Autonomous Train Operation Obstacle Detection Based on Night Vision System

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Abtract: This paper presents the development of an obstacle detection system for autonomous train operation (ATO) using a night vision system. The focus is on the development of the ATO for freight transport that operates in low light and night conditions. An experimental setup featuring an Intensified Charge-Coupled Device (ICCD) camera was employed to acquire images under low-light conditions. A novel computer vision algorithm was developed to ensure robust and reliable obstacle detection. The methodology begins with the detection of rail tracks, which are subsequently used to define a Region of Interest (ROI). Within the ROI, the rail tracks are analyzed for interruptions indicative of obstacles. Obstacle detection is achieved through image segmentation techniques, while the distance between the setup and the detected obstacles is estimated using a homography-based approach. The proposed algorithm was evaluated on a comprehensive dataset comprising images from three representative scenarios. Experimental results demonstrate the system's effectiveness in reliably detecting obstacles under nighttime conditions and accurately estimating distances.

Keywords: night vision; obstacle detection; distance estimation; autonomous train operation; railway

1 Introduction

Railways represent one of the most vital modes of transportation, and their modernization is crucial for increasing safety, efficiency, and capacity. A number recent works addressed various aspects of modern railways, including adequate engineering solutions for railways infrastructure [1, 2], analysis of acting mechanical and thermal loads in railways [3, 4, 5, 6], environmental protection through reduction of emitted noise [7, 8], investigation of the efficiency of rail freight transport [9] – to name but a few. A key aspect of railway modernization is the development of ATO systems, which aim to enhance railway operations by reducing human intervention and improving reliability. ATO has already been widely adopted in public transportation, including metro systems, light rail transit (LRT), and automated guided transit (AGT) [10]. The core principle of ATO involves transferring operational tasks from human operators to automated control systems, such as the European Rail Traffic Management System (ERTMS), ensuring safe and efficient train movement.

One of the fundamental challenges in ATO is the implementation of an Obstacle Detection System (ODS), which is responsible for identifying and classifying obstacles on or near the rail tracks and estimating their distance from the train. The primary objective of the ODS is to enable timely braking and accident prevention, a crucial requirement given that freight trains have significantly longer break distances compared to automobiles—ranging from 500 meters to over 2 kilometers, depending on weight, speed, and braking system efficiency. Unlike autonomous vehicles, where obstacle detection is limited to relatively short distances, autonomous train systems must detect potential hazards much further ahead to allow adequate response time.

A major challenge for ODS is ensuring reliable operation in diverse environmental and lighting conditions. While traditional vision sensors provide effective detection in good lighting, their performance significantly deteriorates in low-light and adverse weather conditions such as fog, rain, and snow. To overcome these limitations, thermal imaging and night vision systems have been increasingly explored as viable solutions. Thermal imaging systems operate in the infrared spectrum and do not rely on ambient light, making them particularly effective for night-time and low-visibility conditions [11, 12, 13, 14]. Use of a night vision system for obstacle detection in those specific conditions enables detection in extremely low-light conditions and at night because this system needs a very small amount of light for good operating.

The authors proposed an AI-powered method for estimating the distance between a camera and objects on railway tracks using image-plane homography and neural networks, with validation showing a 2% error margin in impaired visibility scenarios [14]. Ristić-Durrant et al. in [15] reviewed the state-of-the-art in obstacle detection for railways and outlined the challenges in implementing autonomous obstacle detection systems capable of operating effectively in various environmental conditions. In [16] a two-step method for detection and tracking of pedestrians with single night vision camera installed on a vehicle, is proposed. The detection is performed using support vector machine (SVM) and tracking with a combination of Kalman filter prediction and mean shift tracking. Two new techniques for pedestrian detection using a stereo night-vision system installed on the vehicle are introduced in [17]. Two-stage method for stereo correspondence and motion detection without explicit ego-motion calculation use of characteristics of night-vision video data, in which humans appear.

In this paper, we present an approach to obstacle detection in autonomous train operation using night vision imaging. The proposed method involves rail track detection through image segmentation, followed by ROI analysis to identify track interruptions where obstacles may be present. Detected obstacles are then marked, and their distances from the train are estimated using a homography-based method. The objective is to develop a robust vision-based ODS capable of functioning in real-time across varying environmental conditions, thus ensuring safe and reliable autonomous railway operations.

2 Literature Review

In the field of obstacle detection for autonomous train operations, several approaches have been explored to enhance safety and reliability. One method for long-distance obstacle detection involves using LiDAR to process point cloud data, which offers reliable safety even in low-light and tunnel environments [18]. In addition, Xungu et al. developed a semi-autonomous rail survey inspection device (SID) that travels ahead of trains to detect obstacles, allowing for early hazard identification and significantly improving safety [19]. Assaf et al. introduced a cost-effective gimballing platform designed for long-range obstacle detection using 1D-LiDAR, demonstrating precise targeting at distances beyond 1000 meters [20]. An approach proposed by Brucker et al., uses a shallow neural network that incorporates both local and global information to segment railway images and detect obstacles, outperforming baseline methods on a custom dataset [21]. To improve detection accuracy and adaptability, Tang and Yang developed a multi-sensor obstacle detection system that integrates point cloud data and visual inputs, overcoming the limitations of single-sensor detection [22]. Khobragade et al. also explored real-time track and anomaly detection using computer vision, achieving consistent track continuity and reliable obstacle detection in complex railway environments [23]. Lastly, Gasparini et al. proposed a vision-based anomaly detection system for railway inspection, using RGB and thermal images captured by a rail drone. Their approach proved effective during nighttime operations, offering both computational efficiency and high accuracy [24].

Deep learning methods have been widely adopted in obstacle detection for railway systems, offering improved accuracy and efficiency in challenging environments. Jenefa et al. developed a Deep Convolutional Neural Network (DCNN) model to detect obstacles on railway tracks, achieving an 98% accuracy. Their research demonstrated the potential of DCNNs in real-world applications, though further testing in varying environmental conditions is suggested [25]. Xu et al. proposed another DCNN-based approach, integrating a Single Shot Multibox Detection method with a Residual Neural Network to improve real-time performance. This model outperformed traditional methods with a mean average precision (mAP) of 91.61% and a detection speed of 26 frames per second (FPS) [26].

In complex environments, Qin et al. introduced a robust feature-aware network (RFA-Net) that enhances the detection accuracy of small obstacles, achieving a 92.7% mAP. Their improved algorithm excels in both accuracy and lightweight implementation, making it well-suited for rail transit [27]. Kapoor et al. applied Faster R-CNN with thermal imaging to identify objects on railway tracks in night conditions, showing 83% accuracy and demonstrating the potential of deep learning in improving safety under low-visibility scenarios [28]. Raza et al. developed a novel system for multiple pedestrian detection and tracking in night vision surveillance systems using infrared (IR) images. Their machine learning-based method achieved a 93% segmentation accuracy and 90% detection accuracy, demonstrating high effectiveness in identifying pedestrians in low-light environments. The system was also highly accurate in tracking and classifying detected objects [29].

In nighttime imaging, Patel et al. developed a compact object detector using Depthwise Convolutional Neural Networks (DDCNN), improving detection accuracy while reducing computational complexity. Their model outperforms state-of-the-art methods, with a mAP of 52.39% and 72.7% accuracy for car detection in night-time situations, highlighting the applicability of DDCNNs in real-time use cases [30].

In addition to deep learning methods, several papers have focused on using night vision and sensor-based techniques for obstacle detection, especially in low-light conditions. Yasin et al. leveraged bio-inspired event-based vision sensors for night-time obstacle detection, utilizing the asynchronous adaptive collision avoidance (AACA) algorithm to process high-frequency event data. Their method showed improved detection performance in low-light conditions compared to traditional cameras [31]. Patel et al. addressed the challenge of enhancing night-time image quality by employing the Dark Channel Prior (DCP) filter. Their approach improved visibility and object recognition in traffic surveillance during low illumination, with real-time processing speed optimized through FPGA implementation [32].

3 Night Vision System

Night vision systems use various technologies to enable users to see in complete darkness or low-light conditions. The basic principle of these systems involves collecting small amounts of ambient light, which may be imperceptible or insufficient for the human eye, and amplifying it to a level where the image becomes visible. The night vision system used in this research is an ICCD (Intensified CCD) camera, which consists of an optical lens system, an image intensifier tube, and a CMOS camera sensor coupled to the output screen of the image intensifier tube (Fig. 1). Unlike thermal camera, there is no significant influence of varying ambient temperature on image acquired with ICCD camera.

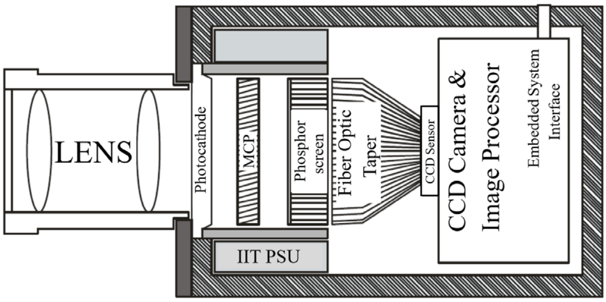


Figure 1
ICCD camera schematics [33]

The optical lens system in a night vision device is responsible for providing the appropriate magnification of an object at specific distances, ensuring that the image captured is clear and focused. This lens system plays a crucial role in directing the incoming light onto the image intensifier, where the real enhancement of the image occurs. The image intensifier's primary function is to increase the intensity of the incoming light by multiplying the photons it receives. This process of photon amplification enables the ICCD camera to capture images even under extremely low-light conditions, where the available light is insufficient for conventional imaging, or during very short exposure times, such as those as brief as 200 ps. In such cases, the total photon flux collected over the short exposure period is typically very low, but the image intensifier ensures that the minimal light available is amplified to produce a visible image.

The image intensifier, as shown in Fig. 2, is composed of three integral components that work in tandem to achieve this amplification [34]. These components are mounted very close each other in order: photocathode, microchannel plate, phosphor screen. The working principle is: photons from light sources is absorbed into the system, then the photocathode (a) receives the incoming light and converts the photons into photoelectrons. These photoelectrons then pass through the microchannel plate (MCP) (b), which multiplies them by a significant factor, enhancing the number of photoelectrons for further processing. Finally, the amplified photoelectrons are directed onto the phosphor screen (c), where they are converted back into photons, creating the intensified image that is captured by the camera sensor. These three stages – photon conversion, electron multiplication, and photon re-emission – are essential for enabling high-quality imaging in low-light environments.

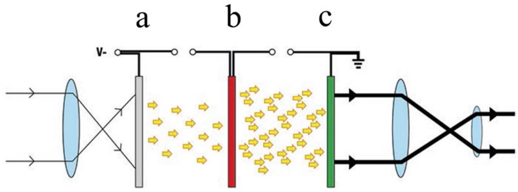


Figure 2
Three functional units of an image intensifier: the photocathode (a), the microchannel plate (b) and the phosphor screen (c) [35]

The functional components of the image intensifier are precisely aligned in close proximity to each other to ensure optimal performance. The operational principle of the image intensifier is as follows: photons incident on the photocathode from the light source are converted into photoelectrons. These photoelectrons are then subjected to significant amplification within the microchannel plate (MCP), after which the phosphor screen re-emits the multiplied photoelectrons as photons. The amplified photons are subsequently directed towards the CCD sensor through an optical system for image acquisition. A critical feature of the image intensifier is its gating capability, which serves as the shutter function for the ICCD camera. When the camera is "gated on," the shutter is open, permitting the transmission of amplified photons to the CCD sensor for image capture. When the camera is "gated off," the shutter is closed, preventing any photon transmission to the CCD sensor. This gating function is essential for enabling the ICCD camera to operate effectively in environments with minimal or no ambient light, thereby facilitating its use in various low-light and no-light imaging applications [34].

4 Obstacle Detection System

The primary objectives were to detect obstacles on or near rail tracks under no-light and low-light conditions and to estimate the distance between the detected obstacles and the system. To achieve this, after image acquisition using the night vision system, rail tracks are identified through a region-based segmentation approach. Specifically, thresholding and region growing techniques, using an optimal threshold range, are employed [13, 36, 37, 38]. The comuter vision flow chart used for obstacle detection and distance estimation is illustrated in Fig. 3.

The proposed obstacle detection and distance estimation system operates through a vision-based algorithm that leverages rail track segmentation and dynamic region of interest (ROI) definition to achieve accurate and efficient obstacle localization.

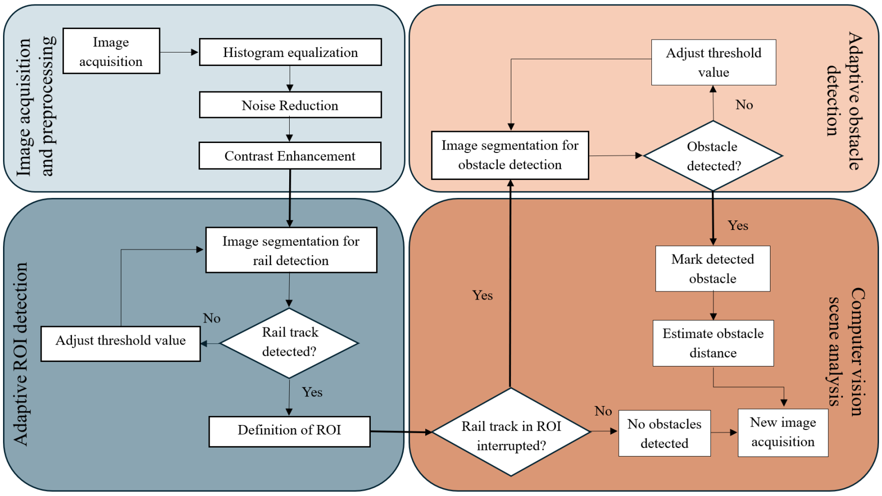


Figure 3

Obstacle detection and distance estimation flow chart

The system begins by continuously acquiring images from a mounted ICCD camera or RGB, and applies image preprocessing techniques such as contrast enhancement, noise filtering and histogram equalization to improve feature visibility. Rail track segmentation is then performed using a threshold-based method to isolate the distinctive linear features of the tracks. If successful, the system defines a dynamic ROI surrounding the detected rails, with margins added laterally and longitudinally to capture the spatial context where potential obstacles are likely to occur. This targeted approach reduces the computational burden by focusing only on relevant parts of the image. Within the ROI, the continuity of rail tracks is analyzed. Discontinuity in the rail structure is interpreted as a potential indication of an obstacle. If such a discontinuity is detected, a second segmentation stage is initiated specifically for obstacle detection. This involves applying an optimized thresholding method to extract non-rail features, followed by blob analysis to identify and localize obstacle candidates. To accommodate diverse lighting and environmental conditions, the algorithm can iteratively adjust threshold values during both segmentation stages. Once an obstacle is confirmed, it is marked within the image and its distance from the camera is estimated using a homography-based transformation, which uses the geometric relationship between the image plane and the real-world ground plane [38, 39].

The homography is also called projectivity, which is defined as *invertible mapping* $\boldsymbol{h}$ *from* $\boldsymbol{P}^2$ *to itself such that three points* x_1, x_2 *and* x_3 *lie on the same line if and only if* $\boldsymbol{h}(x_1)$, $\boldsymbol{h}(x_2)$ *and* $\boldsymbol{h}(x_3)$ *do* [39]. On this way, projectivity is defined in terms of geometry, and an equivalent algebraic definition of projectivity is that *a mapping* $\boldsymbol{h}$*:* $P^2 \rightarrow P^2$ *is a projectivity if and only if there exists a non-singular 3×3 matrix* $\boldsymbol{H}$ *such that for any point in* $\boldsymbol{P}^2$ *represented by a vector* $\boldsymbol{x}$ *it is true that*

h(x)*=*Hx. A planar projective transformation, which was used for estimation of distance, represents linear transformation on homogeneous 3-vectors represented by a non-singular 3×3 matrix:

This is an equation example:

$$\begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{1}$$

or shorter:

$$\boldsymbol{x}' = \boldsymbol{Hx} \tag{2}$$

5 Results and Discussion

5.1 Experimental Setup

The experimental setup used in this research consists of three monocular RGB cameras, one IR camera, one night vision system and one laser scanner. All cameras are mounted in metal housing, especially designed for this purpose (Fig. 4). For an obstacle detection in no light and low-light conditions, IR camera and night vision system are used and tested on field tests performed on rail tracks in different times of the night. During tests, humans were imitating obstacles on the rail tracks and next to them on different distances from |the experimental setup. However, in the research presented in this paper only videos (images) acquired by the CCD camera augmented with image intensifier were used and analyzed.

To obtain high quality videos during experiments in no light and lowlight conditions, night vision system hardware has an optical system with 6x objective, fixed 170 mm focal length and aperture f/1.7. Image intensifier is 3rd generation with 64 lp/mm and auto-gating function, with monochromatic camera resolution 2592x1944 pixels.

For the real time online processing ROS Noetic Ninjemys was used, while using OpenCV library, CUDA 10.1 and working on Ubuntu 20.04 64-bit Qt 4.8.1. For algorithm development, testing and evaluation, as well as data analysis MathWorks MATLAB 2023b was also used.

Figure 4
Experimental setup on field

To prepare needed data for development, testing and evaluation of the proposed method for long-range object (obstacles) detection and distance estimation using CCD camera with image intensifier, field tests were performed on various a Serbian railway test-sites (on a railway Niš-Prokuplje) approved for the experimental use by the Serbian Railway authorities.

5.2 Obstacle Detection

To achieve greater reliability and robustness, image processing algorithm for an obstacle detection was implemented and tested on a large set of images. Those images were continuously captured by experimental setup with a night vision system during night conditions at two different locations. The first location was in the village of Babin Potok, near the city of Prokuplje, Serbia. The chosen location was a level crossing located in a rural and an uninhabited area, so there was no facility or light source in the wider area (marked with a red circle in Fig. 5 (left)). The level crossing was located at the intersection of the local unpaved road and the Niš-Prokuplje-Merdare main railway line. The experiment was carried out on a part of the Niš-Prokuplje railway, between the Rečica and Babin Potok railway stations, in the direction towards Prokuplje (marked with a blue line in Fig. 5 (left)). On that site, the railway line is a single-track and not electrified. The level crossing is marked with vertical signs, it is not illuminated, and it is not equipped with appropriate equipment. The experiment was carried out in night conditions, in clear weather at a temperature of 18°C and the amount of illumination of 0 lux over the whole location. Night vision system was set up at the center of railway between the rail tracks (Fig. 5 (right)) at a height of 1.5 meters from the ground.

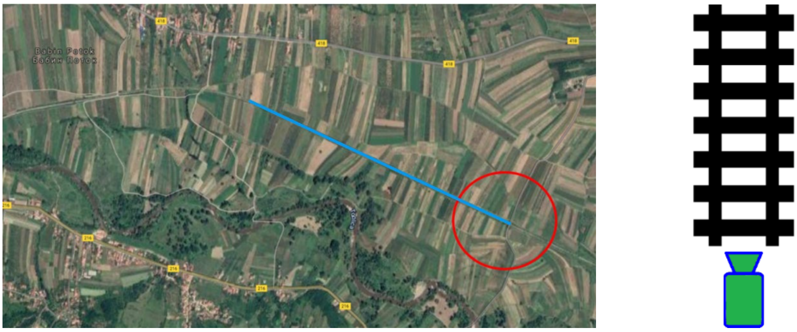


Figure 5
Location of the first level crossing where experimental setup was placed (left) and schematics of the camera orientation (right)

In this experiment, there were three specific cases for obstacle detection. In the first case, one object was between the rail tracks (Fig. 6 (left)). Rail tracks were detected and based on that and the ROI was defined (marked with a purple color in Fig. 6 (right)). Although the object was not directly on rail tracks, its position was in ROI and affected the occurrence of interruption on the rail tracks. In a further image processing, the obstacle was detected in ROI between the rail tracks and marked with a red rectangle (Fig. 6 (right)).

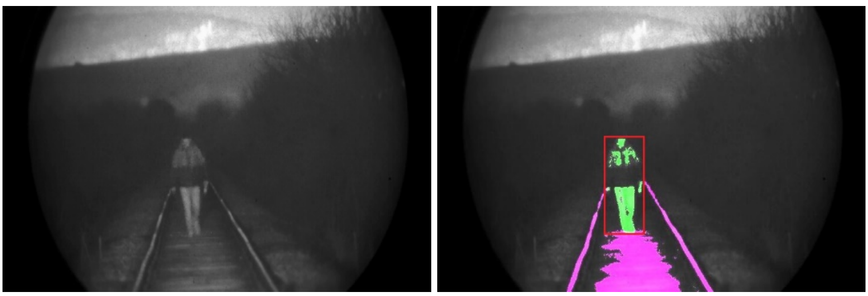


Figure 6
Object between rail tracks (left) and the detected ROI and obstacle (right)

In the second case, there were two objects, one next to the left rail track and another on the right rail track (Fig. 7 (left)). First, rail tracks were detected, and ROI is defined (marked with a purple color in Fig. 7 (right)). However, in this case, there was interruption only on the right rail track, and in a further image processing, the obstacle was detected in ROI and marked with a red rectangle (Fig 7 (right)). An object next to the left rail track was out of ROI, i.e., was not on the rail tracks nor in close vicinity of the rail tracks, it did not affect interruption in rail tracks, and was not detected.

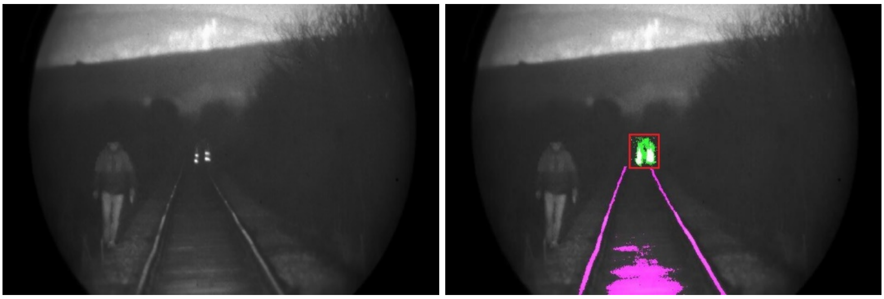


Figure 7
Objects next to left and on right rail track (left) and the detected ROI and obstacle (right)

In the third case, an object was on both rail tracks and far from the night vision system (Fig. 8 (left)). First, rail tracks were detected, and ROI was defined (marked with the purple color in Fig. 8 (right)). Considering that there were interruptions on both rail tracks, in further image processing, othe bstacle was detected in ROI and marked with a red rectangle (Fig. 8 right).

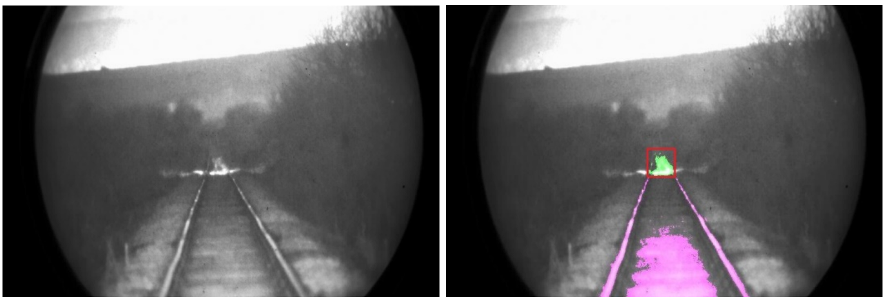


Figure 8
Object on both rail track (left) and the detected ROI and obstacle (right)

The second location was in village Žitorađa, near city of Prokuplje, Serbia (Fig. 9 (left)). This location is in a rural uninhabited area, the level crossing is not illuminated and without signs and equipment. There is a local road next to the location and there are residential buildings at 820 meters from the level crossing. Because of this, occasional and partial occurrence of indirect lighting was expected. This location was chosen considering the real conditions of the mixed environment and the safety aspects of the implementation of the experiments. The experimental setup was mounted on a level crossing (marked with a red circle in Fig. 9 (left)), while the night vision system was directed towards the village Žitorađa (marked with a blue line in Fig. 5 (left). The experiments were carried out in night conditions, in clear weather at a temperature of 2°C and the amount of illumination of 0 lux over thewhole location. The night vision system was placed on the left side of the rail tracks (Fig. 9 right), at a height of 1.5 meters from the ground and directed towards a habited place.

Figure 9
Location of the second level crossing where experimental setup was placed (left) and schematics of the camera orientation (right)

The purpose of this experiment was to inspect operating of the algorithm in the process of object detection during their arbitrary movement on rail tracks and in their vicinity. In the first case, the object was located between rail tracks. Although the object was not on the rail track, its presence caused interruption on the detected rail track, which can certainly indicate its potential presence. The object, i.e., the part that was in the ROI, was successfully detected and marked with a red rectangle. However, the whole object was not detected because the position of night vision system was not set in front.

Figure 10
CCD image (left), CCD image with image intensifier (center) and the detected ROI and obstacle (right)

During experiments, the algorithm showed its robustness through successful detection of obstacles or its parts at different locations, as well as in different weather conditions. However, results showed that positioning of the night vision system has influence on the quality of detection. According to that, the best results of detection were obtained when axis of the night visions systems was perpendicular to the rail tracks. In densely populated or heavily illuminated urban railway scenarios, the use of an ICCD camera is not necessary due to sufficient ambient light. In such conditions, the ICCD's image intensifier should be protected by closing the shutter, and the system should rely on a standard RGB camera instead. To maintain robust performance, algorithmic adjustments will be required – particularly in the image preprocessing pipeline – to account for the different lighting conditions, reduce noise, and enhance feature extraction under varying illumination and background complexity.

5.3 Estimation of Distance

In order to estimate the distance between the night vision system and the detected objects, a homography method was used. At the first location – village Babin Potok, four points – vertex of blue quadrilateral (Fig. 11 (upper left)) was used for calculation of the homography matrix ***H.*** The coordinates obtained during the experiments, in real world, were calculated based on known positions of people on the rail tracks relative to the night vision system. The coordinates in image were determined using of captured image. Calculated homography matrix ***H*** is given in Eq. 3. An estimation of the distance between night vision system and the previously detected objects was performed using an inverse matrix ***H***.

$$\boldsymbol{H} = \begin{bmatrix} 11.3929 & 0.5302 & 592.1667 \\ -2.7321\cdot 10^{-12} & 0.4132 & 1935.667 \\ -7.3347\cdot 10^{-15} & 0.001377 & 1 \end{bmatrix} \tag{3}$$

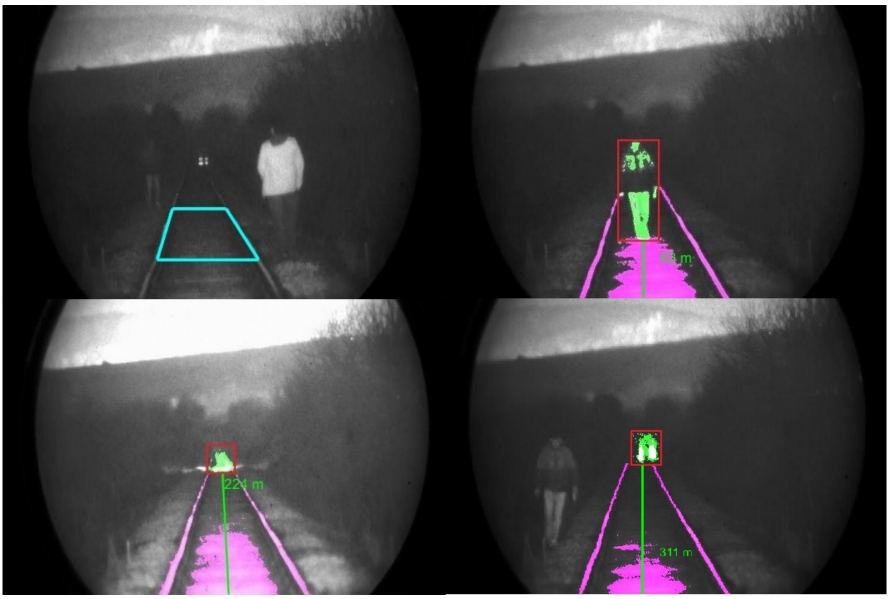


Figure 11

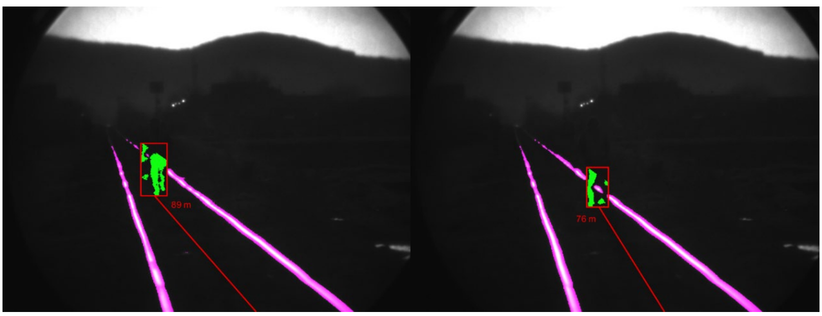
Points for calculation of matrix ***H*** (upper left), estimated distance for the first case (upper right), estimated distance for the second case (lower left) and estimated distance for the third case (lower right)

Also, at the second location – Žitorađa, estimation of distance between night vision system and the detected object was performed using the homography method. The coordinates in real world were calculated as is in first location, while the coordinates in image were determined using two captured images, that were fused (Fig. 12). Calculated homography matrix $\boldsymbol{H}$ for the second location is given in Eq. 4.

Figure 12
Points for calculation of matrix H

$$\boldsymbol{H} = \begin{bmatrix} -24.2809 & -0.5485 & -684.0977 \\ -1.1670 & -0.6427 & -3008.4 \\ -0.0049 & -0.0025 & 1 \end{bmatrix} \tag{4}$$

In Fig. 13 estimated distances between night vision system and detected objects for four scenarios at location Žitorađa are shown.



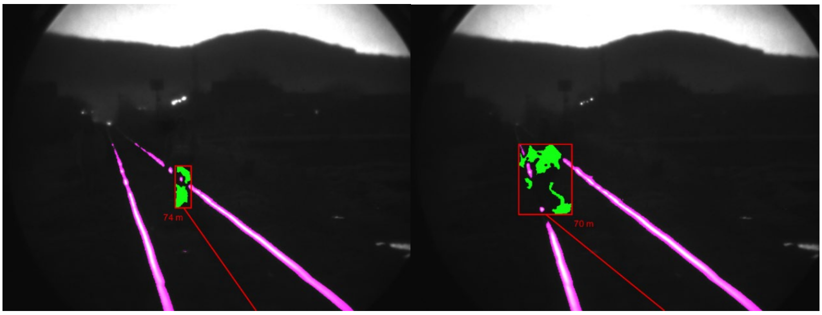


Figure 13
Obstacle detection and distance estimation for the various position of the objects on the rail tracks

In Table 1 estimated and measured distances for both locations are shown, as well as estimation error. Maximum estimation error is 5.76%, and it is for the longest measured distance. Furthermore, results showed that estimation error increases with the increase of the distance. One of the possible causes for error in distance estimation can be uncertainty in homography matrix ***H*** calculation and detection of the exact point on the rail tracks where the obstacle was, while another can be due to detection error because of the night vision system and object's position.

Table 1
Comparison of Measured and Estimated distances from the ICCD camera to the obstacle

Location	***Measured distance [m]***	***Estimated distance [m]***	***Distance estimation error [m]***	***Distance estimation error [%]***
I	65	63	2	3.08
I	330	311	19	5.76
I	235	224	11	4.68
II	89	84	5	5.62
II	76	72	4	5.26
II	74	70	4	5.41
II	70	66	4	5.71

The height of the mounted vision system has a significant influence on the homography matrix and can, therefore, affect the reliability and accuracy of the proposed method. However, since the ODS is intended to be mounted on a locomotive, the height from the ground and railtracks remains constant and it can not influence obstacle detection and distance estimation accuracy.

The accuracy of distance estimation was evaluated across a range of obstacle positions. The minimum observed error was approximately 2 meters, while the maximum error reached 20 meters, primarily at longer distances where small pixel deviations result in larger real-world inaccuracies due to the limitations of homography-based methods. In the critical operational range of 200 to 300 meters, relevant for low-speed railway scenarios, the system maintained an error below 20 meters, which is acceptable for early obstacle detection, warning and breaking. Additionally, the experiments demonstrated that the accuracy improves significantly when the ICCD camera is centrally aligned with the rail tracks, reducing perspective distortion and improving the quality of homography-based transformations.

Conclusions

The continuous development and modernization of railway transportation require the integration of advanced and intelligent technologies, such as Autonomous Train Operation (ATO), to improve operational efficiency, safety, and reliability. One of the most critical components of ATO is an effective Obstacle Detection System (ODS) capable of operating under diverse environmental conditions, including low-light and nighttime scenarios. Traditional vision-based systems often suffer from significant performance degradation in such conditions, necessitating the development of alternative solutions.

In this paper, a novel obstacle detection system using a night vision-based imaging approach was presented. The proposed system employs an advanced image processing algorithm incorporating region-based segmentation techniques to detect rail tracks, define a Region of Interest (ROI), and identify potential obstacles. By analyzing track interruptions within the ROI, the system detects objects in close proximity to the railway and estimates their distances using a homography-based method. The algorithm was tested on a comprehensive dataset consisting of images captured in nighttime conditions across three representative railway scenarios. Experimental results demonstrated that the proposed approach effectively detects obstacles with a high-level of accuracy, achieving a distance estimation error of less than 6%.

These findings suggest that night vision-based ODS can serve as a reliable solution for autonomous train operations, particularly in environments where conventional vision systems struggle due to low-light conditions. The integration of such technology can significantly enhance railway safety by providing real-time, automated obstacle detection, thereby mitigating the risks associated with delayed braking response in freight train operations. However, while the system has demonstrated promising results, further research is needed to improve its robustness and adaptability to extreme weather conditions such as fog, heavy rain, and snow. The integration of additional sensor modalities, such as LiDAR and thermal imaging, can significantly mitigate the limitations of the homography-based distance estimation method, particularly under adverse weather conditions. LiDAR provides accurate depth information independent of lighting, which complements the vision-based system by improving distance estimation at longer ranges. Thermal imaging can detect heat signatures, enhancing obstacle visibility in low-visibility environments such as fog, rain, or darkness. Future work will focus on fusing these modalities to increase overall obstacle detection accuracy and reliability, especially where homography alone may be less effective.

Additionally, optimizing the computational efficiency of the algorithm will be crucial for ensuring real-time implementation in practical railway applications.

In conclusion, the proposed night vision-based ODS represents a significant step toward achieving fully autonomous and safe railway operations. Its ability to function effectively in low-light environments positions it as a viable solution for modern railway systems, with the potential for further enhancements through sensor fusion and deep learning-based methodologies.

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List of Abbreviations

ATO: Autonomous Train Operation
ICCD: Intensified Charge Coupled Device
ROI: Region of Interest
AGT: Automated Guided Transit
LRT: Light Rail Transit
ERTMS: European Rail Traffic Management System
ODS: Obstacle Detection System
SVM: Support Vector Machine
LiDAR: Light Detection and Ranging
SID: Survey Inspection Device
RGB: Red Green Blue
DCNN: Deep Convolutional Neural Network
mAP: mean Average Precision
AACA: Asynchronous adaptive collision avoidance
DCP: Dark Channel Prior
FPGA: Field Programmable Gate Array
CMOS: Complementary Metal Oxide Semiconductor
MCP: Microchannel Plate
IR: Infrared
ROS: Robot Operating System

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