NEUROPROSTHETIC GRASPING IMPROVEMENT USING sEMG AND DEEP GENERATIVE MODELING

Advanced Deep Learning For Robotics

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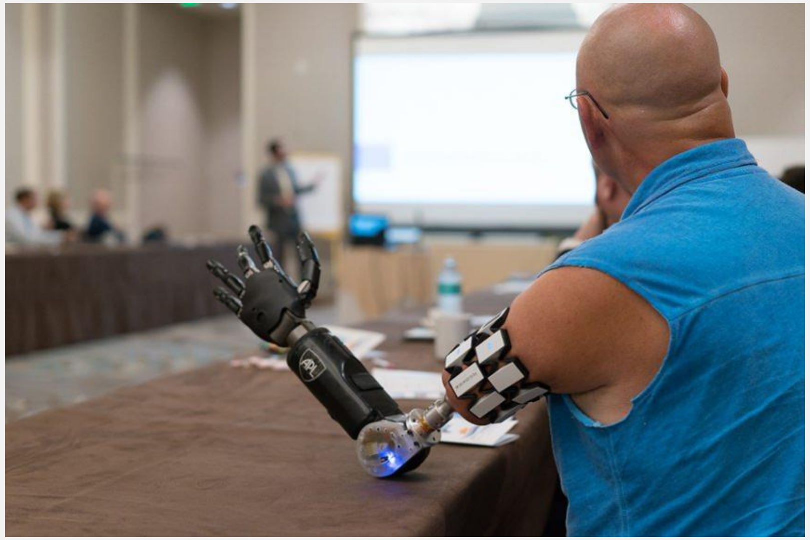
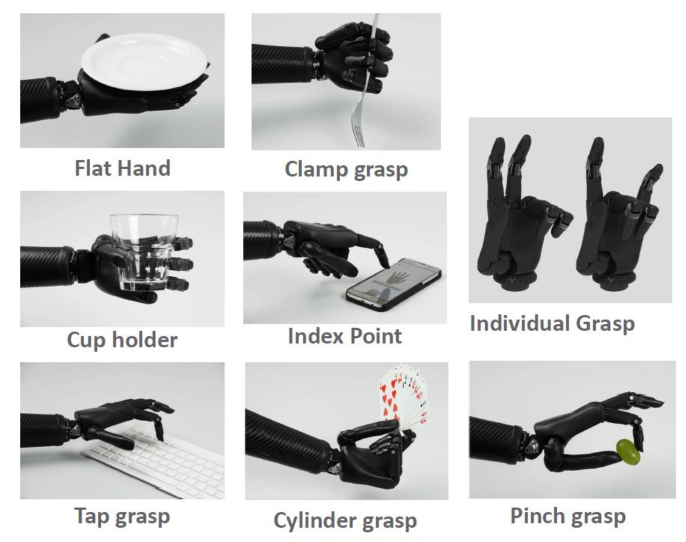
INTRODUCTION AND MOTIVATION

- **Abandon rate** of neuroprosthetic devices for upper limb amputees → **≈ 50%**
- Due to:
  - **Difficulties** in usage control and grasping selection



Upper limb neuroprosthetic

Grasping selection is done with a switch…



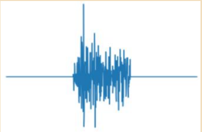
Myoelectric hand graspings

INTRODUCTION AND MOTIVATION

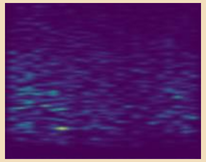
- **Our idea?**
- To develop a **reliable** and **robust** pipeline for **generating graspings**
- Ease neuroprosthetics usage

PIPELINE – 2 STAGES

sEMG Signals



Feature extraction



ResNet-18 DL Classifier

Main Grasping Type
E.g. cylindrical

User selects grasping intention through EMG

Cup holder

PIPELINE – 2 STAGES

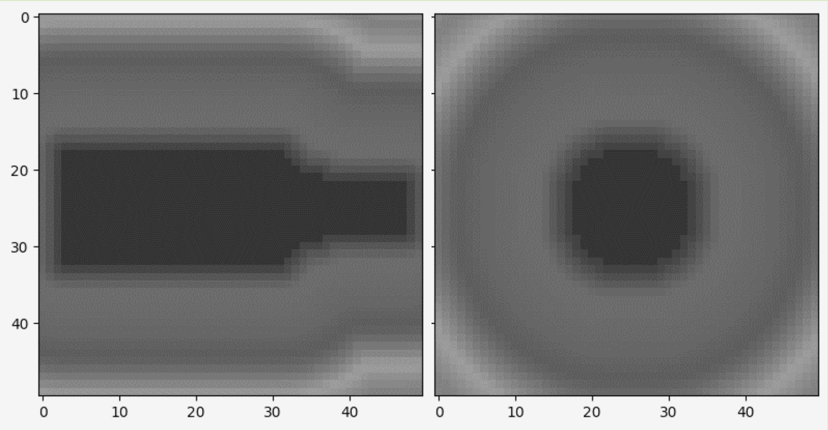
sEMG Signals

User selects grasping intention through EMG

Main Grasping Type
E.g. cylindrical

Cup holder

Extract 3D parameters of the object



PIPELINE – 2 STAGES

sEMG Signals

User selects grasping intention through EMG

Main Grasping Type
E.g. cylindrical

Cup holder

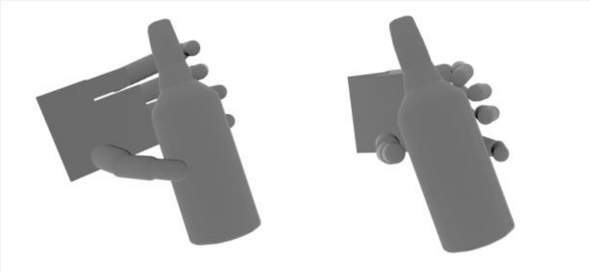
User wants… "cylindrical grasping"

Extract 3D parameters of the object

Bottle has… "characteristics"

Diffusion Model

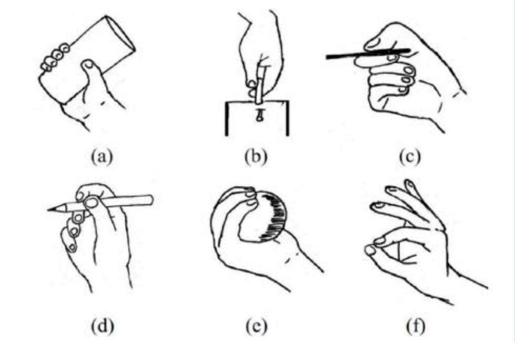
Fine-tuned hand pose



FIRST STAGE – EMG CLASSIFICATION

TECHNICAL OUTLINE RECAP – EMG CLASSIFICATION

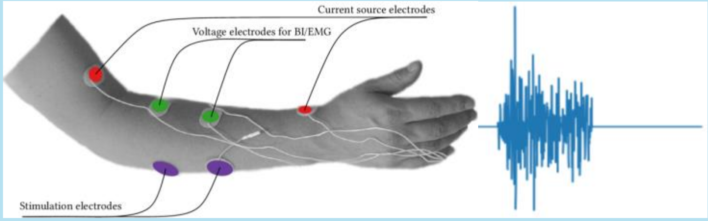
User performs 6 grasps



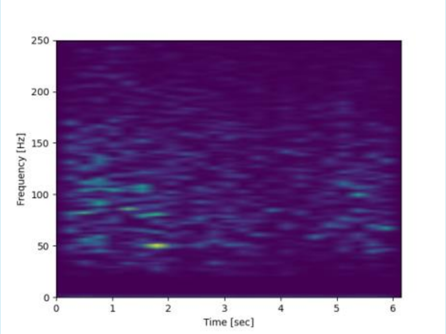
Grasp types

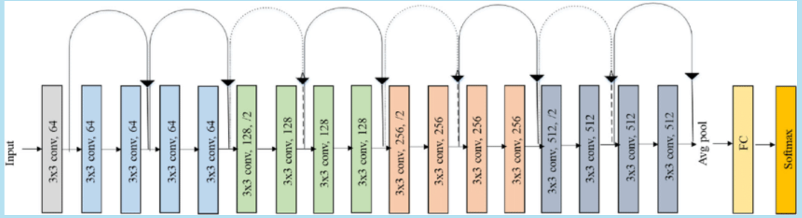
a) Power grasp
b) Hook
c) Lateral
d) Palm
e) Sphere
f) Tip

Raw sEMG is recorded and processed



Spectrograms (2 per trial)





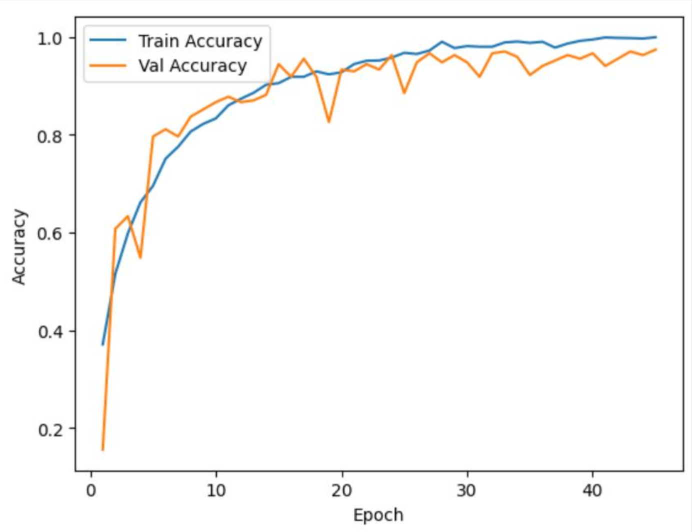
ResNet-18, 18 layers

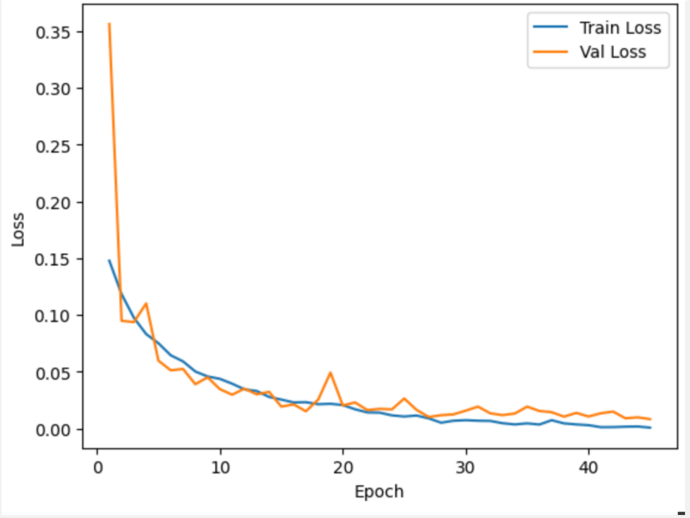
User wants… "cylindrical grasping"

RESULTS – EMG CLASSIFICATION

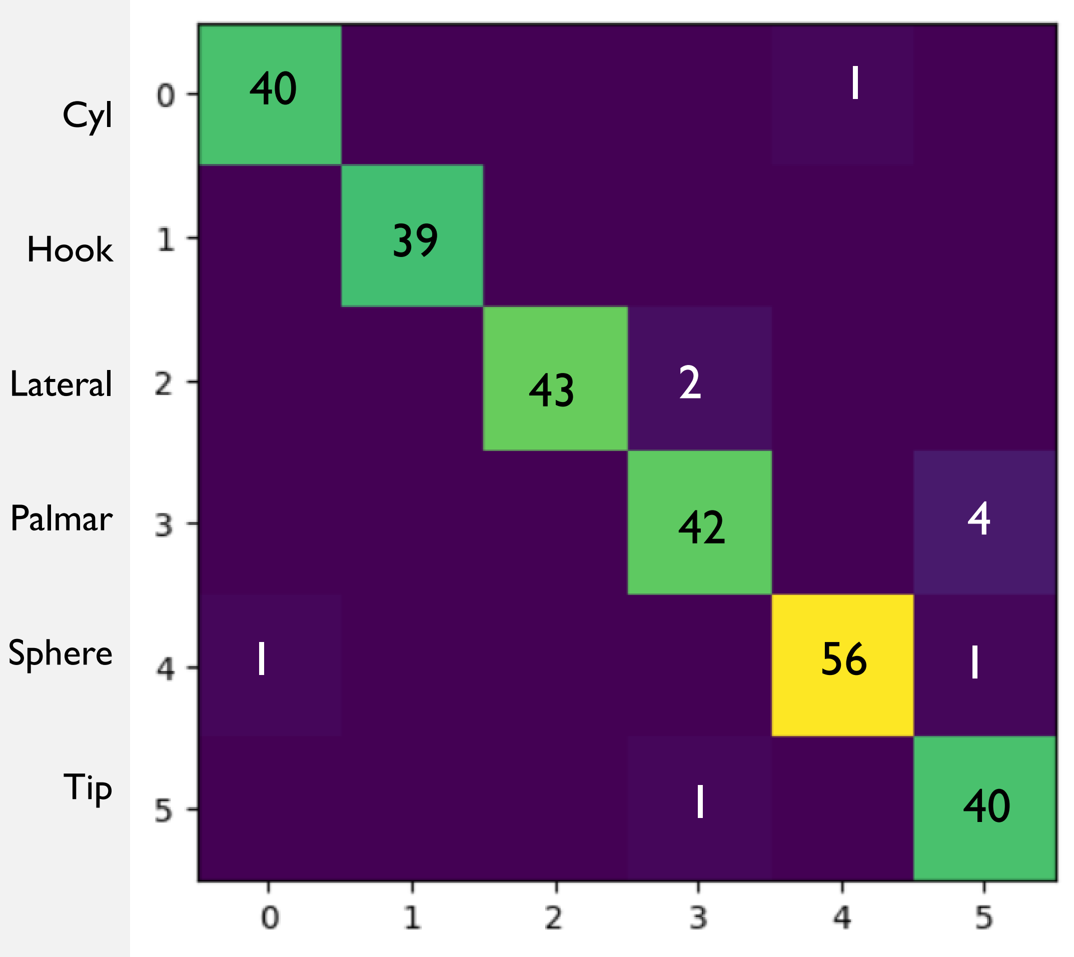
Source	Average (N=5)	Reference
Testing Accuracy	95.5	99.5
Recall	95.5	99.6
Precision	94.9	-
F1-Score	94.7	99.6

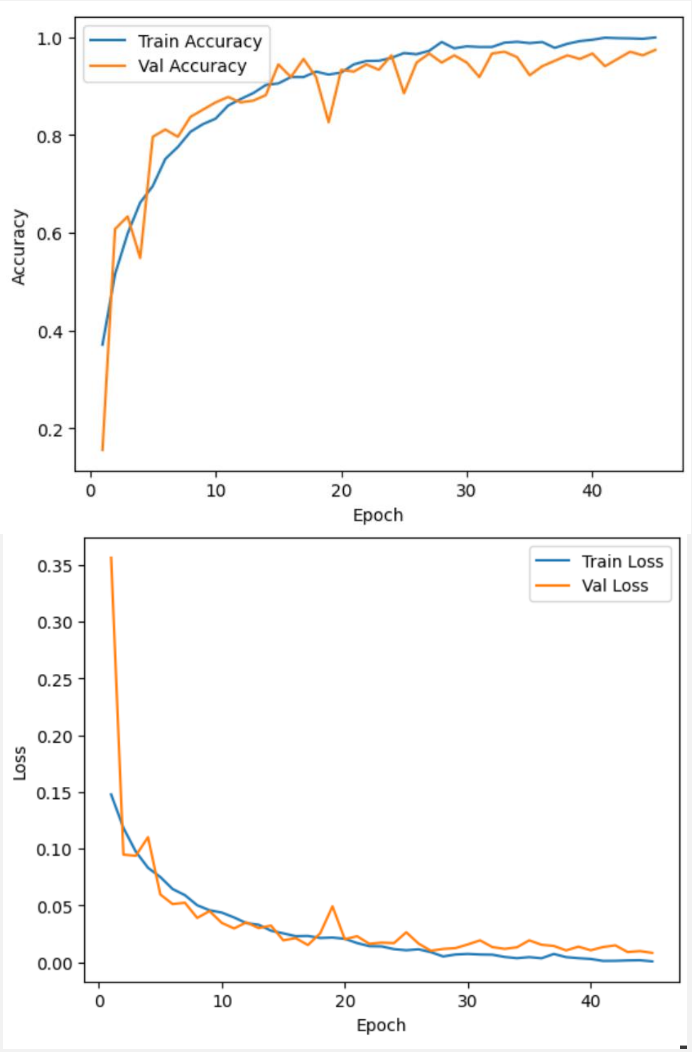
Our results vs. Reference paper





RESULTS – EMG CLASSIFICATION

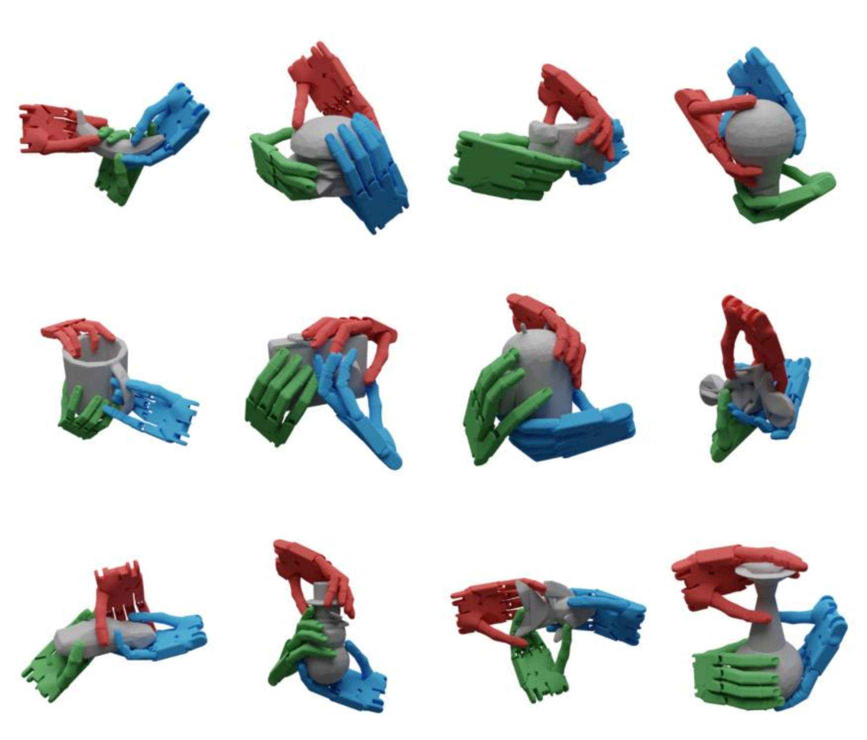




SECOND STAGE – GENERATIVE MODELING

TECHNICAL OUTLINE – DIFFUSION DATASET

Original Dataset – **DexGraspNet**



Large-Scale Robotic Dexterous Grasp Dataset for General Objects Based on Simulation

↓

5.000 CAD objects
and
1.3 M generated grasps

↓

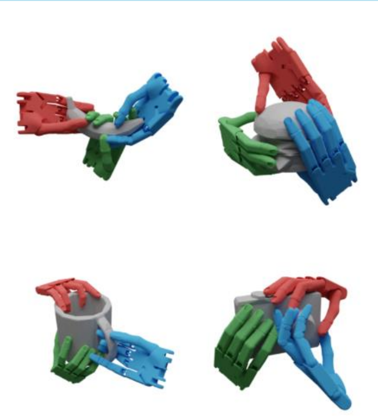
Each grasp consisted of $\{\theta, R, T\}$

$\boldsymbol{\theta}$ → 22 joint angles (e.g. MCP) $\boldsymbol{R}$ → 3 wrist rotation angles

$\boldsymbol{T}$ → position of wrist in space

TECHNICAL OUTLINE – DIFFUSION DATASET

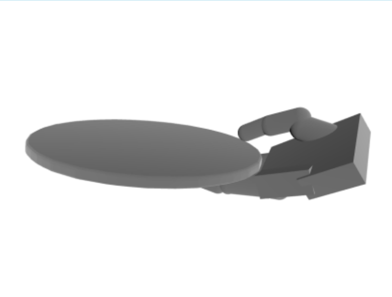
DexGraspNet



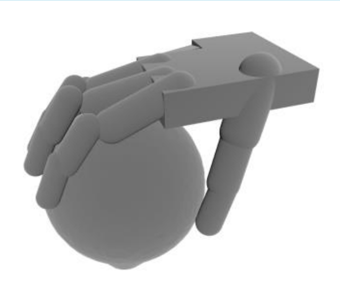
Parameters: $\{\theta, R, T\}$

Selected reference grasps

Cylindrical



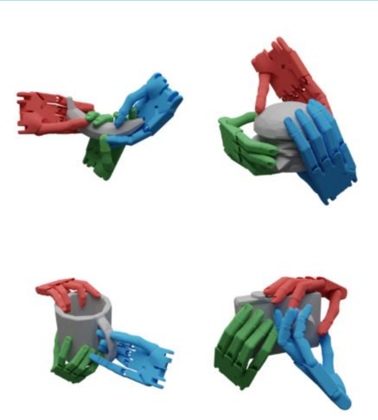
Planar



Spherical

TECHNICAL OUTLINE – DIFFUSION DATASET

DexGraspNet

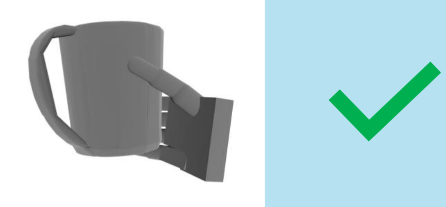


Parameters: $\{\theta, R, T\}$

Selected reference grasps

Cylindrical

Random dataset object + all grasps



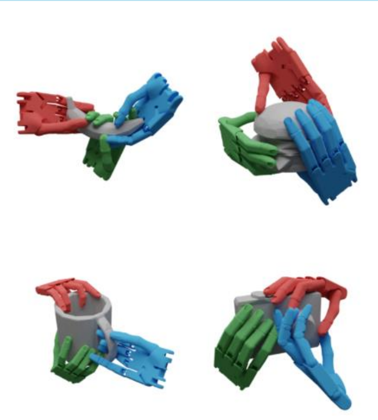
$\{\theta_{cyl}, R_{cyl}, T_{cyl}\} \longleftrightarrow \{\theta_1, R_1, T_1\}$

Euclidean distance for 28 dimensions of grasp

$dist < threshold$

TECHNICAL OUTLINE – DIFFUSION DATASET

DexGraspNet

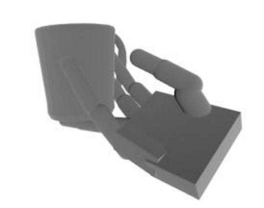


Parameters: $\{\theta, R, T\}$

Selected reference grasps

Cylindrical

Random dataset object + all grasps



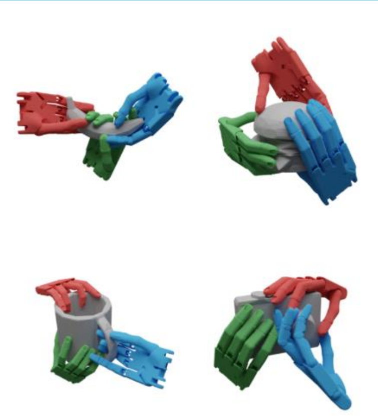
$\{\theta_{cyl}, R_{cyl}, T_{cyl}\} \longleftrightarrow \{\theta_2, R_2, T_2\}$

Euclidean distance for 28 dimensions of grasp

$dist > threshold$

TECHNICAL OUTLINE – DIFFUSION DATASET

DexGraspNet



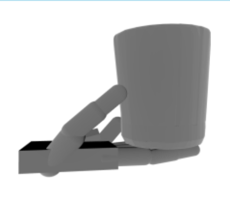
Parameters: $\{\theta, R, T\}$

Selected reference grasps

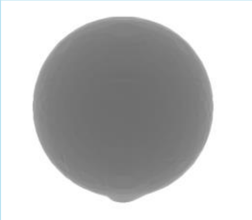
Cylindrical

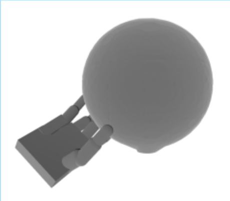
Refined Dataset





… … …





1.000 objects and **21.000 grasps**

TECHNICAL OUTLINE – DIFFUSION MODEL

Refined Dataset

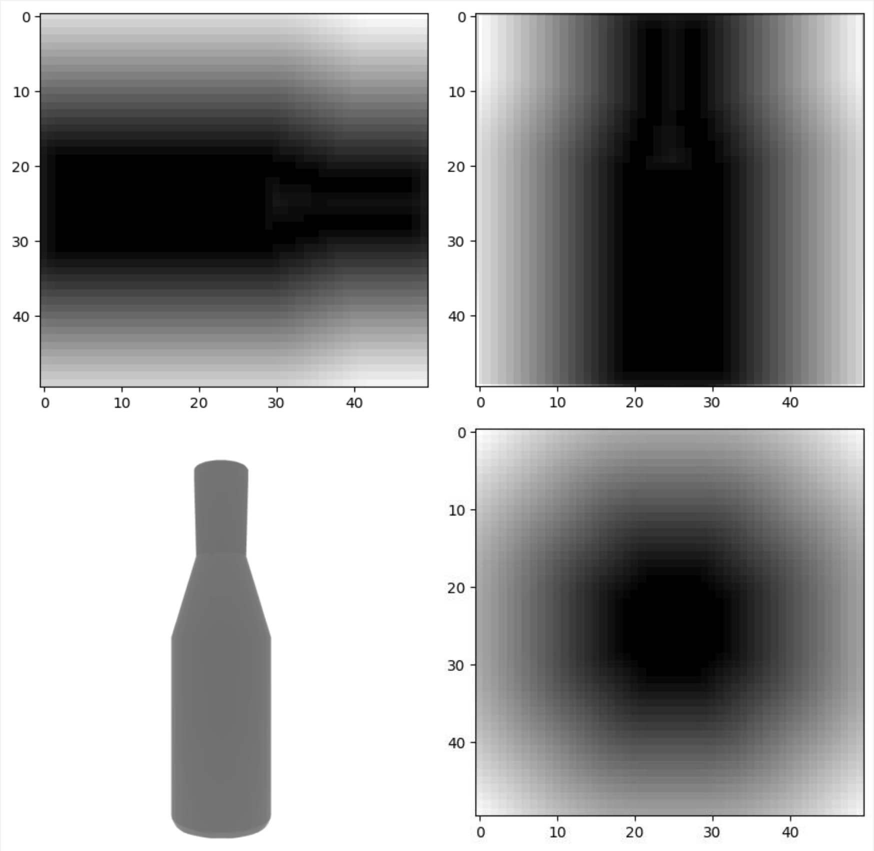
Object embedding:
Euclidean distance map

$50 \times 50 \times 50$

Grasp type:
One-hot vector
E.g., "cyl" = (1,0,0)

Grasp embedding:
Joint angles

22 joint angle
+3 rotation + 3 translation



TECHNICAL OUTLINE – DIFFUSION MODEL

Each Sample

Object embedding:
Euclidean distance map

$50 \times 50 \times 50$

Grasp type:
One-hot vector
E.g., “cyl” = (1,0,0)

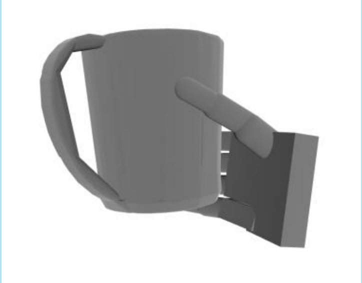
Grasp embedding:
Joint angles

$28 - \text{dimensional}$

Input

DIFFUSION MODEL

Output



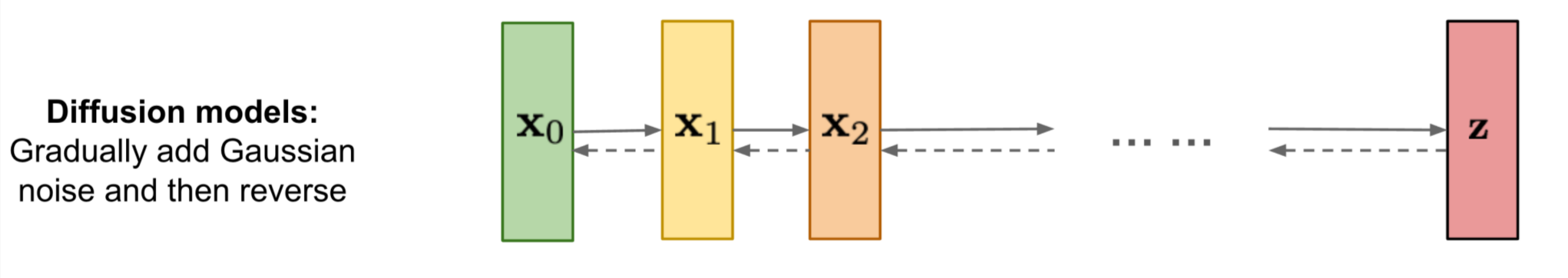
Finetuned Grasp

$28 - \text{dimensional}$

Conditioned on:

Desired grasp type
Input object

DIFFUSION MODEL - CHARACTERISTICS



Euclidean distance map
$50 \times 50 \times 50$

Joint angles:
$28 - \text{dimensional}$

Timesteps vector:
$64 - \text{dimensional}$

Grasp type:
One-hot vector
E.g., "cyl" = (1,0,0)

CONV3D

POSITIONAL EMBEDDING

POSITIONAL EMBEDDING

INPUT

Object embedding
$1x512$

Grasp embedding:
$1x1792$
$(1792 = 64 * 28)$

Timesteps embedding:
$1x64$

Grasp type:
$1x3$

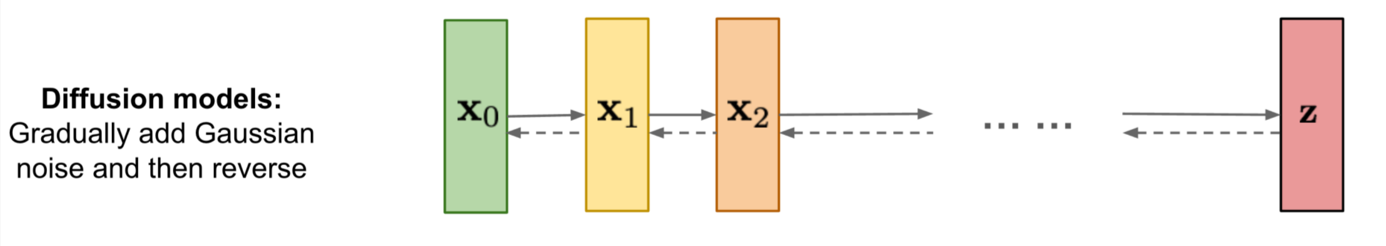
DIFFUSION MODEL - CHARACTERISTICS

Hyperparameters

Batch size	64
Epochs	200 / 250
Learning rate	1e-4 / 1e-5
Time steps	50
β (diffusion rate)	'linear'
Embedding size	64

Optimizer: AdamW

Loss function: MSE Loss



INPUT

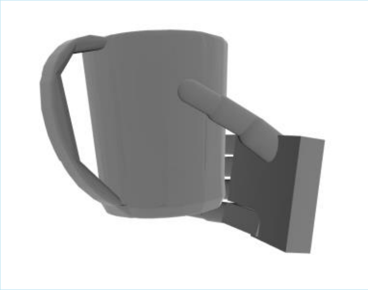
Object embedding
$1x512$

Grasp embedding:
$1x1792$
$(1792 = 64 * 28)$

Time embedding:
$1x64$

Grasp type:
$1x3$

OUTPUT



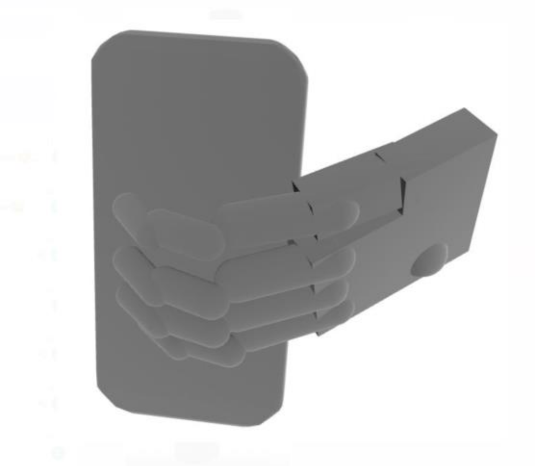
Finetuned Grasp

$28 - \text{dimensional}$

DIFFUSION MODEL – TRAINING AND RESULTS

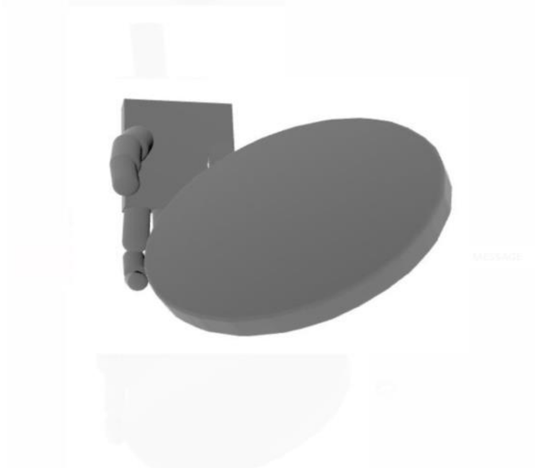
FULL MODEL

PLANAR GRASP



CYL GRASP

PLANAR GRASP

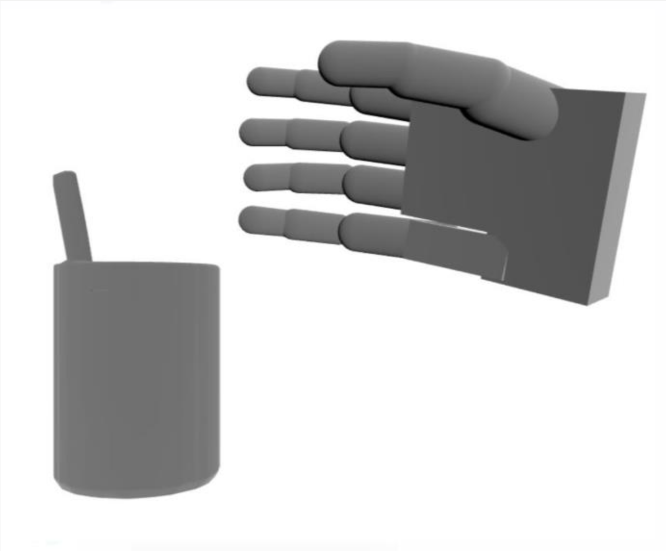


CYL GRASP

DIFFUSION MODEL – TRAINING AND RESULTS

FULL MODEL

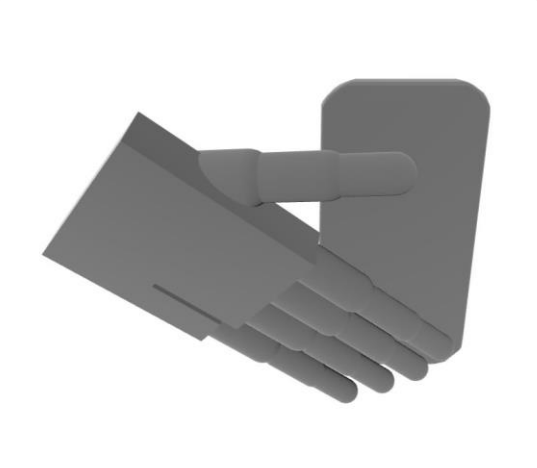
Rotation and translation sometimes fails…



DIFFUSION MODEL – TRAINING AND RESULTS

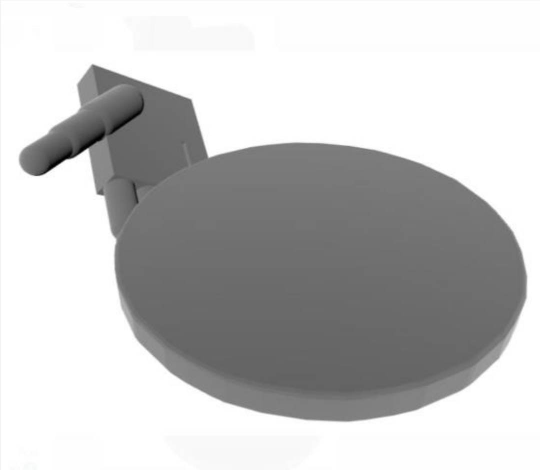
ROTATION-TRANSLATION ONLY

PLANAR GRASP



CYL GRASP

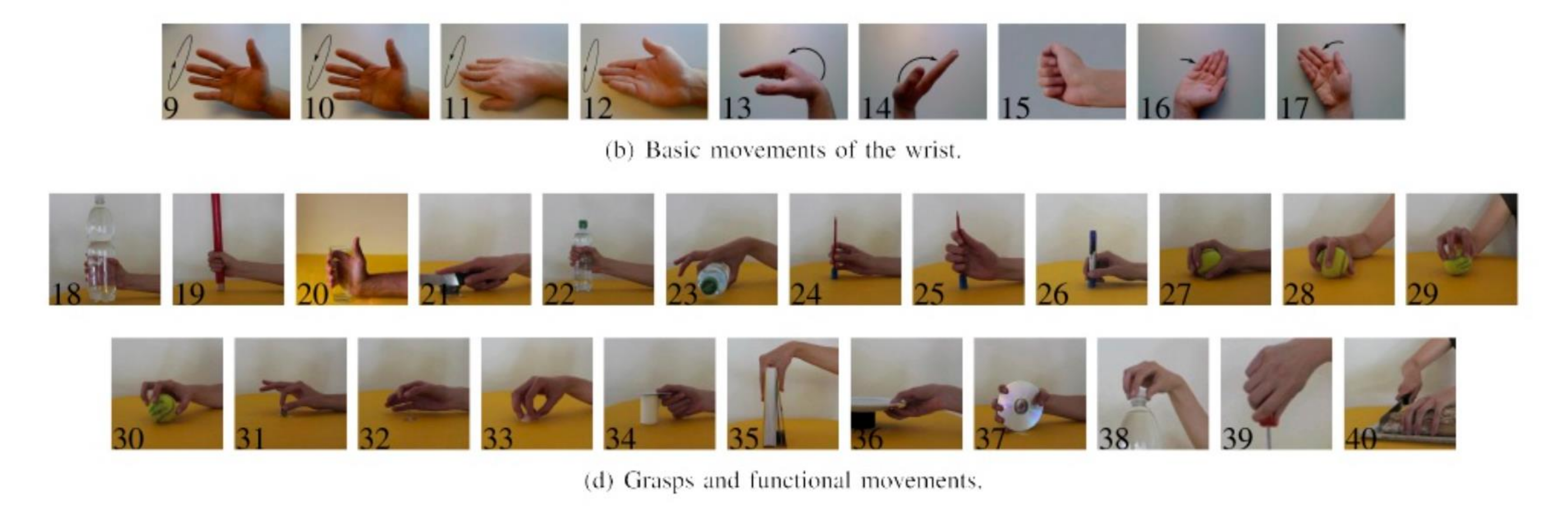
PLANAR GRASP



CYL GRASP

DISCUSSION AND FUTURE WORK

- **First part:**
  - **sEMG** classification provided **good results** → similar to the reference paper
  - **Future steps:**
    - **Extend the sEMG dataset** to more grasping types.



(b) Basic movements of the wrist.

(d) Grasps and functional movements.

DISCUSSION AND FUTURE WORK

- **<u>Second part:</u>**
  - **Joint angles** representation → almost **PERFECT**!
  - **Translation and rotation** representation → **not consistent at all**!
  - → Dimensionality problem? Applying **dimensionality reduction**…

- We also implemented **dimensionality reduction** with **PCA**:
  - → **PCA** did not achieve to represent the reconstructed sample properly.

DISCUSSION AND FUTURE WORK

- **Future steps:**
  - Implement different dimensionality reduction methods.
  - Think about different approaches to solve this problem.

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