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# Rail Fastener Inspection by Clustering of Object Textures

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**ABSTRACT**

Rail line assessment is a supreme task in railway safety, and it is systematically needed for preventing critical situations like derailments, level crossing and miscellaneous accidents. Manual rail inspection is done by skilled human operator, walking by the side of the track and search for visual abnormalities. But, this labor-intensive inspection is gradual and subjective to vary with respect to the competency level of the observer. Motivated by this issue, a vision based rail line inspection system is proposed in this work to mitigate this issue. This work concentrates on segmenting the objects present in the railroad tracks and fault measurement of track components. The appearances of those components vary across different tracks using the Local Binary Pattern (LBP) feature which replaces each pixel by a convex combination of its neighbors. The conventional clustering algorithm, fuzzy c-means (FCM) used. And it is an efficient clustering algorithm used for image segmentation. The investigational result shows that the proposed system can segment the images automatically and efficiently. Especially, FCM can process the different types of textures such as ballast, concrete, rail and fasteners; which are the most difficult task for the image segmentation.

***Keywords:*** Rail inspection, derailments, Local Binary Pattern (LBP), fuzzy c-means algorithm (FCM), Clustering.

## 1. INTRODUCTION

Rail inspection consists of investigating various components in rail tracks as shown in figure 1, for identifying the defects that could lead to derailments and track failures. It is a crucial duty in the railway maintenance, and is periodically required in order to prevent hazardous situations. Habitually, this duty is done manually by a well-trained human operator who periodically walks by the side of the track inquiring for visual abnormalities. This labor-intensive investigation is lengthy, difficult and subjective, since it relies entirely on the ability of the human operator to detect possible anomalies. Since rail traffic is increased at higher speeds and with heavier axle loads today, dangerous crack sizes are shrinking and rail inspection is becoming more important and railway companies are also interested in developing fast and efficient inspection systems for the tracks management by automatically. In the last decade, since computer vision systems have become increasingly powerful, smaller and cheaper, automatic visual inspection systems have become a possibility. These are especially suitable for inspecting the high-speed railway zones with a low resolution camera. Most of the algorithms for object detection problems have been studied by the computer vision community, especially for industrial inspection process. However, only few works can be found on the use of computer vision in the specific area of rail inspection. Existing inspection methods acquire real images by a digital camera installed under a specialized train or the permanent way as track cart moving along the rail line [8]. Earlier approaches available for identifying the status of the materials e.g, testing the steel alloy rely on destructive and non destructive methods. The destructive method is done by coring and the non-destructive method is based on hammer sounding. Non Destructive methods also includes Infrared inspection, Ultrasound inspection, Laser light inspection [1], defect localization based on projection profile [12], morphological component analysis (MCA) [10],

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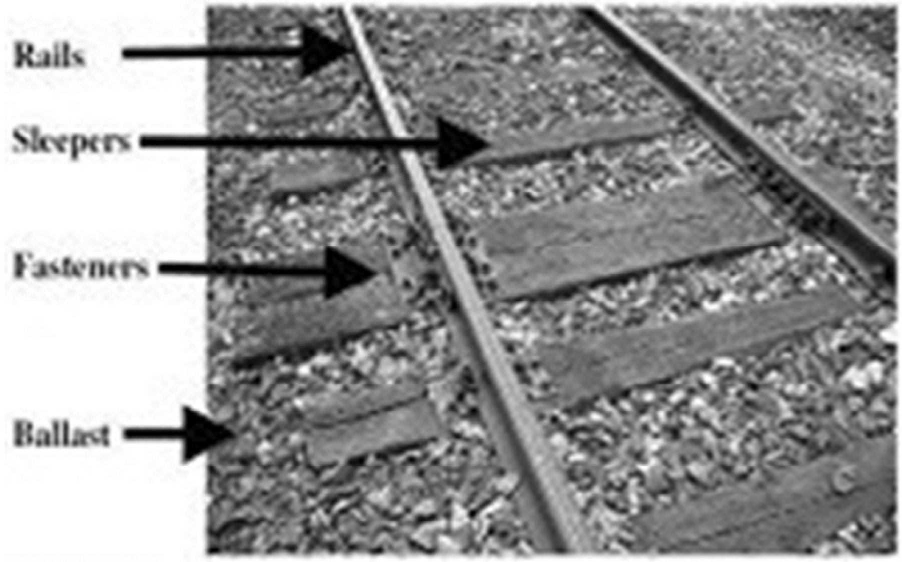



**Figure 1: Illustration of Rail track components**

**Figure 2: Fasteners Under Different Illumination Conditions**

and Spectral analysis of surface waves (SASW),Global Positioning System (GPS) [6] are used to detect the components in the track. Later on, automatic hexagonal-headed bolts detection based on discrete wavelet transform as a local processing step for texture feature extraction and Multilayer Perceptron Neural Classifiers (MLPNCs) are used to identify the presence and absence of the rail component [4]. But these methods simply work on limited rail area and even show poor performance under varying illumination conditions as shown in Fig 2. Hence, this proposed work aims to develop an effective vision-based automatic rail inspection system to detect the parts such as fasteners, concrete, ballast and rail line in the railway track and to cluster these components under different illumination condition.

## 2. PROPOSED METHODOLOGY

In the proposed methodology, automatic railway track inspection is done with the help of vision based system. The system flow diagram of the proposed methodology is shown in Fig 3. The input rail track image is acquired using a digital camera. The texture feature of the railway track are extracted using LBP and the rail components like rail, concrete, sleeper and fasteners are detected by Fuzzy clustering of the Gaussian smoothed texture histogram. Thus, the clustering of the rail track components localize the materials present in the rail track image.

### 2.1. Feature Extraction

The success of detecting fasteners highly rely on the quality of the feature used to represent the component which in turn depends on the feature extraction technique. Hence, in this work, a low level feature referred as texture has been used to cluster the local image regions, since the texture feature can detect roughness

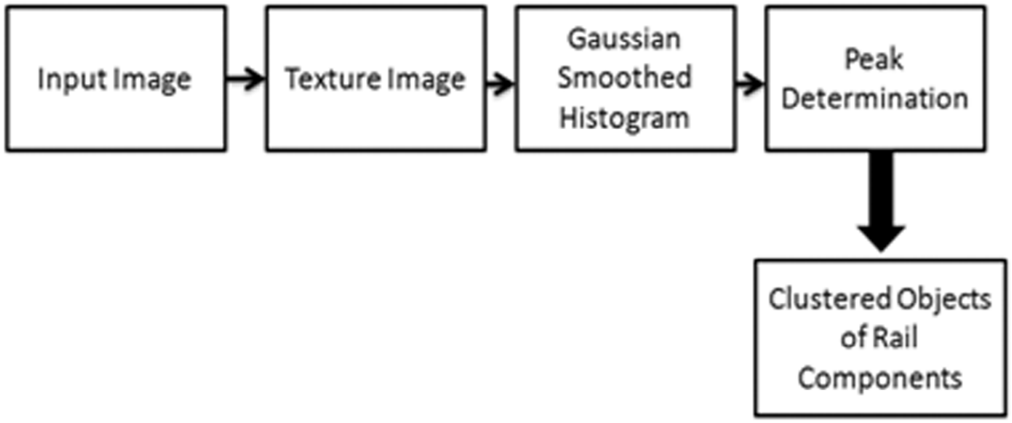



**Figure 3: System Flow**

and smoothness in the image region which can distinguish the rail track components. The proposed methodology uses the classical Local Binary Pattern (LBP) as a texture feature and it is described as follows.

#### *2.1.1. Texture Feature: Local Binary Pattern*

To classify the image regions different types of features are used such as shape feature, color feature and texture feature. In our problem color is not the primary criteria, because the rail line and the fastener having the rusted color of iron. Hence that, here we have using the texture as a feature and this efficient low level feature is used to detect the roughness and smoothness of the different rail components. In this proposed technique, Local Binary Pattern (LBP) has been used to represent the characteristics of the different rail components such as Fasteners, Rail, Concrete and Sleepers. Local binary pattern is a gray scale invariant texture feature. This low level texture descriptor is computed by 3 × 3 local neighborhood pixels. And this descriptor is built by using the thresholding of the pixel which is based on the center pixel of the 3 × 3. Hence that the current pixel value is changed on the basis of the center pixel and then it is labeled as 0 or 1. Likewise, the eight neighbors are labeled as 0 and 1 which is used to form binary code and derives as follows. Let us define the texture $T_x$ in local neighborhood of gray scale image as

$$T_x = T\,(gr_c, gr_0, \ldots\ldots\ldots\ldots\ldots gr_{p-1}) \tag{1}$$

Where $gr_c$ is the center pixel of a local neighborhood, $gr_p$ (p = 0, . . ., I – 1) correspond to the gray values. Where $gr_c$ is the center pixel of a local neighborhood in a gray scale. The local image texture around $(x_c, y_c)$ is given by,

$$LBP_{I,J}(x_c, y_c) = \sum_{p=0}^{p-1} s(gr_p - gr_c)\, 2^p \tag{2}$$

An example for computing LBP for a gray scale image of radius J = 1 is shown in Fig 4. The obtained LBP histogram shows drastic variations in the gray level distribution as shown in Fig 5. which makes the algorithm difficult to find out the number of clusters for grouping the rail components. Hence, the next step is to smooth the LBP histogram.

#### *2.1.2. Gaussian Smoothing*

For smoothing the LBP histogram, the proposed methodology uses well known technique namely, Gaussian smoothing which replaces each pixel by a0 weighted average of its neighbors, and mask weights are computed by sampling a Gaussian function. The spatial smoothing is increased by the signal-to-noise ratio and enables averaging across subjects. Gaussian filtering is used to blur images and remove noises. The 1-D gaussian distribution is described by,

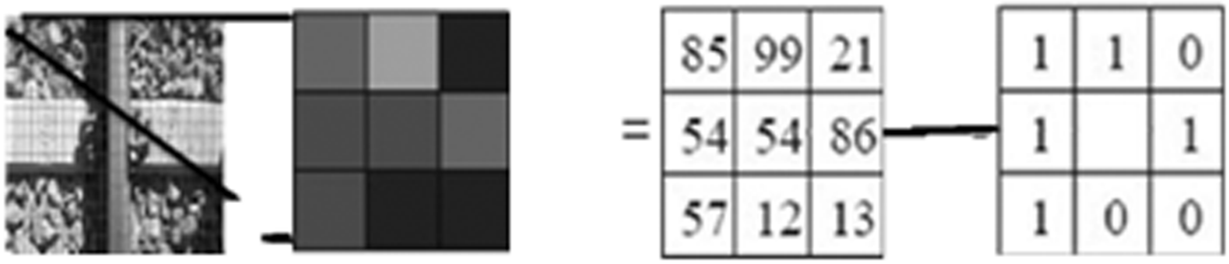



**Figure 4: Local Binary Pattern**

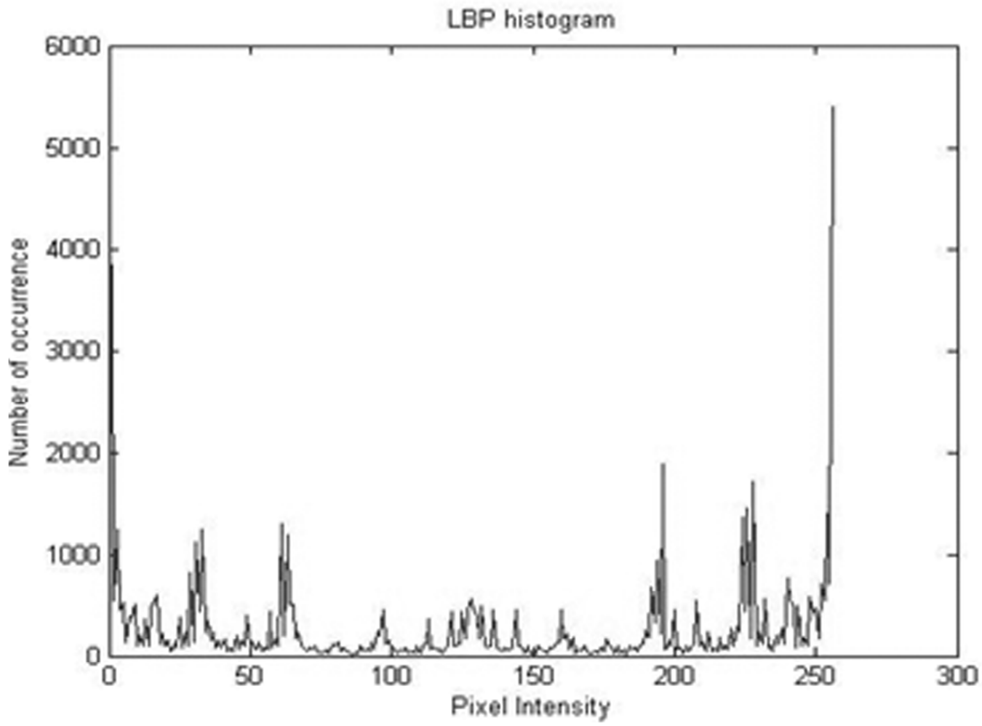



**Figure 5: Histogram of Local Binary Pattern**

$$G(C) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{c^2}{2\sigma^2}} \tag{3}$$

Where σ is the SD (standard deviation) of the given gaussian distribution. The smoothing is determined based on the standard deviation. So that the degree of the smoothing is related to the standard deviation. The larger standard deviation requires larger convolution kernels to represent accurately. This gaussian smoothing is used to remove high spatial frequency components from an image. The LBP histogram obtained for the particular cluster separation and the corresponding Gaussian smoothed texture histogram with σ = 5 is shown in the Fig 6. As depicted in Fig 7, the Gaussian smoothing on the LBP histogram provides the smoothened histogram with visible peaks. Now, it is simple to detect the peaks for clustering the parts in the railway track.

### *2.1.3. Peak Determination*

This step is essential for determining the number of parts in the acquired rail track image. Many different methods are available for peak determination in Literature. The Peak determination algorithm works by finding the real peaks by automatically analyzing the results to determine the dominant cluster. Here, from the Gaussian smoothed texture histogram, the higher edge peak points is computed using threshold. The mean of the smoothened histogram is chosen as the threshold. The detected peaks in the histogram using

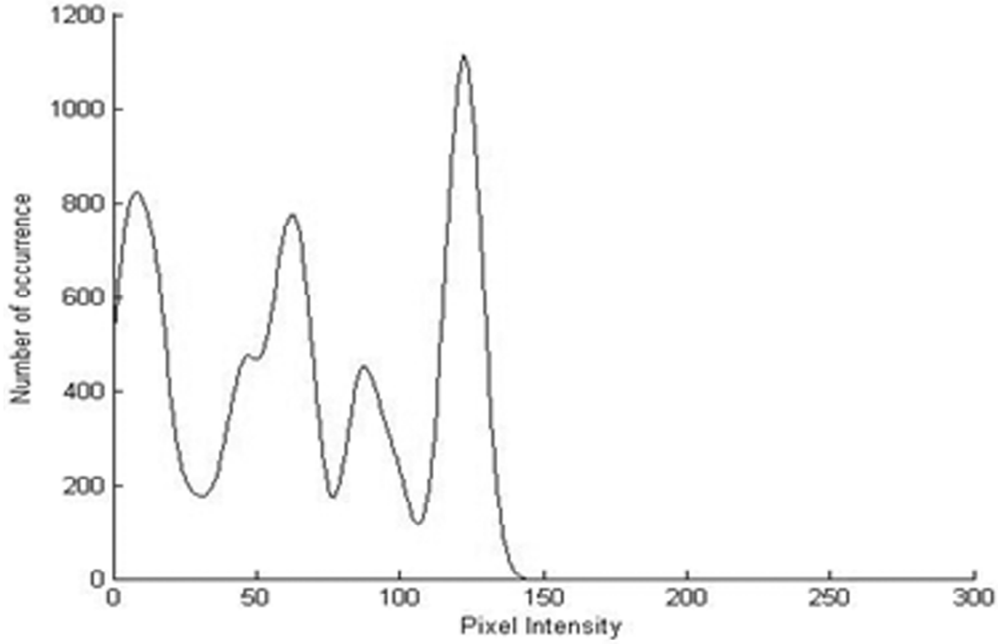



**Figure 6: Gaussian Smoothed Texture Histogram**

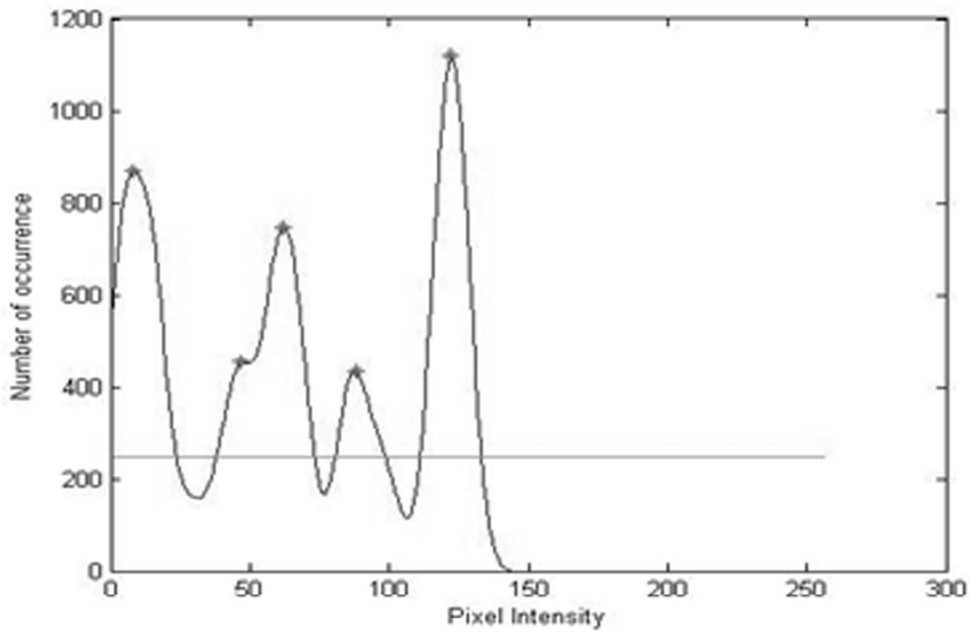



**Figure 7: Histogram of Peak Detection using mean line**

mean line is shown in Fig 7. The number of peaks gives the number of clusters; it shows the clustered objects of the rail track component such as Rail, Concrete, Ballast, Fasteners.

### *2.1.4. Fuzzy C-means Clustering Algorithm*

In fuzzy clustering, each peak points has a probability of neighboring cluster to each cluster in an rail track image. rather than completely belonging to just one cluster as it is the case in the traditional k-means. In this work, the condition of each pixel is determined by the membership values of surrounding neighboring pixels and then is either added to or subtracted from the cluster.The algorithm is an iterative clustering that produces an optimal 'c' partition by minimizing the weighted within group sum of squared error objective function $J_{FUZZY}$

$$J_{FUZZY} = \sum_{k=1}^{n}\sum_{i=1}^{c} (U_{ik})^{q}\, d^{2}(v_k, x_i) \tag{4}$$

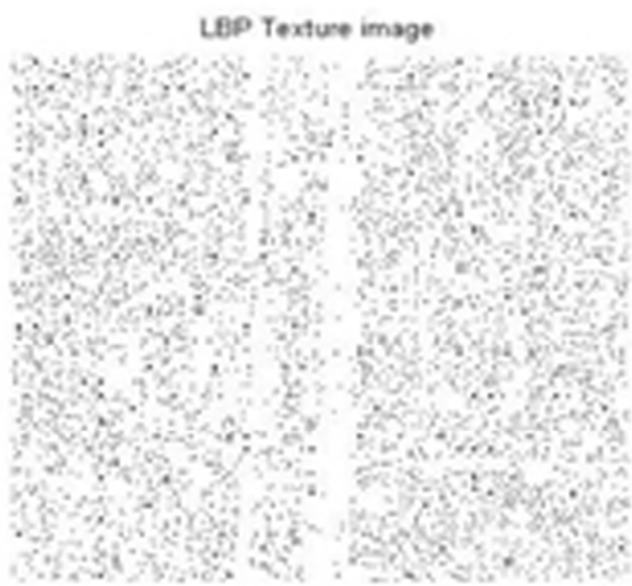
Here, $U_{ik}$ is the degree of relationship of the desired component $v_k$ pertains to the cluster center of $x_{i.}$ The algorithm reduces the intra-cluster variance, but has the same problems as *k*-means; the minimum is a local minimum, and the results depend on the initial choice of weights. This clustered result is based on the components present in the rail tracks.

## 3. RESULTS

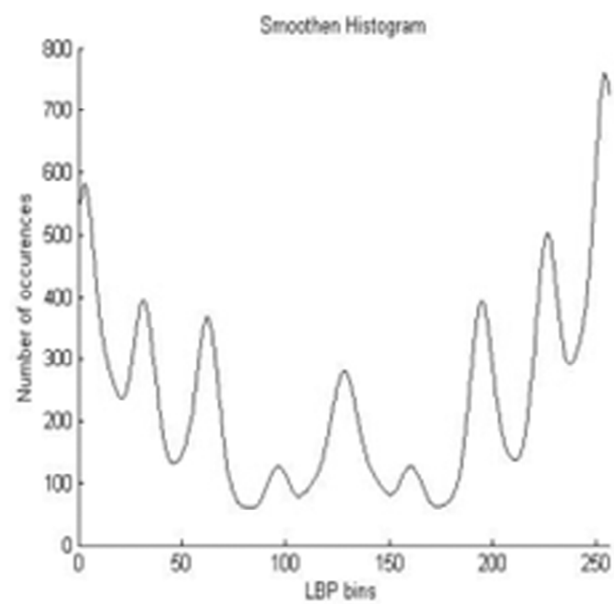
The images of rail track are acquired using mobile camera, in handheld device (Micromax A091). The resolution of the images is 1600 × 1200. The rail line images consist of four components namely, Ballast, Rail line, Fasteners and Concrete bed. The input image is resized to 256 × 256 and it is converted to grayscale. The LBP texture features extracted from the track images are shown in the Fig 8. Then the histogram of LBP texture feature is used to find the number of rail components present in the input image.

**(a)**

**(b)**




**(c)**




**(d)**

**Ballast** **Fastener** **Rail line** **Concrete**

**(f)**

**Figure 8: Result of the proposed Rail components Clustering**
**(a) Input Image (b) Gray scale image (c) Texture image (d) Gaussian Smoothed Texture Histogram (e) Peak detection for finding clusters (f) Clustering of Rail Components**

In order to avoid the spurious peaks, the histogram is smoothen by a Gaussian filter with varying attributes. The number of peaks in the smoothen histogram predicts the number of rail components are clustered using FCM algorithm with the number of cluster determined from the peaks.

## 4. CONCLUSION

In this paper, an algorithm for clustering rail components to develop a instantaneous automatic vision system for the rail inspection is presented. Fuzzy c means clustering algorithm which clusters the four major components of rail track namely ballast, concrete, rail and fastener based on the LBP texture feature. Feature reduction of the LBP histogram is obtained by histogram bins and the use of Fuzzy c means clustering algorithm assures the low complexity of the algorithm. The experimentation of the proposed method over 30 database images clearly shows that the rail components are clustered. The extended work include clustering of rail components from video database.

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