

An Empirical Study of Propagation-based Methods for Video Object Segmentation*

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Abstract

While propagation-based approaches have achieved state-of-the-art performance for video object segmentation, the literature lacks a fair comparison of different methods using the same settings. In this paper, we carry out an empirical study for propagation-based methods. We view these approaches from a unified perspective and conduct detailed ablation study for core methods, input cues, multi-object combination and training strategies. With careful designs, our improved end-to-end memory networks achieve a global mean of 76.1 on DAVIS 2017 val set.

1. Introduction

Video object segmentation (VOS) aims at segmenting one or multiple objects for each frame in a video given the annotated masks in the first frame. It is an extremely challenging task due to fast motions, significant appearance changes, severe occlusions and similar dis-tractors.

One important branch for VOS is based on mask propagation [12] [7], which estimates the segmentation masks by taking advantage of the masks from previous frame. Recently propagation-based methods have shown continuous performance improvements by introducing more cues such as reference frame information [17], embedding matching [15], or dynamic frame memory [11]. Among these techniques, different settings in different papers make it difficult to compare them fairly. To our knowledge, there has been little systematically exploration of how different factors and methods influence performance.

In this paper, we analyze several propagation-based methods [12] [15] [11] in a unified way and conduct extensive empirical experiments to study the impact of different factors and methods on the final performance. We find that input cues, multi-object merging and training paradigms can substantially affect the segmentation in addition to core methods. Based on the findings, we improve the global

mean of baseline memory networks[11] from 74.3 to 76.1 on DAVIS 2017[13] val set in our implementations. It also achieves a global mean of 67.5 on test-dev set of DAVIS.

2. Methods

A typical propagation-based system [12] [15] [11] for VOS can be divided into three components: feature encoder, mask decoder and training paradigms. The models first encode inputs from images and masks into features, including feature extraction and fusion. Subsequently masks are predicted by the decoder, often with multi-object combination. To train such models, several strategies such as off-line training and on-line training are adopted. See Fig. 1 for an overview.

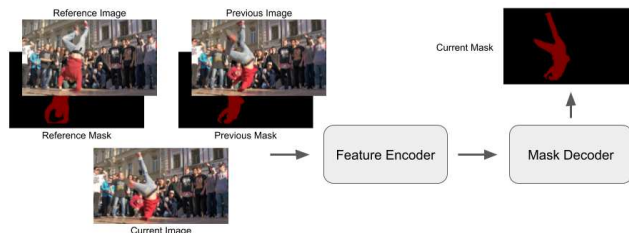


Figure 1. A typical pipeline for a propagation-based system.

Feature encoder. The feature encoder takes concatenated cues (i.e. images, masks) as inputs and outputs feature maps for mask decoder. Because there may be multiple frame inputs, some methods use correlation matching (FEELVOS[15]) or non-local matching (STM[11]) to combine feature maps from different sources. Correlation matching can be approximately seen as a special case of non-local matching, with the feature maps as keys and the masks as values. We investigate different input cues (previous/reference image and mask) and fusion methods [15] [11]. We also test MaskTrack[12] with reference and previous cues for a fair comparison. During testing, most of the propagation-based methods[7][15][11] use soft probability outputs from previous frames instead of masks. We also examine its effect in our experiments.

Mask decoder. The mask decoder takes the output of

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feature encoder and predicts the single-object masks independently. Then the masks are merged into a multi-object predictions using object and background probabilities. After merging, the predictions may be normalized and then feed into the next frame. We compare different strategies for computing the background probabilities (constant of 0.5, probability production[7], or mask tracking [11]) and normalization methods (sum [7] or logit aggregation [11]).

Training paradigms. The training procedure contains off-line stage and on-line stage. In off-line stage, the model is trained on the sampled images from videos of VOS datasets. In [17][11], static image datasets are used to pre-train the network. Moreover, they train their models using back-propagation through time (BPTT) on videos to obtain training samples that reflect the accumulated errors. For on-line training, first frame annotations of test set are used to fine-tune the off-line model [12][7]. BPTT and different on-line fine-tuning patterns (per-dataset[7][9] or per-video[19]) are investigated in the experiments.

Implementation details. We employ the DeepLabv3+ architecture [3] (ResNet-50 with output stride of 16) for feature encoder and mask decoder. The concatenated low-level features in decoder are from the query encoder for STM. In all the experiments, we adopt randomly cropped 480×480 patches for training, with batch size of 32. We minimize the cross entropy loss with Adam optimizer for 50 epochs using "poly" policy[3] as learning rate schedule. The learning rate is set to $1e-5$ for concatenated inputs, $5e-4$ for mask matching, and $5e-5$ for non-local feature matching. For fine-tuning, we apply random translation and scaling on the first frame instead of Lucid augmentation[6] for simplicity and reproducibility. We generate 2000 samples for each objects in per-dataset fine-tuning and 60000 samples in per-video fine-tuning. And the learning rate is fixed to $1e-5$ during on-line training.

3. Experiments

Datasets. Our networks are trained on the DAVIS 2017 [13] training set and YouTube-VOS 2018 [18] training set. In some experiments, only DAVIS dataset is used for faster training. We evaluate our models on DAVIS 2017[13] validation and test-dev sets, with mean intersection-over-union (\mathcal{J}), mean contour accuracy (\mathcal{F}) and their mean (\mathcal{G}) as in [13].

Input cues and fusion methods. We compare different models including MaskTrack[12], FEELVOS[15] and STM[11] with different input cues. All the models are trained on two datasets from scratch without fine-tuning. From Table 3, models with more input cues always achieve better performance because different cues are complementary. Among different fusion methods, non-local matching (STM) significantly outperforms the others on all metrics. This is because STM fuses the information from different

frames in space-time dimension, making the encoded features much stronger than other models.

Table 1. Ablation study of different input cues and fusion methods on DAVIS 2017[13] validation dataset (\mathcal{M} : Last mask. \mathcal{I} : Last image. **Ref**: Reference mask and image.)

Model	Cues	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
MSK[12]	\mathcal{M}	36.9	37.1	36.7
	+ \mathcal{I}	46.6	43.4	49.8
	+ Ref	57.2	54.8	59.7
FEEL[15]	$\mathcal{M} + \mathcal{I}$	46.4	44.5	48.4
	+ Ref	59.1	57.4	60.8
STM[11]	$\mathcal{M} + \mathcal{I}$	64.6	62.6	66.7
	+ Ref	74.2	71.7	76.7

In Table 3 we analyze the effect of the soft input probability during model testing. For FEELVOS and STM, it achieves better global mean with soft input. However, we find that it degrades the results of MaskTrack[12]. This may be because all the mask inputs are in one-hot representation with ground truth for training the models without BPTT. A probability inputs during testing may impair the performance of the model without correlation operator.

Table 2. Ablation study of soft input probability for testing on DAVIS 2017[13] validation dataset.

Model	Prob	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
MSK[12]	\checkmark	50.5	47.3	53.7
		52.8	48.8	56.8
MSK (+Ref)	\checkmark	57.2	54.8	59.7
		62.0	59.5	64.5
FEEL[15]	\checkmark	59.1	57.4	60.8
		58.3	56.3	60.3
STM[11]	\checkmark	74.2	71.7	76.7
		73.2	70.4	76.0

Multi-object combination. Table 3 shows the results of different multi-object combination methods for testing on STM[11]. Because we do not employ recursive training with BPTT, methods with normalization performs consistently worse than those without it. And the approach to compute background probabilities is not vital for final performance. We simply choose the constant background without normalization for our final models.

Training paradigms. We compare different fine-tuning strategies for different models. For per-video fine-tuning, we only test it with MaskTrack[12] due to its long testing time. We also provide fine-tuning-only models without training on off-line datasets as baselines. The results are in Table 3. Per-dataset fine-tuning can improve the accuracy for MaskTrack [12] and STM [11]. The gain from fine-tuning decreases when the base model becomes stronger. And the per-video fine-tuning performs worse than per-dataset fine-tuning in MaskTrack model. This may due to

Table 3. Ablation study of different multi-object combination methods for testing on DAVIS 2017[13] validation dataset with STM[11] (**Const**: constant background probability of 0.5. **Prod**: product background probability[8]. **Track**: tracking the background[11]. **Sum**: normalized by the sum. **Logit**: logit aggregation[17]).

Bg	Norm	FT	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
Const	-	✓	76.1	73.5	78.8
			74.2	71.7	76.7
	Sum	✓	75.3	72.9	77.8
Prod	-	✓	76.3	73.6	78.9
			74.4	71.9	76.9
	Sum[7]	✓	75.6	73.0	78.2
Track	-	✓	76.1	73.5	78.8
			74.4	71.9	76.8
	Sum	✓	75.3	72.7	78.0
	Logit[17]	✓	74.0	71.9	76.1
			74.8	72.0	77.5
		74.3	72.1	76.5	

the simple augmentation instead of commonly used Lucid augmentation in other literatures[6][9][19].

Table 4. Ablation study of different on-line training paradigms on DAVIS 2017[13] validation dataset (**Dataset**: per-dataset fine-tuning. **Video**: per-video fine-tuning. **Only**: fine-tuning without mainly training).

Model	FT	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
MSK[12]	-	50.5	47.3	53.7
	Dataset	66.9	64.2	69.6
	Video	60.8	56.9	64.8
	Only	50.6	47.2	54.1
MSK (+Ref)	-	57.2	54.8	59.7
	Dataset	68.2	65.7	70.7
	Only	48.5	45.5	51.6
FEEL[15]	-	59.1	57.4	60.8
	Dataset	57.1	55.0	59.2
	Only	33.9	32.2	35.5
STM[11]	-	74.2	71.7	76.7
	Dataset	76.1	73.5	78.8
	Only	45.4	43.2	47.7

We also experiment with BPTT training (3 frames) and find that it can greatly improve the performance by a large margin in MaskTrack and STM. But due to limited time, we do not apply it on our final models.

Benchmark. According to the conclusions above, we adopt different models with constant multi-object merging and per-dataset fine-tuning. On the DAVIS 2017[13] validation set (Table 3), our STM model beats most of the approaches even without fine-tuning. The only two methods that better than ours are [9] and [11].

Table 5. Ablation study of BPTT on DAVIS 2017[13] validation dataset with MaskTrack[12] and STM[11].

Method	BPTT	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
MSK[12]		35.3	35.3	35.4
	✓	50.5	47.3	53.7
STM[11]		74.2	71.7	76.7
	✓	77.6	74.8	80.3

Table 6. Evaluation on DAVIS 2017[13] validation set.

Methods	OL	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
OSMN[20]		54.8	52.5	57.1
FAVOS[4]		58.2	54.6	61.8
OSVOS[2]	✓	60.3	56.6	63.9
RGMP[17]		66.7	64.8	68.6
CIMN[1]	✓	67.5	64.5	70.5
OnAVOS[16]	✓	67.9	64.5	71.2
OSVOS-S[10]	✓	68.0	64.7	71.3
AGAME[5]		70.0	67.2	72.7
FEELVOS[15]		71.5	69.1	74.0
DOL[14]	✓	73.4	71.3	75.5
DyeNet[7]	✓	74.1	-	-
MHP-VOS[19]	✓	75.3	71.8	78.8
PRemVOS[9]	✓	77.8	73.9	81.7
STM[11]		81.8	79.2	84.3
Ours (MSK Ref)		57.2	54.8	59.7
Ours (MSK Ref + FT)	✓	68.2	65.7	70.7
Ours (FEEL)		59.1	57.4	60.8
Ours (FEEL + FT)	✓	57.1	55.0	59.2
Ours (STM)		74.2	71.7	76.7
Ours (STM + FT)	✓	76.1	73.5	78.8

As for test-dev set (Table 3), our STM model without fine-tuning also performs better than other off-line models. However, it is not able to reach the other results with on-line fine-tuning[7][19][9].

Table 7. Evaluation on DAVIS 2017[13] test-dev set.

Methods	OL	\mathcal{G} Mean	\mathcal{J} Mean	\mathcal{F} Mean
OSMN[20]		41.3	37.7	44.9
FAVOS[4]		43.6	42.9	44.2
OSVOS[2]	✓	50.9	47.0	54.8
RGMP[17]		52.9	51.4	54.4
OnAVOS[16]	✓	56.5	53.4	59.6
OSVOS-S[10]	✓	57.5	52.9	62.1
FEELVOS[15]		57.8	55.2	60.5
DyeNet[7]		62.5	60.2	64.8
VS-ReID[8]	✓	66.1	64.4	67.8
CIMN[1]	✓	67.5	64.5	70.5
DyeNet[7]	✓	68.2	65.8	70.5
MHP-VOS[19]	✓	69.5	66.4	72.7
PRemVOS[9]	✓	71.6	67.5	75.7
Ours (STM)		63.3	60.5	66.1
Ours (STM + FT)	✓	67.5	64.3	70.7

For the 2019 DAVIS Challenge, our submission achieved a global mean of 69.2.

4. Conclusions

In conclusion, we present an empirical study of propagation-based methods for VOS to analyze the influence of different factors and models. Our results suggest that memory network[11] with more input cues, constant background probability without normalization and per-dataset fine-tuning can achieve better performance for this task.

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