

NA 568 - Winter 2024

Robot Motion and Uncertainty Propagation

Maani Ghaffari

February 7, 2024



- 1 Study robot motion described by $SE(2)$ and $SE(3)$ groups;
- 2 Focus on fully actuated models and without nonholonomic constraints commonly used in state estimation;
- 3 Introduce robot motion model and integration technique for rigid body motion;
- 4 A method for covariance propagation in the Lie algebra.

For convenience, we define the following isomorphism

$$(\cdot)^\wedge : \mathbb{R}^n \rightarrow \mathfrak{g},$$

that maps an element in the vector space \mathbb{R}^n to the tangent space of the matrix Lie group at the identity.

We also define the inverse of $(\cdot)^\wedge$ map as

$$(\cdot)^\vee : \mathfrak{g} \rightarrow \mathbb{R}^n.$$

For any $\phi \in \mathbb{R}^n$, we can define the Lie exponential map as

$$\exp(\cdot) : \mathbb{R}^n \rightarrow \mathcal{G}, \quad \exp(\phi) = \exp_m(\phi^\wedge),$$

where $\exp_m(\cdot)$ is the exponential of square matrices.

We also define the Lie logarithmic map as the inverse of the Lie exponential map

$$\log(\cdot) : \mathcal{G} \rightarrow \mathbb{R}^n \quad \text{and} \quad \log_m(\cdot) : \mathcal{G} \rightarrow \mathfrak{g}.$$

► $\text{SO}(3) = \{R \in \mathbb{R}^{3 \times 3} \mid RR^T = R^T R = I, \det R = 1\}$

► Its Lie algebra

$$\mathfrak{so}(3) = \{A \in \mathbb{R}^{3 \times 3} \mid A = -A^T\}$$

is the space of 3×3 skew-symmetric matrices.

► $\mathfrak{so}(3)$ elements are three-dimensional vectors that describe angular velocities.

- Let $\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix} \in \mathbb{R}^3$ be a vector of angular velocity defined using the \mathbb{R}^3 standard basis as $\omega = \omega_1 e_1 + \omega_2 e_2 + \omega_3 e_3$.

- We define the *wedge* (also called hat) notation:

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

- $S^\vee = (\omega^\wedge)^\vee = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}.$

► We can also write $\omega^\wedge = \omega_1 G_1 + \omega_2 G_2 + \omega_3 G_3$

► $G_1 = e_1^\wedge$, $G_2 = e_2^\wedge$, and $G_3 = e_3^\wedge$



$$G_1 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}, G_2 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix}, G_3 = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

► The matrices G_1, G_2 , and G_3 give a basis for vector space $\mathfrak{so}(3)$ and called generators.

► $\text{SO}(2) = \{R \in \mathbb{R}^{2 \times 2} \mid RR^T = R^T R = I, \det R = 1\}$

► Its Lie algebra

$$\mathfrak{so}(2) = \{A \in \mathbb{R}^{2 \times 2} \mid A = -A^T\}$$

is the space of 2×2 skew-symmetric matrices.

► Let $\omega \in \mathbb{R}$, then $\omega^\wedge = \begin{bmatrix} 0 & -\omega \\ \omega & 0 \end{bmatrix}_{2 \times 2} \in \mathfrak{so}(2)$

► $SE(3) = \left\{ \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix}_{4 \times 4} \mid R \in SO(3), p \in \mathbb{R}^3 \right\}$

► Its Lie algebra is

$$\mathfrak{se}(3) = \left\{ \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}_{4 \times 4} \mid \omega^\wedge \in \mathfrak{so}(3), v \in \mathbb{R}^3 \right\}$$

► We call $\xi := \text{vec}(\omega, v) \in \mathbb{R}^6$ twist where $\omega \in \mathfrak{so}(3)$ is the angular velocity and $v \in \mathbb{R}^3$ is the linear velocity.

3D Rigid Body Transformations

► $X = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in \text{SE}(3)$ and $\xi^\wedge = \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}_{4 \times 4} \in \mathfrak{se}(3)$

► For $\xi^\wedge \in \mathfrak{se}(3)$ we have

$$\xi^\wedge = \omega_1 G_1 + \omega_2 G_2 + \omega_3 G_3 + v_1 G_4 + v_2 G_5 + v_3 G_6$$

where

$$\begin{aligned} G_1 &= \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, G_2 = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, G_3 = \begin{bmatrix} 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \\ G_4 &= \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, G_5 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, G_6 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{aligned}$$

3D Rigid Body Transformations

► $X = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in \text{SE}(3)$ and $\xi^\wedge = \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}_{4 \times 4} \in \mathfrak{se}(3)$

► From the reconstruction equation, we have

$$X^{-1} \dot{X} = \xi^\wedge \in \mathfrak{se}(3)$$

$$\begin{bmatrix} R^\top & -R^\top p \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{R} & \dot{p} \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R^\top \dot{R} & R^\top \dot{p} \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}$$

► or

$$\dot{X} X^{-1} = \xi^\wedge \in \mathfrak{se}(3)$$

$$\begin{bmatrix} \dot{R} & \dot{p} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} R^\top & -R^\top p \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \dot{R} R^\top & -\dot{R} R^\top p + \dot{p} \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}$$

we need to make sense of these (body vs. spatial velocities)!

► $SE(2) = \left\{ \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix}_{3 \times 3} \mid R \in SO(2), p \in \mathbb{R}^2 \right\}$

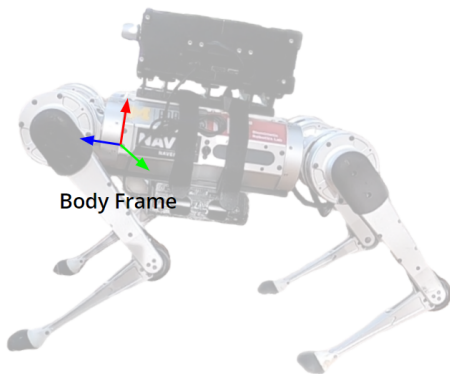
► Its Lie algebra is

$$\mathfrak{se}(2) = \left\{ \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}_{3 \times 3} \mid \omega^\wedge \in \mathfrak{so}(2), v \in \mathbb{R}^2 \right\}$$

► We call $\xi := \text{vec}(\omega, v) \in \mathbb{R}^3$ twist where $\omega \in \mathfrak{so}(2)$ is the angular velocity and $v \in \mathbb{R}^2$ is the linear velocity.

Body vs. Spatial Velocities

Let S and B represent Spatial (World/fixed/inertial) and Body (moving, attached to the robot or sensor) frames.



Spatial Frame



- ▶ The coordinates of a point in frame B , p_b , is related to its coordinates in frame S , p_s , using the action of relative rotation R_{sb} , as

$$p_s = R_{sb}p_b.$$

- ▶ We can also define a vector using the difference of two points as $v_b := p_b - q_b$ and show that

$$v_s = R_{sb}v_b = R_{sb}p_b - R_{sb}q_b = p_s - q_s.$$

- ▶ We can relate the angular velocity in the body frame B , ω_b , to the angular velocity in the spatial frame S , ω_s , via

$$\omega_s = R_{sb}\omega_b \quad \text{or} \quad \omega_b = R_{sb}^\top \omega_s$$

Recall the reconstruction equation $\dot{R} = R\omega_b^\wedge$, and consider ω_b to be in the body frame as the rotation is multiplied in the left.

The consistency with $\dot{R} = \omega_s^\wedge R$ can be proved as follows.

$$\dot{R} = \omega_s^\wedge R = RR^\top \omega_s^\wedge R = R(R^\top \omega_s^\wedge R) = R(R^\top \omega_s)^\wedge = R\omega_b^\wedge.$$

$$\implies \omega_s^\wedge = R\omega_b^\wedge R^\top \quad \text{or} \quad \omega_s = R\omega_b$$

$$\omega_b^\wedge = R^\top \omega_s^\wedge R \quad \text{or} \quad \omega_b = R^\top \omega_s$$

Lemma

For any $R \in \text{SO}(3)$ and $\omega^\wedge \in \mathfrak{so}(3)$, we have

$$R\omega^\wedge R^\top = (R\omega)^\wedge.$$

The adjoint map formalizes the previous derivations for all matrix Lie groups.

The definition of the adjoint is given as

$$\mathrm{Ad}_g(\xi^\wedge) = g\xi^\wedge g^{-1},$$

where $\xi^\wedge \in \mathfrak{g}$ and $g \in \mathcal{G}$

Remark

We're after a matrix transformation called adjoint that takes a group element and maps an element of the Lie algebra to another element of the Lie algebra (change of basis for twist).

Adjoint as a Matrix (Linear Map)

Let $\omega^\wedge \in \mathfrak{so}(3)$ and $R \in \mathrm{SO}(3)$. We have

$$\mathrm{Ad}_R(\omega^\wedge) = R\omega^\wedge R^{-1} = R\omega^\wedge R^\top = (R\omega)^\wedge.$$

So we learn that

$$(\mathrm{Ad}_R\omega)^\wedge = (R\omega)^\wedge \implies \boxed{\mathrm{Ad}_R = R}.$$

Remark

Since we seek a matrix that acts on $\omega \in \mathbb{R}^3$, the leftmost term must be of this form $(\mathrm{Ad}_R\omega)^\wedge$. Notice that we're solving for matrix Ad_R and $\mathrm{Ad}_R(\cdot)$ is a function in the conjugation form.

Adjoint as a Matrix (Linear Map)

SE(3) Case:

$$X = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \in \text{SE}(3) \quad \text{and} \quad \xi^\wedge = \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix}_{4 \times 4} \in \mathfrak{se}(3).$$

$$(\text{Ad}_X \xi)^\wedge = X \xi^\wedge X^{-1} = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix} \begin{bmatrix} R^\top & -R^\top p \\ 0 & 1 \end{bmatrix},$$

$$\begin{aligned} (\text{Ad}_X \xi)^\wedge &= \begin{bmatrix} R\omega^\wedge R^\top & -R\omega^\wedge R^\top p + Rv \\ 0 & 0 \end{bmatrix} \\ &= \begin{bmatrix} (R\omega)^\wedge & -(R\omega)^\wedge p + Rv \\ 0 & 0 \end{bmatrix} \end{aligned}$$

$$(\text{Ad}_X \xi)^\wedge = \begin{bmatrix} (R\omega)^\wedge & p^\wedge R\omega + Rv \\ 0 & 0 \end{bmatrix}.$$

Adjoint as a Matrix (Linear Map)

We can choose to stack the linear velocity $v \in \mathbb{R}^3$ and angular velocity $\omega \in \mathbb{R}^3$ in the following orders.

1 $\xi = \text{vec}(\omega, v) \in \mathbb{R}^6;$

$$\text{Ad}_X \xi = \begin{bmatrix} R & 0 \\ p^\wedge R & R \end{bmatrix} \begin{bmatrix} \omega \\ v \end{bmatrix}, \quad \text{and} \quad \boxed{\text{Ad}_X = \begin{bmatrix} R & 0 \\ p^\wedge R & R \end{bmatrix}_{6 \times 6}}.$$

2 $\xi = \text{vec}(v, \omega) \in \mathbb{R}^6;$

$$\text{Ad}_X \xi = \begin{bmatrix} R & p^\wedge R \\ 0 & R \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}, \quad \text{and} \quad \boxed{\text{Ad}_X = \begin{bmatrix} R & p^\wedge R \\ 0 & R \end{bmatrix}_{6 \times 6}}.$$

- ▶ The kinematic equation of motion is described by the curve $X(t) \in \text{SE}(2)$ or $\text{SE}(3)$ as

$$\frac{d}{dt}X_t = \dot{X}_t = X_t u_t^\wedge, \quad u_t^\wedge \in \mathfrak{g}.$$



- ▶ The kinematic equation of motion is described by the curve $X(t) \in \text{SE}(2)$ or $\text{SE}(3)$ as

$$\frac{d}{dt}X_t = \dot{X}_t = X_t u_t^\wedge, \quad u_t^\wedge \in \mathfrak{g}.$$

- ▶ The control input $u_t = \text{vec}(\omega_t, v_t) \in \mathbb{R}^3$ or \mathbb{R}^6 is a vector of angular velocity, ω_t , and linear velocity, v_t .
- ▶ The reconstruction equation is a simple kinematic model that provides a process model to predict the motion of a rigid body.

- ▶ The integration of the reconstruction equation also makes it convenient to predict rotation and translation simultaneously.
- ▶ To see the separate terms for the rotation and translation, we can write

$$\dot{X}_t = \begin{bmatrix} \dot{R} & \dot{p} \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R & p \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \omega^\wedge & v \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} R\omega^\wedge & Rv \\ 0 & 0 \end{bmatrix}.$$

- ▶ Suppose we integrate this process model for a fixed sampling time $\Delta t = t_{k+1} - t_k$ by assuming a zero-order hold on the input.
- ▶ Define $u_k := u_{t_k} \cdot \Delta t$. Then we have the following discrete-time motion model.

$$X_{k+1} = X_k \exp(u_k) =: X_k U_k.$$

Noisy Process and Uncertainty Propagation

- ▶ The deterministic process model is given by

$$X_{k+1} = f_{u_k}(X_k) := X_k U_k.$$

- ▶ Substituting in the noisy process model, we have

$$X_{k+1} = f_{u_k}(X_k) \exp(w_k),$$

where $w_k \sim \mathcal{N}(0, \Sigma_{w_k})$.

Remark

w_k is the zero-mean white Gaussian noise term defined in the Lie algebra. This is convenient as the Lie algebra is a vector space, whereas the group is a nonlinear space.

Definition (Left and Right Invariant Error)

The right- and left-invariant errors between two trajectories $X_t \in \mathcal{G}$ and $\bar{X}_t \in \mathcal{G}$ are:

$$\eta_t^r = \bar{X}_t X_t^{-1} = (\bar{X}_t L)(X_t L)^{-1} \quad (\text{Right-Invariant})$$

$$\eta_t^l = X_t^{-1} \bar{X}_t = (L \bar{X}_t)^{-1} (L X_t), \quad (\text{Left-Invariant})$$

where $L \in \mathcal{G}$ is an arbitrary element of the group.

Using Adjoint Map to Change Order of Multiplication

The adjoint representation of a Lie group is a linear map that captures the non-commutative structure of the group.

$$\begin{aligned}X \exp(\xi) X^{-1} &= \exp(\operatorname{Ad}_X \xi) \\X \exp(\xi) &= \exp(\operatorname{Ad}_X \xi) X \\ \exp(\xi) X &= X \exp(\operatorname{Ad}_{X^{-1}} \xi).\end{aligned}$$

In the above equations $X \in \mathcal{G}$ and $\xi \in \mathfrak{g}$.

Remark

We used the definition of the adjoint and the property of matrix exponential. In particular, $\exp(XYX^{-1}) = X \exp(Y)X^{-1}$ for any invertible matrix X .

Recall: Baker-Campbell-Hausdorff Series

For $X, Y, Z \in \mathfrak{g}$ with the sufficiently small norm, the equation $\exp(X)\exp(Y) = \exp(Z)$ has a power series solution for Z in terms of repeated Lie bracket of X and Y . The beginning of the series is:

$$Z = X + Y + \frac{1}{2}[X, Y] + \frac{1}{12}[X, [X, Y]] + \frac{1}{12}[Y, [Y, X]] + \cdots .$$

- ▶ The BCH formula can be used to compound two matrix exponentials.
- ▶ If both terms are small, by keeping the first two terms and ignoring the higher order terms, we have:

$$\text{BCH}(\xi_1^\wedge, \xi_2^\wedge) = \xi_1^\wedge + \xi_2^\wedge + \text{HOT},$$

$$\exp(\xi_1) \exp(\xi_2) \approx \exp(\xi_1 + \xi_2).$$

Noisy Process and Uncertainty Propagation

- ▶ We use the *left-invariant error* to track the covariance of the spatial error as seen in the body-fixed frame:

$$\eta = \exp(\xi) = X^{-1} \bar{X}.$$

- ▶ The state X is of the following form where \bar{X} is the mean or estimated value of the true state:

$$X = \bar{X} \exp(-\xi).$$

Noisy Process and Uncertainty Propagation

- ▶ We substitute $X = \bar{X} \exp(-\xi)$ in the noisy process model as follows.

$$\bar{X}_{k+1} \exp(-\xi_{k+1}) = \bar{X}_k \exp(-\xi_k) U_k \exp(w_k),$$

- ▶ using the adjoint to shift all noise terms to the right, we get

$$\bar{X}_{k+1} \exp(-\xi_{k+1}) = \bar{X}_k U_k \exp\left(-\text{Ad}_{U_k^{-1}} \xi_k\right) \exp(w_k).$$

Noisy Process and Uncertainty Propagation

This previous equation shows the relation between noise terms at timesteps k and $k + 1$. Thus,

$$\exp(-\xi_{k+1}) = \exp\left(-\text{Ad}_{U_k^{-1}}\xi_k\right)\exp(w_k).$$

- ▶ Since all noise terms are small, after applying the BCH formula and keeping the first two terms, we arrive at the approximate error dynamics:

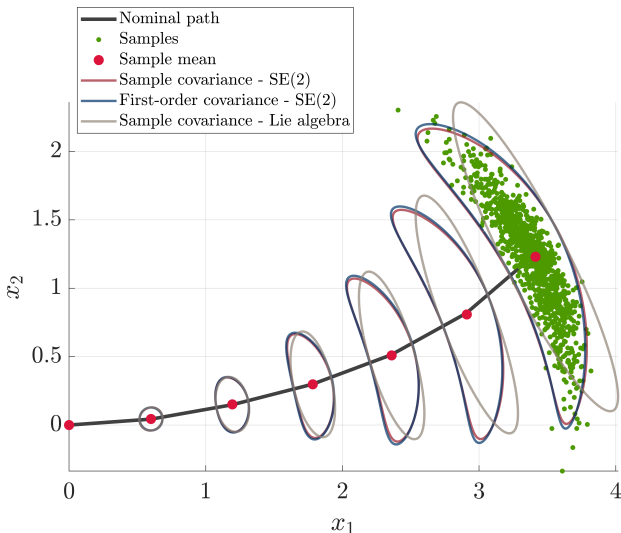
$$\xi_{k+1} = \text{Ad}_{U_k^{-1}}\xi_k - w_k.$$

- ▶ Finally, we arrive at

$$\Sigma_{k+1} = \text{Ad}_{U_k^{-1}}\Sigma_k\text{Ad}_{U_k}^{\top} + \Sigma_{w_k}.$$

Example: Uncertainty Propagation on SE(2)

See Ch. 5 in Lecture Notes for Mobile Robotics and
`odometry_propagation_se2.m` or `.py` for code.



Example: Uncertainty Propagation on SE(3)

See Ch. 5 in Lecture Notes for Mobile Robotics and
odometry_propagation_se3.m or .py for code.

