Goal-directed Imitation Learning from Humans

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Abstract

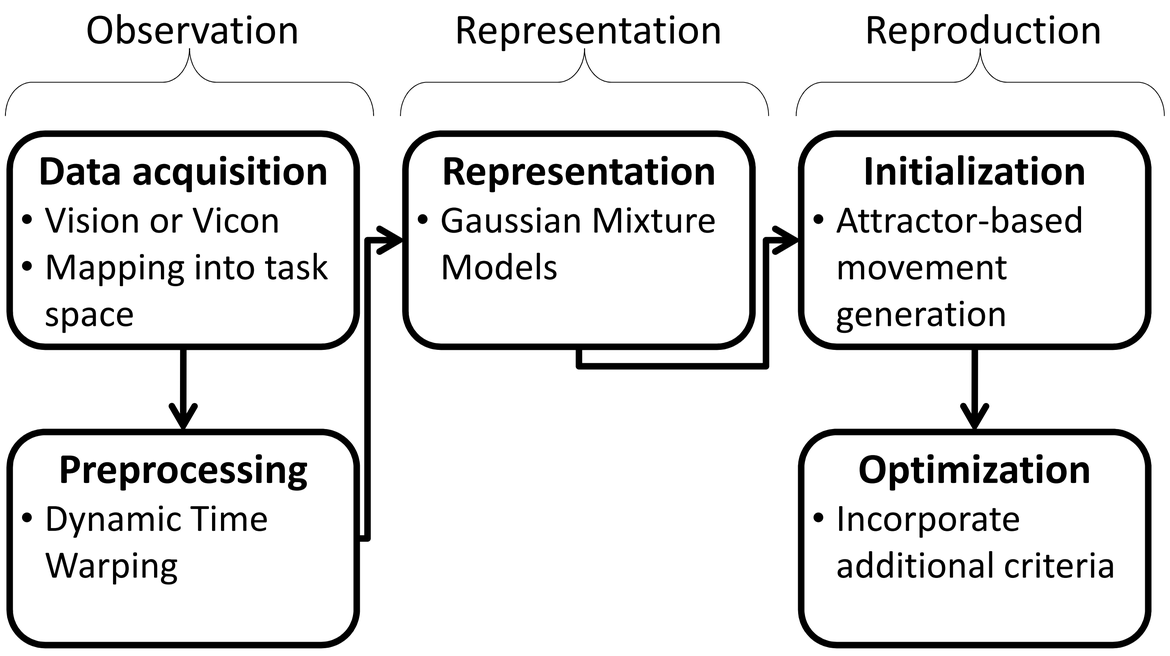
This project aims at learning goal-directed movements by imitation with a humanoid robot. The scope is limited to full-body movements with 2 arms, suited for bimanual tasks. We target to make a significant step from qualitative posture imitation towards capturing the essence of movements. We also see a close link between imitation learning and action recognition, and think that the project will bring us some steps into this direction.

Learning of task representations[1]

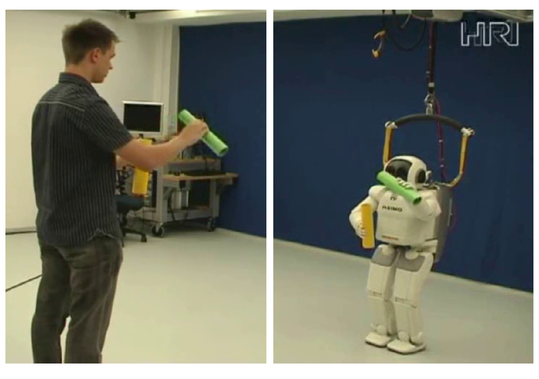
Basic idea

When learning from multiple demonstrations, a high inter-trial variance stands for less important parts of a movement. By allowing the robot to diverge from a learned movement in phases of high inter-trial variance, it is able to fulfill additional criteria (e.g. collision avoidance, center-of-gravity control, …).

Imitation learning framework



- The variance information over several task demonstrations is used as an importance measure. This information is continuously incorporated into the movement generation process.
- Task spaces are used to model the observed movement task. This handles equally dimension reduction, generalization and the correspondence problem.
- The task learning is based on object trajectories only and no assumptions about the teacher's or robot's postures are made.
- To reproduce a learned movement, an attractor-based movement optimization scheme is utilized that also operates on task spaces.



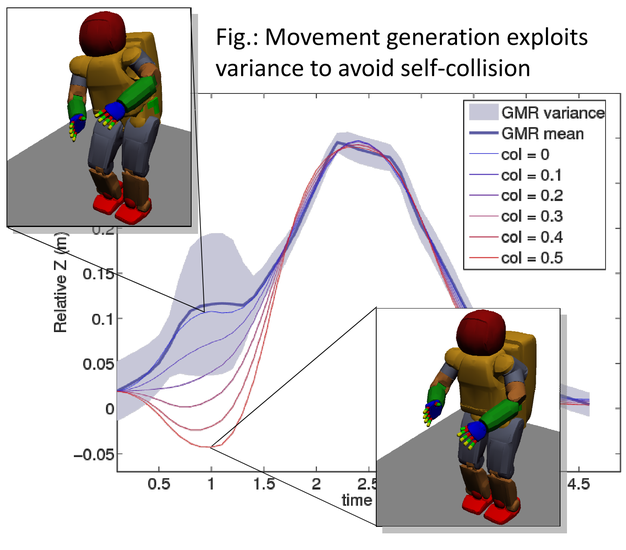
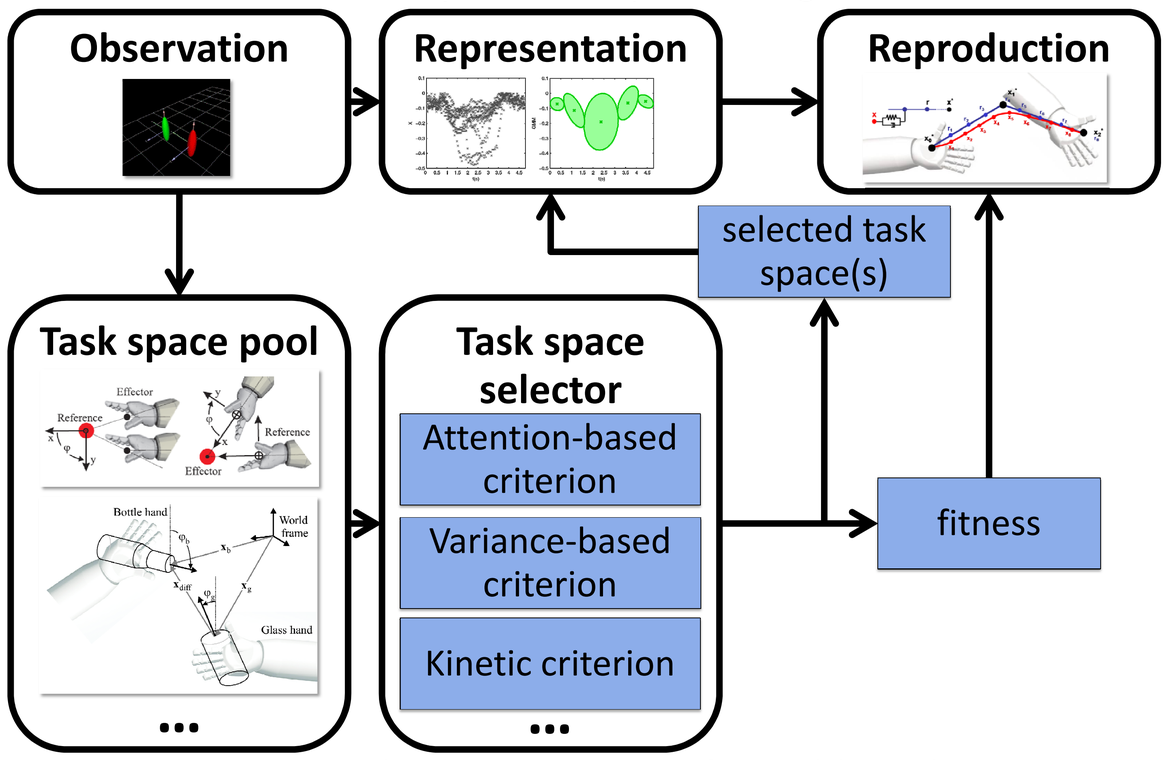


Fig.: Movement generation exploits variance to avoid self-collision

Selection of task spaces[2]

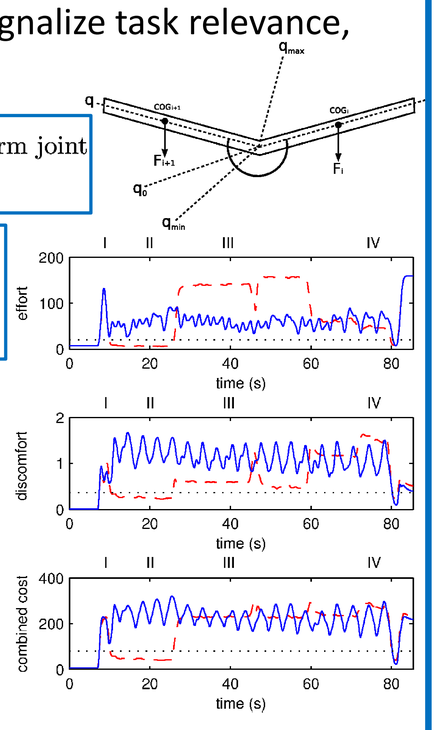
- **Problem:** Which task space for representing a movement?

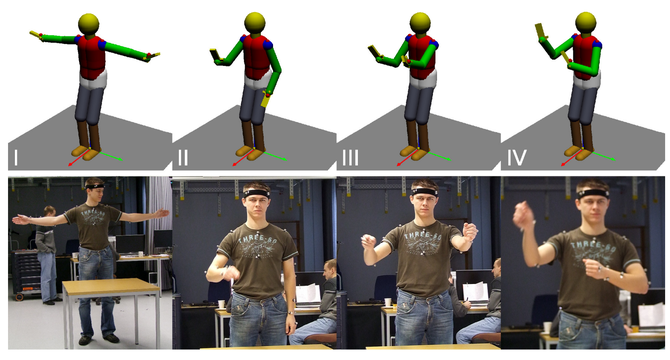


- The task space pool subsumes a set of possible task spaces to choose from
- The task space selector chooses task spaces suitable for the representation and/or adapts the reproduction
- **Attention-based criterion**
  - Reactive gazing behavior (the robot focuses the most salient object)
  - Interactive task space selection (teacher receives direct feedback)
- **Variance-based criterion**
  - When comparing different task spaces, the one that yields the lowest inter-trial variance should be used for the representation
  - Euclidean Dynamic Time Warping for comparing task spaces
- **Kinetic criterion**
  - Low inter-trial variance does not always imply a high task relevance
  - Idea: Model-based approach to estimate internal states of the human demonstrator
  - Uncomfortable and exhausting postures signalize task relevance, otherwise they would have been avoided

$$C_{\text{effort}} = \mathbf{M}^T \mathbf{S} \mathbf{M} \quad \mathbf{M} = \sum_{i \in \text{arm}} \mathbf{J}_{\text{COG}i}^T \mathbf{m}_i \quad \mathbf{S}^{(jk)} = \begin{cases} 1.0 & j = k \text{ is arm joint} \\ 0.0 & \text{else} \end{cases}$$

$$C_{\text{discomfort}} = \sum_{j \in \text{arm}} D_j \quad D_j = \begin{cases} \left(\frac{q_{0_j} - q_j}{q_{0_j} - q_{\min_j}} \right)^2 & \text{for } q_{\min_j} \le q_j \le q_{0_j} \\ \left(\frac{q_j - q_{0_j}}{q_{\max_j} - q_{0_j}} \right)^2 & \text{for } q_{0_j} < q_j \le q_{\max_j} \end{cases}$$





References

1. Manuel Mühlig, Michael Gienger, Sven Hellbach, Jochen J. Steil, Christian Goerick, "Task-level Imitation Learning using Variance-based Movement Optimization", *IEEE International Conference on Robotics and Automation (ICRA),* **2009**
2. Manuel Mühlig, Michael Gienger, Jochen J. Steil, Christian Goerick, "Automatic Selection of Task Spaces for Imitation Learning", *IEEE International Conference on Intelligent Robots and System (IROS), to appear*, **2009**

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