	Attack Against Visual Tracking
	Supplementary Material
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1 Atta	cking Correlation Filter-based Trackers
Completion	c fits (CE) is a dominant tracking framework that can achieve real
Correlation	1 niter (CF) is a dominant tracking framework that can achieve we
trackors ar	tween tracking speed and accuracy. However, most of the CF-based
is difficult	to attack them via the white her setup and is meaningful to explor
if SPARK	could attack CF-based trackers by using deep tracking frameworks
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e.u. Stamt	RPN-based trackers. As shown in Table I, the adversarial example
from Siaml	RPN-based trackers. As shown in Table I, the adversarial example RPN-Alex can reduce all tested CF-based trackers having differen
from Siaml features, w	RPN-based trackers. As shown in Table I, the adversarial example RPN-Alex can reduce all tested CF-based trackers having differen hich demonstrates that the transiferability of our attack across differ
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from Siaml features, wl ent trackers is easier at	RPN-based trackers. As shown in Table I, the adversarial example RPN-Alex can reduce all tested CF-based trackers having different hich demonstrates that the transiferability of our attack across differents and features exists. In terms of different features, the HOG feature tracked when compared with the gray feature, hybird feature (<i>i.e.</i>)
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043 044 three basic attack methods due to the balance between time cost and attack Succ. Rate. Please find details in Section 3.3. Compared with trackers' cost shown in Table. III, the time cost of our attack method increases as the tracking model becomes larger under the white-box attack. In particular, when attacking SiamRPN-Alex, SPARK achieves near real-time attacking. Although the attack speed decreases with more complex models, the corresponding tracking speed is also slower and lets the influence of decreased attacking be smaller. We can

SiamRPN	AlexNet	MobileNetV2	$\operatorname{Res50}$
Track cost per frame (ms)	9.3	37.6	42.1
Attack cost per frame (ms)	41.4	126.9	156.3
Track speed (fps)	108.4	15.3	16.8
Attack speed (fps)	24.3	8.0	6.4

Table II. Time cost of attacks w.r.t. different trackers on OTB100 dataset.

reduce the high time cost of attacking larger models (e.g., MobileNetv2) and Res50) by using the light one (e.q., AlexNet) due to the existence of the trans-ferability between models as discussed in Section 4.3 and Table 4. Specifically, we attack three trackers, *i.e.*, SiamRPN-Alex/Mob./Res50, via SPARK with the adversarial perturbations generated from SiamRPN-Alex. Then, we calculate the attack's online speed as well as the three trackers' speed. As shown in the fol-lowing Table. III, the speed of SPARK base on SiamRPN-Alex can reach near real-time speed (around 25 fps) for different trackers, which means our method is suitable for attacking real-time online trackers.

Table III. Time cost of attacking trackers on OTB100. The adversarial perturbations are generated from SiamRPN-Alex.

SiamRPN	AlexNet	MobileNetV2	Res50
Track speed (fps)	108.4	15.3	16.8
Attack speed (fps)	24.3	23.1	22.7

References

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