# Seminar Presentation

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# Tool Gravity Compensation for the Galen Microsurgical System

The objective of this project is to:

- Develop models of tool gravity in static and dynamic modes
- Integrate the model into the control loop of the Galen robot to compensate for tool's gravity and dynamics
- Identify the deflection model of the Galen's arm in the presence of the operator's hand force

# Paper selection

- *Learning optimal variable admittance control for rotational motion in human-robot co-manipulation.*
  - Dimeas, Fotios & Aspragathos, Nikos. (2015). Learning optimal variable admittance control for rotational motion in human-robot co-manipulation. IFAC-PapersOnLine. 48. 10.1016/j.ifacol.2015.12.021.

Why:

- Tool gravity compensation
- Variable admittance control

# Summary of problem & key result

Problem

- Virtual damping, a key component in admittance control
  - Low damping → less resistance, fine positioning is reduced
  - High damping → fine positioning is increased, more resistance
- Variable damping can improve performance of the cooperative control framework
- Goal: Implement variable admittance control with a systematic approach

# Summary of problem & key result

Key Results

- Implemented variable admittance control using a Fuzzy Model Reference Learning Controller (FMRLC)
- Allowed users to cooperate with a robot in a simple rotation task with significantly less energy exertion, in less time, and with less overshoot

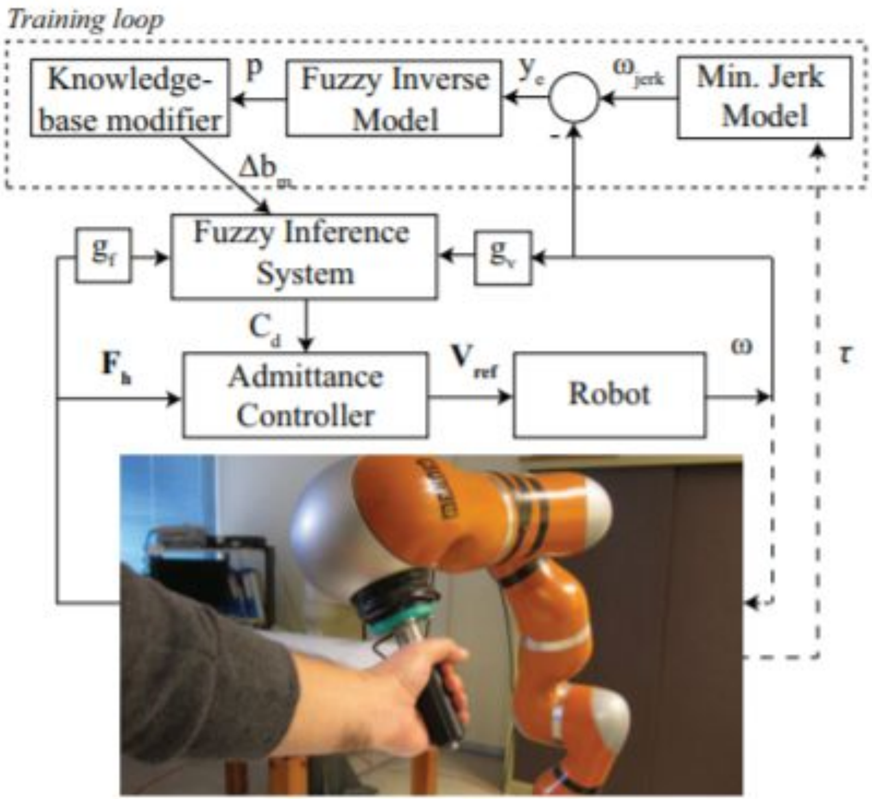
# Significance of key result

- Presents a systematic approach to tune variable admittance control
  - Much of the prior literature tunes parameters using trial and error
- Presents an approach to regulate variable admittance control for rotation tasks
  - Most literature approaches variable admittance control for pure translation tasks

# Necessary background

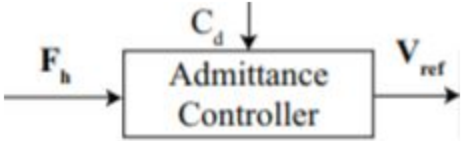
- Prior work by these authors for pure translation variable admittance control
  - Dimeas, F. and Aspragathos, N. (2014). Fuzzy Learning Variable Admittance Control for Human-Robot Cooperation. In IEEE International Conference on Intelligent Robots and Systems, 4770–4775. September 13-18, Chicago, IL, USA.
- Mathematics behind the minimum jerk trajectory model
  - Flash, T. and Hogan, N. (1985). The coordination of arm movements: an experimentally confirmed mathematical model. The Journal of Neuroscience, 5(7), 1688–1703.
- Knowledge of fuzzy control and FMRLCs
  - Passino, K.M. and Yurkovich, S. (1997). Fuzzy Control. Addison Wesley Publishing Company, California.

# Technical Approach




Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Admittance Controller




- Goal: Impose desired velocities on end effector as a function of applied force

- $F_h$ = input forces / torques
- $V_{ref}$ = output velocities
- $q'_{ref}$ = joint velocities
- $M_d$ = virtual inertia
- $C_d$ = virtual damping/viscosity

$$\mathbf{M_d \dot{V}_{ref} + C_d V_{ref} = F_h}$$

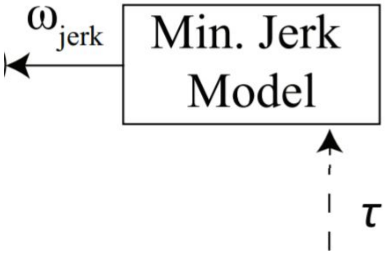
$$\mathbf{V_{ref}} = \begin{bmatrix} \dot{\mathbf{p}}_r \\ \boldsymbol{\omega}_r \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \text{ translational velocities} \\ \in \mathbb{R}^3, \text{ angular velocities} \end{matrix}$$

$$\mathbf{F_h} = \begin{bmatrix} \mathbf{f}_h \\ \boldsymbol{\tau}_h \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \text{ forces} \\ \in \mathbb{R}^3, \text{ torques} \end{matrix}$$

$$\mathbf{\dot{q}_{ref} = J^{-1}(q) V_{ref}}$$

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Minimum Jerk Model




- During rotations, the trajectory followed by the human hand has minimal change in angular acceleration, and can be described by $\theta_{jerk}$

$$\theta_{jerk}(\hat{t}) = \theta_0 + (\theta_f - \theta_0)(6\hat{t}^5 - 15\hat{t}^4 + 10\hat{t}^3)$$

$$\omega_{jerk}(\hat{t}) = \theta_f(30\hat{t}^4 - 60\hat{t}^3 + 30\hat{t}^2)$$

- $t_f$ is the duration of the motion, t^ = $t/t_f$, $\theta_0 = 0$ is the initial angle, and $\theta_f$ is the final angle.

$$y_e = \omega_{jerk} - \omega$$

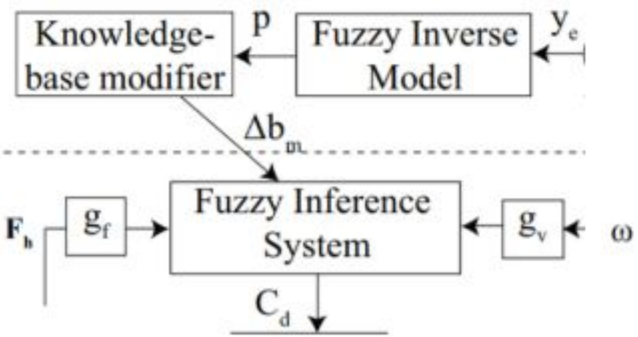

Dimeas, Fotios & Aspragathos, Nikos. (2015)

Flash, T. and Hogan, N. (1985).

# Fuzzy Model Reference Learning Controller

**Initial Fuzzy Inference System rule-base**:
Cd: 1 to 5 (low to high)
Fh & ω: -2 to 2 (neg high to pos high)

Triangular shaped membership functions



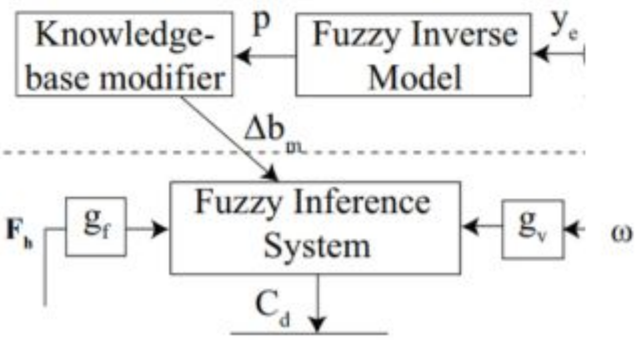

$F_h$ = input forces / torques
ω = angular velocity
$C_d$ = virtual damping

| Cd | | $F_h$ | | | | |
|---|---|---|---|---|---|---|
| | | −2 | −1 | 0 | 1 | 2 |
| ω | −2 | 1 | 2 | 3 | 5 | 5 |
| | −1 | 2 | 3 | 4 | 5 | 5 |
| | 0 | 3 | 4 | 5 | 4 | 3 |
| | 1 | 5 | 5 | 4 | 3 | 2 |
| | 2 | 5 | 5 | 3 | 2 | 1 |

Dimeas, Fotios & Aspragathos, Nikos. (2015)

Dimeas, F. and Aspragathos, N. (2014).

# Fuzzy Model Reference Learning Controller



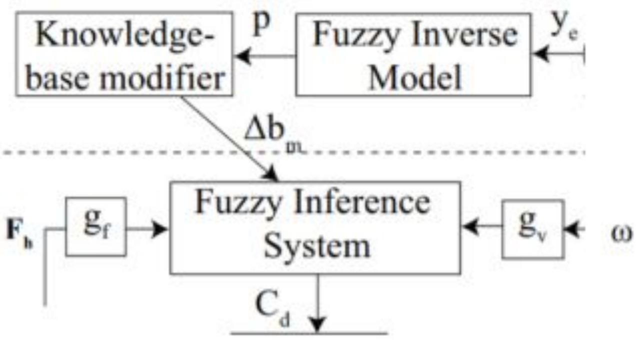

**Fuzzy Inverse Model rule-base**:

IF $y_e$ is zero THEN $p$ is zero.
IF $y_e$ is positive THEN $p$ is negative.
IF $y_e$ is negative THEN $p$ is positive.

$$y_e = \omega_{jerk} - \omega$$

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Fuzzy Model Reference Learning Controller



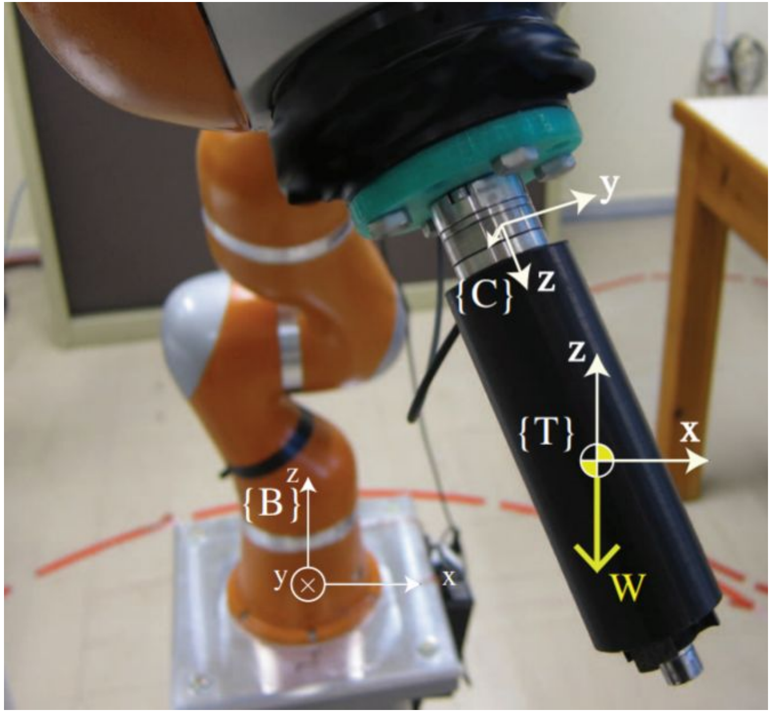

**Knowledge-base modifier**:

$$\Delta b_m(kT) = p\mu_m(\tau_h(kT - T), \omega(kT - T))$$

- The functions $\mu_m$ describes the certainty that a rule applies
- The function $\Delta b_m$ describes how much to shift the output membership function

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Tool weight compensation




Transform forces and torques in tool frame to force sensor frame:

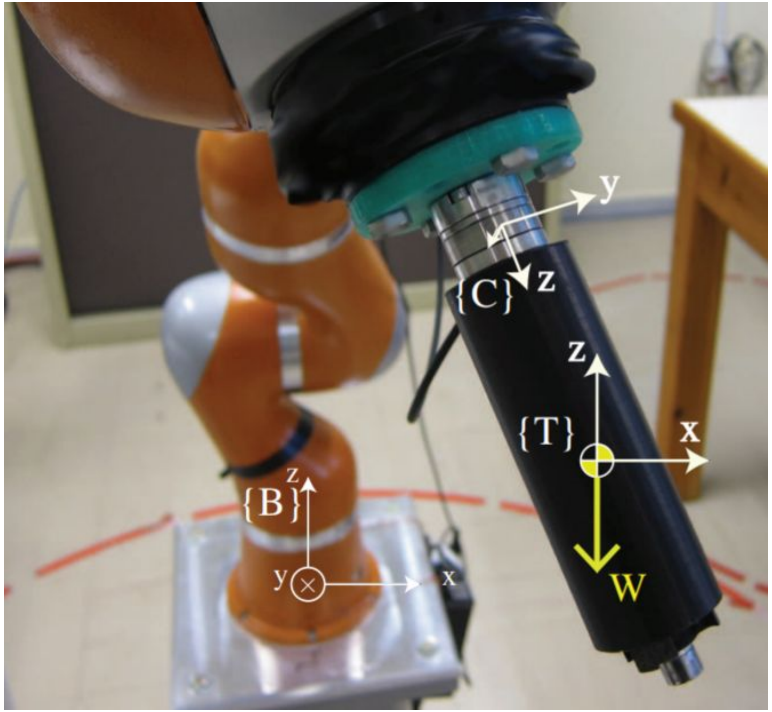
$$\mathbf{W} = \begin{bmatrix} \mathbf{f}_W \\ \boldsymbol{\tau}_W \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \ forces \\ \in \mathbb{R}^3, \ torques \end{matrix}$$

$$\mathbf{f}_W = [0 \ 0 \ -m_t g]^T \quad \boldsymbol{\tau}_W = [0 \ 0 \ 0]^T$$

$$\begin{bmatrix} \mathbf{f}_W^C \\ \boldsymbol{\tau}_W^C \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{CT} & 0 \\ -\mathbf{R}_{CT}\hat{\mathbf{p}}_T & \mathbf{R}_{CT} \end{bmatrix} \begin{bmatrix} \mathbf{f}_W^T \\ \boldsymbol{\tau}_W^T \end{bmatrix}$$

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Tool weight compensation




Removing rebiasing weight and tool weight from force sensor readings

$$\mathbf{F}_{ext} = \mathbf{F}_{tot} - \mathbf{F}_{tot}^{init}$$

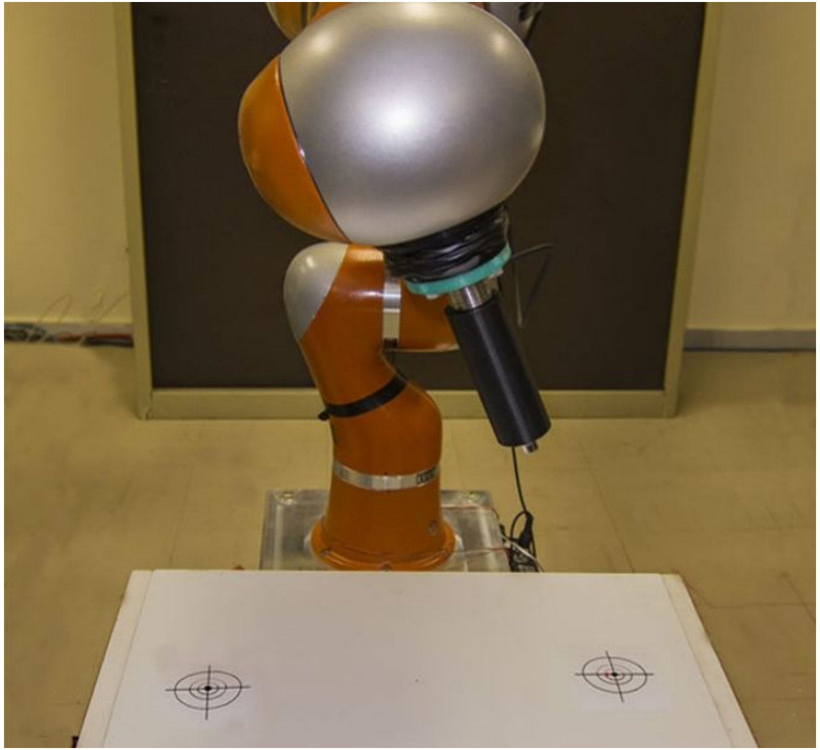
$$\mathbf{F}_{tot}^{init} = \mathbf{F}_{uncal} + \begin{bmatrix} \mathbf{f}_{W,init}^{C} \\ \boldsymbol{\tau}_{W,init}^{C} \end{bmatrix}$$

$$\mathbf{F}_{tot} = \mathbf{F_h} + \mathbf{F}_{uncal} + \begin{bmatrix} \mathbf{f}_{W}^{C} \\ \boldsymbol{\tau}_{W}^{C} \end{bmatrix}$$

$$\mathbf{F_h} = \mathbf{F}_{ext} - \begin{bmatrix} \mathbf{f}_{W}^{C} \\ \boldsymbol{\tau}_{W}^{C} \end{bmatrix} + \begin{bmatrix} \mathbf{f}_{W,init}^{C} \\ \boldsymbol{\tau}_{W,init}^{C} \end{bmatrix}$$

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Experimental Evaluation

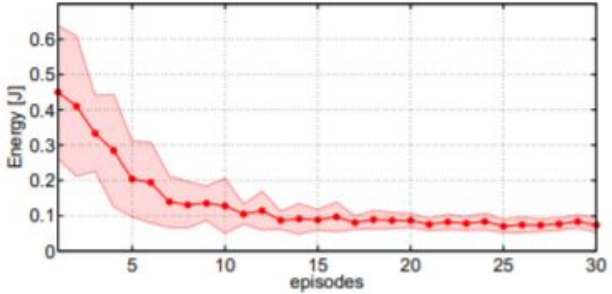


- A user study involving 7 participants
- Each subject rotated the KUKA LWR robot about the x-axis of frame {C}
  - Laser on end effector which points to goal regions, instructing subjects
  - Two sets of 30 transitions were recorded for each subject
- Output membership functions are initialized evenly distributed between 0 and 10 Nms/rad
- Output membership functions are updated throughout

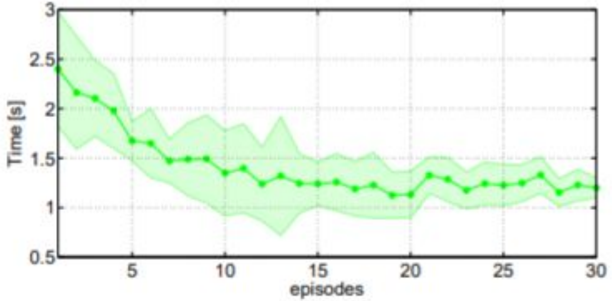
Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Experimental Results

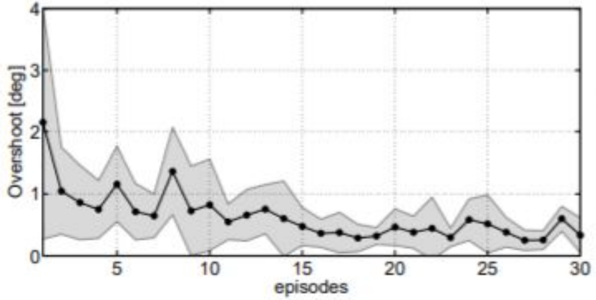
- The FMRLC significantly reduced energy exertion, time taken, and overshoot
- It converged to steady values after 10 episodes
- Thus, the FMRLC is more effective and systematic than manually tuned FISs for variable admittance control




(b)




(c)




(d)

Dimeas, Fotios & Aspragathos, Nikos. (2015)

# Assessment

- Importance
  - Provides systematic approach to tune parameters for variable admittance control
  - Has potential in optimising human-robot cooperation in many settings
- Relevance
  - Provides a solid mathematical background for static gravity compensation and gives insight about adaptive adjustment of admittance gain

# Assessment

- Good and Bad Points

| Good | Bad |
|---|---|
| ● Clear justification of FMRLC approach<br>● Explicit and helpful mathematics<br>● Positive results with clear graphics | ● No explicit validation of weight comp.<br>● Experiment only along a single axis<br>● No trial of 30 episodes without FMRLC |

- Further Work Suggestion:
  - Experimental validation of variable admittance control for translation and rotation about many different axes

# Conclusion

- Introduced unique way for tuning variable admittance control for simple rotation tasks
- Provides a lot of insightful mathematics for performing variable admittance control and static tool gravity compensation
- The experiment section was lacking without control trials without FMRLC training and without gravity tool compensation validation

# Questions

# References


- Dimeas, Fotios & Aspragathos, Nikos. (2015). Learning optimal variable admittance control for rotational motion in human-robot co-manipulation. IFAC-PapersOnLine. 48. 10.1016/j.ifacol.2015.12.021.
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