



Overview

Goal: Given a single RGB image and a 2D hand location as input, we aim to segment hands and handheld objects to better understand contact regions.



For learning, we generate *responsibility maps* in video and use them as pseudo-labels.

Responsibility Map

We use *responsibility* as the notion of synchronous motion for hand and in-hand object, explaining how well each pixel is explained by each hand's motion model or the background.

Given a set of *N* hands, we produce *N* responsibility maps $R \in \mathbb{R}^{H \times W \times (N+1)}$. For the *k*th hand,

$$R_{i,j,k} = \frac{exp_t(-d_k(O_{i,j,:}))}{exp_t(-d_{BG}(O_{i,j,:})) + \sum_{k'=1}^{N} exp_t(-d_k(O_{i,j,:}))}$$

- $0 \in \mathbb{R}^{H \times W \times 2}$: Optical flow.
- d_{BG} , d_k : Distances between an optical flow vector and a model.
- Hand vertices between 2 frames are used to fit a Homography.





COHESIV: Contrastive Object and Hand Embeddings for Segmentation In Video

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Object



Large

non-rigid

object

	100DOH				EPICK				
	All	Pair	Hand	Obj	All	Pair	Hand	Obj	
	51.9	46.5	53.6	29.3	43.2	42.1	60.7	19.5	
	25.2	20.1	8.6	17.0	21.6	15.9	6.0	11.7	
	29.3	21.5	12.9	12.1	15.4	11.9	6.2	6.6	
onsibility	44.5	37.0	-	-	42.9	30.0	-	-	
ng Box	56.9	47.0	56.5	34.9	54.3	44.8	53.8	34.4	

		100	DOH		EPICK				
	All	Pair	Hand	Obj	All	Pair	Hand	Obj	
	51.9	46.5	53.6	29.3	43.2	42.1	60.7	19.5	
	42.8	40.0	-	-	38.1	37.8	-	-	
	25.7	18.3	13.2	22.9	30.0	20.8	24.6	14.4	
Net Backbone	45.8	41.2	48.1	25.2	39.8	39.1	55.2	17.9	
icted Query	47.7	42.8	47.8	28.1	40.0	38.6	55.1	19.4	