Computer Vision as Part of an Advanced Train Control System

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Contribution to the State of the Art

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Abstract: The article addresses the key issues related to the application of computer (machine) vision as part of an advanced train control system. The authors describe the architecture of a multi-layered train control system that uses computer vision as a key element of autonomy and automatic detection of obstacles on track ahead the train. The article provides some overview of computer vision sensors, key stages of dataset preparation for onboard perception, and some issues related to sensor calibration.

Keywords: automatic train control system, computer vision, artificial intelligence (AI), machine learning (ML), datasets, RAMS, SIL, sensor calibration.

The basic principles of the development of advanced train control and protection systems were defined as early as at the beginning of the XXI century. In terms of safety and infrastructure access requirements, they are based on the RAMS (Reliability, Availability, Maintainability, Safety) principles described in the IEC 61508 and EN 50128 standards. In that sense, the train control systems are quite conservative and are designed according to the "safety above all" principle. This approach is based on the method of evaluating the risk of failure per each safety function and defining target failure indicators (both random and systematic) based on the criteria of probability and severity of consequences. The failure targets are conventionally named SIL (Safety Integrity Level), where the highest requirements are specified for SIL 4, for which the probability of wrong-side failure is between 10^{-8} and 10^{-9} [1].

Currently, technological innovations are widely tested and deployed as part of train control systems (TCS). Those include artificial intelligence-based control elements as part of unmanned train control systems that do not completely comply with the adopted RAMS methodology, which requires its possible modification along with a whole number of regulations and operating instructions. Despite the certain conservatism of the railway industry the migration from niche solutions to a mass use of COTS appears to be inevitable, as otherwise it is impossible to reduce the time and cost of innovation deployment [2].

Today, development, testing, and deployment of such innovations are conducted as part of the general digital transformation of the railway industry, one of the key elements of which is the evolution towards robotised train control processes (cyber physical transportation systems) that implies the minimisation of human involvement in the business processes and complete replacement of humans in routine operations [3]. The objective is the transition to command and control 4.0, meaning that all trains are covered by a single broadband communication network, while each smart train continuously calculates its own safe distance to go and controls its speed accordingly based on precise knowledge of its current coordinate and information on the operating situation (location of other trains, status of track and signalling assets) received from a smart TMS [4].

The key point is the migration of the railway infrastructure functionality onto on-board trains (the concept of "smart train"). For instance, while in the past the absence of obstacles and foreign objects on the track ahead of a train could only be guaranteed (partially) by fencing the tracks, now that can be done through the use of a computer (machine) vision system installed at the head end of the train and additionally, if necessary, on the track itself in particularly hazardous locations [5].

The computer vision system (CVS) is to ensure timely detection and classification of foreign objects ahead of a train for the purpose of making a decision as regards the appropriate reaction of the onboard train control system (whistle, speed reduction, emergency braking, etc.). The CVS can play the role of a smart assistant if a human driver is present in the cab or of the primary automatic obstacle detection facility. Over the last few years such systems have been tested in several locations in Russia and other countries.

The onboard CVS consists of a set of sensors of varied nature and purpose, as well as high-performance, large-memory computer systems that process the signals of such sensors in real time using machine learning algorithms (Fig. 1). The above sensors include lidars, video cameras, 3 – 7 and 7 – 14 um thermal cameras, short range ultrasound sensors. Cameras and lidars are used at different ranges, i.e., short (up to 50 – 100 m), medium (up to 500 – 600 m) and long (up to 1000 – 1500 m). The settings are chosen depending on the function of the rolling stock. Shunting engines operate within a short range, commuter trains operate within the medium range, while long-range trains are additionally outfitted with long-range sensors. The sensors operate in various ranges of the electromagnetic spectrum, have their advantages and drawbacks that can manifest themselves under different conditions of lighting, humidity, etc.

Despite the active testing and application of the above systems a whole number of open questions remains regarding the use of computer vision as part of advanced train control systems. For instance, the question remains as to the method of proving the safety of an CVS as part of an TCS, including the definition of SIL for such a system. Obviously, the application of artificial neural networks does not allow classifying a CVS as a system with a high safety integrity level (SIL4). Meanwhile, the many tests conducted on CVS show that the capabilities of machine vision definitively surpass those of a human eye in terms of obstacle detection at various distances and under different lighting conditions.

For the purpose of ensuring safety and certifying a TCS that includes a computer vision system, some experts suggest dividing such TCS into a safe part (safety kernel) in the form of an onboard safety device that operates within a safety envelope, and a computer vision subsystem that operates within a separate control loop (see Fig. 2) [6].

Meanwhile, a TCS can be complemented with an additional element that fulfils the function of super-

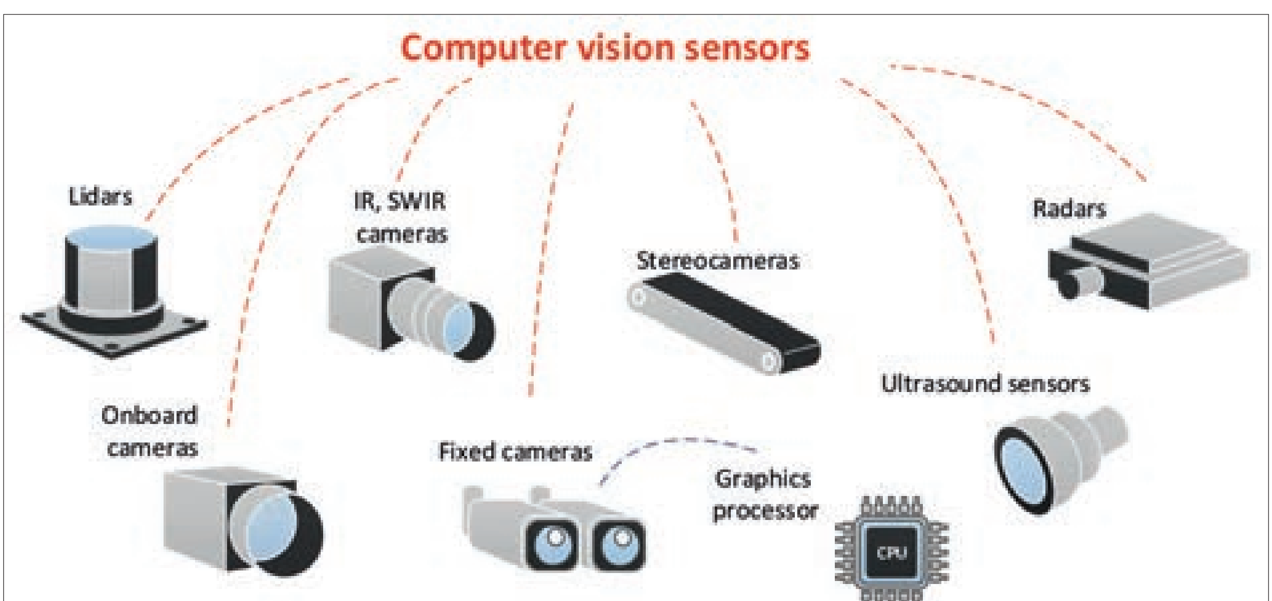

Fig. 1. *Computer vision system with various types of sensors*

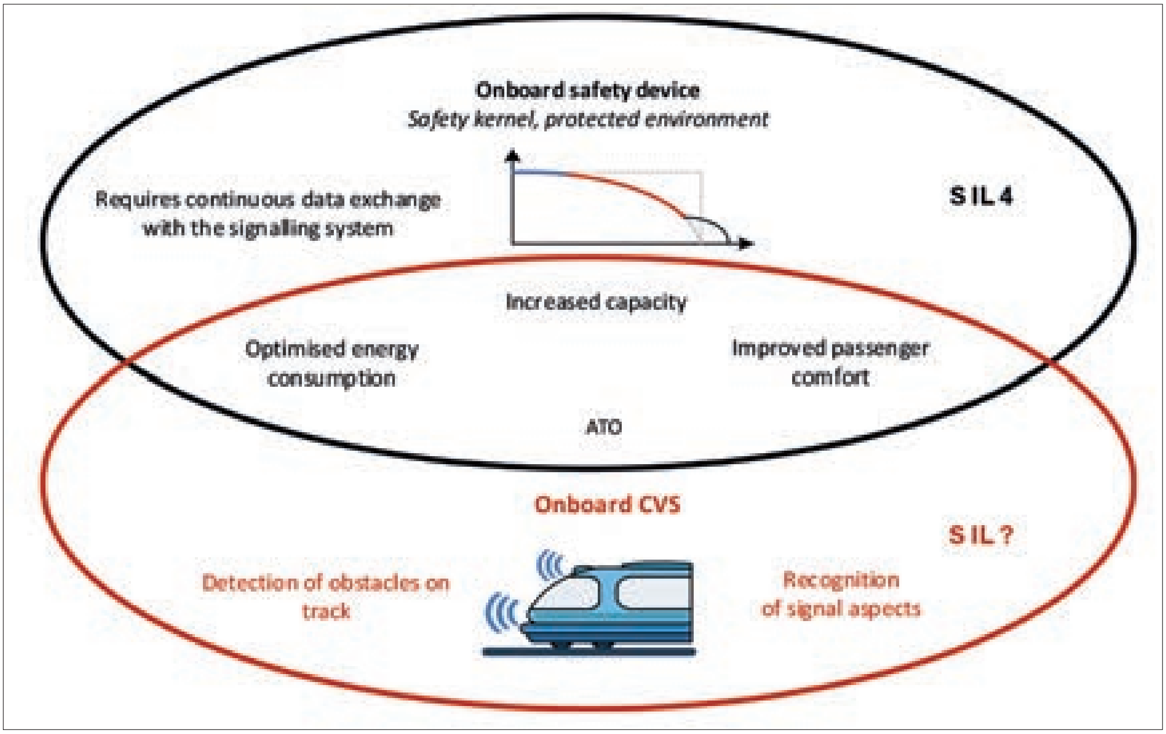

Fig. 2. *Diagram of an advance TCS with smart control*

vision and restriction. In most cases, a remote operating driver is considered as such an element that makes decisions in case of disparity of data between the control loops, yet other, completely automatic, solutions are examined as well [7].

As an example, let us consider the diagram of the TCS implemented on the Moscow Central Circle (MCC). The MCC TCS is designed as a multi-loop control system that supports two control modes, "autonomous" and "remote control". In Fig. 3, the red

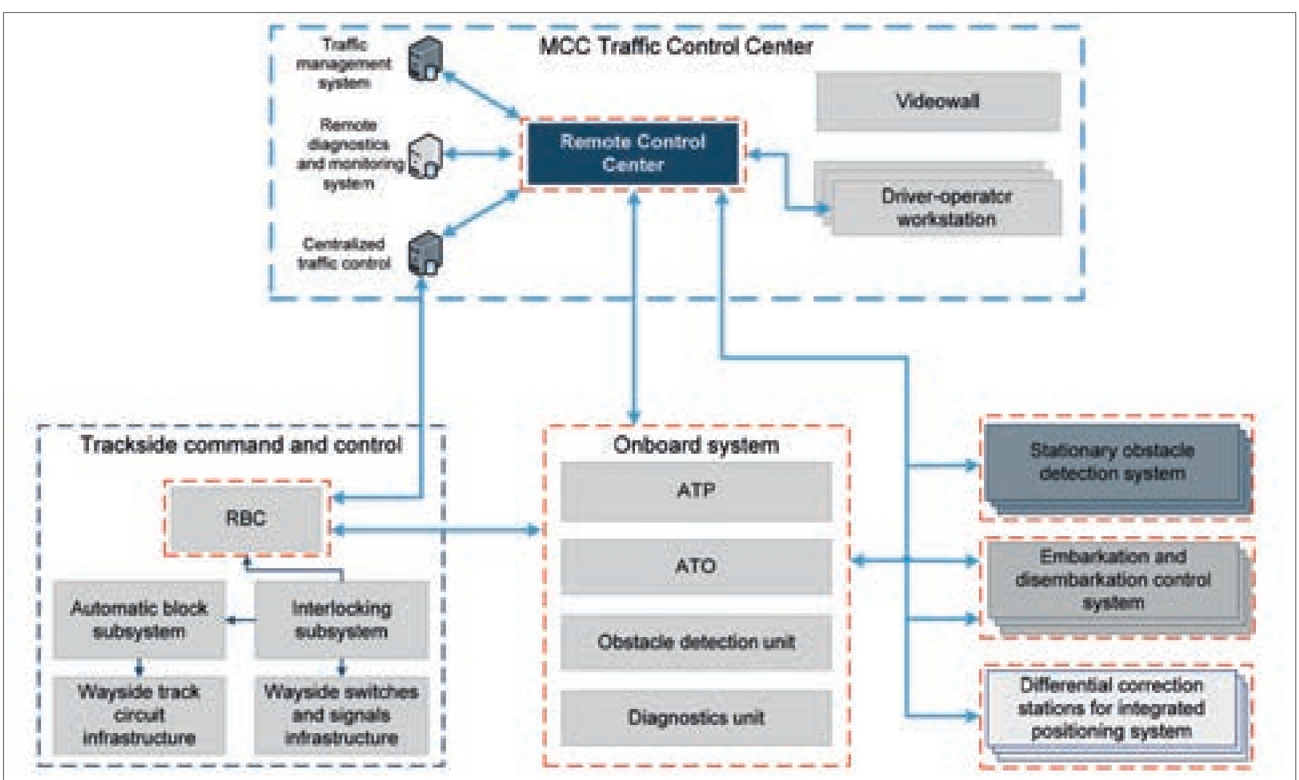

Fig. 3. *General diagram of the MCC TCS*

dashed line shows the subsystems that constitute the safety envelope of the GoA3/4 mode [8]:

The MCC TCS, besides the conventional coded track circuit-based automatic cab signalling, implements radio-based interaction between the trackside and onboard train control systems. Additionally, within a separate control loop, obstacles are automatically detected using onboard and fixed visual detection devices using artificial neural networks with the communication of the collected information to the Remote Supervision and Control Centre (RSCC).

Standardisation and automation of the preparation and verification of datasets for CVS sensors, as well as selection, testing and calibration of machine vision devices remain a question [4].

The process of dataset preparation for CVS includes the creation of digital models of railway lines and training of an artificial neural network to recognise objects. Normally, digital models are created by processing arrays of data obtained using laser scanning and video recording of railway lines during test rides. Besides input data obtained from the sensors, datasets contain target output data. Supervised learning aims to identify the required correlations between the input and output data. A CVS is to recognise not only infrastructure assets, but non-stationary objects (both static, and dynamic) at different distances and in different configurations and positions, namely, people of different age and gender, animals, trees on the track, vehicles, etc.

In case of unsupervised learning, the machine learning algorithms are used for the purpose of analysing and clustering of sets of unlabelled data. The creation (the so-called “annotation” or “labelling”) of correct target output data (labelled data) is normally done by people, which is labour-intensive. Various ways of automating data labelling for CVS are being examined [9].

Correct identification and semantic segmentation of objects (people, cars, trees, buildings, etc.) affects the operational safety of unmanned railway transportation. Reliable and efficient operation of CVS also requires accurate setting, calibration and continuous verification of the machine vision sensor outputs. The existing calibration methods are largely inefficient and unreliable and often cause reduced accuracy and increased error in the operation of the sensors. If CVS are mass-deployed as part of TCS, a whole number of issues will need to be resolved that deal with the organisation of the calibration and verification of CVS sensors as a measuring instrument with the development of an industry-wide method in accordance with GOST R 8.879-2014 [10].

One of the key difficulties as regards the calibration is the comparison of the data collected by sensors of different nature: a set of spatial points collected by a lidar and images collected by cameras. Therefore, calibration requires a special calibration stand including one or several calibration objects (markers) and equally well-identifiable both on a visual image, and within a point cloud, which will allow using its acquisitions as input data for calibration. A synchronised verification of data collected by all types of sensors – video cameras, lidars and thermal cameras – is to be provided for as well, including when an autonomous train operates in automatic mode.

The use of machine vision as part of advanced TCS is becoming a key and long-lasting trend in the development of modern control systems, which defines a wide range of engineering problems that require a comprehensive approach. Their efficient solution will define the mass migration towards completely automatic train control (with no driver) that is primarily enabled by the guaranteed level of safety that is at least not worse than the current one.

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