Thermal Image-Based Wheel-Rail Contact Classification and Analysis Using Convolutional Neural Networks

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Abstract

The purpose of this paper is to outline the integration of thermal imaging measurements and Convolutional Neural Networks (CNNs) in studying the contact state of wheel-rail interaction under real operating conditions. The first part discusses the most important aspects of the mechanics of wheel-rail contact related to wear and heat generation in the context of vehicle operation and tram infrastructure. Special focus is placed on the origin and consequences of the multipoint contact between the wheel and rail. This is followed by a presentation of the methodology of thermal imaging measurement. The subsequent section focuses on the potential of CNNs to detect contact situations in the tram wheel-rail interface. The research concludes with a presentation of the most important research observations and outlines the further stages of the project.

1. Introduction

Lateral, longitudinal and spin wheel and rail relative movements, increasing wear intensity during curving, accelerating and decelerating, result in transformations of the wheel-rail interface. The contact area is subjected to fast displacements (even jumps) and shape alterations. The most welcome kind of wheel-rail contact is a single-point conformal area resulting in mild wear and quiet operation. A specific situation is a multipoint contact resulting in a significant rise of creepage values in the interface which, is believed to contribute to accelerated wheel and rail wear and increased generation of vibration-acoustic phenomena [1][2]. Despite the rolling and sliding nature of the wheel-rail contact, frictional heating resulting from relative motion is disadvantageous. This phenomenon can lead to changes in tangential forces or several forms of wheel and rail wear [3][4][5][6].

The local temperature rises between wheel and rail, which are the outcomes of the creepage increase, are also informative signals, indicating the frictional work generated at the contact [7]. Having the effect of frictional heating (relative motion of wheel and rail), it is beneficial to use these signals to improve the efficiency of rail transport systems. Information on the type of contact, linked to spatial data, can constitute a component of the analysis. In this study, we have designed an automatic classifier, that can be used in the analysis of the relationship between the contact situations and the generated friction work.

Due to the dynamic nature of the wheel-rail interaction and a great amount of recorded data, developing an automatic classification tool is highly desirable, as manual classification is time-consuming and prone to errors. So far, no research has been identified that is directed towards the analysis of wheel-rail thermograms using Convolutional Neural Networks (CNNs). CNNs are a technology with wide applications in various scientific, industrial and service sectors [8]. Thus, the application of this technology to thermal imaging of the wheel-rail interface is a fully justifiable research innovation, part of the general trend of integrating vision and deep learning methods in wheel-rail interface monitoring. It is also worth pointing out that thermal imaging is the only known method of visualizing the number of contact patches between wheel and rail under real operating conditions.

2. Material and methods

2.1.1. Thermal imaging

The thermal imaging measurement was carried out with two FLIR A700 cameras directed at the wheel-rail interfaces of a vehicle. A thermal imaging mirror arm was used to achieve appropriate image composition containing the contact area without directly pointing the camera lens at this area (Fig. 1).

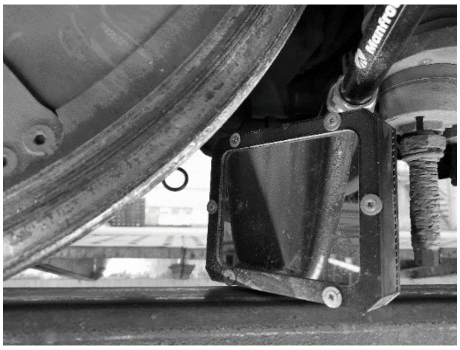

Fig. 1 *IR mirror setup*

The experiment highlighted the advantages of thermal imaging, i.e., the possibility of realizing the measurement under real operating conditions. The vehicle run was carried out on a tram depot experimental track. The measurement was carried out during a warm (21°C) and dry night. The recording parameters are presented in Table 1.

Table 1. *IR imaging parameters*

emissivity coefficient	0.85
measurement distance	0.80 m
relative humidity	50%
ambient temperature	21°C
reflected temperature	21°C
recording frequency	30 Hz

2.1.2. Dataset

The measurement resulted in a set of thermograms. A manual selection within feature engineering was performed. Based on the analysis, three main contact classes were distinguished. In this task, data in radiometric format was used - thus, the dataset was a file with a column containing tensors (3-channel matrixes of temperature data) and the corresponding contact class labels.

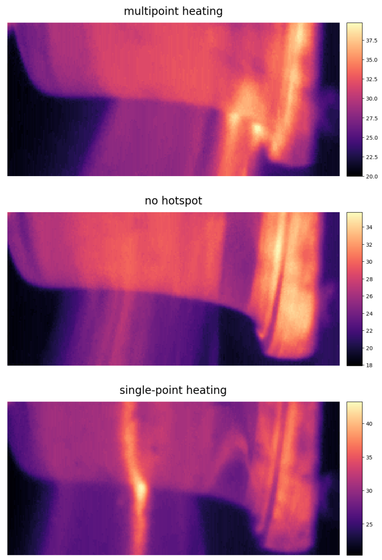

Fig. 2 *Contact classes*

In creating the training dataset, 1800 thermograms from each class were arbitrarily selected. The ratio between the training dataset (including the validation dataset) and test dataset was set at 80:20. Thus, 1440 thermograms from each class were used for training the neural network, while 360 were used for testing.

2.1.3. Network architecture and training

To solve the classification task, a pre-trained on the ImageNet [9] dataset EfficientNetV2S network was used. EfficientNetV2 is a family of Convolutional Neural Networks whose design is geared towards optimizing computational efficiency while providing high-performance operation [10].

Network training in the present task was conducted in two stages, following the transfer learning and fine-tuning paradigm. In the first, the original network classification layer was replaced by one dedicated to classifying contact types (Fig. 3).

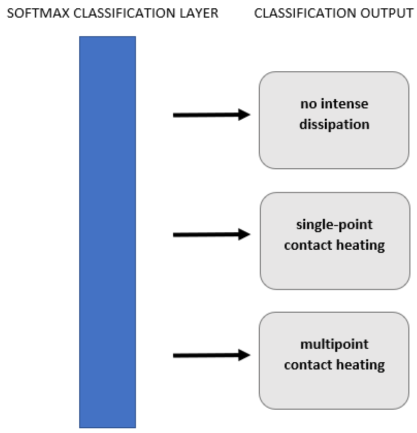

Fig. 3 *Classification layer*

First, the classification layer was trained using the Adam optimizer [11] with an initial learning of 0.001 and a batch size of 32. The model was trained for 10 epochs. Then, in order to improve the performance of the model, a fine-tuning procedure was performed. For this, the model was unfrozen starting at layer 330, corresponding to “block 6d”. Again, the ADAM optimizer was selected, but with a smaller initial learning of 0.0001. The model was trained by performing checkpoints and using early stopping functions. The training was terminated by the function at the 15. epoch.

3. Results

The resulting classifier model was tested on the test set. A global classification value of 98% was obtained. Table 2 shows the basic classification metrics. It can be seen that the model performs very well in distinguishing between contact classes. Relatively high classification results on the test dataset prove that the model is able to generalize well. Analysing the results, it is apparent that the 'no hotspot' class is the one most easily identified.

Table 2. Results of the model evaluation

	no hotspot	**single-point contact heating**	**multipoint contact heating**
precision	0.99	0.96	0.97
recall	0.99	0.97	0.96
F_1 score	0.99	0.97	0.97

4. Conclusions and contributions

Evaluation of the created classification model showed that it is possible to effectively classify the contact classes of wheel-rail contact presented by thermal imaging. Classification of contact types into three groups, which are defined by the number of hot spots, appears to be an accessible and relatively easy-to-solve task. The tool developed will allow automatic labelling of thermograms in terms of their membership of contact classes, thus enabling the finding of relationships between contact types and other variables related to the vehicle-track interaction.

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