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Development of a Rail Flaw Measuring Stick Using Binary Image Classifier

A.A.Shah[1], G.F.Mirza[1], G.H.Palli[1], T.Hussain[1], B.S.Chowdhry[1] and M.Z.Shaikh[1]

[1] NCRA-CMS Laboratory, Mehran University of Engineering & Technology, Jamshoro, Sindh, Pakistan

Abstract

The safety of railway system in most of the developing countries like Pakistan is compromised by railway track surface defects like squat and turn out frogs. The railway system plays a significant role in shaping up a country's economy due to its increasing demand of passengers and cargo. This paper describes development of an instrumentation that is an inspiration from Spherry's walking stick and uses binary classifier for the swift analyzation of a railway track surface-based faults. The algorithm is trained using 500 images of healthy and faulty railway tracks captured at an operational railway junction. The entire process is performed in real time using Raspberry Pi 3 B + and APIs like OpenCV, Tensorflow, Numpy and Keras. The measured accuracy of the algorithm recorded is 93.7% and is validated using visual inspection techniques.

Keywords: railway track surface defects, binary classifier, canny edge detector, image histogram, Tensorflow, Numpy, Keras.

1 Introduction

Most of the railway tracks over the time have endured excessive loading conditions due to which their surface gets deformed. This deformation of the track surface can lead to rail corrugation, which serve as a major cause of the train derailment. Pakistan, in the year 2019 has marred over 100 railway accidents[1]. The majority of the accidents amongst them were due to the train derailment. Upon inspection of those train derailment related accidents, the reason was found to be lack of condition monitoring. As railway condition monitoring plays a pivotal role in making the railway secure and safe mode of transportation. Rail condition monitoring methodologies involve two types of techniques namely: “Walk by inspection” and “Drive by Inspection” . Pakistan uses both of these techniques in which the visual inspection is applied as a primary methodology for the determination of the track faults. Whereas, internationally there are instrumentations either installed on the track or in the vehicle. Those instrumentations involve: Inertial Measurement Units, Image Processing, Fiber Bragg Grating, Tilt sensing, Ultrasound testing, InfraRed Thermography (IRT), etc. With the recent development in Artificial Intelligence (AI) and deep learning have enable researchers to integrate these with the previously discussed instrumentation. Making them to fetch optimal results in the faults identification of the railway track but for a developing country like Pakistan, it is very expensive to adapt technologies like Fiber Bragg Grating or ultrasound testing, therefore, a cost-effective alternative is required. This generates a need of development of an indigenous solution for determination of the surfacebased railway track faults. The developed instrumentation has potential to replace the labour-oriented push trolleys with a portable, image processing based rail flaw measuring stick that detects the railway track surface based faults with an accuracy of 93.7%. The instrumentation operates with the canny edge detector, image histogram and binary classifier. Canny edge detector is applied in order to reduce the illumination effect. The instrumentation is also compared with visual inspection methodology in order to validate its efficiency and accuracy in the Validation section.

2 Methods

The track’s dimension for is considered as 70mm track’s head width so stick’s wheel A and B were separated at 70mm as shown in Figure 1. It could be hovered over track with wheels C and D as shown in Figure 2 and is constructed using metal with laptop holder to identify track faults.

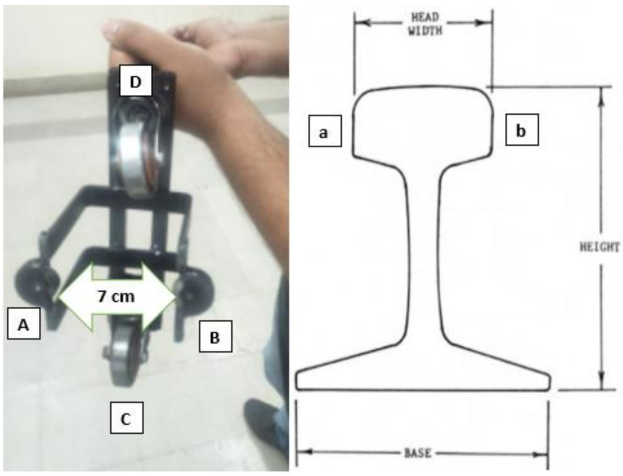


Figure 1: Instrumentation’s Dimensions.

Figure 2: Field Testing of Developed Instrumentation.

The working of Rail Flaw detection stick is shown in Figure 3:

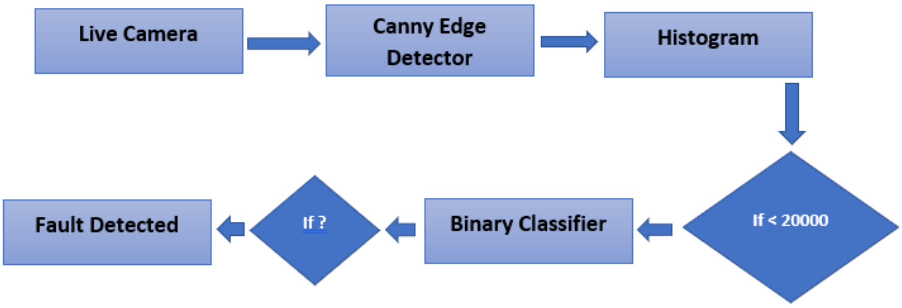


Figure 3: Block Diagram of Rail Flaw Detection Stick.

The stick analyzes faults by capturing live video using 5 MP, 720p Logitech webcam camera. Canny edge detector eliminates lighting condition captured in video as shown in Figure 4.

Figure 4: Overexposed Captured Image due to Lighting Condition.

It splits video into frames and sobel X and sobel Y masks are applied on each image pixels as shown in Figure 5. The webcam generated noises are reduced by Gaussian filter using Equation 1:

$$h(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

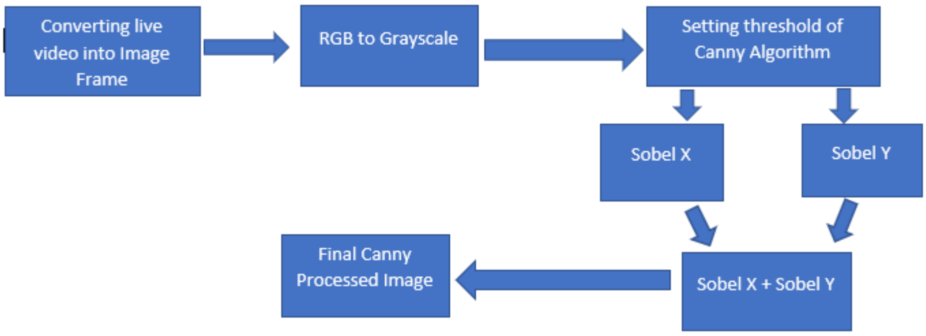


Figure 5: Working of Canny Edge Algorithm.

As image is comprised of horizontal (x) and vertical pixels (y), it requires image smoothing in which masks hx and hy are multiplied with each pixel of grayscale image. The image's gradient value and angle are computed using Equation 2 and Equation 3.

$$grad\ f = mag\ (\nabla G) = [G_x^2 + G_y^2]^{\frac{1}{2}} \quad (2)$$

$$\theta = tan^{-1} \frac{G_y}{G_x} \quad (3)$$

Pixels' alteration can be observed using gradient amplitude. As non-zero gradient is an effective block texture feature, therefore image noise can be calibrated using smaller gradient amplitude which can be adjusted by variable threshold. After experimentations, threshold values were found ranging from 0 to 180 for identification of track damages. The histogram decides faults if it crosses threshold and quantifies image pixels into graphical representation. The Canny Edge processed images are illustrated in Figure 6 and Figure 7. In graphical representation, the X and Y axis are image intensity and pixel count.

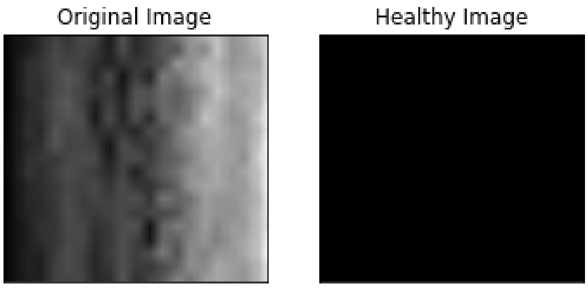


Figure 6: Canny Processed Image of Healthy Track.

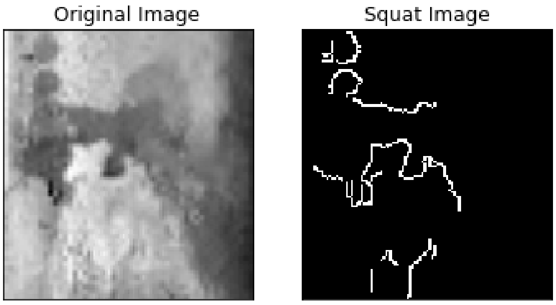


Figure 7: Canny Processed Image of Damaged Track.

The histograms are elaborated in Figure 8 and Figure 9.

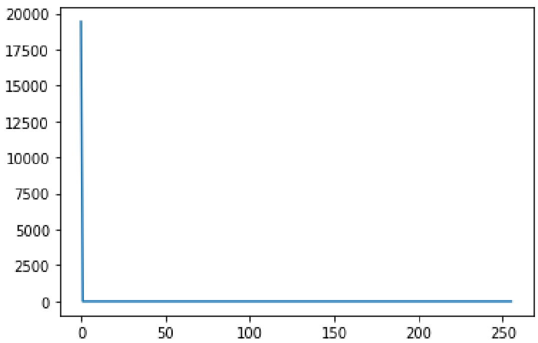


Figure 8: Image Histogram of Healthy Track.

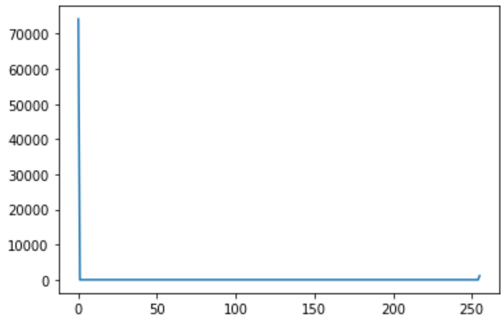


Figure 9: Image Histogram of Damaged Track.

In Figure 9, pixel count of healthy track reaches at 20000 whereas, the damaged track has pixel count of more than 32000. Therefore, conditional statement sends the track image to binary image classifier if track pixel count is more than 32000. To make classifier optimal for identification of railway fault, the convergence speed is increased with control parameters and confusion matrix as shown in Figure 10.

		Actual	
		Damaged Track	Healthy Track
Predicted	Damaged Track	True Positive (TP)	False Positive (FP)
	Healthy Track	False Negative (FN)	True Negative (TN)

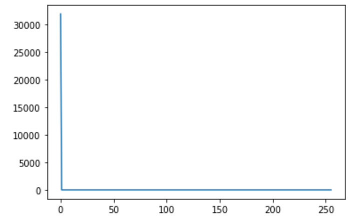
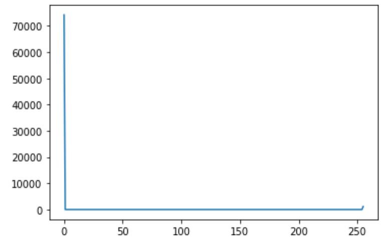
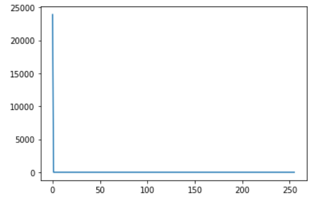
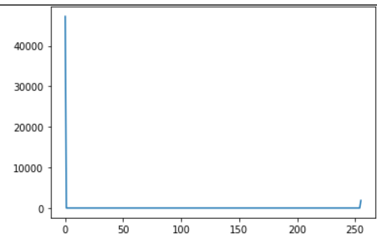
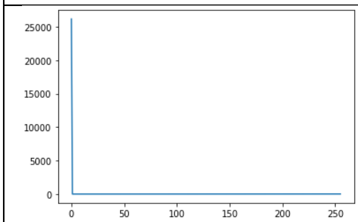
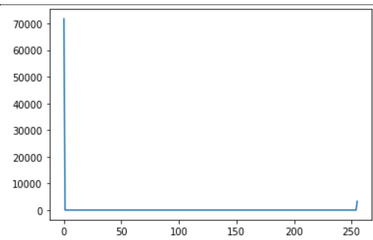
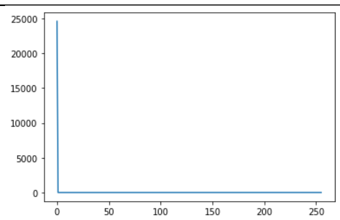
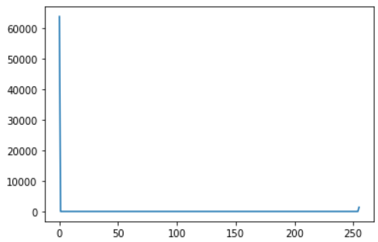
Figure 10: Confusion Matrix.

3 Results

The developed algorithm uses three stage image processing and identifies railway track surface faults. It is tested on 3 km railway track, situated at Kotri junction, Pakistan. There were 7 faults in that region and this test was performed with the permission of Divisional Engineer, Pakistan Railways. The canny edge detector removes faults' illumination effect as mentioned in Table 1. After canny edge processing which takes 400 milli-seconds, the image histograms are generated as illustrated in Table 2:

Original Image	Canny Edge Processed Image

Table 1: Comparative Analysis of Original and Canny Edge Processed Image.

Healthy	Damaged
	
	
	
	

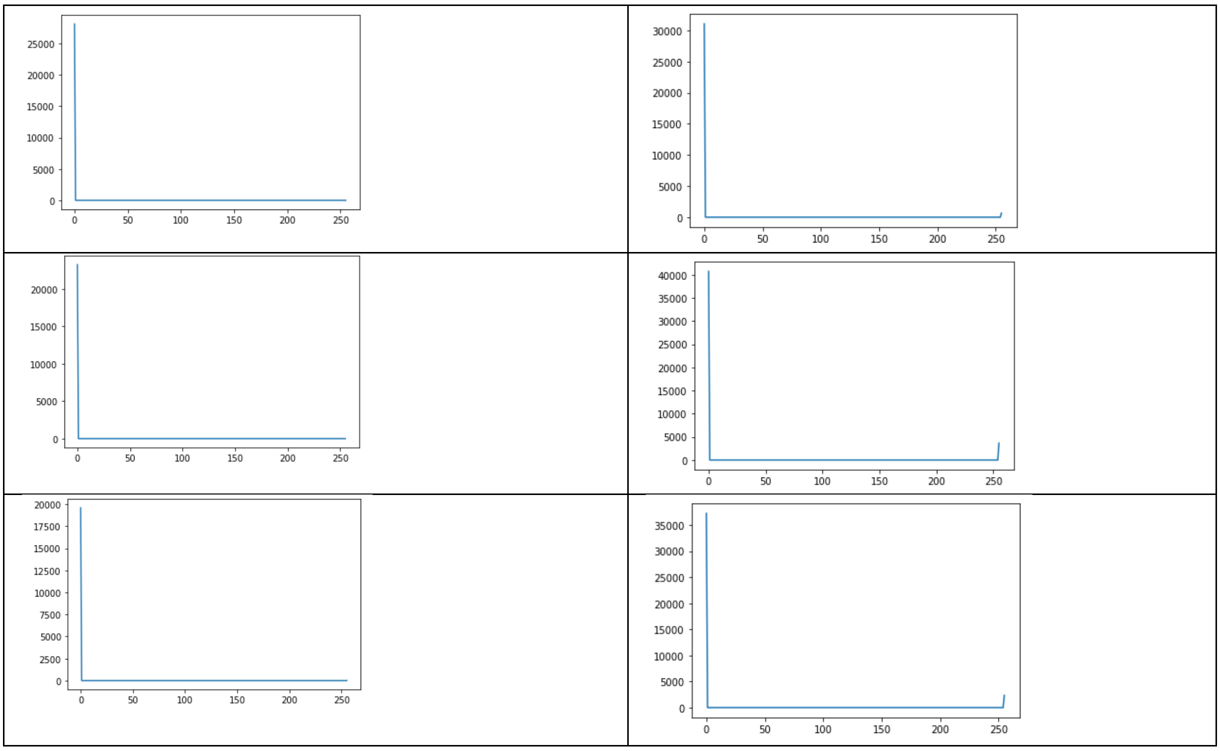


Table 2: Comparative Analysis of Histogram of Intact and Damaged Track.

While comparing thresholds of healthy and damaged track, if threshold of histogram is below 32000 pixel counts, then track has surface fault probability as analyzed from table. Binary image classifier further verifies that works on the logistic regression, which is sigmoid function. If output is 1 (true), track is damaged otherwise (0-false) not. Binary classifier is trained with 500 damaged track images and 500 healthy track images as shown in Figure 11:

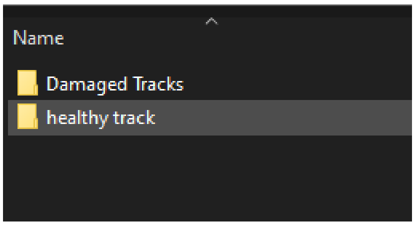


Figure 11: Folders Built for Binary Classifier.

Testing is then performed, for that, a separate folder is created in which healthy and damaged track images are mingled. Each image dimension is put constant that is 200 x 200 x 3, whereas activation function ReLU is applied. The convolution 2D layer is implemented consists of 16 filters and kernel of 3 by 3. For algorithm to work efficiently and fast, MaxPooling layer is added which compresses image dimensions into 100 by 100 x 3. The classifier is trained with 100 epochs. The RoC curves of accuracy and loss are shown in Figure 12 and Figure13 respectively. The results of damaged tracks are 1 and of healthy tracks are 0 and algorithm accuracy computed to be is 93.7%.

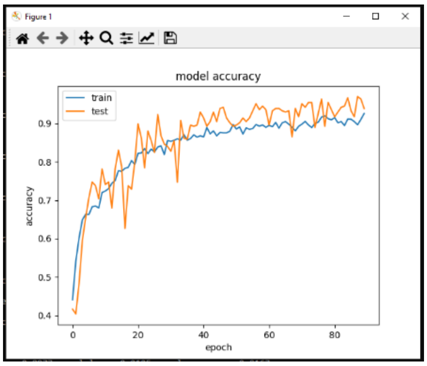


Figure 12: Accuracy Curve.

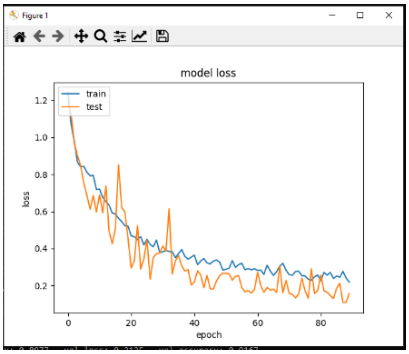


Figure 13: Loss Curve.

The validation was performed with traditional visual inspection from naked eye of the trained Pakistan Railway's official. They were hovered over the same track in which our testing was performed using push trolley as shown in the Figure 14. Through examination, the officials were able to detect three track defects out of seven track defects that were present in that railway junction. Thus, it is easy to compute the efficiency of developed algorithm for determination of the track surface faults.

Figure 14: Visual Inspection.

4 Conclusions and Contributions

The developed device identifies railway track faults with an accuracy of 93.7% and with a loss of 0.12%. It is achieved by developed algorithm using three stages image processing. Stage 1 includes canny edge image filtration for removing the illumination effect. For that, algorithm threshold is kept from 100 to 200, which acts as a marker and highlights track damages as shown in Table 1.
After that a real time histogram function is applied for the analysis of track faults if pixel counts of captured image crosses compared to 32000 pixel counts of intact track as mentioned in Table 2. If such variation is observed in real time, then the captured image is processed in binary classifier for determining track damage with precision resulting into desired accuracy.
The only limitation observed in this study is that the developed instrumentation can analyze one track at a time which will be resolved in our future work.
In various studies it is demonstrated how image processing and Inertial Measurement Units are capable of identification of track faults with an optimal accuracy and precision. A comparison of research works related to image processing and IMUs is presented in Table 3 and Table 4, respectively.

Researchers	Image Processing Algorithms	References
Xiukun Wei et al.	Railway track fastener defect detection using deep learning	[2]
Yungpeng Wu et al.	UAV based visual inspection method for rail surface defect detection.	[3]
Zhang et al.	Multi target defect detection	[4]

Table 3: Studies on Image Processing Algorithms.

Researchers	Inertial Measurement Units	References
D Milne et al.	Use of IMUs for the measurement of railway track faults	[5]
Abdollah Malekjafarian et al.	Implementation of the IMU sensors in the instrumented trains	[6]
Janxiang Zhang	Train induced vibration monitoring of track slab under long term temperature load using fiber optics accelerometer.	[7]

Table 4: Studies on Inertial Measurement Units (IMUs).

Studies show that accelerometers identify joint dipped angles and rail corrugation but not squat and turn out frogs. To identify squats and frogs, complicated signal condition processor may be required. The signal processing unit might produce an error as potential damage due to mud and dirt that remains stuck on tracks because of the rain. Techniques are compared in Table 5.

	Squat	Frog	Drainage	Crack
Image Processing	✓	✓	✗	✓
Accelerometer	✓	✓	✓	✗
Tilt Sensor	✗	✗	✓	✗
Fiber Bragg Grating	✓	✓	✗	✓
Ultrasonic	✓	✓	✗	✓

Table 5: Comparative Studies on Existing Techniques.

As squats and turn out frogs are major cause behind rail deformation so identification of these in timely manner can eliminate train derailment accidents. The techniques like ultrasonic flaw detection and IRT can analyze squats and turn out frogs but are slow in processing than image processing techniques. Hence, canny edge detection is incorporated along with AI based binary classifier.

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