Vision Enhancement Solution for Loco Pilot During Fog, Rain, Curves

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Abstract: ***This project presents a concept for improving locomotive driving visibility and collision avoidance by integrating a smart digital display with layered protective glazing and a thin electrochromic glass layer, supported by an onboard processing unit for real-time vision and navigation functions. The proposed setup combines a transparent display, an infrared thermal camera feed, and embedded image-processing methods for track and obstacle detection under low-visibility conditions such as fog and heavy rain. A compact GPU-CPU class processing board runs the operating system, camera pipelines, and AI-based detection models- including CNN and YOLO-based frameworks- with attention to installation steps and field integration constraints. In parallel, an intra-railway navigation system is proposed using real-time GPS/GNSS tracking to display nearby locomotive positions, speeds, and route geometry on the cab screen, aiming to reduce rail-to-rail accidents, derailment risk, operational delays, and infrastructure losses. This approach complements existing Indian Railway safety initiatives such as the Kavach Automatic Train Protection system by adding a vision-layer and a pilot-accessible navigational display. A supporting business case is discussed using reported accident-loss figures and the growing relevance of service reliability for both public and private rail operations.***

Keywords: electrochromic glass, thermal infrared camera, obstacle detection, onboard image processing, railway GPS navigation, CNN, YOLO, loco pilot vision, intra-railway navigation, Kavach

1. Introduction

In the abstract round, we discussed the problems railways are facing, causing huge losses in terms of infrastructure and finances. We discussed three major things: (1) smart screens, (2) infrared camera, and (3) navigation connection between loco motives. In this paper we present a detailed study of these. Although accidents have reduced because of various improvements in safety and technology, there is still a lot of scope for improvement in railway safety.

1) Smart Digital Screen Setup as Loco Motive Screen

In (1) we saw layers of glass around the smart screen: (a) stretched acrylic glass due to its high optical quality, low weight, and good processability, (b) a layer of urethane for resisting abrasive forces and preventing air leakage, with hydrophobic coating on outer sides so that in any condition moisture doesn't enter.

We will introduce thin Electro Chromatic glass on the outer end of this layer of glass. Electro Chromatic glass is a smart glass that changes its transmittance (i.e., how much light it passes) when stimulated by an electrical signal. This reversible change alters the state of the glass between transparent and opaque (or any state in between). In the center of the structure are the electrochromic layer and the electrolytic layer, which are responsible for the change in transmittance.

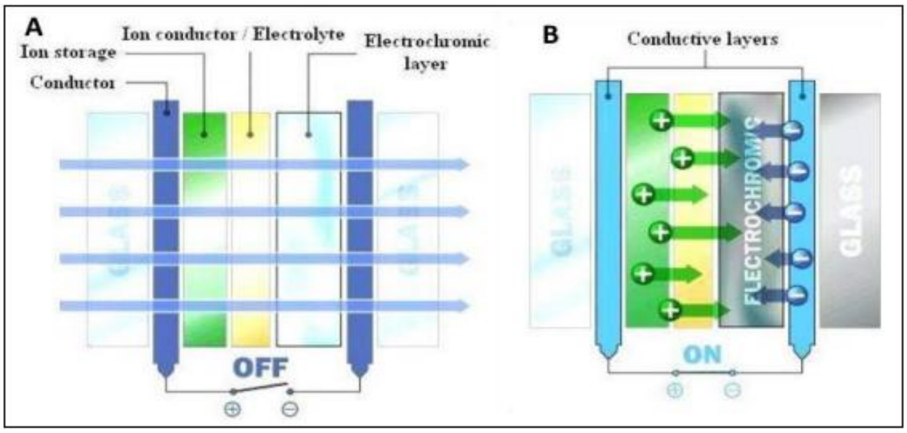

Figure 1: Description of electro chromatic glass (a) when the glass power is cut off. (b) when the glass power is on and ions are activated

When you apply a voltage to the ITO (indium tin oxide), charged particles (normally lithium ions) migrate from the electrolyte into the electrochromic layer (often tungsten oxide, which is transparent in its inactive state). The voltage transformations for electro chromatic glass require 48 Vdc (for aircraft) or 24 Vdc (for automotive applications).

This is also known as switch glass. The motive to use this glass is during extreme weather conditions when the loco engine glass vision is almost blurred (translucent turning to opaque): the loco pilot can then turn on the electro chromatic glass to block disturbing partial light rays and access the smart digital display.

Figure 2: Pictures of loco motive experiencing extreme weather due to fog which is a case where electro chromatic glass should be activated. Transparent screen mostly used as digital signage will be used here. Thin display will have to be attached with processing unit to give basic control to become normal display to smart display

2) Connectivity Between Camera and Screen Through Processing Chip

A chip like Raspberry Pi can be installed here with the required Python coding to process images captured by the camera and run the intra-railways navigation software. It acts as both CPU and GPU in a single integrated circuit. The Raspberry Pi is a compact computer that uses a system-on-a-chip with RAM, USB ports, and other components soldered onto the board for an all-in-one package.

Figure 3: Raspberry Pi 4 processor chip- 1.5 GHz quad-core ARM CPU, 500 MHz VideoCore VI GPU, 1–4 GB RAM, USB-C power, HDMI output

It has an SD card slot to house the operating system and files. The Raspberry Pi 4 upgrades to USB-C power delivery and HDMI for audio/video output. Image captured by camera is sent to the processing unit, where the GPU processes that image according to the code on the processing chip, and the result is displayed on the smart screen.

Previous versions of the Pi use micro-USB for power delivery, but the Raspberry Pi 4 upgrades to USB-C. Need HDMI cable to connect it for audio and video through single cable and SD card for storage

Graphical or display processing unit

Image captured and sent to processing unit then GPU processes that image according to the code given to processing chip and then display to smart screen

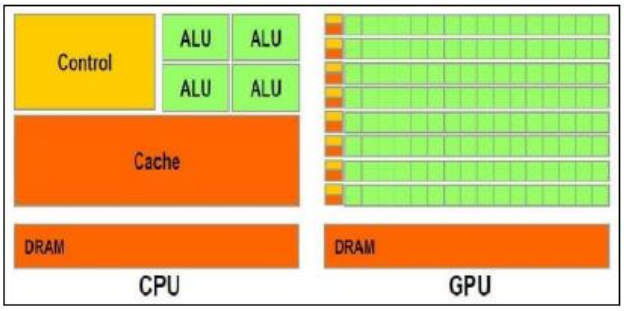

Figure 4: Processing architecture of Raspberry Pi: ARMv6 700 MHz single-core CPU, VideoCore IV GPU, 512 MB RAM. The GPU handles parallel image processing tasks while the CPU manages the OS and navigation software

2(a) Installing the Processing Chip

Step 1: Use Etcher (available for Windows, macOS, and Linux) to write to the SD card. Code should cover image processing, obstacle detection, railway track detection, and obstacle distance detection.

Step 2: Download the Raspbian image file for your specific Pi model (IMG or ZIP).

Step 3: Launch Etcher, click Select Image, choose the downloaded file, select your SD card as the target, and click Flash.

Step 4: Eject the SD card, insert into Pi, connect HDMI to smart display, plug in power. Configure Wi-Fi and install required software from the Raspbian desktop.

3) Cameras

An infrared camera detects the thermal energy or heat emitted by the scene being observed and converts it into an electronic signal. This signal is then processed to produce an image. The heat captured by an infrared camera can be measured with a high degree of precision- the higher the temperature of a body or object, the more radiation it emits. When the camera's sensor picks up infrared radiation, the data is converted into a colored representation of the scene.

Thermal imaging cameras see in total darkness, producing clear, crisp images without the need for any light.

Range of thermal camera in fog vs. naked eyes:

Fog Category	Visual (km)	MWIR (km)	LWIR (km)
Cat I	1.22	3.0 – 9.8	5.9 – 10.1
Cat II	0.61	0.54	2.4
Cat IIIa	0.305	0.294	0.293
Cat IIIc	0.092	0.089	0.087

Figure 4 (table). Fog categories with visual range (naked eye), MWIR (Medium Wavelength Infrared) range, and LWIR (Long Wavelength Infrared) range in km. Infrared cameras far exceed naked-eye visibility in all fog categories.

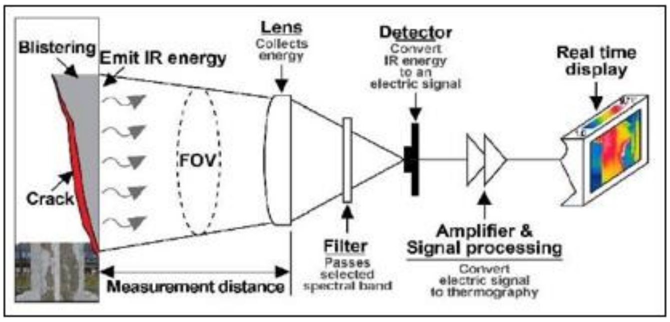

Figure 5: Schematic diagram of an infrared camera: from IR energy emission through lens collection, spectral filtering, IR-to-electric signal conversion, amplification and signal processing, to real-time display output

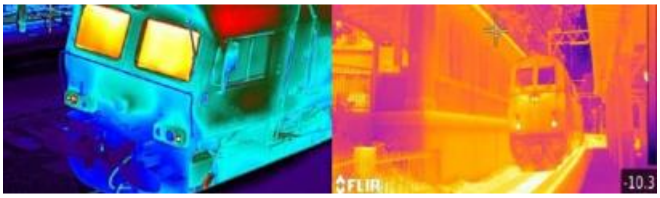

Figure 6: These are pictures captured by thermal infrared camera of moving train. Color grading depends on the temperature of the body detected in camera

3 (a) Image Processing Study

Here image processing will be used to get enhanced image with more desired output such as object detection, track detection, distance estimation as AI system. Already traffic control system of countries has opted this AI system. DL and CNN method is mainly used to detect object which we will discuss further. This will work irrespective of weather condition

3 (b) Image Processing Study

Image processing will be used to obtain an enhanced image with desired outputs such as object detection, track detection, and distance estimation as an AI system. Traffic control systems of multiple countries have already adopted such AI systems. Deep Learning (DL) and Convolutional Neural Network (CNN) methods are mainly used to detect objects and will work irrespective of weather conditions.

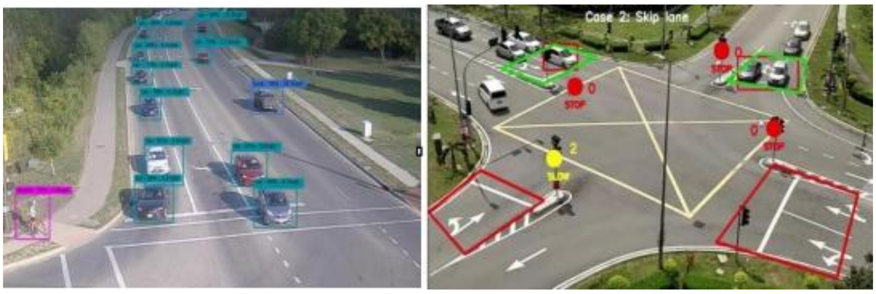

Figure 7: AI camera system for traffic and obstacle detection: image captured, processed, and output with bounding boxes and classification labels showing detected objects.

A DL-based method for detection of obstacles on rail tracks transforms the obstacle detection problem into a target object detection problem. A CNN-based feature extractor using the Faster R-CNN framework is proposed. Input thermal camera images are first transformed to HSV color space to remove noise (unwanted surroundings like trees and buildings appear less bright). After noise removal, Faster R-CNN identifies objects from HSV-segmented frames.

The Feature Fusion Refine Neural Network (FR-Net) consists of three modules: the depth-wise-pointwise convolution module (real-time detection), the coarse detection module (prior anchor approximation), and the object detection module (accurate locations and class labels). An improvement is DFF-Net (Differential Feature Fusion CNN) — an end-to-end detection network with fully convolutional architecture.

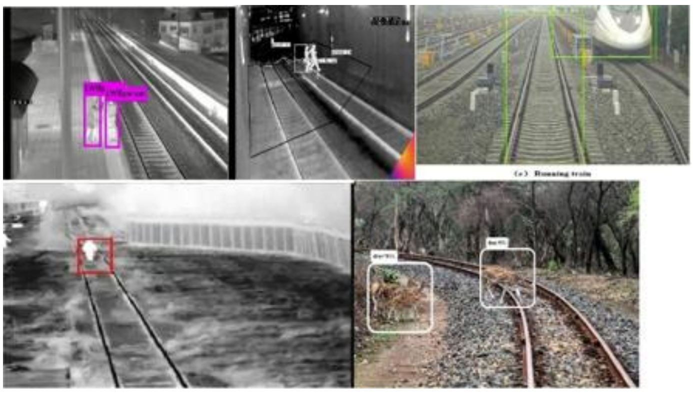

Figure 8: (a) Thermal camera at platform people detection (b) infrabel 30FLIR ITSSeries rail thermal captured photo (c)FR-Net Robustness test performed on running train (d) FLIR thermal camera captured photos

The method is based on CNN and is known as a Feature Fusion Refine Neural Network (FR-Net). It consists of three connected modules: the 'depth-wisepointwise' convolution module, which improves detection in real time; the 'coarse detection module,' which approximates the locations and sizes of prior anchors to provide better initialization for the subsequent module and also reduces the search space for the classification; and the 'object detection module' that provides more accurate object locations and predicts the class labels for the prior anchors. An improvement to the FR-Net method is proposed, an object-detection method that uses the so-called DFF-Net (Differential Feature Fusion CNN). DFF-Net is an end to-end object detection network with a fully convolutional network architecture. DFF-Net includes two modules: the prior object detection module, which produces initial anchor boxes; and the object-detection module, which applies a differential feature fusion sub-module onto the initial anchor boxes to enrich the semantic information for object detection, enhancing the detection performance, particularly for small objects.

A multi-stage obstacle detection method is also proposed. The method has two steps: feature map creation and feature fusion. In the first step, the input image is converted into multi-scale feature maps using a Residual Neural Network (RNN). Multi-scale features maps improve the identification of objects of different sizes at different distances. Specifically, low-level features lack semantic information but provide precise object location information, while high-level features are rich in semantic information but provide only approximate location information. Once the multi-scale features maps are created, a series of convolution layers are added to extract features, and the network calculates a confidence score and bounding boxes for possible obstacles. For training and testing the network, the authors made a custom dataset which contained large-scale urban rail transit video frames taken by an on-board HD camera.

3 (c) Distance Estimation

a novel machine-learning based method named DisNet was presented which works with on-board cameras to detect possible obstacles in front of the train. DisNet consists of two parts: the first part performs DL-based object detection, and the second part is a multi-hidden layer's neural network-based system for distance estimation. An object detector can be any bounding box-based DL-based method which extracts the bounding box of an object detected in the input image as well as the object class. The results presented were obtained using one of the state-of-theart one stage DL-based methods for the prediction of detected objects bounding boxes named YOLOv3. The main advantage of YOLO is its speed, making it appropriate for real-time applications such as on-board OD in railways. The distance estimator is a feedforward artificial neural network that consists of three hidden layers, each containing 100 hidden units. DisNet estimates the distance between each detected object and the on-board camera based on the features of the object Bounding Box (BB) extracted by the YOLO-based object detector. The YOLO model used was first trained with the Microsoft COCO dataset of images of everyday scenes containing common objects in their natural context, consisting of 328,000 images of 80 easily recognizable object classes. There are many works present online and accessible but no work discuss detail on distance estimation for long range an on-board thermal camera was used which had a distance range of up to 1500 m. The paper presents results of object detection within the camera visibility range, on the rail tracks' portions visible in the camera image. However, no details are given on the estimation of distances to individual detected objects. A different on-board thermal camera-based system for finding rails at long-range However, no details on the detection distance range are given.

The only known published work explicitly describing obstacle distance estimation is presented in. The main part of the on-board vision-based obstacle detection system presented in is the distance estimator named DisNet. DisNet estimates the distance between each detected object in the camera images and the on-board camera, using the features of the object Bounding Box (BB) extracted by the DL-based object detector. In other words, DisNet learns the relationship between the size of the object BB and the distance of the object to the on-board camera. The evaluation tests performed in an operational railway environment demonstrated that this integrated on-board vision-based obstacle detection system fulfilled the functional requirements of mid- and long-range obstacle detection. This system extended the state-of-the-art by providing long-range

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object detection and identification of obstacles in the mid-range (from 80 m up to beyond 200 m) and in the long-range (up to 1000 m). Some of the DisNet results on distance estimation of real-world objects are given in

Figure 9: RGBC (red, green, blue) camera captured photos with distance estimation image processed

The distance estimator is a feedforward ANN with three hidden layers of 100 units each. DisNet learns the relationship between the bounding box size of a detected object and its distance from the on-board camera. The YOLO model was trained on the Microsoft COCO dataset (328,000 images, 80 classes). Evaluation in an operational railway environment demonstrated mid-range (80–200 m) and long-range (up to 1,000 m) obstacle detection performance.

4) Intra-Railways Navigation Connection with Real-Time GPS Tracking

The intra-railways navigation system framework proposed here is inspired by cab aggregator apps like Ola and Uber, where multiple vehicles are visible in real-time on a single map frame. The same framework can be adopted for railways, with each locomotive visible on a unified navigation map displayed on each loco motive's smart screen.

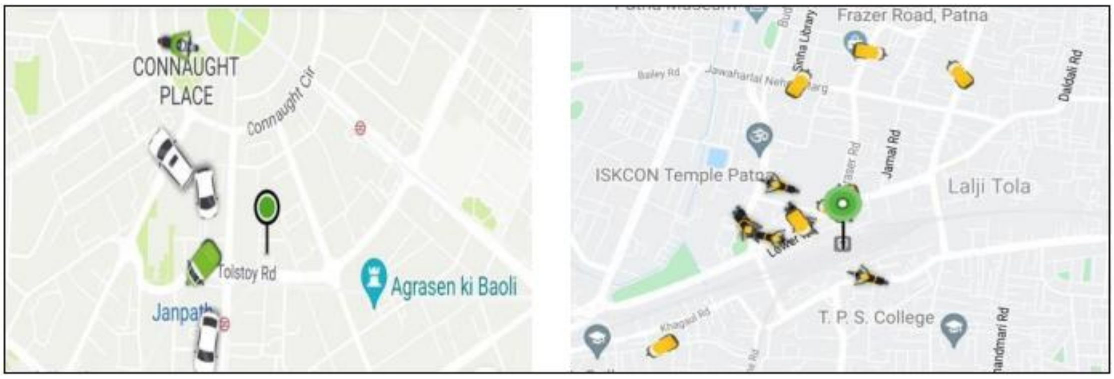

Figure 10: Image taken from a cab aggregator app showing real-time locations of multiple vehicles in a single map frame — the same concept proposed for inter-locomotive navigation.

Same framework I want railways network to opt for, intra railways navigation system which will be displayable on the screen of each loco motive smart displays which will help loco pilot to get to know curves of track and other loco motives travelling nearby or which is few kilometers away and with what speed they are travelling. Pilot can access this in extreme weather or normal weather condition, there will be almost zero chance of rail – rail accident and trains running off the track hence saving infrastructure of railways and solving problem statement of project. We have to develop a navigation software specially for intra-rail network where each loco motive is connectable

This will help loco pilots get to know the curves of the track, and identify other loco motives travelling nearby or a few kilometres away along with their speeds. The pilot can access this in extreme or normal weather conditions, reducing the chance of rail-rail accidents and derailments. A navigation software specially designed for an intra-rail network- where each locomotive is connectable- needs to be developed.

5) How GPS Tracking System Works

The main functionality of a GPS-based tracking system comes from the Global Navigation Satellite System (GNSS) network. This network of satellites emits microwave signals sent to a GPS device installed in each locomotive. Information broadcast includes location, speed, direction, idle time, and diagnostics. The data is transmitted via wireless or cellular network through government providers like BSNL or ISRO, to a server that acts as the "cloud" accessible on the smart display.

The tracking device will be installed into a loco motive (or piece of equipment or asset) to gather all sorts of information including speed, idle time, diagnostics, etc. It uses Global Positioning Systems (GPS satellites) to know the device or loco motive location at all times. The information that is gathered from the device is then stored on the device inside.

The data will be then transmitted by using a wireless, or cellular network through government provider like BSNL or with the help of ISRO. It travels over one of these cellular networks back to a server. The server acts as the "cloud" that will allow to access information on smart display.

As we know even now, we can track real time running status with an accuracy of 10 meters, and latency of 2 minutes of loco motive of a single rail at a time. On 8 th Jan, 2019. RTIS (real time train information system), first device installed in the Indian locomotive that detect the position and speed of train by using GAGAN geo-positioning system developed by ISRO. But our vision is to connect each locomotive in a single mapping system and accessible to pilots with the help of smart displayable screen

Figure 11: Official railway track map edited to show real-time GPS tracking of multiple locomotives in a single map frame: (a) terrain view, (b) satellite view. Black navigation arrow = host locomotive; Red arrows = other locomotives.

As of now, real-time running status can be tracked with an accuracy of 10 meters and a latency of 2 minutes. On 8 January 2019, RTIS (Real Time Train Information System) was first installed in an Indian locomotive, detecting position and speed using the GAGAN geo-positioning system developed by ISRO. The vision of this project is to connect each locomotive in a single mapping system accessible to pilots via a smart display screen.

6) Business Case Development

In 2021-22, a total of 35 "consequential train accidents" were reported; railways incurred a loss of Rs 6,875.42 lakh (provisional) due to these accidents, encompassing loss of human life, human injury, loss of Railways' property, and interruption to rail traffic. As per RTI data, 13 out of 35 consequential accidents were reported in the first three months of 2022. Rail-rail accidents and derailments remain among the major problem categories.

On 8 September 2021, per the Supreme Court's order, Railways are liable to pay compensation for late arrival of trains if delay is not explained or justified. On 12 August 2020, Railways released an official draft with rules for private entities where delays or early arrivals were key compliance points.

Our real-time navigation software with multiple locomotives in a single frame can reduce loss to railways infrastructure and reduce operational delays. Wabtec and similar companies can sell this developed software to private/government railways, creating a strong commercial proposition.

7) Working Model for Multi-Locomotive Navigation Software

We can develop the required software for the railway sector by making targeted modifications to the base code of real-time GPS-based tracking software, tailored specifically to the intra-rail network where each locomotive is connectable and visible on a unified map display for the pilot.

2. Conclusion

A combined approach that links an adaptive smart display, electrochromic glazing, thermal vision, onboard processing, and shared locomotive navigation data can substantially strengthen railway safety in conditions where conventional sight lines fail- particularly in fog, rain, and complex track geometry. By activating the electrochromic layer to block partial and scattered light, routing real-time thermal infrared imagery to the cab-mounted display, and applying proven deep learning-based object detection frameworks such as Faster R-CNN, FR-Net, and YOLOv8, the loco pilot receives clearer, actionable cues about obstacles and track conditions in real time. Recent research confirms that YOLOv8-based systems achieve mAP values above 96% for railway obstacle scenarios [16], validating the AI detection layer proposed in this work.

Extending the system into a networked, map-based intra-rail navigation layer adds another safety barrier by improving awareness of nearby trains, relative speeds, and upcoming curves — directly addressing common causes of collision and derailment. This vision aligns with and complements Indian Railways' Kavach 4.0 Automatic Train Protection system (approved by RDSO in 2024) [20], which provides loco-to-loco communication and automatic braking. While Kavach operates on RFID and radio infrastructure, the proposed intra-railway GPS navigation display adds a pilot-accessible visual map interface that Kavach currently lacks, making both systems complementary rather than redundant.

For deployment, practical priorities include: rugged hardware selection suited to locomotive vibration and temperature ranges; reliable cellular or ISRO SATCOM coverage for GPS data transmission; latency control in the image processing pipeline; dataset quality representative of Indian railway environments (lighting, track geometry, fog density); and careful validation to reduce false alarm rates. With these elements treated as engineering requirements rather than afterthoughts, the concept can evolve from a demonstration model into a scalable safety and operations product- delivering measurable benefits for infrastructure protection, service punctuality, and overall risk reduction across India's railway network.

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