Dynamic Obstacle-Aware Navigation Framework for Complete Coverage in Aerial Exploration

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Abstract

This paper proposes a dynamic obstacle-aware navigation framework for UAV-based complete coverage in aerial exploration missions. Conventional UAV navigation systems predominantly assume static environments, limiting their applicability in real-world scenarios involving moving obstacles. The proposed framework integrates vision-based obstacle detection with a two-tiered motion prediction model that combines short-term estimation using a Kalman filter with long-term trajectory forecasting via a discrete-time Markov chain to enable proactive trajectory replanning in response to environmental dynamics. An energy-aware decision-making module evaluates and selects between active obstacle avoidance and strategic hovering, based on a comparative analysis of maneuvering and waiting costs to enhance exploration efficiency and ensure collision-free operation in cluttered and dynamic environments.

Keywords: Dynamic obstacle avoidance, UAV motion and path planning, coverage planning.

Ⅰ. Introduction

Autonomous exploration is a fundamental task in UAV applications such as inspection, subterranean navigation, and search and rescue. Depending on the application context, exploration planners prioritize different goals, including rapid coverage, accurate mapping, uncertainty reduction, or object-focused navigation. However, due to the limited energy capacity of aerial vehicles, maximizing coverage within minimal time remains a core objective.

Traditional frontier-based and next-best-view (NBV) approaches often neglect global spatial structure, causing redundant revisitations of previously explored regions [1]. While global guidance strategies aim to address this by sequentially visiting frontiers, they still fail to reflect the true exploration goal due to dynamically shifting frontiers [2]. In contrast, coverage path planning (CPP) considers the entire unexplored space, offering more structured global guidance [3].

However, navigating UAVs in complex and dynamic cluttered environments remains a challenging endeavor. Obstacle avoidance in state-of-the-art exploration planners mainly focus on static environments [4]. Path planning algorithms must be capable of avoiding moving objects efficiently. Recent studies proposed several methodologies to address dynamic obstacles for UAVs. Vision-based avoidance models use constant velocity or acceleration models to estimate and predict object's motion [5]. These models didn't estimate and predict the motion of dynamic obstacles for efficient path planning for UAV navigation.

To address these challenges, we propose a framework that estimates obstacle motion, predicts future trajectories, and enables energy-efficient UAV navigation in dynamic, cluttered environments for complete and collision-free coverage.

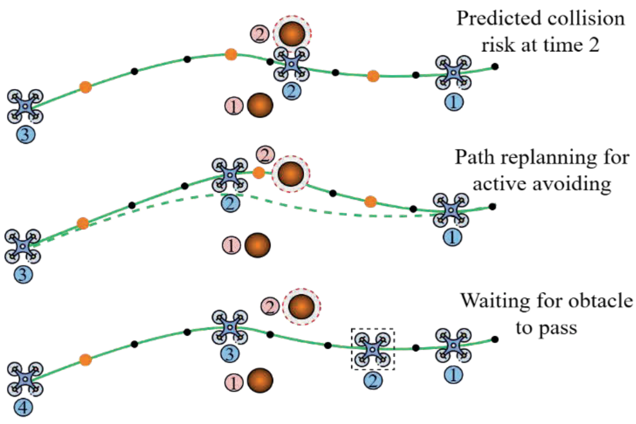

Fig.1: Adaptive replanning strategy to avoid moving objects

Ⅱ. Proposed System

This system integrates dynamic obstacle detection using RGB-D sensing, predictive modeling of obstacle motion using a Kalman filter coupled with a Markov chain-based estimator, and a decision-making module that dynamically selects between active avoidance and waiting strategies based on cost analysis. The adaptive trajectory replanning strategy is illustrated in Fig.1.

Obstacle detection is achieved using an onboard RGB-D camera that continuously captures color and depth data. For each frame, the system extracts the 2D image-space bounding box of an obstacle, defined by the center point p_o^I, the size vector s_o^I, and the average depth d_o where:

$$\mathrm{p}_o^I = \begin{bmatrix} x_o^I \\ y_o^I \end{bmatrix}, \qquad \mathrm{s}_o^I = \begin{bmatrix} w_o^I \\ h_o^I \end{bmatrix}$$

Using the camera intrinsic matrix K, the pixel-space center is converted to a 3D position in the camera coordinate frame by:

$$\mathrm{P}_o^W = \mathrm{K}^{-1} \begin{bmatrix} x_o^I \\ y_o^I \\ 1 \end{bmatrix} . d_o$$

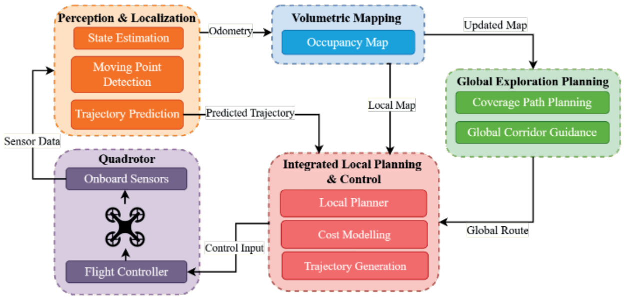

Fig.2: Overview of UAV navigation framework

This provides an estimate of the obstacle's spatial position relative to the UAV at each frame. To predict the future motion of detected obstacles, the system maintains a state estimate using a discrete Kalman filter. The obstacle's state at time step k is represented as a vector:

$$\mathrm{X}_k = \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \end{bmatrix}$$

Where x_k, y_k are position components and $\dot{x}_k$, $\dot{y}_k$ are velocity components in 2D space. The filter performs a prediction step using the linear transition model:

$$X_{k|k-1} = \mathrm{F}\mathrm{X}_{k-1|k-1},\ \mathrm{P}_{k|k-1} = \mathrm{F}\mathrm{P}_{k-1|k-1}\mathrm{F}^T + \mathrm{Q}$$

followed by an update step using the new observation z_k:

$$\mathrm{K}_k = \mathrm{P}_{k|k-1}\mathrm{H}^T\left(\mathrm{H}\mathrm{P}_{k|k-1}\mathrm{H}^T + R\right)^{-1}$$

Here, F is the state transition matrix, H is the observation matrix, Q and R are the process and measurement noise covariances, respectively, and $\mathrm{P}_{k|k}$ is the estimate covariance matrix. This allows the UAV to maintain a running estimate of the obstacle's current position and velocity. For longer-horizon motion prediction, the system integrates a probabilistic model based on a discrete Markov chain. The state transition of obstacle motion directions is modeled using a transition matrix P_{trans}, while the influence of environmental constraints is encoded by softmax-normalized vector P_{env}^{t+1}. The path probabilities of obstacle are recursively updated as:

$$\mathrm{P}_{\mathrm{path}}^{t+1} = \mathrm{P}_{\mathrm{path}}^{t} \cdot \mathrm{P}_{\mathrm{trans}} * \mathrm{P}_{\mathrm{env}}^{t+1}$$

where * denotes element-wise multiplication. $\mathrm{P}_{\mathrm{env}}^{t+1}$ is computed by applying the softmax function to the obstacle-free distances $\{Dist_1, Dist_2, \cdots, Dist_n\}$ to favor safer paths. The interaction between perception, trajectory prediction, mapping, and planning module are shown in Fig. 2.

UAV uses this predictive information to decide whether to wait or to actively avoid obstacles. This decision is governed by an energy-aware cost model. For avoidance, the system estimates the energy required to execute a detour based on UAV dynamics, including acceleration, turning radius, and time to rejoin the original path as:

$$E_{\mathrm{avoid}} = \int_{t_0}^{t_f} P_{\mathrm{maneuver}}(t)\, dt$$

For waiting, the energy cost of hovering in place for the predicted duration of obstruction is calculated as:

$$E_{\mathrm{hover}} = P_{\mathrm{hover}} \cdot t_{\mathrm{wait}}$$

The local planner module then compares both costs from two actions and selects the action that minimizes energy consumption while maintaining collision-free coverage.

Ⅲ. Conclusion and Future Work

This study presents a UAV-based dynamic obstacle-aware navigation framework that integrates RGB-D camera-based perception with Kalman filter and Markov chain-based motion prediction to enable safe and efficient coverage in dynamic environments. The proposed system offers an adaptive solution for autonomous aerial exploration in cluttered and unpredictable settings. Future work will focus on real-world implementation of this navigation framework.

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