## In Defense of Sparse Tracking: Circulant Sparse Tracker (Supplementary Material)

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We present more evaluation results on the tracking benchmark [3]. Here, we show comparisons with the stateof-the-art trackers in [3] and sparse tracking evaluation results. The details are as follows.

**Comparison with State-of-the-Art** We evaluate the proposed CST tracker on the tracking benchmark with comparisons to 29 trackers in [3], whose details can be found in [3]. We report the precision and success plots in Figure 1, thus, illustrating the mean distance and overlap precision over all the 50 sequences. Figure 1 contains the precision and success plots illustrating the mean distance and overlap precision over all the 50 sequences. In both precision and success plots, the proposed CST method registers the best performance among all trackers and significantly outperforms the best existing sparse tracking method (SCM).

In Figure 3 and Figure 4, we show the distance precision plots and overlap success plots on the 50 benchmark sequences [3] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, outof-plane rotation and out-of-view. In Figure 3, the legends contain the average distance precision rate using a threshold at 20 pixels. In Figure 4, the legends contain the scores of the area under the curve (AUC) for each tracker. Overall, the proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

In Figure 5 and Figure 6, we show the center location errors and overlap scores on the 50 benchmark sequences [3], respectively. In Figure 5, we show the fame-by-frame comparison of center location errors of the top 10 trackers (denoted in different colors and lines) in our evaluation. The average center location errors of these trackers are shown in the legends. In Figure 6, we show the fame-by-frame comparison of overlap scores of the top 10 trackers (denoted in different colors and lines) in our evaluation. The average overlap scores of these trackers are shown in the legends.



Figure 1. Precision and success plots over all the 50 sequences using OPE among 29 trackers in [3]. The proposed CST method performs favorably against the state-of-the-art trackers.



Figure 2. Comparisons of different sparse trackers by using precision and success plots over all the 50 sequences. The legend contains the area-under-the-curve score for each tracker. Our CST method performs favorably against the state-of-the-art trackers.

Generally, our method achieves much better performance.

**Sparse Tracking Evaluation** We evaluate the proposed algorithm on the benchmark with comparisons to the top 4 sparse trackers in [3], namely SCM [5], ASLA [2], L1APG [1], and MTT [4]. The details of the 4 trackers in the benchmark evaluation can be found in [3]. We report the results in OPE using the distance precision and overlap success rate in Figure 2, attribute-based evaluation in Figure 7, and qualitative comparison in Figure 8 and Figure 9.

Figure 2 contains the precision and success plots illustrating the mean distance and overlap precision over all the 50 sequences of different sparse trackers. In both precision and success plots, our approach shows the best results and significantly outperforms the best existing sparse method (SCM). In Figure 7, we analyze tracking performance based on some tracking attributes of the video sequences [3]. Note that the benchmark annotates 11 such attributes to describe the different challenges in the tracking problem, e.g., occlusions or out-of-view. These attributes are useful for analyzing the performance of trackers in different aspects. We note that the proposed CST method performs well in dealing with challenging factors including fast motion, occlusion, and out of view.

In Figure 8, we show a qualitative comparison among the sparse trackers on 10 challenging sequences. Overall, the proposed CST tracker performs very well in tracking objects on these challenging sequences. In addition, we compare the center location error frame-by-frame on the 10 sequences in Figure 9, which shows that our method performs well against existing trackers. Tracking results are also attached in the submitted video. Due to the maximum file size limitation, only 20 video results are attached.

## References

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Figure 3. Distance precision plots on the 50 benchmark sequences [3] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the average distance precision rate using a threshold at 20 pixels. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.



Figure 4. Overlap success plots on the 50 benchmark sequences [3] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.



Figure 5. Comparison of center location errors (in pixels) on the 50 benchmark sequences [3]. Here, we show the fame-by-frame comparison of center location errors of the top 10 trackers (denoted in different colors and lines) in our evaluation. The average center location errors of these trackers are shown in the legends. Generally, our method achieves much better performance.



Figure 6. Comparison of overlap scores on the 50 benchmark sequences [3]. Here, we show the fame-by-frame comparison of overlap scores of the top 10 trackers (denoted in different colors and lines) in our evaluation. The average overlap scores of these trackers are shown in the legends. Generally, our method achieves much better performance.



Figure 7. Overlap success plots and distance precision plots over eleven tracking challenges of fast motion, background clutter, motion blur, deformation, illumination variation, in-plane rotation, low resolution, occlusion, out-of-plane rotation, out-of-view, and scale variation. The proposed CST method performs favorably against the state-of-the-art trackers when evaluating with the eleven challenging factors.



Figure 8. Tracking results of the top 5 sparse trackers (denoted in different colors and lines) in our evaluation on 10 challenging sequences (from left to right and top to down are basketball, singer2, car4, jogging-1, subway, david3, liquor, suv, jumping, and tiger1 respectively).



Figure 9. Fame-by-frame comparison of center location errors (in pixels) on 10 challenging sequences in Figure 8. Generally, our method is able to track targets accurately and stably.