



Detection and Prevention of Hazards in Dark Territory using AI

¹Subhadip Kumar,

¹Senior Technology Specialist - SAP,

¹Canadian Pacific Kansas City

Abstract: Non-signal territory, or dark territory, is a type of railway operation where signals and interlockings are absent. More than half of the North American rail network operates in dark territory, which creates safety and operational issues for railroads. In this study, I propose an AI-based solution for enhancing dark territory safety. This solution uses a novel framework that applies AI methods such as computer vision, natural language processing, and machine learning to identify and avoid hazards, improve train scheduling, and facilitate communication and collaboration among train operators, dispatchers, and maintenance staff. I try to show its benefits in lowering accidents, delays, and costs in this research. Our study advances the field of railway safety and efficiency in dark territory and offers directions for future research and development. I also address the cost challenges faced by regional and short-line railroads, which account for more than 90% of the dark territory in the USA and show how our solution can help them leverage the potential of dark territory.

IndexTerms - Dark Territory, Artificial Intelligence, Computer Vision

I. INTRODUCTION

Dark Territory, or non-signal territory, is a term used to describe the tracks that do not have any signals to control the movement of trains. The term refers to rail track in the UK and Australia where the signaling system does not communicate the signal indications or track occupancy to a signal box. This means that signalers cannot see the location of trains, and the track is “dark”. In the past, trains in dark territory had to follow a timetable that specified when and where they could run, but with the advancement of radio communication, most trains now use track warrant control (TWC), where dispatchers directly communicate with the trains and give them instructions. The main purpose of TWC is to prevent collisions by ensuring that there is only one train on a section of the main track at any time. To do this, dispatchers issue warrants to trains and track workers, which allow them to use or work on a specific section of track. For example, a maintainer who needs to repair a track might get a warrant to work on a section of track. Or a train that needs to move from one location to another might get a warrant to move from point A to point B, where it will meet another train. The warrant gives the train or the worker the exclusive right to that section of track until the warrant expires, or they request an extension. TWC is often used in conjunction with CTC system, which is a system that uses signals and switches to control the main lines. TWC helps to coordinate the movements of local and regional roads, which are smaller railroads that connect to the main lines. One of the reasons that warrants must be read back to the control operator word for word is to ensure that there is no misunderstanding or confusion between the dispatcher and the train or the worker. Another common method of controlling trains in dark territory is Direct Traffic Control (DTC). DTC is like TWC, but it simplifies the process by naming the track segments, which are usually between sidings. Sidings are short sections of track that allow trains to pass each other. Instead of giving milepost limits for authority like TWC, the dispatcher gives out block limits, which are the names of the track segments. For example, the dispatcher might tell a train to proceed from the Alpha block to the Beta block. DTC is easier to use, but it is also less flexible, because it does not allow for variations in the track segments.

To operate safely in dark territory, human involvement is crucial. Network users, such as train drivers and track workers, usually need to get verbal authorization from a network controller, who is a person in charge of managing the traffic on the network. The network controller gives them permission to move between specific locations, such as stations or sidings, and tells them the rules they need to follow to avoid collisions with other network users. These rules are called occupancy rules, and they define how many network users can occupy a section of track at a time. Unlike signal-controlled territory, where the network controller can see the position and speed of the trains on a display, and where there are systems that can automatically stop the trains if they violate the rules, in dark territory the network controller has limited visibility and control over the network users. The network controller relies on radio communication to communicate with the network users, but the radio links are not always reliable, especially in remote areas. Therefore, the network controller cannot always monitor the location and actions of the network users, and the network users must be responsible and vigilant to ensure their own safety and the safety of others [2].

Human error is the main cause of most collisions in dark territory, where trains get track authority from the dispatcher to travel in opposite directions or where locomotive engineers enter a single line main track without track authority. A 2010 NTSB report [4] identified these safety issues as factors:

- After-arrival track authorities for train movement on tracks without signals
- Banned use of portable electronic devices

- tiredness
- teamwork among crew members
- missing supervision and regulation by management

The aim of this research paper is to examine some cases of accidents in dark territory and explore how advanced technologies could prevent them in the future. It will also analyze the main causes of each collision and how technology can help reduce them.



Fig 1: Aerial view of collision in dark territory – NTSB report [4]

II. CONCEPT AND CHARACTERIZATION

Artificial Intelligence (AI) stands as a testament to human ingenuity, offering a complementary set of ‘eyes’ that enhances our capabilities without supplanting our efforts. This article delves into the integration of AI in radio communications and the augmentation of 5G, as well as Beyond 5G (B5G) networks, to revolutionize vehicular communication systems. By harnessing the power of the YOLOv5 model, AI extends its vision to the realm of transportation safety, enabling the detection of trains and other objects with unprecedented accuracy. Furthermore, the exploration of Fiber Bragg Grating (FBG) sensors and block detection methods offers innovative ways to ascertain track occupancy, thereby mitigating human error. Additionally, this paper will explore external, non-technical factors that can be optimized to enhance operations in areas with limited infrastructure, known as ‘dark territories.’ Through these advancements, AI not only supports human effort but also propels us towards a future of safer, more efficient transportation networks.

III. ADVANCED TECHNOLOGIES

INTELLIGENT TRANSPORTATION SYSTEM (ITS)

The foundation of intelligent transportation system (ITS) lies on the Internet of Vehicles (IoV), a specialized area within the broader Internet of Things (IoT) framework. Cyber-Physical Systems (CPS) represent a complex, cohesive network that merges data, tangible elements, and regulatory mechanisms. This fusion delivers diverse informational services and enables the continuous surveillance of expansive engineering structures [6]. Vehicle ad hoc networks (VANETs) are crucial components of Intelligent Transportation Systems (ITS). As a specific form of mobile ad hoc network, VANETs enable direct vehicle-to-vehicle (V2V) communication or vehicle-to-infrastructure (V2I) interactions [17]. Recognized for their potential to enhance road safety in numerous projects, VANETs lay the groundwork for such improvements in the dark territory. Wireless sensor networks (WSNs) are integral to the fabric of intelligent transportation systems, serving as the backbone for advanced localization technologies. These networks employ a variety of localization methods, broadly categorized into range-based and range-free techniques. Range-based methods utilize specific measurement metrics such as time of arrival (TOA), time difference on arrival (TDOA), received signal strength (RSS), and angle of arrival (AOA). By analyzing the connectivity within the network and leveraging historical measurement data, these methods can accurately determine the position of individual nodes. This capability is essential for ensuring the precision and reliability of transportation systems, as it allows for real-time tracking and management of vehicles and infrastructure components. The sophistication of WSNs in localization reflects a broader trend in the railroads industry, where AI and IoT are increasingly harnessed to optimize operations and enhance safety.

The TOA method measures the travel time of a signal from the beacon node to the unknown node. The true distance of TOA is modeled as follows:

$$d = c \cdot t$$

where c is the speed of the signal, d is the distance between the two nodes, in this case two train, and t is the travel time of the signal between the two nodes [20].

In the realm of railway transportation, particularly within 'dark territories' where traditional communication systems may fail, the challenge of ensuring safe distances between trains is paramount. The absence of direct line-of-sight (LOS) often renders conventional methods ineffective, posing a significant risk when multiple trains share the same track. To address this, non-line-of-sight (NLOS) channels emerge as a viable solution for location awareness and wireless channel modeling. A notable advancement in this field is the NLOS identification method developed by Zheng et al., which employs a convolutional neural network (CNN) [21]. This method represents a substantial improvement over the Ricean K factor-based identification, boasting an impressive accuracy rate of 0.99 compared to the latter's 0.86. Such technological innovations are critical in enhancing the safety and efficiency of rail operations. The use of CNNs for NLOS identification exemplifies the potential of machine learning in overcoming communication barriers. Installation of low-cost sensors in every train can potentially eliminate collisions in the dark territory.

VEHICLE PLATOONING

Vehicle platooning, a transformative technology in the realm of intelligent transportation, has significantly evolved and is now being implemented in metro systems, building upon its success in truck platooning. This technology is pivotal for collision prevention, primarily through Vehicle-to-Vehicle (V2V) communication, which allows for the real-time exchange of essential data such as speed, position, and braking status between vehicles. The integration of V2V is instrumental in reducing human error, which can lead to severe accidents, like a train inadvertently entering an occupied track due to a dispatcher's error or an engineer's unauthorized maneuver. Furthermore, Cooperative Adaptive Cruise Control (CACC) enhances this system by enabling CACC-equipped trucks to lead a platoon, facilitating the sharing of comprehensive dynamic information among themselves. Conversely, when a CACC-equipped truck follows a non-CACC equipped vehicle, the interaction is limited to Adaptive Cruise Control (ACC), where only headway and speed data are communicated [15,16]. This distinction is essential for optimizing the safety and efficiency of platooning systems, ensuring that vehicles are equipped with compatible technologies to communicate effectively and prevent collisions. The advent of Cognitive Radio and the advent of AI-powered 5G and Beyond 5G (B5G) networks have heralded new possibilities for sophisticated vehicular communication systems. The aim of this work is to highlight the significance of AI-driven radios and networks in improving vehicular communications, thus overcoming major obstacles [7, 10, 11, 12, 13,14]. Train platooning minimizes risk of collisions by ensuring that all trains in the platoon are aware of each other's speed, position, and braking status in real-time in the dark territory.

AI POWERED REAL TIME CHANNEL AWARENESS

In the context of radio communication, collisions in the dark territory can often be attributed to human error. However, this is precisely where AI-powered radio communication can play a crucial role. By complementing human cognitive decision-making, AI engines enhance safety and efficiency. Two notable technologies that stand to benefit from this synergy are Software-Defined Radio (SDR) and Cognitive Radio (CR) systems, particularly in the context of 5G/6G communications. These systems can leverage early digitization managed by AI engines to optimize spectrum utilization, adapt dynamically to changing conditions, and mitigate potential collisions. As we embrace the future of wireless communication, the collaboration between human intelligence and AI-driven capabilities promises exciting advancements in connectivity and reliability. Cognitive Radio (CR) systems, empowered by Artificial Intelligence (AI), are revolutionizing the telecommunications landscape, particularly in regions underserved by traditional 4G/5G networks. These AI-driven radios leverage sophisticated machine learning models for Channel Awareness and Radio Access Network (RAN) Scheduling, optimizing real-time communications through a framework known as CARS. By employing deep learning techniques, CR systems can map the state of mobile networks to the Quality of Service (QoS) experienced by users, thereby enabling more informed and intelligent operational decisions. This is crucial for supporting the triad of services envisioned for 5G: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (uRLLC). The integration of AI into integrated circuits is a cornerstone of digital transformation, enhancing the functionality of electronic devices through advanced digital signal processing. As AI-managed data converters become integral to cyber-physical systems, they facilitate the convergence of analog/digital interfaces, where information is captured or disseminated. Such AI-managed interfaces are particularly beneficial in Software Defined Radio (SDR) and CR systems designed for next-generation 5G/6G communications, exemplifying the potential of AI to manage early digitization processes within mobile telecom systems [18, 19].

IV. PROPOSED ARCHITECTURE

TRAIN INTELLIGENT SYSTEM

The envisioned architecture aims to enhance railway safety and efficiency by integrating a train intelligent system (TIS) that operates as a component of intelligent transportation systems (ITS). This system would be driven by a cognitive radio system, which dynamically adapts its transmission and reception parameters to communicate effectively in varying conditions and avoid interference with other users. Coupled with wireless sensor networks (WSN), the TIS can monitor a range of environmental and mechanical factors in real-time, facilitating a responsive and interconnected network.

Advanced radio communication technologies would enable trains to operate in a platooning formation, closely following one another at optimized speeds and intervals, thereby increasing track capacity and reducing energy consumption through aerodynamic drag reduction. In the event of a wrong track authority, which could potentially lead to a collision, the TIS would act as an autonomous safeguard. By continuously analyzing sensor data and communication signals, the system could detect anomalies and issue alerts to prevent accidents, functioning as an indispensable 'second set of eyes' for train operators. This proactive approach to railway management underscores the potential of AI and machine learning in revolutionizing logistics and supply chain operations, particularly within the railroad industry where safety and precision are paramount.

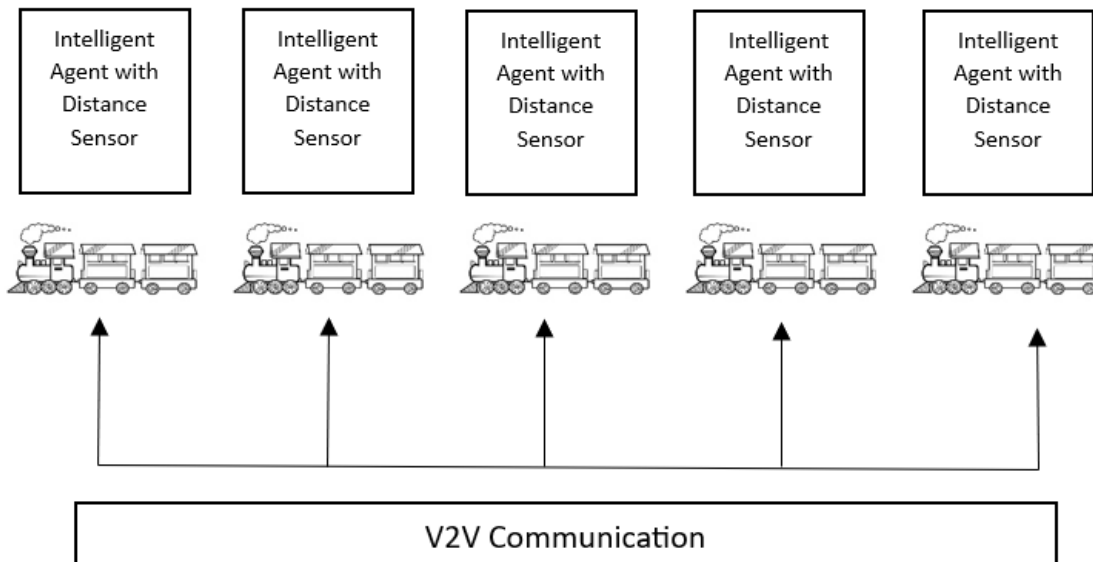


Fig 2: Train Platooning System

Fig 2 depicts a train platooning system equipped with an intelligent agent that includes a distance sensor. This affordable sensor can be mounted on trains to establish a reliable communication method.

AI POWERED RADIO COMMUNICATION

In the realm of railroad operations, the integration of NLP (Natural Language Processing)-powered radio communication systems serve as a pivotal safeguard, enhancing decision-making processes such as switch positioning and track authority assignments. These intelligent systems act as a vigilant secondary check against human error. In instances of discrepancy, the AI intervenes, offering corrective suggestions to reconcile conflicts. For instance, should an operator verbally confirm the alignment of a switch to the left via radio, the AI system could promptly counter-check and notify if that alignment corresponds to an occupied yard track, thereby preventing potential mishaps. This immediate feedback loop allows the operator to swiftly reassess and rectify decisions, ensuring safety and operational efficiency. If necessary, the operator can also seek additional assistance, bolstered by the AI's reliable oversight. On the other side with NLP, train operators can use voice commands to control various aspects of train operation, such as adjusting the speed or switching tracks, which can be particularly useful in situations where manual control is challenging. AI can optimize train scheduling and dispatching by processing vast amounts of data in real-time, ensuring efficient use of the rail network, ensure safety and reducing delays.



Fig 3: AI Powered Radio Communications

V. SUMMARY

The article discusses the integration of Intelligent Transportation Systems (ITS) into railroads, creating a Train Intelligent System (TIS). In the context of smart cities and vehicles, TIS is crucial for enhancing safety in areas with limited visibility, known as dark territories. It utilizes train platooning systems, cognitive AI-powered radios, and wireless sensor networks to mitigate hazards and prevent derailments and collisions. This technology significantly improves vehicle-to-vehicle communication and interaction. The paper also highlights how these advancements can safeguard the lives of locomotive engineers and track workers by preventing accidents.

VI. ACKNOWLEDGMENT

I would like to thank anonymous reviewers for the comments and suggestions.

REFERENCES

- [1] [1] U.S. Department of Transportation, Federal Railroad Administration. (2019). Railroad Safety Advisory Committee Charter. Retrieved February 21, 2024, from [https://rsac.fra.dot.gov/radcms.rsac/File/DownloadFile?id=235]
- [2] MacGregor, C. S., & Bearman, C. (2022). The danger in the dark: Safety and teamwork in Australian dark territory railway operations. *Safety science*, 148, 105638.
- [3] Dark territory. Retrieved from https://en.wikipedia.org/wiki/Dark_territory
- [4] National Transportation Safety Board. (2010). Collision of Two Canadian National Railway Freight Trains near Two Harbors, Minnesota, September 30, 2010 (NTSB/RAR-13/01)
- [5] de Zarzà, I., de Curtò, J., Roig, G., & Calafate, C. T. (2023). Llm adaptive pid control for b5g truck platooning systems. *Sensors*, 23(13), 5899.
- [6] Yang, Y., & Hua, K. (2019). Emerging technologies for 5G-enabled vehicular networks. *IEEE access*, 7, 181117-181141.
- [7] Chai, S., Yin, J., D'Ariano, A., Samà, M., & Tang, T. (2023). Scheduling of coupled train platoons for metro networks: A passenger demand-oriented approach. *Transportation Research Record*, 2677(2), 1671-1689.
- [8] Wang, Y., Gorski, A., & DaSilva, L. A. (2021, April). Ai-powered real-time channel awareness and 5g nr radio access network scheduling optimization. In 2021 17th International Conference on the Design of Reliable Communication Networks (DRCN) (pp. 1-7). IEEE.
- [9] Lesch, V., Breitbach, M., Segata, M., Becker, C., Kounev, S., & Krupitzer, C. (2021). An overview on approaches for coordination of platoons. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 10049-10065.
- [10] Axelsson, J. (2016). Safety in vehicle platooning: A systematic literature review. *IEEE Transactions on Intelligent Transportation Systems*, 18(5), 1033-1045.
- [11] van de Hoef, S., Johansson, K. H., & Dimarogonas, D. V. (2016). Computing feasible vehicle platooning opportunities for transport assignments. *IFAC-papersonline*, 49(3), 43-48.
- [12] Boysen, N., Briskorn, D., & Schwerdfeger, S. (2018). The identical-path truck platooning problem. *Transportation Research Part B: Methodological*, 109, 26-39.
- [13] Larsson, E., Sennton, G., & Larson, J. (2015). The vehicle platooning problem: Computational complexity and heuristics. *Transportation Research Part C: Emerging Technologies*, 60, 258-277.
- [14] Gungor, O. E., & Al-Qadi, I. L. (2020). All for one: Centralized optimization of truck platoons to improve roadway infrastructure sustainability. *Transportation Research Part C: Emerging Technologies*, 114, 84-98.
- [15] Faber, T., Sharma, S., Snelder, M., Klunder, G., Tavasszy, L., & van Lint, H. (2020). Evaluating traffic efficiency and safety by varying truck platoon characteristics in a critical traffic situation. *Transportation research record*, 2674(10), 525-547.
- [16] Yang, J., Peng, W., & Sun, C. (2021). A learning control method of automated vehicle platoon at straight path with ddpq-based pid. *Electronics*, 10(21), 2580.
- [17] Hartenstein, H., & Laberteaux, L. P. (2008). A tutorial survey on vehicular ad hoc networks. *IEEE Communications magazine*, 46(6), 164-171.
- [18] Luo, G., Yuan, Q., Li, J., Wang, S., & Yang, F. (2022). Artificial intelligence powered mobile networks: From cognition to decision. *IEEE Network*, 36(3), 136-144.
- [19] de la Rosa, J. M. (2022). AI-Managed Cognitive Radio Digitizers. *IEEE Circuits and Systems Magazine*, 22(1), 10-39.
- [20] Wang, Y., Wu, X., & Cheng, L. (2018). A novel non-line-of-sight indoor localization method for wireless sensor networks. *Journal of Sensors*, 2018.
- [21] Zheng, Q., He, R., Ai, B., Huang, C., Chen, W., Zhong, Z., & Zhang, H. (2020). Channel non-line-of-sight identification based on convolutional neural networks. *IEEE Wireless Communications Letters*, 9(9), 1500-1504.