



Harmonious Feature Learning for Interactive Hand-Object Pose Estimation

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Understanding hand-object interaction

• Estimating 3D hand and object pose from a single image



• Challenge:

Hands and objects are often self-occluded during interactions

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Related Work

Separate Encoders



One Encoder and Feature Fusion



Hasson et al., 2019

Liu et al., 2021

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Proposed Method



Proposed Method



Feature Extraction Backbone

Interaction Modules

Two separate decoders



1.Feature Extraction Backbone



 single stream backbone -> treats the hand and object both as foreground, competitive in feature learning



 double stream backbone -> large number of parameters, the different feature spaces between backbones



1.Feature Extraction Backbone



- Our backbone keeps the structure of the stage-0, stage-1, and stage-4 layers of the ResNet-50 model unchanged, but adopts independent stage-2 and stage-3 layers for the hand and object.
- The feature maps output by the stage-1 layers are fed into the two sets of stage-2 and stage-3 layers.
- The two sets of feature maps output by the stage-3 layers are fed into the same stage-4 layers.
- Finally, we adopt Feature Pyramid Network (FPN) to combine the features in different scales.



1.Feature Extraction Backbone



- independent stage-2 and stage-3 layers -> regard the hand and object respectively as the sole foreground target
- shared stage-4 layers -> the hand and object features are forced to be in similar feature spaces







2.Interaction Modules



 hand-> non-rigid, flexible, high degree of freedom

- We use the ROIAlign to obtain F^h and F^{oh} from P^h and P^o, according to the hand bounding box.
- And concatenating them along the channel dimension to get F^H.
- Finally, We feed F^H into the Object-to-Hand Enhancement module.

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2.Interaction Modules



• object-> rigid, and less flexible

- We use the ROIAlign to obtain F^o from P^o, according to the object bounding box, and obtain F^{ho} from P^h, according to the overlapped area between the hand and object bounding boxes.
- Finally, We feed F^o and F^{ho} into the Hand-to-Object Enhancement module.



3.Two separate decoders

• Hand decoder output 2D joints, 3D mesh



Hand pose



3D hand mesh parameterized by MANO model



• Object decoder output 2D control points



21 control points pre-defined on object mesh 6D object pose computed by PNP algorithm



Experiments

Methods	Joint↓]	Mesh↓	cleanser↑	bottle↑	`can↑a	average↑	interaction modules	Methods	Joint↓	Mesh↓	cleanser↑	bottle↑	can↑	average↑
Single-Stream	10.4	10.3	80.1	55.3	46.2	60.5		Single-Stream	10.2	10.0	86.2	62.1	42.3	63.5
Double-Stream	9.7	9.6	82.2	74.1	49.4	68.6	-	Double-Stream	9.5	9.4	91.2	73.3	46.8	70.4
Ours	9.8	9.7	84.1	70.3	48.2	67.5		Ours	8.9	8.7	81.4	87.5	52.2	73.3

- The double-stream backbone works better than the single-stream without adding interaction modules, while our approach achieves close to the double-stream effect by adding only a small number of parameters.
- The performance gain of the double-stream backbone after adopting the interaction modules are quite small, while our approach has a larger improvement.













Thanks for listening

code:https://github.com/lzfff12/HFL-Net