

1           **Range-based rail gauge and rail fasteners detection using**  
2                           **high-resolution 2D/3D images**

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## **ABSTRACT**

Defects in railroad tracks are responsible for several incidents every year. Rail gauge is the most important measurement for track maintenance, because deviations in gauge indicate where potential defects may exist. In addition, missing rail fasteners can be considered as a critical defect that should be detected and repaired. In this paper, an automatic inspection system specifically devised to estimate the rail gauge and detect missing rail fasteners is presented. A 3D imaging sensor, which produces high-resolution 2D images and 3D profiles, is used to capture the data. Then a range-based approach is used to inspect the railroad track. We rely on the 3D structure of the rail components (rail heads and rail fasteners) instead of using a vision-based approach which suffers from illumination changes. The system is evaluated using data recorded from real scenarios in two different cities (Metro Madrid and London Underground), with different nominal gauge values and fastening elements. The system is described and results are presented, evaluated and discussed.

**KEYWORDS:** rail gauge detection, rail fasteners detection, rail track inspection, 3D point clouds analysis.

## 1 INTRODUCTION

2 Defects in railroad tracks are responsible for several incidents every year resulting in  
3 fatalities, injuries, extensive material damage, environmental damage (dangerous goods), etc.  
4 According to Federal Railroad Administration's (FRA) Office of Safety Analysis, the 32% of  
5 the train accidents in the United States from the decade 2000-2010 occurred due to defects in  
6 the tracks (1). Although in the European Union most of the fatalities are caused by railway  
7 suicides, rolling stock in motion, and level-crossing accidents, on average, a derailment or a  
8 collision is reported at least every second day in the European Union (2). Most of the  
9 derailment accidents and collisions are also due to defects in the tracks and they are usually  
10 categorized as serious accidents into which National safety authorities mostly decide to open  
11 an investigation. Accordingly, efficient inspection and maintenance of railroad tracks are  
12 fundamental tasks that should be carried out on a regular basis. Human inspectors are usually  
13 the main actors when performing track inspection. Although their efforts are very thorough,  
14 the manual inspection process can be extremely tedious, demanding and time-consuming. An  
15 automatic inspection system able to identify railroad track defects will therefore be a valuable  
16 tool to improve the efficiency of current inspection procedures. Track defects can be  
17 classified into two main categories: (i) Track Geometry, which includes deviation from the  
18 nominal gauge measure, misalignment, etc.; (ii) Track Structure, which includes defects and  
19 missing parts in the tie-plates, fasteners, bolts, etc.

20 The main goal of the proposed work is to present a new non-contact-type railroad  
21 track inspection system by means of a 3D imaging sensor which produces high-resolution 2D  
22 images and 3D profiles. The data supplied by the sensor is analyzed using intelligent 3D  
23 processing techniques, focusing in two main objectives: track gauge monitoring and missing  
24 rail-fasteners detection. On the one hand, rail gauge is obtained by analyzing the 3D cross-  
25 sectional profile with a resolution of 1 millimeter. Rail heads are firstly detected and the  
26 limits of the inner faces are refined by searching the points that appears at a certain distance  
27 below the rail head. On the other hand, missing fasteners detection is carried out using a  
28 generic two-staged approach that combines localization and verification.

29 The proposed range-based railroad track inspection system described in this paper  
30 was developed through an interdisciplinary research collaboration between the company  
31 EUROCONSULT GROUP (Madrid, Spain) and the Innovative Sensing and Intelligent  
32 Systems (ISIS) research group at the University of Alcalá (UAH, Alcalá de Henares, Spain).

## 34 RELATED WORK

35 There is extensive literature on automatic inspection of railroad track and track components.  
36 Inspection technologies are usually installed on board of track geometry cars, including  
37 computers to process and display data gathered by the systems. Although contact  
38 measurement systems exist, they can be considered as obsolete since most of the  
39 measurement devices are now based on non-contact sensors. Well established inspection  
40 techniques such as ultrasonic rail flaw, geometry car testing, inertial accelerometers, etc.,  
41 were surveyed in (3). The authors stated that machine vision is the most applicable  
42 technology given the manual, visual nature of old track inspections. As a matter of fact,  
43 machine vision approaches to assist rail track inspection has attracted much interest in the last  
44 years from both industry and research groups at Universities.

45 A track simulation model used to evaluate camera views and to provide synthetic  
46 images for machine vision algorithm development was proposed by the Computer Vision and

1 Robotics Laboratory (CVRL) at the University of Illinois in (3). Cameras are finally placed  
2 laterally to obtain lateral views of track components. The inspection algorithm follows a  
3 global-to-local scheme, with the most consistent detectable objects being located first (ballast,  
4 rail, ties) followed by smaller components (tie plates, spikes and anchors). Using edge  
5 detection and texture information, the same group presents a robust means of detecting rail,  
6 ties and tie plates (4), which narrows again the search area. Then, prior knowledge of  
7 probable component locations is applied to determine the presence of spikes and rail anchors.  
8 In a most recent works (5), (6), special track components are periodically inspected to detect  
9 turnouts.

10 The Exploratory Computer Vision Group (ECVG) at Watson Research Center  
11 developed a vision-based track condition monitoring system (7), (8), able to detect different  
12 rail components such as spikes, anchors, tie plates and bolts. Hough transform plays here a  
13 very important role, since it is used to locate both tie plates (lines) and spikes (ellipses). Spike  
14 holes and anchors are detected by analyzing edges distribution. The system is evaluated using  
15 their own dataset, resulting in an average detection rate of 98.2%. The authors remark the  
16 high variability of track components appearance that comes from diversities in components  
17 (anchor, tie plate, spikes, etc.) type, size, shape, camera view point, occlusion and light  
18 condition.

19 In (9) and (10), the Computer Vision Lab at University of Central Florida, proposed  
20 the use of SIFT features combined with MACH filters and SVM to detect both rail fasteners  
21 and missing rail fasteners. Rail fasteners hold the steel rail to the perpendicular crossties.  
22 Since these ones can take several geometries and can differ depending upon their purpose and  
23 producer, the problem is addressed as a multi-classification problem. Up to seven classes are  
24 used including steel clips, E-clips, missing, defective, etc. Lighting variance is mitigated by  
25 using normalized correlation filters.

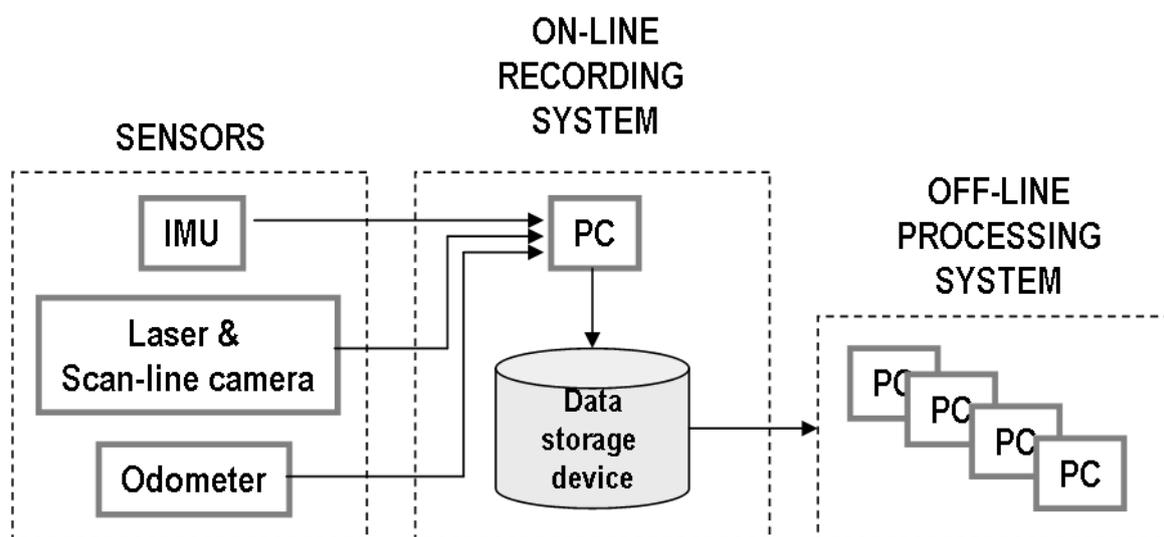
26 Considering the detection of the rail gauge, in (9) and (10), two approaches are  
27 presented: pure laser and pure camera. Vision-based approach makes use of the Hough  
28 transform to detect persistent edge lines and validate the rail limits. Laser-based approach  
29 applies a 3-means clustering technique to isolate the rail head. The rail head surface is then  
30 approximated by a third degree polynomial, and inner rail edge points are obtained by  
31 computing the intersection of a vertical plane tangent to the rail head surface. Finally, rail  
32 gauge is calculated using the distance between matching edge points. Although the methods  
33 are well explained, the evaluation is poor since no comparisons are given with respect to a  
34 specific ground truth.

35 In the context of the industry, various commercial systems are available for  
36 performing rail track inspection. Examples include the AURORA system for inspecting wood  
37 ties, rail seat abrasion, tie plates, anchors and spikes (11). ENSCO developed the *VisiRail*<sup>TM</sup>  
38 Joint Bar Inspection System, using high-resolution scan line cameras and laser sensors (12).  
39 High-speed line-scan cameras are also used by the system developed by MERMEC Group to  
40 detect track surface defects and measures track geometry, rail profile and rail corrugation (13).  
41 Finally, the TrackVue system (14), developed by RailVision, is applied for measuring rail  
42 wear, track gauge and curvature, rail cant and vegetation cover, etc., using an array of  
43 cameras and laser equipment. It is worth to mention that with commercial systems, neither  
44 technical details nor performance reports are available, so it is very complicated to establish  
45 their performance in the context of some reference baseline.

1 In this paper, a range-based rail track inspection system is presented. The nature of  
 2 our data does not suffer from illumination changes as it happens with machine vision  
 3 algorithms. We rely on the 3D structure of the rail components (rail heads and rail fasteners)  
 4 to obtain two main measurements: track gauge and missing rail fasteners. The system is  
 5 evaluated using data recorded from real scenarios in different countries, with different  
 6 nominal gauge values and fastening systems. The system is described and results are  
 7 presented, evaluated and discussed.

## 8 9 **SYSTEM DESCRIPTION**

10 The proposed rail track inspection system can be defined by three main blocks, depicted in  
 11 Figure 1. The measurement device is composed of a set of sensors including an odometer, an  
 12 Inertial Measurement Unit (IMU) and the laser and scan line camera system. The sensors are  
 13 connected to a PC which is responsible for recording all the data provided by the sensors. On-  
 14 line processing is not a critical point for this application. Accordingly, the procedure was  
 15 designed to store all the data in a set of data storage devices that will be used as the input of  
 16 the off-line processing system.



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19  
20 **FIGURE 1 System overview**

### 21 **Measurement Device**

22 The main component of the measurement block is the high-speed laser scanner (15) that  
 23 provides both 2D images and high-resolution 3D profiles of the railroad track (see Figure 2 –  
 24 right-). It can scan at 1-mm image resolution and 3D data at acquisition speeds between 0-50  
 25 km/h. The platform used to storage the data is integrated in a global system devised for tunnel  
 26 inspection (see Figure 2 –left-). The acquisition software makes use of the data provided by  
 27 the laser scanner, the IMU and the odometer to finally storage a 3D cloud of points with  
 28 appearance information coming from the scan line camera. A couple of examples of the data  
 29 supplied by our sensor are shown in Figure 3. As can be observed, the level of detail is very  
 30 rich. All the track components (rail heads, fastening systems, tails, etc.) are perfectly visible  
 31 and distinguishable.

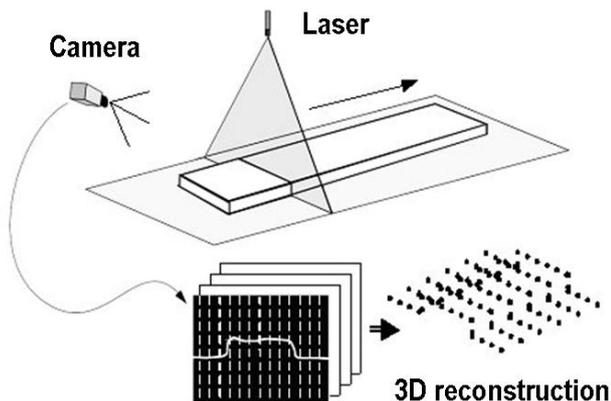
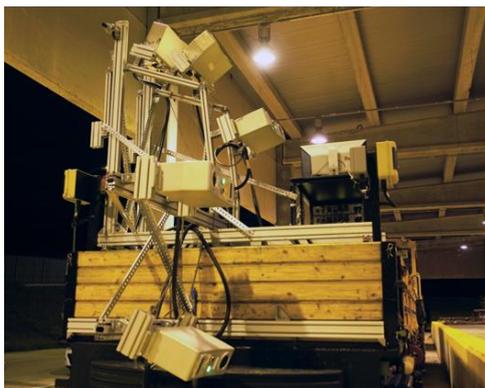


FIGURE 2 Left: tunnel/rail track inspection platform. Right: sensor overview.

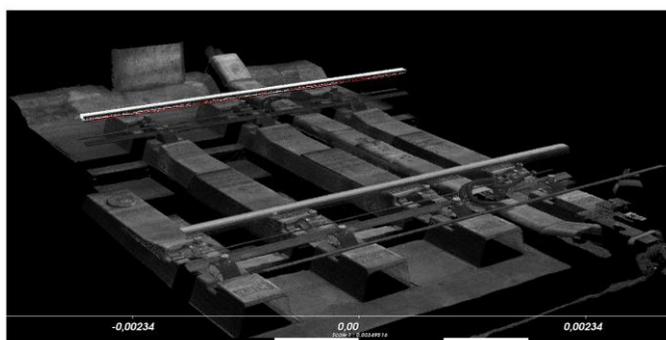
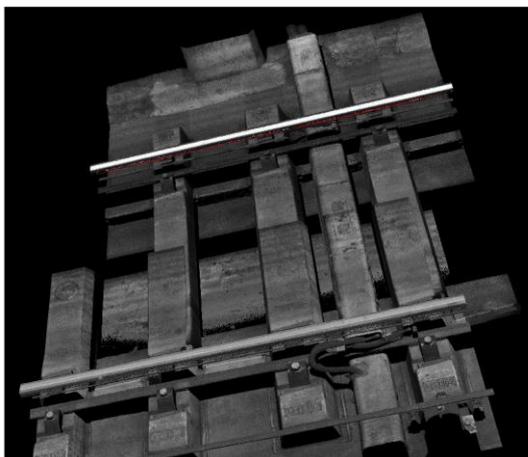


FIGURE 3 Data supplied by the high-speed laser scanner and scan line camera.

### Track gauge detection

The proposed approach used to estimate the rail gauge is depicted in Figure 4. The 3D cloud of points is divided into horizontal scan-lines that are evaluated independently. In order to detect the main changes (edges) of the scan-line profile we use the Derivative of Gaussian (DoG) function. The DoG allows edge detection in only one step in the context of noise. An example of the DoG applied in a single scan-line that corresponds to one rail is depicted in Figure 5.

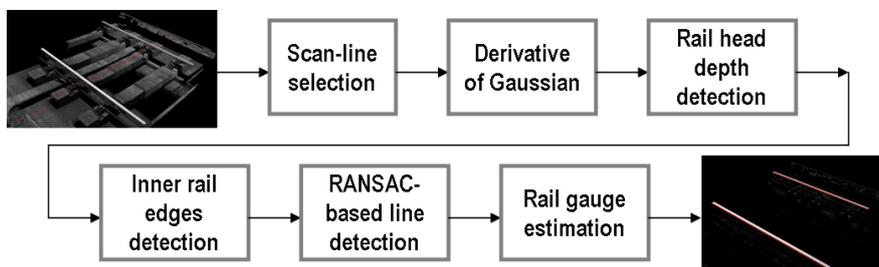
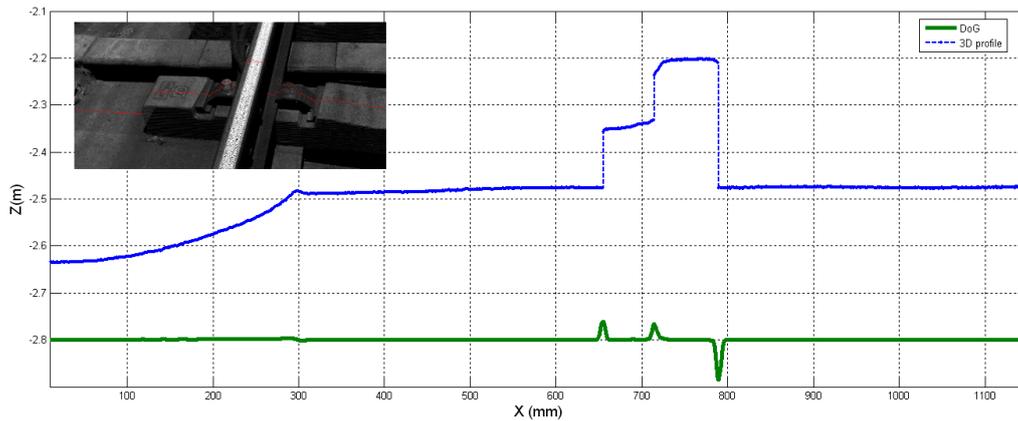


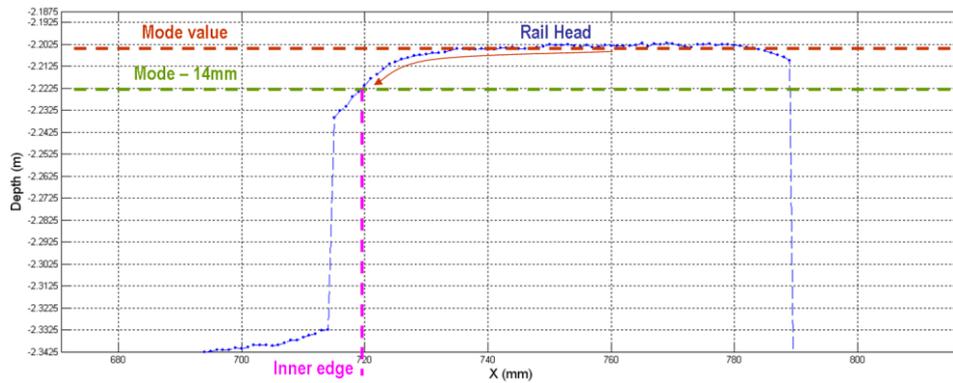
FIGURE 4 Overview of the rail gauge detection procedure.

In order to detect the inner rail edges, we use the definition of rail gauge, which is computed with respect to the two inner points of both rails, defined 14mm below each rail

1 head top. Accordingly, the first step consists in computing the rail head depth. As can be  
 2 observed in Figure 5, the rail head boundaries produce a maximum and a minimum in the  
 3 DoG function. By searching this specific pattern (maximum and minimum) and introducing a  
 4 depth restriction (rail head is considered the closer region with respect to the sensor), the rail  
 5 head limits are finally obtained. The depth of the rail head is computed as the mode value  
 6 between those boundaries. Then, inner rail edges are estimated by selecting the inner point  
 7 that appears at 14mm below the rail head depth. A linear interpolation is applied when no  
 8 point appears at this exact position with respect to the rail head depth. An example of this  
 9 procedure is depicted in Figure 6.



10 **FIGURE 5 Scan-line 3D profile and DoG result.**



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13 **FIGURE 6 Rail head inner edges computation example (right head). A mirrored**  
 14 **version of this procedure is applied over the left rail head.**

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17 Once the inner edges of both the right and left rail are detected for one specific scan-  
 18 line, the same procedure is applied in a pre-defined number of scan-lines. According to the  
 19 sensor resolution, each scan-line represents 1mm. Then, all the inner edges of the rail head  
 20 are robustly modeled by means of a RANSAC-based line fitting procedure (see Figure 7).  
 21 After we determine the inner rail lines, the last step is the calculation of the rail gauge  
 22 between matching points. A post-processing step is applied to the estimated rail gauge curve  
 23 by smoothing it with 1D 1x7 Gaussian filter.  
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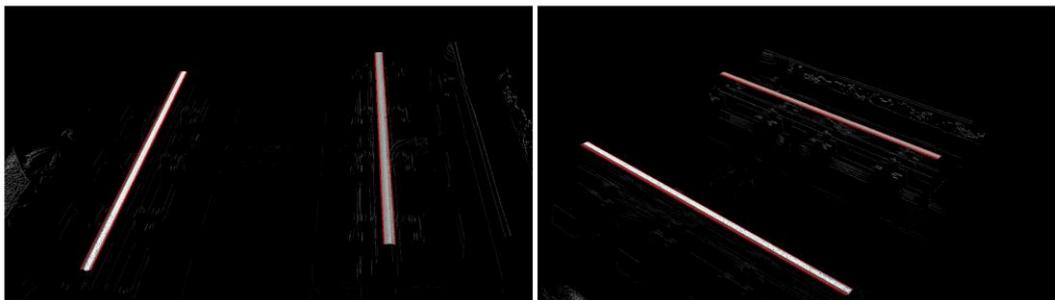


FIGURE 7 Rail head inner lines detection examples.

#### Rail fasteners detection

Rail fasteners detection is carried out using a two-staged approach. First, the base plate is located using a 2D matching scheme applied over depth images directly obtained from the 3D data. Second, a 3D Iterative Closest Point (ICP) is applied using previous knowledge about the fasteners location.

Depth images are obtained by integrating the 3D information given by the laser. The gray color provided to the 2D image is directly related with the distance between the point and the laser. The location of the point is directly related with the X-Y coordinates. The maximum and minimum range used when coding the distance into a gray value is defined using previous knowledge about the sensor height. Some examples of the depth images obtained using this procedure are depicted in Figure 8. The 2D matching approach uses a pre-defined template that has to be given as a manual input. This template should contain the base plate, the rail and the fasteners. This is the unique process that requires manual intervention. Once the 2D template is given, the base plate location system applies a 2D template matching between the template and the depth image, guided by the location of the rail (which is detected following the aforementioned procedure). Two examples of the base plate location approach are showed in Figure 9. Note that in this case, two templates are used depending on the rail (left or right). A red line is showed as the detected inner edge of each one of the rails.

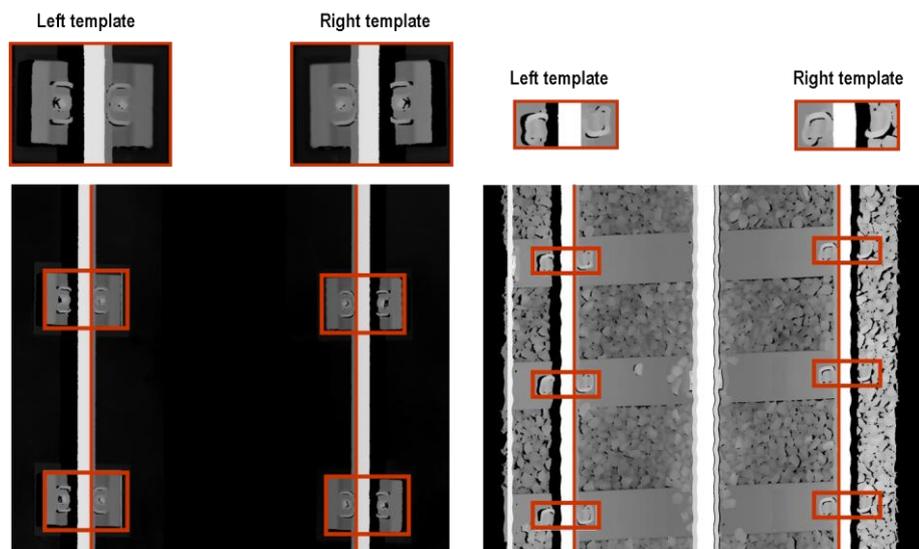


FIGURE 8 Three different depth image examples.

Once the base plate are properly located, a 3D ICP algorithm is applied, using a manually pre-defined 3D model of the fastener and previous knowledge about the expected location of the fastener. The located base plate is firstly isolated in 3D. Then, we extract the 3D cloud of points corresponding to the expected location of the fastener. Finally, we apply ICP with that cloud of points with the pre-defined 3D model. If the difference between both

1 cloud of points is greater than a threshold, we consider that the fasteners is missed. Some  
 2 examples of this procedure are depicted in Figure 10.

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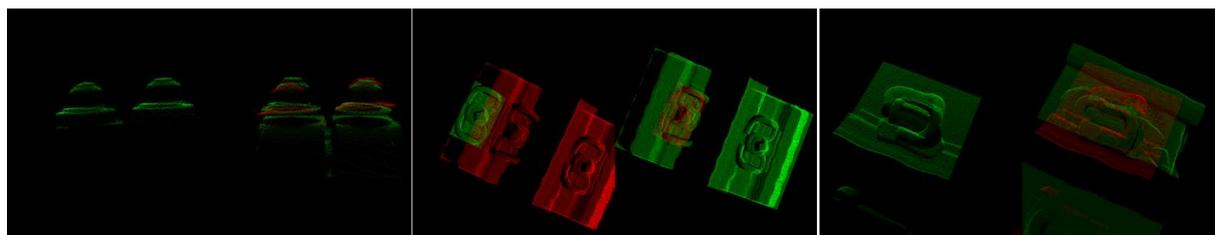


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**FIGURE 9 Base plate location examples. Left: tension clamp. Right: e-Clip.**



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**FIGURE 10 ICP examples. Left: bolt clamp. Middle: tension clamp. Right: e-Clip.**

## 10 EXPERIMENTAL RESULTS

11 In order to validate the proposed automated rail track inspection system, we devised a set of  
 12 experiments using real data obtained from Metro Madrid and London Underground. The  
 13 system is firstly calibrated for rail gauge estimation using data recorded in a controlled  
 14 scenario. Preliminary results are showed in the context of missing rail fasteners detection.

15

### 16 Calibration results

17 Two steel guides (see Figure 11) placed at a set of pre-defined positions in a controlled  
 18 scenario are used to define a ground truth and establish a reference pattern. The rail gauge  
 19 detection system is run and the results are compared with the ground truth. Table 1 shows the  
 20 reported results. As we can observe, the average error is 0.9952%, always below the ground  
 21 truth values. Accordingly, we correct all the rail gauge estimation by a factor of 1.009952 to  
 22 obtain the best estimation. It leads to an average post-calibration error of 0.0103%.

23



FIGURE 11 3D reconstruction of the two steel guides used for sensor calibration.

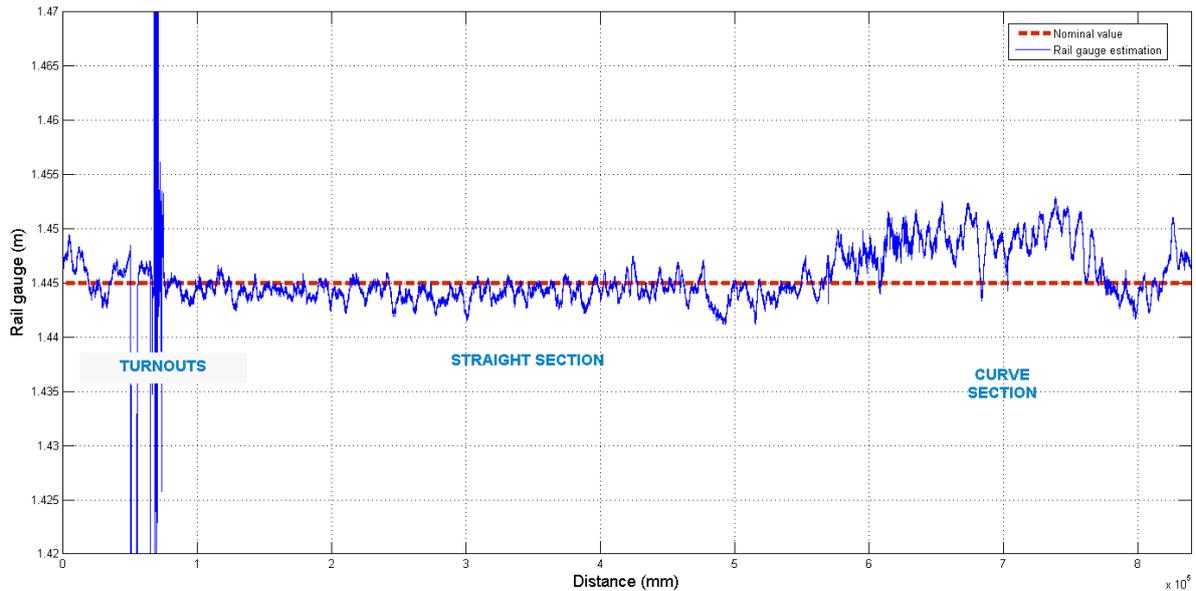
TABLE 1 Ground truth and estimated rail gauge values.

Ground truth (mm)	Before calibration			After calibration		
	Estimated rail gauge (mm)	Error (mm)	Relative Error (%)	Estimated rail gauge (mm)	Error (mm)	Relative Error (%)
1200	1187.9	12.14	1.01	1187.9	0.28	0.02%
1300	1290.4	9.58	0.73	1290.4	-3.24	-0.25%
1400	1388.5	11.47	0.82	1388.5	-2.32	-0.17%
1500	1484.8	15.17	1.01	1484.8	0.42	0.03%
1600	1584.7	15.28	0.96	1584.7	-0.47	-0.03%
1700	1681.1	18.87	1.11	1681.1	2.17	0.13%
1800	1778.5	21.49	1.19	1778.5	3.80	0.21%
1900	1878.7	21.35	1.23	1878.7	2.60	0.14%
Average	--	15.6687	0.9952	--	<b>0.41</b>	<b>0.0103</b>

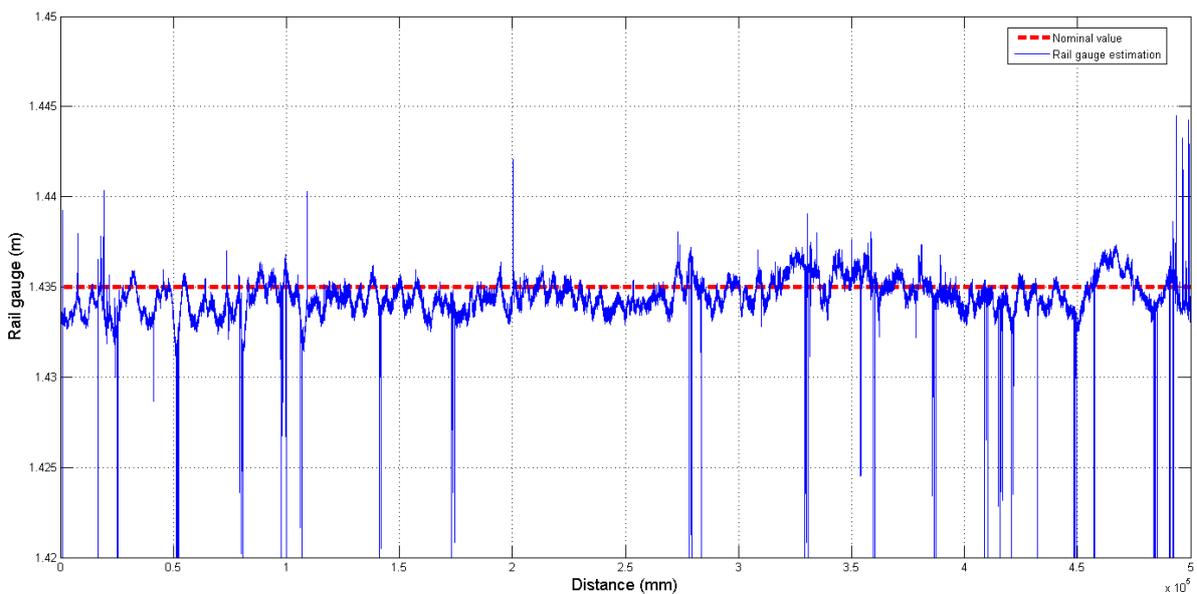
### Rail gauge detection experiments

We collected a considerable amount of data corresponding to two different routes at the Metro Madrid and London Underground. A total of 840 meters were recorded from Metro Madrid whereas a total of 500 meters were collected from the London Underground. The nominal rail gauge at straight sections was 1445mm and 1435mm for Metro Madrid and London Underground respectively. Results obtained from the Madrid route are depicted in Figure 12. The route contains a section with undetected turnouts, a straight section and a curve. Note that nominal values for curve sections are always greater than for straight sections. Results obtained from the London route are supplied in Figure 13. Some spurious values were obtained due to vibrations in the recording platform.

As can be observed in both cases, the estimated rail gauges were very close to the nominal gauge. Although no ground truth values were available for the whole route, some control points were recorded with errors lower than 1mm in all cases. Accordingly, we consider that the obtained results clearly validate our rail gauge detection approach.



1  
2 **FIGURE 12** Estimated rail gauge corresponding to a section of 840m of the Metro  
3 **Madrid.** The section contains turnouts (non-detected), a straight section and a curve.  
4



5  
6 **FIGURE 13** Estimated rail gauge corresponding to a section of 500m of the London  
7 **metro.** The section was mainly a straight section.  
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### 9 Rail fasteners detection experiments

10 The data collected from both Metro Madrid and London Underground, contains two different  
11 types of fastening systems: tension clamp (Madrid) and e-Clip (London). Unfortunately the  
12 data for both routes showed no missing components, so in practice we were only able to  
13 validate our rail fasteners detection approach in terms on false positives. No false positives  
14 were reported.  
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## **CONCLUSIONS AND FUTURE WORK**

In this work a range-based rail gauge and rail fastener detection system was presented. A high-speed laser scanner that provides both 2D intensity images and high-resolution 3D profiles of the railroad track was used to capture data in an off-line fashion. Track gauge is estimated by analyzing edges on the 3D profiles of subsequent scan-lines. The Derivative of Gaussian is applied to isolate edges in the presence of noise. The inner edges of both rails are estimated 14mm below the rail head surface. Then inner lines are robustly estimated using a 3D RANSAC-based line estimator. The base plates that support the rail fastening system are firstly located by means of a 2D template matching technique applied over 2D depth images. Then, rail fasteners are detected by means of a 3D Iterative Closest Point approach. Results were presented from two different scenarios: Metro Madrid metro and London Underground.

Future works should include the detection of turnouts. Some improvements can be introduced in the rail gauge fastener detection procedure using 2D/3D pattern recognition techniques. Other potential defects such as rail cracks or rail burns will be considered in future versions of the system. Finally, more experimental work has to be carried out, using different routes of thousands of meters with the corresponding ground truth obtained by a manual labeling process. Thus, we would be able to validate the whole system for being commercially exploited.

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