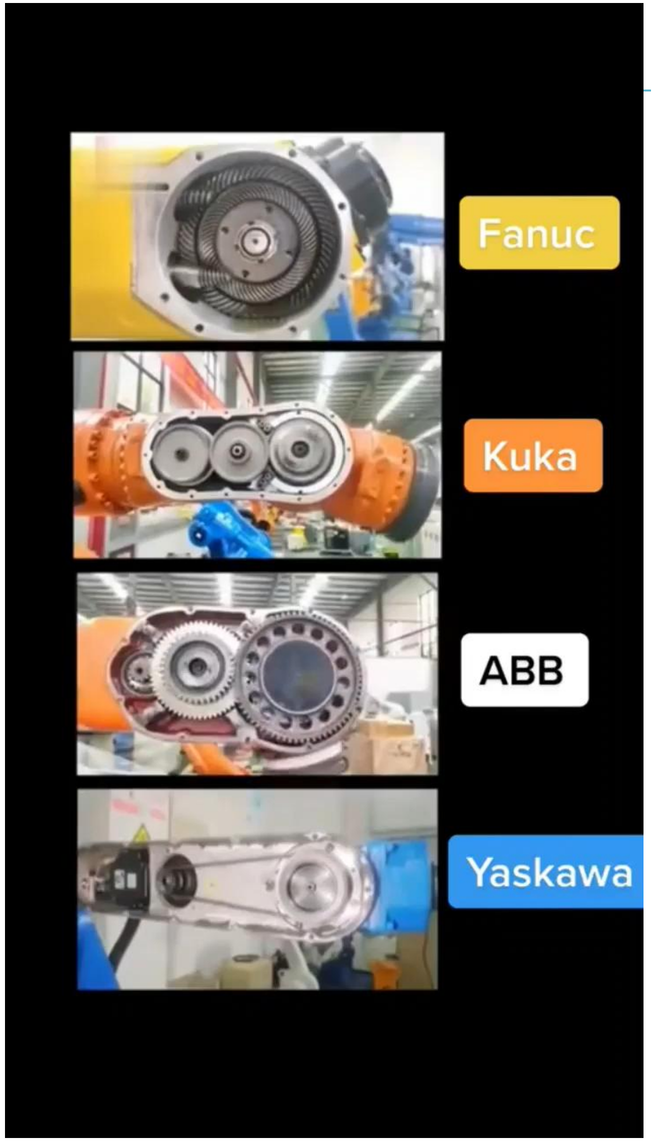
Mechatronics Engineering Department
Faculty of Engineering
Ain Shams University

MCT344/MCT342/CSE373/CSE471: Robotics

Lecture 13: Robot Control II

Presented by : Prof. Mohammed Ibrahim Awad

Robotic Mechanical Components



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https://www.youtube.com/shorts/80aE5XF4T2M

https://www.youtube.com/shorts/NtucDVCYnaw

Joint space control

Consideration #2

The diagonal of the matrix $\mathbf{M}(\mathbf{q})$ is composed by two kinds of elements

- Inertia terms that do not depend on the robot's configuration
- Terms that depend on the robot's configuration.

Therefore:

$$\mathbf{M}(\mathbf{q}) = \bar{\mathbf{M}} + \Delta\mathbf{M}(\mathbf{q})$$

where $\bar{\mathbf{M}}$ is a diagonal matrix with constant elements (i.e. the mean values of the joints inertia). From the robot dynamic model it follows

$$\boldsymbol{\tau}_m = (\mathbf{K}_r^{-1}\bar{\mathbf{M}}\mathbf{K}_r^{-1})\ddot{\mathbf{q}}_m + \mathbf{D}_m\dot{\mathbf{q}}_m + \mathbf{d}$$

where

$$\mathbf{D}_m = \mathbf{K}_r^{-1}\mathbf{D}\mathbf{K}_r^{-1}$$

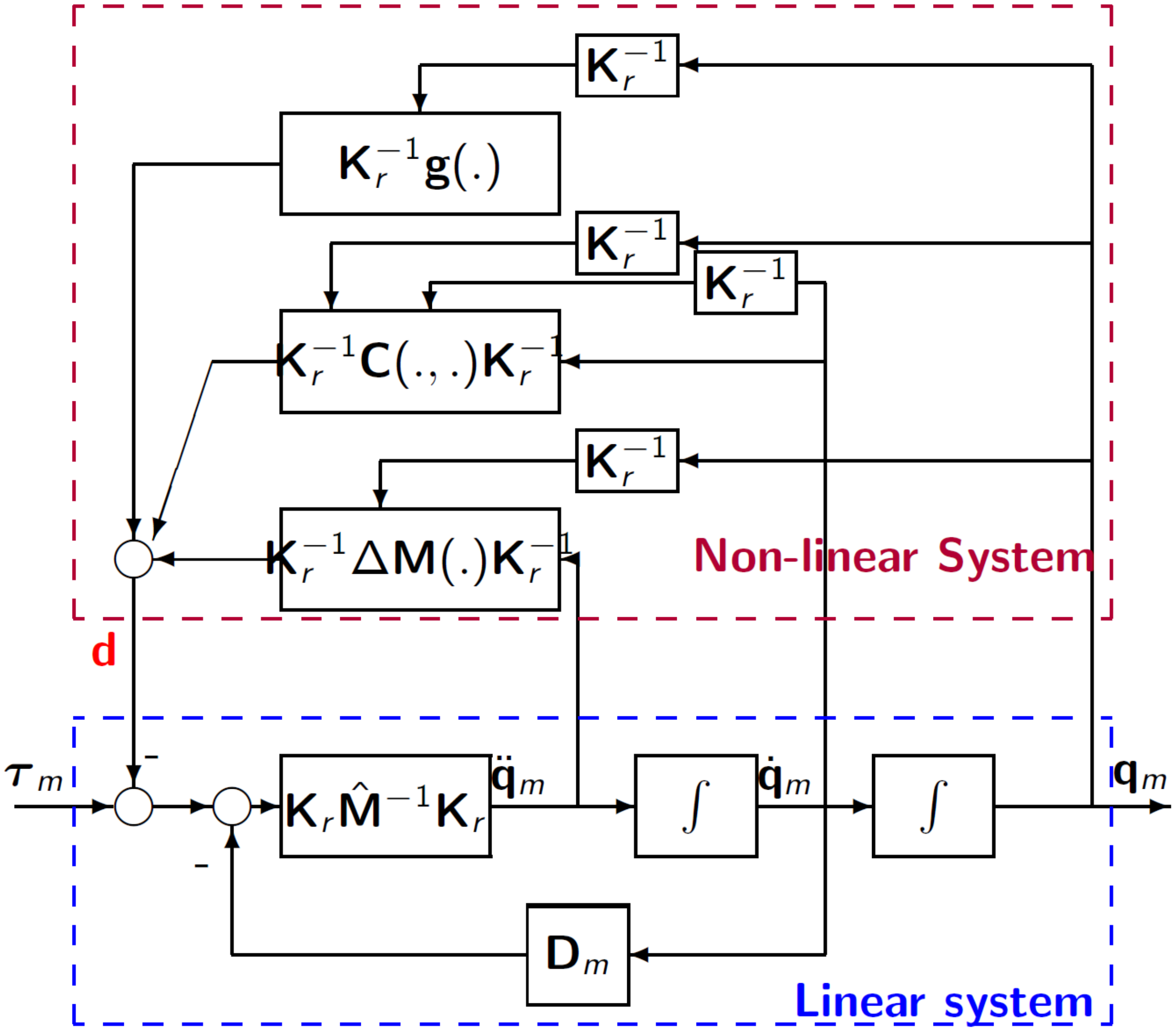
is the matrix collecting the motors friction coefficients, and

$$\mathbf{d} = (\mathbf{K}_r^{-1}\Delta\mathbf{M}(\mathbf{q})\mathbf{K}_r^{-1})\ddot{\mathbf{q}}_m + (\mathbf{K}_r^{-1}\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\mathbf{K}_r^{-1})\dot{\mathbf{q}}_m + \mathbf{K}_r^{-1}\mathbf{g}(\mathbf{q})$$

is a term that can be considered as a disturbance.

Joint space control

$$\ddot{\mathbf{q}}_m = \mathbf{K}_r \hat{\mathbf{M}}^{-1} \mathbf{K}_r (\tau_m - \mathbf{D}_m \dot{\mathbf{q}}_m - \mathbf{d}) \Longrightarrow$$



A manipulator (+ the actuation system) can be regarded as the composition of:

- a system with input $\ddot{\mathbf{q}}_m, \dot{\mathbf{q}}_m, \mathbf{q}_m$ and output $\mathbf{d}$, *non linear and with couplings*
- a system with input τ_m and output $\mathbf{q}_m$, *linear and decoupled*

Centralized control

Dynamic model of a manipulator:

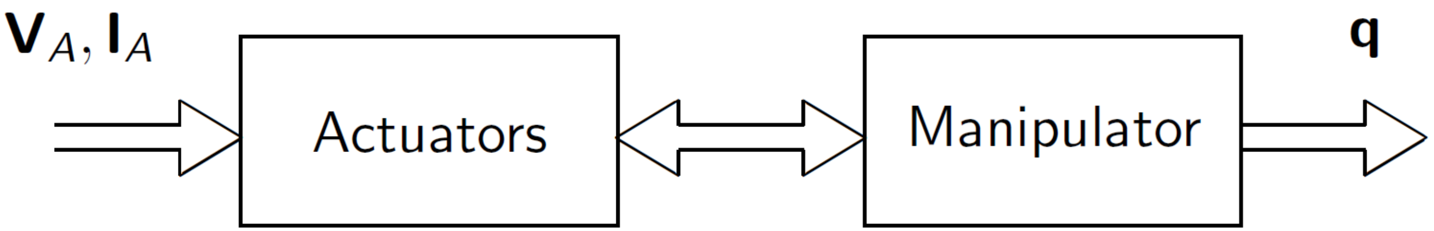
$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{D}_v\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}$$

Actuators and gearboxes may be described by:

$$\begin{aligned}
\mathbf{K}_r\mathbf{q} &= \mathbf{q}_m \\
\mathbf{v}_A &= \mathbf{G}_v\mathbf{v}_c \\
\mathbf{v}_A &= \mathbf{R}_A\mathbf{I}_A + \mathbf{K}_v\dot{\mathbf{q}}_m \\
\boldsymbol{\tau}_m &= \mathbf{K}_t\mathbf{I}_A = \mathbf{K}_r^{-1}\boldsymbol{\tau}
\end{aligned}$$

where $\mathbf{K}_r$ is the matrix with the reduction coefficients; $\mathbf{G}_v$ the gain of the motor drives; $\mathbf{R}_A$ the armature resistances; $\mathbf{K}_v, \mathbf{K}_t$ the electro-mechanic constants of the motors.

Consider the manipulator as a MIMO system with n input and n output.



Centralized control

Voltage control mode:

$$\begin{aligned} \mathbf{I}_A &= \mathbf{R}_A^{-1}(\mathbf{v}_A - \mathbf{K}_v\dot{\mathbf{q}}_m) \\ &= \mathbf{R}_A^{-1}\mathbf{G}_v\mathbf{v}_c - \mathbf{R}_A^{-1}\mathbf{K}_v\mathbf{K}_r\dot{\mathbf{q}} \end{aligned}$$

$$\begin{aligned} \boldsymbol{\tau} &= \mathbf{K}_r\mathbf{K}_t\mathbf{I}_A \\ &= \mathbf{K}_r\mathbf{K}_t\mathbf{R}_A^{-1}\mathbf{G}_v\mathbf{v}_c - \mathbf{K}_r\mathbf{K}_t\mathbf{R}_A^{-1}\mathbf{K}_v\mathbf{K}_r\dot{\mathbf{q}} \end{aligned}$$

Thus, the robot dynamic equaiton becomes:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{D}\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{u}$$

where

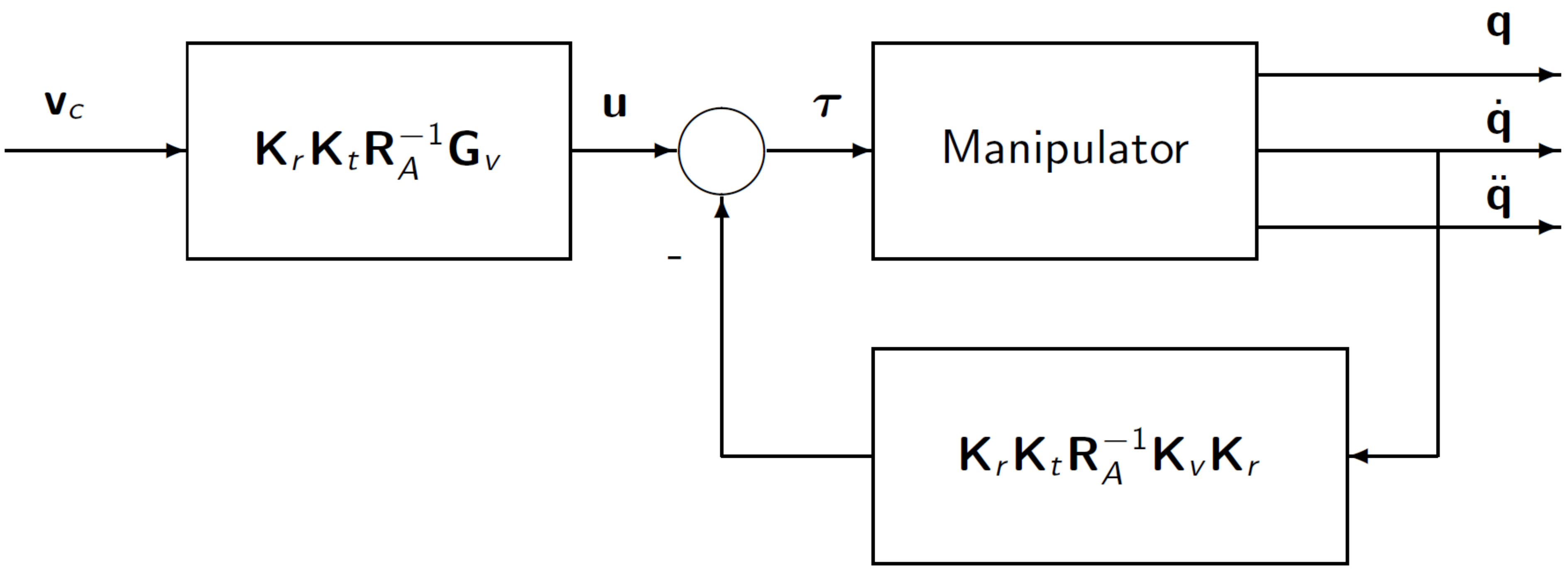
$$\begin{aligned} \mathbf{D} &= \mathbf{D}_v + \mathbf{K}_r\mathbf{K}_t\mathbf{R}_A^{-1}\mathbf{K}_v\mathbf{K}_r & \Longrightarrow & \quad \text{diagonal matrix with friction terms} \\ \mathbf{u} &= \mathbf{K}_r\mathbf{K}_t\mathbf{R}_A^{-1}\mathbf{G}_v\mathbf{v}_c & \Longrightarrow & \quad \text{control input} \end{aligned}$$

Centralized control

Manipulator dynamic model:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{D}\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{u}$$

The torque $\boldsymbol{\tau}$ (real input generating the motion of the manipulator) is not equal to $\mathbf{u}$ (algebraically related to $\mathbf{v}_c$) because of the counter-electromotive force proportional to the joints velocity $\dot{\mathbf{q}}$.



Centralized control

Torque control mode: With the voltage-control mode, it is not possible to directly provide to the joints the exact torques needed to move the robot (complex computation should be introduced to compensate for the velocity-dependent terms). It is preferable to use for the motor a current-control modality: the actuator acts as a torque generator.

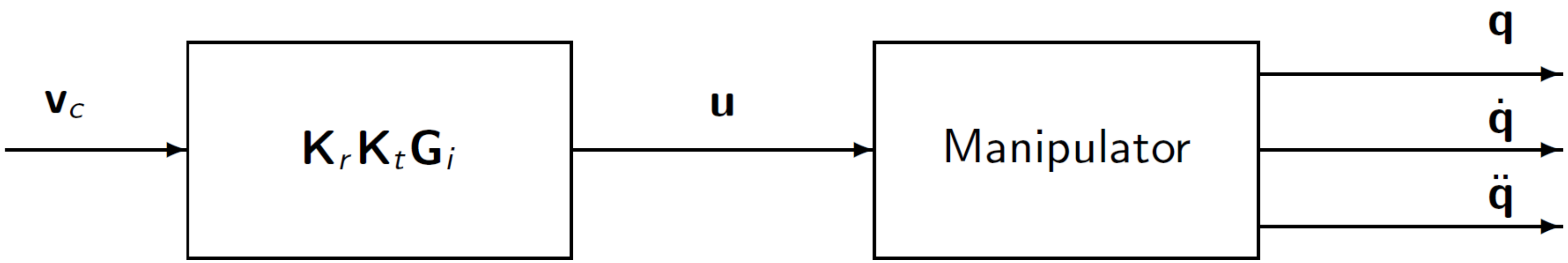
$$\mathbf{I}_A = \mathbf{G}_i \; \mathbf{v}_c$$

It follows:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{D}\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{u}$$

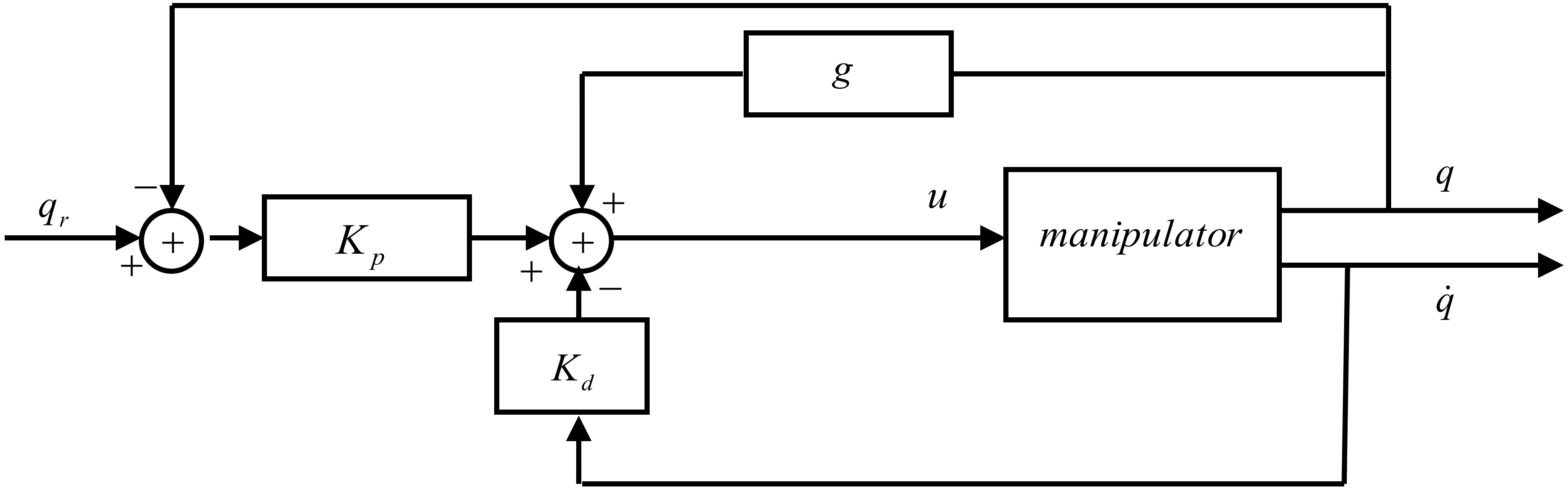
where

$$\mathbf{D} = \mathbf{D}_v \qquad \mathbf{u} = \mathbf{K}_r\mathbf{K}_t\mathbf{G}_i\mathbf{v}_c$$



Compensating for gravity

PD rate feedback control (notice no integrator):



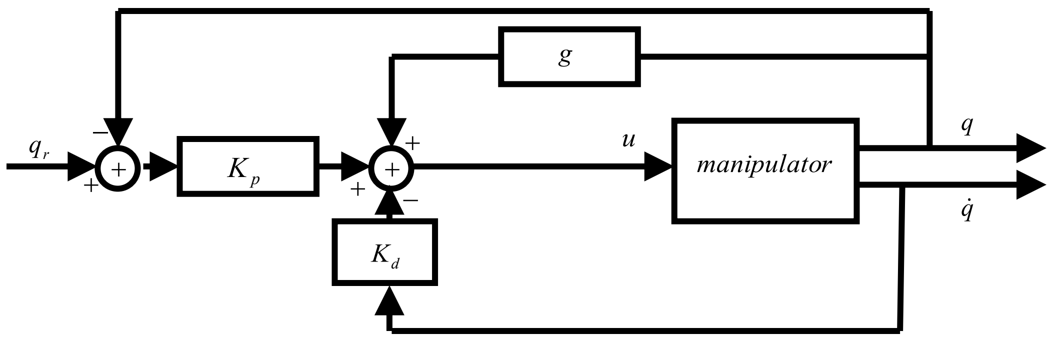
$$u = g(q) + K_p(q_d - q) - K_d\dot{q}$$ where $$g = \sum_{i=1}^{n} m_i g^T \frac{\partial p_i}{\partial q_k}$$

$$M(q)\ddot{q}_i + C(q,\dot{q})\dot{q}_i + g(q) = u$$

$$M(q)\ddot{q}_i + C(q,\dot{q})\dot{q}_i + g(q) = g(q) + K_p(q_d - q) - K_d\dot{q}$$

At equilibrium: $K_p(q_d - q) = 0$

Compensating for gravity



$$u = g(q) + K_p(q_d - q) - K_d\dot{q}$$

$$M(q)\ddot{q}_i + C(q,\dot{q})\dot{q}_i + g(q) = u$$

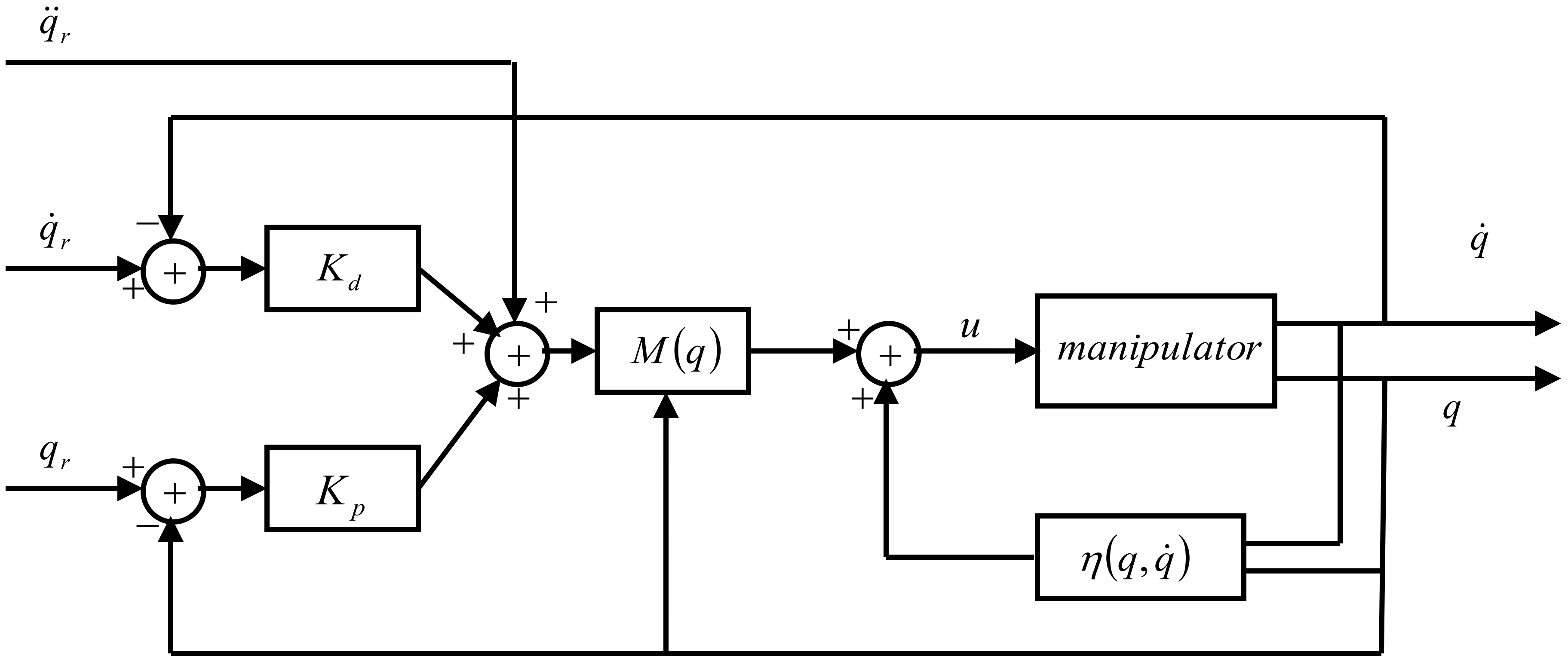
$$M(q)\ddot{q}_i + C(q,\dot{q})\dot{q}_i + g(q) = g(q) + K_p(q_d - q) - K_d\dot{q}$$

Resulting equation of motion:

$$M(q)\ddot{q}_i + (C(q,\dot{q}) - K_d)\dot{q}_i + K_p(q_d - q) = 0$$

At equilibrium: $K_p(q_d - q) = 0$

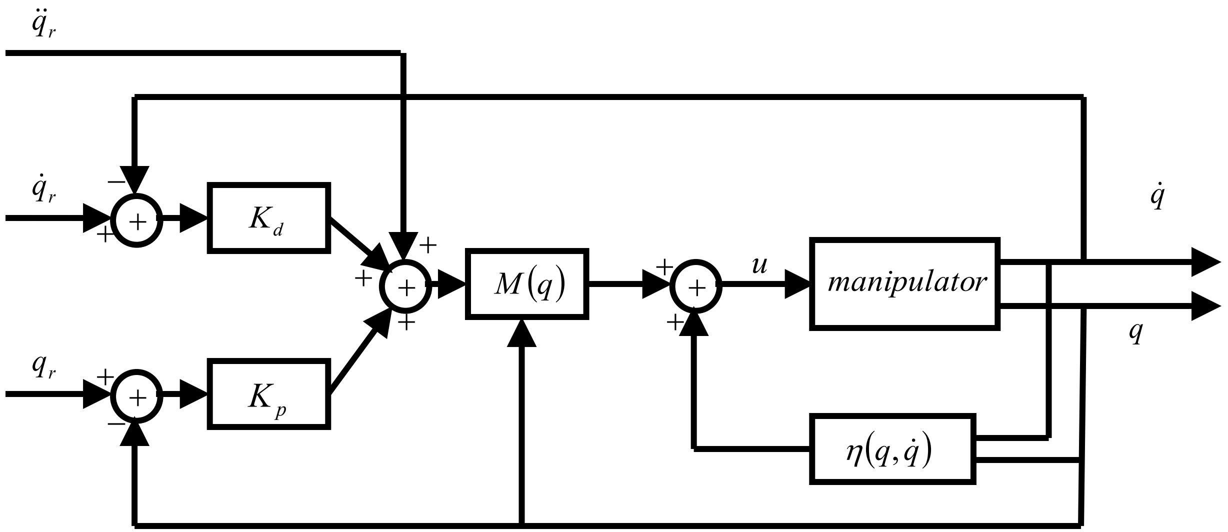
Inverse dynamics control



$$M(q)\ddot{q}_i + C(q,\dot{q})\dot{q}_i + g(q) = u$$

$$u = M(q)\left[\ddot{q}_d + K_d(\dot{q}_d - \dot{q}) + K_p(q_d - q)\right] + C(q,\dot{q})\dot{q}_i + g(q)$$

Inverse dynamics control



$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = u$$

$$u = M(q)\left[\ddot{q}_d + K_d(\dot{q}_d - \dot{q}) + K_p(q_d - q)\right] + C(q,\dot{q})\dot{q} + g(q)$$

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = M(q)\left[\ddot{q}_d + K_d(\dot{q}_d - \dot{q}) + K_p(q_d - q)\right] + C(q,\dot{q})\dot{q} + g(q)$$

$$(\ddot{q}_d - \ddot{q}) + K_d(\dot{q}_d - \dot{q}) + K_p(q_d - q) = 0$$

Force and Interaction Control

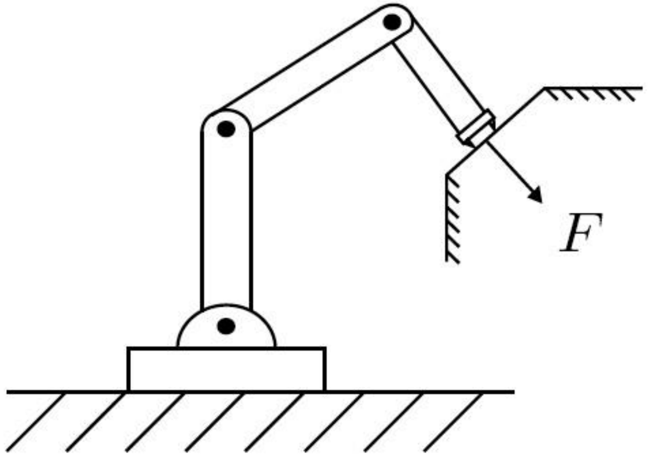


Figure 9.2: Robot end effector in contact with a rigid surface.

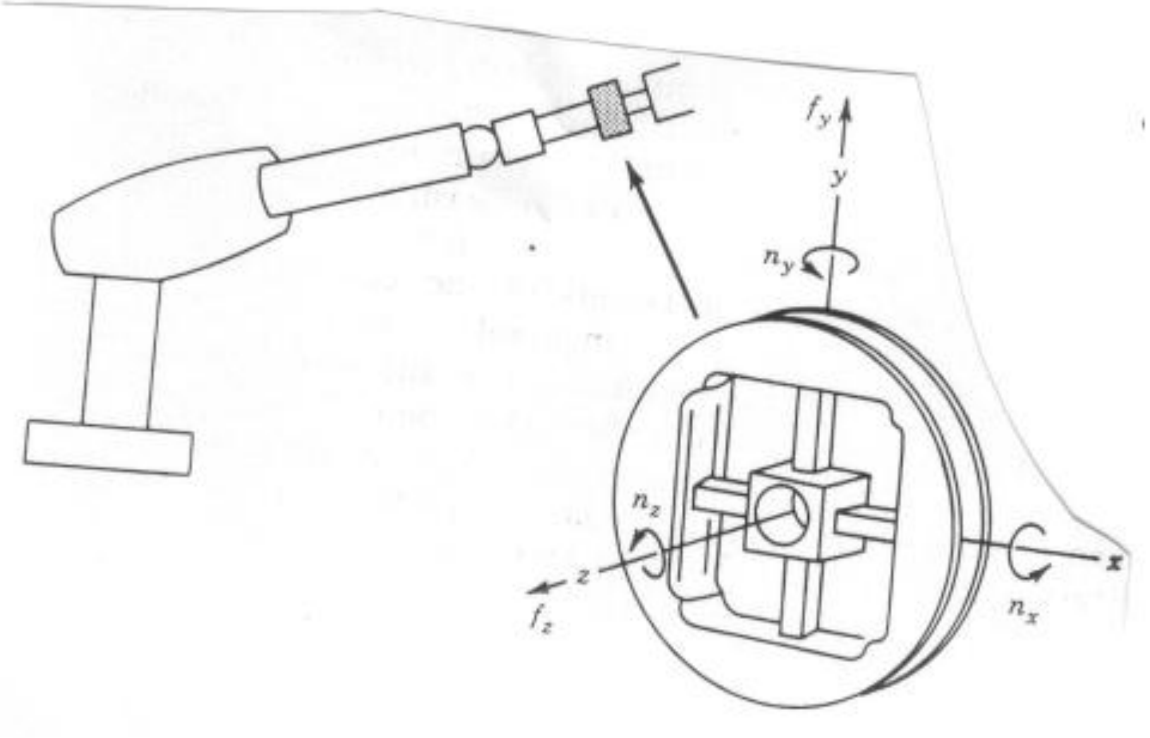
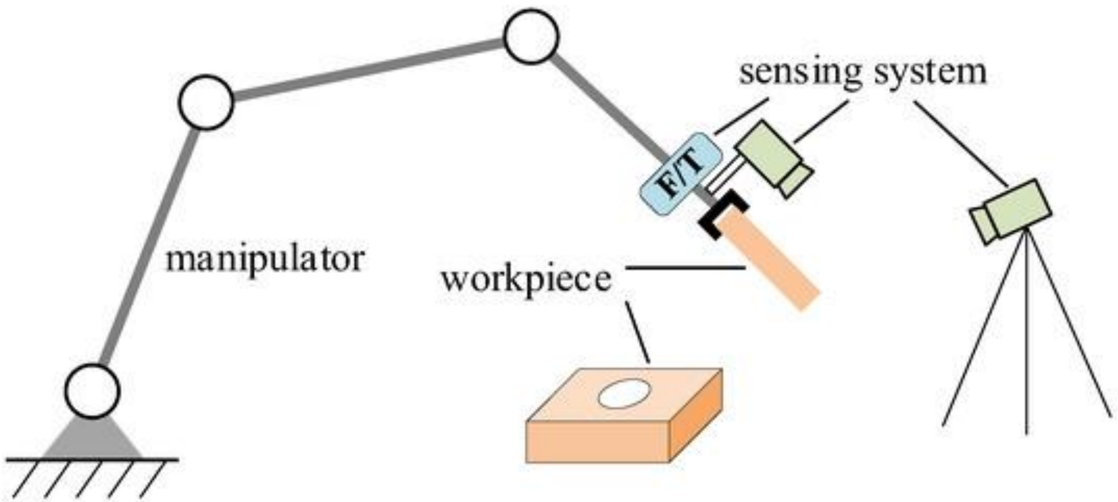
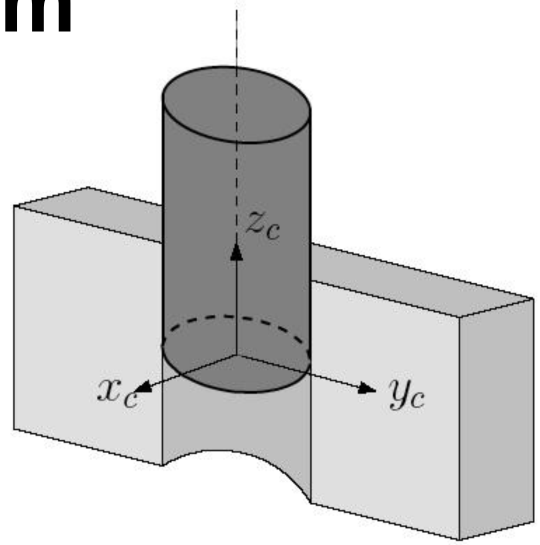


Fig. 9.1 A Wrist Force Sensor.

Peg and Hole Assembly Problem





Natural Constraints	Artificial Constraints
$v_x = 0$	$f_x = 0$
$v_y = 0$	$f_y = 0$
$f_z = 0$	$v_z = v_d$
$\omega_x = 0$	$n_x = 0$
$\omega_y = 0$	$n_y = 0$
$n_z = 0$	$\omega_z = 0$

Figure 9.3: Inserting a peg into a hole.

Peg and Hole Assembly Problem

Performance Analysis of a Robotics Vision System and Localization using Fusion of Vision and Force/Torque Data for Robotic Assembly

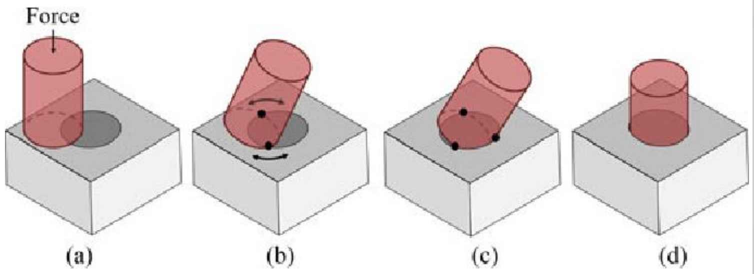
Riby Abraham Boby and Karam Almaghout

Innopolis University

2021

https://www.youtube.com/watch?v=00od51vy7W8

Hole search strategy



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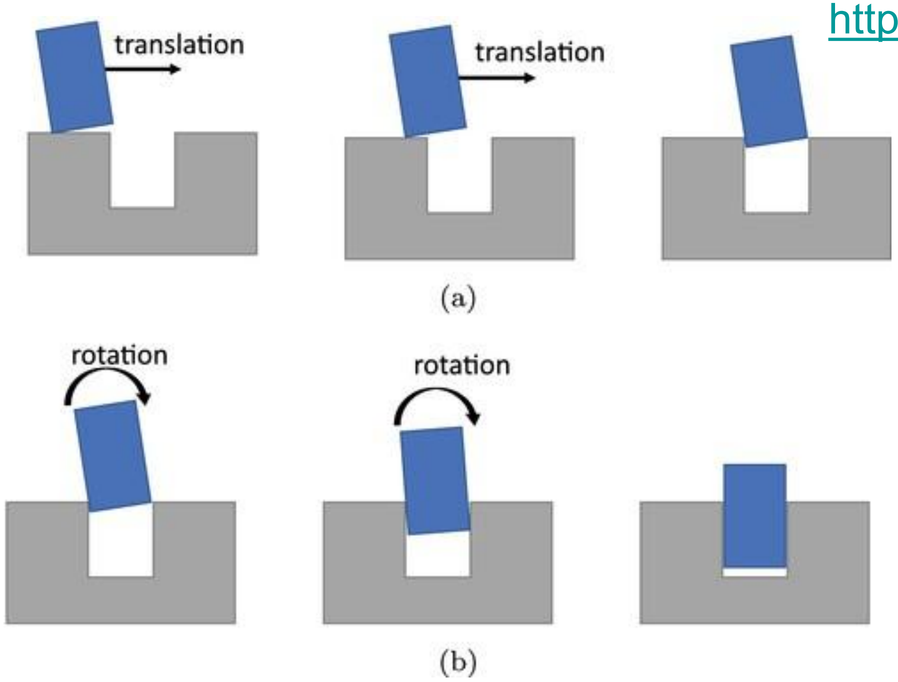

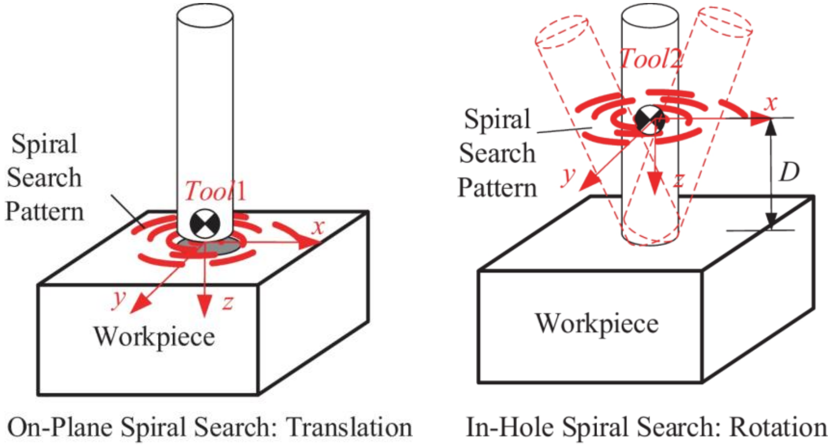

https://www.youtube.com/shorts/stHFbmHeJ9Q

Peg-In-Hole Using 3D Workpiece Reconstruction and CNN-Based Hole Detection

https://www.youtube.com/watch?v=I7Ujij0Y81g

Robot Manipulation: Meta Learning and Aaptive Control

A Framework for Robot Manipulation:
Skill Formalism, Meta Learning and Adaptive Control

Lars Johannsmeier, Malkin Gerchow and Sami Haddadin

Institute of Automatic Control
Gottfried Wilhelm Leibniz Universität Hannover

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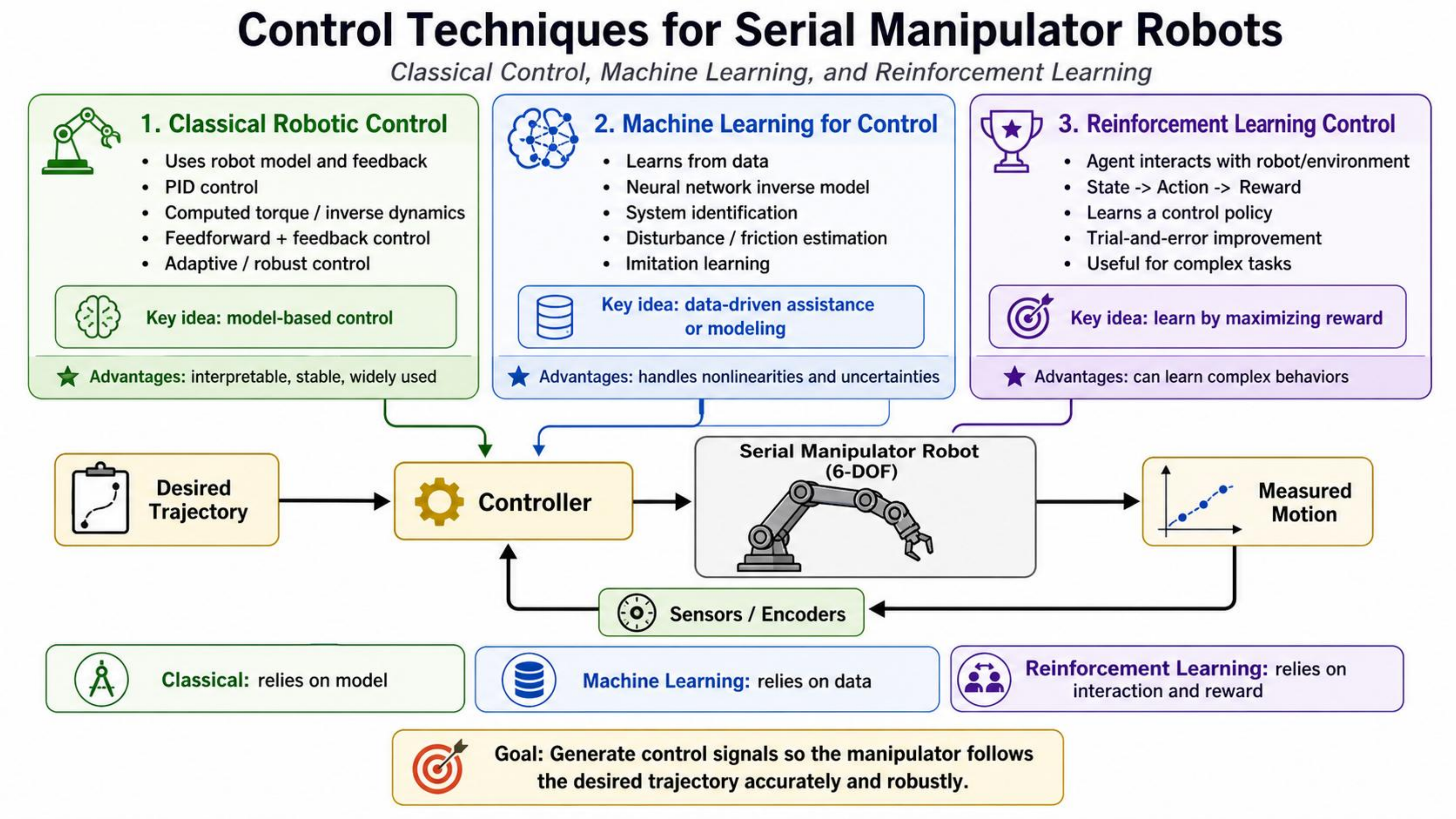
Leibniz Universität Hannover

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



Control Techniques for Serial Manipulator Robots
Classical Control, Machine Learning, and Reinforcement Learning
1. Classical Robotic Control
• Uses robot model and feedback
• PID control
• Computed torque / inverse dynamics
• Feedforward + feedback control
• Adaptive / robust control
Key idea: model-based control
Advantages: interpretable, stable, widely used
2. Machine Learning for Control
• Learns from data
• Neural network inverse model
• System identification
• Disturbance / friction estimation
• Imitation learning
Key idea: data-driven assistance or modeling
Advantages: handles nonlinearities and uncertainties
3. Reinforcement Learning Control
• Agent interacts with robot/environment
• State -> Action -> Reward
• Learns a control policy
• Trial-and-error improvement
• Useful for complex tasks
Key idea: learn by maximizing reward
Advantages: can learn complex behaviors
Desired Trajectory
Controller
Serial Manipulator Robot (6-DOF)
Measured Motion
Sensors / Encoders
Classical: relies on model
Machine Learning: relies on data
Reinforcement Learning: relies on interaction and reward
Goal: Generate control signals so the manipulator follows the desired trajectory accurately and robustly.

https://www.youtube.com/shorts/CbLxJjsm2iA

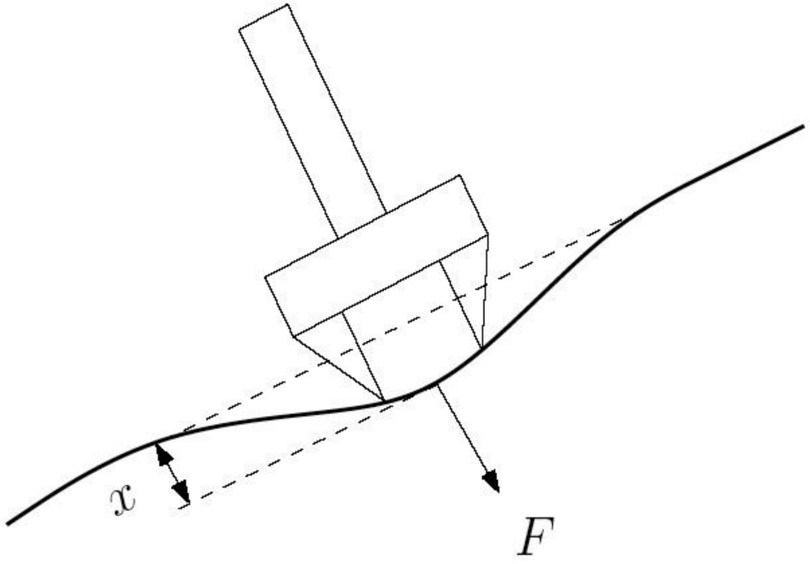
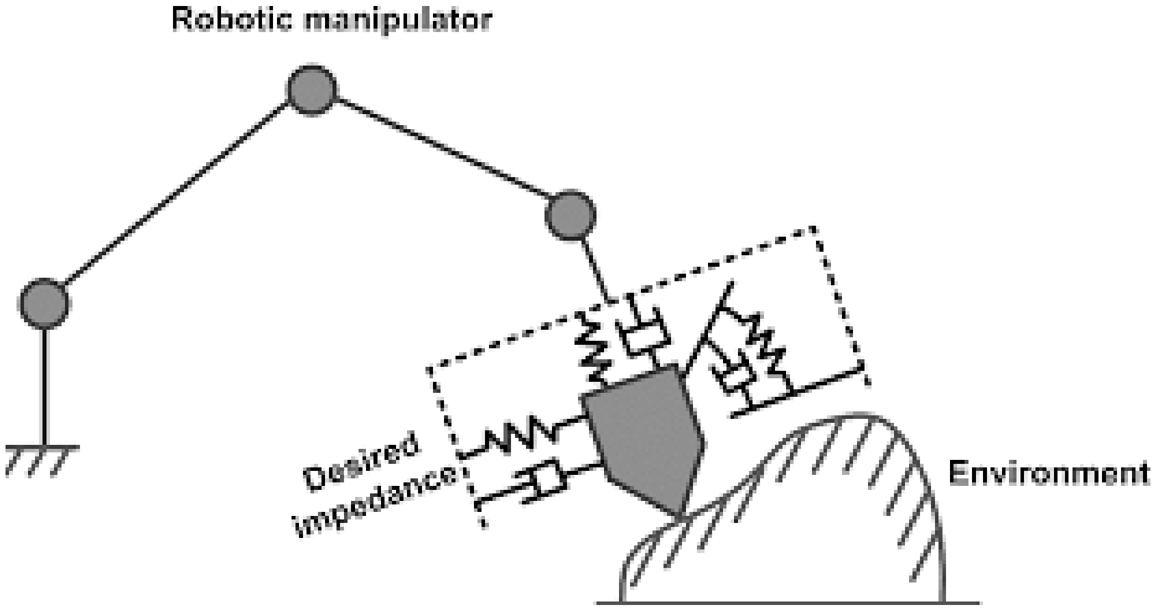
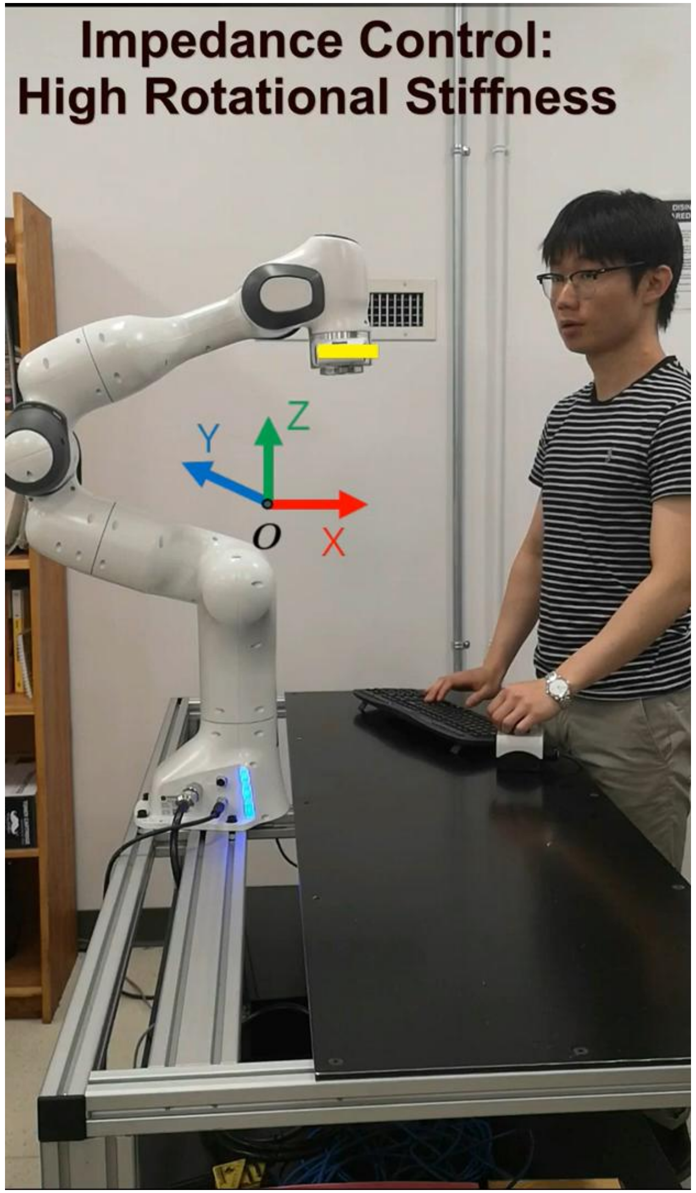
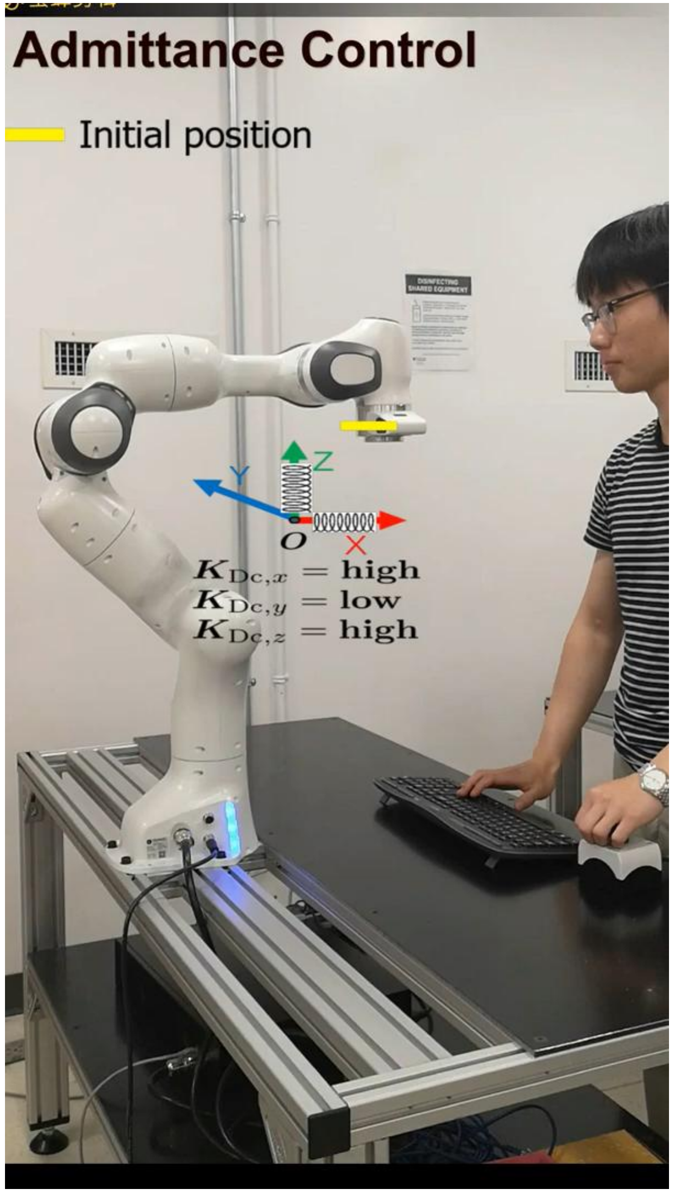


Figure 9.5: Compliant environment.



Impedance Control





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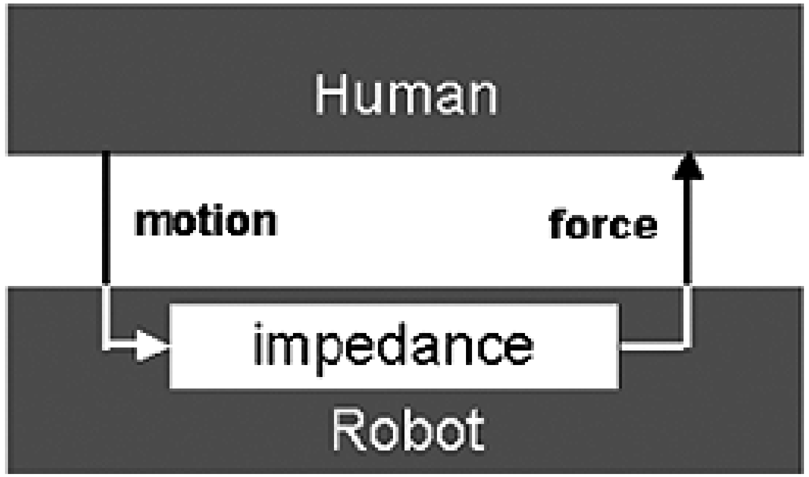
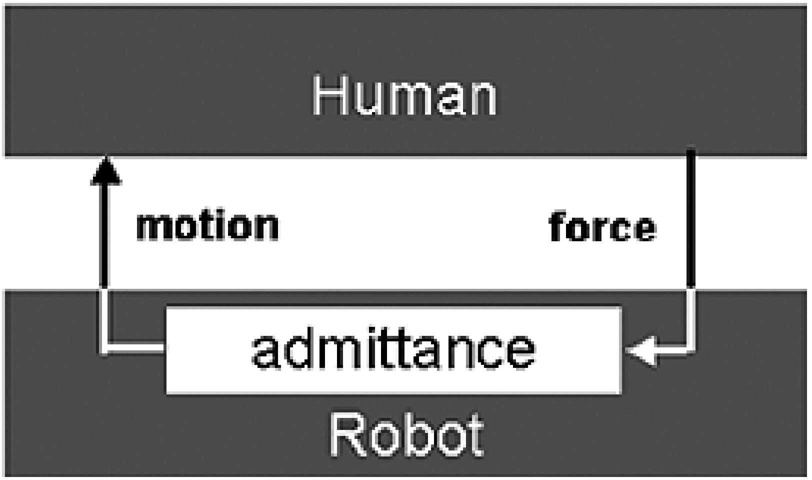
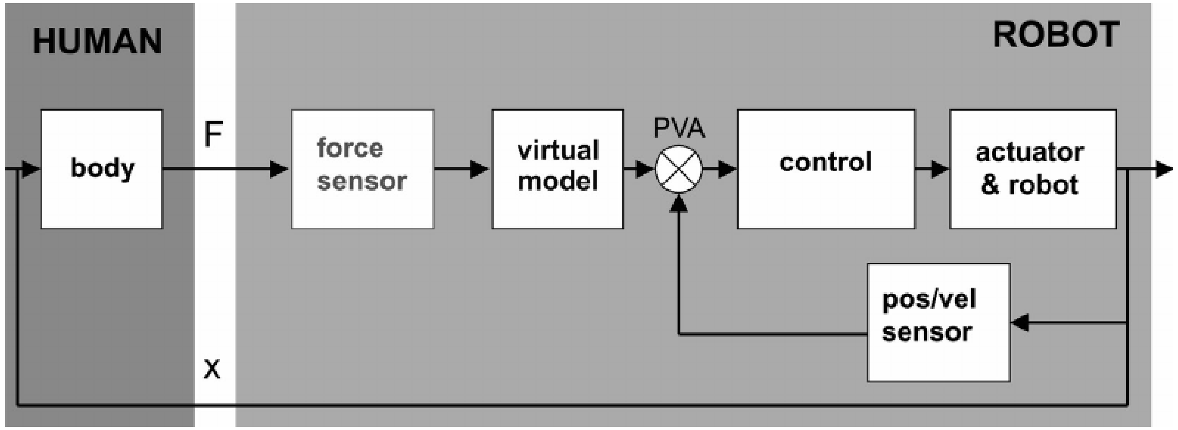
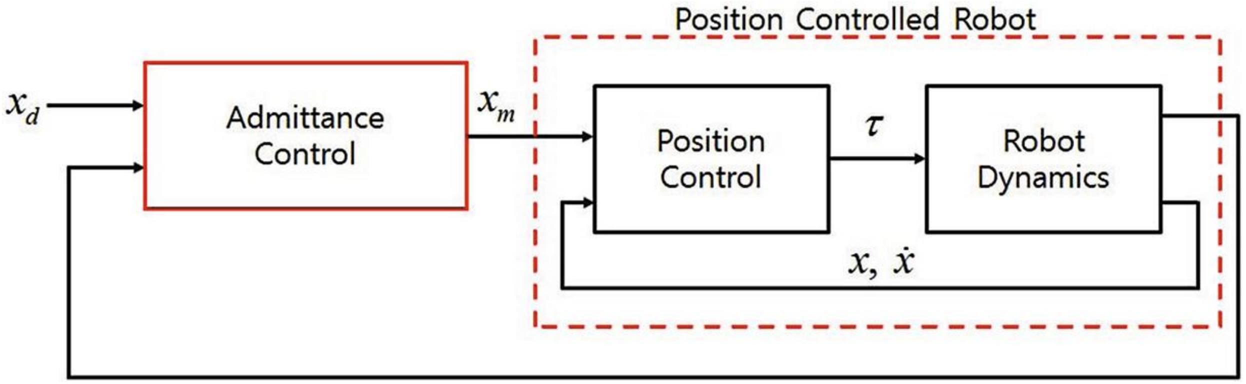
https://www.youtube.com/shorts/cnFiTKgqB9M

Impedance Control Vs Admittance Control

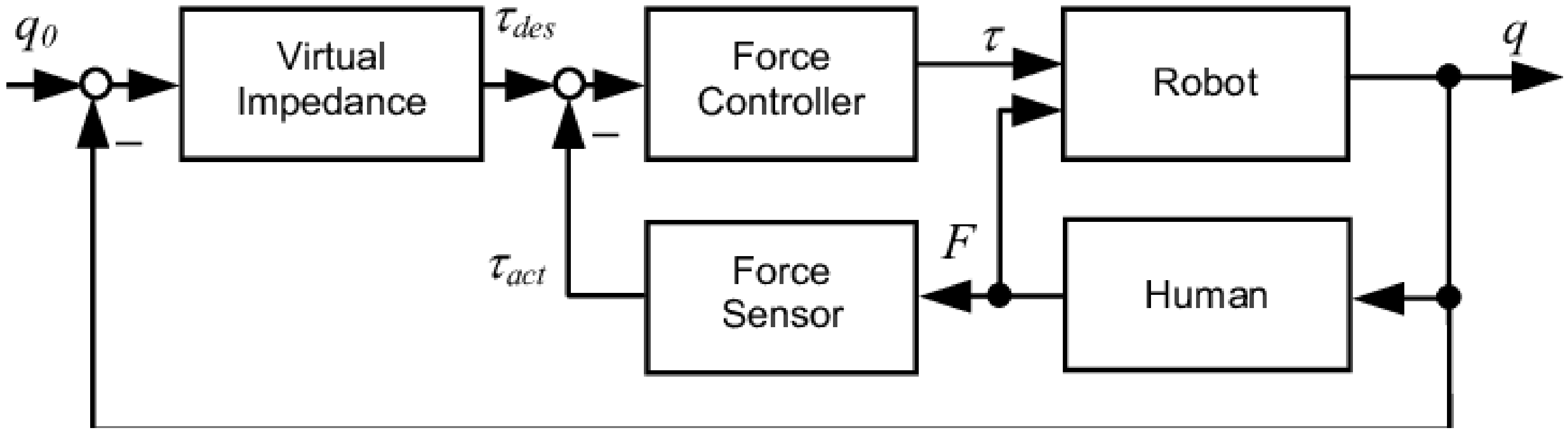


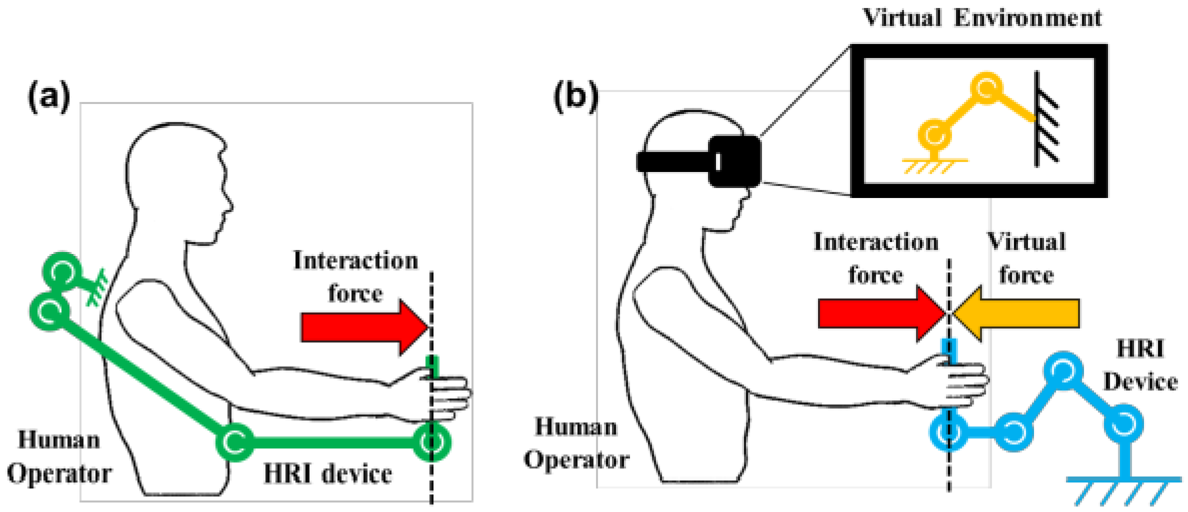


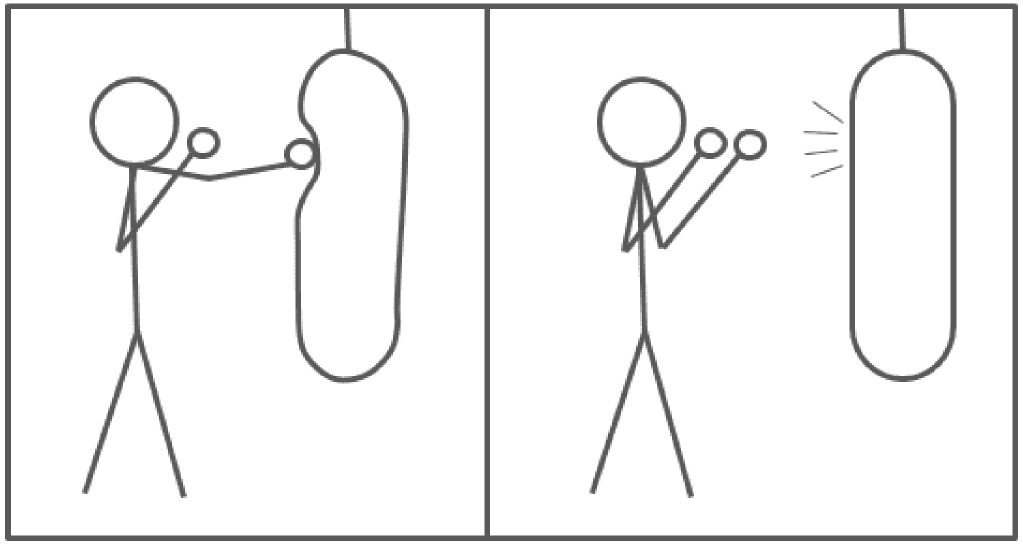




Impedance Control







Robot can be controlled to act as:

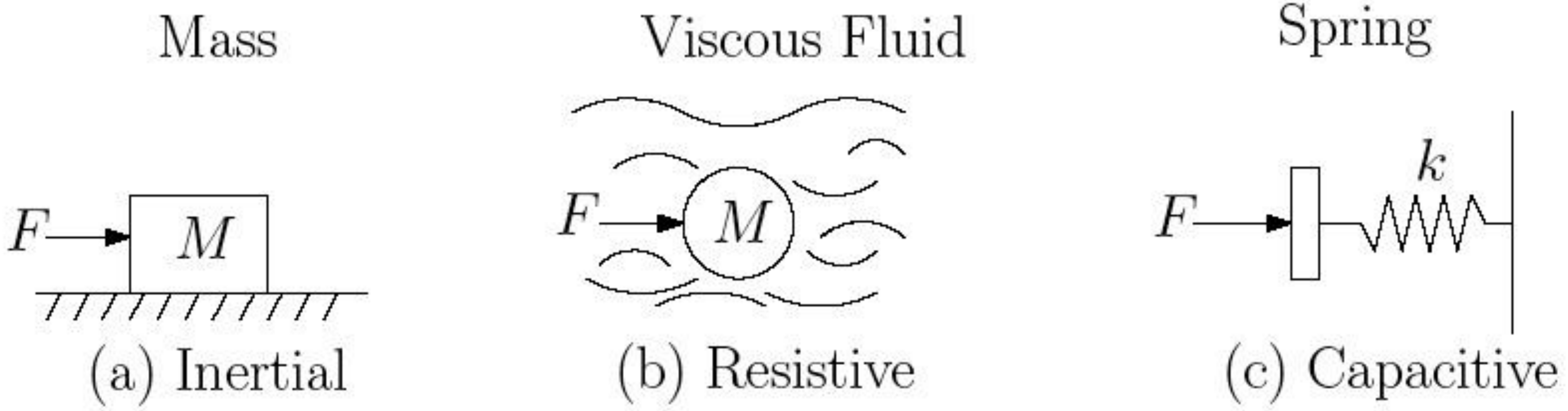
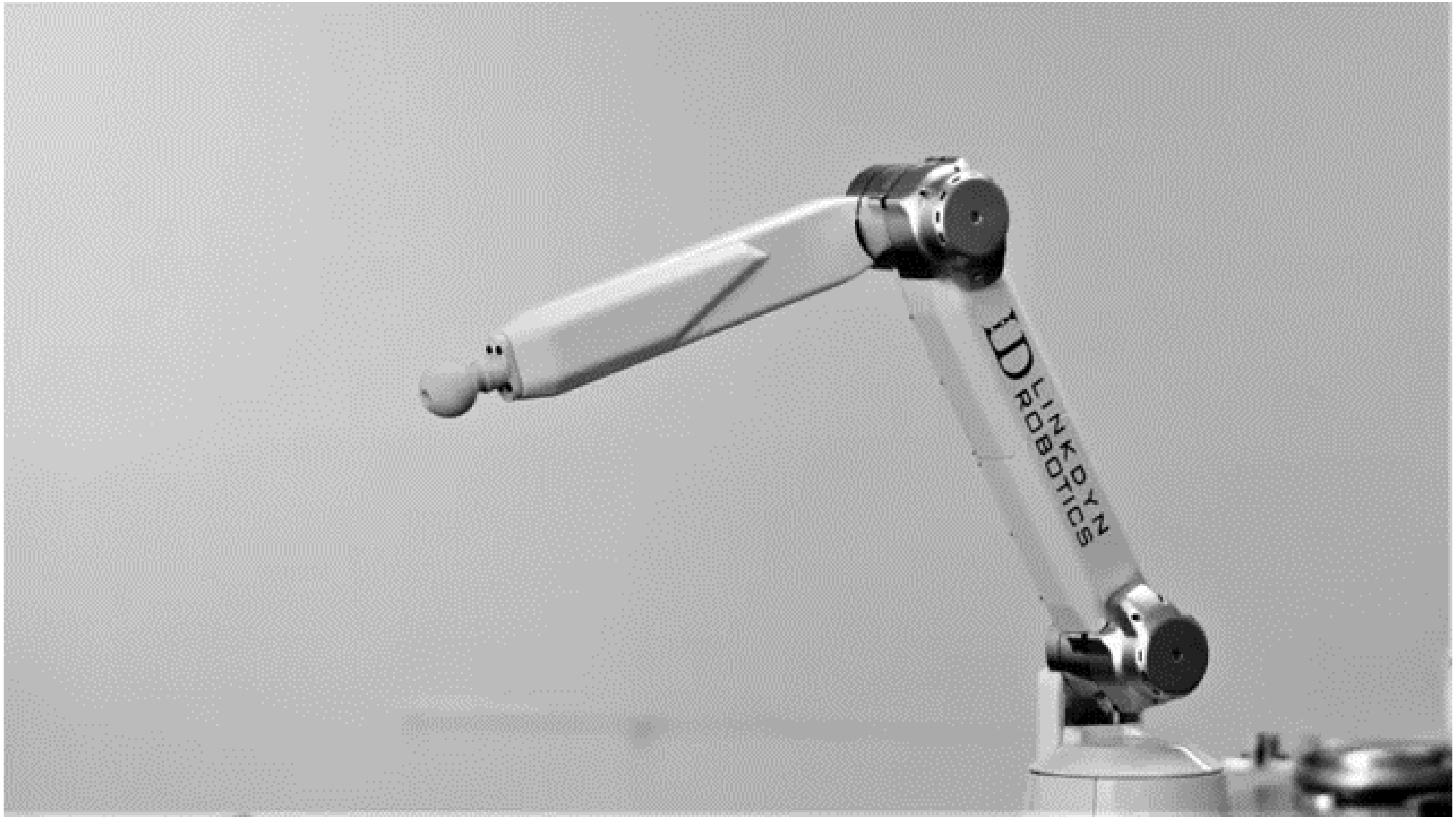


Figure 9.8: Examples of (a) inertial, (b) resistive, and (c) capacitive environments.

Physical Interaction robot



https://www.youtube.com/watch?v=9H32TecFhY8

Questions

Thank You