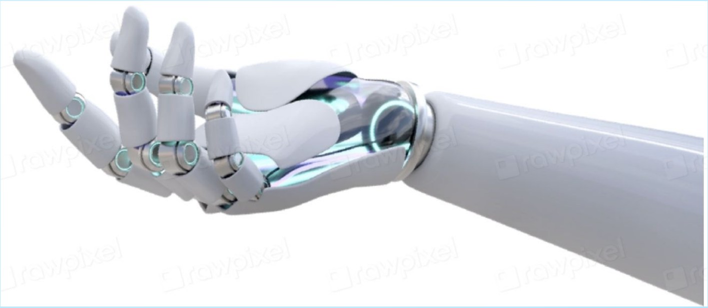
Bio-Inspired Robotic Hand

RSLS Presentation by
Devi Amarsaikhan

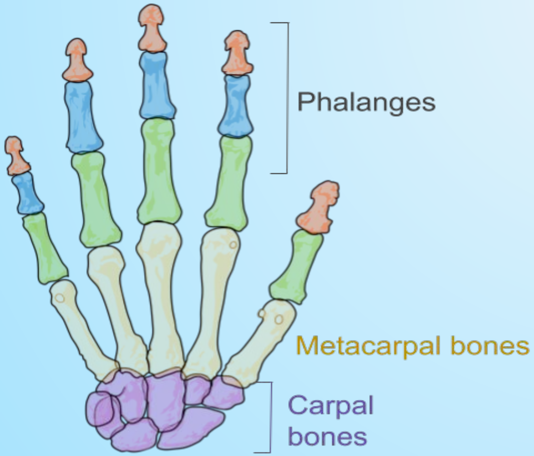
Research Question 1 - Hand Design

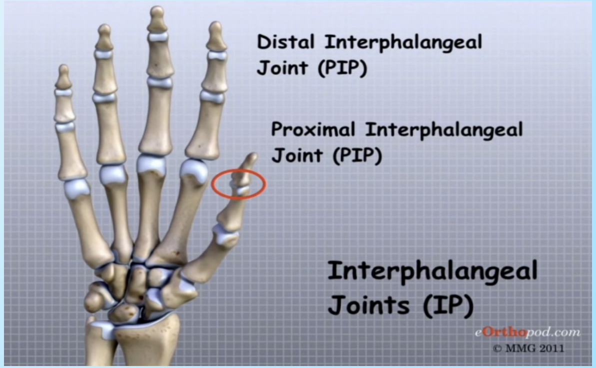
How is the human hand so good at grasping a wide range of objects—and how can we design a robotic hand that is *simpler* but still quite *effective*?



Hypothesis

The key lies in the structure of the bones and muscles in the human hand and their range of motion.





Methodology

1. Insights from biology
2. 3D-print the hand
3. Test using AHAP
4. Research and improve

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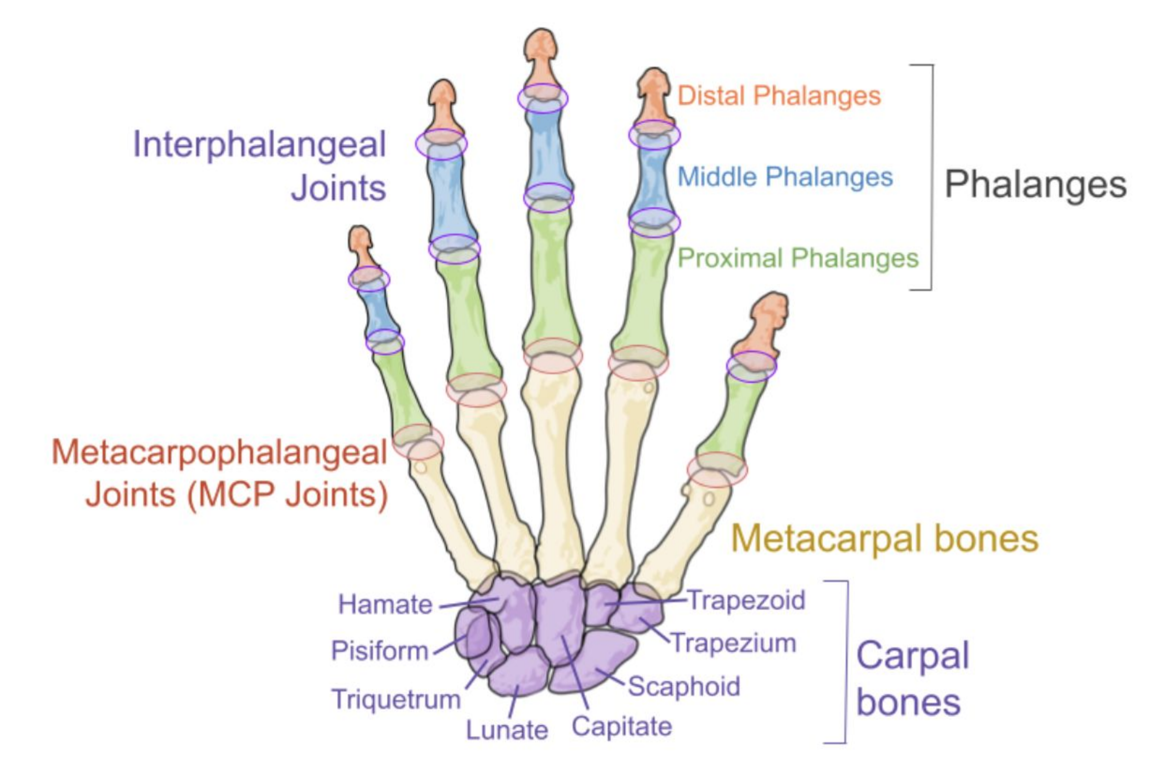
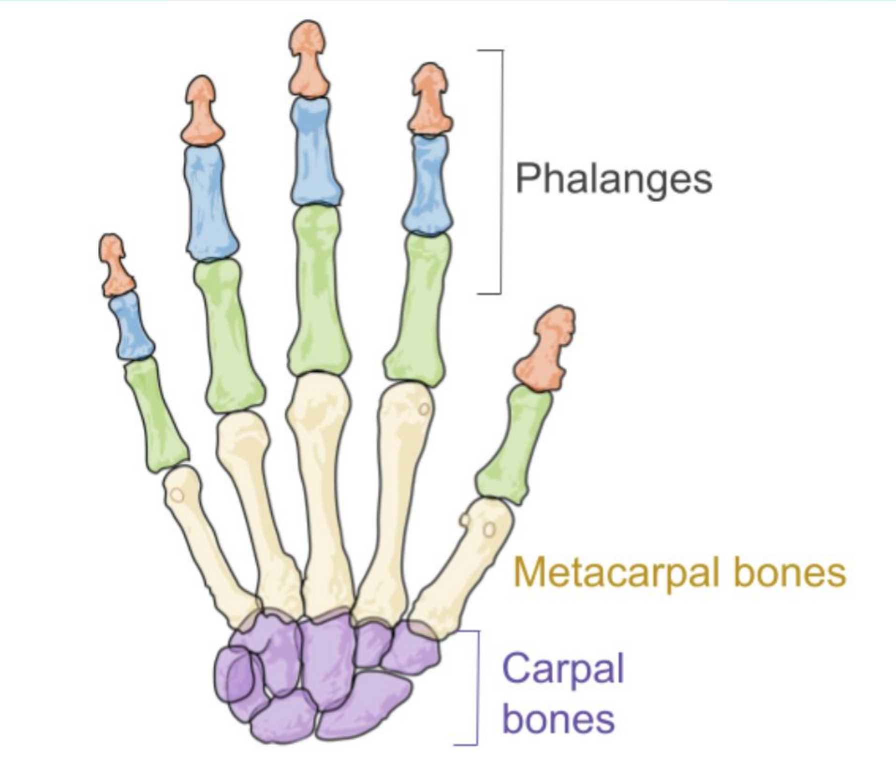
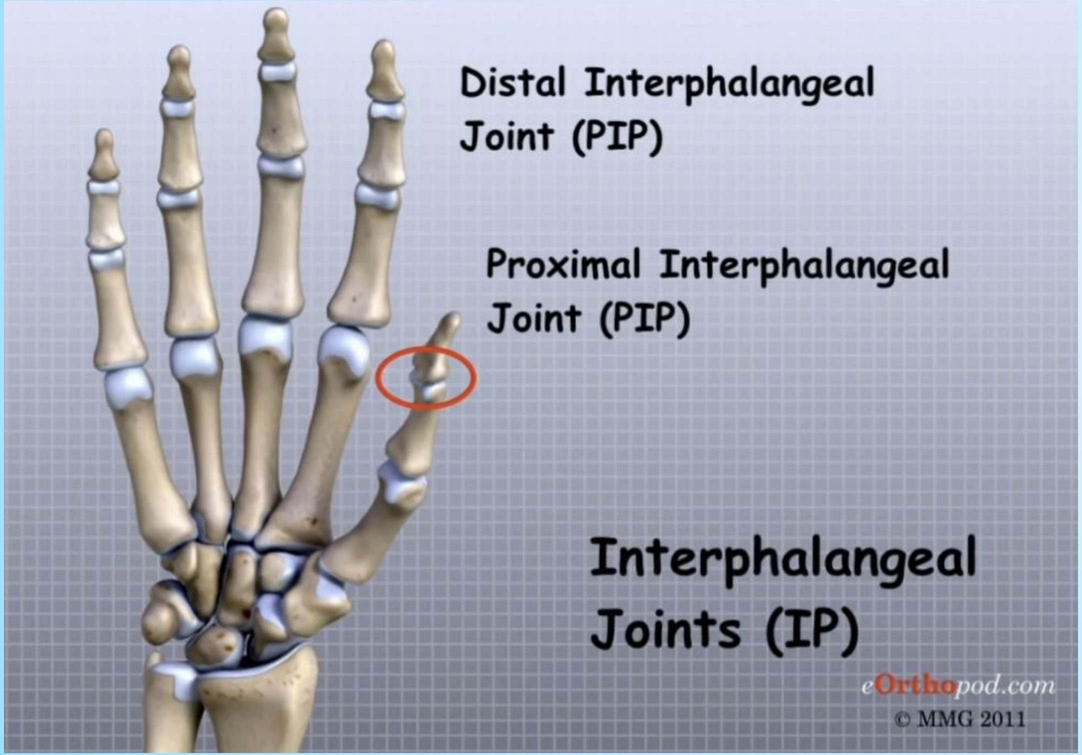
Musculoskeletal Structure



Bones

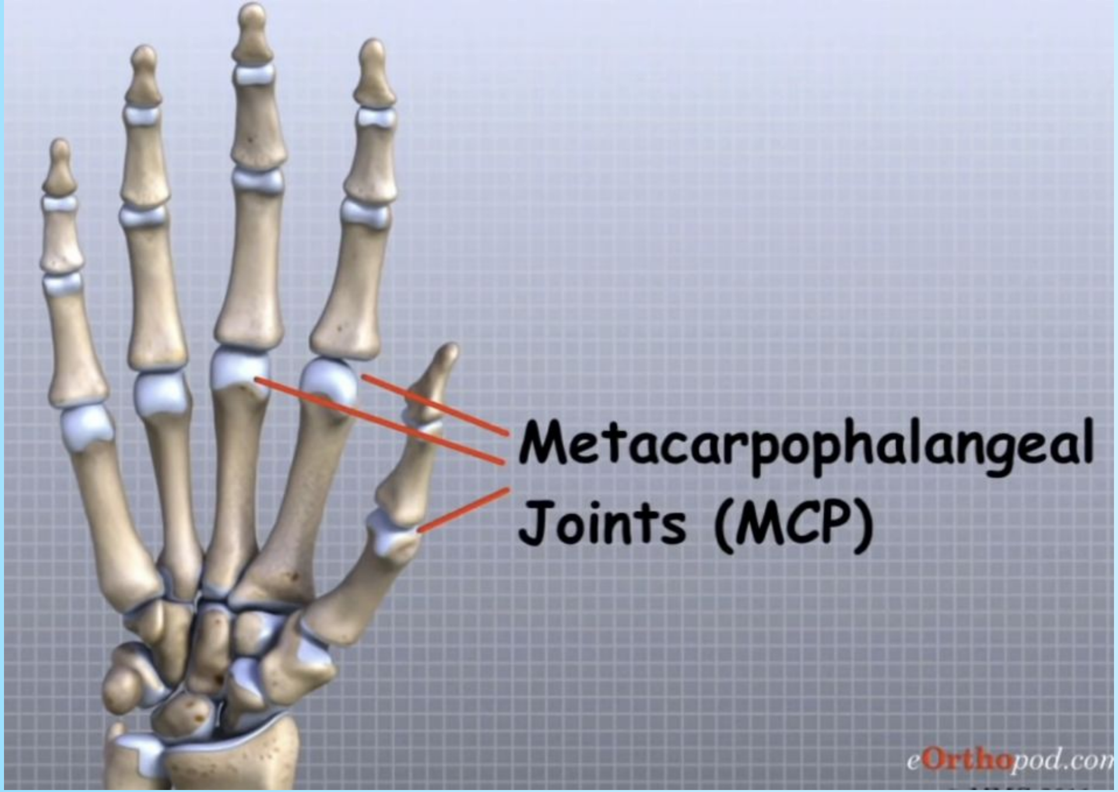


Joints

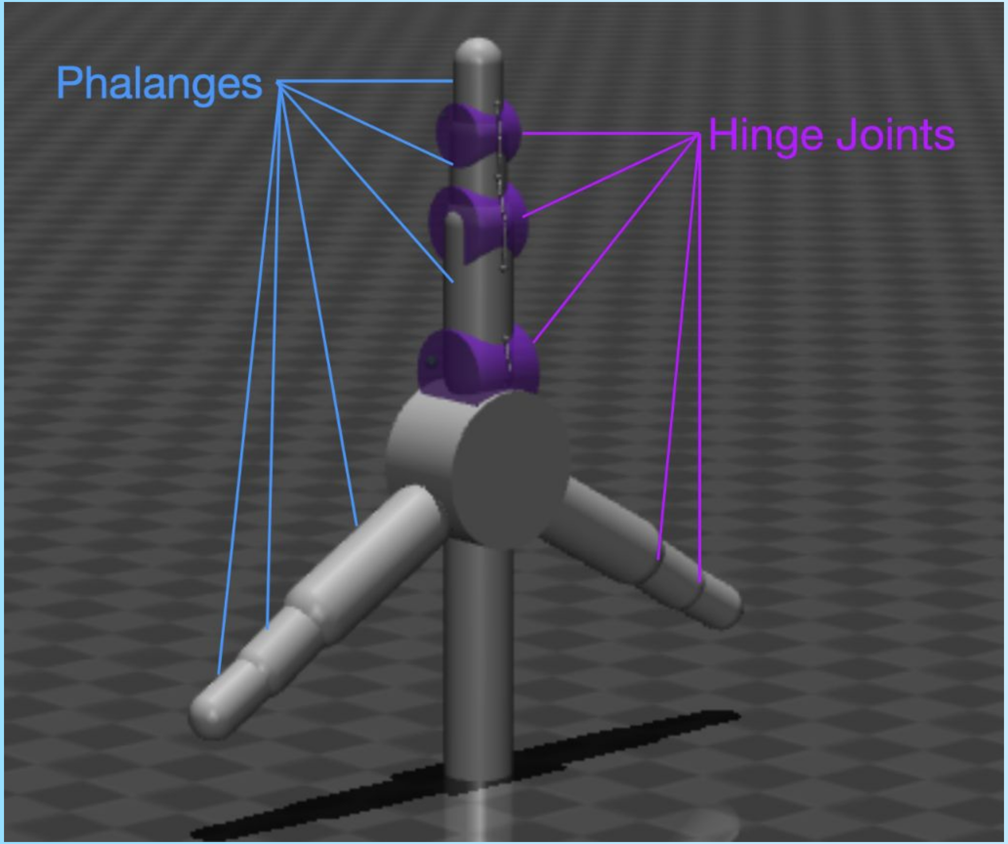

Distal Interphalangeal
Joint (PIP)
Proximal Interphalangeal
Joint (PIP)
Interphalangeal
Joints (IP)
eOrthopod.com
© MMG 2011


Flexor
Muscles

Joints

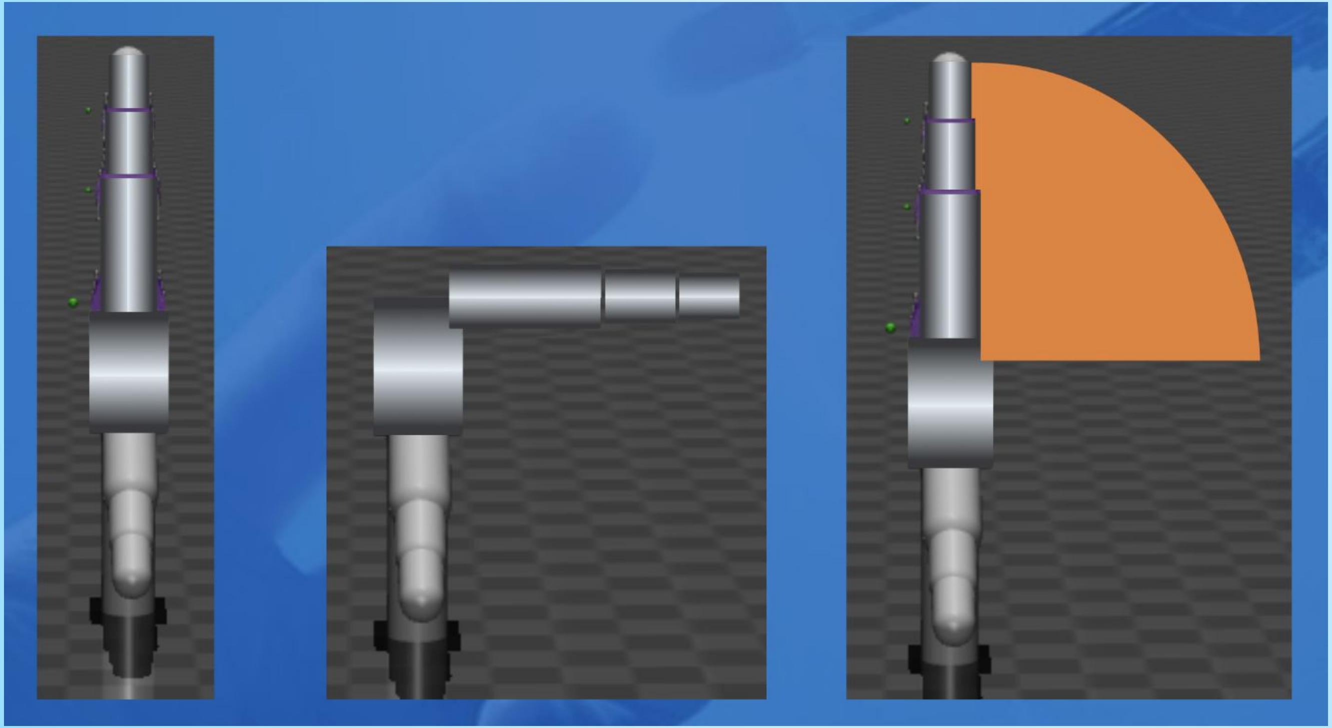


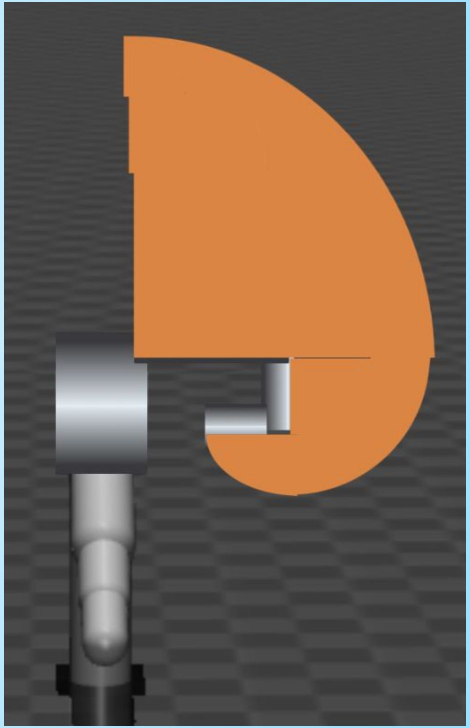
First Hand Design



1. Palm: 2 inches in diameter.
2. Proximal phalanx: 1.8 inches.
3. Middle phalanx: 1.1 inches.
4. Distal phalanx: 0.88 inches.

Reachability Analysis





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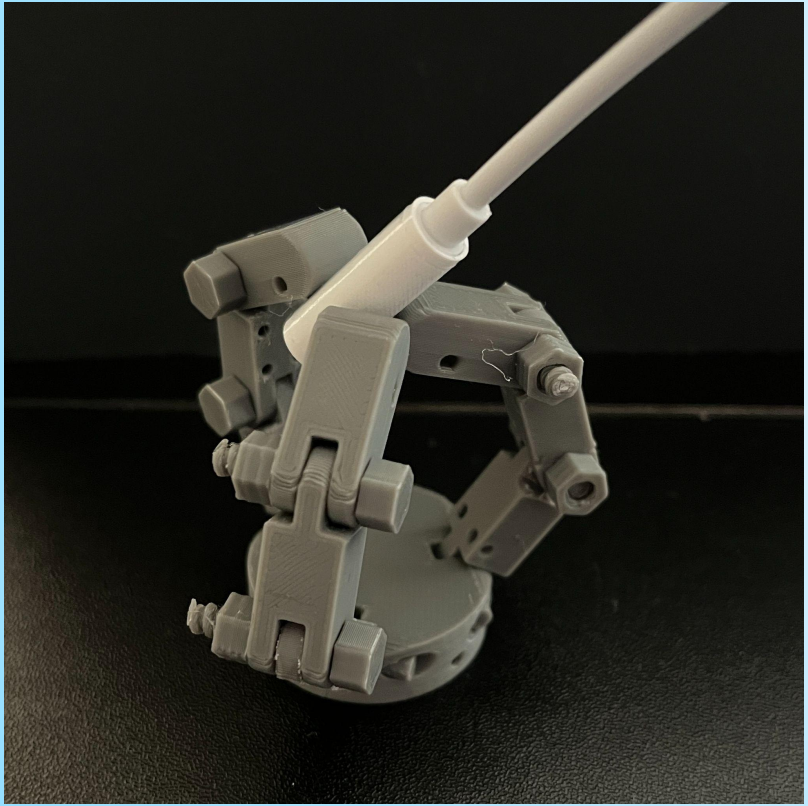
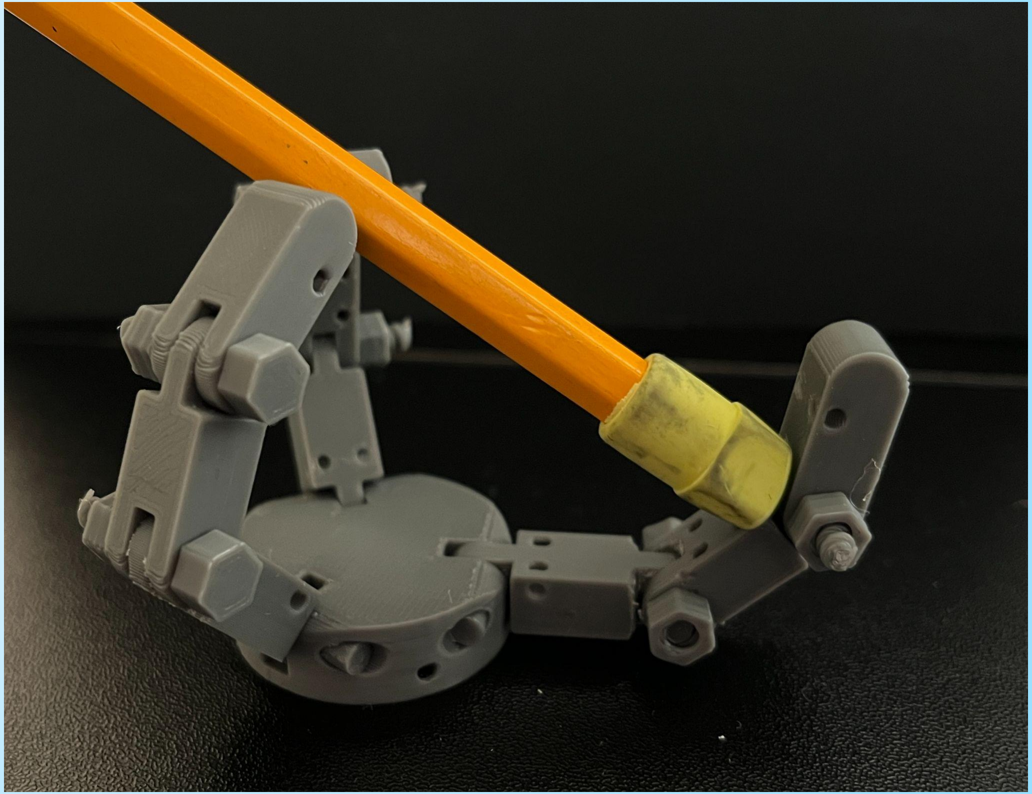
3D Printed Prototype





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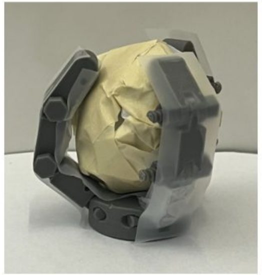
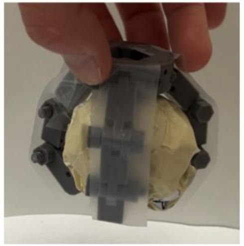
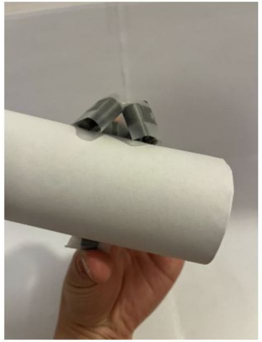
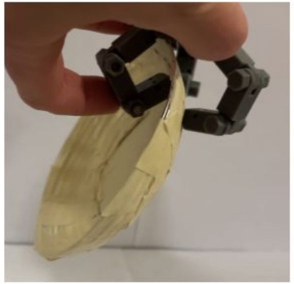
Test 1

Hook (H)	Skillet lid (T_{01}) 
Spherical grip (SG)	Plastic apple (T_{02}) 
Tripod pinch (TP)	Large marker (T_{03}) 

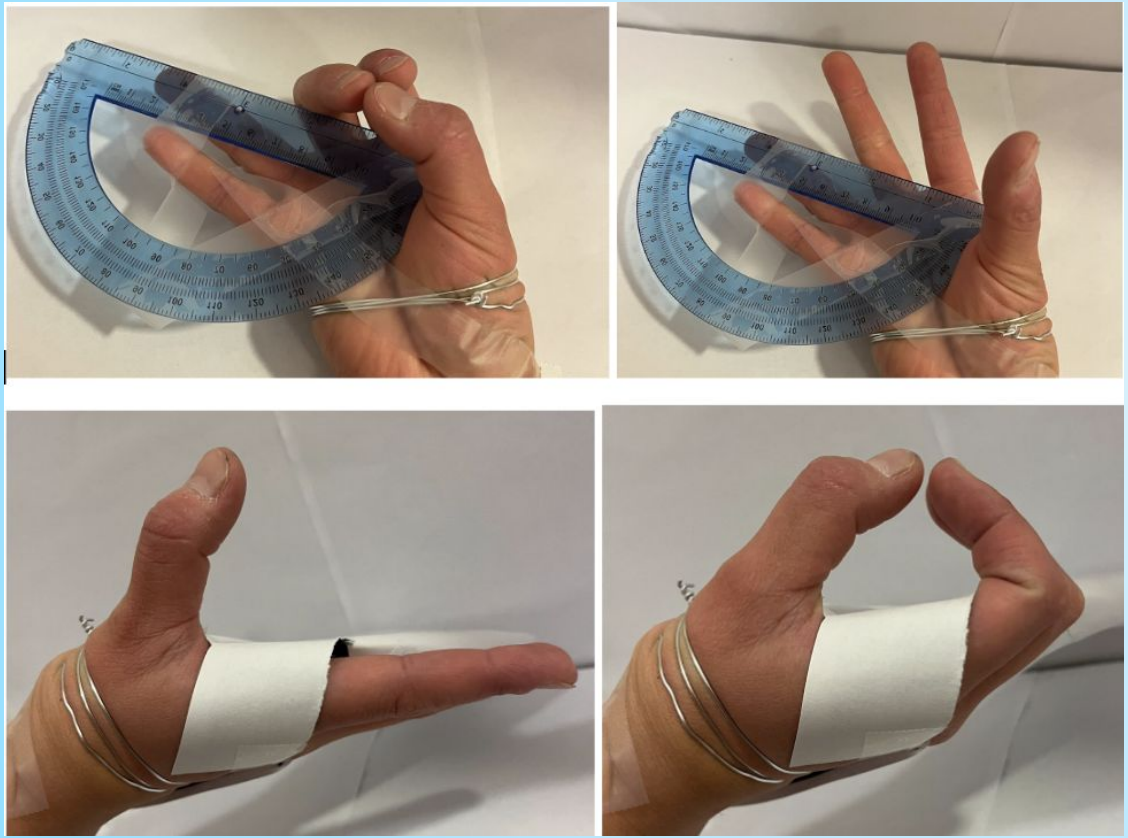
Extension grip (EG)	Plate (T_{04}) 
Cylindrical grip (CG)	Chips can (T_{05}) 
Diagonal volar grip (DVG)	Phillips screwdriver (T_{06}) 

Lateral pinch (LP)	Bowl (T_{07}) 
Pulp pinch (PP)	Small marker (T_{08}) 
Index pointing/pressing (IP)	Timer (T_{09}) 
Platform (P)	Plate (T_{18}) 

Test 1

Grip name	Position 1	Position 2	Notes
Spherical grip			Potentially enough surface area contact
Cylindrical grip			Not enough surface area contact. Object being held up by parts of the screw.
Diagonal volar grip			Not proper DVG because there are no opposing fingers to wrap around the cylindrical portion
Lateral pinch			Not stable grip because one finger is not opposing the surface area of another finger.

Test 2



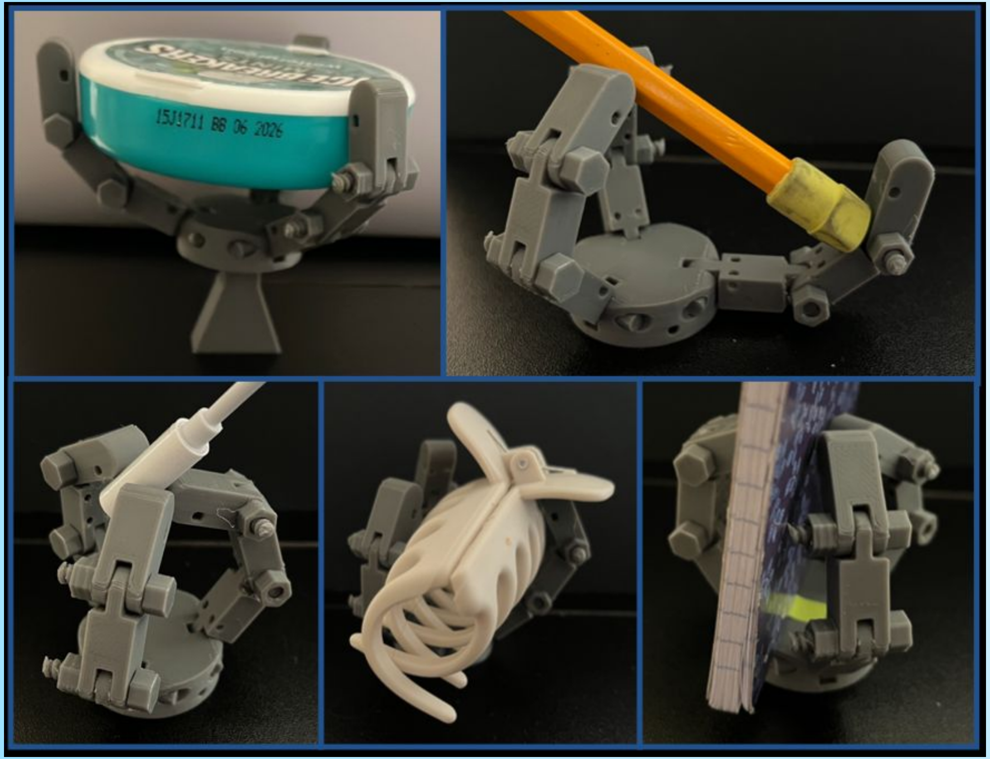
Grip name	Position 1	Position 2	Notes
Spherical grip			Sphere grasped well. Not as well as the first design, but still stable.
Cylindrical grip			More stable than first design

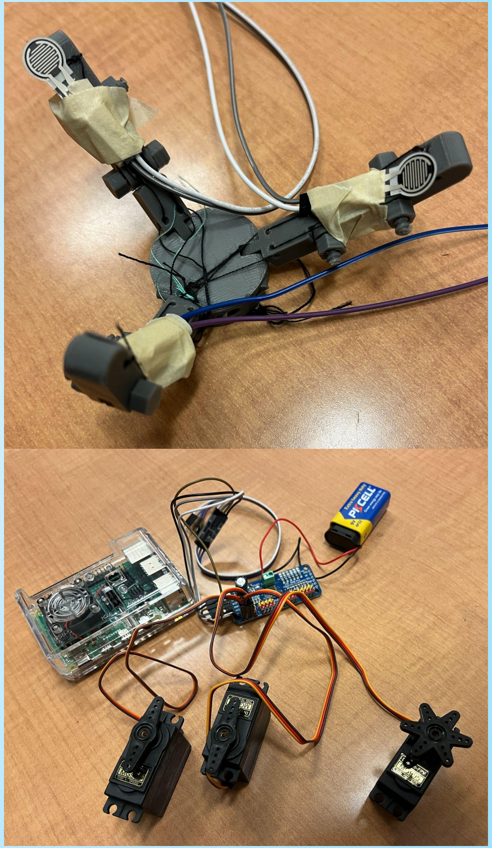
Diagonal volar grip	Not possible because there is no adduction / abduction movement in any of the fingers
Lateral pinch	Not possible because there is no adduction / abduction movement in the thumb

Test 3

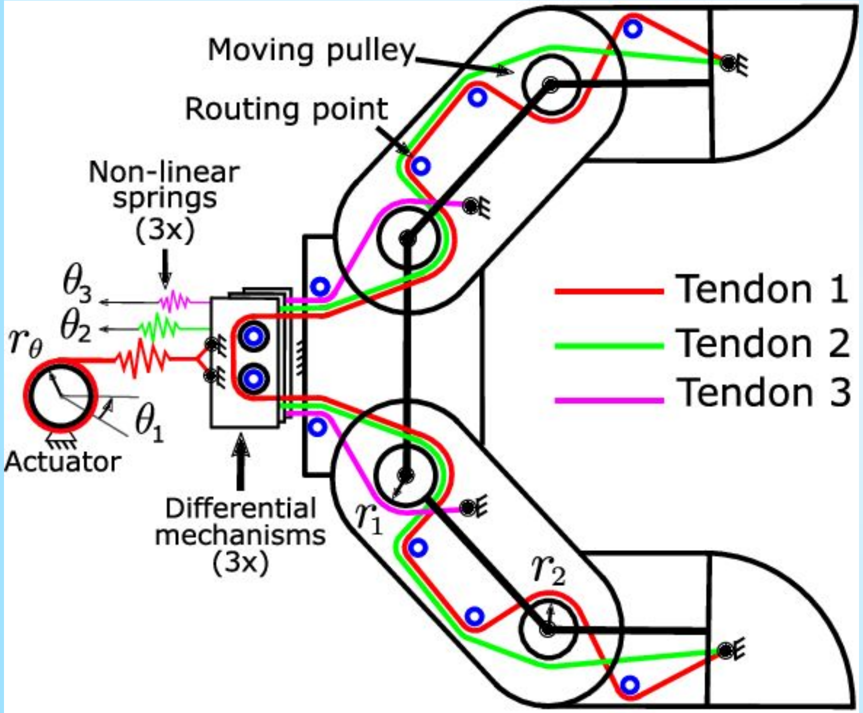
Diagonal volar grip			DVG possible in this configuration
Lateral pinch			LP possible in this configuration

Testing and Electronics





Tendon Routing

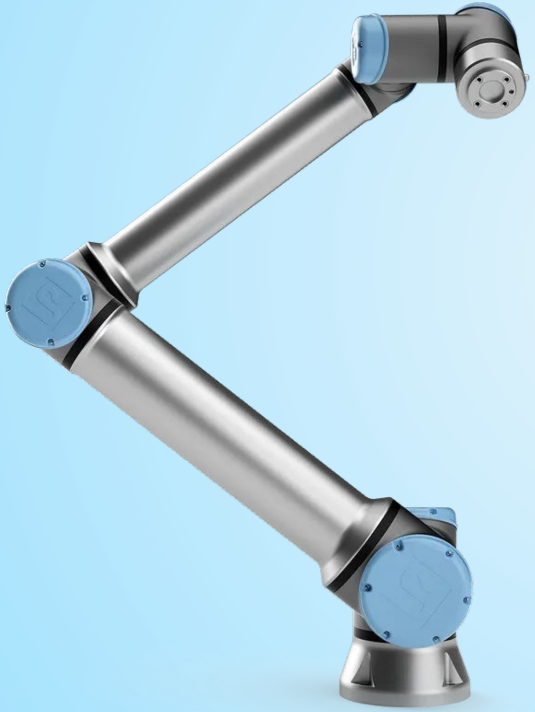


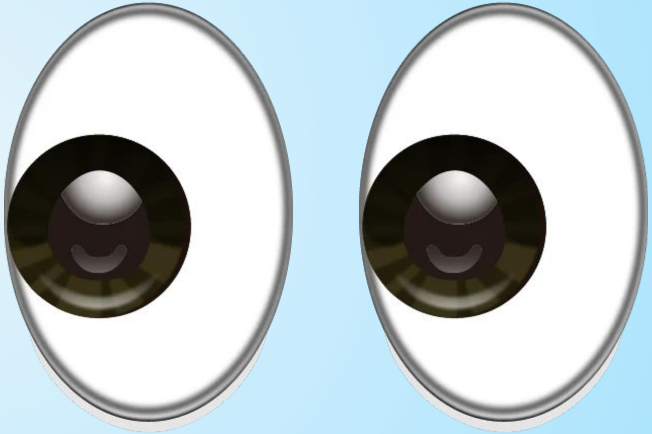
Individual finger control

2 degrees of freedom each

https://www.researchgate.net/figure/Actuation-and-tendon-routing_fig3_374275049

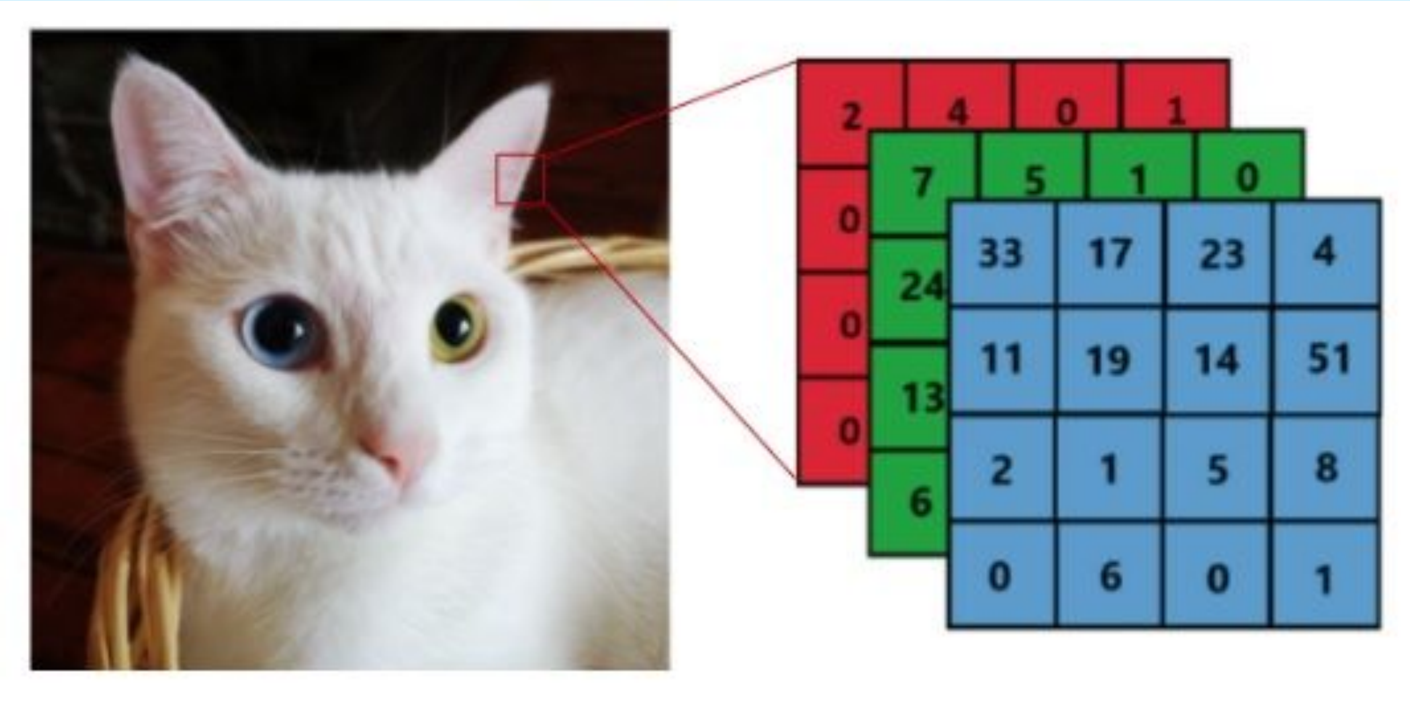
Robotic Hand Control





https://emojiisland.com/products/eyes-emoji-icon

Background Information



https://www.midokura.com/unveiling-the-world-of-computer-vision-a-comprehensive-overview/

Background Information

https://indiaai.gov.in/article/image-segmentation-the-deep-learning-approach

Image Segmentation

Object Detection

Research Question 2 - Perception

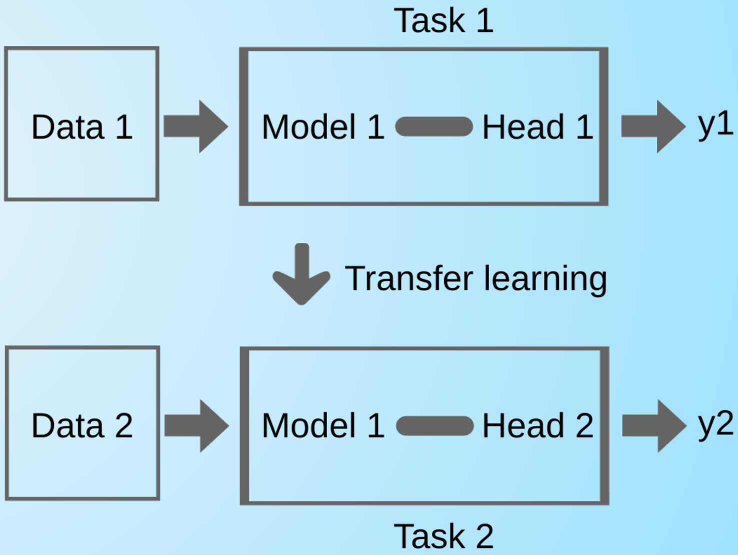
How to train a computer vision model to quickly and reliably determine the 3 dimensional *position* and *shape* of an object from visual data?

Hypothesis

Using images from ***different points of view*** along with ***transfer learning*** from models trained on pose estimation tasks can help reliably determine the ***3D position*** and ***shape*** of an object.

Hypothesis

https://unblast.com/free-mug-on-table-mockup-psd/

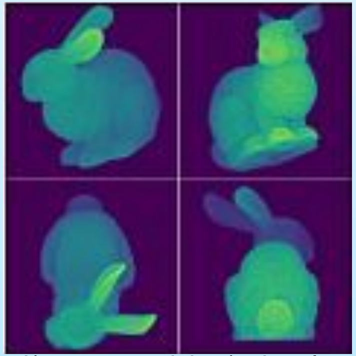


https://en.wikipedia.org/wiki/Transfer_learning

Experiment

Train 3 different types of models to reconstruct 3D position and shape of household objects from images.

Single-image **Multi-image** **Transfer learning**



https://viso.ai/computer-vision/point-cloud-processing/

Things to Measure

3D position accuracy

Euclidean distance error in mm between predicted and ground truth object center.

3D shape similarity

Overlap in terms of surface area of actual and predicted object shapes.

Controls

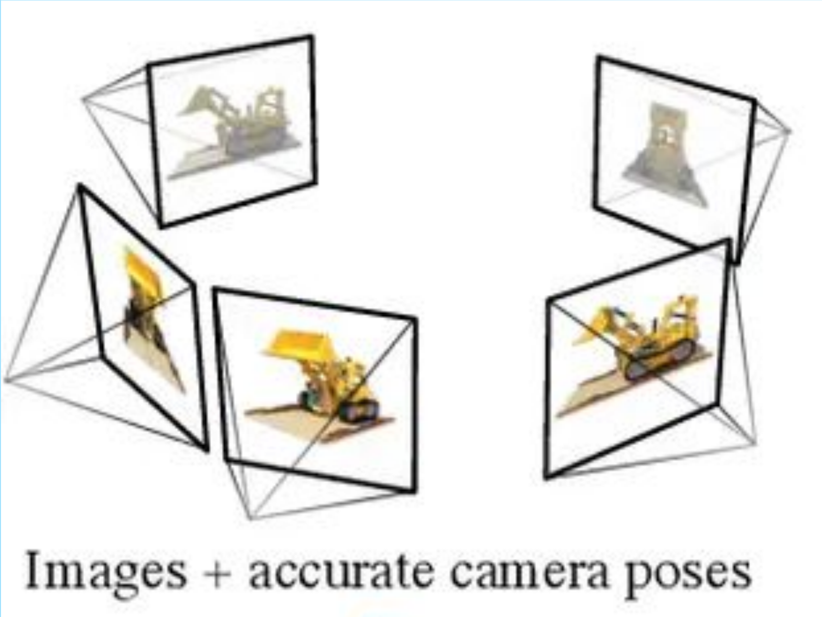
Positive Control

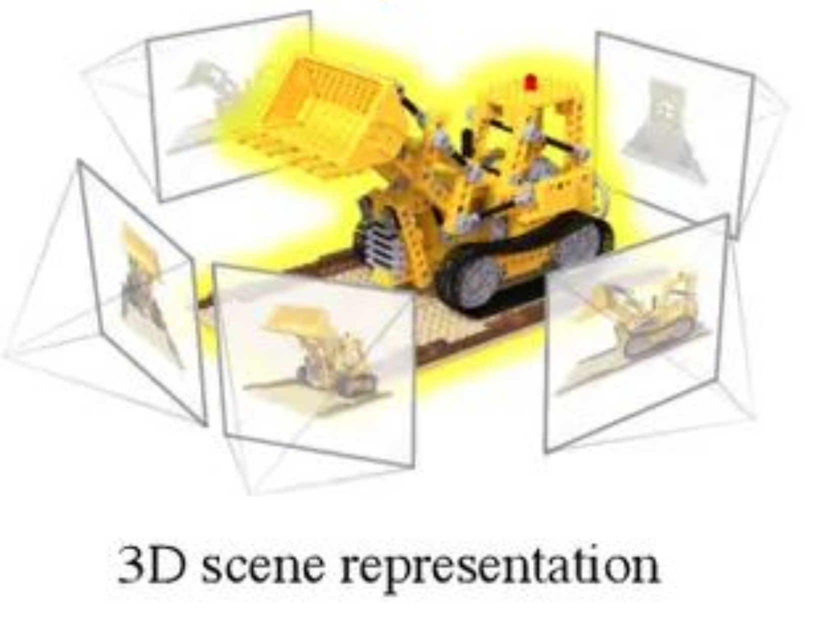
Location that is accurately measured and 3D pose captured by LiDAR.

Negative Control

Model trained on mismatched labels. Should fail to learn meaningful representations.

Neural Radiance Fields (NeRFs)





H-InDex Pre-trained Model

Pretraining

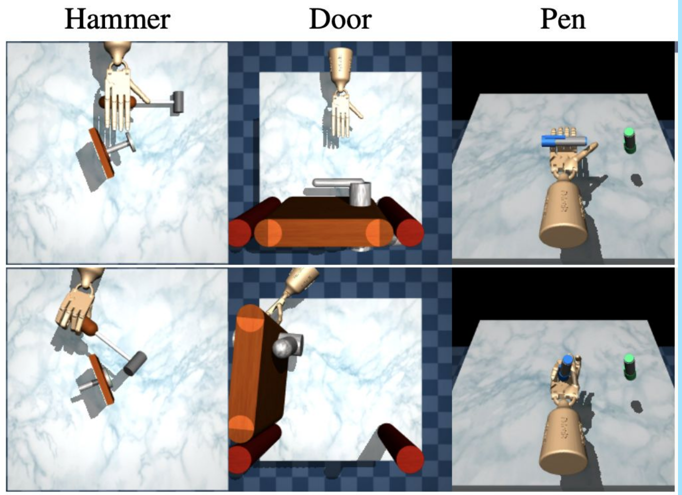
Recognize 3D human hand poses.

Adapting

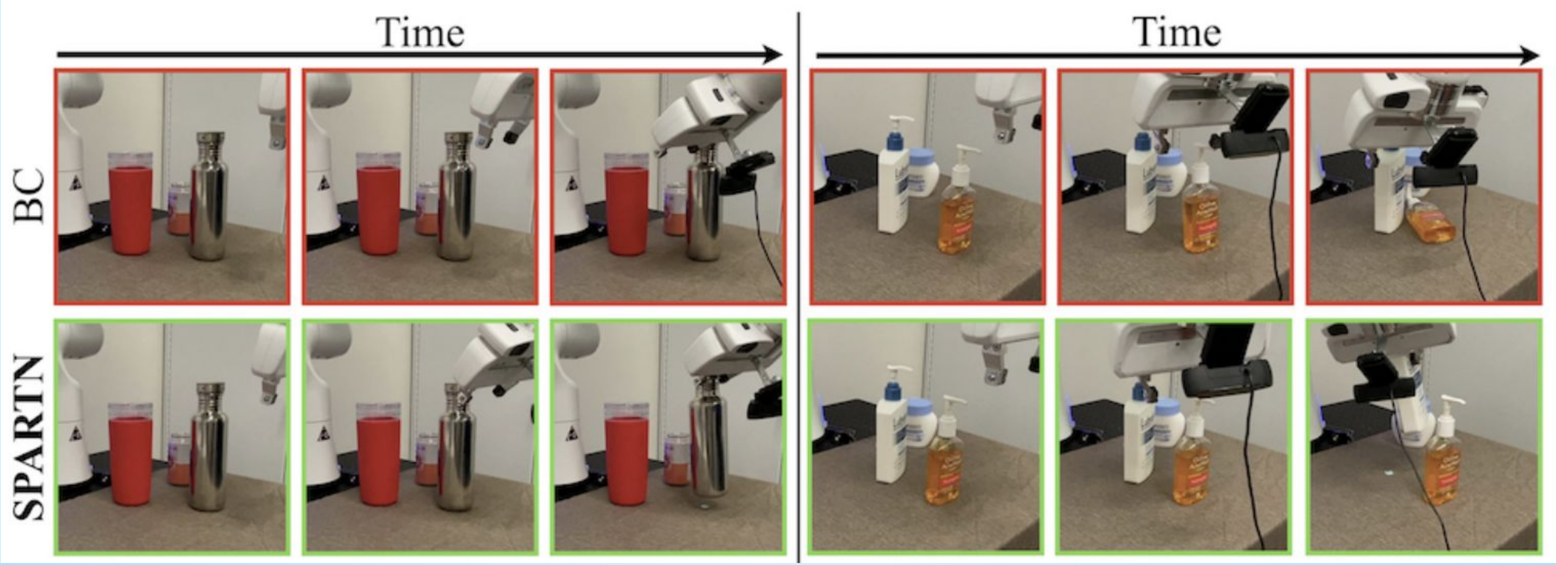
Fine-tunes using a self-supervised method. Learns to find key points like corners or edges without needing labeled data.

Reinforcement Learning

Train through RL with knowledge from original hand-pose model.



SPARTN for Robustness



On 8 complex grasping scenarios (e.g., shiny objects, clutter), it improved grasp success by 22.5% on average.

Further Research

Evaluate **RGB** vs. **depth-sensing** cameras

Mount both types of cameras on a robotic arm to compare autonomous pick-and-place tasks.

Explore ways to **accelerate** the process


Thank you