Generating Manipulation Trajectory Using Motion Harmonics

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

- **Preprocess trajectories**

- **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

\[ M_{\text{robot}}(t) = a_0 + a_1 f_1(t) + a_2 f_2(t) + a_3 f_3(t) \]

\[ \min_{a \in \mathbb{R}^3} \{ \alpha \text{dist}[(M_{\text{robot}}(a, t), M_{\text{demo}}(t))] + \sum_{i=1}^{m} (\text{dist}[M_{\text{robot}}(a, t), C_i]) \} \]

Subject to

\[ M_{\text{robot}}(t) \in [p_{\text{min}}, p_{\text{max}}], \]
\[ \dot{M}_{\text{robot}}(t) \in [v_{\text{min}}, v_{\text{max}}], \]
\[ \ddot{M}_{\text{robot}}(t) \in [a_{\text{min}}, a_{\text{max}}] \]

Passing through constraints

Similarity to demonstrated trajectories
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
    \[ q_n^* = (s_{final}(q_n - \bar{q}) + \bar{q}) + d_{final} \]
  - Then, we compute the average normalized DTW distance as the similarity measure
    \[ \text{similarity}(y) = \frac{1}{N} \sum_{n=1}^{N} DTW(q_n^*, y) \]
- The error of a new trajectory is defined by the distance between the via points and the corresponding points on the trajectory
  \[ \text{error}(y) = \frac{1}{N_c} \sum_{i=1}^{N_c} |y(t_i) - f(e_i)| \]
Where \( f(\cdot) \) represents forward kinematics.
Error and Similarity

\[ \alpha \]

\[ \text{error (millimeter)} \]

\[ \text{Dissimilarity} \]

OMPL
LSPB
ours
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

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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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References


2. Sun, Y., Yun Lin, and Yongqiang Huang (2016) Robotic Grasping for Instrument Manipulations, URAI, 1-3


