Optimizing UAV Navigation through Non-Uniform B-Spline Trajectory for Tracking UAV Enemy

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***Abstract*—This paper proposes optimizing unmanned aerial vehicle (UAV) navigation through a non-uniform b-spline trajectory. The safety of the UAV and successful trajectory execution while avoiding obstacles become paramount in scenarios involving enemy tracking. The proposed system offers optimization in UAV navigation by adjusting time and velocity to address smooth and safe path planning in a dynamic environment for tracking UAV enemies. The tracking enemy relies on a depth camera to classify the enemy with the environment and calculate the distance. Specifically, the UAV capitalizes on the flexibility and smoothness of Non-Uniform B-Spline curves, enabling UAVs to navigate complex environments with precision. The approach is evaluated through comprehensive the experimental result.**

***Index Terms*—UAV navigation, non-Uniform B-Spline trajectories, trajectory optimization, obstacle avoidance, tracking UAV.**

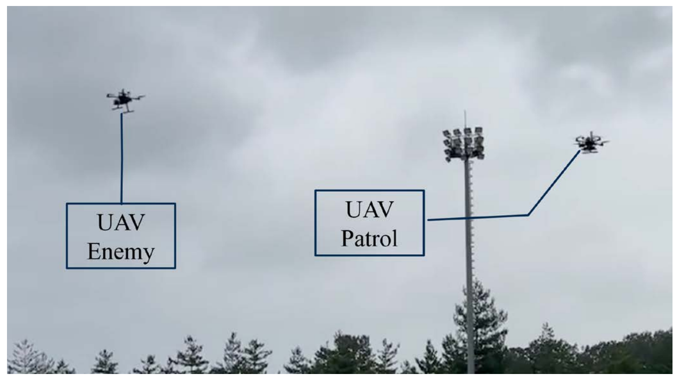

Fig. 1: Tracking UAV Enemy.

I. Introduction

In recent years unmanned aerial vehicles (UAVs) in contemporary society have revolutionized various sectors, including surveillance, logistics, defense, and agriculture [1]. In light of these advancements, the critical imperative in this context is the development of obstacle sensing and avoidance capabilities to ensure the safe navigation of tracking UAV enemies in dynamic environments involving intricate and rapidly changing conditions, where the targeted drone enemy may exhibit swift and unpredictable movements. As a result, UAVs must adapt their trajectories and strategies in real-time to effectively chase and neutralize these drone threats. This dynamic interplay between UAVs and drone enemies introduces a heightened complexity, requiring advanced algorithms and responsive control systems to ensure successful tracking and engagement.

Tracking and engaging an enemy involves crucial steps, each contributing to the operation. At the forefront of these steps is detecting the target itself, which is the foundation for subsequent tracking and avoidance maneuvers. Several methods [2]–[6] have been proposed. In [3] object detection algorithms, predominantly leveraging Convolutional Neural Networks (CNNs). Within target detection, YOLO, SSD, R-CNN, and Faster R-CNN have emerged as prominent players, renowned for their exceptional balance between accuracy and real-time processing capabilities. In [4] undertook a comparative assessment of target detection methodologies, highlighting the importance of considering onboard embedded GPU systems, off-board GPU ground stations, and onboard GPU-constrained systems when evaluating frame rates and accuracy. In [5] addressing constraints imposed by transmission capacity and limited onboard computing power, the integration of the Intel Movidius Neural Compute Stick (NCS) alongside Raspberry Pi proved impactful, with Mobilenet-SSD (5FPS) emerging as a superior choice compared to YOLO (1FPS). Nonetheless, object detection becomes essential for identifying the intended target, while configuring navigation settings becomes necessary for facilitating the pursuit of drone enemies.

Numerous strategies [8]–[12] within UAV trajectory generation have emerged, addressing the intricacies of this multifaceted challenge. In [9], [10] to overcome the difficulties presented by these obstacles, the A* algorithm is employed. This algorithm serves the purpose of preserving the distance between points and searching for the shortest path from the UAV current position. Despite the significant effort put into this field, two critical issues remain unresolved. In [11] concerns the practical constraints of time and computational resources that come with UAV trajectory planning. In [12], current methods suggest optimizing the A* algorithm for path planning trajectory. However, the A* algorithm's performance is suboptimal when it comes to generating trajectories that are both smooth and maintain a safe distance from obstacles. This proposed system offers

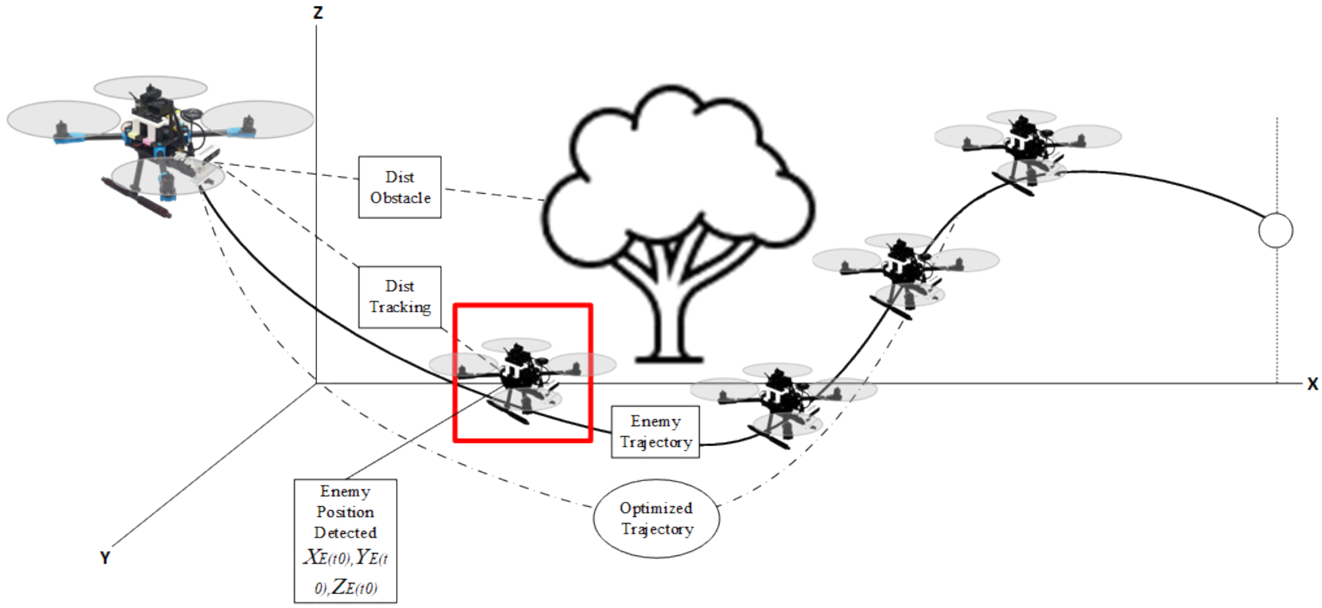

Fig. 2: Tracking UAV enemy scenario with consider distance of obstacle and UAV enemy.

a solution to overcome this challenge involving integrating object detection and smooth trajectory navigation using non-uniform b-spline. The main contributions of this paper are summarized. First, the object detection is formulate to maintain the UAV focus on the target in mission mode tracking UAV enemy based on YOLO V5. Second, a Non-uniform B-spline, a mathematical technique is utilized to optimize the UAV time and velocity while pursuing the UAV enemy. This combination of object detection and trajectory optimization aims to enhance the tracking accuracy and the smoothness of the UAV movement while chasing the UAV enemy.

II. System Model

This section presents a comprehensive overview of the functionalities and capabilities of an UAV equipped with a UAV enemy detection system. The objective is to understand the UAV advanced features to identify and detect aggressive UAV enemies.

A. Detection Algorithm

Object detection is designed based on recognizing UAV enemy. The proposed UAV call patrol UAV through a depth camera mounted on UAV. Fig.1 shows the depth camera calculating distance for obstacles and tracking UAV enemy. Moreover, object detection mainly comprises the Focus module, CBL module which is composed of a convolution layer, batch normalization layer, Concat module, and Up-sample module [5].

The detection algorithm starts with input from a depth image to classify the UAV enemy. The classification result probability for UAV enemy detection. Tracking the UAV enemy relies on a specific position based on a centroid bounding box. In algorithm 1, edge ed given by depth

Algorithm 1: Enemy Detection

Input : ed,$prob_{obd}$,bx_{cur}
Output: x_{ob},y_{ob},z_{ob}
$th \leftarrow prob_{obd}$;
$pos \leftarrow bx_{cur}$;
while *true* **do**
  $Im_{frame} \leftarrow Im_{cur}$;
  $prob_{pos} \leftarrow bx_{cur}$DetectEnemy$Im_{cur}$;
  if $prob_{pos} > th$ **then**
    $x_{ob} =$ centroid$x$;
    $y_{ob} =$ centroid$y$;
    $ed \in ROI\ CDF(c(t+1)) = CDF(c(t)) + CDF(c(t-1))$;
    $z_{ob} = CDF(c(t+1))$;
    if $z_{ob} < En_distance$ **then**
      end
      return;
    end
  end
  $P_x = z_{ob}$;
  $P_y = y_{ob}$;
  $P_z = x_{ob}$;
  return $prob_{pos}$;

camera and pre-processing to probability $prob_{pos}$from object detection to get current bounding box bx_{cur}. The centroid gets position x_{ob} and y_{ob} of the image frame during UAV patrol detected UAV enemy. The distance z_{ob} from the depth image frame calculate by extracting the pixel from a region of interest by object detection. The gaussian smoothing filter (GSF) is utilized [7]. By the GSF algorithm, the distance found with calculate the median of distance estimation can

Fig. 3: UAV enemy detected by object detection.

be written as follow:

$$g(c(t)) = \frac{e^{\frac{-c(t)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}}, \tag{1}$$

$$z_{ob} = \mathrm{CDF}(c(t)) = \frac{1}{2}\left(1 + \mathrm{erf}\left(\frac{c(t)}{\sqrt{2}\sigma}\right)\right), \tag{2}$$

where the pixel extracted $c(t)$ inside ROI with cumulative distribution function CDF to calculate median distance z_{ob} and gaussian error function erf. The goal position is converted by synchronize the position from centroid coordinate bounding box of UAV enemy G_p. The converter can be expressed as follow:

$$\boldsymbol{G}_p = \begin{bmatrix} P_x \\ P_y \\ P_z \end{bmatrix} = \begin{bmatrix} z_{ob} \\ y_{ob} \\ x_{ob} \end{bmatrix}, \tag{3}$$

B. Navigation Algorithm

The optimization of path planning to navigate UAV patrol track the UAV enemy is crucial. Specifically, after detecting the position enemy, the UAV patrol keep the distance between the obstacle and the enemy while planning the trajectory. Therefore, the preceding forward exploration employs a discretized control action space. Consequently, the search process must attain the precise continuous-coordinate goal state. To mitigate this accuracy concern and enhance search efficiency, the hybrid A* is utilized [13]. This system continuously generates a kinematic model. When expanding the nodes, the paths produced by hybrid A* are able UAV to pass through the environment. However, the hybrid state A* is not guaranteed to find the minimal-cost solution because of the discretization of controls and time, as well as the effective pruning of all but one of the continuous-state branches that enter a cell. Therefore uniform B-Spline is adopted for the advantageous properties, namely local control and convex hull property and convenient closed-form evaluation. In this method given $n+1$ control point $Q_0, Q_1, ..., Q_n$ and knot vector $\{t_0, t_1, ..., t_m\}$, the B-spline curve $s(t)$ of degree k is defined as follows:

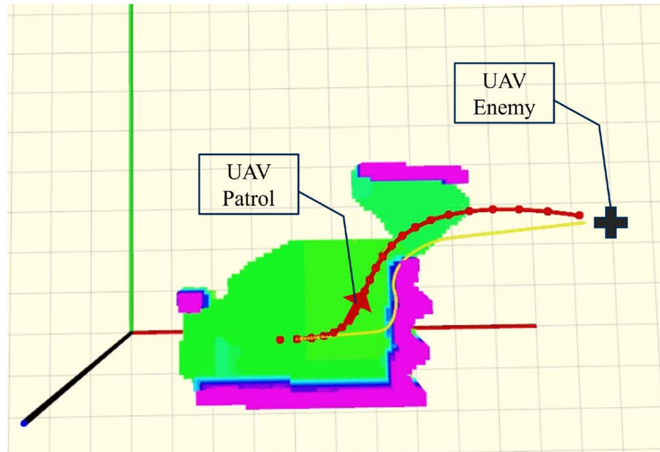

Fig. 4: Trajectory based on Non uniform-B-spiline.

$$\mathbf{s}(t) = \sum_{i=0}^{n} \mathbf{Q}_i N_{i,k}(t), \tag{4}$$

$$N_{i,0}(t) = \begin{cases} 1 & \text{if } t_i \leq t < t_{i+1} \\ 0 & \text{otherwise} \end{cases},$$
$$N_{i,k}(t) = \frac{t - t_i}{t_{i+k} - t_i} N_{i,k-1}(t) + \frac{t_{i+k+1} - t}{t_{i+k+1} - t_{i+1}} N_{i+1,k-1}(t). \tag{5}$$

To optimize time allocation, the trajectory derivative is changed as mention in [10]. The Non-uniform B-spline by independent knot span $\Delta t_m = t_{m+1} - t_m$. The velocity V'_i and the acceleration A'_i derivated as follow:

$$\mathbf{V}'_i = \frac{k\left(\mathbf{Q}_{i+1} - \mathbf{Q}_i\right)}{t_{i+k+1} - t_{i+1}}, \quad \mathbf{A}'_i = \frac{(k-1)\left(\mathbf{V}'_{i+1} - \mathbf{V}'_i\right)}{t_{i+k+1} - t_{i+2}}, \tag{6}$$

where, $\mathbf{Q}_i$ represents the control point of the B-spline at index i, and k denotes the degree of the B-spline curve. These equations allow for the determination of the derivatives of velocity and acceleration, which are pivotal for optimizing the trajectory with respect to time allocation. The non-uniform nature of the B-spline, characterized by its independent knot spans, contributes to its versatility in generating smooth and adaptable trajectories that can accommodate changes in velocity and acceleration, enhancing the overall performance of trajectory planning algorithms.

III. Experimental Result

The evaluation involves the execution of simulations and onboard experiments to demonstrate the performance of the proposed framework, with the integration of a depth camera into this system. In fig.3, the object detection is shown, and the bounding box is marked with a red square achieve the probability 59% . In fig.4, during the UAV in mission mode, a smooth trajectory is generated. In mission mode, the yellow line represents the primitive trajectory from UAV enemy, and the red line is the optimized trajectory. These

TABLE I: UAV trajectory times in mission mode.

Resolution	Trajectory Time(s)			
	Standard Deviation(s)	Average (s)	Minimum (s)	Maximum (s)
0.8m	-	-	-	-
0.05m	5.947	20	14	27
0.03m	2.0	17	15	19

TABLE II: Path planning searching times in mission mode.

Resolution	Search Time(s)			
	Standard Deviation(s)	Average (s)	Minimum (s)	Maximum (s)
0.8m	0.02804	0.06	0.013	0.26
0.05m	0.07602	0.048	0.001	0.141
0.03m	0.00529	0.004	0.001	0.021

experiments aimed to set up the trajectory for the practical approach applicability within real-world contexts. During the phase of onboard testing, numerous essential parameters were specified to ensure a thorough assessment. Notably, the UAV must maintain a maximum separation of 3 meters from the UAV patrol to avert collisions with the UAV enemy, with resolutions of the voxel grid set at 0.8, 0.05, and 0.03. Additionally, practical constraints guided the establishment of a maximum velocity of $1.5m/s$ meters per second and a maximum acceleration of $2m/s^2$.

The comparison is conducted on a map measuring 20 × 10 × 5 meters, featuring random placement of several obstacles. Given the pivotal role of voxel grid resolution in influencing proposed method performance, distinct resolutions facilitate an all-encompassing evaluation. The outcomes presented in table I and table II reveal smoother trajectories and reduced trajectory and search path planning times, particularly when employing lower voxel map resolutions until 0.03.

IV. Conclusion

In conclusion, this paper has introduced an innovative approach for optimizing the navigation of UAV by utilizing non-uniform B-spline trajectories. In scenarios involving enemy tracking, the safety of UAV operations and the successful execution of trajectories while circumventing obstacles are paramount concerns. A depth camera is employed to discern the enemy within the surroundings and ascertain the distance to facilitate effective enemy tracking. The Non-Uniform B-Spline curves, chosen for their flexibility and smoothness, empower UAV to navigate intricate environments with exceptional precision. In the future, it could encompass further optimizing the trajectory planning algorithm, exploring additional sensing modalities for enhanced environmental perception, and extending the framework's applicability to collaborative multi-UAV scenarios for improved efficiency and coordination.

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