Landing UAV on Moving Surface Vehicle: Visual Tracking and Motion Prediction of Landing Deck

Tien-Thanh Nguyen, Augustin Crismer, Geert De Cubber, *Member, IEEE*, Bart Janssens, *Member, IEEE,* and Herman Bruyninckx, *Member, IEEE*

***Abstract* — Landing an uncrewed aerial vehicle (UAV) on a moving surface vehicle in open waters is a formidable challenge due to the dynamic and complicated nature of the environment. The UAV is at risk of damage during the touch-down process, as the oscillatory motion of the surface vehicle can lead to hard impacts or tip-overs. In response, this paper introduces a trajectory optimization strategy for quadrotor for tracking moving surface vehicle using visual feedback from an onboard camera. The visual data is used for real time forecasting of the future motion of the surface vehicle. This prediction leverages a deep learning approach to determine the landing period in future when the surface vehicle's roll and pitch will fall below the critical landing threshold for a certain period, thereby providing a safe window for the impending landing. Our proposed method utilizes visual data from onboard camera on UAV only, obviating the need for external communication between UAV and surface vehicle. The proposed trajectory optimization method has been extensively tested in simulation environment and able to follow the target travel up to 5m/s even with highly maneuvering path. The proposed surface vehicle motion prediction was tested with recorded data and able to achieve the prediction error less than 3º, and in real-time manner.**

***Index terms* — quadrotor, surface vehicle, UAV, trajectory optimization, motion prediction, visual tracking**

I. INTRODUCTION

Uncrewed Aerial Vehicles (UAVs), commonly known as drones, are increasingly utilized in maritime operations to execute tasks that are hazardous or challenging for humans. Nonetheless, a significant challenge in their widespread adoption for maritime operations lies in their ability to autonomously land on moving surface vehicles due to the precipitous and violent nature of the maritime environment. The landing operation of a UAV on a moving surface vehicle contains three phases: approaching phase, following phase and final landing phase as shown in Figure 1. In the approaching phase, the UAV approaches the designated landing area on the moving surface vehicle with correct, well-defined flying direction. In the following phase, the UAV hovers steadily above the moving landing area, gathers the information to estimate and predict the movement of the deck of the moving vehicle before landing. Based on the prediction, a landing period – which is the quiescent period, when the roll and pitch angles of the surface vehicle are below the danger threshold – is determined during the following phase. In the final landing phase, the UAV switches from hovering above the landing area to descend until touchdown right inside the landing period estimated in the following phase.

To land safely on the moving surface vehicle, during the following phase, the UAV must estimate and predict the movement of the landing deck accurately for determining the landing period. In this work, only the visual feedback from the onboard camera of the UAV is used to control the UAV to track the landing deck and for estimating and predicting the landing deck's motion. The visual based solution enables the landing operation to proceed without depending on active communication between the UAV and the surface vehicle. However, in order to obtain high-quality visual data for accurate prediction of the landing deck's movement without relying on communication with the surface vehicle, the UAV's landing deck visual tracking system needs to exhibit stability and resilience characteristics to maintain consistent tracking of the landing deck, even in scenarios involving a highly maneuverable moving surface vehicle, while simultaneously ensuring that the landing deck remains within the field of view (FOV) of the onboard camera.

On other hand, the landing deck's motion prediction aims for determining the landing period when the roll and pitch angles of the landing deck are below the danger threshold – which prevents UAV to tip-over or lead to hard impact during touch down. The danger threshold of the roll and pitch angles and the minimum duration of the landing period are defined in advance and depending on the type of UAV, its descent dynamic and landing gear. The motion prediction of the landing deck must be highly accurate and with low latency – meaning it must be able to predict the landing deck's motion for a relatively long period of time in future based on data recorded in a relatively short period of time in the past, with short processing time and result in low prediction errors in roll and pitch angles.

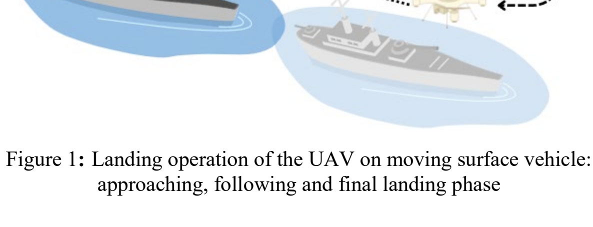

Figure 1: Landing operation of the UAV on moving surface vehicle: approaching, following and final landing phase

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Our contributions in this work are: (1) a visual based trajectory optimization for quadrotor to maintain stable tracking of the landing deck during following phase; (2) a deep learning-based motion prediction of the landing deck for determining the landing period to ensure the safe landing of the UAV on moving surface vehicle in open waters.

The rest of the paper is organized as follows: In Section 2 we discuss various related works on ship motion prediction and UAV target tracking. In Section 3 we present the method for visual tracking and trajectory prediction of the target. Section 4 presents quadrotor trajectory optimization for target tracking. Section 5 presents our landing deck pose prediction and landing period determination approach. The experiments and results to validate our approach are introduced and analyzed in Section 6.

II. Related Works

Predicting ship motion accurately and in real-time is highly relevant to maritime activities such as active ship stability, offloading cargo, fire accuracy of weapon systems and ship deck landing of UAV [1]. Linear estimation methods such as Auto Regressive (AR) from Peng et al. [2] and Auto Regressive Moving Average (ARMA) from Chen et al. [3] have been used, however, due to the nonlinearity of ship motion, the precision of such methods is limited. Chung et al. [4] used Kalman filter with estimated wave-excitation data as input to estimate ship motion online. However, relying on prior knowledge of the ship's transfer functions limits the systems to be used for other surface vehicles. Gupta et al. [5] predicts the uncrewed surface vehicle's (USV) motion from a downward-facing camera without prior knowledge of the USV using fast Fourier transform (FFT) based modeling, a Kalman observer and wave prediction model. Nonetheless, this method required extended recorded data for predicting short future motion, which draws into question the feasibility of implementing it into real applications. A similar approach of using FFT and a Kalman filter to predict ship motion for determined UAV-ship landing period with Go or No-Go intervals is employed by McPhee et al. [6]. Abujoub et al. [7] relies on a LiDAR onboard of the UAV to estimate the roll and pitch angles of the landing deck, learn the dynamic behavior of the surface vehicle while hovering above it then determine the window for safe landing. Deep learning methods are also applied to predict the ship motion: Zhang et al. [8] studied time series prediction using Gate Recurrent Unit (GRU) and Long-Short Term Memory (LSTM) deep learning methods for recorded data of real ship voyages, taking into account weather conditions: wind, wave; maneuvering states: rudder angle, propeller speed; etc. On other hand, Rashid et al. [9] focused more on the real-time aspect for forecasting ship motion based on image recorded on the ship deck, the approach was validated with simulated data.

The visual tracking of UAV for specific visual patterns has remained an active research domain for several years, ranging from autonomous ship deck landing, as demonstrated in Arora et al. [10] to search and rescue operation in maritime condition as presented in Almeshal et al. [11]. In early research work, image moments-based approaches were applied to facilitate helicopter landings on static landing pads with distinct geometric shapes, as detailed in Saripalli et al. [12]. Subsequent advancements extended this method to accommodate landing on moving landing pads, as demonstrated in Saripalli and Sukhatme [13]. Notably, these studies primarily focused on tracking a single dimension, and the image processing was executed offboard. Borowczyk et al. [14] devise a combination of Proportional Navigation (PN) guidance and Proportional-Derivative (PD) control for the purpose of landing a quadrotor onto a rapidly moving ground vehicle (reaching speeds of up to 50km/h). Notably, their strategy requires the combination of visual AprilTag[1] fiducial markers and wireless transmission of GPS and IMU measurements from the ground vehicle to the UAV. Visual servoing approaches using information from onboard cameras of the UAV to facilitate closed-loop pose control, can be broadly classified into two categories: position-based visual servoing (PBVS) and image-based visual servoing (IBVS). Due to their inherent computational efficiency and ability to withstand image noise, IBVS techniques were employed for controlling quadrotor landings on dynamically inclined planar surfaces, as illustrated in Li et al. [15], as well as for landing on moving vehicles, as demonstrated in the work of Keipour et al. [16]. Nevertheless, given that the visual servoing approach heavily relies on the visual pattern detector to provide control feedback, the main problem leading to failures comes from the absence of visual target detection. This problem can be resolved by expanding the field of view of the camera by using a fish-eye camera or multiple cameras system, or an active controlled gimbal system. Another alternative is to use a robust tracker, and future trajectory predictor of the visual target as demonstrated in Han et al. [17]. With predicted trajectory of the tracking target, the UAV trajectory can be computed and optimized for robustness tracking, safety from obstacles and dynamical feasibility as discussed in the same work. The benefit of employing trajectory generation for target tracking lies in its adoption of a cascade control methodology. This approach contains a reliable and system-specific low level attitude controller as an inner-loop, and a model-based trajectory controller as explained in Bangura et al. [18] functioning as an outer-loop. This cascade approach is rationalized by the fact that critical flight control algorithms are running on a dedicated navigation hardware, commonly based on micro-controllers such as Pixhawk[2]. In parallel, high-level tasks are typically managed on a more powerful onboard computer. This design introduces a segregation layer that ensures the secure continuation of critical operations even in the event of potential failures within the high-level computing.

In this work, we implement the hierarchical control approach for UAV target tracking by predicting the trajectory of the tracking target and generating the UAV trajectory for trajectory controller. We focus on analysis of different trackers, predictors, and constraints as well as system integration aspects for landing the quadrotor on a moving surface vessel.

III. Target Tracking and Trajectory Prediction

A. Target detection and pose estimation

Using a fixed downward looking camera from the UAV, for tracking the landing deck on a moving surface vehicle, it

[1] https://april.eecs.umich.edu/software/apriltag

[2] https://pixhawk.org/

requires to have a robust detection of the landing deck and real-time and high accuracy estimation of its pose with respect to UAV coordinate. The fiducial marker is chosen to mark the landing area for visual localization and tracking from the visual feedback. ArUco markers [19], often used in robotics applications, are selected in this work for speed of detection, resistance to occlusion and accuracy of the pose estimation. Other methods such as visual SLAM [20] can be employed for tracking and localization and pose estimation of the landing deck without the presence of the fiducial marker.

B. *Target future trajectory prediction*

After the position of the target is estimated, to achieve robust tracking, the future trajectory of the target is predicted. The main challenge is that the movement dynamic of the target is not specified in this research since our aims is to develop a solution can be used for tracking different types of surface vehicles, and without the necessity of communication between the target and UAV. To solve this challenge, two methods are implemented in this research. The first method involves the estimation of the motion model using a maneuver detection system. In this method, the motion model is dynamically adjusted based on which type of maneuver is detected. A modified version of the Constant Turn Rate and Velocity model (CTRV) explained in Zhai et al. [21] is utilized. Extended Kalman filters (EKF) and unscented Kalman filters (UKF) are used to provide the prediction for the target's future trajectory. The second method is based on Bézier curve regression [17]. These algorithms work as follows; each new measurement of the position is put in a queue of finite length; a weight is associated with each element of the queue according to the time elapsed since the observation, this weight reflects the confidence in the observation. Then a regression process is performed with the elements of the tail and their associated weights as shown in the gradient color in Figure 2. The regression method and the formulation of the curve depends on the algorithm used but it is generally a polynomial formulation.

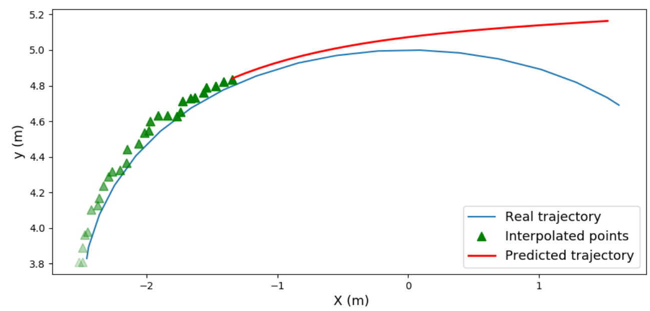

Figure 2: Trajectory regression method example

IV. QUADROTOR TRAJECTORY OPTIMIZATION

Once the target has been detected and its future trajectory estimated, the goal is generate UAV trajectory to track the target while adhering to certain constraints. First, the UAV trajectory must be feasible for the UAV in terms of speed and acceleration, ensuring that the UAV operates within its physical limitations. Additionally, it is desirable for the UAV to stay in close proximity to the target as much as possible. This ensures that the target remains within the field of view of the UAV, allowing for continuous tracking. Moreover, it is important to achieve a smooth and continuous trajectory for the drone. This helps to avoid any jerky movements that could lead to blurring or instability in tracking. These constraints are under the assumption that the target speed is not faster than the maximum speed of the UAV.

A. *UAV trajectory formulation*

UAV trajectory is written as a piecewise polynomial trajectory as introduced by Wang et al. [22]. Each segment is defined by a vector of its states at the beginning and at the end of the segment and the time assigned to it. A trajectory of m segments that pass-through $m+1$ waypoints, with given initial and final states can be efficiently computed for minimize jerk or snap as represented in Wang et al. [23]. The smoothness criterion cost function is written as:

$$J_s(q,T) = \sum_{i=1}^{m} \int_{t_{i-1}}^{t_i} ||T_i^{(r)}(t)||^2 dt$$

With J_s is the cost function for smoothness criterion, q_i is the i-th intermediate waypoint, $t_i - t_{i-1} = T_i$ is the time allocated to the i-th segment. $r = 3$ or 4 to minimize jerk or snap.

B. *Constraints*

1. Corridor constraints

The first constraint to enforce is that the UAV must fly in an area near the predicted trajectory of the target. To do so, we first sample the target trajectory the number of samples which will define the number of segments that the UAV trajectory. Once those waypoints are acquired, a convex polygon $\mathcal{P}_i$ is created around each pair of waypoints. The flight corridor (noted $\mathcal{F}$) is thus defined as the union of the polygons.

$$\mathcal{F} = \bigcup_{i=1}^{m} \mathcal{P}_i$$

The polygons are created in such a way that each polygon has an intersection with the next polygon.

$$\mathcal{P}_i = \{\, x \in \boldsymbol{R}^2 \mid A_i x - b_i \leq 0 \,\}$$

To ensure that the UAV will stay in the corridor $\mathcal{F}$ during its flight, an intermediate waypoint q_i is created in the intersection $\mathcal{P}_i \cap \mathcal{P}_{i+1}$, as illustrated in the Figure 3.

The cost function associated with the corridor constraints J_f is written as a logarithmic barrier term:

$$J_f(q) = -k \sum_{i=1}^{m-1} \sum_{j=i}^{i+1} \mathbf{1}^{\boldsymbol{T}} \ln\left[b_j - \boldsymbol{A_j} q_i\right]$$

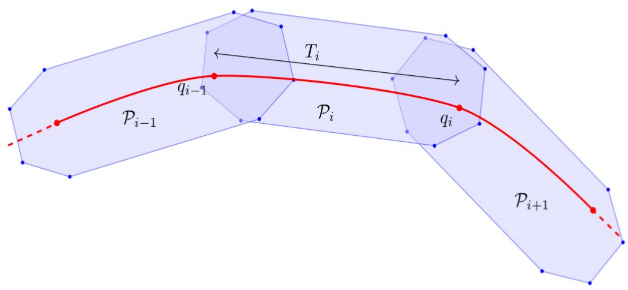

Figure 3: Flight corridor, polygons, and their waypoints

where k is a constant coefficient, $\mathbf{1}$ is an all-ones vector and $\ln[.]$ is the natural logarithm.

2. Velocity and acceleration constraint

The velocity constrain is a soft constraint expressed as a function of the q_i and T_i:

$$J_v(q,T) = \sum_{i=1}^{m-1} \rho_{vi} \cdot g\left(\left\|\frac{q_{i+1} - q_{i-1}}{T_{i+1} + T_i}\right\|^2 - v_{max}^2\right)$$

where ρ_{vi} is a weight associated with each trajectory segment and sets the weight of the constraint for that segment. $g(x) = max(x,0)^3$ is a cubic penalty function and v_{max} the maximum allowed velocity of the UAV. This formula is literally the difference between the maximum velocity of the UAV and the mean velocity considering that it flies from the point q_{i-1} to q_{i+1} in a straight line. Following the same idea, the acceleration constraint is written as :

$$J_a(q,T) = \sum_{i=1}^{m-1} \rho_{ai} \cdot g\left(\left\|\frac{(q_{i+1} - q_i)/T_{i+1} - (q_i - q_{i-1})/T_i}{(T_{i+1} + T_i)/2}\right\|^2 - a_{max}^2\right)$$

where ρ_{ai} is the equivalent of the ρ_{vi} but for acceleration and a_{max} is the maximum acceleration of the UAV.

3. Time constraint

The time constraint is enforced by a term that penalizes the total time of the trajectory:

$$J_t(T) = \rho_t \sum_{i=1}^{m} T_i$$

C. *Cost function*

The cost function can be expressed as the sum of every contribution :

$$J_\Sigma = J_s(q,T) + J_f(q) + J_v(q,T) + J_a(q,T) + J_t(T)$$

This function can be minimized with respect to q and T which are the variables of the problem. A quasi-Newton method, the Limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm (L-BFGS) is applied to solve the optimization problem. With our onboard computer (Intel NUC i7 core processor 2,8 GHz), computation time for the trajectory optimization in general case is shorter than *100ms,* which is sufficient for most missions.

D. *Constraint verification*

Due to the soft nature of the constraints, it is possible for the UAV trajectory to violate the flight corridor boundaries or exceed the speed and acceleration constraints. To address this, a constraint-checking algorithm is implemented, to verify the result trajectory. If all constraints are satisfied, the trajectory is sent to the trajectory tracking controller of the UAV for execution. However, if any constraints are violated, the trajectory is resampled, and the weights assigned to the segments where the violation occurs will be increased. Then the optimization process is launched again. However, this iterative loop should be performed in a limited time to avoid getting stuck in an inefficient optimization loop and to explore alternative options with newly acquired data.

V. LANDING DECK POSE PREDICTION AND LANDING PERIOD DETERMINATION

A. *Landing deck pose prediction.*

The relative position and pose of the landing deck with respect to the UAV have been estimated from the target detection and pose estimation. UAV can estimate its position and pose using GPS, IMU and other onboard localization and estimation methods. Pose, position data of the landing deck and UAV must be filtered and sampling with a defined sampling rate to create the input sequence vector for time series forecasting of the landing deck pose. Figure 4 illustrates the flowchart to generate the input sequence vector. To achieve this, a fully connected network (FCN) is utilized to establish a fusion of the estimated poses and positions of the landing deck. This fusion encapsulates the information of dynamic characteristics of the moving surface vehicle such as speed, heading within the sequence vector.

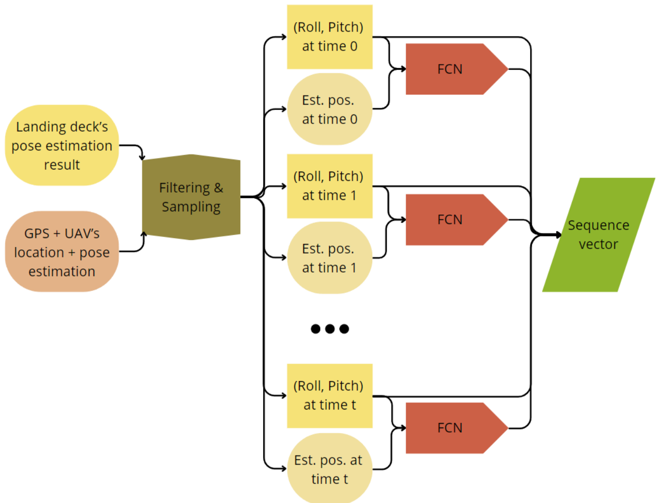

Figure 4: Creating the input sequence vector for landing deck pose prediction.

For predicting landing deck pose from the input sequence vector, a deep learning-based approach commonly used in time series forecasting is utilized. Figure 5 shows the architecture of the implemented pose prediction model. Two LSTMs are used together where the first one acts as an encoder followed by a second decoder LSTM. The first LSTM receives the input sequence vector and a hidden vector. When the data is passed through this network, an encoded latent vector is output together with the hidden state of this first LSTM layer. The second LSTM layer uses this hidden and latent vector and decodes it into a new latent vector. Finally, the latent vector from the decoder is passed through two linear layers that aggregate the vectors into a predicted sequence of pitch and roll angles of the landing deck.

B. *Landing period determination.*

From the predicted sequence of pitch and roll angles of the landing deck, the UAV must determine the safe landing time for limited the impact and reduce the risk of the tip-over during touch down. In higher sea states, the safe landing period is often difficult to come across and only appears in very short periods.

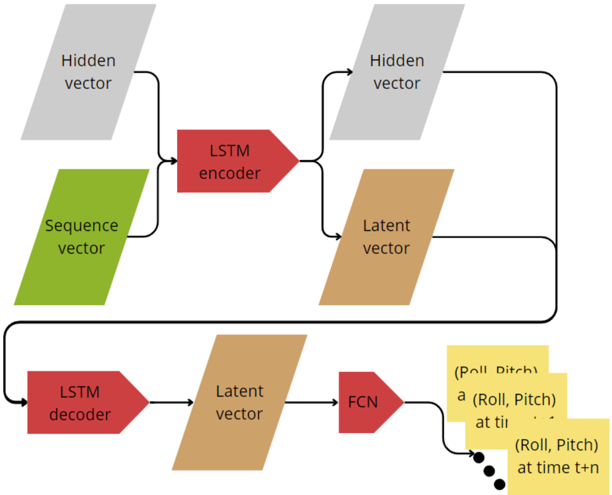

Figure 5: Landing deck pose prediction using LSTM encoder-decoder.

In this research, a threshold of absolute values of roll and pitch angle of the landing deck is defined for determining the safe landing period. When both roll and pitch angles of the landing deck are lower than the defined threshold for a period longer than a pre-defined duration, it is deemed a Go condition, which is a green light for landing. Figure 6 represented an example of a safe landing period determination, with the defined threshold is $\pm 5^o$ for both roll and pitch angles, and the safe landing duration is 5 seconds.

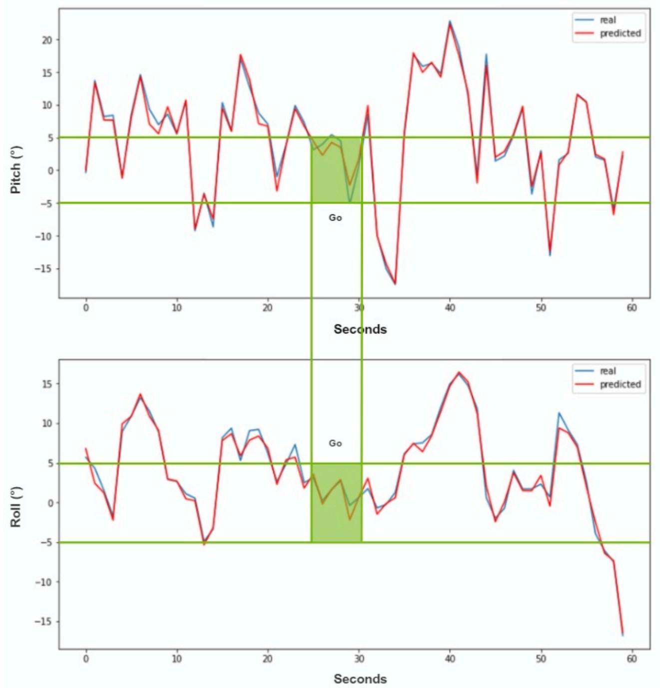

Figure 6: Example of landing period determination using prediction landing deck roll and pitch angles.

VI. Experiments and Results

For validating and analyzing our approaches, we demonstrate the tracking mission with a realistic ROS-based Gazebo simulator [24]. Our research subject drone is custom made from Holybro X500 frame, it is a quadrotor size 50cm, equipped with an RGB-D camera Intel RealSense D435i, fixed under the drone and pointed directly to the ground; and a Garmin LiDaR for measuring the altitude. The camera has relatively limited field of view for tracking task: $87^o$and 55^o. The quadrotor has its own high-fidelity simulator for all the hardware components, including the Pixhawk flight controller, actuator, and sensors. This ensures a smooth transition between simulation and reality.

A simulated version of an USV size $6m \times 3m$, with 2 hulls and actuated by 2 thruster engines. It is affixed with an ArUcO marker size $0.708m \times 0.708m$ for pose estimation. The simulation inherits the buoyancy models in Gazebo, and other weather aspects such as wind, waves, or water flow and resistance are also included and can be adjusted.

For evaluated tracking algorithms, the USV is preprogrammed to follow different defined tracks with different velocity profiles. The UAV starts above the USV at different altitudes and will keep its altitude during tracking.

For acquire training and validating dataset for landing deck pose detection algorithm, USV and UAV are preprogrammed to follow a straight path with fixed velocity. The waves and wind, on the other hand, vary in both magnitude and direction with respect to the USV.

A. *Target future trajectory prediction*

To determine the quality of the different methods for predicting the future trajectory of the target, they will be benchmarked on different trajectories with different velocity profiles of the target. Figure 7 illustrates one of the benchmark trajectories and its velocity profile.

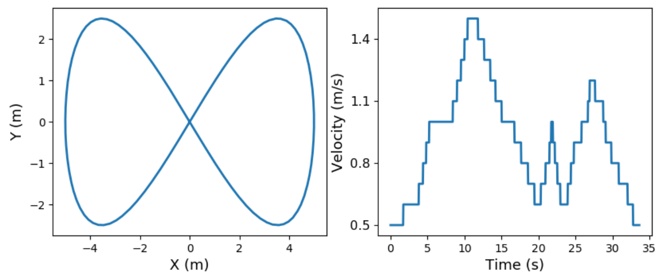

Figure 7: Benchmark target's trajectory (left) and its velocity profile (right)

Figures 8 and 9 show the prediction error for different prediction time for the whole benchmark trajectory using 2 methods: EKF and Bézier curve regression. It is obvious that the further in future that we want to predict, the larger the error we will get. In this specific trajectory, the prediction error from EKF algorithm is smaller than the prediction error from Bézier curve regression. However, when we take into account all the benchmarking results, there is not much of a difference between the prediction error of the two approaches. Kalman Filters excel in accurately estimating the state of a system and predicting its future state in the very short term. They provide a reliable and mathematically grounded approach to state estimation. However, when it comes to predicting the future trajectory of a moving target in the medium term (a few seconds), the Bézier curve regression algorithm offers a more suitable solution. With similar prediction accuracy, the Bézier curve regression algorithm has the advantage of avoiding overestimation of turns from the EKF due to constant turn rate assumption. Moreover, it does not require a motion model for the target.

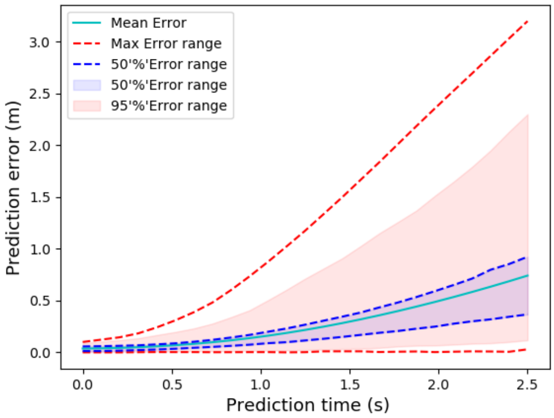

Figure 8: Prediction error for different prediction time for the whole benchmark trajectory using EKF.

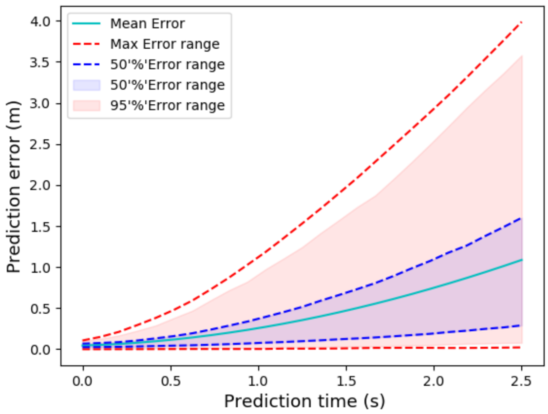

Figure 9: Prediction error for different prediction time for the whole benchmark trajectory using Bézier curve regression.

B. *UAV trajectory optimization*

The tracking result of the UAV for one trajectory is shown in Figure 10 for trajectory comparison and in Figure 11 for velocity comparison. An extensive test and analysis with different trajectories and velocity profiles, as well as different tracking altitudes demonstrates the effectiveness of the trajectory optimization approach, however, the tracking quality depends much on the altitude of the UAV and the movement dynamic of the target.

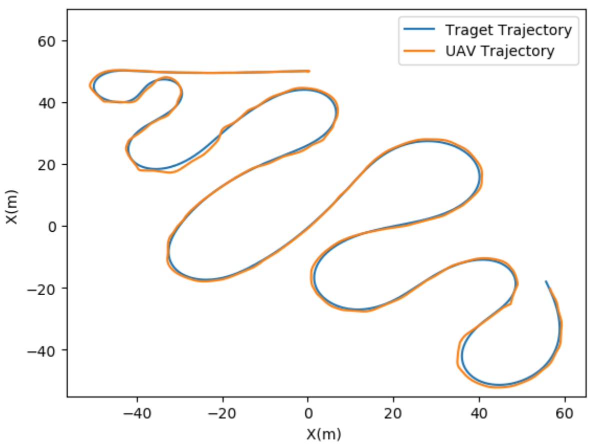

Figure 10: Tracking result of the UAV for a zigzag trajectory

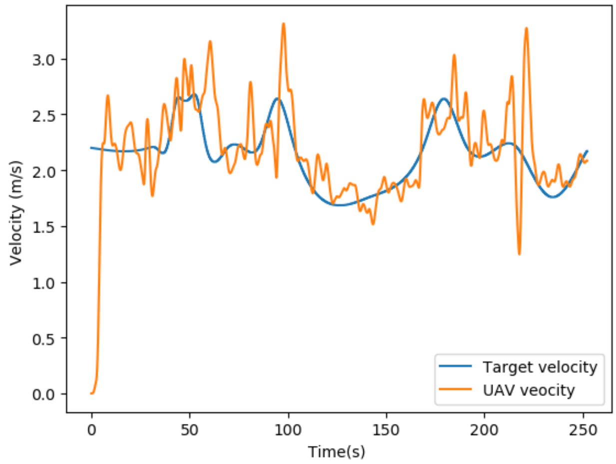

Figure 11: Velocity of the UAV and target in the zigzag trajectory test

Overall, the tracking system demonstrates effective performance for targets with predictable and relatively smooth trajectories. However, it may encounter difficulties in scenarios with rapid and unpredictable movements due to the small field of view from the camera and underactuated nature of the quadrotor. It requires further improvements in terms of tracking algorithms and capabilities to enhance its agility and adaptability to challenging tracking scenarios.

C. *Landing deck pose prediction*

The landing deck motion prediction model was trained and validated for different input sequence lengths and fixed length output of 6 seconds, with the fixed sampling rate at 5Hz. The validated result is presented in Table 1, one predicted sequence sample is illustrated in Figure 6. The model performs very well with the given validation dataset, with straight path and constant speed. Even with the I/O ratio of 10 seconds input to predict 60 seconds in the future, the model can achieve the accuracy of less than 5^oaverage error for both pitch and roll angles. More input data, which means longer data acquiring time, leads to better prediction. To integrate with the landing period determination, we must select a reasonable input, output, and sampling rate so that we can ensure the prediction accuracy and allow sufficient time for defining the land period and executing the landing within the safe period. Another aspect of the integration that should be taken into account is inference time or latency to predict. The inference time for 120/60 I/O ratio is less than 1 second, which is suitable for real-time predictions.

TABLE I. AVERAGE PICHT AND ROLL PREDICTION ERRORS PERFORMED IN VALIDATING DATASET

I/O (seconds)	Average Pitch error (°)	Average Roll error (°)
10/60*	4.7	4.5
30/60	3.2	2.8
60/60	2.6	2.3
90/60	2.2	2.0
120/60	2.1	1.9

*. Sampling rate at 5Hz

CONCLUSION

In this work, we highlighted the importance of the following phase in the landing operation of the UAV onto a moving surface vehicle without any communication between them. In this phase, the UAV must estimate and predict the movement of the landing deck accurately for determining the landing period. To do so, visual tracking of the UAV must be able to track the landing deck of the moving surface vehicle and always keep it in the field of view of its camera. For this purpose, we implemented a UAV's trajectory optimization method for tracking the target by predicting the future target's trajectory and optimizing the UAV's trajectory to satisfy the defined constraints to track the target. We successfully demonstrated the tracking result in simulation as well as investigated the method to determine the tracking operation limit in terms of target dynamic movement, tracking altitude and camera's FOV. A deep learning-based algorithm for landing deck pose prediction has been introduced in this paper and validated with the recorded data. It is able to achieve the prediction error less than 3^o, with short data acquiring time and short inference time which is suitable for the landing operation. Future work will focus on the implementation of the proposed methods into a real demonstration.

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