# Siamese Cascaded Region Proposal Networks for Real-Time Visual Tracking
# — Supplementary Material —

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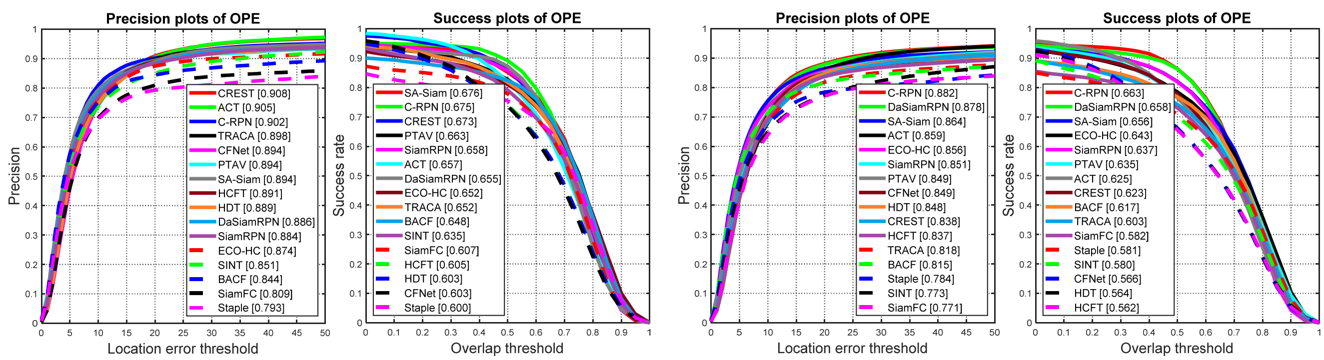
## 1. Detailed experimental results on OTB-2013 and OTB-2015

In this section we show the detailed results on OTB-2013 [19] and OTB-2015 [20]. Following [20], we report the results in *one-pass evaluation* (OPE) using *precision* and *success* plots. The comparison of C-RPN with 15 trackers (SiamRPN [12], DaSiamRPN [21], TRACA [4], ACT [3], BACF [8], ECO-HC [5], CREST [16], SiamFC [2], Staple [1], PTAV [7], SINT [17], SA-Siam [9], CFNet [18], HDT [15] and HCFT [13]) is shown in Fig. 1. Tab. 1 summarizes the comparison.




(a) Comparison on OTB-2013 (b) Comparison on OTB-2015

Figure 1. Comparison of C-RPN with 14 state-of-the-art trackers on OTB-2013 [19] and OTB-2015 [20]. Best viewed in color.

Table 1. Performance of different trackers on OTB-2013 [19] and OTB-2015 [20]. The best two results are in red and blue font, respectively.

| Tracker | Where | OTB-2013 | | OTB-2015 | | Speed (*fps*) |
|---|---|---|---|---|---|---|
| | | PRE | SUC | PRE | SUC | |
| C-RPN | - | 0.902 | 0.675 | 0.882 | 0.663 | 36 |
| DaSiamRPN [21] | ECCV'2018 | 0.886 | 0.655 | 0.878 | 0.658 | 160 |
| ACT [3] | ECCV'2018 | 0.905 | 0.657 | 0.859 | 0.625 | 30 |
| SiamRPN [12] | CVPR'2018 | 0.884 | 0.658 | 0.856 | 0.637 | 160 |
| SA-Siam [9] | CVPR'2018 | 0.894 | 0.676 | 0.864 | 0.656 | 50 |
| TRACA [4] | CVPR'2018 | 0.898 | 0.652 | 0.851 | 0.603 | 101 |
| PTAV [7] | ICCV'2017 | 0.894 | 0.663 | 0.849 | 0.635 | 25 |
| BACF [8] | ICCV'2017 | 0.844 | 0.648 | 0.815 | 0.617 | 35 |
| CREST [16] | ICCV'2017 | 0.908 | 0.673 | 0.838 | 0.623 | 5 |
| ECO-HC [5] | CVPR'2017 | 0.874 | 0.652 | 0.856 | 0.643 | 60 |
| CFNet [18] | CVPR'2017 | 0.785 | 0.603 | 0.777 | 0.566 | 75 |
| SiamFC [2] | ECCVW'2016 | 0.809 | 0.607 | 0.771 | 0.582 | 86 |
| SINT [17] | CVPR'2016 | 0.851 | 0.635 | 0.773 | 0.580 | 2 |
| Staple [1] | CVPR'2016 | 0.793 | 0.600 | 0.784 | 0.581 | 80 |
| HDT [15] | CVPR'2016 | 0.889 | 0.603 | 0.848 | 0.564 | 10 |
| HCFT [13] | ICCV'2015 | 0.891 | 0.605 | 0.837 | 0.562 | 11 |

In addition, we also show the attribute evaluation on OTB-2013 in Fig. 2 and on OTB-2015 in Fig. 3.

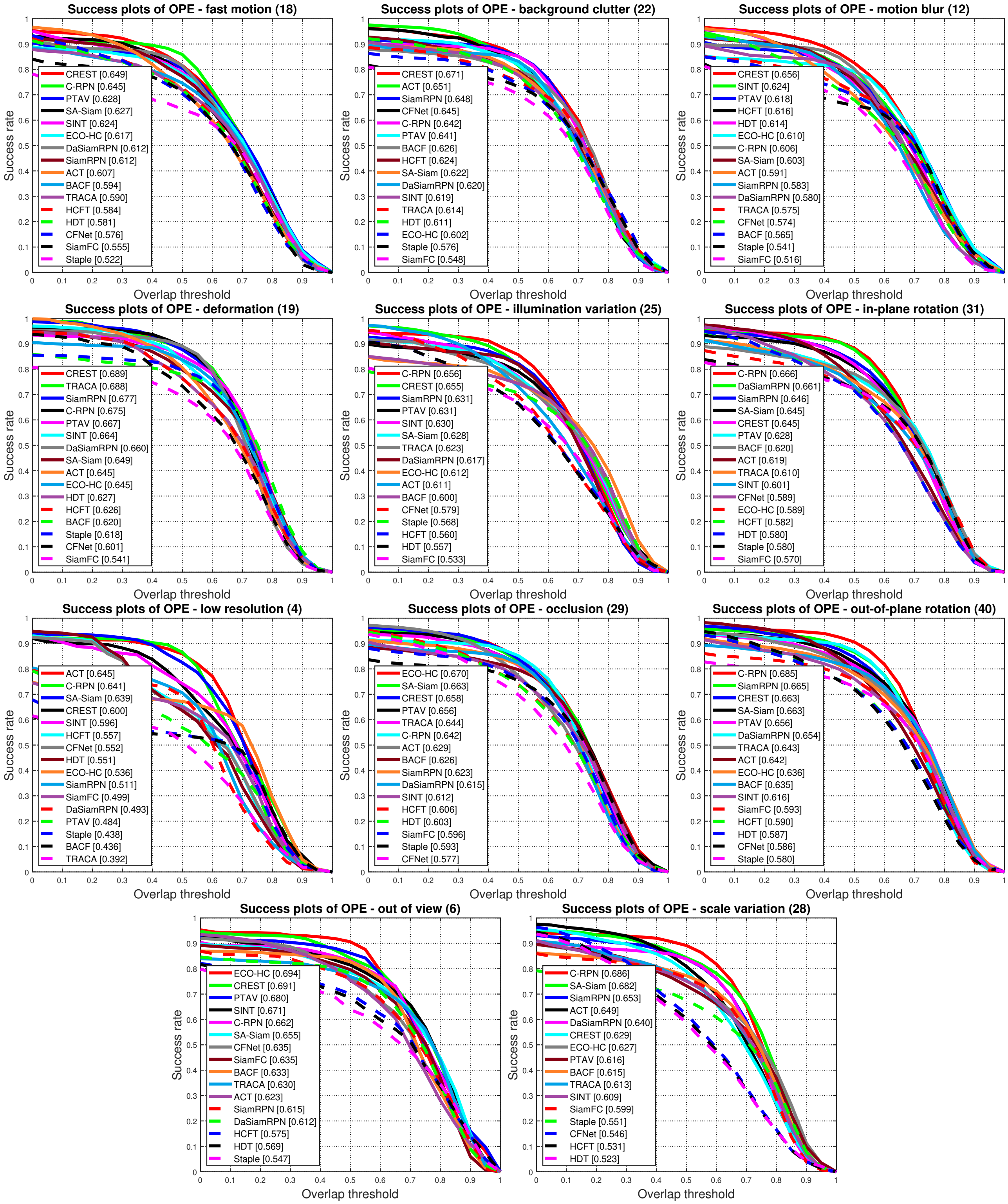



Figure 2. Evaluation on 11 attributes using SUC on OTB-2013 [19], including fast motion (FM), background cluttered (BC), motion blur (MB), deformation (DEF), illumination variation (IV), in-plane rotation (IPR), low resolution (LR), occlusion (OCC), out-of-plane rotation (OPR), out-of-view (OV) and scale variation (SV).

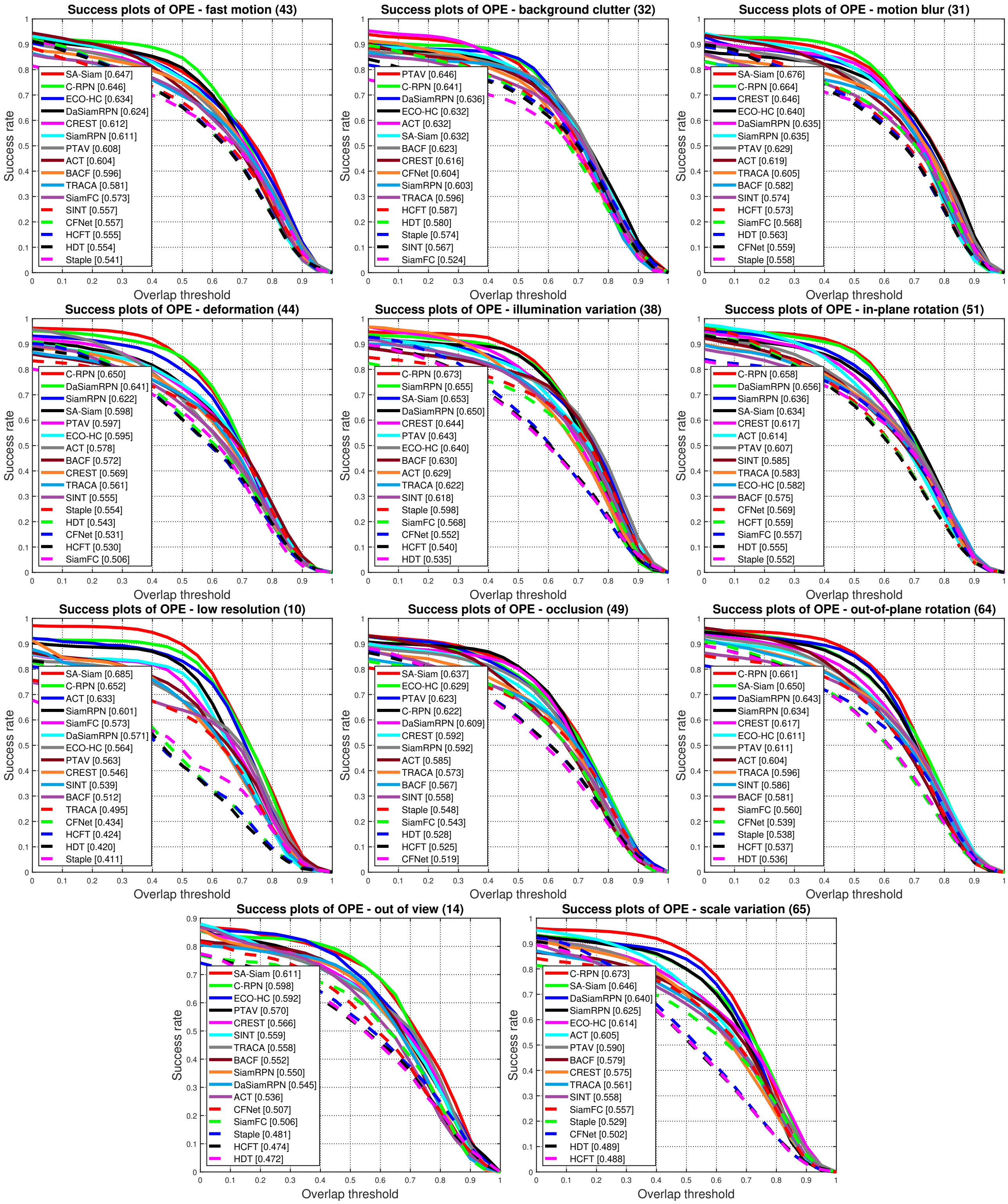



Figure 3. Evaluation on 11 attributes using SUC on OTB-2015 [20], including fast motion (FM), background cluttered (BC), motion blur (MB), deformation (DEF), illumination variation (IV), in-plane rotation (IPR), low resolution (LR), occlusion (OCC), out-of-plane rotation (OPR), out-of-view (OV) and scale variation (SV).

## 2. Detailed experimental results on VOT-2016 and VOT-2017

In this section, we show the full results for baseline experiment on VOT-2016 [10] in Fig. 4. Fig. 5 and Fig. 6 show the results for baseline and real-time experiments on VOT-2017 [11], respectively.

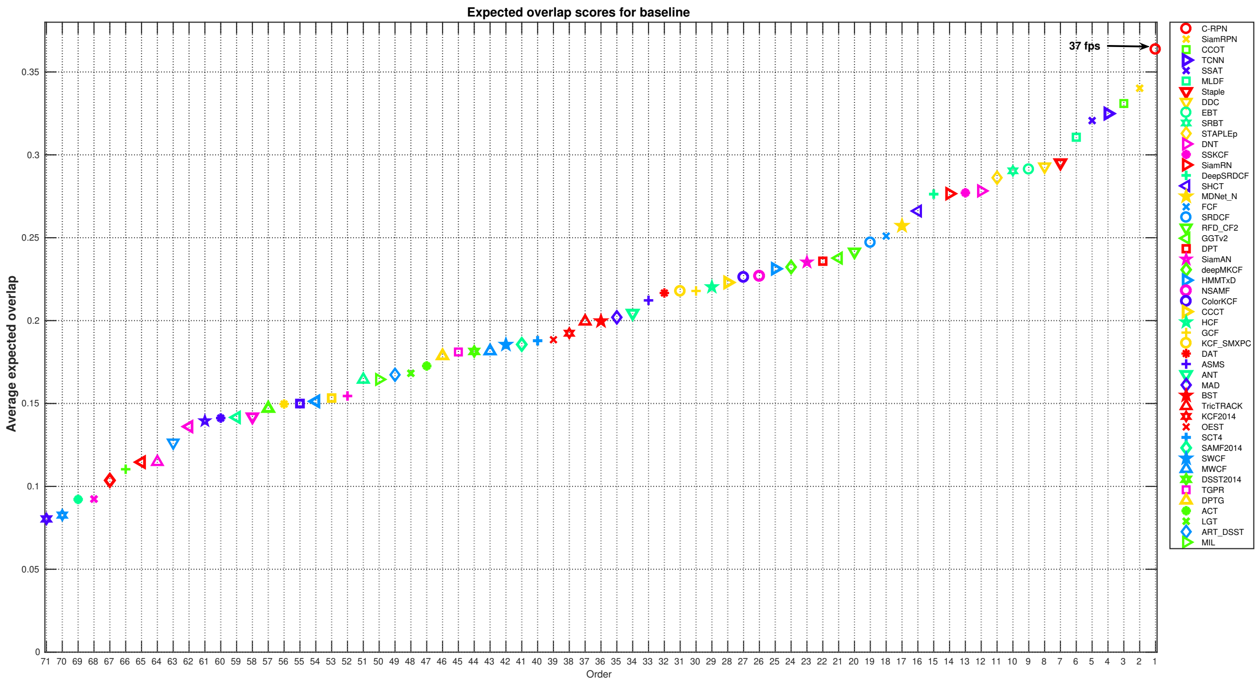



Figure 4. Results for baseline experiment on VOT-2016 [10]. Best viewed in color and when zoomed-in. Our C-RPN ranks the first.

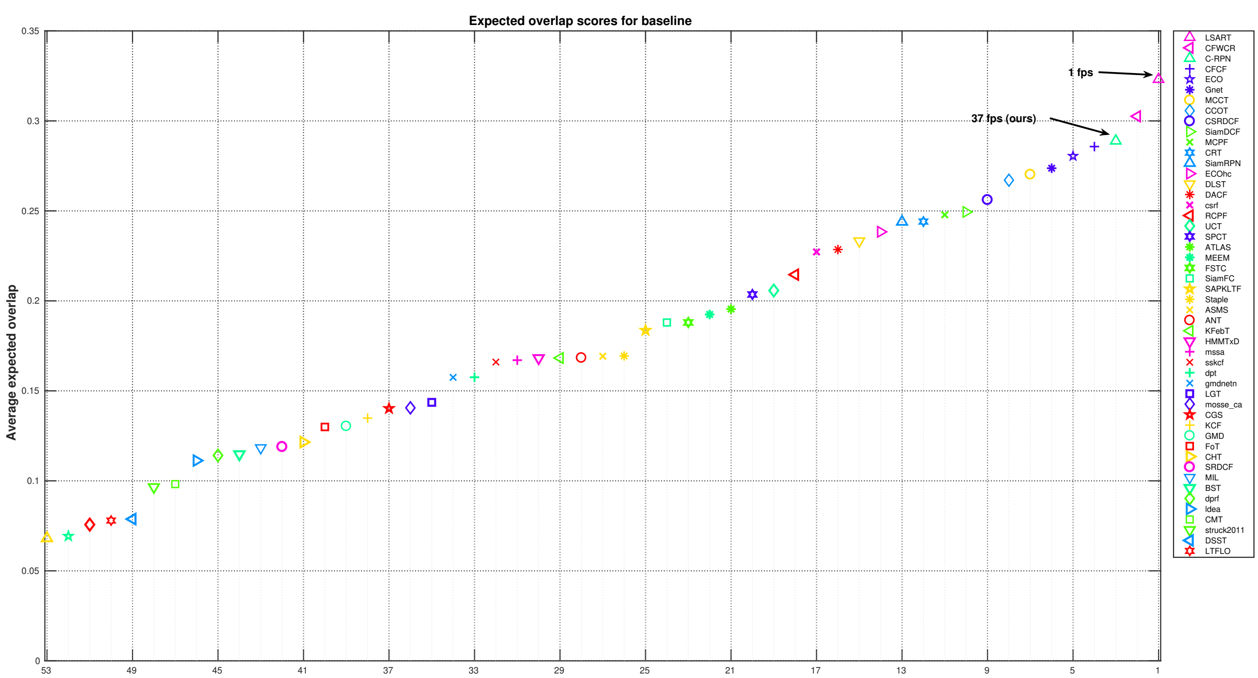



Figure 5. Results for baseline experiment on VOT-2017 [11]. Best viewed in color and when zoomed-in. Our C-RPN shows competitive performance.

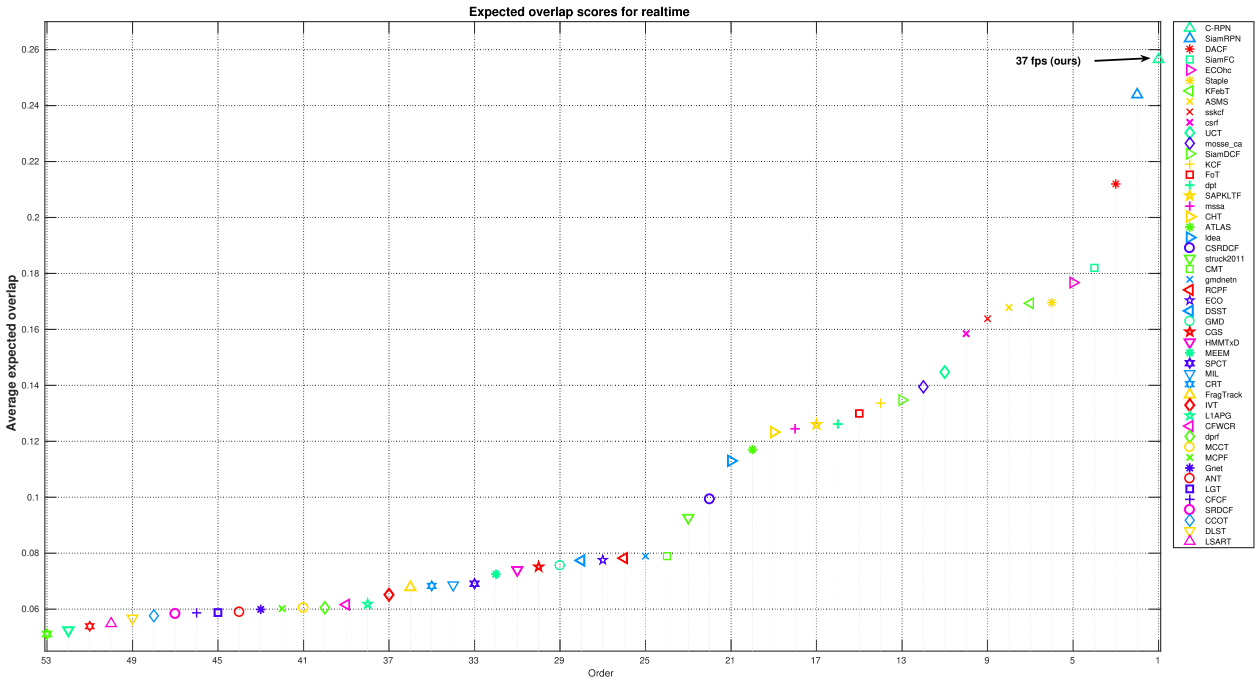
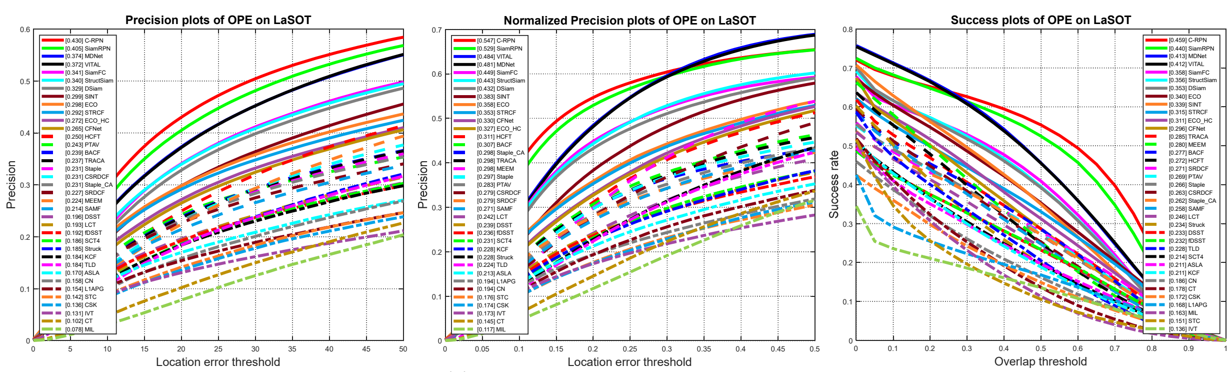


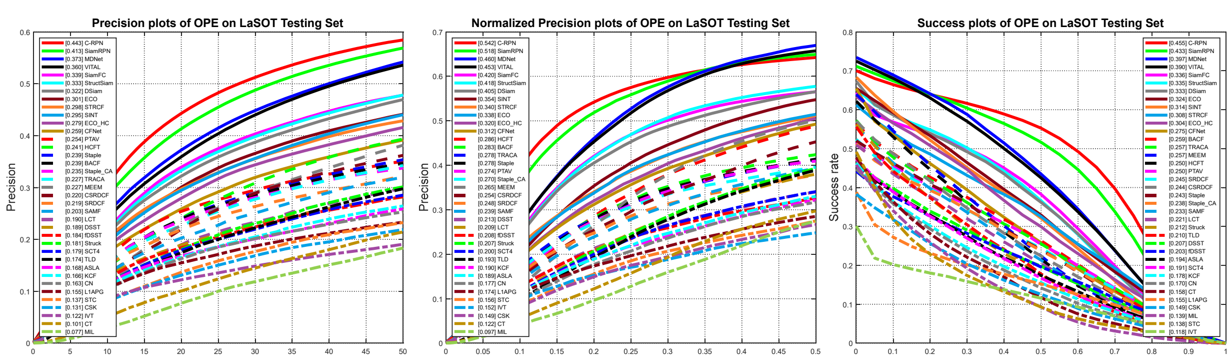

Figure 6. Results for real-time experiment on VOT-2017 [11]. Best viewed in color and when zoomed-in. Our C-RPN ranks the first.

## 3. Detailed experimental results on LaSOT

Fig. 7 demonstrates the results under Protocol I and II. Fig. 8 and 9 show the attribution evaluation under two protocols.




(a) Comparison on LaSOT under Protocol I




(b) Comparison on LaSOT under Protocol II

Figure 7. Comparison of C-RPN with 35 state-of-the-art trackers on LaSOT [6]. Best viewed in color and when zoomed-in.

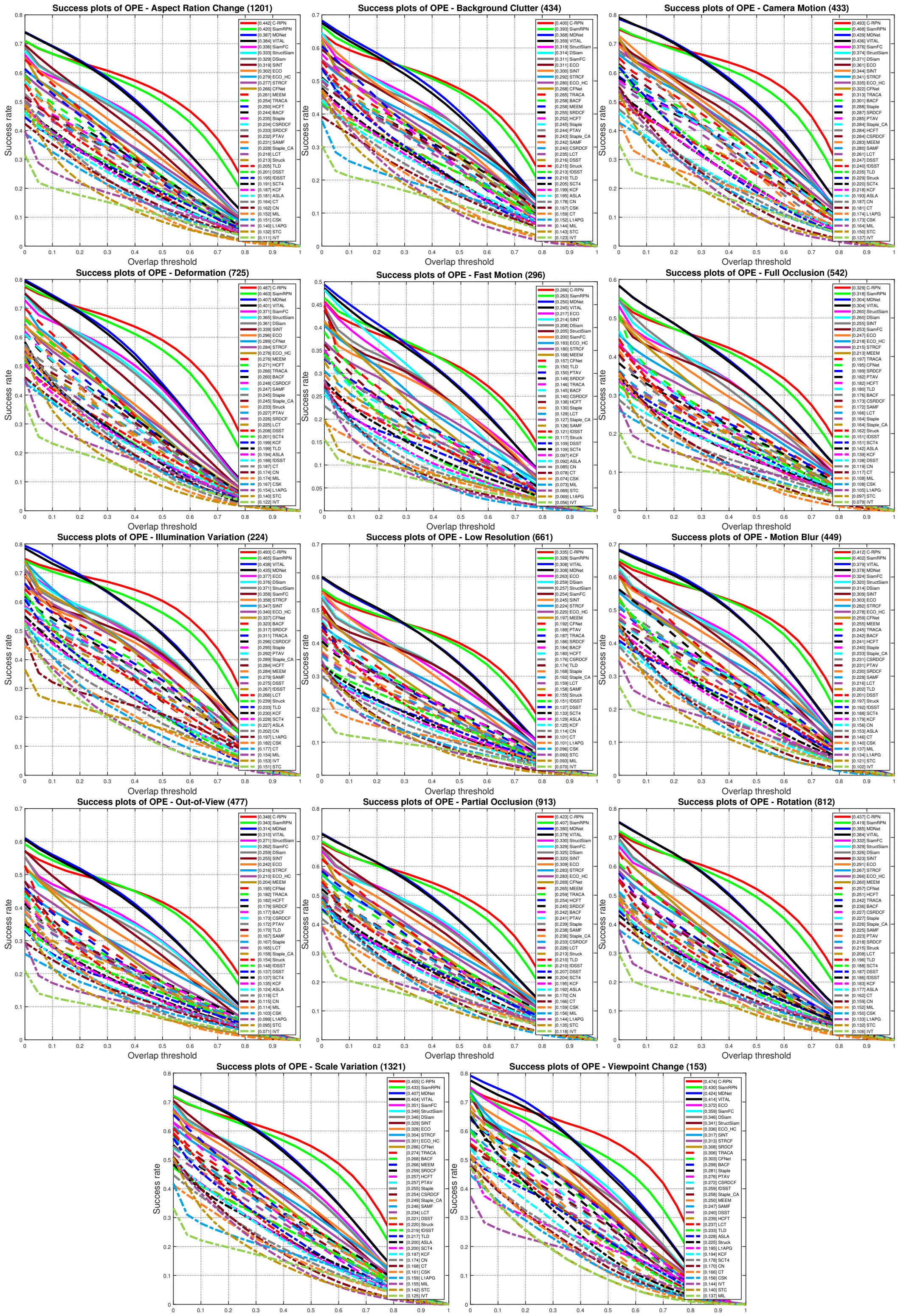



Figure 8. Evaluation on 14 attributes under Protocol I using SUC on LaSOT [20], including illumination variation (IV), full occlusion (FOC), partial occlusion (POC), deformation (DEF), motion blur (MB), fast motion (FM), scale variation (SV), camera motion (CM), rotation (ROT), background clutter (BC), low resolution (LR), viewpoint change (VC), out-of-view (OV) and aspect ration change (ARC).

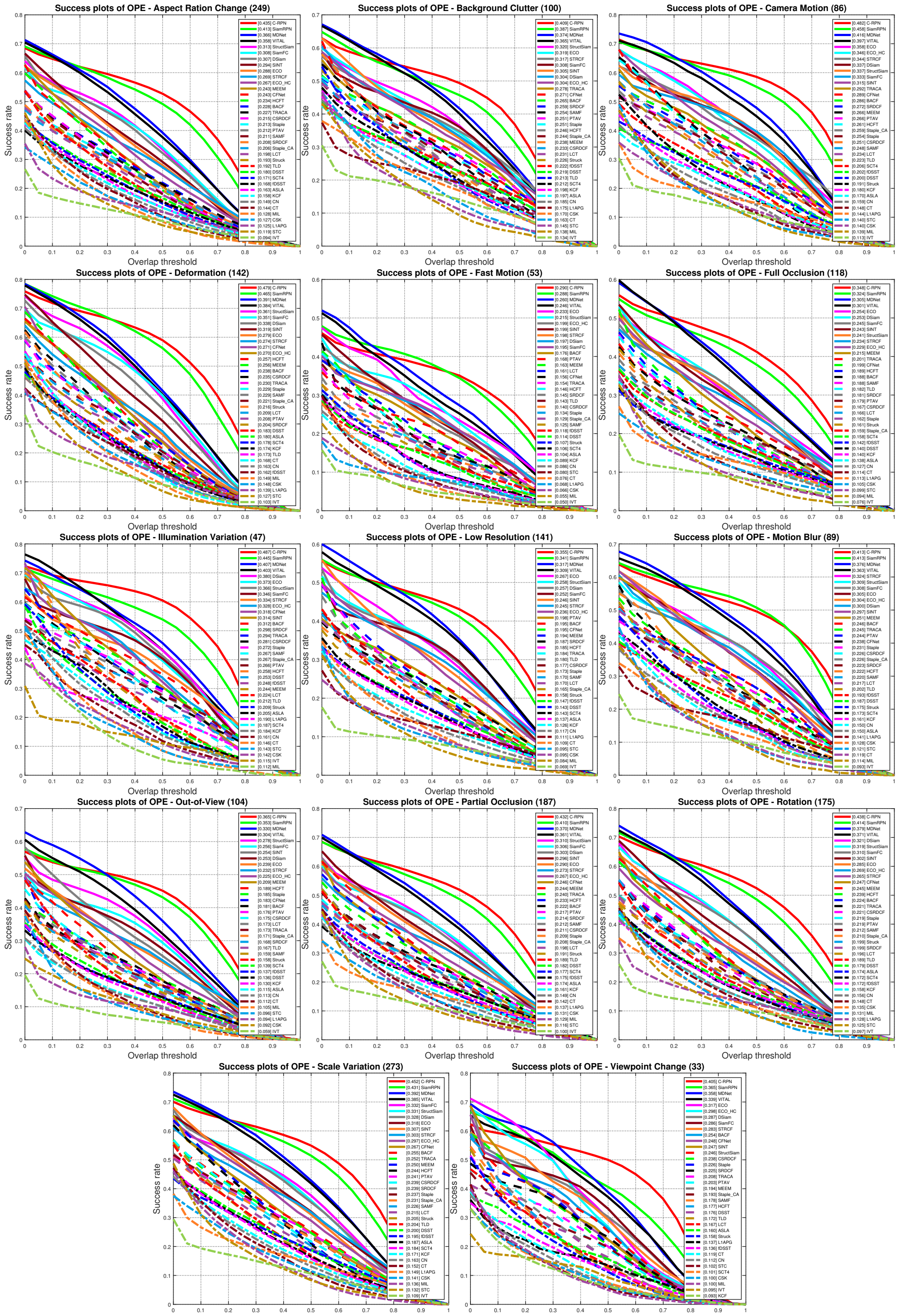



Figure 9. Evaluation on 14 attributes under Protocol II using SUC on LaSOT [20], including illumination variation (IV), full occlusion (FOC), partial occlusion (POC), deformation (DEF), motion blur (MB), fast motion (FM), scale variation (SV), camera motion (CM), rotation (ROT), background clutter (BC), low resolution (LR), viewpoint change (VC), out-of-view (OV) and aspect ration change (ARC).

Moreover, we also show some qualitative results of the proposed C-RPN and comparison to other state-of-the-art trackers on LaSOT [6], as shown in Fig. 10.


Figure 10. Qualitative comparison on ten challenging sequences (from top to bottom: *bicycle-18*, *bird-3*, *boat-3*, *bus-17*, *dog-7*, *horse-1*, *leopard-7*, *person-1*, *turtle-16* and *kite-4*) of LaSOT under the Protocol II. Best viewed in color.

## 4. Detailed experimental results on TrackingNet

This section shows the result of our C-RPN on TrackingNet [14]. Note that the result is evaluated by the server provided by the organizer at http://eval.tracking-net.org/web/challenges/challenge-page/39/leaderboard/

42. Here we list the full comparison of our method with state-of-the-art trackers in Tab. 2. The results of other trackers are reported from the original paper [14].

Table 2. Comparisons on TrackingNet [14] with the best two results highlighted in **red** and **blue** fonts, respectively.

| | Precision | Norm. Precision | Success |
|---|---|---|---|
| C-RPN (Ours) | **0.619** | **0.746** | **0.669** |
| MDNet | **0.565** | **0.705** | **0.606** |
| CFNet | 0.533 | 0.654 | 0.578 |
| SiamFC | 0.533 | 0.663 | 0.571 |
| ECO | 0.492 | 0.618 | 0.554 |
| CSRDCF | 0.48 | 0.622 | 0.534 |
| SAMF | 0.477 | 0.598 | 0.504 |
| ECO-HC | 0.476 | 0.608 | 0.541 |
| Staple | 0.470 | 0.603 | 0.528 |
| Staple_CA | 0.468 | 0.605 | 0.529 |
| BACF | 0.461 | 0.580 | 0.523 |
| DSST | 0.460 | 0.588 | 0.464 |
| SRDCF | 0.455 | 0.573 | 0.521 |
| SAMF_AT | 0.447 | 0.560 | 0.472 |
| DCF | 0.419 | 0.548 | 0.448 |
| KCF | 0.419 | 0.546 | 0.447 |
| DLSSVM | 0.418 | 0.562 | 0.470 |
| ASLA | 0.406 | 0.536 | 0.478 |
| Struck | 0.402 | 0.539 | 0.456 |
| MEEM | 0.386 | 0.545 | 0.460 |
| CSK | 0.368 | 0.503 | 0.429 |
| IVT | 0.336 | 0.460 | 0.417 |
| MOSSE | 0.326 | 0.442 | 0.388 |
| TLD | 0.292 | 0.438 | 0.400 |

## References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