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Detection of Cracks and Missing Fasteners in Railway lines Using Structure Topic Model

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ABSTRACT

The detection of fastener defects is an important task in railway inspection systems, and it is frequently performed to ensure the safety of train traffic. At present, this task is operated manually by a trained human operator who periodically walks along the track searching for visual anomalies. This manual inspection is lengthy, laborious and subjective. So to avoid these drawbacks an automatic visual inspection system was proposed, which uses computer vision based technologies, for detecting partially worn and completely missing fasteners using probabilistic topic model. This project presents a new vision-based technique to automatically detect the presence or absence of parts of interest in rail tracks. STM is one of the probabilistic topic models, which is extension of LDA. Specifically, STM is able to simultaneously model diverse types of fasteners with different orientations and illumination conditions using unlabeled data.

To assess the damages, the test fasteners are compared with the trained models and automatically ranked into three levels based on the likelihood probability. The experimental results demonstrate the effectiveness of this method. Rail inspection is an essential task in railway maintenance. It is periodically needed for preventing dangerous situations and ensuring safety in railways. This inspection system uses real images acquired by a digital line scan camera installed under a train. Data are processed according to a combination of image processing and pattern recognition methods to achieve high performance automated detection.

1. INTRODUCTION

1.1
1.2

Railway inspection is a very critical task for ensuring the safety of railway traffic. Traditionally, this task is operated by trained human inspectors who periodically walk along railway lines to search for any damages of railway components. However, the manual inspection is slow, costly, and even dangerous. With the extension of high-speed railway network, the inspection and maintenance face more challenges than ever before. Recently, the railway companies of all over the world are interested in developing automatic inspection systems, which are specialized trains and are able to detect railway defects very efficiently. An automatic railway inspection system is composed of a number of functions such as gauge measurement, track profile measurement, track-surface defects detection, and fastener defects detection.

Our research focuses on automatically finding and assessing the partially worn and missing fasteners based on computer vision technologies. This manual inspection is lengthy, laborious and subjective, since it relies entirely on the ability of the observer to detect possible anomalies. With increased rail traffic carrying heavier loads at higher speeds, rail inspection is becoming more important and railway companies are interested in developing fast and efficient automatic inspection systems. 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 high-speed, high-resolution and highly repetitive tasks. A large variety of algorithms for object detection problems have been studied by the computer vision community, especially for industrial inspection process. However, few works can be found on the use of computer vision in the specific area of rail inspection. In this project, we propose to develop an effective vision-based automatic rail inspection system. The objective of this system is to detect the presence or absence of parts of interest in rail tracks, such as sleepers or fasteners, by inspecting real images acquired by a digital camera installed under a diagnostic train.

OBJECTIVE

Manual monitoring for rail inspection is unacceptable for slowness and lack of objectivity. Nowadays, railway companies over the world are interested in developing automatic inspection systems that are able to detect rail defects. These automatic systems are to increase the ability to detect defects and reduce the inspection time. The aim of this project is to develop an effective vision-based automatic rail inspection system, which is able to automatically detect the presence or absence of parts

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of interest in rail tracks. This system should be able to detect various objects such as sleepers or fastening elements (such as bolts, insulated block joints,clamps or clips) by inspecting the images acquired by a digital camera installed under a diagnostic train.

Traditional object recognition methods include geometrical approaches, involving the use of rigid geometric models to represent the object to detect. However, railways represent a very rough environment and these methods do not succeed reliably in detecting objects of interest under varying conditions. Significant variety in lighting, viewing directions, sizes or shapes poses challenging problems and actually makes these objects difficult to model. Moreover, these methods usually require a human operator for tuning the parameters of the geometric models. Other approaches include statistical learning techniques.

These approaches involve the use of training sets to automatically learn a classification function that will be able to classify image sub windows and therefore detect the searched objects. These methods are suitable for generic shapes since they assume no geometrical model knowledge of the searched object. These latter approaches provide enabling techniques to build up an effective automatic vision-based system for rail inspection. The next section describes in more detail the state-of-the-art techniques in the areas of rail inspection and object detection.

2. PROJECT DESCRIPTION

AUTOMATIC INSPECTION SYSTEM

To handle the problems in the existing system, 2.1
here a probabilistic structure topic model (STM) is
used to model fasteners. This model is generative, 2.2
data driven, and it can simultaneously learn the probabilistic representations of different objects using unlabelled samples. We train the fastener models using a collection of intact fastener samples. The likelihood probability can be used to measure the 2.2.1
similarity between a test fastener and a model. Generally speaking, the worn fastener has lower likelihood probability than intact ones. We rank fasteners into three levels based on their likelihood probabilities in descending order.

The intact fasteners are ranked into high level; the fasteners in middle level may be partly worn or polluted and the fasteners ranked into low level are severely worn or completely missing.

MATLAB based Railway Fastener Detection for Safe Railway Transportation

- I propose an automatic visual inspection system for detecting partially worn and completely missing fasteners using probabilistic topic model.
- This method is able to simultaneously model diverse types of fasteners with different orientations and illumination conditions using unlabeled data.
- To assess the damages, the test fasteners are compared with the trained models and automatically ranked into three levels based on the likelihood probability. The experimental results demonstrate the effectiveness of this method.

BLOCK DIAGRAM

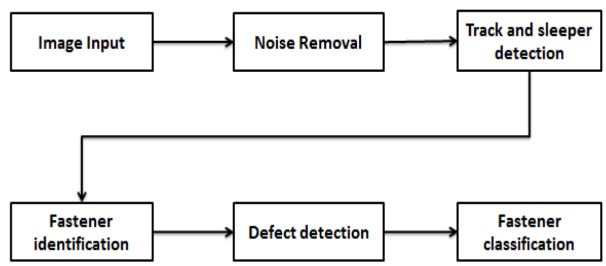

Figure 1. Block Diagram

It shows the data processing module of the automatic railway inspection system.

MODULES

1. INPUT IMAGE
2. FASTENER LOCALIZATION
3. DEFECT DETECTION

Input Image

Input to the system is an image, which is taken from two cameras hanged below a train coach, each of which monitors a side of track. The size of an acquired image will be varying, based on the quality. An example of the acquired image is shown in Figure 2

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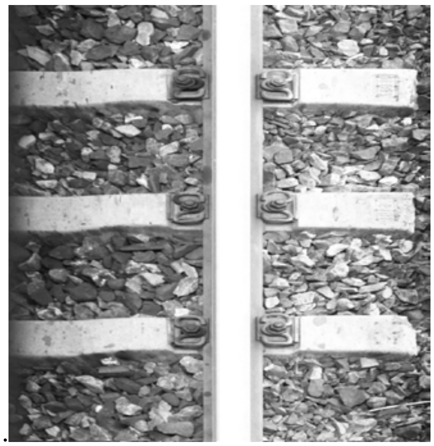

Figure 2 Captured Image

The image is sent to the on board high performance computers as the input of data processing module.

Fastener Localization

RGB to gray converted image is sent as input to next process. Here, the position of the fastener is selected manually. Image crop tool is used to crop the particular portion from the image. The Crop Image tool is a moveable, resizable rectangle that you can position interactively using the mouse.

When the Crop Image tool is active, the pointer changes to cross hairs + when you move it over the target image. Using the mouse, operator specifies the crop rectangle by clicking and dragging the mouse. Operator can move or resize the crop rectangle using the mouse.

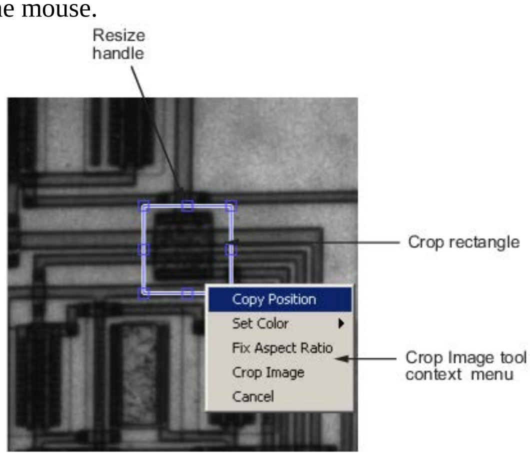

Figure 3..Image Crop Tool

When sizing and positioning the crop rectangle is finished, create the cropped image by double-clicking the left mouse button or by choosing Crop Image from the context menu. I = imcrop creates an interactive Crop Image tool associated with the image displayed in the current figure, called the target image. . imcrop returns the cropped image, I. The following figure 3 illustrates the Crop Image tool with the context menu displayed.

Defect Detection

To effectively model fasteners, we propose a structure analysis approach, which employs the advantages of the LDA model. We named our model as STM. In the first two parts of this section, we first give a brief introduction to LDA and then detail our STM model.

A. Latent Dirichlet Allocation

There are two understandings of LDA:

1. LDA is a probabilistic clustering method, which can be used to cluster words into semantic topics based on the co-occurrence property.
2. LDA is a data-driven model, and it can automatically explore the latent topics from unlabeled discrete data.

On the other hand, LDA suffers from some weaknesses. The most obvious one is that the spatial relationship between words is ignored. Given a collection of M documents denoted by $I_m=\{I_1, I_2, . . . , I_M\}$, each document has N words. LDA groups words $\omega_{n,\, n}= \{1, 2, . . . ,N\}$ into K topics, which is equivalent to assign a latent topic to each word. In Fig. 7, Z_n is an index, which shows the topic label of word ω_n, θ_i represents the distribution of topics for a document (document-topic distribution) and itself has a Dirichlet prior with parameter α, and β is a matrix for the word distributions of each latent topic (topic-word distribution). To apply this model for solving computer vision problems, the concepts of images must be translated to the corresponding concepts of languages. There are two aspects:

- Image features are translated to words (these words are usually called visual words) using bag of features.
- In STM, the topics are translated to fastener classes.

B. Fastener Modeling With STM

STM is the extension of LDA. The STM innovates on the models just described by allowing for the inclusion of covariates of interest into the prior distributions for document-topic proportions and topic-word distributions. The result is a model where each open-ended response is a mixture of topics. Rather than assume that topical prevalence (i.e., the frequency with which a topic is discussed) and topical content (i.e., the words used to discuss a topic) are constant across all participants, the analyst can incorporate covariates over which we might expect to see variance.

We explain the core concept of the model here complete details in the appendix proportions (_) can be correlated, and the prevalence of those topics can be influenced by some set of covariates *X* through a standard regression model with covariates _ ~Logistic Normal (*X*_,_). For each word (*w*) in the response, a topic (*z*) is drawn from the response-specific distribution, and conditional on that topic, a word is chosen from a multinomial distribution over words parameterized by _,which is formed by deviations from the baseline word frequencies (*m*) in log space (_*k* ∝exp (*m* + _*k*)). This distribution can include a second set of covariates *U* (allowing, for example, Democrats to use the word "estate" more frequently than Republicans while discussing taxation).We discuss the difference between the two sets of covariates in more detail in the next subsection.

Thus, there are three critical differences in the STM as compared to the LDA model described above: (1) topics can be correlated; (2) each document has its own prior distribution over topics, defined by covariate *X* rather than sharing a global mean; and (3) word use within a topic can vary by covariate *U*. These additional covariates provide a way of "structuring" the prior distributions in the topic model, injecting valuable information into the inference procedure. The STM provides fast, transparent, replicable analyses that require few a priori assumptions about the texts under study. Yet it is a computer-assisted method, and the researcher is still a vital part of understanding the texts, as we describe in the examples section. As in LDA, each document arises as a mixture over *K* topics. In the STM, topicSTM that considers the spatial information of visual words is an extension of generative topic model. We model the structures of fasteners in topic level. The STM model has the following two advantages when handling our fastener modeling problem:1) it can simultaneously learn multiple types of fasteners from unlabeled samples and produce the models for each fastener class (topic) and 2) the learned model can be used to classify fasteners and offer the consistency scores for assessing the damages.

Suppose that the data set contains M railway images denoted by $\theta_m = \{\theta_1, \ldots, \theta_M\}$. Each image contains fasteners. $Z_n = \{1, \ldots, K\}$ is the class label of a fastener. In fact, θ_m represents the distribution of fastener classes in the m[th] image. A fastener class is represented as the composition of P triples ($W_1 n_l$, $W_2 n_l$, En_l). Specifically, En_l is an index points to two different coordinates denoted by $C(1)En_l$ and $C(2)En_l$, from which the visual words $W_1 n_l$ and $W_2 n_l$ are sampled, respectively. In other words, this triple expresses a truth that for a type of fastener, there must be two specific visual words simultaneously occurred at two given coordinates. It should be noted that En_l can suggest only one or multiple coordinates by simply changing the model. En_l contains only one coordinate.

This simplification results in under fitting when modeling the objects with similar structure configurations. On the contrary, the model places very strict constraints n object structures and leads to over fitted representations. In addition, this model also consumes huge memory and computational resources in the inference and parameter estimation procedures.

From the viewpoint of generative process, θ_m is sampled from a Dirichlet distribution with parameter α. For each image, fastener class Z_n is drawn from a multinomial distribution with parameter θ_m. For a fastener class Z_n, the index of a coordinate pair is first drawn from the multinomial distribution parameterized by γZ_n (class-coordinate distribution). Assuming that $C(1)En_l$ and $C(2)En_l$ are the two coordinates shown by En_l, the visual words $W_1 n_l$ and $W_2 n_l$ are then simultaneously sampled from multinomial distributions with parameters $\eta C(1)En_l,Zn$ and $\delta C(2)En_l,Z_n$, respectively. Both $\eta C(1)En_l,Z_n$ and $\delta C(2)En_l,Z_n$ are the distributions over visual words with respect to the fastener class and coordinate. In summary, the generative process of STM is given as follows.

a) Draw a class-coordinate distribution γ according to Dirichlet(λ).
b) Draw an index En_l according to multinomial (γZ_n). This is equivalent to sample two coordinates $C(1)En_l$ and $C(2)\ En_l$.
c) Draw class-word distributions η and δ according to Dirichlet(π) and Dirichlet(ρ), respectively.
d) Draw visual words $W_1 n_l$ and $W_2 n_l$ according to multinomial($C(1)En_l$, Z_n, η) and multinomial ($C(2)En_l$, Z_n, δ), respectively.

We evaluate the classification results for partially worn and missing fasteners. The partially worn fastener has a few missing or obscured parts, but they are visually recognizable. On the other hand,

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the missing fastener loses its major component such as hook.

They are unrecognizable and most of them are represented as flat image region. Our method achieves 99.5% classification precision for partially worn fasteners. There are two reasons for this result:

1. The illumination variations of the training samples significantly affect the performance of classifiers.
2. The shapes of some fasteners are similar, and the classifiers and features cannot distinguish them effectively.

For STM, the number of classes is automatically determined by the training samples. As a result, the fasteners of different illumination conditions are modelled separately. On the other hand, STM places strict spatial constraints on fastener shapes. Thus, the model is able to identify the differences between similar shapes. We can conclude that the proposed method is able to model various types of fasteners in different visual conditions.

3. HARDWARE AND SIMULATION RESULTS

HARDWARE

In a mobile railway inspection system, Camera Link Full cameras are installed on railcars or service vehicles to detect damage to the rail and track components.

There are two cameras hanged below a train coach or railcars, each of which monitors a side of track. The size of an acquired image is 560*900 pixels. The image is sent to the on-board high performance computers as the input of data processing module.

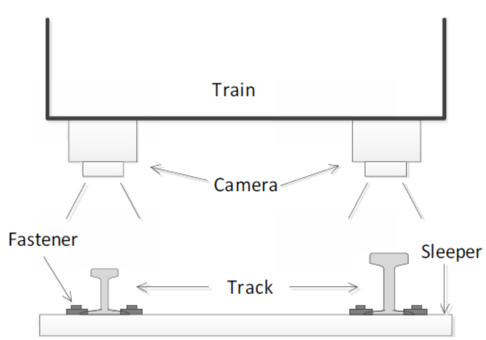

Figure 4 . Hardware implementation

Camera Link Full cameras are typically deployed in railway inspection systems due to their high-bandwidth performance, but designers must compensate for the camera's complex, limited reach cabling and lack of networking support by deploying costly extenders. Alternatively, Pleora's**iPORT CL-Ten Full External Frame Grabber** transforms Camera Link Full cameras into **GigE Vision** -compliant cameras, enabling their integration into multipoint, real-time video networks using low-cost, long-distance Ethernet cabling and off-the-shelf switching.

SIMULATION RESULTS

Input Image

At first, the colored image was converted into gray scale image and quality of the image is increased by removing noise from the image and provide as input to the system is shown in figure 5.

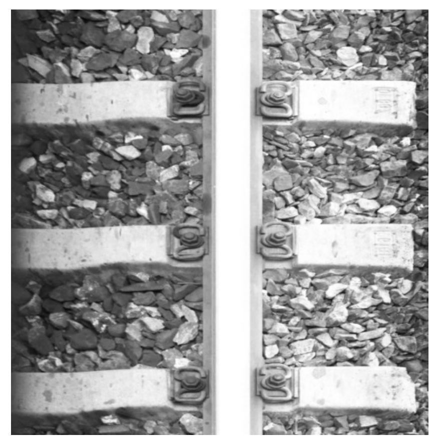

Figure 5. Captured image

Fastener Localization

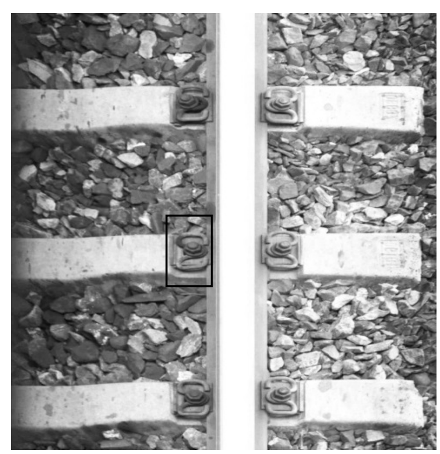

Figure 6. Fastener localization

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Selection of fastener part from an image is done manually. When the Crop Image tool is active, the pointer changes to cross hairs + when operator moves it over the target image. Using the mouse, operator specifies the crop rectangle by clicking and dragging the mouse. Operator can move or resize the crop rectangle using the mouse.

Figure 7. After fastener selection

Octave Generation

Figure 8. First octave generation

Figure 9 Second octave generation

Figure 10 Third octave generation

Figures 8, 9 &10, show three octave generation results, which represents an selected image in different illumination conditions.

Plotting Key points On To The Image

Figure 10. Plotting keypoints on to the image

It shows an image with keypoints mapped on it. Mean of an image is selected from three octaves. Result of mean from octaves shows highlighted spots in different illumination conditions. Keypoints were mapped on highlighted spots of an image.

For every fastener image, detected score has been generated. To get better result, threshold value for detected score is set to 0.1045. If detected score of an processed image is less than or equals to the threshold value, then it is called as normal image. Otherwise it is said to be an abnormal image.

4. CONCLUSION

The detection of worn and missing fasteners is an important task in railway inspection. However, the manual inspection is of poor efficiency. On the other hand, the earlier automatic inspection systems 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. Relying on the topic model, the proposed inspection system has the following three major advantages:

- Different types of fasteners can be simultaneously modeled
- The system is robust to illumination changes
- Condition of the fastener is represented by detection score.

Technically, we introduce a new topic model named STM to model the structures of fasteners. Possibly, STM is the first probabilistic topic model aiming at representing object structure. By which, the modeling of diverse types of fasteners becomes much easier. The detailed evaluation on railway lines is provided. The proposed method has very high performance on recognizing good fasteners as well as detecting worn ones.

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