



# **Boosting Video Object Segmentation via Space-time Correspondence Learning**

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## **Observation**

**Preview** 

- the weakness of previous matching-based video object segmentation (VOS)
- the potential of self-supervised space-time correspondence learning

## Core Idea

• propose a correspondence-aware training framework, which boosts matching-based VOS methods by explicitly encouraging explicit space-time correspondence matching

## Performance

- SOTA quantitative outcome
- impressive qualitative results

## **Contribution**

• elegant training framework





**Background** 

**Motivation** 

#### Framework

## Matching-based VOS Framework

## Video Object Segmentation

- online-learning based
- propagation-based
- matching-based

## Matching-based VOS

- explicit object modeling
- current mainstream





**Introduction** //

## Weakness of previous matching-based VOS (e.g., XMem)

**Background** 



**Motivation** 

**Framework** 

- supervision of gt segmentation masks only
- neglect explicit constraint on space-time correspondence learning
- sub-optimal performance (mismatching)



#### Background

**Motivation** 

## Space-time correspondence-aware training framework

- complementary yet free supervision signals
- pixel-level: spatiotemporally proximate pixels/patches tend to be consistent
- object-level: visual semantics of same object instances at different timesteps tend to retain unchanged.
- deployment friendly



Framework



- complement **implicit**, **segmentation-oriented** supervision signals with **explicit**, **self-supervised** constraint/regularization over the cross-frame correlation estimation.
- correspondence: pixel-level, object-level



**Pixel-level** 

#### **Object-level**



## **Pixel-level** consistency

Method

- local continuity residing in videos
- disambiguate correspondence on both inter- and intra-video levels

• 
$$\mathcal{L}_{PCL} = -\log \sum_{i} \frac{\exp\left(\langle \boldsymbol{K}_{t+1}(i), \boldsymbol{K}_{\tau}(j^*) \rangle\right)}{\sum_{j} \exp\left(\langle \boldsymbol{K}_{t+1}(i), \boldsymbol{K}_{\tau}(j) \rangle\right)}$$







Method

**Pixel-level** 





#### **Object-level** coherence

• the content continuity of videos on the object-level

**Object-level** 

• maximize the similarity of the representations of the same object instance at different timesteps

$$\mathcal{L}_{\text{OCL}} = -\log \sum_{p_i \in \mathcal{Q}} \frac{\exp\left(\langle \boldsymbol{p}_i, \boldsymbol{p}'_{j^*} \rangle\right)}{\exp\left(\langle \boldsymbol{p}_i, \boldsymbol{p}'_{j^*} \rangle\right) + \sum_{o \in \mathcal{O}} \exp\left(\langle \boldsymbol{p}_i, \boldsymbol{o} \rangle\right)}$$





- promote matching-based VOS methods (e.g., STCN and XMem) in a large margin
  - further boost SOTA performance

Method	S	DAVIS2017		YouTube-VOS	
		val	test	2018 val	2019 val
SSTVOS[14]	X	82.5	-	81.7	-
CFBI+[88]	X	82.9	75.6	82.8	-
Joint[44]	X	83.5	-	83.1	-
STCN [12]	X	82.5	73.9	81.2	-
STCN+Ours		<b>84.7</b>	77.3	83.6	-
XMem[10]	×	84.5	79.8	84.3	-
XMem+Ours		86.1	81.0	85.6	-
STM[49]	✓	81.8	72.2	79.4	-
HMMN[58]	✓	84.7	78.6	82.6	82.5
AOT[87]	✓	84.9	79.6	84.1	84.1
PCVOS[51]	✓	86.1	80.2	84.6	84.6
STCN[12]	1	85.4	76.1	83.0	82.7
STCN+Ours		86.8	79.1	85.2	84.9
XMem[10]	1	86.2	81.0	85.7	85.5
XMem+Ours		87.7	82.2	86.9	86.8



# Experiment //

Quantitative





#### **Correspondence** Matching





**Experiment** // Quantitative

**Qualitative** 

# 

#### Video Object Segmentation Results





# Fresh Insight!

**Summary** 

- observe the importance of **explicit supervision signals** for space-time correspondence matching
- take the lead in incorporating **self-constrained correspondence training** target with matching-based VOS

## Impressive performance!

- **SOTA** on DAVIS2017 val/test and YouTubeVOS
- improve matching-based VOS in a large margin
- wonderful qualitative result

## **Charming Framework!**

- no modification on network structure
- no extra annotation budget
- no inference time delay and efficiency burden



