

Mining Cross-Person Cues for Body-Part Interactiveness Learning in HOI Detection

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Code

Motivation

- ■Local perspective (previous works)
 - only focus on the targeted person

• overlook the information of the other persons

human-row-boat human-kick-football

Original **Image**











Interactiveness++ (Li et al., T-PAMI 2021)





- ■Global perspective (ours)
- comparing body-parts of multi-person simultaneously
- more useful and supplementary interactiveness cues

Ours



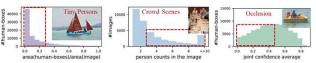


□exploit **contextual** cues from the whole image, easier and more stable

human-eat_atdining_table



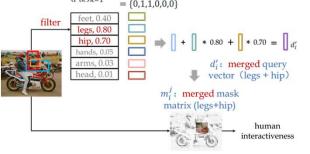
□alleviate the difficulty of HOI hard cases



query vector $d_i \in \mathbb{R}^{D_c}$ feature map DETR $z \in \mathbb{R}^{D_c \times H \times W}$ Ours body-part interactiveness key vector, value vector self-attention $K.V \in \mathbb{R}^{S \times D_c}, S = H \cdot W$ $Att^*(d_i, K, V)$ = $softmax(m_i \circ (d_i K^T)/\sqrt{D_c})V$ mask matrix $m_i \in \mathbb{R}^S, m_{is} = \begin{cases} 1, effective \\ -inf, masked \end{cases}$

- □utilizing **self-attention** calculation in transformer
- Constructing body-part saliency maps via image patches (i.e., transformer tokens) masking
- □ progressively body-part masking to encode diverse visual patterns more flexibly □ different attention mask is applied in successive transformer layers and more tokens are dropped in the late layers





one-time passing via body-parts filtering and merging to improve computation efficiency

Discussion: Sparse vs. Crowded Scene

- We focus on crowded scenes, then what about **sparse** scenes?
 - Our model is **adapted to both** crowded and sparse
 - Crowded scenes is more important in interactiveness learning.
 - Thus, we further propose a novel sparsity adaptive sampling strategy on train set to put more emphasis on crowded scenes.

Experiment & Results

■ With our holistic global-local interactiveness detector, we achieve state-of-the-art for interactiveness detection and HOI detection on HICO-DET & V-COCO.

Method	Full	Sparse/Crowded	Normal/Tiny	Less/More Occ
TIN++	14.35	16.96/9.64	16.11/8.94	16.49/8.06
PPDM	27.34	34.67/26.69	31.79/26.33	29.83/17.25
QPIC	32.96	36.80/27.04	34.02/26.14	32.08/19.75
CDN	33.55	39.92/28.84	36.10/25.11	34.55/21.69
Ours	38.74	43.62/33.10	39.85/32.47	38.60/22.75

		Defa	ult	K	nown (Object
Method	Full	Rare	Non-Rare	Full	Rare	Non-Rare
iCAN [7]	14.84	10.45	16.15	16.26	11.33	17.73
TIN [22]	17.03	13.42	18.11	19.17	15.51	20.26
PMFNet [31]	17.46	15.65	18.00	20.34	17.47	21.20
DJ-RN [17]	21.34	18.53	22.18	23.69	20.64	24.60
PPDM [23]	21.73	13.78	24.10	24.58	16.65	26.84
VCL [11]	23.63	17.21	25.55	25.98	19.12	28.03
IDN [19]	26.29	22.61	27.39	28.24	24.47	29.37
Zou et al. [37]	26.61	19.15	28.84	29.13	20.98	31.57
ATL [12]	28.53	21.64	30.59	31.18	24.15	33.29
AS-Net [2]	28.87	24.25	30.25	31.74	27.07	33.14
QPIC [29]	29.07	21.85	31.23	31.68	24.14	33.93
FCL [13]	29.12	23.67	30.75	31.31	25.62	33.02
GGNet [34]	29.17	22.13	30.84	33.50	26.67	34.89
SCG [34]	31.33	24.72	33.31	34.37	27.18	36.52
CDN [33]	31.78	27.55	33.05	34.53	29.73	35.96
Ours	35.15	33.71	35.58	37.56	35.87	38.06

TIN++ [18]	14.35	29.36		
PPDM [23]	27.34	_3.00		
OPIC [29]	32.96	38.33		
CDN [33]	33.55	40.13		
ours 38	3.74 (+5.19)	43.61 (+3.4		
Method	AP _{role} (S1)	$AP_{role}(S2)$		
iCAN [7]	45.3	52.4		
TIN [22]	47.8	54.2		
VSGNet [30	51.8	57.0		
PMFNet [3]	52.0	-		
IDN [19]	53.3	60.3		
AS-Net [2]	53.9			
SCG [34]	54.2	-		
GGNet [34]	54.7	-		
HOTR [14]	55.2	64.4		
QPIC [29]	58.8	61.0		
CDN [33]	62.3	64.4		
Ours	63.0	65.1		

Method HICO-DET [1] V-COCO [10]

■ Some visualization results, where informative cues are extracted from other persons in the image.

