



# MDQE: Mining Discriminative Query Embeddings to Segment Occluded Instances on Challenging Videos

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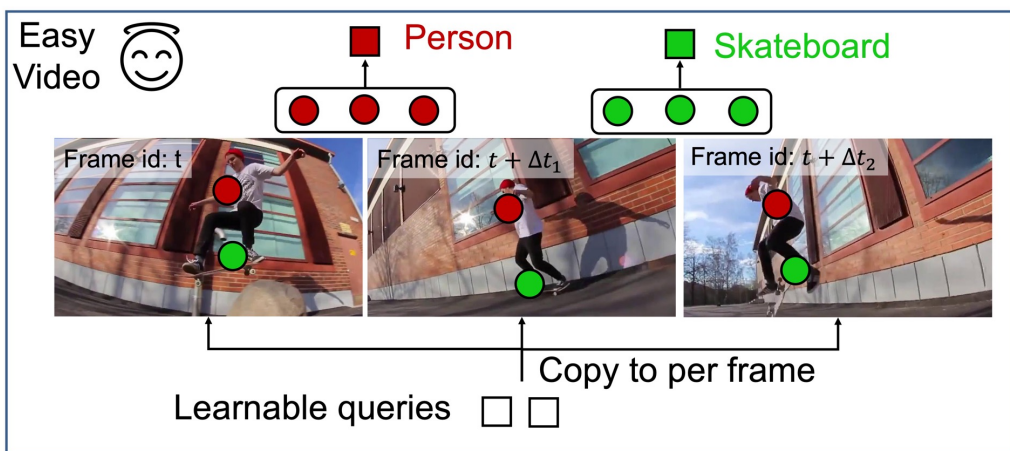
# 1. Motivations

## ➤ Architecture of previous clip-based VIS methods

To distinguish objects depends mainly on:

Positions + Categories

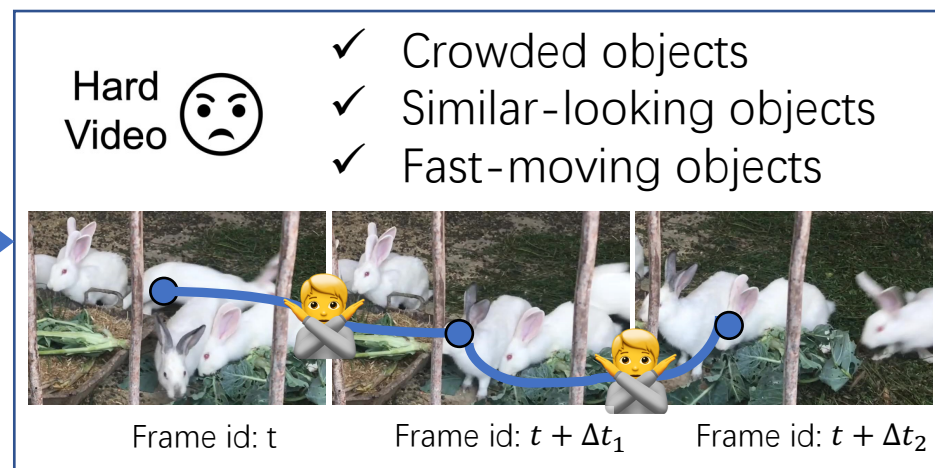
SeqFormer: (ECCV 2022)



## ➤ Our work: mining discriminative object embeddings

- Embedding initialization for object tokens
- Inter-instance mask repulsion loss

poor temporal consistency



Which is the target rabbit in the following frames?

## 2. Methodology

To Mine discriminative object embeddings:

2.1 Query initialization for object tokens

2.2 Inter-instance mask repulsion loss

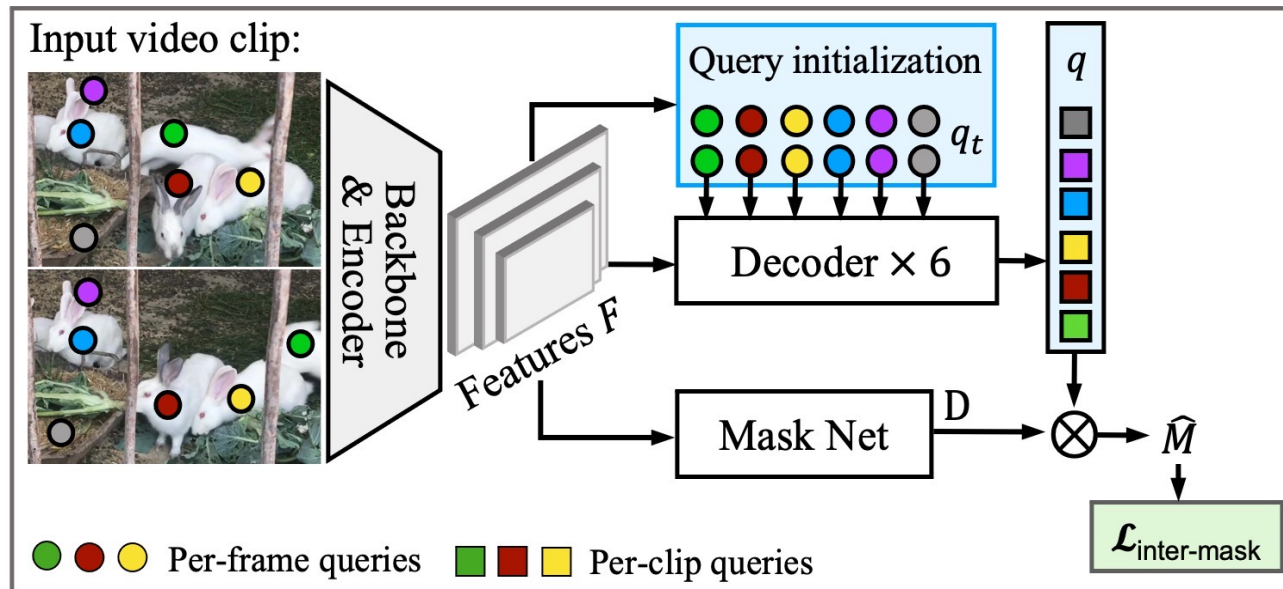
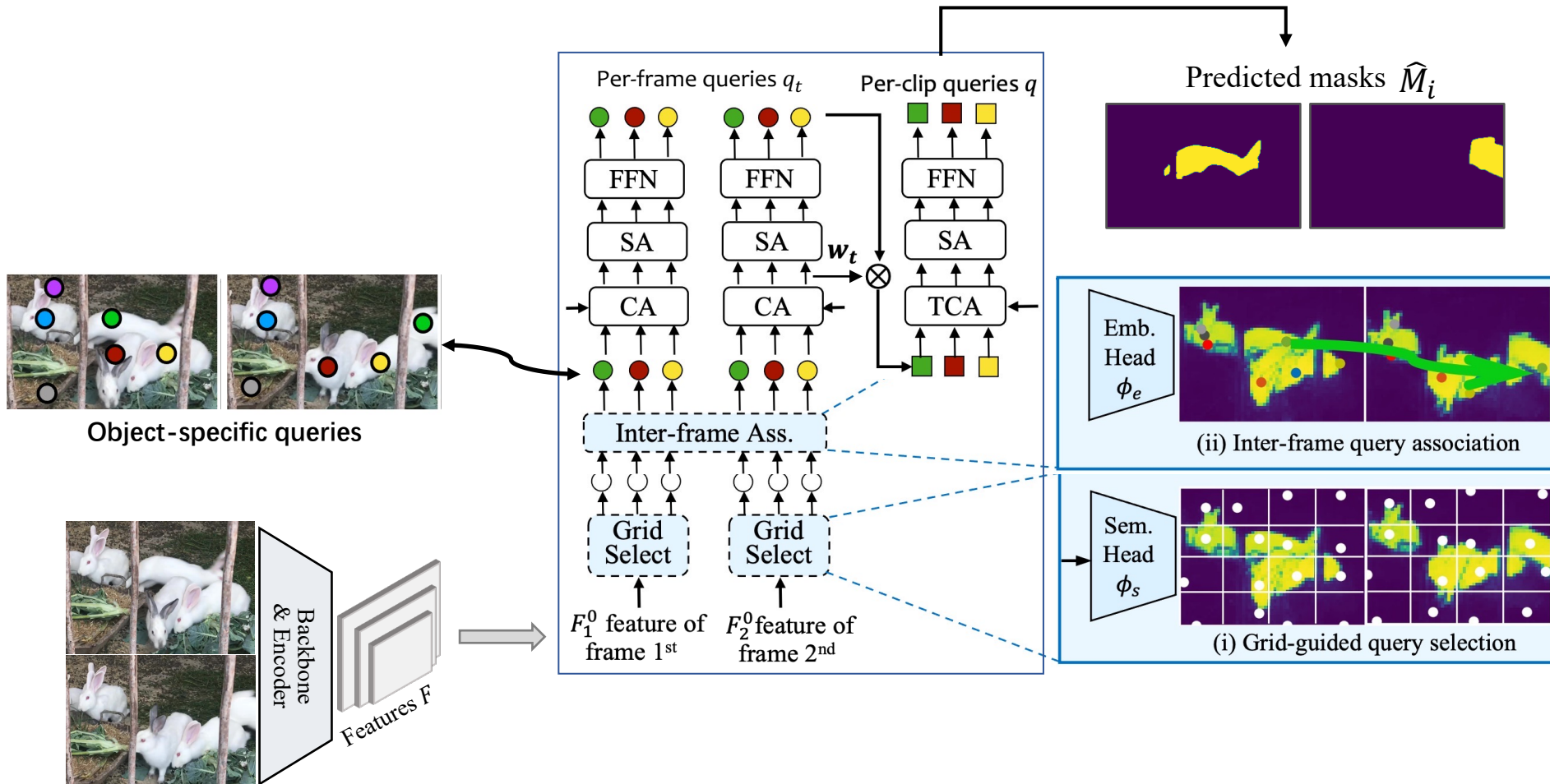


Fig. 1 Overview architecture of our proposed MDQE

# 2.1 Query Initialization

Architecture of the first decoder layer with our proposed query token initialization:





## 2.2 Inter-instance Mask Repulsion Loss

I. Ground-truth masks  $M_i$



Predicted mask  $\hat{M}_i$

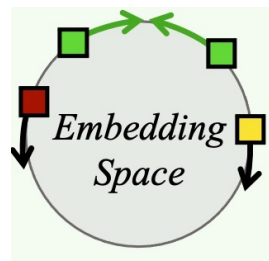
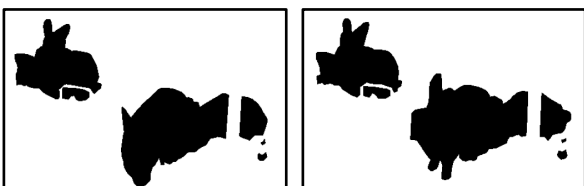


II. Define its nearby non-target instances via box IoU:

$$o_i = \{j \mid \max_{t \in [1, T]} \text{IoU}(B_{ti}, B_{tj}) > \epsilon, \forall j \in [1, K], j \neq i\},$$

III. Complementary GT inter-instance mask:

$$M_{o_i} = \cup_{j \in o_i} M_j,$$



The formula of the inter-instance BCE loss is:

$$\mathcal{L}_{\text{BCE-inter}} = \frac{1}{|W_i|} \sum_{p=1}^N W_{ip} \text{BCE}(\hat{M}_{ip}, M_{ip}), \quad (4)$$

where  $p$  is the pixel position index. if  $M_{ip} \cup M_{o_i p} = 1$ ,  $W_{ip} = 2$  otherwise 1.

The formula of inter-instance Dice loss is:

$$\mathcal{L}_{\text{Dice-inter}} = 1 - \frac{2|\hat{M}_i \odot M_i| + |(1 - \hat{M}_i) \odot M_{o_i}|}{|\hat{M}_i| + |M_i| + |M_{o_i}|} \quad (5)$$

# 3. Experimental Results

3.1 Ablation study

3.2 Main results

3.3 Visualization

# 3.1 Ablation study for query initialization

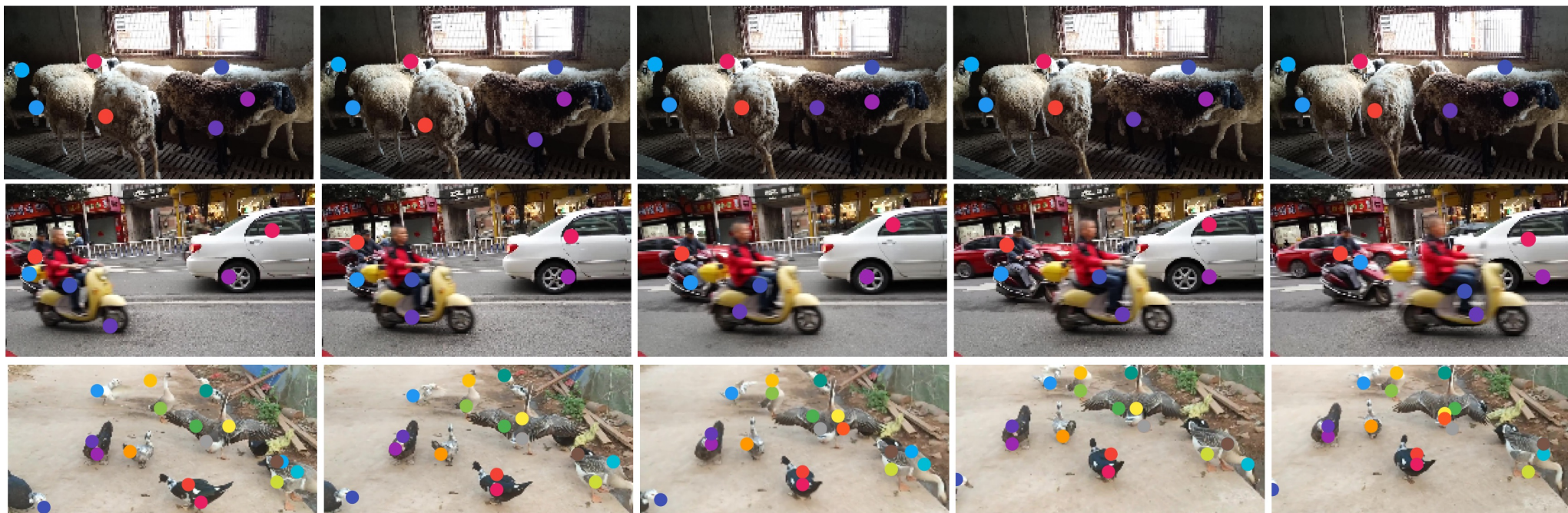
+9.8%

Init.	Arch.	TCA	mAP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>so</sub>	AP <sub>mo</sub>	AP <sub>ho</sub>
	I2O		15.4	31.3	14.3	31.8	17.3	3.2
✓	I2O		19.8	40.6	18.2	36.3	22.6	6.5
✓	O2I		24.2	47.5	22.9	40.9	27.3	8.4
✓	O2I	✓	25.6	49.1	24.9	41.9	29.0	11.2

(a) Initialization for frame-level queries.

$w$	Assoc.	mAP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>so</sub>	AP <sub>mo</sub>	AP <sub>ho</sub>
0		28.5	53.0	26.9	47.6	32.5	11.9
3	✓	29.7	55.6	27.1	48.9	34.5	12.2
5	✓	30.6	57.2	28.2	49.3	35.1	13.6
7	✓	30.5	57.1	28.6	49.1	33.7	13.7

(b) Inter-frame query association, where  $w$  controls the window size.

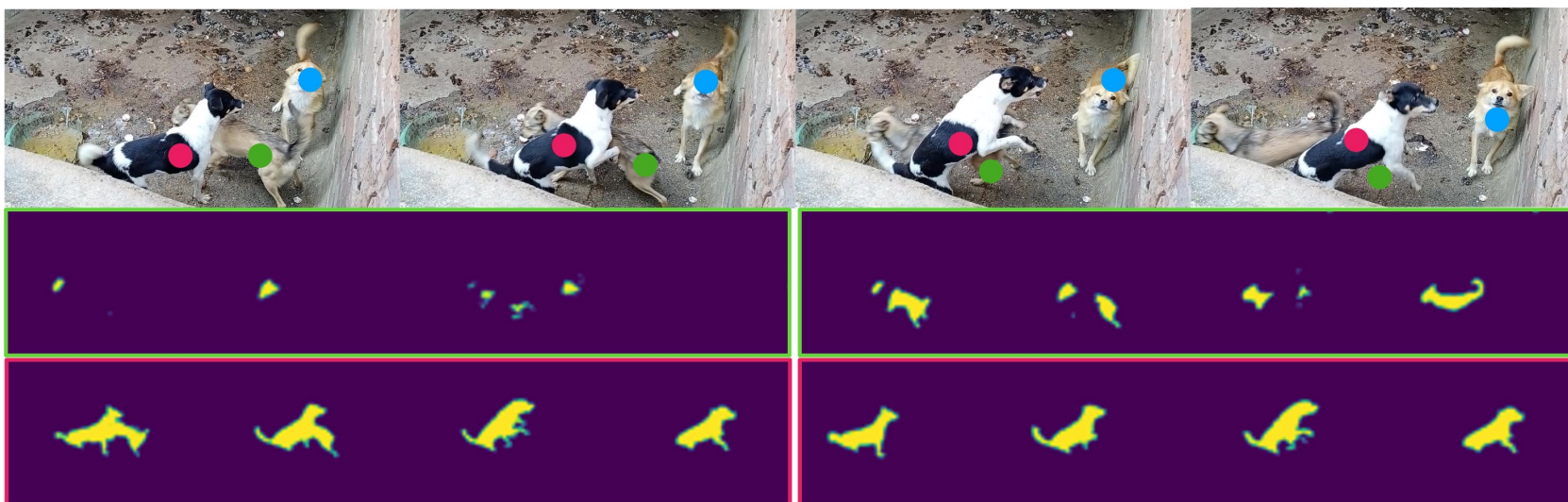




# 3.1 Ablation study for mask repulsion loss

$\mathcal{L}_{\text{BCE-inter}}$	$\mathcal{L}_{\text{Dice-inter}}$	$\epsilon$	mAP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>so</sub>	AP <sub>mo</sub>	AP <sub>ho</sub>
			29.0	51.6	29.5	44.7	31.3	11.8
2		0.1	30.5	55.6	29.5	46.7	33.1	12.9
2	✓	0.1	31.2	56.8	30.4	48.6	34.5	13.5
2	✓	0.5	30.9	56.4	30.5	47.2	34.2	13.3

(c) Inter-instance mask repulsion loss.



(a) Typical mask prediction loss

(b) Our inter-instance mask repulsion loss



# 3.1 Ablation study for clip length

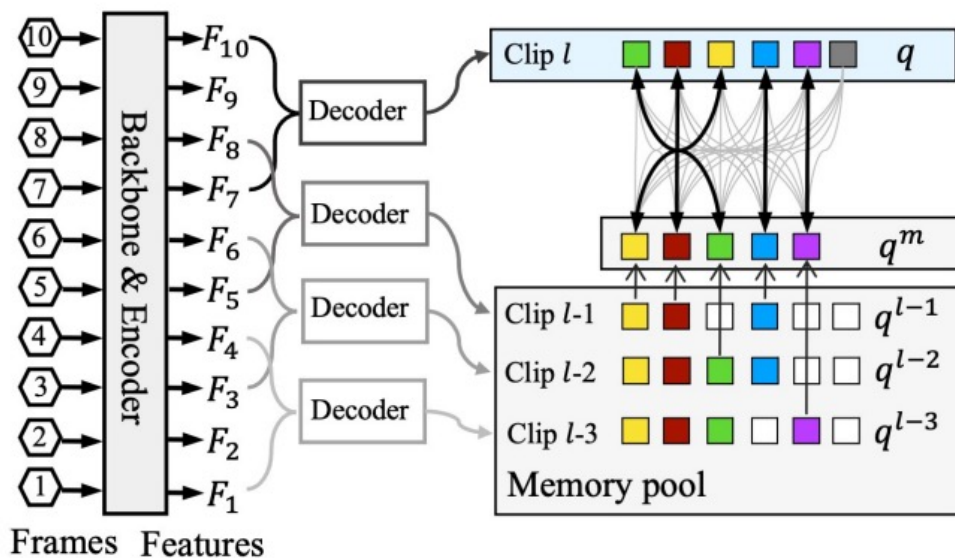


Figure 4. Near-online inference with a clip-by-clip tracker.

$\beta_1$	$\beta_2$	$T_{\text{mem}}$	mAP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>so</sub>	AP <sub>mo</sub>	AP <sub>ho</sub>
1	-	-	29.1	54.1	27.7	46.5	32.8	12.9
	1	10	28.3	53.4	27.1	47.1	31.3	11.6
1	1	10	30.6	57.2	28.2	49.3	35.1	13.6
1	1	5	30.4	56.4	28.7	49.4	35.2	13.2

(d) Tracking.  $\beta_1$  and  $\beta_2$  control the proportions of mIoU and similarity.



Figure 6. Ablation study on clip length with near-online inference.

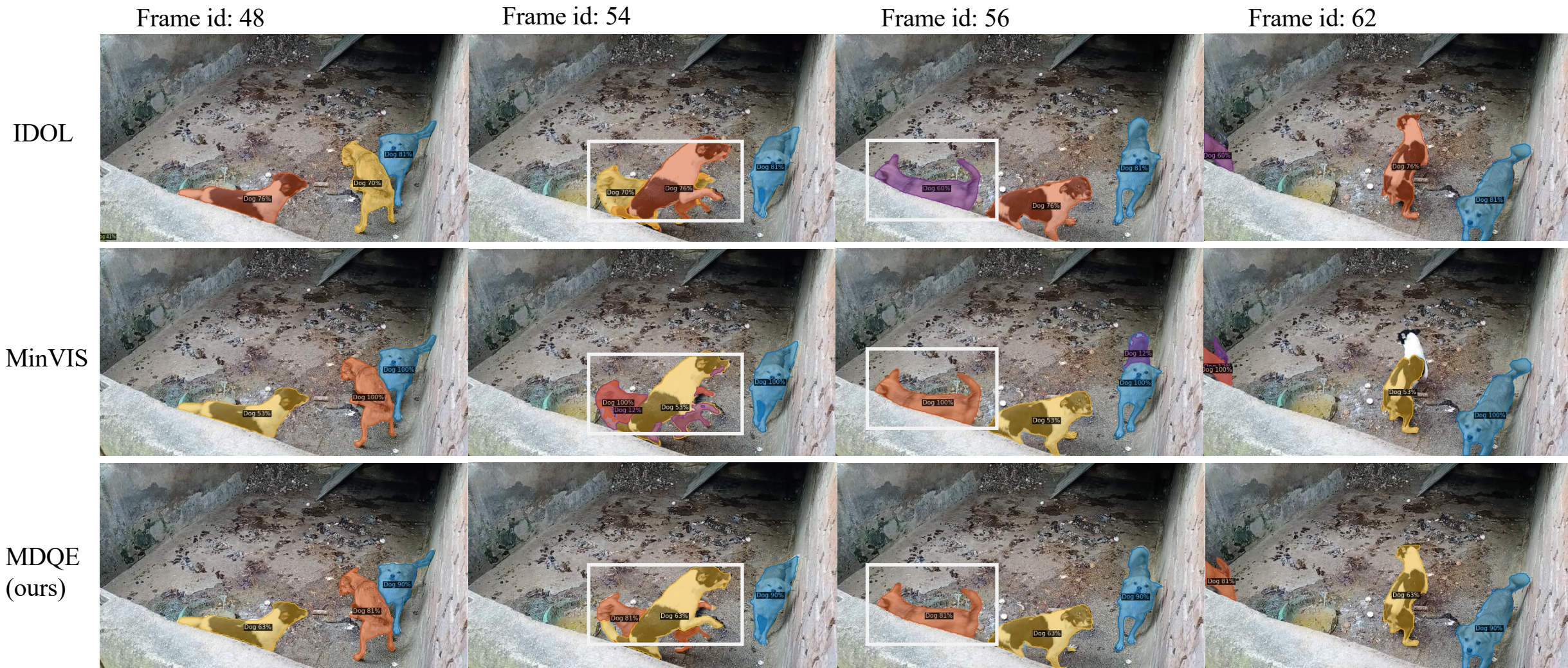
## 3.2 Main Results on R50 Backbone

Type	Methods	YouTube-VIS 2021					OVIS					FPS	Params
		AP	AP <sub>50</sub>	AP <sub>75</sub>	AR <sub>1</sub>	AR <sub>10</sub>	AP	AP <sub>50</sub>	AP <sub>75</sub>	AR <sub>1</sub>	AR <sub>10</sub>		
Per-frame (360p)	MaskTrack [51]	28.6	48.9	29.6	-	-	10.8	25.3	8.5	7.9	14.9	20.0	58.1M
	STMASK [26]	31.1	50.4	33.5	26.9	35.6	15.4	33.9	12.5	8.9	21.4	28.0	-
	CrossVIS [52]	33.3	53.8	37.0	30.1	37.6	14.9	32.7	12.1	10.3	19.8	39.8	37.5M
	InstFormer [24]	40.8	62.4	43.7	36.1	48.1	20.0	40.7	18.1	12.0	27.1	-	44.3M
	IDOL [47]	43.9	<b>68.0</b>	<b>49.6</b>	38.0	50.9	24.3	45.1	23.3	14.1	<u>33.2</u>	30.6	43.1M
	MinVIS [18]	44.2	66.0	48.1	<u>39.2</u>	<u>51.7</u>	<u>26.3</u>	<u>47.9</u>	<u>25.1</u>	<b>14.6</b>	30.0	52.4	44.0M
Per-clip (360p)	VisTR* [45]	31.8	51.7	34.5	29.7	36.9	10.2	25.7	7.7	7.0	17.4	30.0	57.2M
	IFC* [19]	36.6	57.9	39.3	-	-	13.1	27.8	11.6	9.4	23.9	46.5	39.3M
	TeVIT [53]	37.9	61.2	42.1	35.1	44.6	17.4	34.9	15.0	11.2	21.8	68.9	161.8M
	SeqFormer* [46]	40.5	62.4	43.7	36.1	48.1	15.1	31.9	13.8	10.4	27.1	72.3	49.3M
	VITA [17]	<b>45.7</b>	<u>67.4</u>	<u>49.5</u>	<b>40.9</b>	<b>53.6</b>	19.6	41.2	17.4	11.7	26.0	33.7	57.2M
	MDQE (our)	<u>44.5</u>	67.1	48.7	37.9	49.8	<b>29.2</b>	<b>55.2</b>	<b>27.1</b>	<u>14.5</u>	<b>34.2</b>	37.8	51.4M
720p	IDOL [47]	-	-	-	-	-	30.2	51.3	30.0	15.0	37.5	-	43.1M
	MDQE (ours)	-	-	-	-	-	<b>33.0</b>	<b>57.4</b>	<b>32.2</b>	<b>15.4</b>	<b>38.4</b>	13.5	51.4M
	MDQE (ours)	-	-	-	-	-	<b>33.0</b>	<b>57.4</b>	<b>32.2</b>	<b>15.4</b>	<b>38.4</b>	13.5	51.4M

Table 2. Quantitative performance comparison of VIS methods with ResNet50 backbone on benchmark YouTube-VIS 2021 and OVIS datasets. Note that MinVIS and VITA adopt stronger masked-attention decoder layers proposed in Mask2Former [8]. FPS is computed on YouTube-VIS 2021 valid set, and symbol “-” means the results are not available or applicable. Best in **bold**, second with underline.

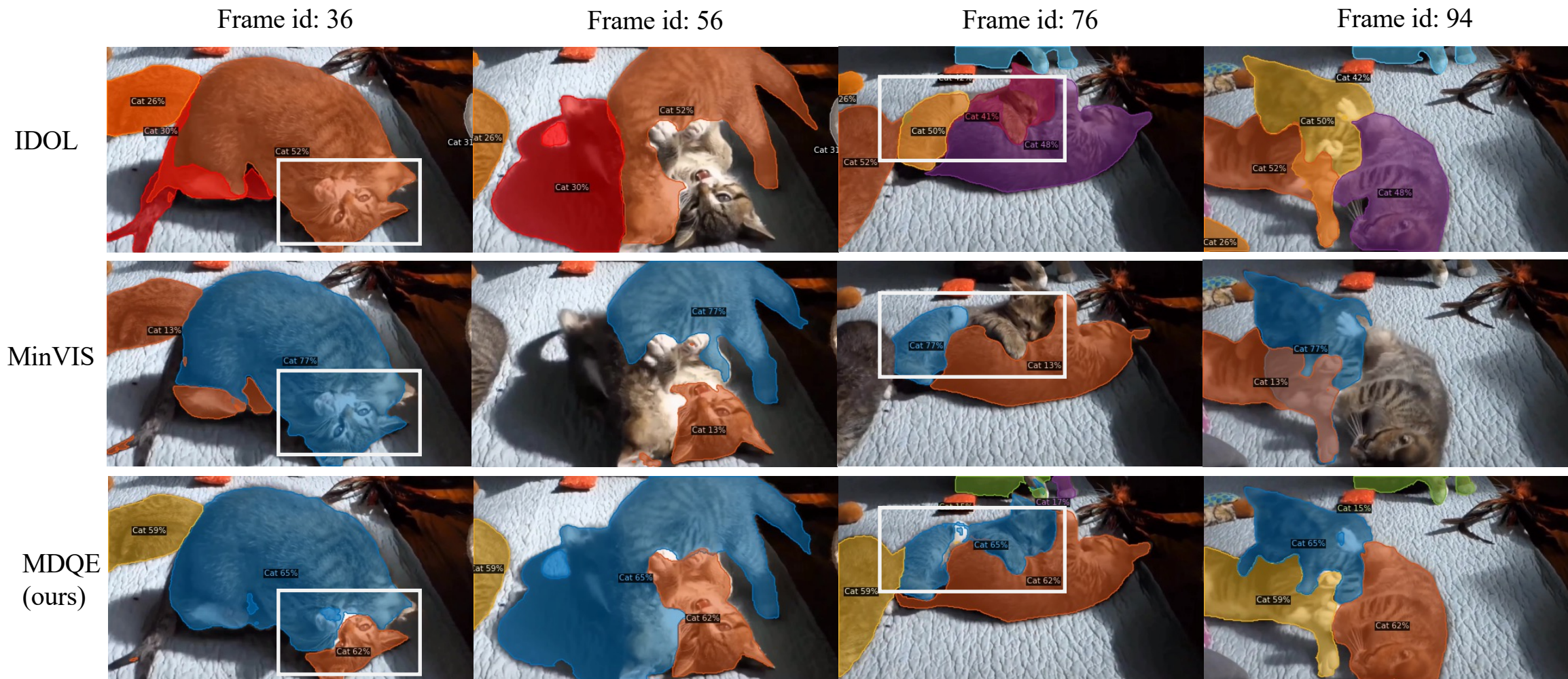


# 3.3 Visualization



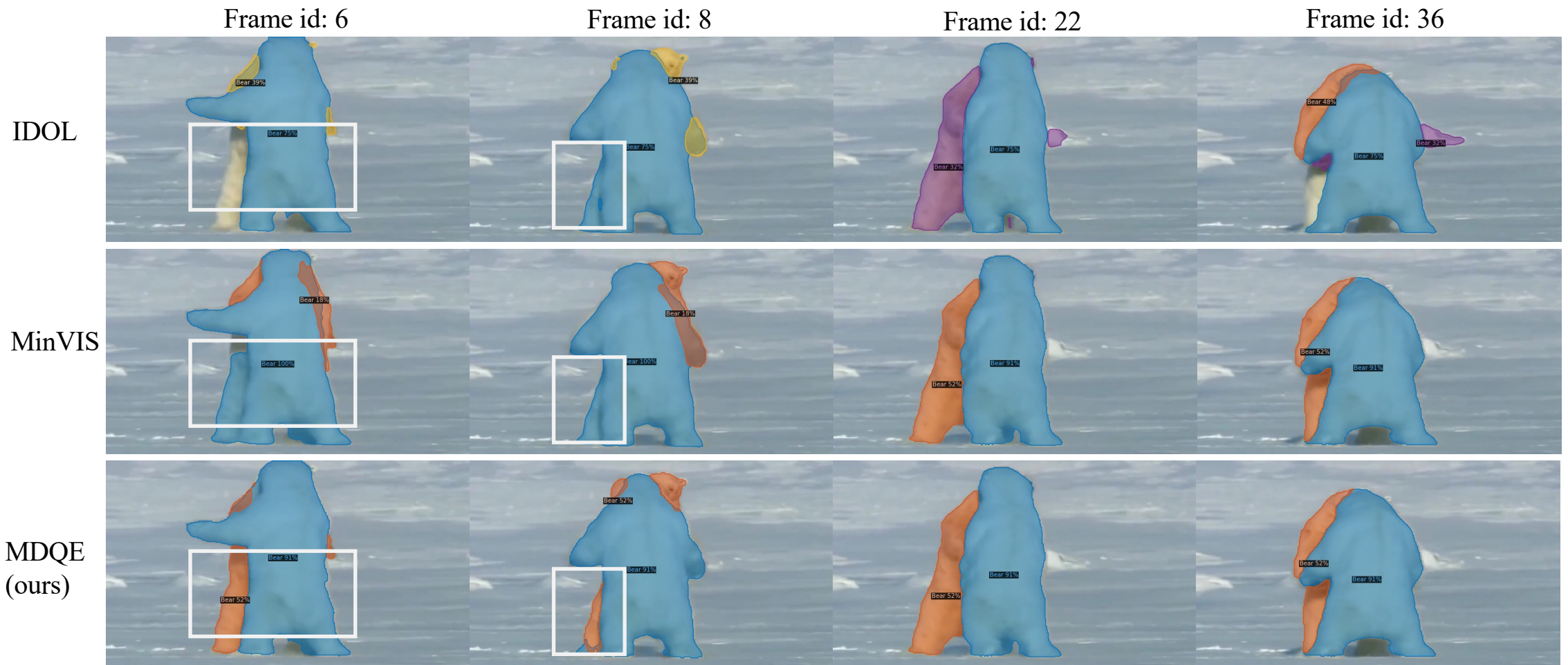


# 3.3 Visualization





# 3.3 Visualization





**Thank you  
for your  
attention!**

