

Provably Correct Shared Control for Human-Embedded Autonomous Systems

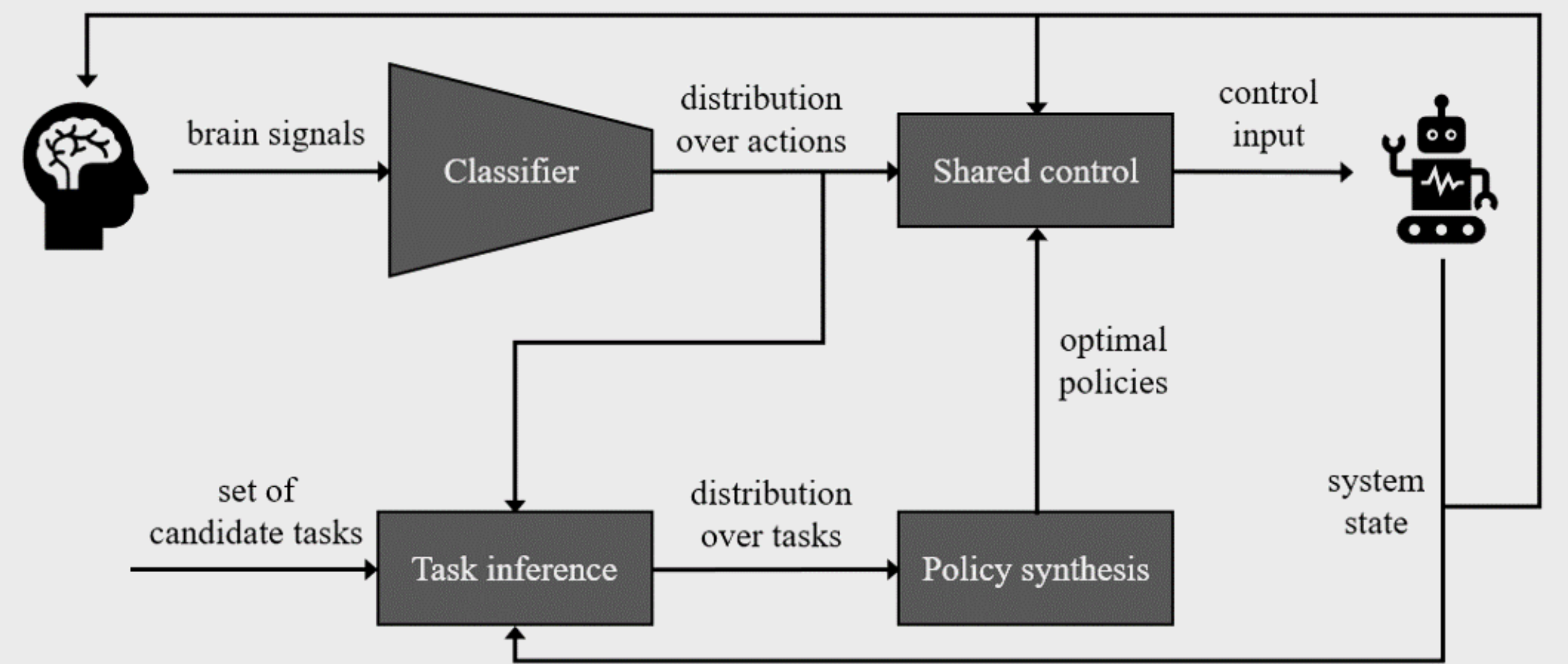
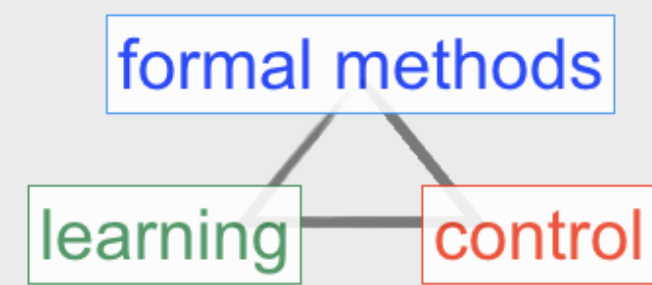
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Human-embedded systems: Humans and autonomy are responsible for collective information acquisition, perception, cognition and decision-making at multiple and varying levels of abstraction.

Objective of the project: Develop languages, algorithms and demonstrations for the formal specification and automated synthesis of *shared control* protocols.

An enabling factor

Convergence between learning, formal methods, and control



Research thrusts

Specifications and modeling for shared control: What does it mean to be provably correct in human-embedded autonomous systems, and how can we represent correctness in formal specifications?

Automated synthesis of shared control protocols: How can we mathematically abstract shared control, and automatically synthesize shared control protocols from formal specifications?

Shared control through human-autonomy interfaces: How can we account for the limitations in expressivity, precision and bandwidth of human-autonomy interfaces, and co-design controllers and interfaces?

Shared Control for Temporal Logic Tasks in Brain-Machine-Interface Applications

An application in brain-machine interface:

A human trying to control a wheelchair through brain signals

human decision-making is prone to error
data gathering and processing are uncertain



How can we design a shared-control framework to augment human's capabilities?

Challenges:

- Human's unknown intent and preferences
- Imperfect interface and uncertain processing
- Online integration of data into sequential decision making

Problem statement:

- Given
- A Markov decision process $\mathcal{M} = (\mathcal{S}, s_{init}, \mathcal{A}, \mathcal{T}, \mathcal{AP}, \mathcal{L})$
 - A safety constraint φ_s along a safety level $\lambda_s \in [0, 1]$
 - A set of template tasks $\mathcal{T} = \{\tau_1, \tau_2, \dots, \tau_k\}$
 - A classifier $C : X \rightarrow Y$ mapping the human brain signals to distribution over actions

The goal is to compute an online policy π_t^* optimizing

$$\max_{\pi_t} \Pr(\mathcal{M}_{s_0}^{\pi_t} \models \varphi^*) + \alpha \sum_{t=0}^T \delta(\pi_t(s_t), y_t)$$

probability of task success
trade-off parameter
divergence from human's intended behavior

subject to $\Pr(\mathcal{M}_{s_0}^{\pi_t} \models \varphi_s) \geq \lambda_s$

safety constraint

Proposed shared-control algorithm:

Blending a data-driven policy with a human rational policy

$$\pi_t^b(a_t = a | s_0, s_1, \dots, s_t) = \gamma_t \bar{\pi}_t^d(a_t = a | s_t) + (1 - \gamma_t) \sum_{\varphi \in \Phi} \Pr(\varphi = \varphi^*) \pi_t^r(a_t = a | s_0, s_1, \dots, s_t, \varphi = \varphi^*)$$

blended policy
blending parameter
data-driven policy

set of candidate tasks instantiated from the template tasks
belief over a tasks obtained through Bayesian inference
rational policy based on the concept of Boltzmann rationality

Effect of perturbing a policy through blending on the task success:

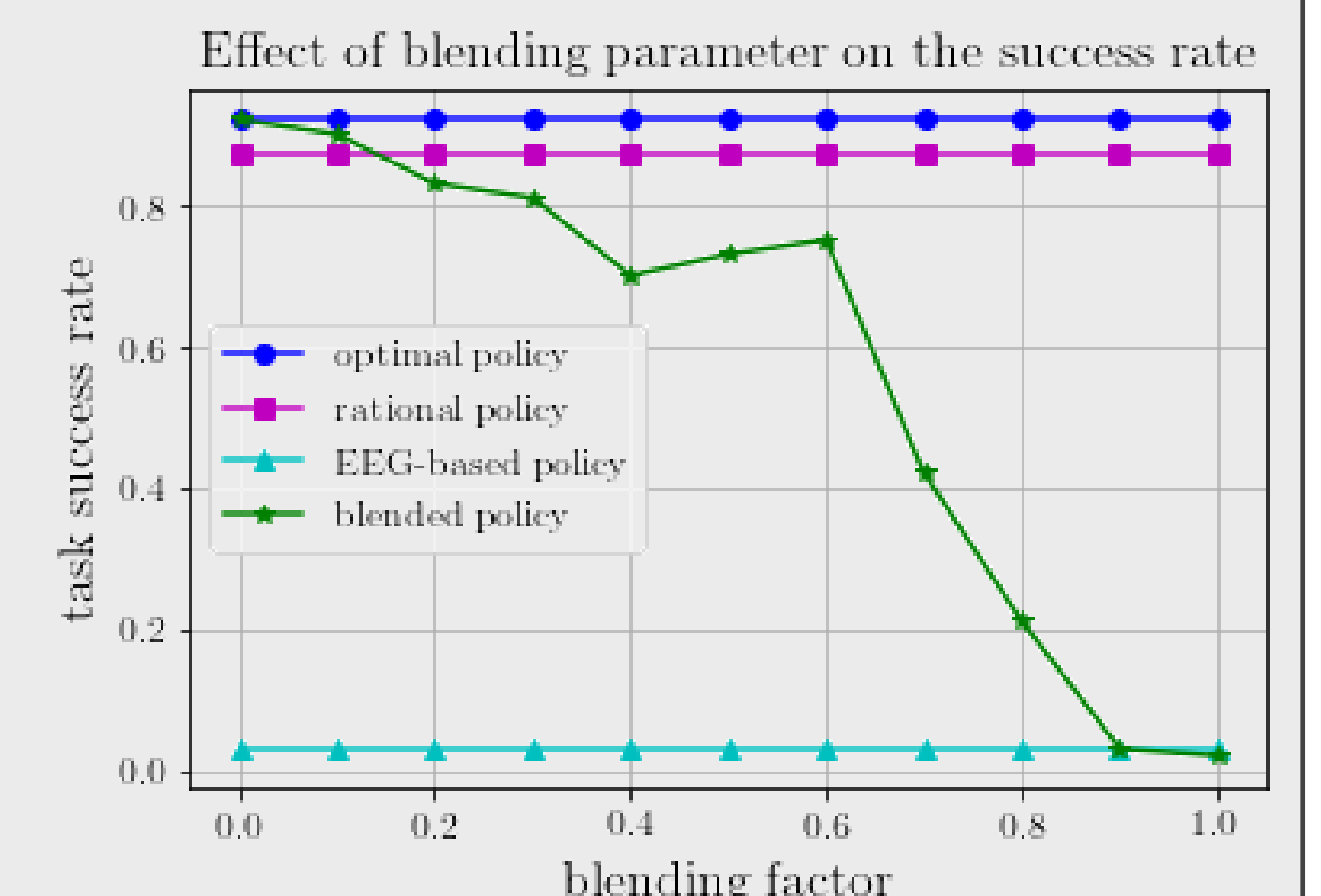
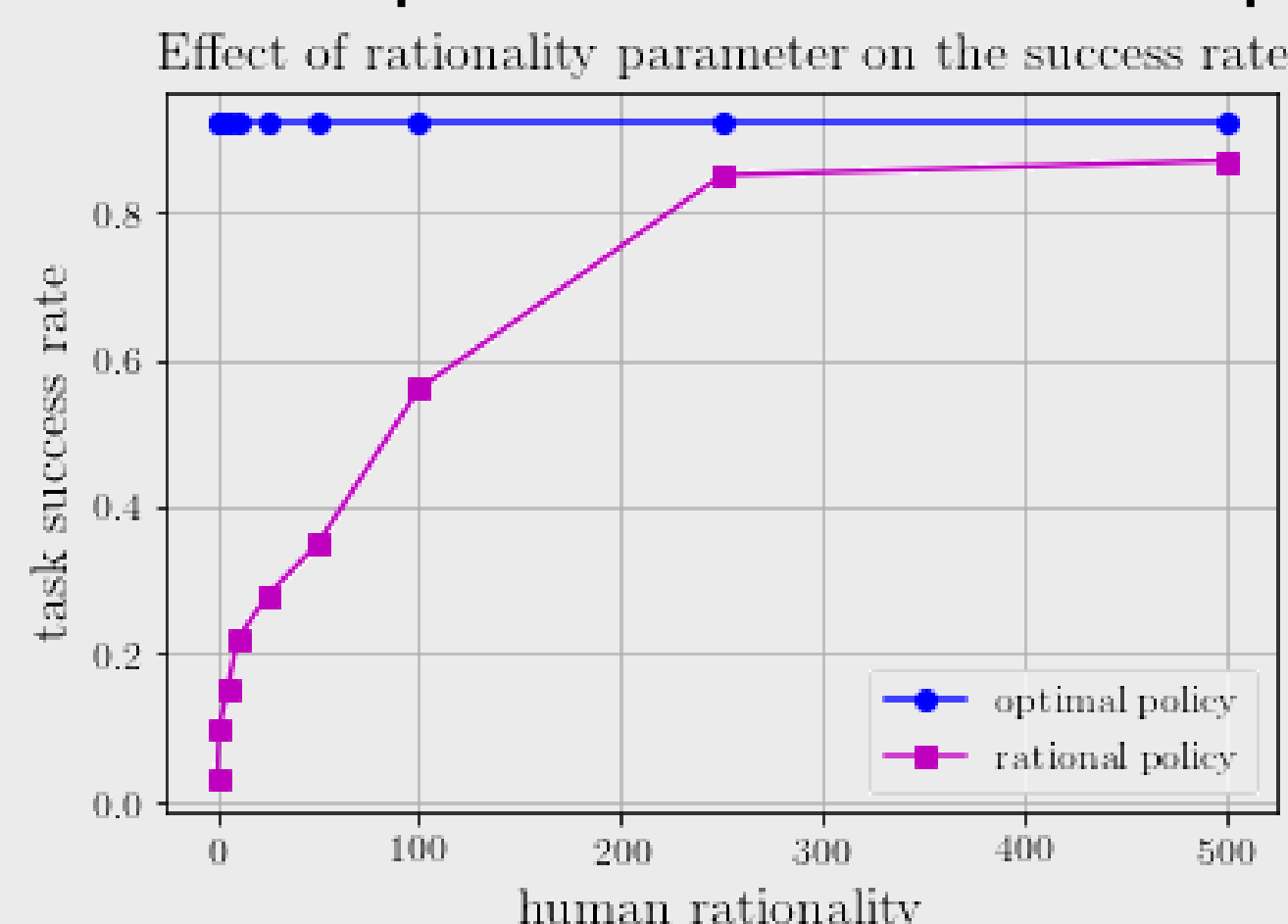
$$|\Pr(\mathcal{M}_{s_0}^{\pi} \models \varphi) - \Pr(\mathcal{M}_{s_0}^{\pi'} \models \varphi)| \leq (1 + \epsilon \delta / \eta)^{2|S|} - 1$$

perturbation amount
properties of the system and policy

Empirical results:

- Classifier's inaccuracy deteriorates the success rate and task completion time
- Lower rationality parameter results in higher suboptimality of the rational policy
- Blending parameter controls the trade-off between performance and compliance with human's preferences

Classifier's noise	Success rate	Completion time
[0.0,0.1]	0.90	27.58 s
[0.2,0.4]	0.77	42.16 s
[0.4,0.8]	0.57	78.11 s



Ongoing and future work:

- Incorporating error-related potential as another human feedback
- Analyzing the theoretical connection between the classifier's performance and shared control's performance
- Evaluating the algorithm through a human user study