A New Rail Inspection Method Based on Deep Learning Using Laser Cameras

Yunus Santur, Mehmet Karaköse, Erhan Akın

{ysantur, mkarakose, eakin}@firat.edu.tr

Computer Engineering, Fırat University
Elazığ, Turkey

Abstract—**Rail systems are one of the most important transportation methods used in today's world. The abnormalities that occur on railway tracks due to various causes result in breakdowns and accidents. For this reason, railway tracks must be periodically inspected. This study proposes a new approach for rail inspection. Today, the railway inspection process is generally performed using computer vision. But the oil and dust residues occurring on railway surfaces can be detected as an false-positive by the image processing software can lead to loss of time and additional costs in the railway maintenance process. In this study, a hardware and software architecture are presented to perform railway surface inspection using 3D laser camera and deep learning. The use of 3D laser cameras in railway inspection process provides high accuracy rates in real time. The reading rate of laser cameras to read up to 25.000 profiles per second is another important advantage provided in real time railway inspection.**

Consequently, a computer vision-based approach in which 3D laser cameras that could allow for contact-free and fast detection of the railway surface and lateral defects such as fracture, scouring and wear with high accuracy are used in the railway inspection process was proposed in the study.

Index Terms— **Rail Inspection, Computer Vision, Fault Diagnosis, Convolutional Neural Network, Deep Learning**

I. INTRODUCTİON

Rail systems are among the most preferred transportation methods around the world due to their speed, reliability and cost-effectiveness. Railway track components must be periodically inspected in order to avoid accidents. Today, this inspection is commonly carried out using computer vision systems (CVS) [1].

A typical rail inspection performed using CVS can be summarized as acquiring an image from the rail track, performing pre-treatment on the image frames, obtaining lower dimensional features on these frames, labeling the data and finally, producing a diagnosis by applying machine learning classifying methods.

A rail inspection process using CVS is expected to be cost-effective, suitable for real-time operation, fast and highly accurate [2].

In the rail inspection process, the camera images constitute the input data of the system using CVS. However, the physical structure of the rail lines causes residues such as oil and dust. This situation may decrease the general accuracy rate of the CVS system [3].

Generally, it is the biggest disadvantage of which is used CVS or image processing based in rail inspection applications.

Another important point in rail inspection applications using CVS is that the system operates at high speeds. Today, rail transport systems can move at speeds of 300 km/h. The fact that the inspection process works at high speeds is extremely important in long-distance inspection applications.

Rail inspection applications using high resolution cameras were shown to be capable of achieving a speed of 75 km/h, depending on the frame sizes of the images taken [1].

Instead of using high-resolution cameras, using 3D-laser cameras is a solution for achieving higher operating speeds. In their study, Qingyong Le et al. used a 3D-laser camera to find rail surface faults and achieved a real-time operating speed close to 100 km/h. Another solution for high-speed operation is to use special field-programmable gate array (FPGA) equipment [4], the biggest disadvantage of which is that the programming and implementation of FPGA-based systems require more effort and time in terms of hardware [5].

In this study, high operating speeds were achieved by performing parallel programming on graphic process units (GPUs) using Nvidia Cuda library, despite the high complexity and the actualization difficulties of hardware of FPGA. The application in which one Nvida GPU and one computer were used was designed in accordance with pipeline architecture [6].

When 3-D laser cameras are compared with normal cameras, they involve both rgb data and precise distance information on the two-dimensional plane. Because of these features, they are widely used with the aim of finding faults in industrial products including rail inspection [7-10].

Although the cost rail inspection with 3-d cameras is higher, it is the most advantageous method in terms of accuracy rate and operating speed. The general components of a 3D computer vision-based rail inspection operation are seen in Fig. 1.

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Consequently, a new approach presented using Deep learning (DP) and 3-d laser camera via GPU programming for rail inspection application proposed in this study.

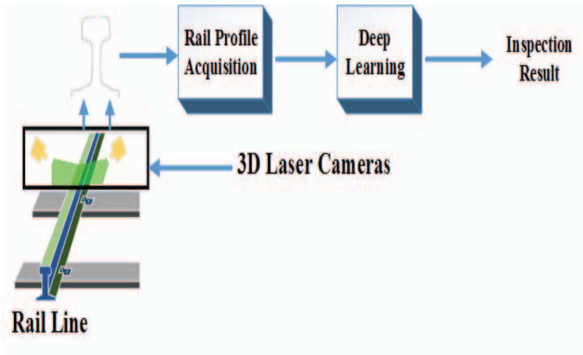


Fig. 1 Railline components and rail profile

II. Rail Surface Faults

Fault types which occur on rail surfaces can be classified into four groups: rail cracks, rail abrasion, corrugation faults and headcheck faults. The definitions and potential causes of these fault types are given below [12].

Cracks: Gaps on the rail surface longer than 50 mm and deeper than 10 mm. Rail cracks can be formed as a result of manufacturing defects, welding defects, operation of trains at a speed exceeding the specified limits, sleeper defects and excess load.

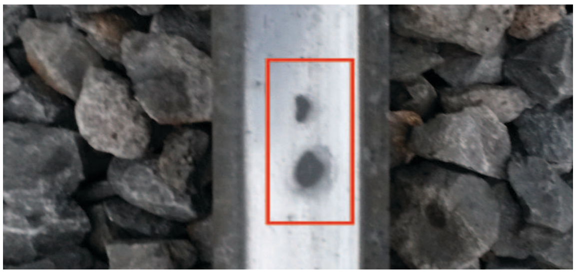
Abrasion: Fault types on the rail surface of less than 60 mm long and 1 mm deep. Locomotive skidding and starting and stopping of the train can cause abrasion-type faults or can increase existing abrasion.

Corrugation: Corrugated wear of varying magnitude occurring on rail surfaces. Deficiencies and defects in rail sleeper connections, excess or unbalanced loads and presence of rail depressions can cause this type of fault.

Headchecks: Hairline cracks occurring on rail surfaces. This type of fault may occur during starting and braking of the railway vehicles.

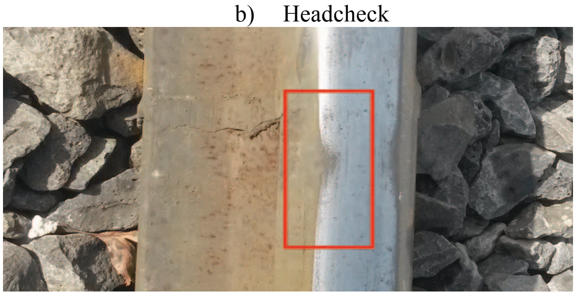
Table 1. Rail Inspections Methods Classifications

	Methods	Advantages	Disadvantages
Contacted Methods	Mechanic devices	Cheap	Very slow Unsafe Low accuary
Contacted Methods	Ultrasonic devices	Fast	Slow Increase existing damage
Contact-Free Methods	CVS	Safe Fast High accuary	Expensive False positive results
Contact-Free Methods	CVS with 3d-laser camera	Safe Very fast Very high accuary	Expensive

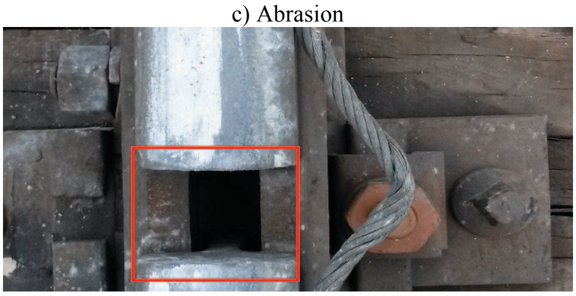


a) Corrugation

b) Headcheck



c) Abrasion



d) Crack

Fig.2. Rail surface faults

III. Rail Inspection Methods

The inspection of rail lines is traditionally performed by manual and visual examination using human labor. However, this type of inspection is slow, unsafe, and most of all, remains limited to the knowledge of a competent person. In this method, the inspector, by walking or driving along the rail, performs the inspection via a rail profile measurement device, such as Robel-A, Robel-B and SKM [13].

Another method is based on the inspection of the rails via mechanical devices. This method, called contact-based, diagnoses faults by using graphs obtained from the friction between the mechanical device and the rail.

It is fast and provides accurate results; however, because it requires contact with the rail, it may damage the rails or increase existing damage. More recently, due to the damage caused by contact-based methods, whether performed under the supervision of an inspector or with mechanical devices.

Rail analysis has been conducted quite accurately and quickly via computer vision-based technologies using cameras or lasers can be shown in Table 1 as a comparable [14].

In the works of Hackel et al., laser cameras were used for the purpose of detecting anomalies such as missing screws and traverse and rail fractures [15].

In a study conducted by Aytekin et.al [16], detection of bolts on rail lines was performed using a laser camera. The most advantage of conducting rail inspection processes using 3D-laser cameras is the higher operating speed and measuring accuracy, while the very high cost constitutes the biggest disadvantage.

Huber-Mörk et al. carried out a study for the classification of rail surface faults using image processing [17]. In the study, faults were classified as wear, puncture, crack, and were grouped by their types. A 99% accuracy performance was achieved with a dataset containing 400 rail pictures. Although the study presented highly accurate results, the method was not fast enough for real-time processing when compared with applications using 3D-laser cameras.

Another approach used in the literature for real-time operations is application performance using special equipment such as FPGA. De Ruvo, to this purpose, proposed an image processing-based method that could operate in real time at 100 km/h using FPGA [18].

However, the biggest disadvantage with this approach is the fact that hardware-based implementation and FPGA programming applications are more difficult to implement.

IV. Proposed Method

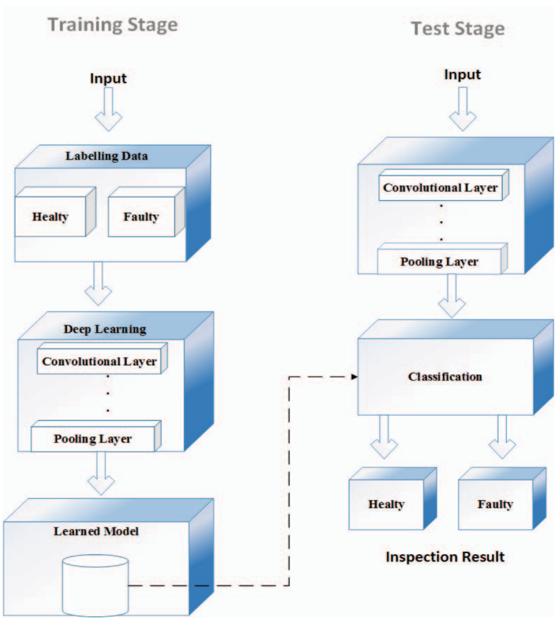


Fig. 3. Proposed method

A general block diagram of the proposal approach method is given in Fig. 4. AT C5-1600CS19-500 3d laser camera was used in this study for taking rail profiles from the rail line [19].

The proposal approach has a two stage. In the learning stage, Nvidia Gtx 930 GPU [20] used building Convolutional Neural Networks (CNN) learning model [21]. In the test stage, the anomaly detection classification was made in a CNN previously trained with data on the computer.

A. 3d Laser Cameras and Getting 3D Data

The ccd/cmos cameras give two-dimensional image on x-y plane. This image is called as three-dimensional if it includes the depth information on the z plane.

The methods of *stereovision, time of flight* and *laser triangulation* are used in obtaining three-dimensional image.

Stereo vision technique is the same as the principle of human vision. It is based on the principle of finding the pixel distance by measuring the projections of each pixel on two separate cameras by geometric methods because the distance and angle between cameras are known in imaging which is performed using two separate calibrated cameras. Although it is low cost, the accuracy performances depend on calibration and the sensitivity of camera parameters [22].

Time of flight cameras containing both rgb camera and an infrared sensor get depth information as well as rgb information by measuring the flight time of the infrared waves. They are particularly used in applications such as game consoles, virtual reality and three-dimensional modeling. They have cost effective and low accuracy solutions [23-25].

Another method used in obtaining three-dimensional image is the use of laser cameras [19]. Laser cameras consist of a calibrated camera and laser line source as shown in Fig. 5.

These components are usually integrated products. The system builds up the three-dimensional profile of the object by benefiting from the profile change in the laser line via constantly taking pictures.

The object needs to move in a controlled manner while performing the profiling process in moving objects with laser cameras. How much the object has moved is determined by means of an encoder. The simple mathematical provision of the process of obtaining three-dimensional profile matrix by reading the rail profile can be given as in "1" from calibrated compact sensor as shown in Fig. 4.

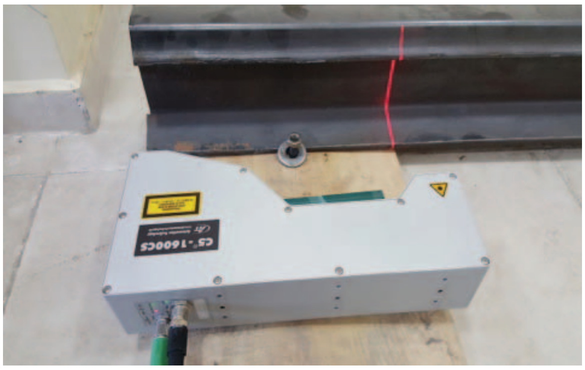
$$z = \frac{x}{\sin(a)} \tag{1}$$

$$P_{Treshold} = \frac{P_L + P_R}{2} \tag{2}$$

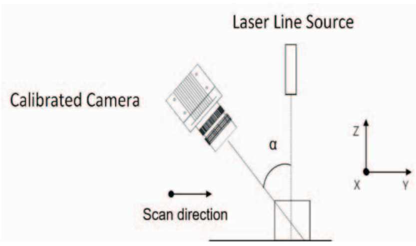
$$I_S = \sum I_P \tag{3}$$

$$M_S = \sum P x I_P \tag{4}$$

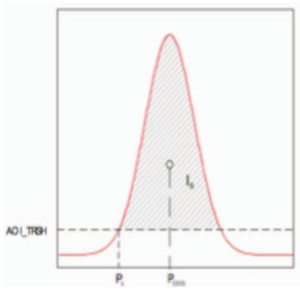
$$P_{COG} = P_L + \frac{M_S}{I_S} \tag{5}$$



a) AT C5-1600CS19-500 3D laser camera



b) Laser triangulation



c) A laser beam

Fig.4. a) Laser camera, b) Laser triangulation, c) A laser beam

Treshold, Center of Gravity (COG), Derivative and Smoothing methods are used in obtaining from laser beam which is shown in Fig.4 (b). A typical laser beam can be shown in Fig.4 (c). In the "2" where P_L and P_R represents the laser beam left and right side. Where Is represents gauss intensity value and M_s represents intensity total moment value which is shown in "3, 4". Consequently $P_{treshold}$ can be found calculate average of laser beam's left and right side which is shown "2", and when P_{COG} can be calculated in "5" [19].

B. Deep Learning

In learning and test stages healthy and faulty rail profiles collected to use in learning algorithms. Every rail profile data size can be select from 1600x1 to 1600x600.

The data of these two classes are trained in compliance with the CNN algorithm. A typical CNN have three main layers shown in Fig.5 [24].

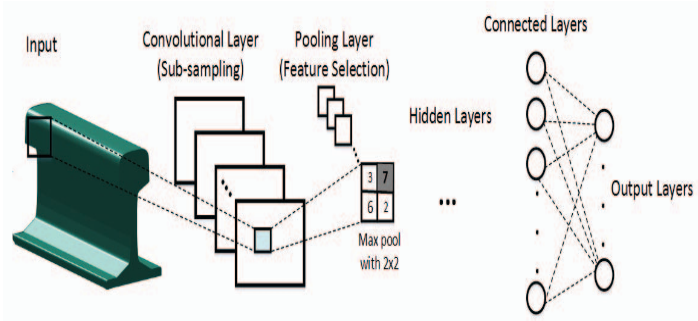


Fig.5. CNN model for deep learning based rails inspection

1) Convolutional layer: The convolutional layer is the core building block of a CNN. This layer's parameters consist of a set of kernels which have a small receptive field, but extend through the full depth of the input volume.

During the forward pass, each filter is convolved across the width and height of the input volume, computing between the entries of the filter and the input and producing a two-dimensional activation map of that filter.

$$C_{ij}^{l} = \sum_{a=0}^{m-1} x \sum_{b=0}^{m-1} W_{ab}\, f_{(i+a)(i+b)}^{l-1} \tag{6}$$

The convolutional layer's mathematical model is given in "6". In the equation, f, representing the input image value, W representing mxn dimension kernel matrix and C representing count of sub-sampling of this layer.

2) Pooling layer (Feature Selection): Pooling layer is a form of non-linear down-sampling. There are several methods to implement pooling among which *max pooling* is the most common. The most common form is a pooling layer with filters of size 2x2 applied (Fig.5).

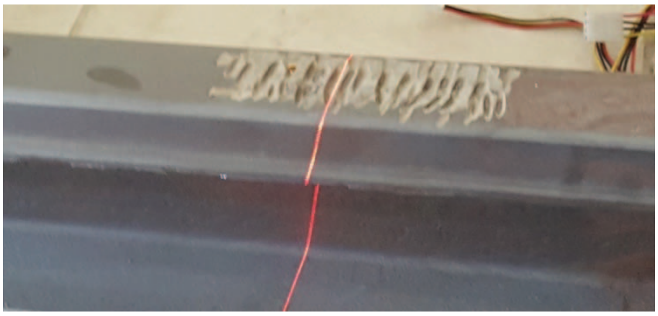
$$P_{vec} = \sum_i C_i {*}\mathrm{p} \tag{7}$$

$$\sum P_{vec} = max \sum C_i \tag{8}$$

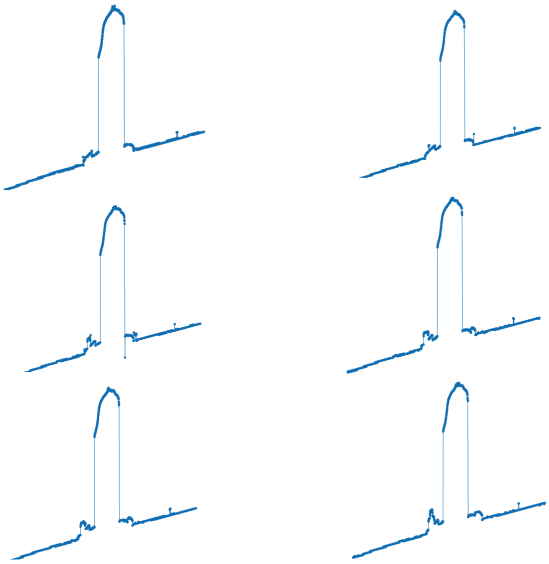
3) Connected Layers: Several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks.

V. Experimental Results

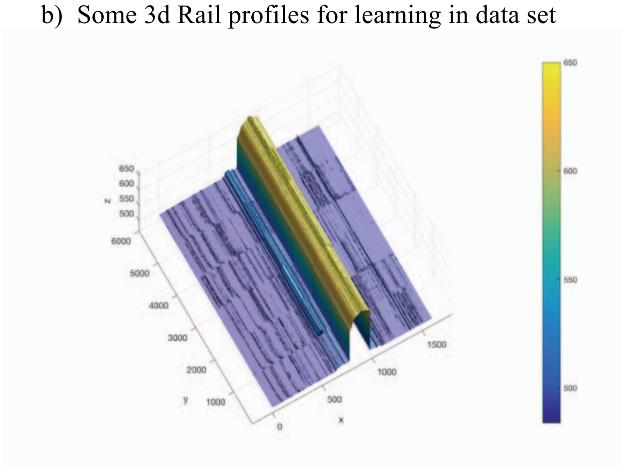
In rail inspection operations conducted using 3d laser cameras, the experimental results include the steps of obtaining rail profiles by preprocessing the three-dimensional data obtained from the calibrated compact cameras. The obtained three-dimensional rail profiles will constitute the input data of the deep learning-based fault diagnosis algorithm.



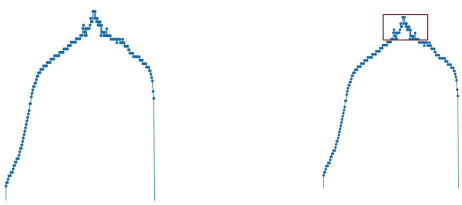
a) Rail surface



b) Some 3d Rail profiles for learning in data set



c) Merged 3d rail profile



d) Faulty rail profile

Fig.6. Experimental results

The most important step of the experimental study was the presence of rail profiles containing anomalies with a CNN trained as a two-class classifier which is labeled as "faulty" or "healthy" which is shown in Fig.6. In the experimental studies training and the classification process with CNN could be performed above 10.000 rail profiles per second with Nvidia Gpu and using Nvidia Cuda DP framework. In this study CNN input size selected 1600*50. AT C5-1600CS19-500 3d laser camera have 313 µm lateral resolutions. Consequently, a cost-effective rail inspection capable of operating in real-time at a speed of 100 km/h.

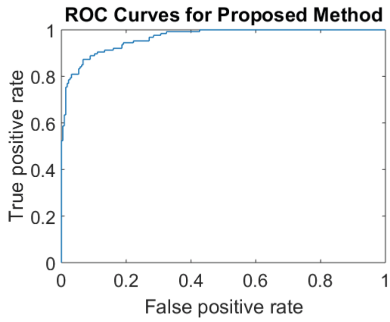


Fig.7. Roc curve for proposed method

The trained system was tested by measuring the operating speed and accuracy performance on a rail line using receiver operating characteristic (ROC) analysis [26]. Rail profiles were collected on a short rail line by the proposed system, and these profiles were trained by labeling as healthy and faulty. 75% of the dataset was used in DP model. The remaining 25% was used for testing purposes. %98 accuracy rate was achieved in the test phase.

VI. Conclusions

Today, rail transportation systems are widely used around the world. The rail lines should be inspected periodically and their maintenance should also be performed to ensure the railway transportation safety. Today, this inspection process is commonly carried out using CVS. In this study, the software architecture is presented for a rail inspection conducted using 3D laser cameras.

In general, there are two major criteria expected from a rail inspection application. These are highly accurate results and high operating speed. In this study rail inspection application was obtained at the high accuracy rate of 98%.

The second criterion of success expected from rail inspection applications is high operating speed. For this purpose, systems using 3D laser ensure high accuracy and high operating speed due to their measurement precision. In this study, it was possible to obtain high operating speeds approaching those of systems using special hardware with classical indexed CPU programming. The GPU programming employed had a similar code structure and was easy to learn and implement. In this system classification process with CNN were performed using Nvidia Cuda library.

Consequently, a new Deep Learning based approach presented using 3-d laser camera via GPU programming for rail inspection application proposed in this study with %98 accuary.

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