A Game-Theoretic Approach for Adaptive Action Selection in Close Proximity Human-Robot-Collaboration (HRC)

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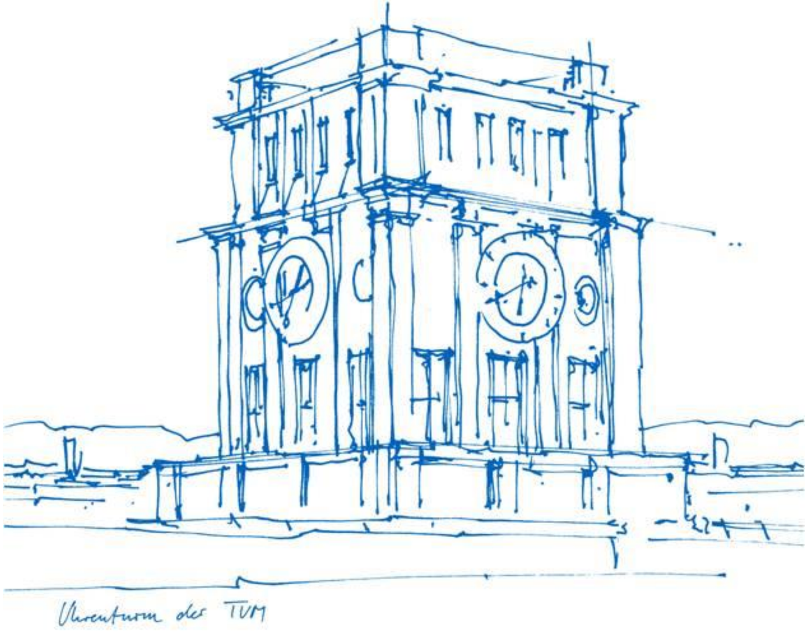


Motivation and General Approach

Autonomous Robots in Human-Robot Collaboration (HRC)

Given are high-level actions [Nau+ 2004] e.g.

```
pick(robot, object1)
pick(robot, object2)
pick(human, object1)
pick(human, object3)
```

The goal is to adapt high-level action-selection such that

- agents' effort is minimized
- team-efficiency is maximized
- human safety is guaranteed

Contribution

Autonomous Decisions in HRC

State of the art: Adapt to human action without reflecting human adaptivity [Mainprice+ 2013; Hawkins+ 2014; Maeda+ 2014; Gombolay+2015]

Contribution: Evaluation of the complete action-space for all involved agents using **normal form games**

Applied Game Theory in HRC

State of the art: Application limited to differential game theory or simulations [Jarrassé+ 2012; Li+ 2015; Bahram+ 2015; Turnwald+ 2016]

Contribution: discrete online action selection in real HRC

General Approach: Adaptive Action-Selection as a Normal Form Game

Iterative Decision Process as a **Game:**

- Finite Game
- Rational Players
- Complete Information
- Non-Zero-Sum
- Non-Cooperative
- Normal Form

Basic Assumptions

Direct mapping of high-level action and estimated trajectory

Interaction heuristics rather than purely data-driven models

Applied Interaction Heuristics

- Task dependent reward r_k
- Native cost c_k^{nat}
- Interactive cost c_k^{inter}

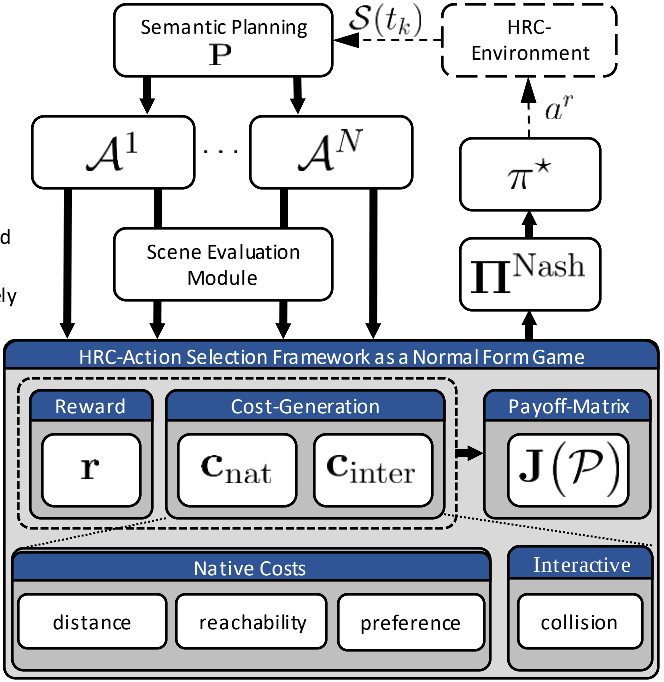
$$J_k(\boldsymbol{\pi}) = r_k - c_k^{\text{nat}}(a_k) - c_k^{\text{inter}}(\boldsymbol{\pi})$$
$$\text{with } a_k \in \boldsymbol{\pi}$$

Retrieve Nash-Equilibrium/-a

$$\boldsymbol{\pi}^\star \leftarrow \underset{\boldsymbol{\pi}^k \in \boldsymbol{\Pi}^{\text{Nash}}}{\operatorname{argmax}} \; u^i(\boldsymbol{\pi}^k)$$

$$\boldsymbol{\pi}^\star \leftarrow \underset{\boldsymbol{\pi}^k \in \boldsymbol{\Pi}^{\text{Nash}}}{\operatorname{argmax}} \; \sum_{i=0}^{N} u^i(\boldsymbol{\pi}^k)$$

$$\boldsymbol{\pi}^\star \leftarrow \underset{\boldsymbol{\pi}^k \in \boldsymbol{\Pi}^{\text{Nash}}}{\operatorname{isPareto}}(\boldsymbol{\pi}^k)$$



Cited Related Work

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D. Nau, M. Ghallab and P. Traverso. Automated Planning: Theory & Practice. Morgan Kaufmann Publishers Inc., 2004, p. 229. isbn: 1558608567.
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Conclusion

Design of a normal form game decision framework

Online application of proposed framework

Confirmed three hypotheses in extensive user-study

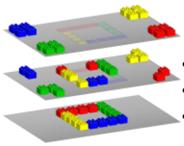
Future Work

Extension to multi-agent systems

Comparison with latest state-of-the-art on complex scenarios

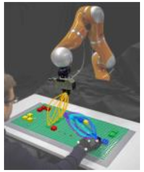
Experimental Insights I – General Overview, Results and Video

Experimental Setup



Baseline comparison to a fixed action policy

- Cooperative pick- and place assembly
- $n = 30$ participants
- All participants build same task under different policies applied



Policies Compared

1. *Fixed* - Non-reactive policy in which the robot is simply following.
2. *Line* - Proposed Framework with straight line human motion prediction
3. *Spline* - Proposed Framework with minimum jerk human motion prediction

Hypotheses

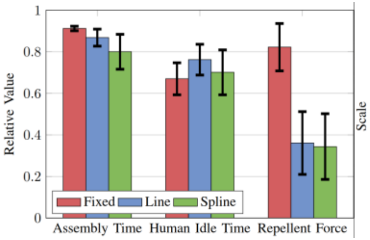
- **H1** - Participants prefer the robot's action-selection when working in the Spline or Line mode over the decisions in Fixed mode.
- **H2** - The decisions of the robot increase the safety for the human in Spline or Line mode, compared to the Fixed mode.
- **H3** - The robot's decisions adapt to the human and therefore decrease the overall completion time in the Spline or Line mode, compared to the Fixed mode.

Experimental Measurements

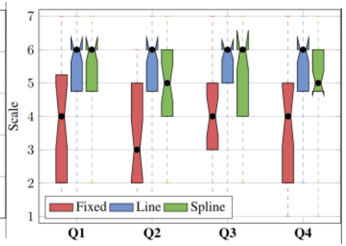
- Subjective questionnaire (**H1**) using a 7-point Likert scale
- Potential field based compliance control around robot end-effector to measure repellent force as a safety measure (**H2**)
- Overall completion time from first robot motion to assembly of last object(**H3**)

Experimental Results

Empirical Measurements



Subjective Feedback



How would you grade the ...

Q1 ... *collaboration with the robot?*
Q2 ... *robot as a helpful co-worker?*
Q3 ... *motion reaction of the robot?*
Q4 ... *action selection of the robot?*

Question	Overall Comparison	Line vs Spline	Line vs Random	Spline vs Random
Q1	**0.0016**	0.6670	**0.0034**	**0.0014**
Q2	**0.0004**	0.9324	**0.0009**	**0.0005**
Q3	**0.0032**	0.9327	**0.0025**	**0.0052**
Q4	**0.0021**	0.7709	**0.0023**	**0.0030**

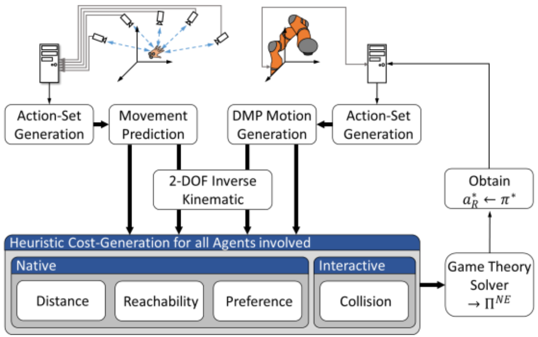
p-Values; statistically significant values shown in bold font

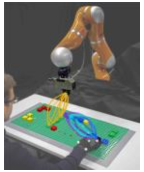
Results

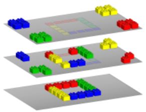
1. Subjective Evaluation proved statistic significant improvements for **H1.**
2. The reduced repellent force of the potential (safety) field confirms **H2.**
3. Except some minor overlap in the variance of the assembly time concerning *Line* vs. *Fixed* comparison, **H3** is confirmed.

Experimental Insights – Applied Heuristics and Video

Experimental Framework







Cost-Generation native components

Distance Based Costs

$$c^i_{\mathrm{nat}} = \alpha\, c^i_{\mathrm{travel}} + \beta\, c^i_{\mathrm{reach}} + \gamma\, c^i_{\mathrm{pref}}$$

$$c^i_{\mathrm{travel}} = \alpha_{\mathrm{L}} \int_{t_k}^{t_e} \dot{\mathbf{p}}^i_{\mathrm{s}}(t)\, dt + \alpha_{\mathrm{T}} \int_{t_k}^{t_e} 1\, dt + \alpha_{\mathrm{D}} ||\mathbf{p}_{\mathrm{e}} - \mathbf{p}^i_{\mathrm{s}}||$$

Reachability Based Costs

$$c^i_{\mathrm{reach}} = \begin{cases} \infty & \text{if } d > d_{\max} \\ \exp\left(w_{\mathrm{r}} \left(\frac{d - d_{\max}}{d_{\max}}\right)^2\right) & \text{else} \end{cases}$$

Preference Based Costs

$$c^i_{\mathrm{pref}} = \begin{cases} 0 & \text{if } ||\dot{\mathbf{p}}^i_{\mathrm{s}}|| < \epsilon_v \\ \varphi_{\mathrm{diff}}\, ||\dot{\mathbf{p}}^i_{\mathrm{s}}|| & \text{else} \end{cases} \qquad \varphi_{\mathrm{diff}} = \left| \cos^{-1}\left(\frac{\langle \mathbf{d}_{\mathrm{dest}}, \dot{\mathbf{p}}^i_{\mathrm{s}}(t) \rangle}{|\mathbf{d}_{\mathrm{dest}}|\, |\dot{\mathbf{p}}^i_{\mathrm{s}}(t)|} \right) \right|$$

Cost-Generation interactive component

Collision risk evaluation given two trajectories in x-y-plane

$$c^{i,j}_{\mathrm{inter,k}} = \begin{cases} c_{\mathrm{col}} & \text{if } d_{\mathrm{t}} < d_{\mathrm{cmin}} \\ \Psi(d_{\mathrm{t,k}}) & \text{if } d_{\mathrm{cmin}} < d_{\mathrm{t,k}} < d_{\mathrm{cmax}} \\ 0 & \text{else,} \end{cases}$$

$$c^{i,j}_{\mathrm{inter,avg}} = \frac{\sum_{k=1}^{N_{\mathrm{smpl}}} w_k^{\mathrm{temp}}\, c^{i,j}_{\mathrm{inter,k}}}{\sum_{k=1}^{N_{\mathrm{smpl}}} w_k^{\mathrm{temp}}}, c^{i,j}_{\mathrm{inter}} = \max(c^{i,j}_{\mathrm{inter,avg}}, c^{i,j}_{\mathrm{inter,max}}),$$

$$c^{i,j}_{\mathrm{inter,max}} = \max_{k \in \{1,2,\ldots,N_{\mathrm{smpl}}\}} \left(w_k^{\mathrm{temp}}\, c^{i,j}_{\mathrm{inter,k}} \right).$$

Robot Motion Control

Use a database of prelearned Dynamic Movement Primitives (DMPs):

$$\tau \ddot{\mathbf{y}} = \alpha_z(\beta_z(\mathbf{g} - \mathbf{y}) - \dot{\mathbf{y}}) + \mathbf{f}, \in \mathbb{R}^3,$$

Robotic Action set therefore given by