Motion Strategy for Autonomous Aerial-videography for a Dynamic target in Dense Obstacle Environments

1. Introduction

Aerial videography has been one of the most popular applications of drones, utilized for various purposes such as surveillance, filming sports events and personal cinematography. To facilitate broader applications of the videography drone, the technology for its automation becomes essential. For example, users might want to film themselves enjoying outdoor activities (e.g. trekking or riding a bicycle) without other photographers. We can also consider the case where an unmanned surveillance agent should be employed to chase a suspicious person. Aligned with this trend, there have been research interests focused on the automation of the filming process by the drone to extend its applicability. Although recent works and commercial drones such as DJI and Skydio efforted to tackle the autonomation, the fully autonomous execution is still an open problem, especially in obstacle environments which the general users often encounter. In particular, the existing methods have not yet developed a chasing strategy which simultaneously satisfies the following five objectives:

A1) Target prediction considering obstacles.

A2) Ensuring flight safety under unstructured obstacles.

A3) Maintaining visibility of the target.

A4) Smooth chasing trajectory and efficient travel.

A5) Optimality and fast computation.

This work introduces a pipeline which effectively resolves A1 – A5 in an integrated manner by proposing a visibility metric and a planning module which consists of an *obstacle-aware target forecaster* and a *hierarchical chasing planner*. The contribution of our work is summarized as the below:

(a) (b)

Fig. 1 (a) Autonomous chasing for a dynamic actor with a drone in a dense forest. The actor moves at 2 m/s speed, whose trajectory is not known a priori to the chaser. **(b)** The translational histories of the drone (sky-blue) and the target (pink). By reducing collision or target-occlusion, the drone operates in a receding horizon manner using the proposed pipeline.

- We propose an online prediction algorithm reflecting the presence of obstacles, based on a covariant optimization framework (A1).

- We introduce a visibility metric for a moving target which can be defined in general environments without restriction on the shape of obstacles (A2). With simple computation, the metric encodes visibility against uncertain future movement of the target.

- We propose the motion strategy in a bi-level structure which includes chasing corridor generation (A2, A3 and A5) and dynamically feasible trajectory generation (A4 and A5).

- We validate the proposed methods with three types of tests: 1) comparison with other state-of-the-art algorithms, 2) high-fidelity simulation in a dense forest, and 3) fully-onboard hardware experiment.

2. Obstacle-aware target forecaster

As the first phase of the pipeline, we focus on the obstacle-aware prediction of the target over a future horizon, which computes a forecasting trajectory z_n $(n = 1, \dots N_T$, where $n > N_o$ corresponds to the future trajectory and $n \leq N_o$ are the fitting terms for past observations) so that it does not intersect the obstacle regions. To solve the problem, we leverage the covariant optimization by minimizing the observation error with past observation $x_{p,n}$ $(n = 1, \dots N_o)$ and penalizing the prediction path ($N_o \leq n \leq N_T$) for the obstacle cost $f_{obs}(z_n)$ (see (2) in the paper for the definition), which is formulated with the following optimization:

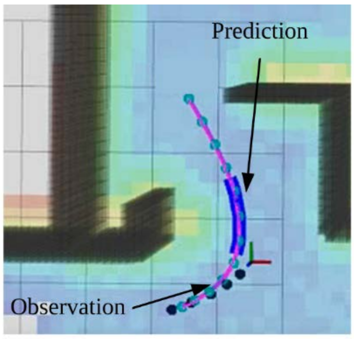

Fig. 2. Prediction example in multiple obstacles.

$$\min_{\xi} \frac{1}{2}\sum_{n=1}^{N_o} exp(\gamma n) \left|z_n - x_{p,n}\right|^2 + \frac{1}{2}\sum_{n=1}^{N_T-2} |z_n - 2z_{n+1} + z_{n+2}|^2 + \frac{1}{\rho}\sum_{n=1}^{N_T} f_{obs}(z_n),$$

Where γ is a positive constant for weighting more recent observation. The above can be re-arranged into the standard form of covariant optimization, which enjoys the stable convergency. The example of prediction in obstacles can be found in **Fig. 2**. In the example, 5 observations (black circles) were used to compute a prediction (thick blue) which does not collide the obstacles. In this way, the forecaster assists the chasing planner by providing a feasible prediction and does not mislead the planner by a infeasible one which intersects with obstacles.

3. Chasing strategy

- ***Safety and visibility metric***

To measure the safety of the drone position $x_c \in \mathbf{R}^3$ and visibility toward the target position $x_p \in \mathbf{R}^3$, we first use the safety score based on Euclidean distance field (EDF) $\phi(x)$ of the *octomap*. $\phi(x)$ is zero inside obstacles and positive for the safe region as illustrated in the left of **Fig. 2**. Next, assuming that the chaser takes $x_p - x_c$ as its bearing vector from the location x_c, we propose the visibility score toward the target position x_p as below:

$$\psi(x_c; x_p) = \min_{x' \in L(x_c, x_p)} \phi(x').$$

The visibility score field $\psi(x; x_p)$ given x_p is illustrated in the right of the **Fig. 2**, where we can note that the visibility

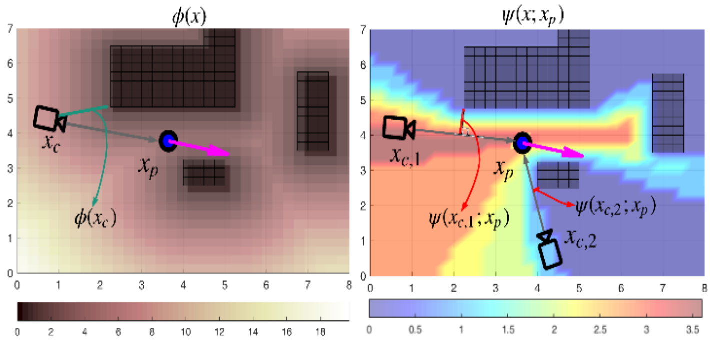

Fig. 3 Score for safety (left) and visibility of x_p (right) fields with colorbars.

score increases as the bearing vector stays away from the ambient obstacles (compare $x_{c,1}$ and $x_{c,2}$). From this, we can evaluate the performance metric in multiple unstructured obstacles not confined to single obstacle of ellipsoidal or box shapes.

- ***Chasing pipeline***

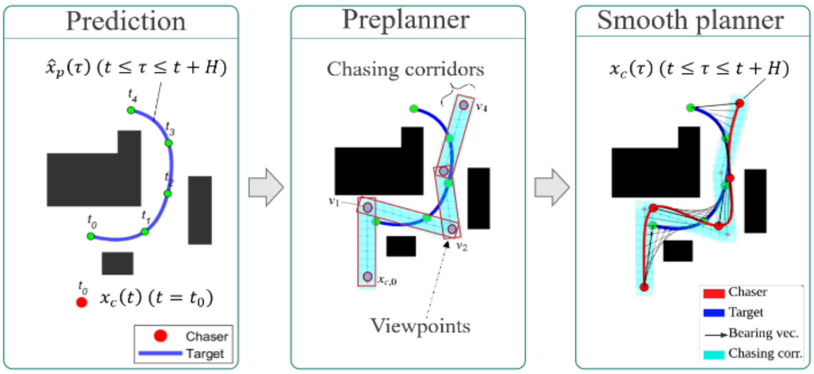

Fig. 4. The proposed chasing pipeline.

Based on the prediction introduced in **section 2**, the proposed chasing framework consists of two parts: 1) building the chasing corridors (*preplanner*) and 2) generating a dynamically feasible chasing trajectory (*smooth planner*) as illustrated in **Fig. 4**. The first phase outputs a *chasing-corridor* (see cyan boxes in the middle of **Fig. 3**) inside of which the safety and target-visibility are ensured. The corridors are found by the efficient graph search. The next phase plugs the corridors as the set of linear constraints into a quadratic optimization which optimizes the travel efficiency of the final chasing trajectory $\hat{x}_c(\tau) \in \mathbf{R}^3$ (see the red curve generated inside of the corridors in right of **Fig. 3**). In this way, the final chasing motion of the drone achieves the travel efficiency while alleviating the collision with obstacles and the occlusion of the target.

4. Results

- ***Simulations***

For the simulations, we performed three types of tests: 1) analyzing the performance scores attained over the missions in complex environments (**Fig. 8-9** in the paper), 2) high-fidelity simulation in dense forest (**Fig. 1**), and 3) comparison with other methods (**Fig. 5**).

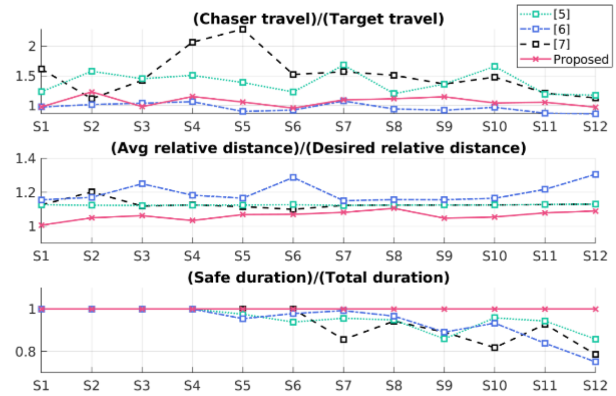

Fig. 5. Systemic comparison with other methods (see reference [5],[6] and [7] in the paper) in 12 scenarios (also see the paper for the description of S1-S12). We conducted comparisons in terms of the 1) travel efficiency, 2) shot distance, 3) safety, 4) target-visibility and 5) computation time. Our algorithm outperforms in terms of stable chasing by strictly guaranteeing the visibility and safety and shows the real-time computation suitable for fully online-chasing.

- ***Real-world experiment***

(a) (b) (c)

Fig. 6. **(a)** the camera-drone with onboard implementation: for algorithm execution, intel NUC is used as core, and camera- and vision-related tasks such as visual odometry and target localization run on Jetson TX2. Pixhawk is employed as the flight controller. **(b)** Autonomous aerial video shooting using a drone for a moving target in plane classroom with cluttered objects. The drone plans a chasing trajectory on-the-fly to incorporate the safety and visibility of the target against obstacles. The target (UGV with a green marker) is driven manually by a human operator who can be found in the figure. The entire drone operation is fully autonomous. **(c)** Path history of target (black) and chaser (magenta). The history of line-of-sight (LOS) of the drone toward the target is visualized with the sky-blue arrow.

5. Conclusion

In this paper, we proposed a target-visibility score metric and a chasing framework incorporating the prediction and motion planner which can handle A1-A5 jointly. Also, we validated the proposed algorithm from multiple types of tests including comparisons and a real-world experiment. From this work, we expect the possible applications of aerial videography to become more practical without the restriction of the filming environment by extending the capability of the autonomous camera drones into the dense obstacle cases. For future plans, we will reflect the artistic factors by actively selecting the shot angle and distance in order to obtain more cinematic videography by drones.