

## Assignment 4: Problem Set

### Question 1

We show that  $Q(X)$  is a stationary distribution of the Markov chain by verifying the detailed balance condition. It suffices to prove that

$$(1.1) \quad Q(Y) P(Y \rightarrow Y') = Q(Y') P(Y' \rightarrow Y), \quad \forall Y, Y' \in U.$$

We consider three cases according to the Hamming distance between  $Y$  and  $Y'$ .

**Case 1.**  $Y$  and  $Y'$  differ in at least two coordinates.

In one transition, the chain updates only a single coordinate. Therefore it is impossible to move from  $Y$  to  $Y'$  (or vice versa) in one step, so

$$P(Y \rightarrow Y') = P(Y' \rightarrow Y) = 0,$$

and (1.1) holds trivially.

**Case 2.**  $Y = Y'$ .

Both sides of (1.1) reduce to

$$Q(Y) P(Y \rightarrow Y),$$

so the equality holds.

**Case 3.**  $Y$  and  $Y'$  differ in exactly one coordinate.

Assume they differ only at index  $k$ . That is,

$$Y_i = Y'_i \text{ for all } i \neq k, \quad Y_k \neq Y'_k.$$

Then

$$Y = (Y_{-k}, Y_k), \quad Y' = (Y'_{-k}, Y'_k), \quad Y_{-k} = Y'_{-k} = Z_{-k}.$$

By the definition of the transition,

$$(1.2) \quad \begin{aligned} Q(Y) P(Y \rightarrow Y') &= Q(Y) \frac{1}{N} Q(X_k = Y'_k \mid X_{-k} = z_{-k}) \\ &= \frac{1}{N} Q(X_{-k} = Z_{-k}, X_k = Y_k) \frac{Q(X_{-k} = Z_{-k}, X_k = Y'_k)}{Q(X_{-k} = Z_{-k})}. \end{aligned}$$

Similarly,

$$(1.3) \quad \begin{aligned} Q(Y') P(Y' \rightarrow Y) &= Q(Y') \frac{1}{N} Q(X_k = Y_k \mid X_{-k} = Z_{-k}) \\ &= \frac{1}{N} Q(X_{-k} = Z_{-k}, X_k = Y'_k) \frac{Q(X_{-k} = Z_{-k}, X_k = Y_k)}{Q(X_{-k} = Z_{-k})}. \end{aligned}$$

The right-hand sides of (1.2) and (1.3) are identical. Hence

$$Q(Y) P(Y \rightarrow Y') = Q(Y') P(Y' \rightarrow Y),$$

and the detailed balance condition (1.1) holds.

Since the chain satisfies detailed balance with respect to  $Q$ , it follows that  $Q$  is a stationary distribution of the Markov chain.

## Question 2

**2.1 Adjoint Operation** The inverse of  $T = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \in SE(3)$  is

$$(2.1) \quad T^{-1} = \begin{bmatrix} R^T & -R^T t \\ 0 & 1 \end{bmatrix}.$$

Any  $\xi \in \mathbb{R}^6$  can be written as two vectors  $\psi, \rho \in \mathbb{R}^3$ :

$$\xi = \begin{bmatrix} \psi \\ \rho \end{bmatrix}.$$

The  $\wedge$  operator gives

$$(2.2) \quad \xi^\wedge = \begin{bmatrix} \psi^\wedge & \rho \\ 0 & 0 \end{bmatrix}.$$

Now compute the adjoint map:

$$(2.3) \quad \begin{aligned} Ad_T(\xi^\wedge) &= T\xi^\wedge T^{-1} \\ &= \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \psi^\wedge & \rho \\ 0 & 0 \end{bmatrix} \begin{bmatrix} R^T & -R^T t \\ 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} R\psi^\wedge R^T & -R\psi^\wedge R^T t + R\rho \\ 0 & 0 \end{bmatrix}. \end{aligned}$$

To extract the  $6 \times 6$  adjoint matrix  $A = Ad_T$ , we apply the  $\vee$  operator to (2.3). Since cross product is rotation invariant:

$$R(x \times y) = (Rx) \times (Ry),$$

we have

$$(2.4) \quad -R\psi^\wedge R^T t = -R(\psi \times (R^T t)) = -(R\psi) \times t = -(R\psi)^\wedge t = t \times R\psi = (t^\wedge R\psi).$$

This holds for any  $t \in \mathbb{R}^3$ . Applying  $(\cdot)^\vee$  to (2.3) and using (2.4), we obtain

$$(2.5) \quad (T\xi^\wedge T^{-1})^\vee = \begin{bmatrix} R\psi \\ t^\wedge R\psi + R\rho \end{bmatrix}.$$

Thus  $A$  satisfies

$$A \begin{bmatrix} \psi \\ \rho \end{bmatrix} = \begin{bmatrix} R\psi \\ t^\wedge R\psi + R\rho \end{bmatrix}.$$

Comparing block-wise, we identify

$$A = \begin{bmatrix} R & 0 \\ t^\wedge R & R \end{bmatrix} = \begin{bmatrix} R & 0 \\ t \times R & R \end{bmatrix}.$$

This is exactly the standard adjoint representation of  $SE(3)$ .

**2.2 Gradient** From the lecture, we know that for any  $T \in SE(3)$ ,

$$(2.6) \quad Te^{\xi^\wedge} T^{-1} = e^{T\xi^\wedge T^{-1}} = e^{Ad_T(\xi)^\wedge} = e^{(Ad_T \xi)^\wedge}.$$

We have already computed  $Ad_T \in \mathbb{R}^{6 \times 6}$  in the previous problem.

Consider now the function

$$(2.7) \quad L(\xi) = \log\left(Te^{\xi^\wedge} T_1 T_2^{-1}\right)^\vee = \log\left(e^{(Ad_T \xi)^\wedge} T T_1 T_2^{-1}\right)^\vee, \quad \xi \in \mathfrak{se}(3).$$

The BCH approximation for small  $\Delta\xi$  states that

$$(2.8) \quad f(\Delta\xi) = \log\left(e^{(\Delta\xi)^\wedge} e^{\xi^\wedge}\right)^\vee = J_l^{-1}(\xi) \Delta\xi + \xi, \quad \|\Delta\xi\| \text{ small}.$$

To match this form, write

$$e^{(\text{Ad}_T \xi)^\wedge} T T_1 T_2^{-1} = e^{(\text{Ad}_T \xi)^\wedge} \exp(z^\wedge),$$

where

$$z = \log(T T_1 T_2^{-1})^\vee.$$

Applying (2.8) with  $\Delta \xi = \text{Ad}_T \xi$  and base point  $z$ ,

$$(2.9) \quad L(\xi) = \log\left(e^{(\text{Ad}_T \xi)^\wedge} e^{z^\wedge}\right)^\vee \approx J_l^{-1}(z) (\text{Ad}_T \xi) + z.$$

Since the linear approximation (2.9) is exact to first order,

$$L(\xi) = J_l^{-1}(z) \text{Ad}_T \xi + z + O(\|\xi\|^2), \quad z = \log(T T_1 T_2^{-1})^\vee.$$

Thus,

$$(2.10) \quad \left. \frac{\partial L}{\partial \xi} \right|_{\xi=0} = J_l^{-1}\left(\log(T T_1 T_2^{-1})^\vee\right) \text{Ad}_T.$$