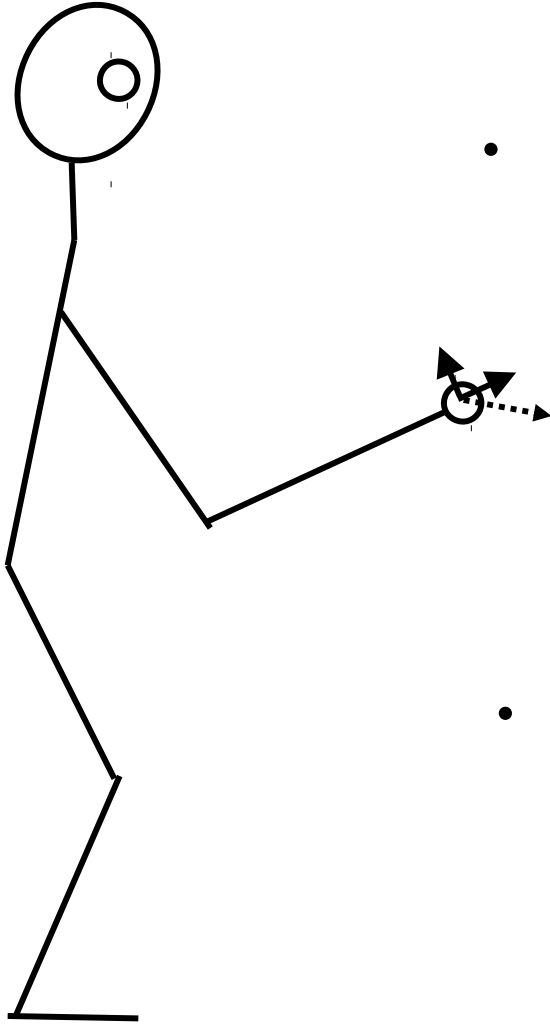


# Cartesian Control

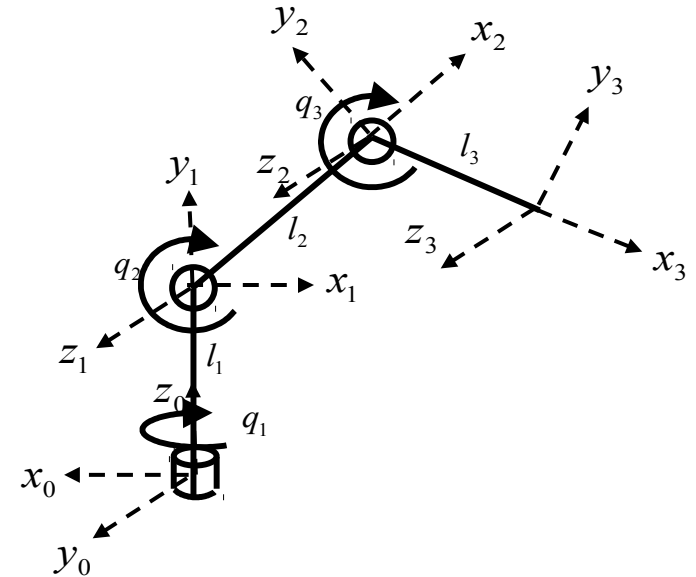


- Analytical inverse kinematics can be difficult to derive
- Inverse kinematics are not as well suited for small differential motions
- Let's take a look at how you use the Jacobian to control Cartesian position

# Cartesian control

Let's control the position (not orientation) of the three link arm end effector:

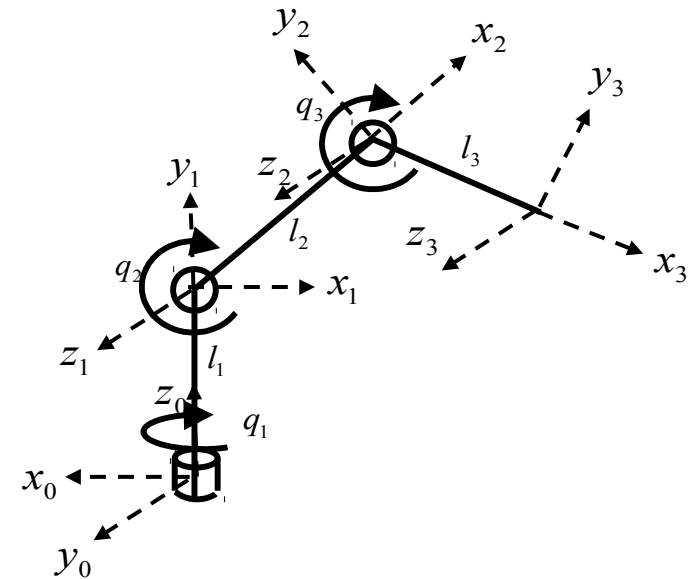
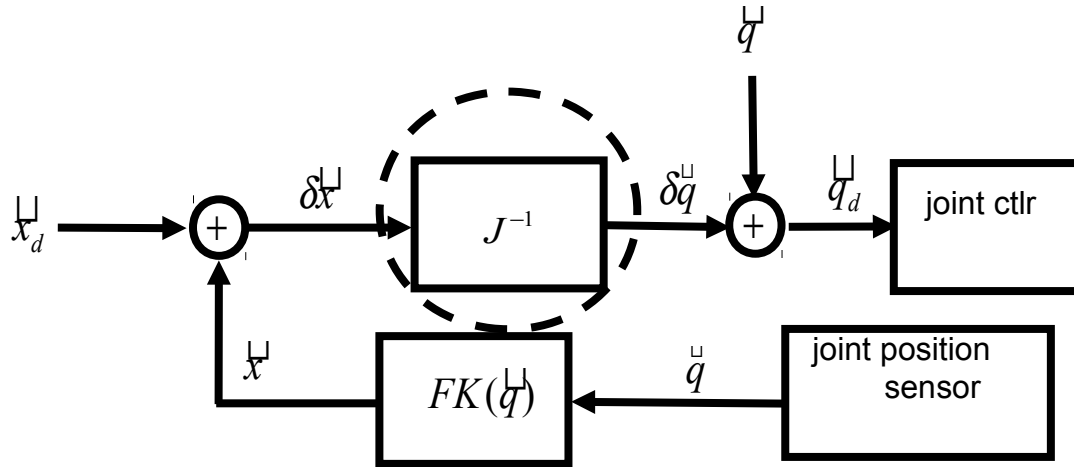
$$J = \begin{pmatrix} -s_1(l_2c_2 + l_3c_{23}) & -c_1(l_2c_2 + l_3c_{23}) & -l_3c_1s_{23} \\ c_1(l_2c_2 + l_3c_{23}) & -s_1(l_2c_2 + l_3c_{23}) & -l_3c_1s_{23} \\ 0 & l_2c_2 + l_3c_{23} & l_3c_{23} \end{pmatrix}$$



We can use the same strategy that we used before:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} = J \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} \longrightarrow \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} = J^{-1} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}$$

# Cartesian control



$$\begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} = J^{-1} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}$$

However, this only works if the Jacobian is square and full rank...

- All rows/columns are linearly independent, or
- Columns span Cartesian space, or
- Determinant is not zero

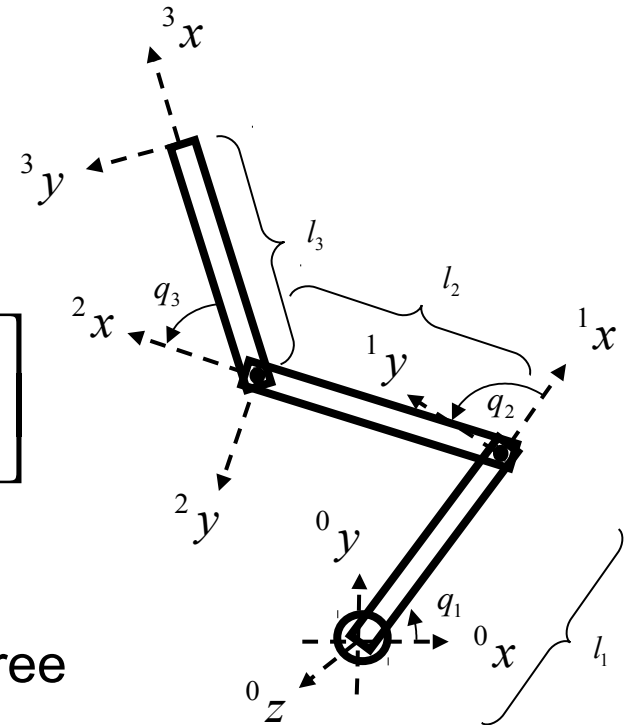
# Cartesian control

What if you want to control the two-dimensional position of a three-link manipulator?

$$J(q) = \begin{bmatrix} -l_1 s_1 - l_2 s_{12} - l_3 s_{123} & -l_1 s_1 - l_2 s_{12} & -l_1 s_1 \\ l_1 c_1 + l_2 c_{12} + l_3 c_{123} & l_1 c_1 + l_2 c_{12} & l_1 c_1 \end{bmatrix}$$

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} = J(q) \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix}$$

← Two equations of three variables each...



This is an *under-constrained* system of equations.

- multiple solutions
- there are multiple joint angle velocities that realize the same EFF velocity.

# Generalized inverse

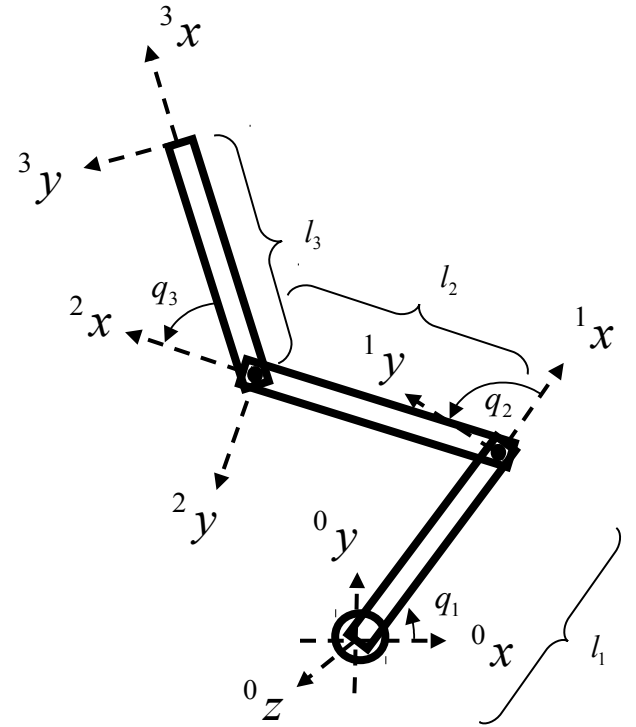
If the Jacobian is not a square matrix (or is not full rank), then the inverse doesn't exist...

- what next?

We have:  $\dot{x} = J\dot{q}$

We are looking for a matrix  $J^\#$  such that:

$$\dot{q} = J^\# \dot{x} \longrightarrow \dot{x} = J\dot{q}$$



# Generalized inverse

Two cases:

- Underconstrained manipulator (redundant)
- Overconstrained

Generalized inverse:

- for the underconstrained manipulator: given  $\dot{x}$ , find any vector  $\dot{q}$  s.t.
- for the overconstrained manipulator: given  $\dot{x}$ , find any vector  $\dot{q}$  s.t.  
$$\|\dot{x} - J\dot{q}\|$$
 is minimized

# Jacobian Pseudoinverse: Redundant manipulator

Pseudoinverse definition: (underconstrained)

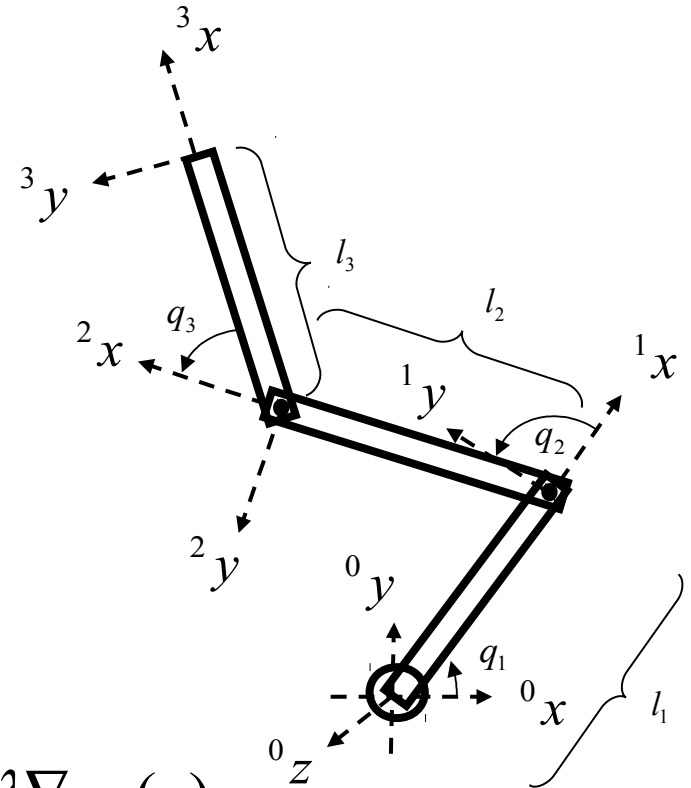
Given a desired twist,  $\dot{x}_d$ , find a vector of joint velocities,  $\dot{q}$ , that satisfies  $\dot{x}_d = J\dot{q}$  while minimizing  $f(\dot{q}) = \dot{q}^T \dot{q}$

Minimize joint velocities

Minimize  $f(z)$  subject to  $g(z) = 0$  :

Use **lagrange multiplier method**:  $\nabla_z f(z) = \lambda \nabla_z g(z)$

This condition must be met when  $f(z)$  is at a minimum subject to  $g(z) = 0$



# Jacobian Pseudoinverse: Redundant manipulator

$$\nabla_z f(z) = \lambda \nabla_z g(z)$$

$$f(\dot{q}) = \frac{1}{2} \dot{q}^T \dot{q} \quad \longleftarrow \text{Minimize}$$

$$g(\dot{q}) = J\dot{q} - \dot{x} = 0 \quad \longleftarrow \text{Subject to}$$

$$\nabla_{\dot{q}} f(\dot{q}) = \dot{q}^T$$

$$\nabla_{\dot{q}} g(\dot{q}) = J$$

$$\dot{q}^T = \lambda^T J$$

$$\dot{q} = J^T \lambda$$

# Jacobian Pseudoinverse: Redundant manipulator

$$\dot{q} = J^T \lambda$$

$$J\dot{q} = (JJ^T)\lambda$$

$$\lambda = (JJ^T)^{-1} J\dot{q} \quad \longleftarrow \begin{array}{l} \text{I won't say why, but if } J \text{ is full rank, then} \\ JJ^T \text{ is invertible} \end{array}$$

$$\lambda = (JJ^T)^{-1} \dot{x}$$

$$\dot{q} = J^T \lambda$$

$$\dot{q} = J^T (JJ^T)^{-1} \dot{x}$$

$$J^\# = J^T (JJ^T)^{-1}$$

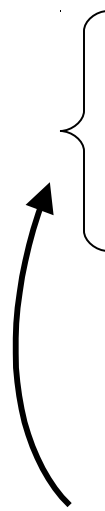
$$\dot{q} = J^\# \dot{x} \quad \longleftarrow$$

So, the pseudoinverse calculates the vector of joint velocities that satisfies  $\dot{x}_d = J\dot{q}$  while minimizing the squared magnitude of joint velocity (  $\dot{q}^T \dot{q}$  ).

- Therefore, the pseudoinverse calculates the *least-squares* solution.

# Calculating the pseudoinverse

The pseudoinverse can be calculated using two different equations depending upon the number of rows and columns:


$$\left\{ \begin{array}{ll} J^{\#} = J^T (J J^T)^{-1} & \text{Underconstrained case (if there are more columns than rows } (m < n)) \\ J^{\#} = (J^T J)^{-1} J^T & \text{Overconstrained case (if there are more rows than columns } (n < m)) \\ J^{\#} = J^{-1} & \text{If there are an equal number of rows and columns } (n = m) \end{array} \right.$$

These equations can only be used if the Jacobian is full rank; otherwise, use singular value decomposition (SVD):

# Calculating the pseudoinverse using SVD

Singular value decomposition decomposes a matrix as follows:

$$J = \underbrace{U}_{m \times m} \underbrace{\Sigma}_{m \times n} \underbrace{V^T}_{n \times n}$$

For an under-constrained matrix,  $\Sigma$  is a diagonal matrix of singular values:

$$J = U \begin{bmatrix} \sigma_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_n & 0 & 0 \end{bmatrix} V^T$$

$$J^\# = V \Sigma^{-1} U^T$$

$$J^\# = V \begin{bmatrix} \frac{1}{\sigma_1} & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{\sigma_2} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\sigma_3} & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{\sigma_n} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} U^T$$

# Properties of the pseudoinverse

Moore-Penrose conditions:

$$1. J^{\#} J J^{\#} = J^{\#}$$

$$2. J J^{\#} J = J$$

$$3. (J J^{\#})^T = J J^{\#}$$

$$4. (J^{\#} J)^T = J^{\#} J$$

Generalized inverse: satisfies condition 1

Reflexive generalized inverse: satisfies conditions 1 and 2

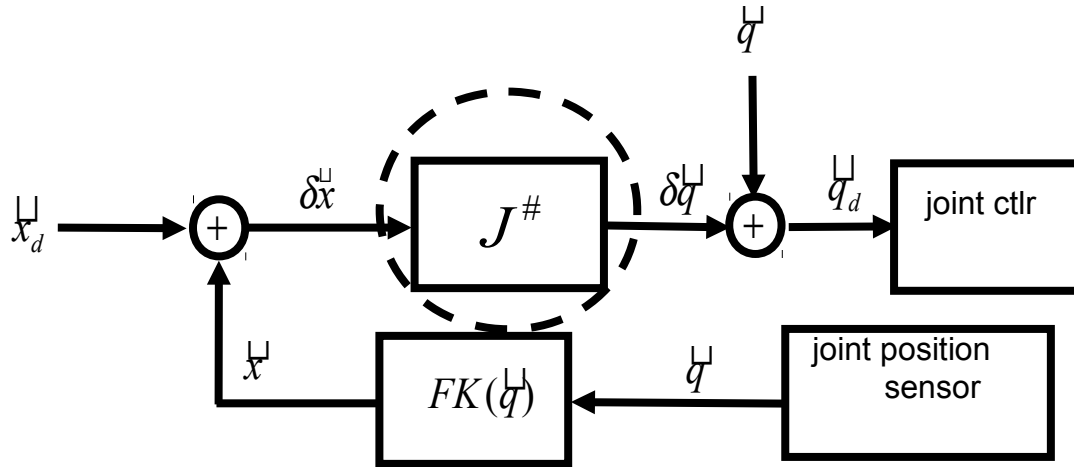
Pseudoinverse: satisfies all four conditions

Other useful properties of the pseudoinverse:

$$(J^{\#})^{\#} = J$$

$$(J^{\#})^T = (J^T)^{\#}$$

# Controlling Cartesian Position



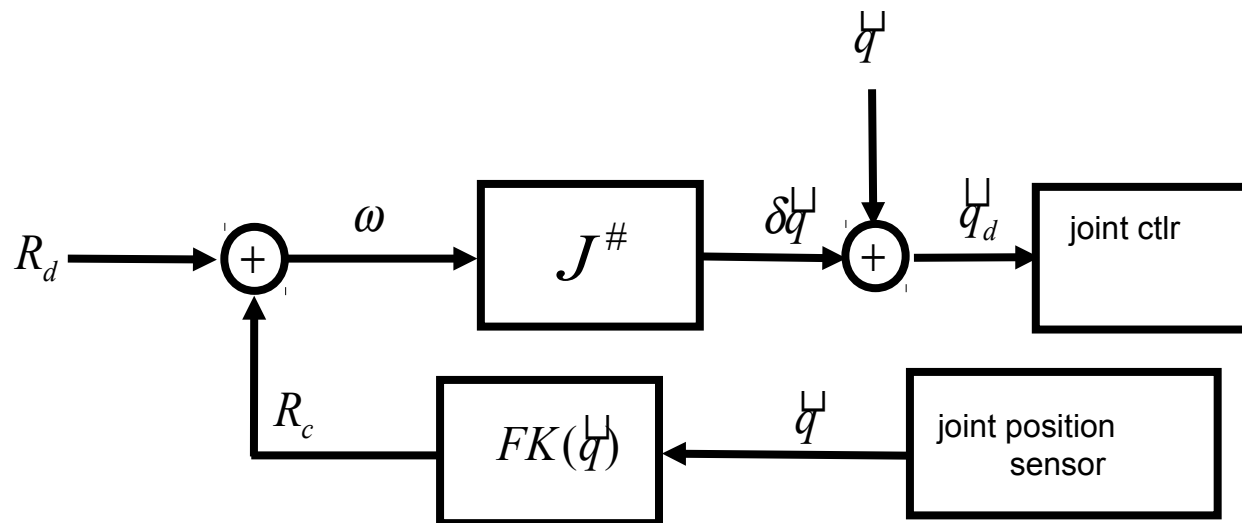
Procedure for controlling position:

1. Calculate position error:  $\mathbf{x}_{err}$
2. Multiply by a scaling factor:  $\delta \mathbf{x}_{err} = \alpha \mathbf{x}_{err}$
3. Multiply by the velocity Jacobian pseudoinverse:  $\dot{\mathbf{q}} = J_v^\# \alpha \mathbf{x}_{err}$

# Controlling Cartesian Orientation

How does this strategy work for orientation control?

- Suppose you want to reach an orientation of  $R_d$
- Your current orientation is  $R_c$
- You've calculated a difference:  $R_{cd} = R_c^T R_d$
- How do you turn this difference into a desired angular velocity to use in  $\dot{q} = J^\# \omega$  ?

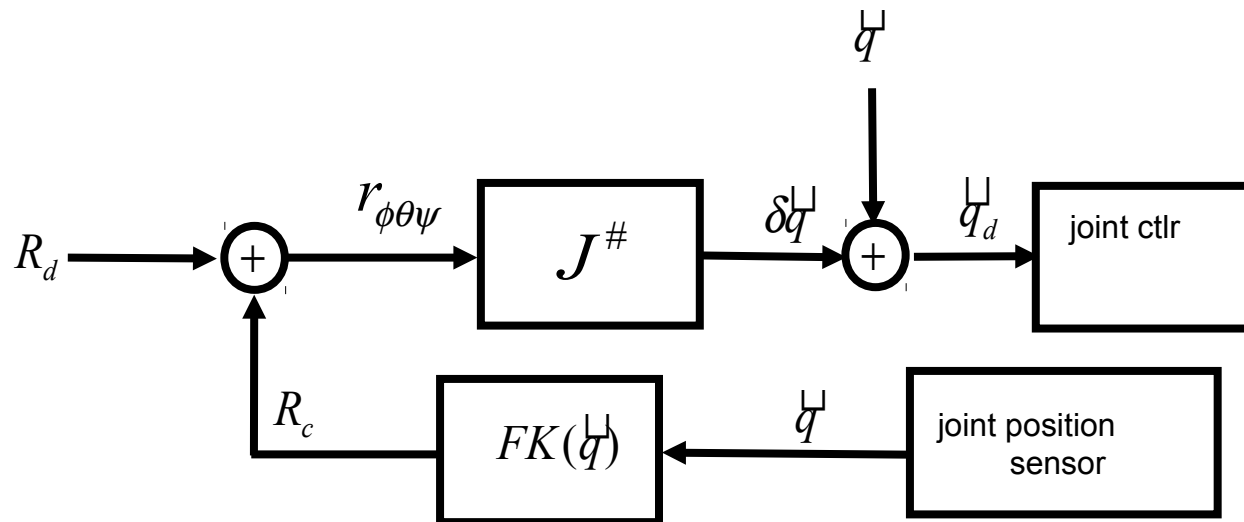


# Controlling Cartesian Orientation

You **can't** do this:

- Convert the difference to ZYZ Euler angles:  $r_{\phi\theta\psi}$
- Multiply the Euler angles by a scaling factor and pretend that they are an angular velocity:  $\delta q = \alpha J^\# r_{\phi\theta\psi}$

Remember that in general:  $J_\omega \neq \frac{\partial r_{\phi\theta\psi}}{\partial q}$



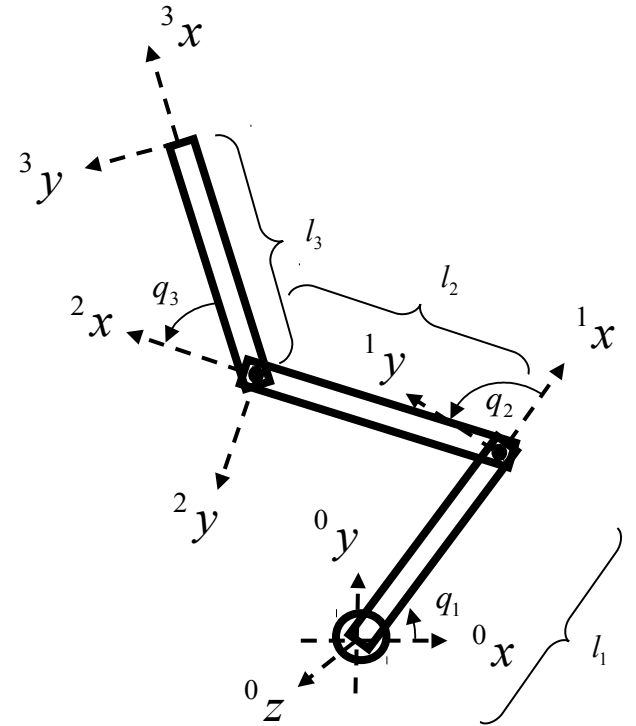
# The Analytical Jacobian

If you really want to multiply the angular Jacobian by the derivative of an Euler angle, you have to convert to the “analytical” Jacobian:

$$\frac{\partial r_{\phi\theta\psi}}{\partial q} = T_A(r_{\phi\theta\psi}) J_\omega \dot{q}$$

$$J_A = T_A(r_{\phi\theta\psi}) J_\omega = \begin{bmatrix} 0 & -s_\phi & c_\phi s_\theta \\ 0 & c_\phi & s_\phi s_\theta \\ 1 & 0 & c_\theta \end{bmatrix} J_\omega$$

For ZYZ Euler angles



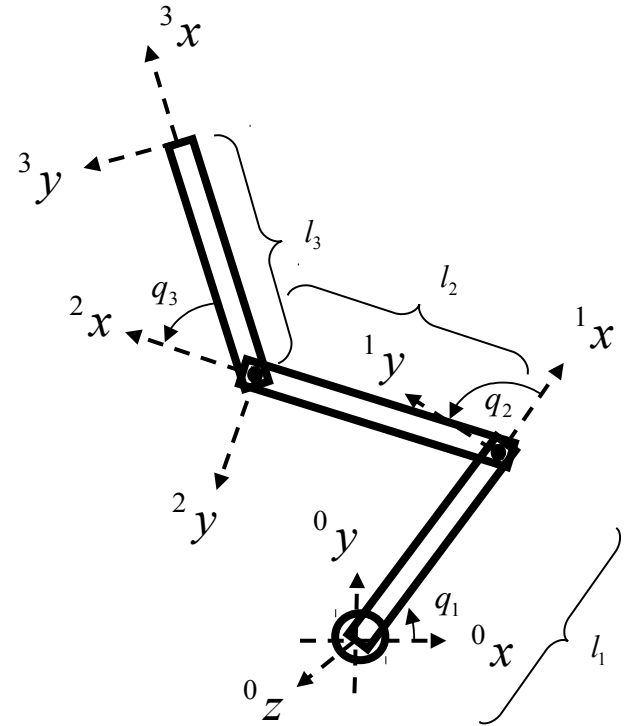
Gimbal lock: by using an analytical Jacobian instead of the angular velocity Jacobian, you introduce the gimbal lock problems we talked about earlier into the Jacobian – this essentially adds “singularities” (we’ll talk more about that in a bit...)

# Controlling Cartesian Orientation

The easiest way to handle this Cartesian orientation problem is to represent the error in axis-angle format

$$\delta \mathbf{r}_k = J_\omega \dot{\mathbf{q}}$$

Axis angle delta rotation



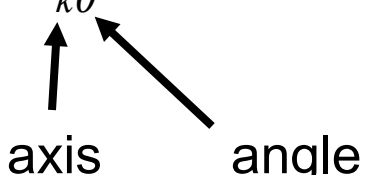
Procedure for controlling rotation:

1. Represent the rotation error in axis angle format:  $\mathbf{r}_{err}$
2. Multiply by a scaling factor:  $\delta \mathbf{r}_{err} = \alpha \mathbf{r}_{err}$
3. Multiply by the angular velocity Jacobian pseudoinverse:  $\dot{\mathbf{q}} = J_\omega^\# \alpha \mathbf{r}_{err}$

# Controlling Cartesian Orientation

Why does axis angle work?

- Remember Rodrigues' formula from before:

$$R_{k\theta} = e^{S(k)\theta} = I + S(k)\sin(\theta) + S(k)^2(1 - \cos(\theta))$$


axis      angle

Compare this to the definition of angular velocity:  ${}^b\dot{p} = S({}^b\omega){}^b p$

The solution to this FO diff eqn is:  ${}^bR_{\omega t} = e^{S({}^b\omega)t}$

Therefore, the angular velocity gets integrated into an axis angle representation

# Jacobian Transpose Control

The story of Cartesian control so far:

1.  $\dot{x} = J\dot{q}$
2.  $\dot{q} = J^\# \dot{x}$

# Jacobian Transpose Control

Here's another approach:

$$e = \frac{1}{2} x_{err}^T x_{err}$$

$$\frac{\partial e}{\partial q} = -\left(x_{err}^T\right) \frac{\partial x}{\partial q}$$

$$\dot{q} \leftarrow -\alpha \left( \frac{\partial e}{\partial q} \right)^T$$

$$\dot{q} = \alpha \left[ \left(x_{err}^T\right) \frac{\partial x}{\partial q} \right]^T$$

$$\dot{q} = \alpha \frac{\partial x^T}{\partial q} (x_{err})$$

$$\dot{q} = \alpha J_v^T (x_{err})$$

Start with a squared position error function (assume the poses are represented as row vectors)

Position error:  $x_{err} = x_{ref} - x$

Gradient descent: take steps proportional to  $\alpha$  in the direction of the negative gradient.

# Jacobian Transpose Control

The same approach can be used to control orientation:

$$\dot{q} = \alpha J_{\omega}^T \left( {}^{curr}k_{ref} \right)$$

orientation error: axis angle orientation of reference pose in  
the current end effector reference frame:  ${}^{curr}k_{ref}$

# Jacobian Transpose Control

So, evidently, this is the gradient of that

↓

$$\dot{q} = J^T(x_{err})$$

↓

$$e = \frac{1}{2} x_{err}^T x_{err}$$

- Jacobian transpose control descends a squared error function.
- Gradient descent always follows the *steepest* gradient

# Jacobian Transpose v Pseudoinverse

What gives?

- Which is more direct? Jacobian pseudoinverse or transpose?

$$\dot{q} = J^T \xi \quad \text{or} \quad \dot{q} = J^\# \xi$$

They do different things:

- Transpose: move toward a reference pose as quickly as possible
  - One dimensional goal (squared distance metric)
- Pseudoinverse: move along a least squares reference twist trajectory
  - Six dimensional goal (or whatever the dimension of the relevant twist is)

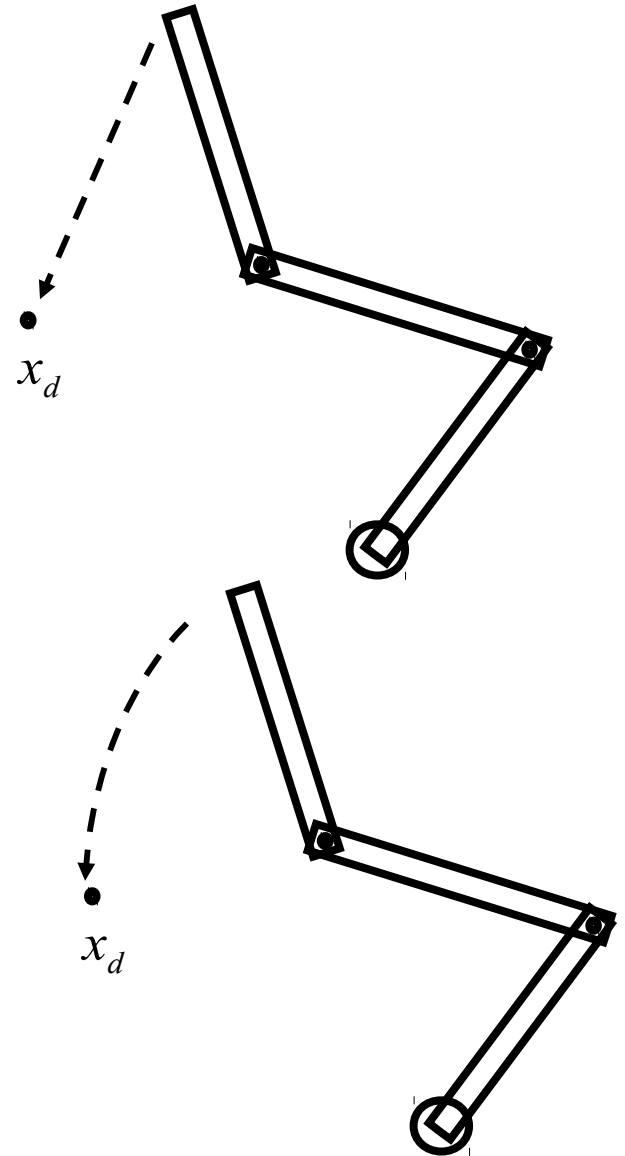
# Jacobian Transpose v Pseudoinverse

The pseudoinverse moves the end effector in a straight line path toward the goal pose using the least squared joint velocities.

- The goal is specified in terms of the reference twist
- Manipulator follows a straight line path in Cartesian space

The transpose moves the end effector toward the goal position

- In general, not a straight line path *in Cartesian space*
- Instead, the transpose follows the gradient in *joint space*



# Using the Jacobian for Statics

Up until now, we've used the Jacobian in the twist equation,  $\xi = J\dot{q}$

Interestingly, you can also use the Jacobian in a statics equation:

Joint torques

Cartesian wrench:

$$\tau = J^T w$$
$$w = \begin{pmatrix} f \\ m \end{pmatrix}$$

force

moment (torque)

The diagram illustrates the statics equation  $\tau = J^T w$ . Two arrows point from the components of the Cartesian wrench  $w$  towards the equation. The first arrow points from the force component  $f$  to the equation, and the second arrow points from the moment component  $m$  to the equation. The text 'Joint torques' is positioned to the left of the equation, and 'Cartesian wrench:' is positioned to the right of the equation. The components of the wrench are labeled 'force' and 'moment (torque)' to the right of the equation.

# Using the Jacobian for Statics

It turns out that both wrenches and twists can be understood in terms of a representation of displacement known as a *screw*.

- Therefore, you can calculate work by integrating the dot product:

$$W = \int (\mathbf{v} \cdot \mathbf{f} + \boldsymbol{\omega} \cdot \mathbf{m}) = \int \begin{bmatrix} \mathbf{v} \\ \boldsymbol{\omega} \end{bmatrix}^T \begin{bmatrix} \mathbf{f} \\ \mathbf{m} \end{bmatrix} \quad \leftarrow \quad \text{Work in Cartesian space}$$

$$W = \int \boldsymbol{\tau}^T \dot{\mathbf{q}} \quad \leftarrow \quad \text{Work in joint space}$$

Conservation of energy:  $\int \boldsymbol{\tau}^T \dot{\mathbf{q}} = \int \begin{bmatrix} \mathbf{v} \\ \boldsymbol{\omega} \end{bmatrix}^T \begin{bmatrix} \mathbf{f} \\ \mathbf{m} \end{bmatrix}$

# Using the Jacobian for Statics

$$\tau^T \dot{q} = \begin{bmatrix} f \\ m \end{bmatrix}^T \begin{bmatrix} v \\ \omega \end{bmatrix} \quad \longleftarrow \quad \text{Incremental work (virtual work)}$$

$$\tau^T \dot{q} = \begin{bmatrix} f \\ m \end{bmatrix}^T J \dot{q}$$

$$\tau^T = \begin{bmatrix} f \\ m \end{bmatrix}^T J$$

$$\tau = J^T \begin{bmatrix} f \\ m \end{bmatrix}$$

Wrench-twist duality:

$$\tau = J^T w \quad \text{vs} \quad \xi = J \dot{q}$$

$$\tau = J^T w$$

# Twist: converting between reference frames

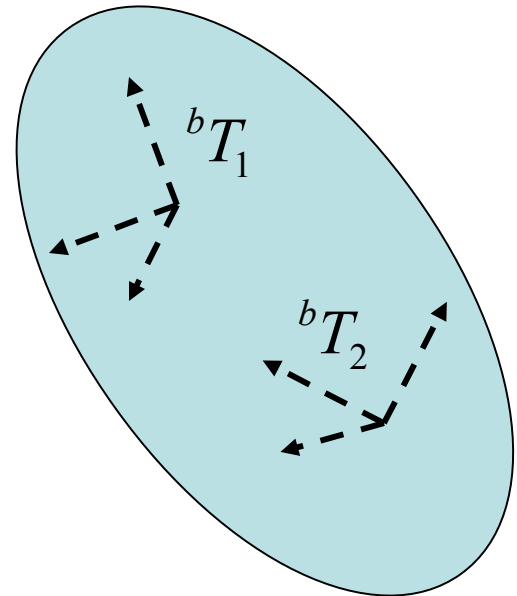
Note that twist can be represented in different reference frames:

$${}^b\xi = \begin{bmatrix} {}^b\mathbf{v} \\ {}^b\boldsymbol{\omega} \end{bmatrix} \quad {}^k\xi = \begin{bmatrix} {}^k\mathbf{v} \\ {}^k\boldsymbol{\omega} \end{bmatrix}$$

Consider two reference frames attached to the same rigid body:

$${}^b\boldsymbol{\omega}_2 = {}^b\boldsymbol{\omega}_1$$

$${}^b\mathbf{v}_2 = {}^b\mathbf{v}_1 + {}^b\boldsymbol{\omega}_1 \times \mathbf{r}_{12}$$



# Twist: converting between reference frames

$${}^b\omega_2 = {}^b\omega_1$$

$${}^b v_2 = {}^b v_1 + {}^b\omega_1 \times r_{12}$$

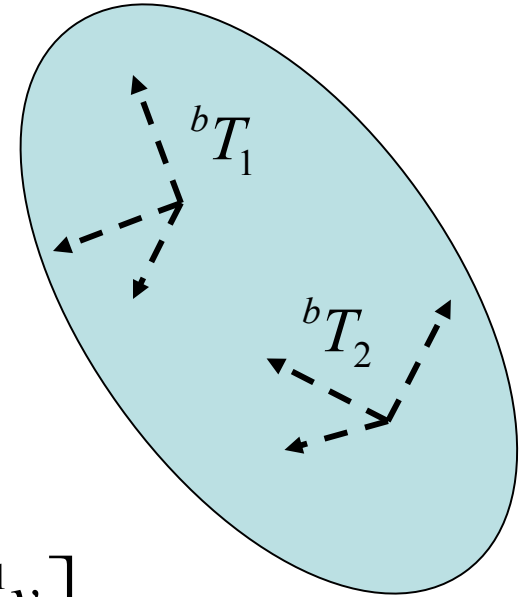
$$\begin{bmatrix} {}^b v_2 \\ {}^b \omega_2 \end{bmatrix} = \begin{bmatrix} I & -S(r_{12}) \\ 0 & I \end{bmatrix} \begin{bmatrix} {}^b v_1 \\ {}^b \omega_1 \end{bmatrix}$$

$$\begin{bmatrix} {}^2 v \\ {}^2 \omega \end{bmatrix} = \begin{bmatrix} {}^b R_2^T & 0 \\ 0 & {}^b R_2^T \end{bmatrix} \begin{bmatrix} I & -S(r_{12}) \\ 0 & I \end{bmatrix} \begin{bmatrix} {}^b R_1 & 0 \\ 0 & {}^b R_1 \end{bmatrix} \begin{bmatrix} {}^1 v \\ {}^1 \omega \end{bmatrix}$$

$$\begin{bmatrix} {}^2 v \\ {}^2 \omega \end{bmatrix} = \begin{bmatrix} {}^2 R_1 & -{}^2 R_1 S({}^1 r_{12}) \\ 0 & {}^2 R_1 \end{bmatrix} \begin{bmatrix} {}^1 v \\ {}^1 \omega \end{bmatrix}$$

Twist in frame 2

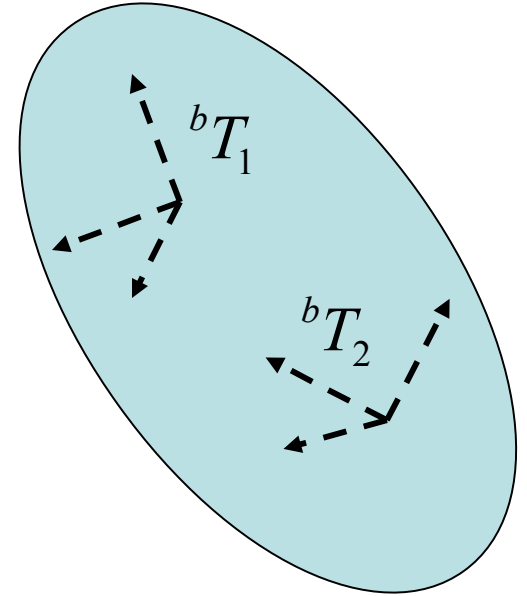
Twist in frame 1



# Wrench: converting between reference frames

Wrench can also be represented in different reference frames:

$${}^b\mathcal{W} = \begin{bmatrix} {}^b f \\ {}^b m \end{bmatrix} \quad {}^k\mathcal{W} = \begin{bmatrix} {}^k f \\ {}^k m \end{bmatrix}$$



# Wrench: converting between reference frames

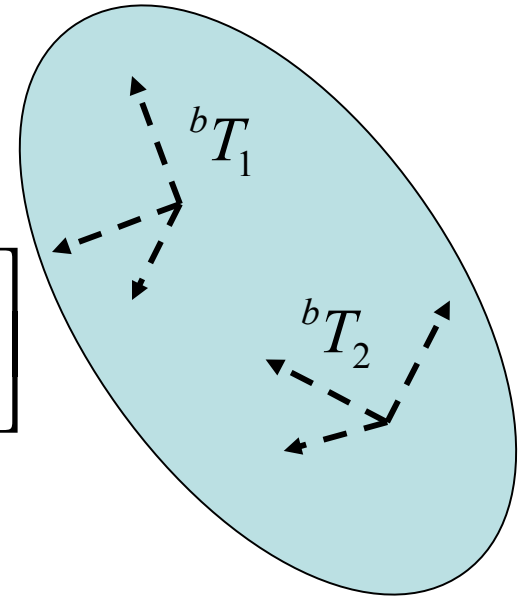
Use the virtual work argument to derive the relationship:

$$\begin{bmatrix} {}^2f_2 \\ {}^2m_2 \end{bmatrix}^T \begin{bmatrix} {}^2v_2 \\ {}^2\omega_2 \end{bmatrix} = \begin{bmatrix} {}^1f_1 \\ {}^1m_1 \end{bmatrix}^T \begin{bmatrix} {}^1v_1 \\ {}^1\omega_1 \end{bmatrix}$$

$$\begin{bmatrix} {}^2f_2 \\ {}^2m_2 \end{bmatrix}^T \begin{bmatrix} {}^2R_1 & -{}^2R_1 S({}^1r_{12}) \\ 0 & {}^2R_1 \end{bmatrix} \begin{bmatrix} {}^1v_1 \\ {}^1\omega_1 \end{bmatrix} = \begin{bmatrix} {}^1f_1 \\ {}^1m_1 \end{bmatrix}^T \begin{bmatrix} {}^1v_1 \\ {}^1\omega_1 \end{bmatrix}$$

$$\begin{bmatrix} {}^2f_2 \\ {}^2m_2 \end{bmatrix}^T \begin{bmatrix} {}^2R_1 & -{}^2R_1 S({}^1r_{12}) \\ 0 & {}^2R_1 \end{bmatrix} = \begin{bmatrix} {}^1f_1 \\ {}^1m_1 \end{bmatrix}^T$$

$$\begin{bmatrix} {}^1f_1 \\ {}^1m_1 \end{bmatrix} = \begin{bmatrix} {}^1R_2 & 0 \\ S({}^1r_{12}) {}^1R_2 & {}^1R_2 \end{bmatrix} \begin{bmatrix} {}^2f_2 \\ {}^2m_2 \end{bmatrix}$$

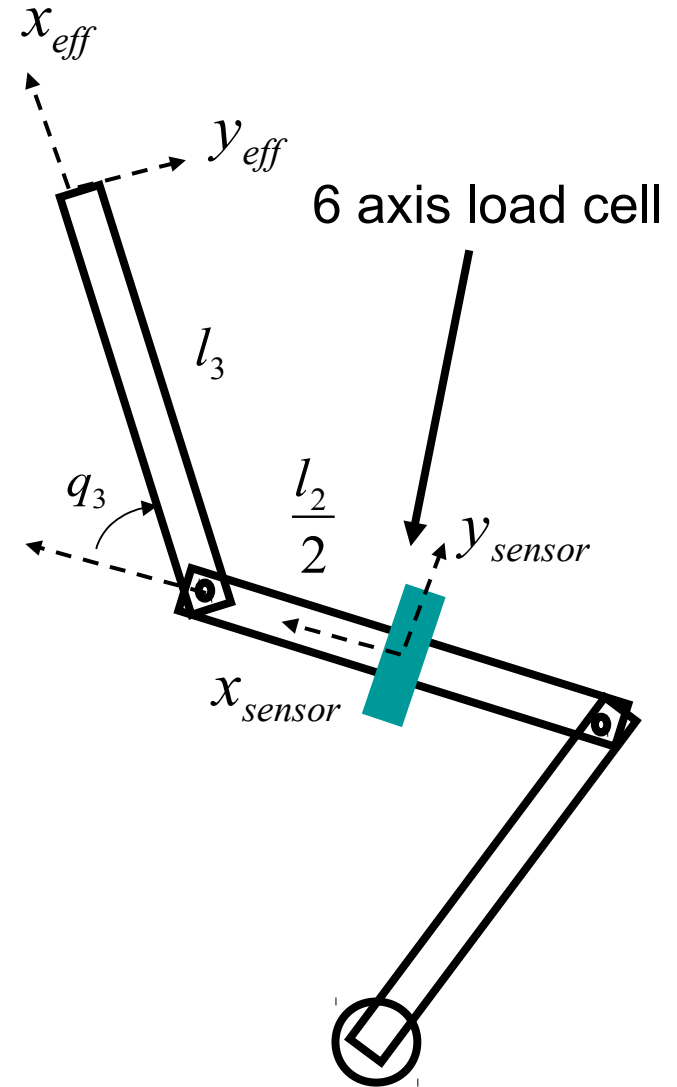


# Converting wrenches: Example

Use a 6-axis load cell bisecting the second link to calculate wrenches at the end effector (the tip of the last link)

$${}^{eff}R_{sensor} = \begin{pmatrix} c_3 & s_3 & 0 \\ -s_3 & c_3 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

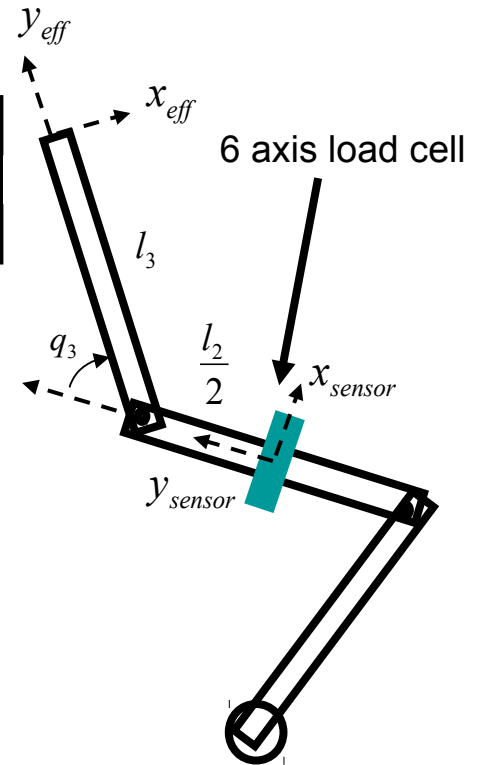
$${}^{eff}r_{sensor} = \begin{pmatrix} -l_3 - \frac{l_2}{2}c_3 \\ \frac{l_2}{2}s_3 \\ 0 \end{pmatrix}$$



# Converting wrenches: Example

$$\begin{bmatrix} {}^{eff}f_{eff} \\ {}^{eff}m_{eff} \end{bmatrix} = \begin{bmatrix} {}^{eff}R_{sensor} \\ S \left( {}^{eff}r_{eff,sensor} \right) {}^{eff}R_{sensor} \end{bmatrix} \begin{bmatrix} {}^{sensor}f_{sensor} \\ {}^{sensor}m_{sensor} \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ {}^{eff}R_{sensor} \end{bmatrix} \begin{bmatrix} {}^{sensor}f_{sensor} \\ {}^{sensor}m_{sensor} \end{bmatrix}$$



$$\begin{bmatrix} {}^{eff}f_{eff} \\ {}^{eff}m_{eff} \end{bmatrix} = \begin{bmatrix} c_3 & s_3 & 0 & 0 & 0 & 0 \\ -s_3 & c_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \frac{l_2}{2}s_3 & c_3 & s_3 & 0 \\ 0 & 0 & l_3 + \frac{l_2}{2}c_3 & -s_3 & c_3 & 0 \\ l_3s_3 & -l_3c_3 - \frac{l_2}{2}c_3^2 - \frac{l_2}{2}s_3^2 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^{sensor}f_{sensor} \\ {}^{sensor}m_{sensor} \end{bmatrix}$$