Learning Motion Trajectories from Phase Space Analysis of the Demonstration

Paul Gesel, Dain La Roche, Momotaz Begum
pac48@wildcats.unh.edu, Dain.LaRoche@unh.edu, mbegum@cs.unh.edu

University of New Hampshire

Cognitive Assistive Robotics Lab

Introduction

- Novel low-level learning from demonstration framework
- Formulation derived from the concept of phase space in dynamic system theory
- Evaluation on several manipulation tasks shows the robustness of our approach

Background

- Gaussian Mixture Model
- Dynamic Motion Primitive
- Stable Estimator of Dynamical Systems

Phase Space Model

Phase space transition function is defined as a dynamic system that reaches a desired phase space state (position, velocity), given any initial state.

$$\ddot{x} = k\left(x + \frac{x_n^2 - x_c^2}{2\,(x_n - x_c)}\right) + \frac{\dot{x}_n^2 - \dot{x}_c^2}{2\,(x_n - x_c)} \tag{1}$$

- Parameter k is learned from the demonstration
- Piece-wise PSTFs reconstructs the demonstration's space space curve
- Cut points are required when velocity changes direction

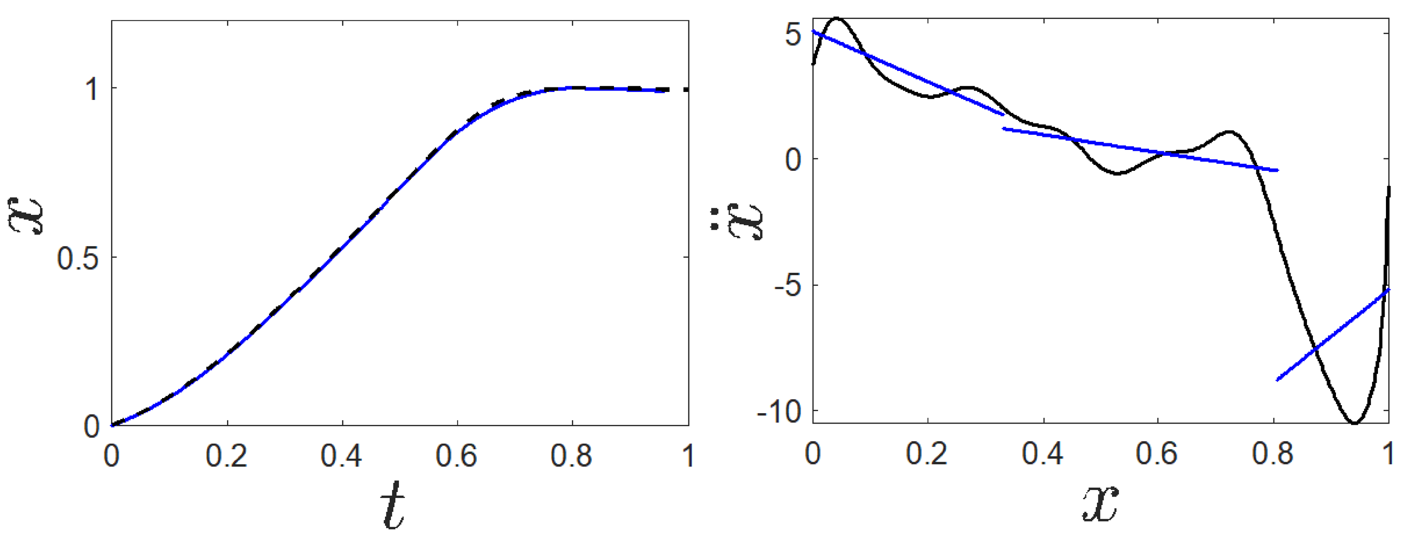

Figure 1: An example trajectory is shown on the left and its position vs. acceleration curve is shown on the right.

Synchronizing multiple dimensions is achieved via coupling each dimension with a braking heuristic.

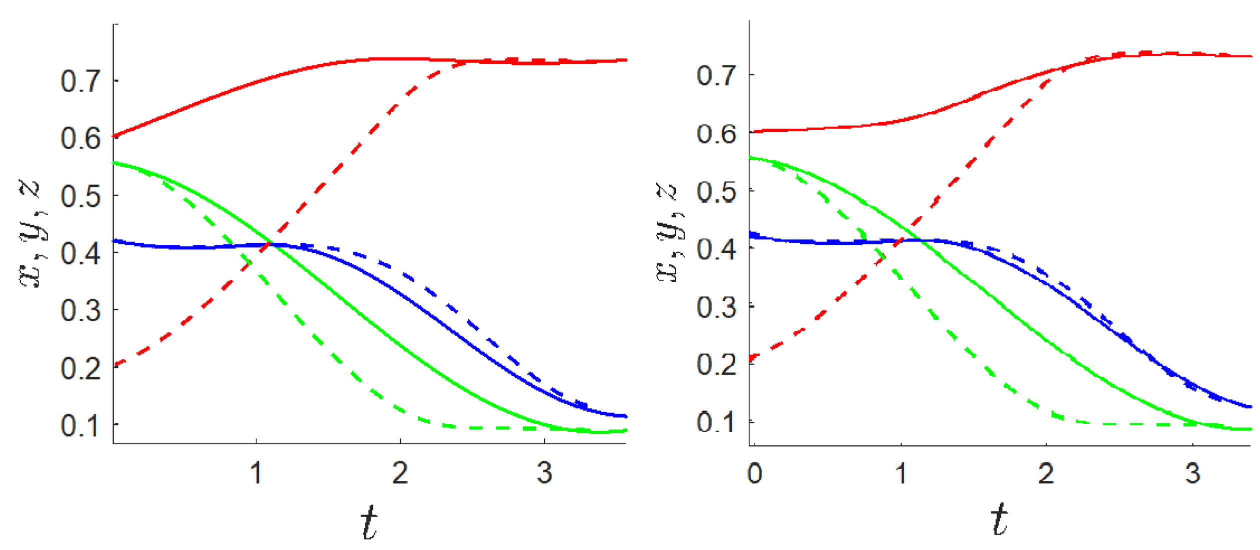

Figure 2: Three dimensional trajectory with and without time synchronization applied is shown in the left and right plots, respectively.

Collision avoidance is achieved via dynamically altering the executing PSTF

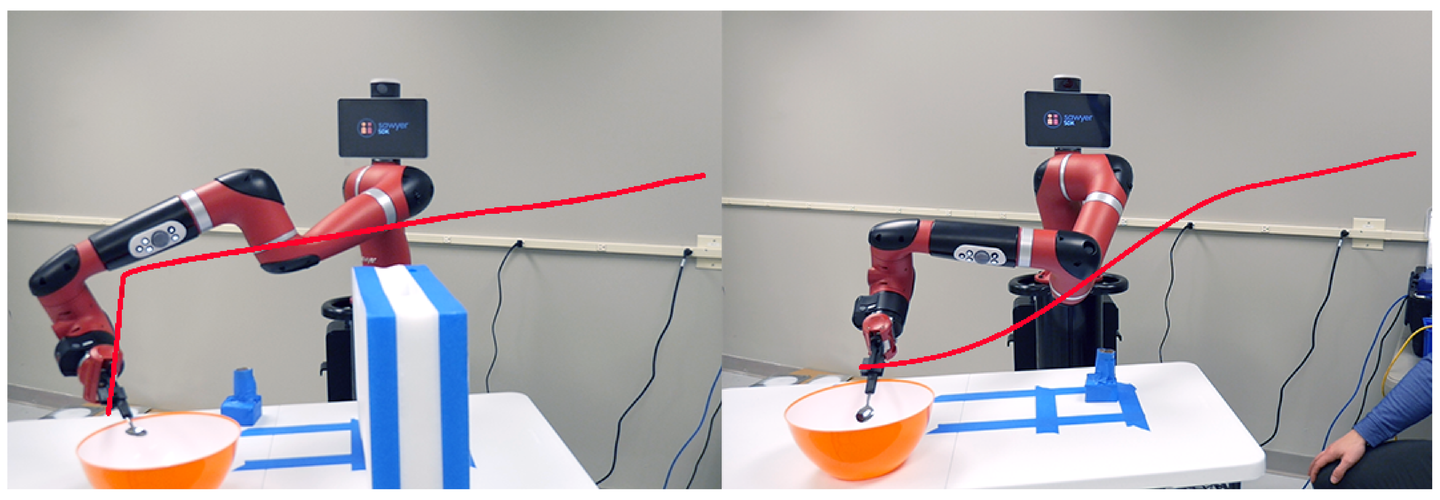

Figure 3: The obstacle free task is shown on the right and collision avoidance task is shown on the left.

Phase Space Model Continued

$$\ddot{x} = \begin{cases} k_n x + c_n - T\dot{x}(t_E - t_e) & \dot{x} \geq \frac{x_n - x_c}{|x_n - x_c|} \\ m & \dot{x} < \frac{x_n - x_c}{|x_n - x_c|} \\ \frac{-\dot{x}_c^2}{2(x_{ob} - x_c)} & CD \end{cases} \tag{2}$$

Experimental Setup and Results

Figure 4: The feeding assistant task setup is shown on the left and the cylinder rolling task setup is shown on the right.

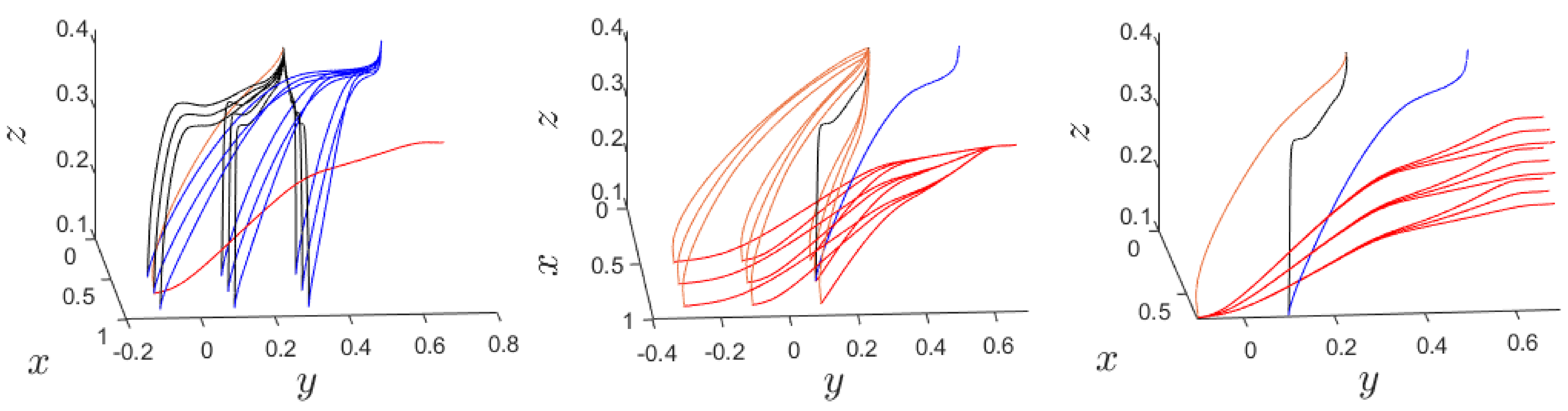

Figure 5: A variety of goal adaptations for three sub-task of the feeding assistant task are shown.

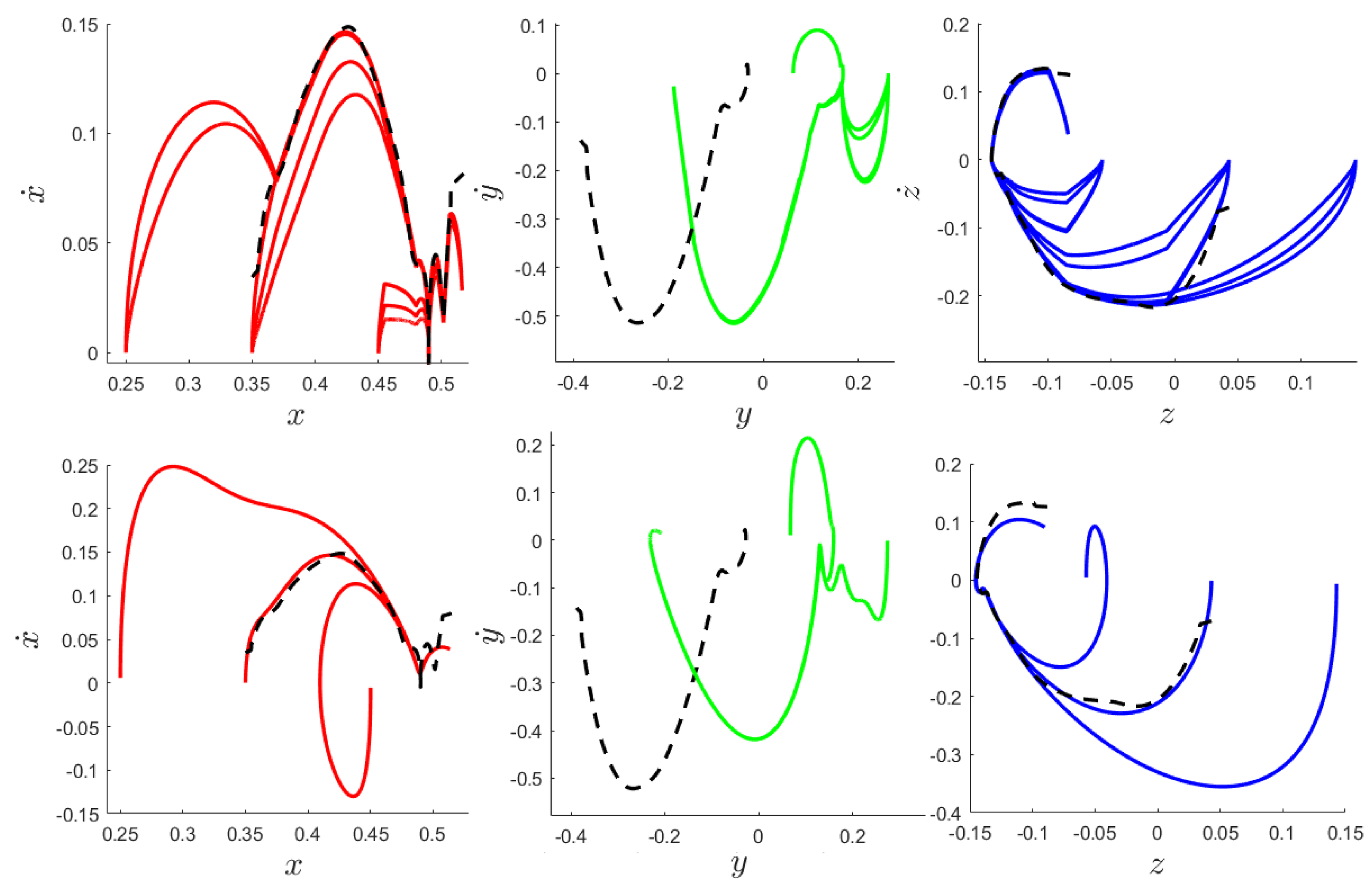

Figure 6: The plots on the top show the phase space curves produced by the PSM for several starting locations. The plots on the bottom show the phase space curves produced by the DMP. The cylinder was place at $y = 0.1\ m$.

Conclusion

- The advantage of the PSM's phase space based goal compared to DMP's time-position based goal is demonstrated in the cylinder rolling task.
- The benefits of this framework are robustness to temporal perturbation via time invariant dynamics, multidimensional synchronization, learning from a single demonstration, and the ability to transition between phase space states with continuous velocity via PSTFs.

Acknowledgements

Research support
IIS 1830597