Intelligent Aerial Drones for Traversability Assessment of Railroad Tracks (Year\Phase 2)

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16. Abstract

Efficient railroad infrastructure monitoring and assessment is a critical issue for safe and sustainable operations. Apart from scheduled inspection and routine maintenance, there is a need for rapid assessment of the rail network after major events. For example, a storm can affect the traversability of a line (downed trees, rocks or flooding can block the line). Since it is impossible to continuously monitor the whole network before and after a major event, there is always the risk of an accident for a train crossing a blocked line if the obstacle\damage ahead is realized too late. In this project, we aim to develop intelligent aerial drones capable of identifying and following railway lines, while assessing the traversability and providing an early warning whenever needed. The drone system can be carried and deployed by the locomotive, with the mission to fly ahead of the train within the railway right of way for a distance that is safe to provide this early warning (2-3 miles). The main characteristics of this system are: i) Visual based identification and autonomous following of the line; the system will be able to work even in GPS-degraded environments (tunnels, dense forests); ii) Collision avoidance capability where the drone senses and avoids obstacles; iii) Track centering capability where the drone follows the same line regardless of the number of tracks in the field of view; and iv) Identification and mapping of any obstacles identified blocking the line.

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List of Abbreviations

AGL	Above Ground Level
ENU	East-North-Up
FLU	Front-Left-Up
HIL	Hardware in the Loop
MPC	Model Predictive Control
MSL	Mean Sea Level
OSDK	Onboard Software Development Kit
ROS	Robot Operating System
SLAM	Simultaneous Localization and Mapping
UAV	Unmanned Aerial Vehicle

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1 SUMMARY

Given the pivotal role of the railroad industry in modern transportation and the potential risks associated with track malfunctions, the inspection and maintenance of railroad tracks emerges as a critical concern. While existing solutions excel in performing accurate measurements and detection, they often rely on large, expensive, and time-consuming platforms for inspections. The goal of this project is to study the use of an Unmanned Aerial Vehicle (UAV) to aid the inspection operations, aiming in reduced operational times and cost, while maintaining efficient detection and traversability assessment capabilities.

This solution is ideal for large-scale, high-level inspections following major events such as floods [1], hurricanes [2] or earthquakes [3]. The project focuses on developing, implementing, and testing a fully functional, vision-based, autonomous track-following system for UAVs, as illustrated in **Figure 1**. The creation (in Phase 1 of this project) of a cutting-edge track detection algorithm, TrackNet [4], is used to identify and interpret railroad tracks from the video stream of an onboard camera. This system is then seamlessly integrated with a customized DJI Matrice 100 UAV to detect and follow railroads in real-time. Notably, this system operates independently of external sensors such as GPS, thanks to its utilization of advanced computer vision techniques. Building off phase 1 of this multi-year project, this report covers recent work in improvement of track detection and following capabilities.

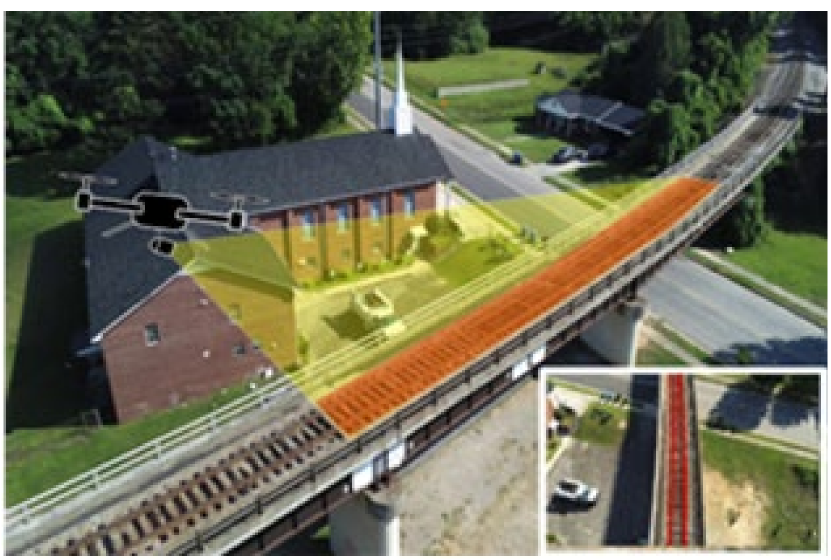

Figure 1: Aerial drone tracking and following a railroad line

2 BACKGROUND

The railroad industry plays a pivotal role in the global transportation network, facilitating the movement of cargo and passengers, while supporting local economies [1], [2]. Despite their significance, railroads can pose substantial risks if not adequately maintained [3]. Maintenance must address two types of track deterioration: the gradual wear from continuous usage and major obstructions resulting from specific incidents [5], [6], [7]. Current methods of track maintenance primarily rely on manual methods or semi-automated track geometry vehicles, where tracks are inspected by inspectors walking along the tracks or riding some type of high-rail vehicle [8]. Although these methods are very common, they are not completely reliable, are labor-intensive, are time-consuming, and subject inspectors to hazardous environments. Additionally, even when utilizing high-rail vehicles, the maximum inspection speed is around 1.4 m/s (5 km/h) [8].

A superior method of track inspection is the utilization of automated track inspection vehicles to measure track and rail geometry. These platforms utilize a host of non-destructive evaluation (NDE) technologies to identify rail surface and track geometry defects [8]. The primary limitations of such techniques, however, are their speed and their cost. The current systems are capable of performing inspection at around 4.2 m/s (15 km/h) but also require significant time for deployment and cause track shutdowns for inspection. Additionally, the average cost of a single-track inspection vehicle is around $8.1 million to purchase or $2.2 million annually for a service contract. Although these platforms are effective in detecting small defects caused by long-term wear, they are less efficient at addressing the second type of deterioration induced by major destructive events. The existing technology, due to its time requirements, unnecessary precision, and reliance on the track's viability, is ill-suited to meet the demands of such scenarios.

To address this challenge, the utilization of Unmanned Aerial Vehicles (UAVs) has been proposed in the literature for track inspection [9]. Although current systems are capable of higher detail of inspection when compared to UAVs, any reduction in their use would allow for significant savings. UAVs can perform many of the same types of inspection at a fraction of the cost and at least at the same speed, without the need for track shutdown or lengthy deployment time. UAVs offer the capability to traverse sections of track, identifying major obstructions at a reduced cost. Moreover, their airborne nature allows for continuous inspections regardless of any obstacles on the track. In Phase 1 of this project, we developed an autonomous railroad line detection system that can aid UAVs in navigating\following railroad lines [4].

3 OBJECTIVES

With the foundational work in Phase 1 serving as a proof of concept, the work described here focuses on improving the performance and utility of the system. Specifically, the major goals of Phase 2 are [10]:

- Continue development of the TrackNet detection algorithm to provide the ability to track a specific rail line, even when there are multiple in frame.
- Increase the processing speed of the TrackNet algorithm.
- Improve the flight control system to more accurately follow the selected line.

4 METHODS

4.1 UAV Implementation

The UAV used for this project is the DJI Matrice 100, a medium size platform designed to be customized for developmental work. An Intel NUC mini-PC provides onboard processing power to the drone. This is used to perform computer vision tasks, determine control inputs, and communicate with a ground station. The drone is fitted with an Intel T265 camera for identifying railroad tracks and any obstructions along them. The camera also comes with built in Simultaneous Localization and Mapping (SLAM). This capability provides a GPS-independent estimate of the drone's position and orientation without adding any computational load to the computer. Finally, the DJI Guidance module provides additional sensing capability. It has a combination of optical flow and ultrasonic sensors that assist in GPS-denied flight and obstacle avoidance. The hardware setup is tied together using a custom Robot Operating System (ROS) software package. The open source Acados library is used to run the MPC and generate command inputs [11] . Commands and sensor data are communicated between the NUC and Matrice using DJI's Onboard Software Development Kit (OSDK). An image of the complete Matrice 100 setup is provided in **Figure 2**.

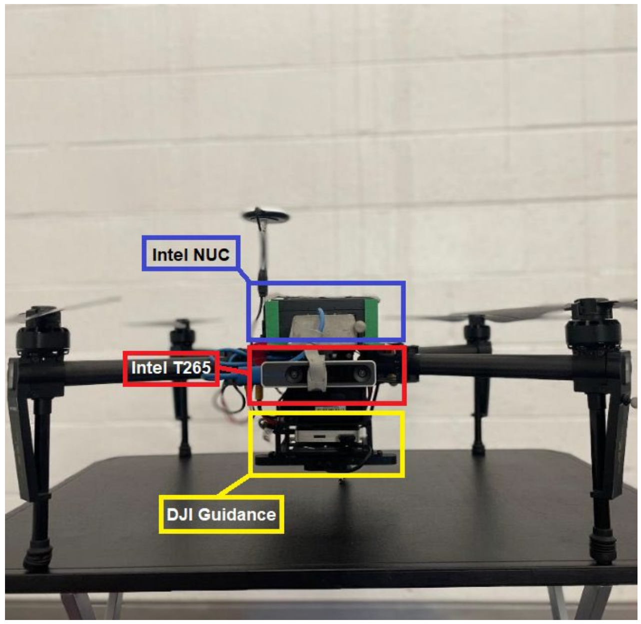

Figure 2: DJI Matrice 100

4.2 Track Detection

The main limitations encountered with the track detection algorithm in Phase 1 were the inability to handle multiple tracks in the image and a slow processing speed that reduced the drone's real time capabilities. To deal with multiple visible lines, the new version of the algorithm now records each individual instance of track region detected by the segmentation network. Having each rail be classified individually provides flexibility when deciding which line the drone should follow. The current rule is to search for the closest rail to the image center and focus on it. However, this can be easily modified to change mid-flight, be manually selected by the user, or other rules to fit a desired mission. Tracking the rail is done by comparing the coordinates of the identified lines between each frame [10]. If the coordinates do not move more than a few pixels between adjacent frames, then the identified rail is considered to be the same as the previous frame.

The segmentation network also got an improvement in computational efficiency. The original Unet model works well to identify rail but is not optimized for our CPU hardware. Intel's OpenVINO toolkit provides optimization tools and is designed to take advantage of Intel computing devices. By optimizing the model, the processing speed saw a nearly 3 times increase in processing speed (10 fps vs 3.5 fps in phase 1) while using fewer CPU cores [10, 11]. Faster processing means smoother flight as the UAV will not deviate as far from the flight path between control loop iterations.

Finally, a rework was done to the way the rail line is determined inside of the segmented region. Instead of a combination of edge detection, line detection, and a line chaining step, the direction of the rail is now represented by the centroid of the segmented region at each pixel row. The original process faced issues with detection of the lines at farther distances and given the reliance on an accurate vanishing point to follow, this led to inconsistent flight behavior. An example of the new centerline detection is shown below in **Figure 2** with the red centerline representing the line being tracked by the UAV.

Figure 3: Multiple lines detected with the main line highlighted in red

4.3 Track Following

The track following flight controller has been entirely reworked from the previous PID based design. The new version uses a model predictive controller (MPC) that controls the drone's position using a velocity control service. This type of control uses a prediction of the system's dynamics to find an optimal control input. The benefits of this approach include explicit handling of multivariable dynamics, constraints, and predictive capability that can be used in obstacle avoidance tasks. This section describes the design of the flight control and navigation system.

4.3.1 System Model

The dynamic modelling for this system is made simple thanks to the platform's built-in control features. The state of the system is described as its 3-D position and its heading angle in an East-North-Up (ENU) inertial frame. The command inputs used are the UAV's velocity along its 3 main axes and yaw velocity in a Front-Left-Up (FLU) body frame. Accounting for the transformation between frames, the dynamic model is as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v_x * \cos(\theta) - v_y * \sin(\theta) \\ v_x * \sin(\theta) + v_y * \cos(\theta) \\ v_z \\ \omega \end{bmatrix} \tag{1}$$

This model conveniently allows the MPC to guide the drone towards points along the railroad track by controlling its velocity. No low-level control is needed as the drone's flight controller handles this in the background.

4.3.2 MPC Formulation

The MPC framework is based on optimizing a series of future inputs across a small window in time called the prediction horizon. This is done by minimizing a cost function that penalizes both deviation from the desired state and excessively large control inputs. Ideally, the lowest cost solution represents the desired behavior. The cost function used here is a standard least squares function and is shown below:

$$J = \sum_{i=0}^{N-1} \left[(x_i - x_{ref})^T Q (x_i - x_{ref}) + (u_i - u_{ref})^T R (u_i - u_{ref}) \right] + (x_N - x_{ref})^T P (x_N - x_{ref}) \tag{2}$$

The matrices Q, R, and P are weighing matrices that influence how much the different cost terms contribute to the overall cost. Q scales the weight of state deviations throughout most of the prediction horizon. P also scales state deviations, but only for the last time step in the prediction horizon. Finally, R scales the deviation of the input from its reference. Based on the dynamic model shown in (1) and the flight mission, the values inside the weight matrices were chosen. For this navigation problem, the desired state is determined by the x and y coordinates found with the track detection algorithm along with a preset altitude and a heading that points towards those coordinates.

The UAV is ideally flying forward, so the reference input is a preset forward velocity with no lateral, vertical, or yaw motion. Although the specific values do not mean much on their own, the relative weights used in this formulation are shown below in **Tables I and II**.

Table I. State Deviation Weights	
X	High to encourage accurate waypoint following
Y	High to encourage accurate waypoint following
Z	Low since the altitude setpoint is relatively constant and UAV will settle easily
θ	Moderate to ensure the UAV orients itself along the flight path

Table II. Input Deviation Weights	
V_x	High to encourage precise forward velocity control
V_y	Low to allow for some lateral correction while following curves
V_z	High to discourage use of vertical velocity unless to correct larger altitude deviations
ω	Moderate to allow for heading corrections without high yaw rates that might interfere with track detection

4.3.3 Reference Generation

Operating under the assumption that railroad tracks are relatively flat, the pixels identified as showing the rail centerline can be translated into 3 dimensional coordinates for the UAV to follow. This technique is a form of inverse projection mapping whereby knowing information about the camera's intrinsic properties (field of view, distortion, resolution, etc.), each pixel can be mapped to a ray in the UAV's 3-dimensional coordinate system. The rays corresponding to track centerline pixels will intersect the ground plane, and these intersection points are reference points that can be fed into the controller. Multiple points can be set as references across the prediction horizon to ensure smooth tracking. Using a downward facing ultrasonic sensor, the UAV's above ground level (AGL) altitude is known. This can be used to ensure the ground plane is always appropriately represented in the UAV's local coordinate frame, even if there is a gradual increase or decrease in the ground's mean sea level (MSL) altitude.

5 EXPERIMENTS

This section discusses the process of experimentally testing the updated system to evaluate its performance. Initial experiments were conducted inside the Unmanned System and Robotics laboratory at the University of South Carolina. Using images of real tracks and simulated position information allowed for hardware-in-the-loop (HIL) testing of track detection and flight control algorithms. These tests confirmed that the UAV could identify and interpret railroad tracks in a simulated environment. Additionally, the MPC was flight tested independently using a motion capture system to look for efficient controller response and verify correct implementation using OSDK.

Figure 4: Satellite images of straight section of track (top) and curved section (bottom)

Subsequently, these systems were tested outdoors on a real track to validate their efficacy. These experiments took place along a couple of sections of railroad situated at the South Carolina Railroad Museum in Winnsboro, SC. An image of these sections of track, taken from Google Maps can be seen in **Figure 4**. This site provides plenty of different environments with which to test the

UAV. In these tests, we mostly utilized a straight section of track with parallel lines that merge. This setup enabled a good baseline of flight control performance as well as the UAV's ability to focus on only one line at a time. More limited testing was done at another section that contains curves, providing a more complex flight path for the control system to handle. Flight testing was mainly done at an altitude of 4 meters above the ground and a velocity of 2 meters per second. Other tests at higher velocities were conducted, but to a lesser extent.

6 RESULTS

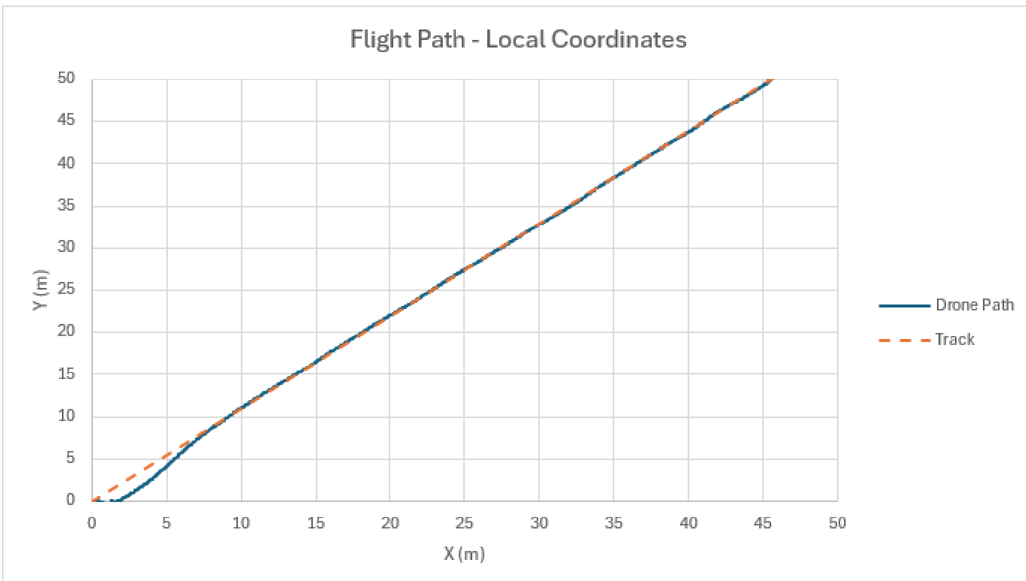

Figure 5: Flight path of the UAV along railroad tracks

In this section we summarize the results obtained in the SC Railroad Museum experiments, after the system was tested in different scenarios to analyze track following performance. **Figure 5** shows the flight path the UAV follows in comparison to the coordinates of the track during one such test. After starting with an initial position and orientation offset from the track centerline, the drone quickly begins correcting itself. Using positioning data from both the GPS (for evaluation purposes only) and camera, the average distance error during the flight was 0.44 meters, which decreases further to 0.28 meters when looking only at the steady-state portion of the flight. This is an improvement over the previous average of approximately 2 meters [4] [10]. The change in controller design as well as the increased fps of the system means the control of the UAV is both more accurate and responsive to changes in real time.

7 CONCLUSIONS

Phase 2 work on this project has significantly improved on the track detection and following capabilities developed during Phase 1. The UAV is now able to distinguish between multiple tracks and focus on a single track. This prevents confusion in more complex environments and gives the user the ability to inspect lines as needed. Increased efficiency of the detection model also improves detection speed and frees up computational resources that can be used for later stages of the project. Finally, a reworked flight control design enables significantly more accurate line following.

8 FUTURE WORK

The experiments show that the drone can very accurately follow rails and distinguish between multiple lines in the image. While this work represents significant progress, there are still more areas to develop. Future work will include developing two major features: collision avoidance and the ability to detect obstructions on the railroad track. These features will improve the system's safety and give the system inspection capability respectively. Implementing collision avoidance means the UAV can safely fly through more congested areas without requiring pilot intervention, maintaining autonomy. Likewise, the ability to identify obstructions to the railroad track is critical to making this system a viable inspection platform. Additionally, we plan to do more testing of the system to more thoroughly analyze its performance.

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