IJTE, Vol. 10, No. 1, Summer 2022, pp. 855-864

Research Paper

Railway Turnout Defect Detection Using Image Processing

Zahra Fathollahi[1], Amir Golroo[1,*], Morteza Bagheri[2]

Received: 2017/07/06 *Accepted: 2018/06/02*

Abstract

Despite other modes of transportation, trains move just along one dimension. However, trains inevitably change their track or move to the opposite track in railway stations and ports using switch systems. Switches are vital for better operation and seamless movement of trains. Furthermore, they are crucial for the safety of movement in tracks due to high derailment potentials at switches; therefore, all parts of switches need to be continuously monitored. An increasing number of accidents in railway systems is highly dependent on switch performance. According to the Islamic Republic of Iran Railways, 90 percent of railway accidents in Tehran stations occur on switches, from which 25 percent happen due to switch defects. Therefore, condition evaluation of switches is of significant importance. Research studies have not been sufficiently conducted on automated condition evaluation of switches. This paper aims to develop a robust automated approach to evaluate switch conditions to be able to measure switch defects. Having taken some pictures from various switches with fixed angles and distance from rails, an image processing technique is applied to determine defects. The first step of image processing is to preprocess the images to increase their quality. The second step is to indicate the type and severity of defects using different algorithms. A Graphical User Interface (GUI) is developed to develop a user-friendly tool to be able to load images, preprocess the images, measure defects, and report the health condition of switches. Finally, the outcomes are validated by applying ground truth, which ends up with high accuracy of approximation of 87 percent.

Keywords: Fatality Severity, Risk Map, Classification, Decision Tree algorithms

[1] Department of Civil Engineering, Amirkabir University of Technology, Tehran, Iran
[2] School of Railway Engineering, Iran University of Science and Technology, Tehran, Iran

1. Introduction

Despite other modes of transportation, trains move just along one dimension. However, trains inevitably change their track or move to the opposite track in railway stations and ports using switch systems. Switches are vital for better operation and seamless movement of trains. Furthermore, they are crucial for the safety of movement in tracks due to high derailment potentials at switches; therefore, all parts of switches need to be continuously monitored.

Derailment, which is one of the most common railway incidents worldwide, annually results in a two million dollars loss of railway infrastructure in the United States [Fernando Molina, et al. 2010]. It has been revealed that the main reason of these incidents is switch defects. In 2009, the official reports showed that 54.3 percent of incidents are due to derailment in major and minor lines in Canada, most of them happened at switches [Canada, 2009]. In Iran, 35 percent of incidents are because of switch defects which clearly shows its importance and negative impacts on railways [Shahni Dezfulian, Jafarpour and Mir Mohammad Sadeghi, 2005].

The condition of switches should be continuously monitored to ensure no crucial defects are present due to their critical role in rail networks. For this purpose, conventional visual inspections are conducted by experts in a non-automatic manner to monitor defects on switches regularly. Generally speaking, the inspectors can capture only significant defects and may miss some minor ones, time-consuming, labor-intensive, and unsafe. Automated

Inspection; however, can considerably contribute to detecting defects before incidents occur [Clark, 2004] with a higher level of safety and a lesser level of bias related to personal judgment. Moreover, the procedure of automated data collection is repeatable, standard, and cost-effective.

The railway condition data would be helpful in railway maintenance planning. Several studies have been conducted on preventive maintenance in industries such as railways to increase reliability [Papaeliass, Roberts and Davis, 2008]. Preventive maintenance requires accurate data from railways, specifically from switches that should be acquired regularly, at a high quality and quantity. Some other researchers focused on risk assessment of the railway system to prioritize the risk to reduce the railway risk [Baradaran, 2017].

In this study, first, a design of experiment has been carried out, including sensor selection (i.e., camera), number, and location of taking images. Then, the images have been processed to make it clear to detect the defect. After that, the defects have been indicated and measured through image processing techniques. Finally, the outcomes have been validated via ground truth data.

2. Literature Review

Rail visual inspection previously was carried out by experts walking along railway tracks to detect any possible defect. However, camera-based inspection systems have been implemented in track inspection, maintenance and operational systems [Gonzalez and Woods, 2007]. Instead of visual inspections, these systems have employed an alternative approach [Fernando Molina, et al. 2010]. In this study, the researchers have applied a machine vision technique to recognize ties, anchors, and cut spikes rather than focus on cracks. Automated rail surface defects detection has been conducted since the early 1990s using cameras and optic sensors [Papaeliass, Roberts and Davis, 2008].

Several machine vision systems are in use or under development worldwide for a variety of railway inspection tasks, including inspection of rails, fastening systems, joint bars and ballast [Luis , Edwards and Barkan, 2011]. These systems have shown their considerable capabilities in the improvement of railway inspection. In many cases, experimental results have shown more than 80 percent accuracy with measurement speed up to 320 kph. Future works consist of more field tests with variable lighting conditions, particularly in dark locations and unfavorable climate. Further research studies should be carried out in order to improve the algorithm processing time, develop a reliability index for rail, and perform real-time data analysis [Alippi, et al. 2000].

Fra and Ensco began the development of a machine-vision-based joint inspection system in 2002 [Aguilar, et al. 2005]. The system applied high-resolution cameras with high-powered xenon lights to capture images of joint bars. It captured images at a maximum speed of 105 Kph. This system primarily found external cracks in joint bars. Experimental results showed an accuracy of 98 percent, whereas the accuracy declined to 85% under non-ideal track conditions.

In 2003, Singh et al. researched developing a machine-vision method for inspecting concrete crossing ties using a stereometric system that measured different surface shapes [Singh, et al. 2006]. The method estimated the deviation of the concrete ties from the required dimensional tolerances in production lines. Two CCD cameras with a resolution of 768*512 pixels were utilized to capture images and lasers for artificial lighting. The researchers came up with promising results at a high level of reliability.

Since 2008, Papaeliass et al. have studied the use of machine vision technology for inspection of timber cross ties [Papaeliass, Roberts and Davis, 2008]. The technology evaluated the condition of the ends of the ties and classified them as good or bad. This classification was performed by evaluating the quantitative parameters such as the number, length, and depth of cracks and the condition of the tie plate. Experimental results demonstrated 90% of accuracy in classifying ties.

In 2008, Cybernetix, in conjunction with the French National Railways, developed a commercial system for inspecting rails, fastening systems, measuring the rail gap between joint bars, and reconstructing the ballast profile [Papaeliass, Roberts and Davis, 2008]. The system applied an optical system and machine vision to capture speed up to 320 kph.

In 2009, the University of Central Florida developed a system measuring track gauges and inspecting fasteners (Babenko, 2009). The system utilized high-speed CCD cameras with a resolution of 1024*768 pixels. The camera was synchronized with strobe lights to minimize the differences in contrast during days. Additionally, sun shields were mounted on a cart to eliminate the effect of shadows on the images. The system detected the edges of the rails. Having known the distance between two cameras, the track gauge was estimated.

Few research studies have focused on switch defects or crossing anomalies due to rail contact fatigue (Grossoni et al. 2021,). Researchers have deployed the image processing and machine learning techniques to detect crack features and their combinations expressing the surface fatigue (Sysyn et al. 2019). However, to date, the automated condition data collection of railway switches has not received enough attention, which is a vital need of the railway industry for enhancing data collection processes to be able to conduct maintenance planning for switches in one hand. On the other hand, automated data collection is the only cost-effective, safe, time-saving, and standardized approach widely used in recent years in the health monitoring of transportation infrastructures. Therefore, this study is to fill the gap of automated condition diagnosis of switches only to detect a few defects, including rail wear, split, and fracture in the frog point.

3. Objective and Scope

The main objective of this research is to conduct condition evaluation of railway switches to inspect only a few switch defects through the application of high-resolution cameras using real-time image processing algorithms. The scope of this research is limited to condition evaluation of switches by detecting a few defects that encompass rail wear, split, and fracture in the frog point. The defect location, type, and severity are measured and reported automatically by a user-friendly Graphical User Interface (GUI).

4. Research Methodology

Having reviewed related literature, an experimental design was completed expressing how to collect data/images. After taking images, an image processing technique was applied to determine defects. The first image processing step was to preprocess the images to increase their quality. The second step was to indicate the type and severity of defects using different algorithms. Finally, the outcomes were validated through the application of ground truth. Figure 1 shows the methodology of this research.

4.1. Data Collection

The experimental design of this study consisted of camera selection, instruction development, and finally, data collection. First, based on the precision needed to detect defects on switches (1 mm) a high-resolution CCD camera (14.5 Mega Pixel) was selected, which could recognize the targeted defects. Images should be taken at high resolution with enough contrast between defects and their background to be able to identify defects. Then, an instruction was prepared to describe how to collect data (distance and angle from/to the rail) to consistently take images. Adopting a monotonous approach to capturing images is necessary for the next steps. Finally, after initial investigations on 226 switches in strict 6 of the central railway station in Tehran, Capital of Iran, 20 switches with the required defects were selected.

To determine optimal distance and the best possible angle resulting in sufficient accuracy and precision of images, sensitivity analysis was conducted in distance and angle i.e.; several images were taken at different heights and angles. This sensitivity analysis concluded an optimum height of 110 centimeters and an angle of 90 degrees. Several images were captured from the switch at the achieved optimum distance and angle in a constant lighting state with (i.e., artificial light) applying sun shields to avoid the negative effect of shadow. A Graphical User Interface (GUI) was developed as illustrated in Figure 2 to develop a user-friendly tool to be able to load images, preprocess the images, measure defects, and report the health condition of switches.

Image processing

The ultimate goal of this step was to indicate the location of any possible defect along with its type and severity with real-time processing. For this purpose, the image processing toolbox of Matlab software was applied. In the initial image processing step, the operators of contrast increase, edge detection, and image parts separation with intensity distribution histogram were utilized. The outputs of this step were images of switches including the frog point with defects that were clearly recognized. In this step, inappropriate images from which defects were not recognizable were removed from database, while the others proceeded to the second processing step. In the second step, the severity of defects was measured by different algorithms to ensure that the acceptable level of accuracy of defect measurement was achieved.

The differences between the algorithms were in the threshold applied for defect isolation [Liu, et al. 2011]. As the lighting system was not rigid and modification of images intensity is the software's ability, applying the threshold was more complicated. So, it was decided to consider two methods of dynamic threshold applications: Quadratic Integral Ratio (QIR) algorithm and Otsu’s algorithm [Benitoa and Peñab, 2007]. Having utilized the two algorithms of applying the threshold, the number of pixels in defective areas was determined [gibert, patel and chellappa, 2014]. Then, the length of defective areas was determined by defining a pixel conversion coefficient and reported in meters.

Subsequently, the length of measured defects was compared with allowable limits to evaluate the switches' health condition.

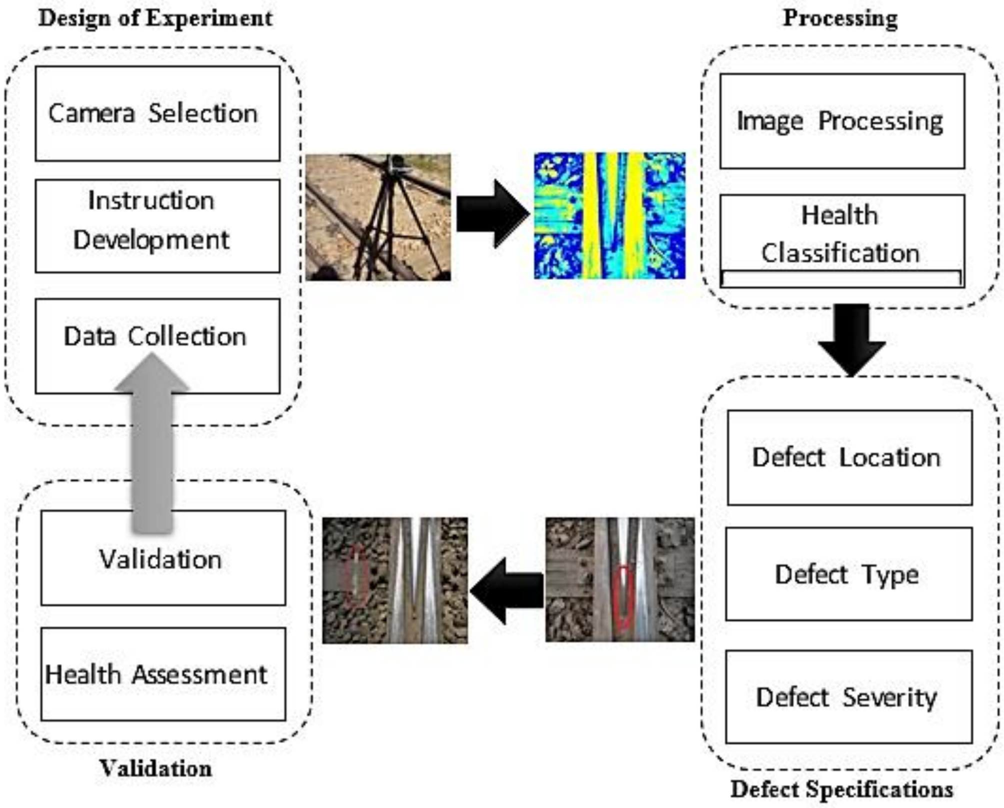

Figure 1. Research Methodology

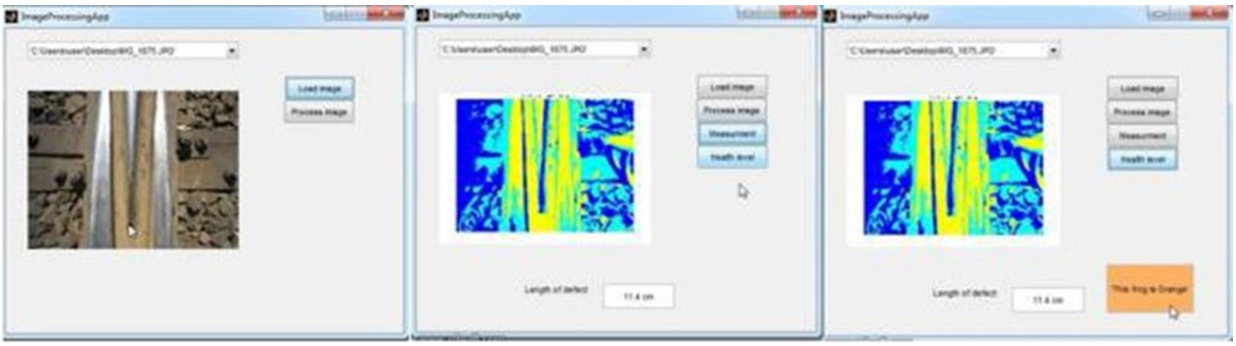

Figure 2. Graphical User Interface displaying image processing steps

4.2. Health Classification

The final step was to classify switch defects according to international codes. According to the ARMA code [standards ,1991], a frog should be restored or replaced if it is chipped, broken, or worn more than 6 inches (15 centimeters) back from the original location. The ARMA code also defines different classes for switches as represented in Table 1.

Table 1. Condition diagnosis classification of the switches

Detected length	Defect percentage based on ARMA code	Defect classification
less than 5cm	0-33	Green
between 5 cm &10 cm	33-67	Yellow

between 10 cm & 15 cm	67-100	Orange
more than 15 cm	more than 100	Red

5. Results and Discussion

The first preprocessing step applied to the images was to recognize the edges. This step was important to detect frog/crossing points (li, et al. 2014). Figure 3 shows an image with the red lines on edges expressing the crossing point location. It is noteworthy that if an image did not include the crossing point, it was ignored from further analysis.

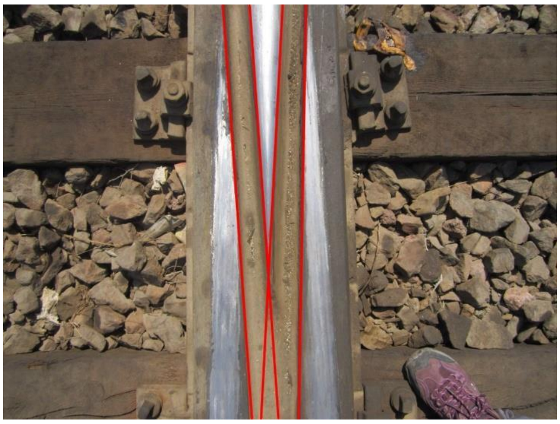

Figure 3. An acceptable image with a frog point

After recognizing a frog point, the image was processed to enhance the contrast to detect the defect. As shown in Figure 4, the left image shows a rail section in which a frog point is detected with Quadratic Integral Ratio (QIR) and Otsu's algorithms. The picture in the middle depicts different features of the frog point more clearly due to the enhancement of contrast. Finally, the right image was changed to the blue background to measure the defects.

As mentioned before, the MATLAB Image Processing Toolbox was applied in this research. After recognizing the defective area by two abovementioned algorithms, the number of pixels in this area was determined. Having applied a defined benchmark, the software calculated the length of the defect based on the number of pixels counted. The next step is to validate the length of defects identified.

In order to validate the length of defects, they were compared with ground truth. The ground truth was manually measured on the entire switches very accurately by professional surveyors. Figure 5 demonstrates the length of defect manually measured as compared to the same length indicated through the application of image processing using both algorithms mentioned above. It is understood from the figure that the results are consistent, and no significant difference among the three measures is realized. Therefore, it generally proves the validity of applied algorithms.

The Analysis of Variance (ANOVA) test was employed to check a statistically significant difference among the mean of the three measures for defect length. It is concluded from the results of the ANOVA test (p-value 0.75 > 0.05) that there was no significant difference among the measures, which perfectly expresses the validity of the algorithms used in this research. The detailed results of the ANOVA test are shown in Table 2.

The other method used to ensure the validity of the algorithms in measuring the length of defect is to develop a linear relationship between manual measurements and the length of defect approximated using two algorithms. In this relationship, the length of defect obtained manually by visual inspection was considered an independent variable (M), and the defect length calculated by both image processing algorithms were addressed by a dependent one (IPi). Therefore, given the above definition for variables, the linear relationships for each algorithm and manual measurements separately were developed using the regression analysis method for 20 samples switches as follows:

$$IP_1 = 1.0286M + 0.5913 \quad (1)$$

$$IP_2 = 1.0395M + 0.7275 \quad (2)$$

M denotes the defect measured manually, IP_1 and IP_2 are the estimated defect using the first and second algorithms, respectively. As displayed in Figure 6, there are strong relationships between real measured defects (ground truth) and estimated ones by the first and second algorithms. Both lines fitted to two sets of data clearly illustrate a negligible difference between real data and estimated ones as the coefficients of M (the slope of the lines) in both Equations 1 and 2 are almost one. In addition, the high value (almost 0.99) of the coefficient of determination (R^2) and a lower amount of Standard Error (almost 0.15) confirms the fact that there is a close relationship between the real and estimated measures.

(a) original photo (b) contrast increased (c) blue background

Figure 4. Defect severity detection

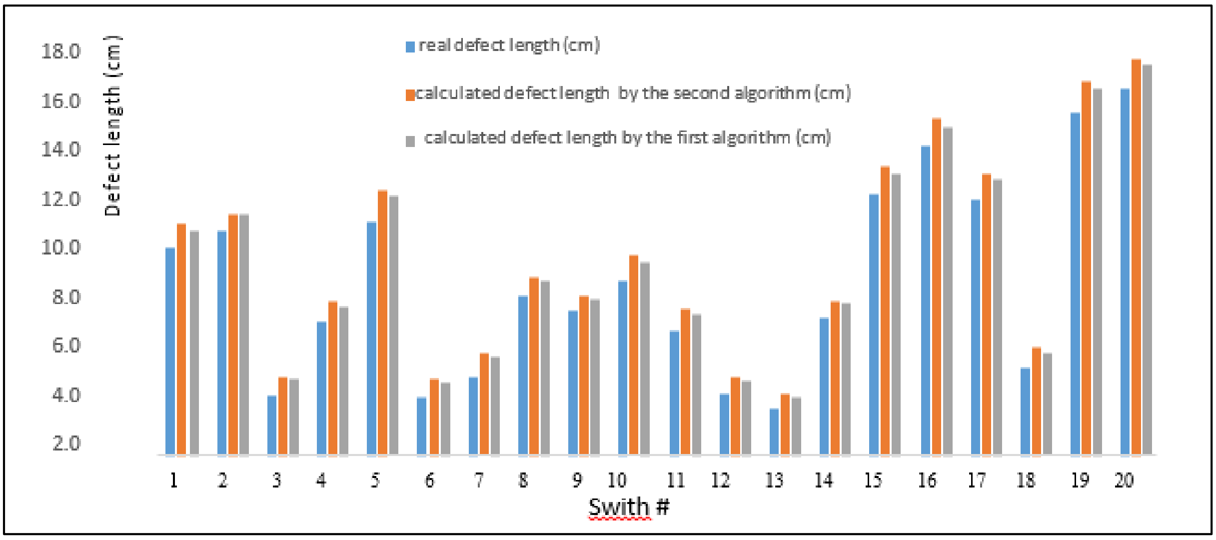

Figure 5. Comparing manual measurements (real defect length) with estimated ones (using algorithms)

Finally, the associated estimation errors were compared to compare the two algorithms. The errors were defined as the differences between defect measures approximated by the algorithms and ground truth. Table 3 shows all defect measurement data with the corresponding errors. As presented in this table, the average errors are 11% and 13% (i.e., the precision of 89% and 87%) for the first and second algorithms, respectively, negligible.

More importantly, the classes of the defect (refer to Table 1) identified through all three methods come up with identical results for all samples. It is concluded that the algorithms are robust in approximating the switch defect.

Generally speaking, the overall condition of the sample switches is promising. Based on the defect classifications, the percentage of Green, Yellow, Orange, and Red classes are 31, 32, 21, and 16. This figure illuminates that about 63% of the sample size had the switch condition over than average. Such information is significantly helpful for decision-makers to be able to plan for resource allocation for maintenance planning on the switches.

6. Conclusion

Switch condition is of crucial importance in the entire railway performance. Automated inspection methods have been widely replaced with manual visual inspections. However, a few attempts have been performed to inspect switch health automatically. This study successfully developed an automated inspection method to capture images from switches. By applying two image-processing algorithms, the captured images were quickly analyzed to come up with type, length, and class of switch defects. The algorithms were validated using ground truth. The following achievements have been obtained in this research.

- Several switch defects (i.e., rail wear, split, and fracture in the frog point) have been detected via image processing on switches
- Through the application of image processing, the detected defects have been measured via counting their image pixels.
- Ground truth data have successfully validated the defect measurements via image processing
- The estimated defect could approximate the real defect with at least 87 percent precision.

Table 2. The ANOVA test on image processing outputs and ground truth

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	12.603	2	6.3015	0.277632	0.758594	3.158843
Within Groups	1293.746	57	22.69729	---	---	---
Total	1306.349	59	---	---	---	---

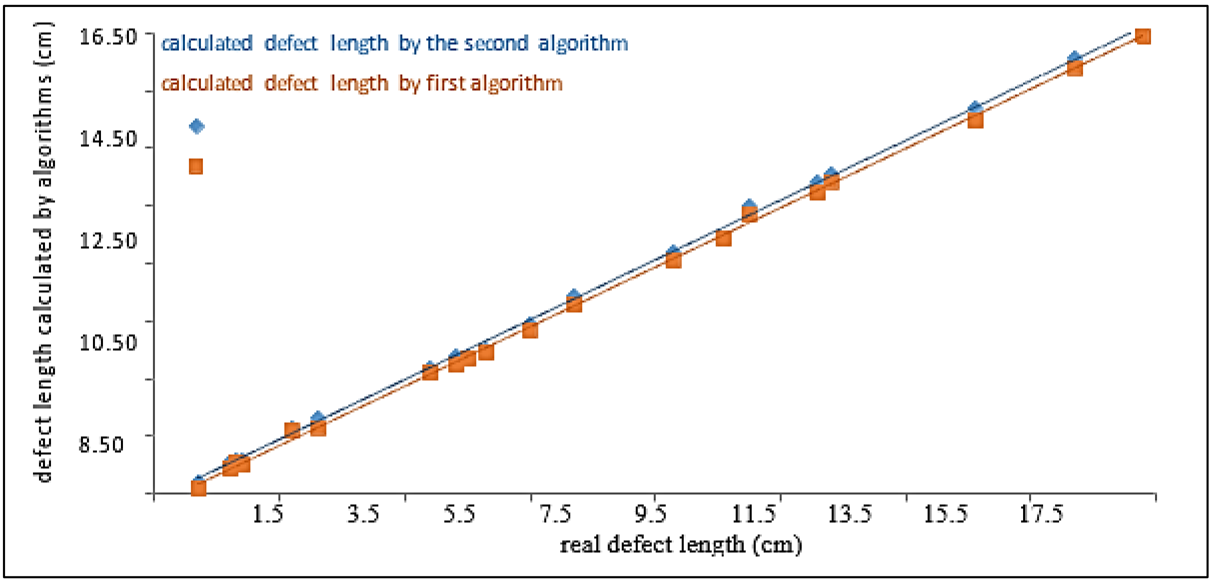

Figure 6. Correlation between estimated and real defect length

Table 3. Sample defect length, percentage, error, and class

Sample	GROUND TRUTH			FIRST ALGORITHM				SECOND ALGORITHM			
#	Length (cm)	%	Class	Length (cm)	%	Error	Class	Length (cm)	%	Error	Class
1	9.8	68	Orange	10.9	70	3	Orange	10.6	72	6	Orange
2	10.6	70	Orange	11.4	76	8	Orange	11.4	76	8	Orange
3	2.8	18	Green	3.7	24	25	Green	3.6	24	25	Green
4	6.3	42	Yellow	7.3	47	11	Yellow	7	48	13	Yellow
5	11	73	Orange	12.5	81	10	Orange	12.2	83	12	Orange
6	2.8	18	Green	3.6	22	18	Green	3.4	24	25	Green
7	3.7	25	Green	4.8	31	19	Green	4.7	32	22	Green
8	7.5	49	Yellow	8.4	55	11	Yellow	8.2	56	13	Yellow
9	6.8	44	Yellow	7.5	49	10	Yellow	7.4	50	12	Yellow
10	8.2	53	Yellow	9.4	61	13	Yellow	9.1	63	16	Yellow
11	5.9	38	Yellow	6.9	44	14	Yellow	6.7	46	17	Yellow
12	2.9	19	Green	3.7	23	17	Green	3.5	25	24	Green

Sample	GROUND TRUTH			FIRST ALGORITHM				SECOND ALGORITHM			
#	Length (cm)	%	Class	Length (cm)	%	Error	Class	Length (cm)	%	Error	Class
13	1.8	11	Green	2.9	18	39	Green	2.7	19	42	Green
14	6.5	42	Yellow	7.3	48	13	Yellow	7.2	48	13	Yellow
15	12.3	80	Orange	13.6	89	10	Orange	13.3	91	12	Orange
16	14.6	95	Red	15.9	103	8	Red	15.5	106	10	Red
17	12.1	79	Orange	13.3	87	9	Orange	13	89	11	Orange
18	4.1	26	Green	5.1	30	13	Green	4.8	33	21	Green
19	16.2	106	Red	17.6	115	8	Red	17.3	117	9	Red
20	17.3	113	Red	18.7	122	7	Red	18.4	124	9	Red
Average	8.16	54	---	9.225	59	11	---	9	61	13	---

7. References

- Aguilar, Juan, Lope, Maria, Torres, Enrique and Blesa, Maria (2005) "Development of a stereo vision system for none-contact railway concrete sleepers measurement based in holographic optical elements", Measurement, Vol. 38, No. 2, pp. 154-165.

- Alippi, Cesare, Casagrande, Ettore, Scotti, Fabio, and Piuri, Vincenzo (2000) "Composite Real-Time Image Processing for Railways Track Profile Measurement", IEEE transaction on instrumentation and measurement, Vol. 49, No. 3, pp. 559-564.

- Baradaran, Vahid (2017) "Assessment and Prioritizing the Risks of Urban Rail Transportation by Using Grey Analytical Hierarchy Process (GAHP)", International Journal of Transportation Engineering, Vol. 4, No. 4, pp. 255-273.

- Benitoa, Mónica, and Peñab, Daniel (2007)"Detecting defects with image data", Computational Statistics & Data Analysis, Vol. 51, No. 12, pp. 6395-6403.

- Canada, Transportation safety board (2009) Statistical summary railway occurrences, communications division. Quebec: Transportation safety board (TSB).

- Clark, Robin (2004) "rail flaw detection: overview and needs for future developments", NDT & E International, Vol. 37, No. 2, pp. 111-118.

- Fernando Molina, Luis, Resendiz, Esther, Edwards, J. Riley, and M. Hart, John (2010) "Condition Monitoring of Railway Turnouts and track components using machine vision." Transportation Research Board (TRB), Washington DC, USA, 23-27.

- Gonzalez, Rafael C, and E Woods, Richard (2010) Digital image processing. New Jersy: Prentice Hall.

- Grossoni, Ilaria, Hughes, Peter, Bezin, Yann, Bevan, Adam, and Jaiswal, Jay (2021) “Observed failures at railway turnouts: Failure analysis, possible causes and links to current and future research.” Engineering Failure Analysis, Vol. 119, No.104987.

- Li, Ying, Trinh, Hoang, Haas, Norman, And Pankanti, Sharath (2014) "rail component detection, optimization, and assessment for automatic rail track inspection", IEEE transactions on intelligent transportation system, Vol. 15, No. 2, pp. 760-770.

- Liu, Ze, Wang, Wei, Zhang, Xiaofei, and Jia, Wei (2011) "Machine vision inspection of railroad track", 2nd International Asia Conference.

- Luis, Camargo Fernando Molina, Edwards, J. Riley, and P. L Barkan, Christopher (2011) "emerging condition monitoring technologies for railway track components and special trackwork", ASME/ASCE/IEEE Joint Rail Conference, Pueblo, Colorado, USA.

- Papaeliass, Mayorkinos, Roberts, Christophe, and Davis, Christina (2008)"A review on non-destructive evaluation of rails: state-of-the-art and future development", rail and rapid transit, Vol. 222, pp. 367-384.

- Shahni Dezfulian, Reza, Jafarpour, Amir, and Mir Mohammad Sadeghi, Seyed Javad (2005) "Investigating the result of setting up a comprehensive Iranian railway network maintenance", 3rd national maintenance conference. Tehran, Iran.

- Sysyn, Mykola, Gerber, Ulf, Nabochenko, Olga, Gruen, Dmitri, and Kluge, Franziska (2019) “Prediction of Rail Contact Fatigue on Crossings Using Image Processing and Machine Learning Methods” Urban Rail Transit 5, 123–132.

- Singh, Maneesha, Singh, Sameer, Jaiswal, John, and Hempshall, John (2006) "Autonomous Rail Track Inspection using Vision Based System", IEEE International Conference on Computational Intelligence for Homeland Security and Personal Safety. Alexandria, Virginia, USA.

- Standards, railroad track. (1991) Army TM 5-628, Air Force AFR 91-44. Washington: departments of the ARMY, and the air force.

- Swely, Kevin, and Reiff, Ray (2000) "An assessment of Railtrack’s methods for managing broken and defective rail", Rail failure assessment for the office of the rail regulator.