Anomalous Tie Plate Detection For Railroad Inspection

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Abstract

This paper describes our latest work on identifying anomalous tie plates to automate railroad inspection using machine vision technology. Specifically, we have developed a completely automatic detection scheme to recognize tie plates with anomalous spiking patterns using various video analytics. In particular, each tie plate is first represented by four characteristic regions-of-interest (ROI), then each ROI is fed into a pre-trained SVM (Support Vector Machine) model, and classified to be either spike- or spike hole-related. Next, the dissimilarity between the current tie plate and a reference set of tie plates in a sliding window is measured and analyzed. Based on that, it is finally recognized as either an anomalous or a normal tie plate. Preliminary experiments conducted on a set of videos captured by our own designed imaging system, has achieved an average precision, recall and false alarm rates of 88%, 92.8% and 2.16%, respectively. This validates the promising direction of applying machine vision technology to assist in railroad inspection.

1. Introduction

To maintain safe and efficient operations, railroads must inspect their tracks for physical defects on a regular basis. While some of them have already been automated using a track geometry car, others are still manually and visually conducted by railroad track inspectors. It is thus of great interest to railroad companies to enhance the current manual inspection process using machine vision technology for more efficient, effective and objective inspections.

We are recently engaged in an exploratory research project with a railroad company, aiming to develop machine vision technologies to automate the inspection of railroad tracks. One of the key tasks that we jointly identified is the monitoring of spiking patterns, which will be the scope of this paper. By spiking pattern, we mean the layout of spikes on a tie plate, which hold the plate in place to prevent the rail from latitudinal movement. A spiking pattern is defined over two tie plates which fasten one tie. There are 8 spike slots on each tie plate. An example of a tie plate (more accurately, one side of a tie plate) is shown in Fig. 1, which contains 3 spikes and 1 spike hole. Consequently, a spiking pattern is determined by the status of 16 spike slots, which could either be spiked, or remain empty.

Based on the class of track, the tonnage and speed of trains traveling on it, and its degree of curvature, a specific spiking pattern will be required for a specific track segment. Applying wrong or non-compliant spiking patterns could potentially lead to derailment. On the other hand, when previously installed spikes are broken or fall off the plate, it will also change the spiking pattern. We will catch both intentional and unintentional pattern changes in this work. For the rest of paper, we refer to a tie plate with non-compliant spiking pattern as anomalous tie plate.

Anomaly detection has been a hot topic in vision-related research areas, especially in video surveillance. Typical examples include the detection of unusual video events, abnormal object/vehicle motion patterns, anomalous object activities, etc. Consequently, such work tends to use trajectory based methods where an appearance model is built to track objects [1], and activity learning techniques where various statistical models such as Hidden Markov Model, Markov Random Field and Bayesian are used to learn object activities [4]. Clustering-based approaches have also been reported, where anomalies are identified as outliers from clusters of normal motion patterns. Machine learning techniques have also been applied to train different models for abnormal behaviors.

For this work, since we focus on tie plates which are static objects, most of existing solutions will not be applicable. On the other hand, while we can derive spiking patterns based on the detection of spikes and spike holes, robustly detecting such rail components is itself a very challenging task. This is validated by the extensive...
work from UIUC [2], where features such as color, edge and Gabor are applied to detect rail fastener components such as tie plate, spikes and anchors. Consequently, we have chosen an appearance-based approach to accomplish our task. To our best knowledge, this is the first work studying anomaly detection in the rail inspection domain.

There are four major steps in our proposed anomalous tie plate detection scheme. Specifically, given a frame, we first localize the tie plate region, then detect four characteristic ROI based on certain criteria. Next, we extract top ten salient features from each ROI and classify it as either a spike-related ROI or a spike hole-related ROI using a pre-trained SVM model. Finally, we measure the dissimilarity between the current tie plate and a reference set of tie plates in a sliding window, analyze it, and identify its abnormality.

Our main contribution lies in representing a tie plate with characteristic ROI, and incorporating ROI classification result into its dissimilarity measurement.

2. Anomalous Tie Plate Detection

Given a frame, we first apply Hough transform to detect the horizontal edges of a tie plate. Then we localize its vertical edges by exploiting the fact that there is much less texture within the plate region than the outside. Fig. 1 shows one detection example, where the blue rectangle indicates the localized tie plate region. Please refer to our earlier work [3] for more details on this module.

2.1. ROI Detection

In this module, we attempt to capture the spike and spike holes by detecting image patches that contain very rich edge information. We term them as regions of interest (ROI).

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**Step 1.** Given a localized tie plate, we first extend its height by a quarter size so as to include any spike heads. One example is shown in Fig. 1 (indicated by the yellow rectangle). The extended tie plate region (ETPR) is then extracted, as shown in Fig. 2 (a).

**Step 2.** For each $4 \times 4$ image cell of ETPR, we extract the following 16 features: 8 Gabor features (mean and deviation for 4 different orientation maps), 4 edge features (average edge magnitude of each orientation), 2 color features (mean and deviation) and 2 location features (the center position).

**Step 3.** We perform a K-means clustering on the ETPR, and classify all cells into either foreground or background. One example is shown in Fig. 2 (a), where white cells represent foreground. We then remove all foreground cells that are at image boundaries, as they very likely relate to foreign objects (such as ballast) and could interfere with subsequent ROI detection. Fig. 2 (b) shows the Sobel edge map of the cleaned ETPR.

**Step 4.** Finally, we divided the ETPR into 4 quadrants, and detect a fixed-sized ROI that has the most amount of edge magnitude within each quadrant. Note that we choose ROI to have approximately the size of a spike hole. Fig. 2 (c) shows the four detected ROI, which as we can see, have well captured the four important elements on a tie plate.

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![Image](image.png)

**Figure 2.** (a) An extended tie plate region where white cells represent extracted foreground, (b) the Sobel edge map, and (c) the four detected ROI.

2.2. ROI Feature Extraction and SVM-based ROI Classification

For each ROI, we extract 38 features to capture its color, texture, edge and structural information.

**Feature 1:** The weight of foreground, which is defined as the ratio of total number of foreground cells over the total number of cells within the ROI. The reason for choosing this feature is that, the spike hole-related ROI tends to contain many more foreground cells than the spike-related ROI.

**Feature 2-15:** 8 Gabor features, 4 edge features and 2 color features, averaged for all foreground cells in the
ROI.

**Feature 16-30:** similar to features 1 to 15, yet calculated for background cells in the ROI instead.

**Feature 31-32:** The horizontal and vertical cross-correlation ratios (HCCR/VCCR), which are meant to capture any horizontally or vertically symmetrical structures that the ROI might have.

**Feature 33:** The edge magnitude ratio of four pre-defined boundary stripes, which reveals the edge distribution within the ROI. This feature intends to capture the rectangular shape of a spike hole.

**Feature 34:** The total amount of edge magnitude in the ROI.

**Feature 35-36:** The distances between the gravitational center and geometric center of the ROI’s edge map, along x and y directions, respectively. These two features also aim to capture the edge distribution within the ROI.

**Feature 37-38:** The differences of edge magnitude between the left and right half of the ROI, and between the top and bottom half of the ROI, respectively.

As there are likely redundancy in the extracted features, we have thus conducted feature saliency analysis and feature correlation analysis to identify top features. A certain amount of training data with both spike and spike hole-related ROIs were collected for that purpose. As a result, we have identified the following top 10 features: Feature 33, 12, 32, 38, 31, 16, 1 36, 34 and 24. For the purpose of efficiency, we propose to represent each ROI with its top 10 features only.

The next step is to classify each ROI to be either spike- or spike hole-related. This is achieved by applying an SVM-based learning approach. Specifically, we first collect some labeled ROI data to train an SVM model, then apply the model to recognize the type of each test ROI.

### 2.3. Tie Plate Dissimilarity Measurement

This module analyzes and measures the dissimilarity between the current tie plate \((P)\) and a reference set of tie plates in a sliding window. More specifically, denote the reference set as \(RS = \{P_1, P_2, ..., P_N\}\), it contains the preceding \(N\) tie plates to the current one. We further denote the dissimilarity between \(P\) and \(P_i (i = 1..N)\) as \(DSM(P, P_i)\), it can be calculated as:

\[
DSM(P, P_i) = \sum_{j=1}^{4} w_j \times dist(P^j, P_i^j),
\]

where \(dist(P^j, P_i^j)\) indicates the distance or dissimilarity between the \(j^{th}\) ROI in tie plate \(P\) and \(P_i\), respectively. It is calculated as the Euclidean distance between their corresponding feature vectors. Meanwhile, \(w_j\) is the weight for the \(j^{th}\) ROI, and is determined based on both ROI classification result and the confidence of such classification. In particular, denote the classification confidences of \(P\) and \(P_i\) as \(C^j\) and \(C_i^j\), which are within the range of 0 and 1, we set \(w_j\) to 1.0 if they are both below a certain threshold \(e.g. 0.8\). Otherwise, when both ROI are classified with a higher confidence, then we set \(w_j\) to \(1 - (C^j + C_i^j)/2\) if they are of same ROI type, and to \(10(C^j+C_i^j)/2\) if they are of different ROI type. As a summary, the underlying principle of determining the weight is, if the two ROI indicate different objects, then we should boost their distance measurement \((i.e. dist(P^j, P_i^j))\); otherwise, if they indicate the same object type with high confidence, the distance measurement shall be deemphasized.

Once we obtain the dissimilarity scores between \(P\) and all \(P_i (i = 1..N)\) in \(RS\), we apply an agglomerative clustering analysis over them, and identify the class that has the most number of data points. We then calculate the average dissimilarity score of this class, and return it as the dissimilarity between \(P\) and \(RS\). The reason for applying the agglomerative clustering is that, due to potential errors in ROI detection and potential inclusion of anomalous tie plates in \(RS\), we could get inconsistent dissimilarity measurements between \(P\) and \(P_i (i = 1..N)\). Yet by identifying the majority class, such inconsistency issue would be under control.

The benefit of fusing the ROI classification result and ROI-feature based distance into the tie plate dissimilarity measurement is that, they can complement each other to achieve a more robust and a higher performance than each of them can individually achieve. This will be validated by our performance study in Section 2.5.

### 2.4. Anomalous Tie Plate Identification

Once we obtain the dissimilarity score between the current tie plate \(P\) and its reference set \(RS\), identifying its abnormality becomes very straightforward. Specifically, if it is above a certain threshold \(T\), it will be declared as an anomalous instance. This tie plate will then be pushed into the \(RS\) for the next incoming tie plate, no matter if it is normal or abnormal. Meanwhile, the farthest tie plate will be removed from \(RS\), so as to maintain a fixed window size.

### 2.5. Performance Study

We have setup a hi-rail truck for capturing videos for this work. For the detailed camera setup, please refer to our earlier work [3]. To validate the proposed anomalous tie plate detection scheme, we selected 6 clips from

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our video collections, which were captured at various times on different days. The average duration of them is 2 minutes (i.e. 2400 frames). The percentage of anomalous tie plates in each clip is shown in Table 1, which averages to 13.2%. Note that we have intentionally included two clips without any anomalous tie plates so as to better observe false alarm cases.

The performance is evaluated in three dimensions: precision, recall and false alarm rate (FAR), where FAR is defined as the total number of false alarms over the total number of tie plates. We specifically report FAR here as it is a very important performance indicator for railroad industry. Table 1 tabulates the evaluation results. Note that the threshold $T$ applied here was empirically determined based on experiments. It was then fixed for all clips. Due to the limit of space, we skip the evaluation for tie plate detection here, but its accuracy is around 99% [3].

Table 1. Performance evaluation of anomalous tie plate detection, where FAR indicates False Alarm Rate.

<table>
<thead>
<tr>
<th>Clip</th>
<th>Anomaly Percentage</th>
<th>Performance Measurements</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Precision</td>
</tr>
<tr>
<td>1</td>
<td>20%</td>
<td>89.6%</td>
</tr>
<tr>
<td>2</td>
<td>28.8%</td>
<td>90.6%</td>
</tr>
<tr>
<td>3</td>
<td>22%</td>
<td>88%</td>
</tr>
<tr>
<td>4</td>
<td>8.5%</td>
<td>84%</td>
</tr>
<tr>
<td>5</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>6</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

From the table, we see that an average of 88% and 92.8% precision and recall rates have been achieved on the first 4 clips, respectively. The average FAR over all 6 clips is 2.16%, which is very encouraging. We also note that the FAR remains quite stable over all clips, regardless of the number of anomalous tie plates in the videos. Another observation is that, while the precision of Clip 4 is relatively low compared to other clips, which is due to the fewer number of anomalies in the clip, its recall rate is however, the highest.

To validate the effectiveness of applying SVM-based ROI classification result in calculating the weight $w_j$ for $\text{dist}(P_j, P^i_j)$ in Equation 1, we have conducted a separate experiment on the same 6 clips, where we dropped the weight and used plain Euclidean distance instead. As a result, we have achieved an average of 78%, 82% and 5.4% on precision, recall and FAR, respectively, which are apparently worse than the results shown in Table 1.

We further performed some gap analysis, and realized that: 1) foreign objects such as leaves and ballast on a tie plate usually result in false alarms, due to their interference with ROI detection. Another major cause is raised spikes, which in fact is another type of exception that our partnering railroad company cares about. Three such examples are shown in Fig. 3; and 2) earlier anomalous tie plates which are missed by the system could lead to more false negatives in later frames due to the use of reference set.

![Figure 3. Examples of false alarms caused by: (a) debris, (b) a raised spike (top left), and (c) a leaf on the tie plate.](image)

3. Conclusion and Future Work

An automatic anomalous tie plate detection scheme based on characteristic ROI detection and classification is presented in this paper. Preliminary experiment on a set of videos has achieved encouraging results. We are currently exploring some statistical modeling approach to hopefully further reduce the FAR while maintaining the precision and recall rates.

References