Wheel tread defect detection for high-speed trains using wheel impact load detector

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ABSTRACT

The problem of wheel tread defects has become a major challenge for the health management of high-speed rail as a defect with small radius deviation may be enough to give rise to severe damages on both the train bogie components and the track structure. It is thus necessary to detect the defects soon after their occurrences and then conduct wheel turning for the defect wheelsets. A promising solution for tread defect detection can be the wheel impact load detector (WILD) which can assess the wheel condition during train passage. This paper presents an FBG-based WILD for high-speed train wheel tread defects. The track-side impact detector consists of two FBG strain gauge arrays mounted on the rail base to measure the dynamic strains of the rails excited by wheelset passages. The FBG arrays has a length of 3m, slightly longer than the wheel circumference to ensure a full coverage for the detection of any potential defect on the tread. A defect detection algorithm is developed for using the online monitoring rail response to identify the potential wheel tread defects. This algorithm consists of three parts: I) strain data preprocessing by using data smoothing technique to remove the trends which can be regarded as the ideal response excited by round wheel; II) novel responses diagnosing by outlier analysis for the normalised data; and III) local defects identification by a further analysis for the novel responses found in Part II. To verify the detection method, a field test was conducted using a test train with defective wheels. The train ran at different speeds on a instrumented track on which the proposed wheel impact load monitoring system was installed. By using the proposed algorithm to process the monitoring data, all the defects were identified and the results agreed well with those from the static inspection for the wheelsets in the depot. A comparison is also drawn for the detection accuracy under different running speeds of the test train and the results show that the proposed method can achieve a satisfying accuracy in wheel defect detection when the train runs at 30~50kph. Some
minor defects with a depth of 0.05mm~0.06mm are also successfully detected.

1. INTRODUCTION

Wheel defects, including wheel flats and wheel polygonisation (periodic out-of-roundness) can give rise to severe damages on train bogie components and rail track structure, especially when the trains run at high speed (Johansson & Nielsen, 2003). The causes of wheel defects are so complex that they may occur unpredictably and have been found on trains operating on many lines with very different operation conditions. To solve the problem and ensure safety operation, railway authorities generally adopt wheel turning (wheel lifting), as a common and effective approach to eliminate wheel defects. Wheel turning is always conducted following a mileage-based schedule for each multiple unit train. A problem thus arises: in wheel turning, all the wheelsets of one EMU including those without defects will be subject to maintenance which can shorten the lifetime of the healthy wheelsets. It is thus important to narrow the coverage of wheel turning to the faulty wheels only based on an effective method to screen out the wheels with defects before turning.

In terms of wheel defect detection, a lot of research has been carried out on the modelling of wheel-rail dynamic interaction based on different contact models (Nielsen & Oscarsson, 2004; Ding et al., 2014; Baeza et al., 2006; Pieringer et al., 2014; Yang & Thompson, 2014). Finite element methods for rail and wheel simulation are also used (Zhao et al., 2011; Bian et al., 2013) to investigate the dynamic response on wheel or rail structure influenced by wheel defects. But relatively fewer focused on the development of online wheel condition monitoring system.

Online monitoring can be more effective than offline/static inspection for wheel condition assessment and defect detection (Barke & Chiu, 2005). Compared with the vehicle-borne wheel defect detection method (Wei & Chen, 2013), the track-side wheel impact load detector (WILD) can be more suitable for great quantity of wheel inspections. The sensors in impact detection system are usually the strain gauge rosettes (Milković et al., 2013; Asplund et al., 2014) or fibre Bragg grating (FBG) strain sensors (Wei et al., 2012; Filograno et al., 2013). But the adaptability of the proposed WILD in high-speed trains still need further investigations and the defect identification methods based on wheel impact load monitoring data may need further development, especially in minor defect detection or when the passage trains run at low speed.

This paper develops an FBG-based trackside WILD for wheel local defect detection. The detector, as an online rail response monitoring system, consists of two FBG strain gauge arrays installed on the rail foot of both sides of rails, an interrogator for data collecting and a computer for system control and data storage. After obtaining the rail response monitoring data from all the FBGs along both arrays, a three-stage process based on outlier analysis is used for wheel potential defect detection. To validate the proposed detection method, an 8-car EMU equipped with wheelsets with artificial local defects was chosen as the test train. The test train ran 20 times at different speed levels - 10, 20, 30, 40 and 50 kph (4 times at each level). By using the proposed defect detection method, it is found that the detection results agree well with the results from the offline wheel tread inspection conducted in the depot, even when the defect depth is as low as 0.05~0.06mm.
2. FBG-BASED TRACKSIDE WHEEL CONDITION MONITORING SYSTEM

This paper uses FBG-based sensing technology to develop a trackside WILD for potential wheel tread defects. It was found by previous research (Ni, et al., 2017) that the excitation of wheel defect will generate novel responses on the rail, so a strain gauge mounted on the rail can collect response data that may reflect potential wheel defects. Also, because the location of wheel defect excitation on the rail head is randomly distributed with a period of the wheel tread perimeter, a strain gauge array installed on the rail can be used to detect local defects on the wheel tread if the length of the array is not shorter than the wheel tread perimeter. The interval can be determined by the identifiability of the novel response features.

2.1 Layout of FBG arrays

To detect potential local defects on the wheel tread, we design an FBG strain gauge arrays that can be mounted at the rail foot along the longitudinal direction. The length of the array is 3m, which is slightly longer than the circumference of the wheel tread and the interval of the FBGs along the array is 0.15m. This can ensure that no less than three FBGs can detect the novel response features when a potential defect hits at any location within the instrumented rail segment. Each FBG can measure the longitudinal strain of rail foot caused by bending moment of the cross-section under the excitation of the wheel impact. The layout consists of two arrays mounted on base of both rails, as shown in Fig. 1. The output rail bending moment can then be obtained as

\[ M_i = \frac{EJ}{y} \varepsilon_i = \frac{EJ}{Ky} \Delta \lambda_i, i = 1, 2, \ldots, N_S \]

(1)

Where \( M_i \) is rail cross sectional bending moment at location \( i \) (refer to Fig. 1) of two rails. \( y \) is the height difference between neutral axis and array. \( \Delta \lambda_i \) is the wavelength changes of the \( i \)th FBG installed on the rail and \( N_S \) is the number of FBGs on the array.

![Fig. 1 FBG Strain gauge array disposition](image)

2.2 System configuration

As shown in Fig. 2, The proposed wheel load detector consisted of: 1) two FBG strain gauge arrays installed on the foot of both sides of rails, as described in 2.1; 2) a high-speed interrogator and 3) a computer with data acquisition software. As a wheel load detector, the monitoring system collects monitoring data of rail responses at a sampling rate of 5000Hz and is triggered to save data during train passage.
automatically. Because the transmission distance of fiber optic sensing system can be as far as 100 km, the interrogator, as data logger can be installed with computer in a control room far away from the instrumented rail section.

![Online wheel load detector for wheel condition monitoring](image)

Fig. 2 Online wheel load detector for wheel condition monitoring

3. WHEEL DEFECT DETECTION BASED ON OUTLIER ANALYSIS

3.1 General description

The process of wheel defect detection based on monitoring data of rail responses can be divided into three parts, as shown in Fig. 3.

Part I: this part is to conduct data preprocesing for the subsequent wheel defect detection. In this part, the amplitude and location of peaks can be found out from the time history of monitoring data, as shown in Fig. 4. The global rail based response collected by different FBGs along the array excited by each wheel can be extracted, as shown in Fig. 5a. The S-G filter is used to normalise the response data and the normalised data, as shown in Fig. 5b, can be further used to detect potential defects. The data normalisation method will be detailed in 3.2.

Part II: this part mainly conduct outlier analysis based on Chauvenet’s criterion to find novel response in the time history of the normalised response data for all of the passage wheelsets. If no novel response of the excitation of the \(i\)th wheel is found, the outlier analysis will be conducted for that of the \((i+1)\)th wheel. The outlier analysis will be detailed in 3.3.

Part III: this part is a further analysis for the novel responses found in Part II, mainly to detect potential defects. When the outlier dataset is not empty (in other words, the dataset contains novel responses), the novel responses and their features will be subject to further investigation. If in an outlier dataset there are no less than three novel responses (collected by different FBGs occur at a same time period), the novel responses in the outlier dataset are likely the responses of the excitation of a potential wheel defect. The features of the potential defect, including the relative response amplitude and its location on the wheel tread, can then be obtained subsequently. The wheel defect identification method will be detailed in 3.4.
3.2 Data normalisation

The original strain response of one FBG on rail base under the excitation of an 8-car EMU (32 wheels) is shown in Fig. 4. The time history of the strain response contains 32 peaks, corresponding to 32 wheels. To identify the defective wheel, the roughness of all the wheel treads should be investigated by the analysis of the corresponding peak signals collected by all the rail base FBGs. Fig. 5 shows the strain data collected by the rail base FBG array under the excitation of a same wheel.

As shown in Fig. 5a, the output strain data contains the major trend that reflect the variation of rail base strain during the process of wheel passage, the disturbance caused by both the wheel tread roughness and the noise signal. To assess the roughness on the wheel tread, we need to eliminate the major trend of the raw data. This paper use Savitzky-Golay filter to smooth the strain data. By introducing 5-point quadratic polynomial to smooth the raw data for m times, the trend term of the strain data can be obtained. For a strain time series $E_{(0)} \ (E_{(0)} = (\varepsilon(0), 1, \varepsilon(0), 2, ..., \varepsilon(0), n))$, the normalised strain data $\hat{E}$ can be expressed as:

$$\hat{E} = E_{(0)} - E_{(m)}$$  \hspace{1cm} (2)

Where $E_{(m)}$ is the result of m times smoothing ($m=1, 2, ...$) and it can be obtained as:

$$E_{(m)} = AE_{(m-1)} = A^m E_{(0)}$$  \hspace{1cm} (3)

Fig. 3 Online wheel load detector for wheel condition monitoring
Where $A$ is the matrix of coefficients specified by 5-point quadratic polynomial, as given by Savitzky & Golay (1964). Using the data smoothing technique, the relative measured strain response of the rail is obtained as shown in Fig. 5b.

![Fig. 4. Measured strain response of one rail base FBG versus time](image)

![Fig. 5. Strain responses of all rail base FBGs excited by one wheel](image)

3.3 Localised response identification

It is seen that the normalised data are approximately normally distributed. When we assign a Gaussian PDF for the data, the parameters $\mu$ and $\sigma$ can then be obtained and updated by the growing of monitoring data collected by every FBG. Considering that the wheel defects rarely occur, the Chauvenet's criterion is a suitable outlier analysis method in this situation. For given $\mu$ and $\sigma$, a threshold for judging the outliers from the normalised data can be set. The upper and lower limits of the probability band given by Chauvenet's criterion are expressed in Eq. (4) and Eq. (5) respectively.

$$x_u = F^{-1}\left(1 - 0.25/N\right|\mu, \sigma)$$  \hspace{1cm} (4)

$$x_l = 2\mu - F^{-1}\left(1 - 0.25/N\right|\mu, \sigma)$$  \hspace{1cm} (5)
where \( x_u \) and \( x_l \) are the upper and lower limits of the probability band, \( F^{-1} \) is the normal inverse function, and \( N \) is the sample size.

Given the lower and upper limits, the outliers on the time history of normalised strain data can then be easily located and the novel responses that possibly excited by potential wheel defects can be drawn, as shown in Fig. 6. Note that in this paper outliers are the data points beyond the the lower or upper limits, and the outlier-centric strain responses are defined as novel response.

![Image](image.png)

**Fig. 6.** Outlier analysis for the normalised strain data: an example of two strain response datasets (blue and green curves: normalised strain time history of two different FBGs; black straight lines: the upper and lower threshold specified by Chauvenet’s criterion; red curves: the novel responses identified by outlier analysis)

### 3.4 Potential local defects detection

In 3.3, the novel responses are obtained based on outlier analysis. But whether the novel responses come from a wheel defect still need further investigation because: 1) the monitoring data contain noise signal generated from the sensing system and other environmental interference, so some abnormal data may be wrongly recognised as outliers; 2) the upper and lower thresholds given by outlier analysis is a screening mechanism rather than being used to identify wheel defects and those data points exceed the threshold are considered as outliers instead of the sign of wheel defects. It is found by previous research that another necessary evidence for the existence of wheel defect is that the novel responses from different strain gauges occur at a same time period. In the view of this, we can scan the normalised strain data along the time history and generate several datasets, each of which correspond to a point in time, called defect excitation time and consists of all the novel responses. These outlier datasets are denoted as \( OD_j (j = 1, 2, ..., N_O) \) where \( N_O \) is the number of outlier datasets in the monitoring data of a certain wheel. If in an outlier dataset, there are no less than 3 novel responses, these novel responses can be regarded as caused by a potential wheel defect.

**Fig. 7** shows a typical monitoring data that are excited by a wheel with potential defects. 7 outlier datasets can be found in the normalised strain response data collected by an FBG array. Each of the outlier datasets \( OD_1, OD_2, OD_3, OD_4, OD_5 \) and
$OD_6$ consists of no less than 3 novel responses and thus theses novel responses can be considered to be generated by potential defects. On the contrary, $OD_1$ has only one novel response detected by only one FBG, so it is screen out of defect detection.

![Fig. 7 Online wheel load detector for wheel condition monitoring ($N_D=7$)](image)

### 4. IN-SITU VERIFICATION

#### 4.1 In-situ test

To verify the monitoring system and the defect detection algorithm, we chose an 8-car high-speed EMU as the test train, as shown in Fig. 8. Some of the wheels with artificial local defects were installed on the EMU, but the defects were unknown before the test. The train was instructed to run on the track at five different speed levels: 10 kph, 20 kph, 30 kph, 40 kph and 50 kph. At each speed level, the train ran four times. Thus for each wheel, we have 20 monitoring datasets.

The detection method proposed in Chapter 3 is used to detect potential local defect from the monitoring data collected by online WILD developed in Chapter 2. The wheel tread defect detection results will then be compared with the results of offline wheel inspection conducted later in the depot, as shown in Fig. 9. The analysis of detection results and validation of the wheel condition monitoring system including the defect detection algorithm will be detailed in 4.2 and 4.3.

#### 4.2 Wheel defect detection results

With the defect detection method developed in Chapter 3, the wheelsets with potential defects can be detected, as listed in Tab. 1. Both the left wheel and right wheel of wheelsets No. 1, 6, 24, 27 are considered having potential defects, as indicated by most of the monitoring datasets. Besides, the left wheel of wheelsets No. 23, the right wheel of wheelset No. 7, 11, 13, 28 and 29 are detected as defective wheels and each of the wheels is detected by no more than three datasets (the total number of datasets is 20).
By comparing the online defect detection results to the offline radius deviation test results listed in right-hand columns of Tab. 1, it is found that the right wheels of wheelsets No. 1, 6, 24 and the left wheel of wheel No. 27 are the wheels with local defects and they are all successfully detected by most of the tests, especially when the train ran at higher speed levels. Fig. 10 and Fig. 11 shows the defect detection results by the online monitoring and the radius deviation by the offline inspection for these four wheels respectively. It can be seen that the defect detection results well match the radius deviation measurement results for most local defects, even in terms of the location and depth of the defect. Also the defects whose depths are as low as 0.05~0.06mm are also found in the detection results. However, the wheels on the opposite side of the defective wheels which are considered by some online tests as “with defects”, are actually all non-defective wheels, as found in offline radius deviation inspection. This is because the defective wheel can affect the dynamic behaviors of the whole wheelsets including the wheel at the opposite side, which can then generate novel excitations on the rail and FBG arrays on that rail can detect the corresponding novel responses. Other potential defects found by online tests are all false alarms caused by unknown factors. An analysis of errors in detection and the accuracy will be given in 4.3.

Tab. 1 Online defect detection results and offline inspection results for wheel tread

<table>
<thead>
<tr>
<th>Wheelset No.</th>
<th>Side</th>
<th>Defect detection results</th>
<th>Offline inspection results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(from online monitoring data)</td>
<td>(from radius deviation test in depot)</td>
</tr>
<tr>
<td>Number of monitoring datasets from which defects are detected (total test number at each speed level is 4)</td>
<td>Number of defects</td>
<td>Depth of actual wheel tread defects (unit: mm)</td>
<td></td>
</tr>
<tr>
<td>10kph</td>
<td>20kph</td>
<td>30kph</td>
<td>40kph</td>
</tr>
<tr>
<td>1</td>
<td>Left</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>Left</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
4.3 Accuracy of online detection

As the test train passed the instrumented rail section for 4 times at each speed level, the number of defect detection tests is 256 under a certain train speed condition. Among the 256 samples, 16 are later proved to be “with defects” and 240 are “without defects”. It should be noted that among the 240 samples, 16 correspond to the wheels on the opposite side of those with defects and the reason for the great opportunity for these wheel to be recognised as defective wheels has been described in 4.2.

To analyse the detection accuracy of the proposed wheel load detector and defect detection method, we count all the false positive errors in the 1200 tests (240 for...
each speed level), the false positive errors in 1120 tests (224 for each speed level) where the samples from wheels on the opposite side of defective wheels have been excluded, and the false negative errors in 80 tests (16 for each speed), as shown in Tab. 2. The rates of type I and type II errors and the detection accuracy are also listed in Tab. 2. It is seen that as the train speed increases, the type I error rate increases while the type II error decreases. The sensitivity of the detection method is highly related to the train speed when it is 30kph or lower. But when the train speed is no lower than 30kph, all the defective wheels can be detected while only few false positives may occur. Thus, it can be concluded that the proposed wheel defect detection method has high accuracy in wheel local defect detection, especially when the train passes the instrumented section at 30 - 50 kph.

\[
\begin{array}{cccccc}
\text{Errors} & 10kph & 20kph & 30kph & 40kph & 50kph & \text{Total} \\
\hline
\text{False positive errors}^* & 0 & 5 & 9 & 9 & 11 & 34 \\
\text{False positive errors}^* & 0 & 2 & 2 & 2 & 3 & 9 \\
\text{False negative errors} & 10 & 2 & 0 & 0 & 0 & 12 \\
\hline
\text{Error rates} & & & & & & \\
\hline
\text{Type I error rate}^* & 0\% & 2.1\% & 3.8\% & 3.8\% & 4.6\% & 2.8\% \\
\text{Type I error rate}^* & 0\% & 0.9\% & 0.9\% & 0.9\% & 1.3\% & 0.8\% \\
\text{Type II error rate} & 62.5\% & 12.5\% & 0\% & 0\% & 0\% & 15\% \\
\hline
\text{Detection accuracy} & & & & & & \\
\text{Accuracy}^* & 96.1\% & 97.3\% & 96.5\% & 96.5\% & 95.7\% & 96.4\% \\
\text{Accuracy}^* & 95.8\% & 98.3\% & 99.2\% & 99.2\% & 98.8\% & 98.3\% \\
\end{array}
\]

\*^1: including all the 240 samples later proved "without defects"; 
\*^2: including 224 samples (the wheels on the opposite side of the defective wheels are excluded from 240 samples)

5. CONCLUSIONS

This paper develops a FBG-based track-side WILD and a data-based wheel local defect detection method for high-speed trains. As a track-side WILD, this system can be more suitable for great quantity of wheel inspections. By using fiber optic sensing technique, the system can allow multiple FBG layouts and remote monitoring. The effectiveness of proposed system and detection method is verified by an in-situ test and results show that the proposed method including the WILD system and the outlier analysis algorithm has high accuracy in wheel local defect detection.

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