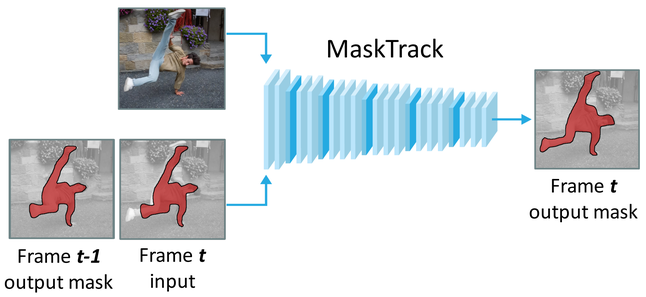
LEARNING VIDEO OBJECT SEGMENTATION FROM STATIC IMAGES

(* equal contribution) *F. Perazzi[1,2] *A. Khoreva[3] R. Benenson[3] B. Schiele[3] A. Sorkine-Hornung[1]
[1]Disney Research, [2]ETH Zürich, [3]Max Planck Institute for Informatics

INTRODUCTION

Goal: Separating **foreground objects** from the **background** in a video given the **1st frame mask annotation**.

- Guided CNN trained for video object segmentation **using only static images.**



- Handle different types of input annotations such as **bounding boxes and segments** while leveraging an arbitrary amount of annotated frames.

- Competitive results on three different datasets, independently from the type of input annotation

Visit the project pages:
https://graphics.ethz.ch/~perazzif/masktrack
https://www.mpi-inf.mpg.de/masktrack
Source code and trained models are available online.

LEARNING FROM STATIC IMAGES

Video Dataset

DAVIS 2016 [Perazzi et al.'16] **50*** videos, **4K** images
SegTrack-v2 [Li et al.'13] **14** videos

Image Dataset

MSRA10K [Cheng et al.'14], **10K** images

➔ lack of large-scale diverse video data for training

***DAVIS 2017 – 150 videos, workshop on 26.07**

TRAINING PHASES

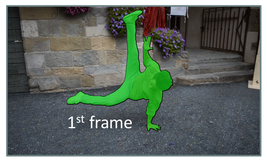
1 Pre-Training

IMAGENET

2 Online Training

MSRA10K

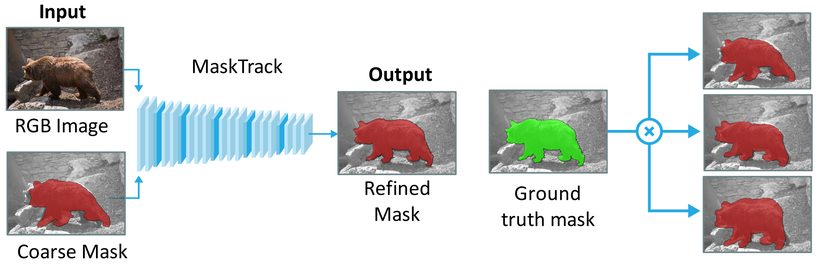
3 Online Fine-tuning



Tuning on the 1st frame mask of the test video

OFFLINE TRAINING

Guided Instance Segmentation



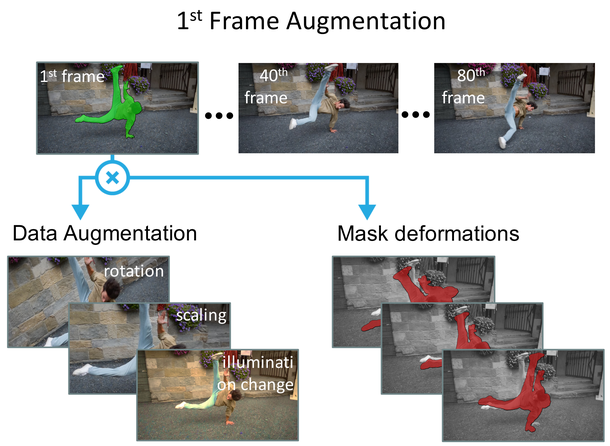
Previous Frame Mask Generation

➔ we train using *static images* only

➔ Non-rigid and affine deformations to simulate the previous frame mask

ONLINE FINE-TUNING

1st Frame Augmentation



EVALUATION

Method	DAVIS, mIoU					
	J			*F*		
	Mean ↑	Recall ↑	Decay ↓	Mean ↑	Recall ↑	Decay ↓
Box oracle	45.1	39.7	**-0.7**	21.4	6.7	**1.8**
Grabcut oracle	67.3	76.9	1.5	65.8	77.2	2.9
NLC [3]	64.1	73.1	8.6	59.3	65.8	8.6
FCP [9]	63.1	77.8	3.1	54.6	60.4	3.9
BVS [6]	66.5	76.4	26.0	65.6	77.4	23.6
ObjFlow [12]	71.1	80.0	22.7	67.9	78.0	24.0
MaskTrack	74.8	87.8	14.1	75.0	84.7	14.3
MaskTrack+Flow+CRF	**80.3**	**93.5**	8.9	**75.8**	**88.2**	9.5

Method	Dataset, mIoU		
	DAVIS	YoutbObjs	SegTrack-v2
Box oracle	45.1	55.3	56.1
Grabcut oracle	67.3	67.6	74.2
ObjFlow [49]	71.4	70.1	67.5
BVS [29]	66.5	59.7	58.4
NLC [15]	64.1	-	-
FCP [35]	63.1	-	-
W16 [50]	-	59.2	-
Z15 [56]	-	52.6	-
TRS [53]	-	-	**69.1**
MaskTrack	**74.8**	**71.7**	67.4
MaskTrack_{Box}	73.7	69.3	62.4

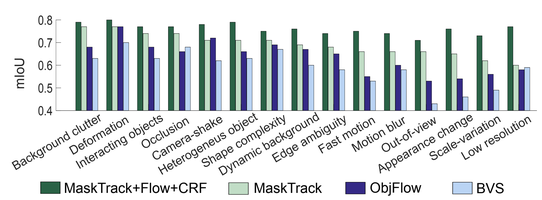
Competitive results despite using the same model and parameters across all videos.

ANALYSIS

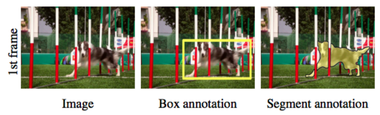
Ablation Study

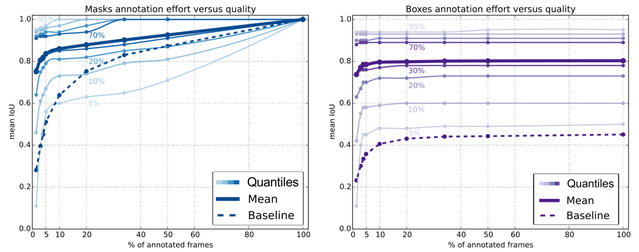
Aspect	System variant	mIoU	ΔmIoU
Add-ons	MaskTrack+Flow+CRF	**80.3**	+1.9
	MaskTrack+Flow	78.4	+3.6
	MaskTrack	*74.8*	-
Training	No online fine-tuning	69.9	−4.9
	No offline training	57.6	−17.2
	Reduced offline training	73.2	−1.6
	Training on video	72.0	−2.8
Mask defor-mation	No dilation	72.4	−2.4
	No deformation	17.1	−57.7
	No non-rigid deformation	73.3	−1.5
Input channel	Boxes	69.6	−5.2
	No input	72.5	−2.3

Attribute Based Analysis



SUPERVISION EFFORT





Segment annotations. Box Annotations.

REFERENCES

ObjFlow: Video Segmentation via Object Flow, Yi-Hsuan Tsai et al, CVPR 201
NLC: Video segmentation by non-local consensus voting. A. Faktor and M. Irani BMVC 2014
BVS: Bilateral Space Video Segmentation, N. Maerki et al. CVPR 2016
FCP: Fully connected object proposals for video segmentation. F. Perazzi et al. ICCV 2015
TRS: Track and segment: An iterative unsupervised approach for video object proposals, Xiao et al. CVPR 2016
W16: Semi-supervised domain adaptation for weakly labeled semantic video object segmentation, Chan et. al.
Z15: Semantic object segmentation via detection in weakly labeled video, Zhang et al. CVPR 2015

Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs, Chen et al, ICLR 2015.