

Provoking Opponents to Facilitate the Recognition of their Intentions *

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Introduction

Possessing a sufficient level of situation awareness is essential for effective decision making in dynamic environments. In video games, this includes being aware to some extent of the intentions of the opponents. Such high-level awareness hinges upon inferences over the lower-level situation awareness provided by the game state. Traditional plan recognizers are completely passive processes that leave all the initiative to the observed agent. In a situation where the opponent's intentions are unclear, the observer is forced to wait until further observations of the opponent's actions are made to disambiguate the pending goal hypotheses. With the plan recognizer we propose, in contrast, the observer would take the initiative and provoke the opponent, with the expectation that his reaction will give cues as to what his true intentions actually are.

Plan recognition is of course only one component of a larger AI system which in addition involves components to make decisions on how to act against the opposing force, execute and monitor planned and reactive actions, and learn from past interactions to adapt accordingly. Our long term objective is to develop plan recognition and planning algorithms that will compete against humans in games and other applications. The unlimited creativity of the human mind coupled with its sometimes chaotic and unpredictable nature makes this challenge very exciting.

Plan Library-Based Approach

To recognize the opponent's goals, a plan recognizer needs as input observations of the environment. It also needs background knowledge on the potential behaviours the observed agent could engage in. Then, plan recognition somewhat amounts to generating hypotheses about goals and plans that are consistent with the observations so far. In many plan recognition systems, the *a priori* behaviours are conveyed by a plan library (Geib and Goldman 2009) or by behavioural constraints (Sadilek and Kautz 2010), while others use prim-

itive action descriptions and generate plans on the fly using planning techniques (Ramírez and Geffner 2009).

Although our provoking-to-observe method is orthogonal to these different plan recognition approaches, we describe it within the context of a plan library-based algorithm. Our hypothesis generation algorithm is based on PHATT (Geib and Goldman 2009), except that we use finite state machines (FSMs) to represent plans and, most importantly, include a mechanism for the provocation of the observed agent to analyze its reactions.

The adoption of FSMs to represent plans is motivated by their widespread use by game developers (Rabin 2002). The syntax and semantics of our FSMs are inspired by timed automata in formal methods (Baier and Katoen 2008), where actions are executed in states and transitions denote events the executing agent reacts to. Transitions must be enabled to change to a new state. An event is a Boolean condition over world state propositions and clock variables, used to specify time constraints. When entering a state, clocks can be initialized or reset. A transition is enabled when the corresponding event holds. An agent cannot stay in a state when there is at least one enabled event.

Provoking a Reaction

As in PHATT, our algorithm generates on the fly a set of hypotheses that explain the sequence of observations to date. Each of these hypotheses indicates the set of behaviours the opponent is believed to be pursuing, as well as the completion status of these behaviours. The generated hypotheses can be ranked by their conditional probabilities given the sequence of observations.

Given an FSM modelling the behaviour of an agent, we can have events for which the corresponding propositions are made true or false by another agent. We call these events *provokable* from the latter agent's standpoint. For plan recognition, we are interested in events affecting the behaviours of the observed agent and which can be provoked by the observing agent.

Provoking an event may cause the opponent to react upon it, thus revealing his intended behaviour. Deciding when and which event to provoke is in fact a planning problem. However, as a starting point to solve the problem, we rather explore a heuristic approach that consists in selecting the event to provoke just based on its expected disambiguation

*The work presented herein was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada and the Fonds québécois de la recherche sur la nature et les technologies (FQRNT).

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of the current set of hypotheses. For each provokable event, we compute the expected reduction of the uncertainty on the opponent’s intentions, knowing how he would react to the provocation. We use entropy as a measure of uncertainty associated with the set of hypotheses, and determine the provokable event that is expected to reduce it the most.

By simulating the opponent’s potential reactions as if he had been provoked, we get new sets of hypotheses. We then average the entropy of each resulting situation over the potential reactions to the provocation of an event, and compare them with the entropy of the current set of hypotheses. The codomain of this *expected disambiguation* \mathcal{D} is $[-1, 1]$, each extreme marking a situation where the ambiguity on the opponent’s intentions has been exacerbated in the worst possible way or completely removed, respectively. Thus, the best event to provoke is the one with the largest \mathcal{D} value. If this value is negative, it might be better to simply wait instead of voluntarily risking to increase the uncertainty on the opponent’s intentions. Accordingly, our goal recognition algorithm takes as input two thresholds, one for the minimal entropy and the other for the minimal expected disambiguation. If both thresholds are met, the provocation of the event is given as a goal to a deterministic forward-chaining planner to produce a plan leading to a state where the event holds.

Experimental Results

We conducted several experiments, producing very encouraging, albeit preliminary, results, given that we adopted a heuristic approach to the problem instead of the fully-fledged provocation planning approach. We scripted the opponent’s goals as pairs of behaviours selected from a set of 5 potential behaviours from an artificial domain with very similar prefixes, making them hard to be identified by a typical goal recognition algorithm. We then let the opponent randomly select actions pertaining to his plans and had the observer try to recognize the opponent’s goals. We generated 500 such scenarios and measured the average probability that the correct goal was recognized properly by each algorithm, with respect to the percentage of completion of the opponent’s plans. The results are reported in Figure 1.

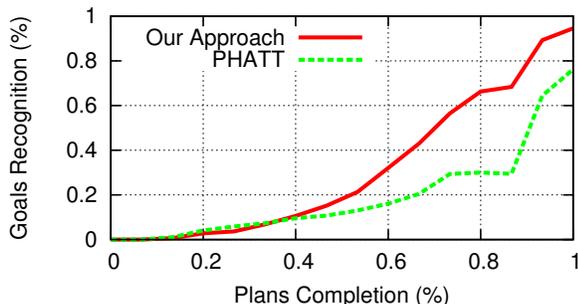


Figure 1: Experimental results

As the figure shows, the average accuracy of the goal recognition process was improved by the enhanced algorithm. The correct goal was, on average, correctly identified with a probability of 0.762 using the PHATT algo-

rithm and with a probability of 0.946 using our algorithm. Moreover, the earliest detection time is preceded by approximately 20 % of the plan’s completion. Although the provocation of events generally improves the goal recognition process, it sometimes increases the probability of some hypotheses that are wrong to begin with. In the experiments, these hypotheses tend to be eliminated later as more actions are observed. This can be seen on the figure where the solid red curve is below the dashed green curve. This means that, with the approach as it stands now, the selection of the best event to provoke is heavily dependent on the accuracy of the underlying recognition system.

Conclusion

We presented a method of provoking the opponent during plan recognition based on the expected disambiguation of the current set of goal hypotheses. A comparison to the PHATT algorithm demonstrated that such a technique is indeed a useful addition to the algorithm to improve its accuracy and earliest time detection.

The current implementation is only a starting step in exploring this idea of provoking to observe the reaction in plan recognition. Currently, we only consider the opponent’s immediate reaction to a provocation. The next step of our investigation is to consider the longer term effect of a provocation on the opponent’s behaviours as well as on the observer’s own goals. Indeed, it is possible that by provoking, the observer may, in turn, make himself vulnerable. We plan to examine an integrated planning and plan recognition approach in which the decision to provoke takes into account the impacts on the observer’s goals, the cost of actions, and the plans he is currently committed to.

An important obstacle to plan library-based approaches in adversarial domains is that it is virtually impossible to script all potential behaviours in a plan library. Learning behaviours remains an important research avenue to face this obstacle.

The ultimate test of a plan recognition algorithm is when it is embedded into an effective planning and plan execution architecture. Future evaluations of our approach will involve comparisons with alternative methods by integrating the compared plan recognizers in a game AI and have them compete against one another to see which one wins.

References

- Baier, C., and Katoen, J.-P. 2008. *Principles of Model Checking*. The MIT Press.
- Geib, C., and Goldman, R. 2009. A probabilistic plan recognition algorithm based on plan tree grammars. *Artificial Intelligence* 117(11):1101–1132.
- Rabin, S. 2002. *AI Game Programming Wisdom*. Rockland, MA, USA: Charles River Media, Inc.
- Ramírez, M., and Geffner, H. 2009. Plan recognition as planning. In *Proceedings of the 21st International Joint Conference on Artificial Intelligence (IJCAI)*.
- Sadilek, A., and Kautz, H. 2010. Recognizing multi-agent activities from GPS data. In *Proceedings of the 24th Conference on Artificial Intelligence (AAAI)*.