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Approaches to Creating a Driver Decision Support System for Digital Analysis of Railway Infrastructure Based on Machine Learning and Machine Vision Algorithms

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Abstract. The paper considers the issues of creating a driver decision support system for digital analysis of the railway infrastructure based on machine learning and machine vision algorithms, which will take into account and analyse the given traffic schedule, infrastructure capabilities, dispatch centre teams, statuses of the nearest traffic participants for unmanned safe control of electric rolling stock. A detailed review of existing control systems in railway transport is made, which are based on technical vision.

1 Introduction

Today, in accordance with the priority areas for the development of science, technology and technology in the Russian Federation, as well as the Strategy for Scientific and Technological Development, an early transition to advanced digital intelligent control systems based on machine learning and artificial intelligence is necessary. For railway transport, this issue is especially relevant and is largely related to the issues of improving the energy efficiency of electric rolling stock with a simultaneous increase in traffic safety.

In the context of the implementation of the "Digital Railway" concept, the solutions of the above tasks reach a new level and must comply with the following requirements of the "Digital Railway" concept [1, 2]:

- Implementation of technological processes for servicing infrastructure and organizing a system of "unmanned train traffic" based on the creation of a digital infrastructure model based on a geocentric coordinate system.
- Unification of traffic control systems for suburban trains and metro trains in large metropolitan areas.
- Creation of a new generation of onboard security systems using computer technologies with elements of artificial intelligence.
- Development of a regulatory framework and technologies for collecting and processing information.

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To improve traffic safety during the operation of rolling stock, various technical means are being introduced, including on-board ones that monitor the state of the infrastructure, the presence of various obstacles along the route, the busyness of hauls, etc. One of such means is the systems of technical vision, the research of which is carried out by many world scientists [3 – 7].

Companies involved in this area in Russia LLC "TMH Intelligent Systems", LLC "AVP TECHNOLOGIA", LLC "Smartvis" JSC "NIIAS", JSC "VNIIZhT" and Cognitiv Pilot. Abroad, these are TTG - Energymiser (Austria, Great Britain, France), RCS -ADL (Switzerland), LEADER (Germany), AVV AZD (Czech Republic), CUBRIS - GREENSPEED (Denmark), Trip Optimizer (USA), EBI Drive 50 (Canada)), CATO – TRANSRAIL (Sweden), FALKO (Germany), Viriato (Switzerland), TRENOPLUS (Italy), TrueLine (Japan).

Technical vision is inextricably linked with various methods and means of image processing, and various methods can be used to solve the same problem. For railway transport, technical vision issues are not simple, for example, the detection and recognition of a traffic light signal on a line is complicated by the fact that the signal of interest to us occupies a very small image area. Traditional image processing methods do not achieve the desired result, they are prone to errors, especially at high speeds and contrasting backgrounds.

Currently, convolutional neural networks with strong learning capabilities are used for recognition, but such methods often require a large number of training samples, which are also publicly available to avoid the risk of overfitting.

Most methods still use signal colour a priori to derive the area of interest in different colour spaces, and then make further judgments based on the signal's unique shape and angle characteristics.

2 Formulation of the problem

A universal solution for solving various problems, which are conventionally grouped into four groups [8]: object detection, inspection, measurement, identification. All four groups, one way or another, use rail transport.

Position recognition. Today, the creation of digital twins and a map of space is more relevant than ever. When managing rolling stock, it is important to understand position relative to other entities such as infrastructure, rolling stock encountered, and position information transmission in a control or controller system (Fig 1).

Fig. 1. Digital map of the railway space.

1) Inspection. A function that allows you to confirm certain properties of an object, such as the state of brake pads, the presence of defects in the car body, etc. So, at the initial stage, objects are classified, the object being diagnosed is identified from a variety of other objects, and the defect is determined based on trained neural networks (Fig. 2).

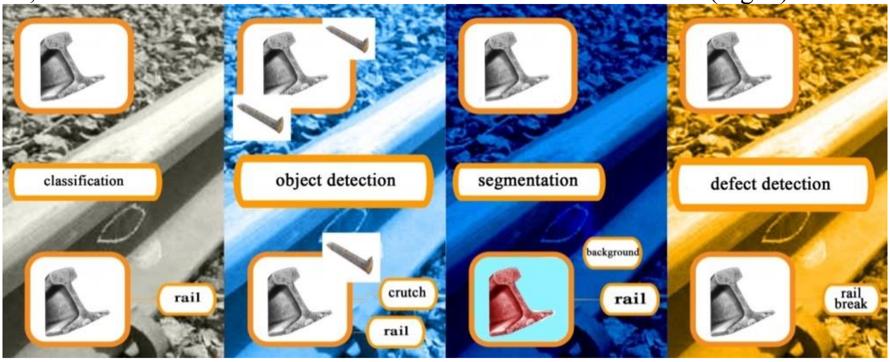

Fig. 2. Finding a defect in rails.

2) Measurement. Installed video cameras measure the dimensions of the rolling stock, the position of automatic couplers with the possible transmission of information both to the driver's screen and to the relevant structural subdivisions of the road in case of deviations from the norm (Fig. 3).

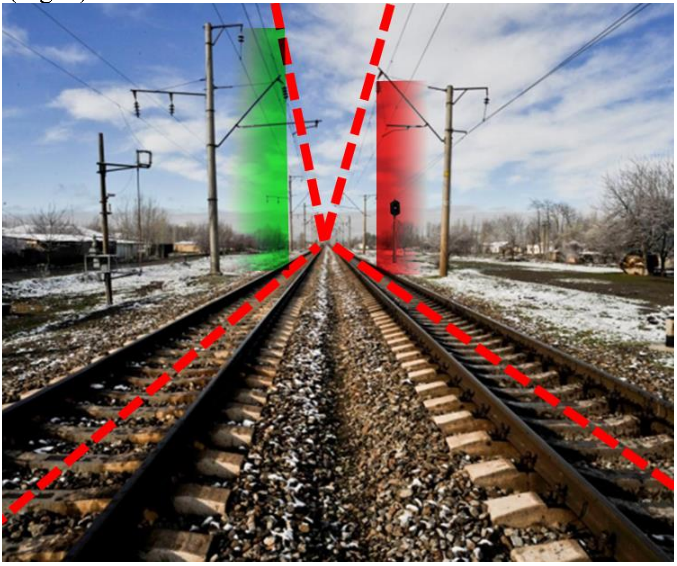

Fig. 3. Measuring the dimensions of the approximation of buildings.

4) Identification. In this task, based on artificial intelligence, traffic signals, personal identification for security purposes, various bar codes, and obstacles along the route are recognized (Fig. 4).

Fig. 4. Railway traffic light identification.

3 Solution options and methods

Let's consider an example of the implementation of the personal identification function for security purposes when proceeding to various railway facilities, including rolling stock. For implementation, we will use the Matlab software package with a large set of different computer vision functions, including the possibility of deep learning of neural networks.

To solve the problem, we will use the Lucas-Kanade and Viola-Jones algorithm, which is widely used in computer vision [9, 10]. The basis of the Lucas-Kanade algorithm is the statement that in the local neighborhood of each pixel the value of the optical flow is the same, so you can write the basic equation of the optical flow for all pixels in the neighborhood and solve the resulting system of equations using the least squares method. The Viola-Jones algorithm uses a variation of the AdaBoost learning algorithm [11] for both feature selection and classifier tuning. In Matlab, the example code would look like this:

```
faceDetector = vision.CascadeObjectDetector();
videoFileReader = vision.VideoFileReader('C:\Users\25.jpg');
videoFrame = step(videoFileReader);
bbox = step(faceDetector, videoFrame);
videoFrame = insertShape(videoFrame, 'Rectangle', bbox);
figure;
imshow(videoFrame);
title('Detected face');
bboxPoints = bbox2points(bbox(1, :))
points = detectMinEigenFeatures(rgb2gray(videoFrame), 'ROI', bbox);
figure, imshow(videoFrame), hold on, title ('Detected features');
plot(points);
```

After the implementation of the code, we determine the admission or prohibition to control the rolling stock (Fig. 5).

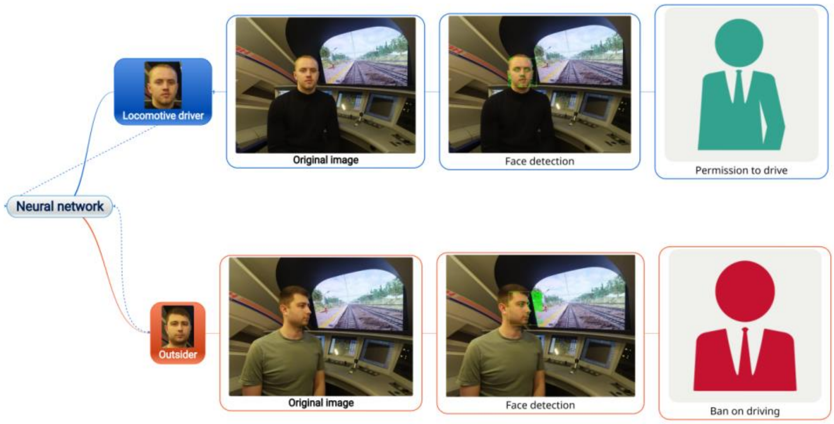

Fig. 5. Raw input image and image with match markers.

The task of determining the signal of a traffic light, its type, other infrastructure objects is somewhat more complicated and requires preliminary preparation of an image of railway objects in order to train a neural network, classify all objects, adjust the size in accordance with the network, perform randomized addition (rotation, color, etc.) to existing files. One of the most time-consuming processes is the need to mark the corresponding objects on each image or frame of the video sequence with the corresponding markers (Fig. 6).

Fig. 6. Raw input image and image with match markers.

To speed up the work, you can use the application of the Matlab system - Automated Driving System Toolbox.

To create a simple neural network, it is also possible to use the Deep Network Designer, which has great machine learning capabilities in order to create computer vision for railway transport (Fig. 7).

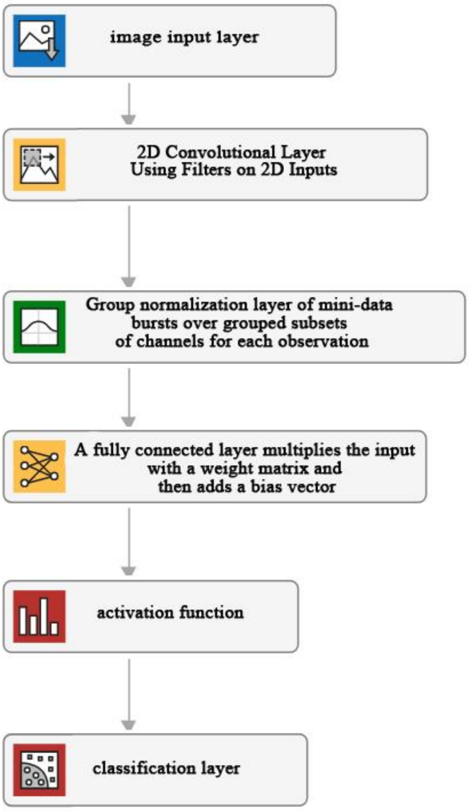

Fig. 7. An example of a network architecture of a convolutional neural network.

4 Conclusion

Thus, the considered options for the implementation of technical vision should improve the safety of traffic on the rolling stock. The variety of options for solving the tasks set speaks for the need for a more detailed analysis of technical solutions, their improvement and testing on the country's railways.

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