

# DeepRob

#### **Discussion 8 Prelude to Rigid Body Objects** University of Michigan and University of Minnesota





# Next Time: Rigid Body Objects

#### Seminar 3: Object Pose, Geometry, SDF, Implicit Surfaces

- SUM: Sequential scene understanding and manipulation, Sui et al., 2017 1.
- 2. <u>DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation</u>, Park et al., 2019
- 3. Implicit surface representations as layers in neural networks, Michalkiewicz et al., 2019
- iSDF: Real-Time Neural Signed Distance Fields for Robot Perception, Oriz et al., 2022 4.

#### Seminar 4: Dense Descriptors, Category-level Representations

- Dense Object Nets: Learning Dense Visual Object Descriptors By and For Robotic Manipulation, Florence et al., 2018 1.
- 2. Normalized Object Coordinate Space for Category-Level 6D Object Pose and Size Estimation, Wang et al., 2019
- 3. <u>kPAM: KeyPoint Affordances for Category-Level Robotic Manipulation</u>, Manuelli et al., 2019
- Single-Stage Keypoint-Based Category-Level Object Pose Estimation from an RGB Image, Lin et al., 2022 4.







#### Last Time: 3D Perception





Data courtesy of Anthony Opipari, Liz Olson, Grant Gibson, and Arden Knoll







DR

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#### Last Time: 3D Perception



## This Time: Rigid Body Objects





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# Example Rigid Body Object







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#### **Rigid body:**

Model of an object that assumes no deformation is possible

I.e. Every pair of points on the object remain at constant distance







## Aside: Digit is an Articulated Object









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Articulated objects are composed of rigid bodies and connecting joints



# Rigid Body Objects









# Rigid Body Objects

#### **Rigid body:**

Model of an object that assumes no deformation is possible

I.e. Every pair of points on the object remain at constant distance





How to represent the 3D geometry of objects?

What roles can deep learning play?



Vertices: set of 3D coordinates







Vertices: set of 3D coordinates







Vertices: set of 3D coordinates



### Rigid Body Objects: Explicit Representation



*O*<sub>torso</sub>=(0, 0, 0)

Object 'origin' or 'coordinate frame'



Vertices: set of 3D coordinates

**Faces:** set of polygons made by connecting subset of vertices







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**Texture Map:** Map from image pixel on texture to object face



### Rigid Body Objects: Explicit Representation



#### **Texture**





Vertices: set of 3D coordinates

**Faces:** set of polygons made by connecting subset of vertices

**Texture Map:** Map from image pixel on texture to object face







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### Rigid Body Objects: Explicit Representation



O<sub>torso</sub>=(0, 0, 0)

#### **Common Geometry File Formats**

- .obj (wavefront)
- .ply (polygon file format)
- .stl (standard tessellation language)
- .dae (collaborative design activity)





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### **Rigid Body Objects: Explicit Representation**

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### Rigid Body Objects: Explicit Representation



Human artists (e.g. <u>Sketchfab</u>, <u>cgtrader</u>) Photogrammetry algorithms (e.g. <u>Matterport</u>)





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**Pose:** Position and orientation of object coordinate frame in world coordinate frame





*O*torso

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world

torso

 $O_{\rm torso}$ 

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#### **Rigid Body Transformations**

From Special Euclidean group, SE(3), meaning they preserve Euclidean distance

Can be decomposed into a rotation (3DoF) followed by a translation transform (3DoF) Rotations commonly expressed as <u>quaternions</u> Translations expressed as residuals (deltas)







## Collections of Rigid Body Objects





Data courtesy of Anthony Opipari, Liz Olson, Grant Gibson, and Arden Knoll



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#### **Explicit Object Representations are Useful** for Model-Driven Robotics

- Knowing object geometry and pose enables Collision-free motion planning Path planning and obstacle avoidance
- - Task planning
  - Goal-directed manipulation



# Rigid Body Objects: Roles for Deep Learning

- 6DoF pose estimation
  - How to perceive from vision or tactile sensors?
- Implicit surfaces and signed distance functions
  - How to model an object's surface implicitly by a learned network?
- Dense object descriptors
  - How to extract features from a learned network that describe local and global object properties?
- Category-level representations
  - How to model geometry and pose for objects of varying shape but same semantic category?



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