Planning of Diverse Trajectories for UAV Control Displays (Extended Abstract)

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ABSTRACT

Unmanned aerial vehicles (UAVs) are more and more often used to solve different tasks in both the private and the public sector. Some of these tasks, can be often performed completely autonomously, while the others are still dependent on the remote pilots. They control an UAV using a command display where they can control it manually using joysticks, or give it a simple task. The command display allow for the planning of the UAV trajectory through the waypoints while avoiding the no-fly zones. Nevertheless, the operator can be aware of other preferences, or soft restrictions, for which it's not feasible to be inserted into the system especially during the time critical tasks. We propose to provide the operator with several *alternative* trajectories which are different from the operator's point of view. So he can choose the best one for the current situation. In this contribution we evaluate previously presented techniques for diverse planning. We focus on an evaluation made by a group of human operators and show how it can be deployed in an UAV control display.

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics—*Operator interfaces*

General Terms

Algorithms,Human Factors

Keywords

Trajectory Planning, UAV, Human-Machine Interface

1. INTRODUCTION

Nowadays, when the operator wants to change a trajectory of an UAV (or other remote controlled robot), he can define the new trajectory, e.g. by means of waypoints and no-fly zones. When the waypoints are updated, the new trajectory is planned (on UAV or within ground control station) by a trajectory planner, e.g. Θ* [4], which plans the optimal trajectory in respect to the fuel consumption, needed time, or other user specified criteria. Nevertheless, the operator can be aware of other preferences, where the plane should fly, or soft restrictions on areas which would be nice to avoid. These can contain, for example, possible future colliding traffic, weather conditions, flights over inhabited areas, etc. It is not feasible to insert all these preferences into the system, especially during the time critical tasks. The operator typically does not accept proposed trajectory in the cases when he sees other, suboptimal but more preferable one. Then, he has to change input values to force the system to give the desired solution. This process can be improved by a system giving several possible trajectories out of which the operator selects one based on his preferences which is then applied. We proposed to use diverse planning and introduced several methods in [5].

In this contribution we summarize several metrics measuring how much the trajectories differ and several approaches to the diverse planning in Section 2. All the proposed approaches have been evaluated by human operators and results are examined in Section 3.

2. DIVERSE PLANNING OVERVIEW

In [5] we defined several trajectory diversity metrics counting different states, distance of the trajectories or how the obstacles are avoided by each trajectory. Based on these metrics we have implemented several diverse planners:

Metrics Based Planners are solely based on the diversity metrics. These planners start with the optimal trajectory found by any trajectory planner. Then it iteratively looks for next trajectories while maximizing the diversity metric.

Obstacle Extension Approach transforms the planning task into several new tasks and then runs a traditional trajectory planner on each task. The transformed task contains obstacles extended in different directions (4 directions in our case).

Voronoi–Delaunay Graph Based Trajectory Planner uses Voronoi graph to find representative trajectories from the start to the target. These trajectories are not locally optimal, thus for each such trajectory we generate a set of obstacles and run classical trajectory planner to get a locally optimal trajectory similar to that Voronoi trajectory. Obstacles are generated from the Delaunay graph [1], which is dual to the Voronoi graph.

3. EXPERIMENTS

We have evaluated all presented diverse planners using metrics described above. In this contribution we focus on

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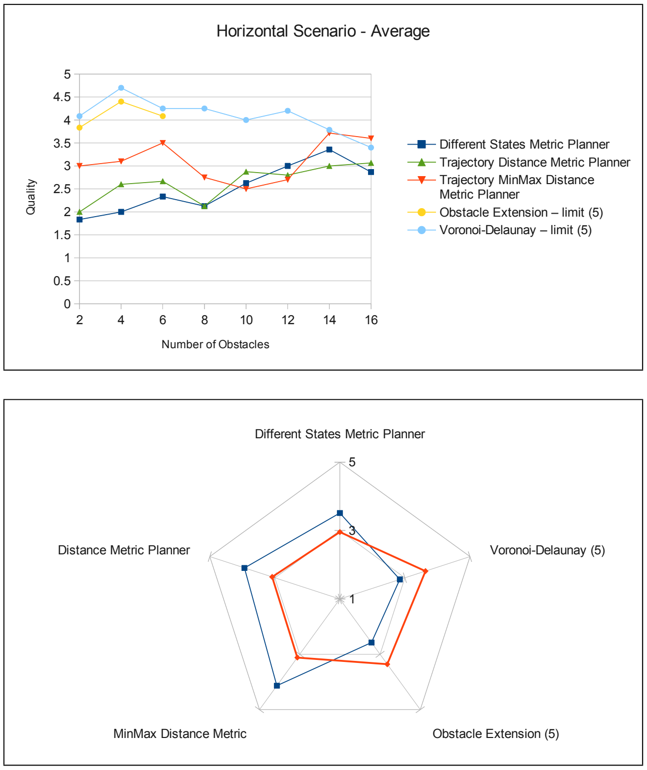

Figure 1: Average quality evaluated by human operator and cluster centroids.

the user evaluation of the methods. A group of 12 people, familiar with the trajectory planning and the UAV control problem, have manually evaluated results of each method. Each user has been presented with a set of 15 problem instances of two scenarios in the 8-grid domain with randomly placed obstacles and 5 trajectories proposed by each method. User grades each solution with 1 to 5 points (more points mean better solution).

Average quality evaluation of each method for different number of obstacles are shown in Figure 1. We can see that the best score was achieved by the Trajectory Distance Metric MaxMin planner and the Voronoi-Delaunay graphs based planner. The Voronoi-Delaunay graphs based planner outperformed other methods mainly in the scenario with up to 12 obstacles. Based on our experience, one segment of the UAV trajectory typically does not avoid more obstacles which makes this method very suitable for use in operators' control panels.

Closer evaluation shows that the users can be divided into two groups. Some have preferred trajectories whose length is closer the to optimum while the others preferred more diverse trajectories. First group of users, graded higher the Voronoi-Delaunay graphs based planner while the latter one preferred the Trajectory Distance Metric MaxMin planner. We used k-means clustering to find centroids of both groups. These centroids of evaluations both groups are shown in the Figure 1. This observation will direct our future research to create a method which will satisfy both groups.

4. CONCLUSION

The human-UAV interaction is a bottleneck of today's unmanned aerial systems. The interface of the trajectory planning can be certainly improved by providing a user with several alternative trajectories from which a user can choose the most suitable one. This problem has not been targeted by the scientific community yet even though it has significant practical impact. This contribution presented experimental results of user evaluation of several methods suitable for trajectory diverse planning for UAV mission displays.

We have implemented the Voronoi-Delaunay graphs based planner together with RRT* (optimal rapid-random trees, [2, 3]) planner into a prototype of UAV control display. When user specifies new waypoints, several diverse trajectories are created and proposed to the user, as shown in Figure 2. User can choose one trajectory or refuse all of them. When a trajectory is accepted, it is sent to the UAV and it starts to follow it.

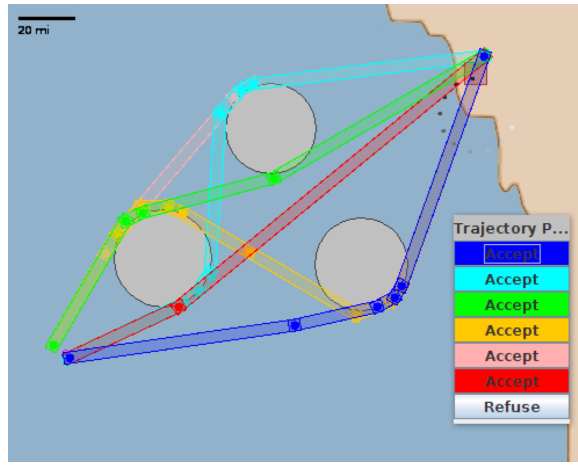

Figure 2: The screenshot shows several trajectories, which are proposed to the user after he set up new waypoint for the UAV.

5. ACKNOWLEDGEMENT

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