Pose Partition Networks for Multi-Person Pose Estimation (Supplementary Materials)

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Figure 1: Qualitative results of the proposed PPN on MPII (1st row), extended PASCAL-Person-Part (2nd row), and WAF (3rd row). PPN performs well even in challenging scenarios, *e.g.*, self-occlusion and other overlapped persons in the 1st example of 1st row, large pose variations in the 2nd example of 2nd row, appearance and illumination changes in the 4th example of 3rd row

1. Qualitative Results

In this section, we show visualization examples of pose partition, local inference, and multi-person pose estimation by the proposed Pose Partition Network (PPN) on benchmarks MPII Human Pose Multi-Person (MPII), extended PASCAL-Person-Part, and WAF.

Figure 1 visualizes some pose estimation results on these three datasets. We can observe that the proposed PPN model estimates multi-person poses accurately and robustly even in challenging scenarios, *e.g.*, joint occlusion caused by a person of interest and other overlapped persons presenting in the first example of MPII dataset, large pose variation shown in the second example of the extended PASCAL-Person-Part dataset, and appearance and illumination changes in the forth example of WAF dataset. These results also verify the effectiveness of PPN for producing reliable joint detections and partitions in multi-person pose estimation.

Figure 2 visualizes the pose partition and local inference results of the proposed PPN on MPII dataset. One can observe that the proposed model can effectively produce robust person detections with joint partitions via votes from all joint candidates in the centroid embedding space relying on the dense regression module. It performs well not only for the common multi-person case (left image of 1st row), but also for some challenging scenarios, *e.g.*, partial or complete joint occlusions (left images of 2nd and 3rd rows), people overlapping (left image of 4th row), crowded and cluttered scenes (left image of 5th row), and large pose variations (left image of last row). Benefiting from the accurate joint partitions, the proposed local inference algorithm can efficiently estimate joint configurations for each person detection independently by exploiting reliable global affinity cues from the centroid embedding space, as shown in right image of each row. More visualization examples for pose partition and local inference of the proposed PPN are provided in Figure 3.

Figure 4, 5, and 6 visualize more multi-person pose estimation results of the proposed PPN on MPII dataset, extended PASCAL-Person-Part dataset and WAF dataset, respectively. One can see that besides the challenging scenarios mentioned above, the proposed PPN can also deal with scale variations (*e.g.*, the first example of the first row in MPII dataset), appearance and illumination changes (*e.g.*, the first example of the last row in PASCAL-Person-Part dataset), and color tone changes (*e.g.*, the third example of the first row in WAF dataset).

These qualitative results further demonstrate the effectiveness of the PPN model for robustly and accurately generating joint partitions and inferring joint configurations to address the multi-person pose estimation problem.

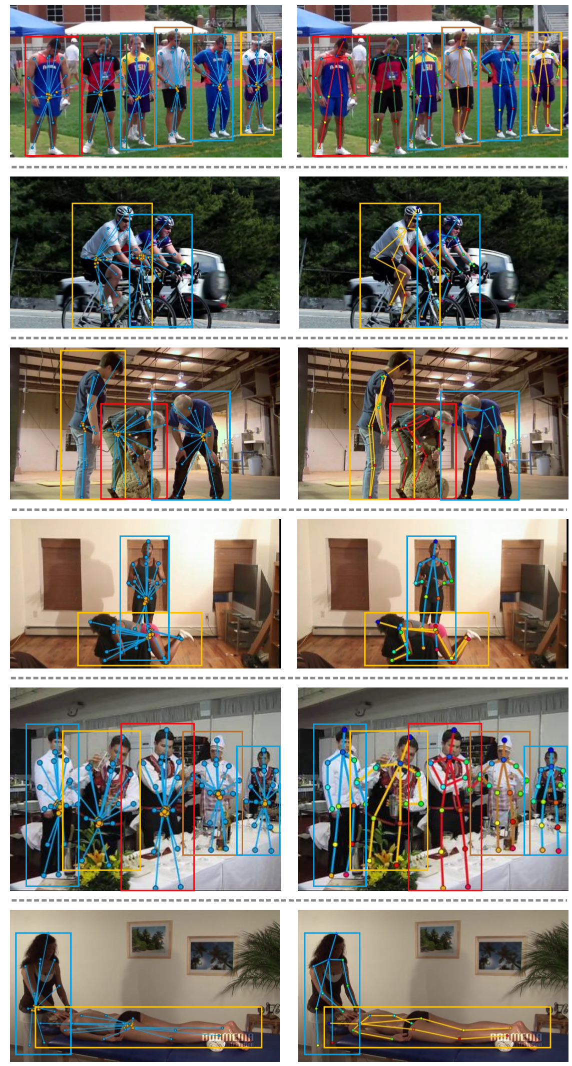

Figure 2: Qualitative results of pose partition and local inference of PPN on MPII dataset, shown in left and right images respectively for each row. For the pose partition examples, the blue points represent predicted joint candidates, the yellow ones represent centroid embedding results, and the blue lines represent predicted dense regressions. The rectangles in different colors illustrate person detections for local inference. Best viewed in color.

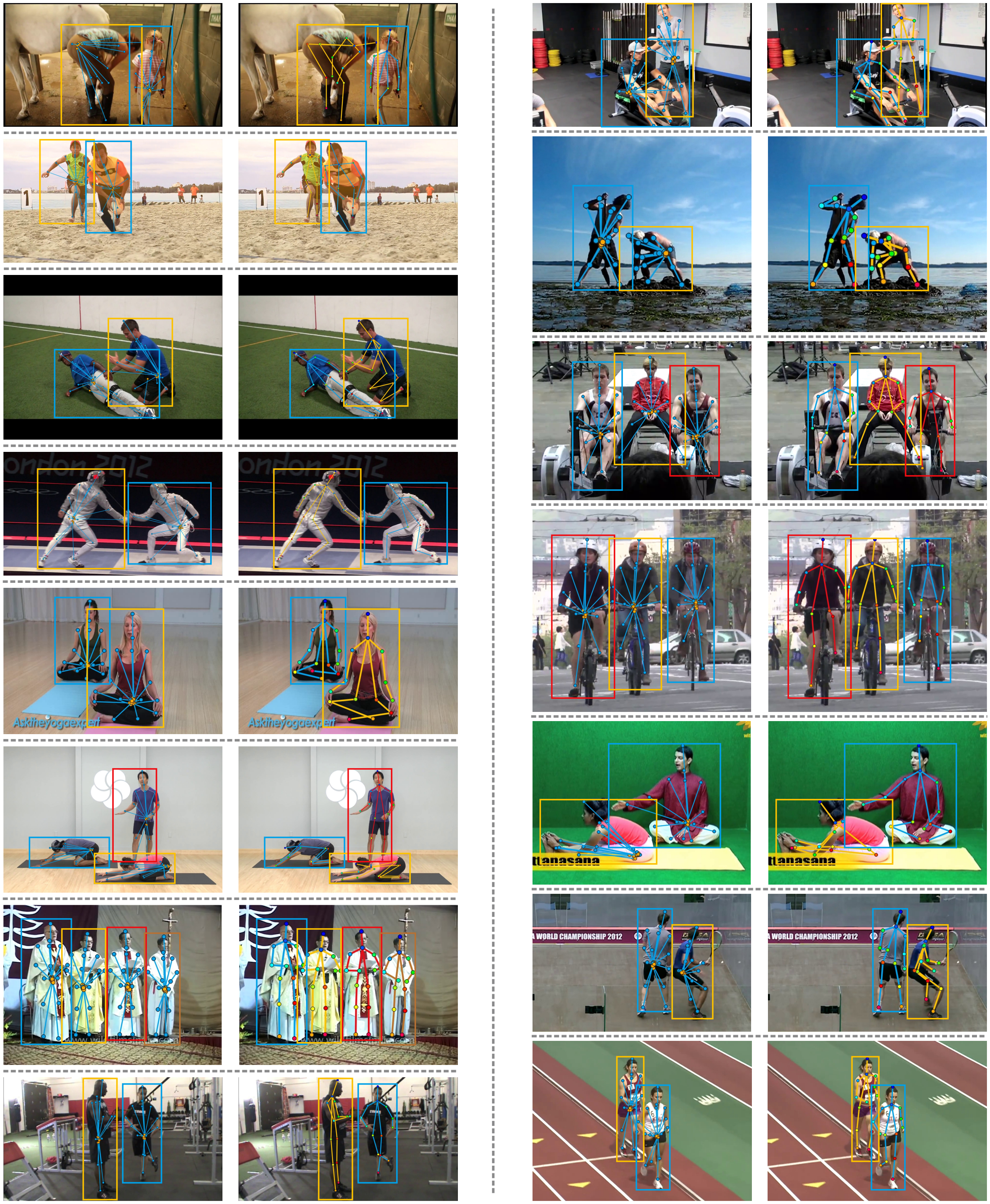

Figure 3: Qualitative results of pose partition and local inference on MPII dataset, shown in left and right respectively for one pair of images in each row. The proposed PPN model can generate robust person detections with joint partitions and accurate joint categorizations and associations even in some challenging scenarios, *e.g.*, pose variations (1st row of left panel), partial or complete occlusions (2nd, 3rd and 6th rows of left panel), and appearance and illumination changes (2nd and 3rd rows of right panel). Best viewed in color.

Figure 4: Qualitative results of multi-person pose estimation of PPN on MPII dataset. PPN performs well even in challenging scenarios, *e.g.*, scales variations (1st example of 1st row), people overlapping (3rd example of 1st row), pose variations (2nd example of 2nd row), appearance and illumination changes (2nd example of 4th row), and occlusions (1st to 3rd examples of last row). Best viewed in color.

Figure 5: Qualitative results of multi-person pose estimation of PPN on extended PASCAL-Person-Part dataset. PPN performs well even in challenging scenarios, *e.g.*, occlusions (1st row), people overlapping (2nd row), scales variations (first two examples of 3rd row), cluttered backgrounds (5th example of 3rd row), pose variations (4th row), appearance and illumination changes (1st example of last row). Best viewed in color.

Figure 6: Qualitative results of multi-person pose estimation of PPN on WAF dataset. PPN performs well even in challenging scenarios, *e.g.*, pose variations (first two examples of 1st row), people overlapping (2nd row), occlusions (3rd row), appearance and color tone changes (3rd example of 1st row and 3rd example of 4th row). Best viewed in color.