2021 Intelligent Sensing Winter School

An Affordance Detection Pipeline for Resource-Constrained Devices

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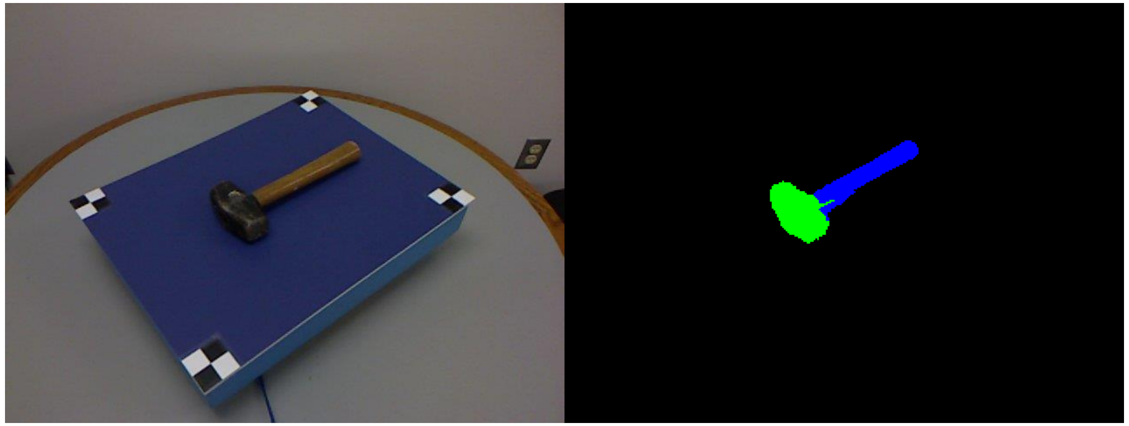
Affordance detection

Segmenting parts of objects based on potential interaction with a human.



Affordance detection

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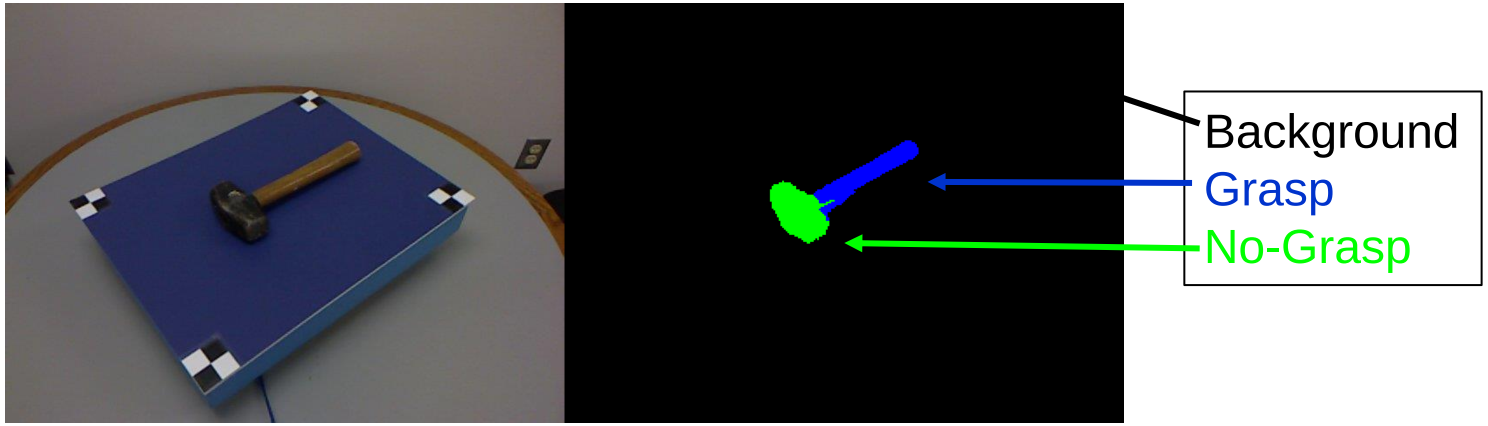

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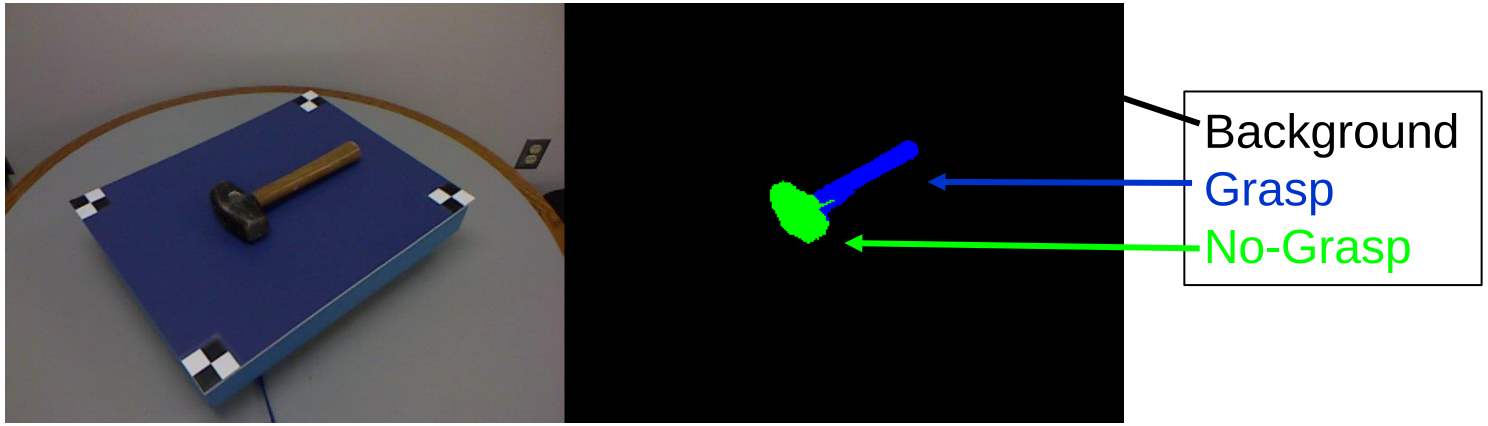


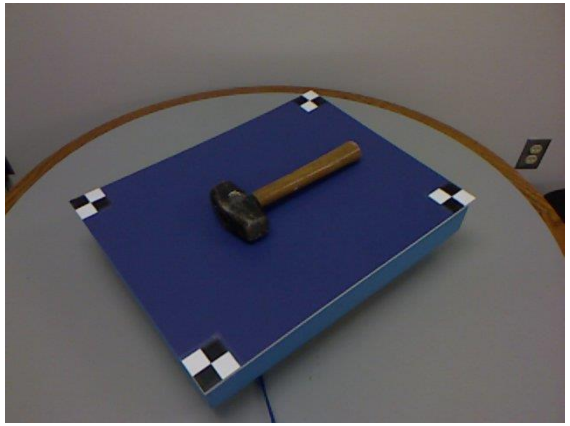
Wearable context (prosthetic):

- Resource-constrained devices
- Robotic solutions require remarkable computational power
- Human-in-the-loop application

Baseline

Models for portable embedded systems [1] assume objects to be:

- In foreground
- Completely visible



[1] Ragusa, E. et al., *"Hardware-Aware Affordance Detection for Application in Portable Embedded Systems",* IEEE Access, 2021.

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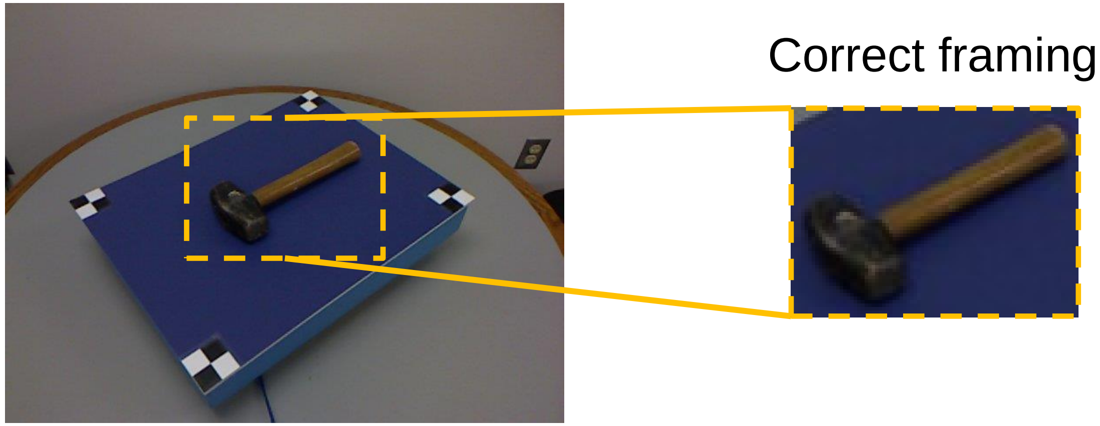
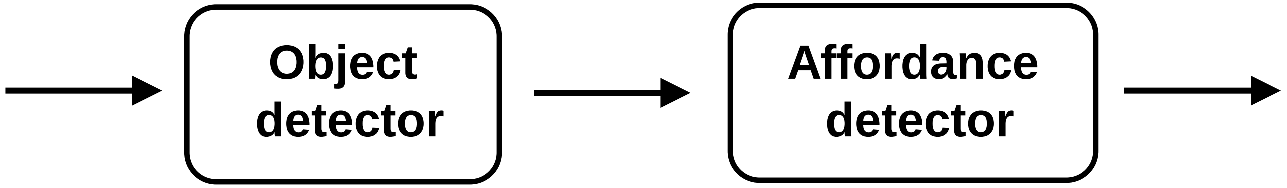


Framing issue: the position of the camera is indirectly controlled by a human

[1] Ragusa, E. et al., *"Hardware-Aware Affordance Detection for Application in Portable Embedded Systems",* IEEE Access, 2021.

Contributions

- Overcome framing issues



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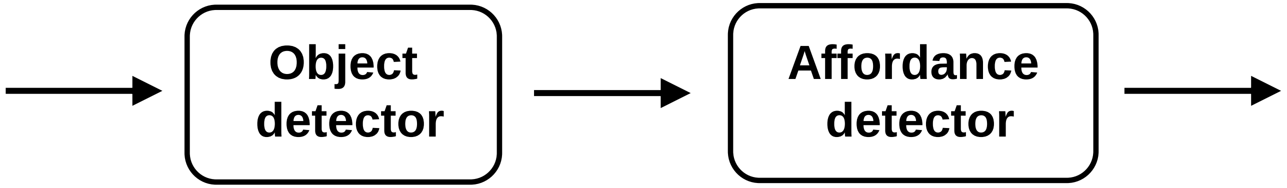
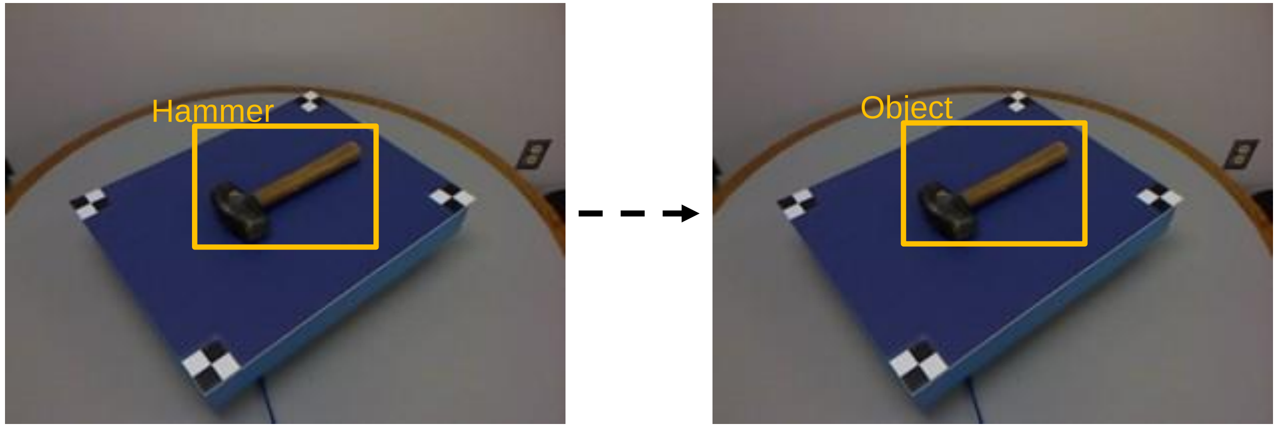


- Leverage human-in-the-loop feature: the object class is known by the human



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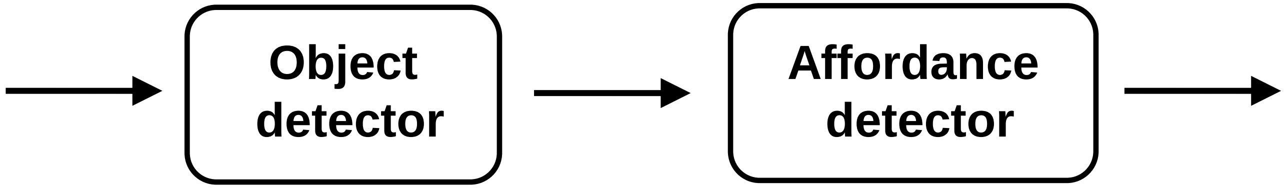

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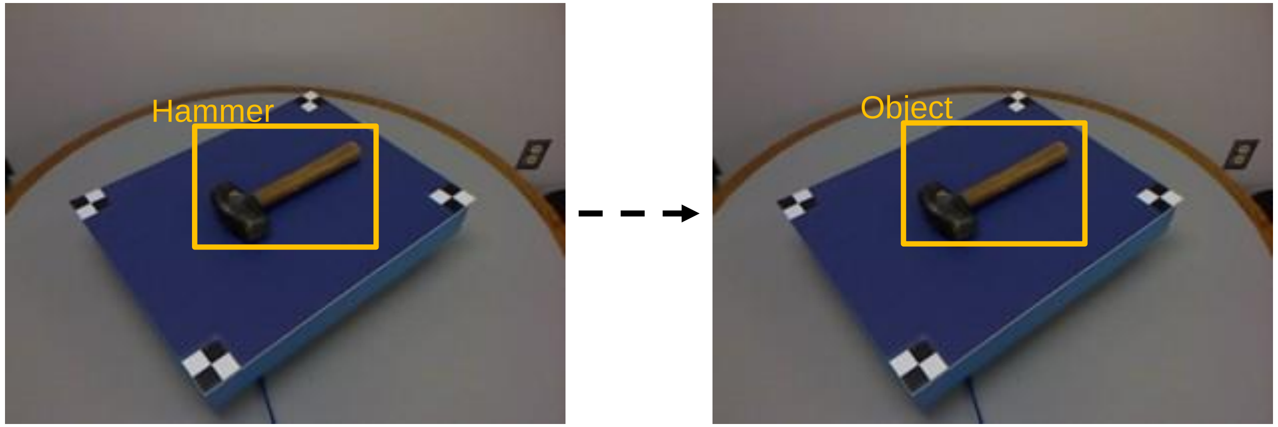
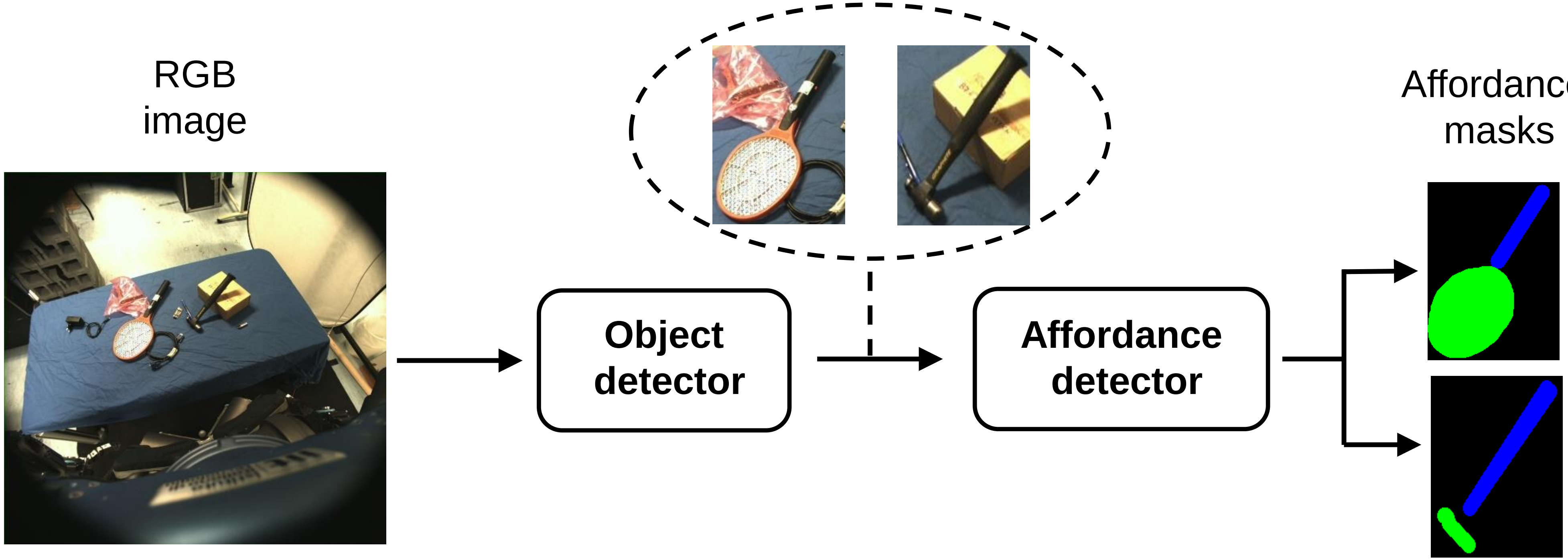


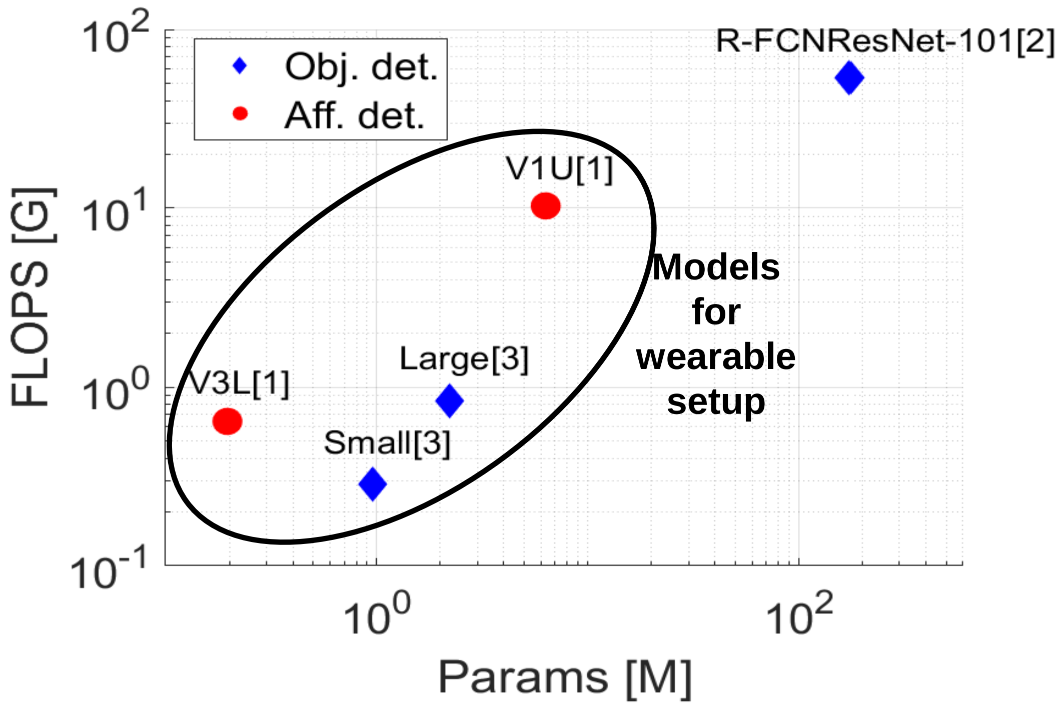
- Target resource-constrained devices employing lightweight models

Proposed Method



Considered models

Comparison: wearable vs robotic



[1] Ragusa, E. et al., *“Hardware-Aware Affordance Detection for Application in Portable Embedded Systems”,* IEEE Access, 2021.

[2] Nguyen, A. et al., *“Object-Based Affordances Detection With Convolutional Neural Networks and Dense Conditional Random Fields”,* IEEE /RSJ IROS, 2017.

[3] Howard, A. et al., *“Searching for MobileNetV3”,* IEEE/CVF ICCV, 2019.

Datasets

UMD [4]

- Simple setting
- Same resolution
- Blue rotating support
- Single object per image

IIT-AFF [2]

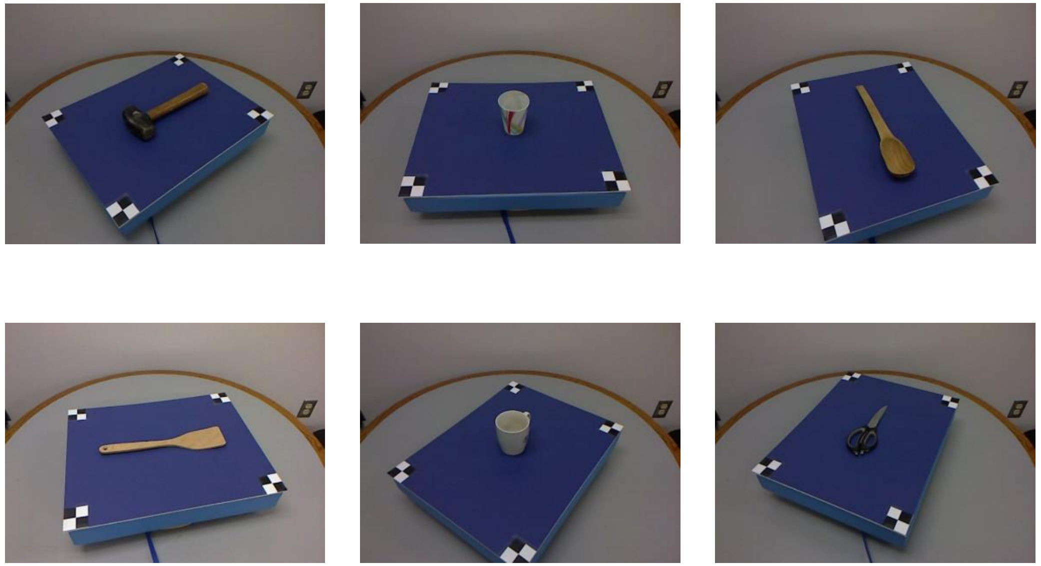
- Challenging setting
- Different resolutions
- Different supports and scenes
- Multiple objects per image

[2] Nguyen, A. et al., *“Object-Based Affordances Detection With Convolutional Neural Networks and Dense Conditional Random Fields”,* IEEE/RSJ IROS, 2017.

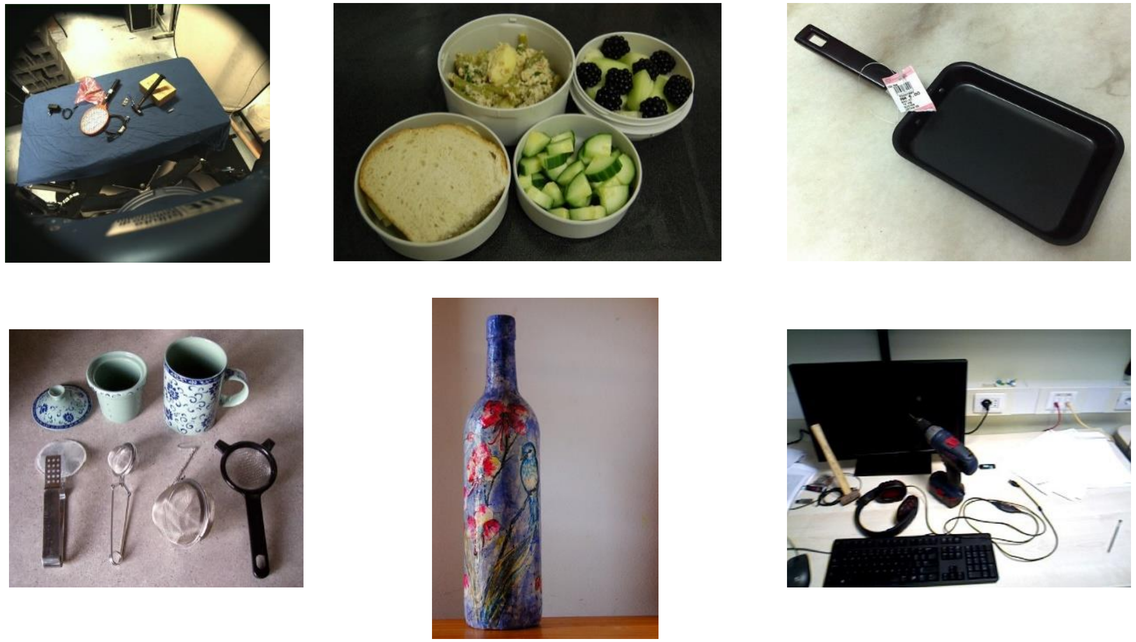
[4] Myers, A. et al., *“Affordance Detection of Tool Parts from Geometric Features”,* IEEE ICRA, 2015.

Datasets

UMD [4]



IIT-AFF [2]



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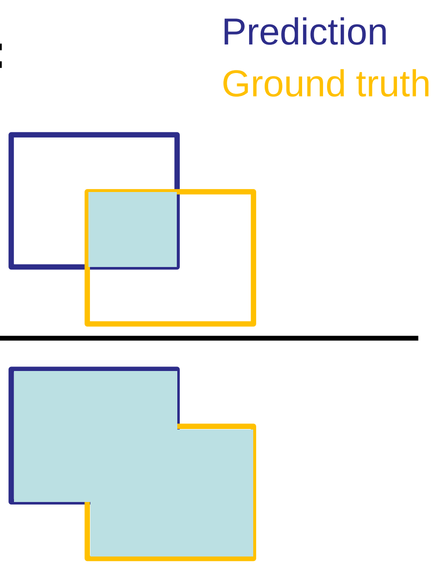
Metrics

Intersection over Union (IoU):



$$\text{IoU} = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

Mean Average Precision (mAP):

- Area under Precision-Recall curve

F_β^w score [5]:

$$F_\beta^w = (1+\beta^2)\frac{Precision^w \cdot Recall^w}{\beta^2 \cdot Precision^w + Recall^w}$$

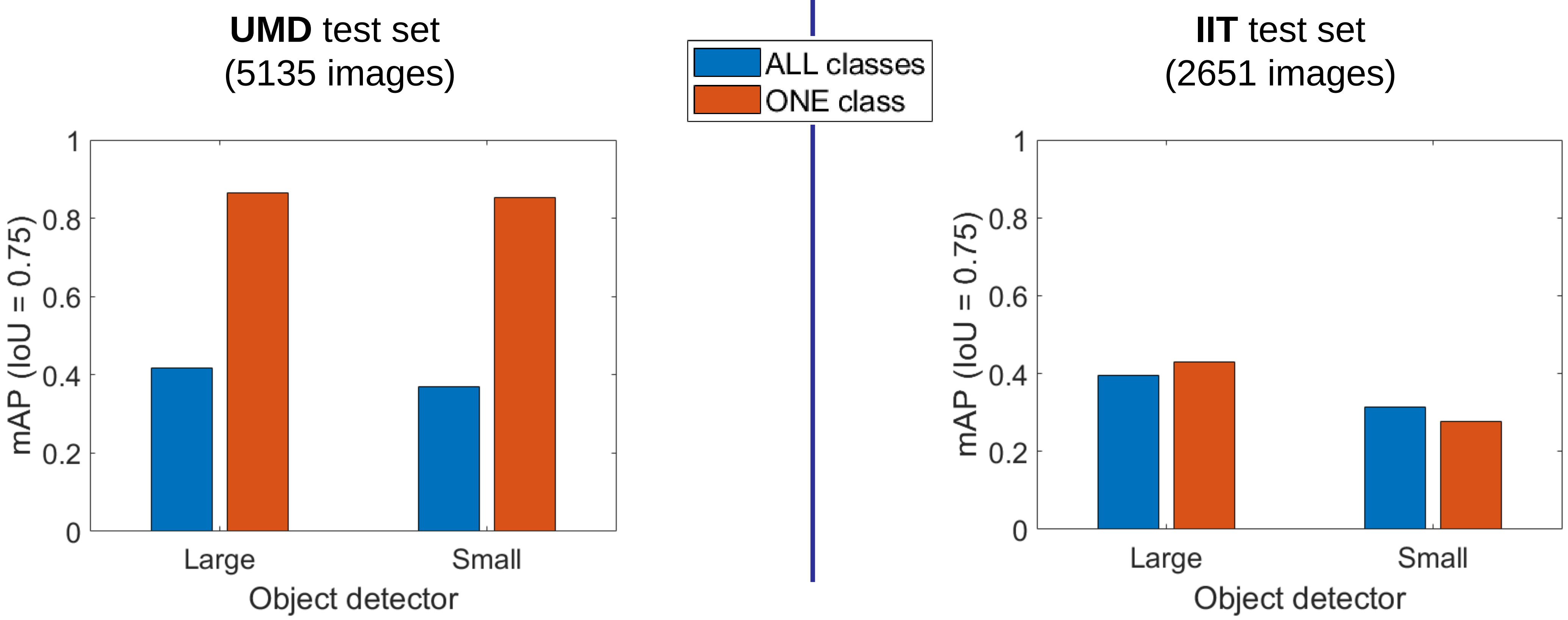
w:

- weights the dependency between ground truth pixels
- weights the errors based on distance with respect to ground truth

[5] Margolin, R. et al., *"How to evaluate foreground maps,"* IEEE Conference on Computer Vision and Pattern Recognition, 2014.

Object detection results

Detection improvement leveraging human-in-the-loop (ONE class)

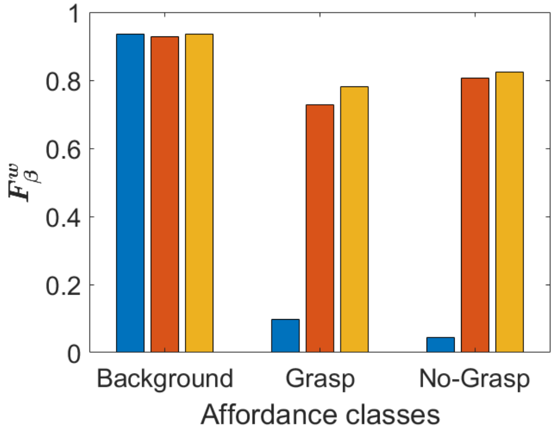


Affordance detection results

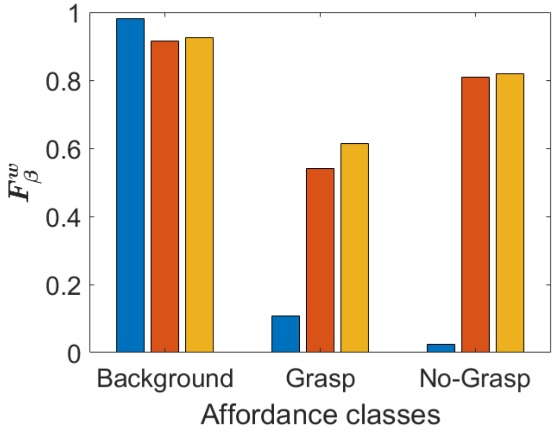
Improvement employing proposed method (Obj. det. + Aff. det.) vs baseline (only Aff. det.)

UMD test set

V1U

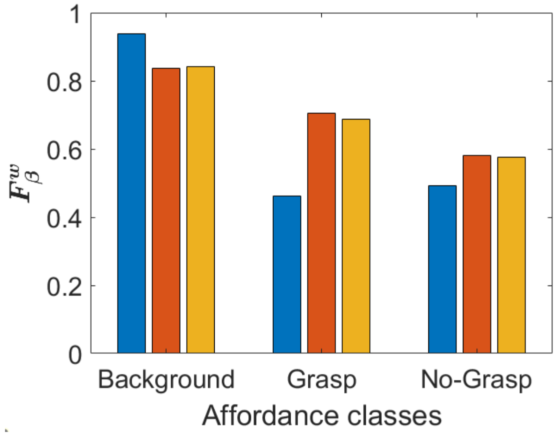


V3L

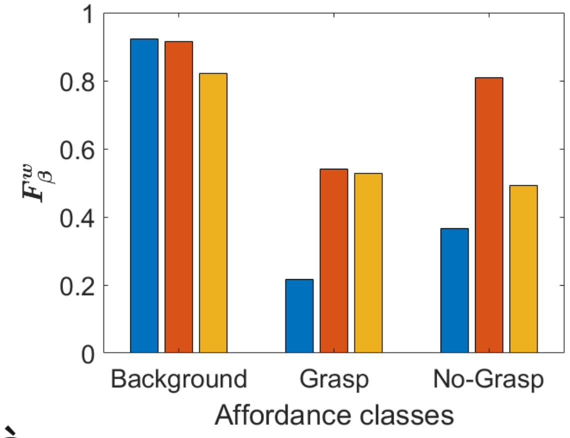


IIT test set

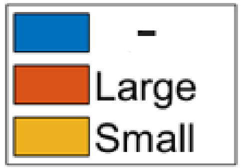
V1U



V3L



Obj. Det.



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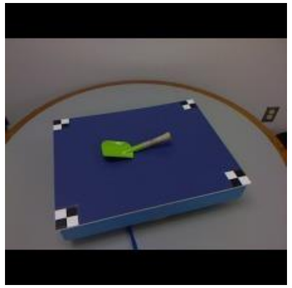
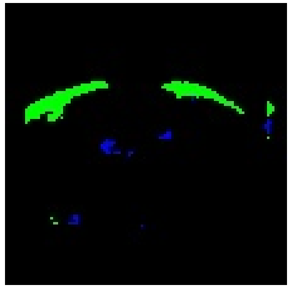
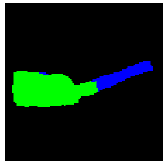
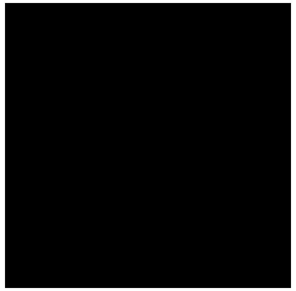
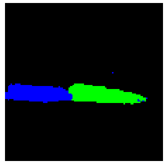
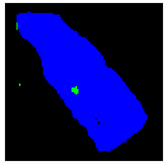
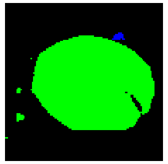
Qualitative results

Image	Baseline	Proposed method	
	Aff. Det.	Obj. det.	Aff. det.
			
		  	  

Conclusions

- Pipeline to overcome framing issue
- Object detection improvement leveraging human-in-the-loop
- Affordance detection improvement
- Target resource-constrained devices employing lightweight models

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https://github.com/SEAlab-unige/ICECS-2021

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