Critical Review
Adam Polevoy
CIS 2
03/09/19

Statement of my Project

My project is 'Tool Gravity Compensation for the Galen Microsurgical System'. The objectives of this project are to integrate models of tool gravity, in static and dynamic modes, into the control loop of the Galen robot to compensate for tool's gravity and dynamics. Once this has been accomplished, we aim to identify the deflection model of the Galen's arm in the presence of the operator's hand force

Paper Selection

The paper I've selected for my critical review is *Learning optimal variable admittance control for rotational motion in human-robot co-manipulation* (Dimeas 2015). This paper contains basic mathematics for performing static tool gravity compensation. Additionally, it discusses an approach to variable admittance control tuning, which provides insight into improving traditional admittance control.

Summary of Goal, Key Results, and Significance

Virtual damping is a key component in admittance control. If the damping is too low, there is less resistance to movement, but the ability to do fine positioning is reduced. If the damping is too high, the ability to do fine positioning is increased, but there is high resistance to movement. Thus, variable damping can greatly improve performance of the cooperative control framework. The goal of this paper was to implement a method to systematically tune variable admittance control parameters.

The authors implemented variable admittance control using a Fuzzy Model Reference Learning Controller (FMRLC). This method was successful in tuning variable admittance control parameters; it allowed users to cooperate with a robot in a simple rotation task with significantly less energy exertion, in less time, and with less overshoot.

These results were significant because they presented a systematic approach to tuning variable admittance control. Much of the prior literature had manually tuned parameters only using trial and error. Additionally, they presented an approach to regulate variable admittance control for rotation tasks. Most literature before this paper only did variable admittance control for pure translation tasks due to tool gravity concerns.

Necessary Background

It is necessary to have knowledge of prior work be these authors in which they performed pure translation variable admittance control (Dimeas, 2014). This paper contains vital information about the FMRLC that is being used.

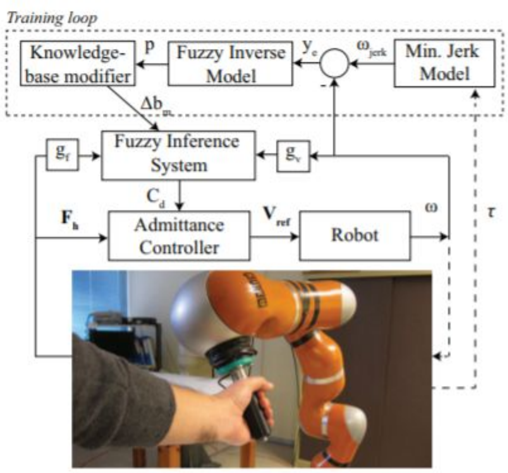
It is useful to know of the minimum jerk trajectory model and the mathematics behind it (Flash 1985). The minimum jerk trajectory describes the rotational trajectory the human hand takes in simple motions. This trajectory is used to form the error signal for the FMRLC.

Additionally, it is necessary to have a basic knowledge of fuzzy control systems and FMRLCs (Passino 1997).

Technical Approach

Overview

Below is a block diagram of the entire system. It includes an admittance controller, the minimum jerk model, and the FMRLC. The goal of this system is to reduce the error between the minimum jerk trajectory and the true jerk trajectory by optimizing the virtual damping.



(Dimeas 2015)

Admittance Controller

The admittance controller imposes desired velocities on end effector as a function of applied force.

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

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

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

(Dimeas 2015)

Where M_d is the virtual inertia, and C_d is the virtual daming. These end effector velocities can then be transformed to joint velocities.

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

(Dimeas 2015)

Where q'_{ref} are the joint velocities.

Minimum Jerk Model

It is theorized that during rotations, the trajectory followed by the human hand has minimal change in angular acceleration, and can be described by θ_{jerk}. By taking the derivative of this equation we can get ω_{jerk}.

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

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

(Dimeas 2015)

Where t_f is the duration of the motion, t^ = t/t_f, $\theta_0 = 0$ is the initial angle, and θ_f is the final angle. The difference between the actual angular velocity, ω, and the minimum jerk angular velocity, ω_{jerk}, is an error signal that can be used by the FMRLC.

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

(Dimeas 2015)

Fuzzy Model Reference Learning Controller

The Fuzzy Inference System (FIS) has two inputs: F_h and ω. Each of these inputs had 5 triangular membership functions. The linguistic values for these go from ‘neg high’ to ‘pos high’ (-2 to 2). The output is C_d, which also had five membership functions. The linguistic values for the output go from low to high (1 to 5). The initial rule base of the FIS is outlined in the chart below.

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 2014)

Fuzzy Inverse Model transforms the error signal to a value that can be used by the Knowledge Base Modifier. The rule base for the Fuzzy Inverse Model is shown below. Note that the magnitude of p is not specified.

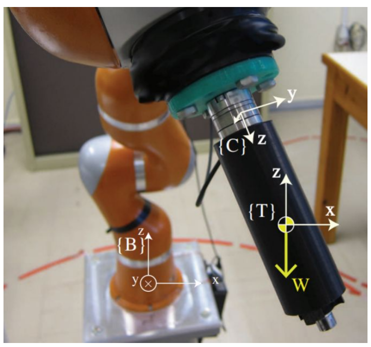
IF y_e is zero THEN p is zero.
IF y_e is positive THEN p is negative.
IF y_e is negative THEN p is positive.

The knowledge-base modifier uses the value from the fuzzy inverse model to shift the output membership functions of the FIS. In the equation below, the function μ_m describes the certainty that each rule applies, and the function Δb_m describes how much to shift the output membership function

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

(Dimeas 2015)

Tool Weight Compensation



(Dimeas 2015)

To perform the tool weight compensation, first the wrench in the tool frame must be converted to the wrench in the sensor frame using the transpose of an adjunct transformation.

$$\mathbf{W} = \begin{bmatrix} \mathbf{f}_W \\ \boldsymbol{\tau}_W \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \ forces \\ \in \mathbb{R}^3, \ torques \end{matrix} \qquad \mathbf{f}_W = [0 \ 0 \ -m_t g]^T \quad \boldsymbol{\tau}_W = [0 \ 0 \ 0]^T$$

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

(Dimeas 2015)

Then, the force readings due to the initial biasing of the sensor must be taken into account.

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

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

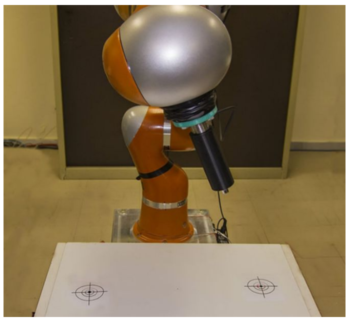
$$\mathbf{F}_{tot} = \mathbf{F}_{\mathbf{h}} + \mathbf{F}_{uncal} + \begin{bmatrix} \mathbf{f}_W^C \\ \boldsymbol{\tau}_W^C \end{bmatrix}$$

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

(Dimeas 2015)

Experimental Evaluation and Results

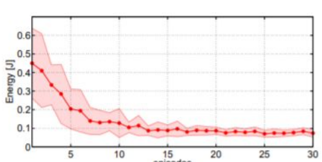
An user study was done with 7 participants. Each subject rotated the KUKA LWR robot about the x-axis of the force sensor frame. A laser was attached to the end effector which points to a goal region, as displayed below.



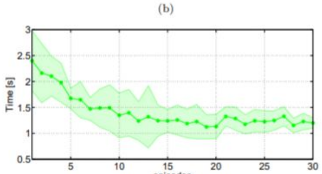
(Dimeas 2015)

The subjects are instructed to move the laser point from one goal region to the other 30 times. Each subject did two sets of these 30 episodes, and only the data from the second set was taken into account. The first set was thrown out because the subjects were still learning to use the robot. The output membership functions of the FIS were initialized evenly distributed between 0 and 10 Nms/rad and were updated throughout the 20 episodes via the FMRLC.

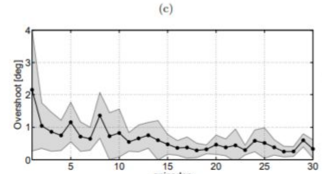
The FMRLC significantly reduced energy exertion, time taken, and overshoot, which all converged to steady values after 10 episodes. Thus, the FMRLC is more effective and systematic than manually tuned FISs for variable admittance control



(b)



(c)



(d)

(Dimeas 2015)

Assessment

This paper was important because it provided a systematic approach to tuning parameters for variable admittance control. Therefore, it has potential in optimising human-robot cooperation in many settings. It is relevant to my project because it provides a solid mathematical background for static gravity compensation and gives insight into adaptive adjustment of admittance gain.

There are several good and bad points to this paper. This paper is good because it provides a clear justification for the FMRLC approach, it had explicit and helpful mathematical formulation, and it has positive results with clear graphics. However, there are several bad points. There is no explicit validation of weight compensation. There is no control trial of 30 episodes without the FMRLC tuning. The experiment is only done along a single axis under the assumption of the minimum jerk model. Thus, it is unclear if this method would be generalizable to more complex motions. Furthermore, several key implementation details were missing from the paper, such as input membership function locations and the scaling of the Fuzzy Inverse Model, p.

A suggestion for further work is experimental validation of variable admittance control for translation and rotation about many different axes

Conclusion

This paper Introduced unique way for tuning variable admittance control for simple rotation tasks. It provides a lot of insightful mathematics for performing variable admittance control and static tool gravity compensation. However, the experiment section was lacking without control trials without FMRLC training and without gravity tool compensation validation, and it is unclear if the method is generalizable.

References

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.

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.

Flash, T. and Hogan, N. (1985). The coordination of arm movements: an experimentally confirmed mathematical model. The Journal of Neuroscience, 5(7), 1688–1703.

Passino, K.M. and Yurkovich, S. (1997). Fuzzy Control. Addison Wesley Publishing Company, California.