



Github page



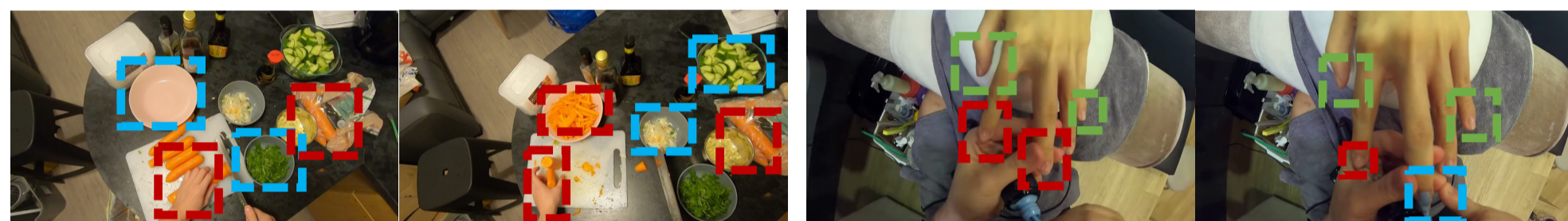
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Introduction

Referring video object segmentation (RVOS) aims at segmenting target objects using natural language expressions.

Challenges: Existing RVOS benchmarks primarily rely on **static attributes** such as object names and colors to describe the target objects.

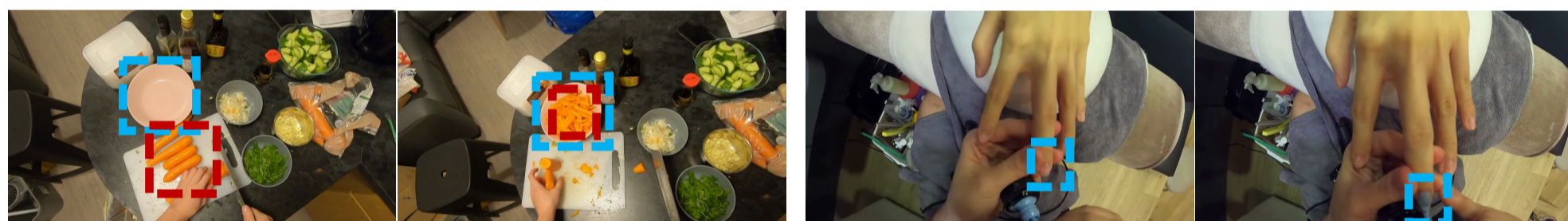
In complex scenarios where **redundant instances** coexist or **object state changing**, such static attributes can not identify the target objects.



Static attributes: carrot bowl

nail pink nail blue nail

Key Idea: Human actions precisely describe the active objects.



Human actions: "put carrot in bowl"

"paint nail"

Our Solution: This work propose a novel action-aware RVOS setting, **ActionVOS**, segmenting **only active objects** by adding **human actions** as language prompts.

ActionVOS Problem Setting



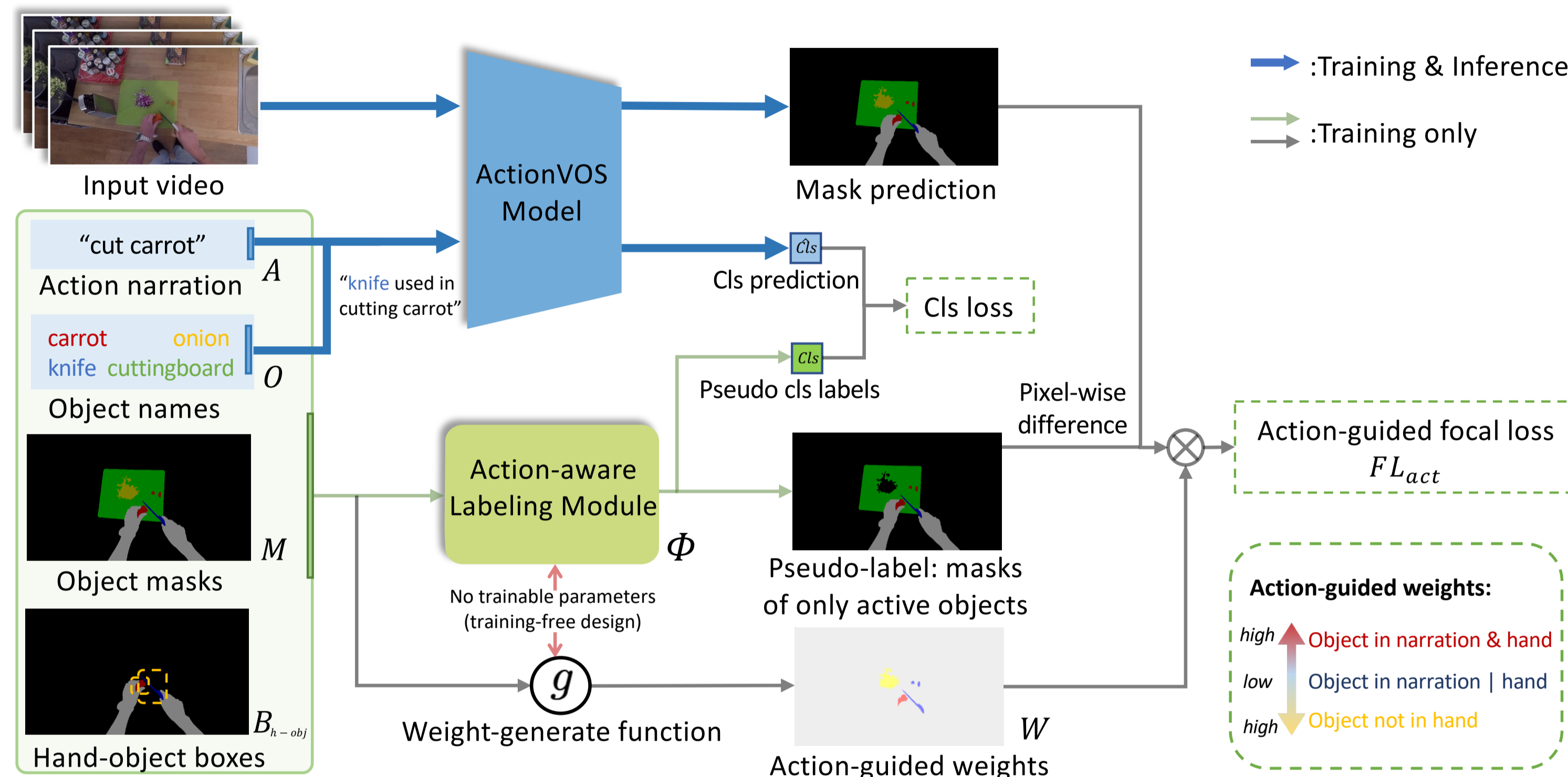
Input:
- Video clip.
- Arbitrary object names.
- Action prompt describing the human action.

Output:
Masks of only active objects corresponding to the action prompt.

Definition of active objects:

- Objects described by the action prompt.
- Hands and hand-tools used in the action.
- Containers and contents interacted in the action.

Proposed Method for ActionVOS



Key Challenge: training an ActionVOS model with existing readily-available annotations. (A, O, M, B_{h-obj})

ActionVOS Model: Any RVOS model with an additional classification head.

Action-aware Labeling Module Φ :

Generate pseudo-labels of positive/negative objects.

Pseudo positive label: 1) object whose name mentioned in the action prompt, e.g., carrot

2) object whose mask intersect with hand-object bounding boxes, e.g., knife, cutting board

$$Cls(O_i) = \begin{cases} 1, O_i \in A \\ 1, M(O_i) \cap B_{h-obj} \neq \emptyset \\ 0, otherwise \end{cases}$$

Action-guided Focal Loss FL_{act} :

Modified segmentation focal loss by adjusting the pixel-wise weights W .

It is designed to reduce the impact of false positives in pseudo-labels. E.g., $W(\text{carrot in hand}) > W(\text{carrot on board})$.

ActionVOS Quantitative Results

ActionVOS results on VISOR. * serve as the upper bound of p-mIoU.

Model	Setting	ActionPrompt	p-mIoU \uparrow	n-mIoU \downarrow	gIoU \uparrow	Acc \uparrow
RF-R101	RVOS*	X	67.7	54.2	43.8	59.1
	ActionVOS	X	56.3	19.9	66.8	72.9
	ActionVOS	✓	65.4	19.0	70.9	82.4
RF-SwinL	RVOS*	X	71.8	59.7	46.8	59.4
	ActionVOS	X	64.4	28.2	65.1	72.8
	ActionVOS	✓	69.1	24.6	70.3	80.7
RF-VSwinB	RVOS*	X	70.5	58.5	45.6	59.2
	ActionVOS	X	61.6	25.2	65.7	72.5
	ActionVOS	✓	68.2	22.0	70.6	81.2

+5-10% p-mIoU gIoU with action prompts

-34% n-mIoU comparing to RVOS (less mis-segmentation on inactive objects)

ActionVOS results on VOST and VSCOS.

Model Dataset	Setting	AP	p-mIoU \uparrow
RF-R101 VOST	RVOS	X	29.3
	ActionVOS	✓	32.3
RF-R101 VSCOS	RVOS	X	46.4
	ActionVOS	✓	49.4

Higher mIoU for state-changed objects

ActionVOS Quantitative Results

Comparison with baseline methods:

Method	p-mIoU \uparrow	n-mIoU \downarrow	gIoU \uparrow	Acc \uparrow	VOST		VSCOS	
					p-mIoU	p-cIoU	p-mIoU	p-cIoU
HOS	56.2	11.4	68.8	77.0	19.4	13.1	34.4	24.1
RVOS+ Φ	65.3	35.2	60.4	75.1	29.3	17.5	46.4	44.9
Ours	65.4	19.0	70.9	82.4	32.3	22.8	49.4	49.6

+10% p-mIoU HOS

-16% n-mIoU RVOS+ Φ

Evaluations on unseen actions:

Method	p-mIoU \uparrow	n-mIoU \downarrow	gIoU \uparrow	Acc \uparrow	VOST		VSCOS	
					p-mIoU	p-cIoU	p-mIoU	p-cIoU
HOS	51.9	9.0	64.9	72.0	13.6	11.4	42.7	38.8
RVOS	60.0	49.0	42.9	65.3	18.6	12.6	31.5	21.4
Ours	60.3	21.0	66.1	79.7	22.5	18.0	44.9	43.1

+20% gIoU on unseen actions

+3-12% mIoU on unseen state changes

ActionVOS Qualitative Results

ActionVOS results trained w/ and w/o action prompts.



ActionVOS for different actions in same scene.



ActionVOS results on state-changed objects.



ActionVOS
video visualization