Human motion prediction for “human-aware” robots

Jim Mainprice, PhD
“HUMANS TO ROBOTS MOTION” (HRM)
Research Group Leader
Human **Space Sharing** Skills

- Dynamic Environment - Reactive - Accurate
- Multi-Agent Coordination - "Body language" - Anticipation
Human **Interactive** Manipulation

- Pick
- Place
  - Give
  - Receive
  - Co-Manipulate
Dynamic Social Movement
Anticipation

Legibility
Human-Robot Interactions

Robot Models
- Model of the human, context of the task and the context of the interaction

Human Models
- Mental model of the robot, social cognition and interpersonal perception difference

Interaction Models
- Models of the communication and interaction

Task
Robot Models

Perception

Uncertainty

State Estimation

Human Estimation

Prediction

Optimal Control

Action

Uncertainty

Robot Models

Perception

Uncertainty

State Estimation

Human Estimation

Prediction

Optimal Control

Action
1. Human Aware Motion Planning
2. Inverse Optimal Control of Collaborative Motion
3. Combining with Data Driven Dynamical Models
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“Human-Aware” extension of motion planning algorithms

Anthropological Studies: Theory of «proxemics» [Hall66]

Elementary Interaction Costs

1 - Distance
2 - Visibility
3 - Musculoskeletal Effort

Trajectory Space
\[ \Xi = \{ \xi | \xi : [0, 1] \rightarrow C \} \]

Configurations Space
\[ C = \{ q \in \mathbb{R}^d \} \]

Workspace
\[ \mathcal{W} = \{ x \in \mathbb{R}^3 \} \]

Explores trajectories globally

Explores trajectories locally

Collaborators: Rachid Alami, Thierry Siméon, Daniel Sidobre, LAAS-CNRS
“Human-Aware” extension of motion planning algorithms

Motion planning with binaire vs. continu cost maps

Motion planning with statique vs. mobile human receiver

RRT

T-RRT + STOMP

Statique

Mobile

Collaborators: Rachid Alami, Thierry Siméon, Daniel Sidobre, et al. LAAS-CNRS
Anticipation of human movement in dynamic motion planning

Solution: Prediction of swept volume

\[ p(x|\xi) = \sum_{m=1}^{M} p(x|C_m)p(C_m|\xi) \]

- Number of classes
- Partial trajectory
- Voxel
- Probability of traverse in class \( m \)
- Probability to belong to class \( m \) encoded in a GMM

Collaborators: Dmitry Berenson, Worcester Polytechnic Institute
Publication: IROS 2013
1. Human Aware Motion Planning
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Imitation of interactive behaviors

How to balance the elementary interaction features in the cost function?

1) Demonstration

2) Features

Perception → State Estimation → Optimal Control → Action

Solution: Inverse Optimal Control

\[
c(\xi) = \int_T \sum_{i=1:N} w_i e^{-\|\xi(t) - x_i\|^2_{RBF}} dt
\]

Collaborators: Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute

Publications: ICRA 2015, TRO 2016
Collaborative Manipulation Experiment

Collaborators: Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute
Publications: ICRA 2015, TRO 2016
Goalset Stochastic Inverse Optimal Control

Learning  PIIRL [Kalakrishnan 13]

- Demonstration
- Trajectory Sampling
- Learned cost landscape

Prediction  STOMP [Kalakrishnan 11]

Trajectory vector

\[ \xi = \begin{bmatrix} q_1 & \ldots & q_N \end{bmatrix}^T \]

Smoothness Metric

\[ R \leftarrow K^TK \]

Goalset Trajectory Sampling

- Modified covariance
- Project the samples to the goal region with respect to the smoothness metric

\[
\begin{aligned}
\minimize_{\Delta \xi} & \quad \frac{1}{2} \|\Delta \xi\|_K^2 \\
\text{subject to} & \quad h(\xi_t + \Delta \xi) = 0
\end{aligned}
\]

Collaborators: Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute

Publications: ICRA 2015, TRO 2016
Learning **Collaborative Motion Objectives**

**Collaborative Experiment**

**Start State**

**Final State**

**Inverse Optimal Control**

\[ \Phi \rightarrow \arg\min_w - \sum_{i=1}^{D} \log \frac{e^{-w^T \Phi_i}}{\sum_{k=1}^{K} e^{-w^T \Phi_{i,k}}} \rightarrow \mathcal{W}^* \]

**Goalset Trajectory Sampling**

**Human Motion Library**

**Collaborators:** Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute

**Publications:** ICRA 2015, TRO 2016
Interactive Features Importance

- **Smoothness**
  - Length
  - Sum of squared velocity, acceleration and jerk

- **Interpersonal distances**
  - Between the center of each link
    - Shoulder
    - Elbow
    - Wrist

- **C-space distance to a resting posture**
  - 12 DoFs considered

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Collaborators: Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute
Publications: ICRA 2015, TRO 2016

Significant interference example

Interpersonal distances

Iterative Re-Planning
Anticipation of Human-Robot movement by Inverse Optimal Control

15 users x 8 execution = 2120 trajectories

IOC better than manual tuning of the cost function and GMMs

- The robot is executing fixed trajectories
- Compare against baseline tunings
  - Conservative: all distances active
  - Aggressive: no-interlink distances
- Compare with multiple metrics
  - Joint center distances
  - Task space metric

\[ d(T_1, T_2) = \| p_1 - p_2 \| + 0.1 \cdot \cos^{-1}(\| v_1, v_2 \|) \]

Collaborators: Rafi Haynes et Dmitry Berenson, Worcester Polytechnic Institute
Publications: ICRA 2015, TRO 2016
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Long-term activity and motion prediction

- Reaching
- Placing
- Pouring
- Drinking
- ....

\[ \xi = \begin{bmatrix} q_1 & \ldots & q_N \end{bmatrix}^T \]
Data gathering of **activity and motion**

PUPIL sensor

Fullbody Data

~1 hour of data
7 different activities
Tracking objects and human

Collaborators: Philipp Kartzer, Jan Hoffman Stuttgart Uni.
Combining Data Driven **Dynamical Models** with **Trajectory Optimization**

- Discrete trajectory of states: $\xi_t = (s_0, \ldots, s_t)$
- **Step 1:**
  - Learn dynamic behavior of humans: $s_{t+1} = f(\xi_t)$
  - We do this using a Gaussian process (GP)
- **Step 2:**
  - Unroll the prediction
  - Iteratively apply $s_{t+1} = f(\xi_t)$
- **Step 3:**
  - Account for constraints e.g. target state
  - **Optimize the trajectory**

**Example Trajectories**

**Step 3: Optimize the trajectory**

![Synthetic 1D data with target state constraint](image)

**Collaborators:** Philipp Kartzer, Jan Hoffman Stuttgart Uni.  
**Publications:** IEEE Humanoids 2018, IROS Workshop 2018, ECCV Workshop 2018
Prediction of human activity

Algorithm:
- Sample Affordances
- Generate Spline Trajectories
- Evaluate the features
- Evaluate Energy/Cost for sampled frame

Collaborators: Jan Hoffman, Philipp Kartzer, Stuttgart Uni.
Publications: IROS Workshop 2018
Architectures for Reactive Manipulation
Integrating feedback at multiple time scales

300+ experiments on 4 dynamic scenarios with dynamical geometries

Collaborators: Nathan Ratliff, Jeannette Bogh et al., Max Planck Institute, Tübingen
Publications: IROS 2016, LBR-ICRA 2017, RA-L 2018
"Gauss-Newton" for motion planning

\[ \xi = \begin{bmatrix} q_1 & \ldots & q_N \end{bmatrix}^T \]

**Constraints**
- Joint Limits
- Collision

**Objectives**
- Joint Postural
- Configuration Space Smoothness
- Task Space Smoothness
- Terminal Potential

**Constraints** \[ \Rightarrow \text{Objectives} \]

**Compute Lagrange Multipliers**

**Unconstrained Proxy**

**Local Approximation**

**Optimization Step**

**Local Optimizer**

**while not StopCondition() do**
\[
\begin{align*}
u & \leftarrow f(\xi_i) \\
g_\xi & \leftarrow \nabla f(\xi_i) \\
\xi_{i+1} & \leftarrow \xi_i - \eta_i B_i^{-1} g_\xi
\end{align*}
\]

**Collaborators:** Nathan Ratliff et al., Max Planck Institute, Tübingen

**Publications:** IROS 2016

"Gauss-Newton" for motion planning

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**Publications:** IROS 2016
Modeling the Environment

Smooth occupancy grids using tri-cubic splines
Conclusion

- Motion planning for manipulation
  ➔ High-DOF, Continuous state-space
  ➔ Sampling-based + local methods

- Human-awareness requires a predictive models of human motion
  ➔ safety, comfort (i.e, social awareness)

- Challenges:
  ➔ Model environment : affordances
  ➔ Model awareness : theory of mind
  ➔ Hierarchical representations
Collaborators Past and Present

Questions

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