High-speed Railway Fastener Detection Using Minima Significant Region and Local Binary Patterns

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Abstract. Railway fastener is an important part of the railway system. Keeping the fasteners effective is essential to ensure the safe operation of the railway, so abnormal railway fastener detection is a main task of railway maintenance. With the development of railway system, the traditional manual fastener detection method has been unable to meet the application requirements, because it is very slow, costly, and dangerous. In this paper, we propose a novel method for abnormal fastener detection based on computer vision, which can detect missing fasteners automatically. In this method, Minima Significant Region is extracted in order to improve the fastener localization accuracy. Then, fastener recognition is operated using local binary features and Support Vector Machine classifier based on the fastener sub-images which are obtained by fastener localization. The proposed method is evaluated in our own database which is obtained by railway inspection system in different environments. The experimental results have shown improved performance against the state-of-the-art algorithm.

1. Introduction
Railway fastener is an important part of the railway system, which is designed to maintain gage by keeping both tracks firmly attached to the sleepers. However, the fastener status may become abnormal due to the vibration generated by rolling wheels or possibly even by theft. Abnormal fasteners will affect the smoothness of the train and even threaten the safety of train operation. Therefore, the inspection of railway fastener is essential to ensure train safety. However, traditional manual detection mode is slow, costly, and can’t meet the high maintenance frequency of modern high-speed railway. In recent years, with the development of computer vision technology, computer vision has been gradually adopted by the railway companies as an inspection technology in some aspects of railway system such as detection of rail surface defects\textsuperscript{[1]}, detection of bird nests in overhead catenary\textsuperscript{[2]}, fault recognition of freight train\textsuperscript{[3]}, diagnosis of isoelectric line in railway\textsuperscript{[4]} and fastener defects detection\textsuperscript{[5]}. In this paper, our research focuses on the algorithm for detecting the missing fastener based on computer vision technology. The images used in this paper are captured by two line-scan cameras installed under the inspection train.

Since the early 2000s, a number of vision-based methods for railway fastener inspection have been proposed. Singh et al.\textsuperscript{[6]} used edge density to locate the clips and detect missing clips, then detected recently replaced blue clips based on color information in the located window. References\textsuperscript{[7-9]} detected hexagonal-headed bolts using two 3-layer neural networks running in parallel and both networks took the 2-level discrete wavelet transform (Daubechies wavelets and Haar wavelets) as an input to generate a binary output indicating the presence of a fastener. Hsieh et al.\textsuperscript{[10]} confirmed the fastener region using characteristics of grey-level variation and wavelet transformation, and then they applied a morphological approach to obtain the outline of fasteners, which can inspect fasteners on the concrete...
or ballasted track. Ruvo et al.\cite{ruvo2010abnormal} applied the error back propagation algorithm to model two types of fastener and implemented the detection algorithm on graphical processing units. Yang et al.\cite{yang2017missing} implemented the detection algorithm on graphical processing units. Yang et al.\cite{yang2017missing} finally they detected the missing fastener by the factor of weighted template matching. Xia et al.\cite{xia2016fastener} firstly located the fastener using gray-level and gradient-based techniques, and then an Ada-Boost approach was followed to determine the state of the fastener based on Haar-like rectangle feature by dividing the fastener region into several parts. Resendiz et al.\cite{resendiz2013fastener} used texture classification using a bank of Gabor filters followed by a Support Vector Machine (SVM) to detect the periodically occurring track components such as rail, ballast, tie plate, spike, and anchors. Liu et al.\cite{liu2016fastener} located the fastener region according to the geometric prior information, and then classify the fasteners by Bayesian compressed sensing model based on the fusion of improved edge gradient features and macro texture features at the head of the fastener. Li et al.\cite{li2016novel,li2017novel,li2018novel} located tie plate by detecting its four edge lines using the Sobel operator, and then applied a Hough transform to detect the roughly elliptical shape of spike heads in tie plate region based on edge features. Feng et al.\cite{feng2018novel} located the fastener region by detecting the lines of rail and sleeper using line segment detector, and then detected partially worn and completely missing fasteners using probabilistic topic model based on Haar-like features. Khan et al.\cite{khan2018improved} used Harris-Stephen and Shi-Tomasi features to detect missing rail clips in image by matching errors. Thanawit et al.\cite{thanawit2019abnormal} estimated coarse regions of possible fastener from the track and tie using edge density map and then employed PHOG features and Epsilon Support Vector Regression to detect missing railway fasteners.

However, most of the algorithms cannot detect the partly missing fastener and the dimension of the fastener features used is high and often lead to classifier over-fitting. The reason is that they cannot localize fastener precisely and lack of robust description of fastener due to surface variations that result from illumination changes, weather changes, occlusions and other elements in the outdoor environment, thereby increasing the difficulty of followed fastener classification. To handle these problems, we propose a novel fastener localization method using Minima Significant Region (MSR), which can provide accurate fastener region and then simplify the followed fastener classification that only need low-dimension features.

![Image](image_url)

**Figure 1.** Normal and abnormal fasteners. (a)-(b) Normal fastener, (c)-(d) partly missing fastener, (e)-(f) completely missing fastener

In this paper, an algorithm for abnormal fastener detection of high speed railway is proposed based on minima significant region and local binary feature, which can effectively recognize the abnormal fasteners (completely missing and partly missing, as shown in Fig. 1) in different environments. As illustrated in Fig. 2, there are four main components in our approach: MSR extraction, fastener localization, feature extraction and fastener classification.

![Flow chart](chart_url)

**Figure 2.** Flow chart of proposed abnormal fastener detection method
2. Proposed Fastener Localization Approach

In order to make the fastener localization more robust, the proposed method uses MSR in the vertical direction to represent fastener. Then, template matching is implemented to get the precise position of fastener.

2.1. MSR Feature Extraction

The salient region of a target is an important feature of the target, which can represent the target robustly when the external environment changes. As railway fastener is always exposed to the external environment, image quality is greatly affected by the environment and the weather. After analyzing the characteristics of fastener image and in order to represent fastener stably in a changing environment, we propose a new MSR extraction algorithm, which only compares the gray levels of central pixel to its neighbors in vertical direction and makes a Boolean operation comparison results. Formally, the MSR extraction at a given center pixel is defined as:

\[
MSR_i(x) = s(g_{c-n} - g_x) \times s(g_{c+n} - g_x)
\]

where

\[
s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}
\]

and where \( g_x \) and \( g_{c-n} \), \( g_{c+n} \) are the grayscale values of the central pixel \( P_c \) and its neighbors \( P_{c-n} \), \( P_{c+n} \) respectively.

MSR extraction algorithm only has one parameter \( n \) and Fig.3 illustrates four examples of extracted MSR\((n=5)\) of normal fastener and missing fastener (The upper half is a part of original image and the lower half is the corresponding MSR map). It can be seen that MSR extraction pays more attention to the clips of fastener. When the external environment and illumination changes, the fastener appearance has undergone strong changes, but MSR can still be stably extracted.

![Figure 3. Fastener images and their corresponding MSR images.](image)

(a)-(b) Normal, (c) partly missing, (d) completely missing.

2.2. Fastener Template Matching

To obtain the precise region of fastener, fastener template matching is conducted using the standard template. To perform template matching, similarity between standard template and sub-window of searching image is evaluated through SAD (Sum of Absolute Differences) metric. The reason we chose SAD is that for binary images, SAD equates to the Hamming distance and can be calculated easily. The SAD template matching formula is as follows:
and where $S(x, y)$ is the searching image with the size of $m \times n$, which has been operated by MSR extraction. $T(x, y)$ is the fastener standard template with the size of $M \times N$, as shown in Fig. 4.

After the template matching is completed, a coefficient matrix $R$ is obtained. We only need to find the smallest element of matrix $R$ to determine the exact location of fastener. Fig. 5 shows some examples of the template matching results, in which we replaced the MSR image with the original image to show clearly and the rectangle indicates the fastener sub-image.

![Figure 4. Fastener template](image)

![Figure 5. Examples of fastener localization results](image)

### 3. Abnormal Fastener Detection

In this section, abnormal fastener detection will be performed based on the fastener sub-image which is obtained by fastener localization approach. In order to make the detection of the partly missing fastener and completely missing fastener more robust, the Center-Symmetric Local Binary Patterns (CSLBP) features are extracted only in the key part of fastener. Then, recognition of missing fastener is carried out using linear SVM classifier based on the CSLBP histogram.

#### 3.1. Fastener Local Binary Feature Extraction

The Local Binary Patterns (LBP) encoding method and its variants are widely used in target recognition because of its simple algorithm, the ability to capture the microstructure information and the illumination invariance. The original LBP operator, proposed by Ojala et al.\textsuperscript{[21]}, compares the central pixel and the surrounding neighborhood. CSLBP is a modified version of LBP, which is closely related to the gradient operator because it compares the gray levels of pairs of pixels in centered symmetric directions instead of comparing the central pixel to its neighbors. In this way, CSLBP features take advantage of the properties of both LBP and gradient based features. For an even number $P$ of neighboring pixels distributed on radius $R$, the CSLBP operator produces $2^{P/2}$ patterns as follows:

\[
CSLBP_{p, R}(x_c, y_c) = \sum_{i=0}^{(P/2)-1} s\left(\|g_i - g_{i+(P/2)}\|\right)2^i, \quad \text{(4)}
\]

\[
S(x) = \begin{cases} 
1, & \text{if } x \geq T, \\
0, & \text{otherwise},
\end{cases} \quad \text{(5)}
\]

where $g_i$ and $g_{i+(P/2)}$ correspond to the gray values of center-symmetric pairs of pixels ($P$ in total) equally spaced around central pixel $(x_c, y_c)$. $T$ is used to threshold the gray-level difference so as to increase robustness of CSLBP feature on flat image regions.
For an image, after computation of CSLBP patterns for each image pixel, the image texture is represented by the histogram of the patterns and the length of a histogram resulting from the CSLBP feature is $2^{P/2}$.

**Figure 6. Illustration of fastener key part**

To represent the fastener more effectively, the feature extraction is operated only in the key part of the fastener and Fig. 6 shows the key part defined in this paper. In this work, eight neighbor points and a 2-pixel radius around the center pixel are set for CSLBP parameters. So the feature dimension of each fastener is 16, which produces a shorter feature set than original LBP and can prevent over-fitting of classifiers effectively.

### 3.2. Fastener Classification

To recognize the missing fastener, the local binary features computed in section 3.1 are fed into a trained linear SVM classifier. In the training dataset, fasteners are only labeled as two classes including missing fasteners (partly missing and completely missing) and normal fasteners.

### 4. Experimental Setup

#### 4.1. Database

The database used in this paper is our own database, which is obtained by railway inspection systems in China high-speed railway from Wuhan to Guangzhou. The database consists of 4,000 original images which are obtained by railway inspection system in different external environments, including new railway, old railway, rainy day, low illumination and so on. In this work, we only detect the fasteners on left side, so there are 12,000 fasteners to detection, including 10,000 normal fasteners, 1000 partly missing fasteners and 1000 completely missing fasteners. Each image has three fasteners to be tested and contains at most one defective fastener. Some examples of fastener sub-images are shown in Fig. 7.

**Figure 7. Sub-images for fastener recognition**

#### 4.2. Evaluation Method

Precision and recall are used to evaluate the detection of abnormal fasteners and they are defined as follows:

Recall = \( \frac{TP}{N} \)  \[ (6) \]

Precision = \( \frac{TP}{TP + FP} \)  \[ (7) \]

where $TP$ is the number of correctly classified samples for a class, $FP$ is the number of unexpected samples classified to this class, and $N$ is the total number of the test samples for this class. For missing
fastener detection, $TP$ is the number of correct alarm for missing fastener, $FP$ is the number of normal fasteners classified to missing fastener and $N$ is the total number of missing fastener.

5. Experiments and Results
In this experiment, missing fastener detection method is tested. In order to evaluate the robustness of our method, we test our missing fastener detection method using 10-fold cross-validation. The dataset is divided into ten parts, in which one part is selected as the test set and the others combined as the training set. Then, linear SVM classifier is executed on the training set and test set. Ten tests are carried out and the average result is compared to that obtained by other three state of art methods based on our image database, as shown in Table 1.

Table 1. Results of missing fastener recognition using different methods.

| Method               | Feng's$^{[18]}$ | Thanawit's$^{[20]}$ | Liu's$^{[15]}$ | Ours     |
|----------------------|-----------------|---------------------|----------------|----------|
| Features for localization | Lines       | Edge density        | Edge detection | MSR      |
| Features for classification | Haar-like | PHOG                | MSLBP          | CSLBP    |
| Recall               | 99.42%          | 98.25%              | 98.96%         | 99.50%   |
| Precision            | 96.14%          | 84.56%              | 96.80%         | 97.32%   |

It can be seen that our method outperforms the others in both recall and precision. There are two main reasons: 1) other methods cannot get the fastener region as precisely as our method and 2) our method only extracts the features in the key part of the fastener, however the other methods extracts the features of the entire fastener. Although the performance of our method is only slightly better than Feng’s, the computational complexity of our method is significantly lower.

6. Conclusions
The detection of abnormal fasteners is an important task in railway maintenance. In this paper, an abnormal fastener detection method based on minima significant region and local binary features is proposed to detect missing fastener under different real conditions. After MSR extraction, template matching is operated to locate the fastener precisely. Then, fastener classification is operated using CSLBP features and linear SVM classifier based on the fastener sub-image which obtained by fastener localization. Thanks to the MSR extraction, we can get the precise position of fastener and then make the followed classification process more robust and efficient. Experimental results showed that the proposed fastener detection method is more robust and effective for abnormal fastener detection in challenging environments.

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8. References
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