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RAILWAY TRACK DERAILMENT INSPECTION SYSTEM USING SEGMENTATION BASED FRACTAL TEXTURE ANALYSIS

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Abstract

Derailments take place when a train runs off its rails and are seriously hazardous to human safety. Most of the Railway Track defects which lead to derailment are detected manually by trained human operators walking along the track. To overcome this difficulty, an Automatic Railway Track Derailment Inspection System using Machine Vision Algorithm to detect the cracks in the railway track is proposed here. The input image is decomposed by Gabor filter and texture features were extracted using Segmentation based Fractal Texture Analysis (SFTA) and the features are classified as defect and defect free classes using AdaBoost Classifier. The proposed algorithm is tested on a set of real time samples collected and the classification rate obtained was satisfactory.

Keywords:

Crack Detection, Gabor Wavelets, Texture Analysis, AdaBoost Classifier

1. INTRODUCTION

Railways provide the cheapest and most convenient mode of passenger transport both for long distance and suburban traffic also it plays a significant role in the development and growth of industries. Railways help in supplying raw materials and other facilities to the factory sites and finished goods to the market. The Indian nationwide rail network, the fourth longest in the world, includes an operating route length of more than 65,000km. The network carried about eight billion passengers (the highest in the world) and 1.01 million tons of freight (fourth highest in the world) in 2013.The Indian railway network is divided into 17 zones and operates more than 19,000 trains per day, including12,000 passenger trains and 7,000 freight trains. Even though there are several advantages in railway transport, the frequency of train accidents is still increasing. Approximately 292 train derailments were reported from 2010 to 2015 throughout the world [1].

A train derailment occurs whenever a train car or cars leaves the railroad tracks. A train derailment can result in severe injuries or even death to passengers. In an early morning train accident near Bengaluru, 10 passengers died and many were injured after several coaches of the Ernakulam-bound Bengaluru City-Ernakulam Intercity express (Train no. 12677) derailed on the city's outskirts. Earlier reports said 12 people had been killed in the accident. The accident has been reported at Belagondapalli near Anekal town on the city's outskirts around 7.35 a.m. with reference to “THE HINDU” dated February 13, 2015. The leading causes of derailments include: (i) Poor and improper maintenance of tracks, (ii) Collisions with other trains, (iii) Improper switch alignment, (iv) Failing to install adequate signals such as lights and gates, (v) Railroad crossing collisions with vehicles and trucks at hazardous crossings, (vi) Mechanical failures of train engines or rail cars, (vii) Overworked and tired train crews, (viii) Improper training of train crews, (ix) Understaffed track maintenance departments, (x) Improper removal of obstructions near railroad crossings, (xi) Excessive speed of trains in poor weather conditions.

The improper maintenance of tracks which have resulted in the formation of cracks in the tracks has been identified to be the main cause of derailment. Some of the defects are worn out rails, weld problems, internal defects, head checks, squats, spelling and shelling. If undetected and/or untreated these defects can lead to rail breaks and derailment. Traditionally, this task is manually conducted by trained railroad track inspectors walking along the track searching for visual anomalies. Tracks that are subjected to heavy-haul traffic necessitate frequent inspection and have more intensive maintenance requirements, leaving railroads with less time to accomplish these inspections. To improve the manual inspection process in an efficient and cost effective manner, machine vision technology can be developed as a robust alternative [2-9].

The wheels transmit the weight of the train to the rails, which then transfer it via the sleepers to the track substructure. When repeated stresses of sufficient magnitude are applied to a rail section, a crack is initiated after a certain number of cycles, which goes on propagating when stresses are repeatedly applied [10]. Rail break or fracture is the final result of the crack development process succeeding crack initiation and propagation.

Two widespread techniques to evaluate the properties of a material: destructive techniques and non-destructive techniques. Because of their limited effectiveness and the limited area covered by the destructive techniques such as Coring, Pullout test, tensile test and Flexure test techniques [11], non-destructive techniques have been recently developed. Machine vision is one of the methods of non-destructive techniques.

Deutschl et al. proposed a vision based inspection technique for rail surface defects is proposed by Deutschl et al. [12]. Color line-scan cameras and a special image acquisition method-the so called spectral image differencing procedure allow the automatic detection of defects on rail surfaces like flakes, cracks, grooves or break-offs. Lin and Luo [13], adopts geometrical analysis directly on a gray-level histogram curve of the smoothed rail head surface image for detecting special Rolling Contact Fatigue. Nitti et al. proposed an algorithm for surface inspection using Gabor filter and Self Organized Map (SOM) network [14].

In the last decade, several methods for automatic crack detection have been proposed. Some of the popular techniques include the morphological operation [15,16], the wavelet analysis [17],the fractal analysis [18] and the edge detection scheme [19], [20] , Hutchinson and Chen [21] employed canny filter and thresholding methods to detect cracks based on Bayesian decision theory in which simple images consisting of clearly observable cracks were considered. Meanwhile, a crack detection and inspection system based on SVM technique were proposed [22] and various schemes of Hough transform were investigated for line and ellipse detection [23], [24].

One of the most popular schemes is based on local approach such as the fixed partitioning method [25] and the sliding window scheme [26]. The main advantage of these techniques is that they give additional information to the descriptor. However, these approaches are computationally inefficient and require every portion of the image to be examined, resulting in thousands of evaluations which need to be performed. A slightly better approach in capturing small but distinct spatial variation in the image is through the use of spatial pyramid scheme [27]. This method is frequently used to compute features at multiple resolution levels to increase the discriminative power of the descriptor. Multilevel image features normally produce different evidences of visual information.

The features can be computed easily and the procedures preserve the spatial information by simply fusing local features at multiple levels; each level in the spatial pyramid presents different information and hence new features. Moreover, this method has the ability to characterize the entire image with a single vector, and hence, it is more sensitive to complex disturbances such as occlusion and small cracks. Also, this image partitioning scheme is expected to generate more useful and salient features, and consequently, classification methodologies can be implemented in a space with vastly reduced dimension and reasonable time. Though the above techniques are effective in crack detection, these techniques are very complex. Therefore to reduce this complexity a machine vision algorithm for crack detection is proposed.

2. PROPOSED METHODOLOGY

The block diagram of the proposed algorithm is shown in Fig.1.

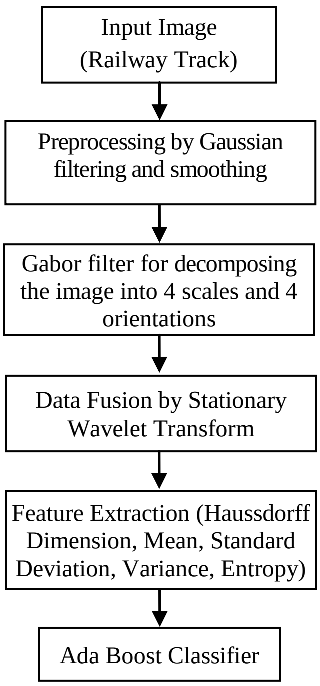


Fig.1. Block Diagram of Crack Detection

2.1 PREPROCESSING

Image pre-processing can significantly increase the reliability of an optical inspection. This uses a small neighborhood of a pixel in an input image to get a new brightness value in the output image. This process is called filtering. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Smoothing aims to suppress noise or other small fluctuations in the image equivalent to the suppression of high frequencies in the frequency domain. Preprocessing is done using Gaussian filtering and smoothing. Gaussian filters are a class of linear filters with the weights chosen according to the Gaussian function. Gaussian smoothing filter is very good in noise removal in normal distribution function. Gaussian functions are rotationally symmetric. This means that the amount of smoothing performed by the filter will be the same in all directions [31]. Hence Gaussian filter is preferred for preprocessing.

The 2D Gaussian smoothing filter is given by the equation,

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{1}$$

where, x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

2.2 GABOR FILTER

Gabor filters are multiscale, multiresolution and tuneable band pass filters. It is useful in many applications such as texture analysis. In this paper, Gabor filter is used in the frequency domain to detect cracks. The filtered images are partitioned into scales and orientations. 2D Gabor filter is a gaussian kernel function modulated by a sinusoidal plane wave. Because of Convolution Theorem, the Fourier Transform of impulse response of Gabor filter is the convolution of Fourier Transform of Harmonic function and Gaussian function. The filter has real and imaginary components.

Real,

$$\begin{aligned}&g(x,y,\lambda,\theta,\psi,\sigma,\gamma)\\&=\exp\left(\left(-x^2+\gamma^2 y'^2\right)/2\sigma^2\right)\cos\left(2\pi\left(x'/\lambda\right)+\psi\right)\end{aligned} \tag{2}$$

Imaginary,

$$\begin{aligned}&g(x,y,\lambda,\theta,\psi,\sigma,\gamma)\\&=\exp\left(\left(-x^2+\gamma^2 y'^2\right)/2\sigma^2\right)\sin\left(2\pi\left(x'/\lambda\right)+\psi\right)\end{aligned} \tag{3}$$

In this equation λ represents the wavelength of the sinusoidal factor, represents the orientation of the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma/standard deviation of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

2.3 DATA FUSION

In machine vision it is not possible to have a single gabor wavelet scale that contains all the information about the cracks in the image. To achieve this fusion of gabor wavelets scales are required. Gabor wavelet scales containing different features corresponding to each orientation are fused to get a single scale retaining important features from each and every scale with extended information context. The most commonly used transform for multiscale fusion is Discrete Wavelet Transform (DWT).But it suffers from lack of translation invariance. To overcome the translation invariance Stationary Wavelet Transform (SWT) is used [32] Wavelet undergoes translation and scaling operations to give similar wavelets as,

$$\varphi(a,b(t)) = \frac{1}{\sqrt{a}}\varphi\frac{(t-b)}{a}(a,b \in R), a > 0 \tag{4}$$

In this equation, *a* is the scaling parameter and *b* is the translation parameter.

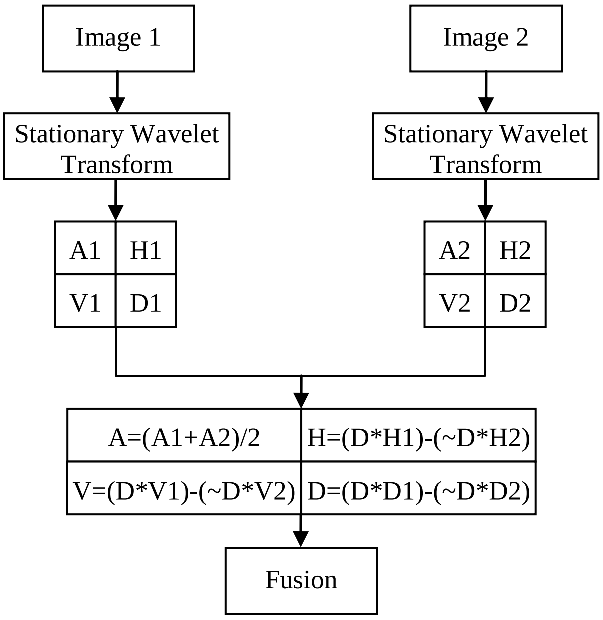


Fig.2. Block Diagram of Fusion Algorithm

In this algorithm, where *A*, *H*, *V*, *D* are approximation, horizontal, vertical and detailed coefficients. Here more precisely the SWT is applied at each scale of an image for a particular orientation and the detailed coefficients (*D*) are extracted.

2.4 FEATURE EXTRACTION - SEGMENTATION BASED FRACTAL TEXTURE ANALYSIS

Texture gives information about the spatial arrangement of color or intensities in an image or selected region of an image. Textures can be used for the classification of images. Texture feature extraction is a time consuming process hence SFTA is used to deal time consuming problems. In SFTA multi-level Otsu thresholding is used to decompose the fused scale corresponding to each orientation. Box counting method is implemented to extract features. Each fused scale has 6 vector features that represent boundaries of fractal dimension (FD).The FD values computes over the block of fused scales. To calculate the box-counting dimension, any structure should be located on square grid with the mesh dimension s, and afterwards, all meshes that contain even the smallest part of the structure are summed up. In this way, the number of filled meshes N is calculated, which is related to the fractal dimension (FD), thereby it is registered as $N(s)$. In practice, the algorithm can be continued until which is restricted by the vector features. Each mesh is further divided into six equal ones and repeats the operation. The fractal dimension is obtained by,

$$H = \sum\nolimits_{S=K}^{2} \log(A(s)) * \log(N(s)) \Big/ \sum\nolimits_{S=0}^{K=2} \log(A(s))^{2} \tag{5}$$

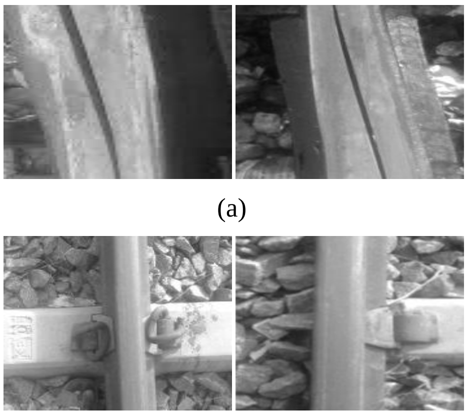
In this equation *H* is slope, $A(s)$ is total number of boxes to all block, $N(s)$ is number of box cover the structure, *k* is highest box size and *s* is box size [33].For fractals that occur in nature, the Hausdorff and box counting dimension coincide.

2.5 CLASSIFICATION - ADABOOST CLASSIFIER

The goal of the AdaBoost classifier is to find the hypotheses barely better than choosing the random number of samples from the training samples. AdaBoost classifier is based on adaptive reweighting and averaging the classes of classifier. The bounded weightage of the classifier is based on the complexity of weak classifiers. Weak classifiers are Adaptive Linear and Weighted Linear classifiers. It follows the changing pattern of the samples. It combines the result of weak classifier into a strong weighted classifier. Weak classifiers which correctly classifies the training data less than 50% by having this assumption the boosting is done here to generate the strong weighted classifier which correctly classifies the training data at 99%-100%.Boosting iterations thereby reduces the classification error of the weak classifiers. AdaBoost classifier focuses on the training points which have been misclassified most by the previous weak classifier. The AdaBoost classifiers with decision trees have been referred to as “the best off-the-self classifier” [34].

3. RESULTS AND DISCUSSIONS

The algorithm is evaluated using the samples collected from the Salem Railway station. The images are captured with the help of 256MB RAM Camera Primary 5MP, 2592 × 1944 pixels having the resolution of 320 × 240 pixels. Some of the samples in our dataset are shown in Fig.3.



(a)

(b)

Fig.3. (a) Cracks in the railway track (b) Railway track without defects

The preprocessed output images are shown in Fig.4.

(a)

(b)

Fig.4. (a) Input image (b) Preprocessed image

3.1 FEATURE EXTRACTION

In the feature extraction phase, the input image is convolved with Log Gabor filters of 4 orientations (00, 450, 900 and 1350) and 4 scales and the 16 different filter responses are shown in Fig.5. The filtered output is subjected to data fusion and 4 Gabor wavelet scales corresponding to each orientation are fused to get single scale per orientation.

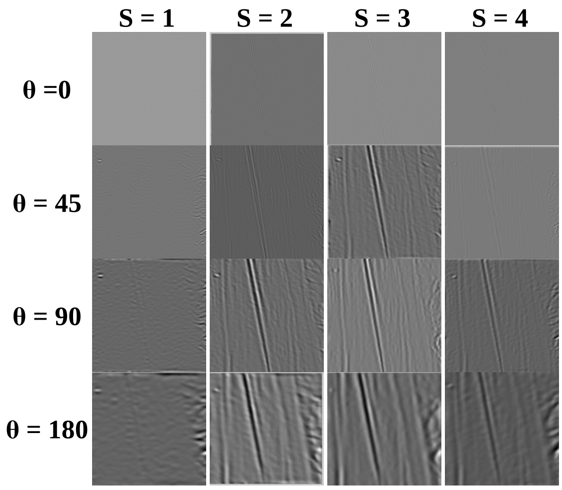


Fig.5. Gabor Transformed Image with 4 scales and 4 orientations

For all the 4 fused sub-images with different orientations, statistical and Fractal features were extracted. When compared with the statistical features fractal dimension shows a significant variation for defect and defect free samples as illustrated in Table.1.

From Table.1 it is found that the image with defects or irregularities has the feature values 0.04% higher than the defect free image.

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Table.1. Extracted Features from the samples

Samples	Features					
	Mean	**Standard Deviation**	**Variance**	**Entropy**	**Moment**	**Fractal Dimension**
Defected Image	1.49	217.20	0.002	45.60	-0.0067	0.0029
Defect Free Image	1.50	221.88	0.003	46.27	-0.0070	0.0180

3.2 CLASSIFICATION

The extracted features are classified with the help of Weka Data Mining software [31]. Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can be applied directly to a dataset. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.

AdaBoost classifier which is barely better than other classifier is used as it gives correct classification rate (CCR) of 100%. Performance of a classifier is visualized by means of confusion matrix. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. A dataset having 4 defected samples and 11 defect free samples are subjected to this algorithm and the results are shown in Table.2, the confusion matrix for a two class classifier.

Table.2. Confusion Matrix

Classes	Track with Defect	Track without Defect
Track with Defect	4	0
Track without Defect	0	11

4. CONCLUSION

The detection of cracks in the railway track plays a major role in the derailment inspection system. The results obtained from this algorithm indicate that the pre-processed image is subjected to Gabor filter and it is decomposed into different scales and orientations have a significant effect in improving the detection accuracy. The Gabor filter is invariant to rotation and robust from the effect of variations in the frequency domain. It was found that the classification of defected and defect free samples from the samples were done by extracting the fractal features and hence it resulted in the highest correct classification rate (CCR) of 100% using collected dataset samples. Therefore, this crack detection technique by machine vision algorithm has a potential to detect even fine cracks in the railway track.

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