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An Efficient Framework to Detect Cracks in Rail Tracks Using Neural Network Classifier

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Abstract: The detection of defects or cracks in rail track plays an important role in railway management, which prevents train accidents in both summer and rainy seasons. During summer, the cracks are formed on the track which slips the train wheel. In rainy environment, the rail tracks are affected by corrosion which also produced cracks on it. In present method, the cracks or defects are detected by humans which consumes more time. Hence, this paper proposes an efficient methodology to detect and segment the cracks in rail track using neural networks classifier. The performance of the proposed system achieves the accuracy rate of 94.9%.

Key words: Cracks · Segmentation · Classifier · Rail Tracks · Train accidents

INTRODUCTION

In the modern world, the role of railway network is an essential for the people around the world. The railway system consists of infrastructure, development and maintenance. The infrastructure of the railway network is the planning and construction of the rail tracks and establishing their contacts in railway junction. The development of the railway network is used to extent the tracks to the rural and interior areas of the village. The rail tracks are maintained by maintenance division of the railway network system. The rail tracks are severely affected by corrosion due to the air and floods during rainy season. They make cracks on the rail track which leads the accident of the trains. The quality of the rail track is important to prevent such defects in rail track and these cracks must be frequently checked to avoid accidents. Fig. 1 shows the procedure for capturing the rail track, in which the pre-checking vehicle is passed over the running track of the rail. The light source in this vehicle passes the light on the track and these running rail tracks are captured by high definition digital camera which is located on the vehicle.

Fig. 2 (a) shows the normal rail track which does not contain any cracks on it and Fig. 2 (b) shows the rail track which contains cracks on it.

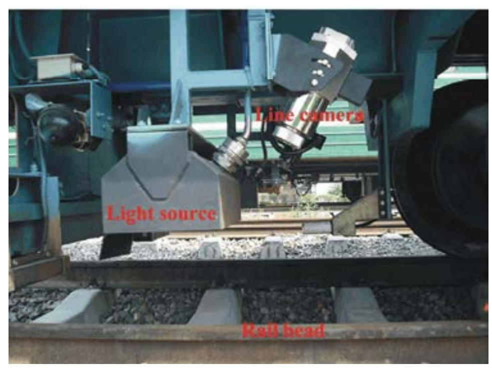

Fig. 1: Rail track capturing

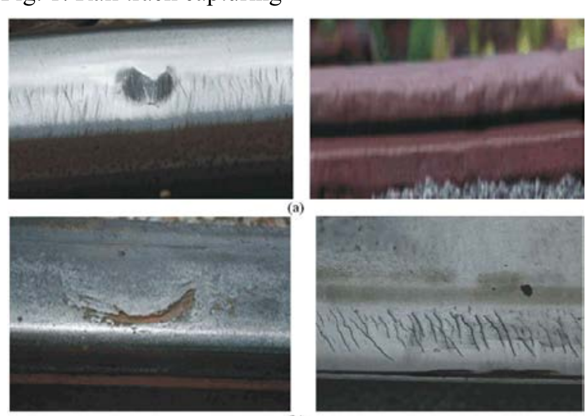

Fig. 2: Rail track images (a) Normal (b) with Cracks

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The detection of rail crack in track is achieved by railway operators and lot of conventional techniques was proposed to detect the cracks in railway track. In present method, manual power is used to detect these defects. It has several limitations as slow processing and it is very harmful during the inspection of the train tracks by human. These limitations are overcome by proposing an automated defect detection system using classification approach in this paper.

This paper is organized as, Section 2 discusses various conventional techniques to detect the defects in rail tracks, Section 3 proposes an efficient technique to detect the cracks in rail track using classifiers, Section 4 discusses the experimental results and Section 5 concludes the paper.

Literature Survey: Marino *et al*. [1] used hexagonal technique and two multilayer perceptron neural classifiers to inspect the bolt system in real time rail track image. The authors achieved 95% of accuracy for the detection and classification of bolts which connected tracks in continuous rail. Thomas *et al*. [2] detected rolling contact fatigue type of cracks or defects in running rail tracks. The authors constructed non-destructive rail inspection methodology to detect the cracks and defects in the obtained image from video sequences. Qingyong Li *et al*. [3] proposed a methodology to detect the surface defect of the rail track using visual inspection system. The authors developed projection profile model to detect the defects based on transversal projection profile technique and they applied different contrast enhancement approaches on the rail track images. The authors achieved 80.41% of Recall rate to analyze the defects in real time track image using their proposed model.

Maria Molodova *et al*. [4] proposed a fully automated method for the detection and segmentation of squats in rail system. The authors constructed an efficient method for the railway system by incorporating the automation technique in it. Ze Liu *et al*. [5] applied the basic principles of Electromagnetic Tomography on rail track image to detect the crack in their running path. The linear backprojection algorithm was constructed to classify the given test source rail track image into either normal or cracked. Based on this classification of rail track, Tikhonov regularization algorithm was applied to validate the experimental results.

Yong Shi *et al*. [6] developed an efficient rail crack detection system using random forest classification technique. The authors extracted integral channel features from real time rail track image and these extracted features were used to detect the crack or defect in rail track images. The topological error of the proposed method was analyzed using the crack detection method. Zhu Qingbo [7] used Pavement Crack Detection Algorithm to detect and segment the crack in railway track through image processing techniques. The noises and other interferences were detected and removed before the segmentation of cracks in rail track to enhance the performance of the crack detection system.

The following points are observed from the conventional methods and they are stated below as:

- The segmentation accuracy of the crack detection system in rail track is low.
- The conventional methods detected the crack only on high resolution rail track images.

The classifier based rail track detection technique is proposed in this paper to overcome the limitations of the conventional methods.

Proposed Methodology: In this paper, cracks in railway track are detected in an efficient methodology. The proposed method contains preprocessing, Gabor transform, feature extraction, classification and segmentation. The flow of crack detection and segmentation methodology is depicted in Fig. 3.

Preprocessing: It is used to enhance the track image to detect the crack in track. The captured track image is converted into grey scale image. Adaptive histogram Equalization technique [5, 7] is applied on the track image to enhance the crack regions in track. It enhances the contrast of the track image which transforms the image value into its intensity value.

Gabor Transform: The multi resolution transform is used to convert the spatial domain image into multi resolution image which is in the form of amplitude, frequency and phase. Conventional multi resolution transforms such as Discrete Wavelet Transform (DWT), Contourlet and Curvelet converted the spatial domain image into multi resolution image with low accuracy. In order to overcome such limitations of the conventional classifiers, Gabor transform is used in this paper to obtain the multi resolution image from the spatial domain rail track image.

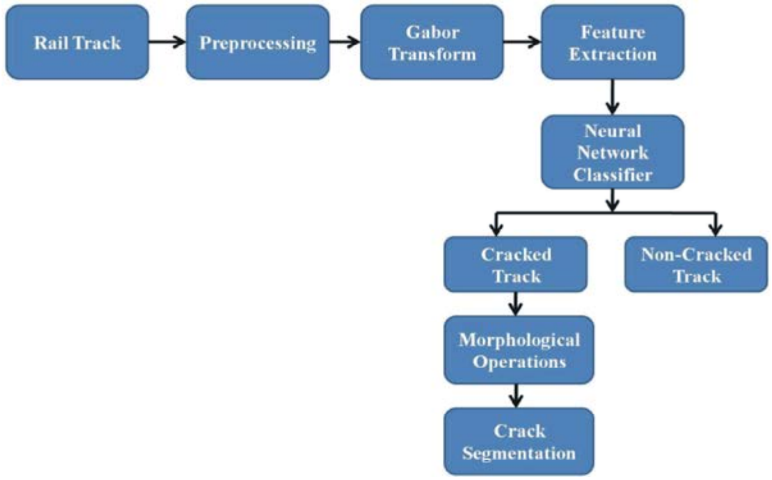

Fig. 3: Proposed Crack Detection Systems

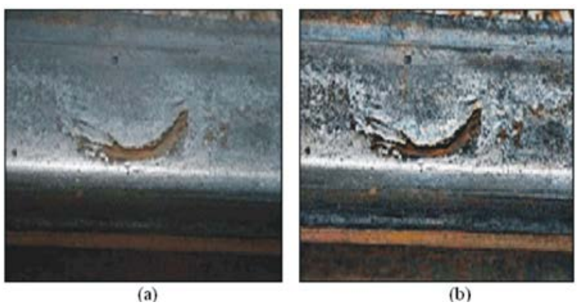

Fig. 4: (a) Source track image (b) Preprocessed track image

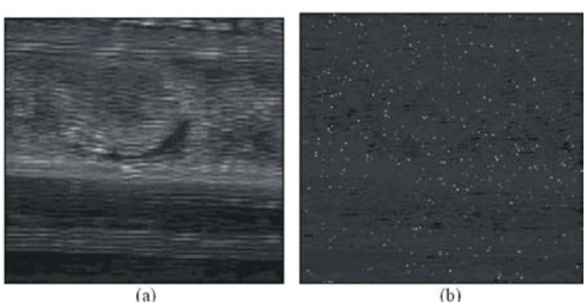

Fig. 4: (a) Gabor Magnitude image (b) Gabor Orientation image

In this paper, the Gabor kernels are designed with five scales f = {1, 2, 3, 4, } and four orientations θ = {45°, 90°, 120°, 180° }. The Gabor kernel is defined as,

$$g(x,y) = \exp\left\{0.5\left(\frac{x'^2+\gamma y'^2}{2\sigma^2}\right)\right\}\exp\left\{i\left(2\pi\frac{x'}{\lambda}+\varphi\right)\right\} \quad (1)$$

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

The Gabor magnitude image and its phase or orientation image are shown in Fig. 4 (a) and Fig. 4(b), respectively.

Feature Extraction: Features are extracted from the Gabor magnitude image and these are used to differentiate the cracked track image from the non-cracked track image by means of its energy characteristics. In this paper, Grey Level Co-occurrence Matrix (GLCM) features are extracted from the Gabor magnitude image for crack image classifications.

GLCM Features: The GLCM features are extracted from the GLCM matrix which can be constructed directly from the Gabor magnitude image at different directions of the pixels such as 0°, 45°, 90° and 135° in the image. In this paper, the GLCM matrix is constructed at the pixel orientations of 45°. The maxima pixel value in the Gabor magnitude image is chosen as the number of rows and columns in the GLCM matrix. Then, the values in GLCM table are obtained by making 45° orientations at each pixel value in the Gabor orientation image. The following GLCM feature are obtained from the GLCM matrix as,

$$\text{Contrast} = \Sigma(|i-j|^2 \times p(i,j)) \quad (4)$$

$$\text{Energy} = \Sigma\, p(i,j)^2 \quad (5)$$

$$\text{Entropy} = -\Sigma p(i,j)[\log_2 p(i,j)] \quad (6)$$

$$\text{Correlation} = \Sigma\,(i-\mu i)(j-\mu j)\,\frac{p(i,j)}{[\sigma i, \sigma j]} \quad (7)$$

where, ‘i’ and ‘j’ relates the row and column of the GLCM matrix and p(i, j) represents the corresponding values in GLCM matrix. ‘σ’ depicts the variance of the GLCM matrix.

Table 1: GLCM features for normal and cracked rail track test image samples

GLCM features	Cracked	Non-cracked
Contrast	$8.17*10^3$	$2.19*10^4$
Correlation	-0.0072	0.02
Energy	$3.21*10^{-5}$	$2.38*10^{-5}$
Homogeneity	0.092	0.012

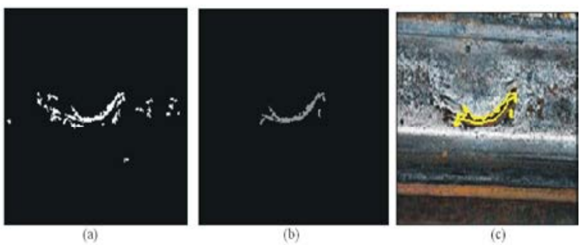

Fig. 5: (a) Morphologically processed image dilated image (b) Eroded image (c) Crack segmented image

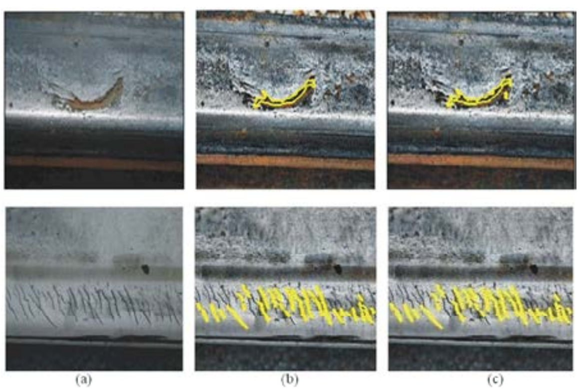

Fig. 6: (a) Source track images (b) Ground truth images (c) Crack detection by proposed method

Table 1 shows the extracted GLCM features from the Gabor magnitude rail track image for the case of normal and cracked rail track images.

Neural Network Classifier: Classifier is used to detect the running rail track image into either crack free or cracked image. Conventional classifiers such as Support Vector Machine (SVM), Principal Component Analysis (PCA) classified the rail track image for defect detection with low classification accuracy. In this paper, Neural Network (NN) classifier is used for the classification of rail track image into either crack free or cracked image. The NN classifier has two types as Radial neural network and Feed Forward Back Propagation (FFBP) neural networks. This paper uses (FFBP) neural networks for the detection of track images which can be operated in training and testing modes. In training mode of this classifier, the extracted features from both cracked and crack free rail track images are trained which produces trained pattern. In testing mode of this classifier, the extracted features from the running rail track image is classified with respect to the trained pattern and its produces either low or high value. The low value of this classifier indicates the test image is crack free and high value of this classifier indicates the test image is cracked. Further, the cracks in the classifier image are detected using morphological operations. It produces dilation and erosion images, which subtracts the eroded image (Fig. 5b) from the dilated image (Fig. 5a) to obtain the cracked regions in the classified image (Fig. 5c).

Fig. 6(a) shows the Source track images, Fig. 6(b) shows the Ground truth images and Fig. 6(c) shows the Crack detection by proposed method.

RESULTS AND DISCUSSION

The proposed rail track crack detection system using feed forward neural network classifier is simulated using MATLAB 2014 version with 1GB RAM in Intel Pentium Core-2-Duo processor. The performance of the proposed crack detection system is analyzed in terms of sensitivity, specificity and accuracy with respect to ground truth images. The performance evaluation parameters are given as,

$$\text{Sensitivity (Se)} = TP/\ (TP+FN) \tag{8}$$

$$\text{Specificity (Sp)} = TN/\ (TN+FP) \tag{9}$$

$$\text{Accuracy (Acc)} = (TP+TN)\ /\ (TP+FN+TN+FP) \tag{10}$$

where, TP is True Positive which is the number of correctly segmented crack pixels, TN is the True Negative which is the number of correctly segmented non-crack pixels, FP is False Positive which is the number of wrongly segmented crack pixels and FN is the False Negative which is the number of wrongly segmented non-crack pixels in rail track. Table 2 shows the performance analysis of the proposed rail crack detection system. The proposed system stated in this paper achieves 89.99% of sensitivity, 98.96% of specificity and 94.9 of accuracy.

Table 3 shows the performance comparisons of the proposed rail crack detection system with conventional techniques as Zhu Qingbo *et al*. [7], Ze Liu *et al*. [5] and Qingyong Li *et al*. [3]. The conventional methods Zhu

Qingbo *et al*. [7] achieved 81.27% of sensitivity, 91.28% of specificity and 87.75% of accuracy; Ze Liu *et al*. [5] achieved 78.93% of sensitivity, 94.96% of specificity and 87.98% of accuracy. Qingyong Li *et al*. [3] achieved 82.18% of sensitivity, 95.37% specificity and 89.71% of accuracy. The reason behind the low accuracy which was obtained by the conventional methods is its low clarity. Another main criteria is that the present conventional methods detected and segmented the rail track crack in high resolution images only. The proposed method for the detection of cracks in rail track works on both low and high resolution rail track images.

Table 2: Performance Analysis

Parameters	Experimental Results (%)
Sensitivity	89.99
Specificity	98.96
Accuracy	94.9

Table 3: Performance comparisons

Parameters	Sensitivity (%)	Specificity (%)	Accuracy (%)
Proposed Method	89.99	98.96	94.9
Zhu Qingbo *et al.* [7]	81.27	91.28	87.75
Ze Liu *et al.* [5]	78.93	94.96	87.98
Qingyong Li *et al.* [3]	82.18	95.37	89.71

CONCLUSION

In this paper, feed forward neural network classifier based crack detection in rail track is proposed to detect and segment the cracks or defects in rail track images. The proposed method enhances the track image using adaptive histogram equalization technique and further feature are extracted from the enhanced rail track image. These extracted features are trained and classified using neural network classifier which classifies the rail track image into either cracked or non-cracked image. The proposed system stated in this paper achieves 89.99% of sensitivity, 98.96% of specificity and 94.9% of accuracy.

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