Long-Term Tracking

Matej Kalc

I. Introduction

While tracking a specific object, it can disappear from the field of view or it can get occluded. short-term trackers fail to track the object when such events occur. In this report, we will modify an existing short-term tracker into a long-term tracker using thresholding. Additionally, we will explore how the tracker performance differs with a different number of re-detections and using a growing gaussian search space.

II. Experiments

A. SiamFC

The performance of SiamFC is shown in Table I.

	car9	all
Precision	0.64	0.59
Recall	0.27	0.30
F-score	0.38	0.40

Table I: Results of the SiamFC tracker on only the sequence car9 and all the sequences.

B. SiamFC with redetection

I added a threshold to SiamFC. When the score is lower than the threshold T, we search uniformly n times across the image. If the search returns a position with a score higher than T, we re-detected the tracked object.

	car9	all
Precision	0.60	0.58
Recall	0.59	0.46
F-score	0.60	0.51

Table II: Results of the SiamFC tracker with re-detection (T = 4, number of re-detections/frame = 50) on only the sequence car9 and all the sequences.

Using re-detections drastically improved our measures (see Table II).

C. Threshold optimization

I tried different constant thresholds (T = 3,4,5). The results are shown in Table III.

	T = 3	T = 4	T = 5
Precision	0.58	0.58	0.55
Recall	0.43	0.46	0.41
F-score	0.49	**0.51**	0.47

Table III: Results of SiamFC with re-detections (re-detections/frame = 50) with different constant thresholds on all sequences.

The best results were given by T = 4. Another approach would be to set the threshold internally using Equation 1.

$$T = \alpha \cdot \text{median}(scores) \tag{1}$$

Instead of setting directly the threshold, we would set the α parameter.

D. Number of re-detections optimization

Higher is the number of re-detections than on average earlier we can re-detect the tracked object. The highest jump in performance is going from 0 to 1 re-detection (see Table IV).

	number of re-detections				
	0	1	10	50	100
Precision	0.64	0.59	0.58	0.55	0.57
Recall	0.26	0.44	0.44	0.41	0.44
F-score	0.37	0.50	0.50	0.47	0.50

Table IV: Results of SiamFC with re-detection on all sequences using different a number of re-detections.

E. Example of re-detection

We will show an example of re-detection in sequence car9 (see Figure 1).

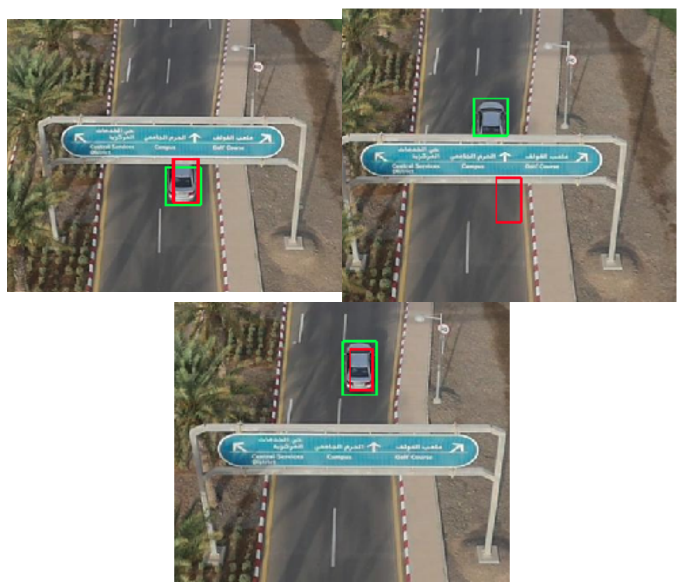

Figure 1: In the top left our tracker is tracking a car. In the top right, the SiamFC tracker with no re-detection failed to track the object. In the bottom image, the tracker SiamFC with re-detection managed to re-detect the car.

We see that the tracker with re-detection managed to re-detect the tracker car right after the occlusion.

F. Growing gaussian search space

Uniform sampling is not the most efficient search space, since when an object is occluded it will probably reappear in a near position. A solution is to use a 2D gaussian search space. Additionally, we must use a growing in time gaussian, since it could happen that the object reappeared but it is not the search space.

Using the 2D gaussian search space did not improve the results, but still, the results are similar to the results of the uniform search space (see Table V).

	σ				
	10	30	50	70	90
Precision	0.59	0.59	0.59	0.54	0.59
Recall	0.42	0.42	0.44	0.40	0.44
F-score	0.49	0.50	0.50	0.46	0.50

Table V: Results of SiamFC with re-detection and a 2D gaussian search space on all sequences for different σ.

III. Conclusion

Transforming a short-term tracker into a long-term tracker drastically improved the F-score. Selecting the ideal threshold is a challenge on its own. Using 2D gaussian sampling did not improve our results, but it could if the ideal starting and ideal growing σ are chosen.