Interactive Robotics Lab

Bayesian Interaction Primitives:

A SLAM Approach to Human-Robot Interaction

Joseph Campbell, Heni Ben Amor
School of Computing, Informatics and Decision Systems Engineering
Arizona State University

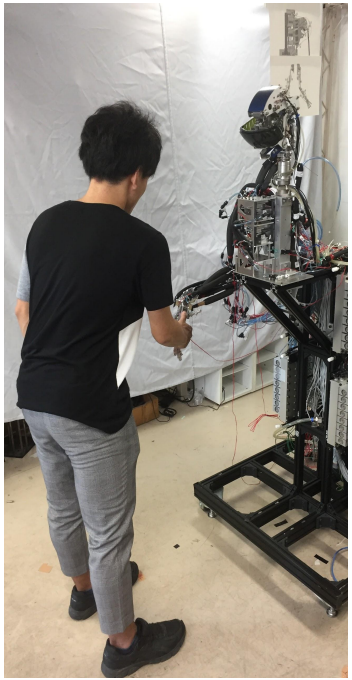
1st Conference on Robot Learning (CoRL 2017)
Mountain View, California
November 13, 2017

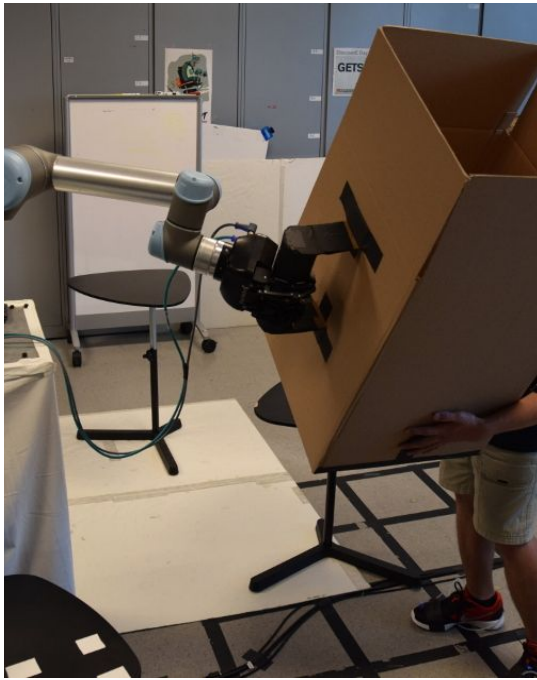
Human-Robot Interaction

- Programming HRI is *hard!*
- Represent interaction in time & space
- Generalize over interaction partners

Robot Learning

- Learning from demonstration
- Multimodal/high-dimensional
- Robust in time & space



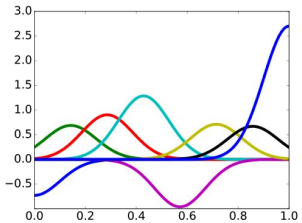


Interaction Primitives

Demonstration

$$\boldsymbol{y}_t = [x_1^o, \ldots, x_{D_o}^o, x_1^c, \ldots, x_{D_c}^c]$$

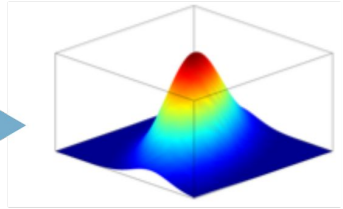
Basis Representation



$$x_d \approx \Phi_t^T \boldsymbol{w}_d + \epsilon_y$$

$$\boldsymbol{w} = [\boldsymbol{w}_0{}^T, \ldots, \boldsymbol{w}_{D_c}{}^T]^T$$

Joint Distribution

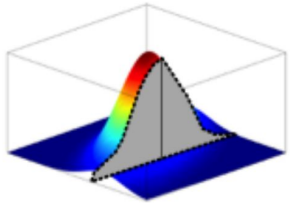


training

Observation

$$\boldsymbol{y}_t^* = [x_1^o, \ldots, x_{D_o}^o]$$

Conditioning



$$p(\boldsymbol{w}|\boldsymbol{y}^*) \propto p(\boldsymbol{y}^*|\boldsymbol{w})p(\boldsymbol{w})$$

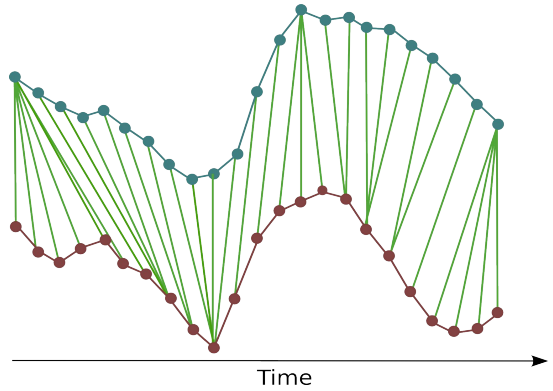
Response

inference

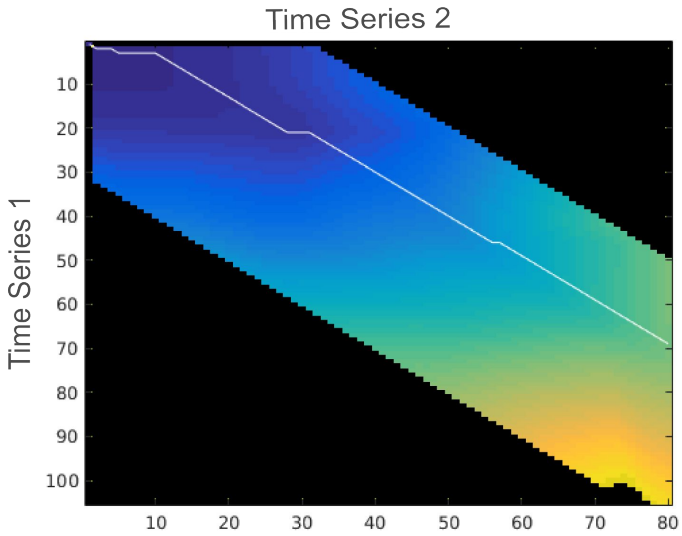
H. Ben Amor, G. Neumann, S. Kamthe, O. Kroemer, J. Peters. Interaction primitives for human-robot cooperation tasks. ICRA, 2014.
G. Maeda, M. Ewerton, R. Lioutikov, H.Ben Amor, J. Peters, G. Neumann. Learning interaction for collaborative tasks with probabilistic movement primitives. Humanoids, 2014.

Problem: Temporal Alignment

Dynamic Time Warp



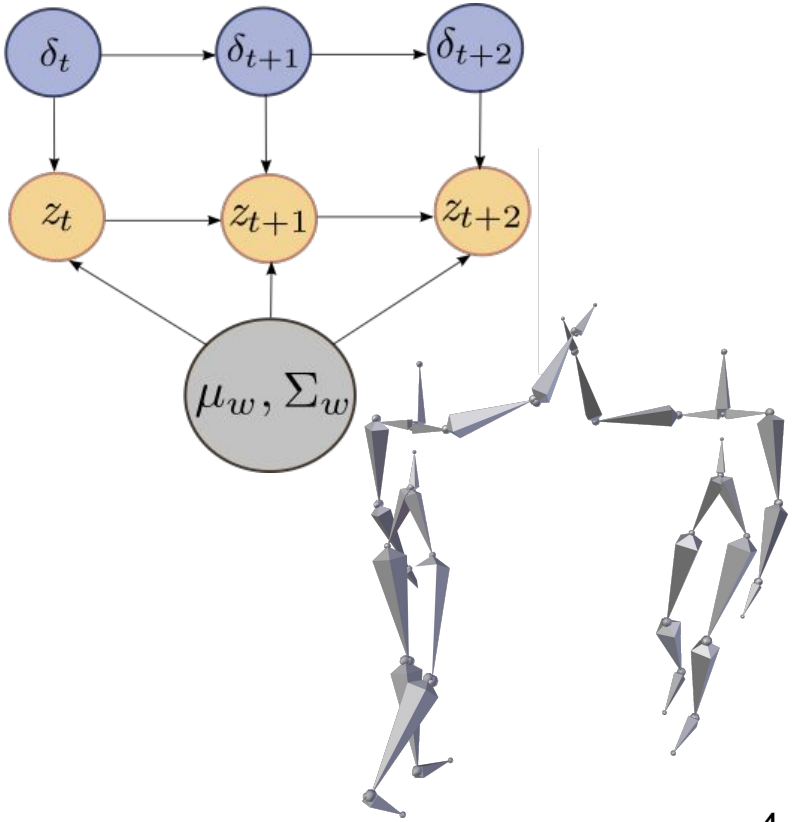
- Poor performance in higher dimensions
- Not probabilistic
- Does not leverage spatial inference
- Difficult to use recursively



Simultaneous Localization and Mapping

Insight:

“Localize in time, generate action in space”

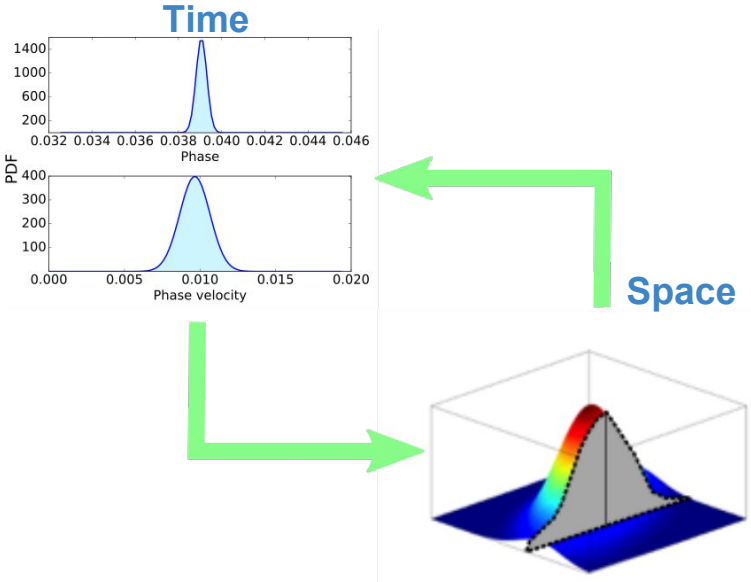


- Probabilistic reasoning over time
- Action generation in space
- Phase = location
- Weights = map

Bayesian Interaction Primitives

Extended Kalman Filter SLAM applied to Interaction Primitives

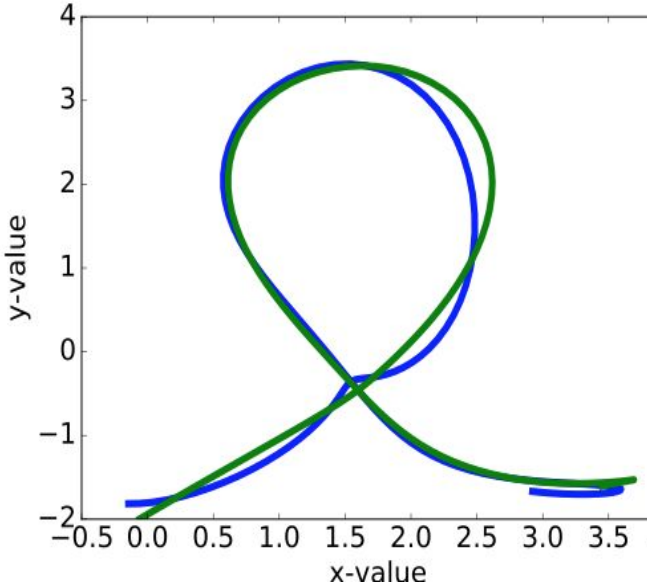
$$p(\boldsymbol{\delta_t}, \dot{\boldsymbol{\delta}}_t, \boldsymbol{w}|\boldsymbol{y}^*) \propto p(\boldsymbol{y}^*|\boldsymbol{\delta_t}, \dot{\boldsymbol{\delta}}_t, \boldsymbol{w}) p(\boldsymbol{\delta_t}, \dot{\boldsymbol{\delta}}_t, \boldsymbol{w})$$

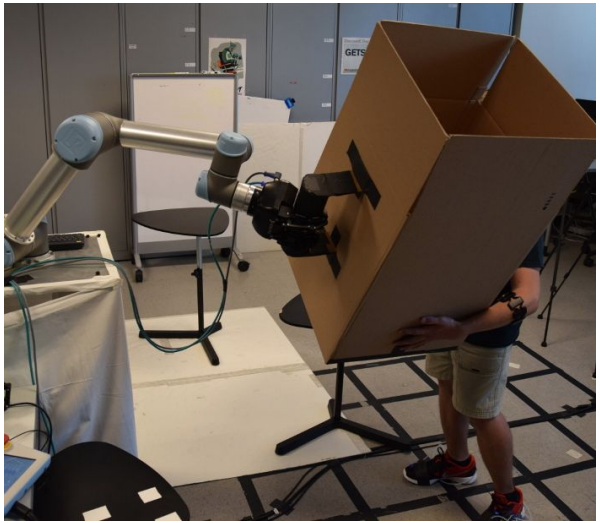


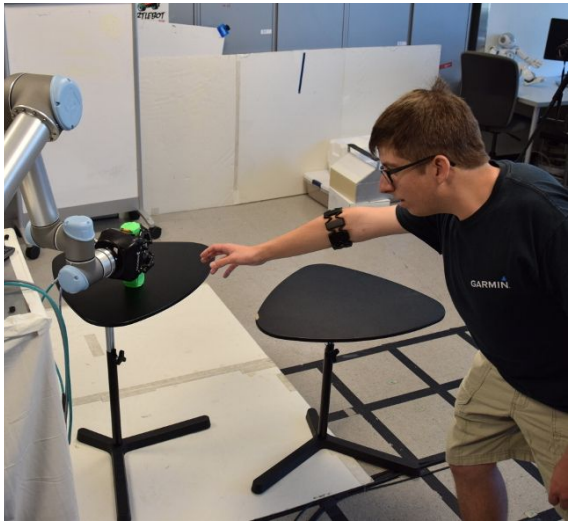
$$\boldsymbol{s}_t = [\delta_t, \dot{\delta}_t, \boldsymbol{w}^T]^T$$
$$p(\boldsymbol{s}_t|\boldsymbol{z}_{1:t}) = \mathcal{N}(\boldsymbol{s}_t|\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$$

$$\boldsymbol{\mu}_t = g(u_t, \boldsymbol{\mu}_{t-1}),$$
$$\boldsymbol{\Sigma}_t = \boldsymbol{G}_t \boldsymbol{\Sigma}_{t-1} \boldsymbol{G}_t^T + \boldsymbol{R}_t,$$
$$\boldsymbol{K}_t = \boldsymbol{\Sigma}_t \boldsymbol{H}_t^T (\boldsymbol{H}_t \boldsymbol{\Sigma}_t \boldsymbol{H}_t^T + \boldsymbol{Q}_t)^{-1},$$
$$\boldsymbol{\mu}_t^+ = \boldsymbol{\mu}_t + \boldsymbol{K}_t(\boldsymbol{z}_t - h(\boldsymbol{\mu}_t)),$$
$$\boldsymbol{\Sigma}_t^+ = (I - \boldsymbol{K}_t \boldsymbol{H}_t)\boldsymbol{\Sigma}_t.$$

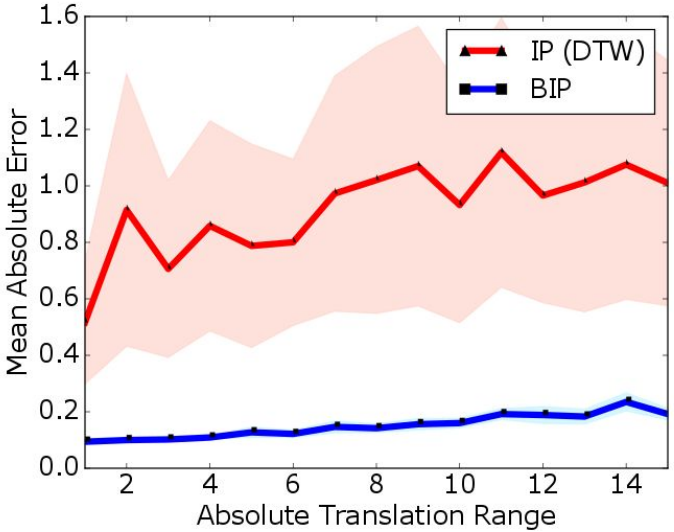
Experiments



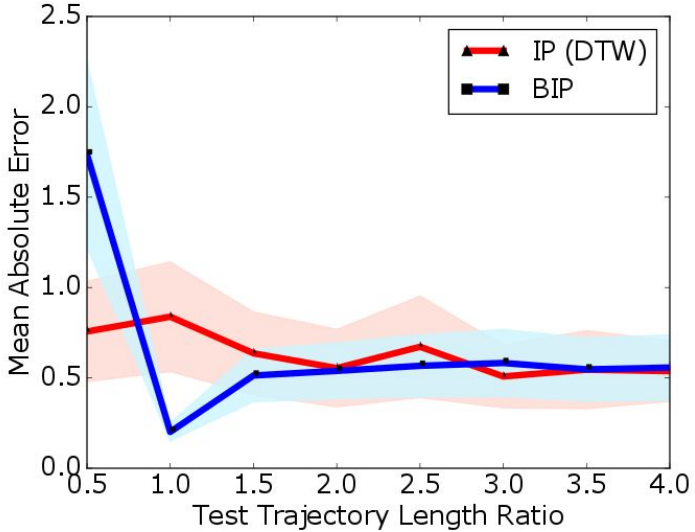




Results

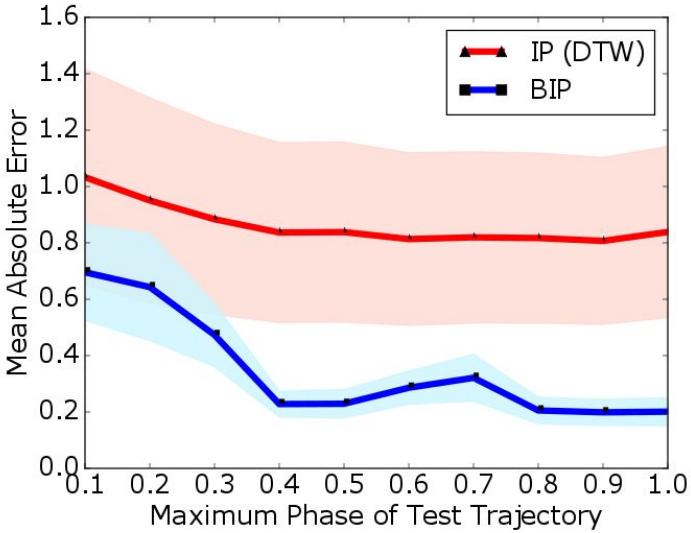


Spatial robustness

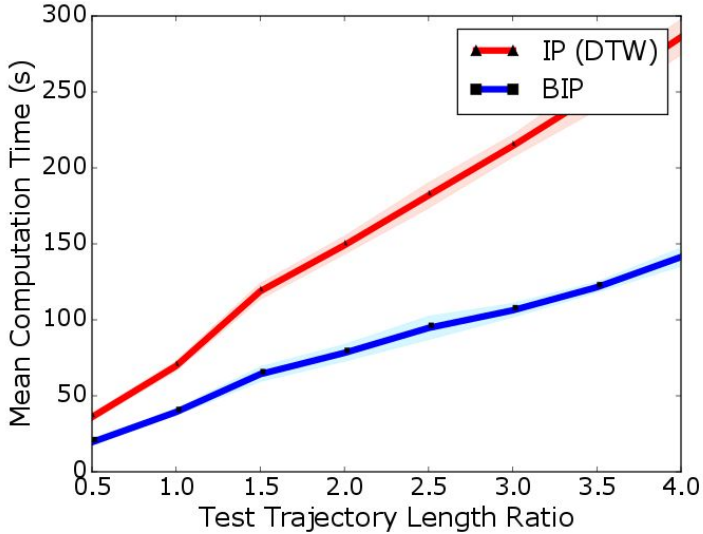


Temporal robustness

Results cont.



Partial visibility



Computational complexity

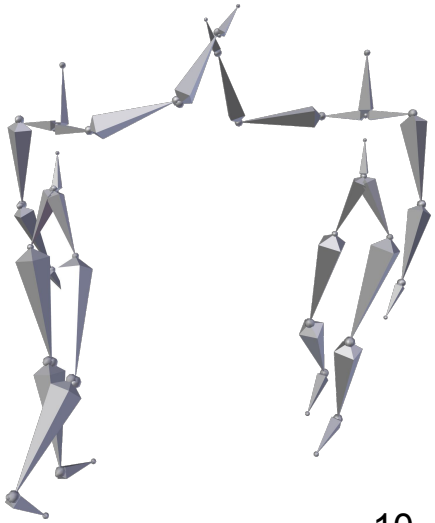
Applications

Conclusions

- Established conceptual link between HRI and SLAM
- Bayesian Interaction Primitives from demonstrations
- Properties:
  - Improved robustness to noise
  - Reduced computational complexity
  - Fully Bayesian inference in time and space
- Applied to multiple, physical human-robot collaboration tasks

Future work:

- Highly multimodal scenarios
- Noise-resilient SLAM algorithms



Acknowledgements

Thank you to all Hosoda Lab members at Osaka University, especially

Prof. Koh Hosoda

Assist. Prof. Shuhei Ikemoto