Validation of Cognitive Models for Collaborative Hybrid Systems with Discrete Human Input

Abraham Vinod*, Yuqing Tang**, Meeko Oishi*, Katia Sycara**, Christian Lebiere†, and Michael Lewis††

(Presented by Hao-Tien (Lewis) Chiang)

*Electrical and Computer Engineering, University of New Mexico, USA

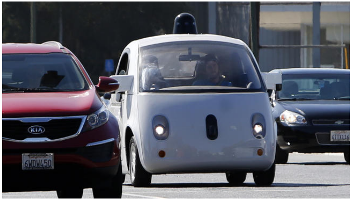
**Robotics Institute, Carnegie Mellon University, USA

†Psychology Department, Carnegie Mellon University, USA

††Information Sciences and Intelligent Systems, University of Pittsburgh, USA

October 12, 2016

Motivation



- Formal methods for human-in-the-loop systems
- Cognitive models to predict human response
- Validation of cognitive models is key

Motivation

- Formal methods for human-in-the-loop systems
- Cognitive models to predict human response
- Validation of cognitive models is key

- Talking points:
  - The need for formal methods in collaborative systems is paramount. As automation becomes more commonplace (consider the recent interest in self-driving cars, for example), rigorous methods to assess performance and safety of human-in-the-loop systems must be developed.
  - A key element is modeling of the human.
  - Human error, for example, is the primary source of 94% of accidents, according to the National Highway Traffic Safety Administration's 2015 report.
  - In systems with input from both the human and the automation, accurate models of human response and decision making are critical.
  - We focus on *cognitive models*, which are derived from principles of human psychology, and pose the question of *validation* of cognitive models.

Related Work

Modeling human-automation systems

Fitts (1951); McRuer (1980); Hess (1996); Bailleiul, Leonard, & Morgansen (2012); Oishi, Tilbury, & Tomlin (2016); Savla, & Frazzoli (2012); Stewart, Cao, Nedic, & Leonard (2012); Reverdy, & Leonard (2016); Srivastava, Surana, & Bullo (2012); Forghani, McNew, Hoehener, & Vecchio (2016); Ding, Powers, Egerstedt, Young, & Balch (2009); Parasuraman, Sheridan, & Wickens (2000)

ACT-R cognitive architecture

Anderson & Lebiere (1998); Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin (2004); Lebiere (1999)

Reachability analysis

Althoff, Stursberg, & Buss (2010); Kvasnica, Grieder, & Baotic (2004); Kurzhanski & Varaiya (2000); Guernic & Girard (2010); Mitchell (2007,2008)

Related Work

Modeling human-automation systems
Fitts (1951); McRuer (1980); Hess (1996); Bailleiul, Leonard, & Morgansen (2012); Oishi, Tilbury, & Tomlin (2016); Savla, & Frazzoli (2012); Stewart, Cao, Nedic, & Leonard (2012); Reverdy, & Leonard (2016); Srivastava, Surana, & Bullo (2012); Forghani, McNew, Hoehener, & Vecchio (2016); Ding, Powers, Egerstedt, Young, & Balch (2009); Parasuraman, Sheridan, & Wickens (2000)

ACT-R cognitive architecture
Anderson & Lebiere (1998); Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin (2004); Lebiere (1999)

Reachability analysis
Althoff, Stursberg, & Buss (2010); Kvasnica, Grieder, & Baotic (2004); Kurzhanski & Varaiya (2000); Guernic & Girard (2010); Mitchell (2007,2008)

- Talking points:
  - Early models for human drivers and pilots were based on transfer functions gathered from experimental data, and allowed analysis of pilot-induced oscillations and other problematic behaviors.
  - However, in modern cyber-physical systems, human inputs may include non-trivial combinations of low-level continuous inputs as well as high-level discrete inputs.
  - Recently several models have been proposed for high-level human decision making for dynamical systems.
  - Cognitive modeling of human behavior is an alternative approach. Cognitive architectures are computationally unified theories of cognition, developed to implement aspects of cognition that do not vary across human subjects, including the mechanisms and structures through which information is processed.
  - We choose ACT-R as the cognitive model because of its generality and ability to incorporate cognitive processes as well as human limitations.
  - Reachability analysis in itself have seen some good foundational studies. A major problem plaguing this domain is the curse of dimensionality. Efficient computation of reachable sets is key.

Main contributions

- Reachability based computation of expected outcome for collaborative human-automation systems with infrequent human inputs
- Validation of cognitive model using different metrics based on expected outcome

Main contributions

- Reachability based computation of expected outcome for collaborative human-automation systems with infrequent human inputs
- Validation of cognitive model using different metrics based on expected outcome

- Talking points
  - In this paper, we provide a framework to validate cognitive models designed for collaborative human-automation systems with infrequent human inputs.
  - The framework builds on existing tools for deterministic reachability analysis.
  - We show that the reachablity computation is reasonable for certain classes of hybrid systems with discrete human input.
  - The validation is done using metrics derived from expected outcome.

Hybrid system

$$q[k+1] = \boldsymbol{g}(q[k], x[k], u_h[k])$$
$$x[k+1] = \boldsymbol{f}(q[k+1], x[k], u_a[k])$$

- discrete state $q[k] \in Q \subset \mathbb{N}$
- continuous state $x[k] \in \mathbb{X} \subset \mathbb{R}^n$
- hybrid state space $S \triangleq \bigcup_{q \in Q} \{q\} \times \mathbb{X}$
- automation input $u_a[k] \in \mathbb{U}_A$
- known deterministic automation policy $\pi_a : S \rightarrow \mathbb{U}_A$
- human input $u_h[k] \in \mathbb{U}_H$
- known stochastic map for human policy $\pi_h : S \rightarrow \mathbb{U}_H$
- time horizon of interest $N < \infty$

The human-automation system is a *Markov Decision Process* since π_h is Markov.

Abate, Prandini, Lygeros, & Sastry, 2008

Hybrid system

$$q[k+1] = \boldsymbol{g}(q[k], x[k], u_h[k])$$
$$x[k+1] = \boldsymbol{f}(q[k+1], x[k], u_a[k])$$

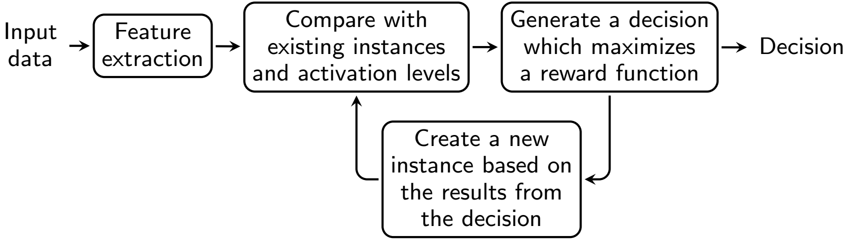
- discrete state $q[k] \in Q \subset \mathbb{N}$
- continuous state $x[k] \in \mathbb{X} \subset \mathbb{R}^n$
- hybrid state space $S \triangleq \bigcup_{q \in Q} \{q\} \times \mathbb{X}$
- automation input $u_a[k] \in \mathbb{U}_A$
- known deterministic automation policy $\pi_a : S \to \mathbb{U}_A$
- human input $u_h[k] \in \mathbb{U}_H$
- known stochastic map for human policy $\pi_h : S \to \mathbb{U}_H$
- time horizon of interest $N < \infty$

The human-automation system is a *Markov Decision Process* since π_h is Markov.

- Talking points:
  - We presume a discrete-time hybrid system with mode q and continuous state x.
  - Note that the automation input u_a only affects the continuous state evolution, and the human input u_h only affects the evolution of the discrete state. We presume that the control policy for the automation is deterministic, and that the policy for the human is stochastic (and based only on the current hybrid state).
  - The input set $\mathbb{U}_H$ is a finite set, but the automation input set $\mathbb{U}_A$ may be infinite.
  - This means that the human-automation system is a Markov decision process since the human policy is also Markov.
  - ((side note, if anyone asks: By definition, the discrete dynamics are propagated before the continuous state dynamics so that the human input $u_h[k]$ at time k influences the continuous state at time $k+1$ $x[k+1]$.))

Abstraction of ACT-R cognitive model to Markov model

- *Instance-based learning* — Instance comprises of
  - context (features) in which the decision is made
  - decision
  - outcomes of the decision



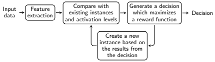
- Markov model is defined for every feature $s[k]$

$$Pr_{s[k]}\left\{u_h = \hat{u}_h\right\} = \sum_{j \in \mathbb{U}_H} Pr_{s[k]}\left\{u_h = \hat{u}_h \middle| u_h^- = j\right\} Pr_{s[k]}\left\{u_h^- = j\right\}$$

Sycara, Lebiere, Pei, Morrison, Tang, & Lewis, 2015

Abstraction of ACT-R cognitive model to Markov model

- *Instance-based learning* — Instance comprises of
  - context (features) in which the decision is made
  - decision
  - outcomes of the decision



- Markov model is defined for every feature $s[k]$

$$Pr_{s[k]}\{u_h = \hat{u}_h\} = \sum_{j \in \mathbb{U}_H} Pr_{s[k]}\{u_h = \hat{u}_h | u_h^- = j\} \, Pr_{s[k]}\{u_h^- = j\}$$

- Talking points:
  - The cognitive model is implemented using a neurally-inspired cognitive architecture, ACT-R, via instance based learning.
  - We define an instance as an object comprised of context, a decision, and outcomes.
  - ACT-R is initialized with instances based on human psychology, and faced with the same decision as human participants.
  - A set of features are extracted from ACT-R's response to the problem.
  - Decision making is done via similarity-based pattern matching of these features with the instances present in memory, and noise-perturbed activation levels of these instances.
  - A new instance is created from the information available after the decision for future decisions.
  - The Markov model is defined for every feature with parameters estimated via relative frequency.

Problem statement

Problem 1.

Given a discrete-time stochastic hybrid system $\mathcal{H}$ with discrete human input captured by a Markov model, and a performance metric R, find the expected performance of the system for a typical human subject (modeled via a given cognitive model).

Problem 2.

Determine the validity of a cognitive model by comparing expected outcome using the cognitive model (Problem 1) with actual outcome from human subject experiments.

- Use expected outcome as the metric for comparison
- Deterministic forward reach tubes $RTube_{\mathrm{auto}}$ and reach sets $Reach_{\mathrm{auto}}$
- Stochastic forward reach tubes $RTube$ and reach sets $Reach$
- Reward functions $R(\cdot)$ are functions of $RTube$

Problem statement

Problem 1.

Given a discrete-time stochastic hybrid system $\mathcal{H}$ with discrete human input captured by a Markov model, and a performance metric R, find the expected performance of the system for a typical human subject (modeled via a given cognitive model).

Problem 2.

Determine the validity of a cognitive model by comparing expected outcome using the cognitive model (Problem 1) with actual outcome from human subject experiments.

- Use expected outcome as the metric for comparison
- Deterministic forward reach tubes $RTube_{\mathrm{auto}}$ and reach sets $Reach_{\mathrm{auto}}$
- Stochastic forward reach tubes $RTube$ and reach sets $Reach$
- Reward functions $R(\cdot)$ are functions of $RTube$

- Talking points:
  - Problem 1 is about finding the expected outcome and Problem 2 is about validating the cognitive model using expected outcome.
  - ((Read Problem 1 and Problem 2 verbatim))
  - Expected outcome is used to validate the cognitive model to understand the typical performance of the human.
  - We define “outcome” in terms of a reward function based on forward reachable tubes and sets.
  - Forward reach tubes are all the states that can be reached *within* time t and forward reach sets are all the states that can be reached *at* time t.
  - Their stochastic counterparts include the influence of the stochastic human input.

Solution to Problem 1: Evaluating expected outcome

- Stochastic reach tube/sets for infrequent human input computed via "stitching"
- Intervals between human input $\Delta\tau = \{I_i\}_{i=0}^{N_\tau}$
- Markov model π_h describes the probability of a sequence of human actions $\hat{\boldsymbol{u}}_h$
- Expected outcome for initial configuration s_0

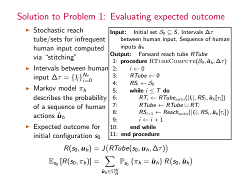
Input: Initial set $\mathcal{S}_0 \subseteq S$, Intervals $\Delta\tau$ between human input, Sequence of human inputs $\hat{\boldsymbol{u}}_h$

Output: Forward reach tube $RTube$

```
procedure RTubeCompute(S_0, û_h, Δτ)
    i ← 0
    RTube ← ∅
    RS_i ← S_0
    while i ≤ T do
        RT_i ← RTube_auto(|I_i|, RS_i, û_h[τ_i])
        RTube ← RTube ∪ RT_i
        RS_{i+1} ← Reach_auto(|I_i|, RS_i, û_h[τ_i])
        i ← i + 1
    end while
end procedure
```

$$R(s_0, \boldsymbol{u}_h) = J\big(RTube(s_0, \boldsymbol{u}_h, \Delta\tau)\big)$$

$$\mathbb{E}_{s_0}\left[R(s_0, \pi_h)\right] = \sum_{\hat{\boldsymbol{u}}_h \in \mathbb{U}_H^N} \mathbb{P}_{s_0}\left\{\pi_h = \hat{\boldsymbol{u}}_h\right\} R\big(s_0, \hat{\boldsymbol{u}}_h\big)$$



- Talking points:
  - Key point: Assuming that the human inputs are *infrequent* allow us to treat the problem of determining stochastic reach sets as a set of deterministic reach problems.
  - Given a sequence of human actions, we can define the set of time intervals beginning at a human action and ending just before the next human action. The dynamics over each of these intervals is determinstic after the human action is seleted.
  - With these, one can compute the stochastic reach tube/set via this algorithm. It iteratively computes the forward reach set and reach tube for the deterministic sections and takes the union appropriately.
  - The Markov model provides the probability measure using which we compute the expected outcome.

Solution to Problem 2: Validation of cognitive model

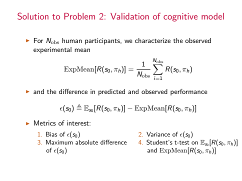
- For N_{obs} human participants, we characterize the observed experimental mean

$$\mathrm{ExpMean}[R(s_0,\pi_h)] = \frac{1}{N_{\text{obs}}}\sum_{i=1}^{N_{\text{obs}}} R(s_0,\pi_h)$$

- and the difference in predicted and observed performance

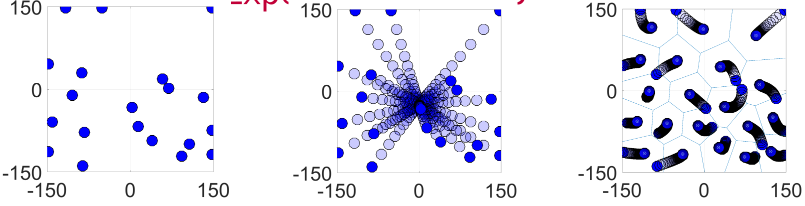
$$\epsilon(s_0) \triangleq \mathbb{E}_{s_0}[R(s_0,\pi_h)] - \mathrm{ExpMean}[R(s_0,\pi_h)]$$

- Metrics of interest:
  1. Bias of $\epsilon(s_0)$
  2. Variance of $\epsilon(s_0)$
  3. Maximum absolute difference of $\epsilon(s_0)$
  4. Student's t-test on $\mathbb{E}_{s_0}[R(s_0,\pi_h)]$ and $\mathrm{ExpMean}[R(s_0,\pi_h)]$



- Talking points:
  - To solve Problem 2, and validate the cognitive model, we compare the outcome using the cognitive model as the decision maker, to the observed outcome obtained experimentally from N_{obs} users.
  - For each trial, we define $\mathrm{ExpMean}$ as the mean outcome, and
  - ϵ as the difference between the observed outcome (experimentally) and the predicted outcome (using the cognitive model).
  - We construct a variety of metrics using these two quantities.
  - *Side note (if there's time):* Our approach relies in particular upon the assumption that human inputs are infrequent (if they were not, we could have to resort to dynamic programming to compute the forward reachable sets, which is computationally prohibitive for even moderate dimension systems). We also exploit the fact that our reward function is a function of the forward reachable set. Other outcomes, based on e.g., the viable set, would also be computationally prohibitive.

Experimental Setup

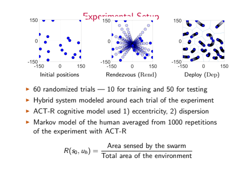


Initial positions Rendezvous (Rend) Deploy (Dep)

- 60 randomized trials — 10 for training and 50 for testing
- Hybrid system modeled around each trial of the experiment
- ACT-R cognitive model used 1) eccentricity, 2) dispersion
- Markov model of the human averaged from 1000 repetitions of the experiment with ACT-R

$$R(s_0, u_h) = \frac{\text{Area sensed by the swarm}}{\text{Total area of the environment}}$$

Bullo, Cortes, & Martinez, 2009; Sycara, Lebiere, Pei, Morrison, Tang, & Lewis, 2015

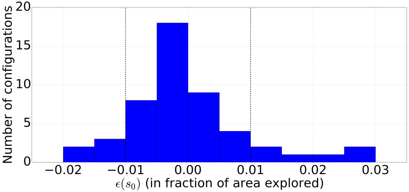


- Talking points:
  - The experiment consists of a series of 60 trials. In the first phase (10 trials) the user can "learn" how the game works, and in the second phase (50 trials) the user completes the testing on their own.
  - In each trial, the user is shown an initial configuration of 20 robots with omnidirectional sensors that cover a predetermined radius. *The user must maximize the total area sensed.*
  - Based on the initial configuration only, the user decides whether to use Rendezvous or Deploy dynamics, in which robots swarm to a common location, or spread out via Voronoi cells. This choice constitutes the human action.
  - In the training phase, the results from both strategies are shown. In the testing phase, only the results from the chosen strategy are known.
  - The ACT-R model makes use of two features: eccentricity and dispersion, to capture the difference between rendezvous and deploy dynamics. Eccentricity is the distance of the mean position of the configuration from the center. Dispersion is the RMS of the robots

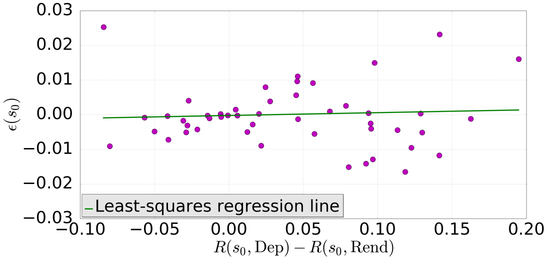
Validating the cognitive model: Results

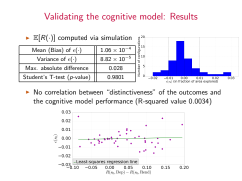
- $\mathbb{E}[R(\cdot)]$ computed via simulation

Mean (Bias) of $\epsilon(\cdot)$	1.06×10^{-4}
Variance of $\epsilon(\cdot)$	8.82×10^{-5}
Max. absolute difference	0.028
Student's T-test (p-value)	0.9801



- No correlation between "distinctiveness" of the outcomes and the cognitive model performance (R-squared value 0.0034)





- Talking points:
  - Very low mean and variance $\epsilon(\cdot)$ indicates the cognitive model predicts outcome fairly well
  - Moderately low value of maximum absolute difference shows that for some outlier configurations for the performance is not within 1% tolerance. (see the histogram)
  - The T-test between the experimental and predicted performance showed that the null hypothesis ("means are equal") cannot be rejected.
  - Additionally, we have showed that there is no correlation between the difference in the outcomes (distinctiveness) and performance
  - The first configuration shows the largest difference between predicted and observed performance and the second shows the least.
  - For the second, it is clear that `Rendezvous` is the right option. This is not true for the first configuration (potentially confused mental model arising from training).

Summary+Future work

Summary

- Human-automation systems with non-trivial dynamics and infrequent human actions
- Model as a hybrid dynamical system with a Markov controller (stochastic human input)
- Expected outcome computed via reachability analysis
- Cognitive model (ACT-R) validated against actual human subject data, via expected outcome

Future work

- Reward functions requiring safety (viability) and safety with guarantees (reach-avoid)
- Predicting conflicts in collaborative human-automation systems
- Identifying additional features to reduce the prediction error

Acknowledgments

This material is based upon work supported by the National Science Foundation.

- NSF CMMI-1254990 (CAREER, Oishi), CNS-1329878, and CMMI-1335038
- CNS-1329986
- CNS-1329762

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Summary+Future work

Summary

- Human-automation systems with non-trivial dynamics and infrequent human actions
- Model as a hybrid dynamical system with a Markov controller (stochastic human input)
- Expected outcome computed via reachability analysis
- Cognitive model (ACT-R) validated against actual human subject data, via expected outcome

Future work

- Reward functions requiring safety (viability) and safety with guarantees (reach-avoid)
- Predicting conflicts in collaborative human-automation systems
- Identifying additional features to reduce the prediction error