

Composition of Movement Primitives

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1 ProMPs

1.1 Recap

From (Paraschos et al., 2013, 2018):

- q_t : joint angle over time
- \dot{q}_t : joint velocity over time
- $\tau = \{q_t\}_{t=0\dots T}$: trajectory
- \mathbf{w} : weight vector of a single trajectory
- ϕ_t : basis function
- $\Phi_t = [\phi_t, \dot{\phi}_t]$: $n \times 2$ dimensional time-dependent basis matrix
- $z(t)$: monotonically increasing phase variable
- $\epsilon_y \sim \mathcal{N}(\mathbf{0}, \Sigma_y)$: zero-mean i.i.d. Gaussian noise

$$\mathbf{y}_t = \begin{bmatrix} q_t \\ \dot{q}_t \end{bmatrix} = \Phi_t^\top \mathbf{w} + \epsilon_y \quad (1)$$

$$p(\tau|\mathbf{w}) = \prod_t \mathcal{N}(\mathbf{y}_t | \Phi_t^\top \mathbf{w}, \Sigma_y) \quad (2)$$

$$p(\tau; \theta) = \int p(\tau|\mathbf{w}) \cdot p(\mathbf{w}; \theta) d\mathbf{w} \quad (3)$$

1.2 Coupling between joints

$$p(\mathbf{y}_t|\mathbf{w}) = \mathcal{N}\left(\begin{bmatrix} \mathbf{y}_{1,t} \\ \vdots \\ \mathbf{y}_{d,t} \end{bmatrix} \middle| \begin{bmatrix} \Phi_t^\top & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \Phi_t^\top \end{bmatrix} \mathbf{w}, \Sigma_y\right) = \mathcal{N}(\mathbf{y}_t|\Psi_t\mathbf{w}, \Sigma_y) \quad (4)$$

with:

- $\mathbf{w} = [\mathbf{w}_1^\top, \dots, \mathbf{w}_n^\top]^\top$: combined weight vector
- Φ_t : block-diagonal basis matrix containing the basis functions and their derivatives for each dimension
- $\mathbf{y}_{i,t} = [q_{i,t}, \dot{q}_{i,t}]^\top$: joint angle and velocity for the i^{th} joint

1.3 Hierarchical Bayesian Model

The Hierarchical Bayesian Model used in ProMPs is illustrated in Fig. 1.

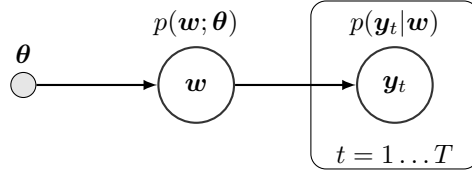


Figure 1: Hierarchical Bayesian Model used in ProMPs.

- $\theta = \{\mu_w, \Sigma_w\}$
- $p(\mathbf{w}; \theta) = \mathcal{N}(\mathbf{w}|\mu_w, \Sigma_w)$: prior over the weight vector \mathbf{w} , with parameters θ , assumed to be Gaussian

$$p(\mathbf{y}_t; \theta) = \int \mathcal{N}(\mathbf{y}_t|\Psi_t^\top \mathbf{w}, \Sigma_y) \cdot p(\mathbf{w}; \theta) d\mathbf{w} \quad (5)$$

$$= \int \mathcal{N}(\mathbf{y}_t|\Psi_t^\top \mathbf{w}, \Sigma_y) \cdot \mathcal{N}(\mathbf{w}|\mu_w, \Sigma_w) d\mathbf{w} \quad (6)$$

$$= \mathcal{N}(\mathbf{y}_t|\Psi_t^\top \mu_w, \Psi_t^\top \Sigma_w \Psi_t + \Sigma_y) \quad (7)$$

See Appendix A for the proof.

1.4 Via-Points Modulation

- $\mathbf{x}_t^* = [\mathbf{y}_t^*, \Sigma_t^*]$: desired observation
- \mathbf{y}_t^* : desired position and velocity vector at time t
- Σ_t^* : accuracy of the desired observation

Using Bayes rule:

$$p(\mathbf{w}|\mathbf{x}_t^*) = \frac{p(\mathbf{x}_t^*|\mathbf{w}) \cdot p(\mathbf{w})}{p(\mathbf{x}_t^*)} \quad (8)$$

$$p(\mathbf{w}|\mathbf{x}_t^*) \propto \mathcal{N}(\mathbf{y}_t^*|\Psi_t^\top \mathbf{w}, \Sigma_t^*) \cdot \mathcal{N}(\mathbf{w}|\mu_w, \Sigma_w) \quad (9)$$

$$\mu_w^{[new]} = \mu_w + \Sigma_w \Psi_t \left(\Sigma_y^* + \Psi_t^\top \Sigma_w \Psi_t \right)^{-1} (\mathbf{y}_t^* - \Psi_t^\top \mu_w) \quad (10)$$

$$\Sigma_w^{[new]} = \Sigma_w - \Sigma_w \Psi_t \left(\Sigma_y^* + \Psi_t^\top \Sigma_w \Psi_t \right)^{-1} \Psi_t^\top \Sigma_w \quad (11)$$

See Appendix B for the proof.

1.4.1 Do we actually get the desired mean by applying the conditioning update?

$$\boldsymbol{\mu}_w^{[new]}(t) = \boldsymbol{\mu}_w + \boldsymbol{\Sigma}_w \boldsymbol{\Psi}_t \left(\boldsymbol{\Sigma}_t^* \boldsymbol{\Psi}_t^\top \boldsymbol{\Sigma}_w \boldsymbol{\Psi}_t \right)^{-1} (\mathbf{y}_t^* - \boldsymbol{\Psi}_t^\top \boldsymbol{\mu}_w) \quad (12)$$

$$\stackrel{?}{=} \mathbf{y}_t^* \quad (13)$$

ToDo

2 Composition of MPs

References

- A. Paraschos, C. Daniel, J. R. Peters, and G. Neumann, “Probabilistic Movement Primitives,” in *Advances in Neural Information Processing Systems*, vol. 26. Curran Associates, Inc., 2013. [Online]. Available: <https://proceedings.neurips.cc/paper/2013/hash/e53a0a2978c28872a4505bdb51db06dc-Abstract.html>
- A. Paraschos, C. Daniel, J. Peters, and G. Neumann, “Using probabilistic movement primitives in robotics,” *Autonomous Robots*, vol. 42, no. 3, pp. 529–551, Mar. 2018. [Online]. Available: <https://doi.org/10.1007/s10514-017-9648-7>
- M. P. Deisenroth, A. A. Faisal, and C. S. Ong, *Mathematics for machine learning*. Cambridge University Press, 2020.
- C. M. Bishop and H. Bishop, *Deep Learning: Foundations and Concepts*. Springer International Publishing, 2024. [Online]. Available: <https://doi.org/10.1007/978-3-031-45468-4>

A Hierarchical Bayesian Model proof

Proof of Eq. (7). From (Deisenroth et al., 2020), we have the joint distribution:

$$p(\mathbf{x}_a, \mathbf{x}_b) = \mathcal{N} \left(\begin{bmatrix} \boldsymbol{\mu}_a \\ \boldsymbol{\mu}_b \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{aa} & \boldsymbol{\Sigma}_{ab} \\ \boldsymbol{\Sigma}_{ba} & \boldsymbol{\Sigma}_{bb} \end{bmatrix} \right) \quad (14)$$

and the marginal distribution $p(\mathbf{x}_a)$ of a joint Gaussian distribution $p(\mathbf{x}_a, \mathbf{x}_b)$:

$$p(\mathbf{x}_a) = \int p(\mathbf{x}_a, \mathbf{x}_b) d\mathbf{x}_b = \mathcal{N}(\mathbf{x}_a | \boldsymbol{\mu}_a, \boldsymbol{\Sigma}_{aa}) \quad (15)$$

Since \mathbf{y}_t and \mathbf{w} are jointly Gaussian, we have:

$$\begin{bmatrix} \mathbf{y}_t \\ \mathbf{w} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \boldsymbol{\mu}_{\mathbf{y}_t} \\ \boldsymbol{\mu}_{\mathbf{w}} \end{bmatrix}, \begin{bmatrix} \text{Cov}[\mathbf{y}_t, \mathbf{y}_t] & \text{Cov}[\mathbf{y}_t, \mathbf{w}] \\ \text{Cov}[\mathbf{w}, \mathbf{y}_t] & \text{Cov}[\mathbf{w}, \mathbf{w}] \end{bmatrix} \right) \quad (16)$$

$$\boldsymbol{\mu}_{\mathbf{y}_t} = \mathbb{E}[\mathbf{y}_t] \quad (17)$$

$$= \mathbb{E}[\boldsymbol{\Psi}_t^\top \mathbf{w} + \boldsymbol{\epsilon}_y] \quad (18)$$

$$= \boldsymbol{\Psi}_t^\top \mathbb{E}[\mathbf{w}] + \mathbb{E}[\boldsymbol{\epsilon}_y] \quad (19)$$

$$= \boldsymbol{\Psi}_t^\top \boldsymbol{\mu}_{\mathbf{w}} + 0 \quad (20)$$

$$= \boldsymbol{\Psi}_t^\top \boldsymbol{\mu}_{\mathbf{w}} \quad (21)$$

$$\text{Cov}[\mathbf{y}_t, \mathbf{y}_t] = \text{Cov}[\Psi_t^\top \mathbf{w} + \epsilon_y] \quad (22)$$

$$= \text{Cov}[\Psi_t^\top \mathbf{w}] + \text{Cov}[\epsilon_y] \quad (23)$$

$$= \Psi_t^\top \text{Cov}[\mathbf{w}] \Psi_t + \Sigma_y \quad (24)$$

$$= \Psi_t^\top \Sigma_w \Psi_t + \Sigma_y \quad (25)$$

$$\begin{bmatrix} \mathbf{y}_t \\ \mathbf{w} \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \Psi_t^\top \mu_w \\ \mu_w \end{bmatrix}, \begin{bmatrix} \Psi_t^\top \Sigma_w \Psi_t + \Sigma_y & \Psi_t^\top \Sigma_w \\ \Sigma_w \Psi_t & \Sigma_w \end{bmatrix} \right) \quad (26)$$

$$p(\mathbf{y}_t; \theta) = \mathcal{N}(\mathbf{y}_t | \Psi_t^\top \mu_w, \Psi_t^\top \Sigma_w \Psi_t + \Sigma_y) \quad (27)$$

□

B Via-Points conditioning proof

Proof of Eq. (10) and Eq. (11). With the joint distribution $p(\mathbf{x}_a, \mathbf{x}_b)$ in Eq. (14), and from (Bishop and Bishop, 2024), the parameters of a conditional multivariate Gaussian $p(\mathbf{x}_a | \mathbf{x}_b) = \mathcal{N}(\mu_{a|b}, \Sigma_{a|b})$ are the following:

$$\mu_{a|b} = \mu_a + \Sigma_{ab} \Sigma_{bb}^{-1} (\mathbf{x}_b - \mu_b) \quad (28)$$

$$\Sigma_{a|b} = \Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba} \quad (29)$$

We want the posterior $p(\mathbf{w} | \mathbf{x}_t^*)$, knowing the likelihood $\mathbf{x}_t^* | \mathbf{w} \sim \mathcal{N}(\mathbf{y}_t^* | \Psi_t^\top \mathbf{w}, \Sigma_t^*)$, and the prior $\mathbf{w} \sim \mathcal{N}(\mu_w, \Sigma_w)$.

$$\begin{bmatrix} \mathbf{w} \\ \mathbf{x}_t^* \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu_w \\ \Psi_t^\top \mu_w \end{bmatrix}, \begin{bmatrix} \text{Cov}[\mathbf{w}, \mathbf{w}] & \text{Cov}[\mathbf{w}, \mathbf{x}_t^*] \\ \text{Cov}[\mathbf{x}_t^*, \mathbf{w}] & \text{Cov}[\mathbf{x}_t^*, \mathbf{x}_t^*] \end{bmatrix} \right) \quad (30)$$

$\text{Cov}[\mathbf{x}_t^*, \mathbf{x}_t^*]$ follows from Eq. (25).

$$\text{Cov}[\mathbf{w}, \mathbf{x}_t^*] = \text{Cov}[\mathbf{w}, \Psi_t^\top \mathbf{w} + \epsilon_y] \quad (31)$$

$$= \text{Cov}[\mathbf{w}, \Psi_t^\top \mathbf{w}] \quad (\text{Cov}[\mathbf{w}, \epsilon_y] = 0 \text{ since } \epsilon_y \text{ is independent of } \mathbf{w}) \quad (32)$$

$$= \mathbb{E}[(\mathbf{w} - \mu_w)(\Psi_t^\top \mathbf{w} - \Psi_t^\top \mu_w)^\top] \quad (33)$$

$$= \mathbb{E}[(\mathbf{w} - \mu_w)(\mathbf{w} - \mu_w)^\top \Psi_t] \quad (34)$$

$$= \text{Cov}[\mathbf{w}, \mathbf{w}] \cdot \Psi_t \quad (35)$$

$$= \Sigma_w \Psi_t \quad (36)$$

$$\begin{bmatrix} \mathbf{w} \\ \mathbf{x}_t^* \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu_w \\ \Psi_t^\top \mu_w \end{bmatrix}, \begin{bmatrix} \Sigma_w & \Sigma_w \Psi_t \\ \Psi_t^\top \Sigma_w & \Psi_t^\top \Sigma_w \Psi_t + \Sigma_t^* \end{bmatrix} \right) \quad (37)$$

Using Eq. (28) we get:

$$\mu_{w|x_t^*} = \mu_w + \Sigma_w \Psi_t \left(\Sigma_t^* + \Psi_t^\top \Sigma_w \Psi_t \right)^{-1} (\mathbf{y}_t^* - \Psi_t^\top \mu_w) \quad (38)$$

Using Eq. (29) we get:

$$\Sigma_{w|x_t^*} = \Sigma_w - \Sigma_w \Psi_t \left(\Sigma_t^* + \Psi_t^\top \Sigma_w \Psi_t \right)^{-1} \Psi_t^\top \Sigma_w \quad (39)$$

□