Generating Manipulation Trajectory Using Motion Harmonics

Yongqiang Huang and Yu Sun
Robot Perception and Action Lab (RPAL)
Computer Science and Engineering
University of South Florida

Motion Learning and Generating

- Observe human manipulation motions
  - Different types of manipulation motion trajectories
- Represent motion
  - Essence of the motion: spatial-temporal patterns
  - Flexibility to adapt
- Generate motion trajectory for new constraints
  - Robot’s kinematic and dynamic models
  - Environment constraints – obstacles
  - New start and goal

Motion Representations

- Hidden Markov model (HMM)
- Directed graph, hierarchical graph, motion graph
- Principal component analysis (PCA)
- Linear dynamical system (LDS)
- Gaussian process (GP) + Newtonian dynamics
- Movement primitive
- Functional data analysis – primarily in motion analysis
- Many others

Approach Overview

Demonstrate world-space trajectories

Preprocess trajectories

- Time alignment
- Spatial adaptation
- Trajectories converted to joint space

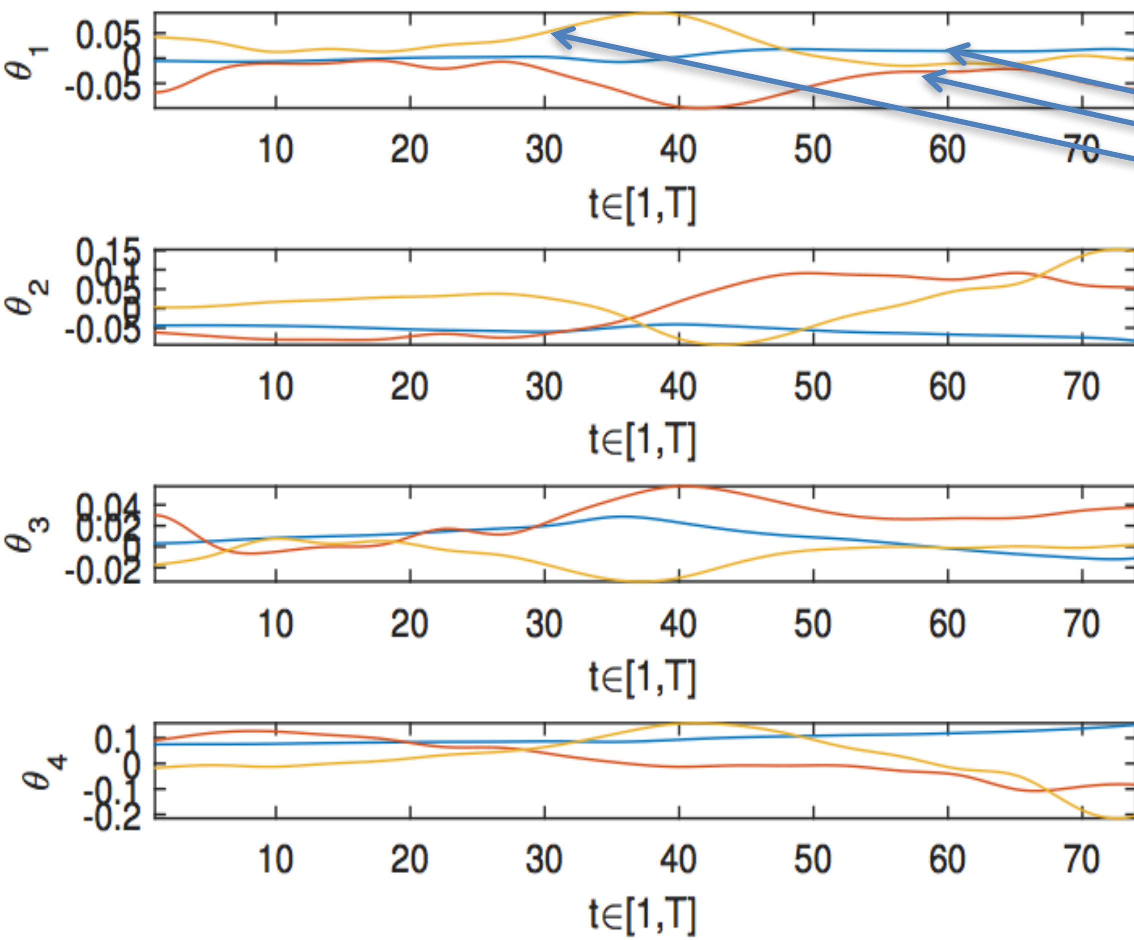
Extract motion harmonics

- Functional representation
- Eigenanalysis

Generate new trajectories

- Using motion harmonics
- Using constraints
- Optimization

Functional Motion Data Analysis and Representation

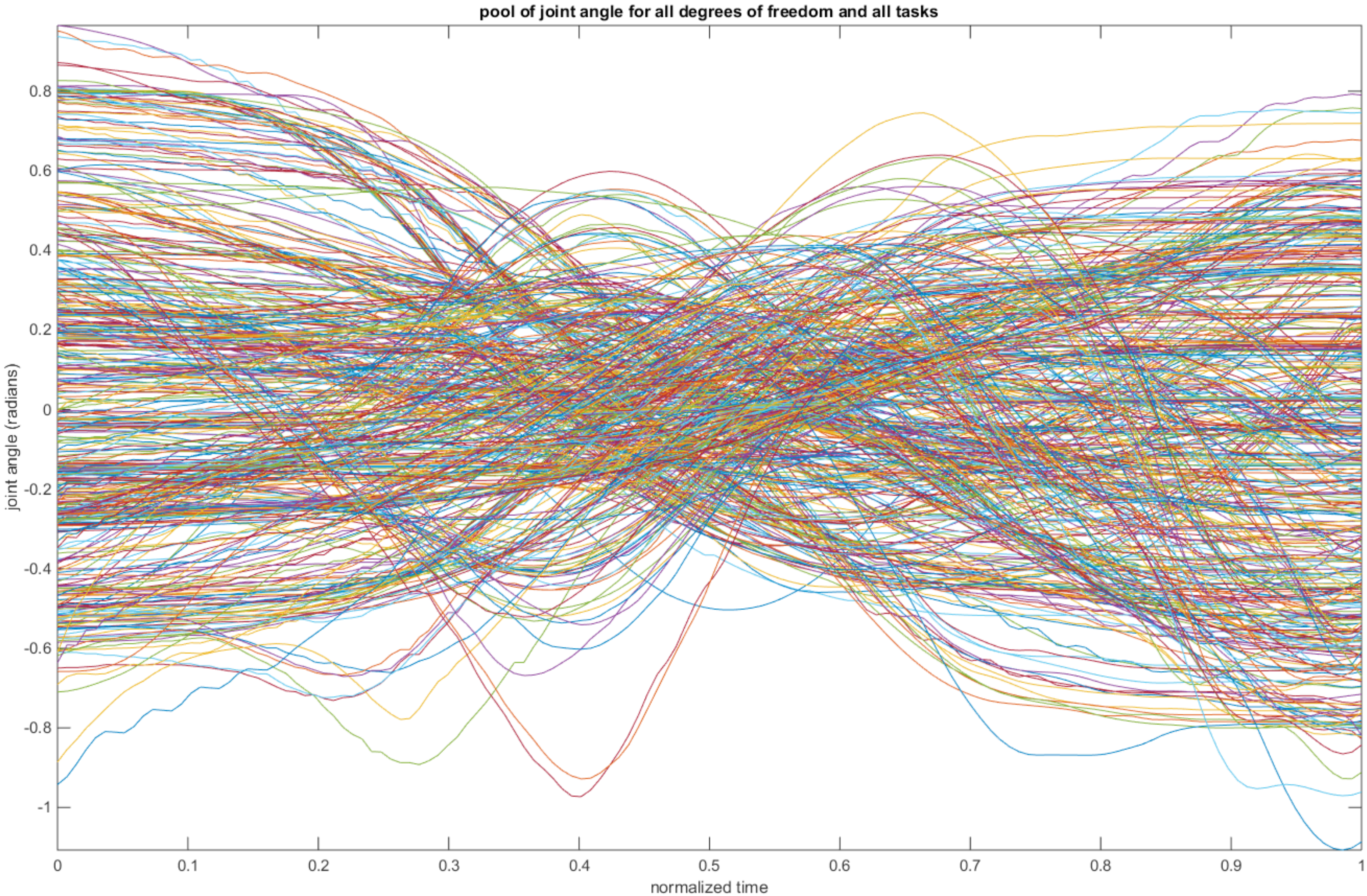


$M(t) = a_0 + a_1 f_1(t) + a_2 f_2(t) + a_3 f_3(t)$

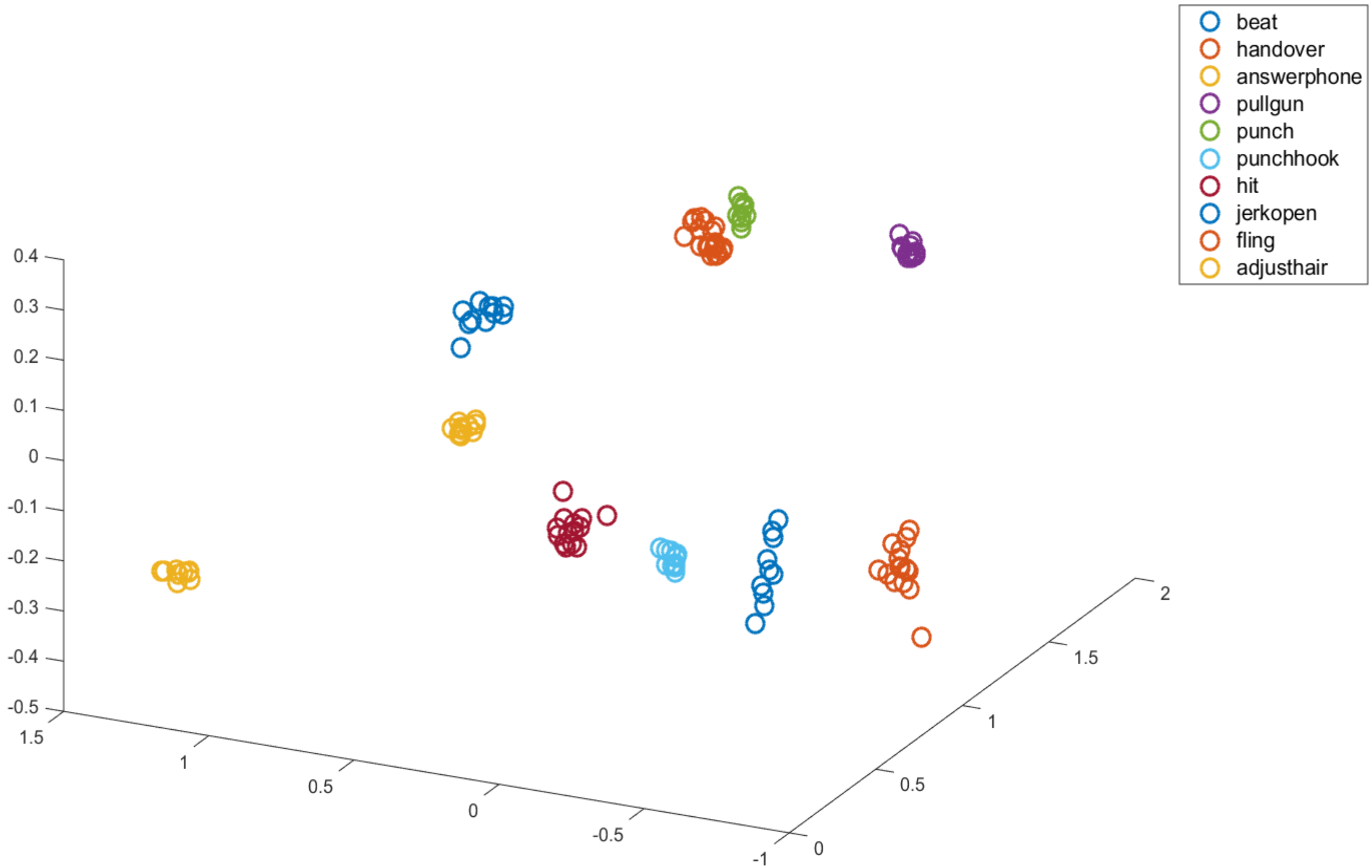
$f_i(t)$ – motion harmonic

- contains a set of basis functions:
  B-spline or Fourier

Demonstrated Motion Trajectories



Motion Clustering



Motion Trajectory Generating

$M_{robot}(t) = a_0 + a_1 f_1(t) + a_2 f_2(t) + a_3 f_3(t)$

$$\min_{a \in R^3} \{\underbrace{\alpha \mathrm{dist}[(M_{robot}(a, t), M_{demo}(t)]}_{\text{Similarity to demonstrated trajectories}} + \sum_{i=1}^{m} \underbrace{(\mathrm{dist}[M_{robot}(a, t), C_i])}_{\text{Passing through constraints}} \}$$

Subject to

$$M_{robot}(t) \in [p_{\min}, p_{\max}],$$

$$\dot{M}_{robot}(t) \in [v_{\min}, v_{\max}],$$

$$\ddot{M}_{robot}(t) \in [a_{\min}, a_{\max}]$$

Evaluation

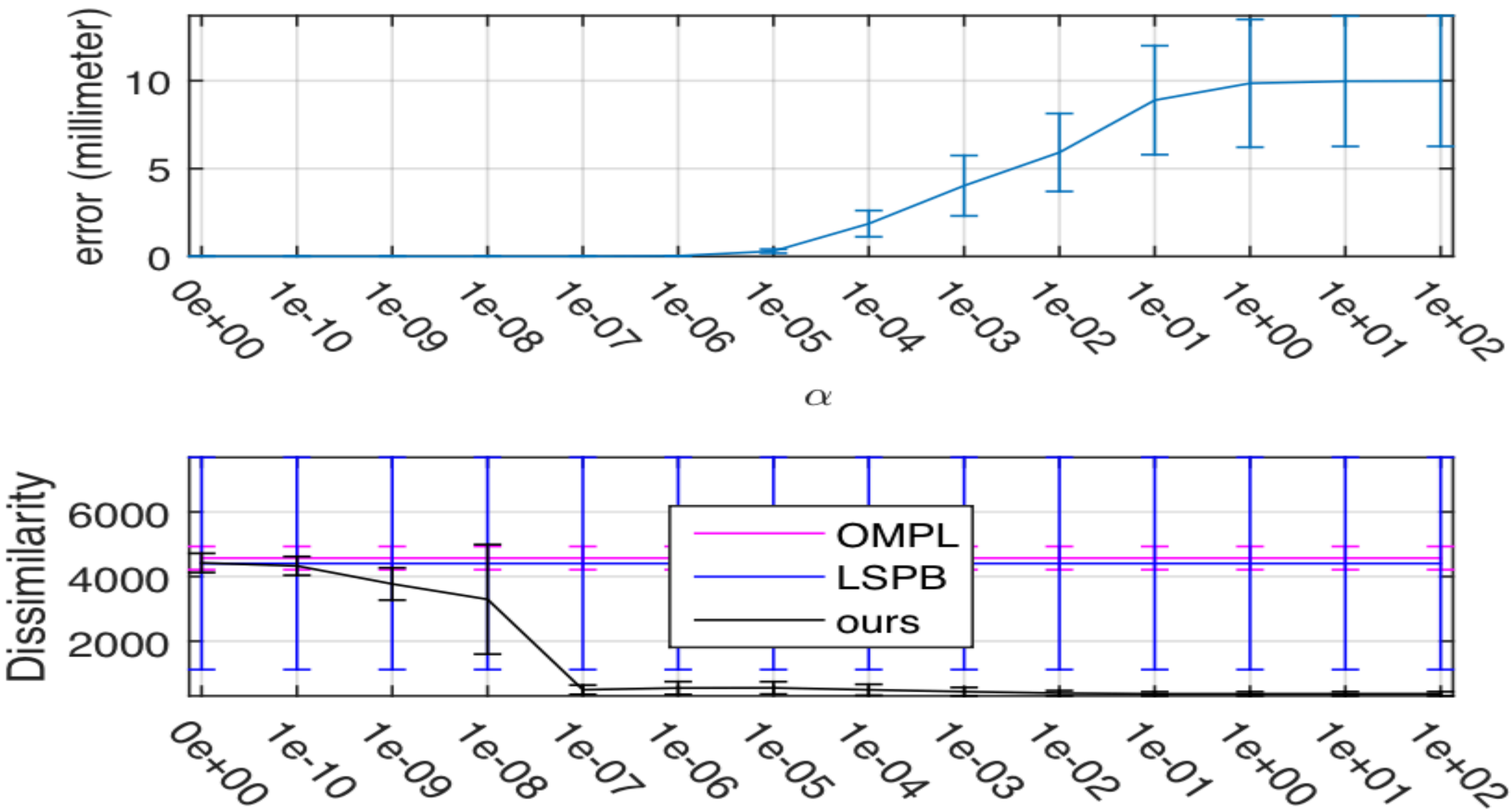
- We evaluate two aspects of our approach
  1. How well does the new trajectory meet the two goals of the optimization?
     - resembling the demonstrated trajectories
     - pass the via points at specified time.
  2. Can the via points guide the new trajectory around obstacles?

Metrics

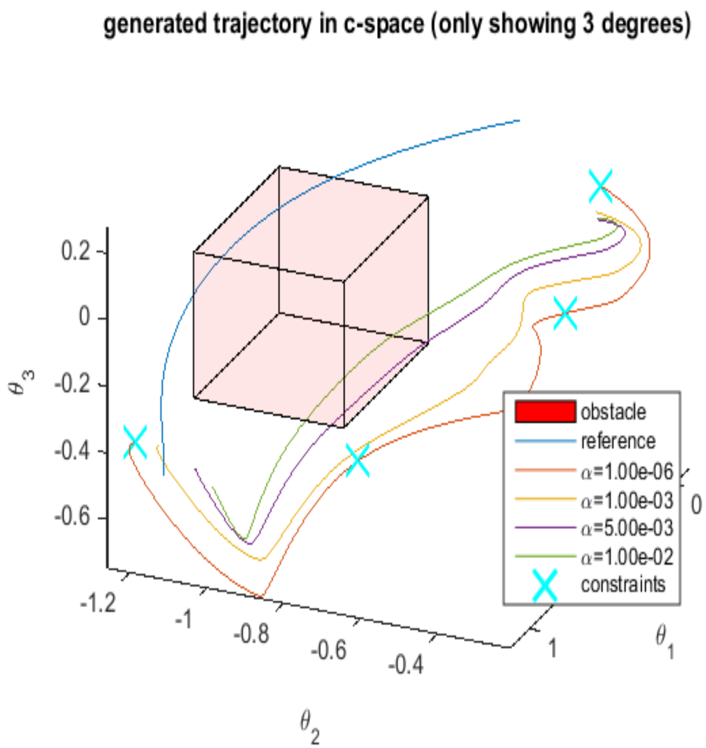
- The similarity of the new trajectory to the demonstrated trajectories is measured by the normalized distance computed by DTW.
  - First, we scale each demonstrated joint-space trajectory
$$q_n^* = \left(s_{final}(q_n - \bar{q}) + \bar{q}\right) + d_{final}$$
  - Then, we compute the average normalized DTW distance as the similarity measure
$$similarity(y) = \frac{1}{N}\sum_{n=1}^{N} DTW(q_n^*, y)$$
- The error of a new trajectory is defined by the distance between the via points and the corresponding points on the trajectory
$$error(y) = \frac{1}{N_c}\sum_{i=1}^{N_c} |y(t_i) - f(e_i)|$$

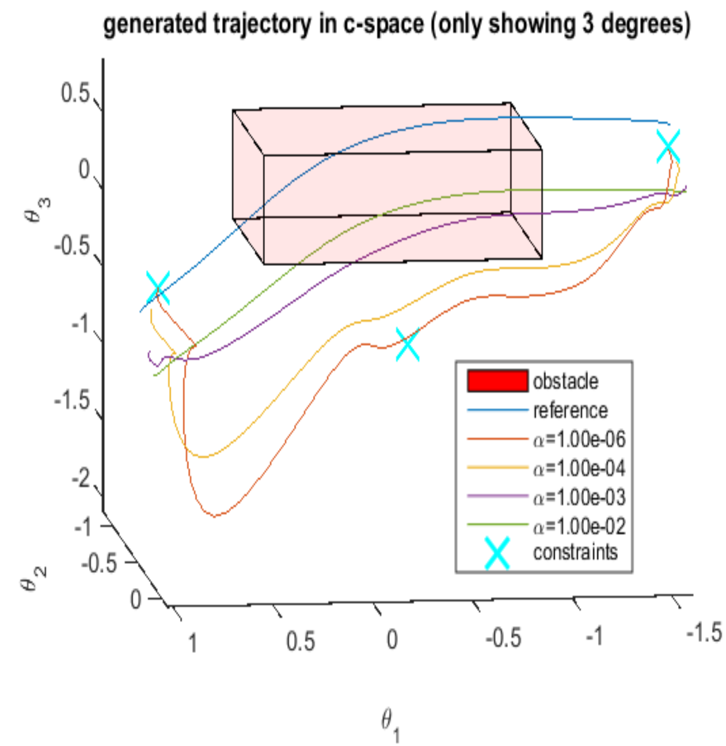
Where $f(\cdot)$ represents forward kinematics.

Error and Similarity



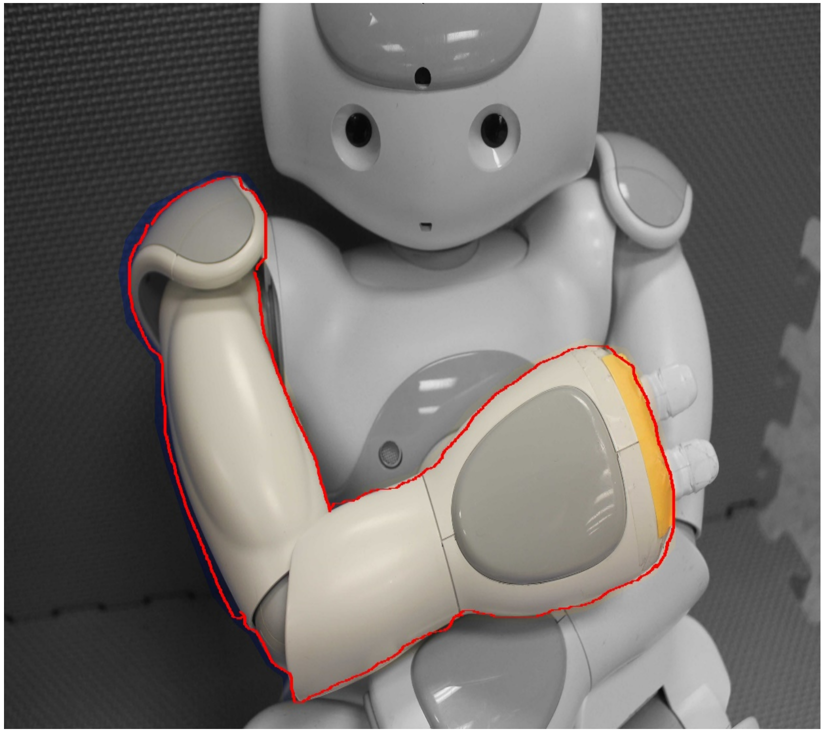
Evaluation: Success at Clearing Obstacles with via Points





Evaluation with NAO

- We used the right upper arm of NAO as the kinematics chain
- We randomly generated sets of start and end points
- We compare with the Linear Segment Parabolic Blend (LSPB) algorithm, and the RRT algorithm from OMPL



Visual Comparisons

Summary

- Represent functional motions with motion harmonics
- Keep spatial-temporal motion patterns and meet constraints
- Use dissimilarity between motion and distance to the constraints to evaluate
- Work with sample-based motion planners
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