Tackling Occlusion in Siamese Tracking with Structured Dropouts

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Paper Id: 1590

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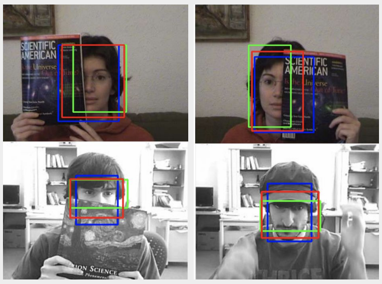
Introduction

Ōcclusion is among the hardest tracking challenges, especially because it is defined by lack of representation. Occlusion is hard to simulate as the occluding object can be anything in any shape.

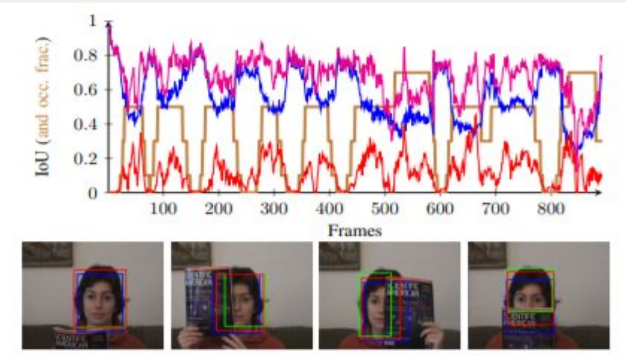
We propose to use *structured dropouts* to adapt the CNN model itself for tackling occlusions in Siamese tracking.



Examples from OTB100 showing groundtruth (blue), prediction from SiamRPN++ (green) snd SiamRPN-SD (red).

Improved localization under occlusion

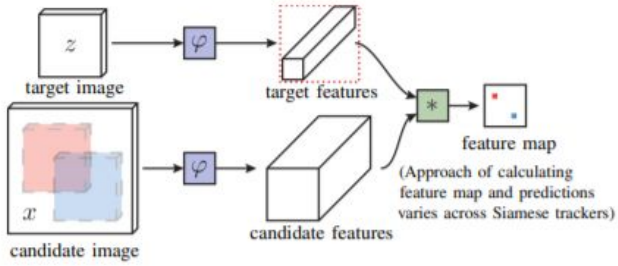
Structured dropouts improve the IoU score under occlusion.



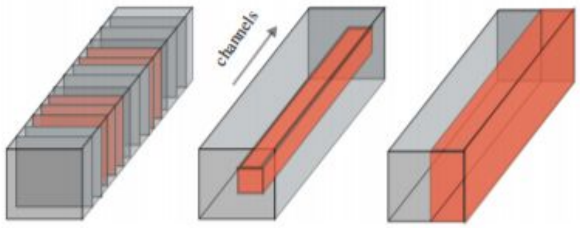
Top: IoU for predictions without (blue) and with (magenta) structured dropouts, and improvement obtained with structured dropouts (red). Occlusion fraction is denoted by brown.
Bottom: examples showing occlusion.

Modeling occlusion with structured dropouts

Structured dropout refers to dropout applied in the latent space of the target subnetwork of siamese networks to mimic target occlusion.



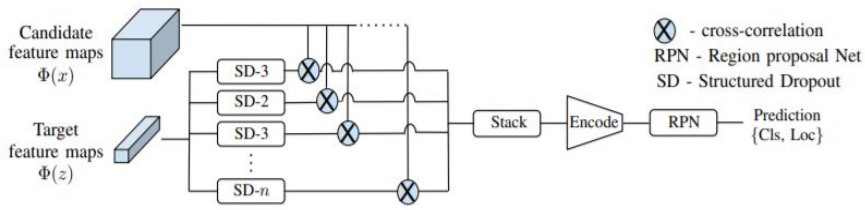
Siamese network architecture. Structured dropout is applied on the target subnetwork



Schematic representation of three different structured dropout methods. (a) channel (b) segment and (c) slice dropouts.

Interpretations of different structured dropouts.

1. *Channel.* Designed to specifically handle feature occlusions. A randomly sampled set of channels from the target feature map are set to 0.
2. *Segment.* Mimics patch occlusion through stochastically sampling parts of the spatial map from the entire set of the latent features of the target.
3. *Slice.* Frequently occurring patch occlusion mimicked through dropping patches from one of the four sides of the feature maps - a nonstochastic dropout method.



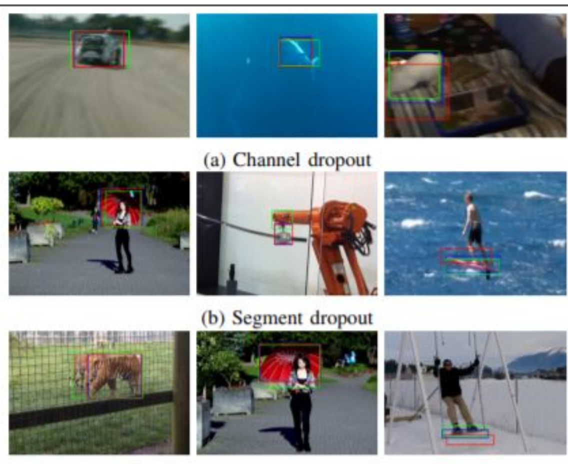
Schematic representation of Siamese Tracking model with structured dropouts.

Experiments on benchmark datasets

Approach	OTB2015 Pr	OTB2015 $SR_{0.5}$	UAV123 Pr	UAV123 $SR_{0.5}$	GOT-10k AO	GOT-10k $SR_{0.5}$	GOT-10k $SR_{0.75}$	VOT2018 EAO	VOT2018 Acc
SiamFC	**0.809**	0.597	0.711	0.513	0.355	0.395	0.118	**0.311**	**0.508**
MC-Dropout	0.807	0.602	0.712	0.515	0.350	0.396	0.116	0.307	0.506
exp-SiamFC-SD	0.807	0.608	0.732	0.526	**0.366**	**0.409**	**0.131**	**0.311**	0.506
SiamFC-SD (Ours)	0.808	**0.610**	**0.736**	**0.535**	0.361	0.402	0.129	0.309	**0.508**

Approach	OTB2015 Pr	OTB2015 Acc	VOT2018 EAO	VOT2018 Acc
SiamRPN++	0.890	0.683	0.414	0.600
DiMP-50	-	0.684	0.440	0.597
UPDT	-	0.702	0.378	0.536
ATOM	-	0.669	0.401	0.590
SiamRPN-MC	0.876	0.681	0.417	0.599
exp-SiamRPN-SD-channel	0.908	0.695	0.416	0.591
SiamRPN-SD-channel	0.912	0.702	0.421	0.601
SiamRPN-SD-segment	0.896	0.698	0.410	0.588
SiamRPN-SD-slice	0.914	0.701	0.418	0.598

Results for SiamFC (top) and SiamRPN++ (left) with and without structured dropouts.



(a) Channel dropout
(b) Segment dropout
(c) Slice dropout