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Reinforcement Learning in Dynamic Environments using Instantiated Information

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Abstract

We study using reinforcement learning in dynamic environments. Such environments may contain many dynamic objects which makes optimal planning hard. One way of using information about all dynamic objects is to expand the state description, but this results in a high dimensional policy space. Our approach is to instantiate information about dynamic objects in the model of the environment and to replan using model-based reinforcement learning whenever this information changes. Furthermore, our approach is combined with an a-priori model of the changing parts of the environment, which enables the agent to optimally plan a course of action. Results on a navigation task with multiple dynamic hostile agents show that our system is able to learn good solutions minimizing the risk of hitting hostile agents.

1. Introduction

Reinforcement learning. Reinforcement learning (Sutton & Barto, 1998; Kaelbling et al., 1996) can be used to learn to control an agent by letting the agent interact with its environment and learn from the obtained feedback (reward signals). Using a trial-and-error process, a reinforcement learning (RL) agent is able to learn a policy (or plan) which optimizes the cumulative reward intake of the agent over time. Reinforcement learning has been applied successfully in particular stationary environments such as in backgammon (Tesauro, 1992). RL has only been used few times in single agent non-stationary environments. Path-planning problems in non-stationary environments are in fact partially observable Markov decision problems (POMDPs) (Lovejoy, 1991), which are known to be hard to solve exactly. Dayan and Sejnowski (1996) concentrate themselves on the exploration problem of detecting changes in a changing environment. Boyan and Littman (2001) use a temporal model to take changes of the environment into account when computing a policy. In this paper we are interested in applying RL to learn to control agents in dynamic environments.

Dynamic environments. Learning in dynamic environments is hard, since the agent needs to stay informed about the status of all dynamic objects in the environment. This can be done by augmenting the state space with a description of the status of all dynamic objects, but this may quickly cause a state space explosion. Furthermore, the agent may not exactly know the status of an object and therefore has to deal with uncertain information. Using uncertain information as part of the state space is hard, since it makes the state space continuous and high dimensional.

Instantiating information in the model. There exists another method for using knowledge about dynamic objects: *instantiate* the information about the dynamic objects in the world model and then use the revised world model to compute a new policy. E.g. if a door can be open or closed, and we know whether the door is closed, we can set new transition probabilities between states in the world model such that this information can be used by the agent. Once the model is updated using the currently available information, dynamic programming-like algorithms (Bellman, 1961; Moore & Atkeson, 1993) can be used to compute a new policy. In this way, we have an adaptive agent which takes currently known information into account for computing actions, and which replans once the dynamic information changes.

Using prior knowledge. Usually, reinforcement learning is used to learn control knowledge from scratch, i.e. without using a-priori knowledge. Sometimes, however, the use of some kind of a-priori knowledge is clearly beneficial, e.g. if particular actions are heavily punished we do not want to explore those actions, but rather reason about the consequences of these actions using an a-priori designed model. A-

priori knowledge could also be used to model a dynamic environment so that this knowledge could be presented to the RL agent. This enables the agent to reason about the dynamics of the environment which may be necessary to solve the problem. In this paper, we study using a-priori knowledge for learning to solve problems in dynamic environments.

Outline of this paper. We will describe model-based RL in section 2. Then using instantiated information is described in section 3. Then we describe the experimental setup and results in section 4. Section 5 provides a discussion which relates our framework to POMDPs and describes the limitations of the approach. Finally, section 6 concludes this paper.

2. Model-Based Reinforcement Learning

2.1 Markov Decision Problems

As a model of the environment and task we use the Markov decision problem (MDP) framework. We consider a finite set of states $S = \{S_1, S_2, \ldots, S_n\}$, a finite set of actions A, and discrete time steps $t = 1, 2, 3, \ldots$. Let s_t denote the state at time t, and $a_t = \Pi(s_t)$ the action, where Π represents the agent's policy mapping states to actions. The transition function P with elements $P_{ij}(a) := p(s_{t+1} = j | s_t = i, a_t = a)$ for $i, j \in S$ defines the transition probability to the next state s_{t+1} given s_t and a_t. A reward function R maps state/action pairs (SAPs) $(i, a, j) \in S \times A \times S$ to scalar reinforcement signals $R(i, a, j) \in I\!R$. A discount factor $\gamma \in [0, 1]$ discounts later against immediate rewards. The agent's goal is to select actions which maximize the expected long-term cumulative discounted reinforcement, given an arbitrary initial state $\in S$. The value $V^{\Pi}(i)$ is a prediction of the expected discounted cumulative reward to be received in the future, given that the agent is currently in state i and policy Π will be used in the future:

$$V^{\Pi}(i) = E(\sum_{k=0}^{\infty} \gamma^k R(s_k, \Pi(s_k), s_{k+1}) | s_0 = i)$$

Action evaluation functions (Q-functions) $Q^{\Pi}(i, a)$ return the expected future discounted reward for selecting action a in state i, and subsequently executing policy Π:

$$Q^{\Pi}(i, a) = \sum_j P_{ij}(a)(R(i, a, j) + \gamma V^{\Pi}(j))$$

where V^{Π} is defined as: $V^{\Pi}(i) = \max_a Q^{\Pi}(i, a)$. By setting $\Pi(i) = argmax_a Q^{\Pi}(i, a)$ for all states i we then iteratively improve the policy.

2.2 Estimating a Model

In reinforcement learning we do not initially possess a model containing the transition and the reward functions, and therefore we have to learn these from the observations received during the interaction with the environment. Inducing a model from experiences can be done by counting the frequency of observed experiences. For this the agent uses the following variables: $C_{ij}(a)$:= number of transitions from state i to j after executing action a. C_i (a) := number of times the agent has executed action a in state i. $R_{ij}(a)$:= sum of all immediate rewards received after executing action a in state i and stepping to state j.
A maximum likelihood model (MLM) is computed as:

$$\hat{P}_{ij}(a) := \frac{C_{ij}(a)}{C_i(a)} \text{ and } \hat{R}(i, a, j) := \frac{R_{ij}(a)}{C_{ij}(a)} \quad (1)$$

After each experience the variables are adjusted and the MLM is updated.

2.3 Prioritized Sweeping (PS)

Dynamic programming (DP) techniques (Bellman, 1961) could immediately be applied to the estimated model, but online DP tends to be computationally very expensive. To speed up DP algorithms, some sort of efficient update-step management should be performed.

Our Prioritized Sweeping:

```
1) Promote the most recent state k to the
   top of the priority queue
2) ∀ a do:
    3 Q(k,a) := Σ_j P̂_kj(a)(R̂(k,a,j) + γV(j))
4) While n < U_max AND the queue is not empty
    5 Remove the top state s from the queue
    6 Δ(s) := 0
    7 ∀ Predecessor states i of s do:
       8 V'(i) := V(i)
       9 ∀ a do:
          10 Q(i,a) := Σ_j P̂_ij(a)(R̂(i,a,j) + γV(j))
       11 V(i) := max_a Q(i,a)
       12 Δ(i) := Δ(i) + V(i) − V'(i)
       13 If |Δ(i)| > ε
          14 Promote i to priority |Δ(i)|
    15 n := n + 1
```

This can be done by prioritized sweeping (PS) (Moore & Atkeson, 1993) which assigns priorities to updating the Q-values of different state/action pairs (SAPs) according to their relative update sizes. Following the update of a state-value, the state's predecessors are inserted in a priority queue. Then the priority queue

is used recursively for backpropagating the update of the states with highest priority. Our implementation (Wiering, 1999) uses a set of predecessor lists $Preds(j)$ containing all predecessor states of state j. We denote the priority of state i by $|\Delta(i)|$, where the value $\Delta(i)$ equals the change of $V(i)$ since the last time it was processed by the priority queue. To calculate it, we constantly update all Q-values of predecessor states of currently processed states, and track changes of $V(i)$. The details are given above. The parameter U_{max} is the maximal number of updates to be performed per update-sweep. The parameter $\epsilon \in \mathbb{R}^+$ controls update accuracy.

3. Instantiating Information

For particular environments with dynamic objects, the agent should have information about the status (e.g. position) of these objects. One way of using this information is to expand the state space to include the state of all dynamic objects. However, suppose that we possess information about a dynamic object in the form of occupancy probabilities. Clearly it is not desirable to include these occupancy probabilities in the state space, since this would result in a high dimensional continuous state space which makes planning and the use of dynamic programming-like algorithms hard.

Instantiating information. Another way is to *instantiate* the information about the dynamic object in the world model. E.g. if we have information about occupancy probabilities of robots in a soccer game, we may adjust the model's transition probabilities to account for possible hits with obstacles. Thus, expected occupancy probabilities of a hostile agent can be used for setting transition probabilities to a (possibly terminal) encounter with the hostile agent.

An example of instantiating information. Suppose that the agent receives new information that the hostile agent has probability $p(j)$ to occupy a specific state j. If the agent makes a step after which she meets the hostile agent, she dies. How do we then change the model to incorporate the information about occupancy probabilities of the hostile agent? Clearly we have to reset the transition counters and reward variables, since this is what our model consists of. We define the transition counter from state i to some terminal state (H for hit) which is occupied by a hostile agent if action A is executed as $C_{iH}(a)$. Now if some state action pair (i,a) can make a transition to state j with probability $\hat{P}_{ij}(a)$ and we know the probability that a hostile agent occupies state j is $p(j)$, we set the transition counter for modelling transitions from i to the terminal state H (hit) to:

$$C_{iH}(a) := \frac{p(j)\hat{P}_{ij}(a)(C_i^{old}(a) - C_{iH}^{old}(a))}{1 - p(j)\hat{P}_{ij}(a)}$$

and

$$C_i(a) := C_i^{old}(a) - C_{iH}^{old}(a) + C_{iH}(a)$$

In this way the new probability $\hat{P}_{iH}(a)$ will become $p(j)\hat{P}_{ij}(a)$. We set the reward $R_{iH}(a)$ to R_{hit}.

General algorithm. In case an action a from a state i can result in multiple states j all with a different probability of being occupied by the hostile agent, we cannot set the transition counter to one of these transitions immediately, but have to add the transition counter over all transitions to states which may be occupied by a hostile agent. For this we first reset all counters to hostile states to 0, and then recompute the counters using the occupancy probabilities. The following algorithm does this:

Instantiating information :

1) For all state-action pairs (i,a) which are in a possible area of the hostile agent do:
  2) $C_i(a) := C_i(a) - C_{iH}(a)$
  3) $C_{iH}(a) := 0$
4) For all hostile areas D do:
  5) For all (i,a) pairs which can lead to some successor state k in D do:
    6a) $C_H := 0$; 6b) $C_T := 0$
    7) For all successor states j of (i,a)
      8) If state j falls inside D
        9) $C_H := C_H + C_{ij}(a)p(j)$
      10) $C_T := C_T + C_{ij}(a)$
    11) $p_{old} := C_{iH}(a)/C_i(a)$
    12) $p_{new} := \hat{P}_{ij}(a)C_H/C_T$
    13) $\Delta C := \frac{C_i(a)*(p_{new}+p_{old})-C_{iH}(a)}{(1-p_{new}-p_{old})}$
    14) $C_{iH}(a) := C_{iH}(a) + \Delta C$
    15) $C_i(a) := C_i(a) + \Delta C$
    16) $\hat{R}(i,a,H) := R_{hit}$

This algorithm exactly recomputes the desired probabilities for transitions from a state/action pair to a hit with some hostile agent (dynamic obstacle). Note that rewards $\hat{R}(i,a,H)$ are set to R_{hit} which is predefined in the reward function.

Using prioritized sweeping to replan. After we instantiated all newly available information, we store all changed states at the top of the priority queue and use prioritized sweeping to recompute the policy. This ensures that the new information is immediately used.

4. Experiments

Wumpus II. We have executed a number of experiments to validate the usefulness of our method. In the first experiment we have a small maze and one hostile spider agent, and in the second experiment we have a larger maze and 5 moving spider agents. The agent needs to find the goal in the least number of steps without hitting a spider. The agent cannot see the spider, however. If the agent hits a spider it dies and knows the region where the spider was. A spider agent occupies a particular nest and moves randomly around the nest so that all states surrounding the spider nest have the same occupancy probability. If the agent finds an active nest, the agent can smell whether there is an active spider in the region or not. Figure 1 shows the first environment used in the experiments which consists of two spider nests. For the region around the spider nest, we use 25 states. After a trial, the spider may move to a different nest or goes to its current nest.

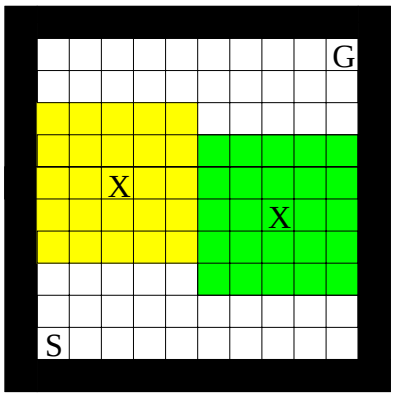

Figure 1. The maze environment containing two spider nests X which may be used by the spider. The start and goal positions are indicated by S and G. The regions around the spider nests denote which states the spider may occupy if it uses a particular nest. The agent and the spider can move in 4 directions.

4.1 The Model of the Environment

The agent knows her exact (X,Y) location at all times, but cannot observe the spider agent. She only knows the exact spider location when she hits the spider, but then she dies so that information is only partially useful, since a new trial starts and the spider is reset to the position of the new active, possibly neighboring, spider nest. After each trial the spider has a particular probability $P_{move} = 1 - P_{stay}$ of moving to one of the neighboring nests.

Modelling occupancy probabilities. In the beginning the agent does not know where the spider nests are. It has to discover these for itself, but once it hits a spider nest, it remembers its location in (X, Y) coordinates. The a-priori knowledge of the agent consists of its knowledge of the size of the region of a spider nest in which the spider moves randomly, and the probabilities that the spider makes a transition to a new neighboring spider nest after each trial[1]. The agent uses a probabilistic model of the spider's location. The occupancy probabilities $P(S\_spider)$ are computed by:

$$P(S\_spider) = \sum_i P(Active_i)P(S\_spider|Active_i)$$

Here, the agent uses for hostile area i the probabilities: $P(Active_i)$ and the conditional probabilities $P(S\_spider|Active_i)$ to compute the probabilities $P(S\_spider)$. The probability $P(S\_spider|Active_i)$ is set to $\frac{1}{M}$ for the M (25) states surrounding a spider region and 0 to other states. Note that we model the stationary distribution of the spider's location.

Computing active nest probabilities. The first probability $P(Active_i)$ follows from the properties of the dynamic stochastic system. There are several ways to get new information about the state of the system: (1) The agents finds a nest and observes whether it is used or not, (2) The agent hits the spider around some nest, (3) A new trial starts, and the agent knows that the spider may have migrated to a neighboring nest. In case the agent finds a spider nest, it can see whether the nest is active or not. In case the nest is active it sets the probability $P(Active_i)$ to 1.0, and sets the probabilities for the other nests to 0. If the nest is not active the agent sets the probability $P(Active_i)$ to 0.0 and renormalizes the probabilities of the other nests.

Hitting the spider. In the same way, in case the agent hits the spider, the agent knows that the region in which it was walking contained the active nest, and sets the probability $P(Active_i)$ to 1.0 and the other nest probabilities to 0.0. After an encounter with the spider, the agent dies and a new trial is started.

Transition probabilities between nests. After each trial, the spider may change its nest. In the small maze given above, the spider has probability $P_{stay} = 0.9$ of staying in the same nest and probability 0.1 of moving to the other nest after each trial. Therefore we recompute the active nest probabilities of the model after each trial by:

$$P(Active_1) = 0.9P(Active_1) + 0.1P(Active_2)$$

And vice versa for the other nest.

[1] Although learning this information is possible, it would require many interactions with the spider or with spider nests and therefore take a very long time.

Discovering nests. Since the agent can only set probabilities to non-zero for nests it has discovered and knows that the spider can only move between nests which are closer than a particular distance Manhattan D (which is set to 7 and defines the neighbourhood relation between nests), the probability cannot be exactly computed in case the agent has not yet discovered all spider nests. Therefore exploration is important to ensure all spider nests have been found.

Using additional a-priori information. Finally, we use a-priori information in the form of an initial state transition model. For each action in a state (X,Y), we set the transition counter to 1 for the successor state (i.e. state (X+1,Y) for action East) as if actions were deterministic and no states are blocked. This initial information can be easily obtained and used in case of maze environments, and makes it easier to implement the instantiating information procedure (to deal with unvisited states which may contain a spider). Of course, initially the position of the goal and spider's nests are unknown and should be discovered by the agent. Furthermore, in case of maze-like environments as in the second maze (see figure 3), the initial transition model in the maze is less helpful, since maze-locations may be occupied. For this maze, we therefore initialize the transition counters to 0.0001.

4.2 Experiments with the Small Maze

First we have executed experiments with the small maze given in figure 1.

Systems. We compare using the a-priori spider model using instantiated information to using model-based RL without using the spider model and instantiated information. The second algorithm computes probabilities of hitting the spider based on previous experiences resulting in a confrontation with the spider. It does not use any kind of a-priori knowledge. With each system we perform 10 simulations.

Problem description. The reward for hitting the spider is -5000, the reward for reaching the goal state is 1000. The reward for an individual step is -1. We experimented with a deterministic environment, with 10% noise, and with 25% noise. If a noisy action is executed, the agent has probability 25% of executing each of its actions.

Parameters. After a coarse search through parameter space to find the best learning parameters, we used the following setup: We use max-random exploration with $P_{exp} = 0.5 \rightarrow 0.0$ (we anneal the exploration probability). The discount factor γ when using the spider model is set to 0.9999, the discount factor without spider model is set to 0.95. The update accuracy ϵ is set to 1.0. Finally, the maximal number of updates $U_{max} = 500000$ (which we used to make almost optimal use of the instantiated information possible).

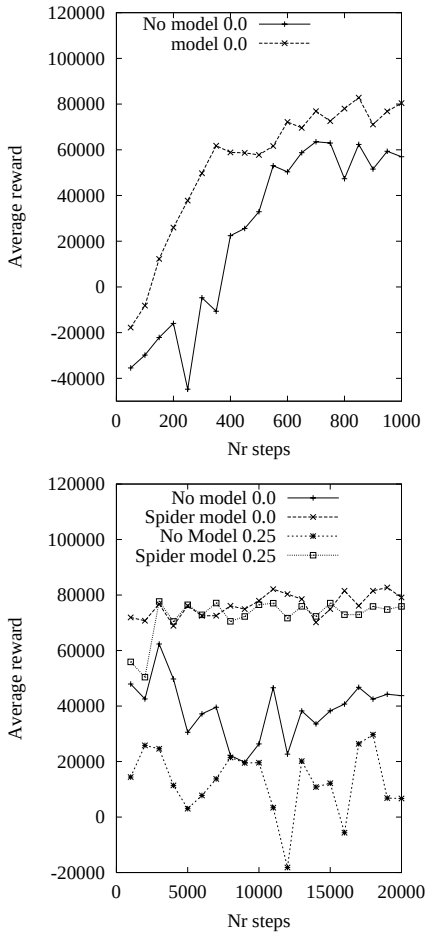

Figure 2. The results for the small maze environment containing two spider nests. (A) shows learning results for the first 1000 steps. (B) shows the results for much longer simulations.

Results. Figure 2(A) shows the average cumulative reward in 100 test trials after each 50 steps during the first 1000 training steps in the deterministic environment. Within 1000 steps, both methods have learned to find good solutions, but using the model results quickly in near optimal performance. Figure 2(B) shows the obtained cumulative reward intake during each 100 test trials after each 1000 learning steps of the two different algorithms for the small maze with deterministic actions and with 25 % randomness in the action selection. The figure clearly shows that using the spider-model outperforms not using the model. Basically, the agent can reason about the spider's location and use its marginal information to compute op-

timal dynamic policies. Thus, the agent always prefers to go through the region with the smallest probability of containing the spider. This is impossible to learn without using the spider model, although it is clearly beneficial in particular dynamic environments. The simulation for 20,000 trials costs 358 seconds for using the spider model and 12 seconds for not using it.

Table 1 shows the total number of goal hits and spider hits in a total of 2000 test trials (100 test trials after each 1000 steps in a 20,000 step simulation) and the average reward intake during the last 100 test trials.

Table 1. Results for the systems with (With) and without (No) the spider model. Noise refers to the amount of noise in the action execution. Goal/Spider hit refers to the number of test trials resulting in a hit with the goal/spider. Final R denotes average reward of the last 100 test trials.

Model (noise)	Goal hit	Spider hit	Final R
With (0.0)	1927 ± 8	73 ± 8	79K ± 10K
With (0.1)	1917 ± 12	83 ± 12	68K ± 9K
With (0.25)	1910 ± 41	80 ± 19	76K ± 11K
No (0.0)	1802 ± 20	198 ± 20	44K ± 31K
No (0.1)	1782 ± 20	218 ± 20	36K ± 23K
No (0.25)	1717 ± 24	283 ± 24	7K ± 25K

The table clearly shows that using the spider model leads to fewer hits (4% vs. 11%) with the spider (and therefore a larger number of times the goal was reached). It should be mentioned that it is impossible to avoid spider hits completely — the position of the spider can never remain completely known. What the table also shows, however, is that when the spider model is used, additional randomness does not lead to more hits with the spider. The reason is that the agent learns to circumvent the dangerous region, and therefore does not suffer from random actions which let the agent stay there longer. An interesting phenomena when using the spider model is that in particular simulations, the agent has learned a path traversing the spider nest's location so that it is able to get more information whether the current path is safe (nest is not active). If not, the agent plans a new path.

4.3 Experiments with a Large Maze with Multiple Spiders

We have also experimented with a larger maze of size 50 × 50 (see figure 3) containing 30 possible locations for spider nests, and 5 spiders traversing 30% of the maze. The maze also contains about 20% randomly distributed blocked states and 20% penalty states.

Reward function. For hitting the goal, the agent receives a reward of 2500. For hitting the spider, the reward is -10,000. For hitting a blocked state, the reward is -2, for hitting a penalty state, the reward is -10, and other steps are rewarded by -1.

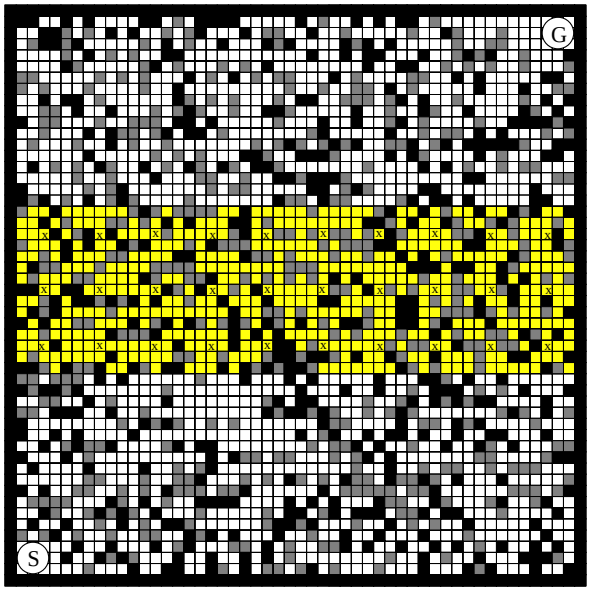

Figure 3. The large maze environment containing 30 spider nests (indicated by an X in the shaded area) and 5 active spiders. Black fields denote impassable walls. Dark grey fields denote penalty fields.

Parameters. The discount factor when using the model is set to 0.99999 which was used to make almost optimal use of the model possible. The discount factor without spider model which worked best is 0.99. The exploration rule Max-Random is used where the probability of selecting a random action is annealed from 0.5 to 0.0. The maximum number of updates is 50,000. The accuracy parameter ϵ is set to 0.5.

Simulation set-up. The number of steps in a simulation is 200,000. After each 1,000 steps the systems are tested a single trial using a maximum number of 10,000 test actions. Thus, in total there are 200 tests. For these tests we compute the total number of times the goal has been found and the number of times one of the spiders is hit.

Results. Table 2 shows the number of times the goal has been found and the number of times a spider has been hit for different noise levels when P_{stay} is set to 0.4. The table clearly shows that using the spider model leads to many fewer hits with the spider. The number of hits with a spider is reduced by a factor of 3 when the spider model is used. It is clear that the agent is able to discover spider nests and to use the acquired information to plan paths which circumvent going through locations with a large probability

of containing a spider.

Table 2. Results for the system with and without using the spider model. Noise refers to the amount of noise in the action execution. Spider hits refers to the number of test trials resulting in a hit with the spider.

System	Noise	Goal hits	Spider hits
With Model	0.0	173 ± 3	9 ± 2
With Model	0.1	173 ± 5	12 ± 4
With Model	0.25	173 ± 5	11 ± 3
No Model	0.0	163 ± 6	26 ± 6
No Model	0.1	160 ± 6	31 ± 7
No Model	0.25	152 ± 7	42 ± 7

Table 3 shows the number of times the goal has been found and the number of times a spider has been hit for values of P_{stay} where the noise is set to 0. It shows that our approach works better when the environment is more predictable. This indicates that the agent makes efficient use of the model. Both systems find very good solutions to the deterministic task.

Table 3. Results for the system with using the spider model for different values of the P_{stay} parameter. Evidently, using a larger value for P_{stay} leads to more predictable environments so that the spider model is more accurate.

Model (P_{stay})	Goal hits	Spider hits	Time (min)
With (0.1)	167 ± 6	12 ± 5	122 ± 25
With (0.4)	173 ± 3	9 ± 2	117 ± 21
With (0.9)	183 ± 3	4 ± 2	84 ± 6
With (1.0)	196 ± 2	0 ± 0	31 ± 15
No (0.1)	165 ± 5	23 ± 5	0.5 ± 0.2
No (0.4)	163 ± 6	26 ± 6	0.5 ± 0.2
No (0.9)	168 ± 5	19 ± 7	0.5 ± 0.3
No (1.0)	184 ± 4	4 ± 2	0.2 ± 0.0

Although instantiating information and replanning works very well, the computational time is significantly larger, since after each trial large portions of the policy have to be updated. We have not explored using other learning parameters to speed up the learning time, however. We are currently studying more efficient heuristic algorithms which recompute smaller parts of the policy.

5. Discussion

POMDPs. Path-planning problems in environments with dynamic obstacles are partially observable Markov decision problems (POMDPs), since the transition and reward functions are non-stationary, and there is uncertainty about the true state of the world. Usually POMDPs are solved by using a belief vector which models the probabilities an agent is in each of the possible states. In case of an environment with dynamic agents, we use a belief vector modelling probabilities of being in each possible world (with locations of other agents). Solving POMDPs exactly can be done by particular dynamic programming algorithms (Lovejoy, 1991) which compute the best action given each possible belief vector. However, this approach is intractable when the number of possible worlds is quite large (as in our second environment).

Using the underlying MDP. There exist a number of heuristic algorithms trying to find sub-optimal solutions to POMDPs more quickly. The most relevant to our current algorithm is the Q_{MDP} value method (Littman et al., 1995). Here, first the MDP is solved, and then the optimal action is selected by computing the sum of the Q-values of possible states times the occupancy probabilities. This algorithm can perform quite well (Littman et al., 1995), but is not able to perform actions to obtain information.

Our approach. We model the POMDP using a single MDP (possible world). Although the dynamic agents may be at different places, and in reality there are multiple possible worlds, we use the certainty equivalence assumption and set transition probabilities to account for all possible worlds. In this way we can use DP on the single world, otherwise we would need to solve each possible world, which would be quickly intractable. As with Q_{MDP}, our method does not take into account that actions can be used for gaining information about the environment. In principle, the MDP is unchanged as long as no additional information is acquired.

Computing information values. We can extend our algorithm so that information gains can be computed. We can compute the information value of going to a state by instantiating the possible outcomes of an observation received in this state in the MDP. Our current policy would obtain a reward which can be computed by policy evaluation. By taking into account the instantiated information and recomputing the policy afterwards (by value iteration), we would receive the reward received with the optimal policy given the observation. By subtracting the value of the current policy (found by policy evaluation) of the value of the optimal policy (found by value iteration) and weighing these values over all possible observations, we can compute the information value of going to this state. This will be 0 if no change to the policy is made, and large if the current policy would behave quite bad compared

to the optimal policy. Then, this information value can be instantiated in the reward function for this state, and the agent can act to gain information. Unfortunately this becomes intractable if the agent wants to explore sequences of observations.

Dual Control. Dayan and Sejnowski (1996) focus on the exploration problem in which barriers may block the shortest path with some probability. They also changed the transition and reward functions to account for the dynamic probabilities of the existence of each barrier. After this, they used DP to compute a new policy. Although their approach is similar, our algorithm was designed for modelling dynamic agents moving around in the environment and was made much more efficient by using prioritized sweeping. Our algorithm can also instantiate information acquired by sensors, communication, or reasoning in the transition and reward functions, so that the approach is more general. We did not study exploration issues in this paper, however.

We also used instantiating information in (Wiering, 2000) where traffic light controllers communicated with each other to determine paths through the traffic network containing the least number of waiting cars.

Dynamic Replanning. Multiple researchers have designed dynamic replanning algorithms. Most relevant to our research is the D^* algorithm (Stentz, 1995), which uses A^* planning in a dynamic way and a focusing technique to backpropagate the effects of changed parts of the environment. Stentz ran experiments in deterministic 100×100 and 1000×1000 mazes and found a large improvement for only backpropagating partial state-update values which may change the agent's plan. His method used an heuristic to find the goal, however, and cannot deal with probabilistic information.

6. Conclusion

We developed a new adaptive dynamic replanning method using reinforcement learning. Our method can learn a model of the environment, and replan if it observes that the environment has changed. The method uses model-based reinforcement learning and instantiates dynamic information about the environment in the model so that the agent can reason about the current environmental state. Our method was successfully tested on maze problems with dynamic obstacles.

Future work. For very fast changing environments, we may need to include time in the state description (Boyan & Littman, 2001), and our current method may need too much computation. Therefore we need to make Prioritized Sweeping's update management smarter, taking into account the position and plan of the agent. Then, we want to test our method on robot soccer and forest fire control.

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