Progressive Graph Matching: Making a Move of Graphs via Probabilistic Voting <Supplementary Material>

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1. Experimental Results

In this supplementary material, we provide additional details and experiments of Sec.4 of our main paper which we could not provide due to the shortage of space.

1.1. Progress of Progressive Graph Matching

In the first experiment of Sec.4.1 in our paper, we tested progressive graph matching on a severely deformed face, and showed its 1-step progressive result in Fig.5 of our paper. The more results of subsequent progressive matching are shown in Fig. 1. The related performance plot is already shown in Fig.6(b) of our main paper. Other additional progressive results are provided in Fig. 2 whose final results are the same as those contained in Fig.7 of the main paper. In the performance plots

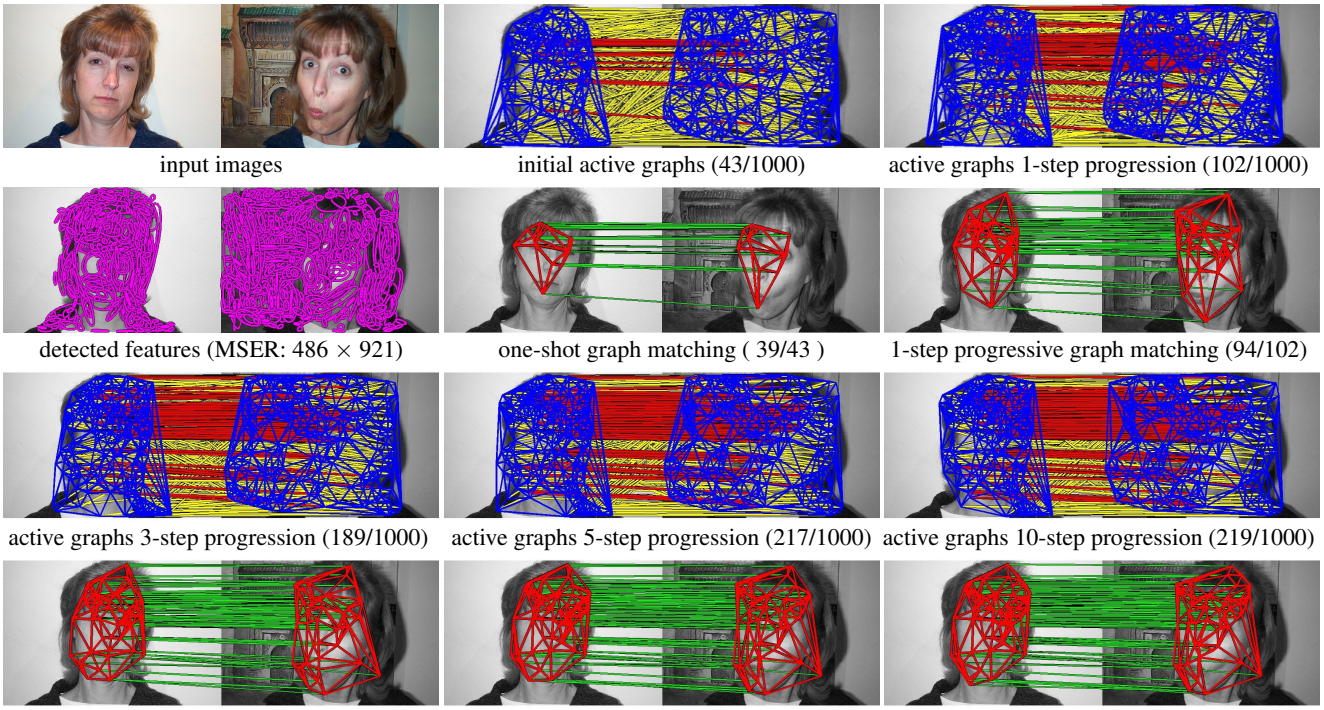


Figure 1. Boosting effects of progressive graph matching. At the first and third rows, to visualize active graphs, the candidate matches are drawn by yellow (false) and red (true) lines, and their related features are represented by blue triangulations. At the second and fourth rows, the true matches obtained by graph matching are shown with green lines with red triangulations. As the graph matching module, RRWM is used.

of Fig. 2, the number of true matches tends to increase with the graph matching score. For better visualization, the score curves were scaled close to other curves in each plot. These results clearly shows the effect of progressive graph matching; graph progression significantly increase the true candidate matches in active graphs, thus boosting the performance in the subsequent graph matching.

1.2. Other Results

Besides the results shown in the main paper, we tested the proposed method on various image pairs from the VOC 2010 dataset[1], the Caltech dataset[2], and the ETHZ toys dataset[3]. The ground truth feature pairs were manually constructed for each image pair as we mentioned in the main paper: the ground truth pairs are labeled by hands on landmark points and then extrapolated to neighboring features within 10 or 20 pixels (considering the image size).

All these results are shown in Fig. 3∼7 where the results of one-shot matching and progressive matching are shown with the plot of performance growth. Significant improvement in scores and inliers is clearly observed in almost all results. In all these experiments, the size of active graphs are set to $N_c = 3000$ and the settings and parameters are fixed as in the main paper ($k_1 = 25$ and $k_2 = 5$). If we increase N_c, the overall performance usually improves but the algorithm requires more memory and time. $N_c = 3000$ was close to the maximum size which we can cope with in our environment. The values of k_1 and k_2 determines the computation cost of graph progression. $k_1 = 25$ and $k_2 = 5$ were already sufficient in our experiments. For feature detection, MSER [1] is used as the default detector. When the number of MSER features are not sufficient in an image pair, the Harris-affine and Hessian-affine features [2] are additionally employed.

Figure. 3∼7 clearly show that progressive graph matching greatly enhances one-shot graph matching and find still more inliers even from a very weak result of initial graph matching. Especially, in Fig. 7, we tested the robustness to the quality of initial active graphs. In this experiment, we started progressive graph matching from a very small size of initial active graphs ($N_c = 50$ when t = 0), and compared the results with a large size of initial active graphs ($N_c = 3000$). The result of the initial active graphs with 3000 candidate matches is shown at the top, and the two results of the initial active graph with 50 candidate matches is shown at the middle and the bottom. Although they have just 1 and 3 initial true matches, their final results are comparable to the result at the top which started from 82 true matches. This robustness is consistently observed in the experiments. The results demonstrate that progressive graph matching is not sensitive to the starting active graphs.

References

[1] J. Matas, O. Chum, M. Urban, and T. Pajdla. Robust wide baseline stereo from maximally stable extremal regions. *BMVC*, 2002. 2

[2] K. Mikolajczyk and C. Schmid. Scale and affine invariant interest point detectors. *IJCV*, 60(1):63–86, Oct. 2004. 2

[1] http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2010/

[2] http://www.vision.caltech.edu/archive.html

[3] http://www.vision.ee.ethz.ch/~calvin/datasets.html

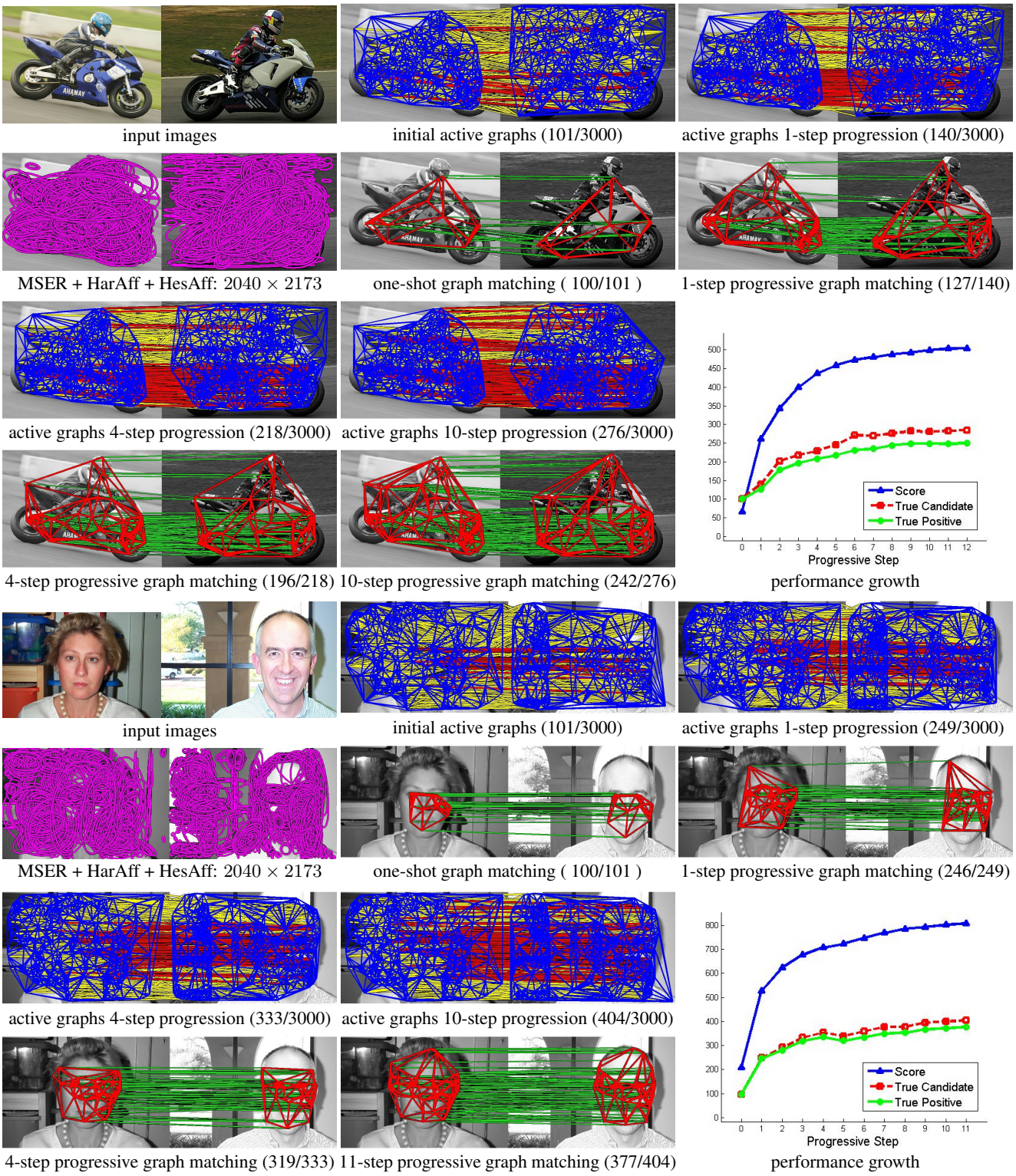


Figure 2. Progressive graph matching.

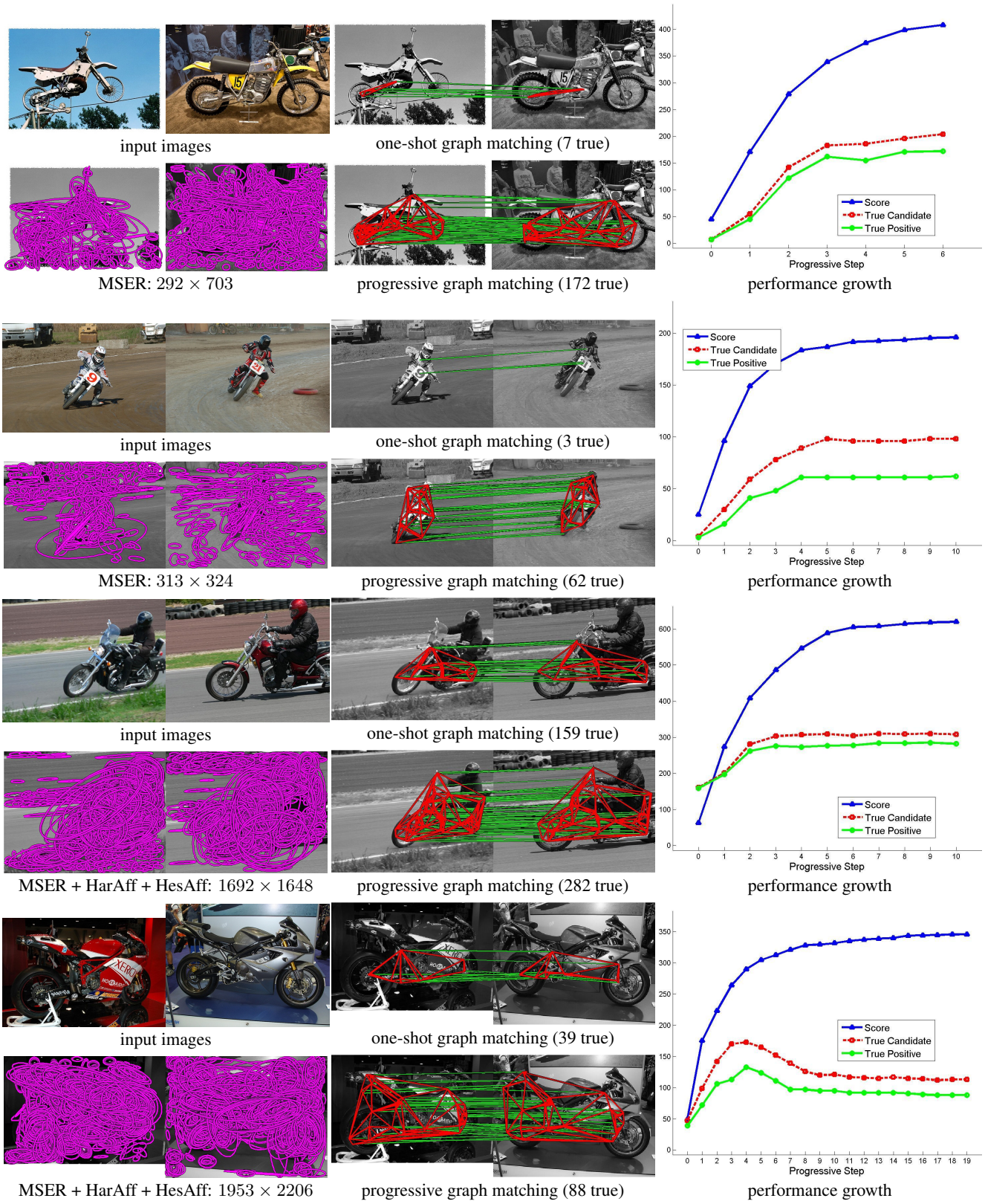
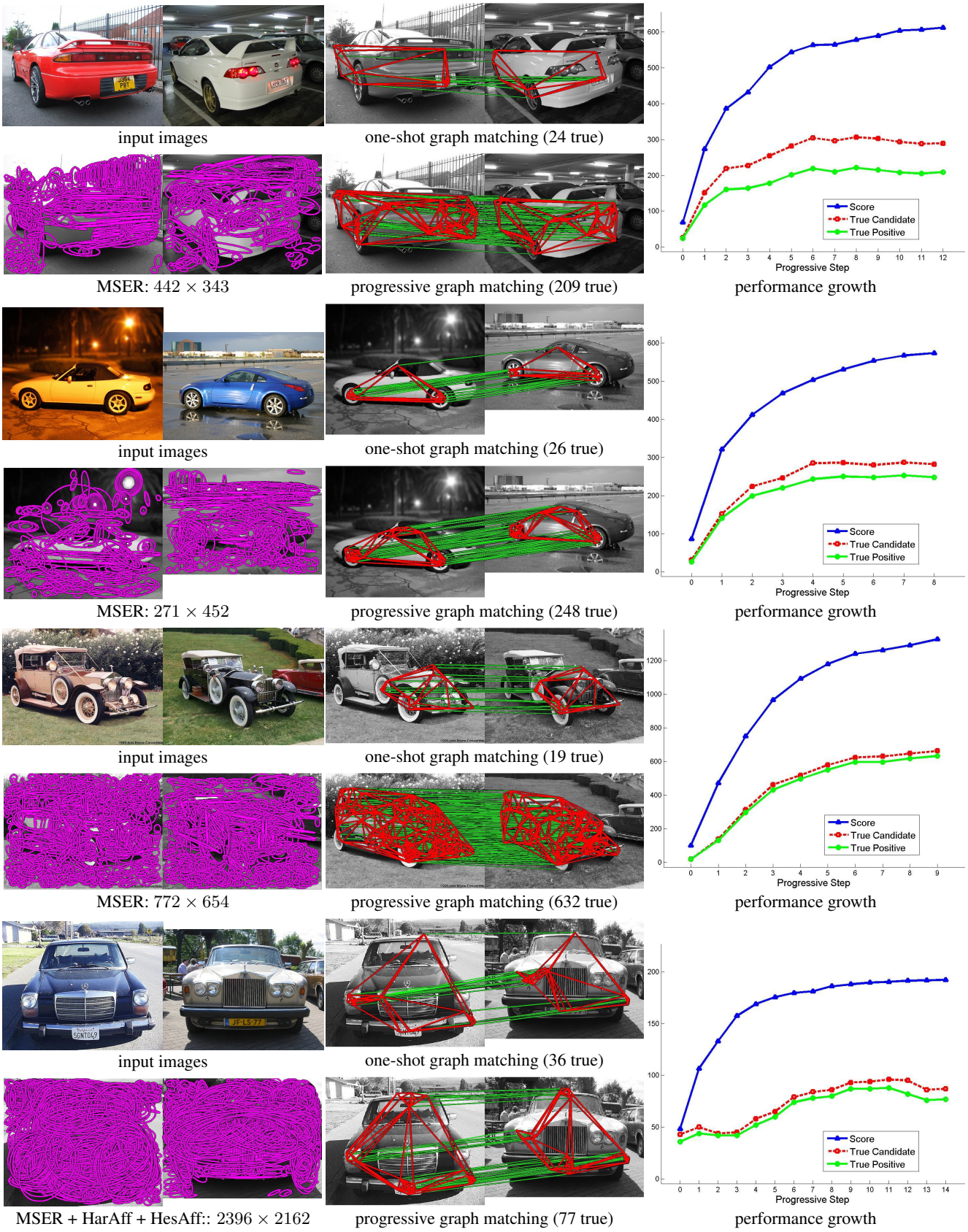


Figure 3. Progressive graph matching.



input images | one-shot graph matching (24 true)

MSER: 442 × 343 | progressive graph matching (209 true) | performance growth

input images | one-shot graph matching (26 true)

MSER: 271 × 452 | progressive graph matching (248 true) | performance growth

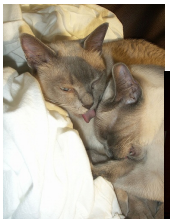
input images | one-shot graph matching (19 true)

MSER: 772 × 654 | progressive graph matching (632 true) | performance growth

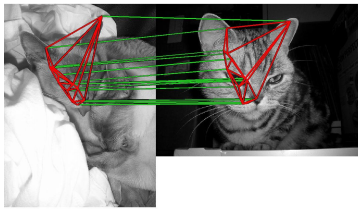
input images | one-shot graph matching (36 true)

MSER + HarAff + HesAff:: 2396 × 2162 | progressive graph matching (77 true) | performance growth

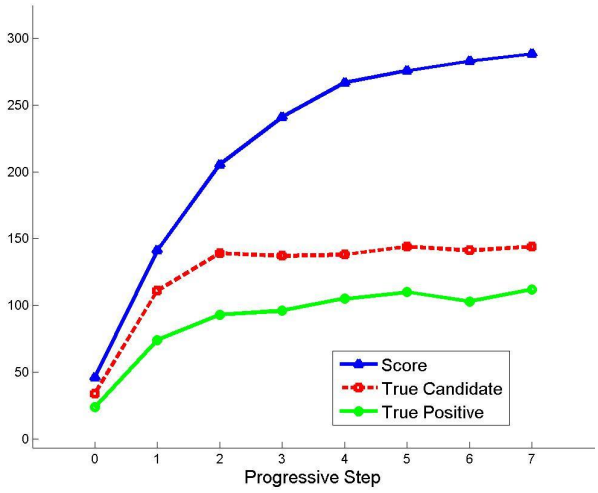
Figure 4. Progressive graph matching.



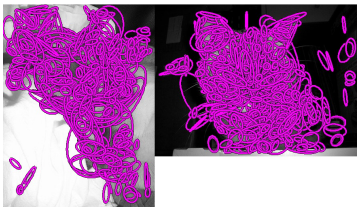
input images



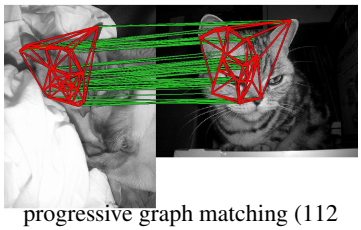
one-shot graph matching (24 true)



performance growth

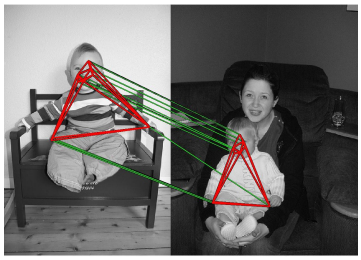


MSER: 318 × 391

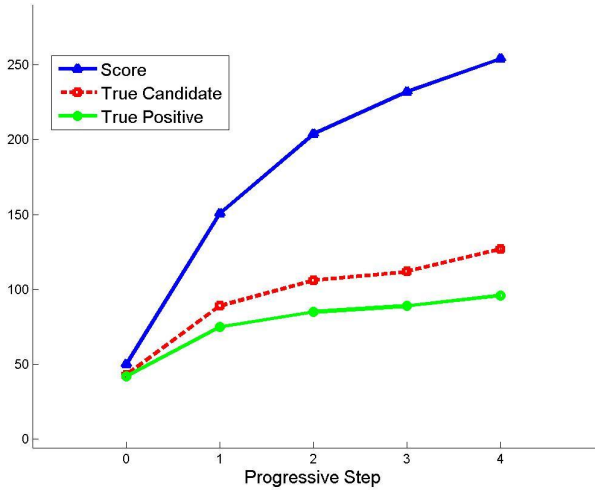


progressive graph matching (112 true)

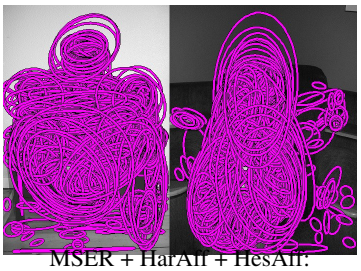
input images



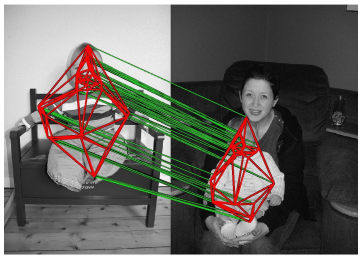
one-shot graph matching (42 true)



performance growth



MSER + HarAff + HesAff: 1425 × 717



progressive graph matching (96 true)

Figure 5. Progressive graph matching.

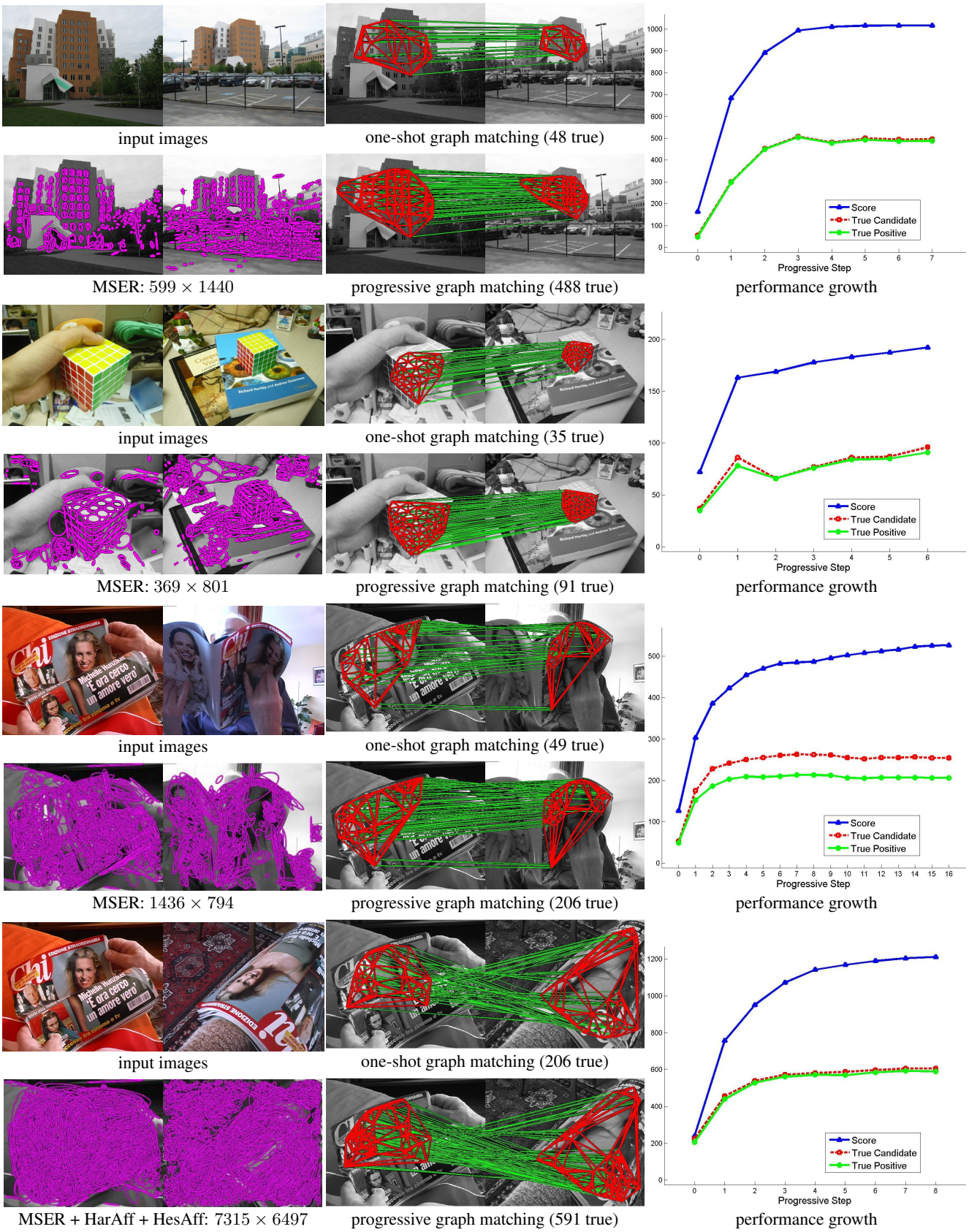


Figure 6. Progressive graph matching.

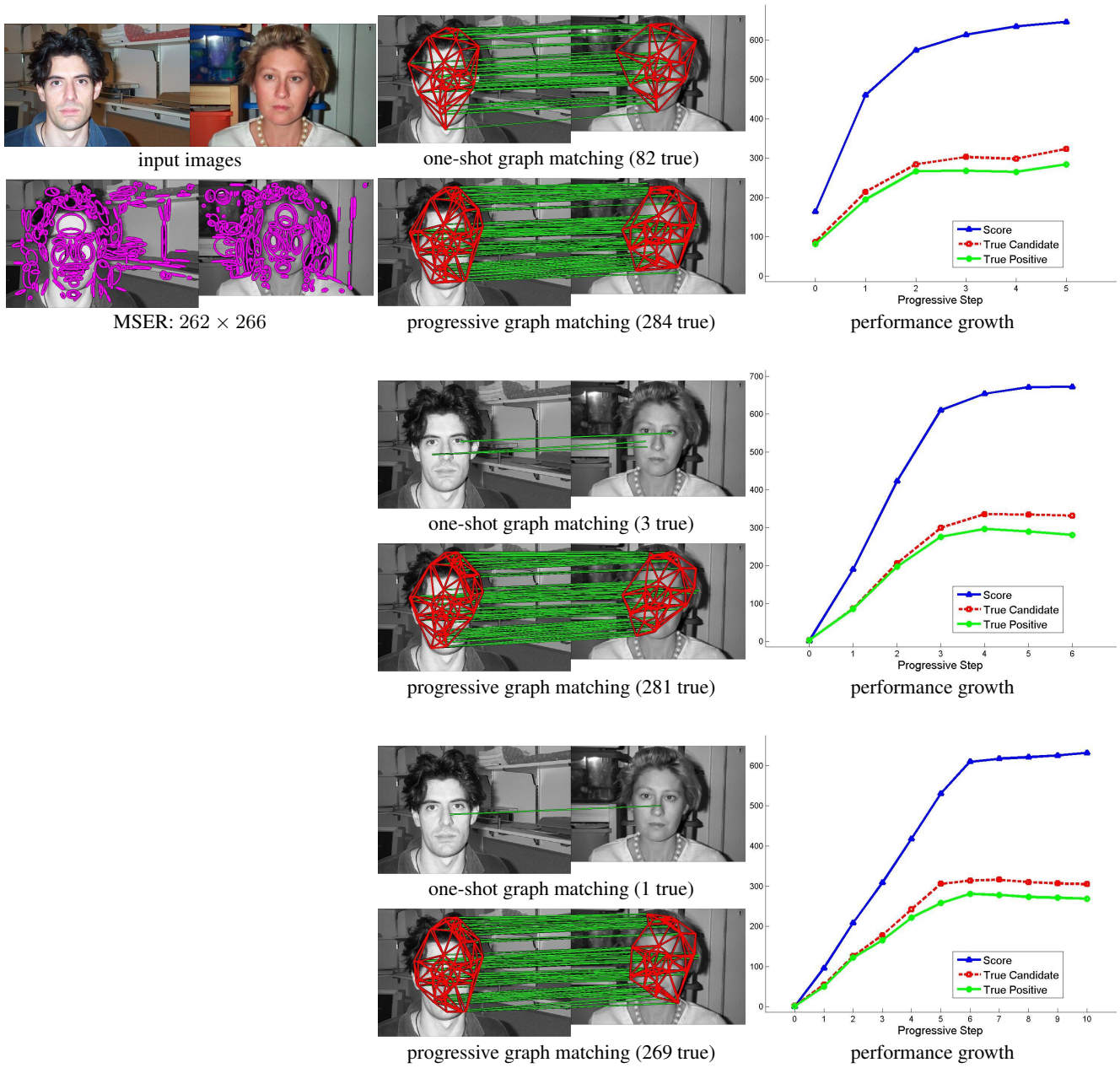


Figure 7. Robustness to initial active graphs. In this experiment, we started progressive graph matching from a very small size of initial active graphs, and compared the results with a large size of initial active graphs. The result of the initial active graphs with 3000 candidate matches is shown at the top, and the two results of the initial active graphs with 50 candidate matches is shown at the middle and the bottom. Algthough they have just 1 and 3 initial true matches, their final results are comparable to the result at the top which started from 82 true matches. This results demonstrate that progressive graph matching is not sensitive to the starting active graphs.