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Machine Vision Technology for Locomotives to Identify Railway Colour-Light Signals

Vitaly A. MINAKOV

Valentin K. FOMENKO

***Minakov, Vitaly A.,** Omsk State Transport University (OSTU), Omsk, Russia.*
***Fomenko, Valentin K.,** Omsk State Transport University (OSTU), Omsk, Russia*.*

ABSTRACT

Improving quality of transport and logistics services in modern conditions is associated with introduction of new technology and improvement of existing technologies of informatization and digitalization of transport. A particular task of introducing digital technologies into the technological processes of railway transport is to increase safety of train traffic.

The analysis of the works of domestic and foreign authors on issues of improving safety of train traffic revealed that at present there is a task of introduction of digital devices for analyzing infrastructure objects along the route of a locomotive. This is of importance when increasing speed of trains or when the trips are long, and it is difficult for a person (a driver) to correctly assess the situation and make a right decision.

The objective of this work is to develop a method for automatic monitoring of railway infrastructure facilities, by equipping the locomotive with machine vision technology, namely, to ensure the ability to visually control the indications of railway colour-light signals along the route. The locomotive is equipped with a video module for fixing the streaming image along its movement, and with the microprocessor equipment for analyzing the resulting image. As an algorithm for recognizing railway signals in a fixed image, a mathematical apparatus based on models of convolutional neural networks is used.

The work performed showed good results in identifying colour-light signals in the analyzed images. Equipping traction rolling stock with technical vision will allow timely identification of track signals, this is especially important on railway tracks where there is no coding in the track circuit, which helps to increase the level of train safety. The development of the presented technology contributes to digitalization of railway transport, which makes it competitive in the world market.

Keywords: railway, locomotive, machine vision, signalling, traffic safety, machine vision, convolutional neural networks.

*Information about the authors:
Minakov, Vitaly A. – Ph.D. (Eng), Associate Professor of the Department of Locomotives of Omsk State Transport University (OSTU), Omsk, Russia, vitalya_13@mail.ru.
Fomenko, Valentin K. – Ph.D. (Eng), Associate Professor of the Department of Locomotives of Omsk State Transport University (OSTU), Omsk, Russia, fomenkovk@mail.ru.

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Background. Machine vision is a subsection of engineering, namely it is a general set of methods that allow computers to «see» using digital cameras. Today, machine vision is an integral part of many automated processes. The scope of its implementation in transport field is varied, for example, it is intended for identifying car plates or for counting people in vehicles. The tasks of machine vision is the analysis of images or video stream.

International companies, such as Siemens, Rio Tinto, General Electric, show great interest in development of machine vision for railways. They proposed systems that allow for automated visual monitoring of the condition of track, monitoring the technical condition of systems in real time, and automated control of autonomous locomotives.

Machine vision is significantly important for ensuring growth of traffic safety, particularly through modernization of existing signalling systems.

If we address practices used in Russia, the main device of railway equipment in ensuring traffic safety and increasing transit capacity of the railway network of the Russian Federation is an automatic continuous locomotive signalling system (ACLSS). When a train (locomotive) is moving, ACLSS, through a continuous communication channel which is provided by rails, receives encrypted information about the readings of the forward light-colour signal device. The ACLSS operation consists in transmitting the readings of track colour-light signals to a locomotive colour-light device and to devices monitoring the vigilance of the driver, controlling traffic speed, providing automatic train stop, etc. [1].

On sections of the railway track where temporary track signals are located, or there is no coding of the railway track (lack of a coded electrical signal in the rail circuits), the signal readings are not transmitted to traffic safety systems of traction rolling stock, thus reducing the level of safety when a locomotive moves within a given section.

In such cases, the function of additional control can be carried out using modern computer monitoring tools by equipping traction rolling stock with machine vision.

The *objective* of the work is to develop a technology for visual control of readings of railway signals by locomotives. Equipping a locomotive with machine vision technology will allow it to «see» railway signals, while visual analysis methods based on a convolutional neural network will allow it to identify their readings.

The use of machine vision for locomotives to visually control railway signals will allow detection, classification of objects and tracking their condition. Using this approach, railway signals will act as objects, and readings of railway signals will serve as a classification attribute. It should be noted that the use of machine vision can only be used as an additional control, together with ACLSS system, to eliminate errors that periodically occur in the rail circuit [2].

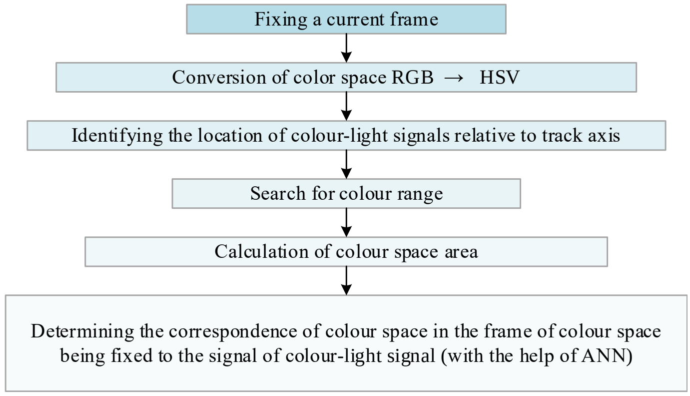
When traction rolling stock moves along a section of a railway track, a video control device captures a digital image along the train route. The zone of machine vision is determined depending on technical requirements and operating conditions. Interval capture of a digital image within the control zone (locomotive vision zone) will allow for detection, tracking and classification of railway infrastructure facilities.

The analysis of a fixed frame (digital image) of railway signals is carried out by technical means using various libraries of open source code algorithms. The search for correspondence of colour components in a digital image, when identifying certain railway signals, consists in analyzing each pixel and determining colour clusters, followed by pattern recognition using artificial neural networks.

TASK SETTING

The tasks of machine vision technology for locomotives is to develop algorithms for analyzing colour space, determining the location of colour-light devices and identifying them in a digital image.

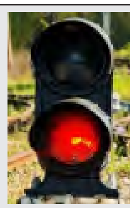
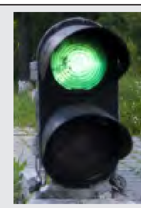
The difficulty in identifying railway signals is that the background medium is not monotonous and is changing during the image analysis period. Therefore, the value of the railway signal cannot be segmented from the background by the difference in colour. The colour model RGB (*red, green, blue*) has many limitations when used to describe colour [3]. Unlike *RGB*, the *HSV* (hue, saturation, value) colour model is less sensitive to the external environment, to brightness of light and shadow, it is easier to separate it from the background. One of the tasks of the algorithm (Pic. 1) is the



Pic. 1. Algorithm of machine vision technology. Authors' design.

Table 1

Correspondence of identified signals of a colour-light signal device to the colour space[1]

Colour space			
RGB (red, green, blue)	{255, 0, 0 ÷ 100, 50, 50}	{0, 0, 255 ÷ 50, 50, 100}	{0, 255,0 ÷ 50, 100, 50}
HSV (hue, saturation, value)	{0, 155, 155 ÷ 15, 255, 255}	{255, 50, 50 ÷ 255, 100, 100}	{120, 155, 155 ÷ 150, 255, 255}

[1] According to the authors' data.

conversion of a fixed frame from RGB to HSV space and their comparison with a range of identifiable colours. An identifiable colour is the ratio of the colour palette to which the colour range of the signal pointers belongs.

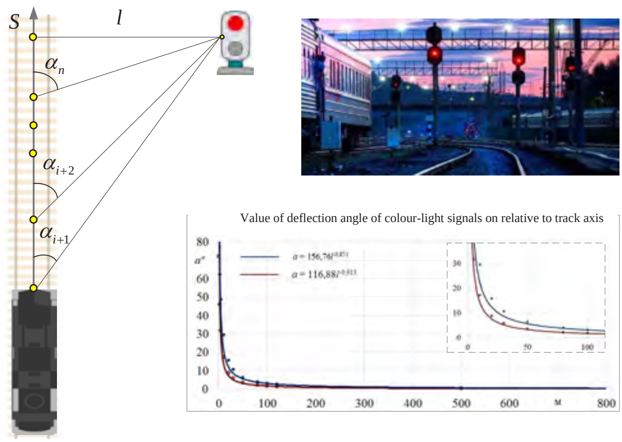
Thus, to search for a colour palette corresponding to the identified signals of colour-light device, the range of the colour model in HSV is set. When identifying a colour palette, it is necessary to determine the area of the colour space to exclude random glare, interference, and noise in the captured image. This area parameter is set empirically when developing the algorithm (Table 1).

When controlling the railway light signalling using the machine vision method, while the locomotive is moving along station tracks, it is important to fix the machine vision on the colour-light signal device that is intended for the track, along which the train moves. This becomes a difficult task, since the colour-light signals in the station are located at a small distance from each other, and in the process of image analysis, identification of «alien» signal device is probable. To determine «one's own» colour-light signal device, knowing the distance to the signalling device (l) according to the devices controlling locomotive's motion parameters, and the remoteness distance of the device from the track (S) [2], the angle between the line of sight and the light indicator is calculated by the formula:

$$tg\alpha = \frac{l}{S}. \qquad (1)$$

Thus, the search area for the light signalling is determined, which also reduces the number of operations required to detect an object in the image. Pic. 2 shows the identification pattern and the results of calculating the angle of the line of sight, considering the location of colour-light signals at the station.

A method of processing digital images is based on machine learning methods using a convolutional neural network (CNN) of deep learning, which is an effective tool for pattern recognition [4; 5]. The convolutional neural network consists of two blocks: the first is responsible for selection of features (attributes),



Pic. 2. Determining attribution of a colour-light signal to the track that the locomotive uses. The authors' picture is based on the work [2].

and the second one is responsible for their classification.

The input data for training the neural network are segmented images of track colour-light signals installed on the public tracks (we use the example of Omsk station for illustrating the described case). Image data is divided into two subgroups: training subgroup and test one. The total number of samples is more than 500 images.

To learn CNN, standard methods for calculating the values of each neuron according to the formulas [6; 7] are accepted:

$$x_j^l = f\left(\sum_i x_i^{l-1} w_{i,j}^l + b_i^{l-1}\right), \qquad (2)$$

where x_i^l is map of attributes j of the output layer l;

f is activation function;

b_i^l is shear coefficient of the layer l;

$w_{i,j}^l$ are weight coefficients of the layer l.

As an activation function are accepted [8; 9]:

– for hidden layers, the *ReLU* (*rectified linear unit*) function:

$$f(s) = \max(0, s); \qquad (3)$$

– for the output layer the *softmax* function:

$$f(s) = \exp(q_i) / \sum_{i=1}^{m} \exp(q_i), \qquad (4)$$

where q_i is signal of the i-th neuron.

To measure the quality of recognition of the objects in the image, the root-mean-square error function is used:

$$E = \frac{1}{2}\sum_{i=1}(t_i - y_i)^2, \qquad (5)$$

where t_i is desired result of the i-th neuron;

y_i is output signal of the i-th neuron.

To reduce the number of network retraining cases, which can be estimated in a thousand eras, the Dropout regularization function is applied, i.e. the network structure is changed by each neuron's ejection with a certain probability p. In general, a function is described as:

$$f(s) = D \cdot f(s), \qquad (6)$$

where D is dimensional vector of random variables.

A convolutional neural network for searching for light signalling in digital images is implemented in the Python 3.6 programming language using open access libraries, e.g. Keras, NumPy, TensorFlow, Scikit-learn [2], which have the ability to stream data.

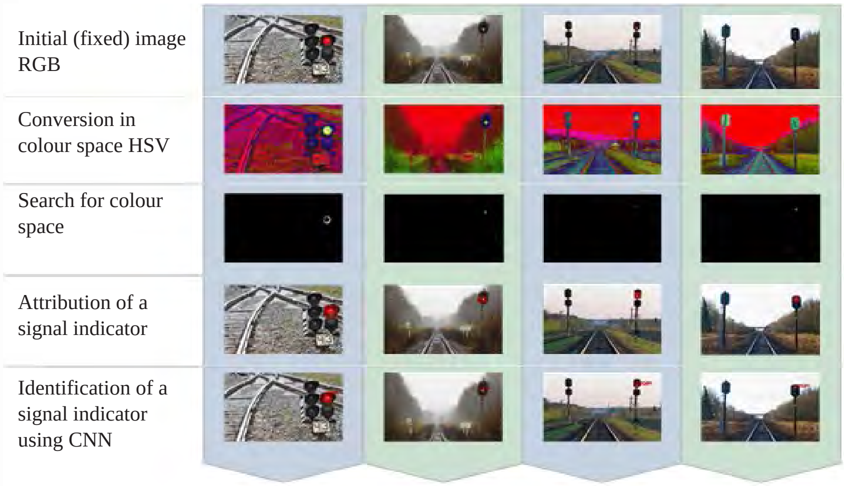
Results.

According to the results of the training of the developed CNN, estimates of accuracy of the response were obtained, for the training sample the estimate is of 88,3 %, for the test one it is of 87,15 %.

An algorithm has been developed for the technology of machine vision, extended from the moment of fixing the current frame (image) to identifying the presence of a colour-light signal in it, shown in Pic. 1.

As an example, test evaluations of the developed technology were carried out, digital images of the stop signals of colour-light signals were used, which had not been previously used in the training of CNN. The results are presented in Pic. 3.

Improving the quality of CNN assessment for identifying colour-light signals in the analysed images is possible by changing the number of convolution layers, increasing the digital images of the training sample, and



Pic. 3. Testing results of the developed technology. Authors' picture.

improving the quality of the analysed images [10].

Conclusion

The developed algorithm based on the convolutional neural network provides finding, selection and identification of the readings of colour-light signals. The use of on board machine vision technology will allow computer monitoring of railway signals, both temporary and constant ones, increased vigilance of a locomotive driver, which is an integral condition of train traffic safety.

Currently, the department of locomotives of Omsk State Transport University works carries out research to solve the problem of tracking and identifying objects under various transformations related to railway signals, technical devices of rolling stock, fixed movable units, and other devices, as a further development of the described study.

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НОВАЯ ГЛОБАЛЬНАЯ СЕТЬ КОСМИЧЕСКОЙ ПОГОДЫ ДЛЯ АВИАЦИИ

В ноябре 2019 года введена в действие новая служба круглосуточного непрерывного предоставления обновлённой информации о глобальной космической погоде в режиме реального времени.

Новая служба будет генерировать и предоставлять международной авиации консультативные сообщения о космической погоде, используя существующую авиационную фиксированную службу и данные, полученные от целевых глобальных центров космической погоды, созданных в 14 странах: консорциум с участием Австралии, Канады, Франции и Японии (ACFJ); консорциум PECASUS с участием Австрии, Бельгии, Кипра, Финляндии, Германии, Италии, Нидерландов, Польши и Соединённого Королевства; и третий центр, управляемый Соединёнными Штатами Америки.

Не позднее ноября 2022 года также будут созданы два новых региональных центра обнаружения явлений космической погоды. Первый из них будет управляться консорциумом с участием Китая и Российской Федерации, а второй – Южной Африкой. Все глобальные и региональные центры будут уделять основное внимание проявлениям солнечной активности, которые могут потенциально оказывать влияние на связанную с воздушным транспортом высокочастотную (ВЧ) связь, навигацию и наблюдение, основанные на GNSS, а также уровни радиации на борту гражданских воздушных судов.

«Эта новая возможность позволит лётному экипажу и специалистам по производству полётов пользоваться самой свежей информацией о любых проявлениях солнечной активности, которые могут потенциально повлиять на работу авиационных систем или здоровье пассажиров», – отметила генеральный секретарь ИКАО д-р Фан Лю.

На основе материалов ИКАО: https://www.icao.int/Newsroom/Pages/RU/New-global-aviation-space-weather-network-launched.aspx ●

NEW GLOBAL AVIATION SPACE WEATHER NETWORK

A new 24/7 service has been launched in November 2019 to provide real-time and worldwide space weather updates for commercial and general aviation.

The new service will generate and share space weather advisories using the existing aeronautical fixed network for international aviation using data collected from dedicated space weather centers established by 17 countries: the ACFJ consortium of Australia, Canada, France and Japan; the PECASUS consortium comprising Austria, Belgium, Cyprus, Finland, Germany, Italy, Netherlands, Poland and the United Kingdom; and a 3rd center operated by the United States.

Two new regional space weather detection centers are also going to be established, no later than November 2022. The first of these will be operated by a consortium of China and the Russian Federation, and the second by South Africa. All of the global and regional centers will be focusing on solar events which can potentially impact air transport-related High Frequency (HF) communications, GNSS-based navigation and surveillance, and radiation levels on board civilian aircraft.

«This new capability will permit flight crew and flight operations experts to make use of the most updated information possible on any solar events which could potentially impact aircraft systems or passenger health», commented ICAO Secretary General Dr. Fang Liu.

Compiled from ICAO news: https://www.icao.int/Newsroom/Pages/RU/New-global-aviation-space-weather-network-launched.aspx ●