Point cloud classification and track centre determination in point cloud collected by MMS on rail

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Abstract

Mobile Mapping Systems (MMS) provide huge amounts of data that require algorithms that allow them to be quickly and correctly processed. In this article, the problem of automating the processing of data acquired by mobile mapping systems, that use laser scanning, on the railroad is discussed. An algorithm for automatic point cloud classification was created. It was designed to recognize railheads of track being monitored, as well as to determine track centre.

The algorithm uses several consecutive steps. As a pre-processing step the search for rail heads is limited both horizontally and vertically according to the MMS trajectory. Then in small sections perpendicular to the trajectory point cloud is analysed. Firstly point classification is performed according to a set of geometric constrictions. Then two formations of two perpendicular lines are fit into classified points to depict simplified rail geometry – separately, one to the right side and one to the left side from trajectory. Best fit is achieved with use of modified RANSAC algorithm. In the end, based on the determined geometry, track centre is calculated.

Created solutions have been tested on a large data set of almost 90 km cumulative railway track. The measurements were performed three times using Riegl VMX-250 and Riegl VMX-450 systems and divided into four data sets according to the MMS system used, the date of survey and the direction of the survey (southbound/northbound). Algorithm correctly classified points and properly determined track centre in over 99% of analysed sections.

Key words: LiDAR, mobile mapping, point cloud classification, railway monitoring

1 INTRODUCTION

There are over one million kilometres of railroads in the world. For them to be in use they have to be regularly monitored. There are several types of surveys that have to be carried out regularly. They include assessing track parameters such as chainage, cant, twist, gradients, gauge, and also clearance gauge monitoring (Glaus, R. 2006). Traditionally this type of work was done using a trolley operated by an operator walking on foot (Wei, H. et al. 2013). Nowadays Mobile Mapping Systems (MMS) mounted on rail platform are also employed. Though their accuracy can't compete with aforementioned trolleys they definitely can compete within speed and cost (Pastucha, E. 2016). The problem is, that while MMS provides data far faster, the trolley operator decides what is important to measure and point clouds include multiple measurements to single objects. With the existing technology, massive amounts of data are obtained after each survey mission, the processing of which still requires a lot of manual work. Also MMS provided point clouds are expressed in one of the spatial coordinate systems, but clearance gauge monitoring is done with respect to track axis – planar coordinate system moved along the track. As this is a requirement, most basic problem of MMS on rail is the determination of track axis.

Since the moment point clouds came to existence the problem of processing them came to be. There are numerous algorithms created for this task, some of them created solely for the purpose of processing point cloud registered for MMS on rail. They include mostly rail detection, sometimes catenary wires (Arastounia, M. 2016)(Neubert, M. et al 2008) and catenary support structures (Zhu, L. et al 2014, Pastucha, E. 2016, Neubert, M. et al 2008, Arastounia M., 2015). Most algorithms limit the search area in point clouds, by segmentation, buffering or a basic classification process. For this purpose, some algorithms use the approximated position derived from orthophotomaps (Beger, R. 2011), embankments detected by moving window operators (Yang, B. et al. 2014) or the trajectory of the MMS (Pastucha, E. 2016, Neubert, M. et al. 2008). Actual rail detection is usually performed by the local analysis of elevation differences
(Rodríguez-Cuenca, B. et al. 2015, Arastounia, M. et al. 2016, Beger, R. et al. 2011,
Elberink, S.O et al. 2015). Methods using the analysis of local height jumps often incorrectly classify points belonging to the railway sleepers or various railway line control devices (Yang, B. et al. 2014). Because of that most algorithms use a combination of height differences and some kind of a clarification step, like RANSAC algorithm (Stein, D. et al. 2016), fitting rail model into the data (Neubert, M. et al. 2008, Stein, D. et al. 2016), or search by continuity and parallel position properties of rails (Elberink, S.O et al. 2015).

2 METHODOLOGY

2.1 GEOMETRICAL PROPERTIES AND SPATIAL RELATIONS

The objective of this work is to automatically detect and classify points registered on rails of controlled track and to determine track centre. In Poland, survey of railway gauge is done in local, planar coordinate system, with its origin in track centre. So as to be able to use MMS data in this kind of survey providing information about accurate track centre position is a necessity.

According to Polish law, track centre is defined as spatial curve represented by consecutive points measured in sections along railway track, at the intersection of the headlines of the rails, with a perpendicular line defined midway between the inner side surfaces of the two rails (fig.1).

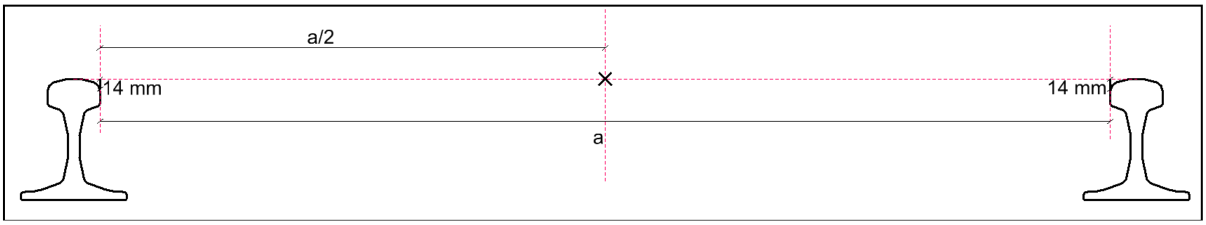


Fig. 1 Determination of rail track centre. a – nominal rail spacing

Therefore, to determine track centre, in point cloud collected by MMS on rail, it has to be calculated continuously along the track.

2.2 ALGORITHM STRUCTURE

Designed algorithm workflow can be divided into four consecutive steps (fig.2). First step limits the area of the search for rails according to their typical geometrical properties and position of MMS on the platform. Second step locates possible rail heads and performs classification according to their geometrical features. In the third step classification is being clarified. In the last step track centre is being determined.

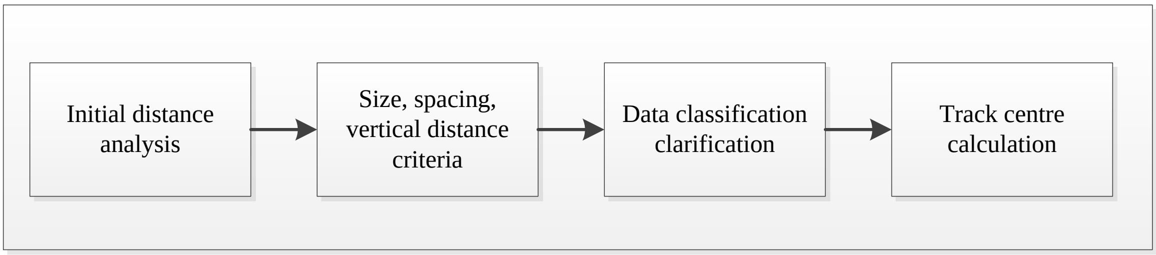


Fig. 2 Simplified algorithm structure

Whole algorithm is based on calculation in consecutive point cloud sections, more or less perpendicular to the run of the railway at a given location. The same idea of processing and indexing point cloud was presented in a previous paper (Pastucha, E. 2016).

The processed point cloud is divided into sections along the route. Subsequent sections are given unchangeable index i {1,2,3...}. Each section is defined by its trajectory key point (*KPi*), directional point (*DPi*) and section depth. Sets of consecutive key points (*KPi*) and directional points (*DPi*) are derived from the trajectory in established, even intervals. Each *KPi* together with its corresponding *DPi* forms a horizontal line perpendicular to the trajectory in said *KPi*. Section i is then a set of points lying within half a section depth from the vertical plane containing appropriate *KPi* and *DPi* (fig.3).

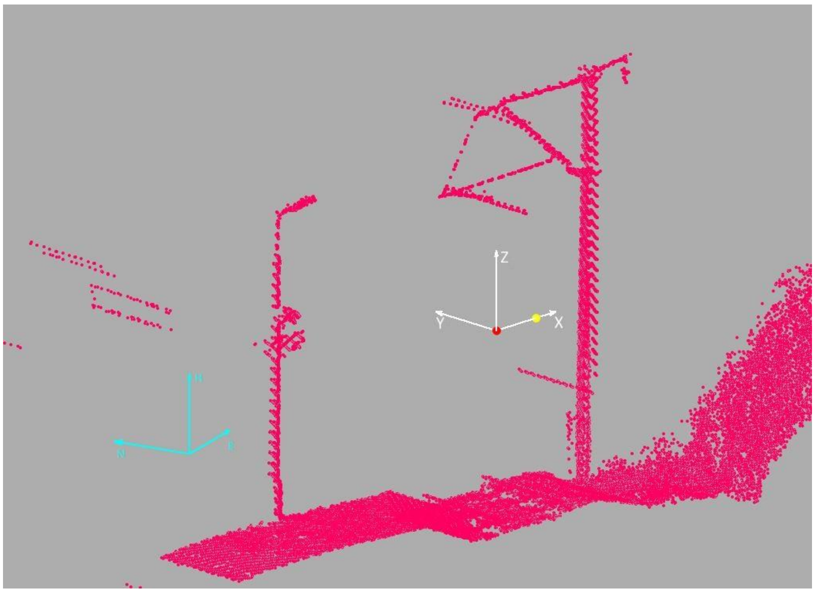


Fig. 3 Sample point cloud section, global coordinate system (teal), section local coordinate system (white), section key point (red), section directional point (yellow) (Pastucha, E. 2016)

2.2.1 Initial distance analysis

Railways are highly regular and defined by a set of strict rules and regulations. The value of maximum cant between rails or minimum arc radius on bend are specified. Thus it is easy to set basic values to limit the search for desired objects both vertically and horizontally (fig.4). Maximum horizontal and vertical distance to trajectory is relative to MMS position towards the track. Due to MMS placement some distance above the rails and inclinations on bend, range of trajectory-rail distance can differ along the track. Those distances are easily determined with use of a couple of representative point cloud sections.

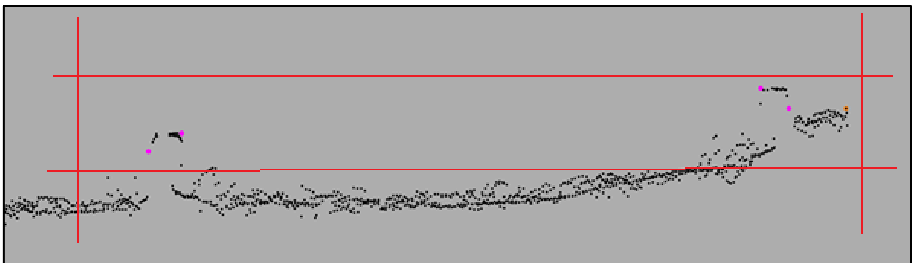


Fig. 4 Limiting search for rail heads vertically and horizontally within point cloud section

For the purpose of this work distance calculations were split into two steps. Firstly the horizontal buffer to trajectory is calculated and point cloud is divided into two sets, one containing all points within trajectory buffer and one containing remaining points.

Second step, vertical distance, is done already in consecutive point cloud sections. Points within set vertical distance are being divided into two groups based on their position left or right to trajectory. Then in each group the highest point is being found. Within 5 cm vertically to this point the whole rail head should be positioned. For those points bounding box is determined.

Bounding box is represented by section index, side index (right or left), and two points – inner upper corner and the outer lower corner in the local section coordinate system, thus providing unequivocal description (fig.5). It must be mentioned that all calculations and records are being kept in local 2D coordinate system set in said section plane.

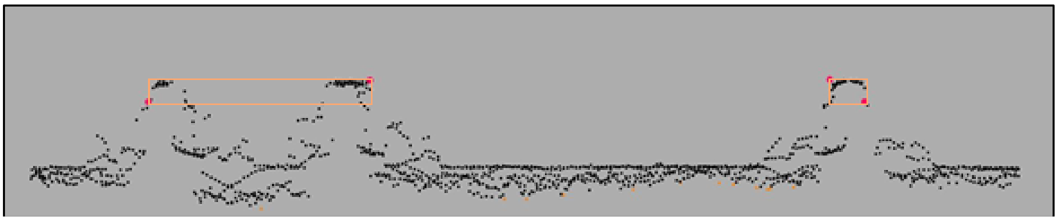


Fig. 5 Calculated bounding boxes against their point cloud section

2.2.2 Determination of problematic sections

Obviously, due to some railway structures like check rails, turnouts and railway crossings, or point cloud noise, bounding box will not always contain only sought after rail head (fig.6).

(a) *(b)* *(c)*

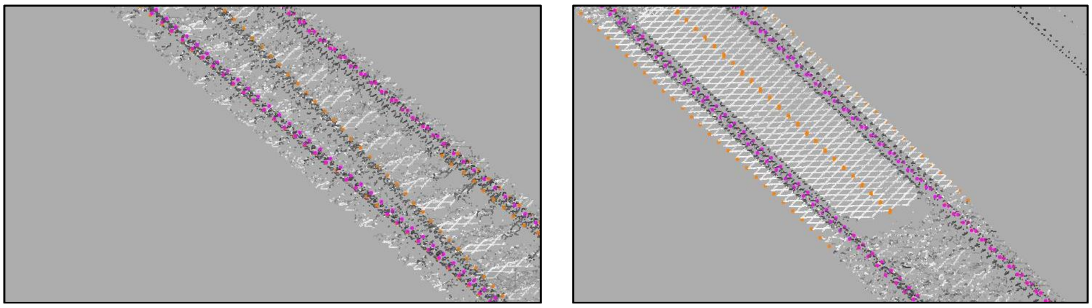
Fig. 6 Check rails (a), turnouts (b) and railway crossings (c)

To extract problematic sections all bounding boxes are checked against three geometric conditions:

- railhead size condition – correct bounding box diameter should fall within set values,
- rail spacing condition – distance between corresponding bounding boxes should be close in value to nominal rail spacing,
- cant condition – cant calculated from determined bounding boxes should not exceed value specified in rules and regulations.

2.2.3 Data classification clarification

In the previous step all problematic sections were identified. The assumption is made, that most of bounding boxes were calculated correctly. Thus can be used to determine correct bounding boxes in problematic sections. This is done with a use of RANSAC algorithm. New bounding box is calculated on the basis of the 20 nearest bounding boxes (fig.7).



(a) *(b)*

Fig. 7 Corrected bounding boxes (pink) against first determined bounding boxes (orange) on a turnout (a) and a crossing (b)

In the end, for every section points lying within appropriate bounding box are assigned class ‘rail’ (fig.8).

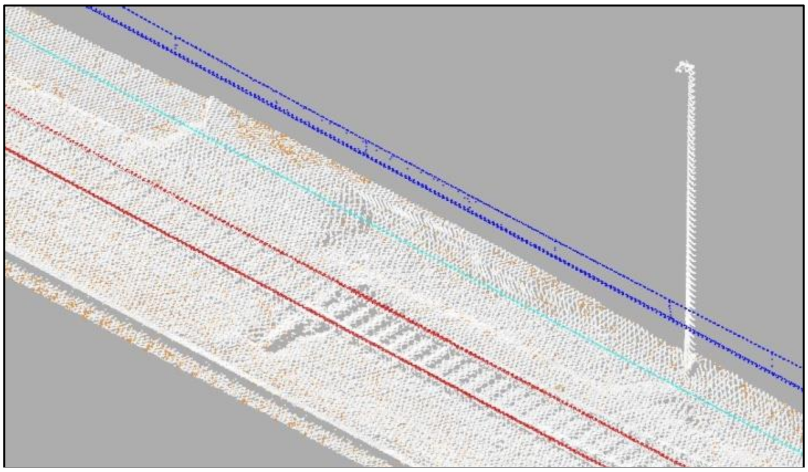
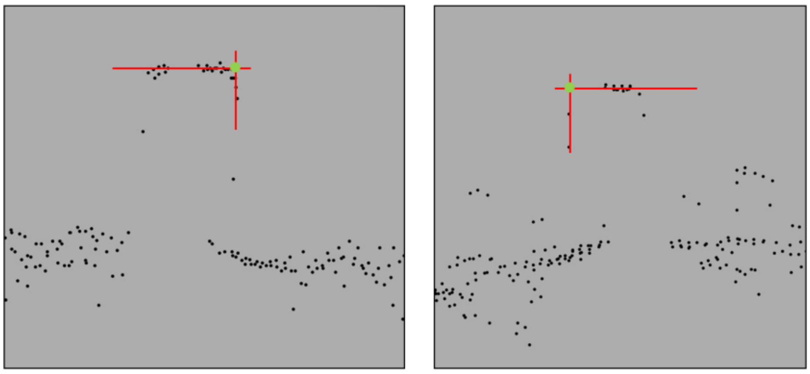


Fig. 8 Classified point cloud. Rails (red), catenary (blue), ground (orange), noise (turquoise)

2.2.4 Track centre calculation

To determine track centre a defining point has to be found both on the left and right rail. Halfway between these points is the track centre. Defining points are located at the intersection of a line fitted to top surface of rail head and a line fitted to the inner side surface of rail head. Due to small amount of points unevenly registered at the rail head, this approach was simplified. There are two lines being fitted to each rail head, one is horizontal and one is vertical (fig.9).

The process for one rail head go as follows. Horizontal line is fitted to all points classified as rail in said section. Going every 1 mm from the highest point to the lowest the possible height of a horizontal line is tested. The final height value is chosen as the one, which within 2.5 mm buffer has the most points. Similarly, is the search for the vertical line. One difference is due to very small amount of points registered at inner side surface. The horizontal distances being tested begin at the most inner point of rail head and end 1 cm going outside.



(a) *(b)*

Fig. 9 Lines fitted to top surface and inner surface of railhead (left (a) and right (b)). Defining points (green)

Defining point is calculated at the intersection of those two lines. Having two defining points, one for the left and one for the right railhead, halfway between them the rail track is being determined (fig.10).

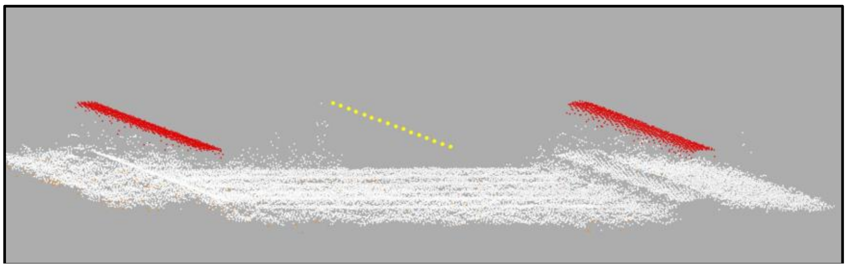


Fig. 10 Determined rail track centre (yellow) against classified point cloud (rails – red)

3 RESULTS

3.1 DATASETS' DESCRIPTION

Data used in this study have been obtained in the framework of a research project (No. 5.72.130.151) conducted by the AGH University for PKP Polskie Linie Kolejowe S.A. in Warsaw, Poland. Data were collected in 2011 and 2012 using RIEGL MMS VMX-250 and VMX-450 on an approx. 30 km rail route between Cracow and Warsaw in Poland. Both point clouds and trajectory coordinates were provided in the Polish National Coordinate System Poland CS2000 zone 7. Collected data were divided into four datasets, according to the MMS system used, the date of survey and the direction of the survey (southbound/northbound) (tab.1). Each set was then split into a number of point clouds.

Table 1. Datasets used in the algorithm verification process

Set	MLS System	Date of Measurement	No. of Points	Route Length (m)	Direction
I	RIEGL VMX-250	September 2011	780 468 277	31 711	northbound
II	RIEGL VMX-250	December 2012	609 748 916	20 065	northbound
III	RIEGL VMX-450	November 2012	677 251 514	18 938	southbound
IV	RIEGL VMX-450	November 2012	666 585 270	18 739	northbound

The survey was conducted mostly on the same part of the rail route. During surveys, the MMS were stabilized on the rail platforms differently, and so, all set distances had to be established individually. The test route length and location enabled the algorithm to be verified in various environments, the railway stations and areas between them, bends and straight sections.

3.2 ALGORITHM PARAMETERS

All parameters and thresholds in the algorithm were set according to Polish law rules and regulations and specificity of positioning of MMS on railway wagon (tab.2).

Table 2. Set algorithm parameters and thresholds

Dataset	buffer [m]	section step[m]	section depth [m]	vertical distance to trajectory [m]	railhead size condition [m]	rail spacing condition [m]	cant condition [m]
I	1.10	0.25	0.40	-2.85 ÷ -3.40	0.07 ÷ 0.12	1.35 ÷ 1.50	-0.20 ÷ 0.20
II	1.10	0.25	0.40	-2.90 ÷ -3.45	0.07 ÷ 0.12	1.35 ÷ 1.50	-0.20 ÷ 0.20
III	1.10	0.25	0.40	-3.15 ÷ -3.60	0.07 ÷ 0.12	1.35 ÷ 1.50	-0.20 ÷ 0.20
IV	1.10	0.25	0.40	-3.15 ÷ -3.60	0.07 ÷ 0.12	1.35 ÷ 1.50	-0.20 ÷ 0.20

Horizontal buffering distance and vertical distance to trajectory were set according to measurements taken in a couple of representative sections for each dataset. That included sections on a bend as well as sections on straight rail route. To those measurements an additional buffer was added to maximize probability of all rails falling within its borders.

Section step was set according to regulations (Regulations Id-14), as a step corresponding to continuous measurement. Section depth was expanded due to low density of points in some parts of the test route. Three geometric check conditions were set according to properties of surveyed railroad.

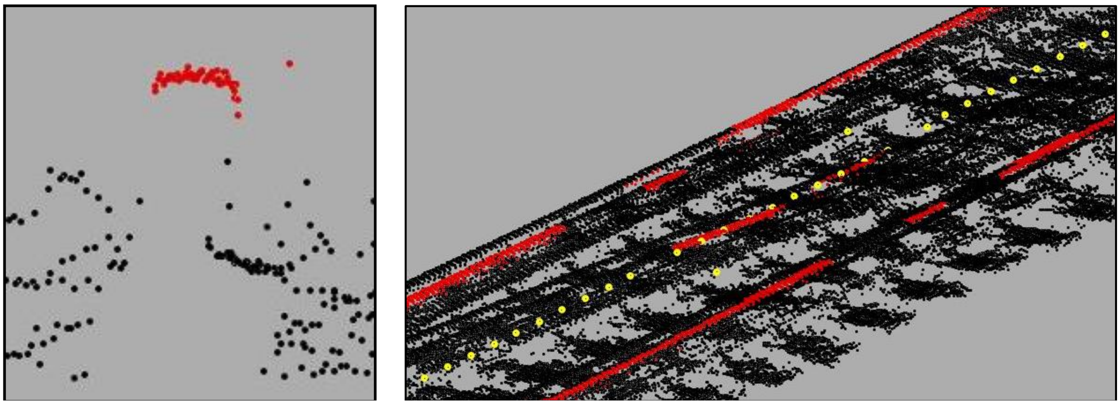
3.3 RAIL CLASSIFICATION

To determine correctness of rail classification each section was checked visually. For every section, that had incorrect classification in any part, its length was recorded. Table 3 presents summarised results.

Table 3. Results of point cloud classification

Dataset	Route length [m]	incorrectly classified rails [m]	correctly classified rails [%]	incorrectly classified rails [%]
I	31 711	338.49	98.93	1.07
II	20 065	80.55	99.60	0.40
III	18 938	28.24	99.85	0.15
IV	18 739	22.89	99.88	0.12

There are various reasons for classification failures. That includes single noise points, that didn't trigger geometric check conditions, or very long segments of turnouts (fig.11).



(a) (b)

Fig. 11 Incorrect classification due to noise (a) and turnout (b)

3.4 RAIL TRACK CENTRE DETERMINATION

Similarly to classification check, rail track centre determination check was conducted using visual inspection. Intuitively results should be the same, though the difference can be noticed for sections, where incorrectly classified single point noise is placed above the rail head (fig.12). Due to iterative characteristics of algorithm this noise will not affect the calculations. On the other hand, one incorrectly classified point would cause incorrect classification for 1 cm of track, while it might cause 25 cm incorrect track centre determination. Table 4 presents summarised results.

Table 4 Results of determination of rail track centre

Dataset	Route length [m]	incorrectly determined rail track centre [m]	correctly determined rail track centre [%]	incorrectly determined rail track centre [%]
I	31711	339.25	98.93	1.07
II	20065	81.25	99.60	0.40
III	18938	28.65	99.85	0.15
IV	18739	23.55	99.87	0.13

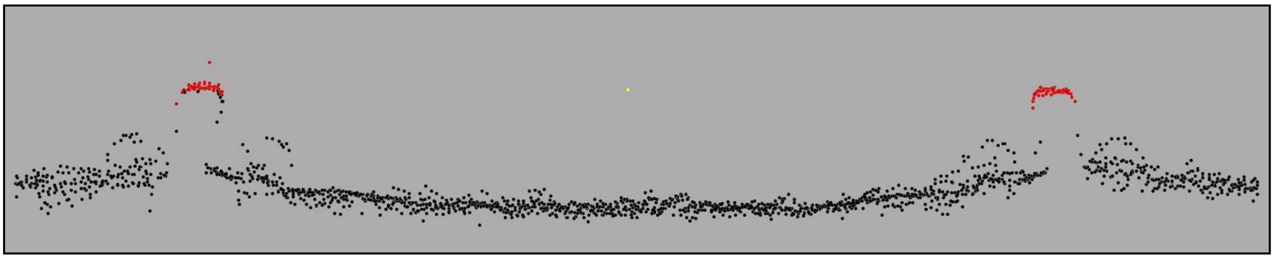


Fig. 12 Correctly determined rail track centre with single point noise on the left

4 CONCLUSIONS

Created method was tested on extensive data. It was collected for a track that included railway bridges, railway stations, turnouts, crossings, straight sections and bends. For 89 453 m of test route, only 470.17 m of track was incorrectly classified, and only 472.70 m of track centre was incorrectly determined. This means the method proved successful for 99.47% of tested railroad.

The presented algorithm has its drawbacks. Perhaps the most important is limiting its use only to one track. In future works implementation of other methods of rail detection is planned, as to also include all neighbouring tracks. Another drawback is in the usage of modified RANSAC algorithm for fitting lines into detected railhead. In case of one point noise it sometimes fails. Perhaps use of different algorithm might help to overcome this defect. Though the question arises if it is necessary considering how rarely single point noise occurs.

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