Tracking and Understanding Object Transformations

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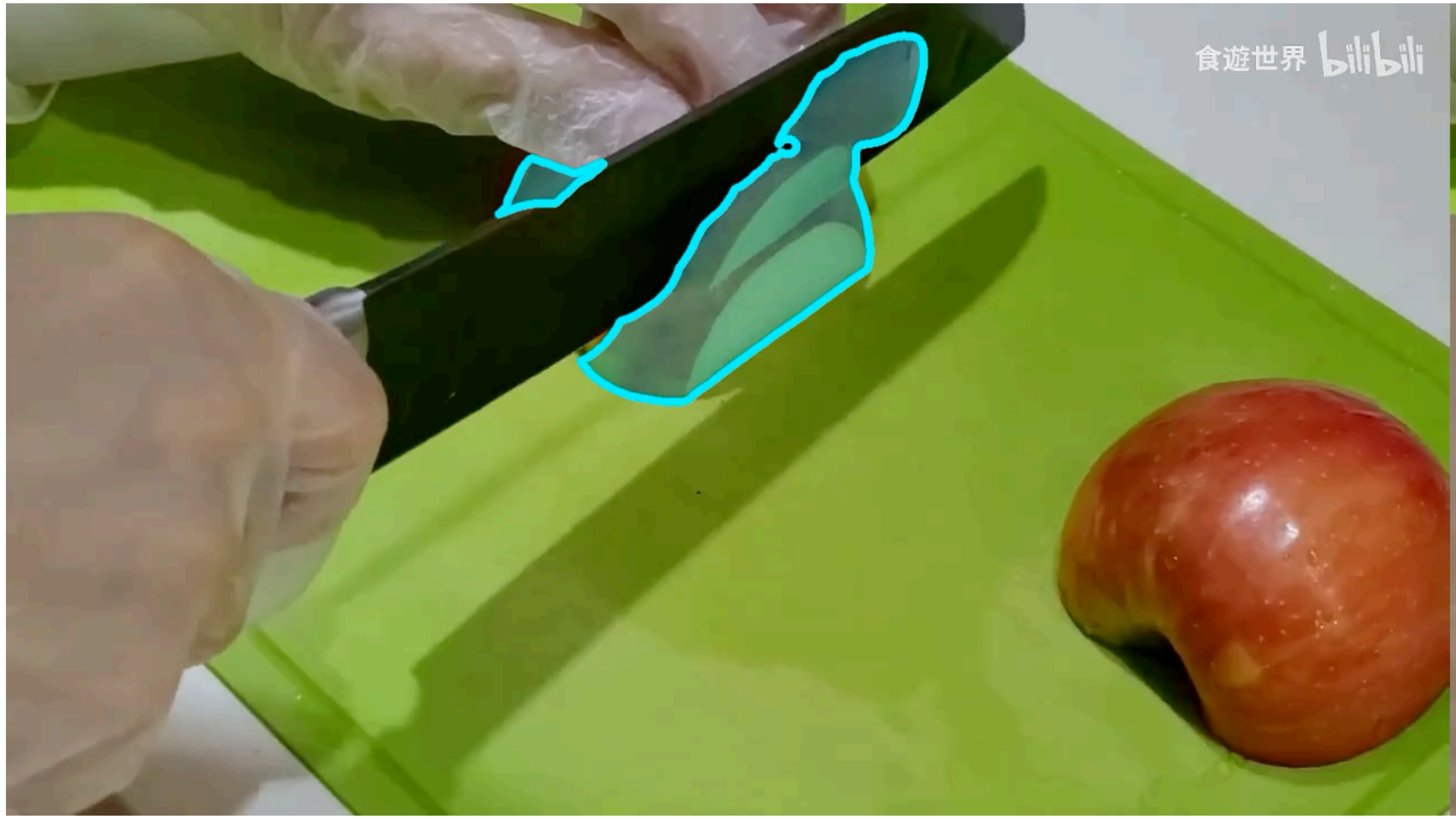
Main challenge

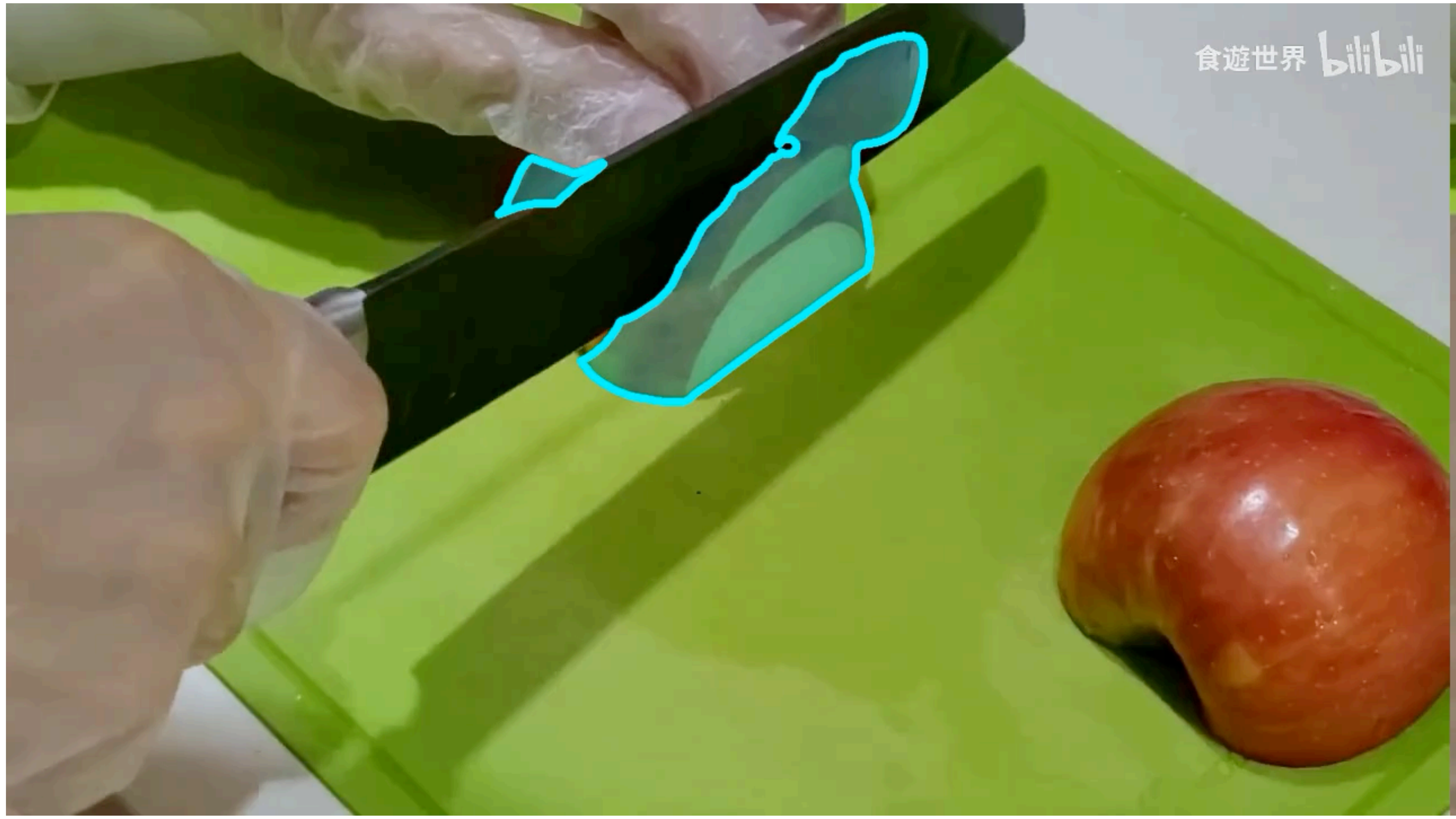


Ground Truth

SAM2.1

Main challenge

- Existing object trackers often fail to keep track of the **complete object** after transformation.



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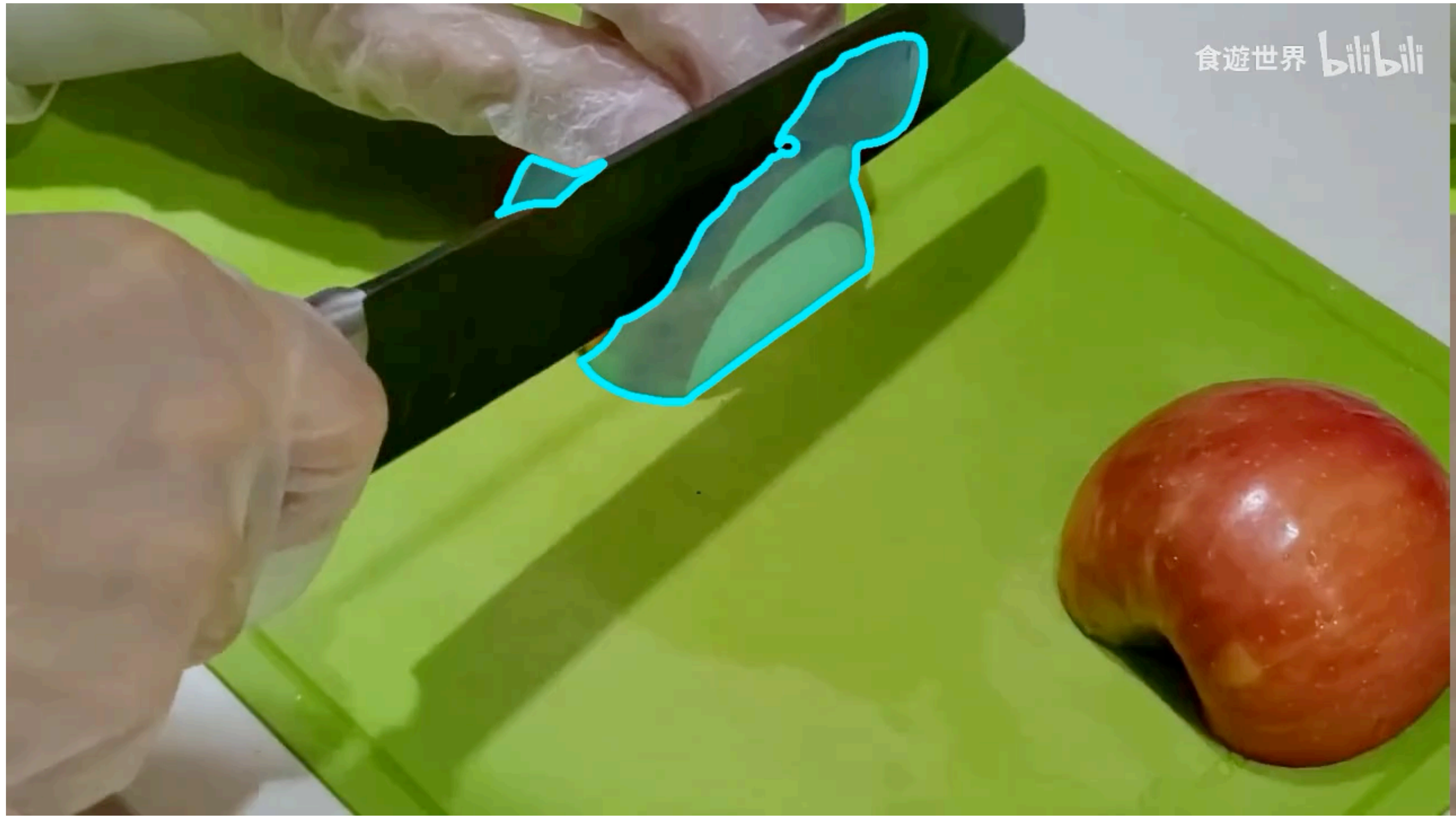
Main challenge

- Existing object trackers often fail to keep track of the **complete object** after transformation.
  - These failures are often caused by object-part separations, appearance changes, shape deformations, etc.



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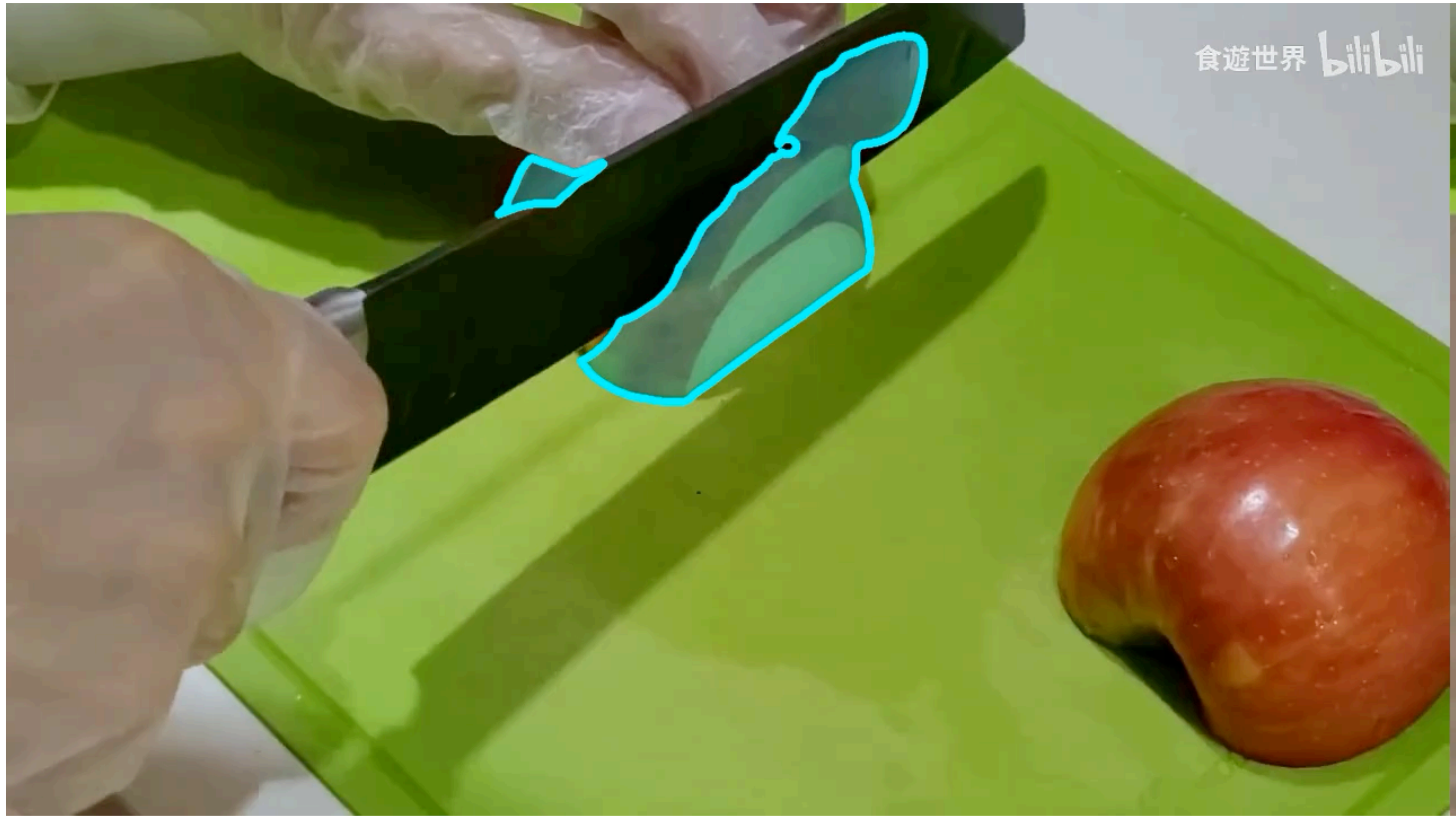

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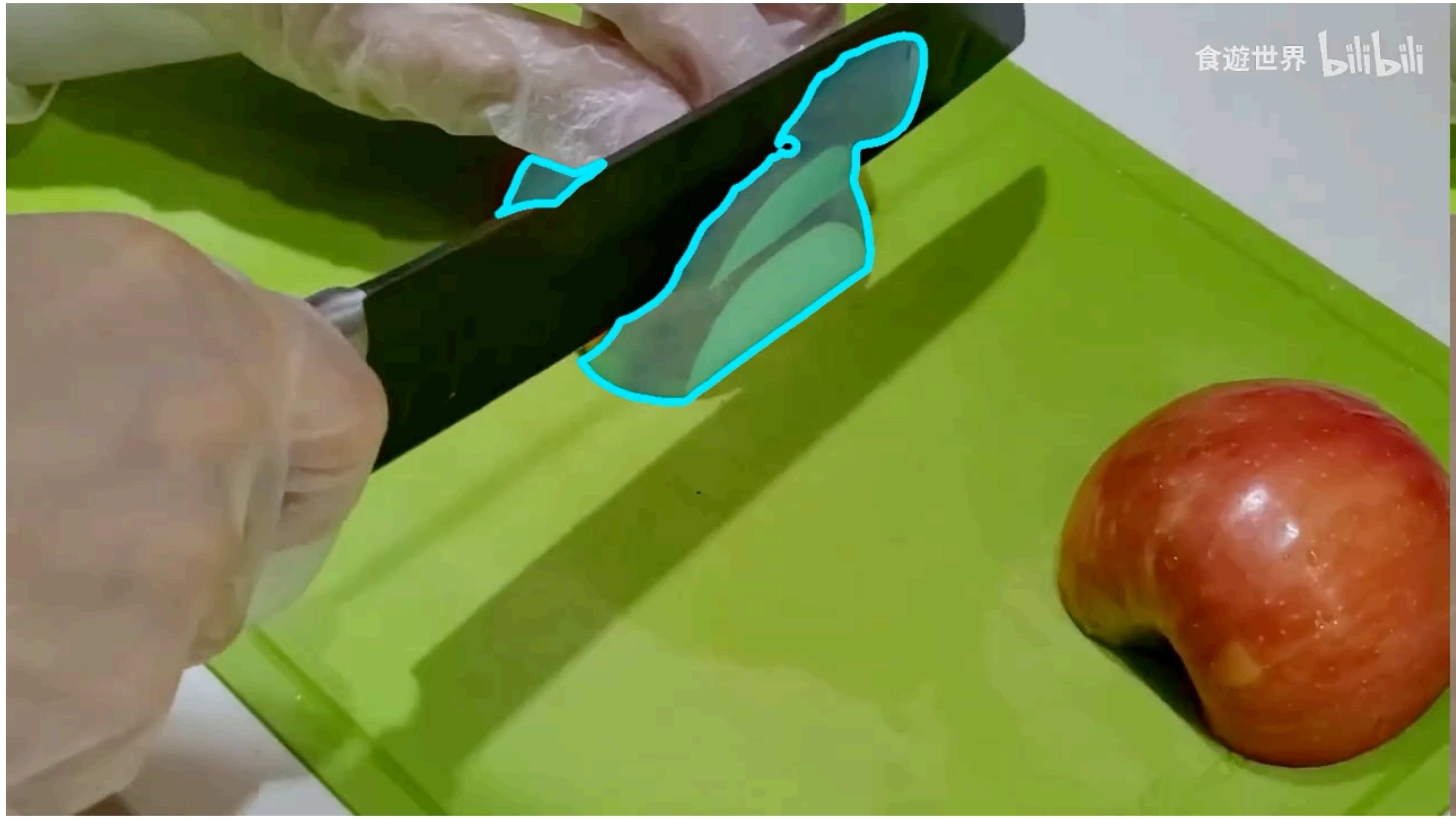

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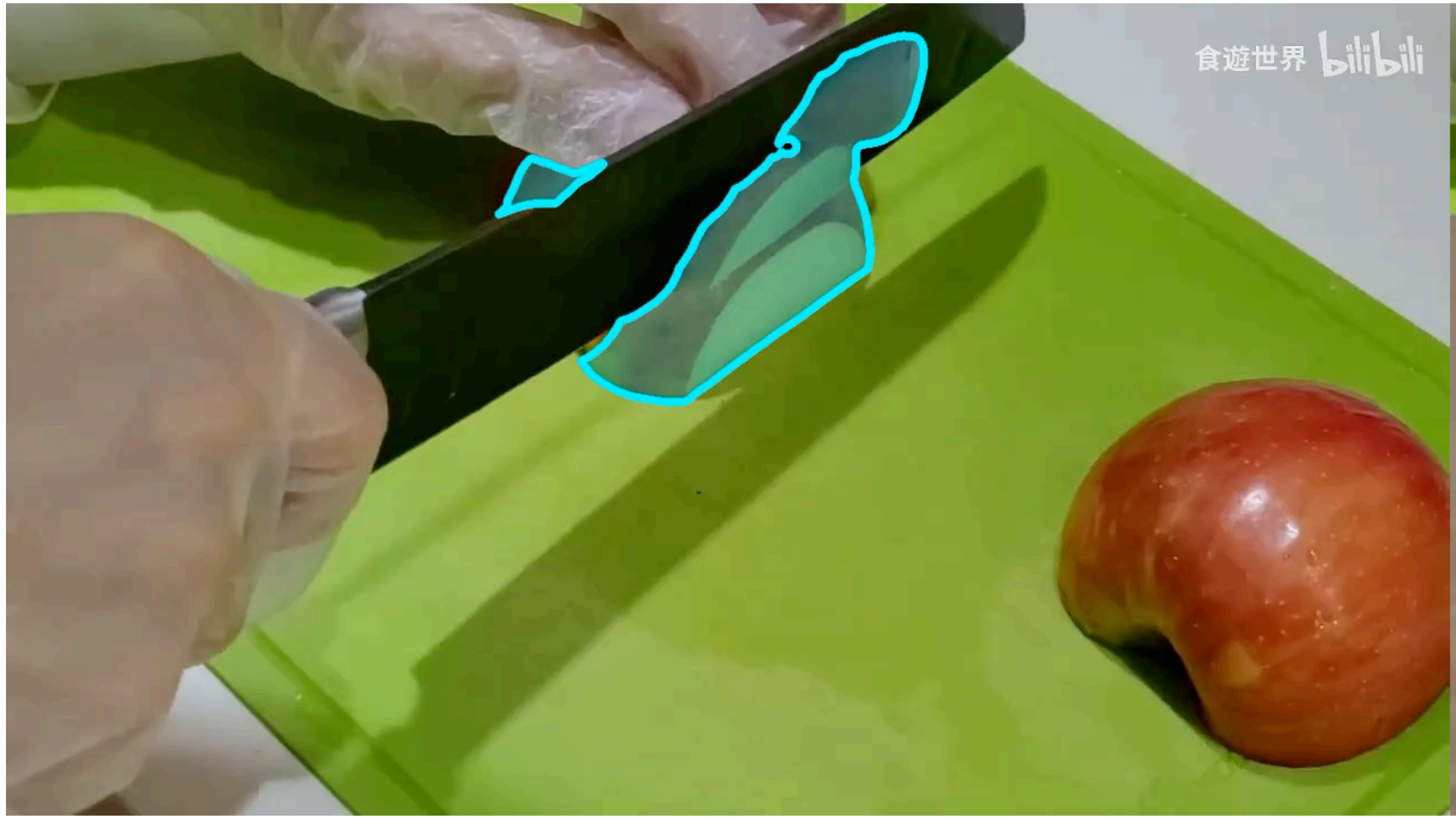
- Object tracking errors are **asymmetric**: false negatives >> false positives
  - The missing objects (false negatives) are often caused by appearance-altering **transformations**.



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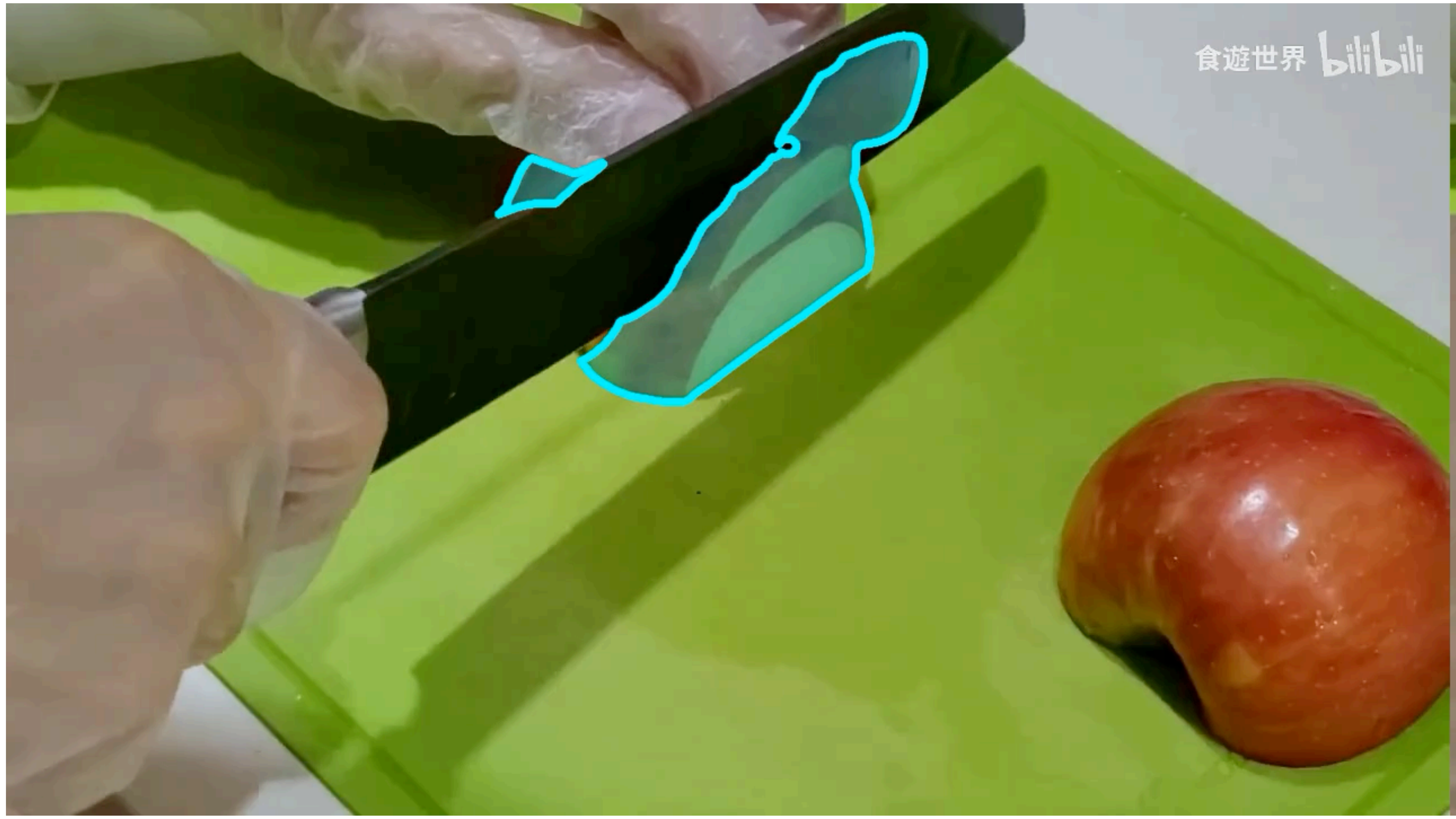
Key Insight

- Object tracking errors are **asymmetric**: false negatives >> false positives
  - The missing objects (false negatives) are often caused by appearance-altering **transformations**.
- Recovering them reveals **when and where** these transformations occurred!



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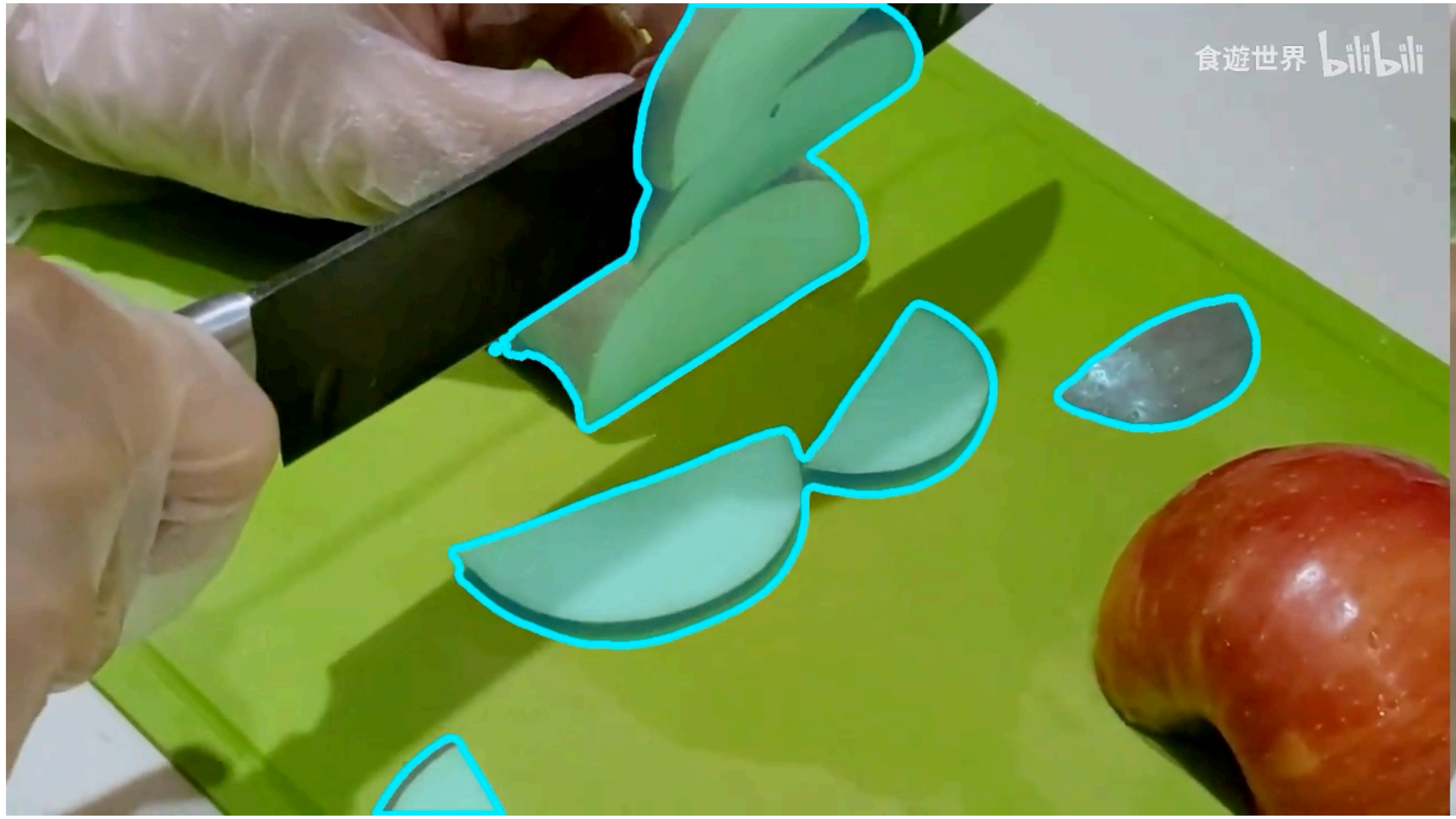
Our Solution

- We propose **TubeletGraph**, a zero-shot framework that recovers missing objects post-transformation and constructs a state graph to detect and describe the underlying transformations.



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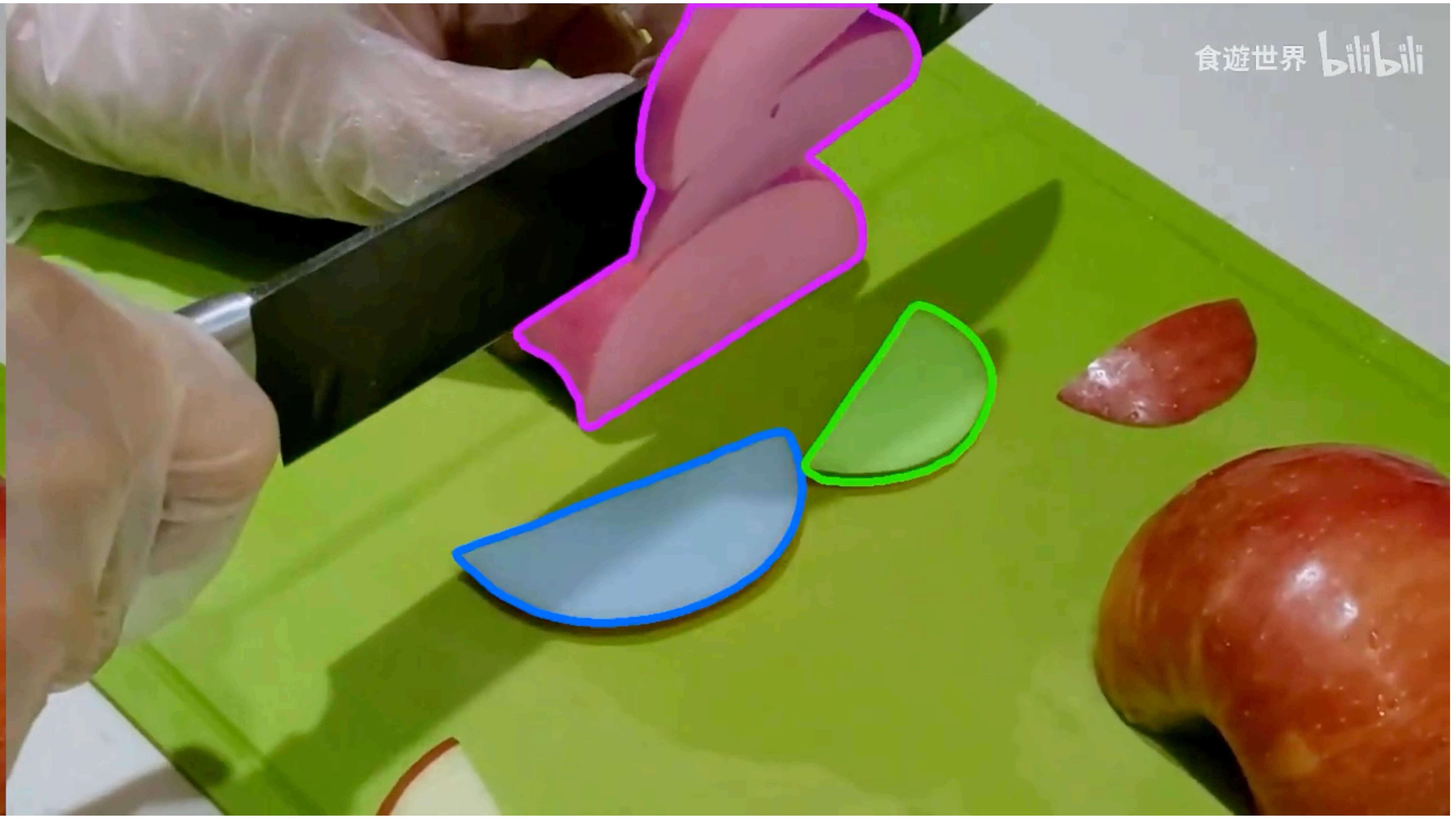

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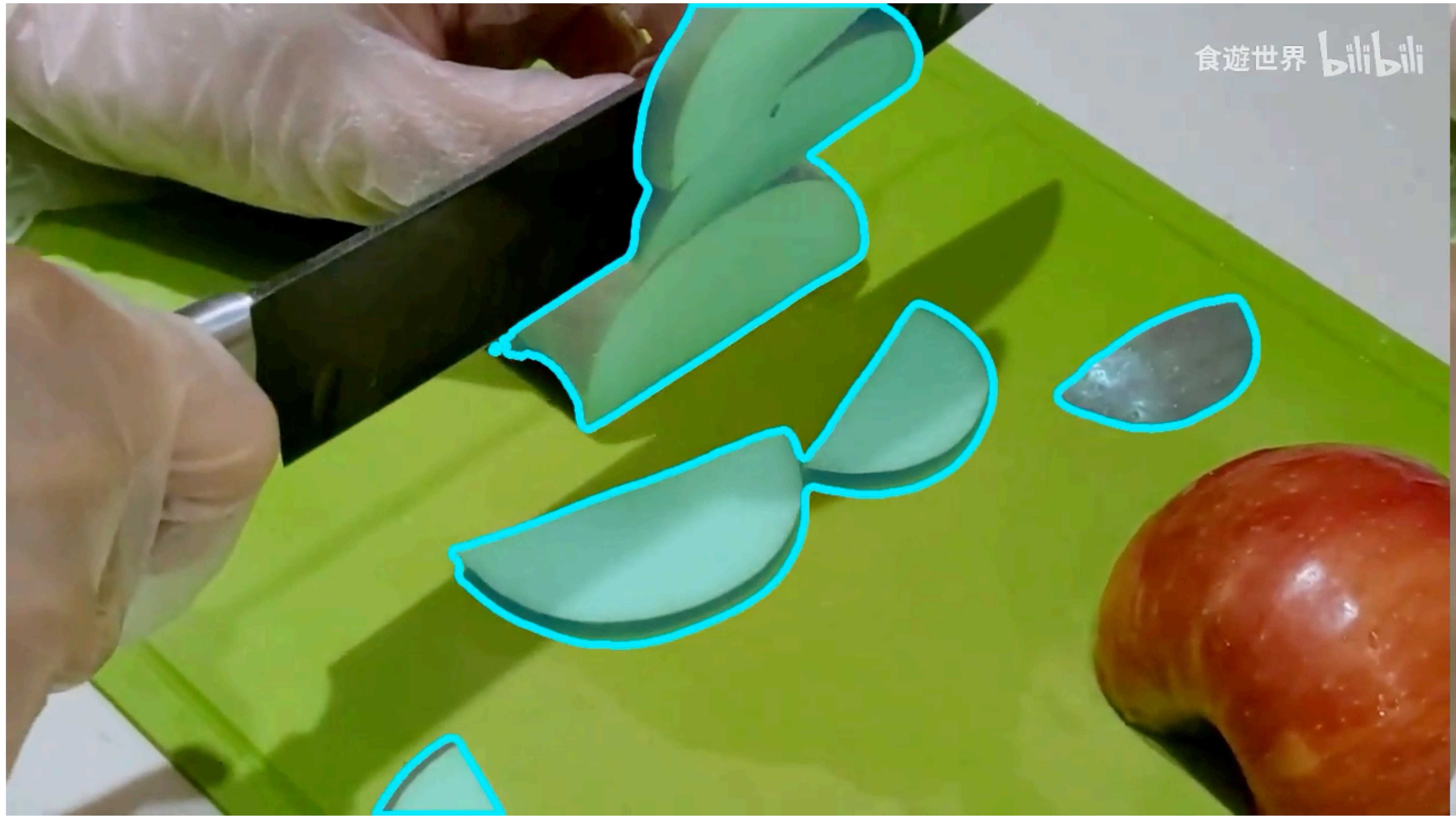

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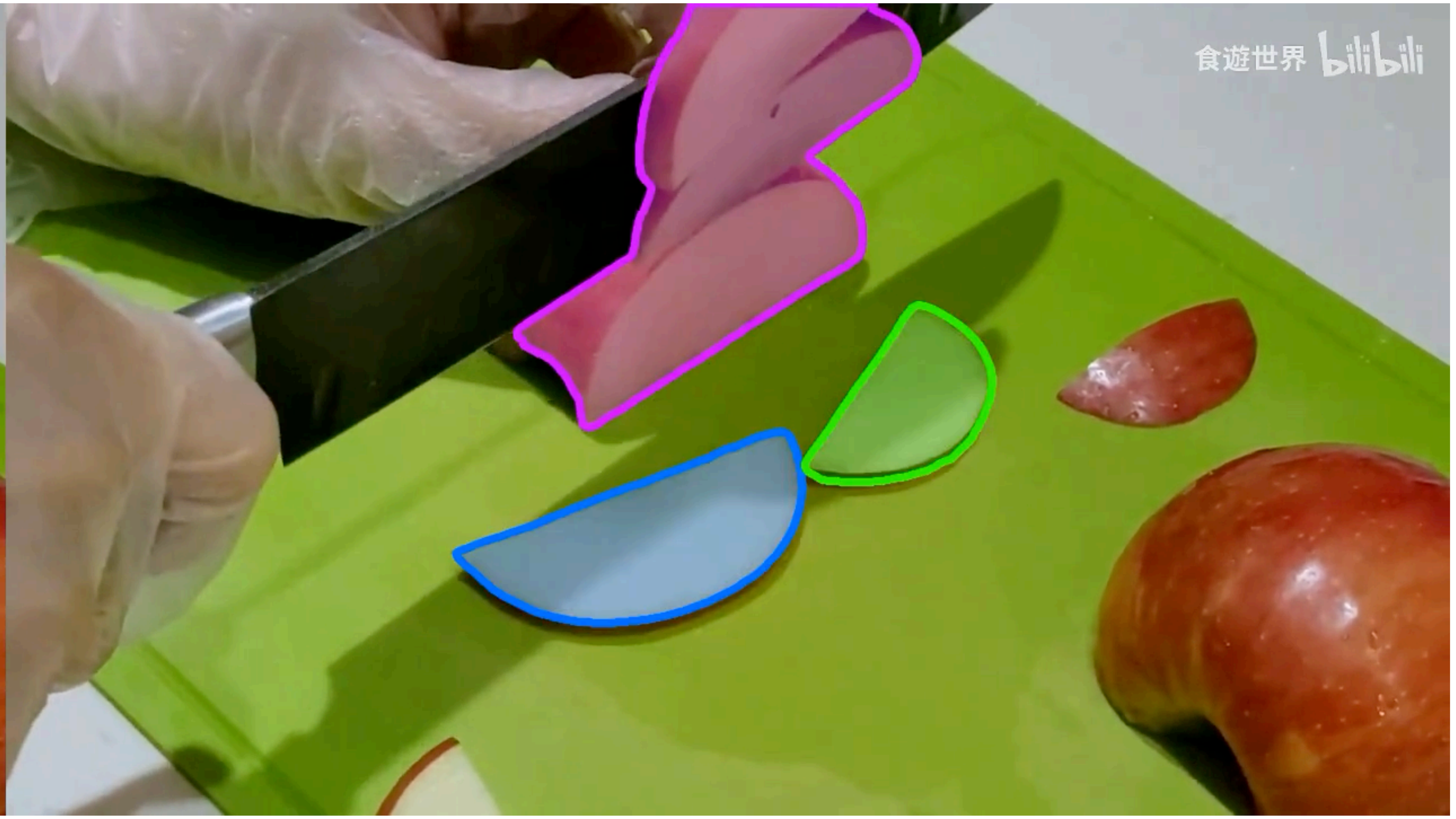

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    - It constructs a **spatiotemporal partition** of the video by tracking all regions and recovers missing objects via semantic and spatial proximity priors.
    - Recovered objects serve as **transformation markers**: It then prompts VLMs for descriptions

Method Overview

1. We first obtain a spatiotemporal partition of the input video with provided object prompt.
   - Track all regions from the first frame and initiate new tubelets when untracked pixels emerge.

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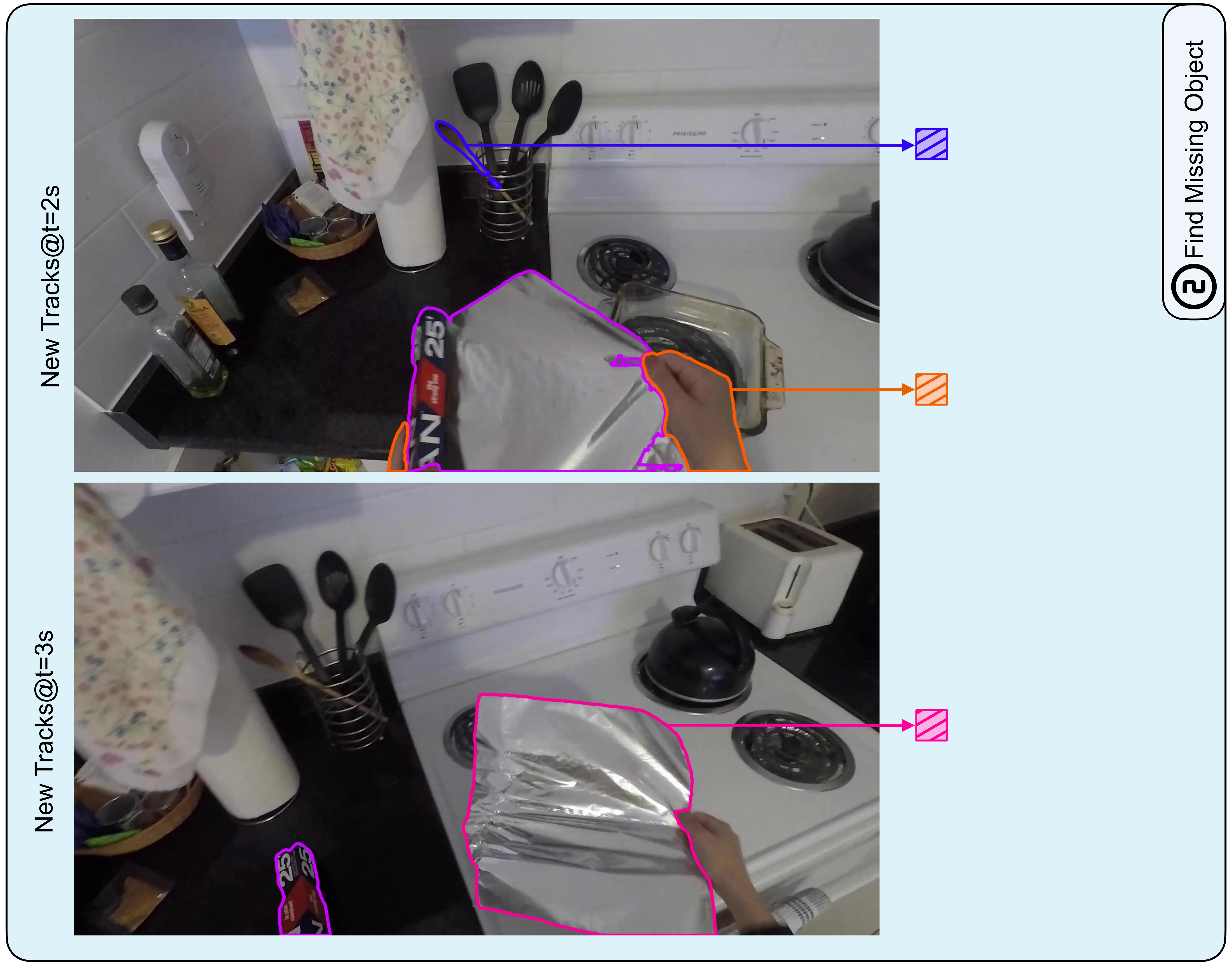
2. For each newly-emergent entity region, we reason about its proximity and semantic consistency and only keep the candidates that satisfy both.



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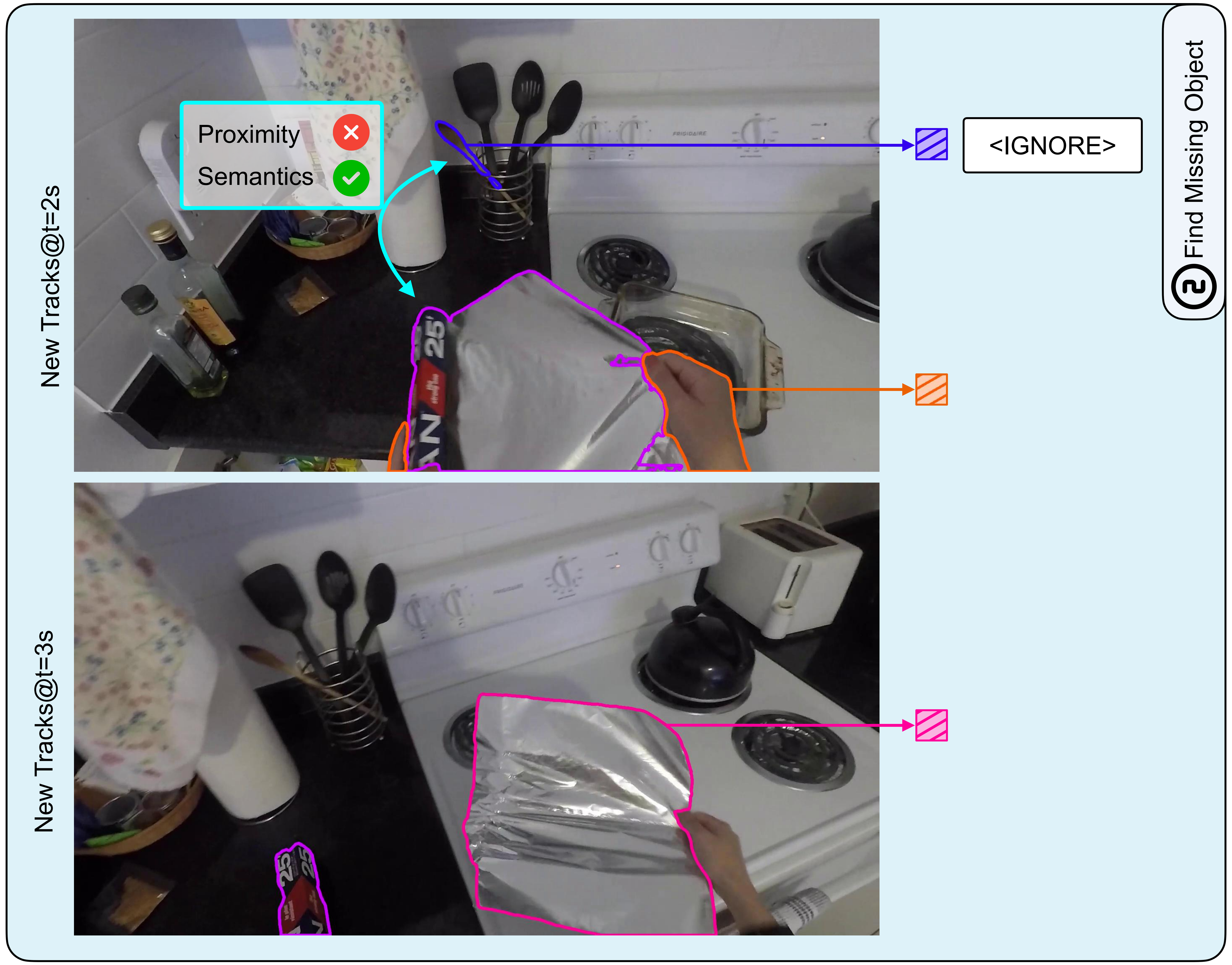

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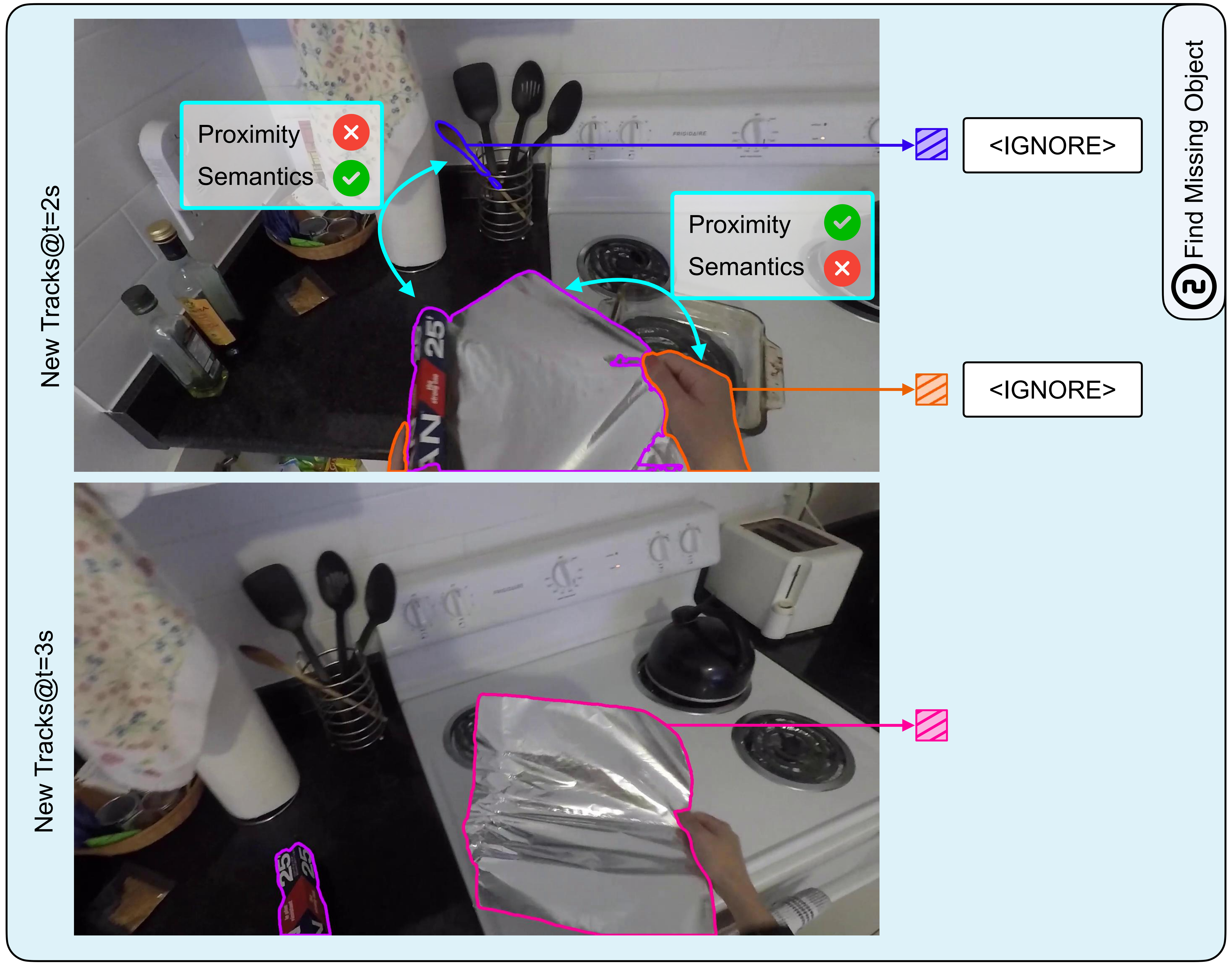

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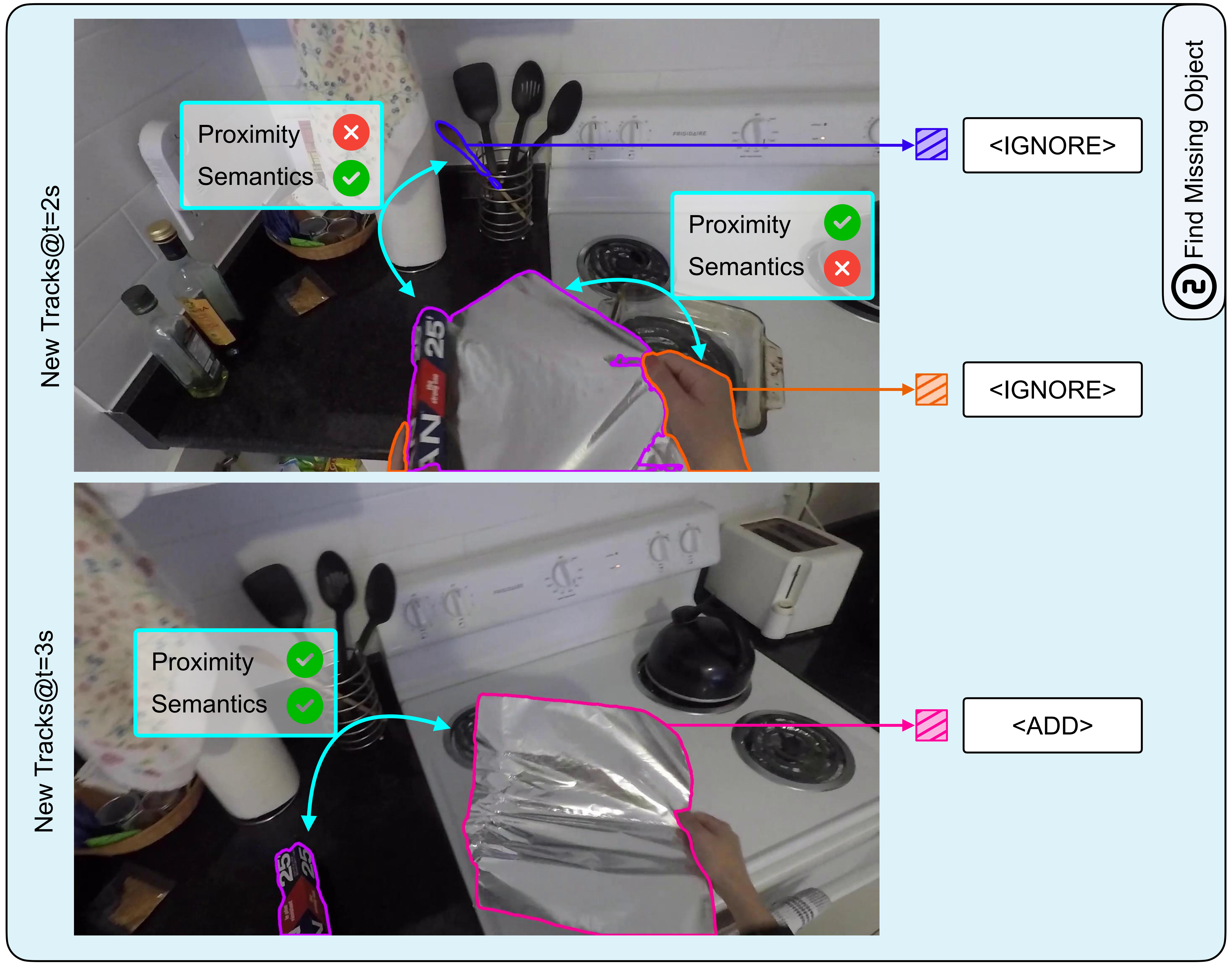

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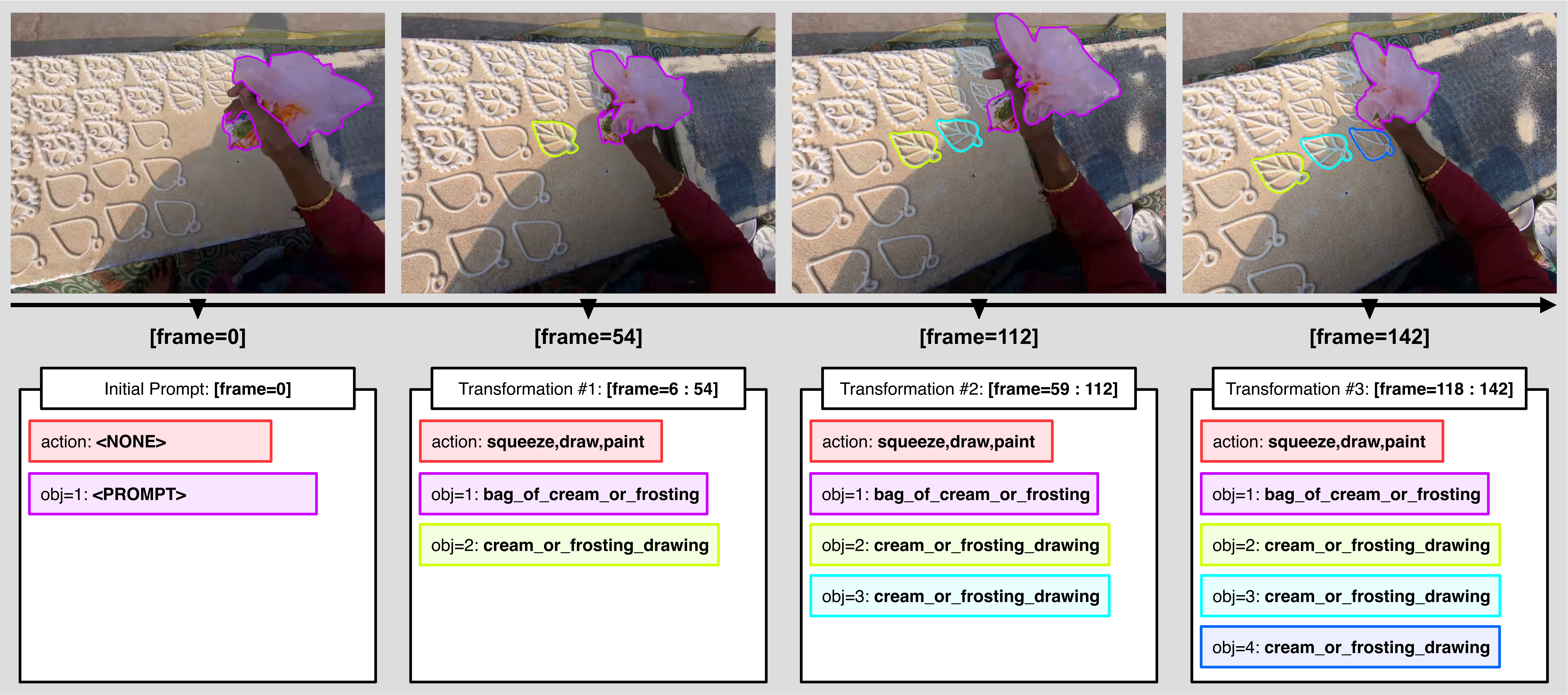
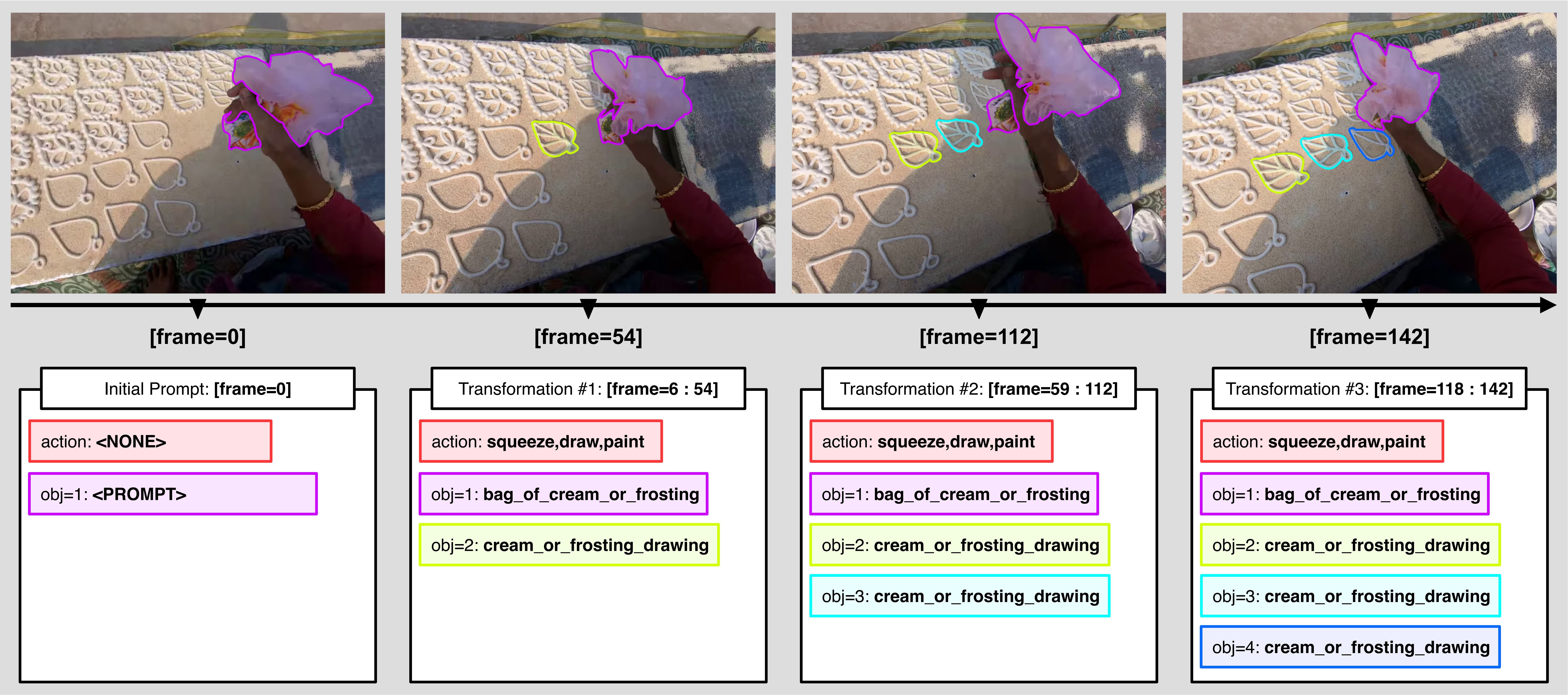
4. Finally, we obtain the complete object tracks along with the predicted state graph.

VOST-TAS


[frame=0]
[frame=54]
[frame=112]
[frame=142]
Initial Prompt: [frame=0]
action: <NONE>
obj=1: <PROMPT>
Transformation #1: [frame=6 : 54]
action: squeeze,draw,paint
obj=1: bag_of_cream_or_frosting
obj=2: cream_or_frosting_drawing
Transformation #2: [frame=59 : 112]
action: squeeze,draw,paint
obj=1: bag_of_cream_or_frosting
obj=2: cream_or_frosting_drawing
obj=3: cream_or_frosting_drawing
Transformation #3: [frame=118 : 142]
action: squeeze,draw,paint
obj=1: bag_of_cream_or_frosting
obj=2: cream_or_frosting_drawing
obj=3: cream_or_frosting_drawing
obj=4: cream_or_frosting_drawing

VOST-TAS

- Finally, we introduce VOST-TAS (TrackAnyState), an extended version of the VOST validation set with explicit transformation annotations for tracking and understanding object state changes in videos.
    - It contains 57 video instances, 108 transformations, and 293 annotated resulting objects.



Results

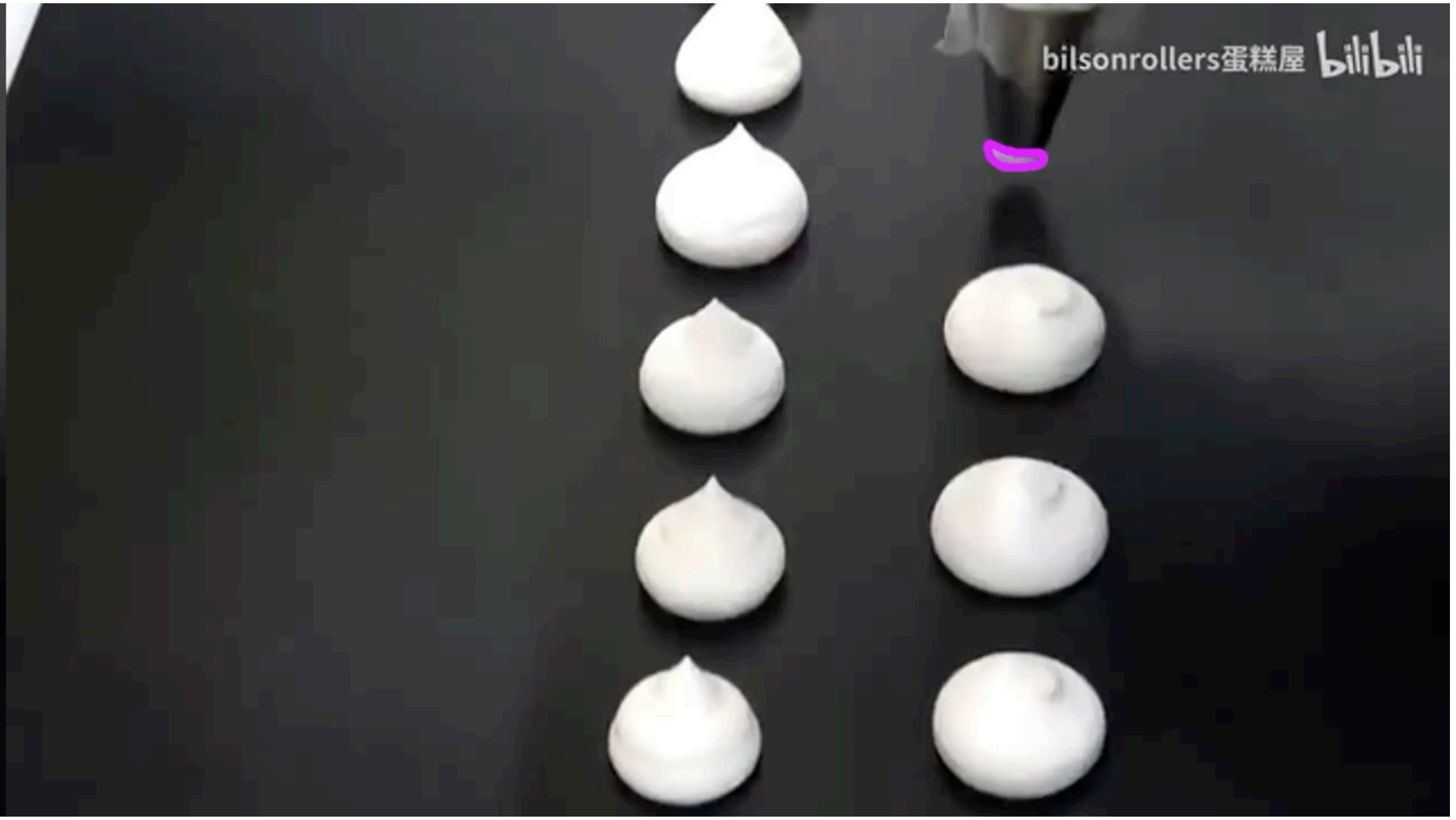
- **State-of-the-art tracking:** TubeletGraph achieves superior performance on transformation datasets (e.g., VOST, VSCOS).
- **Novel state graph capabilities:** It demonstrates promising capabilities in state graph prediction, as evaluated on VOST-TAS, with strong semantic accuracy and temporal precision, though overall transformation recall remains challenging.

Method	Tracking						State Graph					
	VOST		VSCOS		M^3-VOS		Sem. Acc.		Temp. Loc.		Overall	
	$\mathcal{J}$	$\mathcal{J}_{tr}$	$\mathcal{J}$	$\mathcal{J}_{tr}$	$\mathcal{J}$	$\mathcal{J}_{tr}$	$\mathcal{S}_V$	$\mathcal{S}_O$	$\mathcal{T}_P$	$\mathcal{T}_R$	$\mathcal{H}_{ST}$	$\mathcal{H}$
SAM2	46.1	29.4	72.5	67.1	71.3	59.8	-	-	-	-	-	-
SAM2Long	46.4	29.1	<u>73.0</u>	<u>68.6</u>	70.2	58.7	-	-	-	-	-	-
SAM2.1	48.4	32.4	72.0	66.9	71.3	59.3	-	-	-	-	-	-
DAM4SAM	48.8	33.6	71.3	66.0	72.2	61.3	-	-	-	-	-	-
SAMURAI	<u>49.8</u>	<u>34.0</u>	71.8	66.9	<u>72.6</u>	<u>61.6</u>	-	-	-	-	-	-
Ours	**51.0**	**36.9**	**75.9**	**72.2**	**74.2**	**64.4**	81.8	72.3	**43.1**	**20.4**	**12.0**	**6.5**

Results

Input Video + Prompt Object

Predicted Object Tracks



Piping bag tip

Predicted State Graph

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bilsonrollers蛋糕屋 bilibili
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Piping bag tip
t=1s dispense
t=2s dispense
t=4s dispense
t=6s dispense
t=6s dispense
t=6s dispense
t=7s dispense
t=8s dispense
t=8s dispense
Piping tip metal
meringue dollop white
meringue dollop white
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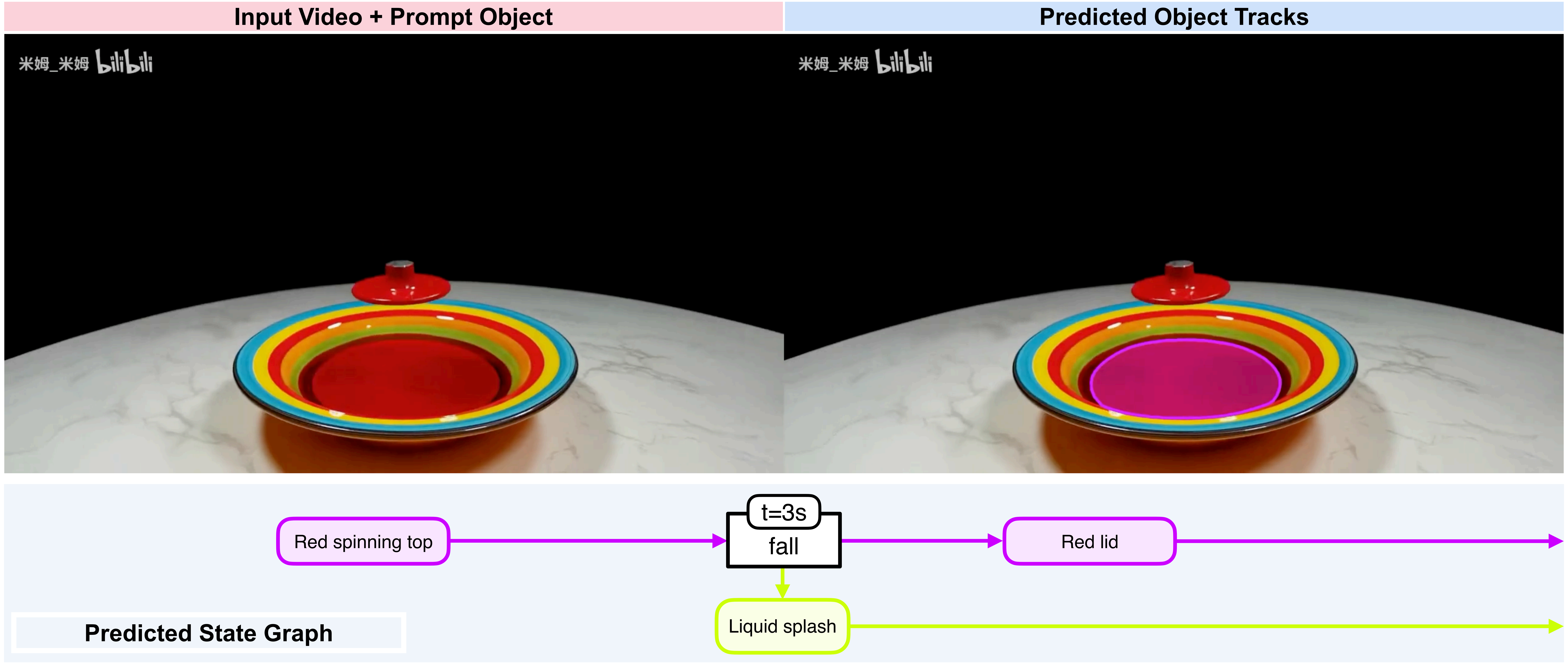
Predicted State Graph

Thank you!

For more results, data and code, please visit

tubelet-graph.github.io



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