Control for an Upper Limb Exoskeleton

Wen Yu

Departamento de Control Automatico
CINVESTAV-IPN (National Polytechnic Institute)
Mexico City, Mexico

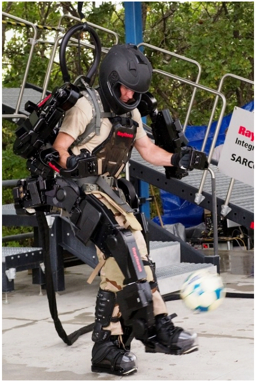
Outline

Exoskeleton robot

- Exoskeletons are wearable robot
- The exoskeleton links, joints and workspace correspond to those of the human body.
- Applications
  1. Human-amplifier
  2. Rehabilitation
  3. Teleoperation

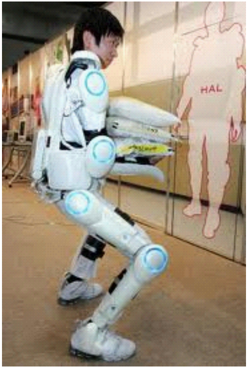
Top 5 Exoskeletons

Raytheon Sarcos XOS 2: Best Inventions of 2010 by Time Magazine.
Raytheon Company, $25 billion, 75,000 people, real “Iron Man”



Top 5 Exoskeletons

Hybrid Assistive Limb (HAL). Dr. Yoshiyuki Sankai, University of Tsukuba, Cyberdyne Inc, Full Body weight 23kg,Lower body:15kg. Continuous operating time:2:40.



Top 5 Exoskeletons

Human Universal Load Carrier (HULC): Berkley Bionics UC-Berkley, Prof. Homayoon Kazerooni, Lockheed Martin, 20kg

Top 5 Exoskeletons

Honda Experimental Walking Assist Device, 2 motors, Lithium battery 2hrs

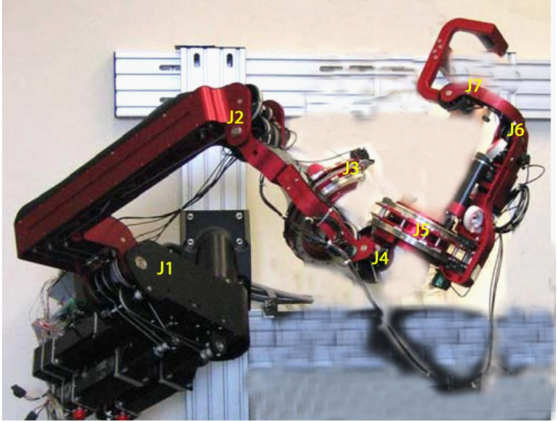
Top 5 Exoskeletons

MIT Exoskeleton, 2 watts

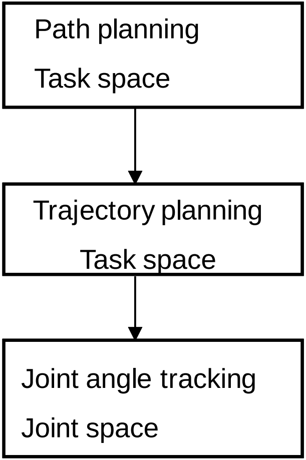
UCSC Exoskeletons

7 DOF upper limb exoskeleton (EXO-UL7)

UCSC Exoskeletons



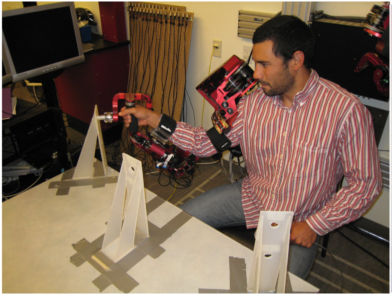
Contrl of exoskeletons

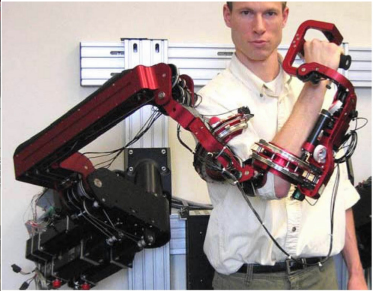


Control problems in exoskeletons

- Human-machine interface: input signals
  1. Electromyography (EMG): electrical activity produced by skeletal muscles, noise and models
  2. force sensor: weight
- Control algorithms
  1. lower level (motor): PID, PD, PD+
  2. upper level: trajectory (desired position) for each joint (motor)
  3. Redundant robot
- Gravity compensation:
  1. mechanical structure
  2. model

Lower level control (motors)





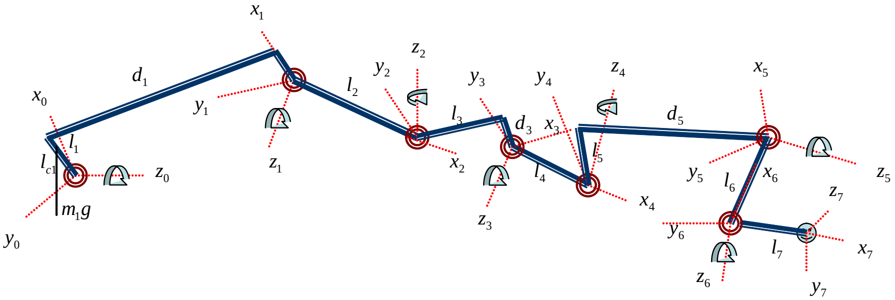


Figure: Frames of the 7-DOF exoskeleton

Dynamic model

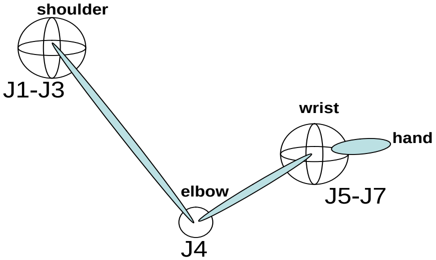


Figure: Human arm

From Euler-Lagrange equation

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

PD control

$$u = K_p \tilde{q} + K_d \dot{\tilde{q}}$$

where $\tilde{q} = q^d - q$. In regulation case $\dot{q}^d$

$$u = K_p \tilde{q} - K_d \dot{q}$$

Define Lyapunov function

$$V = \frac{1}{2} \dot{q}^T M \dot{q} + \frac{1}{2} \tilde{q}^T K_p \tilde{q}$$

IF $g(q) + F(\dot{q}) = 0$,

$$\dot{V} = -\dot{q}^T K_d \dot{q} \leq 0$$

Using LaSalle's Theorem, $\dot{q} \to 0$, $\tilde{q} = 0$. It is asymptotically stable. It is model-free control

PD control with gravity and friction compensation

If $g(q) + F(\dot{q}) \neq 0$ and $g(q) + F(\dot{q})$ is known, simplified Coulomb friction

$$F(\dot{q}) = -B\dot{q}$$

PD control with gravity and friction compensation

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

$$\dot{V} = -\dot{q}^T (K_d - B)\dot{q} \leq 0$$

PD control with gravity and friction compensation

If $g(q) + F(\dot{q}) \neq 0$ and $g(q) + F(\dot{q})$ is partially known

$$u = K_p \tilde{q} - K_d \dot{q} + \hat{g}(q) + \hat{F}$$

which is valid for any $X,\ Y \in R^{n \times m}$ and any $0 < \Lambda = \Lambda^T \in R^{n \times n}$

$$\dot{V} \leq -\dot{q}^T \left(K_d - B - \Lambda^{-1} \right) \dot{q} + \bar{g}$$

It is bounded $\|\tilde{q}\|_K^2 \to \bar{g}$.

PD control in tracking case

$\dot{q}^d \neq 0$. Define

$$\tilde{q} = q^d - q, \qquad r = \dot{\tilde{q}} + \Lambda \tilde{q}$$

PD control is

$$\tau = Kr + f + G + F$$
$$f(x) = M\left(\Lambda \dot{e} + \ddot{q}^d\right) + C\left(\Lambda e + \dot{q}^d\right)$$

The Lyapunov function is

$$V = \frac{1}{2} r^T M r$$

PD control with gravity and friction

$$\tau = Kr + \hat{f} + \hat{G} + \hat{F}$$

$$\dot{V} \leq -r^T \left(K - \Lambda^{-1} - \Gamma\right) r + \bar{g} + \bar{q}^d$$

PID control

PID control

$$u = K_p\tilde{q} + K_i\int_0^t \tilde{q}(\tau)\,d\tau + K_d\dot{\tilde{q}}$$

Regulation$\dot{q}^d = 0$, $\dot{\tilde{q}} = -\dot{q}$

Theorem

Consider robot dynamic controlled by linear PID controller, the closed loop system is semiglobally asymptotically stable at the equilibrium $x = \left[\xi - g\left(q^d\right), \tilde{q}, \dot{\tilde{q}}\right]^T = 0$, *provided that control gains satisfy*

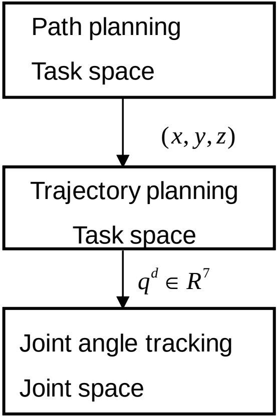
$$\begin{array}{l} \lambda_m(K_p) \geq \frac{3}{2}k_g \\ \lambda_M(K_i) \leq \beta\frac{\lambda_m(K_p)}{\lambda_M(M)} \\ \lambda_m(K_d) \geq \beta + \lambda_M(M) \end{array}$$

where $\beta = \sqrt{\frac{\lambda_m(M)\lambda_m(K_p)}{3}}$, k_g *satisfies* $\|g(x) - g(y)\| \leq k_g\|x - y\|$

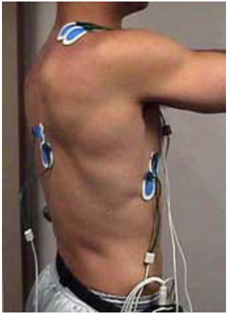
PID control: tracking

No

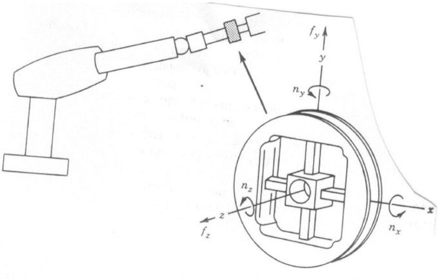
Upper level control



Human–Exoskeleton Interface Utilizing Electromyography (EMG)



- Biomechanical model of the human body:
  1. reflect properties of the individual human operator and his or her current body state
  2. calibration algorithm for these parameters
- Noise problems



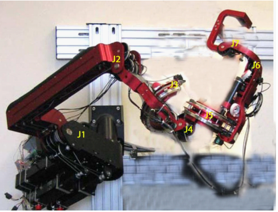
The six-axis wrist sensor

$$F = [F_x, F_y, F_z, n_x, n_y, n_z]$$

where F_i are components of the force at the end-effector, n_i are the components of the torque at the end-effector.

UCSC Exoskeletons

Redundant problem



$$F = [F_x, F_y, F_z, n_x, n_y, n_z] \in R^6 \rightarrow u \in R^7$$

The joint space to the task space is

$$x_1 = K(q), \qquad K(\cdot) \in R^7 \rightarrow R^6$$

Redundant problem

We define one constraint task as

$$x_a = h(q)$$

where x_a is a scalar. The augmented task space is defined as

$$x = \begin{bmatrix} x_1 \\ x_a \end{bmatrix} \in R^7$$

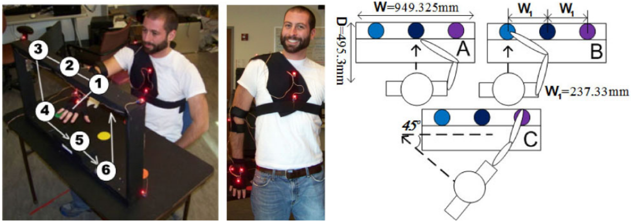
The derivative of x is given as

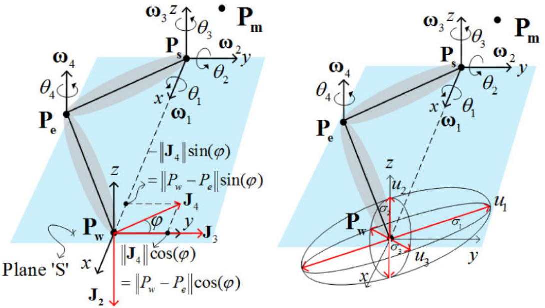
$$\dot{x} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_a \end{bmatrix} = \begin{bmatrix} \frac{\partial K}{\partial q} \\ \frac{\partial h}{\partial q} \end{bmatrix} = \begin{bmatrix} J_1 \dot{q} \\ \dot{h} \dot{q} \end{bmatrix} = J\dot{q}$$

The dynamics of exoskeleton robots

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = u - J^T f$$

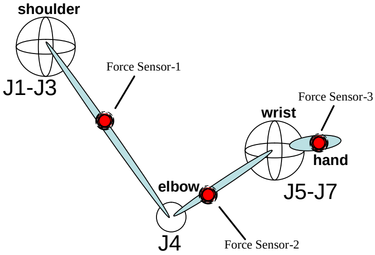
Redundant problem





Swivel angle

UCSC Exoskeletons: force sensors



Human arm

Force sensors fusion

$$f_1 = R_1^3 F_1, \quad f_2 = R_1^5 F_2, \quad f_3 = R_1^7 F_3$$

$$\tau_1 = R_1^3 \Gamma_1 + r_3 \times F_1, \quad \tau_2 = R_1^5 \Gamma_2 + r_5 \times F_2, \quad \tau_3 = R_1^7 \Gamma_3$$

$$f_0 = \sum_{i=1}^{3} w_i f_i, \quad \tau_0 = \sum_{i=1}^{3} v_i \tau_i$$

The dynamics of exoskeleton robots

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = u - J^T f$$

Impedance/admittance Control

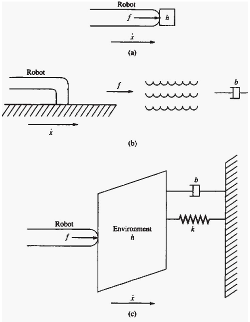


Figure 9.4.1: Environmental impedances.

spring model

$$f = -Kx$$

impedance

$$V = Ri$$

linear transfer function relationship

$$f(s) = \left(hs + b + \frac{k}{s}\right)\dot{x}(s)$$

f represents the force exerted on the environment, $\dot{x}$ represents the velocity of the manipulator at the environmental contact point. Z_e represents the environmental impedance.An impedance $Z(s)$ is said to be. Inductance hs, resistance b, capacitive $\frac{k}{s}$

Impedance/admittance Control

- In electrical engineering, the admittance (Y) is the inverse of the impedance (Z)

$$Y = \frac{1}{Z}$$

- In mechanical systems (particularly in the field of haptics), an admittance is a dynamic mapping from force to motion

$$\dot{x}(s) = Y(s)\, f(s)$$

An admittance device would sense the input force and "admit" a certain amount of motion.

Impedance/admittance Control

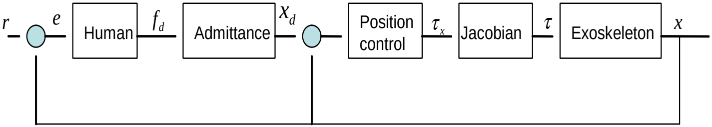


Figure: Human-robot system

Jiont space vs task space model

- Task space

$$M_x \ddot{x} + C_x \dot{x} + g_x = u_x - f$$

1. $M_x = f(M, J)$, however PID control is model-free
2. Impedance/admittance relation is $f \rightarrow \dot{x}$

- Joint space

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = u - J^T f$$

Task space model

The augmented task space is defined as

$$x = \begin{bmatrix} x_1 \\ x_a \end{bmatrix} \in R^7$$

$$\begin{aligned}
&\dot{x} = J\dot{q}, \quad J = \left[J_1, \dot{h}\right]^T \in R^{7\times 7} \\
&\dot{h}^T = \left[I - J_1^T \left(J_1 J_1^T\right)^{-1} J_1\right] \\
&M_x = J^{-T} M J^{-1}, u_x = J^{-T} u, g_x = J^{-T} g, \\
&C_x = J^{-T}\left[C - M J^{-1} \dot{J}\right] J^{-1}
\end{aligned}$$

Task space model properties

$$M_x\ddot{x} + C_x\dot{x} + g_x = u_x - f$$

where

$$\begin{array}{c} 0 < \lambda_m\left\{M_x\left(x\right)\right\} \leq \left\|M_x\right\| \leq \lambda_M\left\{M_x\left(x\right)\right\} \leq \beta \\ x^T\left[\dot{M}_x\left(x\right) - 2C_x\left(x,\dot{x}\right)\right]x = 0 \\ \left\|g_x\left(x\right) - g_x\left(y\right)\right\| \leq k_g\left\|x - y\right\| \end{array}$$

Admittance Control: impedance filter

Mechanical impedance describes a force/velocity relation of the end-effector

$$\frac{f_e(s)}{\dot{x}(s)} = Z(s) = M_i s + B_i + \frac{D_i}{s}$$

The admittance relation is

$$x_d(s) = \frac{1}{M_i s^2 + B_i s + D_i} f(s)$$

The parameters M_i, B_i and D_i are designed such that the closed-loop system is stable.
But it is discomfort, the impedance filter can not guarantee zero contract force.

Target impedance

The impedance behavior can be assigned independently of the manipulator dynamics. With the impedance control

$$a = \ddot{x}_d + \frac{B_d}{M_d}\left(\dot{x}_d - \dot{x}\right) + \frac{D_d}{M_d}\left(x_d - x\right) - \frac{f}{M_d}$$

The closed-loop system is

$$M_d\left(\ddot{x}_d - \ddot{x}\right) + B_d\left(\dot{x}_d - \dot{x}\right) + D_d\left(x_d - x\right) = f$$

The goal of impedance control is to achieve desired impedance between the end-effector position and interaction, here M_d is mass, B_d is damping, and D_d is stiffness of the desired impedance. But it needs feedback linearization control

$$\begin{aligned} & u = M(q)\, J^{-1}\left(a - \dot{J}\dot{q}\right) + C(q, \dot{q})\, \dot{q} + F(\dot{q}) + g(q) + J^{T}(q)\, f \\ & \ddot{x} = a \end{aligned}$$

Admittance Control: reference regulation

$$\frac{\dot{x}(s)}{f(s)} = R(s) = M_a s + B_a + \frac{D_a}{s}$$

$$\dot{x}_d(s) = \left(M_a s + B_a + \frac{D_a}{s} \right) f_d(s), \quad x_d(t) = \int_0^t \dot{x}_d(\upsilon)\, d\upsilon$$

It has the same form as PID control and the control parameters can be chosen based on the kinematics and dynamics of the human arm.

Stability

Regulation error

$$\tilde{x} = x_d - x$$

A linear PID control in task space

$$u_x = K_p \tilde{x} + K_i \int_0^t \tilde{x}(\tau)\, d\tau + K_d \dot{\tilde{x}} + f$$

Theorem

The closed loop system is semiglobally asymptotically stable at the equilibrium $X = \left[\xi - g\left(x^d\right), \tilde{x}, \dot{\tilde{x}}\right]^T = 0$, *provided that control gains satisfy*

$$\lambda_m(K_p) \geq \frac{3}{2} k_g$$
$$\lambda_M(K_i) \leq \beta \frac{\lambda_m(K_p)}{\lambda_M(M_x)}$$
$$\lambda_m(K_d) \geq \beta + \lambda_M(M_x)$$

where $\beta = \sqrt{\frac{\lambda_m(M_x)\lambda_m(K_p)}{3}}$,

Experiment setup

Experiment setup

- Intel Pentium4@2.4 GHz processor and 512 Mb RAM.
- PC104 control computer
- Software, windows XP, Matlab, C++, Real-Time Target
- sampling frequency of $1kHz$. The reference signals are generated by admittance control in task space. These references are sent to joint space.

Lower-level PID control

$$\lambda_m(K_p) \geq \frac{3}{2}k_g$$
$$\lambda_M(K_i) \leq \beta\frac{\lambda_m(K_p)}{\lambda_M(M)}, \qquad \beta = \sqrt{\frac{\lambda_m(M)\lambda_m(K_p)}{3}}$$
$$\lambda_m(K_d) \geq \beta + \lambda_M(M)$$

- we use $k_g = 10$
- because $\lambda_M(M) \leq \beta$ and $\beta \geq n\left(\max_{i,j}|m_{ij}|\right)$,where m_{ij} stands the ij-th element of M. The upper and lower bounds of the eigenvalues of the inertia matrix $M(q)$ are selected as $\lambda_M(M) = 3$, $\lambda_m(M) = 1$.
- The joint velocities are estimated by

$$\tilde{\dot{q}}(s) = \frac{18s}{s+30}q(s)$$

Lower-level PID control: PID gains

If the linear PID gains are as follows, the conditions for the theorems are satisfied.

$$K_p = diag\left[150, 150, 100, 150, 100, 100, 100\right]$$
$$K_i = diag\left[2, 1, 2, 2, 0.2, 0.1, 0.1\right]$$
$$K_d = diag\left[330, 330, 300, 320, 320, 300, 300\right]$$

- robot dynamic is open-loop unstable, it is danger to send step commands to the exoskeleton
- The linear PID control, PID_0 can guarantee closed-loop stability, considering gravity compensation, the closed-loop system is

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + \tilde{g}(q) = PID_0 - \hat{g}(q)$$

- We use the following four linear system:

$$G_1 = \frac{0.93}{60s^2+9s+1},\ G_2 = \frac{1}{20s^2+3s+1}$$
$$G_3 = \frac{0.9}{5.5s^2+4s+1},\ G_4 = \frac{0.85}{30s^2+8s+1}$$

to approximate the closed-loop responses of the robot.

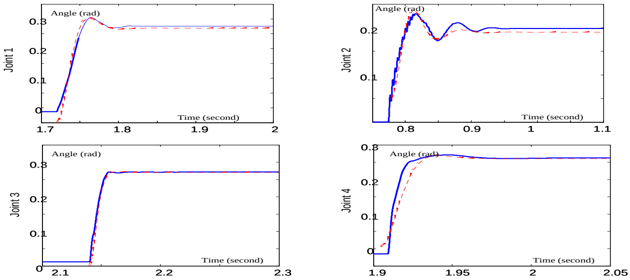


Figure: PD control of the exoskeleton and step responses of linear models

Lower-level PID control: PID gains

Since the step responses (regulation) of the robot are similar with the linear open loop systems. We use the following tuning rule:

$$PID_1 = K_c\left(\tilde{q} + \frac{1}{T_i}\int_0^t \tilde{q}(\tau)\,d\tau + T_d\dot{\tilde{q}}\right)$$
$$K_c = \frac{20\xi_m T_m}{K_m},\ T_i = 15\xi_m T_m,\ T_d = \frac{T_m^2}{10}$$

The above rules are similar with linear systems Huang, Chien

$$K_c = \frac{5T_{m1}\xi_m}{K_m T_{m3}},\ T_i = 2T_{m1}\xi_m,\ T_d = \frac{T_{m1} + 0.1\xi_m}{0.8T_{m1}\xi_m}$$

They are a little different with the other two famous rules, Ziegler-Nichols and Cohen-Coon methods.
Their rules are suitable for the process control, our rules are for mechanical systems.

Lower-level PID control: PID gains

A new PID control, PID_1, for the closed-loop robot system is

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + \tilde{g}(q) - PID_0 + \hat{g}(q) = PID_1$$

The final control torque is $u = PID_1 + PID_0 - \hat{g}(q)$. After this refine turning, the final PID control gains are

Further adjustment

	Rise Time	Overshoot	Settling Time	Steady State Error	Stabilit
P↑	Decrease	Increase	Small Increase	Decrease	Degrad
I↑	Small Decrease	Increase	Increase	Large Decrease	Degrad
D↑	Small Decrease	Decrease	Decrease	Minor Decrease	Improv

$$K_p = diag\,[320, 280, 210, 250, 210, 210, 220]$$
$$K_i = diag\,[5, 4, 5, 6, 3, 4, 2]$$
$$K_d = diag\,[410, 400, 420, 430, 410, 410, 410]$$

Lower-level PID control: PID gains

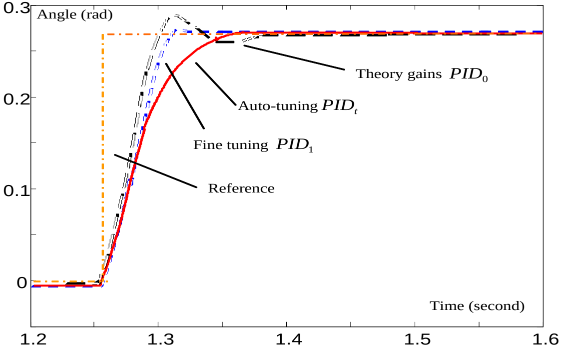


Figure: PID tuning for the joint-1

Upper-level admittance PID control

- The PID admittance control in task space

$$\dot{x}_d = B_a f_d + D_a \int_0^t f_d(v)\,dv + M_a \dot{f}_d$$
$$u = J^T K_p \tilde{x} + J^T K_i \int_0^t \tilde{x}(\tau)\,d\tau + J^T K_d \dot{\tilde{x}} + J^T f$$

B_a, D_a, M_a are human impedance parameters

- The PID admittance control in joint space

$$\dot{q}_d = B_a \left(J^T f_d\right) + D_a \int_0^t J^T f_d(v)\,dv + M_a \frac{d}{dt}\left(J^T f_d\right),$$
$$u = K_p \tilde{q} + K_i \int_0^t \tilde{x}(\tau)\,d\tau + K_d \dot{\tilde{x}} + f,$$

- Manual control (back-driven with no control effort)

Experimental results

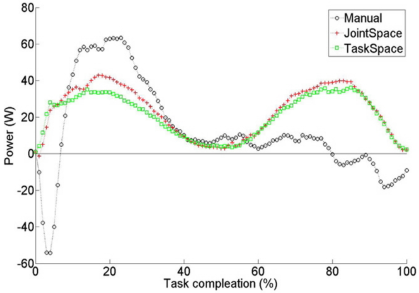


Figure: Average power exchange

Open problem: lower level

- $\lambda_m(K_d) \geq \beta + \lambda_M(M) \rightarrow$ other compensation
- $\lambda_M(K_i) \leq \beta \frac{\lambda_m(K_p)}{\lambda_M(M)}$ does not need
- task space

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

Open problem: upper level

- Force sensors fusion
- Model-based simulation
- Human impedance parameters
- Learning from Demonstration (LfD)

Open problem: applications

Rehabilitation

Conclusions

- Exoskeleton control: two-level
- Stable PID control: joint space and task sapce
- Experiments