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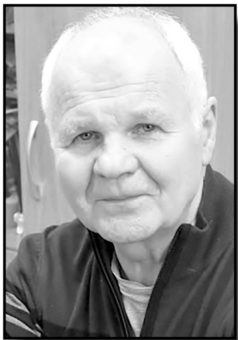
Implementation of Intelligent Monitoring for the Marshalling Yard



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ABSTRACT

The railway marshalling station occupies a central place in the technological chain of freight transportation processes, since the speed of processing trains at marshalling yards determines the volume and cost of transportation. Therefore, development of automation and computerization of sorting processes results in growing efficiency of freight transportation in general.

The objective of the study is to formalize the problem of cars' monitoring within the railway marshalling yard and to develop a method for solving it with the use of algorithms of recognizing and positioning of dynamic objects through the intelligent data analysis of streaming video.

The article presents a new approach to solution of the problem of monitoring moving units in the hump (sorting) yard of marshalling stations. The article suggests core criteria for identifying speed and positioning of the railway wagons when they are running after been separated at the hump. The article specifies that monitoring of moving units at hump yard is less automated in comparison with the monitoring at the hump itself, and that confirms the relevance of the research. To get the problem of the automation monitoring of moving units in the hump yard solved, the authors have suggested an algorithm that is based on the image data intelligent analysis, that is on computer vision, and have described the model of its implementation at a station.

The methods used are based on the theory of computer vision and are aimed at recognizing key dynamic objects in streaming video and at their subsequent positioning.

The study has resulted in substantiation of acceptability of the use of computer vision in the process of separation and formation of trains. It is planned to proceed with further improvement of the presented approach to develop a software product allowing to objectify information about hump yard in order to increase the efficiency of targeted braking at the hump.

Keywords: *transport, railway, classification process automation, classification yard track occupancy, positioning of railway vehicle units, intelligent analysis of video data, digitalization.*

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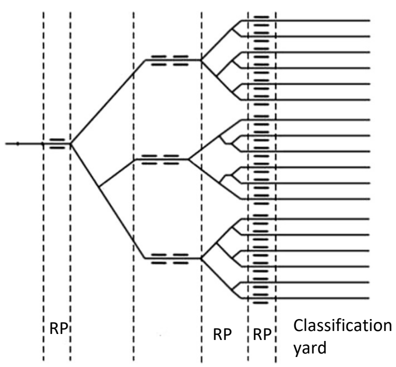
Background. The railway marshalling station is the most important segment of transportation process chain, since transportation costs mainly and directly depend on wagons' idle time spent at them [1]. Growth in efficiency of technological processes at the marshalling yards and hump yards is achieved through improving the IT and automation equipment. The modern automation equipment of classification processes, such as KSAU SP [2], MSR-32 [3], DDC-III [4] *et al.,* provides for complete monitoring of railway vehicle units (identification of a wagon speed and location) while they are moving along the hump yard. After a moving unit leaves the hump towards marshalling yard tracks, the speed is not identified and only the last wagon that enters the yard can be localized, that results in the need for simulation modeling of wagons' motion based on statistical data using manual labour of yard controllers. All this reduces the accuracy and objectivity of monitoring of railcar moving within the marshalling yard and, as a result, causes wagons' collisions at overspeed and probability of appearance of time intervals on the yard tracks, that negatively affects the efficiency of the marshalling process as a whole.

Objective. The objective of the work is to formalize the problem of positioning control of cars when they exit the hump and follow the tracks of the railway marshalling yard with identifying speed of their movement and collision. In addition, the paper presents a method for solving a formalized problem, based on the use of algorithms for recognizing and positioning key dynamic objects on the stage through the intellectual analysis of streaming video data using computer vision.



Pic. 1. Schematic division of the hump yard into control sections with an adjacent classification yard (RP means a retarder position).

Methods. Two groups of computer vision methods are used, the first of which implements recognition of key moving objects against the surrounding background, the second implements positioning of previously known objects on the scene.

Statement of the problem

The current rail marshalling process automation systems [2–5] provide for complete monitoring of railcar groups (cuts) movement in the hump yard when they are passing the control sections (Pic. 1): yard retarder positions (RP) are monitored by radar speed meters, track sections between retarder positions are monitored by speed measurement using axle counter transmitter. The control section equipment permits to precisely determine a wagon's speed, to correlate it with the simulation model received from Automatic Speed Control system and quickly correct brake operation algorithms and algorithms of cut routing systems if needed.

After the cut leaves the wagon retarder yard RP to the sorting track, the speed of the cut and the velocity of its unification with other cars on the tracks is not determined. The calculation is based on the Automatic Speed Control simulation model considering statistical data on the state of the vertical alignment of track, current meteorological conditions, running characteristics of railcars (weight, box type, nominal length).

According to «Procedure for checking the wagon collision speed on the tracks of marshalling (hump) yards» [1], each yard inspector must measure speed of unification of 20 wagons in the hump yard per shift using radar speed meters. Metering accuracy of this device is ±0,2 km/h that is equivalent to 4,3 % of car average speed in the yard.

Number of the cars to be marshalled at large marshalling yard, equipped with two humps, is about 9000 pcs. per day [6]. Thus, 80 wagons measured by inspectors per day (two shifts at two humps) is equivalent to the coverage of about 0,9 % of the number of marshalled wagons. Besides, in poor weather conditions both the quantity and the reliability of the data decrease sharply, which is confirmed by the

[1] Directive of JSC Russian Railways dated August 12, 2010, No. 1735p.

analysis made by the computer-aided classification process control system (KSAU SP) [2]. Due to growing automation of train separation processes, reliable knowledge of the characteristics of movement of mobile units along the tracks of marshalling yards is a must-have for automatic and telemetry control railway units.

With reference to the above, the problem of monitoring the speed of wagons' movement and unification on the tracks of the classification yards when conducting train separation at automated humps is now of great relevance.

By material and performance criteria, the problem solving in the classical way (installation of a group of axle counter transmitters all over the length of the classification yard tracks) is not efficient (the total classification yard track length is on average of above 50 km). To solve this problem it is necessary to develop a tool, which allows monitoring the cuts in the classification yard. Video surveillance cameras mounted on the yard lighting towers can be used as such tool (Pic. 2).

For automatic conversion of video signal into quantitative characteristics of the monitored cars (speed and position), it is proposed to use the intelligent video data recognition method which is a computer vision. It has been already well developed for the commercial railroad freight activities when identifying car numbers [7], when monitoring the railway track conditions [8], when providing the transportation safety [9] and for other activities.

For solving the car movement monitoring problem in terms of computer vision [10] it is necessary to solve two sub-problems:

1. Key object recognition (segmentation);
2. Positioning of key objects within streaming video.

The further sections describe the basic steps toward a solution of the above problems, as well as provide alternative implementation methods.

Key object segmentation

Segmentation problem solution means the key object edge extraction against the environment background. When segmenting moving objects, the edges are determined for entities whose position is different in at least two consecutive frames [11]. Thus, the key object segmentation's first stage is to determine points whose position varies from frame to frame. For its implementation, this article uses the interframe difference (ID) method [12] that suggests to use the difference between the pixel intensities of two consecutive frames I_t и I_{t-1}.In this case, to identify moving points, it is necessary to choose the boundary value of the difference, above which the image area will be assigned to moving objects or to the background, if otherwise (Pic. 3b):

$$I(x,y)=\begin{cases}1, & \text{if} \quad \left|I_t(x,y)-I_{t-1}(x,y)\right|>\tau \\ 0, & \text{otherwise}\end{cases}, \quad (1)$$

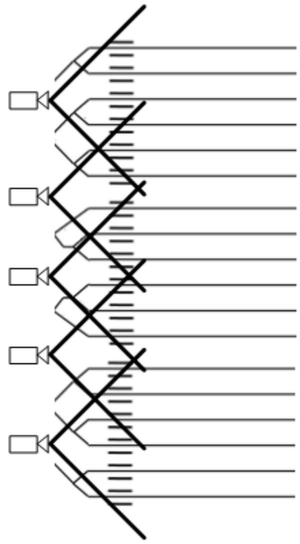
where x, y are pixels coordinates;

τ – boundary value of the pixel intensity difference.

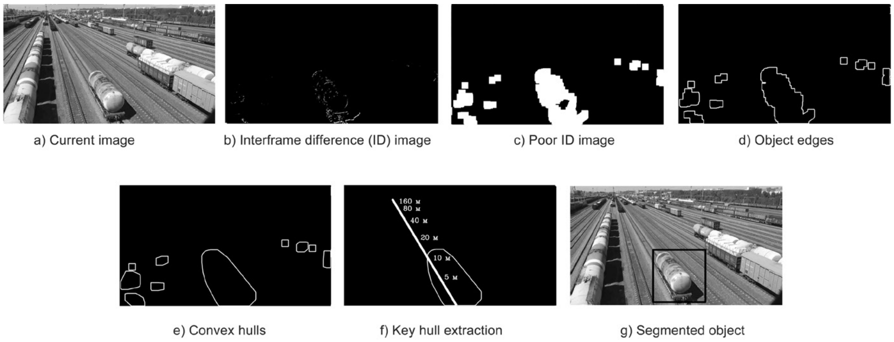
The choice of τ is based on the empirical calculation of the minimum value when background noise is still absent.

The next stage consists in object's edge extraction. For its implementation, this research uses the edge extraction algorithm suggested in [13]. The algorithm essence is to detect the moving object's edge (Pic. 3d) in a morphologically expanded interframe difference image (Pic. 3c), followed by their transformation to convex hulls (Pic. 3d).

The size of the morphological expansion structural block [14] was chosen equal to half the minimum distance (in pixels) between the track concerned and the next one to obtain non-overlapping object's edges. White pixels, which have even one adjacent pixel with zero intensity, are used as edge points. For obtaining



Pic. 2. Arrangement of Video Surveillance Cameras for monitoring.



Pic. 3. Segmentation of the key moving object (wagon) by interframe difference analysis.

the edges as convex hulls, the research uses Jarvis's Algorithm forming a set of edge points $P = \{p_1, p_2, ..., p_n\}$, so that the angle between $p_{i1}p_i$ and p_ip_{i+1} straight lines is maximum.

The resulting edges characterizing the object location have to be classified as key and non-key ones. The edges meeting two following criteria would be considered as key:

1. The edge is located in the line of the analyzed classification yard track;

2. The edge sizes are comparable to the cut length value, known beforehand, and which is obtained from the corresponding hump yard control automation system.

The verification of compliance with first criterion is trivial and is self explanatory. The verification of compliance with second criterion requires matching the image pixels with actual coordinates of the yard tracks. To do this, it is possible to use the camera calibration formula stated in [15], which allows calculation of the actual distance on the track in meters using the image distance in pixels:

$$D = \frac{L \cdot K}{W / x - 1 + K}, \qquad (2)$$

where D is required distance to the object, m;

L – track length, m;

W – track length, pixels;

x – distance from the beginning of the track to the analyzed point in the image, pixels;

K – camera slope coefficient calculated by the following formula:

$$K = \frac{W - M}{M}, \qquad (3)$$

where M – distance from the beginning of the track to the midway, pixels.

Pic. 3g shows the analyzed hump yard track line traced by the expert along with the scale of distance in meters, obtained by formula (2). According to the data obtained from the computer-aided classification process control system, the car length is 14 meters that corresponds to the marked object length on the calculated scale. Hence, the edge in Pic. 3f characterizes the key object and is the segmentation problem solution.

Pic. 3g shows the segmented key object marked with a rectangle of minimum sizes allowing to outline all its edges.

Positioning of key objects within video streaming

Positioning task is to calculate the change in the position of an object with known initial coordinates relative to the surrounding background based on the known object's characteristics in the previous frame. Because of the use of a priori information about the object to be positioned as input data, this approach is more efficient and less time consuming than repeated segmentation of the key object in each new frame [16].

This research uses the image with the marked object position area (Pic. 3g) as a prior information on the object to be positioned.

Contrary to the segmentation algorithm, which allows, when using the basic approaches, to obtain an acceptable solution to the first research subproblem, positioning needs to select the efficient integrated approach since the basic Adaboost algorithm [17], which generates the similarity value of each pixel next to the rectangular area marked in the training image, is unsuitable for positioning (Pic. 4, first column).

Below is a comparison of three advanced positioning algorithms that allow to get the most acceptable results for positioning the cuts: Multiple Instance Learning, MIL [16], Minimum Output Sum of Squared Error, MOSSE [18], Discriminative Correlation Filter with Channel and Spatial Reliability, DCF-CSR [19].

The MIL algorithm is based on the same idea as the Adaboost. Though there is a great difference between the two algorithms as that algorithm considers both the initial data and the adjacent image areas, which potentially are considered as an object's location with a certain confidence value. This allows to refine the positioning in the case of incorrect determination of the object's boundaries at the previous step.

The MOSSE algorithm searches for the area in the frame that is as similar as possible to the image from the set obtained by small affine transformations of the input image (the area with an object). As a search criterion of a new area with an object in the current frame, the authors offer to use the maximum correlation value G between image I that is a potential area with an object in the test image and an ideal filter h characterizing the input image in the Fourier domain:

$$G = F(I) \odot F(h)^{*}, \quad (4)$$

where $F(\cdot)$ – fast Fourier transformation;

$\odot$ – step-by-step matrix multiplication;

* – complex matrice conjugation.

The problem is confined to search an ideal filter h, the Fourier transformation of which satisfies the formula:

$$\min_{F(h)^{*}} \sum_{i} \left| F(I_i) \odot F(h)^{*} - F(g_i) \right|^2, \quad (5)$$

where I_i – i-th input image affine transformation;

g_i – ideal response to i-th affine transformation.

The ideal response is shown as Gaussian-type function:

$$g = \exp\left(\frac{(x - x_c)^2 + (y - y_c)^2}{2.0} \right), \quad (6)$$

where x_c, y_c are coordinates of the area center;

x, y – coordinates of the point in the image.

The DCF-CSR algorithm is one of the most advanced positioning algorithms. Similar to MOSSE, it uses correlation filters. A distinctive feature of the algorithm is the use of the spatial reliability map, which allows to ignore known noise by assigning each point with a value of belonging to the object to be positioned that result in formula (5) as follows:

$$\min_{F(h)^{*}} \left(\sum_{i} w_i \left| F(I_i) \odot F(h)^{*} - F(g_i) \right|^2 \right), \quad (7)$$

where w_i is mass of the corresponding filter based on degree of the affine transformation which it implements in the input image.

In term of accuracy, the DCF-CSR algorithm is the most efficient positioning algorithm. For comparison between the other algorithms provision has been made for using the general-to-mean positioning area overlapping point number ratio of DCF-CSR. Comparison results are stated in Table 1.

Table 1

Positional Precision Comparison

Algorithm	Accuracy
Adaboost	0.53
MIL	0.91
MOSSE	0.67
DCF-CSR	1

Table 2 shows comparison of algorithm rate using Intel Core i5 4200U ((8 GB DDR3) including the OpenCV 4.0 libraries.

Table 2

Positioning Speed Comparison

Algorithm	FPS
Adaboost	24
MIL	15
MOSSE	45
DCF-CSR	7

For specifying the cut speed and mileage, the scale stated in Pic. 3f was used. The original and processed video with DCF-CSR positioning have been uploaded to YouTube[2, 3]. The research results have been put to use as a pilot project in the downyard shunting at Insk classification yard of West Siberian Railway.

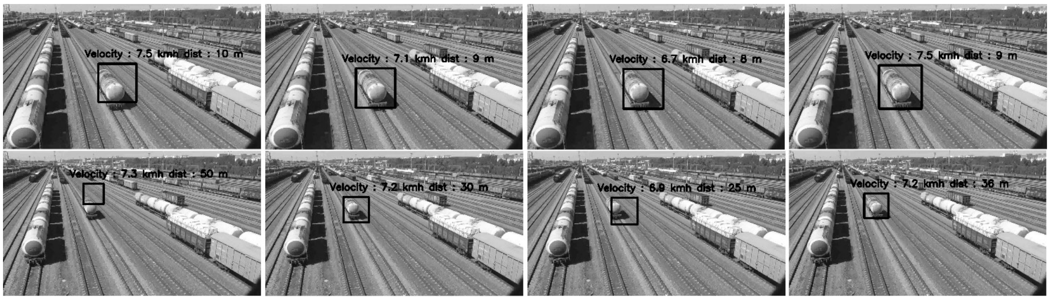
Conclusion

The article considers a problem of monitoring of railway vehicle units in the hump yard and presents the solution algorithm. The proposed development is well-timed in the context of the inefficiency of using traditional approaches existing at the hump yard. The paper describes the main criteria of the problem and presents the steps of a possible solution, as well as shows the result of monitoring the single cut moving in the yard.

As follows from the above research, the developed algorithm is the most urgently needed for use at the rail classification yards, as well as in other fields requiring monitoring for speed and location of the objects relative to the video camera position.

[2] Vehicle tracker NIIAS. [Electronic resource]: https://youtu.be/x-lV7zwyp6k.

[3] Video for vehicle tracking (NIIAS) [Electronic resource]: https://youtu.be/tGm9mKFyQ4U.



Pic. 4. Comparison of positioning algorithms (the first column for Adaboost, the second column for MIL, the third column for MOSSE, the fourth column for DCFCSR).

The result of this work is substantiation of the relevance of using computer vision in the field of railway classification processes. The implementation of the developed algorithms in the automation systems of railway classification processes (for example, KSAU SP) allows to objectify the received information about the state of the classification yard. As a result, this will create the possibility of a more precise adjustment of the targeted braking subsystem at the hump, reducing thus the number of dangerous collisions and avoiding appearance of «windows» between cuts on the classification tracks.

As further studies, it is planned to improve the presented algorithm for monitoring moving cuts containing two or more cars, as well as testing the developed approach under poor visibility (night time and adverse weather conditions).

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