Hierarchical Approach to Transfer of Control in Semi-Autonomous Systems

Kyle H. Wray, Luis Pineda and Shlomo Zilberstein

College of Information and Computer Sciences
University of Massachusetts Amherst

July 12th
Motivation

Many application domains can benefit from partial autonomy, even though fully-autonomous systems are not yet feasible in these domains.
Motivation

- These systems almost universally require human intervention at some point
- Commonly resort to default hard-coded behaviors instead of integrating human capabilities into the planning process
Semi-Autonomous Systems (SAS)

- Explicitly capture this collaborative process of sharing control over the system
- Smoothly transfer control over the system, while proactively considering each actor’s capabilities [Zilberstein, 2015]
Semi-Autonomous Systems (SAS)

Challenges in implementing SAS:

- Factor inherent uncertainty and unpredictability associated with human behavior
- Constantly monitor of the human availability for taking over control
- Provide a measure of safety for the system in terms of actors/state compatibility
Our contributions

1. A formal definition of SAS and its key properties
2. A general transfer of control model
3. A hierarchical approach for integrating domain action planning with transfer of control
4. An analysis showing the hierarchical model is a strong SAS
Formalizing SAS - Key ideas

- Extend a Markov Decision Process to support semi-autonomy
- Include factors representing the actors (controlling entities) in state and action sets
- Factor the transition model into two components:
  - An actor state transition function
  - A control transfer function
- Employ a hierarchical approach to the transfer of control problem
- Characterize policies and systems in terms of the ability to maintain live states
A semi-autonomous system is represented by a tuple $\langle \mathcal{A}, S_+, A_+, T_+, C_+, G, L \rangle$:

- $\mathcal{A}$ is a set of actors (controlling entities)
- $S_+ = S \times \mathcal{A}$ is a set of factored states: a standard state set $S$ and the current controlling actor $\mathcal{A}$
- $A_+ = A \times \mathcal{A}$ is a set of factored actions: a standard action set $A$ and the next desired actor $\mathcal{A}$
A semi-autonomous system is represented by a tuple \( \langle \mathcal{A}, S_+, A_+, T_+, C_+, G, L \rangle \):

- \( T_+ : S_+ \times A_+ \rightarrow \triangle^{\mid S_+\mid} \) is a transition function, comprised of a state transition \( T_a : S \times A \rightarrow \triangle^{\mid S\mid} \) for each actor \( a \in \mathcal{A} \), and control transfer function \( \rho : S_+ \times A \rightarrow \triangle^{\mid A\mid} \)
- \( C_+ : S_+ \times A_+ \rightarrow \mathbb{R}^+ \) is a cost function
- \( G \subseteq S_+ \) is a set of goal states
- \( L \subseteq S_+ \) is a set of live states, such that for actor capability function \( \psi : S \rightarrow 2^A \), \( L = \{ \langle s, a \rangle \mid a \in \psi(s) \} \)
SAS transition function

Definition

The **SAS state transition function** for $s_+ = \langle s, a \rangle$, $a_+ = \langle a, \hat{a} \rangle$, and $s'_+ = \langle s', a' \rangle$ is:

$$T_+(s_+, a_+, s'_+) = \begin{cases} T_a(s, a, s'), & \text{if } a = \hat{a} = a' \\ T_a(s, a, s')\rho(s_+, \hat{a}, a'), & \text{if } a \neq \hat{a} \\ 0, & \text{otherwise} \end{cases}$$

- $T_a : S \times A \rightarrow \Delta^{|S|}$: **actor state transition function**
- $\rho : S_+ \times A \rightarrow \Delta^{|A|}$: **control transfer function**
Optimal policy for SAS

Given a policy $\pi$, the agent incurs a cost per time step given by $C_+: S_+ \times A_+ \rightarrow \mathbb{R}^+$ as it tries to reach a goal state from $G \subseteq S_+$. A policy is optimal if it minimizes:

$$V_+(s^0) = \mathbb{E}\left[ \sum_{t=0}^{\infty} C^t_+(s^t, \pi^*(s^t)) | s^0 \right]$$

Given an initial state, this defines a Stochastic Shortest Path (SSP) MDP. Bellman’s optimality equation for state $s$ is:

$$V_+(s) = \min_{a \in A_+} \{ C_+(s, a) + \sum_{s' \in S_+} T_+(s, a, s') V_+(s') \}$$
Strong, conditionally strongly, and weak policies

- A policy is **strong** if every state that could be reached following this policy, from any initial state, is a live state.

- A policy is **conditionally strong** if there exists some initial state from which all states that can be reached following this policy are live states.

- A policy $\pi$ is **weak** if it is not strong or conditionally strong.

A SAS is said to be **strong** (**conditionally strong**) if there exists a strong (conditionally strong) policy $\pi^*$ that is optimal. Otherwise, the SAS is said to be **weak**.
Transfer of Control (TOC)

- TOC decisions are executed concurrently to domain level actions.
- TOC relies on a sequence of messages to the human that are designed to prompt them to reengage in the control process.
- These messages present trade-offs between efficacy and the burden on the human.
- This sequential decision process is formulated as a Partially Observable MDP (POMDP).
Formalizing TOC POMDP - Key ideas

- State space includes factors for the (hidden) human state, time, state of notification, and the success of the TOC.
- Action space includes the messages for the human plus an abort action.
- Observations provide partial information about the human state and perfect information about the TOC success.
Formalizing TOC POMDP - Key ideas

- Transition function relies on two probabilistic models:
  - One for the change in human state as a function of their previous state and messages sent to them
  - One for the success of transferring control as a function of the human state and the messages sent
- The reward function penalizes failure in transferring control
Semi-Autonomous VEHicle (SAVE) model

- Actors include *human*, *vehicle*, and *no active actor*
- States form a road network graph with edges representing roads
  - *human* can operate on all roads
  - *vehicle* can operate on select autonomy-capable roads
- Goal: minimize combined cost of travel time and manual driving
SAVE model - Theoretical results

- **Proposition 1:** SAVE satisfies the live state constraints
- **Proposition 2:** A TOC POMDP’s optimal policy always succeeds or safely aborts the transfer of control
- **Proposition 3:** SAVE is a strong SAS
SAVE model - Experimental results

- Distant start and goal locations in 10 cities
- Compare human only ($\lambda$), vehicle only ($\nu$), and both ($\lambda \& \nu$)
- Metrics: goal reachable ($G$), autonomous driving ($\%$), and time ($T$)
- Collaboration quickly reaches goal and drives autonomously
### SAVE model - Experimental results

| City    | |S| |A| |G| |%| |T| |G| |%| |T| |G| |%| |T| |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Austin  | 303 | 12  | Y   | 0.0 | 128 | N   | 1.0 | —   | Y   | 0.13 | 128 |
| Balt.   | 315 | 12  | Y   | 0.0 | 146 | Y   | 1.0 | 232 | Y   | 0.46 | 154 |
| Boston  | 912 | 18  | Y   | 0.0 | 136 | N   | 1.0 | —   | Y   | 0.95 | 140 |
| Chic.   | 258 | 12  | Y   | 0.0 | 99  | N   | 1.0 | —   | Y   | 0.85 | 142 |
| Denver  | 348 | 15  | Y   | 0.0 | 128 | N   | 1.0 | —   | Y   | 0.81 | 132 |
| L.A.    | 291 | 12  | Y   | 0.0 | 120 | N   | 1.0 | —   | Y   | 0.42 | 120 |
| N.Y.C.  | 960 | 15  | Y   | 0.0 | 294 | N   | 1.0 | —   | Y   | 0.54 | 313 |
| Pitts.  | 198 | 12  | Y   | 0.0 | 81  | N   | 1.0 | —   | Y   | 0.08 | 89  |
| San Fr. | 504 | 18  | Y   | 0.0 | 151 | Y   | 1.0 | 183 | Y   | 0.80 | 174 |
| Seattle | 366 | 12  | Y   | 0.0 | 111 | Y   | 1.0 | 138 | Y   | 0.00 | 111 |
Conclusion

- Formal definition of SAS and its key properties
- General transfer of control problem and POMDP model
- Hierarchical integration of domain planning with transfer of control
- Analysis showing the hierarchical model is a strong SAS
- Semi-autonomous vehicle experiments on 10 cities
- Currently integrating the model with a realistic full-scale driving simulator