

Material Covered up until now,

- forward kinematics • how to determine end-effector configuration given joint-configuration
- inverse kinematics • " joint configuration " end-effector configuration
- Jacobian (manipulator) • relate <sup>configuration</sup> velocities to joint velocities.  
(end effector)
- exp & ln • convert configuration differences into velocities / trajectories.

⇒

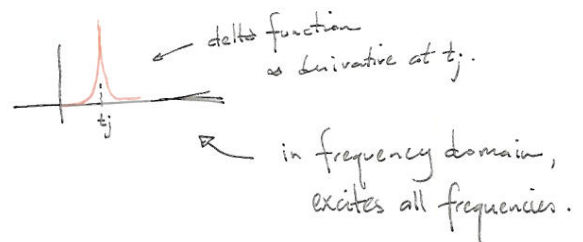
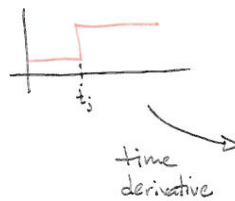
Goal: how do we design realistic/feasible trajectories connecting different configurations.

- ① joint-configurations.
- ② group configurations.
- ③ both levels?

→ sometimes not possible using only one configuration space.  
may need to switch between the two.

### Trajectory design

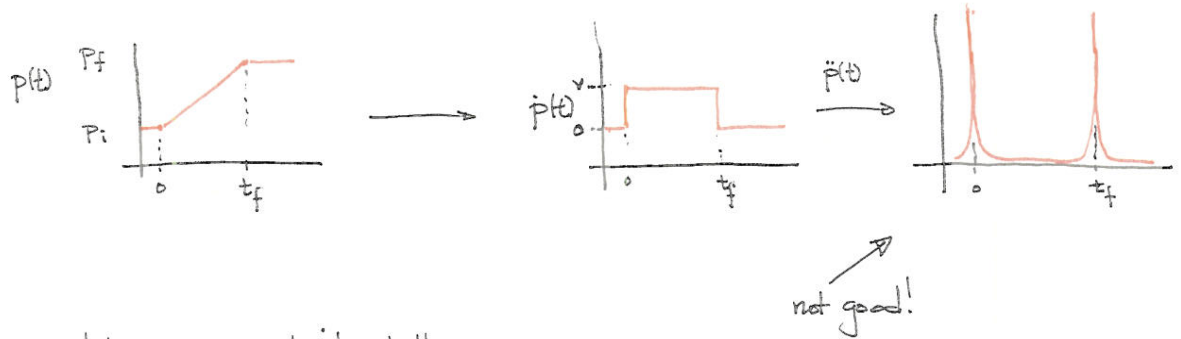
- \* now, considers the time history: position, velocity, and/or acceleration.
- \* want sufficiently smooth trajectories (cts. derivatives)
  - no jerky motions →
    - cause wear
    - induce vibrations (excite resonances)



- \* may require intermediate points between initial and final configurations.  
(AKA: way-points, via-points)

So, how are trajectories generated / designed?

simplest approach is linear (1D)



need to manage velocity better.

let's add velocity constraints on initial & final configurations.

Cubic polynomials / splines

B-Splines

four constraints on polynomials:

1) initial point	$p_i$
2) final point	$p_f$
3) initial velocity	$\dot{p}_i$
4) final velocity	$\dot{p}_f$

⇒ cubic polynomial required (at least)

$$p(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3$$

such that:

$$\begin{aligned} p(0) &= p_i \\ p(t_f) &= p_f \\ \dot{p}(0) &= \dot{p}_i = 0 \\ \dot{p}(t_f) &= \dot{p}_f = 0 \end{aligned}$$

Note:

$$p(t) = a_1 t + 2a_2 t^2 + 3a_3 t^3$$

$$\dot{p}(t) = 2a_2 + 6a_3 t$$

⇒

$$p(0) = a_0 = p_i$$

$$p(t_f) = a_0 + a_1 t_f + a_2 t_f^2 + a_3 t_f^3 = p_f$$

$$\dot{p}(0) = a_1 = 0$$

$$\dot{p}(t_f) = a_1 + 2a_2 t_f + 3a_3 t_f^2 = 0$$

⇒

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & t_f & t_f^2 & t_f^3 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 2t_f & 3t_f^2 \end{bmatrix} \vec{a} = \begin{bmatrix} p_i \\ p_f \\ 0 \\ 0 \end{bmatrix} = \vec{p}_0$$

⇒

$$\vec{a} = P(t_f) \vec{p}_0 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ -3/t_f^2 & 3/t_f^2 \\ 2/t_f^3 & -2/t_f^3 \end{bmatrix} \begin{bmatrix} p_i \\ p_f \end{bmatrix}$$

↑ smaller matrix & vector  
since last two components vanish.

$$a_0 = p_i \quad a_2 = 3/t_f^2 (p_f - p_i)$$

$$a_1 = 0 \quad a_3 = 2/t_f^3 (p_i - p_f)$$

What value should  $t_f$  take?

- certainly should be some short enough time, so trajectory doesn't take forever
- not too short : actuator limits.  
end-effector velocity limits.

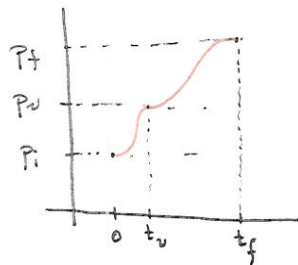
- have decent initial guess based on limits,

$$v \cdot t = d$$

↑ distance  
↑ time.  
↑ velocity.

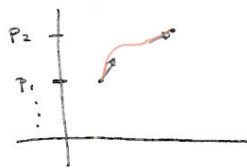
What if there are way points?

- do not want to connect as a series of cubic polynomials w/ zero velocity conditions



← slows down at this point.  
is there a need to?

- use non-trivial velocities at way points.



achieve end-point constraints + match velocities

$$p(0) = p_i \quad p(t_f) = p_f$$

$$\dot{p}(0) = \dot{p}_i \quad \dot{p}(t_f) = \dot{p}_f$$

⇒

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & t_f & t_f^2 & t_f^3 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 2t_f & 3t_f^2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} p_i \\ p_f \\ \dot{p}_i \\ \dot{p}_f \end{bmatrix}$$

⇒

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -3/t_f^2 & 3/t_f^2 & -2/t_f & -1/t_f \\ 2/t_f^3 & -2/t_f^3 & 1/t_f^2 & 1/t_f^2 \end{bmatrix} \begin{bmatrix} p_i \\ p_f \\ \dot{p}_i \\ \dot{p}_f \end{bmatrix}$$

⇒

$$\vec{a} = P(t_f) \vec{p}_0$$

$$a_0 = p_i \quad a_2 = \frac{3}{t_f^2}(p_f - p_i) - \frac{2}{t_f} \dot{p}_i - \frac{1}{t_f} \dot{p}_f$$

$$a_1 = \dot{p}_i \quad a_3 = \frac{2}{t_f^3}(p_i - p_f) + \frac{1}{t_f^2}(\dot{p}_i + \dot{p}_f)$$

- connecting in this manner matches velocities, but not accelerations
  - if accelerations close enough, not a problem
  - if far apart, then may lead to jerky motions.

Let's connect two cubic splines w/ a cts acceleration profile.

achieve positions  $P_i, P_u, P_f$  at times  $0, t_u, t_f$

$$f(t) = \begin{cases} p(t) & \text{if } t \in [0, t_u] \\ q(t - t_u) & \text{if } t \in (t_u, t_f) \end{cases}$$

where,

$$p(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3, \quad t \in [0, t_u]$$

$$q(t) = b_0 + b_1 t + b_2 t^2 + b_3 t^3, \quad t \in [0, t_f - t_u]$$

constraints are:

position :

$$\begin{aligned} p(0) &= P_i \\ p(t_u) &= P_u \\ q(0) &= P_u \\ q(t_f - t_u) &= P_f \end{aligned}$$

velocity :

$$\begin{aligned} \dot{p}(0) &= 0 \\ \dot{q}(t_f - t_u) &= 0 \end{aligned}$$

$$\dot{p}(t_u) = \dot{q}(0)$$

acceleration :

$$\ddot{p}(t_u) = \ddot{q}(0)$$

matching conditions

define:  $t_1 = t_0$ ,  $t_2 = t_f - t_0$

⇒

$$p(0) = a_0 = p_i$$

$$p(t_1) = a_0 + a_1 t_1 + a_2 t_1^2 + a_3 t_1^3 = p_0$$

$$q(0) = b_0 = p_0$$

$$q(t_2) = b_0 + b_1 t_2 + b_2 t_2^2 + b_3 t_2^3 = p_f$$

$$\dot{p}(0) = a_1 = 0$$

$$\dot{q}(t_2) = b_1 + 2b_2 t_2 + 3b_3 t_2^2 = 0$$

$$\dot{p}(t_1) - \dot{q}(0) = a_1 + 2a_2 t_1 + 3a_3 t_1^2 - b_1 = 0$$

$$\ddot{p}(t_1) - \ddot{q}(0) = 2a_2 + 6a_3 t_1 - 2b_2 = 0$$

⇒

$$\vec{a} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & t_1 & t_1^2 & t_1^3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & t_2 & t_2^2 & t_2^3 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 2t_2 & 3t_2^2 \\ 0 & 1 & 2t_1 & 3t_1^2 & 0 & -1 & 0 & 0 \\ 0 & 0 & 2 & 6t_1 & 0 & 0 & -2 & 0 \end{bmatrix} \vec{a} = \begin{Bmatrix} p_i \\ p_0 \\ p_0 \\ p_f \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix} = \vec{p}_0$$

⇒

||  
A

$$\vec{a} = A^{-1}(t_1, t_2) \vec{p}_0 = P(t_1, t_2) \vec{p}_0$$

↑ note structure of  $\vec{p}_0$  allows for simplification.

if we simplify things, we get

$$\vec{a} = P_{\text{simp}}(t_1, t_2) \begin{Bmatrix} p_i \\ p_v \\ p_f \end{Bmatrix}$$

where

$$P_{\text{simp}}(t_1, t_2) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ -\frac{3(2t_1+t_2)}{2t_1^2(t_1+t_2)} & \frac{3(t_1+t_2)}{2t_1^2 t_2} & -\frac{3}{2t_2(t_1+t_2)} \\ \frac{4t_1+t_2}{2t_1^3(t_1+t_2)} & -\frac{3t_1+t_2}{2t_1^3 t_2} & \frac{3}{2t_1^2 t_2 + 2t_1 t_2^2} \\ 0 & 1 & 0 \\ -\frac{3t_2}{2t_1(t_1+t_2)} & \frac{3}{2}\left(\frac{1}{t_1} - \frac{1}{t_2}\right) & \frac{3t_1}{2t_2(t_1+t_2)} \\ \frac{3}{t_1^2 + t_1 t_2} & -\frac{3}{t_1 t_2} & \frac{3}{t_1 t_2 + t_2^2} \\ -\frac{3}{2t_1^2 t_2 + 2t_1 t_2^2} & \frac{t_1 + 3t_2}{2t_1 t_2^3} & -\frac{t_1 + 4t_2}{2t_2^3(t_1+t_2)} \end{bmatrix}$$

if  $t_1 = t_2 = t \Rightarrow 0, t, 2t$

we get

$$P_{\text{simp}}(t, t) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ -\frac{9}{4t^2} & \frac{3}{t^2} & -\frac{3}{4t^2} \\ \frac{5}{4t^3} & -\frac{2}{t^3} & \frac{3}{4t^3} \\ 0 & 1 & 0 \\ -\frac{3}{4t} & 0 & \frac{3}{4t} \\ \frac{3}{2t^2} & -\frac{3}{t^2} & \frac{3}{2t^2} \\ -\frac{3}{4t^3} & \frac{2}{t^3} & -\frac{5}{4t^3} \end{bmatrix}$$

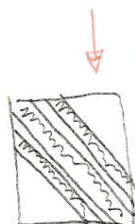
this is much easier to deal with.

\* The above procedure can be implemented for  $n$  waypoints

Leads to a  $[4(n+1) \times 4(n+1)]$  matrix which is invertible.

Has a tri-diagonal form  $\Rightarrow$  ① sparse matrix

② there are fast solvers.





Suppose have manipulator:



$$\left(\frac{\pi}{3}, -\frac{\pi}{8}, -\frac{\pi}{2}\right)$$

$$\left(\frac{\pi}{8}, \frac{\pi}{6}, \frac{\pi}{2}\right)$$

max speed something like  $\frac{\pi}{4}$  rad/sec.

$\Rightarrow$

$$\frac{\pi}{\pi/4} = 4 \text{ sec.}$$

$$t_f = 4 \text{ sec.}$$

$\Rightarrow$

$$\theta_1(t) = \frac{\pi}{3} - \frac{5\pi}{128} t^2 + \frac{5\pi}{768} t^3$$

$$\theta_2(t) = -\frac{\pi}{8} + \frac{7\pi}{128} t^2 - \frac{7\pi}{768} t^3$$

$$\theta_3(t) = -\frac{\pi}{2} + \frac{3\pi}{16} t^2 - \frac{\pi}{32} t^3$$

if we examine  $\dot{\theta}_3(t)$ , it actually goes  $> \frac{\pi}{4}$  rad/sec.

need 7 seconds.

$$\theta_1(t) = \frac{\pi}{3} - \frac{5\pi}{392} t^2 + \frac{5\pi}{4116} t^3$$

$$\theta_2(t) = -\frac{\pi}{8} + \frac{\pi}{5} t^2 - \frac{\pi}{588} t^3$$

$$\theta_3(t) = -\frac{\pi}{2} + \frac{3\pi}{49} t^2 - \frac{2\pi}{343} t^3$$

# Multiple Waypoints, Equidistant in Time

$$p^i(t) = a_0^i + a_1^i t + a_2^i t^2 + a_3^i t^3$$

$$f(t) = p^k(t - kT) \quad \text{where} \quad k = \left\lfloor \frac{t}{T} \right\rfloor = \text{floor}\left(\frac{t}{T}\right) \cdot T$$

Points are  $p_0, p_1, \dots, p_n, p_{n+1}$

position constraints

$$p^1(0) = a_0^1 = p_0$$

$$p^1(T) = a_0^1 + a_1^1 T + a_2^1 T^2 + a_3^1 T^3 = p_1$$

$\vdots$

$2(n+1)$

$$p^k(0) = a_0^k = p_{k-1}$$

$$p^k(T) = a_0^k + a_1^k T + a_2^k T^2 + a_3^k T^3 = p_k$$

$\vdots$

$$p^{n+1}(0) = a_0^{n+1} = p_n$$

$$p^{n+1}(T) = a_0^{n+1} + a_1^{n+1} T + a_2^{n+1} T^2 + a_3^{n+1} T^3 = p_{n+1}$$

velocity constraints:

$$\text{boundary conditions} \rightarrow \dot{p}^1(0) = a_1^1 = 0$$

$n+2$

matching

$$\begin{aligned} \dot{p}^1(T) - \dot{p}^2(0) &= a_1^1 + 2a_2^1 T + 3a_3^1 T - a_1^2 = 0 \\ \vdots \\ \dot{p}^k(T) - \dot{p}^{k+1}(0) &= a_1^k + 2a_2^k T + 3a_3^k T - a_1^{k+1} = 0 \\ \vdots \\ \dot{p}^n(T) - \dot{p}^{n+1}(0) &= a_1^n + 2a_2^n T + 3a_3^n T - a_1^{n+1} = 0 \\ \dot{p}^{n+1}(T) &= a_1^{n+1} + 2a_2^{n+1} T + 3a_3^{n+1} T^2 = 0 \end{aligned}$$

acceleration constraints:

$$\boxed{n} \quad \ddot{p}^k(T) - \ddot{p}^{k+1}(0) = 2a_2^k + 6a_3^k T - 2a_2^{k+1} = 0$$

↓

Total =  $4(n+1)$  equations       $4(n+1)$  variables

⇒

$[4(n+1) \times 4(n+1)]$  matrix.

This determines a curve with  $n$  waypoints between initial and final points.

If velocity is known, then can do differently.

- ORGANIZATION TO OBTAIN TRIDIAGONAL MATRIX.
- SPARSE MATRIX SOLVERS.

## Multiple Waypoints w/ desired velocities.

- easier solve, easier setup
- possible discrete acceleration.

allow controller to handle this.

suppose we have  $p_0, p_1, \dots, p_n, p_{n+1}$

$$0, \dot{p}_1, \dots, \dot{p}_n, 0$$

max times:  $T_0, T_1, \dots, T_n, T_{n+1}$  of polynomials.

$$0, t_1, \dots, t_n, t_{n+1}, t_f \quad T_k = t_{k+1} - t_k$$

$$T_{n+1} = t_f - t_{n+1}$$

recall equations

$$p^k(0) = a_0^k = p_0$$

$$p^k(T_k) = a_0^k + a_1^k T_k + a_2^k T_k^2 + a_3^k T_k^3 = p_1$$

$$\dot{p}^k(0) = a_1^k = \dot{p}_0$$

$$\dot{p}^k(T_k) = a_1^k + 2a_2^k T_k + 3a_3^k T_k^2 = \dot{p}_1$$

$$\vdots$$

$$p^k(0) = a_0^k = p_{k-1}$$

$$p^k(T_k) = a_0^k + a_1^k T_k + a_2^k T_k^2 + a_3^k T_k^3 = p_k$$

$$\dot{p}^k(0) = a_1^k = \dot{p}_{k-1}$$

$$\dot{p}^k(T_k) = a_1^k + 2a_2^k T_k + 3a_3^k T_k^2 = \dot{p}_k$$

also

$[4(n+1) \times 4(n+1)]$

matrix.

$$p^{n+1}(0) = a_0^{n+1} = p_n$$

$$p^{n+1}(T_{n+1}) = a_0^{n+1} + a_1^{n+1} T_{n+1} + a_2^{n+1} T_{n+1}^2 + a_3^{n+1} T_{n+1}^3 = p_{n+1}$$

$$\dot{p}^{n+1}(0) = a_1^{n+1} = \dot{p}_n$$

$$\dot{p}^{n+1}(T_{n+1}) = a_1^{n+1} + 2a_2^{n+1} T_{n+1} + 3a_3^{n+1} T_{n+1}^2 = 0$$

## Manipulator Trajectories.

if we have two joint configurations  $\vec{\theta}_1$  and  $\vec{\theta}_2$ ,  
we can connect with a sufficiently smooth curve,

$$\vec{\theta}(t), \quad \vec{\theta}_1 = \vec{\theta}(0) \quad \& \quad \vec{\theta}_2 = \vec{\theta}(t_f)$$

- does curve satisfy actuator limits?  
possible to check by finding peak velocity or acceleration.
  - if not just dilate time until velocity is low enough.
- sometimes need to check that curve does not violate any workspace constraints
  - if so, need to modify curve.  
can add waypoints that force trajectory to respect workspace constraints.
- may need to refer to associated  $\dot{g}$  or  $(\dot{g}^b)$   
use Jacobian  $\dot{g} = J(\theta)\dot{\theta}$ .

What if trajectory is given by  $g(t)$ ?

can convert to trajectory in joint space by using  
inverse kinematics,

$$\vec{\theta}(t) = \theta_e(g(t)) \quad \theta_e: \text{configuration} \rightarrow \text{joint angles.}$$

$$g_e \circ \theta_e = \text{id}$$

$$\theta_e \circ g_e = \text{id?}$$

↑ recall that there may  
be multiple solutions.



may need to break  
into segments & use  
a local joint controller.

or if  $g(t) = \exp(\hat{\xi}t)$ , then

$$\xi^b = J(\theta) \dot{\theta}$$



$$\dot{\theta} = J^\#(\theta) \xi^b, \quad \theta_0 = \theta_e(g_0)$$

↑ pseudo-inverse.

↑ integrate for  $t \in [0, t_f]$

- PROBLEM: the further away the point, the worse the trajectory is.

## Manipulator Trajectories

can define a trajectory in joint space or in group (configuration) space.

recall that velocities are related via Jacobian:

$$\dot{\mathbf{g}} = \mathbf{J}(\theta) \dot{\theta}$$

↑  
will have invertible subspace

① if  $\mathbf{J}$  is square and invertible, then

$$\dot{\theta} = \mathbf{J}^{-1}(\theta) \dot{\mathbf{g}}$$

else

$$\dot{\theta} = \mathbf{J}^{\#}(\theta) \dot{\mathbf{g}}$$

↑  
pseudo-inverse

"least squares" fit to  $\dot{\theta}$  given  $\dot{\mathbf{g}}$ .

$$\mathbf{J}^{\#} = (\mathbf{J}^T \mathbf{J})^{-1} \mathbf{J}^T \quad \text{if on left}$$

or

## Redundant manipulators

$m$  = dimension of task space

$n$  = # independent variables (joints) OK

kinematically insufficient if  $m > n$ .

kinematically redundant if  $m < n$ .

Given  $g_e^*(t)$ , trajectory generation problem for robotic manipulators is to find  $\bar{\theta}(t)$  such that the actual trajectory  $g(t)$  matches the desired trajectory  $g_e^*(t)$  of the end-effector.

• common approach is to 'spline' together the inverse kinematic solution for a set of knot points to get a joint trajectory

① solve inverse kinematic problem at each  $g^*(t_k)$  to get  $\bar{\theta}^*(t_k)$ ,  $t_0, \dots, t_n$  = # knot points.

② interpolate smooth trajectories  $\bar{\theta}(t)$  through  $\bar{\theta}^*(t_k)$ .

• problems may occur when choosing joint trajectory since inverse is not unique for redundant manipulators.



## Inverting the Manipulator Jacobian.

$$\dot{g} = J(\theta) \dot{\theta} \quad \text{or} \quad \xi^b = J^b(\theta) \dot{\theta}, \quad \xi^s = J^s(\theta) \dot{\theta}$$

↑ better because  $\xi$  really is a vector.

or, can use hybrid Jacobian,

$$\xi^h = J^h(\theta) \dot{\theta}$$

hybrid

$$\xi^h = \begin{Bmatrix} \dot{p} \\ \omega^s \end{Bmatrix} \leftarrow \text{this is position velocity of } J(\theta)$$

↑ this is angular velocity vector from spatial Jacobian,  $J^s(\theta)$ .

• this is what most books use

recall,

$$J^h(\theta) = \text{Ad}_R J^b(\theta),$$

$$\text{where } g_e(\theta) = (p(\theta), R(\theta)).$$

let's work in body coordinates,

$$\cancel{\xi^b = J^b(\theta) \dot{\theta}} \quad \xi^b = J_{\text{body}}(\theta) \dot{\theta}$$

To get joint velocities from body velocities,

$$\dot{\theta} = J_{\text{body}}^{-1}(\theta) \xi^b$$

• but, is  $J_{\text{body}}(\theta)$  really invertible?

A: depends on the manipulator

let  $m$  = dimension of task space

$n$  = # independent variables (joints)

1) kinematically insufficient if  $m > n$

• ~~need~~ <sup>best</sup> to reduce dimension of task space.

2) kinematically redundant if  $m < n$

• it's tricky, but we can handle this case.

3) kinematically sufficient if  $m = n$

• but we need to make sure we are in  
dexters workspace for maximal mobility control.  
• e.g. away from singularities.

How do we handle the Jacobian in these cases?

1) reduce dimension until Jacobian is invertible or use pseudo-inverse.

2) use pseudo-inverse (aka. Moore-Penrose inverse)

3) is invertible, so long as we are away from singularity.

## Linear Algebra Preliminaries to Solution.

a) row space of  $A$ , denoted  $\text{row}(A)$ , and the null space of  $A$ , denoted  $\text{null}(A)$ , are orthogonal.

b) any vector  $\vec{y}$  can be decomposed into  $\text{row}(A)$  &  $\text{null}(A)$  components,

$$\vec{y} = \vec{y}_{\text{row}} + \vec{y}_{\text{null}}$$

c)  $A\vec{y} = A(\vec{y}_{\text{row}} + \vec{y}_{\text{null}}) = A\vec{y}_{\text{row}}$

d) All solutions  $\vec{y}^*$  to  $\vec{b} = A\vec{y}^*$  have the same row space component  $\vec{y}_{\text{row}}^*$ .

- difference between two solutions  $\vec{y}_1^*$  &  $\vec{y}_2^*$  is in the amount of null space contribution.

e) by (a)  $\|\vec{y}\|^2 = \|\vec{y}_{\text{row}} + \vec{y}_{\text{null}}\|^2 = \|\vec{y}_{\text{row}}\|^2 + \|\vec{y}_{\text{null}}\|^2$

f) the Moore-Penrose solution is the solution w/ no null-space component

$$\vec{y} = A^+ \vec{b}, \quad \vec{y} \in \text{row}(A).$$

OK, so what is it?

To compute pseudo-inverse, need to check out different cases.

①  $m=n$ , then  $A^\# = A^{-1}$ .  
 $\S A$  full-rank

②  $m < n$ , then  $A^\# = A^T (AA^T)^{-1}$   
 $\S A$  is full-rank

note that  $AA^\#A = AA^T(AA^T)^{-1}A = A$

$A^\#AA^\# = A^\#AA^T(AA^T)^{-1} = A^\#$

$m \begin{bmatrix} n \\ \end{bmatrix}$

$\Rightarrow AA^T = m \begin{bmatrix} n \\ \end{bmatrix} n \begin{bmatrix} n \\ \end{bmatrix} = m \begin{bmatrix} m \\ \end{bmatrix}$

$(AA^T(AA^T)^{-1})^T = ((AA^T)^{-1})^T A^{\#T} = (A^T)^T A^T$

$= (AA^T)^T (AA^T)^{-1} = I$

$(A^T(AA^T)^{-1}A)^T = A^T(AA^T)^{-1}A = A^\#A$

$(AA^T)^T$   
 $(AA^T)^T$   
 $(AA^T)^{-1}$

③  $m > n$ , then  $A^\# = (A^TA)^{-1}A^T$

$n \begin{bmatrix} n \\ \end{bmatrix}$

$A^TA = n \begin{bmatrix} m \\ \end{bmatrix} n \begin{bmatrix} n \\ \end{bmatrix} = n \begin{bmatrix} n \\ \end{bmatrix}$

OK, so what is this pseudo-inverse thing?

It is defined by its properties.

Suppose we seek

$$\vec{b} = A\vec{y} \quad b \in \mathbb{R}^m, y \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}$$

Moore & Penrose found a solution  $A^+$  (or  $A^\#$ ) such that:

~~$A^\#$  is the unique matrix with the properties:~~

- 1)  $AA^\#A = A$
- 2)  $A^\#AA^\# = A^\#$
- 3)  $(AA^\#)^T = AA^\#$
- 4)  $(A^\#A)^T = A^\#A$

Interpretation:

- a) if  $m=n$  &  $A$  is fullrank, then  $A^\# = A^{-1}$ .
- b) if  $m > n$  the  $\vec{y} = A^\# \vec{b}$  is solution that minimizes  $\|\vec{b} - A\vec{y}\|_2$
- c) if  $m < n$  then  $\vec{y} = A^\# \vec{b}$  is solution that minimizes  $\|\vec{y}^T \vec{y}\|$

so, now we have

$$\dot{\vec{\theta}} = J_{body}^{\#}(\vec{\theta}) \cdot \vec{\xi}^b$$

appropriate inverse is chosen based on particulars of  $J_{body}(\vec{\theta})$ .