

# Classification of Systems' Health Condition Using the New Adaptive Fuzzy-Based Feature Classification Approach AFFCA in Comparison to a Macro-Data-Based Approach

Sandra Schiffer, Sandra Rothe, Dorra Baccar, Dirk Söffker

► **To cite this version:**

Sandra Schiffer, Sandra Rothe, Dorra Baccar, Dirk Söffker. Classification of Systems' Health Condition Using the New Adaptive Fuzzy-Based Feature Classification Approach AFFCA in Comparison to a Macro-Data-Based Approach. Le Cam, Vincent and Mevel, Laurent and Schoefs, Franck. EWSHM - 7th European Workshop on Structural Health Monitoring, Jul 2014, Nantes, France. 2014. <hal-01020457>

**HAL Id: hal-01020457**

**<https://hal.inria.fr/hal-01020457>**

Submitted on 8 Jul 2014

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# CLASSIFICATION OF SYSTEMS' HEALTH CONDITION USING THE NEW ADAPTIVE FUZZY-BASED FEATURE CLASSIFICATION APPROACH AFFCA IN COMPARISON TO A MACRO-DATA-BASED APPROACH

Sandra Schiffer<sup>1</sup>, Sandra Rothe<sup>1</sup>, Dorra Baccar<sup>1</sup>, Dirk Söffker<sup>1</sup>

<sup>1</sup> Chair of Dynamics and Control, University of Duisburg-Essen,  
Lotharstr. 1, 47057 Duisburg, Germany

sandra.rothe@uni-due.de

## ABSTRACT

In this contribution a recently developed new modeling and classification approach to be used with streamed measurement data of industrial processes is applied.

This briefly repeated approach can be used for condition-based maintenance or structural health monitoring. The approach is based on a fuzzy-like modeling using statistical features from training data. Based on the trained model classification can be realized allowing to distinguish unknown data sets to the given number of data classes each related to states.

Beside the detailed illustration of the approaches to be used, the results applying the automated classification using the AFFCA approach are shown. As data, complex and problem-specific Acoustic Emission (AE) signals and also signals taken from the operating level (called hydraulic pressure data) are used and compared. The results show that based on the AE-based and also on the hydraulic pressure based AFFCA systems health state classification, the changes of the system can be detected very early and detailed.

**KEYWORDS :** *classification, SHM principles, monitoring*

## 1. INTRODUCTION

Despite the usage of analytical, rule-based, or even heuristic-oriented approaches to model diagnostic or condition evaluation rules, these approaches usually need an exact model or experienced-based understanding of the considered technical processes for design. In order to avoid analytical modeling task or even to detail heuristics especially within the application fields of condition-based maintenance or structural health monitoring, data driven or machine learning approaches can be applied ([1], [2], and [3]). The main idea behind is to use raw or filtered signals in combination with suitably designed algorithms able to learn or even adapt internal schemes representing the signals input - classified output relations to be learned.

Realizing system's health condition evaluation, besides the availability of task-/process-specific sensors two major issues are important:

- Preparation of the measured data (filtering) and
- Interpretation, in detail classification of filtered data with respect to the machines state.

The classification approach detailed within this contribution is - as prototype algorithm - firstly published in [4]. Here a qualitative model-based method using fuzzy logic for internal representation is used and combined with a feature generation for statistical methods describing the signal properties. The developed approach is based on an internal adaption scheme to find the best representative features to map the signals to the externally given classifications as a supervised learning and classification scheme. It can be shown, that the new approach works well for a number up to 5-7 classes to be distinguished. Recently also additional numerical improvements could be realized [5].

The system and the related data to be discussed are related to the evaluation of sliding friction wear. Therefore a test rig has been built to generate the experimental data to be used for further examination. As data, complex and problem-specific Acoustic Emission (AE) signals and also signals taken from the operating level (called macro data: here pressure data from the hydraulic cylinder) are used and compared.

Beside the detailed illustration of the approaches to be used, the results applying the automated classification using the AFFCA approach are shown and compared to the development of the task-specific macro-data-based approach focused to the observable changes of friction coefficients. The results show that based on the AE-based and also on the hydraulic pressure-based AFFCA systems health state classification, the changes of the system can be detected very early and detailed. In comparison to the friction-coefficients-based evaluation it can be stated that the approach works independent from further physical knowledge of the process.

## **2. THE NEW ADAPTIVE FUZZY-BASED FEATURE CLASSIFICATION APPROACH AFFCA**

Due to the nonavailability of related wear models, due to the complexity of wear phenomena here a data-driven approach is used building models for different wear states. Therefore it will be assumed that training data from previous test runs are available and have classified by experts to given wear states. The goal of the approach to be introduced is to developed a supervised learning approach using classified data able to be used without no further knowledge or information.

### **2.1 Basic Structure of AFFCA**

The AFFCA approach is based on preliminary versions (AFBA) [4], detailed and improved [6] (submitted) and therefore will only be repeated here briefly.

A block diagram of AFFCA, which comprises a training and modeling stage in training module and classification stage in testing module, is shown in Figure 1. The central considerations for this approach are concentration on continuous measurement data to be evaluated online (sliding window technique), use of data characteristics (e.g. statistical characteristics), and definition of boundary parameters by the data itself.

In the training module, the training data generated from the system are used to determine the states considered. These states are determined based on human expertise, previous experience and/or operational observations.

In the context of this study, structured data are data in a matrix, whose rows are the process features generated for the data and whose columns are the data samples. These transferred time-series or structured data are modeled using an embedded modeling process to generate the fuzzy model. The modeling process includes fuzzy partition, fuzzy partition selection, fuzzy rule generation, and adaptation processes.

In the testing module, the information mask from the training module, which contains the necessary information, is used to classify the unknown data.

### **2.2 Feature Extraction Based On A Sliding Window Embedded Modeling**

Measured data in engineering applications are usually time series (online, but buffered and therefor considered as block) or streamed data (measured online without buffering and used for control or classification at the time of measurement). The suggested approach is based on a sliding-window concept (Figure 2). The feature extractor transfers the data continuously into the feature space so that the states considered can be distinguished. The feature extractor can be adjusted using the first and the

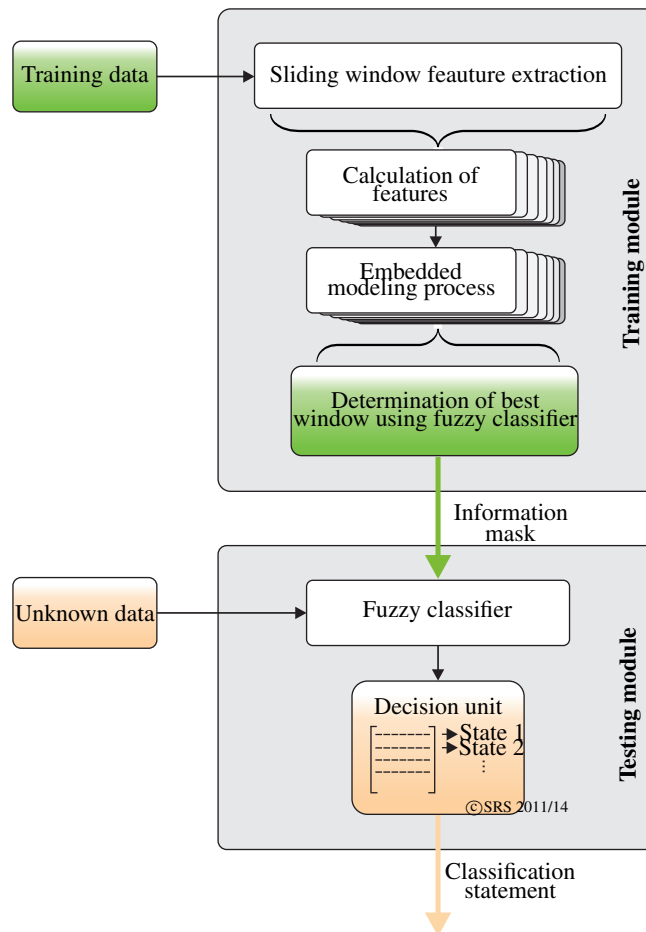


Figure 1: Basic structure of AFFCA [6]

last desired parameter for the window, denoted  $SW_{BE}$  and  $SW_{EN}$ , respectively. Thus a vector of time series or streamed data consisting of  $n$  samples can be scanned by  $NW$  subvectors, which continuously shift by one sample value.

Each subvector generates a new vector HSV consisting of  $p$  features. The statistical, mathematical, geometric, and other features of the system can be used to build the HSV. Finally, all the HSVs generated are combined to construct the hybrid state matrix HSM with  $p$  rows and  $NW$  columns. In combination with these steps, a suitable concept to divide the state or feature space into several regions is introduced, called homogeneity-oriented vector.

The objective is to divide the state or feature space into several regions. The principle used for assignment has an important effect on the performance of the design approach. Using the H-OV concept, the function will represent for all states to be included within the range as follows ([4]).

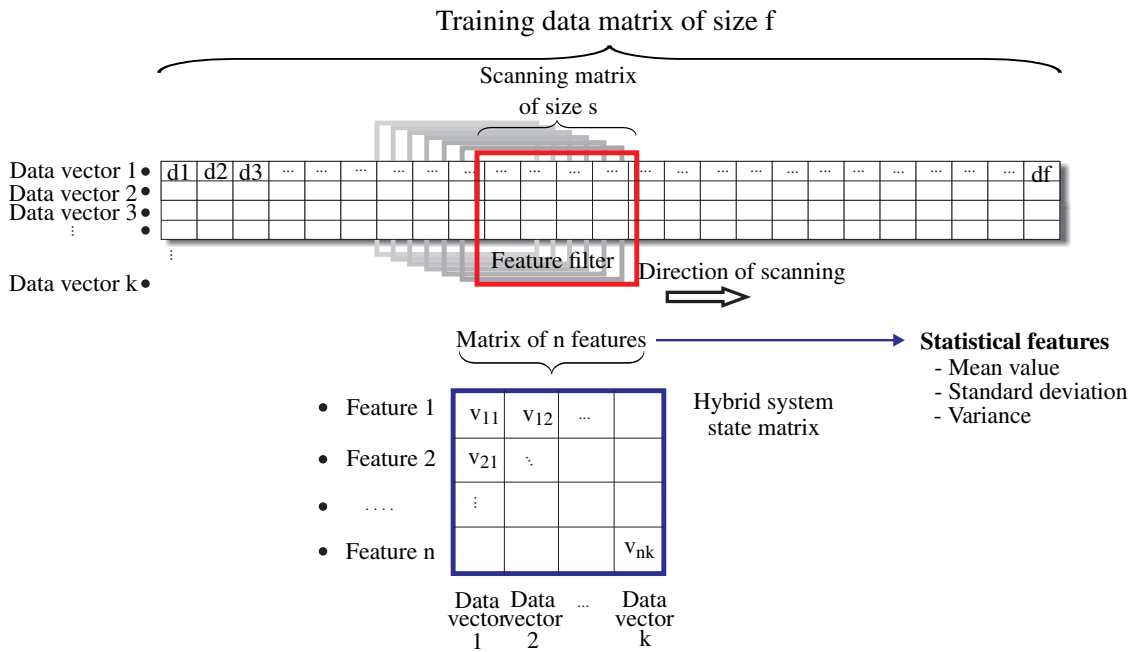


Figure 2: Feature extraction process using sliding window [6]

### 2.2.1 Fuzzy Partition Process

The proposed approach uses a triangular fuzzy membership function, defined as

$$\mu_F(x) = \begin{cases} 1 - (b - x) / (b - a), & \text{for } x \in [a, b] \\ 1 - (x - b) / (c - b), & \text{for } x \in [b, c] \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

### 2.2.2 Adaptation of Boundary Parameters in the Feature Space

Adaptation plays an important role in the proposed approach and uses a two-dimensional adaptation criterion. The criterion is realized by adjusting the boundary parameters for the central and secondary functions for each state considered within the range for each suggested feature. The procedure for adaptation is as follows ([4]):

Initial values of the boundary parameters for the central and secondary functions are defined for each state within the range for each suggested feature using the fuzzy partition process. Adaptation of the initial values of the boundary parameters for the central and secondary functions is realized. The suggested fuzzy model consists of a combination of features. Feature selection for the combination is realized in the proposed approach using suitable dimension adaptation. The goal of this adaptation process is to define the best boundary parameters, the best features describing the states considered, and deleting redundant features.

### 2.2.3 Fuzzy Model and Classification

Fuzzy partition and adaptation generate a specific set of fuzzy partitions in the feature space to describe each state. The suggested fuzzy model is based on a set of  $M$  fuzzy rules and evaluates the state of any sample as: The  $p$  features of a sample are used as the input for the fuzzy model, where each of the  $M$

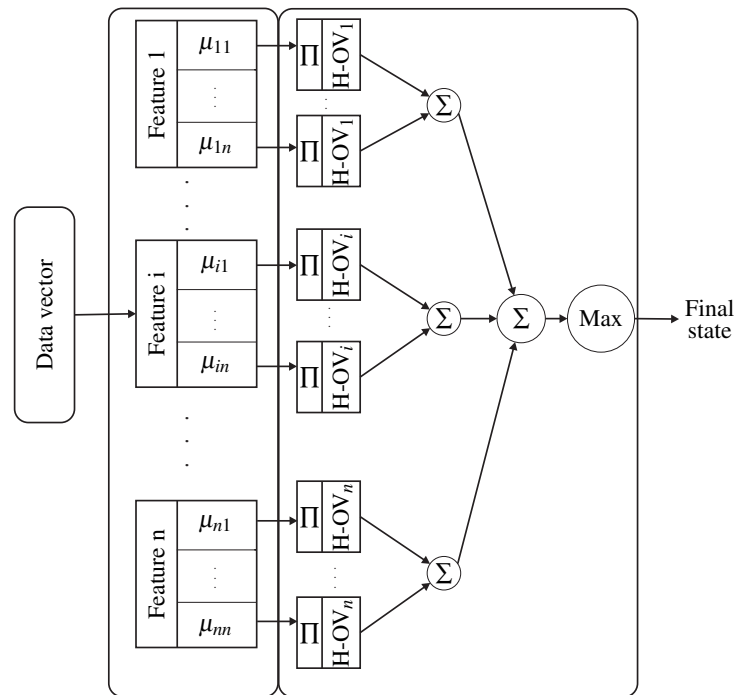


Figure 3: Classification process [6]

fuzzy rules generates a number of fuzzy membership values equal to the number of fuzzy partitions or antecedents.

The fuzzy model generates the number of fuzzy membership values for each of the input samples according to the number of rules and fuzzy partitions. The objective in the classification step is to obtain one fuzzy membership value for each state.

The procedure illustrated in Figure 3 involves four steps. The multiplication process in the first step guarantees that the individual fuzzy membership value represents all possible states in range of corresponding function, with percentages based on H-OV values. In the second and third step all classification values are summarized to generate one classification value for each state. A maximum operator is applied to the values from the third step to define the final state of the input sample.

### 3. SYSTEM AND PROBLEM DESCRIPTION: HEALTH STATES, MEASUREMENTS, AND FILTERED DATA TO BE CONSIDERED

For the applicability of the introduced approaches data are taken from a test rig build for studying friction and wear processes. The motivation using such a test rig is to use measurements showing the whole complexity of the problem. Inner material effects can damage a system internally before it can be detected visually at the material ([7]). Up to now no related model is known. Known monitoring procedures may not prevent the systems' failure, so there is a need to develop health monitoring methods, to classify the systems' states and detect damages beforehand. This includes the distinction of several classes between "Good/Functioning" and "Bad/Out of order".

The used test rig contains two wear resistant plates which are sliding against each other with an applied normal load, driven by a hydraulic cylinder (Figure 4).

From previous contributions it is known, that it is possible to classify the wear state using signals based on an acoustic emission (AE) analysis - according to [8], [9], [10], and [11], solid bodies under mechanical load emit acoustic signals - or with the use of hydraulic pressure data which is proportional

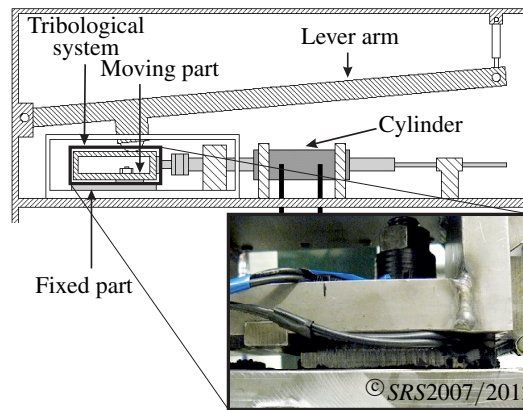


Figure 4: Test rig as tribological system, SRS, U DuE.

to the force and thus also to the friction between the wear surfaces [12].

Within this contribution the usability of the two different data sets, acoustic emission and hydraulic pressure, to distinguish different wear states is examined and compared. The three wear states of the tribological system are illustrated in Figure 5, where the AE energy distribution over system usage is shown.

#### 4. EXPERIMENTAL RESULTS AND COMPARISON OF THE APPROACHES

For the comparison between acoustic emission and hydraulic data, data sets from the same experiment Z15 are used. The underlying question is: Is it possible to classify the systems' states with both

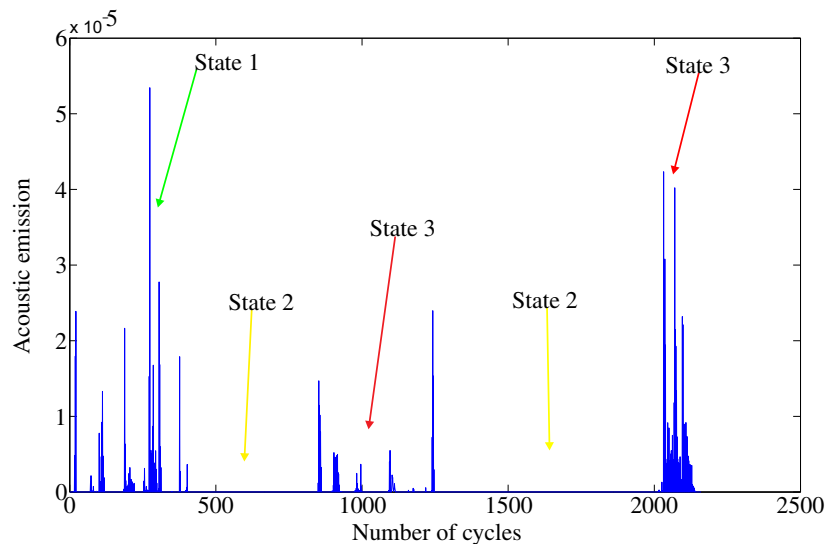


Figure 5: Acoustic emission energy distribution over system usage

- State 1: Run-in phase (Early failure, high probability to fail)
- State 2: Permanent wear phase (Constant failure rate)
- State 3: Changes of surface conditions

approaches?

For comparison, 10-20 cycles of each state-of-wear of Z15 (acoustic emission vs. hydraulic pressure) are used as training data as

- 10 cycles from State 1: Run-in phase,
- 20 cycles from State 2: Permanent wear phase I, and
- 20 cycles from State 3: Changes of surface conditions.

For the testing, 10-20 different cycles for each state-of-wear from Z15 are used. The results for the comparison between acoustic emission and hydraulic pressure data for two different experiments are illustrated in Figure 6. In the figure the classification results of AFFCA are shown. The different colors show the belonging of each data cycle to the correct state. From the graphs it can be concluded, that for the acoustic emission data as well as for the hydraulic data, AFFCA is able to classify the systems' states quiet reliable. This means, for the acoustic emission data there is a correct classification result of about 72.00% and for the hydraulic pressure data of about 68.00 %.

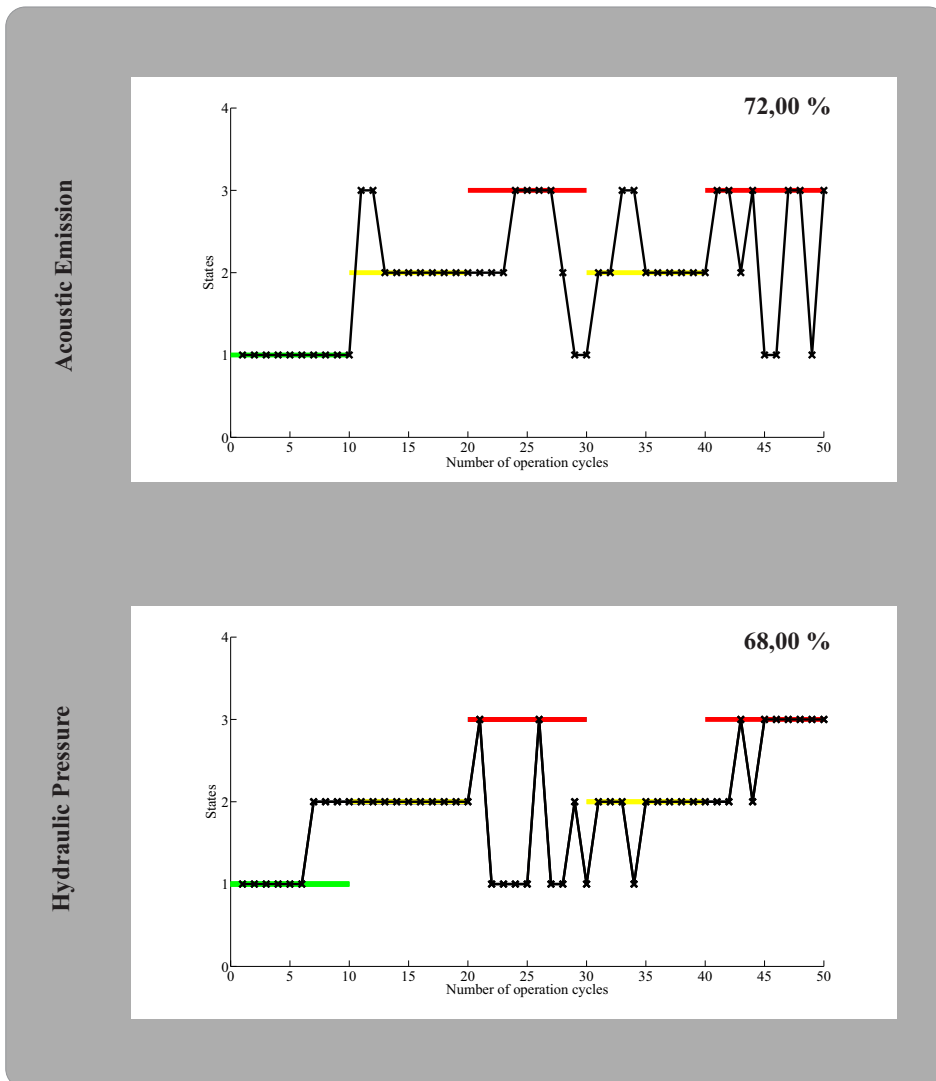


Figure 6: Comparison between acoustic emission data and hydraulic pressure data for the same experiment Z15



This results should be improved with further work. Core idea of the improvement will be the analysis about features to be used characterizing the different states, the definition of the suitable number of the states as well as the definition of the training data.

## 5. CONCLUSION

In this contribution a recently developed new modeling and classification approach is proposed. The framework provides new solutions for automated and improved generation of fuzzy-based rule sets. The evaluation results show that the proposed approach is able to separate different states automatically and to classify unknown data only with information used during training. Furthermore the evaluation results show that the proposed approach is able to classify different wear phases of a tribological system. Here different data sets from acoustic emission and hydraulic pressure measurements are taken and compared. From an engineering point of view it can be stated that the introduced approach is suitable for structural health monitoring purposes.

## 6. REFERENCES

- [1] M.N. Murty and V.S. Devi. *Pattern Recognition, An Algorithmic Approach*. Springer Science & Universities Press, India, 2011.
- [2] I. Guyon, S. Gunn, M. Nikravesh, and L. Zadeh. *Feature Extraction, Foundations and Applications*. Springer-Verlag, Berlin, Heidelberg, New York, 2006.
- [3] Z. Kovačić and S. Bogdan. *Fuzzy Controller Design, Theory and Applications*. Taylor & Francis Group, LLC, 2006.
- [4] H. Aljoumaa and D. Söffker. Multi-Class Approach based on Fuzzy-Filtering for Condition Monitoring. *IAENG International Journal of Computer Science*, 38(1):66–73, 2011.
- [5] S. Schiffer. Further development of a fully automatic classification method for diagnosis and control (in german). Diploma thesis, University of Duisburg-Essen, Duisburg, March 2013.
- [6] S. Schiffer, H. Aljoumaa, and D. Söffker. Classification of complex machine data to be used for structural health monitoring purposes. *ASME Dynamic Systems and Control (DSC) Conference*, San Antonio, Texas, October 22-24, 2014.
- [7] I.M. Hutchings. *Tribology: friction and wear of engineering materials*. CRC Press LLC, UK, 1992.
- [8] S. Theodoridis and K. Koutroumbas. *Pattern Recognition*. Elsevier Inc., USA, 2009.
- [9] J. Zhiaho and G. Bin. Analysis of acoustic emission signals from stainless steel with different wavelet bases. *Proc. IEEE International Symposium on Knowledge Acquisition and Modeling*, pages 892–895, December 2008.
- [10] P. Kalyanasundaram, B. Raj, and T. Jayakuma. Characterization of microstructures in metallic materials using static and dynamic acoustic signal processing techniques. *7th International Workshop, Advances in Signal Processing for Non Destructive Evaluation of Materials*, pages 43–50, 2005.
- [11] J. Takatsubo and T. Kishi. Quantitative acoustic emission source characterisation of microcrackings in steel. *Research in Nondestructive Evaluation*, 1990.
- [12] D. Söffker, S. Rothe, S. Schiffer, H. Aljoumaa, and D. Baccar. Smart, tough, and succesful: Three new innovative approaches for diagnosis and prognosis of technical systems. *F. K. Chang (Ed.): Structural Health Monitoring 2013*, pages 81–88, 2013.