2011 American Control Conference
on O'Farrell Street, San Francisco, CA, USA
June 29 - July 01, 2011

UAV Cooperative Control with Stochastic Risk Models

Alborz Geramifard, Joshua Redding, Nicholas Roy, and Jonathan P. How

Abstract— **Risk and reward are fundamental concepts in the cooperative control of unmanned systems. This paper focuses on a constructive relationship between a cooperative planner and a learner in order to mitigate the learning risk while boosting the asymptotic performance and safety of agent behavior. Our framework is an instance of the intelligent cooperative control architecture (iCCA) where a learner (Natural actor-critic, Sarsa) initially follows a "safe" policy generated by a cooperative planner (consensus-based bundle algorithm). The learner incrementally improves this baseline policy through interaction, while avoiding behaviors believed to be "risky". This paper extends previous work toward the coupling of learning and cooperative control strategies in real-time stochastic domains in two ways: (1) the risk analysis module supports stochastic risk models, and (2) learning schemes that do not store the policy as a separate entity are integrated with the cooperative planner extending the applicability of iCCA framework. The performance of the resulting approaches are demonstrated through simulation of limited fuel UAVs in a stochastic task assignment problem. Results show an 8% reduction in risk, while improving the performance up to 30%.**

I. Introduction

Risk mitigation is a particularly interesting topic in the context of the intelligent cooperative control of teams of UAVs [1,2]. The concept of *risk* is common among humans, robots and software agents alike. Amongst the latter, risk models combined with relevant observations are routinely used in analyzing potential actions for unintended or risky outcomes. In previous work, the basic concepts of risk and risk-analysis were integrated into a planning and learning framework called *iCCA* [3,4]. This research generalizes the embedded risk model with the goal of learning to mitigate risk more effectively in stochastic environments.

In a multi-agent setting, task assignment and planning algorithms implicitly rely on knowing agent capabilities to provide any guarantees on resulting performance. In many situations however, an agent remaining capable of its advertised range of tasks is a strong function of how much risk the agent takes while carrying out its assignments. Taking high or unnecessary risks jeopardizes an agent's capabilities and thereby also the performance/effectiveness of the cooperative plan. Cooperative control algorithms are often based on simple, abstract models of the underlying system. Using simplified models may aid computational tractability and enable quick analysis, but at the cost of ignoring real-world complexities, thus implicitly introducing the possibility of significant risk elements into cooperative plans. The notion of "risk" here may include noise, unmodeled dynamics and uncertainties in addition to no-fly zones. The research question addressed here can then be stated as:

> *How can a cooperative planner and domain knowledge be used to mitigate the risk involved in learning, while improving the performance and safety of the cooperative plans over time in the presence of noise and uncertainty?*

A. Geramifard and J. Redding, Ph.D. Candidates, Aerospace Controls Lab, MIT, N. Roy, Associate Professor of Aeronautics and Astronautics, MIT, J. How, Richard C. Maclaurin Professor of Aeronautics and Astronautics, MIT {agf,jredding,nickroy,jhow}@mit.edu

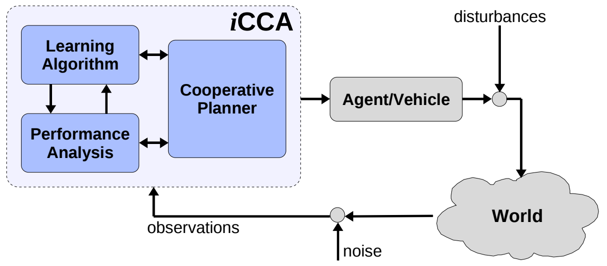


Fig. 1. **i**ntelligent **C**ooperative **C**ontrol **A**rchitecture, a template framework for the integration of cooperative control algorithms and machine learning techniques [4].

We adopt the intelligent cooperative control architecture (*iCCA* [4]) as a framework for more tightly coupling cooperative planning and learning algorithms. Fig. 1 shows the *iCCA* framework which is comprised of a cooperative planner, a learner, and a performance analyzer. Each of these modules is interconnected and plays a key role in the overall architecture. In this research, the performance analysis module is implemented as risk analysis where actions suggested by the learner can be overridden by the baseline cooperative planner if they are deemed too risky. This synergistic planner-learner relationship yields a "safe" policy in the eyes of the planner, upon which the learner can improve.

Here, we extend our previous work [3] in two ways:

- The risk analyzer component is extended to handle stochastic models
- By introducing a new wrapper, learning methods with no explicit policy formulation can be integrated within the iCCA framework

The first extension allows for accurate approximation of realistic world dynamics, while the second extension broadens the applicability of iCCA framework to a larger set of learning methods.

The paper proceeds as follows: Section II provides background information and Section III highlights the problem of interest by defining a pedagogical scenario where planning and learning algorithms are used in conjunction with stochastic risk models. Section IV outlines the proposed technical approach for learning to mitigate risk, and the performance of the approach is then analyzed in Section V.

II. Background

A. Markov Decision Processes

Markov decision processes (MDPs) provide a general formulation for sequential planning under uncertainty [5]–[9]. MDPs are a natural framework for solving multi-agent planning problems as their versatility allows modeling of stochastic system dynamics as well as inter-dependencies between agents. An MDP is defined by tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}^a_{ss'}, \mathcal{R}^a_{ss'}, \gamma)$, where $\mathcal{S}$ is the set of states, $\mathcal{A}$ is the set of possible actions. Taking action a from state s has $\mathcal{P}^a_{ss'}$ probability of ending up in state s' and receiving reward $\mathcal{R}^a_{ss'}$. Finally $\gamma \in [0, 1]$ is the discount factor used to prioritize early rewards against future rewards.[1] A trajectory of experience is defined by sequence $s_0, a_0, r_0, s_1, a_1, r_1, \cdots$, where the agent starts at state s_0, takes action a_0, receives reward r_0, transits to state s_1, and so on. A policy π is defined as a function from $\mathcal{S} \times \mathcal{A}$ to the probability space $[0, 1]$, where $\pi(s, a)$ corresponds to the probability of taking action a from state s. The value of each state-action pair under policy π, $Q^\pi(s, a)$, is defined as the expected sum of discounted rewards when the agent takes action a from state s and follow policy π thereafter:

$$Q^\pi(s,a) = E_\pi\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t \middle| s_0 = s, a_0 = a, \right].$$

The optimal policy π^* maximizes the above expectation for all state-action pairs: $\pi^* = \text{argmax}_a Q^{\pi^*}(s, a)$.

B. Reinforcement Learning in MDPs

The underlying goal of the two reinforcement learning algorithms presented here is to improve performance of the cooperative planning system over time using observed rewards by exploring new agent behaviors that may lead to more favorable outcomes. The details of how these algorithms accomplish this goal are discussed in the following sections.

1) Sarsa: A popular approach among MDP solvers is to find an approximation to $Q^\pi(s, a)$ (policy evaluation) and update the policy with respect to the resulting values (policy improvement). Temporal Difference learning (TD) [10] is a traditional policy evaluation method in which the current $Q(s, a)$ is adjusted based on the difference between the current estimate of Q and a better approximation formed by the actual observed reward and the estimated value of the following state. Given $(s_t, a_t, r_t, s_{t+1}, a_{t+1})$ and the current value estimates, the temporal difference (TD) error, δ_t, is calculated as:

$$\delta_t(Q) = r_t + \gamma Q^\pi(s_{t+1}, a_{t+1}) - Q^\pi(s_t, a_t).$$

The one-step TD algorithm, also known as TD(0), updates the value estimates using:

$$Q^\pi(s_t, a_t) = Q^\pi(s_t, a_t) + \alpha \delta_t(Q), \tag{1}$$

where α is the learning rate. Sarsa (state action reward state action) [11] is basic TD for which the policy is directly derived from the Q values as:

$$\pi^{Sarsa}(s,a) = \begin{cases} 1-\epsilon & a = \text{argmax}_a Q(s,a) \\ \frac{\epsilon}{|\mathcal{A}|} & \text{Otherwise} \end{cases}.$$

This policy is also known as the ϵ-greedy policy[2].

2) Natural Actor-Critic: Actor-critic methods parameterize the policy and store it as a separate entity named *actor*. In this paper, the actor is a class of policies represented as the Gibbs softmax distribution:

$$\pi^{AC}(s,a) = \frac{e^{P(s,a)/\tau}}{\sum_b e^{P(s,b)/\tau}},$$

in which $P(s, a) \in \mathcal{R}$ is the preference of taking action a in state s, and $\tau \in [0, \infty)$ is a knob allowing for shifts between greedy and random action selection. Since we use a tabular representation, the actor update amounts to:

$$P(s,a) \leftarrow P(s,a) + \alpha Q(s,a)$$

following the incremental natural actor-critic framework [12]. The value of each state-action pair ($Q(s, a)$) is held by the *critic* and is calculated/updated in an identical manner to Sarsa, mentioned in Eqn. (1).

III. Problem Statement

This section uses a pedagogical example to explain: (1) the effect of unknown noise on the planner's solution, (2) how learning methods can improve the performance and safety of the planner solution, and (3) how the approximate model and the planner solution can be used for faster and safer learning.

A. The GridWorld Domain: A Pedagogical Example

Consider a grid world scenario shown in Fig. 2-(left), in which the task is to navigate a UAV from the top-left corner (●) to the bottom-right corner (⋆). Red areas highlight the danger zones where the UAV will be eliminated upon entrance. At each step the UAV can take any action from the set $\{\uparrow, \downarrow, \leftarrow, \rightarrow\}$. However, due to wind disturbances, there is 30% chance that the UAV is pushed into any unoccupied neighboring cell while executing the selected action. The reward for reaching the goal region and off-limit regions are $+1$ and -1 respectively, while every other move results in -0.001 reward.

Fig. 2-(middle) illustrates the policy (shown as arrows) calculated by a planner that is unaware of the wind together with the nominal path highlighted as a gray tube. As expected, the path suggested by the planner follows the shortest path that avoids directly passing through off-limit areas. The color of each cell represents the true value of each state (*i.e.,* including the wind) under the planner's policy. Green indicates positive, white indicates zero, and red indicates negative values[3].

The optimal policy and its corresponding value function and nominal path are shown in Fig. 2-(right). Notice how the optimal policy avoids the risk of getting close to off-limit areas by making wider turns. While the new nominal

[1] γ can be set to 1 only for episodic tasks, where the length of trajectories are fixed.

[2] Ties are broken randomly, if more than one action maximizes $Q(s, a)$.

[3] We set the value for blocked areas to $-\infty$, hence the intense red color

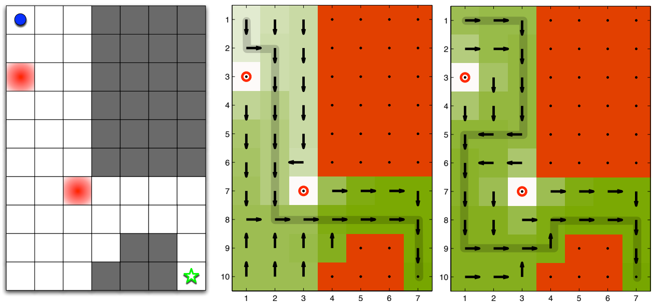


Fig. 2. GridWorld domain (left), the corresponding policy calculated with a planner assuming deterministic movement model and its true value function (middle) and the optimal policy with the perfect model and its value function (right). The task is to navigate from the top left corner highlighted as ● to the right bottom corner identified as ⋆. Red regions are off-limit areas where the UAV should avoid. The movement dynamics has 30% noise of moving the UAV to a random free neighboring grid cell. Gray cells are not traversable.

path is longer, it mitigates the risk better. In fact, the new policy raises the mission success rate from 29% to 80%, while boosting the value of the initial state by a factor of ≈3. Model-free learning techniques such as Sarsa can find the optimal policy through mere interaction, although they require many training examples. More importantly, they might deliberately move the UAV towards off-limit regions just to gain information about those areas. However, when integrated with the planner, the learner can rule out intentionally poor decisions. Furthermore, the planner's policy can be used as a starting point for the learner to bootstrap on, reducing the amount of data the learner requires to master the task.

Though simple, the preceding problem is similar to more meaningful and practical UAV planning scenarios. The following sections present the technical approach and examines the resulting methods in this toy domain and a more complex multi-UAV planning task where the size of the state space exceeds 200 million state-action pairs.

IV. Technical Approach

This section provides further details of the intelligent cooperative control architecture (*iCCA*), describing the purpose and function of each element. Fig. 3 shows that the consensus-based bundle algorithm (CBBA) [13] is used as the cooperative planner to solve the multi-agent task allocation problem. The learning algorithms used are the natural actor-critic [12] and Sarsa [11] methods. These algorithms use past experience to explore and suggest promising behaviors leading to more favorable outcomes. The performance analysis block is implemented as a risk analysis tool where actions suggested by the learner can be overridden by the baseline cooperative planner if they are deemed too risky. The following sections describe each of these blocks in detail.

A. Cooperative Planner

At its fundamental level, the cooperative planner yields a solution to the multi-agent path planning, task assignment or resource allocation problem, depending on the domain. This means it seeks to optimize an underlying, user-defined *objective function*. Many existing cooperative control algorithms

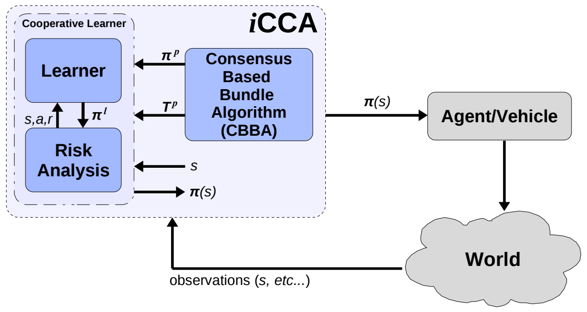


Fig. 3. iCCA framework as implemented. CBBA planner coupled with risk analysis and reinforcement learning modules, where the latter two elements are formulated within an MDP.

use observed performance to calculate *temporal-difference errors* which drive the objective function in the desired direction [14,15]. Regardless of how it is formulated (*e.g.,* MILP, MDP, CBBA), the cooperative planner, or cooperative control algorithm, is the source for baseline plan generation within *iCCA*. The formulation of CBBA as the cooperative planner for this work is nearly identical to that shown previously [3], with the exception that this research adds additional constraints on fuel supply to ensure agents cannot bid on task sequences that require more fuel than they have remaining or that would not allow them to return to base upon completion of the sequence. For further details, the reader is referred to previous work [3,13,16].

B. Risk/Performance Analysis

As discussed earlier, learning algorithms may encourage the agent to explore dangerous situations (*e.g.,* flying with low fuel level) in hope of improving the long-term performance. While some degree of exploration is necessary, unbounded exploration can lead to undesirable scenarios such as losing a UAV. Hence in this research, akin to our previous work [3], we implemented the performance analysis module as a risk analysis element where candidate actions are evaluated for their risk level. Actions deemed too "risky" are replaced with another action of lower risk. The next section details the process of overriding risky actions. It is important to note that the risk analysis and learning algorithms are coupled within an MDP formulation, as shown in Fig. 3, which implies a fully observable environment.

C. Learning Algorithm

A focus of this research is to integrate a learner into *iCCA* that suggests candidate actions to the cooperative planner that it sees as beneficial. Suggested actions are generated by the learning module through the learned policy. In our previous work [3], we integrated natural actor-critic through iCCA framework. We refer to this algorithm as Cooperative Natural Actor-Critic (CNAC).

Algorithm 1 illustrates this algorithm in more detail. In order to encourage the policy to initially explore solutions similar to the planner solution, preferences for all state-action pairs, $P(s, a)$, on the nominal trajectory calculated by the planner are initialized to a fixed number $\xi \in \mathbb{R}^+$. All other preferences are initialized to zero. As actions are pulled

Algorithm 1: Cooperative Natural Actor-Critic (CNAC)

```
Input: $\pi^p, \xi$
Output: $a$
$a \sim \pi^{AC}(s,a)$
if not $safe(s,a)$ then
    $P(s,a) \leftarrow P(s,a) - \xi$
    $a \leftarrow \pi^p$
$Q(s,a) \leftarrow Q(s,a) + \alpha\delta_t(Q)$
$P(s,a) \leftarrow P(s,a) + \alpha Q(s,a)$
```

Algorithm 2: safe

```
Input: $s, a$
Output: $isSafe$
$risk \leftarrow 0$
for $i \leftarrow 1$ to $M$ do
    $t \leftarrow 1$
    $s_t \sim T^p(s,a)$
    while not $constrained(s_t)$ and not
    $isTerminal(s_t)$ and $t < H$ do
        $s_{t+1} \sim T^p(s_t, \pi^p(s_t))$
        $t \leftarrow t + 1$
    $risk \leftarrow risk + \frac{1}{i}(constrained(s_t) - risk)$
$isSafe \leftarrow (risk < \psi)$
```

from the policy for implementation, they are evaluated for their safety by the risk analysis element. If they are deemed unsafe (*e.g.,* may result in a UAV running out of fuel), they are replaced with the action suggested by the planner (π^p). Furthermore, the preference of taking the risky action in that state is reduced by parameter ξ, therefore dissuading the learner from suggesting that action again, reducing the number of "emergency overrides" in the future. Finally, both the critic and actor parameters are updated.

Previously, we employed a risk analysis component which had access to the exact world model dynamics. Moreover, we assumed that the transition model related to the risk calculation was deterministic (*e.g.,* movement and fuel burn did not involve uncertainty). In this paper, we introduce a new risk analysis scheme which uses the planner's inner model, which can be stochastic, to mitigate risk. Algorithm 2, explains this new risk analysis process. We assume the existence of the $constrained$ function: $\mathcal{S} \rightarrow \{0,1\}$, which indicates if being in a particular state is allowed or not. Risk is defined as the probability of visiting any of the constrained states. The core idea is to use Monte-Carlo sampling to estimate the risk level associated with the given state-action pair if planner's policy is applied thereafter. This is done by simulating M trajectories from the current state s. The first action is the suggested action a, and the rest of actions come from the planner policy, π^p. The planner's inner transition model, T^p, is utilized to sample successive states. Each trajectory is bounded to a fixed horizon H and the risk of taking action a from state s is estimated by the probability of a simulated trajectory reaching a risky state within horizon H. If this risk is below a given threshold, ψ, the action is deemed to be safe.

The initial policy of actor-critic type learners is biased quite simply as they parameterize the policy explicitly.

Algorithm 3: Cooperative Learning

```
Input: $N, \pi^p, s, learner$
Output: $a$
$a \leftarrow \pi^p(s)$
$\pi^l \leftarrow learner.\pi$
$knownness \leftarrow \min\{1, \frac{count(s,a)}{N}\}$
if $rand() < knownness$ then
    $a' \sim \pi^l(s,a)$
    if $safe(s,a')$ then
        $a \leftarrow a'$
else
    $count(s,a) \leftarrow count(s,a) + 1$
$learner.update()$
```

For learning schemes that do not represent the policy as a separate entity, such as Sarsa, integration within iCCA framework is not immediately obvious. In this paper, we present a new approach for integrating learning approaches without an explicit actor component. Our idea was motivated by the concept of the R_{max} algorithm [17]. We illustrate our approach through the parent-child analogy, where the planner takes the role of the parent and the learner takes the role of the child. In the beginning, the child does not know much about the world, hence, for the most part s/he takes actions advised by the parent. While learning from such actions, after a while, the child feels comfortable about taking a self-motivated actions as s/he has been through the same situation many times. Seeking permission from the parent, the child could take the action if the parent thinks the action is safe. Otherwise the child should follow the action suggested by the parent.

Algorithm 3 details the process. On every step, the learner inspects the suggested action by the planner and estimates the knownness of the state-action pair by considering the number of times that state-action pair has been experienced following the planner's suggestion. The N parameter controls the shift speed from following the planner's policy to the learner's policy. Given the knownness of the state-action pair, the learner probabilistically decides to select an action from its own policy. If the action is deemed to be safe, it is executed. Otherwise, the planner's policy overrides the learner's choice. If the planner's action is selected, the knownness count of the corresponding state-action pair is incremented. Finally the learner updates its parameter depending on the choice of the learning algorithm. What this means, however, is that state-action pairs explicitly forbidden by the baseline planner will not be intentionally visited. Hence, if the planner's model designed poorly, it can hinder the learning process in parts of the state space for which the risk is overestimated. Also, notice that any control RL algorithm, even the actor-critic family of methods, can be used as the input to Algorithm 3.

V. Experimental Results

This section compares the empirical performance of cooperative-NAC and cooperative-Sarsa with pure learning and pure planning methods in the GridWorld example mentioned in Section III, and a multi-UAV mission planning scenario where both dynamics and reward models are stochastic. The optimal solution for both domains were calculated using dynamic programming (took approximately two days for the UAV scenario). As for the planning, the CBBA algorithm was executed online given the expected deterministic version of both domains. Pure planning results are averaged over $10,000$ Monte Carlo simulations. For all learning methods, the best learning rates were calculated by

$$\alpha_t = \alpha_0 \frac{N_0 + 1}{N_0 + \text{Episode\#}^{1.1}}.$$

The best α_0 and N_0 were selected through experimental search of the sets of $\alpha_0 \in \{0.01, 0.1, 1\}$ and $N_0 \in \{100, 1000, 10^6\}$ for each algorithm and scenario. The best preference parameter, ξ, for NAC and CNAC were empirically found from the set $\{1, 10, 100\}$. τ was set to 1. Similarly, the knownness parameter, N, for CSarsa was selected out of $\{10, 20, 50\}$. The exploration rate (ϵ) for Sarsa and CSarsa was set to 0.1. All learning method results were averaged over 60 runs. Error bars represent 95% confidence intervals.

A. GridWorld Domain

Fig. 4 compares the performance of CSarsa, CNAC, Sarsa, NAC, the baseline planner (Fig 2-middle), and the expected optimal solution (Fig 2-right) in the pedagogical GridWorld domain. The X-axis shows the number of steps the agent executed an action, while the Y-axis highlights the cumulative rewards of each method after each $1,000$ steps. Notice how cooperative methods outperformed pure learning approaches. In particular CNAC outperformed the planner (red) after $6,000$ steps by navigating farther from the danger zones. NAC, on the other hand, could not outperform the planner by the end of $10,000$ steps. While Sarsa was also inferior to CSarsa, it outperformed NAC. We conjecture that Sarsa learned faster than NAC because Sarsa's policy is embedded in the $Q-$value function, whereas NAC's policy requires another level of learning for the policy on the top of learning the $Q-$value function.

B. Multi-UAV Planning Scenario

Fig. 5-(a) depicts the mission scenario introduced in our previous work [3], where a team of two fuel-limited UAVs cooperate to maximize their total reward by visiting valuable target nodes in the network and return back to the base (green circle), targets are shown as blue circles and agents as triangles. The total amount of fuel for each agent is highlighted by the number inside each triangle. For those targets with an associated reward it is given as a positive number nearby. The constraints on the allowable times when the target can be visited are given in square brackets and the probability of receiving the known reward when the target is visited is given in the white cloud nearest the node.[4] Each reward can be obtained only once and traversing each edge takes one fuel cell and one time step. UAVs are allowed to

[4]If two agents visit a node at the same time, the probability of visiting the node would increase accordingly.

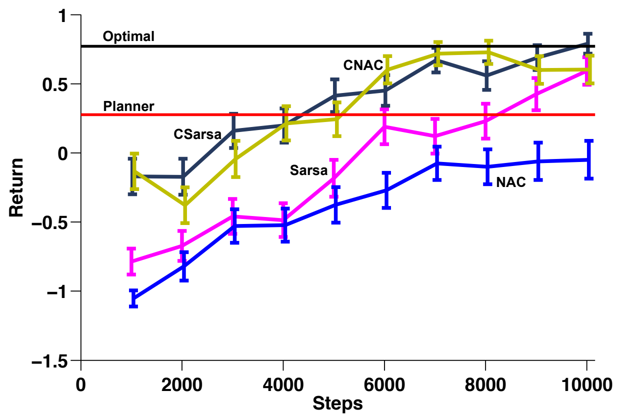


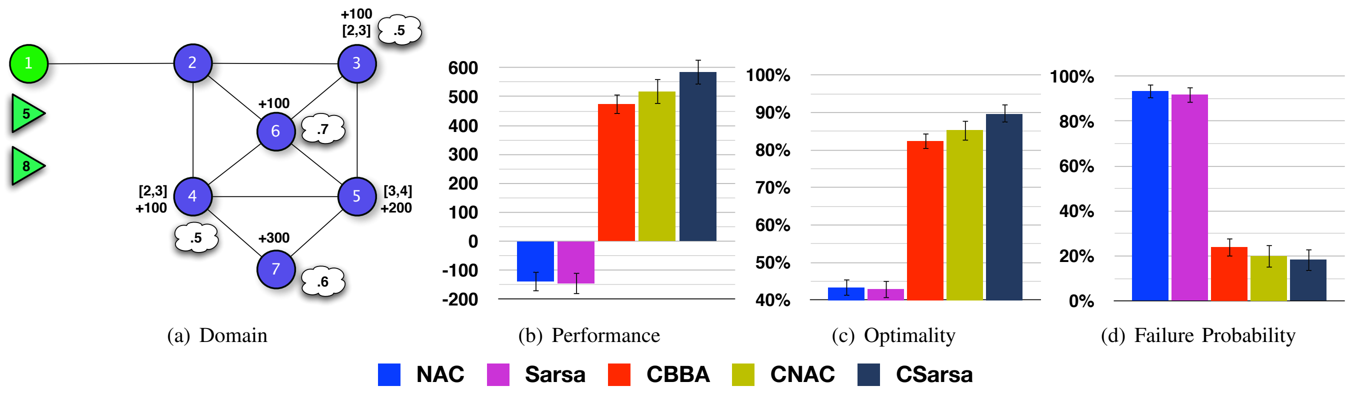
Fig. 4. In the pedagogical GridWorld domain, the performance of the optimal solution is given in black. The solution generated by the deterministic planner is shown in red. In addition, the performance of NAC, CNAC (left) and Sarsa and CSarsa (right) are shown. It is clear that the cooperative learning algorithms (CNAC and CSarsa) outperform their non-cooperative counterparts and eventually outperform the baseline planner when given a sufficient number of interactions. This result motivates the application of the cooperative learning algorithms to more complex domains, such as the Multi-UAV planning scenario.

loiter at any node. The fuel burn for loitering action is also one unit, except for any UAV at the base, where they are assumed to be stationary and thus there is no fuel depletion. The mission horizon was set to 10 time steps. If UAVs are not at base at the end of the mission horizon, or crash due to fuel depletion, a penalty of -800 is added for that trial. In order to test our new risk mitigation approach, we added uncertainty to the movement of each UAV by adding 5% chance of edge traverse failure. Notice that our previous risk analyzer [3,4] could not handle such scenarios, as it assumed the existence of an oracle knowing catastrophic actions in each state.

Figs 5(b)-(d) show the results of the same battery of algorithms used in the GridWorld domain applied to the UAV mission planning scenario. In this domain, we substituted the hand-coded policy with the CBBA algorithm. Fig. 5-(b) represents the solution quality of each method after 10^5 steps of interactions. Fig. 5-(c) depicts the optimality of each solution, while Fig. 5-(d) exhibits the risk of executing the corresponding policy. At the end of training, both NAC and Sarsa failed to avoid the crashing scenarios, thus yielding low performance and more than a 90% probability of failure. Both these methods are below 50% optimal. This observation coincides with our previous experiments with this domain where the movement model was noise free [4], highlighting the importance of biasing the policy of learners in large domains. On average, CNAC and CSarsa improved the performance of CBBA by about 15% and 30% respectively (translated into 3% and 7% optimality improvement). At the same time they reduced the probability of failure by 6% and 8%.

VI. Conclusions

This paper extended the capability of the previous work on merging learning and cooperative planning techniques through two innovations: (1) the risk mitigation approach



(a) Domain (b) Performance (c) Optimality (d) Failure Probability

Fig. 5. (a) Mission scenarios of interest: A team of two UAVs plan to maximize their cumulative reward along the mission by cooperating to visit targets. Target nodes are shown as circles with rewards noted as positive values and the probability of receiving the reward shown in the accompanying cloud. Note that some target nodes have no value. Constraints on the allowable visit time of a target are shown in square brackets. (b,c) Results of NAC, Sarsa, CBBA, CNAC, and CSarsa algorithms at the end of the training session in the UAV mission planning scenario. Cooperative learners (CNAC, CSarsa) perform very well with respect to overall reward and risk levels when compared with the baseline CBBA planner and the non-cooperative learning algorithms.

has been extended to stochastic system dynamics where the exact world model is not known, and (2) learners without a separate policy parametrization can be integrated in the iCCA framework through the cooperative learning algorithm. Using a pedagogical GridWorld example, we explained how the proposed algorithms can improve the performance of existing planners. Simulation results verified our hypothesis in the GridWorld example. We finally tested our algorithms in a multi-UAV planning scenario including stochastic transition and rewards models, where none of the uncertainties were known a priori. On average, the new cooperative learning methods boosted the performance of CBBA up to 30% (7% optimality improvement), while reducing the risk of failure up to 8%.

For future work, we are interested in increasing the learning speed of cooperative learners by taking advantage of function approximators. Function approximation allows generalization among the values of similar states often boosting the learning speed. However, finding a proper function approximator for a problem is still an active area of research, as poor approximations can render the task unsolvable, even with infinite amount of data. While in this work, we assumed a static model for the planner, a natural extension is to adapt the model with the observed data. We foresee that this extension will lead to a more effective risk mitigation approach as the transition model used for Monte-Carlo sampling resembles the actual underlying dynamics with more observed data.

Acknowledgments

This work was sponsored by the AFOSR and USAF under grant FA9550-09-1-0522 and Boeing Research & Technology. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the Air Force Office of Scientific Research or the U.S. Government.

References

[1] J. Kim, “Discrete approximations to continuous shortest-path: Application to minimum-risk path planning for groups of uavs,” in *In Proc. of the 42nd Conf. on Decision and Control*, 2003, pp. 9–12.
[2] R. Weibel and R. Hansman, “An integrated approach to evaluating risk mitigation measures for UAV operational concepts in the NAS,” in *AIAA Infotech@Aerospace Conference*, 2005, pp. AIAA–2005–6957.
[3] J. Redding, A. Geramifard, H. Choi, and J. How, “Actor-critic policy learning in cooperative planning,” in *AIAA Guidance, Navigation and Control Conference*, 2010.
[4] J. Redding, A. Geramifard, A. Undurti, H. Choi, and J. How, “An intelligent cooperative control architecture,” in *American Control Conference*, 2010.
[5] R. A. Howard, “Dynamic programming and Markov processes,” 1960.
[6] M. Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. Wiley, 1994.
[7] M. L. Littman, T. L. Dean, and L. P. Kaelbling, “On the complexity of solving Markov decision problems,” in *In Proc. of the Eleventh International Conference on Uncertainty in Artificial Intelligence*, 1995, pp. 394–402.
[8] L. P. Kaelbling, M. L. Littman, and A. R. Cassandra, “Planning and acting in partially observable stochastic domains,” *Artificial Intelligence*, vol. 101, pp. 99–134, 1998.
[9] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Pearson Education, 2003.
[10] R. S. Sutton, “Learning to predict by the methods of temporal differences,” *Machine Learning*, vol. 3, pp. 9–44, 1988.
[11] G. A. Rummery and M. Niranjan, “Online Q-learning using connectionist systems (tech. rep. no. cued/f-infeng/tr 166),” *Cambridge University Engineering Department*, 1994.
[12] S. Bhatnagar, R. S. Sutton, M. Ghavamzadeh, and M. Lee, “Incremental natural actor-critic algorithms.” in *NIPS*, J. C. Platt, D. Koller, Y. Singer, and S. T. Roweis, Eds. MIT Press, 2007, pp. 105–112.
[13] H.-L. Choi, L. Brunet, and J. P. How, “Consensus-based decentralized auctions for robust task allocation,” *IEEE Trans. on Robotics*, vol. 25 (4), pp. 912 – 926, 2009.
[14] R. Murphey and P. Pardalos, *Cooperative control and optimization*. Kluwer Academic Pub, 2002.
[15] D. P. Bertsekas and J. N. Tsitsiklis, *Neuro-Dynamic Programming (Optimization and Neural Computation Series, 3)*. Athena Scientific, May 1996.
[16] S. Ponda, J. Redding, H.-L. Choi, J. P. How, M. A. Vavrina, and J. Vian, “Decentralized planning for complex missions with dynamic communication constraints,” in *American Control Conference (ACC)*, July 2010, pp. 3998–4003.
[17] R. I. Brafman and M. Tennenholtz, “R-MAX - a general polynomial time algorithm for near-optimal reinforcement learning,” *Journal of Machine Learning*, vol. 3, pp. 213–231, 2001.