Evaluating the Impact of Anticipation on the Efficiency and Believability of Virtual Agents

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Abstract. We propose a model of cognitive process allowing virtual agents to exhibit anticipatory abilities. With user experiments, we show that this mechanism brings about an improvement in the efficiency of the behavior generated, and check that external observers are able to perceive it. We also confirm that this improvement in efficiency leads, up to a point, to an improvement in believability as judged by human observers. Beyond this level of efficiency, believability reaches a plateau.

Keywords: virtual agents, hybrid architectures, anticipation, believability, user evaluation, agent-based simulation.

1 Introduction

The field of virtual agents is particularly rich, and finds applications in various domains. In this paper we address primarily applications to urban simulation, though our results are relevant to other domains. In urban simulation, one has to be able to deal with a large number of agents, in real-time, and in a rich environment. These constraints often lead toward using reactive agents which are known to have limitations in terms of believability [1] and are not adequate when the behaviors to simulate become complex. For that reason, the idea of combining reactive and cognitive abilities in hybrid agent architectures is useful [4]. In this paper we tackle the issue of enriching the decision process of virtual agents with anticipatory abilities, one of the most important skills recognized as cognitive. Our claim is that these abilities increase the behaviors efficiency of the virtual agents, and consequently the believability (as perceived by human observers) of these behaviors. We study this claim by integrating the corresponding module in a agent architecture [2] and by evaluating it with a user experiment focusing on the perceived efficiency and believability of the agent's behaviors.

We consider classically that believability is the capacity of an agent to "suspend the disbelief" of observers [3]. Over the last years, the role of anticipation has appeared as an important feature in agent's decision processes and in virtual agent's

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believability, to such an extent that [1] claimed: "only cognitive systems with anticipation mechanisms can be credible, adaptive, and successful in interaction with both the environment and other autonomous systems and humans".

2 Anticipatory Module

The anticipatory module proposed here takes some inspiration from [5]. Its goal is to provide agents with an ability to make predictions about themselves and their environment, using predictive models. This module is based on an evaluation of future individual satisfaction levels rather than future states as often done in state anticipation. This leads to a better generality, because it is possible to provide the agents with their own model of satisfaction, largely independent from the environment used.

Our anticipatory module uses predictive models. These include a model able to calculate a level of *satisfaction* based on the internal states of the agent. It also includes predictive models about the *environment*, the *actions*, and the *internal states*, which are traditionally used in anticipatory mechanisms. Additionally, a decision model is required to produce predictions on the future *decisions* of the agent. These models can come from several sources: they can be handcrafted by the agent designer, but they can also be learned. A third possibility is to assume that the anticipatory module is fully introspective: it can directly use the various models at work in the agent architecture to run them for predicting their future outputs. We made this simplifying assumption in the experiments reported further below.

We give below a synthetic algorithm of the anticipatory process proposed:

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Data:
A is an agent;
tc is the current time;
Initialization:
t = tc;
while (StoppingCondition is
false), repeat:
PredictNextAction(A,t);
PredictEndOfAction(A,t);
PredictFutureState(A,t);
EvaluateFutureSatisfaction(A,t);
SearchAnticipatoryPlan();
end
```

StoppingCondition(A,t): is the stopping condition of the algorithm.
PredictNextAction(A,t): predicts the action of A at time t.
PredictEndOfAction(A,t): uses the action model to estimate the time remaining until the completion of the predicted action.
PredictFutureState(A,t): uses the environment model to predict the changes occurring in the environment.
EvaluateFutureSatisfaction(A,t): uses the satisfaction model and the predicted situation to predict the satisfaction (S) at time t .
SearchAnticipatoryPlan: attempts to find a plan that leads to a satisfaction (SP) higher than S. Each plan found by this method is called an *anticipatory plan*: a plan using prediction abilities to attempt to be more efficient. These plans have a grade attached Q, depending on both G the predicted gain in satisfaction, and C a confidence level. In this paper, we consider that the goal of the anticipatory module is only to propose these plans.

3 Empirical Evaluation

In order to validate our model, the anticipatory module is integrated in an agent hybrid architecture, described in [2,6]. Agents are driven by a set of behavior sources (*high-level modules*) that propose behaviors. These proposals are fed into a *decision module*, in charge of the integration of all behavior proposals. By default two simple high-level modules were used: a module based on motivations [7], and a schedule module. The anticipation module is therefore introduced as a third high-level module.

In the following experiments, we assume a fully introspective anticipatory module. Satisfaction is based on the number and priority levels of all behavior proposals received by the agent's decision module, and the stopping condition for anticipation is defined as a maximum number of anticipated actions, set to 3.

Experiments were carried out with the simulator described in [7], and all simulations take place in the virtual environment of Place de la République area in Paris, which covers 1.6 km², 5000 buildings, and 100 points of interest, with about 20 actions available to the agents.

The goal of these experiments is to evaluate the following hypotheses: (H_1) the anticipatory module improves the behaviors efficiency; (H_2) the anticipatory module improves the behaviors believability; (H_3) an improvement in the behaviors efficiency brings an improvement in the behaviors believability. The user experiments were conducted through an online survey and involved 144 participants.

Table 1. The participants were presented with two short videos showing the proceedings of an agent's morning. The agent starts at home and then goes to work and stays there until noon. Only in the second video, the agent has an anticipatory module activated. Participants were first asked to grade the *efficiency* of the behaviors shown in both videos on a Likert scale, from 1 to 7 (results in Table 1), then the *believability* of the same behaviors (results in Table 2).

Table 1. Efficiency of behaviors with and without anticipation, on a Likert scale from 1 to 7

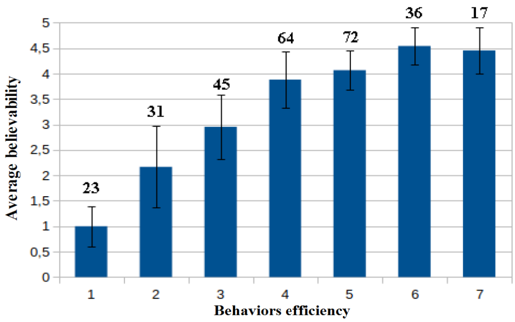
	Average score	st. dev.	Mode
Without anticipation	3.69	1.60	4
With anticipation	4.64	1.74	6

Table 2. Believability of behaviors with and without anticipation, on a Likert scale from 1 to 7

	Average score	st. dev.	Mode
Without anticipation	4.44	1.53	5
With anticipation	4.96	1.65	6

We can see that both efficiency and believability are improved by anticipation, the first more markedly. Both improvements are significant as confirmed by two student's t-tests (with a confidence level below 0.01). Hence both H_1 and H_2 are validated.

We consider now the evolution of behavior believability as a function of behavior efficiency, in order to check H_3, and based on the graph shown in Figure 1.



Graph obtained by gathering results from two previous questions: two sets of 144 couples of efficiency and believability scores. From these 288 couples, we obtain the average believability score associated with each efficiency grade. Standard deviations appear as vertical segments, and number of observations on top of bars.

Fig. 1. Average Behavior Believability, Function of Behavior Efficiency

At first, each gain in efficiency brings a significant gain in believability. Above an efficiency score of 4, believability reaches a plateau, and one could even hypothesize the beginning of a decrease in believability. One could say that H_3 is confirmed only when the perceived efficiency is low or medium.

4 Conclusion

In this paper we presented a model of anticipatory module based on the maximization of an agent satisfaction level, that was integrated within a virtual agent architecture. We confirmed that anticipation brings an improvement in the perceived efficiency and believability. Furthermore, we showed a link between the efficiency and the believability of a behavior, though gains in believability are only obvious when efficiency is low or medium. In conclusion, we can argue that adding anticipatory abilities is a crucial step toward increasing agents believability even though we highlighted some limitations to this result, which would require further research.

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