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Is Reinforcement Learning a Panacea for Solving All Contingencies in UAVs?

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Abstract

We would like to point out that reinforcement learning (RL) needs to be used with caution in contingency planning for UAVs. A more practical approach is proposed in this opinion.

Keywords: Contingency planning; UAVs; Reinforcement learning

Introduction

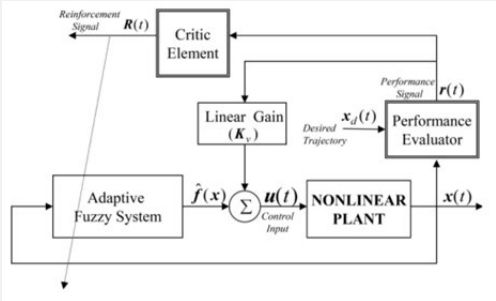

Figure 1: Application of RL to Nonlinear Systems [1].

Reinforcement learning (RL) has two important elements: "critic" and "reward" based on performance. As shown in Figure 1, the "reward" is generated based on a performance evaluator for a system and the "critic" element generates proper actions to a system. In recent years, RL has gained a lot of attention because of its success in games such as the Alphago, which beat the human world champion in straight sets [1]. However, there are several recent blogs [2-4] by researchers in artificial intelligence (AI), who heavily criticized the capability of RL in numerous applications. Some notable criticisms include the requirement of huge amount of training data, lack of mechanism to incorporate metadata (rules) into the learning process, the requirement of starting from scratch in the learning process, etc. In short, those researchers think that RL is not a mature technology yet and has found success in only a few applications such as games, collision avoidance, etc.

Drones, also known as Unmanned Air Vehicles (UAVs), have much higher failure rates than manned aircraft [5]. In 2019, there is a Small Business Innovative Research (SBIR) topic [6] seeking ambitious ideas by using RL to handle quite a few contingencies in drones, including 1) preset lost-link procedures; 2) contingency plans in case of failure to reacquire lost links; 3) abort in case of unexecutable commands or unavoidable obstacles; 4) terminal guidance. After carefully analyzing the requirements in this topic, we believe that a practical and minimal risk approach is to adopt a hybrid approach, which incorporates both conventional and RL methods. Some of the requirements in this topic can be easily handled by conventional algorithms developed by our team. For instance, we have developed preset lost-link procedures to deal with lost links for NASA. Our procedures can satisfy FAA and air traffic control (ATC) rules and regulations. We also have systematic procedures to deal with contingency in case of failure to re-acquire lost links. All these procedures can be generated using rules and do not require any RL methods. We believe that RL should be best used in collision avoidance in dynamic environments be-

cause there is mature development in using RL to tackle clutter and dynamic environments for mobile robots.

Practical Approach

In the past seven years, our team has been working on contingency planning for UAVs to deal with lost links for NASA and contingency planning for engine failures, change of mission objectives, missed approach, etc. for the US Navy. We also have a patent on lost link contingency planning [7]. To tackle the contingencies in drones, a practical approach has several components. First, we propose to apply our previous developed system [7-10] to deal with lost-link and other contingencies. Our system requires some pre-generated databases containing FAA/ATC rules, locations of communication towers, emergency landing places, etc. for a given theater. Based on those databases, we can generate preset plans to handle many of the contingencies related to lost-link, engine failures, mission objective changes, etc. Our pre-generated contingency plans can also handle terminal guidance. We plan to devise different plans to handle different scenarios in the terminal guidance process. For example, if the onboard camera sees a wave-off signal, the UAV can immediately activate a contingency plan to guide the UAV to an alternative landing place. Second, we propose to apply RL to handle some unexpected situations such as dynamic obstacles in the path. RL has been successfully used in robot navigation in clutter and dynamic environments and hence is most appropriate for collision avoidance in UAVs.

Figure 1 shows the relationship of our Advanced Automated Mission Planning System (AAMPS), Joint Mission Planning System (JMPS), and Common Control System (CCS). Our AAMPS first uses JMPS to generate a primary flight plan for a given mission. JMPS has the advantage of containing airport and constraint zone information in its database. Second, we applied Common AAMPS to generate contingency plans for the primary flight path. The Ground Control System contingency plans can deal with major situations such as engine out, lost communications, retasking, missed approaches, etc. To avoid damage to ground structure, we propose to apply an automatic landing place selection tool, which selects appropriate landing places for UAVs so that UAVs can use these landing sites during WEB Route normal flight or emergencies.

In our approach, RL is used for path planning to avoid dynamic threats and obstacles. Recent works showed that RL could be used for autonomous crowd-aware robot navigation in crowded environments [11-12]. However, the performance of these techniques degrade as the crowd size increases since these techniques are based on a one-way human-robot interaction problem [13]. In a recent paper [13], the authors introduces an interesting work which uses RL for robot navigation in crowded environments. The authors of [13] name their method Self- Attention Reinforcement Learning (SARL). They also use the name local map SARL (LM-SARL) for the extended version of SARL. The authors approach the crowd-aware navigation problem different than other techniques and the human-human interactions which affects robot's anticipation capability for navigation are also considered in their method, SARL [13]. SARL can anticipate crowd dynamics resulting in time-efficient navigation paths and outperforms three state-of-the-art robot navigation in crowded scenes methods which are Collision Avoidance with Deep Reinforcement Learning (CADRL) [11], Long Short-Term Memory-RL (LSTM-RL) [12], and Optimal Reciprocal Collision Avoidance (ORCA) [14]. We find similarities between the crowd-aware robot navigation application and the autonomous collision-free UAV navigation in crowded air traffic and SARL can be used as a promising technique along this line. We believe that we can customize SARL for autonomous collision-free UAV navigation in contingency situations such as when the link between operator and UAV is lost and the UAV needs to make a forced emergency landing.

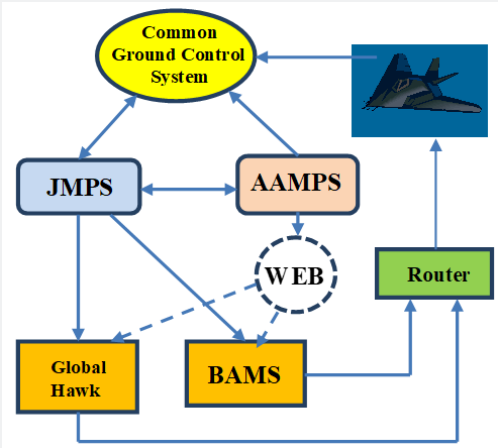

Figure 2: Role of our AAMPS in the Overall Drone Mission Planning and Management Process.

Conclusion

It was argued that RL may not be able to solve contingency planning for UAVs. Instead, we advocate a practical approach to solving this problem.

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