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Deep Imitation Learning with Virtual Reality for Robot Manipulation Tasks

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Outline

Goal

Acquiring robotic manipulation skills in real world environment through learning neural network policies by using Deep Imitation Learning

Challenges

Imitation Learning is an effective approach for skills acquisition, however:

- Obtaining high-quality demonstration is difficult
- Complex kinesthetic teaching and trajectory optimisation
- Expensive tele-operation system

Definition

Imitation learning is a class of methods for acquiring skills by observing demonstrations

A robot observe a human instructor performing a task and imitating it when needed.

It is also referred to deep imitation learning as programming by demonstration

Main Focus

Imitation learning focuses mainly on three issues:

- Efficient motor learning
- The connection between action and perception
- Modular motor control in form of movement primitives

Presenting Imitation Learning

In order to describe a learning process as imitation learning

1. The imitated behaviour is new for the imitator

2. The same task strategy as that of the demonstrator is employed

3. The same task goal is accomplished

Viewpoint of Neuroscience

A connection between the sensory systems and the motor systems is essential

Some neurones were active *both* when:

a) The monkey *observed* a specific behaviour

b) When it *executed* it itself

Those particular neurones are called

“Mirror Neurones”

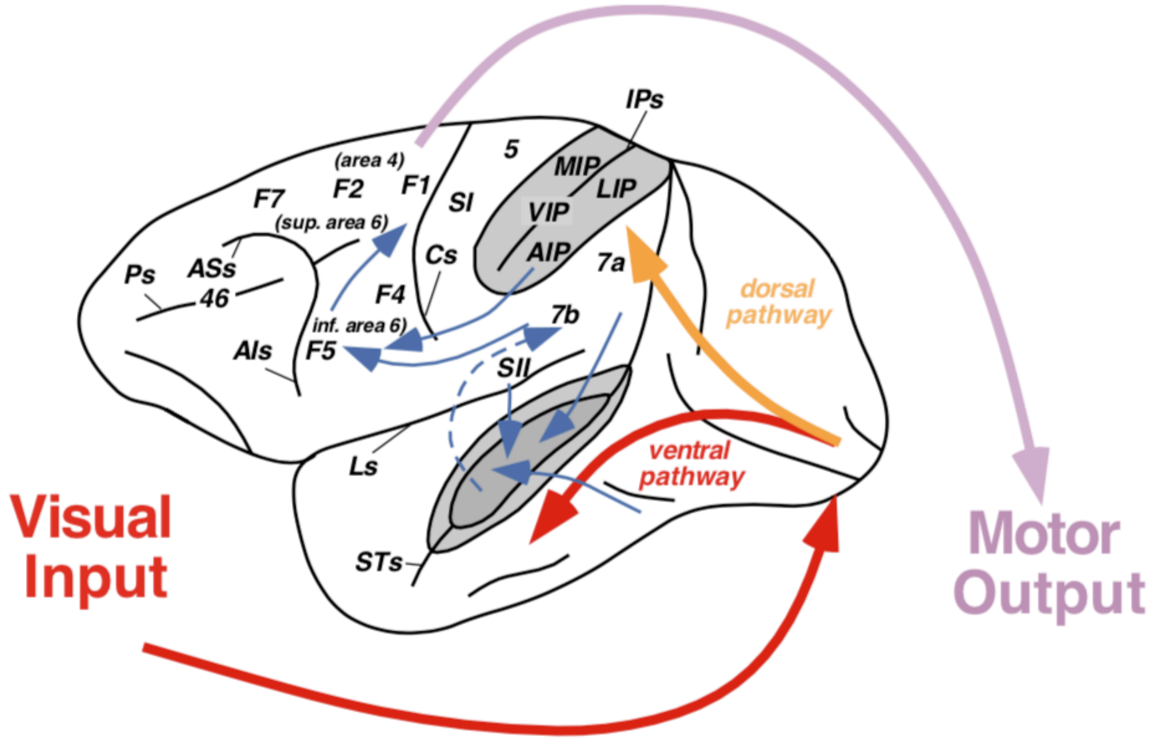


Fig. 1

Fig. 1: https://www.cell.com/cms/attachment/d4ed4e90-982d-4afe-9118-00609928eaf3/gr2.jpg

Viewpoint of Robotics and AI

How imitation learning was approached and represented?

- Symbolic Approaches to Imitation Learning
- Inductive Approaches to Imitation Learning
- Imitation Learning of Novel Behaviours
- Implications for Computational Models of Imitation Learning

Imitation learning system

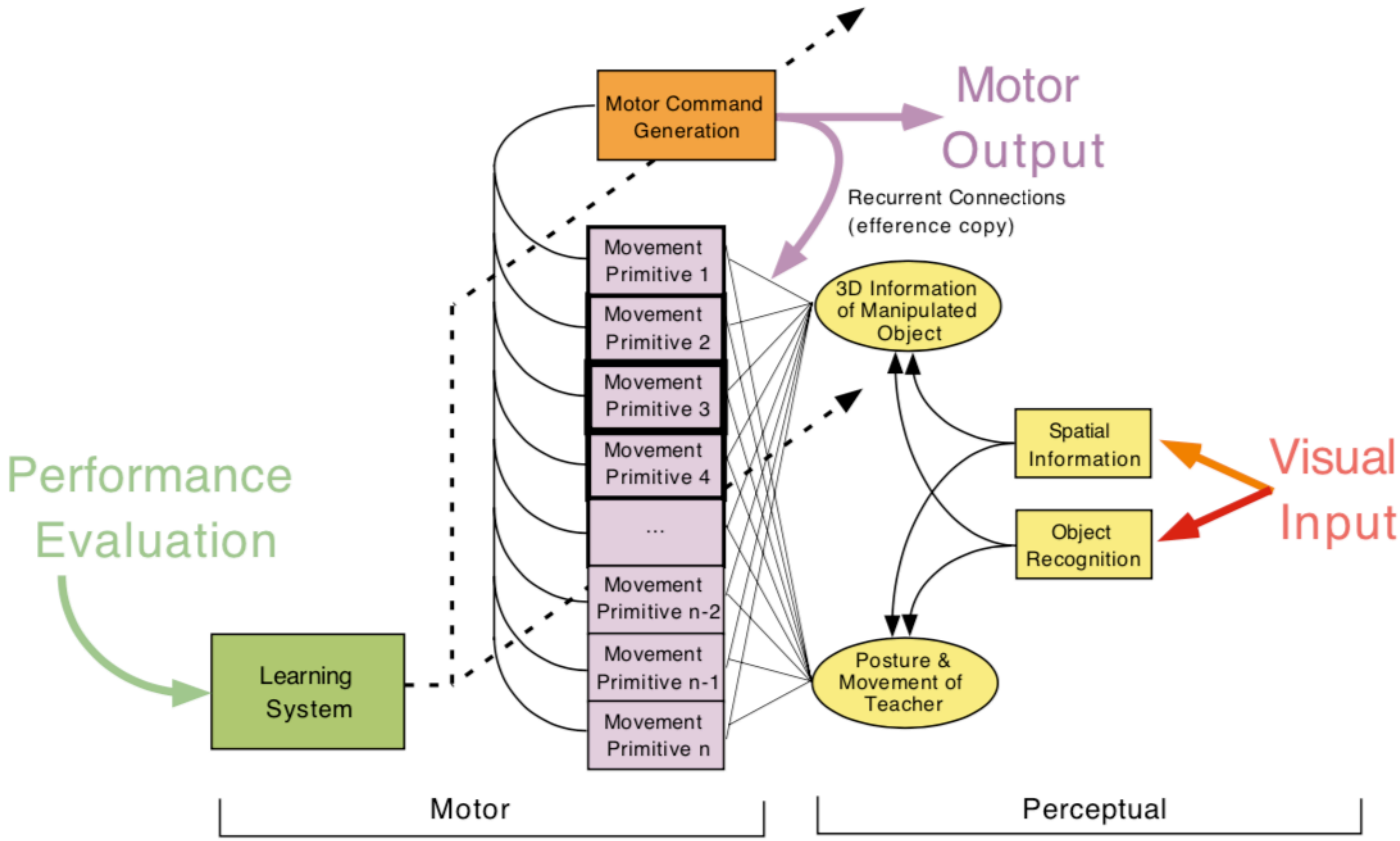


Fig. 2

Fig. 2: https://www.researchgate.net/figure/Conceptual-sketch-of-an-imitation-learning-system-The-right-side-of-the-figure-contains_fig3_24379198

Examples

Fig. 3: Autonomous helicopter flight

Fig. 4: Autonomous driving

Fig. 4: Gesturing and manipulation

Fig. 3: https://www.iitk.ac.in/aero/images/dept-images/heli_small.jpg
Fig. 4: https://ai4sig.org/2018/08/carla-imitation-learning-training/
Fig. 5: https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcSkwIA-wjMhe7vGiTPS8tEJt-D1uc41v2o3-X2I31SJFuDUXmpPtQ&s

Imitation learning Related Work

- Behavioural cloning

  Which performs supervised learning from observations to actions

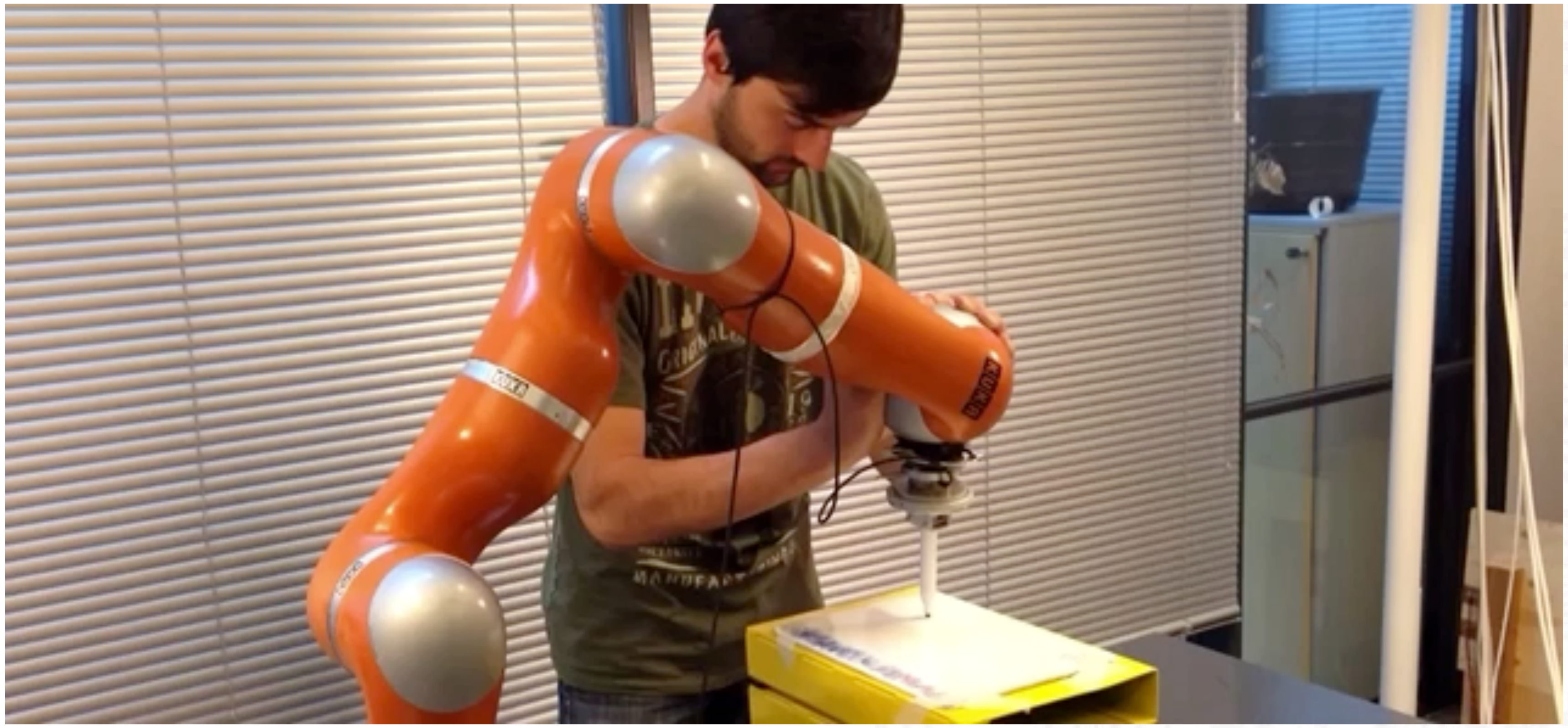
- Inverse reinforcement learning

  Where a reward function is estimated to explain the demonstrations as (near) optimal behaviour

Collecting Demonstrations

- Kinesthetic teaching

In this method, the teacher physically manoeuvres the robot.



https://www.youtube.com/watch?v=SCy4hdP-IeY

Collecting Demonstrations Cont.

- Teleoperation

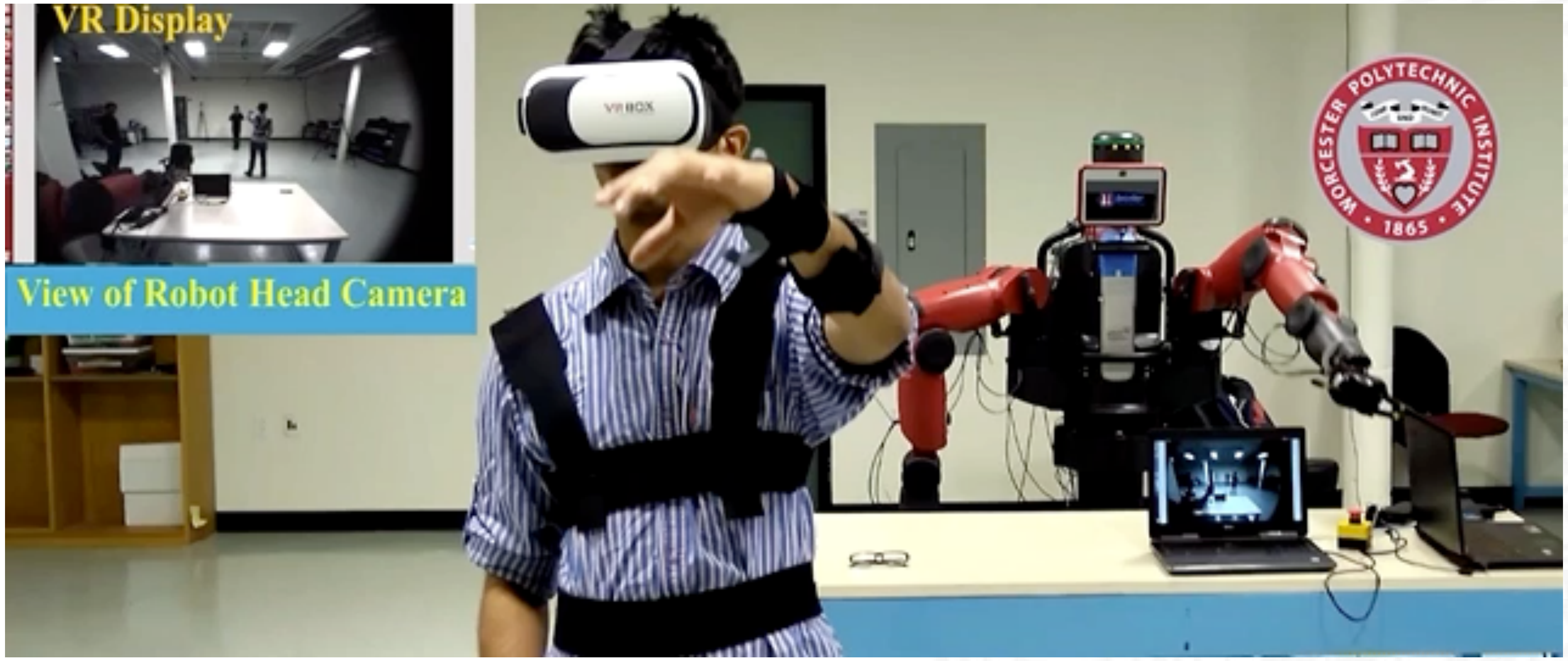
  This method is performed with the help of haptic device.

https://www.youtube.com/watch?v=YLEUBFu5qgI

Collecting Demonstrations Cont.

- Teleoperation with Virtual Reality

This mode is also performed with the help of haptic device in addition to VR Headset



https://www.youtube.com/watch?v=Bae0rvgySBg

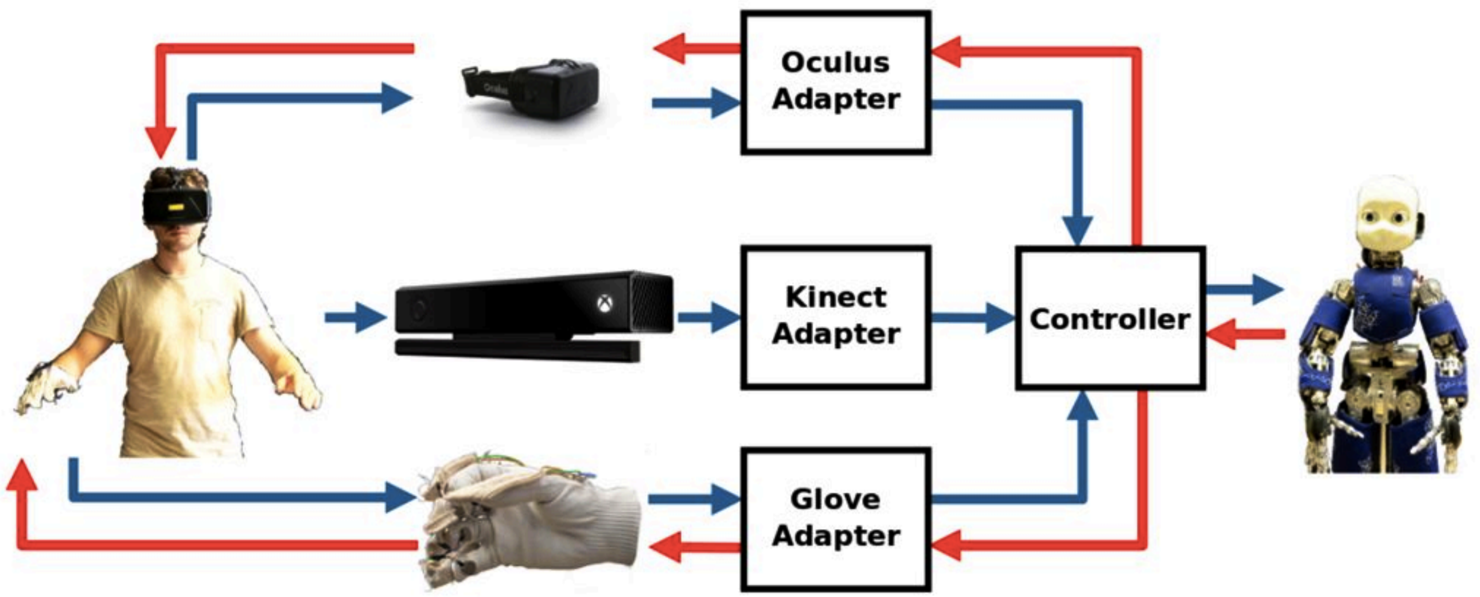
VR Teleoperation

Virtual Reality teleoperation allows:

- Direct mapping of observations and actions between the teacher and the robot
- Leveraging the natural manipulation instincts that the human teacher possesses
- Eliminating the possibility of hidden information for both parties
- Preventing any visual distractions from entering the environment

VR Teleoperation Models

- Microsoft Kinect Version 2
- Oculus Rift Development Kit 2
- SensorGlove
- The Humanoid Robot iCub



"First-person tele-operation of a humanoid robot".

Fig. 5: Control Architecture

Fig. 5: https://www.semanticscholar.org/paper/First-person-tele-operation-of-a-humanoid-robot-Fritsche-Unverzag/47a9dedab44f2c7f1b7da16d24ae05bc2630723d

VR Teleoperation Models Cont.

- Vive VR system
- PR2 robot
- Primesense Carmine 3D Cam
- Vive hand controllers

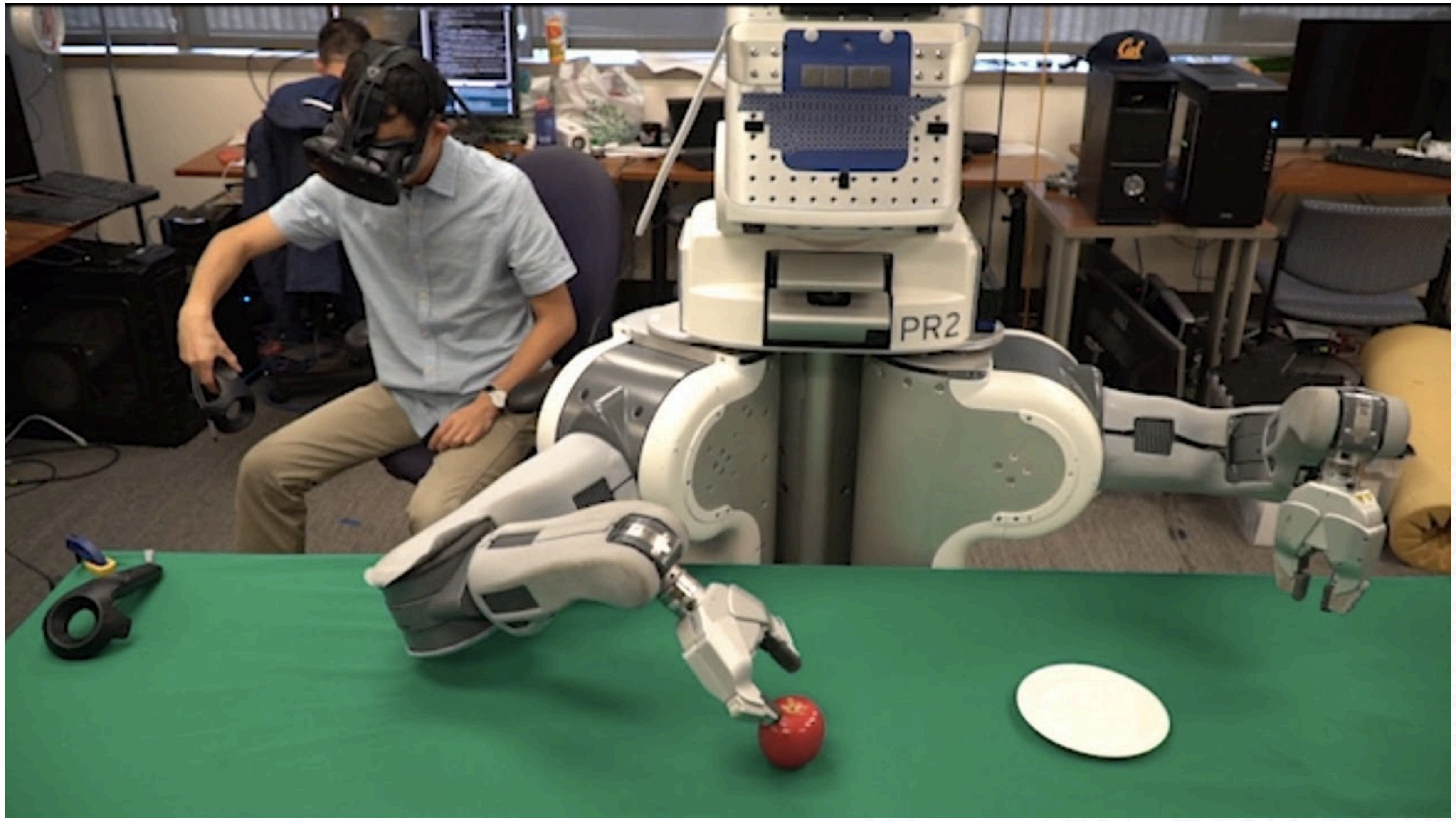


Fig. 6: Control Architecture

Fig. 6: https://techxplore.com/news/2017-11-startup-robots-puppets.html

Behavioural Cloning

"Performs supervised learning from observations to actions"

- Deploying behavioural cloning algorithm to learn neural network control policies

- Collecting and presenting a data set which consist of:

  1. Observation
  2. Corresponding controls

$$D_{task} = \{(o_t^{(i)}, u_t^{(i)})\}$$

$$\pi_\theta(u_t | o_t)$$

Neural Network Control Policies

$$o^t = (I_t, D_t, p_{t-4:t})$$

as an input

I: current RGB image — $I \in R^{160\times120\times3}$

D: current depth image — $D_t \in R^{160\times120}$

$p_{t-4:t}$: three points on the end effector — $p_{t-4:t} \in R^{45}$

Neural Network Control Policies Cont.

$$u_t = \pi_\theta(o_t)$$

as an output

ω_t: angular velocity — $\omega \in R^3$

v_t: linear velocity — $v \in R^3$

g_t: desired gripper — $g \in \{0, 1\}$

Neural Network Architecture

The neural network architecture can be decomposed into three modules:

$$\theta = (\theta_{vision}, \theta_{aux}, \theta_{control})$$

$$f_t = CNN(I_t, D_t; \theta_{vision})$$

$$s_t = NN(f_t; \theta_{aux})$$

$$u_t = NN(p_{t-4:t}, f_t, s_t; \theta_{control})$$

Neural Network Architecture Cont.

The neural network architecture overview:

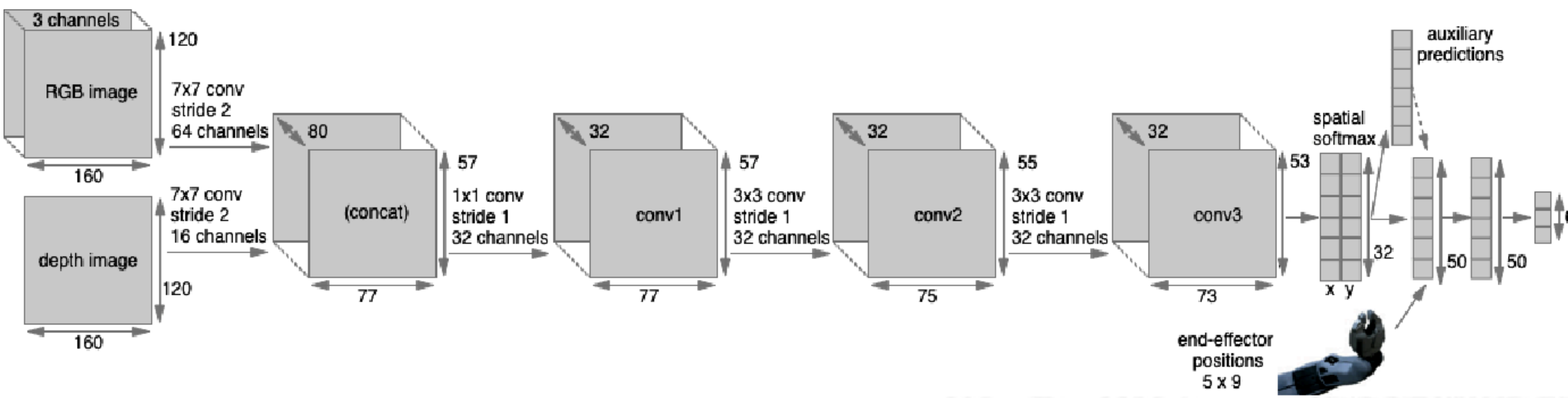
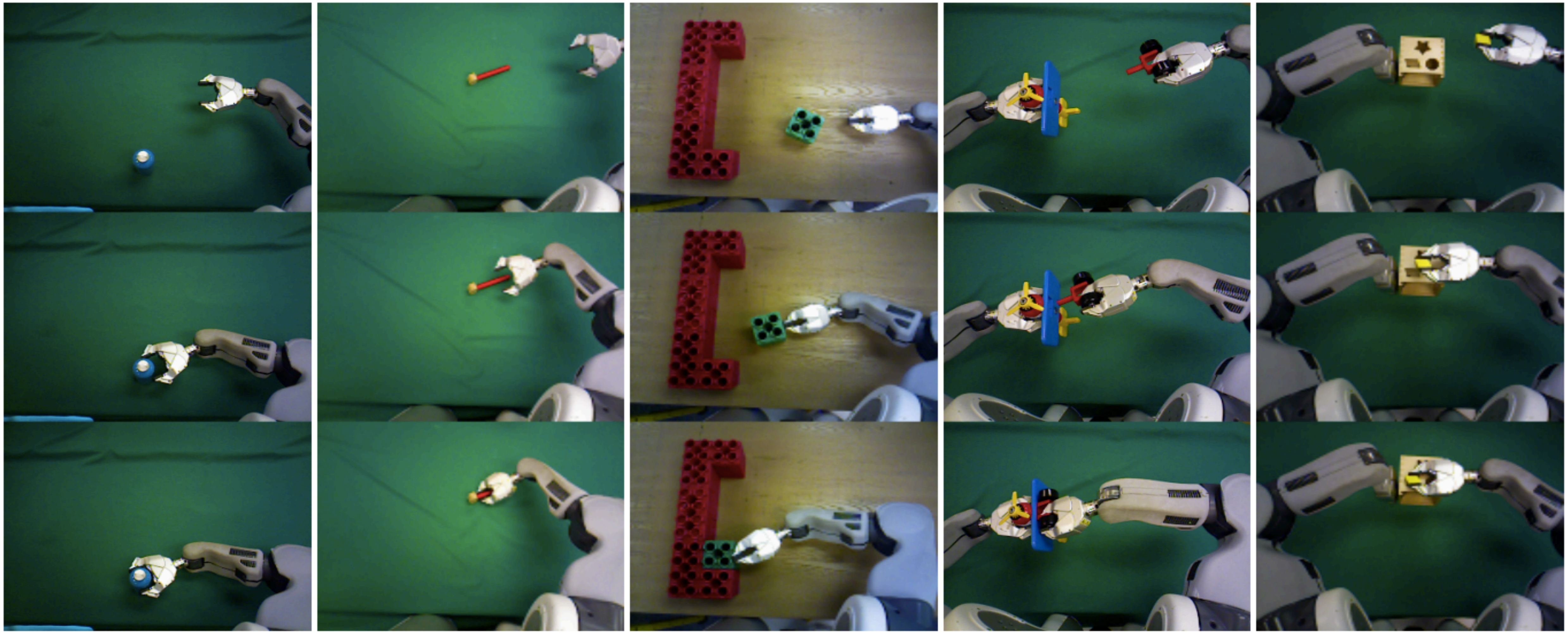


Fig. 7: Architecture of the neural network policies

Fig. 7: https://www.semanticscholar.org/paper/Deep-Imitation-Learning-for-Complex-Manipulation-Zhang-McCarthy/b864f89eaa91120e04e8c62eb0b36568ab4244a8

Manipulation Tasks

A range of challenging manipulation task were chosen:

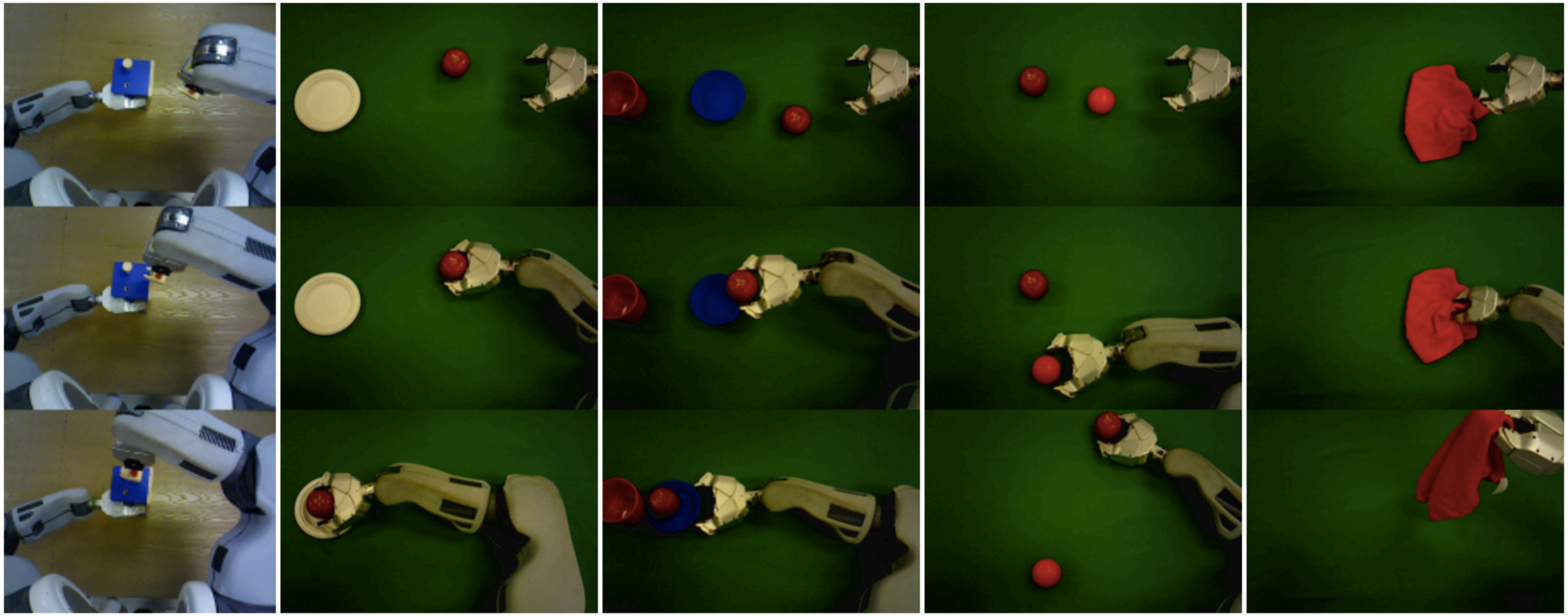


(a) reaching (b) grasping (c) pushing (d) plane (e) cube

Fig. 8: Examples of successful trials

Fig. 8: https://www.semanticscholar.org/paper/Deep-Imitation-Learning-for-Complex-Manipulation-Zhang-McCarthy/b864f89eaa91120e04e8c62eb0b36568ab4244a8/figure/5

Manipulation Tasks Cont.



(f) nail (g) grasp-and-place (h) grasp-drop-push (i) grasp-place-x2 (j) cloth

Fig. 9: Examples of successful trials

Fig. 9: https://www.semanticscholar.org/paper/Deep-Imitation-Learning-for-Complex-Manipulation-Zhang-McCarthy/b864f89eaa91120e04e8c62eb0b36568ab4244a8/figure/5

Results

task	reaching	grasping	pushing	plane	cube
test	91.6%	97.2%	98.9%	87.5%	85.7%
demo time (min)	13.7	11.1	16.9	25.0	12.7
avg length (at 10 Hz)	41	37	58	47	37
# demo	200	180	175	319	206

task	nail	grasp-and-place	grasp-drop-push	grasp-place-x2	cloth
test	87.5%	96.0%	83.3%	80%	97.4%
demo time (min)	13.6	12.3	14.5	11.6	10.1
avg length (at 10 Hz)	38	68	87	116	60
# demo	215	109	100	60	100

Table. 1: Success rates and statistics of training data

Table. 1: https://www.semanticscholar.org/paper/Deep-Imitation-Learning-for-Complex-Manipulation-Zhang-McCarthy/b864f89eaa91120e04e8c62eb0b36568ab4244a8/figure/7

Conclusion and Future Work

- VR teleoperation system facilitates collecting high-quality demonstrations
- Imitation learning can be quite effective in learning deep policies
- Achieving high success rate regardless of small data size

Further work can be investigated such as:

- Collecting additional demonstration signals
- Introducing richer feedback to demonstrators such as haptics and sound
- Learn policies with bimanual manipulation or hand-eye coordination

Resources

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