Detection and Recognition of Cracks In Railway Track Image

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Abstract- *The objective of this project is to detect and classify the cracks in Railway Tracks. Surface analysis is a very important measurement for track maintenance for Railroad tracks, because deviations in surface geometry indicate where potential defects may exist. A rail surface defect inspection method based on computer vision system has been proposed in the project. Various algorithms for de-noising, filtering thresholding; segmentation and feature extraction are applied for processing the images of Railroad surface defect and cracks. for better speed and complexity, the employed algorithm need to be implemented on embedded platforms. Then accurate area of interest in respective to defect is extracted and recognized by adaptive thresholding and feature matching methods. In addition to the detection of cracks in railway track image and classifying them into low, medium, and high cracks. The various steps involved in the development of the proposed system are i) Pre-processing ii) Detection of cracks iii) Feature Extraction iv) Classification of cracks (Small, Medium, Large). The application of the system is to analyze the Railway Tracks, and if any defects found (cracks), classify the risk and inform obtained from a standard speed-tonnage curve inspection (either manually or by using high speed trains), the defects found are coded (classified) according to an existing standard. Each code contains information the nearest Station Master to avoid the incoming Rail Accidents. The Experimental results show the accuracy 83.00% for SIFT and SVM.*

Keywords- Scale invariant feature transform (SIFT), Support vector machine (SVM), Median Filtering, Segmentation

I. INTRODUCTION

The increased traffic on the rail network and the growing demand for high speed, high capacity trains across the INDIA means that the maintenance of railway assets a significant concern to the railway industry. The maintenance should be carried out on a regular basis to minimize the threats associated with failure of tracks (e.g. rail track breaks and/or train derailments). One of the common causes of rail track failure is due to the cracks which is a known threat to the rail industry. After the Hatfield accident in year 2000, rail industries around the world have begun to track inspection, in particular cracks, more seriously than before increases in train speed and axle load intensity the risk of track failure due to cracks. Although there have been considerable improvements in maintenance in the past Few decades due to employing novel non-destructive testing methods to detect defects (e.g. guided waves, non-contact ultrasonic etc.), there are large areas for potential improvement through increasing the reliability and accuracy of the current NDT inspections and hence optimizing the maintenance schedule. At present, rail inspection is carried out manually using hand-held systems (e.g. ultrasonic Sperry sticks) by high speed dual purpose rail/road vehicles equipped with various NDT sensors. From the reference [14] and [8] the optimized system required to sensor for moving train has mentioned. The frequency of inspection is dependent on the track category which is about the minimum action to be taken and also the time scale. Different codes signify a different defect type and severity (size) which is determined based on the amplitude of the measured signal. The maintenance action to be taken is then determined from the code. The time scale may change from one to a couple of weeks depending on the size of the defect. Rail crack detection and recognition is the field of study that can be used to aid the development of a rail inspection system. A rail crack detection and recognition system could in principle be developed as part of an Intelligent System that continuously monitors the crack images, of the rails in order and classifiers them into low, medium and high crack sizes. The system focuses on integrating information technology into rail inspection infrastructure. These systems can include camera, and a computer on which the system runs, after taking images of the cracks the images are processed with the system which gives the classified results.

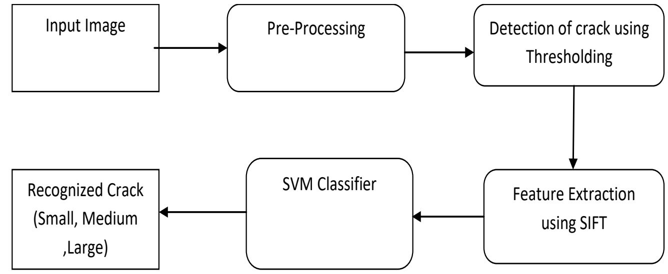

Fig1.Block Diagram of proposed work.

II. PREPROCESSING

The pre-processing in this stage we use median filter. The median filter leads to a high noise removal and smoothing of the image. The median filter is effectively used [3] to reduce noise in an image. It considers each pixel in the image in turn at looks at its nearby neighbors to decide whether are not its representative of its surrounding instead of simply replacing the pixel value with the mean of its neighbor pixel values. It replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

Neighborhood values 115,119, 120, 123 124, 125, 126, 127, 150Median value: 124 Median is calculated by using the following equation

$$g(x,y) = median\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1} f(x-i, y-j)\right)$$

III. DETECTION OF CRACKS

Image segmentation is the process concerned with partitioning of images by determining similarity or, discontinuity or equivalently by finding edges or boundaries. Image segmentation is currently divided into two following categories based on two different aspects of image properties. First, Tracking difference in intensity for example edge detections, second is tracking similarity in regions for example thresholding region growing splitting and merging. Edge is intensity variation between two pixels in an image. Edges are boundaries between different textures. Edge detection is used for image segmentation and feature extraction. Image intensity edges can be profiled as step edge, Line edge, Ramp edge Roof edge. In this project the adapting local block process techniques using OTSU thresholding has been carried out for detecting cracks In railway track. This method minimize the weighted within class variance and turns out to be the save has maximizing the between class variance. It operates directly on the gray level histogram.

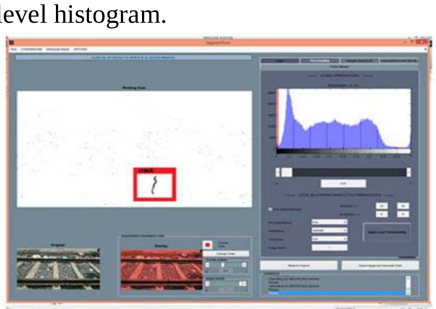

Fig2. Detection of Crack with Bounding Box

IV. FEATURE EXTRACTION

4.1 SCALE INVARIANT FEATURE TRANSFORM

(SIFT)Scale invariant feature transform (SIFT) is a calculation for concentrating stable gimmick depiction (stable feature description) of items call key indicates that are strong changes in scale, introduction, shear, position, and light. The following steps to compute the SIFT features are:

Detection of scale space extrema
Keypoint localization
Orientation assignment
Keypoint descriptor

i) Detection of Scale-Space Extrema

Construct Gaussian scale space function for the input image. This is constructed by convolution operation of the original image with Gaussian functions. The scale space of an image is characterized as a function L(x,y,σ) that is produced from the convolution of a variable scale Gaussian, G(x,y,σ) with an input image, I(x,y):

L(x,y,σ)=G(x,y)*I(x,y,) (2)

G(x,y,σ)=1/(2πσ^2) e^(-(x2+y2)/2σ2) (3)

To efficiently detect stable keypoints difference of gauusians are calculated by simple image image subtraction of two nearby scales separated by a constant multiplicative factor k.

DoG(x, y, k)= (G(x, y, k***σ***) - G (x ,y, ***σ***)) * I(x, y) (4)

=L(x, y, k***σ***)-L(x, y, ***σ***) (5)

To find the local maxima and minima of D(x,y,σ) of each pixel is compared with 8 neighbours at the same scale, and its 9 neighbours up and down one scale. If this value is the minimum or maximum of all these points then this point is an extrema.

ii) Keypoint Localization

Extraction of extrema points produces too different keypoints Low-contrast key points and edge key points are eliminated.

iii) Orientation Assignment

The orientation assignment is to ensure the key points are invariant to rotation. The orientation histogram has 36 bins covering the 360 degree range of orientations. The gradient magnitude m(x,y) and orientation is computed using the introduction task is to guarantee the key focuses are invariant to revolution. The introduction histogram has 36 receptacles convering the 360 degree scope of introduction.

m(x,y)=
$\sqrt{(\boldsymbol{L}(\boldsymbol{x}+\mathbf{1},\boldsymbol{y})-\boldsymbol{L}(\boldsymbol{x}-\mathbf{1},\boldsymbol{y}))\mathbf{2}+(\boldsymbol{L}(\boldsymbol{x},\boldsymbol{y}+\mathbf{1})-\boldsymbol{L}(\boldsymbol{x},\boldsymbol{y}-\mathbf{1}))\mathbf{2}}$
$(\boldsymbol{\theta}(x,y) = \mathbf{tan}\ -\mathbf{1}\ (\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}$ (6)

iv) Key point Descriptor

For each keypoint a squared region considered partitioned in 4x4 parts. A histogram with 8 bins is used for representing the orientation of the points in each of the sub-region of R.

Fig.3 show, a Keypoint descriptor is created by first computing the gradient magnitude and orientation at each image sample point an region around the Keypoint location. These are weighted by a gauusian window, indicated by the overlaid circle. These samples are then accumulated into orientation histograms summarizing the contents over 4x4 sub regions, the length of each arrow corresponding to the sum of the gradient magnitudes near that direction within the region. A 2x2 descriptor array computed from an 8x8 set of samples.

V. RECOGNITION USING SVM

Support vectors machine(SVM)[26]is focused around the standard of structural risk minimization. It is characterization model. Support vector are utilized to discover hyper plane between two classes. Support vectors are the preparation tests that characterize the ideal differenting hyper plane. Support vectors are near the hyper plane. Like RBFNN, support vector machines can be utilized for example order and nonlinear relapse. For straightly divisible information, SVM discovers a differentiating hyper plane, which differentiates the information with the biggest edge. Support vector machine (SVM) can be utilized for arranging the got information. SVM are a situated of related directed learning technique. Give us a chance to mean a feature vector by x=(x1,x2,..xn) and its class mark by y such that y={+1,-1}. Subsequently, consider the issue of dividing the set of n-preparing examples fitting in with two classes.

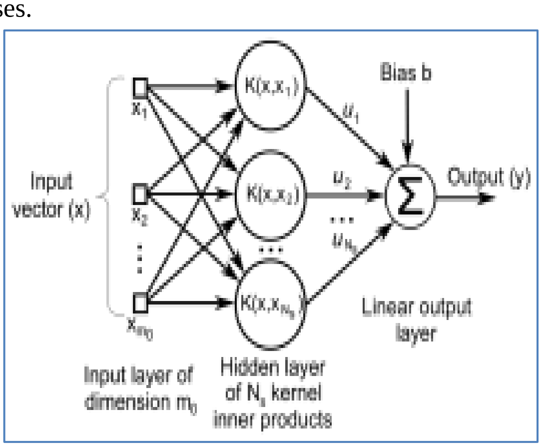

Fig. 3 Architecture of the SVM

VI. EXPERIMENTAL RESULTS

6.1 Railway Track Cracks Recognition

6.1.1 SIFT Features with SVM

In training phase, SIFT is applied to all traffic sign categories. Seven features are extracted from each point by using SIFT features. Number of pixels extracted from an input image is differ from image to image, as well as depends on the complexity of an image. The seven features are x position, y position, scale(sub-level), size of feature on image, edge flag, edge orientation, cracks curvature of response through scale space. SIFT performs extra ordinary robust matching technique. It can handle changes in viewpoint, it can handle significant changes illumination, it is fast and efficient-can run in real time, but compared with SURF is slow.

In testing phase, SIFT is applied to the test sample and depends upon the complexity of an image it extract some pixels, in each pixel seven features are extracted. SVM recognize the sign by using the test features compared with trained features of different traffic signs.

6.2 Performance Measures

The correctness of a classification can be evaluated by computing the number of correctly recognized class examples (true positives), the number of correctly recognized examples that do not belong to the class(true negatives), and examples that either were incorrectly assigned to the class (false positives) or that were not recognized as class examples(false negatives).

6.2.1 Precision

Precision is a measure of the accuracy provided that a specific class has been predicated. It is defined by:

Precision=$\frac{\boldsymbol{number\ of\ true\ posiive}}{\boldsymbol{number\ of\ true\ positive+false\ positives}}$ (6)

6.2.2 Recall

Recall is a measure of the ability of a prediction model to select instances of a certain class from a data set. It is commonly also called sensitivity, and corresponds to the true positive rate. It is defined by the formula.

Recall=$\frac{\boldsymbol{number\ of\ true\ positives}}{\boldsymbol{number\ of\ true\ positives+false\ negatives}}$ (7)

6.2.3 Accuracy

Accuracy is the overall correctness of the model and is calculated as the um of correct classification divided by the total number of classification.

Accuracy

$$=\frac{number\ \ of\ true\ positive+true\ negative}{number\ of\ true\ positive+false\ negative+false\ positive+true\ negative}$$ (8)

6.2.4 F-score

A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional f-measure or balanced

$$\text{F-score}=\frac{2*precision*recall}{precision+recall}$$

Table 2 Performance table for recognition cracks on railway track images with SIFT and SVM

Features	**Model (%)**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F-score (%)**	**Time(sec per Test Image)**
SIFT	**SVM with Gaussian kernel**	83.00	83.00	89.00	83.33	0.599

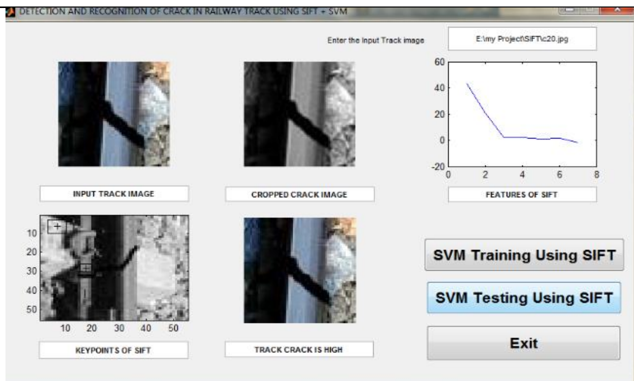

Fig 6.1 Recognition of Small Crack using SIFT and SVM

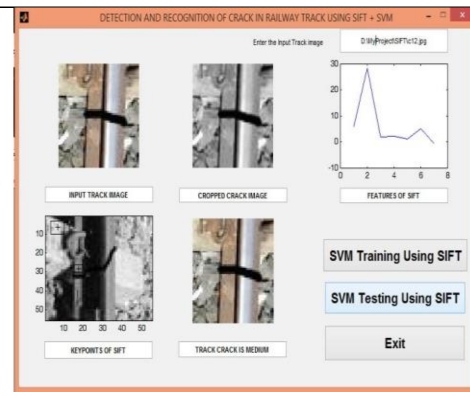

Fig 6.2 Recognition of Medium Crack using SIFT and SVM Crack

Fig 6.3 Recognition of Large Crack using SIFT and SVM

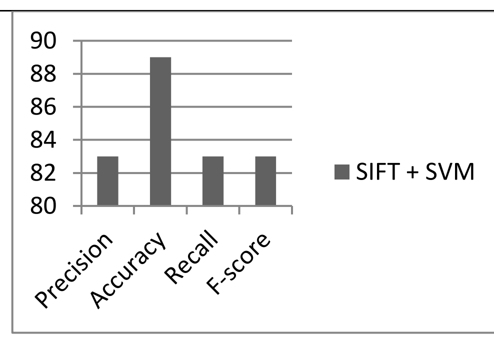

Fig 6.4 Performance chart for recognition of cracks using SIFT and SVM

VII. CONCLUSION AND FUTURE WORK

This project work described an effective method to detect and recognize the cracks in rail track image in an automated manner. The rail crack detection and recognition for railway track inspection system comprises of stages: 1) Pre-Processing and detection of cracks 2) Feature Extraction 3) Classification. The pre-processing is done by median filter. Median filtering leads to the removal of noises and smoothing of the image. Then, rail crack features are extracted using SIFT. Finally rail cracks are recognized using SVM classifier. The experimental results shows the accuracy of 83.00% for SIFT and SVM.

FUTURE WORK

The rail track crack recognition system recognizes the all kinds of rail cracks. the performance of the system can be improved by new feature extraction techniques. By implementing Real-Time processing the visual inspection systems can also be developed to reduce the manpower and time involved in rail track inspection.

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