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Rail Defect Detection and Classification with Real Time Image Processing Technique

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ABSTRACT

Rail defect detection has a great importance for railway transportation. Because faults on the rails cause to problems such as the cost, the disruption of transportation and the safety. In this study, based real-time video processing algorithm used Morphological feature extraction is recommended to detection defects on railroad. The rail is detected by applying Hough Transform and image processing techniques to rail images obtained from the real time camera. Features of the detected rail images are extracted with applying morphological operations and defected regions are identified. Headcheck, fracture, scour and undulation failures are detected through proposed method. And then the classification of defects is performed. In the classification step, Haar-like features based AdaBoost classifier is utilized. In this study, results with low uptime and high success rate are acquired by performing all steps of proposed algorithm to the images of rail taken under different lighting and direction.

Keywords: *Rail Track Detection, Rail Defects, Defects Classification, Hough Transform, Morphological Operation*.

1. INTRODUCTION

The railway transportation has a major significance in the world. It is required that the railways to be examined in more detail with the improved railroad technology. Contact measurement technique is used to detect failures in the rails obtain low sensitivity and low accuracy rate results [1]. So it remains insufficient about meeting the needs of today's advanced railway technology [2]. The failures upon rails with advanced railway technology is identified without contact [3].

In time, the ascending wears on the rails bring about the disruption of transportation security, the off-road accidents, the interruption of the harmony between the rails and the wheels [4]. Detection of most critical components for the safe operation of trains is important [5]. The analysis of the rail profile must be repeated at regular intervals in order to prevent these situations and detect early failures that can occur in rail [6]. Nevertheless this process is costly and it needs that the railway track should be temporarily disabled [7].

The developed methods to detect failures in railway as contactless are available in literature. Shah [8], did work detection place and type of rail defect. He increased the quality of the image acquisition with controlled lighting and the use of superior computing power technology. Breakage failure in the rail is determined by following the block diagram. Block diagram of rail breakage failure detection in literature is shown in Figure 1.Vijaykumar and Sangamithirai [9], offered method that analysis the texture of rails through the help Gabor filter of various frequency and orientation. Defects were identified based on the size of the defects. However, rating of defects was not be accomplished with Gabor method of defect detection. Yaman [6], detected failures happened on the rail surface by associating images taken from two different cameras. The accuracy of proposed method was ascended by using the images taken from two different cameras.

Bettemir [10], which edges belongs to railway track was identified with Heuristic method by utilizing the geometric properties of the railway track and the brightness values of the edges. Shen et al. [11], inquired the feature extraction of the turnout defects based on the bogie acceleration measurement. The normal and faulty turnout model based on SIMPACK were established first. Then the acceleration signal was analyzed in time-frequency domain. Hu et al. [12], detected the heavy rail surface defects based on the mathematical morphology of multi-scale and dual-structure elements according to the characteristics of heavy rail surface defects, uneven brightness and noise. When compared with the traditional edge detection methods, Hu's method is superior.

Sun et al. [13], the non-destructive testing method which carries out the photoacoustic detection technology proposed for the rail defect detection and established a real-time photoacoustic imaging system for the rail non-destructive testing based on the ultrasonic sensor. Li et al. [14], improved rail control system based on real time automatic vision. The Batch algorithm to determine the node layer and the model switching and multiple classifiers algorithm to determine the fasteners was employed in this improved system.

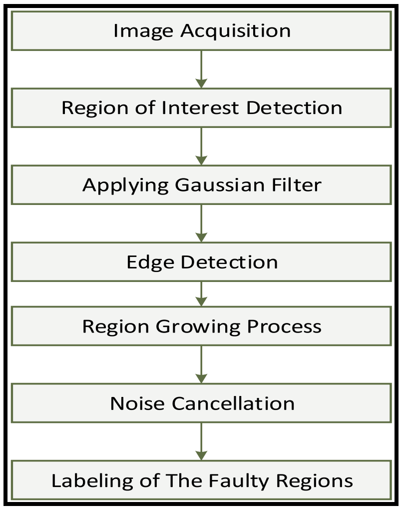


Fig. 1. Block diagram of rail breakage failure detection in literature [8].

Molodova et al. [15], developed an automatic method which use axle box acceleration (ABA) measurements on trains for detecting railway surface defects. Trinh et al. [16], investigated the rail surface defects and detected the rail by combining the speed information obtained from the GPS information and distance measurements with all the camera images obtained from the video stream before did data analysis and advanced data integration for the rail defect detection. Chen et al. [17], applied image processing techniques as image enhancement, noise cancellation, feature extraction and adaptive threshold to rail images for the rail surface defect detection.
In this study, rail detection process is primarily done on the rail images taken from the real time video camera. Then Headcheck, fracture, scour and undulation failures that are on the rail images are detected by using image processing techniques. The detected defect regions are classified bu using AdaBoost classifiers. The defect type of rail track surface is decided with classification. The recommended method of rail defects both runs faster than most algorithms in literature and detects stated all failures with a single algorithm.

2. RAIL DEFECTS

Failures in railway track can be expressed as wear, breakage, scour, undulation, headcheck and oxidation [18]. Horizontal and vertical wears occur in surface which rails contact with wheel. If the amount of rail wear is greater than 33 degree, the boden climbing occurs. So the rail is exchanged with new rail or navigational restriction is made. Rail abrasions happen in horizontal curves, scissors languages and middle of scissors. Rail abrasions are divided into two as vertical and lateral wear. Vertical wear
is a wear shaped of spread and bending that occurs in the track mushrooms of the curve, middle of scissors and head rail of joints [18]. Whereas lateral wear occurs in the scissors languages and the inner cheeks of outer rail by the effect of the centrifugal force [18]. The rail fracture is deeper than 10 mm and longer than 50 mm space in the movement place of the rail [18].
Headcheck defect is found around the gauge corner of outer rail and this fault ascending inclines to happen when cracks reach 30 mm in surface length [20]. The undulation failure can be expressed that different collapses happen in the rail surface [18]. An example of undulation defect that can occur in the rail is shown in Figure 4. The scour fault that can happen in the rail is one or several places of the rail due to the spinning of the locomotive. It should be exchanged rails exceeding the amount scour [18]. An example of scour fault that can occur in the rail is shown in Figure 5. Rail oxidation is that crusting, decay, rust and small holes occur in the rail by effecting humidity, soil and water [18].
Earlier detection of rail defects is important for both preventing accidents that can happen and preventing greater than a costly problem.

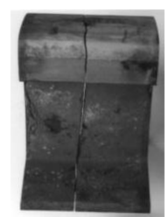


Fig. 2. An example picture of the rail fracture [19].

Fig. 3. An example of headcheck failure that occur in the rail [20].

Fig. 4. An example of undulation defect that occur in the rail [18].

Fig. 5. An example of scour defect that can happen in the rail [20].

3. THE PROPOSED METHOD

Failures in railway track can be expressed as wear, breakage, scour, undulation, headcheck and oxidation. A contactless vision based image processing algorithm is recommended in order to detect and classify defects that can happen on the rail surface. The block diagram of rail defect detection and classification is shown in Figure 6.

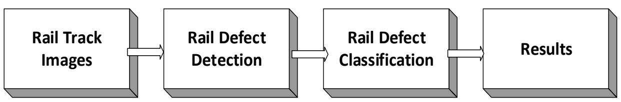


Fig. 6. The block diagram of the proposed method.

3.1 Rail Defect Detection Method

In first step of the proposed detection method, rail object is determined in railway image which is received from a camera placed on train. Then, the detected rail track is given to defect detection algorithm as a parameter to detect failures on the rail surface and the faulty regions on the rail surface is detected by being used image processing techniques.
The detection method of defects on the rail surface both runs faster and gets more correct results than contact measurement technique through utilizing the proposed method. Furthermore, damage doesn't occur on the rail surface during this process. The block diagram of the proposed detection method is shown in Figure 7.

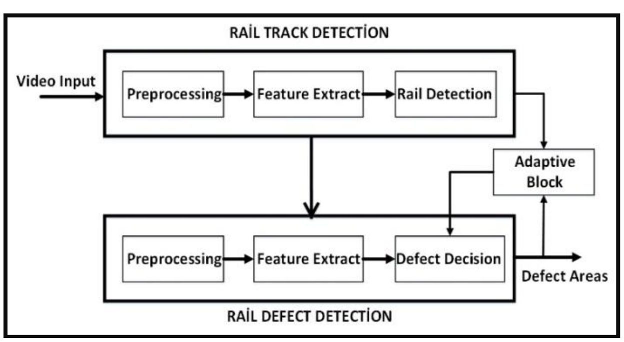


Fig. 7. Block diagram of the proposed detection method.

The rail track image that is obtained from rail detection algorithm is given to the defect detection algorithm as a parameter. Then, preprocessing, feature extraction and defect decision operations are performed. In the rail defect decision process, it is judged whether to be defective of the region by using area feature.
While in the adaptive block, exchange of the stated area threshold value is investigated. In this way, rail detection process, rail fault is detected more accurately and labeling of noisy areas as rail defect is prevented. Flow chart of this proposed detection method is shown in Figure 8.
RGB format images obtained from video frames are primarily converted to Grayscale format images in order to facility algorithm processes. Then image sharpening and Canny edge detection are performed to this image. It is subtracted the last image which the Morphology operations were implemented to from the image which the image sharpening and Canny edge detection were applied to. Thus the difference image is obtained by this subtraction operation. Background removal process is carried out by applied Morphology operations to the difference image [30]. The image whose background was removed has solely rail and some noises. The accuracy rate of rail detection is risen by the background removal operation. The Hough transform finds line segments on the image [21, 22]. Accordingly the line segments are determined by applying Hough Transform to the result image. So the rail object is detected with coordinate informations of the detected line segment.

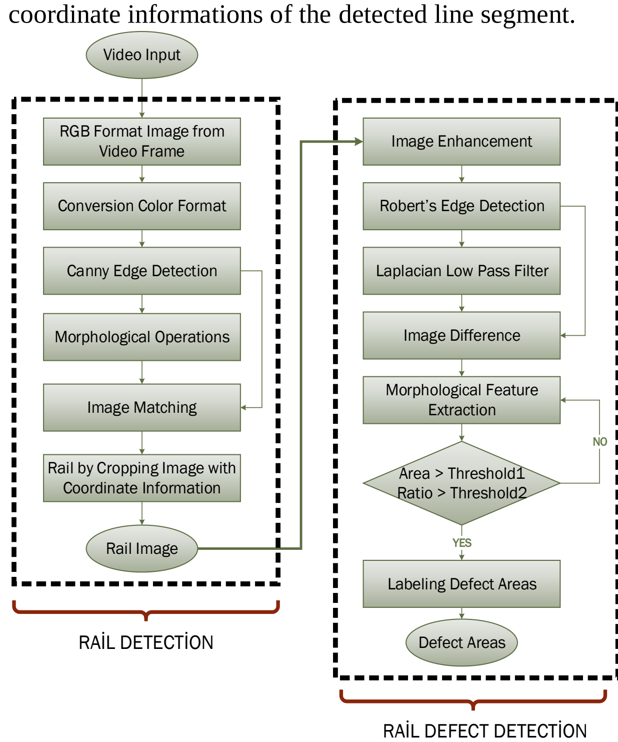


Fig. 8. Flow chart of the proposed detection method.

The rail object which was acquired by the rail detection algorithm is given to the defects detection algorithm as a parameter. The image sharpening and image adjustment is performed in the defects detection algorithm. Rail defects are more prominent than previous appearance with applied the image sharpening and adjustment to the rail image. Then Robert's edge detection is enforced to the resulted image. Robert's edge detection basically finds vertical and horizontal edges on image [23].

In the next step, Laplacian low pass filter is applied to the rail image in order to extract limits of defect areas. Low pass filter removes high frequency information while tends to hold low frequency information. Laplacian filter finds to variation on the neighbor pixels. Laplacian low pass filter softens to the image by reducing disharmony between averaging nearby pixels and pixels values [24]. It is subtracted image applied Laplacian low pass filter from image applied Robert's edge detection in order to remove noise from the image. The difference image is image which this subtraction operation is applied to.

The feature extraction is applied to the difference image by carrying out morphology operations. Applied morphology operations are respectively bridge, close and fill. In this morphology operations, it is investigated statements that are connection to each other of the neighbor pixels, size of white and black pixels and whether gaps between pixels.

The morphology bridge operation provides significant faults to appear in the image. The morphology close operation enables the detection of any faults which are independent of one another and the morphology fill operation closes gaps between pixels. In the latest step, labeling of the fault regions is performed. In order to perform this, 'Area' and 'Ratio' features in Matlab are used. The ratio parameter is shown in Equation (1). The area and ratio parameters are used the separation parts of the limit and feature extraction of the region [25].

$$Ratio = MajorAxisLength \div MinorAxisLength \qquad (1)$$

If 'Area' value of the identified regional is greater than identified threshold value and 'Ratio' feature is used to decision, this regional is labeled as defect. The area parameter can be expressed as total value of white pixels in white-black image which is applying image processing techniques. The ratio parameter can be expressed as ratio value of white pixels. In defect detection, accuracy rate was achieved higher results than a literature algorithm [26] with 'Area' and 'Ratio' features.

3.2 The Defect Classification Method

The AdaBoost classifier based on Haar-like features is utilized to classify defects of rail track. The detected rail defects are input parameters of the classification algorithm. The Haar-like features that are the most popular weak classifiers used with AdaBoost algorithm are consisted of several black and white rectangles [27]. The term of integral image was introduced to compute the sum of pixel value in black and white rectangles. The following pseudo code shows the execution of the proposed AdaBoost algorithm. The flowchart of AdaBoost algorithm is shown in Figure 9.

Algorithm: AdaBoost Classifier Algorithm

$D_k(i)$: Example i weight after learner k
$\propto_k$: Learner k weight
$\forall i : D_0(i) \leftarrow 1/N$: Set uniform example weights
for k=1 to K **do**
  D ← data sampled with D_{k-1}
  h_k ← base learner trained on D
  $\varepsilon_k \leftarrow \sum_{i=1}^{N} D_{k-1}(i)\delta\,[h_k(x_i) \neq y_i]$: Test base learner
  $\alpha_k \leftarrow \frac{1}{2} log \frac{(1-\varepsilon_k)}{\varepsilon_k}$: Set learner weight with weighted error
  $D_k(i) \leftarrow \frac{D_{k-1}(i)e^{-\alpha_k y_i h_k(x_i)}}{Z_k}$: Set example weights based
end for

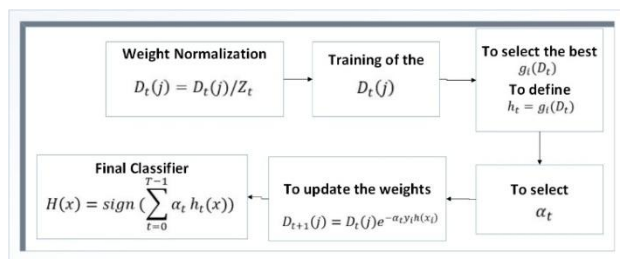


Fig. 9. The flowchart of AdaBoost algorithm.

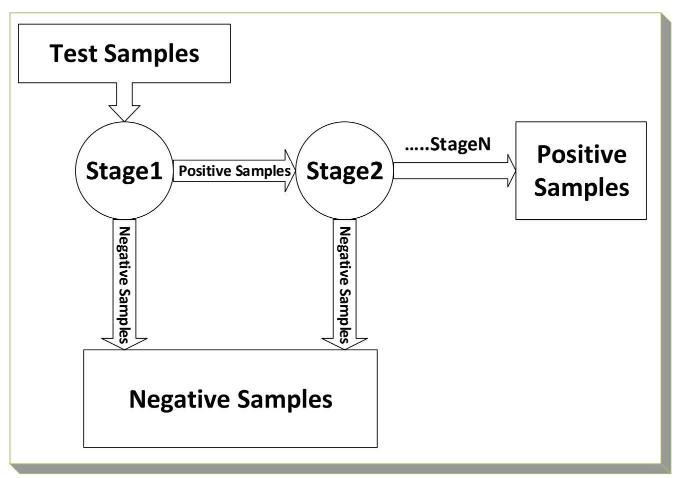


Fig. 10. The cascade strong classifiers.

The strong classifiers are acquired after training [28]. Then using the AdaBoost algorithm, a set of single classifiers are utilized to establish a strong cascade classifier, as shown in Fig. 10. A cascade of classifiers is a degenerated decision tree where at each stage a classifier is trained to detect almost all objects of interest [29].

4. EXPERIMENTAL RESULTS

A computer which has Intel (R) Core (TM) i5-2400 M CPU, 2.5 GHz, 6.00 GB RAM and 64 bit operating system features is used to perform the proposed method. This algorithm is run on variable rail images. Resolution of camera placed on train is important parameter for defect detection process. The more resolution of camera is good, the more algorithm performance is high. Performance of three algorithms which are used in the proposed method is shown in Table 1.

Table 1: Performance of the rail detection and rail defect detection algorithms

Algorithm	***Elapsed Time (Sec)***	***Accuracy Rate (%)***
Rail Detection	0.57	84.80
Rail Defect Detection	0.04	94.73
Defect Classification	0.10	81.52

In this work, rail defect detection method is improved according to the previous work [26]. Accuracy rate of the defect detection is increased with adaptive block. Value of the area parameter is greater than previous work [26]. Thus both accuracy rate of the algorithm is enhanced and noisy areas of the image aren't labeled as defect areas. When the proposed detection method is compared with algorithm existed in literature, this algorithm is superior. Because this algorithm can detect with a single algorithm multiple faults. Moreover this algorithm is not affected from foreign objects which are existed around the rail track and from the reflection of sunlight. After detection of rail defects, these defect regions are subjected to the classification process. The classification process is performed in the OpenCV platform. The AdaBoost classifier algorithm is used to classify defect regions. The relationship between the classification rate and number of weak classifiers is shown in Figure 11. Experimental results of the rail track detection, the rail defect detection are respectively shown in Table 2 and Table 3.

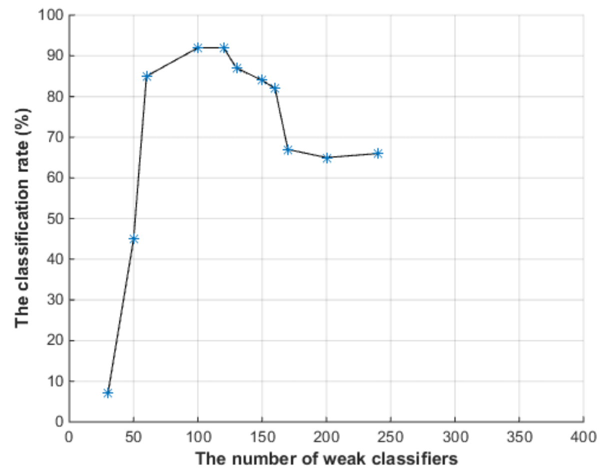


Fig. 11. Relationship between classification rate and number of weak classifiers.

As seen in Figure 11, the classification rate of the AdaBoost algorithm with the increasing in the number of weak classifier does not always increase. Because the resulting is not correct classification. While the AdaBoost algorithm has reached the maximum classification rate with the increasing of the number of weak classifiers, the classification rate decreased. It is indicated that the AdaBoost algorithm can prevent from the deterioration fact. After the AdaBoost algorithm was trained, the output weight (α_t) was computed for rail defects classifier. The output weight is fairly straightforward. It is based on the classifier's error rate(e_t). e_t is the number of misclassifications over the training set divided by the training set size. The relationship between error rate and the output weight is shown in Figure 12.

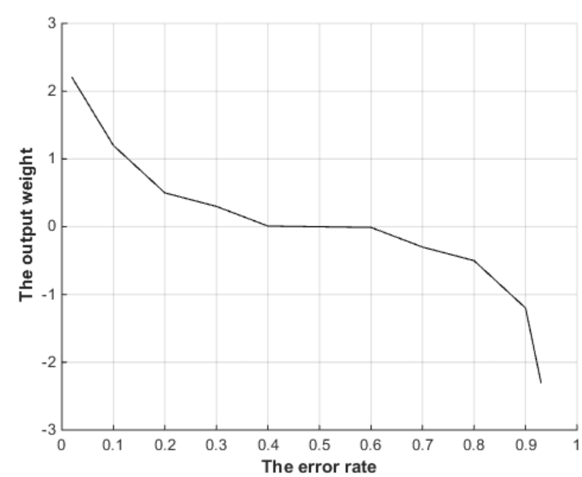


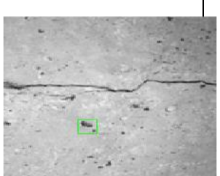
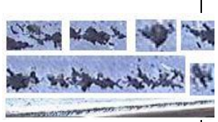
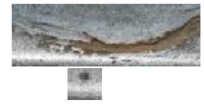
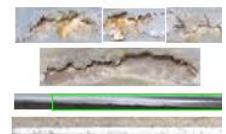
Fig. 12. Relationship between output weight and error rate.

Fig. 12 shows what α_t will look like for classifiers with different error rates. The classifier weight grows exponentially as the error approaches 0. Better classifier are given exponentially more weight. The classifier weight grows exponentially negative as the error approaches 1.

Table 2: Experimental results of the rail track detection

Input Image	***Detected Rail Track***	***Elapsed Time (sec)***
		0.70
		0.59
		0.56
		0.68

Table 3: Experimental results of the rail defect detection

Input Image	***Detected Rail Defects***	***Elapsed Time (sec)***
		0.041
		0.035
		0.030
		0.032
		0.028
		0.038
		0.035
		0.040
		0.056

5. CONCLUSIONS

An algorithm based contactless image processing was suggested to detect rail defects. Rail images were used in the size of 320x240 pixels. Headcheck, undulation, scour and fracture defects were detected on the rail images. And then detected defects were classified by utilizing AdaBoost classifier algorithm. Hough transform, Morphological operations and edge detection were applied to ınput images and line segments were detected. Rail track was identified with detected line segments. Image enhancement, Laplacian low pass filter and morphological feature extraction were enforced to detected rail track image and ıt was detected defect areas. The proposed defect detection method was improved with adaptive block. So it was increased in 94.73% accuracy rate of defect detection method. After the defect detection was done, the classification of rail defects was performed by using AdaBoost classification algorithm. These faults were classified into headcheck, breakage, scour and undulation. With the classification of rail faults, the importance degree of faults can be determined. In the AdaBoost algorithm, it was only needed to choose that weak classifier might work best to solve their given classification problem, the number of boosting rounds that should be used during the training phase. The proposed detection method was performed in Matlab and an average of 0.23 seconds and the average accuracy rate of 87% was obtained for each application by running rail input image.

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