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SLAM 101

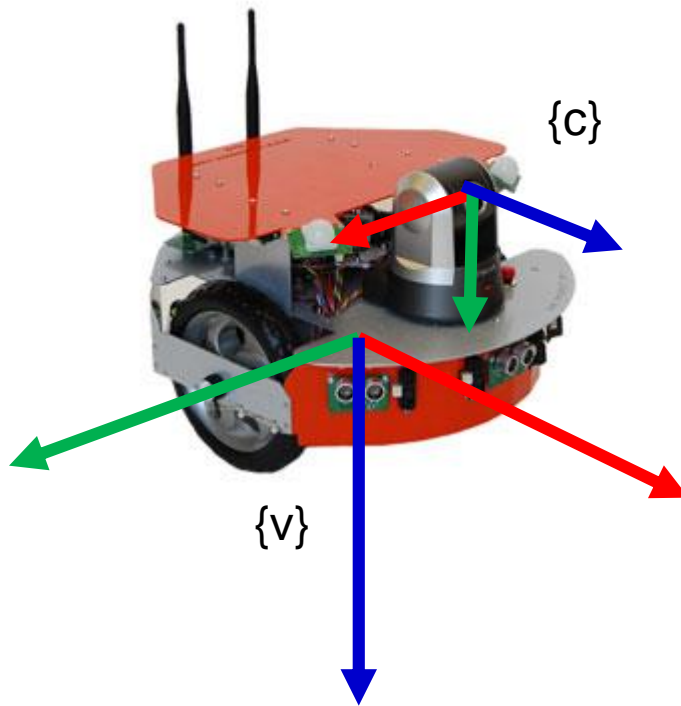
Lecture 03 Uncertainty Representation

Ayoung Kim



Mobile Robot State Representation

► Mobile robots



$$X = [x, y, z, r, p, h]$$

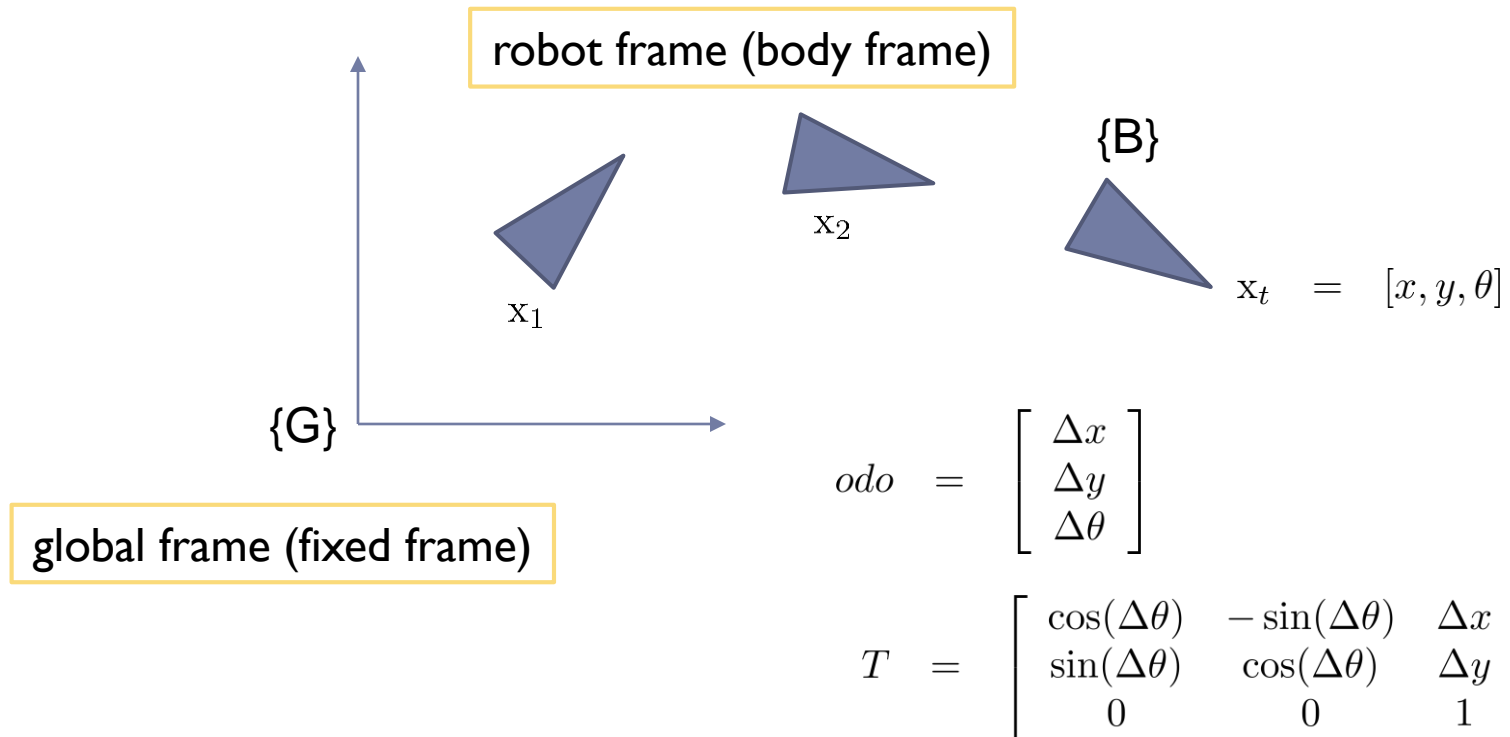
$$T = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in SE(3)$$

Pose = position and orientation



Poses and Trajectory

- ▶ We need a robot trajectory (a set of poses)
 - ▶ Pose in SE(3) and/or vector form



Probabilistic Robotics

▶ Robot pose in Gaussian distribution

Discretized robot trajectory



Pose-graph



$$x_1 \sim \mathcal{N}(\mu_1, \Sigma_1)$$

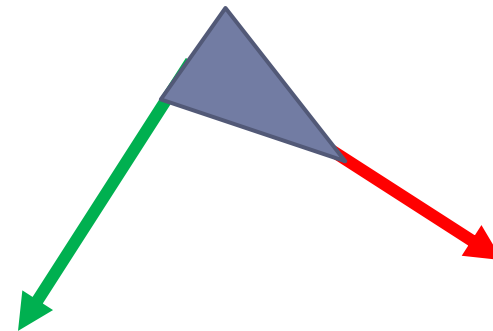
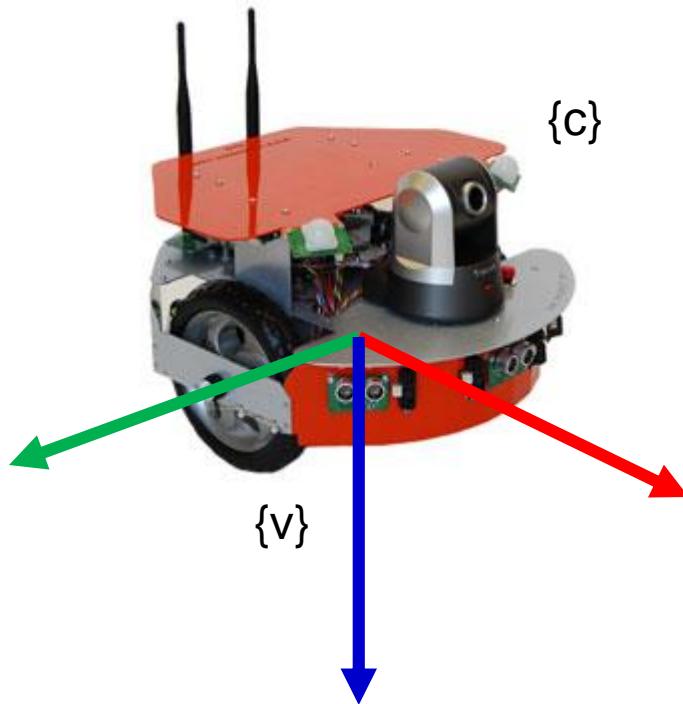
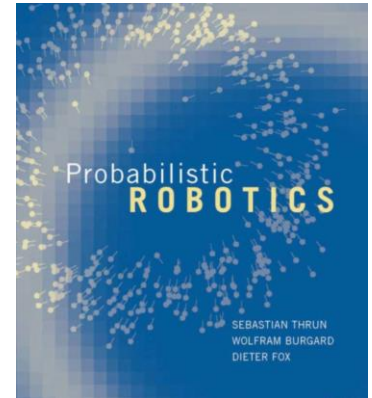
$$x_2 \sim \mathcal{N}(\mu_2, \Sigma_2)$$

Uncertainty propagation



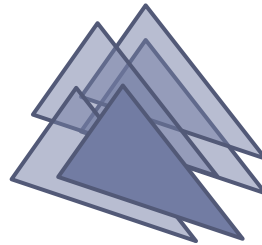
Uncertainty Propagation

- ▶ The core of the SLAM
 - ▶ Robot pose & map are **uncertain**
 - ▶ Probabilistic robotics



Pose Uncertainty

- ▶ Robot pose **uncertainty** representation

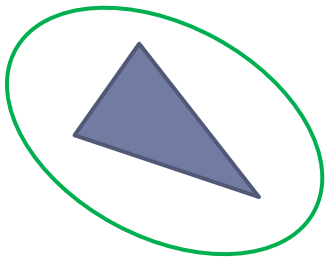


- ▶ Using Gaussian

- ▶ Univariate
- ▶ Mean & covariance

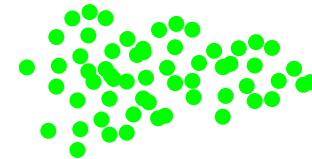
- ▶ Using sample

- ▶ Arbitrary distribution
- ▶ Need N samples

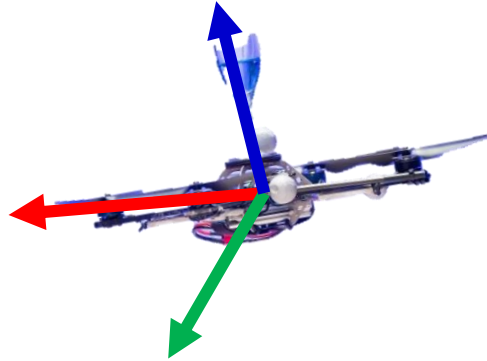


$$X \sim \mathcal{N}(\mu, \Sigma)$$

$$\mu = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \Sigma = \begin{bmatrix} 4 & 1 \\ 1 & 4 \end{bmatrix}$$



Uncertainty Modeling using Gaussian



Position

$$p = [x, y, z]$$

Orientation

$$\begin{aligned} &[r, p, h] \\ &R \in SO(3) \end{aligned}$$

► Vector space

- Position, Euler, quaternion

$$\tilde{p} = p + \epsilon \quad \epsilon \sim \mathcal{N}(0, \Sigma)$$

$$\tilde{r} = r + \epsilon_r \quad \epsilon_r \sim \mathcal{N}(0, \Sigma_r)$$

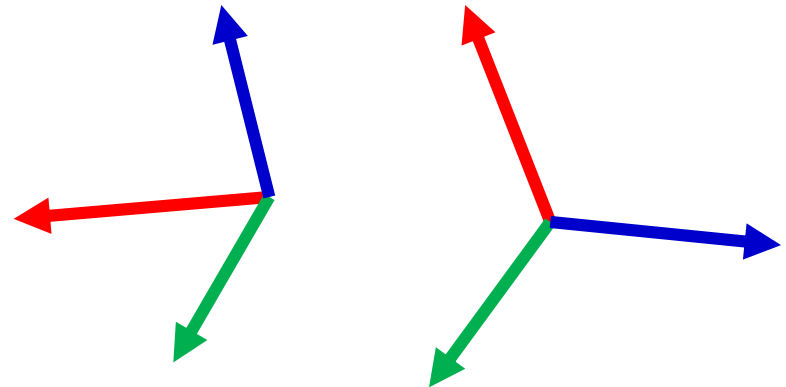
$$\tilde{p} = p + \epsilon_p \quad \epsilon_p \sim \mathcal{N}(0, \Sigma_p)$$

$$\tilde{h} = h + \epsilon_h \quad \epsilon_h \sim \mathcal{N}(0, \Sigma_h)$$

Additive “noise” ok ← linear

► Manifold

- Orientation, SE(3), SO(3)

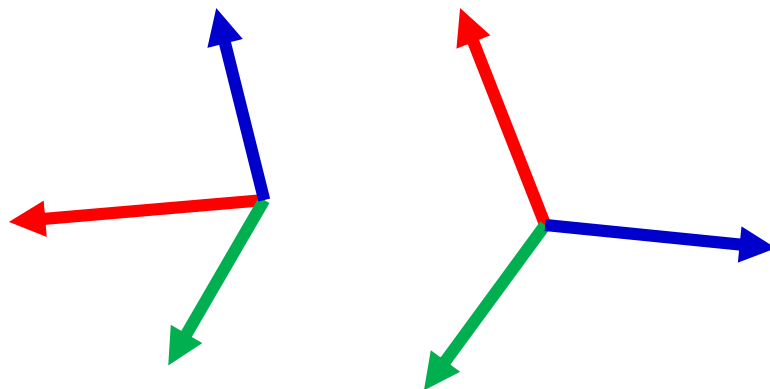


Additive “noise” to a matrix??



Uncertainty Modeling using Gaussian

► Additive noise to SO(3)



$$R_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

$$\tilde{R} = R \oplus \epsilon \quad \epsilon \sim \mathcal{N}(0, \Sigma)$$



Uncertainty Modeling

▶ Vector space

- ▶ Additive noise to a vector
- ▶ Position

$$X = [x, y, z, r, p, h]$$

→ Linearized vector representation

▶ Manifold

- ▶ Additive noise in a locally linear space
- ▶ Rotation (*not* linear)

$$T = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in SE(3)$$

→ Nonlinear SE(3) representation



Uncertainty Representation

Vector Space



Uncertainty in a Vector Space

$$\tilde{p} = p + \epsilon \quad \epsilon \sim \mathcal{N}(0, \Sigma) \quad \begin{array}{lll} \tilde{r} & = & r + \epsilon_r \quad \epsilon_r \sim \mathcal{N}(0, \Sigma_r) \\ \tilde{p} & = & p + \epsilon_p \quad \epsilon_p \sim \mathcal{N}(0, \Sigma_p) \\ \tilde{h} & = & h + \epsilon_h \quad \epsilon_h \sim \mathcal{N}(0, \Sigma_h) \end{array}$$

Estimating Uncertain Spatial Relationships in Robotics*

Randall Smith[†] Matthew Self[‡] Peter Cheeseman[§]

SRI International
333 Ravenswood Avenue
Menlo Park, California 94025

In this paper, we describe a representation for spatial information, called the *stochastic map*, and associated procedures for building it, reading information from it, and revising it incrementally as new information is obtained. The map contains the estimates of relationships among objects in the map, and their uncertainties, given all the available information. The procedures provide a general solution to the problem of estimating uncertain relative spatial relationships. The estimates are probabilistic in nature, an advance over the previous, very conservative, worst-case approaches to the problem. Finally, the procedures are developed in the context of state-estimation and filtering theory, which provides a solid basis for numerous extensions.

- ▶ R. Smith (1990)
 - ▶ Good start paper for SLAM
- ▶ Representation
- ▶ Operation



Uncertainty in a Vector Space

▶ Mobile robot motion & uncertainty

- ▶ Motion has uncertainty
- ▶ Control action corrupted with Gaussian noise

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, u_t) + w$$

$$w \sim \mathcal{N}(0, Q)$$

▶ Mobile robot motion

- ▶ Two operators: oplus and omius (Smith 1998)
- ▶ State = 6 DOF
 - ▶ 6 tuple vector
 - ▶ Not SE(3)...



Uncertainty in a Vector Space

- Pose (2D case)

$$\mathbf{x} = \begin{bmatrix} x \\ y \\ \phi \end{bmatrix}$$

- Estimate

$$\hat{\mathbf{x}} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{\phi} \end{bmatrix}$$

- Covariance

$$\mathbf{C}(\mathbf{x}) = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\phi} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{y\phi} \\ \sigma_{x\phi} & \sigma_{y\phi} & \sigma_\phi^2 \end{bmatrix}$$



Uncertainty in a Vector Space

- State vector = list of poses

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{bmatrix}, \quad \hat{\mathbf{x}} = \begin{bmatrix} \hat{\mathbf{x}}_1 \\ \hat{\mathbf{x}}_2 \\ \vdots \\ \hat{\mathbf{x}}_n \end{bmatrix},$$

$$\mathbf{C}(\mathbf{x}) = \begin{bmatrix} \mathbf{C}(\mathbf{x}_1) & \mathbf{C}(\mathbf{x}_1, \mathbf{x}_2) & \cdots & \mathbf{C}(\mathbf{x}_1, \mathbf{x}_n) \\ \mathbf{C}(\mathbf{x}_2, \mathbf{x}_1) & \mathbf{C}(\mathbf{x}_2) & \cdots & \mathbf{C}(\mathbf{x}_2, \mathbf{x}_n) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}(\mathbf{x}_n, \mathbf{x}_1) & \mathbf{C}(\mathbf{x}_n, \mathbf{x}_2) & \cdots & \mathbf{C}(\mathbf{x}_n) \end{bmatrix}$$

$$\begin{aligned} \mathbf{C}(\mathbf{x}_i, \mathbf{x}_j) &\triangleq E(\tilde{\mathbf{x}}_i \tilde{\mathbf{x}}_j^T), \\ \mathbf{C}(\mathbf{x}_j, \mathbf{x}_i) &= \mathbf{C}(\mathbf{x}_i, \mathbf{x}_j)^T \end{aligned}$$



Uncertainty Representation

Lie Group



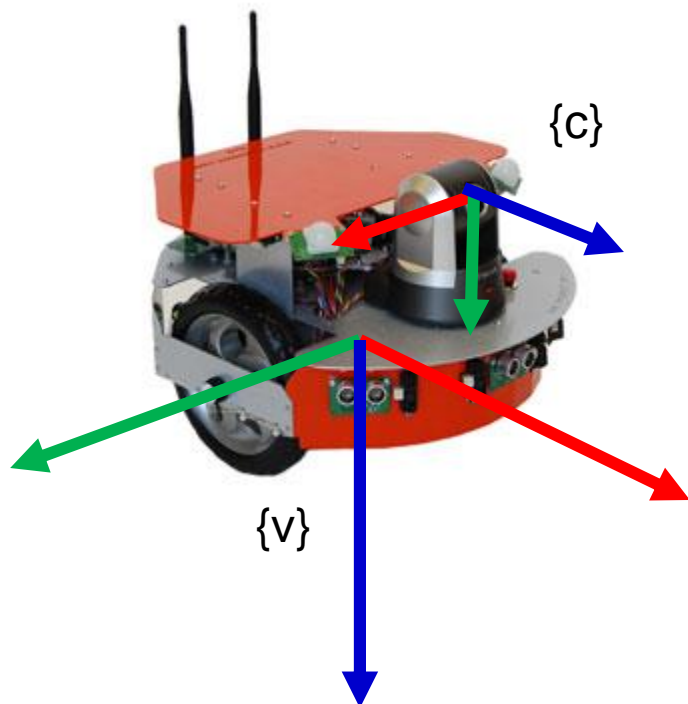
Uncertainty on a Manifold

► Pose representation

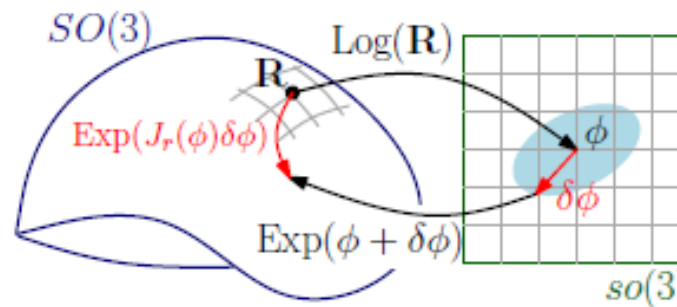
- Translation: vector
- Rotation: $SO(3)$

$$T = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in SE(3)$$

Associated uncertainty for a matrix?



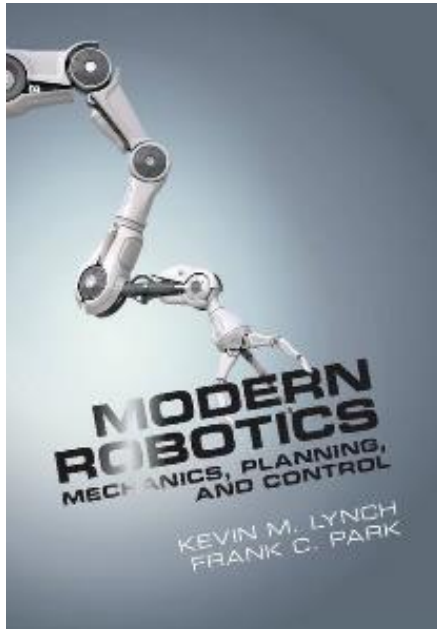
Lie algebra!



References

▶ SNUON

- ▶ Introduction to robotics



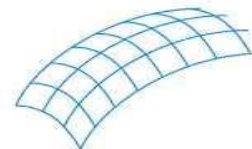
▶ Joan Sola's presentation at IROS 2020

- ▶ Lie theory for the Robotician
- ▶ IROS'20 Workshop on Bringing Geometric Methods to Robot Learning, Optimization and Control.

The Lie Group

Def: a **group** that is also a **smooth manifold**

- Smooth manifold



Non-smooth manifold



Put otherwise:
Def: a **Lie group** is a **smooth manifold** whose **elements** satisfy the **group axioms**



Review: Angular Velocity

► Angular velocity in space / body coordinate

$$\dot{R} = w_s \times R = [w_s]R$$

$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \in \mathbb{R}^3 \quad [w] = \begin{bmatrix} 0 & -w_3 & w_2 \\ w_3 & 0 & -w_1 \\ -w_2 & w_1 & 0 \end{bmatrix}$$

Skew-symmetric matrix

$$\omega^\wedge = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}^\wedge = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix}$$

$$\mathbf{a}^\wedge \mathbf{b} = -\mathbf{b}^\wedge \mathbf{a}, \quad \forall \mathbf{a}, \mathbf{b} \in \mathbb{R}^3$$

$$[w_s] = w_s^\wedge = \dot{R}R^{-1} \quad \text{Space coordinate angular velocity}$$

$$[w_b] = w_b^\wedge = R^{-1}\dot{R} \quad \text{Body coordinate angular velocity}$$

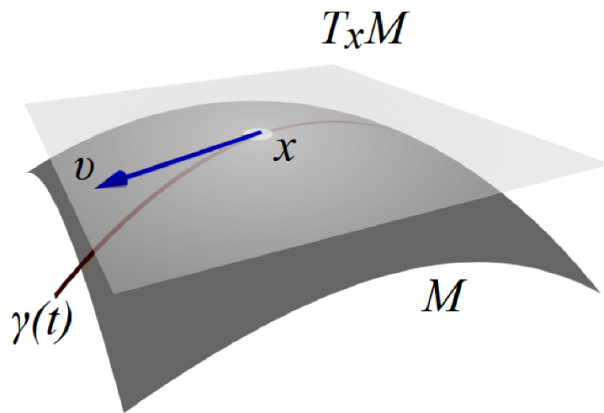


Review: Lie Algebra

- ▶ Set of skew-symmetric matrices $\mathfrak{so}(3)$ is Lie Algebra of the Lie Group $SO(3)$

$$\{A | A^\top + A = 0\} \quad w^\wedge = \begin{bmatrix} 0 & -w_3 & w_2 \\ w_3 & 0 & -w_1 \\ -w_2 & w_1 & 0 \end{bmatrix}$$

- ▶ Tangent space



If $x \in M$ is a point in the manifold, then the space of *all possible* tangent vectors is called the *tangent space* and is denoted by $T_x M$.

Tangent space at **identity** I is **Lie algebra**



Review: Lie Algebra Operator

- ▶ Lie algebra *hat* operator
 - ▶ Vector to skew symmetric matrix

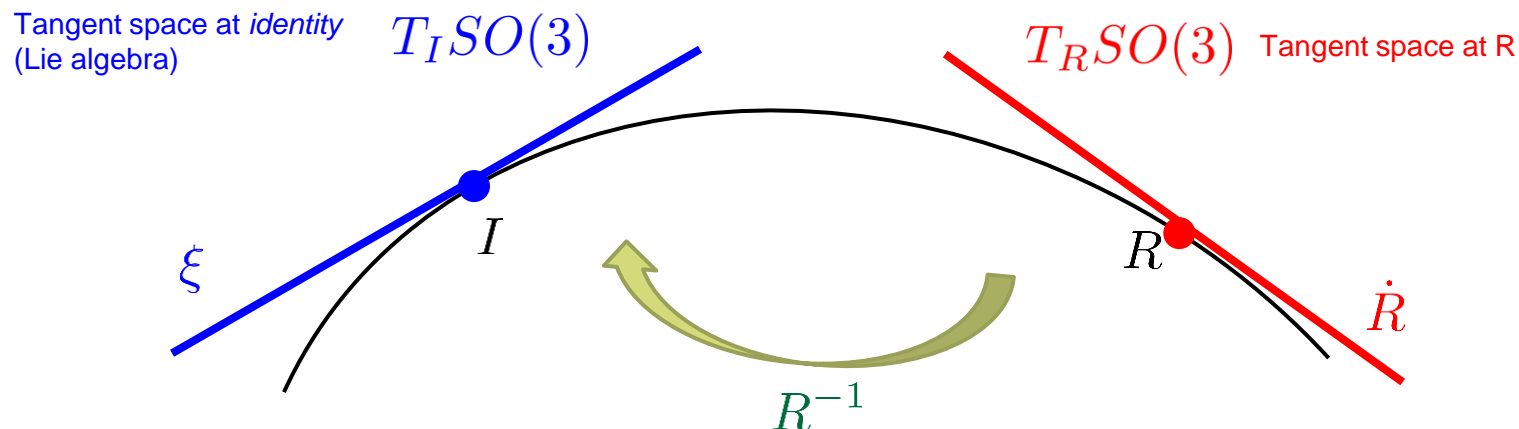
$$\omega^\wedge = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}^\wedge = \begin{bmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{bmatrix} \in \mathfrak{so}(3)$$

- ▶ Lie algebra *vee* operator
 - ▶ Skew symmetric matrix to vector



Review: Tangent Space & Lie Algebra

- ▶ Consider two rotation matrices $I, R \in SO(3)$



- ▶ Using change of basis

$$\dot{R} = R\xi \quad \xi = R^{-1}\dot{R}$$

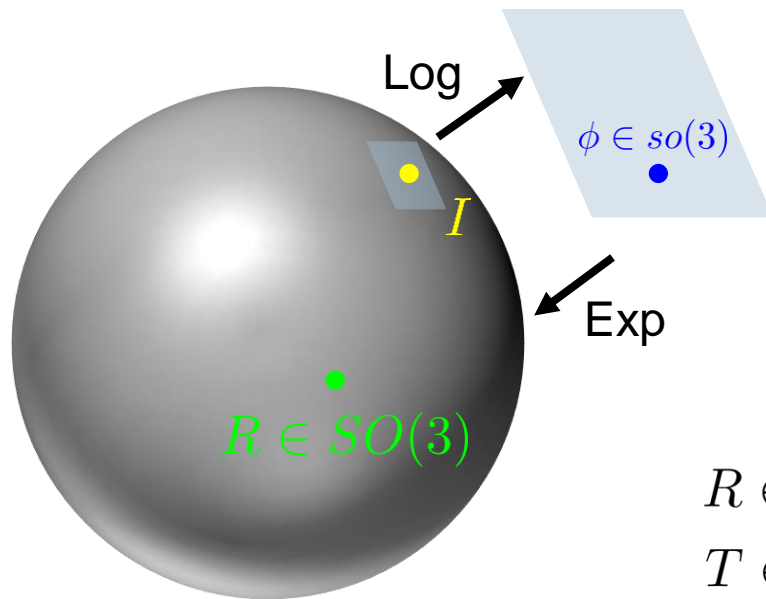
- ▶ Tangent space is a vector space! \rightarrow Additive noise!
- ▶ Tangent space at identity == Lie algebra

- ▶ Lie algebra consists of all possible \dot{R} at $R = I$



Review: Exp/Log

- ▶ Exponential and log mapping between Lie Group and Lie Algebra



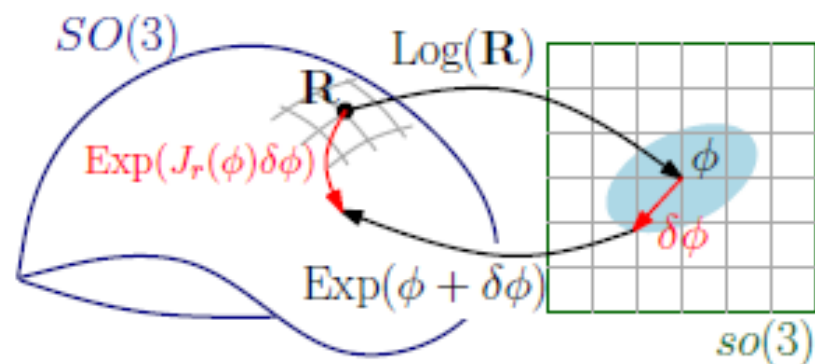
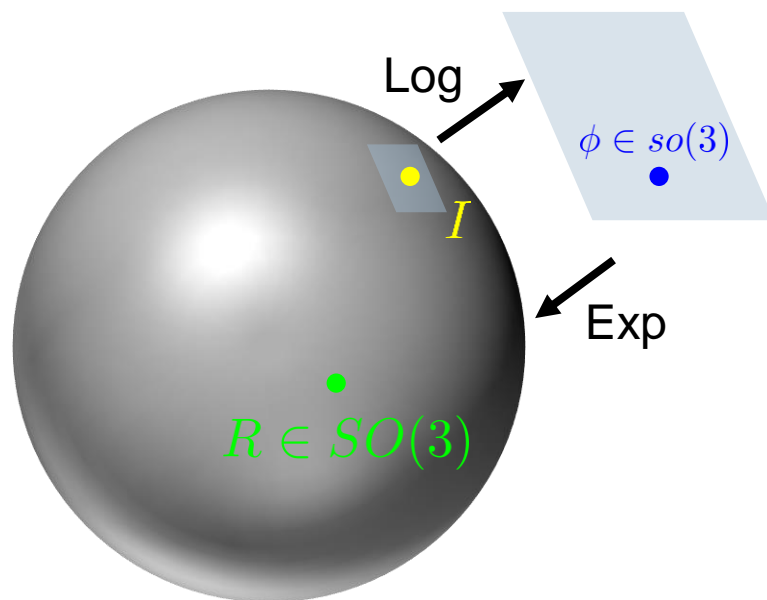
$$\text{Exp}(\underbrace{\phi^\wedge}_{\text{so}(3)}) = \mathbf{I} + \frac{\sin(\|\phi\|)}{\|\phi\|} \phi^\wedge + \frac{1 - \cos(\|\phi\|)}{\|\phi\|^2} (\phi^\wedge)^2. = \mathbf{R} \rightarrow \text{SO}(3)$$

$$\text{Log}(\mathbf{R}) = \frac{\varphi \cdot (\mathbf{R} - \mathbf{R}^\top)}{2 \sin(\varphi)} \text{ with } \varphi = \cos^{-1} \left(\frac{\text{tr}(\mathbf{R}) - 1}{2} \right)$$

$$\begin{array}{ccc} R \in \text{SO}(3) & \xrightarrow{\text{Log}} & \phi \in \text{so}(3) \\ T \in \text{SE}(3) & \xleftarrow{\text{Exp}} & \chi \in \text{se}(3) \end{array}$$

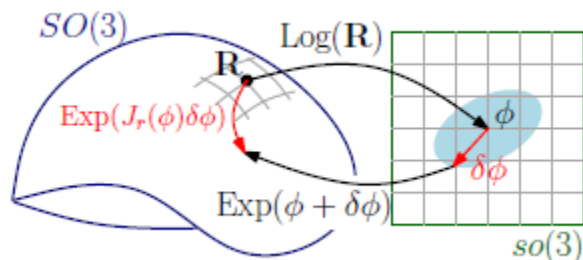
Uncertainty on a Manifold

- ▶ Log and Exp mapping between $SO(3)$ and $so(3)$
 - ▶ Lie algebra lives in a locally linear space
 - ▶ Consider perturbation in Lie algebra



Uncertainty on a Manifold

► First-order approximation for Lie Group $SO(3)$



Consider noise in Lie algebra

► First-order approximation

$$\text{Exp}(\phi + \delta\phi) \approx \text{Exp}(\phi) \text{Exp}(J_r(\phi)\delta\phi).$$

$$\text{Log}(\text{Exp}(\phi) \text{Exp}(\delta\phi)) \approx \phi + J_r^{-1}(\phi)\delta\phi.$$

Right Jacobian

$$J_r(\phi) = \mathbf{I} - \frac{1 - \cos(\|\phi\|)}{\|\phi\|^2} \phi^\wedge + \frac{\|\phi\| - \sin(\|\phi\|)}{\|\phi\|^3} (\phi^\wedge)^2.$$

$$J_r^{-1}(\phi) = \mathbf{I} + \frac{1}{2} \phi^\wedge + \left(\frac{1}{\|\phi\|^2} + \frac{1 + \cos(\|\phi\|)}{2\|\phi\| \sin(\|\phi\|)} \right) (\phi^\wedge)^2$$

► Distribution in the tangent space, then map it to $SO(3)$ via Exp mapping

$$\tilde{\mathbf{R}} = \mathbf{R} \text{Exp}(\epsilon),$$

$$\epsilon \sim \mathcal{N}(0, \Sigma)$$





Thank you very much !!

