Prediction Time in Anticipatory Systems*

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1 Introduction

How important is it to anticipate what will happen in the future? Is it better to anticipate far into the future or to focus on the next few seconds? We have investigated this question within a multi-agent framework where four simulated robots try to collect gold from two buildings without being seen by two patrolling guard agents. The success of the task depends fundamentally on an ability to anticipate.

Rosen [3] proposed that "an anticipatory system is: [...] a system containing a predictive model of itself and/or its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a latter instant". Davidsson [1] used simulations to investigate the benefits of anticipation. In the experiments, the task of the agents were to pick up targets in a two dimension grid world in a particular order and by using a linearly quasi-anticipatory agent architecture, cooperation between the agent lead to decreased total time for fetching all target objects.

In previous work we investigated the importance of anticipation in navigation task [2]. The results of this work show that a multi-robot system will benefit from anticipation compared to a system without anticipation. However, the models used to predict must have high precision, otherwise a reactive or a pure planning strategy will perform equally well as anticipation. The benefits of anticipation also depends on the task. A complex task will increase the usefulness of anticipation and in a simple task, the reactive or planning strategies could perform better then the anticipation strategies. In this paper we will study one additional variable that affects anticipation. By varying the time for how long the agents will predict, we will try to answer the question of how the prediction time influences the success of a task.

2 A Task with Guards And Thieves

In this paper we use a multi-agent system, which has been developed primarily for robots, but it can also run as a pure simulation. The system can be adjusted to simulate different types of robots although here we use the kinematics of

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the E-puck robot.The size of the area where the agents are allowed to navigate is 2x2 m Fig. 1. Within the navigation area there are two buildings, with the approximate size of 60x30 cm. Each building has a 20 cm opening that makes it possible for the agents to sneak into the building. There is also a safe zone where the agents can hide.

The environment is similar to that used in a previous task where the robots had to switch places with each other in environments of different complexity [2]. Here we use a guards and thieves scenario which is a bit more complex. The task for the thieves is to collect gold in the two buildings. In our setup we use two guards and four thieves. The guards protect the buildings that contains the gold by patrolling the area around the buildings on a fixed route. The thieves are hiding in the nearby safe zone, but when there is an opportunity, they sneak out and try to collect the gold. Each time a thief enter the building it collects a gold and tries to return to the safe zone with it. If a thief is seen by the guards, the thief seeks shelter in the safe zone.

In this setup, the guards have been made intentionally less gifted and slower than the thieves. The behavior of the guards is to follow an already set route around the buildings. We have chosen this behavior to reduce the complexity and to better control the thieves anticipatory behaviors. One could enrich the guards with more complex and more realistic behavior like letting the guards anticipate the thieves and having them patrol in an autonomous way. Behaviors like that would give the guards and thieves scenario more dynamic and interesting behaviors, but at the expense of results that would be much harder to interpret. In this scenario, we are not interested in the guard's behavior and we only measure the anticipatory behaviors of the thieves.

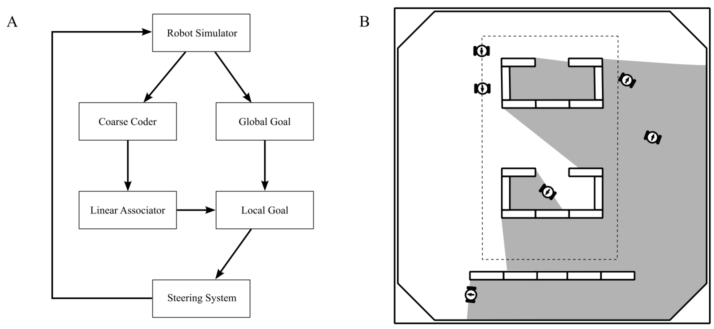

FIG. 1: *A: The Robot Simulator provide an input to the learning system, which is used to predict future position of the guards. This is used to determine a local goal for the agent. B: The agent creates a map over areas that are visible for the guards using the prediction of where the guards will be in the future*

An overview of the control system is shown in figure 1. The global goal module gives the final goal position for the agent. In this simulation, the global goal is either to collect gold in the buildings or to return to its safe zone.

Each agent uses a set of linear associators to learn the guards' routes around the buildings. The input for these associators is coded using coarse coding to get a faster learning rate. These are later used to predict the path of the guarding agents. The learning is made during simulation. Using the learned route of the guards, the thieves can predict the position of the guards t time steps ahead based on its current observation of the guards. This knowledge from the prediction system is used to build a map of regions that are visible and will be visible for the guards and the thieves try to avoid these areas (Fig. 1). The visible parts of the environment are formed as the union of all the visibility polygons generated by each location where the guard is predicted to pass in the next t time steps.

3 Simulations

The simulation system was developed using the Ikaros framework where a large number of modules were developed to control the real and simulated robots. The experiment simulates 35 minutes for real robots in a fixed environment.

Initially, the thieves are located in the safe zone and are not seen by the guards who are located in the upper left corner of the environment. As soon as the experiment begins the thieves try to find a safe way to collect gold and the guards start to guard the buildings. The experiment is repeated ten times with different prediction times for the thieves which stretches from 0 to 40 seconds.

The result of the experiment showed that the thieves collected an almost constant number of gold while prediction time is less then 15 seconds. After this the gold rate quickly drops to a minimum Fig. 2. The time that the thieves are visible for the guards does not vary much with a prediction time less than 6 seconds. From 6 to 15 seconds prediction time, the thieves become more visible for the guards and then the visible value decrease.

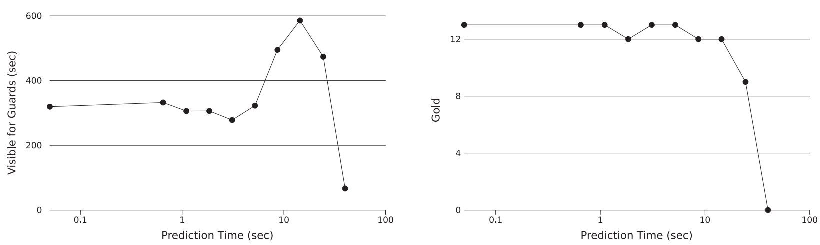

Fig. 2: *A: The graph shows the mean number of gold collected by the thieves. B: The time the thieves are visible for the guards.*

4 Discussion

The current implementation was used to investigate how the prediction time influences the success of a guard and thieves task described in this paper. The result of the experiment shows that a too long prediction time reduces performance. The thieves could not collect any gold if they considered states too far into the future since this would make them afraid of being seen by the guards which resulted in less gold. Although the task for the agents where to collect gold without being seen by the guards. With a prediction time over 6 seconds the thieves is actually more visible for the guards then with a prediction time less than 6 seconds. This may seem strange but this is due to the restrictions of anticipation. The agents are using anticipation to find an opportunity to collect gold but with longer prediction time the time slots between visible and not visible for the guards decrease. With a shorter prediction time, the agent only take a guard into account when it is about to be visible for the agent. This will give the agent more time to collect the gold compared to a longer prediction time. A longer prediction time gives the agent shorter time to actually navigate to the building and to collect the gold. This suggests that to benefit from anticipation with longer prediction time, the demand for the agent is increased. The agent must be able to compensate for the time lost when anticipating. In this paper, the agent builds the map using the predicted position of the guards. The prediction could be more effective if the robot maximized the time slot to fetch the gold. More than 15 seconds prediction time change the behavior of the agent to a more restricted behavior and with 40 seconds the robot does not manage to leave the safe zone once to collect gold.

However, to find an optimal prediction time, a number of features have to be taken into account. The complexity of the task and ability for the agent to plan its own action and how this will influence the environment will likely give different optimal prediction times.

In previous experiments, we have shown that the anticipation depends on precise models to benefits the most. In this paper we show how the demands of the agent increase when prediction time increase.

References

[1] P. Davidsson, Learning by linear anticipation in multi-agent systems. *In 12th European Conference on Articial Intel ligence (ECAI-96) workshop on Learning in Distributed Articial Intelligence Systems*, 1996.

[2] B. Johansson and C. Balkenius, An Experimental Study of Anticipation in Simple Robot Navigation. In Butz, M. et al. (Ed.) *Anticipatory Behavior in Adaptive Learning Systems: From Brains to Individual and Social Behavior.* LNAI, 4520, Springer-Verlag, 2007.

[3] R. Rosen, *Anticipatory Systems.* Pergamon Press, 1985.