Interactive Tuning of Robot Program Parameters via Expected Divergence Maximization

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ROBOT END-USER PROGRAMMING

Main motivation: **End-User Programming makes robots accessible to novice users**
AIDING END-USER PROGRAMMING

Robot actions are the building blocks for EUP programs, with each varying number and complexity of parameters.

PARAMETERS
- Goal Pose
- Translational Speed
- Collision Threshold (move until you sense a contact)
AIDING END-USER PROGRAMMING

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Challenges faced by end-users

- What robot actions to use to achieve the goal?
- How to set the action parameters?
- How to evaluate the program (debug and fix)?
PARAMETER TUNING FOR ROBOT ACTIONS

How are parameter values usually specified?

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- Collision Threshold (move until you sense a certain amount of force)

→ Kinesthetic Teaching
→ GUI elements (e.g. 1-D sliders)
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Trial-and-error tuning strategy (tedious and time consuming):

- often effects of changes to parameter values are not immediate
- sometimes specifying a single value is not enough
AIDING 1-D PARAMETER TUNING

Idea: what if the robot proposes the parameter values to try? instead of the user selecting them with sliders
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Formulation: we formulate this as an Active Learning (AL) problem.

AL agent iteratively:

1. selects informative parameter values to try \textit{(query selection)}
2. action is reproduced with selected parameter \textit{(actual querying)}
3. user gives feedback \textit{(answering)}
4. parameter range estimation is updated \textit{(model update)}
TUNING PIPELINE IN ACTION

A Panda Program

Current Primitive's parameters:

Motion Speed
0.228 m/s

I will execute this Linear Motion now with Motion Speed = 0.228 m/s

Robot State

READY

Go to start state

Execute one step

Recover From Error
Bayesian approach: **priors over parameter values** (e.g. from expert programs)
FEEDBACK AFTER THE ACTION

**Directional answers:** given the 1-D nature of the estimated parameters, the user’s feedback can be directional (higher, lower, fine)
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“The motion was too fast! I want it slower”
SELECTING THE VALUE TO PROPOSE

How to select the parameter value?

- **At random** (complexity O(1))
- **Uncertainty sampling** (O(k)) ~ basically a weighted binary search on the prior
- **Expected Divergence Maximization** (O(k^2))
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\[
S_{ij} = \mathbb{E}_a[J_S(f(x|v, a), f(x))]
\]

\[
= \sum_a p(a|v, f(x)) J_S(f(x|v, a), f(x))
\]
EXPERIMENTS

1. synthetic priors and simulated oracle users
2. priors from expert programs (8 experts) and simulated oracle users
3. usability study: 8 novice users, using expert priors
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Domain Specific Language (DSL) -- 5 actions each with 1 or 2 parameters

Tasks for priors: handover, 2 pushing tasks, and a pick and place
EVALUATION WITH NOVICE USERS

Task: tune the parameters of a provided handover program
Conditions: Baseline (GUI sliders) vs Active tuning
RESULTS and OBSERVATIONS

- **SUS score:** baseline 73.7 *vs* Active tuning 73.1 (good usability)
- **With Active tuning,** novice users produced parameter ranges **closer** to the expert ones
- **With Active tuning,** faster tuning *(8 min *vs* 13 min)*
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From participants’ feedback:

- **Active tuning** helped at the beginning but had strict control over the process
- Participants reduced tuning attempts over time with the baseline
  Active tuning did not → perceived as slower and less efficient!
INTERESTING FUTURE DIRECTIONS

Interaction side:

- **Control issue:** more discreet ways of suggesting parameter values to try out e.g. overlaying information on the GUI sliders or Active tuning only on demand
- **Time consuming:** can (some) executions be handled in simulation/visualization tools? can users still express feedback?
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Learning side:

- **Different querying schemes:** if action has 2 or more parameter, let AL agent **pick** which parameter to tune
- **Tune single or multiple parameters at a time?** can users still express feedback?
CONCLUSIONS

We framed the tuning of parameters of robot actions as an Active Learning problem and proposed a novel interactive tuning method.

We validated the tuning approach both in simulation and in a real robot scenario.

Experiments showed the usability of the method with novice users, and allowed us to identify several promising future directions.
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Code available at github.com/mattiaracca/eupanda
Showcase video at vimeo.com/mattiaracca/hri20
Paper available on ACM Digital Library!

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