COLLABORATIVE GOAL AND POLICY LEARNING

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OBJECTIVES

Our goal is to develop a robust solution framework that enables co-robots to

- learn to decompose loosely defined task into semantics-based subgoals by learning from skilled human operators
- guide novice operators in efficiently decomposing the task to speed up their learning

CONSTRUCTION CO-ROBOTS

- Robots that work with humans
- Complete automation impossible: safety critical decisions require human presence
- Human-robot collaborative learning and task execution
- Co-robots can train novice operators allowing experts to remain in field

ALGORITHM

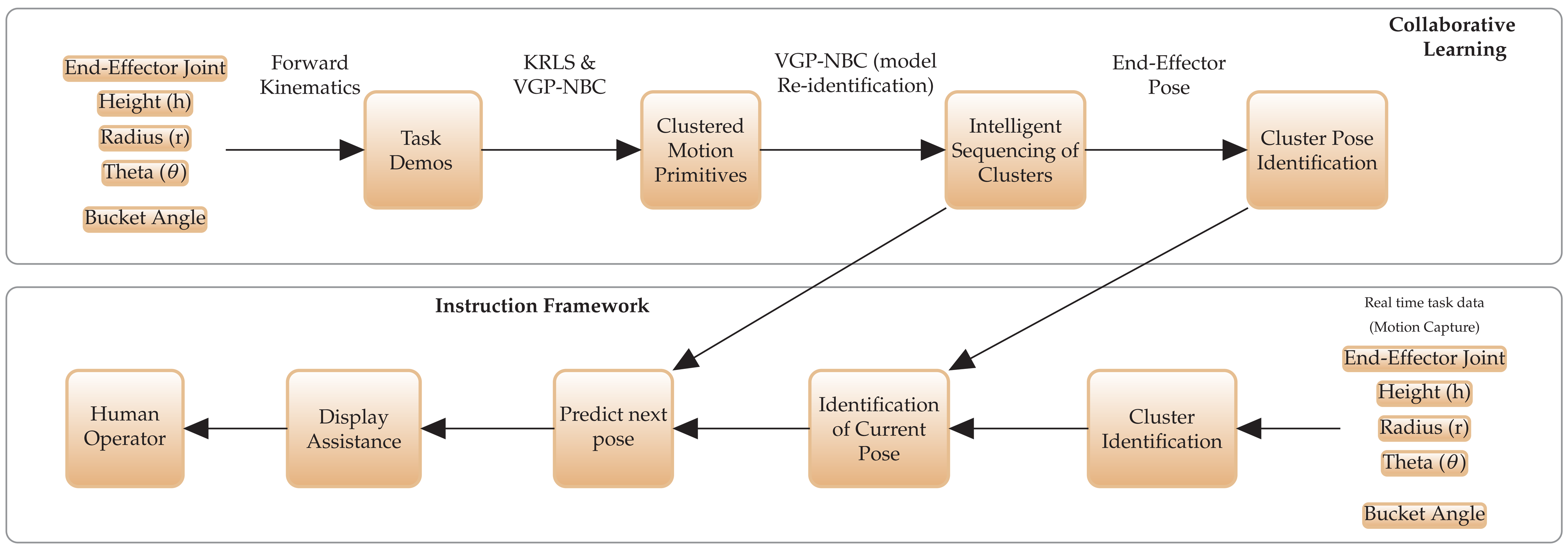
Algorithm 1 VGP Clustering

Input: Data (X, Y), lps size l, model deviation η
Initialize VGP Model 1 for (X, Y).
Initialize set of least probable points $S = \emptyset$.
while new data is available **do**
  Expand the current VGP model M_c using updated KRLS data
  If data is unlikely with respect to M_c, include it in S and build corresponding KRLS model K_S
  if $|S| == l$ **then**
    for each model M_i **do**
      - Calculate $D \times D$ log-likelihood matrices of data set S with respect to each M_i using (3)
      - Calculate the Frobenius norm for each of these matrices and find M_h, having lowest norm.
      - Make M_h the current model M_c.
      - Create new VGP M_S from K_S.
      - $KL \leftarrow \frac{1}{l}(\log(S|M_S) - \log(S|M_c))$
    if $\|KL\|_F > \eta$ **then**
      Add M_S as a new model.
    end if
    end for
  end if
end while

CONTRIBUTIONS

- New scalable nonparametric task models and learning algorithms
  - Computationally efficient Vector-valued Gaussian Process Non-Bayesian Clustering (VGP-NBC)
- Automatic subgoal decomposition and real-time adaptive controllers for executing motions generated by human operators
- Expertise elicitation, characterization and skill transfer interface design
  - Semantically motivated instructional framework
- Corroboration of algorithms through simulation and hardware experimentation

OVERVIEW OF LFD AND INSTRUCTION FRAMEWORK



METHODOLOGY AND RESULTS

Step 1: Vector-valued Gaussian Process and Non-Bayesian Clustering (VGP-NBC)

- VGP model: Actuator positions were observed; end-effector joint position (h, r, θ) and bucket angle were inputs

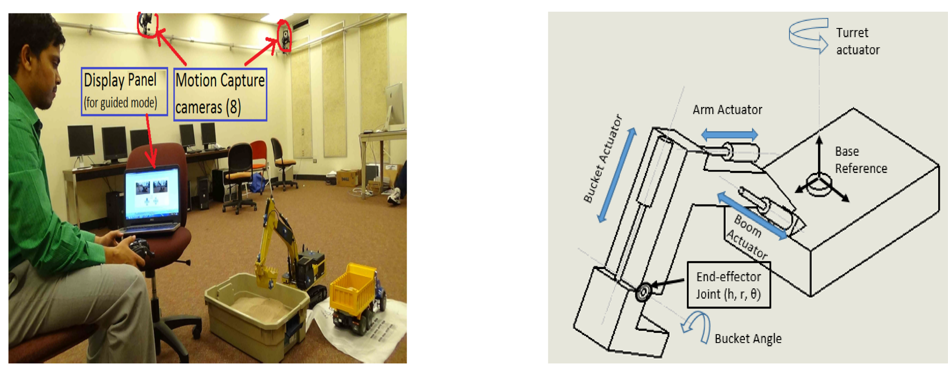


Figure 1: Experimental setup and excavator skeleton

- Motion primitives such as BOOM-RAISE or BUCKET-CURL arise from different VGP models.
- Non-Bayesian Clustering [1]: Hypothesis test used to determine and cluster different VGP models (Figure 2).

$$\frac{P(y \mid M_i)}{P(y \mid M_j)} \underset{\hat{M}_j}{\overset{\hat{M}_i}{\gtrless}} \eta \qquad (1)$$

- Changepoints for the clusters match actual end-effector poses which a human trainer might utilize to train novice operators.

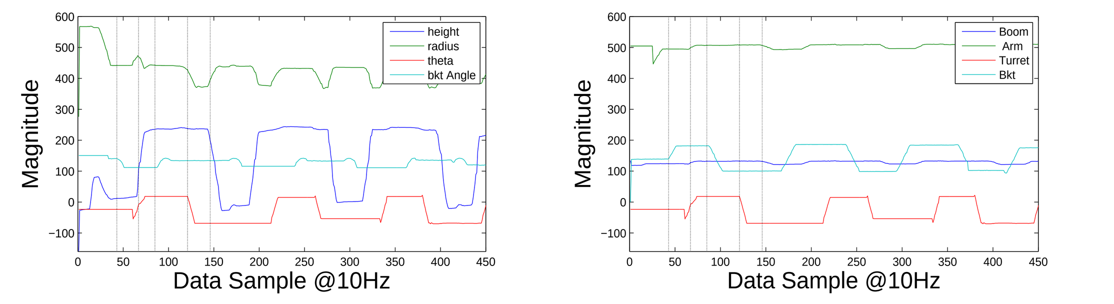


Figure 2: Cluster segments identified by the algorithm for a truck loading task

- Algorithm yields similar clusters for data with different temporal properties (Figure 3).

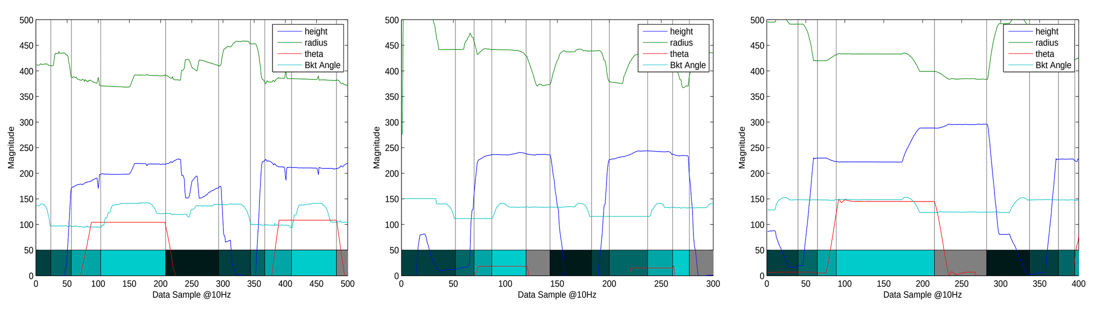


Figure 3: Segmentation with different temporal characteristics

Step 2: Instruction Framework

- On-line re-identification of clusters, coupled with learned sequence of clusters.
- Automated Flash-card instructions to guide a novice operator, learning a task.

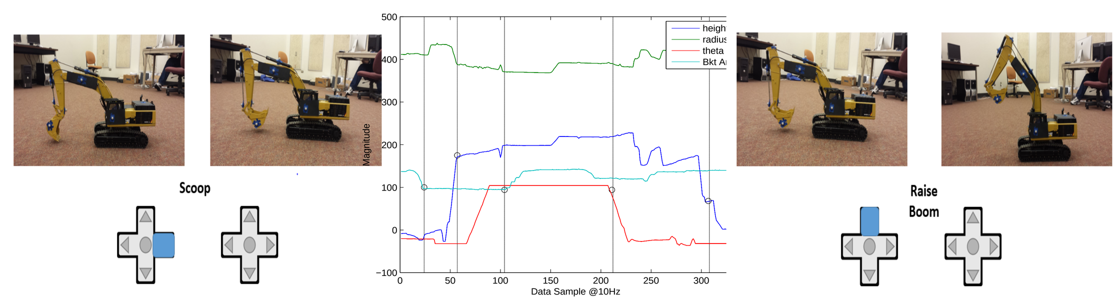


Figure 4: Flash cards and cluster poses

GUIDED VS UNGUIDED

- Comparison for truck loading task: Better performance in guided mode

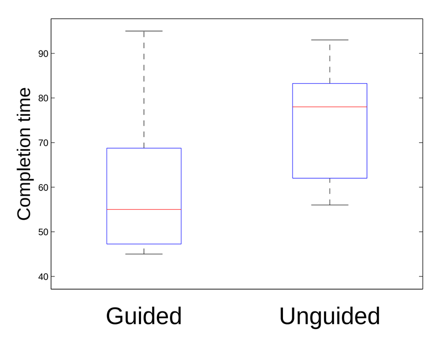
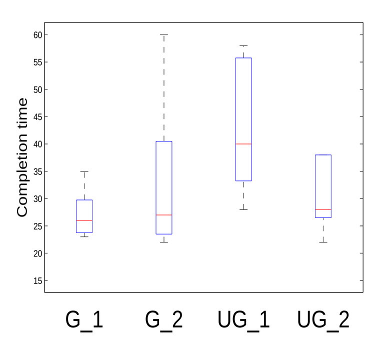


Figure 5: Completion time for the two modes

- Performance comparison between first and second cycle.



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[1] R Grande, T Walsh, S Fergusson, G Chowdhary, and J How. Online regression for non-stationary data using gaussian processes and reusable models. *Transactions on Neural Networks and Learning Systems*, 2013.

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[3] Y Engel, S Mannor, and R Meir. The kernel recursive least-squares algorithm. *IEEE Transactions on Signal Processing*, 52(8):2275–2285, 2004.