Lecture on Motor Control: Manipulation

Angelo Cangelosi
Department of Computer Science, Kilburn Building,
The University of Manchester

Content

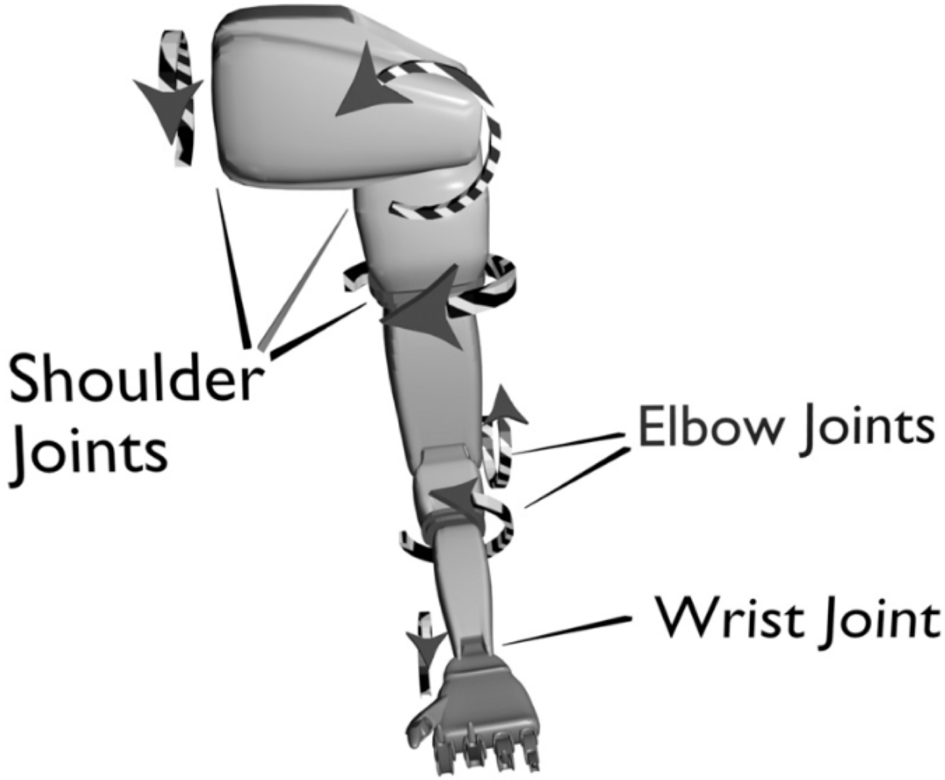
- Types of manipulation actions
  - Reaching & Grasping
- Manipulator and endeffector
- Kinematics and dynamics
- Control
  - Closed loop: Feedback
  - Open loop: Forward
- Cognitive, developmental robotics models
- Deep learning Models

Robot Motion

- **Navigation**: *Moving the entire robot from one location to another (destination planning)*
  - Locomotion
  - Localisation and mapping
- **Manipulation**: *Moving body part to manipulate the environment*
  - Reaching
  - Grasping

Manipulation

- Robotic **manipulator**
  - One or more **links** connected by **joints**, and the **endeffector**



Mataric 2007

Manipulation

- Robotic **manipulator**
  - One or more **links** connected by **joints**, and the **endeffector**
  - Endeffector (e.g. gripper, hand, arm, or body part): used to affect and move objects in the environment

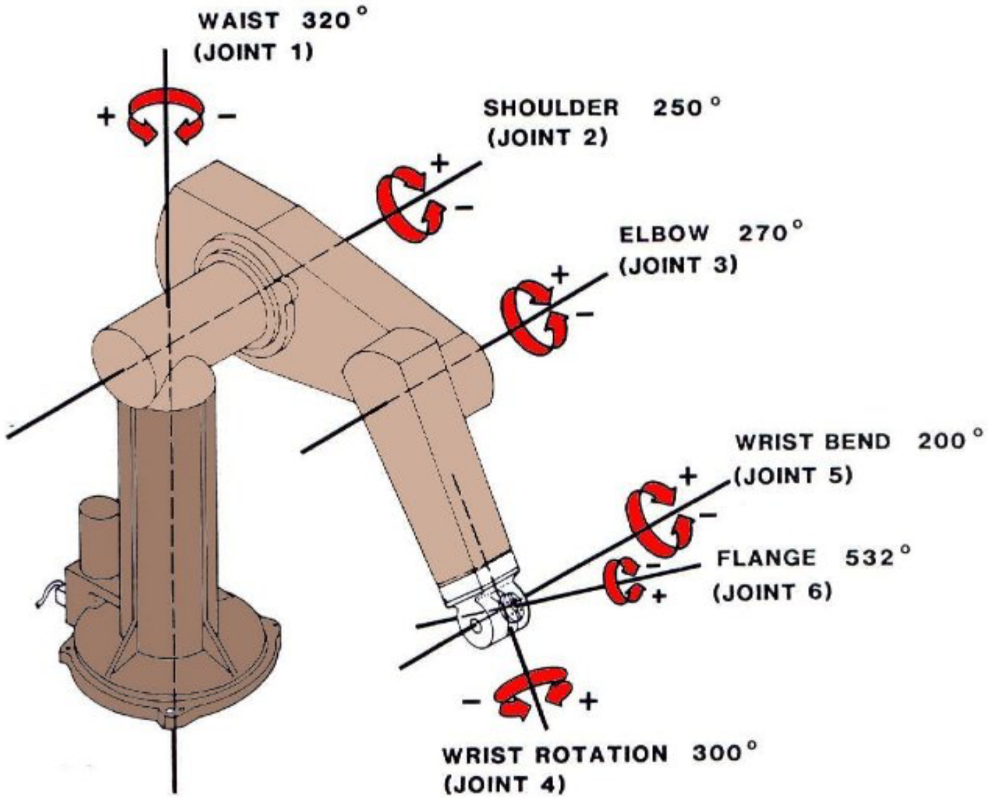
Manipulator: Endeffector

Manipulation

- Robotic **manipulator**
  - One or more **links** connected by **joints**, and the **endeffector**
  - Endeffector (e.g. gripper, hand, arm, or body part): used to affect and move objects in the environment
- Manipulation
  - The goal-driven movement of a manipulator

Manipulator: Joint Limit

- Joint limit
  - the extreme of how far the joint can move

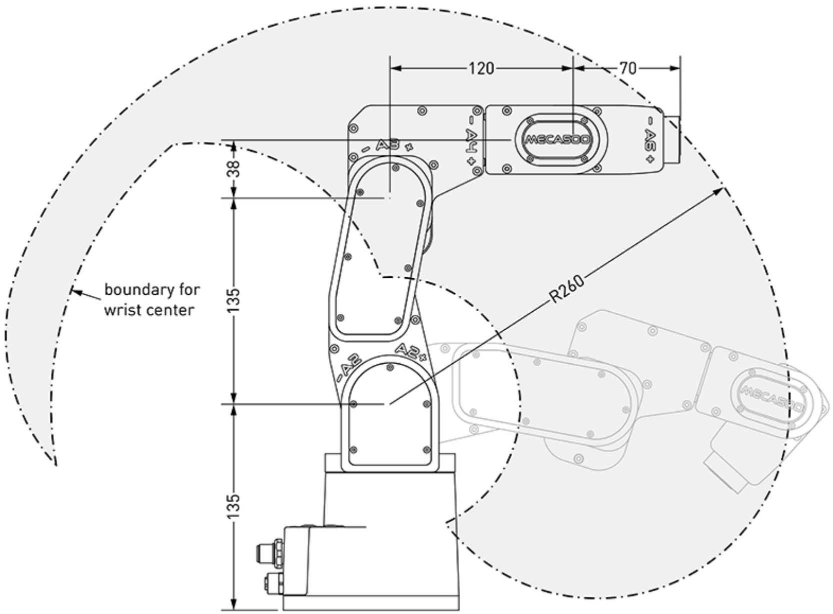


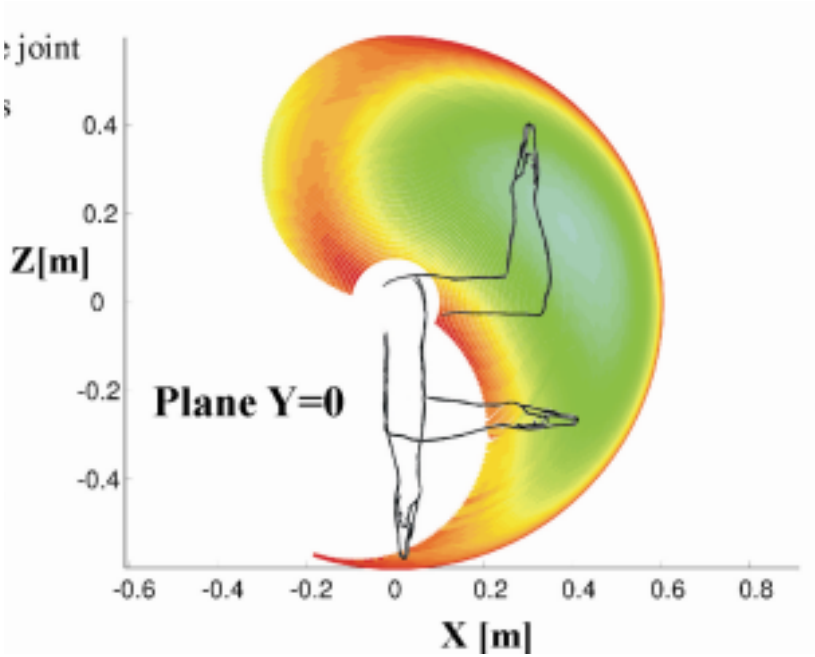
rutherford-robotics.com/PUMA

Manipulator

- Joint limit
  - the extreme of how far the joint can move
- Workspace
  - set of all poses attainable by a particular endeffector mounted on the manipulator (arm)

Manipulator: Workspace





www.mecademic.com

scmero.ulb.ac.be

Manipulator

- Joint limit
  - the extreme of how far the joint can move
- Workspace
  - set of all poses attainable by a particular end-effector mounted on the manipulator (arm)
- Manipulation problem
  - The manipulator/arm must move within the free workspace, avoiding its own joint limit, the body, and obstacles

Manipulator: Human Arm

- 7 DOF for human arm (not including hand)
  - 3 shoulder (up-down, side-to-side, rotation about the axis of the arm)
  - 1 elbow (open-close)
  - 3 wrist (up-down, side-to-side, again rotation)

- Note…
  - Shoulder: based on a ball-and-socket joint
  - Wrist: rotational DOF from the muscles and ligaments in the forearm

Kinematics & Dynamics

Kinematics

- Correspondence between actuator motion and resulting effector motion
  - The rules about the structure of the manipulator: what is attached to what, how many joints, how many DOF for each joint…
  - Determines where the endpoint is, given joint angles
- Manipulation problems
  - **Where the endpoint is** relative to the rest of the arm
  - How to **generate paths** for the manipulator to achieve the goal

Inverse and Forward Kinematics

- **Inverse** Kinematics: Position→Angle conversion
  - from a **Cartesian (x,y,z) position** of the endeffector
  - to the **angles of the joints** of the manipulator
- Maths
  - Computationally intense: iterative optimization of approximate solutions (cf. Schaals' slides)
    - e.g. Jacobian inverse technique (with Hessian matrix)

- **Forward** kinematic: Angle⟶Position
  - From joints' angles to endeffector's cartesian position

Dynamics

- The properties of motion and energy of a moving object
- Different impact in robot motion
  - Behaviour of slow-moving mobile robot not very strongly impacted by its dynamics
  - Behaviour of a fast-moving tennis-ball-juggling robot highly impacted by dynamics
- Expensive computation of direct and inverse dynamics

Compliance

- Compliance
  - The yielding to the environment forces (required for tasks with close contacts)
    - E.g. to follow/clean a surface
    - Safety for contact with humans
- Solutions
  - Spring in joints
  - Soft materials
  - Software compliance

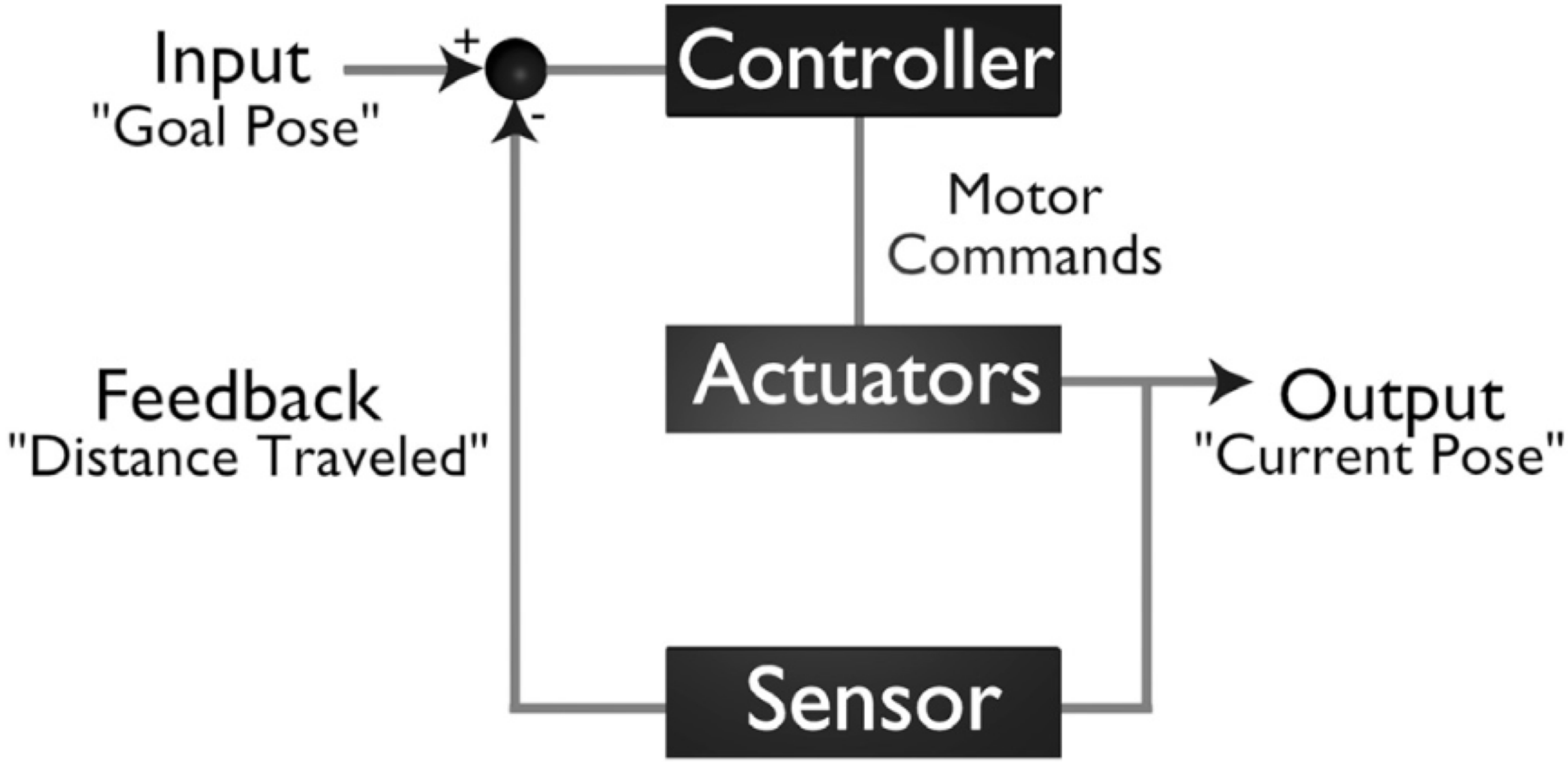
Control

Control

- Actuator **uncertainty**
  - Impossible to know the exact outcome of an action

- **Closed loop** control (*Feedback* control)
  - **Achieve and maintain** a desired state, by continuously comparing its current state with its desired state
  - **Feedback**: information sent back (fed back)
  - **Desired state** (**Goal state**): where system wants to be
  - **Error**: difference between current and desired states

(Closed-Loop) Feedback Control

- 

Mataric 2007

Control

- Actuator **uncertainty**
  - Impossible to know the exact outcome of an action
- Closed loop control (*Feedback* control)
  - Achieve and maintain a desired state, by continuously comparing its current state with its desired state
  - Feedback: information sent back (fed back)
  - Desired state (Goal state): where system wants to be
  - Error: difference between current and desired states
- **Open Loop** control (*Feedforward* control)
  - Apply force to joints towards desired state (no check)

Types of Feedback Control

- Proportional control (P)
  - System responds in **proportion to the error** (direction and magnitude of the error)
  - **Gain**: parameter that determines the magnitude of the system's response (hard to determine in advance; trial and error)
  - **Oscillation**: undershoot or overshoot of desired state (+gain, +oscillation)
  - **Damping:** process of systematically decreasing oscillation

https://vivekbose.com/introduction-to-pid-controller-with-detailed-ppipd-pd-control

Types of Feedback Control

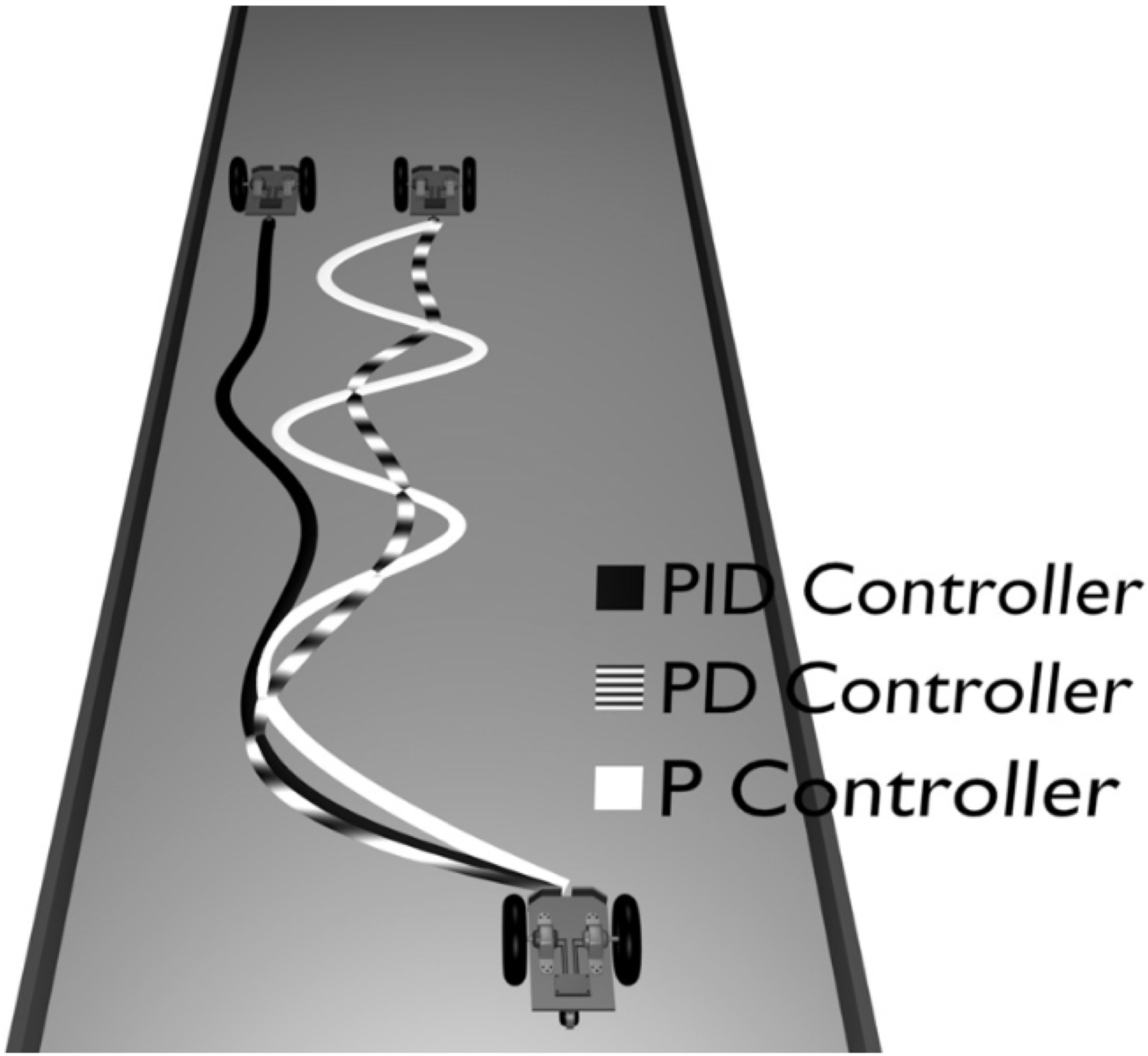
- Derivative Control (PD)
  - Proportional error signal added **with derivative of the error signal**
  - Solve gain/oscillation problem
  - When the system is close to the desired state,
    it needs to be controlled differently than when it is far
  - Correct the momentum as the system approaches the desired state
    - subtract amount proportional to the velocity: $-(\text{gain} * \text{velocity})$

- Used widely in industrial robotics

Types of Feedback Control

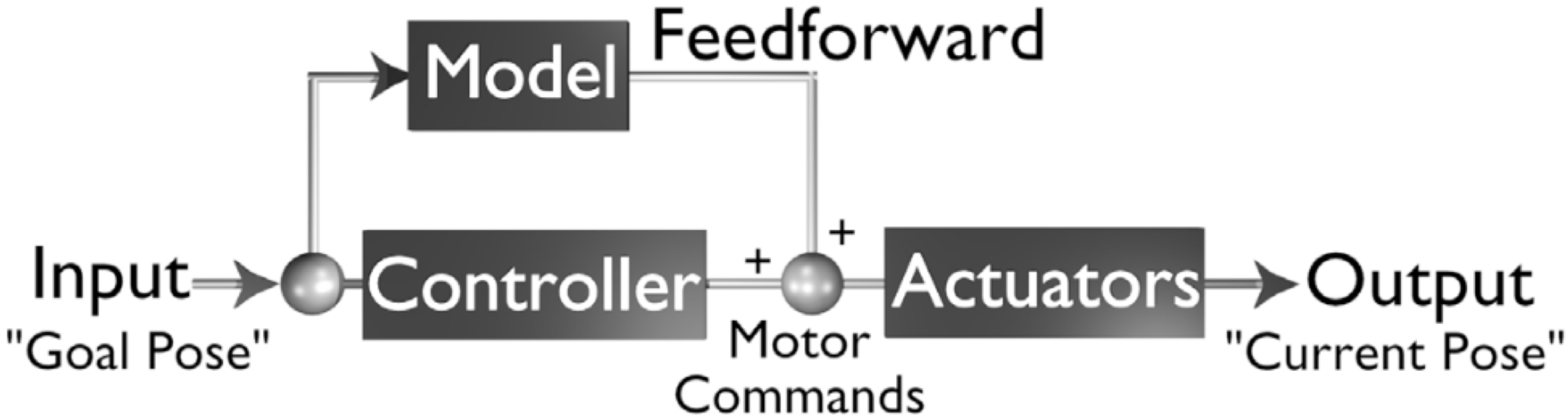
- PID: <u>Proportional Integral Control</u>
  - Integral Term I: The system integrates (sums up) incremental errors over time
  - No steady state errors: repeatable, fixed errors
  - When I reaches threshold (i.e. large cumulative error), the system compensates/corrects
- Many joints have PID controllers

- Feedback Control
  - FC good for low-level motor actions and errors
  - AI / Cognition good for high-level behaviour


PID Controller
PD Controller
P Controller

Open Loop control (Feedforward control)

- Looking ahead (forward) to predict the state of the system
- Apply predicted force to joints (no check!)
  - No sensory feedback, no error



Lecture on
Motor Control: Manipulation

Lecture c
Cognitive Approaches

Angelo Cangelosi
Department of Computer Science, Kilburn Building,
The University of Manchester

Developmental Milestones

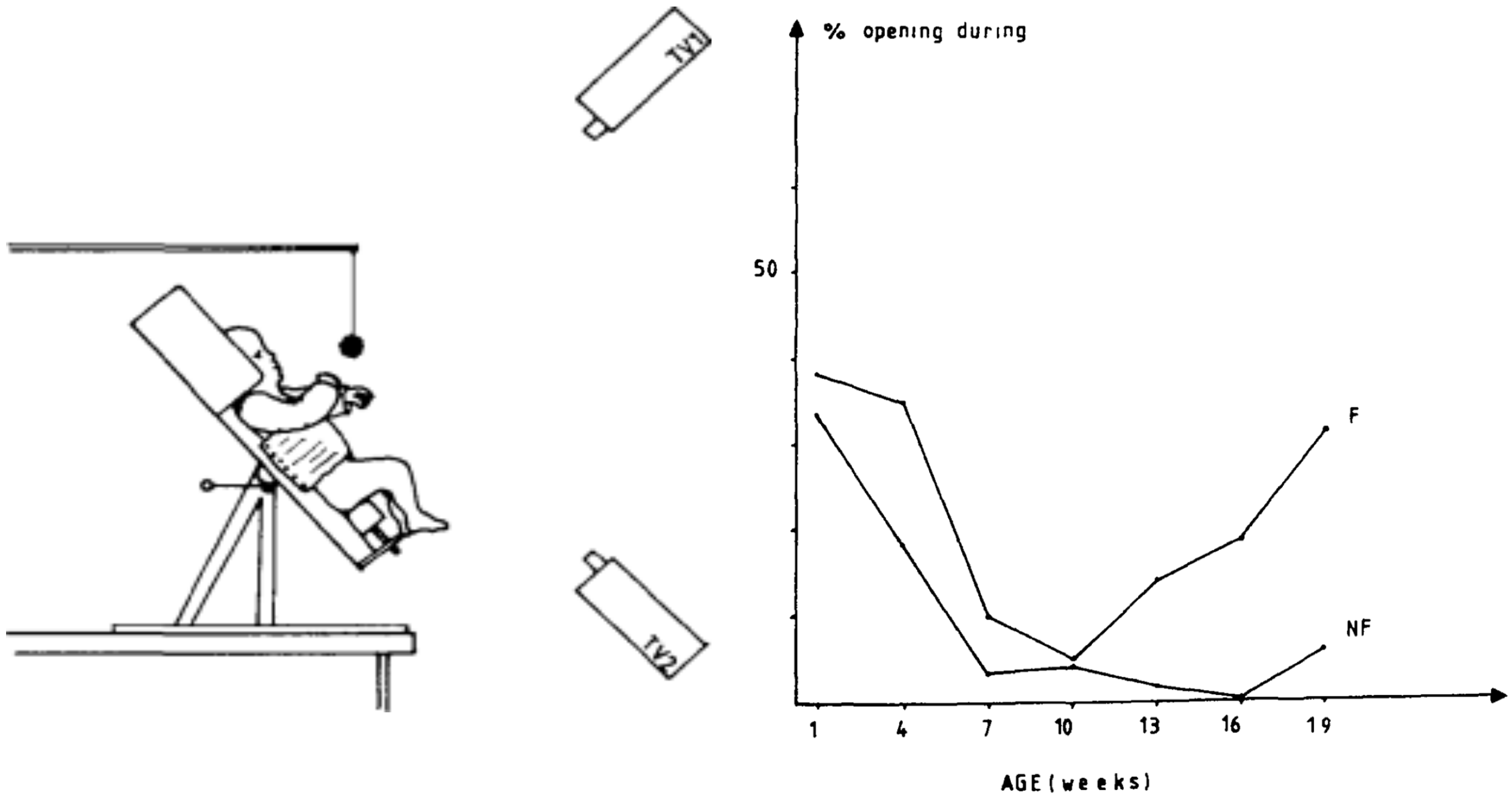
Age (months)	Competence
0-2 months	Grasp reflex Prereaching appears and increases in frequency
2-3 months	Prereaching declines in frequency
3-4 months	Onset of reaching (motor babbling) Hands held predominately open
4-6 months	Hand preshape emerges Palmar/power grasp
6-8 months	Radial-palmar grasp Scissor grasp Hand preshape predominates
8-12 months	Radial-digital grasp Pincer/precision grasp Online reach corrections
12-24 months	Adult-like reaching kinematics Prospective (pre-reach) arm control

Reaching and Motor Babbling

- Infant learns to control their bodies by actively generating trial-and-error arm movements
- Reaching U-shape development (von Hofsten, 1984)
  - “Prereaching” movements toward objects (0-2)
  - Decline of prereaching movements (2-3)
  - Reaching with grasp preshape, corrective movements (3+)

von Hofsten, Claes. "Developmental changes in the organization of prereaching movements." *Developmental psychology* 20.3 (1984): 378.

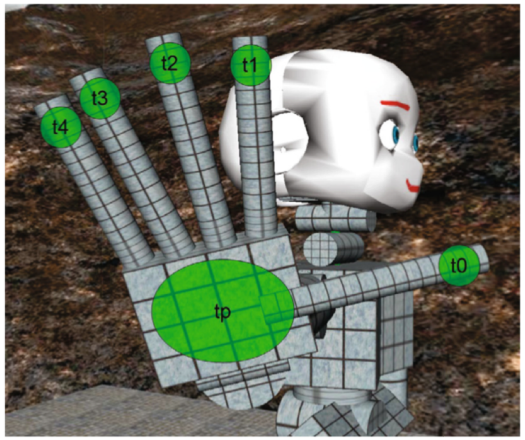
Reaching and Motor Babbling

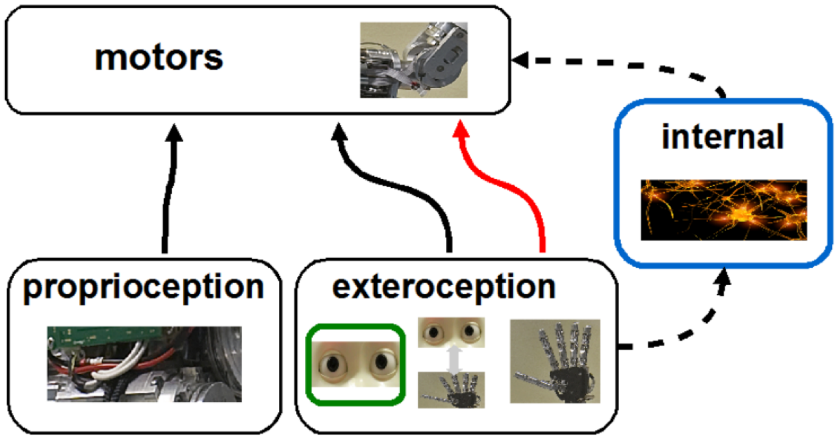


von Hofsten, Claes. "Developmental changes in the organization of prereaching movements." *Developmental psychology* 20.3 (1984): 378.

Evolutionary Robotics Reaching Model

- Replication of von Hofsten's study (Savastano & Nolfi 2012)
  - Simulated iCub and Genetic Algorithm for neural controller weights (aka evolutionary robotics)
  - Maturation model
    - Initial training with low-acuity visual input; gradually improves
    - Internal neurons for cortical control inactive until the midpoint of training



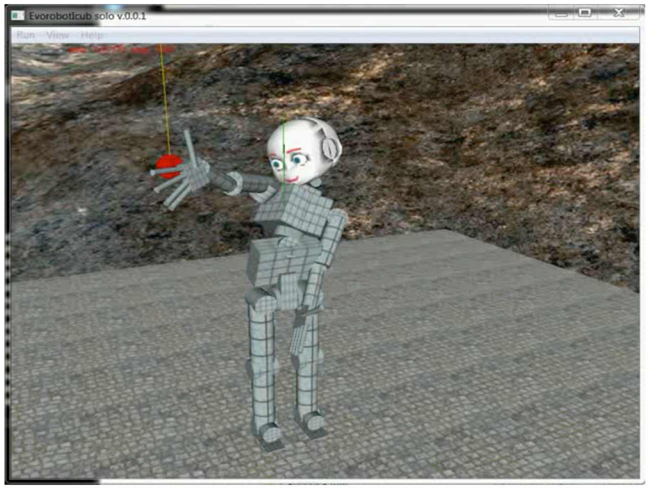


[Savastano & Nolfi (2012). Incremental learning in a simulated iCub robot: Modeling infant reach/grasp]

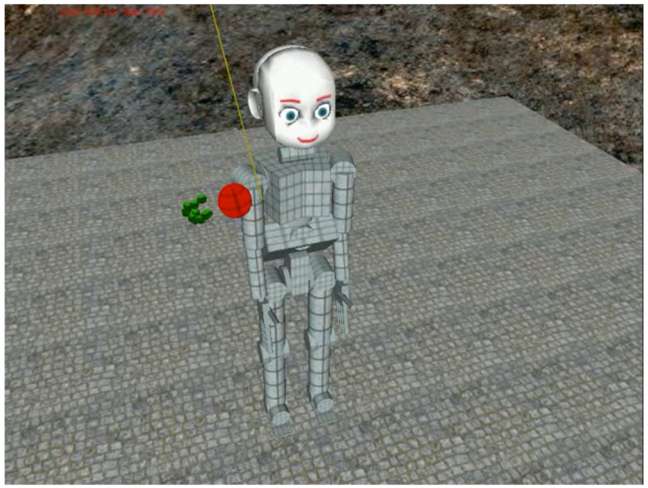
Robot Reaching Model

- Replication of von Hofsten's study (Savastano & Nolfi 2012)
  - Results
    - As visual acuity improves, percent of prereaches declines
    - With experience, reaches become progressively straighter, (as in Berthier & Keen 2006)
    - In non-incremental condition, reaching performance is lower

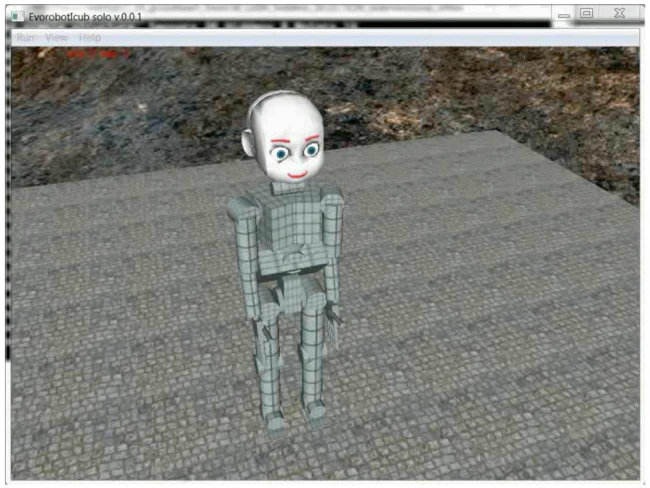
laral.istc.cnr.it/res/reachdev



Phase 1



Phase 2



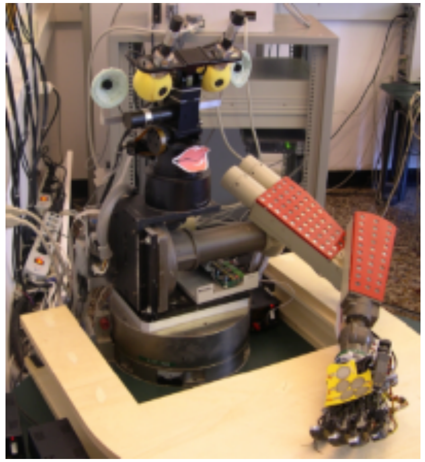
Phase 3

Visually Guided Reaching

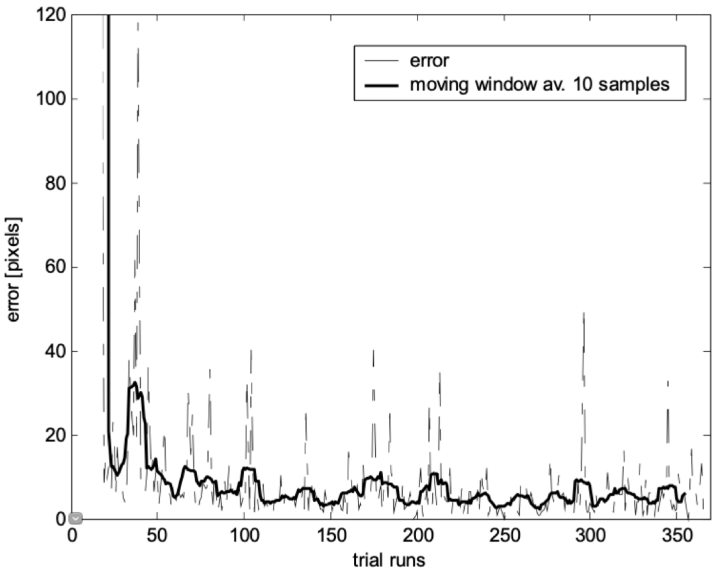
- Model
  - Direct gaze toward visual target (“foveate”)
  - Eye position = proprioceptive cue for target location
  - Learn mapping eye position - arm movement to target
    - ATNR Asymmetric Tonic Neck Reflex (“fencer’s pose”)
  - 4 DOF robotic platform
- Learned solution:
  - directing gaze to hand if in visual field (“hand regard”)
    - when the hand is fixated, the model quickly learns to calibrate the sensory maps that link eye and arm positions

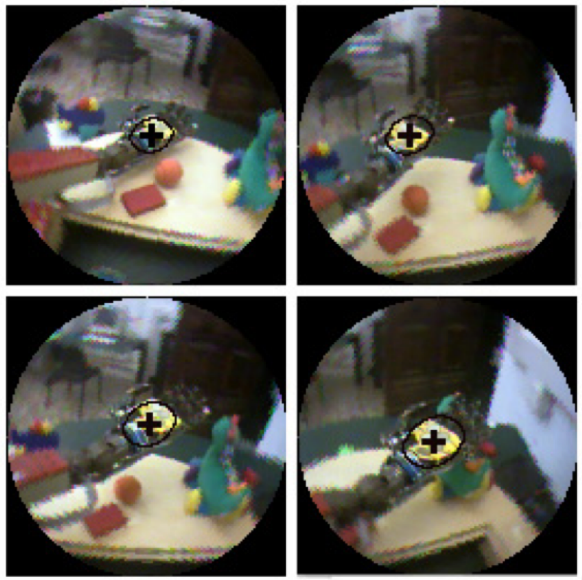
Metta, G., Sandini, G., & Konczak, J. (1999). A developmental approach to visually-guided reaching in artificial systems. *Neural networks*, *12*(10), 1413-1427.

Learning to Reach and Grasp



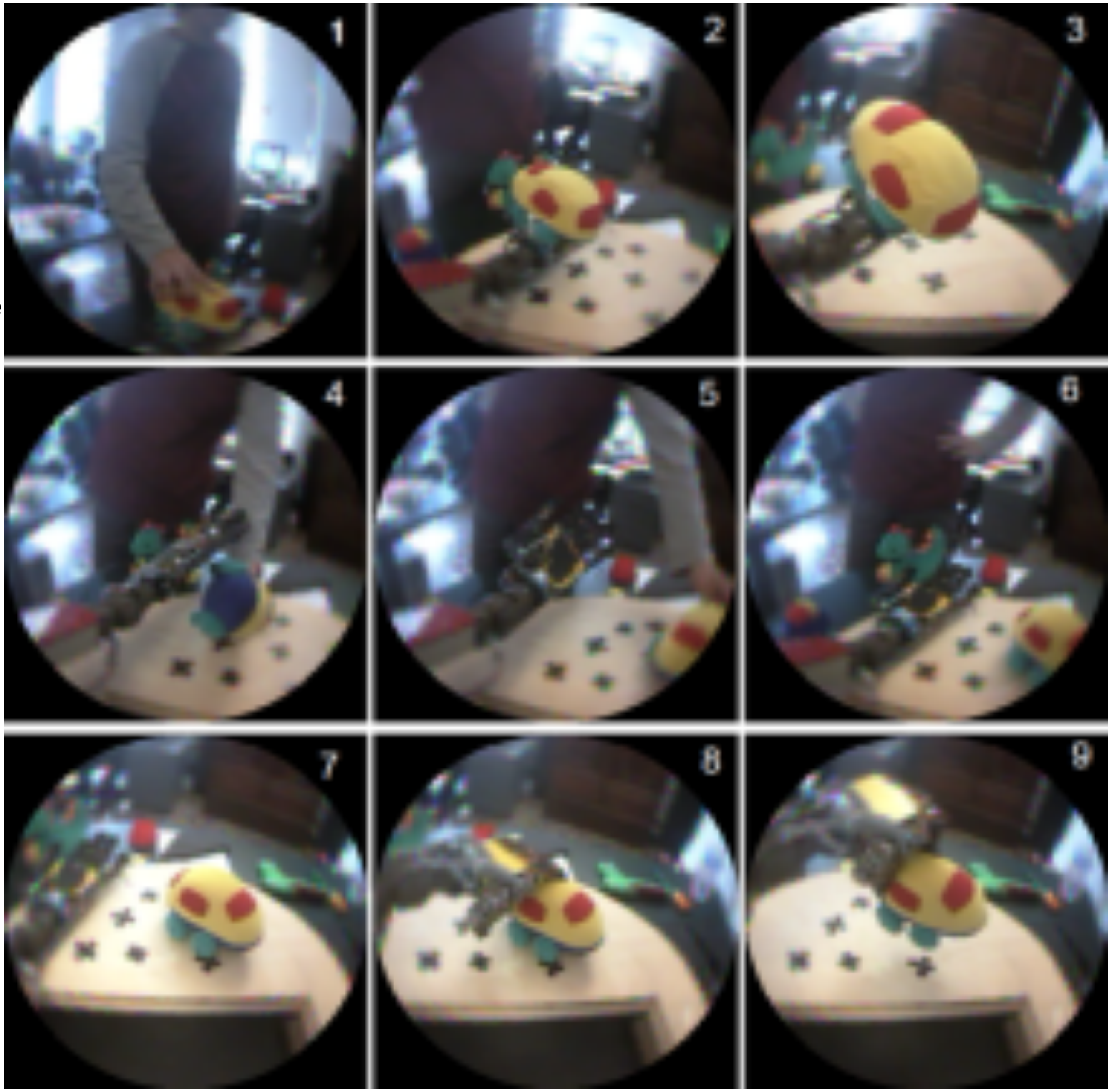
- Learning a body map
  - Babybot (precursor of iCub)
  - Motor babbling to learn to fixate its hand
- Learning to reach





[Natale, L., Metta, G., & Sandini, G. (2005, March). A developmental approach to grasping. In *Developmental robotics AAAI spring symposium* (Vol. 44)]

Learning to Reach and Grasp



Results

•1-3
Object placed in Babybot’s hand
(pre-programmed palmar grasp)
Object brought to visual field centre

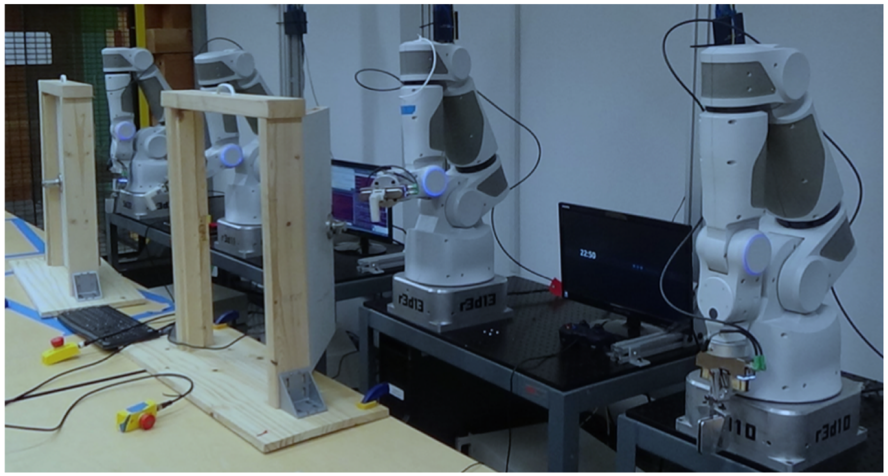
•4-6
Object returned to the workspace
Babybot searches for it

•7-9
Robot tocalises the object
Guides the hand toward object
Grasps it

Deep Learning for Manipulation

Deep Learning for Manipulation

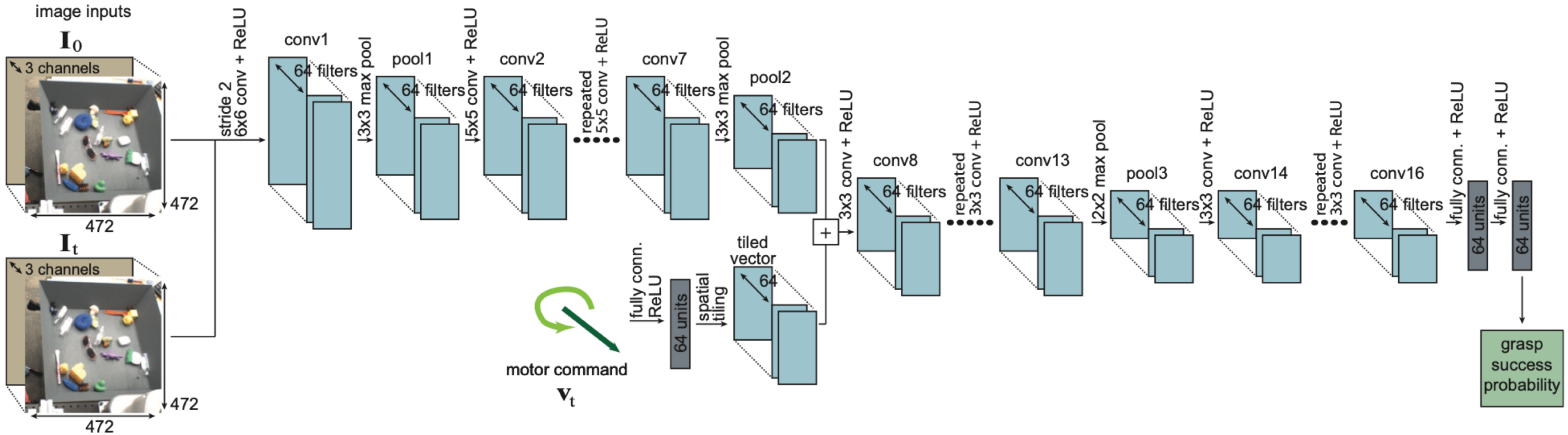
- Deep Q Reinforcement Learning (Gu et al. 2017)
  - Random target reaching and door opening
  - Parallelizing the algorithm across multiple robots, pooling their policy updates asynchronously
  - Training in simulation, then physical robot testing



Gu, S., Holly, E., Lillicrap, T., & Levine, S. (2017). Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates. *IEEE ICRA-2017*

Deep Learning for Grasping

- Hand-eye coordination for grasping (Levine et al. 2018)
  - 14 robots, 800,000 training grasp examples
  - CNN for grasp prediction (input: pregrasp and grasp images)
  - CNN then uses network to successful servo the gripper in real time



Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *IJRR*

Summary

- Types of manipulation actions
  - Reaching & Grasping
- Kinematics and dynamics
- Control: Closed vs. Open loop
- Developmental and deep learning models

- Reading
  - Choose one sample model do understand/discuss