CAREER: Robust Perception and Customization for Long-Term Autonomous Service Mobile Robots

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Perception for Long-Term Autonomy

- How can a robot reason about possible reconfigurations of the world?
- How can a robot iteratively build probabilistic models of semantically meaningful entities over time?
- How can a robot perform real-time inference using such a formulation?

Introspective Perception

- How can a robot autonomously build models of competency of perception, and identify causal factors of competency?
- How can a robot improve competency over time?

End-User Customization

- How can a robot learn preferences from a minimal set of examples?
- How can a robot learn new tasks from minimal demonstration?

Technical Formulation And Preliminary Results

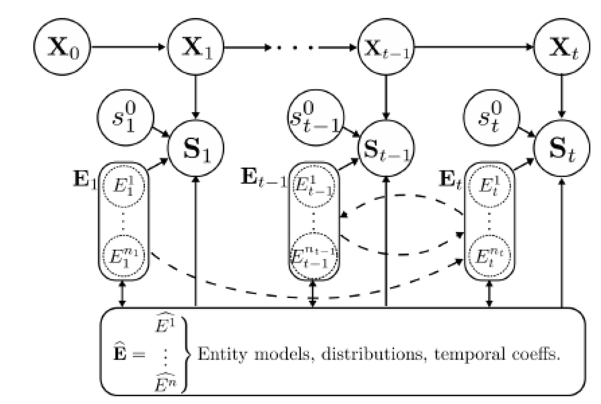


Figure 1: Varying Graphical Network of the Joint Perception Formulation. Robot states are $\mathbf{X}_t$, environment states $\mathbf{E}_t$, observations $\mathbf{S}_t$, and the long-term environment $\widehat{\mathbf{E}}$. Each environment state $\mathbf{E}_t$ consists of n_t sub-states $E_t^1 \dots E_t^{n_t}$, where n_t may vary at every time-step. Varying nodes and correlations (dashed edges) are unknown a-priori.

Mathematical Expressions

$e ::= x$ Inputs
$\mid p$ Parameters
$\mid op_1(e)$ Unary Op.
$\mid e_1\ op_2\ e_2$ Binary Op.

$op_1 ::= - \mid \texttt{norm} \mid \texttt{sin} \mid \cdots$

$op_2 ::= - \mid + \mid * \mid \texttt{cross} \mid \cdots$

Boolean Expressions

$b ::= b_1\ \texttt{\&\&}\ b_2$ Conjunction
$\mid b_1\ \texttt{||}\ b_2$ Disjunction
$\mid e > p$ Parameter -
$\mid e < p$ comparison

Conditionals

$C ::= \texttt{if}(b_1)\{e_1\}$
$\texttt{else if}(b_2)\{e_2\}$
$\dots$
$\texttt{else}\{e_n\}$

Mathematical Types

$T ::= u$
$\mid v$
$u ::= [M, L, T]$
$\mid [0, 0, 0]$
$v ::= \mathrm{Vec}(n, u)$

Type Environment

$\Gamma ::= e : T$
$\mid op_1 : T_1 \to T_2$
$\mid op_2 : T_1 \times T_2 \to T_3$

Figure 2 Grammar for *CusPs*

Expression	Input Dim. Constraints	Result Dim.
$a + b, a - b$	$a : u, b : u$	u
$a + b, a - b$	$a : \mathrm{Vec}(n, u), b : \mathrm{Vec}(n, u)$	$\mathrm{Vec}(n, u)$
a dot b	$a : \mathrm{Vec}(n, u), b : \mathrm{Vec}(n, u)$	u
$a * b$	$a : u_1, b : u_2$	$u_1 + u_2$
a / b	$a : u_1, b : u_2$	$u_1 - u_2$
$a * b$	$a : u_1, b : \mathrm{Vec}(n, u_2)$	$\mathrm{Vec}(n, u_1 + u_2)$
$\sin(a)$	$a : [000]$	$[000]$

Figure 3 Unit checking of mathematical operators

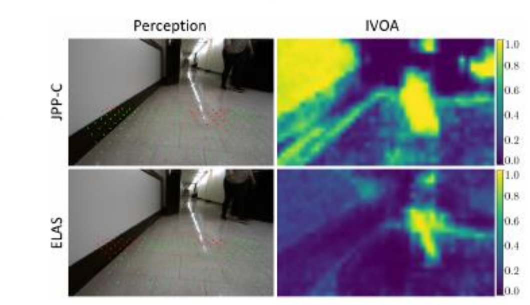


Figure 4 IVOA over two QPAs: JPP-C (top row) and ELAS (bottom). Left: QPA-predicted obstacles (red dots) and free space (green dots). Right: IVOA Predictions.

Algorithm	TE %	RE. (deg/m)	MDBF (m)
IV-SLAM	**5.85**	**0.523**	**621.1**
ORB-SLAM	9.20	0.558	357.1

Figure 5 IV-SLAM *vs.* ORB-SLAM on real robot data: translation error (TE), rotation error (RE), mean distance between failures (MDBF).

Policy	**Attacker**		**Deflector**	
	(%)	N	(%)	N
LSTM-Full	78	778408	70	440385
LSTM-Half	32	389204	61	220192
LSTM-Synth	25	750	38	750
LDIPS	87	750	81	750

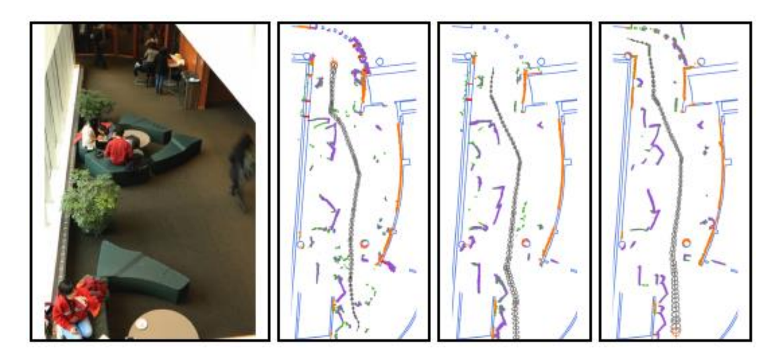
Figure 6 Performance *vs.* # of examples (N).

Scenario	**Attacker**			**Deflector**		
	Ref	**LSTM**	**LDIPS**	**Ref**	**LSTM**	**LDIPS**
Sim	89	78	87	86	70	81
Real	42	48	50	70	16	52
Repaired	70	-	64	78	-	72

Figure 7 LDIPS performance (%) *vs.* LSTM.

Policy	**# Enumerated**			**Success Rate %**		
	Atk	**Def**	**Pass**	**Atk**	**Def**	**Pass**
LDIPS-L3	175	174	345	87	81	74
Dimension Pruning	696	696	1230	87	81	74
Signature Pruning	4971	5013	366	78	76	60
No Pruning	14184	14232	7528	-	-	-

Figure 8 Features enumerated at depth 3.



- Jarrett Holtz, Arjun Guha, Joydeep Biswas (2020). Robot Action Selection Learning via Layered Dimension Informed Program Synthesis. In Conference on Robot Learning
- Sadegh Rabiee, Joydeep Biswas (2020). IV-SLAM: Introspective Vision for Simultaneous Localization and Mapping. In Conference on Robot Learning
- Sadegh Rabiee, Joydeep Biswas (2019). IVOA: Introspective Vision for Obstacle Avoidance. In Intelligent Robots and Systems (IROS), IEEE/RSJ International Conference on
- Jarrett Holtz, Arjun Guha, Joydeep Biswas (2018). Interactive Robot Transition Repair With SMT. In International Joint Conference on Artificial Intelligence (IJCAI)

Thrust 1: The long-term joint perception formulation (LT-JPF) to reasoning about the state of the world in terms of its composing entities, and their long-term distributions.

Thrust 2: Introspective perception (IPr) as a self-supervised approach to empower robots to identify perception failures by relying on online supervisory sensing or offline post-hoc analysis.

Thrust 3: Physics-informed customizable program synthesis (PI-CusPS) as a class of symbolic approaches to generate and repair human-interpretable symbolic programs from a limited set of human guided demonstrations.

Societal Impact

- Service robots deployed autonomously in real human environments over extended periods of time
- Reduced reliance on expert supervision
- End-user adaptability of service robots

Teaching

Hands-on robotics with the UT AUTOmata:

(a) UT AUTOmata cars (b) Touchscreen GUI (c) Remote web visualizer

Outreach: Introduction to computing with UT AUTOmata and robot soccer

Broader Impact

- Wider deployability of service mobile robots in human environments
- Curation of long-term datasets to identify open challenges
- Ability to conduct longitudinal studies of robots embedded in human environments