Position Paper: Modeling Multiple Human-Automation Distributed Systems using Network-form Games

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ORIGIN AND UNDERLYING PRINCIPLES

The focus of the modeling framework is on interactions between human and automation agents in large, distributed agent networks/systems. This model combines Bayes nets with Game Theoretic methods to model human behavior and predict the behavior of a composite system involving humans and automation. In general, some of the nodes of the Bayes net will be set by the humans in the system, some will be set with known conditional distributions (e.g., noise models of sensors), and some might be "black boxes" provided by the proposer that simulate behavior of automated devices. Novel algorithms are required for sampling and prediction with this model.

Bayes nets have been widely studied to describe stochastic systems [1-3]. A Bayes net is a directed acyclic graph in which nodes represent random variables and edges represent conditional dependencies between these variables. The variables can be observable quantities or unknown quantities (or hypotheses). An edge between two nodes indicates that the random variables represented by the nodes are conditionally independent of each other. Each node is assigned a probability function that takes as inputs the random variables of the parent node and that gives the probability assigned by to the random variable associated with the node. There exist many algorithms to calculate the interference and learning in Bayesian networks.

Game Theory is also a well-know technique, which has been used to describe the behavior of interacting humans [4, 5]. It has been widely studied in economics contexts to represent human behaviors and study how decisions are made in auctions and negotiations for examples. The field first addressed zero sum games (so that gains and losses between participants are perfectly balanced), but it has evolved beyond that and can now study different models of equilibrium (Nash equilibrium, Quantal Response equilibrium, Quantal Level-K and Cognitive Hierarchy).

Wolpert has combined Bayes nets and Game Theory in a novel framework, called semi network-form games, to model systems in which humans interact with other humans and with automation. The semi network-form game is a specialization of the complete framework "network-form games" formally defined in [6, 7] by Wolpert. Currently it is relying on level-K equilibrium.

In a semi network-form game, a Bayes net is used to describe probabilistic interactions between agents (humans or automation) in a system using random variables. Automation (and physical sub-systems) is represented by a "chance" node while a human is represented by a "decision" node. The conditional probability distributions associated with "chance" nodes are pre-specified. The "decision" nodes also differ in the sense that they are associated with a utility function, which maps an instantiation of the net to a real number quantifying the player's utility. Utility functions are used to encode the goals of a player. In other words, it represents what a human tries to optimize during the game. A semi network-form game allows a player to control only one decision node while a complete network-form game make no such restriction allowing a player to control multiple decision nodes in the net. Network-form games bear a resemblance to Multi-Agent Influence diagrams [8], except that network-form games consider bounded rational agents and uses utility functions rather than utility nodes.

We illustrate the use of network-form games with the example of a 2-aircraft mid-air encounter (similar to the infamous Überlingen accident). The corresponding Bayes net is shown in Figure 2. At time t, the system is represented by a layer of observation (of the world state) nodes (for both pilots and TCAS boxes), a layer of TCAS nodes, a layer of pilot nodes, the world state as an input node and an outcome node. The state of the pilot node is influenced by both the pilot's observations and the TCAS outcome. The final outcome state is calculated by simulating the aircraft states forward in time using a model of the aircraft kinematics. The social welfare of the system is then calculated from the outcome state. The observational layer is necessary to model observational noise and incomplete information resulting from pilots and TCAS imperfectly observing the world state.

MODELED RELATIONSHIPS

The relationships modeled with network-form games are different from traditional techniques in human factors and user interaction perspectives. The modeling framework is best suited to capture the following types of relationships:

(1). The model strength resides in its ability to capture non-deterministic pilot behavior. For example, TCAS assumes that a pilot receiving an RA will delay for 5 seconds and accelerate at ¼ g to execute the RA maneuver. Despite their

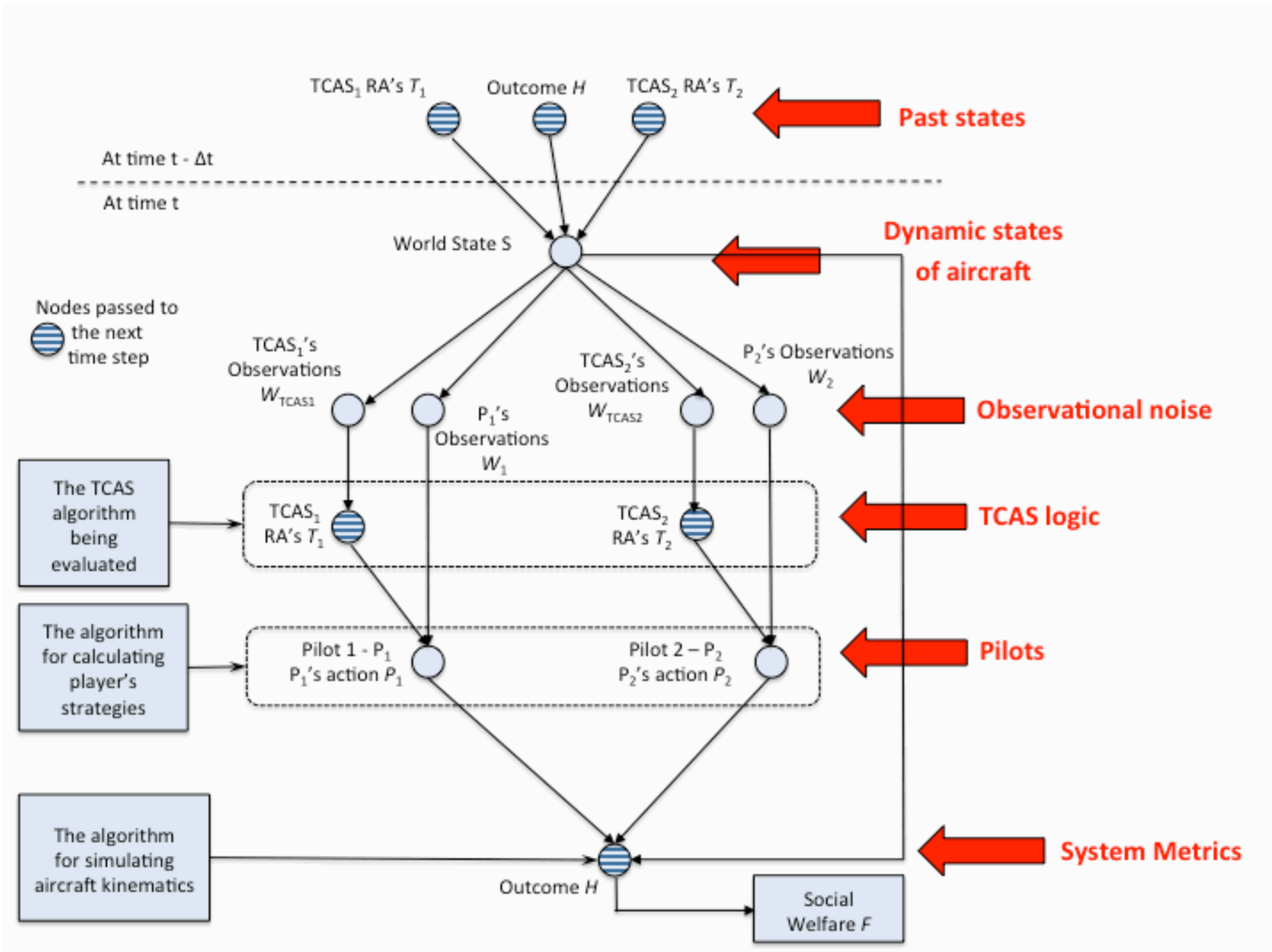

Figure 1. A Bayes net for a 2-aircraft mid-air collision example.

training, pilots actually have different reactions to TCAS RAs. A recent study [9] in the Boston area has found that

- 13% of RAs are obeyed in compliance
- 64% of RAs are obeyed in partial compliance, i.e., the aircraft is moved in the right direction but with an improper timing, and,
- 23% of RAs are ignored and the aircraft is moved in the opposite direction.

Clearly, pilots are not always responding in the same way to TCAS RAs. In fact, pilots make up their mind using more than just the TCAS information, taking into accounts other sources of information, including their own visual clues. The network-form game framework is able to capture this non-determinism by using probability distributions.

(2). The included game theory framework is also very useful to model the "gamesmanship", or guessing game, that may happening when humans interact with other humans. In a mid-air collision possibility, it is important to model the fact that a pilot is always wondering if the other pilot is going to react according to the training he received. Will the other person/pilot make the right move? What if he doesn't? What is my back-up strategy? When do I need to decide which strategy to follow? These types of questions are best answered in a game theory framework.

PROBLEMS ADDRESSED

The idea is to describe human and machine interactions within a large multi-agent system, e.g., airplane crew interacting with air traffic controllers and automation such as TCAS or ADS-B. From a safety point of view, problems can occur because of misunderstanding between

- humans, e.g., a pilot misunderstanding the orders issued by a controller, or, the pilots of two planes encroaching on their respective runways in order to optimize their on-time gate arrival time, or,
- humans and automation, e.g., a pilot doubting, or misunderstanding, the outputs of an automated box, or, a pilot following a TCAS advise when the controller is actually issuing a contradictory command.

The framework can be used at different level of granularity. It works for modeling human/machine interaction problems as well as new air traffic concepts of operation.

An interesting aspect of network-form games is its ability to model the fact that a human might reason about what another human is thinking of doing. Basically, the framework can explore how human reasons about the possible moves of an opponent. In the aeronautics case, one can model how pilots modify their actions based on the actions of another pilot on another plane, e.g., a plane on a collision course. One can model situations where the pilot is weighing his options based on his thinking that the pilot on the other plane is actually paying attention to a TCAS box or not. This can potentially affect his own reactions towards what his own TACS box is advising him to do.

In network-form games, this type of reasoning is captured by an equilibrium concept such as level-K thinking, which is defined recursively as follows. A level-K player plays as if all the other players are playing at level K-1. These players are playing in turn as if others at playing at level K-2, and so on until level 0 is reached, where the players play according to a known prior distribution. So, if we have two players A and B and K=2 and player A is a level 2 player, A plays as if Player B is a level 1 player that assumes that A plays a level 0 player. Note that those are assumptions made by player A. Player B might in reality be a level 2 player, not a level 1 who thinks A is level 0.

Now, this feature is also important when the automation is actually closer to autonomy than automation. Here we are using autonomy to describe situations in which control is not exercised by humans but by a computer of an algorithm with a certain degree of "intelligence". This is the case in Aeronautics when UAS (Un-piloted Aerial Systems) are operating autonomously in the National Airspace System and freely mix with piloted planes. The reasoning is not about another human, but about a system capable of fairly complex reasoning.

APPLICATIONS

This approach is also being used to discover and correct problems in cyber-security (cyber physical attack on smart power grid, denial of service).

LIMITATIONS AND DEVELOPMENT OPPORTUNITIES

The presented framework focuses on human factors issues such as decision making and (in some ways) perception. Issues such a cognition, and, physical limitations are hard to model. At this stage, the biggest limitation is that the analysis relies on having valid probability distributions for human behavior. The best solution would be to get access to results of high-fidelity, human-in-the-loop studies done by the FAA. However, getting access is difficult, and, the number of simulations in those studies does not lend to estimating statistically-valid probability distributions. This problem is being currently addressed by studying the possibility of using multi-fidelity simulations.

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