www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

MACHINE VISION BASED MISSING FASTENER DETECTION IN RAIL TRACK IMAGES USING SVM CLASSIFIER

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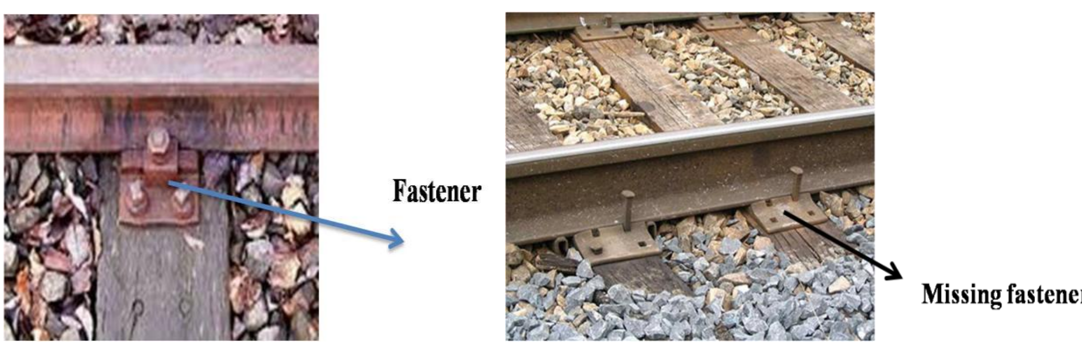
Submitted: May 27, 2017   Accepted: June 15, 2017   Published: Sep 1, 2017

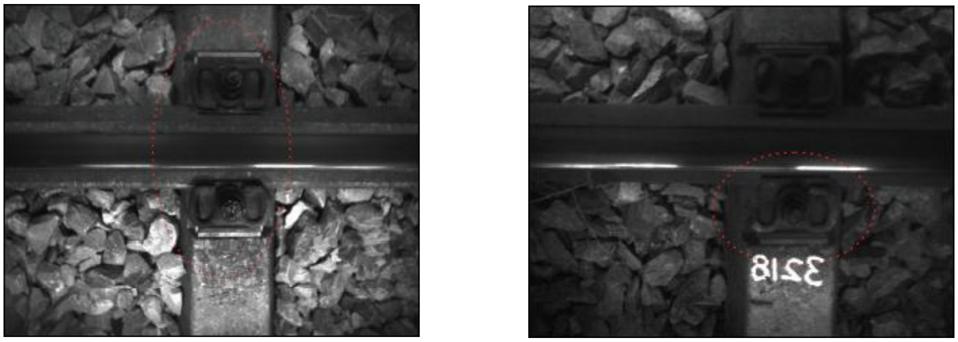
Abstract- Missing fastener detection is a critical task due to its similar characteristics with surrounding environments. In this paper, a machine vision based fully automatic detection and classification of missing fastener detection system is proposed using Support Vector Machine (SVM) classifier. This proposed system consists of preprocessing, transformation, feature extraction and classifications. Image resizing is performed as preprocessing step and Gabor transform is used as transformation technique. Grey Level Cooccurence Matrix (GLCM) features, Local Binary Pattern (LBP) features and Discrete Wavelet Transform (DWT) are used as features in this paper. SVM classifier is used as classifier in order to classify the test rail track image into either track image with fastener or track image without fastener.

Index terms*:* Fastener, classifier, features, track image, transformation.

I. INTRODUCTION

Now a day, Railway system requires proper and regular maintenance of the rail track for safe of the passengers who are travelling in train. This present system requires lot of man power to inspect the rail track for detecting any crack in track. It is also required to get some trained experts in this field. It is time consuming and costly process and it is not suitable for long rail tracks. This manual verification of rail track sometimes leads to accident and it is very dangerous for humans who are inspecting the rail tracks in rainy seasons. At present, lot of researchers is developing an automatic rail track inspection system without any man power. This is very safe process and cost effective process [9]. This automatic detection system consists of automatic rail track defects detection, automatic fastener defects detection and rail track gauge determination. Fasteners are the connectors which connects two subsequent rail tracks in linear manner. Intact, Partially worn and missing fasteners are the types of fasteners. Most of the rails accidents are occurring due to the missing fasteners in rain track. Most of the train accidents and train derailment are occurred due to these missing fasteners in rail track. Hence, this paper proposes an automatic computer aided approach for the detection of fasteners in rail track. In this paper, computer vision algorithms are developed to detect the missing fasteners in rail track in an automated manner. Fig.1 (a) shows the Rail track image with fastener and Fig.(b) shows the Rail track image with missing fastener.





(a) (b)

Figure 1 (a) Rail track image with fastener (b) Rail track image with missing fastener

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

II. Literature survey.

Rubel Biswas et al. (2016) proposed Harris – Stephen feature detection based SVM classification approach for the detection of missing fasteners in rail track images. The authors achieved 81.25% of classification accuracy for their proposed missing fastener detection algorithm. Jiajia Liu et al. (2015) used SVM classification method to classify the test rail track image into either tack with fastener or track without fasteners. The authors achieved recall rate of 87.3% for detecting the missing fasteners in rail track images.

Y. Xia et al. (2010) applied a methodology for the detection of hook-shaped fastener in rail track images. The authors used linear adaboost algorithm for the detection process and achieved 93.7% of classification accuracy for their proposed classification methods. This method was suitable for both low and high resolution rail track images. M. Singh et al. (2006) applied various edge detection methods on rail track images inorder to detect the missing fasteners in rail track images. The authors achieved 78% of precision and 76% of recall rate of their proposed missing fastener detection system. P. L. Mazzeo et al. (2004) developed a fastener detection methodology which efficiently detected missing fasteners in rail track images. The authors used adaboost classifier to classify the preprocessed rail track image into either track with fastener or track without fastener. The authors achieved 92% of classification accuracy for their proposed classification methods. E. Stella et al. (2002) applied wavelet transformation technique on rail track image in order to obtain the wavelet coefficients. These coefficients are optimized using Principal Component Analysis (PCA). The authors applied neural network classification approach on the optimized set of features for the detection of missing fasteners in rail track images.

III. Proposed System

The modules which are used in proposed fastener detection process is illustrated in Fig.2. This proposed system consists of preprocessing, transformation, feature extraction and classifications. Image resizing is performed as preprocessing step and Gabor transform is used as transformation technique. GLCM features, LBP features and DWT are used as features in this paper. SVM classifier is used as classifier in order to classify the test rail track image into either track image with fastener or track image without fastener.

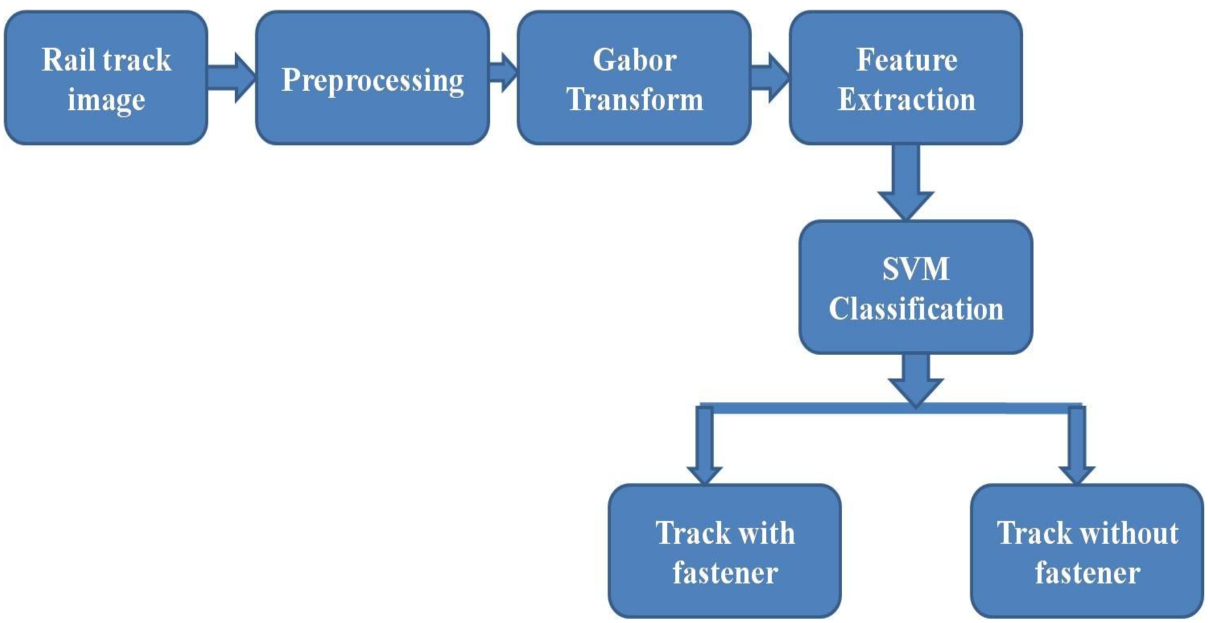


Figure 2 Proposed fastener classification system

3.1 Preprocessing

The rail track images are RGB image in its nature. Preprocessing is used to convert the RGB image into grey scale image due to its speed processing. Then, this grey scale image is resized into 128 width *128 height image as fixed image size. Fig.3 (a) shows the track image with fastener in RGB format and Fig.3 (b) shows the preprocessed rail track image.

(a) (b)

Figure 3 (a) Track image with fastener (b) Preprocessed image

3.2 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.

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 transformed rail track image with fastener is shown in Fig.4

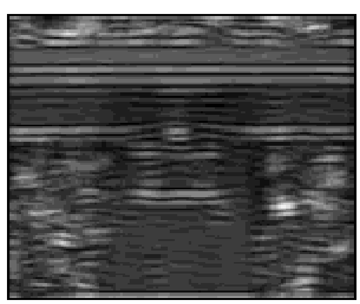


Figure 4 Gabor transformed image

3.3 Feature Extraction

Features are the key elements in differentiating the track image without fastener from track image with fastener. In this paper, GLCM, LBP and DWT features are extracted from the Gabor transformed rail track image.

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 45^0. 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 45^0 orientations at each pixel value in the Gabor orientation image. The following GLCM features are obtained from the GLCM matrix as,

$$\text{Contrast} = \sum\left(|i-j|^2 \times p(i,j)\right) \tag{4}$$

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

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

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

Where, ‘i’ and ‘j’ relates the row and column of the GLCM matrix and p(i,j) represents the corresponding values in GLCM matrix.$'\sigma'$ depicts the variance of the GLCM matrix. These four extracted GLCM features are given as input pattern for SVM classifier.

Table 1 GLCM features

Parameters	**Track with fastener**	**Track without fastener**
Contrast	$3.99*10^3$	$4.53*10^3$
Correlation	$2.89*10^3$	$2.79*10^3$
Energy	$2.55*10^{-3}$	$-9.73*10^{-3}$
Homogeneity	$2.55*10^{-3}$	$-9.73*10^{-3}$

DWT features

In this paper, wavelet decomposition is achieved by applying DWT on Gabor transformed image. The decomposition leads to the formation of four sub bands having equal size as named as Approximation band which constitues low frequency components, Horizontal band which constitutes horizontal pixels, Vertical band which constitutes vertical pixels and Diagonal band which constitutes diagonal pixels. All these sub bands are used as feature set. These decomposed four sub bands are given as input pattern for SVM classifier.

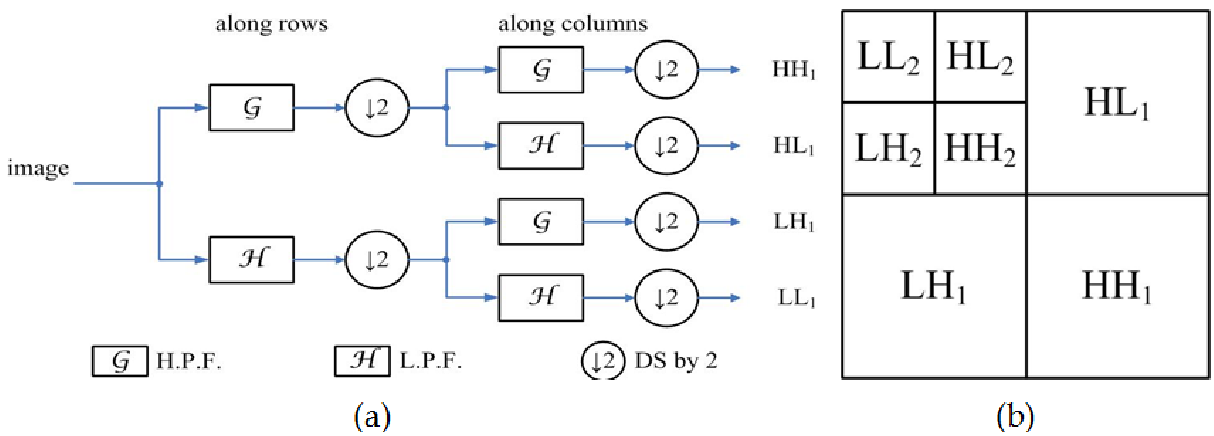


Figure 5 (a) Decomposition of image into sub bands (decomposition level 1) (b) Decomposition sub bands at level 1 and level 2 by DWT

Fig.5 (s) illustrates the decomposition of image into four sub bands at level 1 by down sampling factor 2. Initially, the image is passed through High Pass Filter (HPF) and Low Pass Filter (LPF). The filtered image components are next down sampled by down sampling factor 2 inorder to reduce the sampling rate. The down sampled image components are further filtered by its corresponding LPF and HPF filters, respectively, inorder to obtain four sub bands as Approximate (HH_1), Horizontal (HL_1), Vertical (LH_1) and Diagonal (LL_1). The HH_1 sub band can be decomposed again into four sub bands if needed. In this paper, first level decomposition of image is used as feature for the fastener classifications.

Fig.6 (a) shows the approximate band, Fig.6 (b) shows the horizontal band, Fig.6 (c) shows the vertical band and Fig.6(d) shows the diagonal band, respectively.

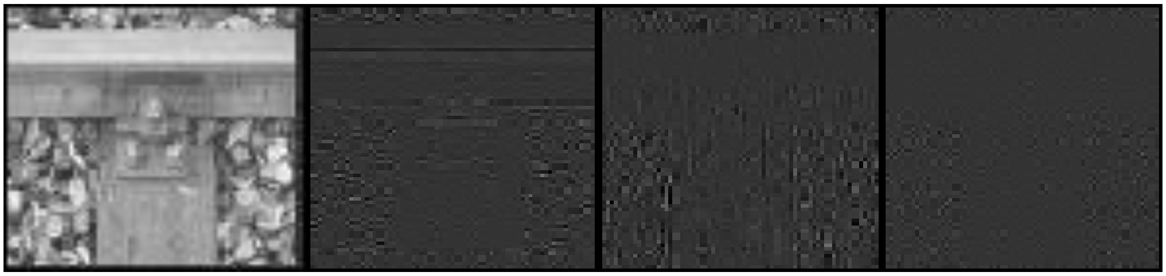


Figure 6 DWT transformed subbands (a) Approximate (b) Horizontal (c) Vertical (d) Diagonal

LBP features

This feature correlates the center pixel with its surrounding pixels. Each surrounding pixel is compared with center pixel inorder to produce the binary patterns. Surrounding pixel is greater than the center pixel, it will produce binary 1 and surrounding pixel is less than the center pixel, it will produce binary 0. These eight binary bits generates the single decimal value as binary pattern. The extraction procedure of LBP feature for the center pixel in 3*3 windows is given as,

$$LBP\ feature\ of\ center\ pixel\ in\ 3*3\ window = \sum_{p=0}^{P-1} s(g_p - g_c) * 2^p \qquad (8)$$

Where as, g_p is surrounding pixels in 3*3 window, g_c is the center pixel in 3*3 window and P is the number of surrounding pixels for center pixel in 3*3 window.

The function's' is given as,

$$(g_p - g_c) = 0;\ \text{if}\ g_p > g_c$$

$$s(g_p - g_c) = 1;\ \text{if}\ g_p \leq g_c \qquad (9)$$

The extracted LBP feature from the Gabor transformed rail track image is shown in Fig.7. This LBP feature is given as input pattern for SVM classifier.

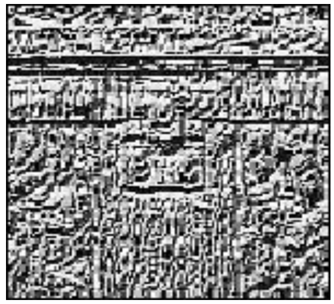


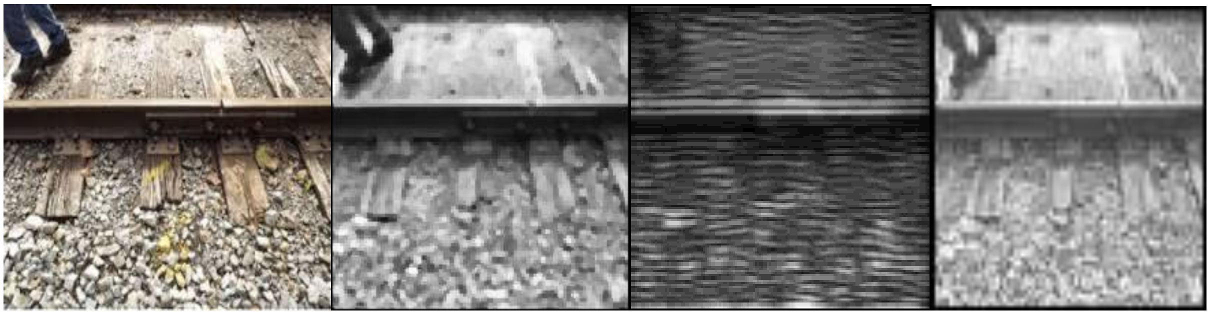
Figure 7 Extracted LBP Image

Feature vector is constructed by concatenating the extracted features of GLCM, DWT and LBP. This feature vector is given as input pattern for SVM classifier.

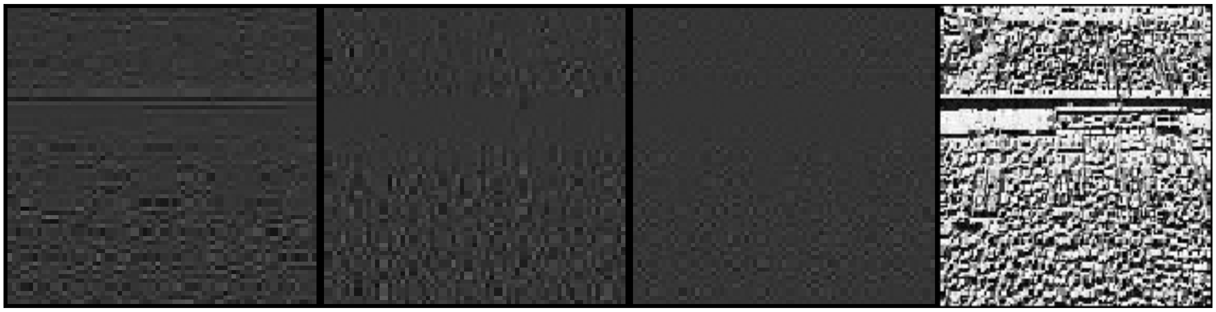
3.4 Detection of fastener using SVM

Classification is used to classify the test rail track image into either track image with fastener or track image without fastener. In this paper, SVM classifier is used for the rail track classifications. It has two pattern modes as training and classification. In case of training phase of this classifier, the features are extracted from both track image with fastener and track image without fastener. In case of classification phase of this classifier, the features are extracted from test rail track image and these extracted features are classified with respect to trained patterns. In this paper, the fastener image classification is done by implementing SVM classifier with various kernel functions as ‘Linear’, ‘Polynomial’ and ‘Sigmoidal’[10].

Fig.8 (a) shows the rail track image with fastener, Fig.8 (b) shows the rail track image without fastener, Fig.8 (c) shows the Gabor transformed track image, Fig.8 (d) shows the Approximate sub band image, Fig.8 (e) shows the Horizontal sub band image, Fig.8 (f) shows the Vertical sub band image, Fig.8 (g) shows the Diagonal sub band image and Fig.8 (h) shows the Extracted LBP Image.



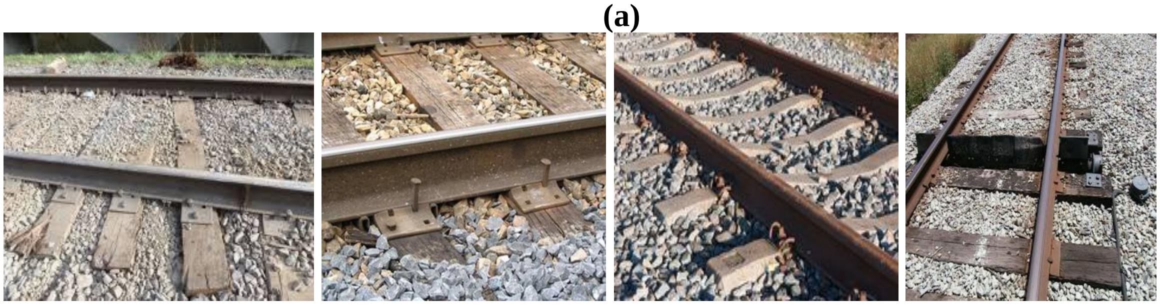
(a) (b) (c) (d)



(e) (f) (g) (h)

Figure 8 (a) Track image with fastener (b) Track image without fastener (c) Gabor transformed image (d) Approximate (e) Horizontal (f) Vertical (g) Diagonal (h) Extracted LBP Image

(a)



(b)

Figure 9 (a) Track images with fasteners (b) Track images without fasteners

Fig. 9(a) shows the rail track images with fasteners and Fig.9 (b) shows the rail track images without fasteners.

IV. Results and Discussion

In this paper, fastener detection methodology is proposed to detect the presence of fastener on rail track images. The proposed methodology is tested on 85 rail track images which are obtained from different environmental conditions with different illumination effects and orientations. The test rail track images are categorized into track image with fastener and track image without fastener. In this paper, 45 track images with fastener and 40 track images without fastener is considered. In training mode of the proposed method, 20 track images with fastener and 20 track images without fastener is considered. In classification mode of the proposed method, 45 track images with fastener and 40 track images without fastener is considered. The proposed system is evaluated using detection rate. It is defined as the ratio between number of images correctly classified and the total number of images considered for evaluation. The detection rate for track images with fastener is defined as the ratio between the number of track images with fastener as track images with fasteners and the total number of track images with fastener. It is given as,

$$Detection\ rate\ of\ fastner\ images = \frac{Number\ of\ detected\ images\ with\ fastners}{Total\ number\ of\ images\ with\ fastners} \quad \text{-(10)}$$

In this paper, 38 track images without fasteners are detected out of 40 track images without fasteners. Hence, the proposed system stated in this paper achieves 95% of detection rate for the case of fastener missing on rain track images.

The detection rate for track images without fastener is defined as the ratio between the number of track images without fastener as track images without fasteners and the total number of track images without fastener. It is given as,

$$Detection\ rate\ of\ fastner\ missing\ images = \frac{Number\ of\ detected\ images\ without\ fastners}{Total\ number\ of\ images\ without\ fastners} \text{-(11)}$$

This proposed method also detects 40 track images with fasteners out of 40 track images with fasteners. Hence, the proposed system achieves 100% of classification accuracy for the case of rain track images with fasteners. The overall detection rate of the proposed methodology is 97.5%.

Table 2 shows the performance analysis of detection rate for both cases as track images with fasteners and track images without fasteners.

Table 2 Performance Analysis of Detection Rate of with and without Fastener

	Track with fastener	**Track without fastener**

Images categories	Actual images	Correctly Detected images	Actual images	Correctly Detected images
Tested images	45	45	40	39
Detection Rate (%)	-	100	-	95

Table 3 Impact of Extracted Features with various SVM Kernels on Detection Rate for Fastener Classifications

Features Index	SVM kernel	Detection rate (%)
1	Linear	87.37
	Polynomial	90.32
	Sigmoidal	91.65
1 and 2	Linear	92.68
	Polynomial	93.01
	Sigmoidal	93.26
1,2 and 3	Linear	94.74
	Polynomial	95.15
	Sigmoidal	97.5

*feature index of GLCM is 1; feature index of DWT feature is 2; feature index of LBP is 3;

Table 3 shows the impact of extracted features on detection rate of fastener classifications. The SVM classifier (Sigmoidal kernel) with feature index 1 achieves 91.65% of detection rate. The classifier (Sigmoidal kernel) with feature index 1 and 2 achieves 93.26% of detection rate and classifier (Sigmoidal kernel) with feature index 1, 2 and 3 achieves 97.5% of detection rate.

Table 4 Performance Analysis of Detection of Fastener interms of elapsed time

Image Sequence	Elapsed Time (sec)	Image Sequence	Elapsed Time (sec)
Fastener Image 1	0.0620	Fastener missing Image 1	0.0025
Fastener Image 2	0.0052	Fastener missing Image 2	0.0016
Fastener Image 3	0.0031	Fastener missing Image 3	0.0072
Fastener Image 4	0.0016	Fastener missing Image 4	0.0021
Fastener Image 5	0.0021	Fastener missing Image 5	0.0031
Fastener Image 6	0.0069	Fastener missing Image 6	0.0028

Fastener Image 7	0.0016	Fastener missing Image 7	0.0028
Fastener Image 8	0.0028	Fastener missing Image 8	0.0017
Fastener Image 9	0.0018	-	-
Fastener Image 10	0.0016	-	-
Average	**0.0088**	**Average**	**0.0029**

Table 4 shows the performance analysis of the proposed method interms of elapsed time. It is defined as the time taken for the classification of the test image into either track with fastener or track without fastener. It is measured in seconds. The proposed system consumes 0.0088 sec for the classification of track with fastener image and it also consumes 0.0029 sec for the classification of track without fastener image. It is clear from Table 3; the elapsed time for the classification of track without fastener is superior to the elapsed time for the classification of track with fastener. This analysis will be very useful for preventing train accidents due to the missing of fasteners on rail track.

V. Conclusion

This paper proposes a computer aided detection and classification of missing fasteners in rail track images using SVM classification approach. The proposed system consumes 0.0088 sec for the classification of track with fastener image and it also consumes 0.0029 sec for the classification of track without fastener image. The proposed system stated in this paper achieves 95% of detection rate for the case of fastener missing on rain track images. The proposed system achieves 100% of detection rate for the case of track images with fasteners. The overall detection rate of the proposed methodology is 97.5%.

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