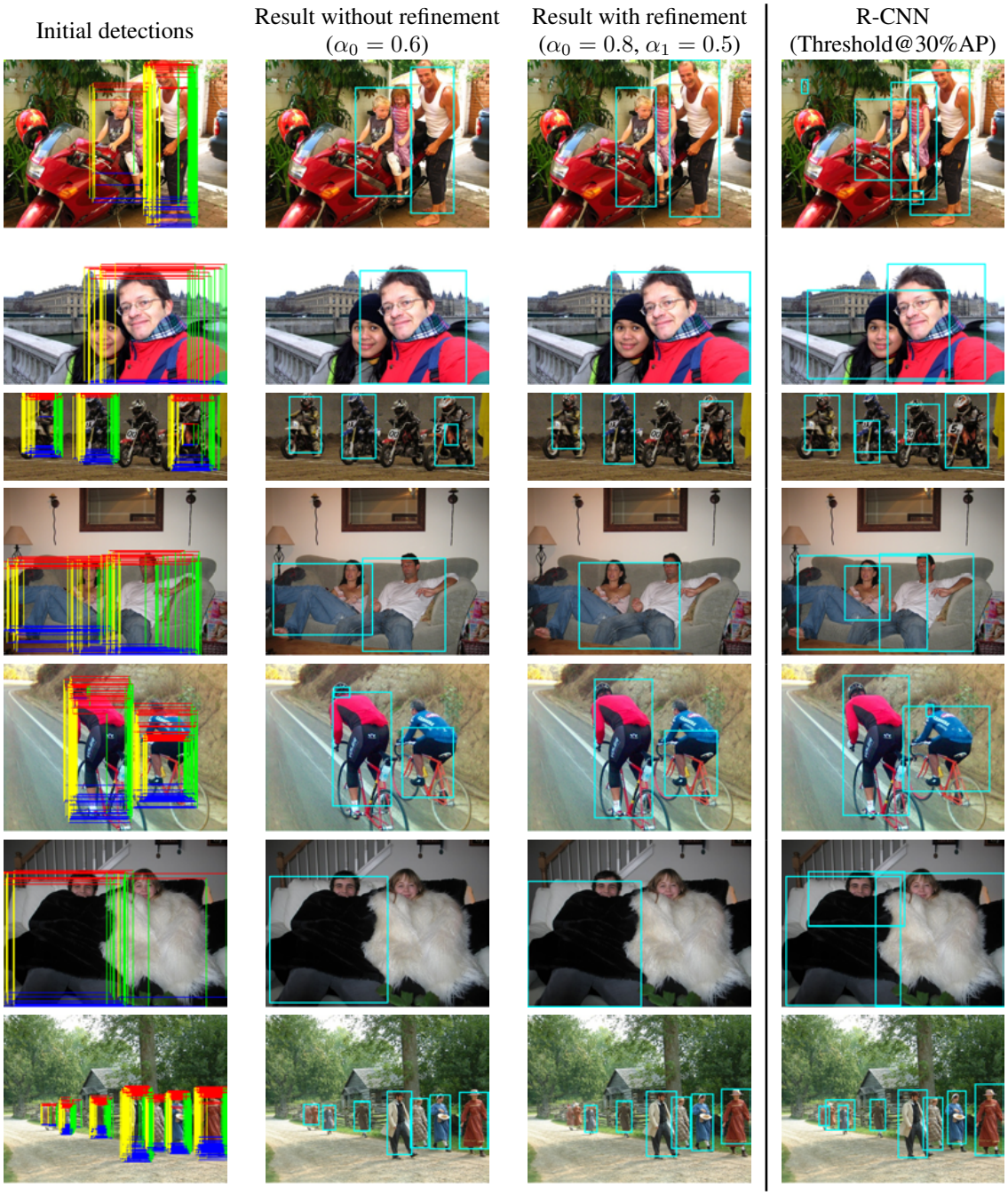


Figure 9: Examples when our result is **inferior** to that of R-CNN in PASCAL VOC 2007 "person".

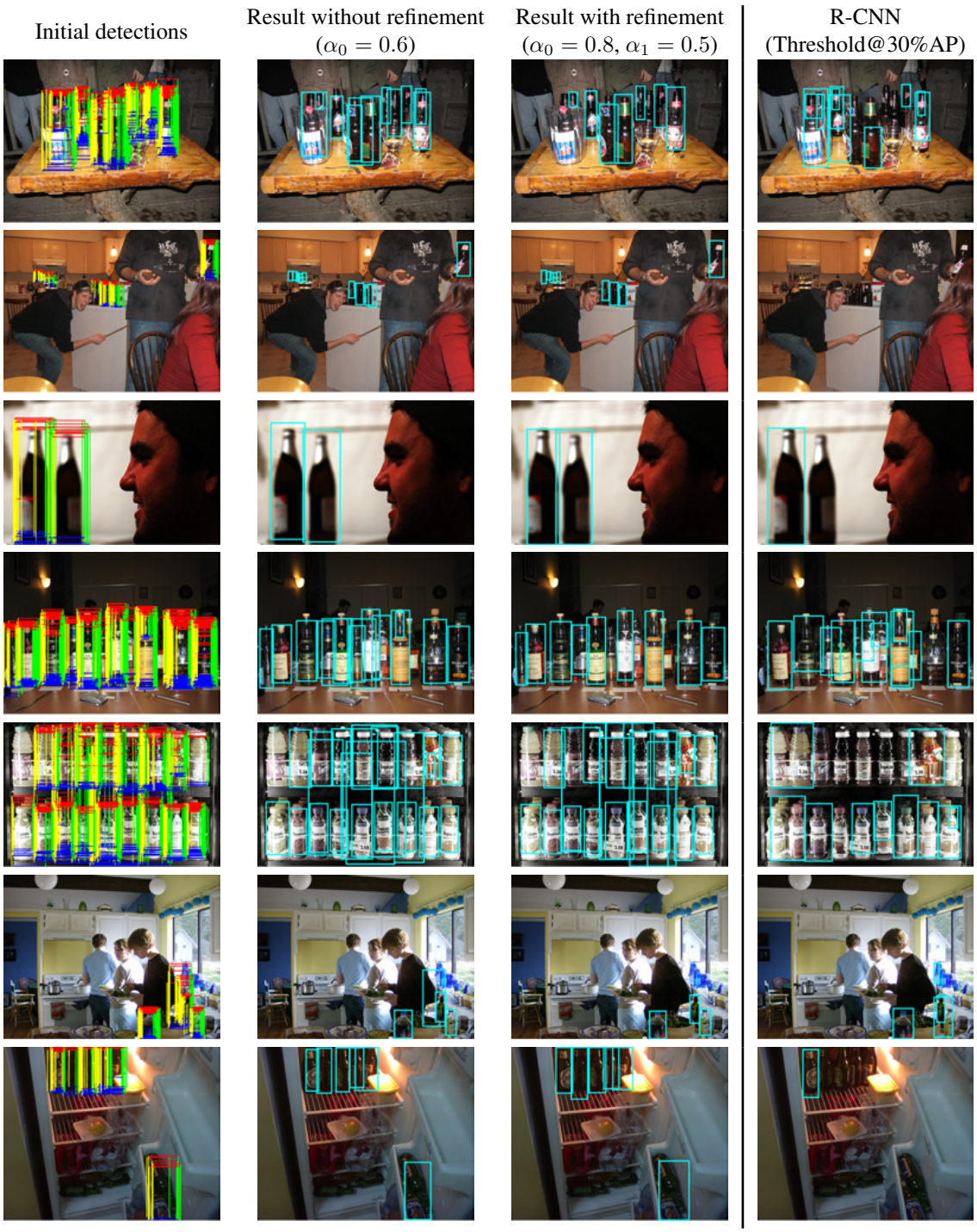


Figure 10: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "bottle".

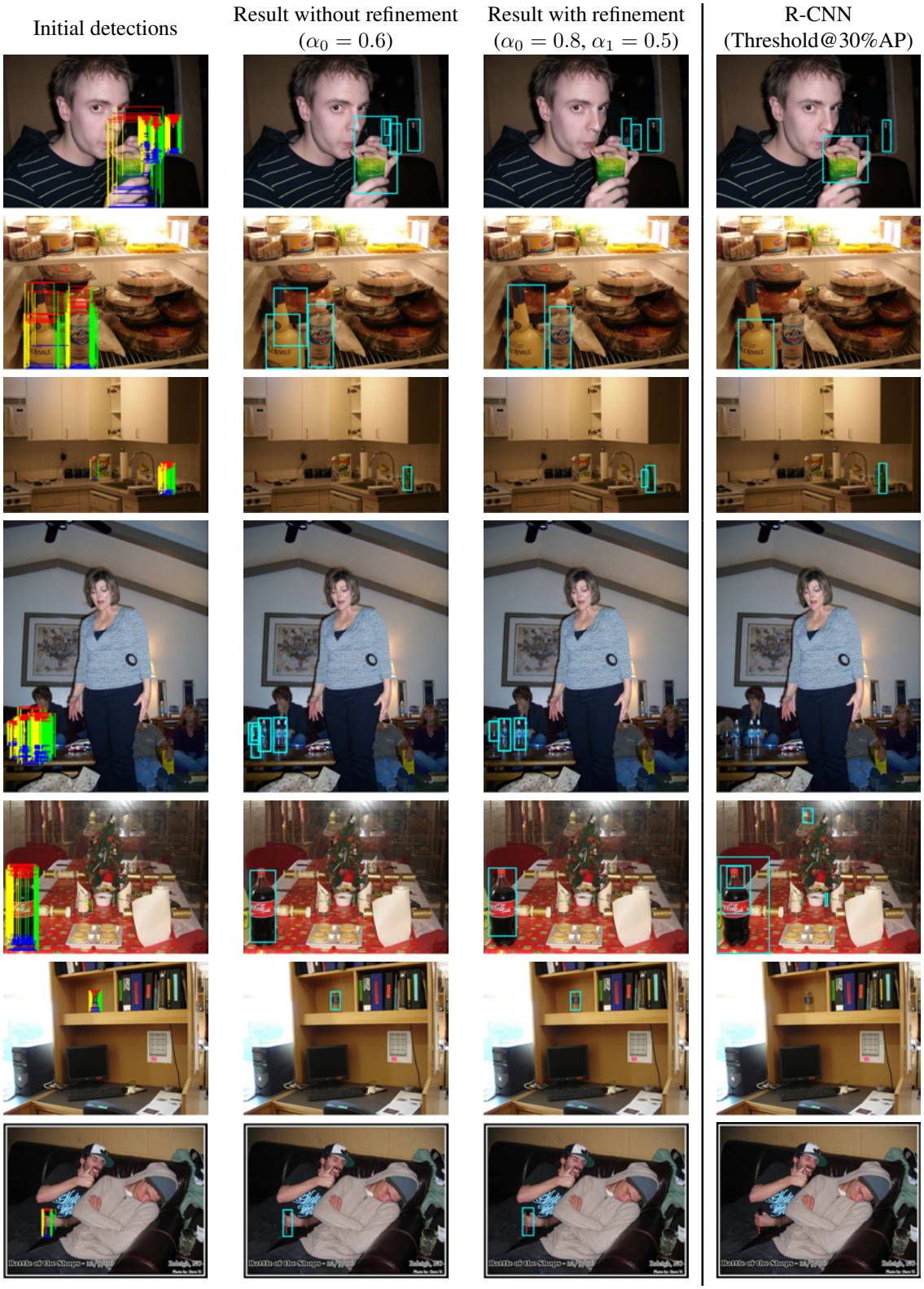


Figure 11: Examples when our result is **superior** to that of R-CNN in PASCAL VOC 2007 "bottle".

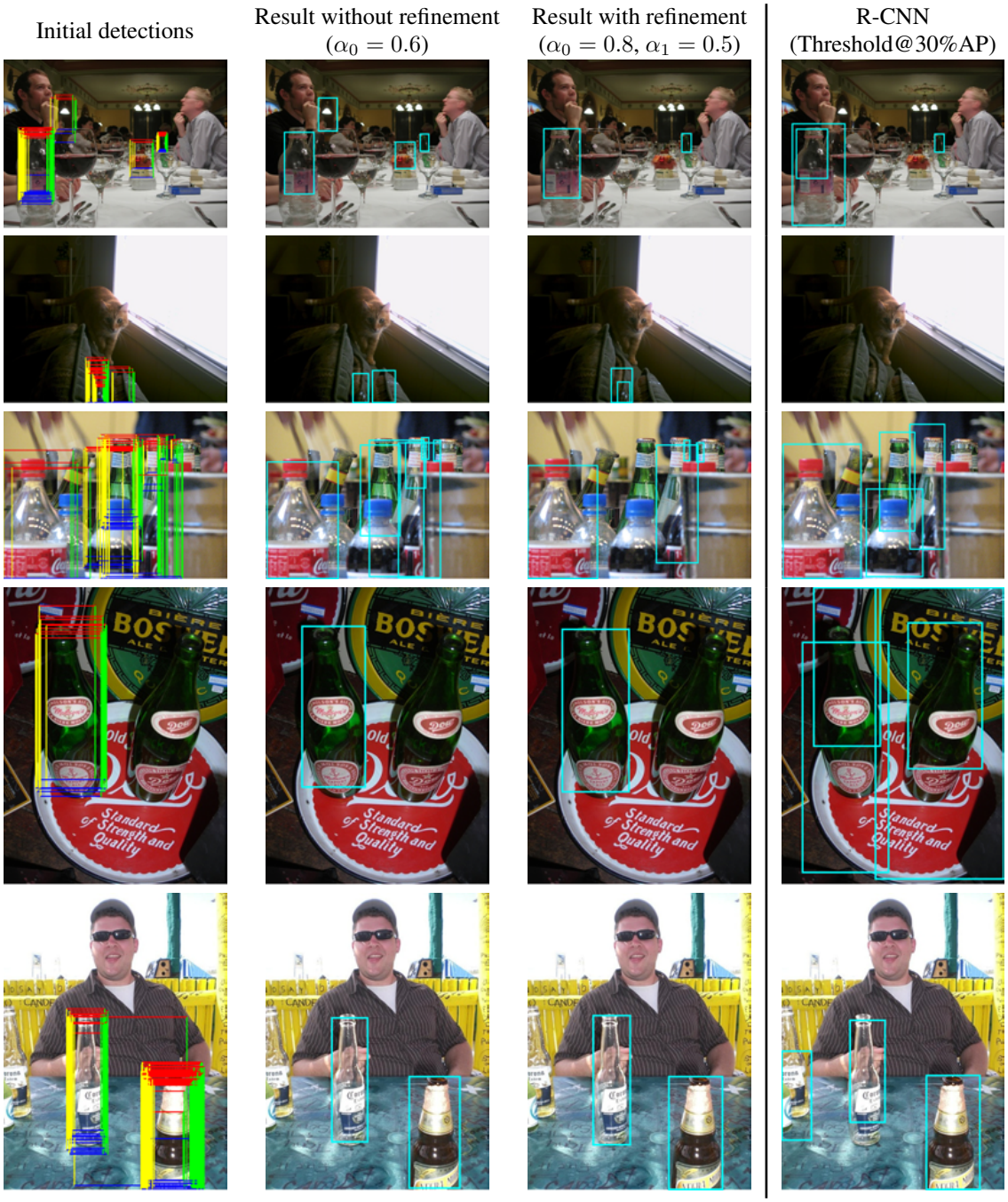


Figure 12: Examples when our result is **inferior** to that of R-CNN in PASCAL VOC 2007 "bottle".

References

[1] R. B. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.

[2] D. Yoo, S. Park, J.-Y. Lee, A. S. Paek, and I. S. Kweon. Attentionnet: Aggregating weak directions for accurate object detection. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2015.