

# Implementation of Track Inspection Cars to Detect the Defection of Fastener in Track Based on Vision System

Mr. S. Prince Samuel  
M.Tech, AP/ECE dept,  
Oxford Engineering college,  
Trichy, Tamilnadu, India.

M. Tharini,  
M.E(Embedded system technologies),  
Oxford Engineering College,  
Trichy. TamilNadu. India.

Mr. C. Arivalan,  
M.E,(Communication system)  
Sudharasan Engineering College,  
Trichy.Tamilnadu. India.

**Abstract-**The defections of railway tracks are inspected manually and using NDT methods, Railway track consists of components like fastener and sleeper, in tracks fastener plays a vital role, fastener is used as the connecting component between the sleeper and the vertical lines of the track. Identifying the defections of fastener using manual inspection and NDT methods are slow and sometimes leads to accidents. This paper proposes an automatic visual inspection of damaged fastener, by modeling the structure of damaged fasteners and comparing with the trained modules the damaged score of the fastener is identified. This method is used to analyze the condition of fastener.

**keywords:** Fastener, structure modelling (STM), visual inspection

## I. INTRODUCTION

Track is one of the most important technical elements in track operations. Track technology has developed in parallel with the railway itself. Current concerns of railways are also technical issues for tracks. The first railway was built in japan using a narrow gauge to meet geographical conditions and the need for economy. Tracks are long structures stretching long kilometers. The design is a rational

structure for supporting heavy fast train on a soft ground. Many attempts have made over thousand years to develop other designs to replace over this conventional design, but none have been good enough. A rail fastening system is a means of fixing rails to rail road ties or sleepers. The terms rail anchors, tie plates, chairs and track fasteners are used to refer to parts or all of a rail fastening system. Various types of fastening have been used over the years. New fastening designs are proposed to withstand the more severe loading conditions and to improve durability. To assess the suitability of these designs it is of utmost importance to perform repeated loading tests on the sleeper/fastening assembly in a laboratory environment. Fastener testing methods are clamping Force Measurement, Longitudinal Restraint test Vertical stiffness measurement.

Fasteners are used to hold the track on sleepers; it is used as a connecting element between the sleeper and the vertical lines of the track, fastener are of two types Hexagonal-headed bolts and Hook shaped fasteners. Hook shaped fasteners are currently used in railway lines, their diverse shapes give rise to significant difficulties in modeling and inspecting. Classifiers used in traditional fastener inspection methods are Multilayer perceptron neural model and Wavelet transformation



Fig. 1. Various types of fasteners installed in tracks

Problems with current inspection methods are:

1. Tracks are constructed using different types of fastener, it is difficult to analyze each type of fastener in manual inspection, and therefore they are able to identify only the missing ones and not the damaged fasteners.
2. A railway tracks are installed with various types of fasteners for various reasons. Therefore, it is necessary for an automatic inspection system to recognize all these types of fasteners without manual intervention
3. The images captured by the cameras placed under the track inspections car are subjected to different illumination conditions.

To handle these problems, a new probabilistic structure topic model (STM) based on vision system is proposed to model fasteners. This model generative, data driven, and it can simultaneously learn the probabilistic representations of different objects using unlabeled samples. This method is designed for detecting the defects of various types of fastener and is able to find both the partially worn and the completely missing ones.

## II. AUTOMATIC INSPECTION OF FASTENER BASED ON VISION SYSTEM

Automatic visual inspection system is used for detecting partially worn and completely missing fasteners, using probabilistic topic model. In this method different types of fastener with different illumination conditions are modeled using unlabeled data. To identify the damages, the test fasteners are compared with the trained models and automatically ranked into three levels based on the likelihood Probability. This method is designed for detecting the defects of various types of fastener and is able to find both the partially worn and the completely missing fasteners.

The adaboost algorithm is used to detect the fastener detection work. Here the fastener components are splitted into four parts and each part is independently trained. Thus, this method has the ability of detecting partially worn fasteners. Similarly, image processing methods are used to detect the components of fastener

zones of the image where the gray level is changing fast enough from dark to light or the opposite. The algorithm starts by computing the level-line angle at each pixel to produce a level-line field, i.e., a unit vector field such that all vectors are tangent to the level line going through their base point. Then, this field is segmented into connected regions of pixels that share the same level-line angle up to a certain tolerance  $\tau$ . These connected regions are called line support regions. The LSD algorithm takes a gray-level image as input and returns a list of detected line segments. The auxiliary image Status has the same size as the scaled image, and is used to keep track of the pixels already used. LSD was designed as an automatic image analysis tool. As such it must work without requiring any parameter tuning. The algorithm actually depends on several numbers that determine its behavior; but their values were carefully devised to work on all images. The result of LSD is different when the image is analyzed at different scales or if the algorithm is applied to a small part of the image. This is natural and corresponds to the different details that one can see if an image is observed from a distance or if attention is paid to a specific part. As a result of the contrario validation step, the detection thresholds automatically adapt to the image size that is directly related to the number of tests. The scale of analysis is a choice left to the user, who can select it by cropping the image. Otherwise LSD processes automatically the entire image. The first step of LSD is, nevertheless, to scale the input image to 80% of its size. This scaling helps to cope with aliasing and quantization artifacts (especially the staircase effect) present in many images. Blurring the image would produce the same effect but affecting statistics of an image in the contrario model: some structures would be detected on a blurred white noise. When correctly sub-sampled, the white noise statistics are preserved. Note that the contrario validation is applied to the scaled image and the  $N \times M$  image size used in the NFA computation corresponds to an input image of size  $1.25N \times 1.25M$ . The scaling is performed by a Gaussian sub-sampling: the image is filtered with a Gaussian kernel to avoid aliasing and then sub-sampled. The standard deviation of the Gaussian kernel is determined by  $\sigma = \Sigma/S$ , where  $S$  is the scaling factor. The value of  $\Sigma$  is set to 0.6, which gives a good balance between avoiding aliasing and avoiding image blurring.

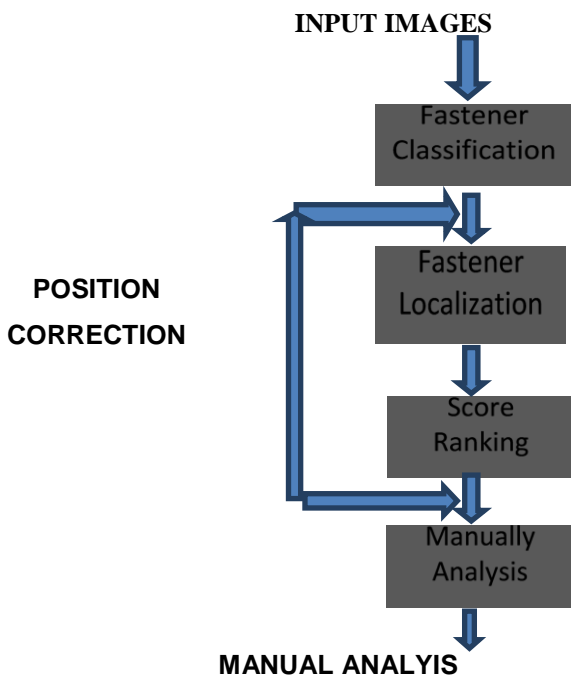


Fig.2. Flow chart of the data processing module.

### A. Fastener localization:

In localization process, first images are captured using camera and those images are processed using image processing. In this method track detection and sleeper detection is done to localize the tracks and sleepers. Track detection and sleeper detection is done using LSD algorithm. Localization plays a major role which is used for detecting the damages, using these information further processing are carried.

### Line segment detection

LSD is aimed at detecting locally straight contours on images. This is what we call line segments. Contours are

### B. Fastener classification

Classification is done based on localization data, here we are using trained samples using this images captured in localization is compared with the trained samples to detect the percentage of failure, and also there are different types of fasteners are installed, so it necessary to develop a model for each type and to compare and to identify the deflection.

### latent Dirichlet allocation

(LDA) is a generative probabilistic model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an

underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. LDA assumes the following generative process for each document  $w$  in a corpus  $D$ :

1. Choose  $N \sim \text{Poisson}(\xi)$ .
2. Choose  $\theta \sim \text{Dir}(\alpha)$ .
3. For each of the  $N$  words  $w_n$ :
  - (a) Choose a topic  $z_n \sim \text{Multinomial}(\theta)$ .
  - (b) Choose a word  $w_n$  from  $p(w_n | z_n, \beta)$ , a multinomial probability conditioned on the topic  $z_n$ .

### Fastener modeling with STM

Structural Topic Model, which simultaneously discovers topics and reveals the latent topical structures in text through explicitly modeling topical transitions with a latent first-order Markov chain. Experiment results show that the proposed Structural Topic Model can effectively discover topical structures in text, and the identified structures significantly improve the performance of tasks such as sentence annotation and sentence ordering.

The generative process of STM is given as follows.

- 1) For each image, draw a fastener class distribution  $\theta_m$  according to Dirichlet( $\alpha$ ).
- 2) Draw a fastener class  $z_m$  from multinomial ( $\theta_m$ ).
- 3) For each fastener sample, do the following steps  $P$  times.
  - a) Draw a class-coordinate distribution  $\gamma$  according to Dirichlet( $\lambda$ ).
  - b) Draw an index  $Enl$  according to multinomial ( $\gamma z_m$ ). This is equivalent to sample two coordinates  $C(1)$ ,  $Enl$  and  $C(2)$ .
  - c) Draw class-word distributions  $\eta$  and  $\delta$  according to Dirichlet( $\pi$ ) and Dirichlet( $\rho$ ), respectively.
  - d) Draw visual words  $W1nl$  and  $W2nl$  according to multinomial( $C(1)Enl, z_n, \eta$ ) and multinomial ( $C(2)Enl, z_n, \delta$ ), respectively.

### C. Score ranking

Ranking the fasteners into three levels based on the likelihood probability, which measures the consistency between a fastener and the corresponding model. The fastener which is ranked into the low level are severely worn or missing, which need to be immediately replaced, the fasteners ranked into middle level are partly worn. These fasteners require further assessment by human inspectors, the fasteners ranked in higher level are the fasteners in good condition, here a threshold value is gained by testing a fastener in good condition, and this value is used as a reference value to check the differences between normal and abnormal fastener.

### D. Position correction

The results obtained from score ranking is used for decision making whether the fasteners need manual correction or automatic correction. The fasteners that are ranked at first level and second level are subjected to automatic position correction because those fasteners are only damaged at low percentage. The position correction is done by hardware system.

### E. Manual analysis

The fasteners that are ranked at low level cannot be corrected automatically thus we need manual corrections; because the fasteners that are in very worsen conditions are subjected to manual correction or replacement of fasteners. The final results are summarized on an interactive user interface for further manual inspection and analysis. The automatic correction is made by the system for adjusting the positions of fastener. In case of automatic correction not possible, manual analysis is done for repairing or replacing the fastener. Manual works are done by the labours, who are authorized and having more experience in this inspection field

## III MATLAB SIMULATION

### Matlab description

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or FORTRAN. MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

MATLAB features a family of application-specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow you to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

Image processing steps

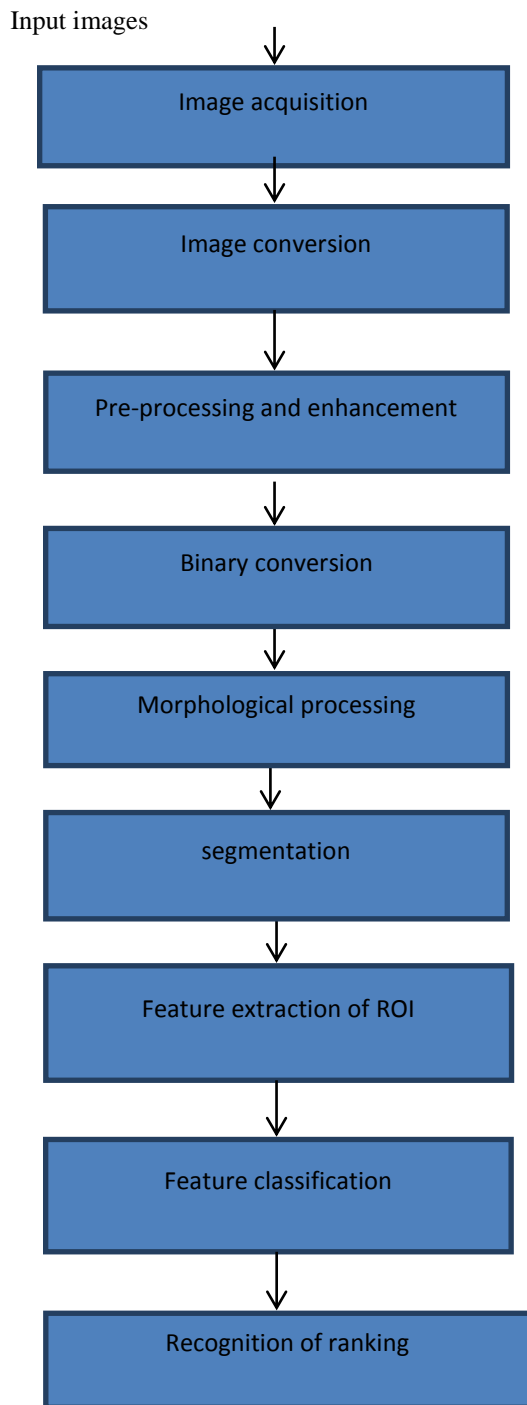


Fig. 3. Steps in image processing

Implementation details:

- 1.The fastener is detected using LSD algorithm
- 2.The detected fastener is captured and analysis is done. The captured image is checked for its plane, if plane is three it is converted into two planes and image is converted in gray image for further processing.

- 3.Histogram is calculated for the captured image,and the noises in the image are filtered using median filter using Gaussian distribution.
4. Morphological processing steps are carried such as eroding and dilation, the gray image is converted into binary image.
5. This binary image is processed by considering each pixel, and for each pixel value magnitude, orientations and locations are calculated and maximum value is considered for further processing.
- 6.The maximum pixel values are considered as the keypoint value and for those value descriptors are calculated using texture based representation.
- 7.Mean is calculated for maximum keypoint value. This value is compared with the normal threshold value; this normal threshold value is obtained by doing structure modeling for the normal fastener. The threshold valuefor normal fastener is 0.1045.
- 8.Mean value for tested fastener is compared with threshold value, if the resulting value is greater than the threshold value, then the fastener is in abnormal condition, or if the resulting value is equal or lesser than the threshold value, then the fastener is in normal condition.

V.EXPERIMENTAL RESULTS

Experiments are done with two types of fastener which is in normal and abnormal fastener, first the input image is acquired , if the input image colour it is converted into gray for further processing, and then the image is smoothed and preprocessing is done, then converted into binary, this binary image is dilated and eroded, segmentation is done for finding the defects, the segmented image is further extracted for finding keypoints and descriptors.these image gives the result of damages from that ranking is done.

Experimental results for normal image



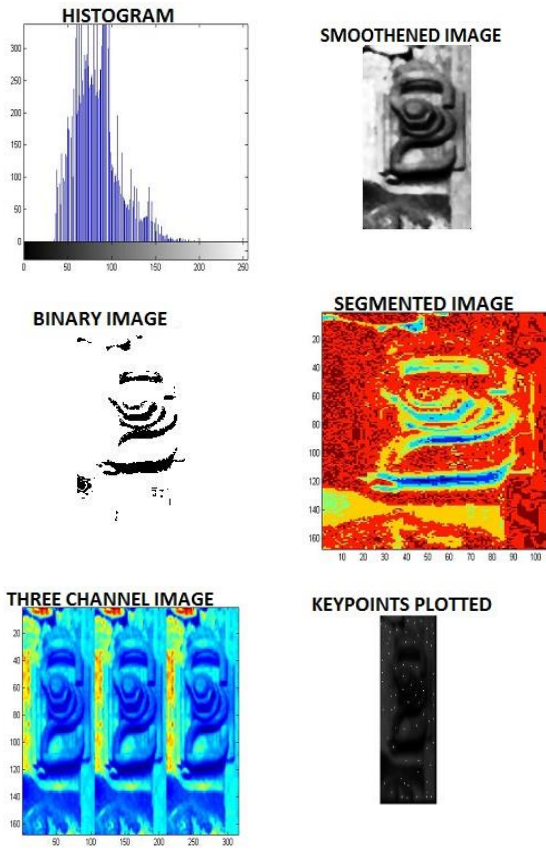


Fig. 4. simulation results of normal fastener

**Experimental results for abnormal image**

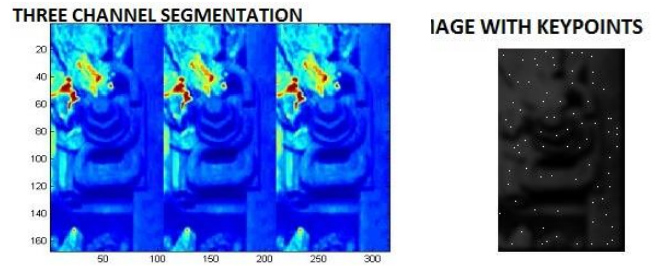
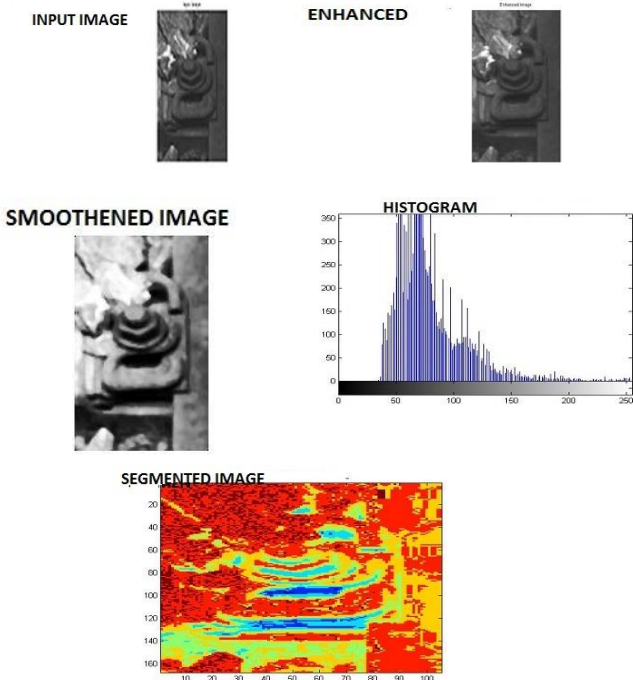


Fig. 5. simulation results of abnormal fastener

To prove the effectiveness of our approach, here the fasteners are trained and classification is done under several illumination conditions and ranking is done based on the damaged score.

**V. TRACK INSPECTION VEHICLE:**

**BLOCK DIAGRAM:**

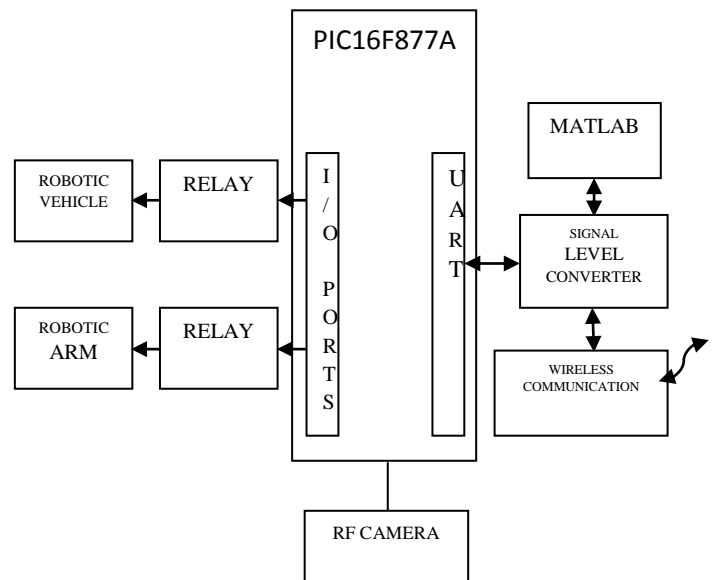


Fig. 6. Transmitter end

**RECEIVER END:**



Fig. 7. Receiver end

**DESCRIPTION:**

The robotic vehicle is placed in the railway track and it is controlled by PIC microcontroller. RF camera is placed below the robotic vehicle and RF receiver is connected with Mat lab. The robotic vehicle starts moving

to the sleeper and sends the video of fastener position. The fastener position is analysis by the mat lab, if it is normal vehicle move to the next sleeper continue same process. If the position is abnormal, it check the range whether robotic vehicle can solve the problem or need of human analysis. The range is low the robotic adjust the fastener by using the robotic arm else sends the alert for human analysis by using ZigBee.

## VI.CONCLUSION

The detection of worn and missing fasteners is an important task in railway inspection. However, the manual inspection leads to some hazards. The inspection methods based on classifiers are of low reliability .in this paper, a novel railway inspection system is proposed, which is able to simultaneously assess the damage of multiple types of fasteners, based on the topic model; the proposed inspection system has the following three major advantages:

- 1) Different types of fasteners can be simultaneously modeled using unlabeled data;
- 2) The system is robust to illumination changes; and
- 3) The statuses of fasteners are ranked.

## ACKNOWLEDGMENT

I am very much indebted to my guide and my parents for their valuable guidance, assistance and support throughout my studies and also for all the given valuable information that might help me for my future career.

## REFERENCES

- [1] Hao Feng, Zhiguo Jiang, Fengying Xie, Ping Yang, Jun Shi, and Long Chen "Automatic Fastener Classification and Defect Detection in Vision-Based Railway Inspection Systems" Ieee Transactions On Instrumentation And Measurement, Vol. 63, No. 4, April 2014
- [2] R. Edwards, S. Dixon, and X. Jian, "Characterization of defects in the railhead using ultrasonic surface waves," *NDT & E Int.*, vol. 39, no. 6, pp. 468–475, Sep. 2006.
- [3] P.L. Mazzeo, M. Nitti, E. Stella, and A. Distanto, "Visual recognition of fastening bolts for railroad maintenance," *Pattern Recognit. Lett.*, vol. 25, no. 6, pp. 669–677, Apr. 2004.
- [4] Y. Xia, F. Xie, and Z. Jiang, "Broken railway fastener detection based on adaboost algorithm," in *Proc. Int. Conf. Opto electron. Image Process.*, vol. 1. Haiko, China, Nov. 2010, pp. 313–316.
- [5] E. Stella, P. Mazzeo, M. Nitti, G. Cicirelli, A. Distanto, and T. D'Orazio, "Visual recognition of missing fastening elements for railroad maintenance," in *Proc. IEEE Int. Conf. Intell. Transp. Syst.*, Singapore, Sep. 2002, pp. 94–99.
- [6] J. Yang, W. Tao, M. Liu, Y. Zhang, H. Zhang, and H. Zhao, "An efficient direction field-based method for the detection of fasteners on high-speed railways," *Sensors*, vol. 11, no. 8, pp. 7364–7381, Jul. 2011.
- [7] D. Blei, A. Ng, and M. Jordan, "Latent dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Jan. 2003.
- [8] Y. Rubinsztein, "Automatic detection of objects of interest from railtrack images," M.S. thesis, School Compute. Sci., Univ. Manchester, Manchester, U.K., 2011.
- [9] Y. Li, C. Otto, N. Haas, Y. Fujiki, and S. Pankanti, "Component-based track inspection using machine-vision technology," in *Proc. 1st ACM Int. Conf. Multimedia Retr.*, Trento, Italy, 2011, no. 60.
- [10] P.L. Mazzeo, N. Ancona, E. Stella, and A. Distanto, "Visual recognition of hexagonal headed bolts by comparing ICA to wavelets," in *Proc. IEEE Int. Symp. Intell. Control*, Houston, TX, USA, Oct. 2003, pp. 636–641.
- [11] Y. Rubinsztein, "Automatic detection of objects of interest from railtrack images," M.S. thesis, School Compute. Sci., Univ. Manchester, Manchester, U.K., 2011.
- [12] Y. Li, C. Otto, N. Haas, Y. Fujiki, and S. Pankanti, "Component-based track inspection using machine-vision technology," in *Proc. 1st ACM Int. Conf. Multimedia Retr.*, Trento, Italy, 2011, no. 60.
- [13] P.L. Mazzeo, N. Ancona, E. Stella, and A. Distanto, "Visual recognition of hexagonal headed bolts by comparing ICA to wavelets," in *Proc. IEEE Int. Symp. Intell. Control*, Houston, TX, USA, Oct. 2003, pp. 636–641.
- [14] C. Mandriota, M. Nitti, N. Ancona, E. Stella, and A. Distanto, "Filter-based feature selection for rail defect detection," *Mach. Vis. Appl.*, vol. 15, no. 4, pp. 179–185, Oct. 2004.
- [15] M. Singh, S. Singh, J. Jaiswal, and J. Hempshall, "Autonomous railtrack inspection using vision based system," in *Proc. IEEE Int. Conf. Comput. Intell. Homeland Security Personal Safety*, Alexandria, VA, USA, Oct. 2006, pp. 56–59.
- [16] D. Blei, A. Ng, and M. Jordan, "Latent dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Jan. 2003.
- [17] B. Zhao, L. Fei-Fei, and E. P. Xing, "Image segmentation with topic random field," in *Proc. 5th Eur. Conf. Compute. Vis.*, Heraklion, Greece, Sep. 2010, pp. 785–798.
- [18] X. Wang, X. Ma, and W. E. L. Grimson, "Unsupervised activity perception in crowded and complicated scenes using hierarchical Bayesian models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 3, pp. 539–555, Mar. 2009.
- [19] L. Fei-Fei and P. Perona, "A Bayesian hierarchical model for learning natural scene categories," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, vol. 2, Jun. 2005, pp. 524–531.
- [20] P. Orbanz and J. M. Buhmann, "Nonparametric Bayesian image segmentation," *Int. J. Compute. Vis.*, vol. 77, nos. 1–3, pp. 25–45, May 2008.