



Robot Devices, Kinematics, Dynamics,
and Control.

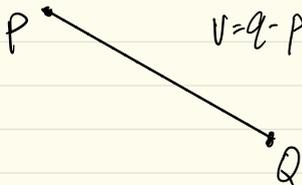
Office hour: Monday after class

Points & Vectors

Point: location in 3D space

Vector: Distance & Direction

can subtract points
can't add them.



Representation of points & vectors.

An array of n numbers

$P = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \in \mathbb{R}^n$ might represent a point or vector.

MLS (course Text) uses p, q for points (non-bold, Roman)

bold face V, W for vectors.

Definition: Linear Vector space is a set X and a field F together with two operations.

Vector addition, scalar-vector multiplication.

such that for $x, y, z \in X$, $\alpha, \beta \in F$

$x + y \in X$ and $\alpha \cdot x \in F$

closure

and the following actions are satisfied.

$$i) x+y = y+x$$

$$ii) (x+y)+z = x+(y+z)$$

$$iii) \exists \vec{0} \in X \text{ such that } x + \vec{0} = x$$

$$iv) \alpha(x+y) = \alpha x + \alpha y$$

$$v) (\alpha+\beta)x = \alpha x + \beta x$$

$$vi) (\alpha\beta)x = \alpha(\beta x)$$

$$vii) 0x = \vec{0}$$

\downarrow \uparrow
F x

$$x+(-x) = 0$$

$$viii) 1 \cdot x = x$$

Let V^n be normed n -dimensional real vector space.
An element of V^n is just of real numbers

$$V = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}, \quad v+w = [v_1+w_1, v_2+w_2, \dots, v_n+w_n]^T$$

A norm, $\|\cdot\|$, is a real-valued function that satisfies,
for all $\alpha \in \mathbb{R}$, $x \in V^n$

$$i) \|\alpha x\| = |\alpha| \|x\|$$

$$iv) \text{ if } \|x\| = 0 \Rightarrow x = \vec{0}$$

$$ii) \|x+y\| \leq \|x\| + \|y\|$$

Example:

$$\|x\|_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$$

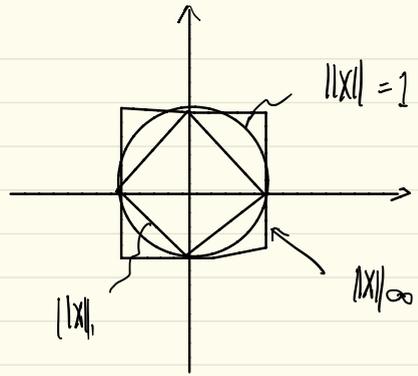
$$iii) \|x\| \geq 0$$

$$= \sqrt{x^T x}$$

$$\|x\|_1 = |x_1| + |x_2| + \dots + |x_n|$$

$$\|x\|_\infty = \max |x_i|$$

$$\|x\|_p = \sqrt[p]{\sum x_i^p}$$



Inner Product on V^n

$$x, y \in V^n$$

$$\langle x, y \rangle = x^T y = x \cdot y, \quad \|x\|_2 = \sqrt{x \cdot x}$$

MLS uses \mathbb{R}^n for real LVS

Physical vectors in 3D space can be represented by element V^n . but to do so, we have to establish a basis $\{i, j, k\}$.

$$\text{If } \tilde{v} \text{ is a physical vector, then } v = \begin{pmatrix} \tilde{v} \cdot i \\ \tilde{v} \cdot j \\ \tilde{v} \cdot k \end{pmatrix}$$

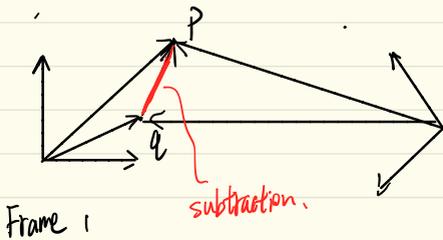
Physical points can be represented as elements of \mathbb{R}^3 once we've established a frame $\{\theta, i, j, k\}$, where θ is the origin

so if \tilde{p} is a physical point, we write:

$$P = \begin{pmatrix} (\vec{p}-\theta) \cdot i \\ (\vec{p}-\theta) \cdot j \\ (\vec{p}-\theta) \cdot k \end{pmatrix}$$

A universal frame is implied / understood

If $p, q \in \mathbb{R}^3$ are points, then $v = p - q$ is a well-defined vector.



Points are not addable

$$V = \begin{bmatrix} p_1 - q_1 \\ p_2 - q_2 \\ p_3 - q_3 \end{bmatrix} \in V^n$$

Distance between points and lengths of vectors

We will treat \mathbb{R}^n as Euclidean space, with the standard two-norm used as a distance metric between points.

ie. $p, q \in \mathbb{R}^n$,

$$d(p, q) = \|p - q\|_2 = \sqrt{\sum_{i=1}^n (p_i - q_i)^2}$$

Let $\theta \in \mathbb{R}^2$ denote the origin. frame, then $\sqrt{p_1^2 + p_2^2 + p_3^2}$ can only have meaning as $\|p - \theta\|$. ie. distance to the origin.

Some Important Facts

with the same field.

\forall = for all \exists = there exists
 $\exists!$ " " unique.

- Let x, y be LVS's and let $f: x \rightarrow y$. we say f is linear if it satisfies
 - i) superposition $\forall x_1, x_2 \in X, f(\alpha x_1 + x_2) = \alpha f(x_1) + f(x_2)$
 - ii) scaling $\forall x \in X, f(\alpha x) = \alpha f(x) \forall \alpha \in \mathbb{F}$

Theorem

Let X, Y be LVS over F , and let $\alpha, \beta \in F$ and $x_1, x_2 \in X$.

then a function $f: X \rightarrow Y$ is linear if and only if

$$f(\alpha x_1 + \beta x_2) = \alpha f(x_1) + \beta f(x_2)$$

Proof: (Both Direction)

$$\begin{aligned} \text{Let } \alpha = \beta = 1, \quad f(x_1 + x_2) &= f(1 \cdot x_1 + 1 \cdot x_2) = 1 \cdot f(x_1) + 1 \cdot f(x_2) \\ &= f(x_1) + f(x_2) \end{aligned}$$

Proves (i) Superposition.

To prove (ii).

$$\begin{aligned} f(\alpha x_1) &= f(\alpha x_1 + \vec{0}) && \text{by axiom (3)} \\ &= f(\alpha x_1 + 0 \cdot x_2) && \text{by axiom (2) of LVS} \\ &= \alpha f(x_1) + 0 \cdot f(x_2) && (\beta = 0) \\ &= \alpha f(x_1) + \vec{0} && \text{by axiom 7} \\ &= \alpha f(x_1) \end{aligned}$$

"Only if"

$$f(\alpha x_1 + \beta x_2) = f(\alpha x_1) + f(\beta x_2) \quad \text{axiom (1)}$$

$= \alpha f(x_1) + \beta f(x_2)$ by axiom (ii) Q.E.D.

• A set of vectors \uparrow is said to be Linearly Dependent.

$x_1, \dots, x_n \in X$ \nearrow not all $\alpha = 0$

if $\exists \alpha_1, \dots, \alpha_n \in \mathbb{F}$ such that $\alpha_1 x_1 + \dots + \alpha_n x_n = 0$

• A set of vectors is said to be Linearly Independent, if no such α 's exist

Example:

$\begin{bmatrix} 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \end{bmatrix} \in \mathbb{R}^2$, Linearly dependent since $\alpha_1 = 1, \alpha_2 = 1, \alpha_3 = -1$

Standard Basis in \mathbb{R}^n

$\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \dots, \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$ are LI

Given $x_1, \dots, x_n \in X$, the space of $\{x_1, \dots, x_n\}$ is the set of all vectors $V \in X$ of the form

$$V = \sum_{i=1}^n \alpha_i x_i \quad \text{for any scalars } \alpha_1, \dots, \alpha_n$$

Related idea: column space of a matrix

$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \end{pmatrix} \in \mathbb{R}^{p \times n}$ where $a_i \in \mathbb{R}^p$, column space $\{a_1, \dots, a_n\}$

A set of n linearly independent vectors x_1, \dots, x_n such that $X = \text{span}\{x_1, \dots, x_n\}$ is a Basis for X .

Example $e_1 = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \dots, e_n = \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix}$ where $e_i \in \mathbb{R}^n$

is called the standard basis.

Consider the 2nd-order linear ODE

$$\ddot{x} + 3\dot{x} + 2x = 0 \quad (*)$$

claim: real-valued solutions to $(*)$ form a LVS over \mathbb{R} .

Proof: Let $x_1(t), x_2(t), x_3(t)$ be solutions to $(*)$, and let

$$a, b \in \mathbb{R}.$$

Closure

$x_1(t) + x_2(t)$ is also a solution. To check, plug into $(*)$,

$$\begin{aligned} & \frac{d^2}{dt^2}(x_1 + x_2) + 3 \frac{d}{dt}(x_1 + x_2) + 2(x_1 + x_2) \\ &= \underbrace{(x_1'' + 3x_1' + 2x_1)}_{=0} + \underbrace{(x_2'' + 3x_2' + 2x_2)}_{=0} \\ &= 0 \end{aligned}$$

\Rightarrow

closed under vector addition. Likewise ax_1 is a solution, seen by plugging into the LHS of $(*)$.

\Rightarrow closed under scalar multiplication.

Defining $\vec{0} = 0(t)$, axioms all follow from perspective of \mathbb{R}

Noted to show $\vec{0}$ is in the LVS. but obviously $\vec{0} + 3\vec{0} = 2\vec{0} = \vec{0}$.

By facts of differential equations, all solutions to (*) can be expressed as linear combination of $v_1(t) = e^{-2t}$, $v_2(t) = e^{-t}$

Call the solution to (*) x . Clearly, $X = \text{span}\{x_1(t), x_2(t)\}$

Must also show $v_1(t)$ and $v_2(t)$ are LI to prove they are basis.

$$a_1 e^{-t} + a_2 e^{2t} = 0 \quad \Rightarrow \quad a_1 e^{-t} = -a_2 e^{2t}$$
$$-a_1 e^t = a_2$$



call only when $a_1 = a_2 = 0$ for all t .

Now we can represent all members of X w.r.t $\{v_1(t), v_2(t)\}$

$$x(t) = a_1 v_1(t) + a_2 v_2(t) = [v_1(t) \quad v_2(t)] \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$y(t) = b_1 v_1(t) + b_2 v_2(t) = [v_1(t) \quad v_2(t)] \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

$a = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$ is the representation of x w.r.t $\{v_1(t), v_2(t)\}$

and $b = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$

- Choice of basis is not unique.
 - However, the number of basis elements is constant (for a given LVS)
- Call the number n , then we say we have an "n-dimensional LVS"

MATRIX Facts.

- A square matrix is said to be singular if $\det M = 0$
- The columns of a non-singular matrix are LI \Rightarrow they span \mathbb{R}^n
- the rows are also LI
- A matrix $M \in \mathbb{R}^{n \times n}$ is said to be SKEW SYMMETRIC if $M = -M^T$. example: $M = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$
- $M \in \mathbb{R}^{n \times n}$ is SYMMETRIC if $M = M^T$
eg $M = \begin{bmatrix} 1 & -3 \\ -3 & 7 \end{bmatrix}$
- The cross product of two vectors. $x, y \in \mathbb{R}^3$

$$x \times y = \underbrace{\begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix}}_x \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} -x_3 y_2 + x_2 y_3 \\ x_3 y_1 - x_1 y_3 \\ -x_2 y_1 + x_1 y_2 \end{bmatrix}$$

$$\text{Also } x \times y = -y \times x = -\hat{y}x$$

Note: $x \times y$ is Bilinear

Consider $x \in \mathbb{R}^3$. What are the eigen values of \hat{x} ?

Direct Computation:

$$\det(\lambda I - \hat{x}) = 0$$

$$= \lambda(\lambda^2 + \|x\|^2) = 0$$

$$\Rightarrow \lambda = 0, \pm i\|x\|$$

Rigid Transformations (Follow MLS)

• Let $p(t) \in \mathbb{R}^3$ be a function of time, interpreted as a moving point.

$$p(t) = \begin{bmatrix} x(t) \\ y(t) \\ z(t) \end{bmatrix} \in \mathbb{R}^3$$

Likewise for $q(t) \in \mathbb{R}^3$. a rigid body is one that for any two points $p(t), q(t)$

$$d(p(t), q(t)) = \text{constant}$$

• A rigid motion of points satisfies ✓

• A rigid displacement is the net movement of a rigid body from one location to another under rigid motion.

• Let $g = \mathbb{R}^3 \rightarrow \mathbb{R}^3$ mapping of points.

Natural way to define a corresponding actions on vectors.

Pick an arbitrary base point $p_0 \in \mathbb{R}^3$

define $g_*: V^3 \rightarrow V^3$ via $g_*(v) = g(p_0 + v) - g(p_0)$

• A mapping $g: \mathbb{R}^3 \rightarrow \mathbb{R}^3$ is a rigid displacement if

1. length is preserved $\|g(p) - g(q)\| = \|p - q\|$

2. Cross product of vectors is preserved in this sense:

$$g_*(v \times w) = g_*(v) \times g_*(w)$$

$\forall v, w \in V^3$ (orientation preserving)

Facts about rigid displacement.

• The induced action g_* is linear of a rigid displacement.
 $g_*(\alpha v + \beta w) = \alpha g_*(v) + \beta g_*(w)$

• Inner products are preserved. $v \cdot w = \frac{1}{4} (\|v+w\|^2 - \|v-w\|^2)$
polarization identity -

$$= \frac{1}{4} (\|g_*(v+w)\|^2 - \|g_*(v-w)\|^2) \Rightarrow g_* \text{ is length preserving}$$

since g is preserve.

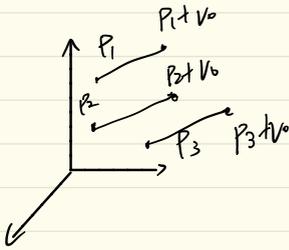
$$= \frac{1}{4} (\|g_*(v) + g_*(w)\|^2 - \|g_*(v) - g_*(w)\|^2) - \text{linearity of } g_*$$

$$= g_*(v) \cdot g_*(w)$$

polarization un-done!

Translations.

$g(CP) = P + v_0$. where $v_0 \in V^2$ is a (pure) translation.



Rotations :

Define $SO(n) = \{ R \in \mathbb{R}^{n \times n} \mid \underbrace{R^T R = I}_{\text{distance preserving}}, \underbrace{\det R = +1}_{\text{orientation preserving}} \}$ such that

SO : is the set of "special Orthogonal" matrices.

claim : Elements of $SO(n)$ are rigid transformations.

Proof : Let $p, q \in \mathbb{R}^n$. let $g(p) = R_p$, then g preserves length.

$$\|R_p - R_q\| = \|(RCP - R) \| = \sqrt{(RCP - R)^T (RCP - R)}$$

$$\sqrt{\underbrace{(CP - q)^T R^T R}_{I} (CP - R)} = \sqrt{(CP - q)^T I (CP - R)} = \sqrt{(CP - q)^T (CP - R)} = \|P - q\|$$

$$g_*(V) = g(CP + V) - g(CP) = R(CP + V) - RP = RV$$

$$\text{Claim: } R(V \times W) = (RV) \times (RW)$$

Pf: P.S 1.

• General Displacements in 3 dimensions

Given $R \in SO(3)$, $V \in V^3$

Define $g(CP) = RP + V$

claim: g is a rigid transformation.

Overview of 530.646

1) Kinematics.

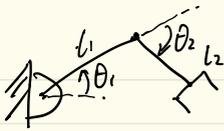
- Forward
- Inverse
- Differential

2) Dynamics

3) Control

- of serial link
- fully actuated
- robot manipulator.

Example to cover (12, 13, 13)



CCW

Description: Planar, two-link solid, revolute manipulator

1) Kinematics.

Forward position: orientation of end-effector as a function of θ_1, θ_2

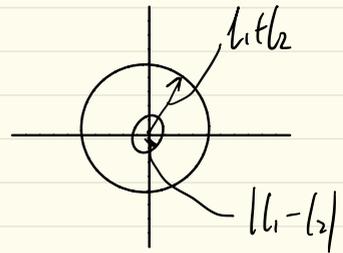
Kinematic map $\rightarrow SO(2) \times \mathbb{R}^2$

$f: \mathbb{T}^2 \rightarrow SE(2)$ or simply but slightly inaccurate:

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^3 \quad f: \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} \rightarrow \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

$$f(\theta_1, \theta_2) = \begin{pmatrix} l_1 \cos \theta_1 + l_2 \cos(\theta_1 + \theta_2) \\ l_1 \sin \theta_1 + l_2 \sin(\theta_1 + \theta_2) \\ \theta_1 + \theta_2 \end{pmatrix} \quad \left. \vphantom{\begin{pmatrix} l_1 \cos \theta_1 + l_2 \cos(\theta_1 + \theta_2) \\ l_1 \sin \theta_1 + l_2 \sin(\theta_1 + \theta_2) \\ \theta_1 + \theta_2 \end{pmatrix}} \right\} \bar{f}(\theta_1, \theta_2)$$

Also part of kinematics



(b) Inverse Kinematics.

Given end-

"pose" \rightarrow position + orientation

find θ_1, θ_2

these since dim of co-domain is 3
 but the dim of domain is 2
 The problem is ill-posed.

so let's consider

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \bar{f}(\theta_1, \theta_2) = \begin{bmatrix} l_1 \cos \theta_1 \\ 0 \end{bmatrix}$$

(c) Differential Kinematics

Idea: compute $\begin{vmatrix} \dot{x} \\ \dot{y} \end{vmatrix}$ given $\theta_1, \dot{\theta}_1$ using the chain rule.

$$\begin{vmatrix} x \\ y \end{vmatrix} = \bar{f}(\theta_1, \theta_2)$$

$$\Rightarrow \begin{vmatrix} \dot{x} \\ \dot{y} \end{vmatrix} = \begin{vmatrix} \frac{\partial \bar{f}_1}{\partial \theta_1} \cdot \dot{\theta}_1 + \frac{\partial \bar{f}_1}{\partial \theta_2} \cdot \dot{\theta}_2 \\ \frac{\partial \bar{f}_2}{\partial \theta_1} \cdot \dot{\theta}_1 + \frac{\partial \bar{f}_2}{\partial \theta_2} \cdot \dot{\theta}_2 \end{vmatrix} = \overbrace{\begin{vmatrix} \frac{\partial \bar{f}_1}{\partial \theta_1} & \frac{\partial \bar{f}_1}{\partial \theta_2} \\ \frac{\partial \bar{f}_2}{\partial \theta_1} & \frac{\partial \bar{f}_2}{\partial \theta_2} \end{vmatrix}}^{\text{Jacobian Matrix}} \begin{vmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{vmatrix}$$

$$\begin{vmatrix} x \\ y \end{vmatrix} = \begin{bmatrix} \bar{f}_1(\theta_1, \theta_2) \\ \bar{f}_2(\theta_1, \theta_2) \end{bmatrix}$$

$$\bar{f}_1(\theta) = l_1 \cos \theta_1 + l_2$$

$$\bar{x} = \begin{bmatrix} x \\ y \end{bmatrix} \quad \bar{x} = \bar{f}(\theta) \quad \Rightarrow \dot{\bar{x}} = J(\theta) \cdot \dot{\theta}$$

$$\dot{\bar{x}} = \frac{\partial \bar{f}}{\partial \theta} \cdot \dot{\theta}$$

2) Dynamics

Larg... Equation

3) Controls

Group

Def: A group is a set y together with a binary operator

$f: y \times y \rightarrow y$ that satisfied
closed

for all $a, b, c \in y$

1. closure : $f(a, b) \in y$

2. assoc : $f(a, f(b, c)) = f(f(a, b), c)$

$$a \cdot (b \cdot c) = (a \cdot b) \cdot c$$

3. $\exists e \in y$ st. $ae = a$

4. For each $a \in y$, $\exists a^{-1}$ st $a \cdot a^{-1} = e$

Recap

1) Kinematics

FWD - $f: \text{"Joint Space"} \rightarrow \text{"End-effector", configuration space}$

$$f: Q \rightarrow SE(n), n=2,3$$

$\leftarrow Q = \text{Joint Space}$

Example

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

Then consider -

$$\tilde{f}: \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} \rightarrow \begin{pmatrix} x \\ y \end{pmatrix}$$

$$f: \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} \rightarrow \begin{pmatrix} x \\ z \end{pmatrix}$$

Inv ...

• Differential kin...

$$\dot{\tilde{x}} = \underbrace{J(\theta)}_{\frac{df}{d\theta}} \dot{\theta}$$

supposed I want $\dot{\tilde{x}} = V^*$, a desired velocity, knowing θ , and being able to command $\dot{\theta}$

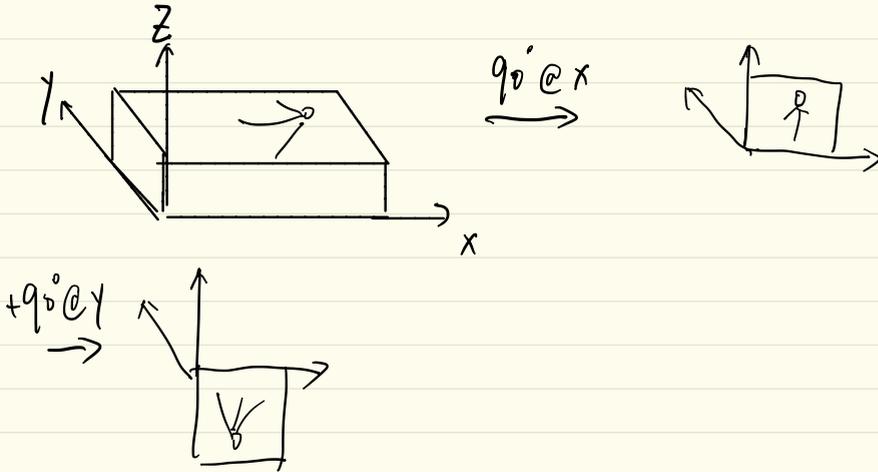
$$\text{Then set } \dot{\theta} = \overset{\text{matrix inv.}}{J^{-1}(\theta)} V^*$$

Inverting J requires L.I. of columns.

Group

Def: a set and a binary operator, $\circ: \mathcal{Y} \times \mathcal{Y} \rightarrow \mathcal{Y}$ (closed)
that satisfies

1. Associativity. $\forall a, b, c \in \mathcal{Y}, a \cdot (b \cdot c) = (a \cdot b) \cdot c$
2. $\exists e \in \mathcal{Y}$, s.t. $a \cdot e = a$, $\forall a \in \mathcal{Y}$
(Also, $e \cdot a = a$, can be proved)
3. For each a in \mathcal{Y} , $\exists a^{-1} \in \mathcal{Y}$, s.t. $a \cdot a^{-1} = e$
(also true: $a^{-1} \cdot a = e$)



$$\underline{90^\circ @ Y} \quad \underline{90^\circ @ X}$$



Representing 3D Rotations

• Rotation matrices, $R \in SO(3)$

Plusses • Sequential Rotations. R_1, R_2, R_3 are easily combined via matrix multiplication to compute net rotations.

If R_1 , then R_2 .

$$x \rightarrow (R_1 x)$$

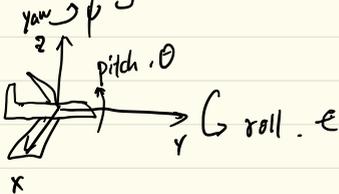
$$(R_1 x) \rightarrow R_2(R_1 x)$$

$$\Rightarrow x \rightarrow (R_2 R_1) x$$

• Inverse is easy $R^{-1} = R^T$

Minuses: 9 numbers of 3 DOF

Euler angles



$R_y(\theta) =$ Rotation about y , angles θ

$R_x(\phi) = \dots$ x , ϕ

$R_z(\psi) = \dots$ z

$$R = R_z R_y R_x$$

Pluses: 3 numbers for 3 DOF

Minuses: Singularities.

* Look up in unbinding.

Representing Rotations (Recap)

- $SO(3) \rightsquigarrow$ - 9 numbers for 3 DOF
 - No singularities
 - Group easy to composite.

- Euler Angle \rightsquigarrow - 3 numbers for 3 DOF
 - small angles
 - singularities

- ^{unit} Quaternion \rightsquigarrow 4 variable number slightly redundant.

$$Q = (\alpha, \vec{q}) \quad \text{where } \alpha \in \mathbb{R}, \vec{q} \in \mathbb{R}^3$$

$$\text{require } \alpha^2 + \|\vec{q}\|^2 = 1$$

$$Q = (\alpha, \vec{q}) = \left(\cos \frac{\theta}{2}, \mathbf{w} \sin \frac{\theta}{2} \right) \quad \text{where } \mathbf{w} \in \mathbb{R}^3, \text{ with } \|\mathbf{w}\| = 1, \theta \in \mathbb{R}$$
$$\|Q\| = 1$$

$$\text{Note: } SO(3) = S^3 / \mathbb{P} \sim \mathbb{P}$$



Another way to write Quaternion: $a + ib + jc + kd$ $i^2 = j^2 = k^2 = -1$. Not commutative.

Def: A group G with its operator \circ , acts on a space X . If there is a mapping $f: G \times X \rightarrow X$ satisfying:

1. identity action: if $e \in G$ is the identity element $\overset{\text{in } G}{\vee} f(e, x) = x, \forall x \in X$

2. Associativity: $\forall g, h \in G$ and $x \in X$, then $f(g, f(h, x)) = f(gh, x)$

Example

Translation Group

Recall V^n is LVS $\Rightarrow V^n$ is a group under addition

We can say V^n acts on points in R^n in the usual way: vector, point addition.

Proof: $G = V^n, X = R^n$, here $f = "+"$, also $\circ = "+"$ \leftarrow Group operator.
action

Closure: $\forall v, w \in V^n, p \in R^n, v + p \in R^n$ by properties of point-vector addition.

1. $e = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ is identity element of V^n and $e + p = p, \forall p \in R^n$, obviously.

2. Associativity: $v + (w + p) = (v + w) + p$ by properties of $\overset{\text{vector}}{\vee}$ point-vector addition.
action action Group operator.

Example: $(\mathbb{R}, +)$ Group.

$$X = \mathbb{R}$$

candidate action $f(a, x) = ax + x + 1$
 $\begin{matrix} \uparrow & \uparrow \\ a \in \mathbb{R} & x \in \mathbb{R} \end{matrix}$

Fails both axioms.

1) $e = 0$, $f(e, x) = x + 1 \neq x$

2) $a, b \in \mathbb{R}$, $x \in \mathbb{R}$. $f(a, f(b, x)) = a + b + x + 2 \neq f(a \circ b, x) = a + b + x + 1$

Group Products

Given two groups (G, \circ) and (H, \diamond)

Direct Product : Given $g_1, g_2 \in G$, $h_1, h_2 \in H$
then $(g_1, h_1) \in G \times H$
 $(g_2, h_2) \in G \times H$

And the direct group product would be

$$(g_1, h_1) \circ (g_2, h_2) = (g_1 \circ g_2, h_1 \diamond h_2)$$

Example = $G = SO(3)$ (matrix multiplication)
 $H = \mathbb{V}^3$ (vector addition)

Direct Product: $G \times H$ if $(R_1, v_1), (R_2, v_2) \in G \times H$
then $(R_1, v_1) \circ (R_2, v_2) = (R_1 R_2, v_1 + v_2)$

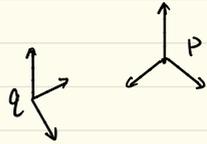
Consider $SE(3)$ acting on \mathbb{R}^3 , $G = (R, v) \in SE(3)$

we know $g(p) = Rp + v$

Example: 90° Yaw, make l-m along x-axis.

$$R_1 = \begin{bmatrix} c\phi & -s\phi & 0 \\ s\phi & c\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad v_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad p = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$R_1 p + v_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$



$$R_2 = I \quad v_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad r = R_2 q + v_2 = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}$$

$\cdot r$

Apply in another order

$$R_2 p + v_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = q$$

$$R_1 q + v_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

Doesn't match $R_1 R_2 p + v_1 + v_2 = \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix}$

Roll \Rightarrow Pitch \Rightarrow Yaw world

Yaw \Rightarrow Pitch \Rightarrow Roll "Nested." frames.

Fix the model for how to combine groups to model rigid transformations.

Apply (R_2, v_2) to p , then apply (R_1, v_1) to the result.

$$g_2 \circ p = R_2 p + v_2 = q \quad g_1 \circ (g_2 p) = R_1 q + v_1 = R_1 (R_2 p + v_2) + v_1$$

$$= R_1 R_2 p + (R_1 v_2 + v_1)$$

!!!
≠ $v_1 + v_2$

Semi-direct group product

$$g_1, g_2 = (R_1, R_2, R_1 V_2 + V_1)$$

\uparrow \uparrow \uparrow
 (R_1, V_1) (R_2, V_2)

Works B/C $SO(2)$ acts on V^3

Homogeneous Representation of points, vectors & rigid transformation.

Points $P = \begin{vmatrix} P_1 \\ P_2 \\ P_3 \\ 1 \end{vmatrix}$ vectors $V = \begin{vmatrix} V_1 \\ V_2 \\ V_3 \\ 0 \end{vmatrix}$

$P + Q = \begin{vmatrix} P_1 + Q_1 \\ \vdots \\ P_3 + Q_3 \\ 2 \end{vmatrix}$ → Not a point
Not allowed

$P + V = \begin{vmatrix} P_1 + V_1 \\ P_2 + V_2 \\ P_3 + V_3 \\ 1 + 0 \end{vmatrix}$ is a point

$\bar{V} + \bar{W} = \begin{vmatrix} V_1 + W_1 \\ \vdots \\ 0 \end{vmatrix}$ is a vector

Rigid Transformations

$$\bar{g} = \begin{vmatrix} R & V \\ \underline{0^T}_{1 \times 3} & 1 \end{vmatrix}$$

In this Rotation

$$\bar{g}\bar{P} = \begin{vmatrix} R & V \\ 0^T & 1 \end{vmatrix} \begin{vmatrix} P \\ 1 \end{vmatrix} = \begin{vmatrix} RP + V \\ 1 \end{vmatrix}$$

$$\bar{g}\bar{W} = \begin{vmatrix} R & V \\ 0 & 1 \end{vmatrix} \begin{vmatrix} W \\ 0 \end{vmatrix} = \begin{vmatrix} RW \\ 0 \end{vmatrix} = \begin{vmatrix} g + cW \\ 0 \end{vmatrix}$$

Usually abuse notation and write homogeneous representation without "-"

$$\Rightarrow gp = (R_p + v) = \begin{bmatrix} R & v \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} p \\ 1 \end{bmatrix} = \begin{bmatrix} R & v \\ 0 & 1 \end{bmatrix} p$$

Recap:

- Basic Math Def...

- LVS, Linearity
- Euclidean Space.
- Points vs. Vectors
- Groups
- Group Action

- Rigid Transformations

- Def n

- Two key examples.

- Translations \mathbb{R}^3

- Rotations $SO(3)$

- Semi-direct Product: $SE(3)$

$$SE(3) = SO(3) \ltimes \mathbb{R}^3$$

↑

special Euclidean
Group

↑
semi-direct product.

- Homogeneous Representation.

$$\sigma: (R, v) \mapsto \begin{bmatrix} R & v \\ 0^T & 1 \end{bmatrix}$$

Homomorphism \downarrow
g

$$\Rightarrow R = g(1:3, 1:3)$$

$$\Rightarrow v = g(1:3, 4)$$

$$p \mapsto \begin{bmatrix} p \\ 1 \end{bmatrix} \quad \text{homo point}$$

$$v \mapsto \begin{bmatrix} v \\ 0 \end{bmatrix} \quad \text{homo vector.}$$

$$R_p + v = g_p$$

• Representing Rotation

- [Represent Translation : 3-vector)
- Euler Angles
- Quaternions, S^3/PP
- Axis angle. (w, θ) , $w \in \mathbb{R}^3$, $\|w\|=1$, $\theta \in \text{Rad} \cdot \pi$

Degree of Freedom

- (Locally) The dimension of the configuration space.
- minimum # of real parameters to coordinate/parameterize the space.

Given a set of \underbrace{n}_{n} parameters subject to a set of n constraint equations.
(Assume $m \leq n$)

so, s_1, \dots, s_n subject to f

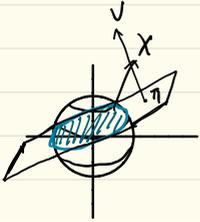
If $\text{rank } J = m$, then the constraints are independent. and there are $r = n - m$ DOF.

In general, there are $r = n - \text{rank}(J)$ DOF

Consider $S^2 = \{x \in \mathbb{R}^3 : x_1^2 + x_2^2 + x_3^2 = 1\}$ $x^T x = 1$

$n=3$, $m=1$, $f(x_1, x_2, x_3) = x^T x - 1$

$J = [2x_1 \ 2x_2 \ 2x_3]$ which is always rank 1 on S^2 , $r=3-1=2$ DOF



$$\pi = \{x \in \mathbb{R}^3 : x^T v = 0\}$$

$$X = S^2 \cap \pi = \{x \in \mathbb{R}^3 : \underbrace{x^T x - 1 = 0}_{f_1(x)}, \underbrace{x^T v = 0}_{f_2(x)}\}$$

$$J = \begin{bmatrix} 2x^T \\ v^T \end{bmatrix}$$

x cannot be parallel (and therefore L.D upon) v !

i.e. $\text{rank}(J) = 2$ on X



Matrix Exponentials

Exponential Review:

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

solves among other things how to deal with irrational exponents.

Also

$$e^{i\theta} = \cos \theta + i \sin \theta$$

Exponential function (or "map") is smooth and is the eigen function of differentiation.

$$\boxed{\frac{d}{dx}} e^x = e^x$$

linear operator.

$$\frac{d}{dx} e^{ax} = a e^{ax}$$

eigen value.
eigen function

$$e^{At} = I + At + \frac{1}{2!} A^2 t^2 + \frac{1}{3!} A^3 t^3 + \dots \in \mathbb{R}^{n \times n}$$

where $A \in \mathbb{R}^{n \times n}$, $t \in \mathbb{R}$ ($A \in \mathbb{R}^{n \times n}$)

$$\text{Look at } \frac{d}{dt} e^{At} = \frac{d}{dt} (I + At + \frac{1}{2!} A^2 t^2 + \dots)$$

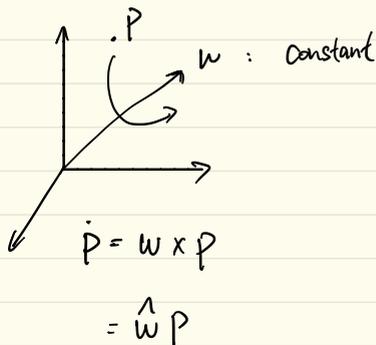
$$= 0_{n \times n} + A + A^2 t + \frac{1}{2!} A^3 t^2 + \frac{1}{3!} A^4 t^3 + \dots$$

$$= A (I + At + \frac{1}{2!} A^2 t^2 + \frac{1}{3!} A^3 t^3 + \dots)$$

$$= A e^{At}$$

Could have factored out and to the right $\Rightarrow \frac{d}{dt} e^{At} = A e^{At} = e^{At} \cdot A$

In general $e^{At} \cdot B \neq B \cdot e^{At}$



Claim $p_0(t) = e^{\hat{w}t} p_0$ where p_0 is the initial position.

$$\text{Proof: } \frac{d}{dt} p(t) = \frac{d}{dt} (e^{\hat{w}t} p_0)$$

$$= \frac{d}{dt} (e^{\hat{w}t}) p_0$$

$$= \hat{w} e^{\hat{w}t} p_0$$

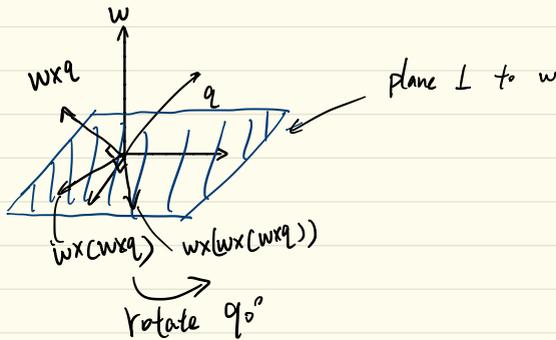
$$= \hat{w} p(t) \Rightarrow \text{which satisfy } \dot{p} = \hat{w} p$$

$e^{\hat{w}t}$ has a lot of structures.

$$e^{\hat{w}t} \cdot q, \quad q \text{ is a point}, \quad t=1$$

$$= q + \hat{w}q + \frac{1}{2!} \hat{w}^2 q + \frac{1}{3!} \hat{w}^3 q + \frac{1}{4!} \hat{w}^4 q + \dots$$

Look at $\hat{w}^k q = (C \dots (C w \times (w \times (w \times \dots)))$



$$\hat{w}^3 q = \|w\|^2 (-\hat{w}q)$$

$$= -\|w\|^3 \hat{w}q$$

In general k odd $\hat{w}^k = \pm \|w\|^{k-1} \hat{w}$

\uparrow alternating sign.

k even $\hat{w}^k = \pm \|w\|^{k-1} \hat{w}^2$

Group terms

$$e^{\hat{w}} = I + (\sin \theta) \hat{w} + (1 - \cos \theta) \hat{w}^2$$

$$\theta = \|w\|$$

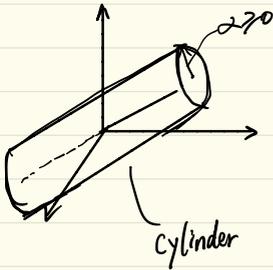
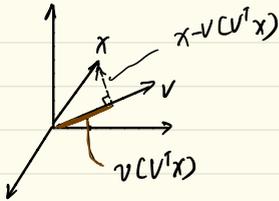
n parameters m constraints "independent"

$$r = n - m = \text{DOF}$$

$$\text{Example: } X = \{x \in \mathbb{R}^3 : \underbrace{\|x - vv^T x\|^2}_{\| (I - vv^T)x \|^2} = 0\}$$

$$\|v\| = 1$$

$$\| (I - vv^T)x \|^2$$



$$X_{\alpha} = \{x \in \mathbb{R}^3 : \underbrace{\| (I - vv^T)x \|^2}_{m=1 \text{ constraint}} - \alpha^2 = 0\}$$

$m=1$ constraint

$$r = n - m = 3 - 1 = 2 \text{ DOF}$$

Constraint Function

$$f: \mathbb{R}^3 \rightarrow \mathbb{R}^3$$

symmetric, doesn't matter.

$$f(x) = x^T \underbrace{(I - vv^T)^T (I - vv^T)}_{(I - vv^T)} x - \alpha^2$$

$$(I - vv^T)(I - vv^T) = I - 2vv^T + vv^T vv^T = I - vv^T$$

$$f(x) = x^T (I - W^T) x - \alpha^2$$

Fact: $\frac{\partial}{\partial x} (x^T P x) = 2x^T P$. P is symmetric.

$$\Rightarrow \frac{\partial f}{\partial x} = 2 \overbrace{x^T (I - W^T)}^{\neq 0} \in \mathbb{R}^3$$

$$\text{rank} \left(\frac{\partial f}{\partial x} \right) = 1 \quad \text{if} \quad \frac{\partial f}{\partial x} \neq 0$$

$$\| \left(\frac{\partial f}{\partial x} \right)^T \|^2 = 4 \| (I - W^T) x \|^2 = 2^2 > 0$$

When $\alpha = 0$. $f(x) = x^T (I - W^T) x$

$$\frac{\partial f(x)}{\partial x} = 2x^T (I - W^T) = [0 \ 0 \ 0]$$

rank is 0, and \therefore can not apply

Rank is a robust property

convex argument

An alternative de of X

$$X = \{ x \in \mathbb{R}^3 : \underbrace{(I - W^T) x}_{f(x)} = 0 \}$$

$$\frac{\partial f}{\partial x} = (I - W^T)$$

$$\text{rank}(I - W^T) = 2$$

$$r = n - 2 = 3 - 2 = 1$$

Derivative Notation

$$f : \mathbb{R}^p \rightarrow \mathbb{R}^q$$

$$f(x) \in \mathbb{R}^q, \text{ when } x \in \mathbb{R}^p$$

$$\frac{\partial f}{\partial x} = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_p} \\ \vdots & \vdots & \dots & \vdots \\ \frac{\partial f_q}{\partial x_1} & \dots & \dots & \frac{\partial f_q}{\partial x_p} \end{pmatrix}$$

If $\varphi: \mathbb{R}^n \rightarrow \mathbb{R}$ is scalar-valued function.

Define $\nabla\varphi = \left[\frac{\partial\varphi}{\partial x} \right]^T \in \mathbb{R}^n$

Reading: Implicit Function Theorem

Skew Symmetric Matrices.

$$\text{so}(n) = \{ S \in \mathbb{R}^{n \times n} : S = -S^T \}$$

If $M \in \mathbb{R}^{n \times n}$, we call $S = \frac{1}{2}(M - M^T)$ the "skew-symmetric part"

$$\text{Note: } S^T = \frac{1}{2}[M - M^T]^T = \frac{1}{2}(M^T - M) = -\frac{1}{2}(M - M^T) = -S$$

Likewise the symmetric part

$$Q = \frac{1}{2}(M + M^T)$$

we say M is "decomposed" into symmetric and skew-symmetric parts.

$$\text{Hence, } S + Q = M$$

$$\text{Let } \Lambda: \mathbb{R}^3 \rightarrow \text{so}(3)$$

$$V: \text{so}(3) \rightarrow \mathbb{R}^3$$

$$\Lambda = \begin{pmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{pmatrix}$$

and V call "inv" as to matrix

S^V

Two facts proved:

$$R \hat{U} R^T = \hat{R} \hat{V}$$

Matrix Exponentials.

$$a^b = e^{b \ln a} = \exp(b \ln a)$$

↳ Taylor Series.

$$e^{A\theta} = I + A\theta + \frac{1}{2!} A^2 \theta^2 + \dots$$

Also Matrix log: $(\ln A = I - \text{something})$

Matrix log is an inverse of exp, on the image of $\mathbb{R}^{n \times n}$ under exp.

Matlab

$$\Rightarrow A = \text{rand}(3,3)$$

$$\Rightarrow eA = \text{expm}(A);$$

$$\Rightarrow A_{\text{test}} = \text{logm}(eA)$$

$$\Rightarrow A - A_{\text{test}}$$

When we restrict $A \in \mathbb{R}^{3 \times 3}$ to be a skew-symmetric matrix.

$$A = \hat{W} \theta, \quad \|\hat{W}\| = 1$$

Then $R = e^A = e^{\hat{W} \theta} = I + \sin \theta \hat{W} + (1 - \cos \theta) \hat{W}^2$ is always a rotation.

And $\exp: \text{SO}(3) \rightarrow \text{SO}(3)$ is onto $\text{SO}(3)$

Image of $so(3)$ under \exp is $SO(3)$

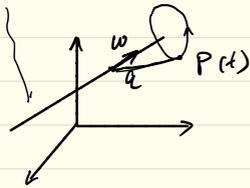
In this case, $\log(CR)$

Inverse is not one-to-one.

Generalize \exp to rigid Transformations via twists.

Motivation \rightarrow consider a $p \in \mathbb{R}^3$ moving with angular velocity
by a unit vector w , $\|w\|=1$

$$\mathcal{L} = \{x \in \mathbb{R}^3 : x = q + \alpha w, \alpha \in \mathbb{R}\}$$



$$\dot{P} = w \times (P - q)$$

$$\text{Let } \hat{\xi} = \begin{bmatrix} \hat{w} & v \\ 0^T & 0 \end{bmatrix}, \quad v = -w \times q$$

$$\Rightarrow \begin{bmatrix} \dot{P} \\ 0 \end{bmatrix} = \hat{\xi} \begin{bmatrix} P \\ 1 \end{bmatrix} = \begin{bmatrix} \hat{w} & v \\ 0^T & 0 \end{bmatrix} \begin{bmatrix} P \\ 1 \end{bmatrix} = w \times P + v = w \times (P - q)$$

Let $\bar{P} = \begin{bmatrix} P \\ 1 \end{bmatrix}$ be homogeneous coordinates for P .

$$\dot{\bar{P}} = \hat{\xi} \bar{P} \quad \Rightarrow \text{Linear System form.}$$

$$\Rightarrow \bar{P}(t) = \exp\{\xi t\} \begin{bmatrix} P \\ 1 \end{bmatrix}$$

This motivates a generalization of $SO(3)$

$$SE(3) = \{ (v, \hat{w}) : v \in \mathbb{R}^3, w \in \mathbb{R}^3 \}$$

↑
 3×3 skew symmetric.

$$SE(3) = \left\{ \begin{bmatrix} \hat{w} & v \\ 0^T & 0 \end{bmatrix} : v \in \mathbb{R}^3, w \in \mathbb{R}^3 \right\}$$

Let $q = (v, w) \in \mathbb{R}^3$ be twist coordinates.

Let $\hat{q} = \begin{bmatrix} \hat{w} & v \\ 0^T & 0 \end{bmatrix}$ and v is the inverse.
↳ overloaded hat

so given 4×4 twist S

$$S^v = (v, w) \in \mathbb{R}^6$$

Cool kid formula for $e^{\hat{q}\theta}$

$$e^{\hat{q}\theta} = I + \theta \hat{q} + (1 - \cos\theta) \hat{q}^2 + (\theta - \sin\theta) \hat{q}^3$$

Matrix Exponential of a twist:

$$\xi = \begin{bmatrix} v \\ w \end{bmatrix} \in \mathbb{R}^6 \quad (v, w) \in \mathbb{R}^3 \times \mathbb{R}^3, \quad \theta \in \mathbb{R}$$

Assume $w \neq 0$, $\|w\| = 1$, without loss of generality?

$$\hat{\xi} = \begin{bmatrix} \hat{w} & v \\ 0^T & 0 \end{bmatrix}$$

$$\exp\{\hat{\xi}\theta\} = I + \theta\hat{\xi} + (1 - \cos\theta)\hat{\xi}^2 + (\theta - \sin\theta)\hat{\xi}^3$$

From MLS

$$\text{Let } \hat{\xi} = (v, w) \in \mathbb{R}^3 \times \mathbb{R}^3$$

$$e^{\hat{\xi}\theta} = I + \hat{\xi}\theta + \frac{1}{2!}\hat{\xi}^2\theta^2 + \frac{1}{3!}\hat{\xi}^3\theta^3 + \dots$$

$$\hat{\xi}^n = \begin{bmatrix} \hat{w}^n & \hat{w}^{n-1}v \\ 0^T & 0 \end{bmatrix}$$

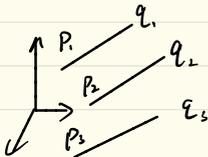
Case 1: Assume $w = 0$

$$\hat{\xi}^n = 0 \quad \text{except for } n=1, \quad \hat{\xi} = \begin{bmatrix} 0 & v \\ 0^T & 0 \end{bmatrix}$$

$$e^{\hat{\xi}\theta} = \begin{bmatrix} 1 & v\theta \\ 0^T & 1 \end{bmatrix}$$

[can assume WLOG $\|v\| = 1$]

Translation of magnitude θ along v .



$$q_i = e^{\hat{\xi}\theta} p_i$$

$$q_1 = p_1 + v\theta$$

Case 2: $\|\omega\| = 1$

Upper 3×3 Block is $e^{\hat{\omega}\theta} = I + \sin\theta \hat{\omega} + (1 - \cos\theta) \hat{\omega}^2$

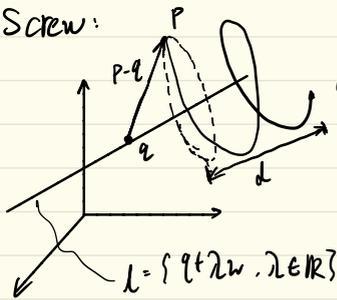
Derivation of $\begin{matrix} 3 \times 1 \\ \text{upper} \end{matrix}$ Block.

$$\text{Let } g = \begin{bmatrix} R & d \\ 0^T & 1 \end{bmatrix} = \exp\{\hat{\omega}\theta\}$$

$R = R_{o,q,h}$ formula

$$d = [I\theta + (1 - \cos\theta)\hat{\omega} + (\theta - \sin\theta)\hat{\omega}^2]v$$

Screw:



q : any point on the axis

$$q + e^{\hat{\omega}\theta}(p - q) + h\omega$$

$$h = \frac{d}{\theta} \quad \text{pitch of screw}$$

A screw is given by $\{l, h, M\}$

axis \uparrow pitch \uparrow Magnitude \uparrow
(θ)

If $h = \infty$, then we have a pure translation.

$$g = \begin{bmatrix} I & w/M \\ 0^T & 1 \end{bmatrix}$$

If $h \neq \infty$.

$$g = \begin{bmatrix} e^{\hat{\omega}\theta} & (I - e^{\hat{\omega}\theta})q + h\omega \\ 0^T & 1 \end{bmatrix}$$

$$gP = \begin{bmatrix} e^{\hat{w}\theta} & (1 - e^{\hat{w}\theta})q + h\theta w \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} P \\ 1 \end{bmatrix}$$

$$= e^{\hat{w}\theta} P + (1 - e^{\hat{w}\theta})q + h\theta w$$

$$= e^{\hat{w}\theta} (P - q) + q + h\theta w$$

Let $q_2 = P + \tau w$

Calculate g_2 based on q_2 (instead of q) and show $g = g_2$.

Given screw, compute twist.

Given a screw (l, h, θ) , $h \neq 0, h \neq \infty$

$$\tilde{\xi} = \begin{bmatrix} -w \times q + h w \\ w \end{bmatrix}$$

Recap: $\{q + w, \exists \in \mathbb{R}\} \quad \|w\|=1$

soem: $\{l, h, M\}$

$h = \infty \Rightarrow$ pure translation

$$\Rightarrow g = \begin{bmatrix} I & wM \\ 0^T & 1 \end{bmatrix}$$

$h \neq \infty, M = \theta$

$$\Rightarrow g = \begin{bmatrix} e^{\hat{w}\theta} & (I - e^{\hat{w}\theta})q + hw \\ 0^T & 1 \end{bmatrix} \quad *$$

which looks similar to...

$$e^{\hat{z}\theta} = \begin{bmatrix} e^{\hat{w}\theta} & (I - e^{\hat{w}\theta})(w \times v) + ww^T v \theta \\ 0^T & 1 \end{bmatrix} \quad *$$

$$v = \begin{bmatrix} U \\ w \end{bmatrix}, \quad \|w\|=1$$

To bring these into agreement, set $v = - (w \times q + hw)$

plug $v \Rightarrow (*)$

$$\begin{aligned} & (I - e^{\hat{w}t}) [w \times (-w \times q + hw)] + ww^T [-w \times q + hw] \theta \\ &= (I - e^{\hat{w}t}) (-w \times (w \times q) + hw \times w) - (ww^T (-w \times q) + \underbrace{(ww^T w)h}_1) \theta \\ &= (I - e^{\hat{w}t}) (-w \times (w \times q) + wh \theta) \\ &= - (I - e^{\hat{w}t}) \hat{w}^2 q + wh \theta \end{aligned}$$

$$\begin{aligned} * &= - (I - I - \hat{w}t - \frac{1}{2!} \hat{w}^2 t^2 - \frac{1}{3!} \hat{w}^3 t^3 - \dots) \hat{w}^2 q \\ &= + \hat{w}^2 (\hat{w}t + \frac{1}{2!} \hat{w}^2 t^2 + \dots) q \quad \leftarrow n^{\text{th}} \text{ term: } \frac{1}{n!} \hat{w}^{n+2} t^n q \end{aligned}$$

$$\underbrace{w \times (w \times (w \times q))}_{n+2}$$

$$\underbrace{(-w \times (w \times (w \times q)))}_n$$

make argument when computing Rodri. Formula

Fold that back into expansion.

$$\begin{aligned} \star &= - \left(\hat{w} t + \frac{1}{2} \hat{w}^2 t^2 + \dots \right) q \\ &= + \left(I - e^{\hat{w} t} \right) q \end{aligned}$$

Recap: finite pitch screw.

$$\{t, h, u\} \longleftrightarrow \xi = \begin{bmatrix} v \\ w \end{bmatrix} \quad \text{with } v = -w \times \xi + h w$$

see back for all cases. screw \leftrightarrow twists.

(only one more case, $h=0$)

Special Case

1) Zero pitch screw \Rightarrow pure rotation about l

2) Infinite Pitch Screw \Rightarrow pure translation

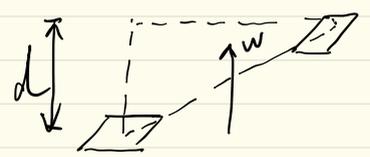
Usually, we factor twists like this: $g = e_{\hat{f}}^{\theta}$

i) $\|w\| = 1$ unit twist

ii) $\begin{cases} \|w\| = 0 \\ \|v\| = 1 \end{cases}$

Charles Theorem

Every rigid body motion can be realized by a rotation about an axis, combined with a translation along that axis.



$$h \frac{\pi}{2} = d \Rightarrow h = \frac{2d}{\pi} \quad (\text{pitch})$$

Proof of Charles Theorem, follows this logic:

1) If $g \in SE(3)$, $\exists \hat{\eta} \in se(3)$, st $e^{\hat{\eta}} = g$

(From surjectivity of exp)

2) given $\hat{\eta}$ (twist), there is a corresponding screw motion

(prop. 2^o in MLS)

Preview of rigid body velocities,

$$R(t) = [X_B^a \quad Y_B^a \quad Z_B^a]$$

Start w/ Rotation

$$R(t) = SO(3), \text{ what is } \dot{R}$$



$$CR^T R = I$$

X_B^a : rep of X-axis of rotated frame wRT original frame.

Rigid Body Velocity

start with rotational (angular) velocity.

start with $R^T R = I$, where we assume $R(t) \in SO(3)$ is a smooth motion, ie. each element of $R(t)$ is differentiable in wrt t .

$$R(t) = \begin{bmatrix} r_{11}(t) & \dots & \\ \vdots & \dots & \\ \vdots & \dots & r_{33}(t) \end{bmatrix} \Rightarrow \frac{d}{dt} R(t) = \dot{R}(t) \text{ and } ij \text{th element is } \dot{r}_{ij}(t)$$

R by itself is not a great way to keep track of rotational velocities.

starting with (*) $R^T R = I$

$$\downarrow$$
$$\frac{d}{dt} R^T R = \frac{d}{dt} I$$

side fact: if $A(t)$, $B(t)$ have compatible dimensions, and are smooth functions of time,

$$\frac{d}{dt} (AB) = \dot{A}B + A\dot{B}$$

$$\Rightarrow \frac{d}{dt} (R^T R) = \frac{d}{dt} R^T R + R^T \frac{d}{dt} R = 0_{3 \times 3}$$

$$= \dot{R}^T R + R^T \dot{R}$$

$$= (R^T \dot{R})^T + R^T \dot{R}$$

$$\Rightarrow (R^T \dot{R})^T = -R^T \dot{R}$$

$\Rightarrow R^T \dot{R}$ is a skew-symmetric matrix.

Therefore, we can define $\omega^b = (CR^T \dot{R})^v$ as so called **Body Angular Velocity**

likewise, starting with $RR^T = I$
 \downarrow
 $\frac{d}{dt} \dots$
 \downarrow

$\omega^s = (CRRT)^v$: **Spacial Angular Velocity**

Look at $\hat{\omega}_b = R^T \dot{R}$

Premultiply by R . Post-multiply by R^T on both sides.

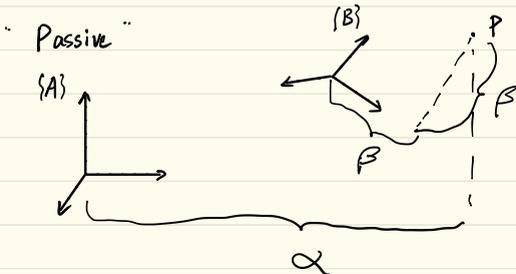
$$R \hat{\omega}_b R^T = \underbrace{R(R^T \dot{R})}_I \underbrace{R^T}_{\hat{\omega}^s} = \hat{\omega}^s$$

$$\Rightarrow \hat{\omega}^s = R (\hat{\omega}_b) R^T$$

$$\Rightarrow \omega^s = R \omega^b$$

likewise, $\omega^b = R^T \omega^s$

Two interpretations of rigid transformation.



$P_b = \text{rep of } P \text{ wrt } \{B\}$

$P_a = \dots \{A\}$

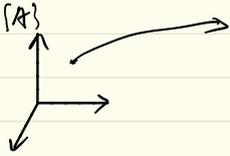
$$P_a = \begin{bmatrix} \alpha \\ 0 \end{bmatrix} \quad P_b = \begin{bmatrix} \beta \\ \beta \end{bmatrix}$$

Passive interpretation of $g_{a,b} \in SE(3)$ is the change of coordinate.

$$P_a = g_{a,b} P_b$$

Active interpretation of $g_{a,b} \in SE(3)$ is the movement of the points via mult by $g_{a,b}$.

$$P \rightarrow gP$$



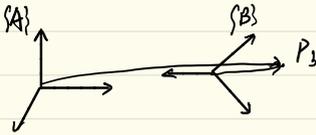
Consider motion of a point under a motion $P_{ab}(t)$

$$P_a(t) = R_{ab}(t) P_b$$

← constant.

velocity of point

$$v_a = \dot{P}_a = \dot{R}_{ab} P_b + R_{ab} \dot{P}_b$$



$$\Rightarrow v_a = \dot{R}_{ab} P_b$$

Put v i P in same frame

Note: $P_b = R_{ab}^T P_a$
 $(P_a = R_{ab} P_b)$

$$\Rightarrow v_a = \dot{R}_{ab} (R_{ab}^T P_a) = (\dot{R}_{ab} R_{ab}^T) P_a$$

$$v_a = \hat{W}_{ab}^a P_a = \mathcal{W}_{ab}^a \times P_a$$

Body velocity

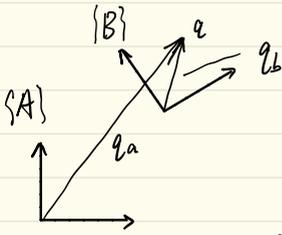
$$v_b \neq \frac{d}{dt} P_b = 0$$

Rather:

$$v_b = \hat{W}_{ab}^b P_b = \mathcal{W}_{ab}^b \times P_b$$

SE(3) Motion

$$g_{ab}(t) = \begin{bmatrix} R_{ab}(t) & P_{ab}(t) \\ 0^T & 1 \end{bmatrix}$$



$$q_b \equiv \text{const.}$$

$$v_{q_a} = \frac{d}{dt} q_a(t) \quad (\text{B/C } \{A\} \text{ is considered stationary})$$

$$\Rightarrow v_{q_a} = \frac{d}{dt} (g_{ab}(t) q_b)$$

$$= \dot{g}_{ab} q_b$$

$$\underbrace{\hspace{10em}}_{g_{ab}^{-1} q_a}$$

$$\Rightarrow v_{q_a} = (\dot{g}_{ab} g_{ab}^{-1}) q_a$$

$\hat{v}_{ab}^s = \text{spatial Body Velocity.}$

$$\text{Let } g(t) = \begin{bmatrix} R(t) & P(t) \\ 0 & 1 \end{bmatrix}$$

Twist

$$\dot{g} g^{-1} = \begin{bmatrix} \dot{R} & \dot{P} \\ 0^T & 0 \end{bmatrix} \begin{bmatrix} R^T & -R^T P \\ 0^T & 1 \end{bmatrix} = \begin{bmatrix} \dot{R} R^T & -\dot{R} R^T P + \dot{P} \\ 0^T & 0 \end{bmatrix}$$

$$\Rightarrow v^s = \begin{bmatrix} v^s \\ w^s \end{bmatrix} = \begin{bmatrix} -\dot{R} R^T P + \dot{P} \\ (\dot{R} R^T)^v \end{bmatrix}$$

$$\text{ie. } \hat{v}^s = \dot{g} g^{-1}$$

$$\Rightarrow v^s = (g \dot{g}^{-1})^v$$

and likewise,

$$\hat{v}^b = g^{-1} \dot{g}$$

$$\Rightarrow v^b = (g^{-1} \dot{g})^v$$

where

$$\hat{v}^b = \begin{bmatrix} R^T & -R^T P \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} \dot{R} & \dot{P} \\ 0^T & 0 \end{bmatrix} = \begin{bmatrix} R^T \dot{R} & R^T \dot{P} \\ 0^T & 0 \end{bmatrix}$$

$$v^b = \begin{bmatrix} R^T \dot{P} \\ (CR^T \dot{R})^v \end{bmatrix} = \begin{bmatrix} v^b \\ w^b \end{bmatrix}$$

Go back to $v_{q_a} = \underbrace{(g_{ab}^{-1} \dot{g}_{ab}^{-1})}_{V_{ab}^s} q_a$

$$= \begin{bmatrix} \hat{w}_{ab}^s & V_{ab}^s \\ 0^T & 0 \end{bmatrix} \begin{bmatrix} q_a \\ 1 \end{bmatrix}$$

$$= \hat{w}_{ab}^s q_a + V_{ab}^s$$

Where $\hat{w}_{ab}^s = \dot{R}_{ab} R_{ab}^T$

$$V_{ab}^s = -\dot{R}_{ab} R_{ab}^T P_{ab} + \dot{P}_{ab}$$

Recap.

$$\hat{V}^s = \dot{g}g^{-1} \Rightarrow V^s = \begin{bmatrix} -RR^T P + \dot{P} \\ (RR^T)^v \end{bmatrix}$$

$$\hat{V}^b = g^{-1}\dot{g} \Rightarrow V^b = \begin{bmatrix} R^T \dot{P} \\ (R^T R)^v \end{bmatrix}$$

These are related by a similarity transformation!

$$g^{-1}\hat{V}^s g = \underbrace{g^{-1}}_{\hat{V}^b} \underbrace{(\dot{g}g^{-1})}_I g = \hat{V}^b$$

$$\hat{V}^b = g^{-1}\hat{V}^s g$$

$$\hat{V}^s = g\hat{V}^b g^{-1}$$

Can we turn this into a relationship between V^s and V^b

See P55 - P56 MLS

$$V^s = \underbrace{\begin{bmatrix} R & \dot{P}R \\ 0 & R \end{bmatrix}}_{\substack{\text{6x6 matrix} \\ \parallel \\ \text{Ad}_g}} V^b$$

$$\Rightarrow V^b = (\text{Ad}_g)^{-1} V^s$$

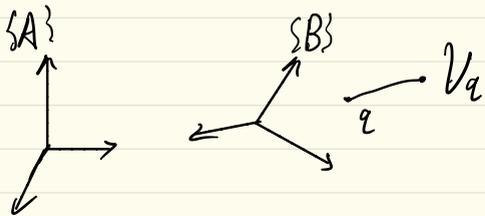
$$= \underbrace{\begin{bmatrix} R^T & -\widehat{(R^T \dot{P})} R^T \\ 0 & R^T \end{bmatrix}}_{\text{Ad}_{g^{-1}}} V^s$$

$$\Rightarrow \text{Ad } g^{-1} = [\text{Ad } g]^{-1}$$

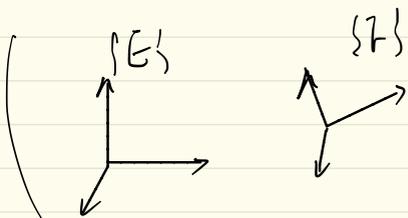
"Inverse of Adjoint is the Adjoint of the inverse"

Recall $v_{q_a} = \hat{V}_{a_b}^s q_a$

What is vel of q written wrt $\{B\}$? (Instantaneous Frame)



$$v_{q_b} = (g_{ab})^{-1} v_{q_a}$$



$$v_{q_e} = \hat{V}_{e_f}^s q_e$$

$$v_{q_f} = (g_{ef})^{-1} v_{q_e}$$

$$\begin{aligned} v_{q_b} &= g_{ab}^{-1} \hat{V}_{a_b}^s q_a \\ &= g_{ab}^{-1} \hat{V}_{a_b}^s \underbrace{g_{ab} q_b}_{\hat{V}_{a_b}^b} \end{aligned}$$

$$\Rightarrow v_{q_b} = \hat{V}_{a_b}^b q_b$$

Velocity of a screw motion

$$\text{Let } g(t) = e^{\hat{f}(t)} g(\omega) \quad g(\omega) = \text{const}$$

$$\Rightarrow \dot{g} = \hat{\xi} \dot{\theta} e^{\hat{f}\theta} g(\omega) \quad \Rightarrow \hat{V}^s g g^{-1} = \hat{\xi} \dot{\theta} e^{\hat{f}\theta} g(\omega) \left[\begin{array}{c} e^{\hat{f}t} \\ g(\omega) \end{array} \right]^{-1} = \hat{\xi} \dot{\theta}$$

$$\text{However, } \hat{V}^b = \dot{g} g^{-1} = g^{-1} \hat{\xi} g(\omega) \dot{\theta} \Rightarrow \hat{V}^b = (\text{Ad } g^{-1} \hat{\xi}) \dot{\theta}$$

Does the choice of Body Frame affect \hat{V}^b ?

$$\begin{aligned} \hat{V}_{ac}^b &= g_{ac}^{-1} \cdot \dot{g}_{ac} \\ &= (g_{bc}^{-1} g_{ab}^{-1}) (\dot{g}_{ab} g_{bc}) \\ &\quad \underbrace{g_{bc}^{-1} \quad \hat{V}_{ab}^b \quad g_{bc}} \end{aligned}$$

$$\therefore \hat{V}_{ac}^b = \text{Ad } g_{bc}^{-1} \hat{V}_{ab}^b$$

A: Yes, Body Velocity is not invariant to body Frame.

Spacial Velocity.

$$\hat{V}_{ac}^s = g_{ac} \dot{g}_{ac}^{-1} = (g_{ab} \dot{g}_{bc}) (g_{ab} g_{bc})^{-1} = g_{ab} \dot{g}_{bc} g_{bc}^{-1} g_{ab}^{-1} = \hat{V}_{ab}^s$$

\Rightarrow Invariant

Sum up:

- spacial Velocity:
- is invariant to body frame
 - is NOT invariant to spacial frame.

{A} Fixed {B} Move

$$\begin{aligned}\hat{V}_{ac}^s &= \dot{g}_{ac} g_{ac}^{-1} = (\dot{g}_{ab} g_{bc} + g_{ab} \dot{g}_{bc}) (g_{bc}^{-1} g_{ab}^{-1}) \\ &= g_{ab} \underbrace{\dot{g}_{bc} g_{bc}^{-1}}_{\hat{V}_{bc}^s} g_{ab}^{-1}\end{aligned}$$

$$\Rightarrow \hat{V}_{ac}^s = \text{Ad}_{g_{ab}} \hat{V}_{bc}^s$$

↓

Not invariant to spacial frame.

- Body Velocity:
- is invariant to spacial frame $\Rightarrow V_{ac}^b = V_{bc}^b$
 - is not invariant to body frame, $\Rightarrow V_{ac}^b = \text{Ad}_{g_{bc}^{-1}} V_{ab}^b$

Suppose {A} is fixed, {B} moves relative {A} $\Rightarrow g_{ab}(t)$
{C} moves relative {B} $\Rightarrow g_{bc}(t)$

$$\Rightarrow \{C\} \dots \{A\} \Rightarrow g_{ac} = g_{ab} \cdot g_{bc}$$

$$\begin{aligned}\hat{V}_{ac}^s &= \dot{g}_{ac} g_{ac}^{-1} = (\dot{g}_{ab} g_{bc} + g_{ab} \dot{g}_{bc}) (g_{bc}^{-1} g_{ab}^{-1}) \\ &= \dot{g}_{ab} g_{bc} g_{bc}^{-1} g_{ab}^{-1} + g_{ab} \dot{g}_{bc} g_{bc}^{-1} g_{ab}^{-1} \\ \hat{V}_{ac}^s &= \hat{V}_{ab}^s + g_{ab} \hat{V}_{bc}^s g_{ab}^{-1}\end{aligned}$$

$$\Rightarrow V_{ac}^s = V_{ab}^s + \text{Ad}_{g_{ab}} V_{bc}^s$$

Similarly, $V_{ac}^b = V_{bc}^b + \text{Ad}_{g_{bc}^{-1}} V_{ab}^b$

Adjoint, $\bullet V^s = \text{Ad}_g V^b$

$\bullet V_{ac}^s = V_{ab}^s + \text{Ad}_{g_{ab}} V_{bc}^s$

$\bullet V_{ac}^b = V_{bc}^b + \text{Ad}_{(g_{bc}^{-1})} V_{ab}^b$

$\bullet \xi' = \text{Ad}_g \xi$ (Transform of screw)

Overview :

- Points . vectors
- Rigid Transformations
- Groups : group action . group product . homomorphism .
- Representing rigid transformation

- Homog Transformations

- Exponentials of Twists C Rodrigues, cool-kid formula

- Euler Angles . $e^{\hat{w}\theta}$. $w_x = \begin{vmatrix} 1 & 0 \\ 0 & 0 \end{vmatrix}$

- Axis . Angle

- screw \leftrightarrow twists

- Rigid Body velocities.
- Adjoints.
- DOF : constraints.

• Linear Vector Spaces - Linearity.

$$G : SO(2) \rightarrow SO(3)$$

$$G(R) = \begin{bmatrix} R & \mathbf{0} \\ \mathbf{0} & 1 \end{bmatrix}$$

• Twists as velocities.

Final 12/21

This class : serial-link, open chain manipulators, typically with a sequence of single DOF joints

Joints can be

• 1 DOF

- revolute
 - Prismatic
 - Helical
- } Screw Motion

• 2 DOF

cylindrical
rev. + Prismatic

• 3 DOF

- Planar
- Spherical
ball in a socket.

"Lower Pairs"

Goal in Forward Kinematics: Find a mapping from joint space to configuration space

$$g: Q \rightarrow SE(3)$$

Where $Q =$ joint space. $Q = \mathbb{R}^n$, where $n = \#$ of joints.

(Technically, $Q = T^n$ for all revolute joint: $T^n = \underbrace{S^1 \times S^1 \times \dots \times S^1}_n$)

We say if $Q = \mathbb{R}^n$, then it's an n -DOF robot.

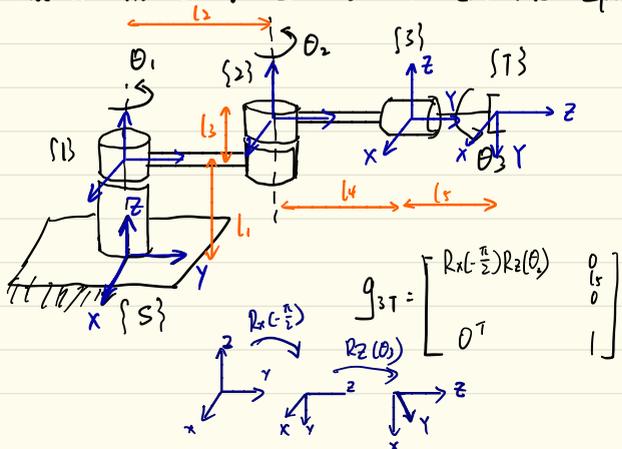
If $n < 6$, under actuated robot

$n = 6$ fully actuated robot.

$n > 6$, redundant manipulator

Classical Kinematics: eg. in Craig

Attach Frames to each link, calculate (passive) link-to-link transformation.



$$g_{s1}(\theta_1) = \begin{bmatrix} R_z(\theta_1) & \begin{matrix} 0 \\ 0 \\ l_1 \end{matrix} \\ 0^T & 1 \end{bmatrix}$$

$$g_{12}(\theta_2) = \begin{bmatrix} R_z(\theta_2) & \begin{matrix} 0 \\ l_2 \\ l_3 \end{matrix} \\ 0^T & 1 \end{bmatrix}$$

$$g_{23}(\theta_3) = \begin{bmatrix} I & \begin{matrix} 0 \\ l_4 \\ 0 \end{matrix} \\ 0^T & 1 \end{bmatrix}$$

$$g_{3T} = \begin{bmatrix} R_x(-\frac{\pi}{2})R_z(\theta_3) & \begin{matrix} 0 \\ l_5 \\ 0 \end{matrix} \\ 0^T & 1 \end{bmatrix}$$

(D-H came up a standard procedure.)

Final Mapping

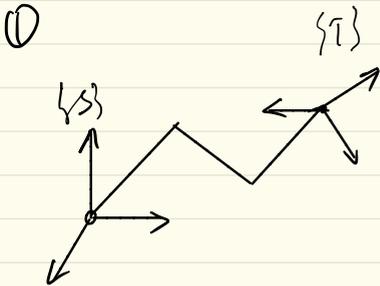
$$g_{st}(\theta_1, \theta_2, \theta_3) = g_{s1} \cdot g_{12} \cdot g_{23} \cdot g_{3T}$$

Transform points from tool frame $\xrightarrow{g_{st}}$ spatial frame
 $\xleftarrow{g_{st}^{-1}}$

Active Perspective.

Product of Exponential Formulation.

Define two frames.



② Choose a home configuration, and call this $\theta = 0 \in \mathbb{R}^n$

③ Calculate g

④ POE

$$g_{st}(\theta) = e^{\hat{z}_1 \theta_1} \dots e^{\hat{z}_n \theta_n}$$

Correction : $f: Q \rightarrow SE(3)$
 \uparrow contains workspace.
 C-space or joint space

Product of Exponential Formula.

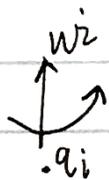
$$g(\theta) = e^{\hat{\xi}_1 \theta_1} e^{\hat{\xi}_2 \theta_2} e^{\hat{\xi}_3 \theta_3} \dots e^{\hat{\xi}_n \theta_n} g_{st}(0)$$

STEP 1 : Place $\{S\}$ and $\{T\}$ to tool

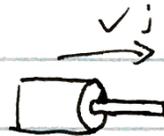
STEP 2 : Pick $\theta=0$ configuration. and compute $g_{st}(0)$

STEP 3 : At $\theta=0$, determine ξ_1, \dots, ξ_n .
 (e.g. by calculating the associated screws)
 \downarrow wrt. $\{S\}$

STEP 4 : $g_{st}(\theta) = e^{\hat{\xi}_1 \theta_1} \dots e^{\hat{\xi}_n \theta_n} g_{st}(0)$



$$\xi = \begin{bmatrix} -w_i q_i \\ w_i \end{bmatrix}$$



$$\xi = \begin{bmatrix} v^j \\ 0 \end{bmatrix}$$

Does the order matter?

$$e^{\hat{\xi}_n \theta_n} e^{\hat{\xi}_2 \theta_2} e^{\hat{\xi}_1 \theta_1} g_{st}(0) \stackrel{?}{=} g_{st}(\theta)$$

Look @ $n=2$ case

After applying a rotation θ_1 , the axis associated with $\hat{\xi}_1$,

How do we move $\hat{\xi}_2 \rightarrow \hat{\xi}'_2$

$$\hat{\xi}'_2 = \text{Ad}_{e^{\hat{\xi}_1 \theta_1}} \hat{\xi}_2$$

$$\begin{aligned} \Rightarrow e^{\hat{\xi}'_2 \theta_2} &= e^{(\text{Ad}_{e^{\hat{\xi}_1 \theta_1}} \hat{\xi}_2) \theta_2} \\ &= \exp \left\{ e^{\hat{\xi}_1 \theta_1} \hat{\xi}_2 [e^{\hat{\xi}_1 \theta_1}]^{-1} \theta_2 \right\} \end{aligned}$$

Aside:

$$e^{ABA^{-1}} = I + ABA^{-1} + \frac{[ABA^{-1}]^2}{2!} + \dots$$

$$(ABA^{-1})^n = AB^n A^{-1}$$

$$= A(e^B)A^{-1}$$

$$\Rightarrow = e^{\hat{\xi}_1 \theta_1} e^{\hat{\xi}'_2 \theta_2} e^{-\hat{\xi}_1 \theta_1}$$

$$\Rightarrow \text{For } n=2, \quad e^{\hat{\xi}'_2 \theta_2} e^{\hat{\xi}_1 \theta_1} g_{st}(\omega)$$

$$= [e^{\hat{\xi}_1 \theta_1} e^{\hat{\xi}'_2 \theta_2} e^{-\hat{\xi}_1 \theta_1}] e^{\hat{\xi}_1 \theta_1} g_{st}(\omega)$$

$$= e^{\hat{\xi}_1 \theta_1} e^{\hat{\xi}'_2 \theta_2} g_{st}(\omega) \quad \mathbb{1}$$

Jacobian: Mapping from joint-space velocities to end-effector velocities. It's calculated using chain rule.

"Easy" Case: End-effector pose is written using local condition, eg. position + Euler angle

$$r = \begin{pmatrix} x \\ y \\ z \\ \alpha \\ \beta \\ \gamma \end{pmatrix} \left. \begin{array}{l} \text{position} \\ \text{Euler angles.} \end{array} \right\}$$

$$r = f(q), \quad f: \mathbb{R}^6 \rightarrow \mathbb{R}^6$$

↑ joint-space ↙ pose

$$\dot{r} = \underbrace{\frac{\partial f}{\partial q}}_{J(q)} \cdot \dot{q}$$

Using Euler angles introduces artificial singularities!

To avoid this, we compute the manipulator Jacobian based on either the body velocity V_{st}^b or the spatial velocity V_{st}^s

$$V_{st}^b = J_{st}^b(q) \dot{q}$$

$$V_{st}^s = J_{st}^s(q) \dot{q}$$

The Jacobian is a linear Mapping between joint-space velocities and end-effector velocities.

To calculate V_{st}^b or V_{st}^s , go back to the definition.

$$\hat{V}_{st}^b = g_{st}^{-1} \dot{g}_{st}$$

$$\hat{V}_{st}^s = \dot{g}_{st} g_{st}^{-1}$$

POE

$$g_{st}(q) = e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_n \theta_n} g_{st}(0)$$

Start with

$$\begin{aligned} \hat{V}_{st}^s &= \frac{d}{dt} [e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_n \theta_n} g_{st}(0)] [e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_n \theta_n} g_{st}(0)]^{-1} \\ &= \dot{q}_1 \hat{q}_1 e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_n \theta_n} g_{st}(0) + e^{\hat{q}_1 \theta_1} \dot{q}_2 \hat{q}_2 e^{\hat{q}_2 \theta_2} \dots g_{st}(0) \\ &\quad + \dots + e^{\hat{q}_1 \theta_1} e^{\hat{q}_2 \theta_2} \dots e^{\hat{q}_{n-1} \theta_{n-1}} \dot{q}_n \hat{q}_n e^{\hat{q}_n \theta_n} g_{st}(0) \end{aligned}$$

Multiply together

$$\begin{aligned} &= \dot{\theta}_1 \hat{q}_1 + \dot{\theta}_2 e^{\hat{q}_1 \theta_1} \hat{q}_2 e^{-\hat{q}_1 \theta_1} + \dot{\theta}_3 e^{\hat{q}_1 \theta_1} e^{\hat{q}_2 \theta_2} \hat{q}_3 e^{-\hat{q}_2 \theta_2} e^{-\hat{q}_1 \theta_1} \\ &\quad + \dots + \dot{\theta}_n e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_{n-1} \theta_{n-1}} \hat{q}_n e^{\hat{q}_n \theta_n} \dots e^{-\hat{q}_1 \theta_1} \end{aligned}$$

\uparrow linear in θ_i

$$\hat{q}_i = \text{Ad}_{e^{\hat{q}_1 \theta_1} \dots e^{\hat{q}_{i-1} \theta_{i-1}}} \hat{q}_i$$

$$\left(\mathcal{L} = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \right)$$

$$\stackrel{\text{"Vee"}}{\Rightarrow} V_{st}^s = \dot{\theta}_1 \hat{q}_1 + \dot{\theta}_2 \hat{q}_2 + \dots + \dot{\theta}_n \hat{q}_n, \quad \uparrow$$

$$\Rightarrow \underset{\in \mathbb{R}^6}{V_{st}^s} = \underbrace{[q_1' \dots q_2' \dots q_n']}_{J_{st}^s(q)} \underbrace{\begin{bmatrix} \dot{\theta}_1 \\ \vdots \\ \dot{\theta}_2 \\ \vdots \\ \dot{\theta}_n \end{bmatrix}}_{\dot{q} \in \mathbb{R}^n}$$

see book for $J_{st}^b(q)$

Recall

$$\hat{V}_{st}^b = g_{st}^{-1} \dot{q}_{st} = g_{st}^{-1} \underbrace{[\dot{q}_{st} g_{st}^{-1}]}_{I} g_{st} = \underbrace{Ad_{g_{st}^{-1}}}_{I} V_{st}^s$$

$$\Rightarrow J_{st}^b(q) = Ad_{g_{st}^{-1}} J_{st}^s$$

Recall If $g_{st}(q)$ is the forward kinematic map and say $J_{st}^s(q)$ is the spatial Jacobian matrix.

A singularity is a point $q_{st} \in \mathcal{Q}$, st $J(q)$ loses rank from its usual rank.

If $\mathcal{Q} \in \mathbb{R}^6$, then look at $\det(J(q))$ and if $\det(J(q))$ is a non trivial (scalar) function, then the usual rank is 6.

The job of finding singularities reduces to finding q vector that cause $\det(J(q)) = 0$

Other cases:

$$n < 6$$

$$\text{Rank}(J) \leq n < 6$$

Assume $\text{rank}(J)$ is "usually" n , then a singularity would be when $\text{rank}(J) < n$

$$n > 6:$$

redundant manipulators

$$\text{Typically } \text{rank}(J) = 6$$

- Enhance dexterous workspace.
- provides extra to solve sub-tasks, (say, avoiding collision)
- singularity when $\text{rank} < 6$

Two physical ramifications of singularities.

1) loss of (local) DOF of end-effector.

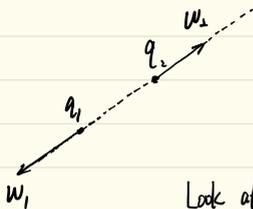
(can't achieve certain end-effector velocities)

2) Inability to transmit certain end-effector forces into torques

Characterizing singularities using twists.

$$\text{Recall for all revolute robots, } J(q) = \begin{bmatrix} -w_1 x q_1 & -w_2 x q_2 & \dots & -w_n x q_n \\ w_1 & w_2 & \dots & w_n \end{bmatrix} \in \mathbb{R}^{6 \times n}$$

Example 1 co-linear parallel joints.



$$\textcircled{1} w_1 = \pm w_2$$

$$\textcircled{2} w_i \times (q_1 - q_2) = 0$$

Look at $q_1 - q_2 = \begin{bmatrix} -w_1 \times q_1 \\ w_1 \end{bmatrix} - \begin{bmatrix} -w_2 \times q_2 \\ w_2 \end{bmatrix}$

say $w_1 = w_2$

$$= \begin{bmatrix} -w_1 \times (q_1 - q_2) \\ 0 \end{bmatrix}$$

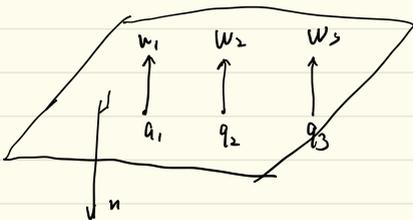
if $w_1 = -w_2$, then add $q_1 + q_2$

, q_1 and q_2 are linearly dependent.

Example 2: parallel co-planar revolute joints.

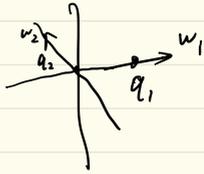
$$\Rightarrow 1) w_i = \pm w_j, \quad i, j = 1, 2, 3$$

$$2) \exists n \neq 0 \cdot n^T C(q_1 - q_2) = 0$$



Example 3. 4 co-intersecting revolute

$$w_i \times (q_i - q) = 0 \text{ for some } q.$$

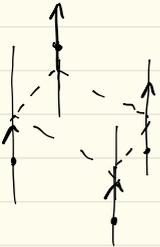


Example 4. (Not in book)

Four Parallel (not nec. coplanar) axes.

Assume $w_i = (w)$ for some w . $i = 1 \dots 4$.

If only are neg, deal w/ one sep time)



$$J = \begin{bmatrix} -w_1 x_1 & -w_2 x_2 & -w_3 x_3 & -w_4 x_4 \\ w_1 & & & \\ & w_2 & & \\ & & w_3 & \\ & & & w_4 \end{bmatrix}$$

Follow through mathematica notebook.

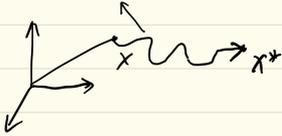
subtract last col from 1st three

$\hat{w} [abc]$ for upper left 3×3 block.

What are Jacobian Matrices good for?

First: A rudimentary Cartesian controller. Let $x \in \mathbb{R}^3$ be the position of a point under our control.

$\dot{x} = u$ $u \in \mathbb{R}^3$, where u is our control input.



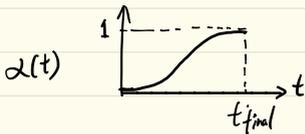
Suppose our goal is to drive $x(t) \rightarrow x^*$, where $x^* \in \mathbb{R}^3$ is a fixed goal.

"CS" approach.

Compute a path for our initial state to x^* . $x_p(t)$



$$x_p(t) = \alpha(x^*) + (1-\alpha)x$$



Now let $u(t) = \frac{d}{dt} x_p(t)$

"EE" approach = a feedback algorithm.

Define a control policy.

$$u(t) = k(x^* - x(t))$$

↑ scalar feedback gain

$$[k] = \frac{m/s}{m} = \frac{1}{s}$$

$$\Rightarrow \dot{x} = u = k[x^* - x]$$

Error

$$e(t) = x - x^*$$

$$\Rightarrow \frac{d}{dt} e = \dot{e} = \dot{x} - \dot{x}^* = -ke = -k|e$$

$$e(t) = e^{-kt} e_0 \quad (\dot{x} = Ax \Rightarrow x(t) = e^{At} x_0)$$

$$\Rightarrow e(t) \rightarrow 0 \text{ as } t \rightarrow \infty$$

Pick k so that $\tau = \frac{1}{k}$ is short enough for our purpose.

Asymptotic convergence practicing at x^* w/in s^t .

Resolved rate control

control model.

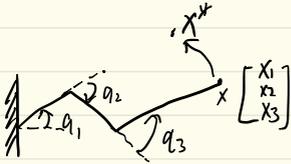
Let $x = f(q)$, $\dot{q} = u$. where $q \in \mathbb{R}^3$ (joint variable)

$x \in \mathbb{R}^3$ tool-tip position.

Define $J(q) = \frac{\partial f}{\partial q} \in \mathbb{R}^{3 \times 3}$

Recall $\dot{x} = \underbrace{J(q)}_{\text{linear map.}} \dot{q}$

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



Calculate algorithm:

$$u = K J^{-1}(q) [x^* - x]$$

↑
joint space velocities.

chain rule.

$$\text{Plug in } \Rightarrow \dot{x} = \frac{d}{dt} f(q) = J(q) \cdot \dot{q}$$

$$\Rightarrow \dot{x} = J(q) u = J(q) [K J^{-1}(q) \cdot [x^* - x]]$$

$$\Rightarrow \dot{x} = K [x^* - x]$$

from the force.

$$x \rightarrow x^* \quad \text{as} \quad t \rightarrow \infty$$

Must worry about singularities

Discrete time implementation

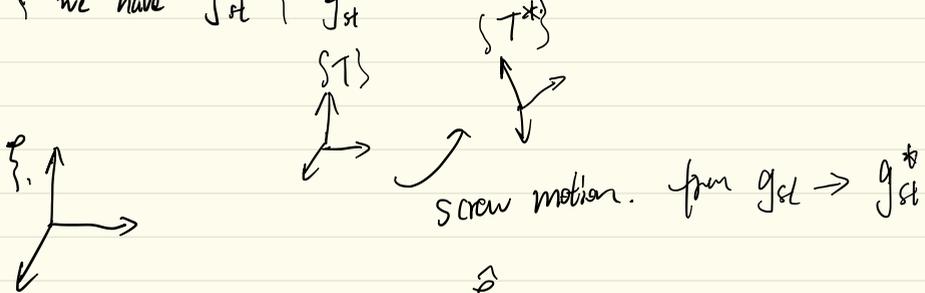
$$\frac{q(k+1) - q(k)}{\Delta T} \approx \dot{q} = K J^{-1}(q) [x^* - x]$$

$$\Rightarrow q(k+1) = q(k) + \underbrace{\Delta T K J^{-1}(q)}_{\text{two variable.}} [x^* - x]$$

6 DOF POE generalization:

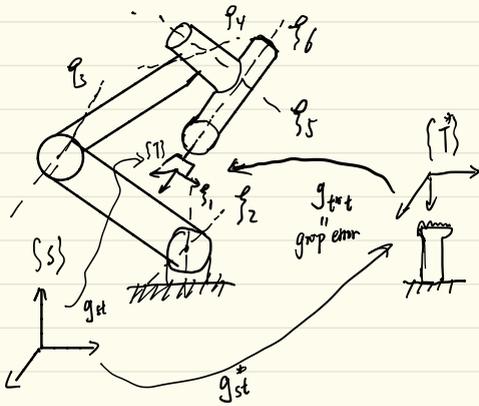
$$g_{st}(q) = e^{\tilde{\xi}_1 \theta_1} \dots e^{\tilde{\xi}_6 \theta_6} g_{st}(0)$$

{ we have J_{st}^b | J_{st}^s



$$g_{st} (g_{st}^*)^{-1} = e^{\theta \tilde{\xi}_e}$$

where ξ_e is the twist coordinate vector of the group error.



$$e = x - x^*$$

$$g_{st} = g_{st}^* g_{t+t}$$

$$g_{t+t} = g_{st}^{-1} g_{st}$$

error

We want $g_{t+t} \rightarrow I$

At time $t=0$, suppose $g_{t+t} = e^{\hat{s}_0 \theta}$. where s_0, θ are extracted using the usual formula.

Our goal: Make g_{t+t} stay along the same screw (associated with s_0)

but make $\theta(t) \rightarrow 0$ as $t \rightarrow \infty$



$$e' = x^* - x$$

$$\dot{e}' = \dot{x}^* - \dot{x} = -u$$

$$\Rightarrow u = -k(x - x^*) = k(x^* - x) = +k e'$$

$$\Rightarrow \dot{e}' = -u - (k e') = -k e'$$

Idea: make V_{t+t}^b point along the screw

$$\hat{V}_{t+t}^b = g_{t+t}^{-1} \dot{g}_{t+t} = g_{st}^{-1} g_{st}^* \underbrace{[g_{st}^{-1} \dot{g}_{st}]}_{g_{t+t}}$$

I g_{t+t}

$$= g_{st}^{-1} \dot{q}_{st} = \hat{V}_{st}^b$$

$$V_{t+t}^b = V_{st}^b = J_{st}^b(q) \dot{q}$$

We will use this later to determine \dot{q} . First find a good choice for V^b .

Let $V_{t+t}^b = -k\xi$, where ξ is the current unnormalized twist, i.e. $\xi = \rho \cdot \rho_0$

We will now show $\dot{\xi} = -k\xi$

$$\text{If } \dot{\xi} = -k\xi$$

$$\Rightarrow \xi(t) = e^{-kt} \underbrace{\xi_0}_{\text{initial condition}}$$

$$\Rightarrow g_{t+t} = \exp(\theta_0 e^{-kt} \hat{\xi}_0)$$

$\theta(t)$

$$\Rightarrow V_{t+t}^b = g_{t+t}^{-1} \dot{q}_{t+t} = e^{-\theta(t) \hat{\xi}_0} [\dot{\theta} \hat{\xi}_0 e^{\theta(t) \hat{\xi}_0}]$$

$= \dot{\theta} \hat{\xi}_0$

$$\Rightarrow V^b = \dot{\theta} \xi = -k \theta_0 e^{-kt} \xi$$

$= -k\xi$

aside:

could choose

$$V_{t+t}^b = \frac{k\xi}{\|\xi\| + \epsilon}$$

$\|\xi\|$ larger than ϵ

$$V_{t+t}^b = -k \frac{\xi}{\|\xi\|}$$

\Rightarrow count velocity

When $\|\xi\| < \epsilon$

$$\Rightarrow V_{t+t}^b = -\frac{k}{\epsilon} \xi$$

\Rightarrow if we choose $V_{st}^b = V_{t^*t}^b = -k \xi$
↑
measure at every time step.

$$\Rightarrow \ddot{q} = -k \xi(t)$$

$$\Rightarrow \xi \rightarrow 0 \text{ as } t \rightarrow \infty$$

$$\Rightarrow q_{t^*t} \rightarrow I$$

$$\Rightarrow \dot{q} = J_{st}^b (q)^{-1} [-k \xi]$$
 Resolved into control joints

MIT Linear Alg G.S.

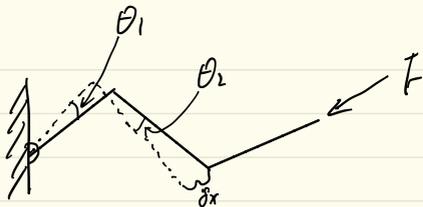
The transpose Jacobian

Generalized Forces $\tau \in \mathbb{R}^n$ ($n = \# \text{ joints}$) are just quantity st.

the virtual work δW done by virtual displacement $\delta \theta$ is given

$$\text{by } \delta W = \sum_{i=1}^n \tau_i \delta \theta_i$$

At the end-effector, the virtual work is given by $\delta W = F \cdot \delta x$, where δx is a virtual displacement.



Conservation of energy \Rightarrow Principle of Virtual Work:

We can equate virtual work at end-effector with the virtual work done by joints.

$$\delta W = F \cdot \delta x = \tau \cdot \delta \theta$$

vector dot product

$$= F^T \delta x = \tau^T \delta \theta$$

\uparrow \uparrow \uparrow \leftarrow
 \mathbb{R}^3 \mathbb{R}^3 \mathbb{R}^n $\in \mathbb{R}^n$

Let's assume $x=f(\theta)$, $f: \mathbb{R}^n \rightarrow \mathbb{R}^3$. forward kinematics.

$$\Rightarrow \delta x = \left. \frac{\partial f(\theta)}{\partial \theta} \right| \delta \theta$$

infinite descent

$$\Rightarrow \underbrace{F^T}_{1 \times 3} \underbrace{J(\theta)}_{3 \times n} \delta \theta = \underbrace{\tau^T}_{1 \times n} \delta \theta$$

Can not mindlessly cancel $\delta \theta$.

but since the expression is true for all $\delta\theta \Rightarrow$

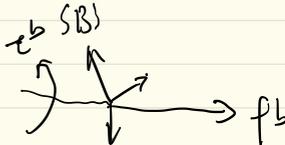
$$F^T J(\theta) = \tau^T$$

$$\Rightarrow \tau = [J(\theta)]^T F$$

To generalize this to Force / Torque @ end-effector.
moment

We need a way of expressing

Force/torques: WRENCHES.



$$F^b = \begin{bmatrix} f^b \\ \tau^b \end{bmatrix}$$

Linear forces.
Torque.

Body Wrench can be written wrt other body frames.

We can also define a spatial frame. See chapter 2

F^b is define so that $\delta W = F^b \cdot \underbrace{V^b \delta t}_{\substack{\text{virtual displacement} \\ \text{(not a velocity)}}}$.
Nash's fix on unit.

Now, for a n-DOF robot with kinematics

$$g_{st}(\theta) = e^{S_1 \delta\theta_1} \dots e^{S_n \delta\theta_n} g_{st}(0)$$

We have $J_{st}^b(\theta)$, st. $\underbrace{V^b \delta t}_{\text{virtual displacement}} = J_{st}^b(\theta) \delta\theta$

$$\delta W = (F^b)^T J_{st}^b(\theta) \delta \theta$$

and, like before

$$\delta W = \tau^T \delta \theta$$

$$\Rightarrow \tau = J_{st}^b(\theta)^T F^b$$

↓

joint torque

$$g = \dots$$

$$X_i = g_0 + X_i'(g)$$

$$g_{test} = \exp(\text{hat}(X_i')),$$

$$(g_{test} \setminus g) \quad \leftarrow \text{ml divide}$$

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$AB = C$$

$$B = A^{-1}C$$

$$B = A \setminus C$$

$$B = \text{inv}(A) * C$$

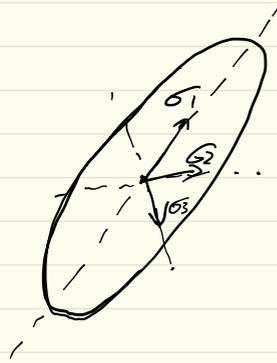
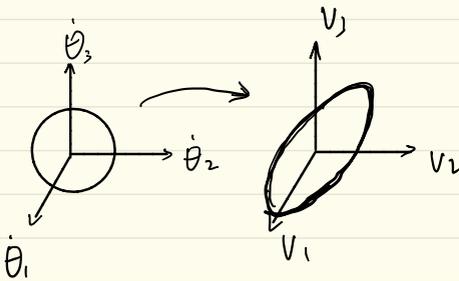
Manipulability :

Affordance over the velocities of end-effector.

↑ Manipulability \Rightarrow can achieve 6 DOF of velocity \nearrow of end-effector with reasonable joint velocities.

Recall that the Jacobian is (of any joint configuration) linear mapping

$$V = J(\theta) \dot{\theta}$$



σ_i 's are the square roots of the non-zero eigenvalues of

$$CJ^T J) \text{ or } (CJ J^T)$$

look at case $n=6$, $J \in \mathbb{R}^{6 \times 6}$

Look at $\|V\|^2 = V^T V = (J\dot{\theta})^T (J\dot{\theta}) = \dot{\theta}^T J^T J \dot{\theta}$ (Quadratic Form)

Level sets of this are ellipsoids.

Eigenvalues of $J^T J$ are all non negative

$$\sigma_i = \sqrt{\lambda_i(J^T J)} \quad (\text{sorted!})$$

Manipulability Measure.

1. σ_{\min} , smallest singular value.

Aside: If $J \in \mathbb{R}^{6 \times 7}$ 7 DOF manipulator take σ_i

$$J = U \Sigma V^T = \underbrace{\begin{bmatrix} U & \begin{matrix} \sigma_1 & & & & & & \\ & \sigma_2 & & & & & \\ & & \ddots & & & & \\ & & & \sigma_6 & & & \\ & & & & & & 0 \end{matrix} \end{bmatrix}}_{\text{orthogonal}} \begin{matrix} \left[\begin{matrix} V^T \end{matrix} \right] \end{matrix} \leftarrow \begin{matrix} \text{dimension of domain} \\ (7 \text{ space}) \end{matrix}$$

2. Inverse of condition # of J

$$\text{cond}(J) = \frac{\sigma_{\max}}{\sigma_{\min}}$$

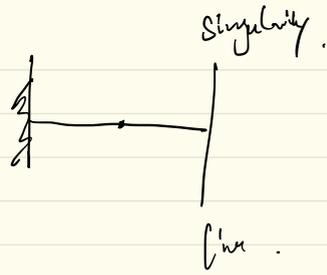
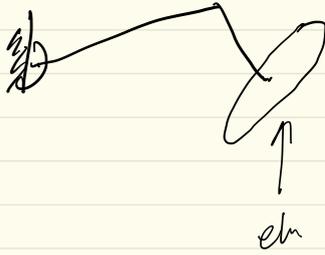
so we take $\frac{\sigma_{\min}}{\sigma_{\max}} = \frac{\sigma_6}{\sigma_1}$ are manipulability measure.

3. Det of J

→ only works if $n=6$

→ not great numerically

$\det J = \lambda_1 \cdots \lambda_n$ product of eigs of J



① Clean up SVD

$$J = U \Sigma V^T \in \mathbb{R}^{6 \times n} \quad n > 6$$

$$\Sigma = \begin{bmatrix} \underbrace{\bar{\Sigma}}_{6 \times 6} & \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \\ \underbrace{0}_{6 \times (n-6)} & \end{bmatrix}$$

U = eigen vector of JJ^T , e-value are $(\sigma_1^2, \dots, \sigma_6^2)$

V = " " of $J^T J$, e-value are $(\sigma_1^2, \dots, \sigma_6^2, \underbrace{0, \dots, 0}_{n-6})$

U, V orthonormal

Facts:

since JJ^T is symmetric, it has orthogonal e-vectors.
($J^T J$)

since JJ^T is positive, semi-definite \Rightarrow eigen values are all non-negative.
($J^T J$)

Note:

$$JJ^T = U \Sigma V^T V \Sigma U^T = U \begin{bmatrix} \bar{\Sigma} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \bar{\Sigma}^T \\ 0^T \end{bmatrix} U^T$$

$$\begin{aligned}
 &= U [\bar{\Sigma} \bar{\Sigma}^T + 00^T] U^T \\
 &= U \bar{\Sigma}^2 U^T \quad \leftarrow \text{orthogonal.} \\
 &= U \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_n^2 \end{bmatrix} U^T
 \end{aligned}$$

verify relation between SVD eigen structures

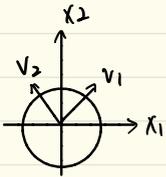
Likewise.

$$J^T J = V \begin{bmatrix} \Sigma^2 & 0 \\ 0 & 0 \end{bmatrix} V^T$$

2x2 case

$$y = Ax, \quad x, y \in \mathbb{R}^2, \quad A = U \Sigma V^T$$

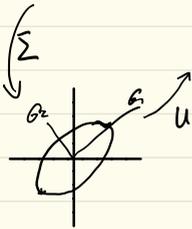
2x2 2x2 2x2



$$x = x_1 a_1 + x_2 a_2$$

$$y = Ax = U \Sigma V^T x$$

$$= U \Sigma \begin{bmatrix} v_1^T \\ v_2^T \end{bmatrix} [a_1 v_1 + a_2 v_2] = \begin{pmatrix} a_1 v_1 v_1^T + a_2 v_2 v_2^T \\ a_1 v_1 v_1 + a_2 v_2 v_2 \end{pmatrix}$$



$$= U \Sigma \begin{pmatrix} a_1 \\ a_2 \end{pmatrix}$$

$$= [U_1 \ U_2] \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$= [U_1 \ U_2] \begin{bmatrix} \sigma_1 a_1 \\ \sigma_2 a_2 \end{bmatrix}$$

$$= \sigma_1 a_1 U_1 + \sigma_2 a_2 U_2$$

② Transposed Jacobian Control.

Recall $\dot{\theta} = u$ control system $u = \text{input}$ $\dot{\theta} = \text{joint velocities}$.

$$u = -k [J_{st}^b(\theta)]^{-1} p$$

where $\exp\{p\} = g_{st}^{-1} g_{st}$

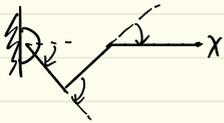
Turns out, we can also use $u = -k [J_{st}^b(\theta)]^T p$

Transpose, not inverse.

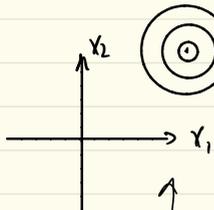
Motivation: Gradient-based control of a 3 DOF manipulator.

Let $x = f(\theta)$. $x \in \mathbb{R}^2$

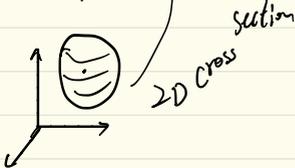
↳ position of "tool"



Define error $V = \frac{1}{2} \|x - x^*\|^2$



level sets of V gradient vector orthogonal to level sets.

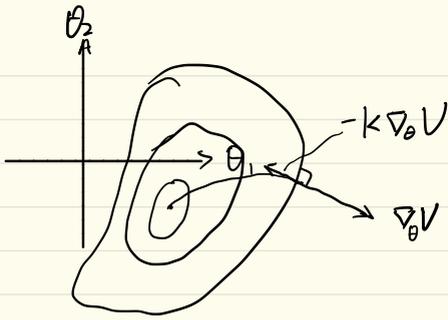


$$V(\theta) = \frac{1}{2} \left\| \underbrace{f(\theta)}_x - x^* \right\|^2$$

$$\dot{\theta} = -\nabla V(\theta)$$

Aside

$$\nabla V = \begin{pmatrix} \frac{\partial V}{\partial \theta_1} \\ \vdots \\ \frac{\partial V}{\partial \theta_n} \end{pmatrix} = \left| \frac{\partial V}{\partial \theta} \right|^T$$



$$\begin{aligned}
 \delta V &= \left(\frac{\partial V}{\partial \theta} \right)^T \\
 &= \left(\frac{\partial V}{\partial x} \cdot \frac{\partial x}{\partial \theta} \right)^T \\
 &= \left(\frac{\partial x}{\partial \theta} \right)^T \left(\frac{\partial V}{\partial x} \right)^T \\
 &= J^T \nabla_x V
 \end{aligned}$$

$$\begin{aligned}
 \dot{\theta} &= -k \nabla_{\theta} V \\
 &= -k J^T \nabla_x V
 \end{aligned}$$

$$\nabla_x V = (x - x^*)$$

Inverse Kinematics

Given end-effector pose, find joint angles.

In Prob Set 4, You solved for θ_1, θ_2 when $x \in W$.

More general set of methods:

works for 6 DOF manipulators w/ spherical wrist & some others.

Break down inverse kinematics into so-called Paden-Kohlan sub problems.

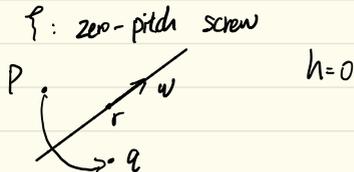
Three s.p. in MLS:

S.P. 1

Zero pitch

Given ξ, P, q

$$e^{\xi \theta} P = q$$



Find θ : $\theta = \text{atan2} (w^T (u' \times v'), u'^T v')$

$$u' = u - ww^T u \quad u = p - r$$

$$v' = v - ww^T v \quad v = q - r$$

solution exists if $w^T u = w^T v, \|u'\| = \|v'\|$

S.P. 2

Let ξ_1, ξ_2 be zero-pitch, unit magnitude twist with intersecting axes.

Find θ_1, θ_2 , such that

$$e^{\xi_1 \theta_1} e^{\xi_2 \theta_2} P = q.$$

⋮

0, 1 or 2 solutions. (see book)

S.P.3

ξ = zero pitch, unit magnitude.

$$P, q \in \mathbb{R}^3$$

Find θ s.t. $\|q - e^{P\theta} p\| = \delta$, for some given δ

\vdots

again, 0, 1 or 2 solutions.

Dynamics & Mechanics.

↓

$$\dot{x} = f(x)$$

↓

$$F = m\ddot{x}$$

In Robotics, we are often interested in dynamical systems and often such systems can be modeled via a set of 1st order differential equations.

$$\dot{x} = f(x, u) \quad . \quad x \in \mathbb{R}^n, u \in \mathbb{R}^p$$

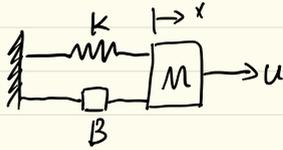
$$\dot{x}_1 = f_1(x_1, \dots, x_n, u_1, \dots, u_p)$$

\vdots

$$\dot{x}_n = f_n(x_1, \dots, x_n, u_1, \dots, u_p)$$

there, $x \in \mathbb{R}^n$ are the state variables, $u \in \mathbb{R}^p$ are the inputs.

Sometimes, particularly in mechanics problems, it is convenient to write a system of 2nd-order ODE's. for example:



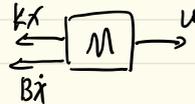
$x=0 \iff$ spring at rest

$$m\ddot{x} = \sum F$$

$$= -kx - B\dot{x}$$

$$\Rightarrow M\ddot{x} + B\dot{x} + kx = u$$

F.B.D.



Define state variables.

$$z = \begin{bmatrix} x \\ \dot{x} \end{bmatrix} \in \mathbb{R}^2 \quad \text{state variables.}$$

STATE: Minimum information at time t_0 , such that, together with all future inputs, you can predict the evolution of the system.

Delay: Infinite state

$$u(t) \rightarrow \boxed{\text{Delay}} \rightarrow v(t) = u(t - T)$$

$$T = \text{delay}$$

Information needed (ie. state). to predict $u(t)$, $t \geq 0$
is $u(t)$, $t_0 - T \leq t < t_0$

Thus, together with $u(t)$, $t \geq t_0$

Let's we predict $x(t)$, $t \geq t_0$.

$$\mathcal{L}\{u(t-T)\} = e^{-sT} U(s) + \text{I.C. term.}$$

$$e^{-sT} = \frac{e^{sT/2}}{e^{sT/2}} = \frac{1 - sT/2}{1 + sT/2}$$

Back to $M\ddot{x} + B\dot{x} + kx = u$

$$z = \begin{bmatrix} \dot{x} \\ x \end{bmatrix} \in \mathbb{R}^2$$

$$\dot{z} = \begin{bmatrix} \dot{\dot{x}} \\ \dot{x} \end{bmatrix} = \begin{bmatrix} z_2 \\ \frac{1}{m}(u - Bz_2 - kz_1) \end{bmatrix}$$

$$\ddot{x} = \frac{1}{m}(u - B\dot{x} - kx)$$

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{B}{m} \end{bmatrix}}_A \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix} u$$

$$\text{Any } W = PZ \quad A$$

↑
non-singular matrix.

would be OK choices for state variables.

Taxonomy

1. Linear vs Non-linear.

$$\dot{x} = Ax + Bu = f(x, u)$$

Linear-system



$$\begin{aligned} u_1(t) &\rightarrow x_1(t) \\ u_2(t) &\rightarrow x_2(t) \\ \alpha u_1(t) + \beta u_2(t) &\rightarrow \alpha x_1(t) + \beta x_2(t) \end{aligned}$$

set $u=0$, $\dot{x} = Ax$

If $x_1(t)$, $x_2(t)$ are solutions. $\alpha x_1(t) + \beta x_2(t)$ is a solution.

$u=0$ case $x(t) = e^{-At} x_0$

$f(x) = Ax$ is a linear function, i.e. $f(\alpha x_1 + \beta x_2) = \alpha f(x_1) + \beta f(x_2)$

Range $(J) = \text{span}\{u_1\}$

Ker $(J) = \text{span}\{v_2\}$

$$\begin{aligned} J &= U \Sigma V^T = G_1 u_1 v_1^T + G_2 u_2 v_2^T \\ &\Rightarrow \dot{x} = G_1 u_1 v_1^T \dot{\theta} = \text{scalar} \cdot u_1 \end{aligned}$$

$$A = [U_1 \dots U_n] \begin{bmatrix} \sigma_1 & & & \\ & \dots & & \\ & & \sigma_{t_0} & \\ & & & \dots \\ & & & & 0 \end{bmatrix} \begin{bmatrix} v_1^T \\ \vdots \\ v_n^T \end{bmatrix}$$

$\underbrace{\hspace{10em}}_{n-t}$

$$\text{Range}(A) = \text{span}\{U_1, \dots, U_t\}$$

$$\text{Ker}(A) = \text{span}\{V_{t+1}, \dots, V_n\}$$

Jacobian:

time-derivative of coords.

① Chain Rule Jacobian $\dot{x} = J\dot{\theta}$

Coordinates on both sides of a mapping
of DOF

② Manipulator Jacobian. $V = J\dot{\theta}$ twist coordinate vector. $(V = (g^1 g^t)^v)$
 ${}^{t-1}(g^{t-1} g^t)^v$

in SE(2) for pose. don't want to use Euler Angles.



$$g = \begin{bmatrix} e^{-s} & x \\ s & y \\ 0 & 1 \end{bmatrix}$$

relate $(\dot{x}, \dot{y}, \dot{\theta})$ & $(g^t g)^v$

$$w^s = (R^T R)^v \cdot J \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix}$$

Taxonomy of systems

I. Linear vs. Non-linear.

$$\dot{x} = f(x, u), \quad x \in \mathbb{R}^n, \quad u \in \mathbb{R}^D$$

$$\text{Linear: } f(x, u) = \underset{\substack{\uparrow \\ n \times n}}{A}x + \underset{\substack{\uparrow \\ n \times D}}{B}u$$

$$u \rightarrow \boxed{\text{system}} \rightarrow x$$

$$u_1(t) \rightarrow \boxed{\text{sys}} \rightarrow x_1$$

$$u_2(t) \rightarrow \boxed{\text{sys}} \rightarrow x_2$$

$$\Rightarrow \alpha u_1(t) + \beta u_2(t) \rightarrow \boxed{\text{sys.}} \rightarrow \alpha x_1 + \beta x_2$$

$$\text{assuming } x(0) = x_0 = 0$$

$$\text{Aside: } x(t) = e^{At}x + \int_0^t e^{A(t-\tau)} B u(\tau) d\tau$$

Non-linear: everything else.

$$\dot{x} = x^2 = f(x)$$

f is not linear in x .

I. Autonomous vs Non-autonomous

time-invariant

time-variant.

Given a system Σ , and $x(t), u(t)$ (state input) that solves Σ , then $x(t-t_0)$ and $u(t-t_0)$ also solves Σ .

e.g. Any system of the form $\Sigma: \dot{x} = f(x, u)$

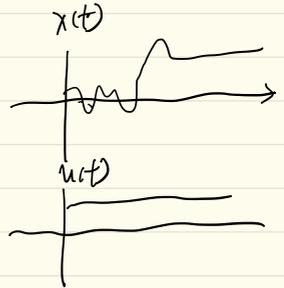
Pf:

Let $x(t), u(t)$ be a solution to Σ . Let $\bar{x}(t) = x(t-t_0)$,

$$\bar{u}(t) = u(t-t_0)$$

If f explicitly depends on time,

Σ is time-varying



III Mechanical System.

Those that aside from Newton's laws!

We will focus on These. (Typically Autonomous, nonlinear)

IV. ∞ : lots of other -- of systems.

Dynamics of Rigid bodies

point masses:

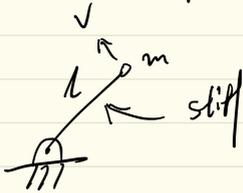
In an inertial frame, Newton's second law:

$$F = m\ddot{p} \quad , \quad F \in \mathbb{R}^3$$

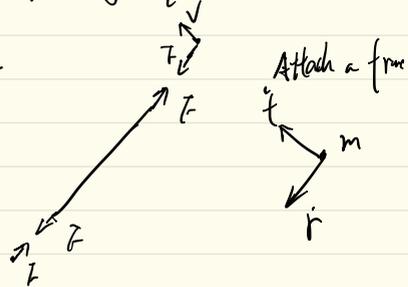
where $F = \sum_i F_i$. sum of all forces acting on the point mass.



Example: Centripetal Forces (inward-pointing forces)



F.B.D.



Decompose force

$$F_t = 0$$

$$F_n = F = \text{unknown.}$$

$$a_r = \frac{v^2}{L}$$

$$\Rightarrow F = m \frac{v^2}{L}$$

Real force! Centripetal Force.

No outward force on mass. There is one on string.

System of rigidly connected points.

$$\ddot{r}_i = m_i \ddot{r}_i \quad r_i \cdot p \in \mathbb{R}^3, \quad i = 1, 2, \dots, n$$

Constraint

$$\|p_i - p_j\|^2 - l_{ij}^2 = 0$$

More generally

$$l_{ij}(p_1, \dots, p_n) = 0 \quad l_{ij}: \mathbb{R}^3 \rightarrow \mathbb{R}$$

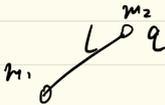
such a constraint (on position variables) is holonomic constraint.

Constraint forces are orthogonal to the constraints of the form.

$$\Gamma_j = \left[\underbrace{\frac{\partial h_j}{\partial p_{i,1}}}_{x_i}, \underbrace{\frac{\partial h_j}{\partial p_{i,2}}}_{y_i}, \dots, \underbrace{\frac{\partial h_j}{\partial p_{i,3}}}_{z_i} \right]^T = \nabla h_j$$

Example:

Two masses, connected by a massless rod:



$$h(p, q) = \|p - a\|^2 - L^2$$

Constraint Forces are \perp to the constraints.

$$\text{So, if } \vec{x} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \in \mathbb{R}^{3n}$$

And $h_j: \mathbb{R}^{3n} \rightarrow \mathbb{R}$, then.

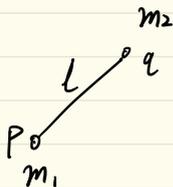
The constraint forces are of the form

$$F_j = \lambda_j \Gamma_j \in \mathbb{R}^{3n}$$

$$\text{where } \Gamma_j = \nabla h_j = \begin{bmatrix} \frac{\partial h_j}{\partial x_1} \\ \vdots \\ \frac{\partial h_j}{\partial x_{3n}} \end{bmatrix}$$

Example

Massless rod connecting two point masses.



$$h(p, q) = \|p - q\|^2 - l^2$$

$$= (p - q)^T (p - q) - l^2$$

$$\Rightarrow \Gamma = \nabla h = \underbrace{\left[\frac{\partial h}{\partial p} \right]}_{1 \times 3}, \underbrace{\left[\frac{\partial h}{\partial q} \right]}_{1 \times 3}^T \in \mathbb{R}^6$$

$$\frac{\partial h}{\partial p} = 2(p - q), \quad \frac{\partial h}{\partial q} = 2(q - p)$$

$$\Gamma \Rightarrow \begin{bmatrix} p - q \\ q - p \end{bmatrix} \leftarrow \begin{array}{l} \text{direction of force on 1st particle} \\ \text{direction of force on 2nd particle.} \end{array}$$

Back to n-point case.

$$h_j(p_1, \dots, p_n) \stackrel{(4.2)}{=} 0, \quad j = 1 \dots k \quad \text{constraints}$$

$$F_i = m_i \ddot{p}_i \quad \text{Newton's law.}$$

Stack up:

$$\begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_n \end{bmatrix} = \begin{bmatrix} m_1 \\ & m_2 \\ & & \ddots \\ & & & m_n \end{bmatrix} \begin{bmatrix} \ddot{p}_1 \\ \vdots \\ \ddot{p}_n \end{bmatrix}$$

Break up

$$F_{\text{all}} = F_{\text{ext}} + F_c$$

↑ constraint forces.

$$F_{\text{ext}} = \begin{bmatrix} m_1 \\ \vdots \\ m_n \end{bmatrix} \begin{bmatrix} \ddot{p}_1 \\ \vdots \\ \ddot{p}_n \end{bmatrix} + \sum_{j=1}^k \lambda_j \Gamma_j \quad (4.3)$$

3n equations.

(Where $F_c = - \sum_{j=1}^k \lambda_j \Gamma_j$)

$$\Gamma_j = \nabla h_j$$

$\lambda_1, \dots, \lambda_k$ are called Lagrange Multipliers.

We have $3n + k$ unknowns
 p_1, \dots, p_n $\lambda_1, \dots, \lambda_k$

$3n + k$ equations,
↑
 \dot{p} equations $h_j = 0$ equations

Read Principle of least Action by Feynman

Recap

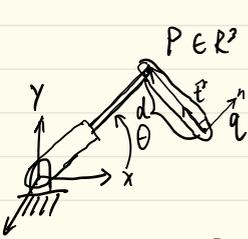
$$P_i = f_i(\theta_1, \dots, \theta_m) \quad i=1, \dots, n$$

$$m = 3n - k$$



$$h_j(P_1, \dots, P_n) = 0, \quad j=1, \dots, k$$

Generalized Coordinates: $\theta_1, \dots, \theta_m$



$$h_1(p) = e_3^T p \Rightarrow p \in \mathbb{R}^3$$

$$h_2(p) = (p - q)^T n, \quad \text{with } q^T e_3 = 0, \quad n = \text{const}, \quad q = \text{const}.$$

$$p \in \mathbb{R}^3$$

$$h(p) = \begin{bmatrix} e_3^T p \\ n^T (p - q) \end{bmatrix}$$

$$\frac{\partial h}{\partial p} = \begin{bmatrix} e_3^T \\ n^T \end{bmatrix} \quad e_3 \neq \lambda n$$

∞ choices of coordinates

① θ , with f st. $f(0)$

② \hat{t} such that $\hat{t} \perp e_3, \perp n$

$$\hat{t} = \frac{n \times e_3}{\|n \times e_3\|}$$

Consider a generalized coordinate, d .

$$\bar{f}(d) = q + \hat{f}d.$$

$$\begin{aligned} \Rightarrow h(\bar{f}(d)) &= \begin{bmatrix} e_3^T q + \hat{f}d \\ [q + \hat{f}d]^T n \end{bmatrix} \\ &= \begin{bmatrix} \cancel{e_3^T q} + \cancel{e_3^T \hat{f}d} \\ \underbrace{(\hat{f}d)^T n}_{\hat{f} \perp n} \end{bmatrix} = \begin{bmatrix} 0 \\ d \end{bmatrix} \end{aligned}$$

" \Leftarrow " Assume $d(p) = 0$

$$\text{Let } d = (p - q)^T \hat{f}$$

check if $\bar{f}(d) = p$:

$$\bar{f}(d) = q + \hat{f} (p - q)^T \hat{f}$$

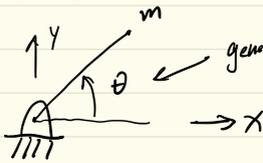
Principle of least action

Let $\theta_1, \dots, \theta_n$ be generalized coordinates. write $\theta \in \mathbb{R}^n$

Define kinetic energy and potential energy
 $T(\theta, \dot{\theta})$ $V(\theta)$

e.g.

Pendulum



generalized coordinate

$$f(\theta) = l \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$$

$$\begin{aligned} T &= \frac{1}{2} m \| \dot{p} \|^2 = \frac{1}{2} m \left\| \frac{d}{dt} f(\theta) \right\|^2 = \frac{1}{2} m \left\| \dot{\theta} \begin{bmatrix} -l \sin \theta \\ l \cos \theta \end{bmatrix} \right\|^2 \\ &= \frac{1}{2} l^2 m \dot{\theta}^2 \end{aligned}$$

$$V = mgl \sin \theta$$

Define Lagrangian

$$L(\theta, \dot{\theta}) = T(\theta, \dot{\theta}) - V(\theta)$$

And the action

$$S = \int_{t_0}^{t_f} L(\theta, \dot{\theta}) dt$$

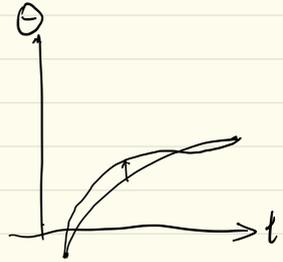
Principle of least action: the trajectory of system minimize S

$$\Rightarrow \delta \int L(\theta, \dot{\theta}) dt = 0$$

↑
Variational derivative.

$$\delta \int L(\theta, \dot{\theta}) dt = 0$$

$$= \int \left(\frac{\partial L}{\partial \theta} \delta \theta + \frac{\partial L}{\partial \dot{\theta}} \delta \dot{\theta} \right) dt$$



$$= \int \left(\frac{\partial L}{\partial \theta} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}} \right) \delta \theta dt = 0$$

↓

$$\frac{dL}{d\theta} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}} = 0$$

$$S = \int L dt$$

$$\delta S = \int \left(\frac{dL}{d\theta} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}} \right) \delta \theta dt = 0$$

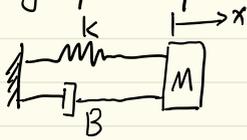
Generating n DOF

$$\frac{\partial L}{\partial \theta_i} - \frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}_i} = 0 \quad (\text{no external forces})$$

If we add external forces:

$$\frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}_i} - \frac{\partial L}{\partial \theta_i} = \Gamma_i \quad (\text{upsilon})$$

Obligatory Example



$$T(x, \dot{x}) = \frac{1}{2} m \dot{x}^2$$

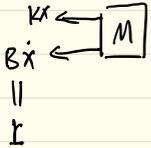
$$V(x) = \frac{1}{2} k x^2 \quad (\text{Hookean Spring})$$

$$L(x, \dot{x}) = T - V = \frac{1}{2} m \dot{x}^2 - \frac{1}{2} k x^2$$

$$\frac{\partial L}{\partial x} = -kx \quad \frac{d}{dt} \frac{\partial L}{\partial \dot{x}} = m\ddot{x}$$

$$\Rightarrow \frac{d}{dt} \frac{\partial L}{\partial \dot{x}} - \frac{\partial L}{\partial x} = m\ddot{x} + kx = \Gamma$$

Look at F.B.D to figure

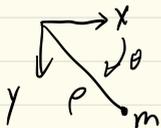


$$\Rightarrow M\ddot{x} + kx = -B\dot{x}$$

$$M\ddot{x} + kx + B\dot{x} = 0$$

Specific equations you get depend on what you choose for generalized coordinates, but what the system does does not!

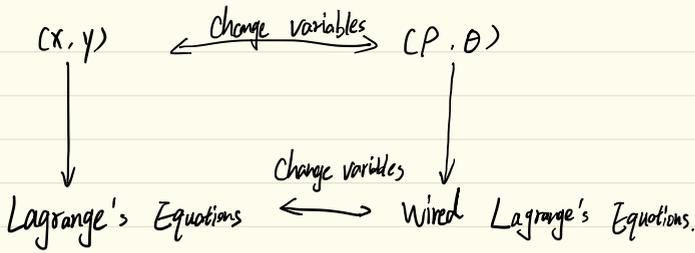
Example.



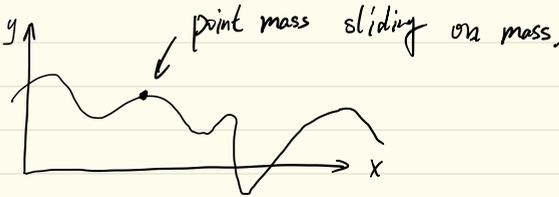
Two choices:

$$\begin{pmatrix} x \\ y \end{pmatrix}$$

$$\begin{pmatrix} p \\ \theta \end{pmatrix}$$



Example



Generalized coordinate choices.

$$\theta = x$$

Another choice : $\theta = s$. $s = \text{distance along curve.}$

Let $\theta = x$

$$L = \frac{1}{2} m (\dot{x}^2 + \dot{y}^2) - mgy$$

$$= \frac{1}{2} m [\dot{x}^2 + (f'(x)\dot{x})^2] + mgf(x)$$

$$\frac{\partial L}{\partial x} = m(f'(x)\dot{x}) f''(x) - mgf'(x)$$

$$\frac{d}{dt} \frac{\partial L}{\partial \dot{x}} = \frac{d}{dt} (m\dot{x} + m f'(x)\dot{x} f'(x))$$

$$= m\ddot{x} + m\ddot{x} f'(x)^2 + 2m f'(x)\dot{x} f''(x)$$

$$\frac{d}{dt} \frac{\partial \mathcal{L}}{\partial \dot{x}} - \frac{\partial \mathcal{L}}{\partial x} = 0$$

conservative
↓

$$m(1 + f(x)^2) \ddot{x} + \underbrace{m f'(x) f''(x)}_{\text{circled}} \dot{x}^2 + mg f(x)$$

$$m\ddot{x} + B\dot{x} + kx = 0$$

dissipated

Lyapunov Stability (\dot{q} Control)

Consider a time-variant system

$$\dot{x} = f(x) \quad (\text{not } f(x, t))$$

If $M(q)\ddot{q} + (C(q, \dot{q})\dot{q} + N(q)) = 0$

$$x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix} \text{ and get it in form}$$

Can make this a control problem by introducing an INPUT:

$$\dot{x} = f(x, u)$$

Many (many!) definitions of stability.

▼ Input-to-state stability

Roughly, finite input leads to finite state values.

▼ Input-output stability

Roughly if we define
say $y = y(t)$

▼ Linear stability

Stability of linearization around an equilibrium.

▼ Lyapunov stability.

(*) Consider a system $\dot{x} = f(x)$, $x(0) = x_0$, $x \in \mathbb{R}^n$

Suppose $x^* = 0$ is an equilibrium.

(If equilibrium is not 0, change ~~state~~ coordinate)

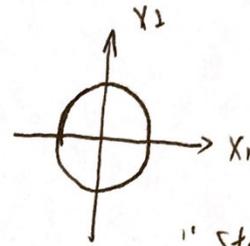
Equilibrium:

$$f(x^*) = 0$$

Definition: Stability

(In the sense of Lyapunov)

The equilibrium $x^* = 0$ of (*) is stable if for any $\epsilon > 0$, $\exists \delta > 0$ s.t. for all $\|x\| < \delta$, $\|x(t)\| < \epsilon \forall t \geq 0$



"Start close
↓
Stay close"

Definition: Asymptotic Stability

$x^* = 0$ is asymptotically stable if:

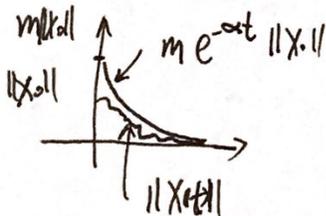
1. $x^* = 0$ is stable in the sense of Lyapunov
2. $\exists \delta > 0$ s.t. $\|x\| < \delta \Rightarrow \lim_{t \rightarrow \infty} x(t) = 0$

Definition: Exponential Stability

The equilibrium $x^* = 0$ is exponentially stable if:

$$\exists m, \alpha, \epsilon > 0 \text{ s.t. } \|x_0\| < \epsilon \Rightarrow \|x(t)\| < m e^{-\alpha t} \|x_0\|$$

The largest ~~constant~~ constant α is called the convergence rate.



Example of a system that is

□ Stable (Not Asymptotically)

$$\ddot{y} + y = 0$$

$$\text{State space: } x = \begin{bmatrix} y \\ \dot{y} \end{bmatrix} \Rightarrow \dot{x} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} x$$

Solutions:

$$y(t) = A \sin(t + \phi) \quad (A, \phi \text{ depend on } y(0), \dot{y}(0))$$

$$\Rightarrow X(t) = \begin{bmatrix} A \sin(t + \phi) \\ A \cos(t + \phi) \end{bmatrix}$$

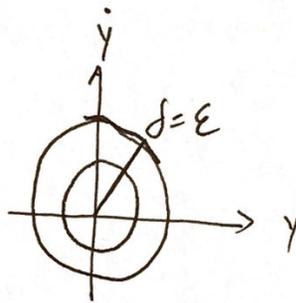
$$\Rightarrow \|X(t)\| = |A| \quad \text{for all } t.$$

Stability:

For all $\epsilon > 0$, let $\delta = \epsilon$

Now, if $\|y_0\| = |A| < \delta$

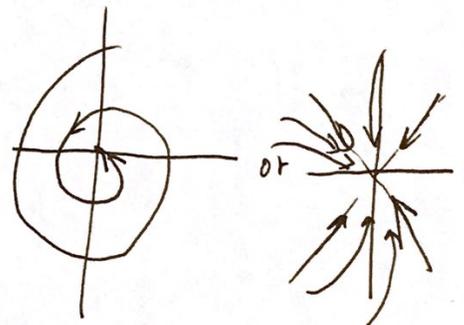
$$\Rightarrow \|X(t)\| = |A| < \epsilon$$



□ Asymptotically stable:

$$m\ddot{x} + b\dot{y} + ky = 0$$
$$X = \begin{bmatrix} y \\ \dot{y} \end{bmatrix} \Rightarrow \dot{X} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{b}{m} \end{bmatrix} X$$

Assume $m, k, b > 0$



"Easy" to show:

$$\lim_{t \rightarrow \infty} X(t) = 0$$

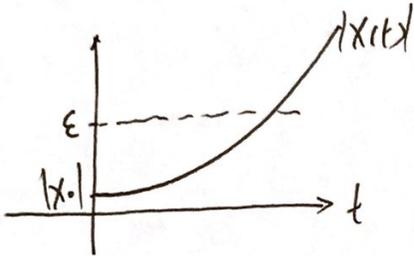
Also "Easy" to show:

Stable (in the sense of Lyapunov)

□ unstable

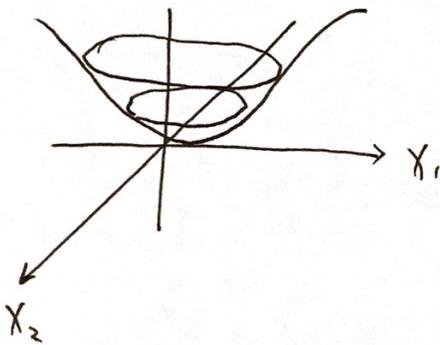
$$\dot{x} = \alpha x, \alpha > 0, x \in \mathbb{R}$$

$$\Rightarrow x(t) = x_0 e^{\alpha t}$$



Definition: A continuous function $V: \mathbb{R}^n \rightarrow \mathbb{R}$ is locally positive-definite if for some $\epsilon > 0$; for some strictly increasing function $\alpha: \mathbb{R}^+ \rightarrow \mathbb{R}$.
s.t. $V(0) = 0$

$$V(x) \geq \alpha(\|x\|), \forall x \in B_\epsilon = \{x \in \mathbb{R}^n : \|x\| < \epsilon\}$$



If $V(x)$ is locally definite and $\dot{V} \leq 0$.
(neg definite)
 \Rightarrow stability