Co-Robotics for Off-road and Construction Equipment

Girish Chowdhary

Asst. Professor
Agricultural and Biological Engineering
Aerospace Engineering
University of Illinois at Urbana Champaign

ILLINOIS
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

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Co-robots

- Robots that work with humans,
- Complete automation is futile as safety critical decision requires human presence,
- Co-robots can learn from expert Human operators,
- Train/Guide novice operator allowing experts to remain in field.

http://www.hulcher.com/

Robot Learhing from Demonstration

- Successful examples: Tennis Swings, Walking gaits, pick 'n' place, Complex Helicopter maneuvers
- Generic approaches: RL, IRL, DMP, Options framework
- Recently: BNPs for auto-segmentation of demonstrations

Tennis Swing [6]

Challenges

- Computationally efficient method for high dimensional continuous state-action spaces
- Performing meaningful segmentation of demonstrated tasks, to enable reuse of skills learned
- Intelligent sequencing of motion primitives for novel tasks
- Shared-Control to aid users in executing complex tasks, without hindering takeover

Human-robot Collaborative Learning and Task Execution

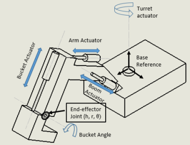
Goal: To develop robust solution framework that enables co-robot to

- Perform segmentation of multi-output, multi-input demonstration data,
- These segmentation should lead to human understandable subgoals,
- Guide a novice operator in efficiently decomposing their task to speed up their learning without hindering take-over

Methodology

Vector-valued Gaussian Process and Non-Bayesian Clustering (VGP-NBC):

- Define observations & inputs for VGP: Actuator positions were observed, and the end-effector joint position (h, r, θ) and the bucket angle were the inputs.



- Motion primitives such as Boom Raise or Bkt Curl, arise from different VGP models.
  - Non-Bayesian Clustering [4]: Hypothesis test used to determine and cluster different VGP models representing motion primitives.

$$\frac{P(y \mid M_i)}{P(y \mid M_j)} \underset{\hat{M}_j}{\overset{\hat{M}_i}{\gtrless}} \eta$$

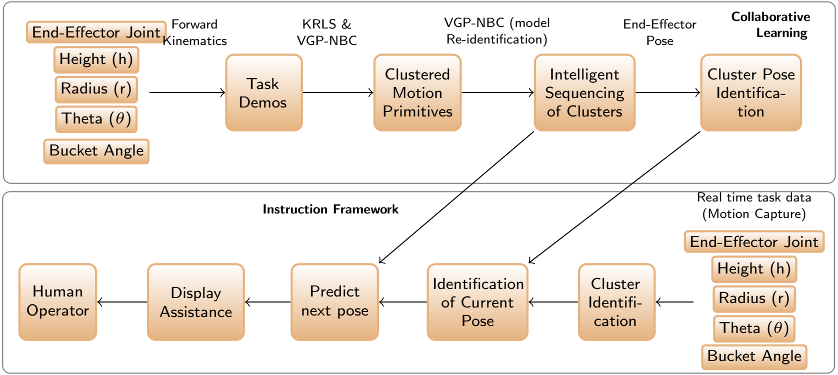
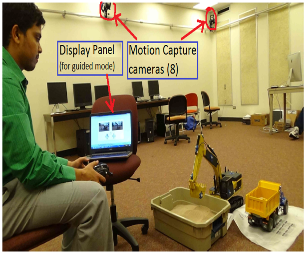


Figure: Overview of LfD and Instruction Framework

Learning from demonstration for off-road equipment

- Challenge: Task efficiency and performance depends on operator skill
  - Skill at the controls
  - Experience in decomposing complex tasks (task understanding)
- Hypothesis: Co-robots can learn latent task-decompositions from expert demonstrators and guide novices

Demonstration and Clustering VGP models



Demonstration under motion capture set-up

- Identification of Motion Primitives.
- Human Understandable ?

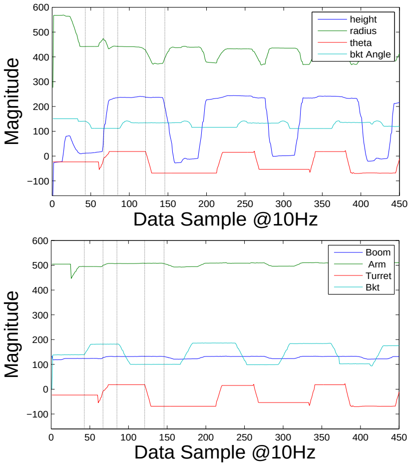
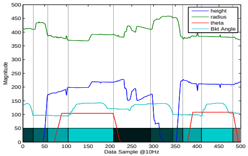
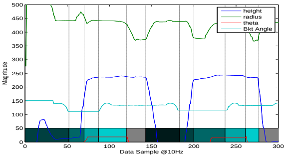
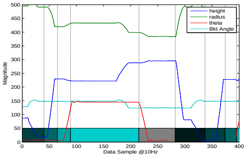


Figure: Demonstrated data for three cycles of the truck loading task with cluster segmentation overlaid.

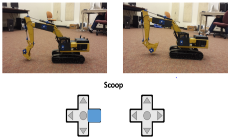
- For data with different temporal characteristics, algorithm yields similar end-effector poses.

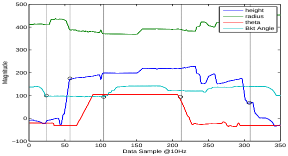


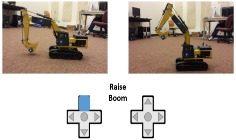




- **Instruction Framework:** Communicate to Novice
- End-Effector Method: Association of End-effector state changes with actuator mechanisms.



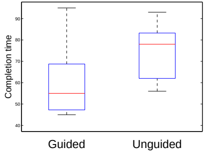




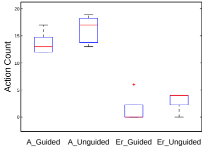
Guided versus Unguided Demos

Task was performed more efficiently in the Guided (G) mode as compared to the Unguided (UG) mode for two cycles of truck loading operation,

- Better completion time,
- Reduced total number of actions taken (A), and minimal Erroneous actions (Er),



(a) Completion time



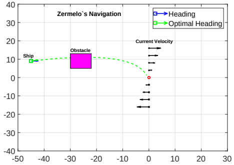
(b) Action counts

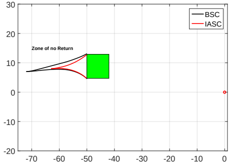
Assistive Training

- Assistive reinforcement: direction of joystick movement
- Eventually can be replaced with color only

Collaborative Task Execution: What Happens in Off-Nominal Situations

- Shared-control: Aid the human without boring them, and let them take over as needed
- Challenge Problem: Zermelo's navigation [2]: Autonomous agent and Human operator collaborate to navigate ship to the Origin,
- Off-nominal situation: Obstacle known to Human, and optimal path known to Autonomous agent
- Smaller zone of return ⇒ greater reaction time available to the operator





Intent ($\dot{\gamma}$) is the rate at which the human operator's input differ from that of the optimal. Mathematically,

$$\begin{aligned}\dot{\gamma} &= \frac{d}{dt}(|\theta_0 - \tilde{\theta}|), \text{ or} \\ &= \frac{d}{dt}(|\Delta|) \end{aligned} \tag{1}$$

where, θ_0 is the operator's input, and $\tilde{\theta}$ is the optimal. Resulting three facets to human intention,

- $\dot{\gamma} > 0 \Rightarrow$ human intends to differ,
- $\dot{\gamma} < 0 \Rightarrow$ human intends to follow,
- $\dot{\gamma} = 0 \Rightarrow$ human is in passive agreement.

Blended Shared Control

Zermelo's Navigation
using
Blended Shared Control

Intent Aware Shared Control

Zermelo's Navigation
using
Intent Aware Shared Control

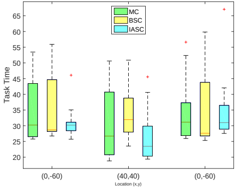


Figure: Boxplot comparison of completion times, from three different starting locations, for Manual Control (MC), Blended shared control (BSC), and IASC.

Table: Obstacle Collision: Design of IASC controller is responsive to Off-nominal situations.

Location (x, y)	Obstacle (x, y)	Manual Control	BSC	IASC
$(0, -60)$	$(-45, 8)$	1	10	2
$(40, 40)$	$(25, -8)$	0	4	3
$(0, -60)$	$(-75, 3)$	0	7	1

Contributions

- A computationally efficient Vector-valued Gaussian Processes Non-Bayesian Clustering (VGP-NBC) algorithm for real time clustering of vector-valued motion primitives.
- A semantically motivated instructional framework to train or assist novice users of construction co-robots that allows the corobot to transfer learned skills from experts to novice human operators.
- Validation of our approach through experimentation on a construction co-robot (a fully-functional 1:14 scale hydraulic excavator).
- Intent aware shared control design responsive to off-nominal situations, at the same time efficient over existing methods.

Non-stationary Markov Models

- Typically the transition model is assumed stationary, i.e. $p(x_t|x_{t-1})$ being time-invariant.
- Limits capability of Markov models to capture time-varying transitions between states.
- Modeling human dance or playing sports, co-robots performing complex tasks, fluctuations in stock index, require **time-varying Markov models**.

Key Ingredients to Model Non-stationary Markov Models

- Capability to detect the time-point of change in the transition model,
- Distinguish between two different transition models,
- Modeling the switching dynamics between Transition Probability Matrices(TPMs).
- Non-parametric modeling to capture potentially infinite TPMs.

Previous Work

- Jilkov et. al. (2004) [5]: Online Bayesian estimation of unknown TPM. Responds slowly to model changes.
- Fox et. al. (2007) [3]: Sticky HDP-HMM, a hierarchic Bayesian non-parametric approach. Learns a single averaged out TPM.
- Bertuccelli and How (2012) [1]: Online estimation of unknown, non-stationary Markov chain transition models with perfect state observation. Does not capture previous transition models.

Deep Markov Model

A non-parametric prior, that

- Learns an unknown number of Transition Probability Matrices (TPMs) from the data,
- Models the switch between TPMs using another hierarchic Markov chain.

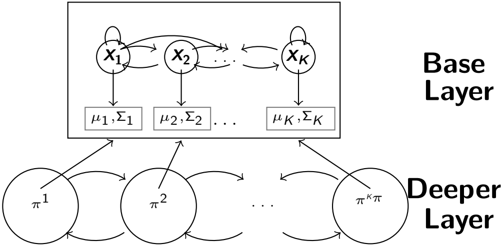
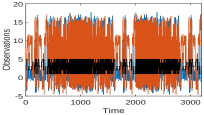
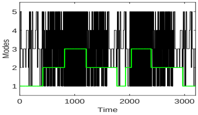


Figure: 1-layer deep Hidden Markov Model: Base layer is a HMM with K modes with Gaussian emissions, and a Deep layer that models Markovian dynamics among the set of K_π (TPMs).

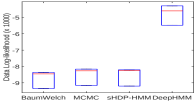
Preliminary Investigation on Synthetic data



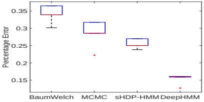
- Latent mode sequence (black) and true state sequence for a five mode HMM (with 2−d Gaussian emissions)



- Latent mode sequence overlaid with identified TPMs (green). Patterns reflect original TPMs.



- Predictive likelihood over 100 timeseries data generated by randomly switching TPMs,



- Viterbi assignment errors.

Team

PIs:

- Girish Chowdhary
- Prabhakar Pagilla
- Christopher Crick

Students:

- Harshal Maske
- Denis Osipychev
- Emily Kieson

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