Intelligent Aerial Drones for Traversability Assessment of Railroad Tracks

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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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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 solve the same problem with the use of an unmanned aerial vehicle (UAV), significantly reducing time and cost while maintaining detection and traversability assessment capabilities.

In particular, 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 of a cutting-edge track detection algorithm, TrackNet, 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.

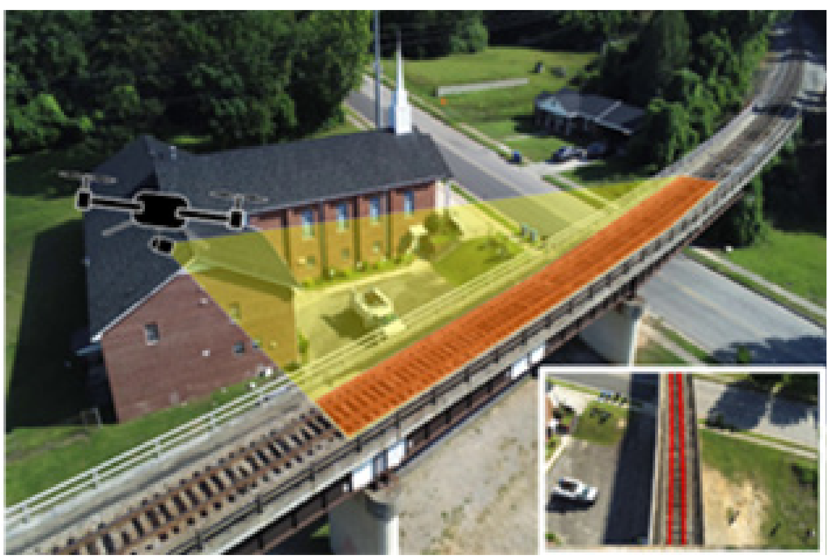


Figure 1: Aerial drone tracking and following a railroad line

Two distinct approaches utilizing differing camera configurations were developed, tested, and compared. Both systems were found to successfully detect and follow railroad tracks 300 meters in length containing curved and straight sections. The first approach required a forward-facing camera and detected the vanishing point of the track as a control reference. The second approach required a downward-facing camera and detected the center line of the track to be used as a control reference. These two systems were developed and improved to achieve a average track position errors of 1.9766 meters and 2.0342 meters for the forward-facing approach and the downward-facing approach, respectively.

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]. This maintenance must address two types of track deterioration: the gradual wear from continuous usage and major obstructions resulting from specific incidents [4], [5], [6]. 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 [7]. 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) [7].

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 [7]. 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 [7]. 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 [7]. 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) is proposed for track inspection [8]. 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 are capable of performing many of the same types of inspection at a fraction of the cost and at least the same speed (at least 4 m/s or 14.4 km/h), 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.

3 OBJECTIVES

This work aims in developing a novel method for railroad track inspection utilizing a UAV system. The goal of this system is to provide the foundational track detection and following techniques that can be utilized for any number of specific inspection applications. Specifically, the objectives of this work are:

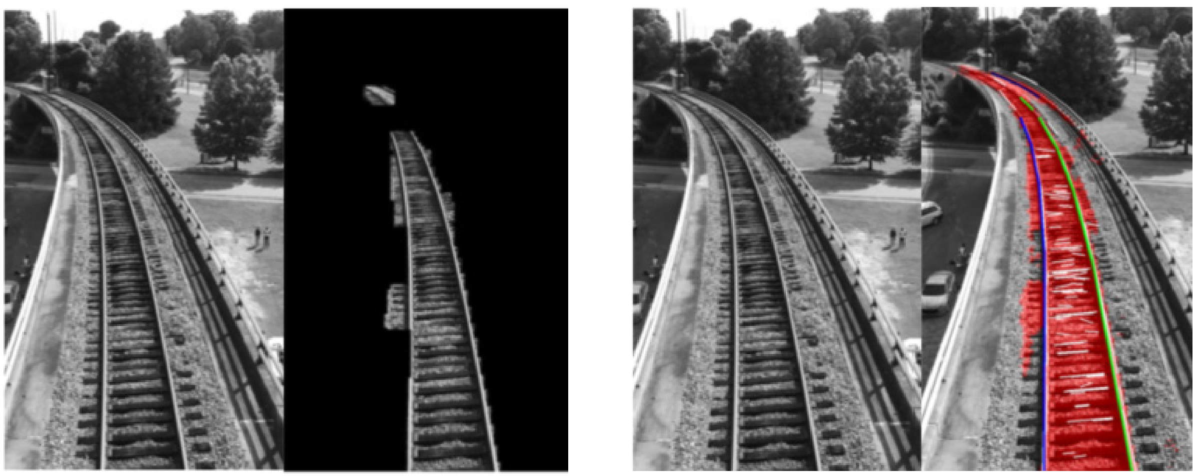
- The development of a track detection system (TrackNet) that is a compound region-rail approach utilizing state-of-the-art techniques for both region detection and rail detection in a way not yet seen in the literature. This is followed by a novel line chaining method for rail identification as the final step in the TrackNet system.
- The first series of thorough experiments validating the implementations of two track following systems, one based on a forward-facing camera orientation and the other a downward-facing orientation.

4 METHODS

4.1 Track Detection

Three primary approaches for track identification (region detection, rail detection, and compound region-rail detection) were considered. Region detection involves a more comprehensive identification of the entire track area, including the rails, the ties, the surrounding land, etc. On the other hand, rail detection targets a specific feature within this region, namely the rail lines. The literature underscores that region detection is a powerful, yet costly method. Often utilizing machine learning techniques, it can be quite computationally heavy when properly implemented.

Conversely, rail detection is often distilled to a few simple and efficient processes, greatly decreasing its required computational load. Despite its computational efficiency, however, rail detection faces challenges in accurately selecting rail lines, particularly in complex scenarios and environments. In this work we develop a compound method integrating both track region detection and rail line detection, and we introduce the novel track detection algorithm named TrackNet, shown in **Figure 2.**



(a) (b)

Figure 2: Steps of the TrackNet algorithm: (a) track region detection using trained Unet network; (b) rail detection results using edge and line detection

4.2 Track Following

Between the completion of track detection and the initiation of track following, a few tasks must be completed. The system needs to interpret the rail lines and determine the flight maneuvers required for the UAV to follow the track. As described earlier, these interpretation methods are contingent upon the configuration of the camera onboard the UAV system. This divergence prompted the development of two distinct approaches for the sake of comparison, namely a forward-facing camera approach and a downward-facing camera approach.

4.3 UAV Implementation

The UAV chosen for our implementation was a DJI Matrice 100, a quadrotor equipped with an integrated flight controller, DJI N1. Mounted on the UAV's frame is an Intel NUC 11 Performance Mini PC Kit, providing onboard processing power, along with an Intel RealSense D435 Camera. These components are affixed to the UAV's frame using custom 3D-printed parts. The widely used Robot Operating System (ROS) framework facilitates communication among these three primary devices, specifically utilizing the RealSense2camera ROS package and the DJI SDK ROS package, along with a custom TrackNet ROS package developed for this application. This package performs the function of processing the RealSense camera's video and sending control outputs to the Matrice's flight controller. The process utilizes two ROS nodes, one for TrackNet processing and one for sending control commands. The TrackNet processing node subscribes to the RealSense2 camera's /camera/image raw topic, acquiring the video feed. These images are then processed by the TrackNet system, and control outputs are calculated. This process is completed at around 3.5 frames per second and the control effort is published to a ROS topic. The control node monitors this topic and sends the control effort to the Matrice's flight controller. An image of the complete Matrice 100 setup is provided in **Figure 3**.

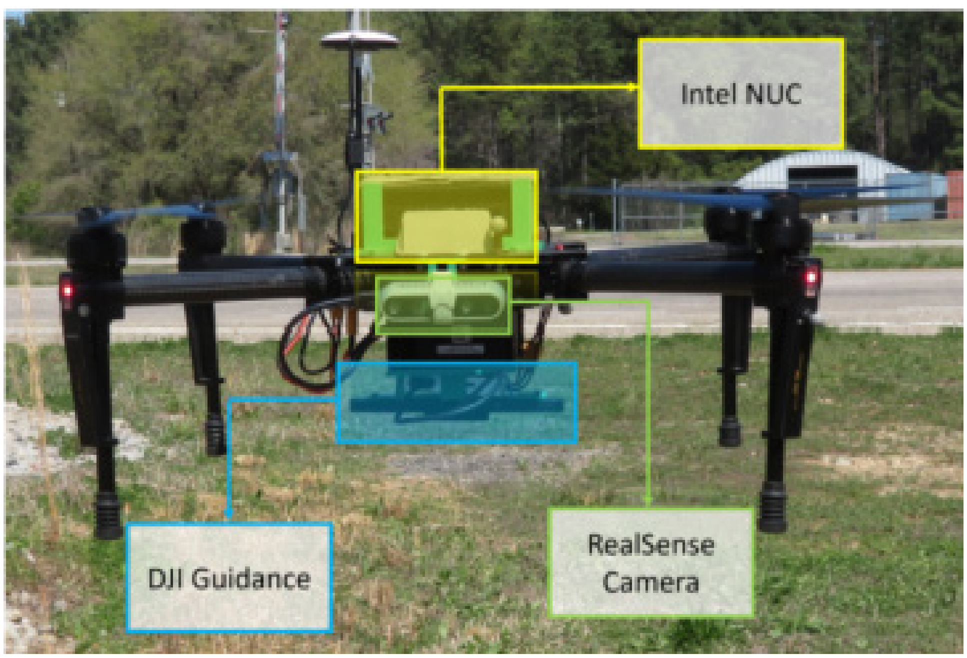


Figure 3: DJI Matrice 100 UAV

5 EXPERIMENTS

A series of experiments were conducted, firstly on a dataset to validate the track detection system, then live and onboard the UAV. With the complete TrackNet system developed and tested offline on prerecorded data, testing of the implementation onboard the UAV system was the next stage of experimentation. This includes both the forward-facing camera and the downward-facing camera approaches. For each approach, several stages of testing were conducted, starting with stationary indoor tests to establish proof of concept and to provide initial gains for each controller. This series of tests was conducted inside the Unmanned System and Robotics laboratory at the University of South Carolina. Simple images of tracks, from both a forward-facing perspective and a downward-facing perspective were utilized as a simulated track environment.

(a) (b)

Figure 4: Satellite images of the test locations; (a) University of South Carolina Athletic Village, (b) South Carolina Railroad Museum in Winnsboro SC

Subsequently, these systems were tested outdoors on a real track to validate their efficacy as well as in effort to determine issues in the first versions of the systems. These experiments took place along a 45-meter section of railroad situated in Columbia, South Carolina, next to the University of South Carolina's athletic center. An image of this section of track, taken from Google Maps can be seen in **Figure 4a**. The track was simple and is mostly straight and located in an urban environment with nearby buildings and power lines. After learning from these initial tests, more extensive outdoor experiments were carried out at the South Carolina Railroad Museum in Winnsboro, South Carolina. This track contained varying track configurations, including a sharp curve in both directions as well as a longer straight section and was situated in a more rural, forest environment. An image of this location can be seen in **Figure 4b**. Over several experiments two sections of this track were utilized at different times and these sections are shown **in Figure 4b**. The shorter section began with a straight track followed by a left curve and was a total of 165 meters. The longer section began with a right curve then a straight section followed by a left curve and was a total of 300 meters.

6 RESULTS

In this section we summarize the results obtained in the SC Railroad Museum experiments, after the system was extensively tested and optimized for best performance in each case (forward-facing vs downward facing camera). A presentation and analysis of all experiments (both indoor and outdoor in all locations) are given in [9] and [10]. **Figure 5** shows the flight path the UAV follows in comparison to the actual path. It is clear that the system tracks the line very well and the UAV manages to follow the line with a small error.

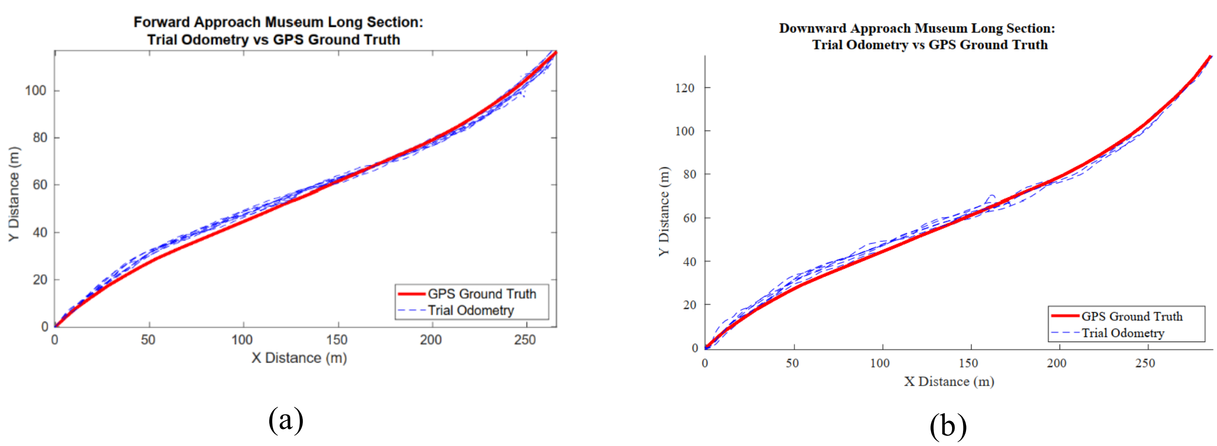


Figure 5: Flight path followed by the UAV compared to GPS Ground Truth (actual railroad line in the SC Railroad Museum) in the two different system configurations, (a) forward-facing camera and (b) downward facing camera

Table 1 shows a comparison between the two approaches (forward-facing vs downward facing camera). There is not a clean victor that is superior in all circumstances, instead it depends on the needs of the application. In this table there are several factors that may be important for any given application and which approach is more suited to that case. From the testing outlined here the forward-facing approach is likely to be the best option if travel speed, altitude variety, or safety are the aspects of greatest concern. On the other hand, the downward-facing approach is a better choice if following efficacy or ease of inspection are of the most importance.

Table 1: Forward-facing approach and downward-facing approach comparison

Critical Factor:	Forward-Facing:	Downward-Facing:
Following Efficacy		X
Travel Speed	X	
Altitude Variety	X	
Safety	X	
Ease of Inspection		X

7 CONCLUSIONS

The primary contribution of this work lies in presenting the first thoroughly tested implementation of a UAV system designed for following railroad tracks, leveraging cutting-edge computer vision-based track detection algorithms. The system demonstrates the development of a highly effective track detection algorithm using computer-vision technologies and its integration onboard a customized DJI Matrice 100 UAV. The track detection algorithm, TrackNet, utilizes a compound region-rail detection approach. In addition to the development of TrackNet, two flight control systems were implemented based around the track interpretation methods of TrackNet. These approaches differ in the configuration of the onboard camera: one employing a forward-facing camera configuration and the other utilizing a downward-facing configuration.

8 FUTURE WORK

Moving forward, a more robust system would integrate both a forward-facing camera as well as a downward-facing camera. The utilization of both cameras would allow for the benefits of either option. Additionally, an integration of the control systems would then be possible and would increase the robustness and improve the overall following efficacy. Moreover, in the next stage of this work, the computer vision system will be enhanced with the capability of identifying obstacles on the track and providing the traversability assessment, i.e. aid engineers to safely proceed with traversing the line.

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