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Automatic System Identification for Robust Fault Detection of Railway Suspensions

H. Jung[1], O. Nelles[2], P. Kraemer[3], K. Weinberg[4], G. Kampmann[2] and C.-P. Fritzen[1]

[1]Arbeitsgruppe Technische Mechanik, University of Siegen, Germany
[2]Arbeitsgruppe Mess- und Regelungstechnik - Mechatronik, University of Siegen, Germany
[3]Lehrstuhl für Mechanik mit Schwerpunkt Schädigungsüberwachung, University of Siegen, Germany
[4]Lehrstuhl für Festkörpermechanik, University of Siegen, Germany

Abstract

Vehicle dynamics and safety against derailment are directly influenced by the primary and secondary suspension of a railway vehicle. During the operation faults of components like broken springs or dampers can occur. To prevent a complete system failure, the early detection of faults in the suspension of trains is thus of high importance. A novel approach to sensitive and robust structural health monitoring is proposed. It is based on (i) acceleration measurement, (ii) time-series modeling, (iii) eigenfrequency and possibly mode-shape extraction, (iv) probability density estimation, and finally (v) classification. Compared to traditional approaches the new kernel-based probability density estimation allows to aggregate the results from different data sets. This approach suppresses the spurious eigenfrequencies and emphasizes the physical ones. If, in addition, the mode-shapes are incorporated into the system, the probability density estimator becomes multivariate and the diagnosis accuracy improves further.

Keywords: structural health monitoring, automatic fault diagnosis, subspace identification, eigenfrequency density estimation.

1 Introduction

The safety and the dynamics of railway vehicles are strongly influenced by their suspension system. To prevent derailments or complete failures of vehicles, the early detection of faulty springs or dampers is of high importance [1, 2].

This publication is widely based on [3] and presents an automated fault detection approach based on data driven system identification using accelerometer signals installed on the bogie. The signals are sampled simultaneously and evaluated by means of online monitoring methods. The signal evaluation consists of two steps. First, a stochastic subspace-based system identification algorithm (SSI) is used to extract damage sensitive dynamical features. In our case the features are: eigenfrequencies (f) and their corresponding mode-shapes (Ψ) and modal dampings (d). In a second step, a probabilistic approach based on kernel density estimation is applied for fault detection to distinguish between different failure causes. Here probability density functions are used to describe the most likely values of the eigenfrequencies in the fault-free and faulty case. Comparing new data to the density functions determined in a previous training phase allows to assess if a failure has occurred or is likely to occur and what type of fault is the most likely one.

Subspace-based algorithms for dynamical properties identification are well-known [4]. It is important to note that this procedure represents only a numerical way to extract dynamical properties from measured data of a linear dynamical model under unknown random excitation. Due to the sensor quality, the assumptions violation regarding the excitation, and possible system non-linearity, etc. the extracted dynamical properties can be of physical or numerical (spurious modes) nature. In conclusion a procedure to extract only the physical modes is necessary.

In the past the automated feature extraction was usually performed using so-called stabilization diagrams. This required experience-based knowledge about setting parameters and the application of a high number of criteria for classifying the features in the diagrams [5].

The motivation for this paper is to overcome this and to improve the automatic feature extraction by using the statistical modelling of the eigenfrequencies by means of density functions. A physical pole will be represented in the data set by a high eigenfrequency density. Spurious poles are suppressed and less noticeable by a lower density. Frequencies calculated online can be now automatically assigned to one or other density function belonging to one or other damaged state.

2 Methods

A multi-body model is used to investigate different failure scenarios and to generate acceleration signals. The modelled test train, the test track and the ground model are based on the Manchester Benchmark [6]. Four accelerometers are located directly above the primary suspensions of the leading bogie. A damage was induced at the left leading primary suspension by reducing the spring stiffness by 5 to 70 % in 5 % steps. The model is excited by random track irregularities according to the power spectral densities defined in ERRI B176 while running along the test track.

The proposed method shown in Figure 1 is divided in a training and operating phase. In the training phase different probability density functions for n several fault cases

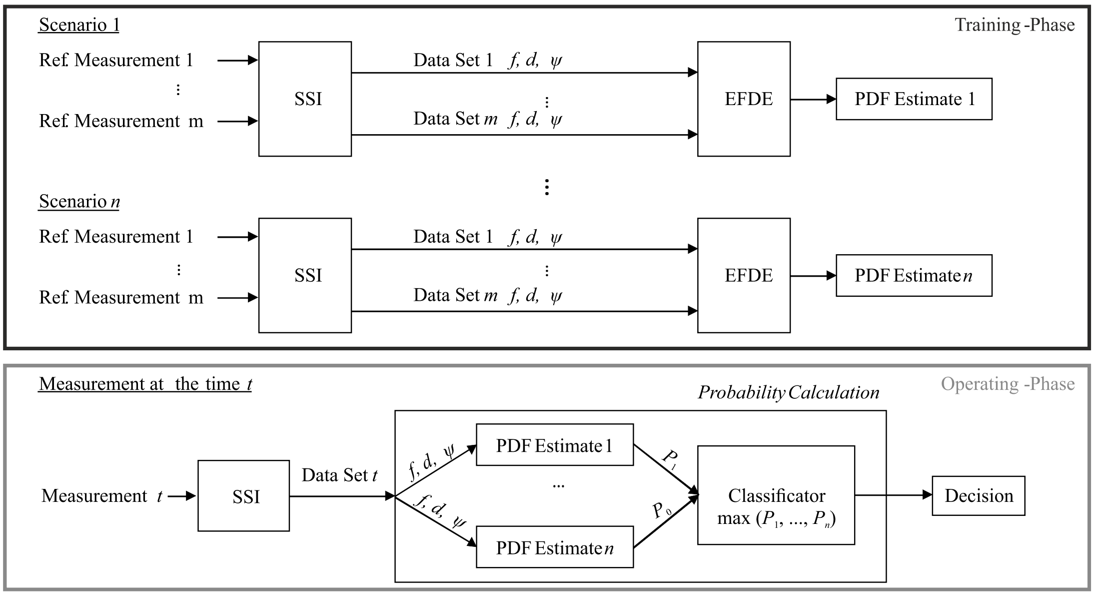


Figure 1: Schematic diagram of the automatic system identification procedure for fault detection.

are estimated by application of the eigenfrequency density estimator (EDFE). For this purpose, first the dynamical properties are determined using the SSI algorithm. To account for the statistical variation of these properties, the calculation is repeated for *m* measurements belonging to a system state.

Afterwards the *m* data sets are passed to a kernel density estimator with a Gaussian kernel to estimate a probability density function (PDF) p_n. In the case of physically meaningful frequencies there will be a high density. Figure 2 shows an example for a healthy and a faulty case with m = 20 different data sets for a p = 8 order state-space-

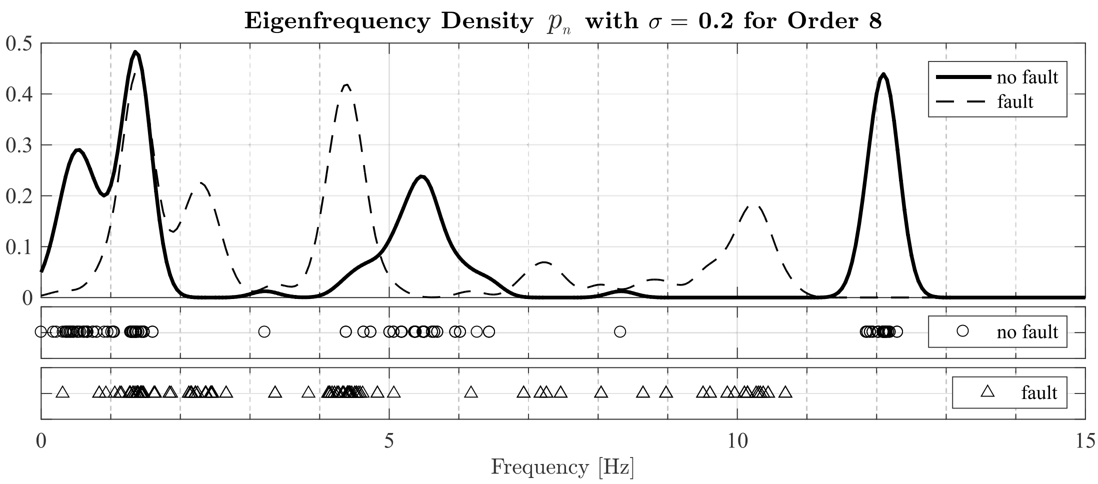
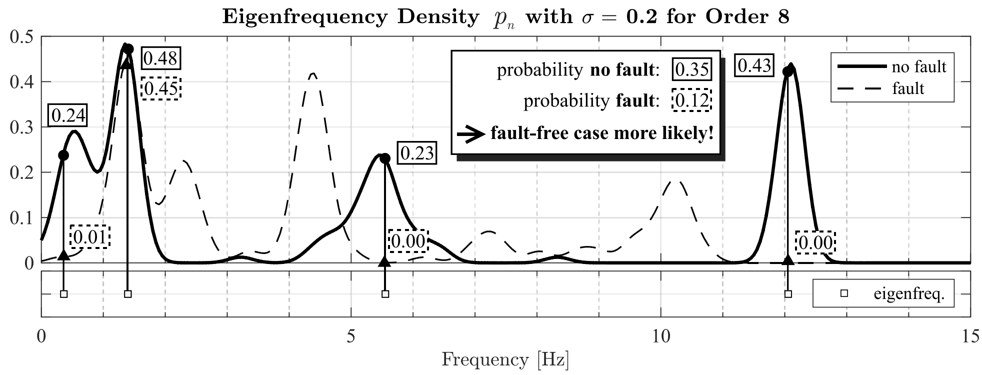


Figure 2: Top: Eigenfrequency density function p_n calculated from 20 different data-sets for the fault-free and faulty case. Bottom: Positions of the available $8 \cdot 20 = 160$ eigenfrequency values.

model. The eigenfrequencies are depicted by circles and triangles. As shown, both cases have a different distribution of the frequencies. At 12 Hz only the fault-free case and at 4.5 Hz only the faulty case has a high p_n. This example shows that the EFDE provides a suitable, sensitive and robust tool for obtaining the physical eigenfrequencies for different system states automatically.

To monitor the system health in the operating phase, the actual SSI results will be calculated from online data and form the data set *t*. This data set is then assessed using the *n* PDFs obtained beforehand by calculating the probability P_n with regard to each *n* fault cases. Comparing the *n* different probabilities, a decision about the systems health can made by a classification. This procedure is illustrated in Figure 3 for a healthy and a faulty data set. As in Figure 2 four eigenfrequencies are considered. In this case the data set belongs to the fault-free case, due to of the higher probability.



$$P_{\text{no fault}} = \frac{1}{N}\sum_{i=1}^{N} p_{\text{no fault}}\,(f_{\text{i}}) = (0.24{+}0.48{+}0.23{+}0.43)/4 = 0.35$$

$$P_{\text{fault}} = \frac{1}{N}\sum_{i=1}^{N} p_{\text{fault}}\,(f_{\text{i}}) = (0.01{+}0.45{+}0.0{+}0.0)/4 = 0.12$$

$$P_{\text{no fault}} > P_{\text{fault}} \quad \rightarrow \quad \text{healthy}$$

Figure 3: Health assessment: The probability is higher when comparing to the healthy density function than to the faulty density function, therefore a healthy system is assumed.

3 Results

Before the concept can be used in a health monitoring scheme, a robust approach is required. For this purpose, the probability density functions for a model order p = 26 were calculated 60 times with 20 randomly selected data sets from 100 data sets (for each scenario). The confidence and prediction intervals in Figure 4 show only moderate deviations. The main frequencies appear clearly in both states of health. This behaviour indicates a robust operation of the EDFE method independent of the measured signals. An advantage of a higher order model is the possibility to determine higher eigenfrequencies. It should be considered that especially the higher eigenfrequencies are more sensitive to damage than the lower ones.

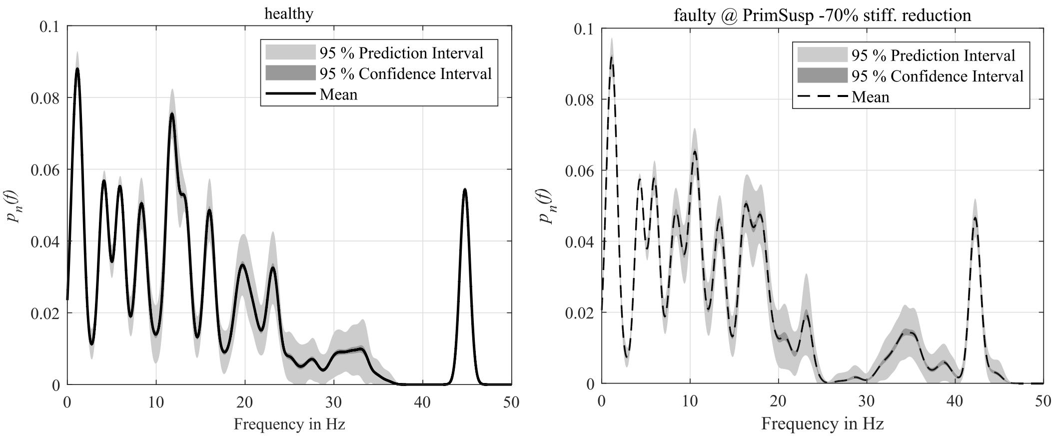


Figure 4: Robustness of classification: Eigenfrequency densities p_n for the fault-free (left, solid) and faulty case (right, dashed).

To evaluate the sensitivity of the proposed fault detection method under consideration of the SSI model order, simulations with a spring stiffness reduction in the range of 5 to 70 % in 5 % steps were used for health monitoring with the classification error as criterion. The classification error is a measure of the false-positive and false-negative classifications relative to the total number of performed classifications. For each fault case m = 80 randomly chosen data sets out of 100 available data sets were used to calculate the probability density estimate in the training phase and 20 randomly chosen data sets from the same 100 available data sets are used for the health assessment in the operating phase. This procedure is repeated 100 times for each model order and fault case combination. The mean values of the 100 classification

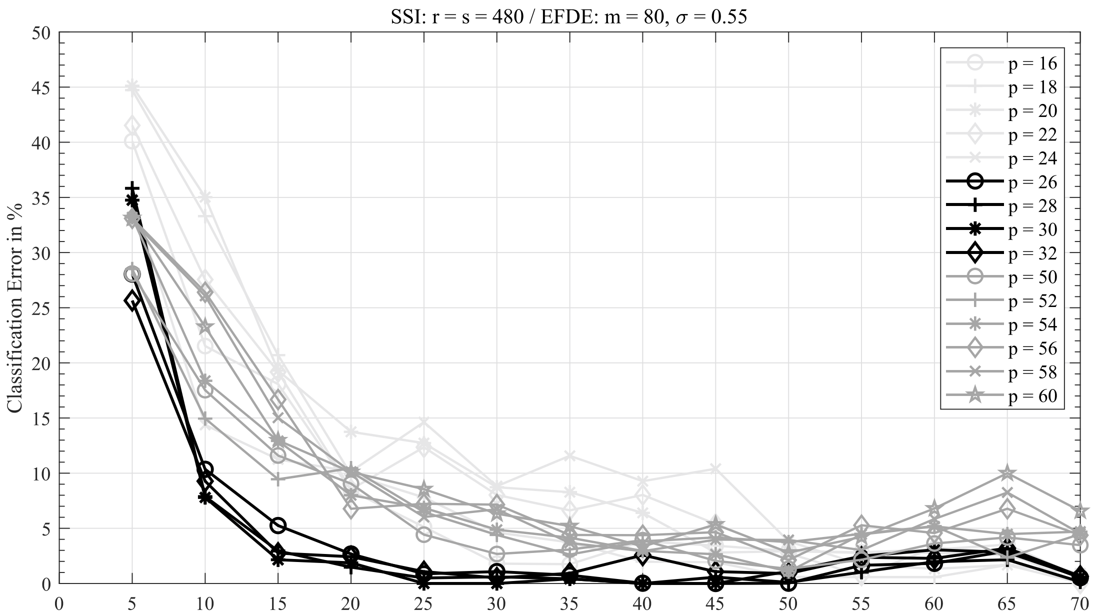


Figure 5: Sensitivity of fault detection with consideration of SSI model order; Classification error over amount of damage.

runs are presented in Figure 5. Generally, damages of 15 % stiffness reduction using model orders between 26 and 32 are detected with an error of 5 % and less.

If more than one sensor is available for health monitoring the eigenvectors (mode shapes) can also be used to construct multivariate probability density functions with additional dimensions derived from the eigenvector values (e.g. ratio of the magnitude of the values for each sensor). An example for such eigenfrequency/mode densities is shown in Figure 6. It can clearly be seen that the healthy/faulty cases not only differ in the frequency but also in the mode dimension, which improves the fault detection.

4 Conclusions and Contributions

In this contribution the faulty front left primary suspension on the leading bogie was investigated by using the probabilistic approach of an eigenfrequency density estimator (EFDE). First, a state-space-model of order 8 was used to describe the density estimator for the health monitoring procedure. The main reason for choosing this low order was to gain a more manageable number of 4 eigenfrequencies for a clearer presentation of the procedure. But the classification in this case relies heavily on the 10 and 12 Hz eigenfrequencies of the faulty and fault-free systems, respectively. When the model order is about 26, the eigenfrequencies around 42 and 45 Hz can additionally be utilized to differentiate between the faulty and fault-free state, respectively. This was shown during the robustness analysis and confirmed by the sensitivity study. In the future the simulations will be extended to the detection and separation of multiple different faults. Also, an investigation related to the robustness (varying masses, velocities and the influence of the rail-wheel-contact) and the practical application will be essential topics.

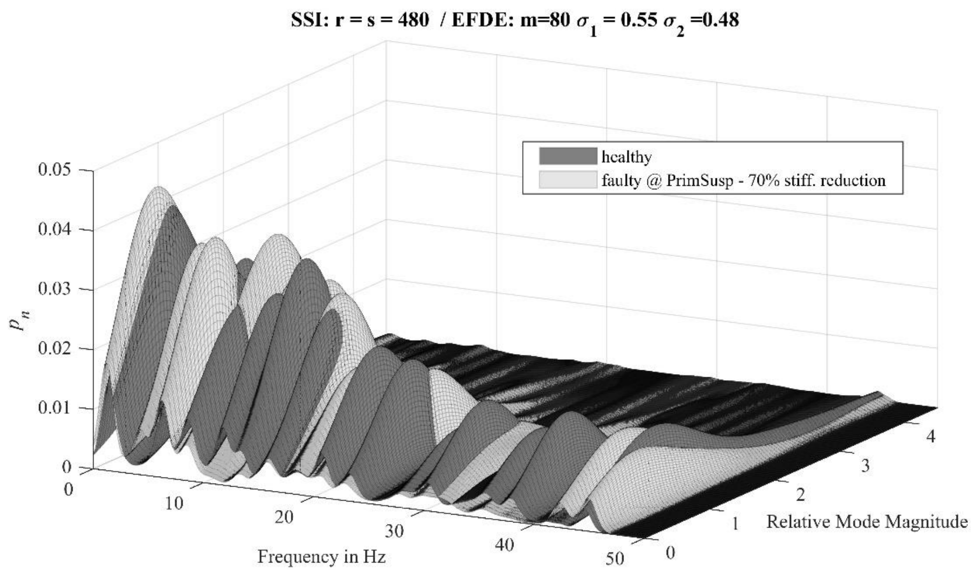


Figure 6: Eigenfrequency/Mode Densities p_n for the fault-free (black) and faulty case (grey).

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