Computational sensorimotor learning and control:
a game-theoretic approach for human/machine interaction

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The challenge

- Natural model for interaction between human/machine is an *imperfect information game.*
- While interacting with a machine, humans will naturally formulate beliefs about the machine's behavior, and these beliefs will affect the interaction.
- Little work on **continuous sensorimotor games** that arise in dynamic closed-loop human/machine interaction.

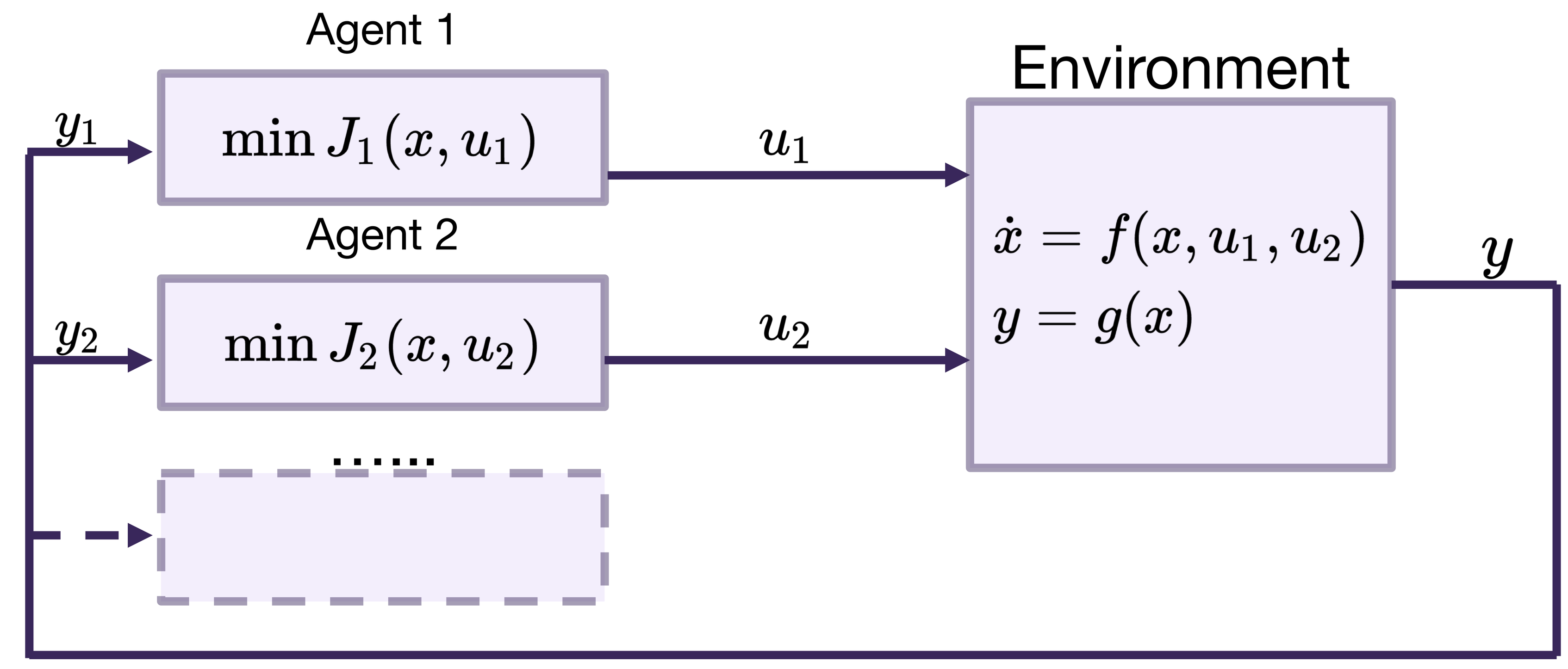
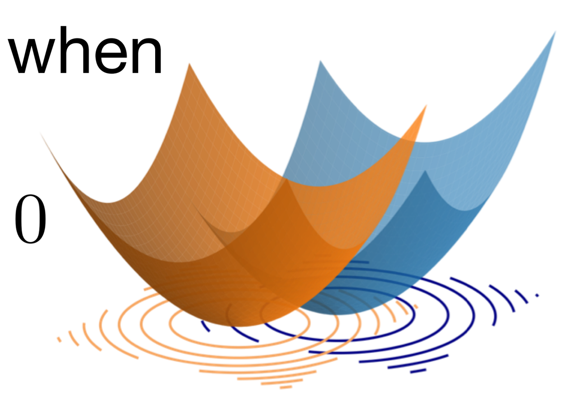


Figure 1: Computational model of multiple *optimal control agents* in a dynamic environment. Agent i observes y_i and outputs action u_i to control the environment's state x such that its cost J_i is minimized.

Mathematical model

- Rational agents in a dynamic world asymptotically converge to an equilibrium with each other, see *Figure 1*. Modeling rationally is the premise of the field of game theory.
- We study these games experimentally and theoretically through following concepts:
  - Markovian system with **continuous dynamics**
    $x \in \mathbb{R}^p,\ f \in C^2,\ u_i \in \mathbb{R}^q, \quad \dot{x} = f(x, u_1, \ldots, u_n)$
    e.g. linear: $\dot{x} = Ax + B_1 u_1 + \cdots + B_n u_n$
  - Rational agent model via **optimal control**
    $\text{minimize } J_i(x, u_i, u_{-i}) \text{ subject to } \dot{x} = f(x, u_i, u_{-i})$
    e.g. maximize utility, minimize energy
  - Fixed point (u_i^*, u_{-i}^*) is a **Nash equilibrium** when
    $J_i(u_i^*, u_{-i}^*) \le J_i(u_i, u_{-i}^*),\ \forall u_i, \forall i$
    e.g. continuous games: $D_i J_i = 0,\ D_{ii}^2 J_i \succeq 0$



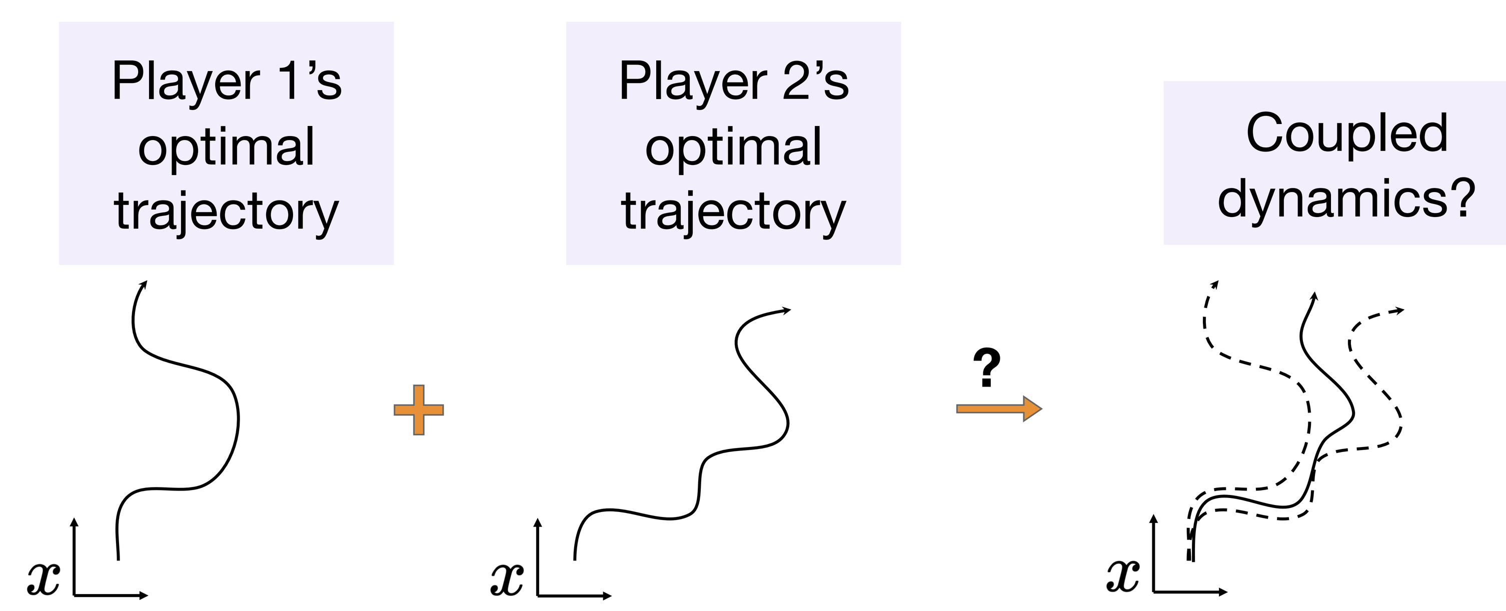


Figure 2: We study the interaction of rational agents in a dynamically coupled environment by "combining" optimal controllers in a coupled settings. Do agents learn equilibria?

Experimental setup

- We study trajectories of agent-agent and agent-human interactions with a **dynamics simulator**, see *Figure 2.*
- In human interactions, user is provided with **visual** and **haptic** feedback. Various **cost models, information structures**, and **belief estimation** explored, see *Figure 3*.

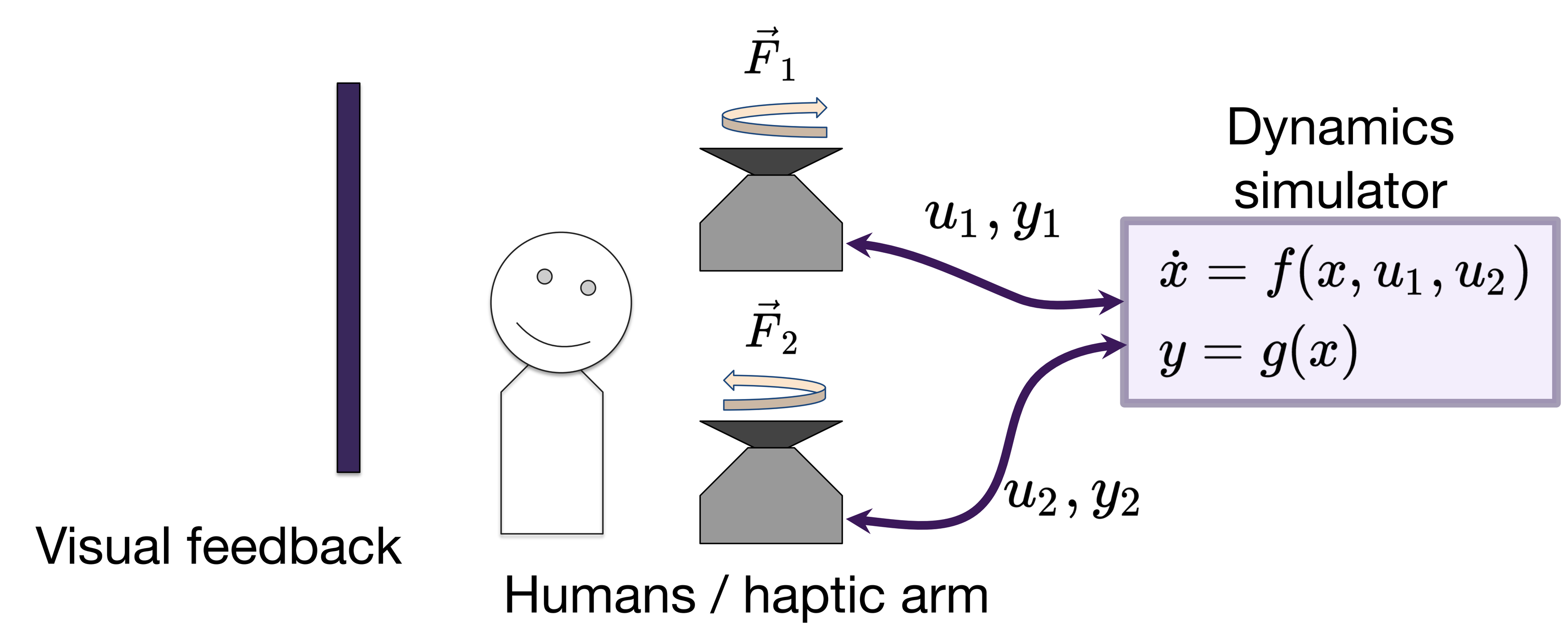
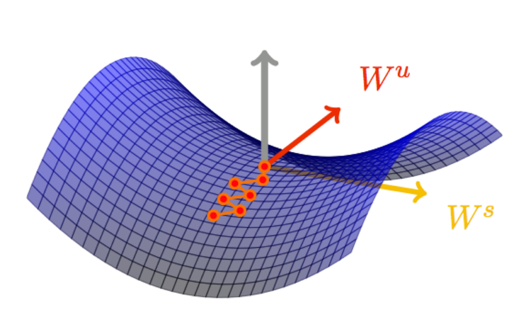
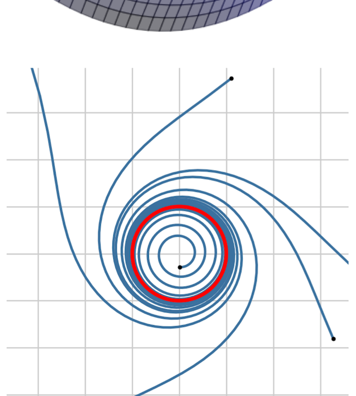


Figure 3: Testbench with multiple haptic controllers interfaced with a dynamics simulator. User receives information via visual and force feedback, and controllers estimate belief and cost models.

Theoretical results

- We derive **predictive models** for behaviors of humans interacting with other agents (humans and machines).
  - Steady-state behaviors *(i.e. equilibrium)*
  - Transient *(i.e. learning)*
- Provably convergent computational model using **gradient-based learning.** [1] Suppose agent i's controller is parameterized by θ_i, then the learning mechanism is
  $$\theta_i^+ = \theta_i - \gamma_i D_i f_i(\theta_i, \theta_{-i})$$
- *Negative result*: Learning converge to **non-Nash equilibrium** points. [2]
  - Non-Nash stable points *(i.e. saddles)*
  - Limit cycles *(i.e. period orbits)*





Next steps

- Design experiments for hypothesis testing
  1. Agents learn to **minimize a quadratic cost** function in environment with linear dynamics?
  2. Convergence to equilibrium depends on **information structure**?
  3. Belief estimation improves **mutual prediction**?
- Extend theoretical work to other settings
  - Learning and **optimization with constraints** for bounded-rationality model of cognition.
  - Develop **coordination methods** for effective learning with multiple agents.

References

[1] Benjamin Chasnov, Lillian J. Ratliff, Daniel Calderone, Eric Mazumdar, and Samuel A. Burden. **Finite-Time Convergence of Gradient-Based Learning in Continuous Games.** In *AAAI Workshop on RL in Games*, 2019.
[2] Eric Mazumdar and Lillian J. Ratliff. **On the Convergence of Competitive, Multi-Agent Gradient-Based Learning.** *arXiv:1804.05464*, 2018.

Acknowledgements

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