Creating Safe Corridors for Urban Air Mobility

Jakub Sláma Jan Faigl

***Abstract*— Personal air transportation on short to medium distances, so-called Urban Air Mobility (UAM), is an emerging trend in modern aviation. Risk mitigation approaches based on no-flight zones over city centers are not suitable for the upcoming UAM as the small aircraft are expected to fly in urban environments. Therefore, further approaches of risk-aware planning are needed. Since such planning can be computationally exhaustive, common low-risk areas used in risk-aware trajectories can be determined and used in a roadmap to support risk-aware planners. Determination of such safe corridors is not well-studied within the UAM domain, but a similar task of road centerlines estimation from GPS tracks is studied in the traffic domain. Thus, we propose to elaborate on the applicability of the existing methods in the UAM domain.**

I. INTRODUCTION

Urban Air Mobility (UAM) stands for personal air transportation on short to medium distances [1], where the number of small aircraft flying in urban environments is expected to rise [2]. Air traffic can be considered highly safe due to its advanced engineering, physical redundancies, and regulations. Namely, small aircraft are not allowed to fly over the most risky areas to minimize the crash risk. However, further restrictions on flyable areas are not sustainable for the upcoming UAM, as the aircraft are expected to fly over densely populated areas. Hence, novel approaches to risk mitigation are necessary.

The risk in a crash case can be ranked based on evaluation ranging from caused damage to a number of casualties [3], [4]. Regardless of the risk definition, it can be minimized by risk-aware trajectory planning. Failure-specific risk maps are proposed in [5] based on the Risk-A* for finding the least risky trajectory. The trajectory planner minimizes the motion cost using heuristic risk-to-goal estimation, exploiting assumptions about the risk limits. Only failures leading to total loss of the aircraft control (total failures) are assumed by the authors. In these failures, the crash location is given solely by the location of failure occurrence and failure type.

If a failure leading to a partial loss of control (partial failure), such as loss of thrust, occurs, an emergency landing is still possible. Thus, the task is to find the least risky landing location and an emergency landing trajectory toward it [6], [7], [8]. We proposed a risk-aware trajectory planner that accounts for partial and total failures in [9]. The RRT*-based planner evaluates the risk of the samples in the trajectory planning as a sum of risks induced by each considered failure. The risk induced by partial failures is estimated from a riskmap obtained by space sampling and risk propagating inspired by kernel operations. The risk of total failures is then determined on demand during the planning.

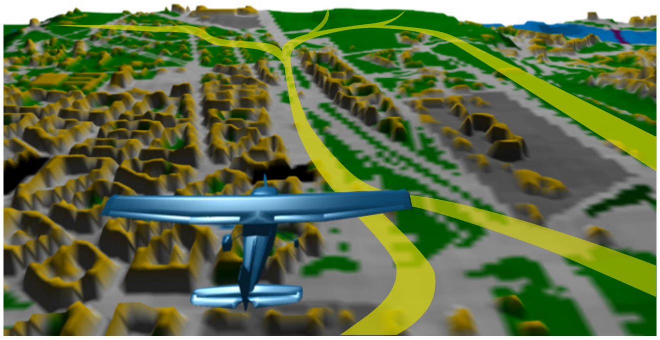

Fig. 1. Risk-aware trajectories pass over low-risk areas such as rivers, parks, or brownfields, forming safe corridors usable if flying nearby. Safe corridors roadmap (in yellow) can be used for risk-aware trajectory planning.

The risk-aware trajectory planning [9] can be demanding, but risk-aware trajectories tend to be over similar, low-risk areas called safe corridors. Thus, a safe corridors roadmap can support risk-aware trajectory planning similarly to roads for ground traffic; see the concept in Fig. 1.

Safe corridors can be determined from a large set of pre-computed risk-aware trajectories. Two approaches for safe corridor extraction have been proposed: (i) based on k-means clustering [10]; and (ii) self-supervised learning based on Growing Neural Gas (GNG) [11]. Both methods provide roadmaps yielding trajectories competitive to the reference planner. Nevertheless, more advanced graph-fitting techniques might achieve a simpler roadmap.

Therefore, we propose applying methods from similar road estimation tasks based on GPS tracks studied in the traffic domain. The creation of the so-called principal (best fitting) graph is proposed in [14] to minimize the distance of all GPS samples to the roadmap and the overall network length. The fitting is based on the reversed graph embedding technique, and the graph originates from the minimum spanning tree. An incremental track insertion algorithm is proposed in [12] with a guaranteed bound on the output map complexity. The algorithm starts with a partial track-map matching. Then, the unmatched portions of the track are inserted into the map, creating new graph vertices and edges. Finally, the map edges are updated by the matched portion of the track by the minimum-link algorithm.

II. CURRENT CHALLENGES

Although the former approaches [10], [11] provide roadmaps that significantly decrease the computational bur-

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The authors are with the Faculty of Electrical Engineering, Czech Technical University in Prague, Technická 2, 166 27 Prague, Czech Republic. `{slamajak|faiglj}@fel.cvut.cz`

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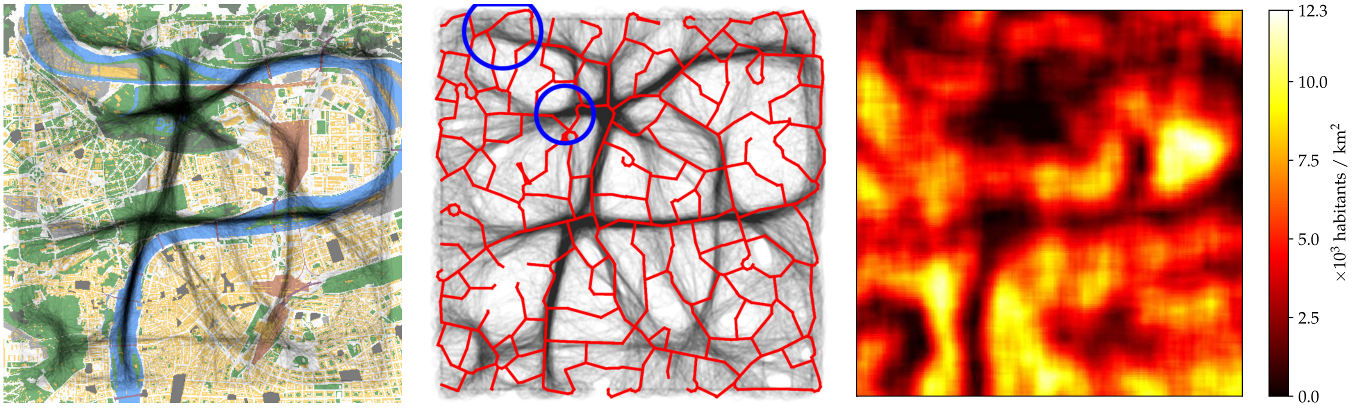

(a) Trajectories over city map (b) Safe corridors roadmap (c) Population density

Fig. 2. A heatmap of risk-aware trajectories and results of the safe corridors estimation: (**a**) risk-aware trajectories over the city map, (**b**) estimated safe corridors roadmap (implementation of [12] taken from [13]), and (**c**) population density layer of the map. The darker the area, the more trajectories pass through it; the trajectory heading is omitted, and only 2D projection is shown. A strong network of highly used low-risk areas (safe corridors) can be noticed. The predicted roadmap contains several areas (examples in blue) with wrongly estimated corridors, mainly due to varying widths of safe corridors.

den while yielding competitive risk-aware trajectories to the reference planner, the resulting roadmaps are relatively too complex with overlapping edges. So, we propose employing graph-fitting techniques to determine simplified roadmaps.

Based on our initial deployments, we found that the methods can be easily employed for a fixed flight altitude. Example results of direct applying [12] are depicted in Fig. 2.

The results suggest obtaining a neat, efficient roadmap of safe corridors using traffic domain methods. However, there is a possibility for improving the results as two main drawbacks have been identified.

The methods used in the traffic domain assume roads of similar width, often narrow. Contrary to the width of safe corridors, that varies significantly. Narrow safe corridors occur over rivers; wide ones can be found over parks; see Fig. 2a. Thus, the method struggles over wide low-risk areas, where multiple corridor segments are found instead of a reasonable safe corridor, as highlighted by blue circles in Fig. 2b.

Furthermore, roads are mostly bi-directional, so the traffic domain methods do not consider trajectory or road orientations. The safe corridors, however, are one-directional; the risk at a given configuration is given by possible ground casualties and damage in the case of failure at that configuration, which strongly depends on the aircraft heading at that configuration.

III. CONCLUSION

Safe corridors are low-risk areas used to increase the performance of risk-aware trajectory planning. Thus, a roadmap of safe corridors can be an alternative to computationally exhaustive risk-aware trajectory planning. Determining safe corridors from existing risk-aware trajectories has been found to be similar to the task of road centerlines estimation from GPS tracks studied in the traffic domain. Although these methods are generally applicable in the studied risk-aware trajectory planning, their current results are not satisfying enough as the assumption of road geometry is not valid on safe corridors in the UAM domain. Thus, a generalization of the methods toward the UAM remains open, with the main challenges being the varying width of corridors and introducing orientation on the roadmap edges.

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