



YouRefIt: Embodied Reference Understanding with Language and Gesture

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Embodied Reference

- Referential behavior is a typical form of human communication, which acts as the first step to understand the surrounding world by establishing joint attention and common ground with other agents.
- Embodied reference: An agent refers to an object to another agent in a shared physical space.



Embodied Reference

Key difference with Referential Expression Understanding (REF):

• The reference participants and referred object are in the same shared physical space.



The white phone on the table



The picture on the wall

- Referrer will use both gestural and verbal information for reference.
- Embodied reference involves **visual perspective-taking**, i.e., the awareness that other people see things from different viewpoints and the ability to imagine what others see from their perspectives.
- Previous REF task takes images from Internet (MSCOCO/Flickr) or simulation(CLEVR). There's a natural domain gap compared with daily life picture.

Data Collection

• YouRefIt dataset is collected using the Amazon Mechanic Turk (AMT) platform

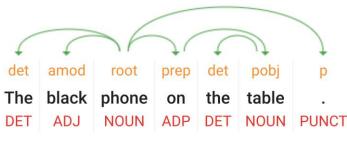
Task: Refer to an object in the scene to an imagined person (camera) Steps:

- 1. Refer to one object using both pointing gesture and language.
- 2. After the reference, tap the target object to confirm.
- 3. Repeat until no more objects.
- 4. Write down the sentences in the same order as during the recording.
- 5. Submit both the videos and sentences.



Data Annotation

- Reference segments
- Canonical frames: "keyframes" that the referrer holds the steady pose to clearly indicate what is being referred
- Bounding boxes of target objects
- Semantic parsing



'The black phone on the table."



Canonical Frames

		— Segments and Bounding Bo
reference segment	canonical frames	tapping
Text: The black phone of	on the table	Semantic Parsing
Audio:	in a share and in the second	
Sentence:	a feaderan an galaithe an an galaithe an	
The black phone on the table	2	
Parse-Target:		
The phone		
Parse-Attribute:		
black		
Parse-Spatial-Relation:		
on the table		
Parse-Spatial-Object(put None	if no object):	
table		
Parse-Comparative-Relation:		
Comparative relation, e.g., sn	nallest, bigger than	
Parse-Comparative-Object(put	None if no object):	

Dataset Sample



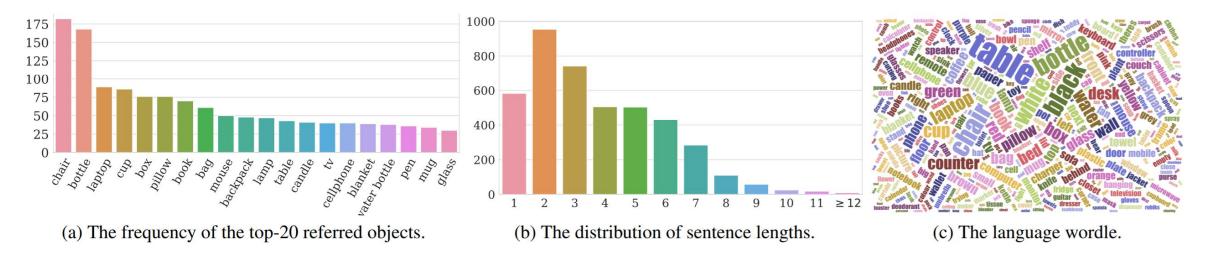


Statistics

Datasets	Lang. Gest. Embo. Type Source		No. of images	No. of instances	No. of object categories	Ave. sent. length			
PointAt [44]	×	1	1	image	lab	220	220	28	1.2
ReferAt [43]	1	1	\checkmark	video	lab	_	242	28	
IPO [46]	×	1	\checkmark	image	lab	278	278	10	13
IMHF [47]	×	1	1	image	lab	1716	1,716	-	
RefIt [21]	\checkmark	×	×	image	image CLEF	19,894	130,525	238	3.6
RefCOCO [64]	1	×	×	image	MSCOCO	19,994	142,209	80	3.6
RefCOCO+ [64]	1	×	×	image	MSCOCO	19,992	141,564	80	3.53
RefCOCOg [35]	\checkmark	×	×	image	MSCOCO	26,711	104,560	80	8.4.
Flickr30k entities [38]	\checkmark	×	×	image	Flickr30K	31,783	158,915	44,518	
GuessWhat? [8]	\checkmark	×	×	image	MSCOCO	66,537	155,280	-	
Cops-Ref [4]	1	×	X	image	COCO/Flickr	75,299	148,712	508	14.4
CLEVR-Ref+ [31]	\checkmark	×	×	image	CLEVR	99,992	998,743	3	22.4
YouRefIt	1	1	1	video	crowd-sourced	497,348	4,195	395	3.7

Statistics

- We retrieved 8.83 hours of video during the post-processing and annotated 497,348 frames.
- In total, YouRefIt includes 432 recorded videos and 4,195 localized reference clips with 395 object categories.
- The total duration of all the reference actions is 3.35 hours, with an average duration of 2.81 seconds per reference.



Embodied Reference Understanding (ERU)

- Image ERU:
 - Input: one canonical frame, the transcribed sentence
 - Predicts the bounding box of the referred object



- Video ERU:
 - Input: the video of reference segment, the transcribed sentence
 - Identifies the canonical frames and predicts the target bounding box



Framework

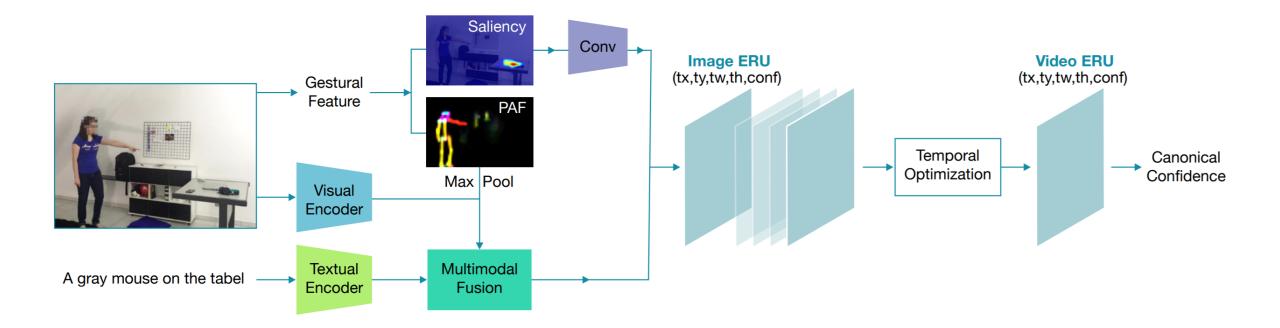
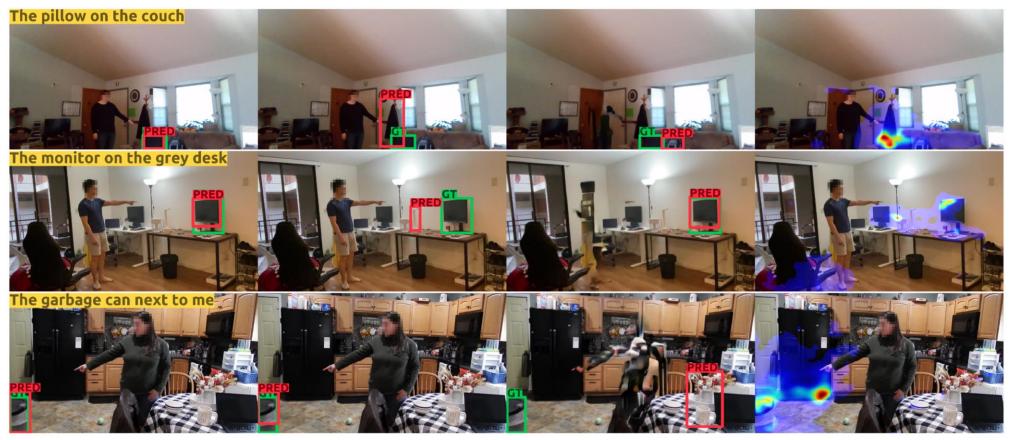


Image ERU

• Our proposed framework, which explicitly considers all information sources (Language + Gesture) yields the best performance compared to the baseline models. Gesture information is essential in embodied reference understanding.

Model	IoU=0.25				IoU=0.5				IoU=0.75			
Model	all	small	medium	large	all	small	medium	large	all	small	medium	large
Language-only												
MAttNet _{pretrain}	14.2	2.3	4.1	34.7	12.2	2.4	3.8	29.2	9.1	1.0	2.2	23.1
FAOA _{pretrain}	15.9	2.1	9.5	34.4	11.7	1.0	5.4	27.3	5.1	0.0	0.0	14.1
FAOA _{inpaint}	23.4	14.2	23.6	32.1	16.4	9.0	17.9	22.5	4.1	1.4	4.7	6.2
ReSC _{pretrain}	20.8	3.5	17.5	40.0	16.3	0.5	14.8	36.7	7.6	0.0	4.3	17.5
ReSCinpaint	34.3	20.3	38.9	44.0	25.7	8.1	32.4	36.5	9.1	1.1	10.1	16.0
Gesture-only												
RPN+Pointing ₁₅	15.3	10.5	16.9	18.3	10.2	7.2	12.4	11.0	6.5	3.8	9.1	6.6
RPN+Pointing ₃₀	14.7	10.8	17.0	16.4	9.8	7.4	12.4	9.8	6.5	3.8	8.9	6.8
RPN+Saliency[27]	27.9	29.4	34.7	20.3	20.1	21.1	26.8	13.2	12.2	10.3	17.9	8.6
Ours _{no_lang}	41.4	29.9	48.3	46.3	30.6	17.4	37.0	37.4	10.8	1.7	13.9	16.6
Language + Gesture												
FAOA[59]	44.5	30.6	48.6	54.1	30.4	15.8	36.2	39.3	8.5	1.4	9.6	14.4
ReSC[58]	49.2	32.3	54.7	60.1	34.9	14.1	42.5	47.7	10.5	0.2	10.6	20.1
Ours _{PAF_only}	52.6	35.9	60.5	61.4	37.6	14.6	49.1	49.1	12.7	1.0	16.5	20.5
Ours _{Full}	54.7	38.5	64.1	61.6	40.5	16.3	54.4	51.1	14.0	1.2	17.2	23.3
Human	94.2±0.2	93.7±0.0	92.3±1.3	96.3±1.7	85.8 ± 1.4	81.0±2.2	86.7±1.9	89.4±1.7	53.3±4.9	33.9±7.1	55.9±6.4	68.1±3.0

Image ERU



(a) Ours_{Full}

(b) Ours_{no_lang}

(c) ReSC_{inpaint}

(d) Saliency Map

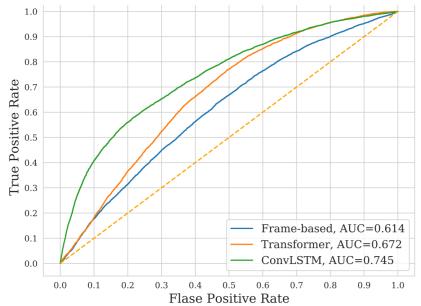
Video ERU

Model IoU=0.25						IoU=0.5				IoU=0.75			
widdei	all	small	medium	large	all	small	medium	large	all	small	medium	large	
Frame-based	55.2	42.3	58.9	64.8	41.7	22.7	53.4	48.8	16.9	1.6	21.8	27.0	
Transformer	52.3	40.2	55.6	58.3	38.8	21.2	54.1	47.1	13.9	1.5	20.8	22.7	
ConvLSTM	54.8	43.1	57.5	60.0	39.3	22.5	54.8	46.7	17.3	1.8	24.3	25.5	
Ours _{Full}	54.7	38.5	64.1	61.6	40.5	16.3	54.4	51.1	14.0	1.2	17.2	23.3	

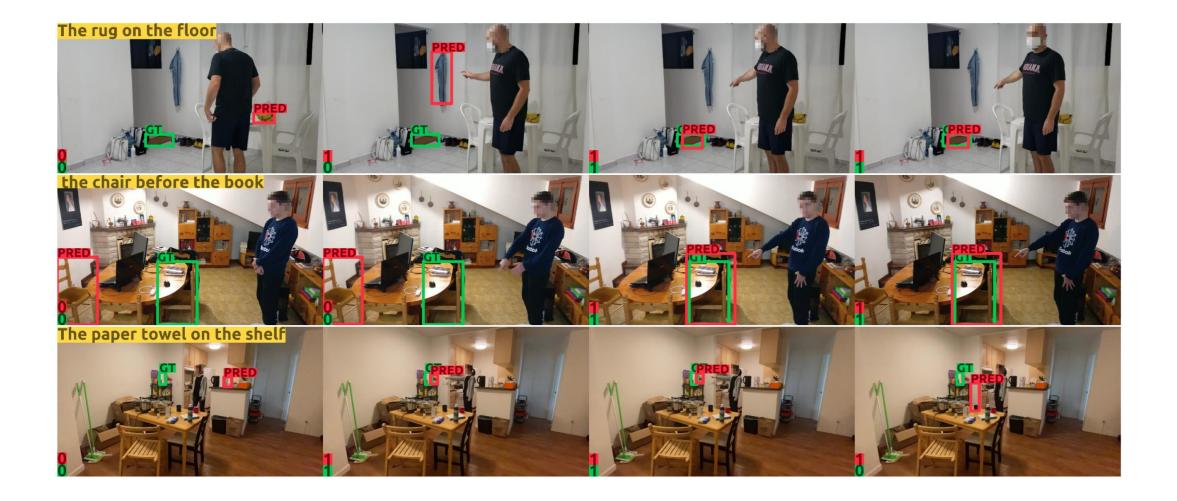
Canonical frames can provide sufficient gestural and language information for clear reference

Method	Avg. Prec	Avg. Rec	Avg. F1
Frame-based	31.9	37.7	34.5
Transformer	35.1	44.2	39.1
ConvLSTM	57.0	37.9	45.4

• Temporal information can greatly improve performance on canonical frame detection



Video ERU



Future Direction

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- Embodied reference in multi-round dialogues
- Referential behavior generation
- Active learning with referential interaction

Thank you

Check our website at https://yixchen.github.io/YouRefIt