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Pre-Grinding Surface Defect Identification using Supervised Machine-Learning and Laser Triangulation Data

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Abstract

This paper proposes a novel technique to identify rail surface defects using laser triangulation optoNCDT 2300-10LL. Two defect types, squat and flaking, are artificially applied on the surface of a rotary steel ring setup. Various supervised binary classification algorithms are implemented, and their performance in defect identification are compared against each other. Linear classifiers, Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA), are observed to be the most performant. The results also show that in spite of 2-dimensional longitudinal measurement, the collected sensory data can be used effectively to detect defects and potentially be extended to other types along with consideration of multiclassification.

Keywords: rail surface defects, laser triangulation sensor, automated defect detection, supervised classification, feature analysis, machine learning

1 Introduction

Maintenance of rails is a relevant topic which has a significant influence on the costs of the rail transportation system. Magel [1] describes the technical implications of rolling contact fatigue (RCF) and how to deal with the defects from detection to removal. Fedorko et al. [2] emphasize the safety implications of rail defects for operation. The EN 13231-5 [3] standard classifies rail surface defects that can be removed by reprofiling the rail. To date, it is often necessary to rely on human-based monitoring of the rail condition as described. It is, therefore, of relevant interest to develop systems that allow automated monitoring of the rail condition. Liang et al. [4] have developed a system for automated rail defect detection based on the application of CCD industrial cameras. Ye et al. [5], instead, have developed a methodology based on a 2D laser signal to create a 3D model of the surface. In other approaches, as used by Afzalan et al. [6], recorded acceleration data from the train is used and deep learning to detect rail defects. Instead of using acceleration data, it would be possible to directly measure a longitudinal profile of the rail with a laser triangulation sensor from the train and thus directly obtain information about defects and their dimensions (length and depth). In this study, artificially created rail surface defects on laboratory test bench are to be detected automatically using the signal of a laser triangulation sensor. As described by Kuffa et al. [7], the setup is used in a slightly modified form. Machine learning techniques are applied for defect detection. For this purpose, an experimental setup in the laboratory is used, which includes a steel ring clamped on a vertical lathe as an artificial rail. The rail surface defects Flaking and Squats are introduced as artificial defects on the ring surface. It is investigated which classifier is suitable for this specific application and to what extent the structure can be transferred to an application on a train.

2 Methods

The experimental setup is shown in Figure 1.

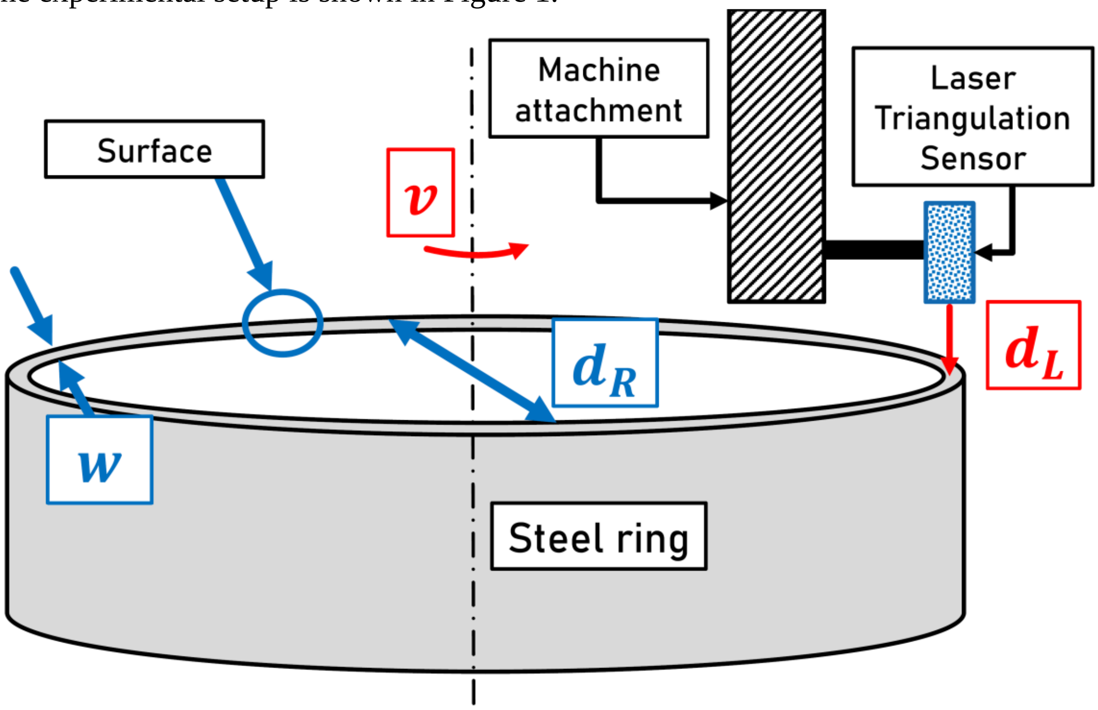

Figure 1: Setup to detect artificial defects.

The structure's base is a steel ring (58CrMoV4), which is clamped on the rotary table of a vertical lathe. A turned facet width w of the ring which serves as an artificial rail surface is approx. $10-12\ mm$. The diameter d_R of the ring is $2\ m$. The rotary table is set in rotation at a speed v of 1.6 rpm ($\sim 0.6\ km\ h^{-1}$). Speeds of up to 80 rpm ($\sim 30.16\ km\ h^{-1}$) would be technically possible to simulate faster driving speeds. Artificial defects are manually introduced with tools onto the ring surface. A selection of the defects introduced is shown in Figure 2.

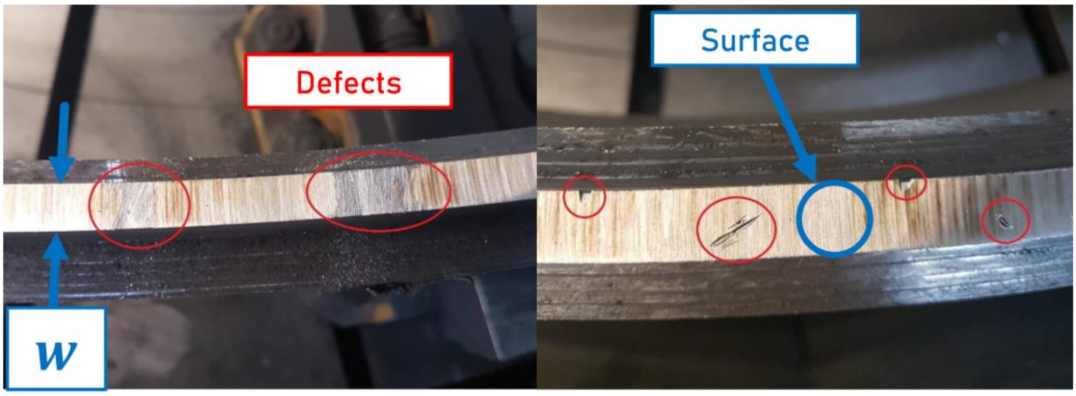

Figure 2: Manually implemented artificial defects on the ring surface.

A total of 81 defects distributed around the circumference of the ring were implemented (36 artificial squats, 45 artificial flaking defects). The defect interpretations are shown in Figure *2*. For the purpose of defects identification, the vertical lathe is equipped with a laser triangulation optoNCDT 2300-10LL sensor from Micro-Epsilon Messtechnik attached to the vertical lathe's tool connection. The signal d_L of the sensor is measured in the range from $-10\ V$ to $10\ V$ and a sampling ratio f_S of $30\ kHz$. The data point distance is $\Delta x = 56\ \mu m$. Figure 3 shows the workflow overview of the study, from data collection to defects detection.

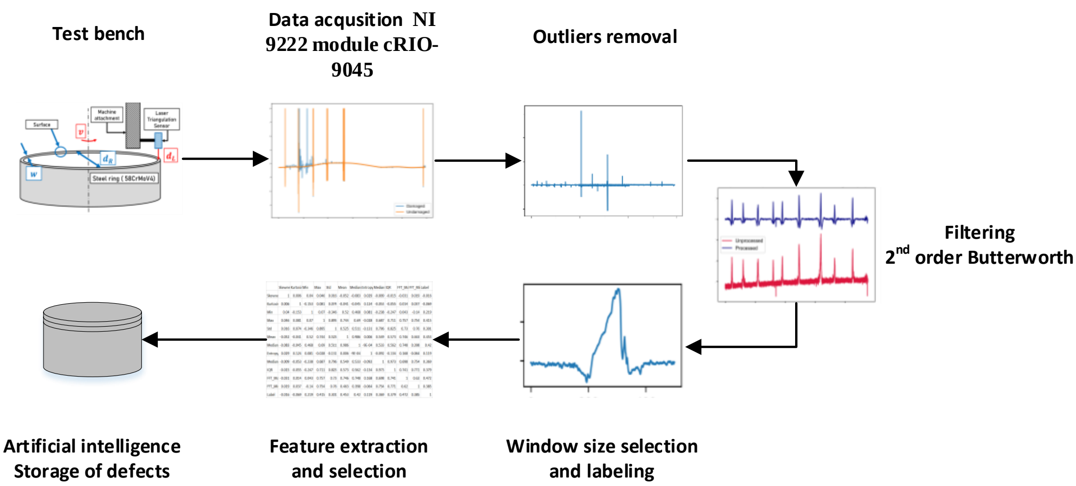

Figure 3: Workflow of the study.

An NI 9222 module in a cRIO-9045 from National Instruments (NI) was used for data acquisition. The data is filtered by a second-order Butterworth filter, and outliers were removed in advance. Then, the processed data is used for supervised binary classification with manually assigned labels of "damaged" and "undamaged". In order to label and train models, 66 % of the total dataset is used as a training dataset, and 34 % is used for evaluation. Initially, 13 statistical features are used, which are reduced to eight after a dimensionality reduction via principal component analysis (PCA). Figure 4 includes the list of all features ranked based on the correlation with the labels.

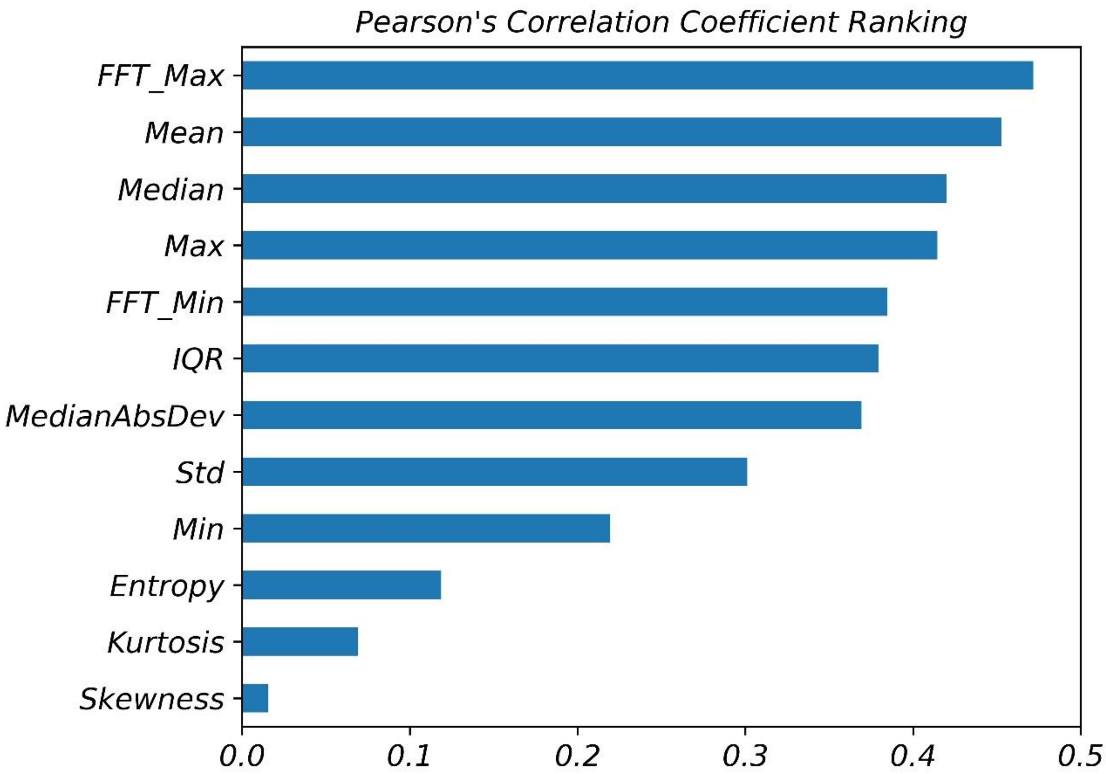

Figure 4: Ranked statistical features based on the absolute value of Pearson's correlation coefficient with regard to.

Different trained models are compared with each other:

- Linear & radial basis function (RBF) Support Vector Machine (SVM)
- Linear Discriminant Analysis (LDA)
- K-Nearest Neighbour (KNN)
- Gaussian Process
- Decision Tree
- Random Forest
- Artificial Neural Network (ANN)
- Adaptive Boosting (AdaBoost)
- Gaussian Naïve Bayes

3 Results

The data-set is biased towards the defective label. Accuracy is not a reliable performance parameter. Instead, precision and recall, respectively the combination of both efficiency parameters, the F-score are used for comparison. Table 1 gives an overview of the results (precision, recall & F-Score) of the trained models.

Classifier	Precision [%]	Recall [%]	F-Score [%]
Linear Support Vector Machine (SVM)	82	86	83.95
Linear Discriminant Analysis (LDA)	87	95	90.82
Radial Basis Function (RBF) Support Vector Machine (SVM)	69	99	81.32
K-Nearest Neighbour (KNN)	3	100	5.83
Gaussian Process	4	100	7.69
Decision Tree	2	100	3.92
Random Forest	3	100	5.83
Artificial Neural Network (ANN)	3	100	5.83
Adaptive Boosting (AdaBoost)	3	100	5.83
Gaussian Naïve Bayes	5	100	9.52

Table 1: Precision, Recall and F-score for different models.

Non-linear models show desirable properties for the recall of 100 % for the precision, on the other hand, only low values below 5% can be achieved. If both values are combined to the F-score, values between 5.83 % and 9.52 % are obtained. An exception is a support vector machine based on a radial basis function. This model achieves a value of 99 % for recall and a value of 69 % for precision, which combined results in an F-Score of 81.32 %. Linear models show the best results in precision with 82 % for the linear support vector machine and 87 % for the linear discriminant analysis. This results in an F-score of 83.95 % and 90.82 %, respectively. It is shown that the linear discriminant analysis outperforms the linear support vector machine by approximately 7 %. The different implemented artificial defects show a low correlation among each other. The correlation reaches a maximum of 1 %, indicating a poor linear correlation. Based on this value, it would be possible to perform a multi-classification with the implemented artificial defects

4 Conclusions and Contributions

It was shown that a binary classification, whether a defect or no defect is present, is generally possible with the recorded data of a longitudinal profile. With the artificial defects implemented, it would theoretically be possible to perform even a multi-classification. Linear classifiers predominantly outperform non-linear classifiers. When comparing the F-score, the linear discriminant analysis approach outperforms the linear support vector machine by approximately 7 percentage points. It is recommended to use the linear discriminant analysis approach to detect defects within a recorded length profile. This study is based on the detection of artificial defects and differences are to be expected when applied to the actual railway network and new training of the classifiers will become necessary. In addition, only a limited number of artificial defects could be applied to the ring. More data would therefore be desirable for better training. Since a longitudinal profile was recorded, it may be difficult in reality to record every defect since the hunting motion of the train was not considered in this study. Nevertheless, it can be assumed that a significant amount of defects could be recorded in order to make a statement about the condition of the rail segment. The proposed approach should be compared to the widely tested concept of capturing image data to compare the performance. Furthermore, a combination of both approaches seems to make sense. For example, it may be advantageous to evaluate the dimensions of the defect in the surface via recorded image data, while the depth of the defect can be determined via the laser sensor.

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