Towards... 3D Human-centric Perception and Synthesis



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Research Direction

Understand how real **people**:

- Look
- Move
- Interact

Long term goal:

- Develop *human-centered AI*
- Assistive AI that:
 - **Perceive** humans in their environment
 - Understand their **behavior**
 - Help them achieve their **goals**



Research Direction

Holistic 3D Scene Understanding:

- Modelling how people, objects, spaces look
- Estimating their 3D shape and pose
- Inferring their semantics and spatial relationships
- Employing all above information to reason about:
 - how people act
 - how they interact with objects & people
 - how they perform tasks

Effortless for *humans* and *animals*

Challenging for *computers*

- → Challenges exist at *all* levels of abstraction
 - Ill-posed 3D inference from a 2D image
 - Semantic interpretation









SMPL Body Model

 $M(\theta, \beta) =$

SMPL specs:

Look like real people Move like real people Small number of parameters Easy to animate Easy to fit to data



SMPL Model

[1] - Loper et al. "SMPL: A Skinned Multi-Person Linear Model". ToG/SIGA 2015



3dMD Scanner









Scans







Shape Space (PCA)

Pose Space (PCA)

Diff. Background \rightarrow Diff. PCA Component



Input Output





Personalized 3D Hand Mesh

Automatically





Hands: Only part of the story















Input Output

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HOMUNCULUS

SMPL-X SMPL eXpressive

- [1] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh
- [2] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, and M. J. Black
- [3] G. Pavlakos, V. Choutas, N. Ghorbani, T. Bolkart, A. A. A. Osman, D. Tzionas and M. J. Black
- [4] F. Bogo, A. Kanazawa, C. Lassner, P. Gehler, J. Romero, M.J. Black

- Real-time multi-person 2D pose estimation using part affinity fields SMPL: A skinned multi-person linear model Expressive Body Capture: 3D Hands, Face, and Body from a Single Image Keep it SMPL: Automatic estimation of 3D human pose and shape from a single image
- CVPR 2017 SIGA 2015 CVPR 2019 CVPR 2019

Goal: Train a DNN to directly map RGB pixels to SMPL-X Problem: No existing training data ! Impossible to manually annotate full-3D bodies !

$$\begin{split} \mathbf{E}_{\mathbf{J}} &= \|J_{2D-est} - \Pi_{\mathbf{K}}(\mathbf{J}_{3D})\|_{2}^{2} \\ \textbf{Solution: Optimization methods need no training} \\ \text{Proxy 2D joints are easy to annotate / detect} \end{split}$$

[1] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh. *Real-time multi-person 2D pose estimation using part affinity fields*. CVPR, 2017

Objective Function to Optimize – SMPLify-X

2D Joints data term

Shape & Expression priors

Self-penetration penalty


```
M(\beta, \theta, \psi) \in \mathbb{R}^{10475 \times 3}
   \psi Facial Expression
Body Pose: \theta = [\theta_b, \theta_f, \overline{\theta_h}]
   \theta_f Jaw Pose
   \theta_h Hand Pose
   \theta_h Main Body Pose
       Body Shape
    ß
```

Optimizationbased Fitting

OpenPose [1]

SMPLify-X [2] Convergence Visualization

[1] Cao et al. TPAMI'19[2] Pavlakos et al. CVPR'19

Humans in 'Interaction'

Reference RGB

SMPLify-X Overlay on RGB

Reference RGB

3D Scan

SMPLify-X Overlay on RGB

SMPLify-X in 3D scene SMPLify-X in 3D scene

SMPLify-X in 3D scene

Contact constraints:

- Object cannot *inter-penetrate*
- Interaction means proximity

Penetrations

• 3D Distance Field @ room level

- Manually annotate likely contact vertices V_P
- Encourage close proximity between:
- V_P & Scene M_S
- If vertices V_P are "close by" in distance & orientation

[1] G. Pavlakos, V. Choutas, N. Ghorbani, T. Bolkart, A. A. A. Osman, D. Tzionas and M. J. Black. Expressive Body Capture: 3D Hands, Face, and Body from a Single Image. CVPR 2019

2D Joints data term

Shape & Expression priors

self-Penetration (penalty) Human-Scene Penetration (penalty) Contact (encourage)

PROX Dataset – Key for training ML

Example Application: Learn to Populate a 3D Scene

"Populating 3D Scenes by Learning Human-Scene Interaction" M. Hassan, P. Ghosh, J. Tesch, D. Tzionas, M. Black CVPR 2021

Research Map

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Research Map

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What is a SMPL-like generative model for Objects?

What is a SMPLify-like reconstr. method for Objects?











What is a SMPL-like generative model for Objects?

What is a SMPLify-like reconstr. method for Objects?







[2] **ShapeNet**, Chang et al., arXiv 2015

[3] Mask R-CNN, He et al., ICCV 2017

[4] SAM 2, Ravi et al., arXiv 2024





[2] DeepSDF, Park et al., CVPR 2019











SDFit - Framework



Category-level models

Morphable SDF (mSDF) model

Deep Features +PnP Corresp



SDFit - Framework

Needs good initialization: - Shape Or Pose



Category-level models

Morphable SDF (mSDF) model

Deep Features +PnP Corresp







Pose Initialization





SDFit - Framework























SDFit:



Recovers Self-Occluded parts via its inherent Shape Prior

[1] **ZeroShape:** Regression-based Zero-shot Shape Reconstruction, Huang et al., CVPR 2024



3D Shape Reconstruction



[1] **ZeroShape:** Regression-based Zero-shot Shape Reconstruction, Huang et al., CVPR 2024

Research Map



not interesting ~_~

Research Map



Human-Object Interaction with Whole Bodies











High-res & 54-camera Vicon MoCap system 1.5mm radius hemi-spherical markers Semi-automatic MoCap data cleaning & labeling

[ContactDB, CVPR'19]







High-res & 54-camera Vicon MoCap system 1.5mm radius hemi-spherical markers Semi-automatic MoCap data cleaning & labeling





High-res & 54-camera Vicon MoCap system 1.5mm radius hemi-spherical markers Semi-automatic MoCap data cleaning & labeling Adapt MoSh++ [1] for SMPL-X (body + face + hands) Rigid fitting for object meshes to markers

[1] N. Mahmood, N. Ghorbani, N. F. Troje, G. Pons-Moll, M. J. Black. AMASS: Archive of Motion Capture as Surface Shapes. ICCV 2019



4 Interaction Intents





Whole-Body Interaction





Data-driven likely contacts





GrabNet: Grasp Synthesis





GrabNet: Grasp Synthesis





GrabNet: Grasp Synthesis



Research Map



Scarce data

Constrained settings

Methods struggle generalizing



Research Map





3D Grasp Synthesis

How do we go **beyond (scarce) data?**

Promising → **FLEX** [1] method

- Divide & conquer!
- Generate a hand-only grasp [2]
- Sample random bodies in scene
 (500 samples, random location & pose)
- Optimize:
 - Hand-only grasp to match body
 - Body to match hand-only grasp
 - **Prune** implausible Bodies

FLEX: Full-Body Grasping Without Full-Body Grasps. Tendulkar et al., CVPR 2023
 GrabNet, Taheri et al., ECCV 2020



3D Grasp Synthesis

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- Optimize:
 - Hand-only grasp to match body
 - Body to match hand-only grasp Let's solve
 - **Prune** implausible Bodies

FLEX: Full-Body Grasping Without Full-Body Grasps. Tendulkar et al., CVPR 2023 [2] GrabNet, Taheri et al., ECCV 2020

Great idea! Exhaustive sampling Intensive post-processing **Roots of limitations: Non-controllable** components [2] Too late reasoning: body & scene



3D Grasp Synthesis

Grasping hands



Only condition @ inference: Object shape



Draw 5 different samples

Hands with random palm direction



[1] **GRAB:** A Dataset of Whole-Body Human Grasping of Object, Taheri et al., ECCV 2020


Grasping hands

with palm-direction control



CGrasp → 'Controllable **Grasp** synthesis'



Draw 5 different samples



Reaching bodies

with arm-direction control



CReach → 'Controllable **Reach** synthesis'









Where does the **3D direction come from ?**

Answer the question: Where can an object be ? reached from?



'Local scene' reasoning

• Object on a receptacle





- Object on a receptacle
- Sample a sphere around object





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- Shoot rays





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 - Project rays \rightarrow parallel to floor





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 - Shoot rays to floor → Check collisions w. receptacles





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 - Project rays \rightarrow parallel to floor
 - Shoot rays to floor → Check collisions w. receptacles
 - Also wiggle around a bit \rightarrow Check collisions (arms take up volume)





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 - Shoot rays to floor → Check collisions w. receptacle
 - Also wiggle around a bit \rightarrow Check collisions again
- Final set of filtered rays





'Local scene' reasoning

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ReachingField

\rightarrow \rightarrow Sample a 3D ray \leftarrow \leftarrow





































[1] FLEX: Full-Body Grasping Without Full-Body Grasps. Tendulkar et al., CVPR 2023



Perceptual study: CWGrasp vs FLEX

- 33 participants (+2 filtered out)
- 24 samples (+4 catch trials)
- Each sample (gif):
- Full-body & hand-zoom view (rated separately – random order)







Participants preferring **CWGrasp**:



	#Body Samples ↓	Time (sec) ↓
FLEX	500	357
CWGrasp	1	23
	500x less	10x less

Research Map



Summary

Publications / Preprints



Embodied Hands: Modeling and Capturing Hands and Bodies Together J. Romero* · **D. Tzionas*** · M. J. Black SIGGRAPH-Asia 2017



Expressive Body Capture: 3D Hands, Face, and Body from a Single Image G. Pavlakos* · V. Choutas* · N. Ghorbani · T. Bolkart · A.A.A. Osman · D. Tzionas · M. J. Black CVPR 2019





Resolving 3D Human Pose Ambiguities with 3D Scene Constraints M. Hassan · V. Choutas · D. Tzionas · M. J. Black ICCV 2019



Publications / Preprints



SDFit: 3D Object Shape and Pose by Fitting a Morphable SDF to a Single Image Dimitrije Antić · S. K. Dwivedi · S. Tripathi · T. Gevers · D. Tzionas arXiv, Sep. 2024



GRAB: A Dataset of Whole-Body Human Grasping of Objects Omid Taheri · N. Ghorbani · M. J. Black · D. Tzionas ECCV 2020





3D Whole-body Grasp Synthesis with Directional Controllability Georgios Paschalidis · R. Wilschut · D. Antić · O. Taheri · D. Tzionas 3DV 2025



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Work funded by:



UNIVLESTY OF AMS EL DAM

