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ACOUSTIC EMISSION-BASED IDENTIFICATION AND CLASSIFICATION OF FRICTIONAL WEAR OF METALLIC SURFACES

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ABSTRACT

Diagnostic and monitoring approaches, able to detect and classify the damage and wear process, are becoming of increasing importance. Especially for friction wear-related phenomena which are difficult to measure directly during the operation and their diagnostic has been usually restrained to offline examinations. Permanent contact and repetitive sliding motions between two surfaces lead to material changes. Due to different wear mechanisms, sudden structural changes appear, emitting energy in form of elastic waves known as Acoustic Emission (AE). Therefore, a correlation between the emitted AE and damage level can give important information about the process state and the related knowledge can be used for automated supervision. This contribution introduces an advanced method for wear states identification and classification by means of AE technique and fuzzy-based multi-class classification approach. Compared to the previous publications, here the sequential effect of the motion trajectory is investigated. To establish a relationship between wear mechanism and AE signals, frequency-based feature selection using Continuous Wavelet Transform (CWT) was performed. Five wear process stages were detected during experiments. Results show that the behavior of individual frequency components changes when the wear-related effect changes. Using the CWT transformed signals, state-specific pattern are generated to classify signal features related to specific states. Results show that the introduced method can be used as an online monitoring method for material detection and characterization.

KEYWORDS : *Frictional wear, Acoustic Emission , Continuous wavelet Transform, Fuzzy logic*

INTRODUCTION

The definition of wear qualities depends on the particular application and the related tolerable level of deterioration as well as to the load history of the system. Hence, this is an individual characteristic that can be quantized and quantified beforehand, so that the related knowledge can also be used for automated supervision, for example in the context of condition-based maintenance concepts. Due to the complexity of wear phenomena, damage and wear detection has been restrained, usually to offline measurement, i.e., during the measurement the wear process needs to be interrupted and the specimen to be removed from the test rig. Therefore, an online, automated, and continuous monitoring of safety relevant structures, in which the wear process is not interrupted and the wear environment (temperature, humidity, lubrication, etc.) is not changed, may be useful to fit SHM or CM-related goals [1]. Non-destructive technique, observing/measuring those signals allows the evaluation of the fatigue progression. The non-destructive testing allows bridging the gap between the discrete information obtained from time-discrete inspection and the desired wish of continuously monitoring of damage progression.

Acoustic Emission technique is one of the most efficient non-destructive methods able to solve the condition monitoring, evaluation in real time. Acoustic emission (AE) is defined by the American

Society of Testing and Materials Terminology for Non-destructive Examinations as the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material [2]. For over the last two decades, properties of AE signals are used as an indicator for different effects affected by material changes due to aging, wear, etc [3–5]. Those signals occur due to different wear phenomena and stages, indicating the main sources of failure due to fatigue [6, 7].

In this contribution, frictional wear generated during sliding motion is investigated. The main idea here is to study the effect of the motion trajectory by analyzing the AE signals emitted during forward stroke and backward stroke separately. The measurement chain and the filtering applications, firstly presented in [8], are applied. To identify the different wear mechanisms, AE signals are examined using CWT and frequency based features which reveal the wear state are selected. The classification of the frequency pattern is performed by an advanced fuzzy-based feature classification approach. The used feature recognition approach is a revision of the firstly in [9] introduced multi-class classification approach. The central idea is to realize a qualitative method based on fuzzy logic in combination with statistical signal properties [9]. On this basis the feature recognition approach is able to generate a set of class-specific features to describe related different states of a system. For a verification of the developed approach, data for classification are required.

The contribution is structured as follows: in the next section, the measurement chain, including the tribological system is introduced and application of suitable filtering algorithms defining relevant data are explained. In the following section, results based on experimental data distinguishing different wear-related effects during different stages and their classification are discussed. In the last section a summary and a conclusion are given.

1. EXPERIMENTAL TESTS

1.1 Measurement Chain

The tribological system analyzed consists of two plates of different sizes (with area ratio 1:5) sliding against each other. Contact pressure and adjustable normal load are applied to the system to accelerate the wear process. Piezoelectric sensors are bonded to the structures, realizing a continuous measurement of relevant signals during the wear process. It can be shown that the AE analysis is principally able to sense material changes of relatively small dimensions. To guarantee a minimum attenuation of the emitted AE signals, the sensor is bonded to the surface. The coupling between the surface and the material is permanent and very stiff. The used sensor is a disc with a diameter of 10 mm and a thickness of 0.55 mm. The measured voltage is fed to an impedance converter and the high-speed AD-converter on the FPGA board. The measured signal is subsequently analyzed by various signal processing methods. This paper focuses on the analysis of the signal frequency contents. An appropriate sampling rate (4 MHz) of the ADC is chosen, this assures a high resolution of the discretized piezoelectric voltage. The FPGA-based measurement chain is shown in figure 1.

1.2 Signal Processing

The recorded AE signals are non-stationary and appear as transient signals with undefined waveform. The first goal is to detect characteristic frequencies for these stochastically appearing effects and to assign them to their unique wear mechanism. Time-frequency analysis provides the possibility to evaluate the time change character of the frequency components. To preserve the time information within the analysis of the recorded AE signals, the CWT is performed for extraction relevant frequencies indicating transient events. In recent years, CWT has been successfully used and became the

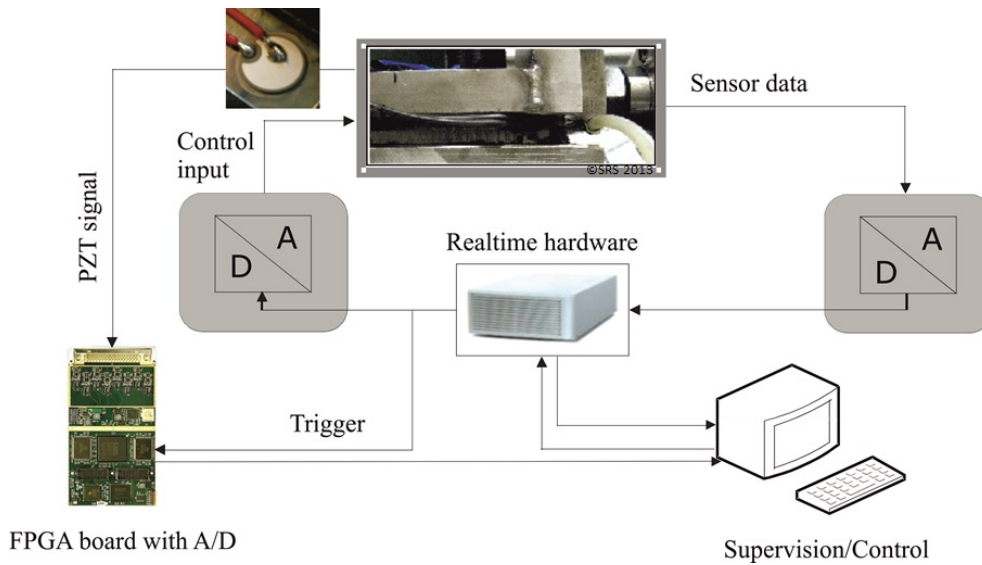


Figure 1 : FPGA-based measurement chain implemented at the Chair of Dynamics and Control, U DuE

most informative in the analysis of AE signals [10]. This method provides excellent time-frequency localized information, which are analyzed simultaneously with high resolution in different frequency ranges [11, 12].

Beside the filtered signals, the actual operating phase has to be known and a criterion for distinguishing between normal and abnormal operation has to be defined. Significant distinction between AE signals measured during different positions of cylinder (forward stroke and backward stroke) has to be detected. Therefore, signals under normal operation in different operating phases are recorded. By correlating the CWT with process signals; recurrent phase-specific patterns can be identified. Those baselines arise from structural excitations. All deviations from those baselines are an indicator for abnormal conditions, which are defined as damage. Therefore, only the frequency contents of the residual CWT pattern are used in the examinations of AE signals. In figure 2 the signal processing chain is shown.

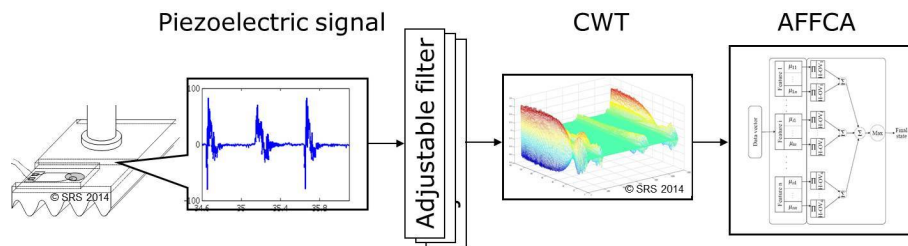


Figure 2 : Signal processing chain

1.3 Classification Approach

The classification approach detailed within this contribution is a new Adaptive Fuzzy-based Features Classification Approach AFFCA- a prototype algorithm. A former preversion is published in [9], details of the revised approach are given in [13]. Here a qualitative model-based method using fuzzy logic for internal representation is used and combined with a feature generation approach using

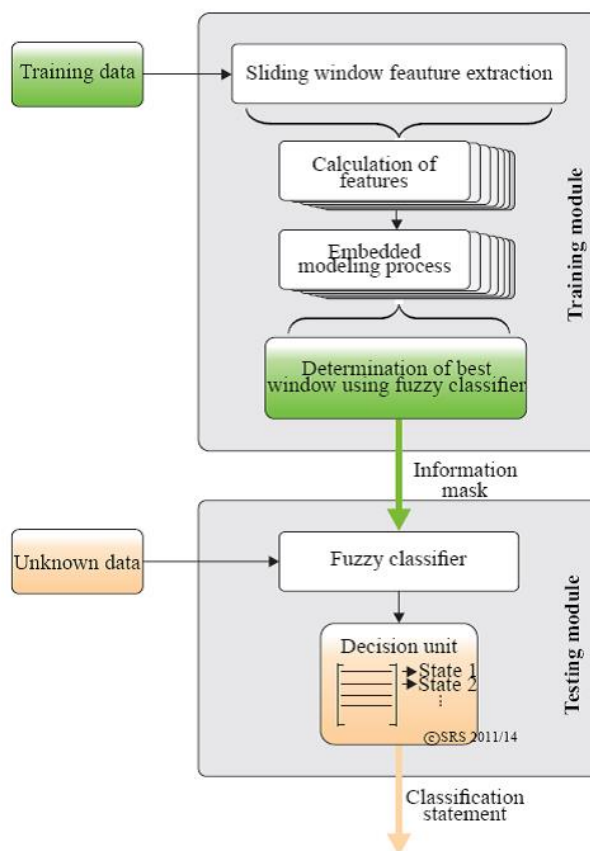


Figure 3 : Basic structure of AFFCA [13]

statistical properties describing signal properties of streaming data.

The developed approach is based on an internal adaption scheme to find the best representative features to map the signals to the externally classified states. 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.

The principle of AFFCA comprises a training and modeling stage in training module and classification stage in testing module. The central considerations for this approach are concentrated 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 testing module, the information mask from the training module, which contains the necessary information, is used to classify the unknown data. Basic structure of AFFCA is shown on figure 3.

2. EXPERIMENTAL RESULTS

Referred to previous works [1, 8], focussing on the same tribological system, the AE energy distribution allows the distinction of the three main characteristic states of system failure. These major phases are classified as (a) run-in phase (self-accommodation), (b) permanent wear phase

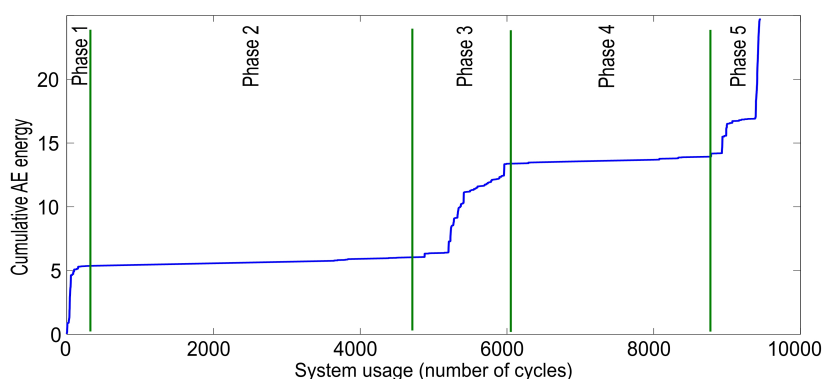


Figure 4 : Cumulative AE energy over system usage during

(steady state) and (c) wear-out phase (catastrophic damage). Within the run-in phase, systems have a high probability to fail. This effect is also called the early failure region. The end of this phase is clearly indicated by a reduction of AE events. In the phase of permanent wear the failure rate is ideally constant until the wear-out phase begins. Within the last region, the systems fail due to the exceedance of their designated life time. This representation is useful to visually detect wear zones and abnormalities. Furthermore, stochastically occurring events can be also distinguished from nominal, process-induced energy events.

The AE energy distribution and the cumulative AE energy were supposed to be effective parameters estimating the evaluation of damage. A careful study of AE energy distribution is given in [8]. Here, the focus is on cumulative AE energy to extract relevant characteristics distinguishing different wear stages from related AE signals.

From the progression of the cumulative AE energy shown in figure 4, five process states could be identified. The run-in phase (phase 1) is characterized by a high increase in AE activity within a short period of time (from cycle nr. 1 till cycle nr. 40). The permanent wear phase (phase 2) is the longest process phase (from cycle nr. 41 till cycle nr. 5000) and is clearly indicated by a reduction of AE events which stayed constant. This stable phase ends when AE activity re-increase, revealing the beginning of the phase 3. Phase 4 is characterized by steady AE energy which remains constant until cycle nr. 8800. Phase 5 shows a rapid and important AE activity increase that indicates the failure of the system. Investigation of wear process based on cumulative AE energy provides qualitative information, about wear state and the level of deterioration.

During operation, process, position, and wear specific frequencies appear in the measured signal. For reasons of consistency and comparability the analysis of the AE signal is always performed at the same position, identical duration, and direction of movement of the cylinder. The points in time of AE measurement are at the beginning of the cylinder movement. To extract more information characterizing the different process phases, frequency components of 5 cycles during the two direction movements were examined using CWT. The analyzed cycles were selected as follows:

- five cycles representing the forward stroke: 1 for the first gradient, 1 for the first stable phase, 1 for the second gradient, 1 for the second stable phase and 1 for the last gradient
- five cycles representing the backward stroke: 1 for the first gradient, 1 for the first stable phase, 1 for the second gradient, 1 for the second stable phase and 1 for the last gradient

Signal segments of the five process phases during forward stroke and backward stroke and the corresponding time-frequency analysis are illustrated in figure 5 and figure 6 respectively. It can be

observed that each phase is indicated by specific frequency components. It can be also shown that CWT results of the backward stroke permit a better distinction between the different states specially by phases 3 and 5 where the energy content is notable higher than during the forward stroke.

Phase 1 and phase 5 are characterized by both low and high frequency components while phase 3 is mainly characterized by frequency components higher than 700 kHz. Signals measured during phase 2 and phase 4 have the same behavior in both forward and backward strokes. They do not show any significant event indicating changes in the material surface.

It can be concluded firstly that time-frequency-analysis is appropriate to describe the incremental damage and to distinguish between different frequencies occurring during the process and secondly, that AE signals generated during backward stroke are more appropriate for wear-state identification. The classification of wear-related frequencies can be used as features in the AFFCA classification module.

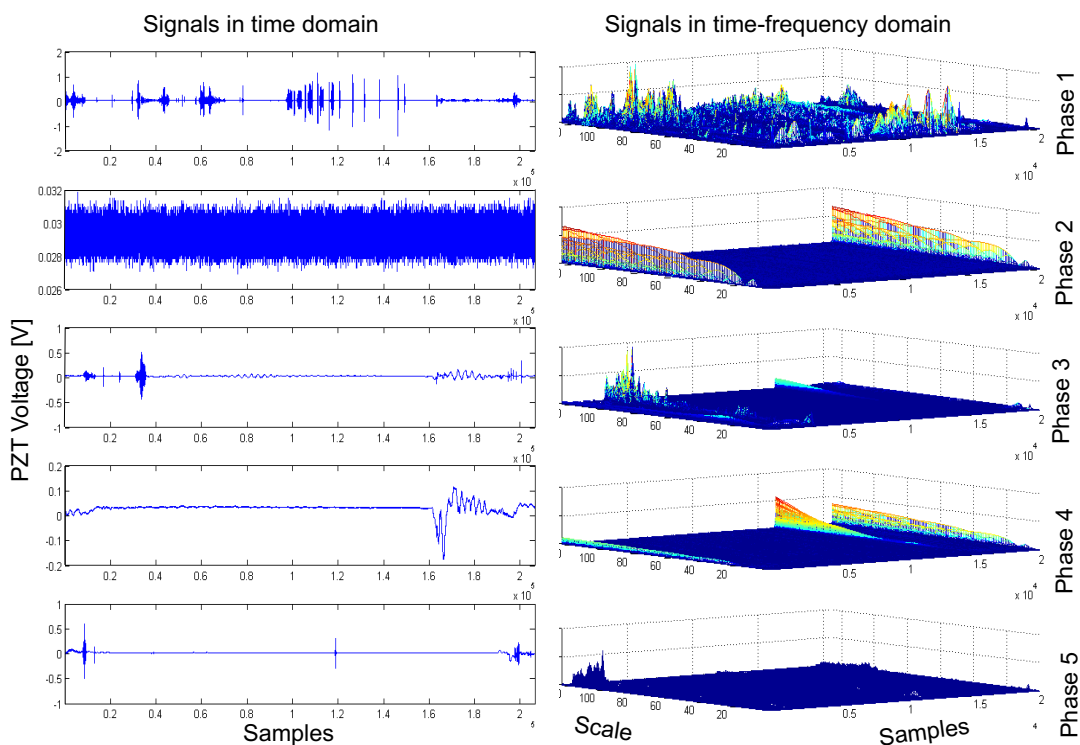


Figure 5 : Acoustic Emission signals and the corresponding CWT results during forward stroke

For the comparison between forward and backward stroke, the underlying question is: Which stroke leads to better signals with respect to system's state distinction? It can be assumed that the backward stroke is more suitable for classification, because there are no more shavings between the plates and the signals measured are more precise. To verify this assumption, 10 cycles of each state-of-wear are used as training data as

- 10 cycles from: Run-in-phase,
- 10 cycles from: Permanent wear phase I,
- 10 cycles from: Phase with surface changes,
- 10 cycles from: Permanent wear phase II, and
- 10 cycles from: Wear-out phase.

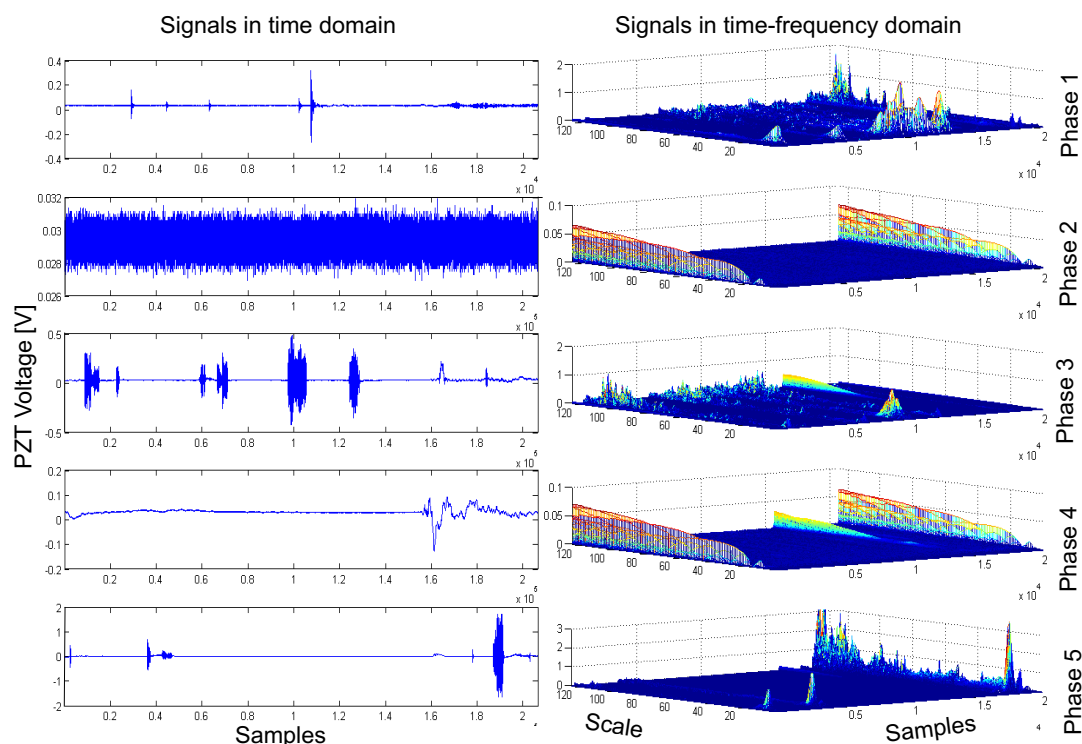


Figure 6 : Acoustic Emission signals and the corresponding CWT results during backward stroke

The result of the comparison between forward and backward stroke of the test data are illustrated in figure 7. There, the correlation of the different states of wear is shown. For testing, 10 different cycles for each state-of-wear are used. In figure 7 (left) the classification results of the forward stroke are illustrated. A misclassification exists, when the classified states do not match the colored lines. From the results it can be concluded, that the backward stroke shown better with respect to the classification. The reliability of the classification of the states 1 to 4 is acceptable, state no. 5 can not be classified. To improve the results a better and more detailed understanding of signal properties with respect to wear states is necessary.

SUMMARY AND CONCLUSION

In this contribution, a correlation between wear mechanisms and AE signals generated during sliding motion was investigated. In this context, the measured AE signals were examined regarding their frequency components as well as the sequential effect of the motion trajectory using CWT. Results show that based on the frequency contents, five different process phases can be distinguished. It could be also concluded that signals measured during backward stroke are better appropriate for system state distinction. In addition, frequency-based features which reveal the wear state were extracted and classified using advanced fuzzy-based feature classification approach. Classification result shows that using the backward stroke of the test data, better classification results can be achieved. As demonstrated, the AE technique can be used as an efficient tool for structural health monitoring applications, which allows wear-state supervision based on automatically running online routines.

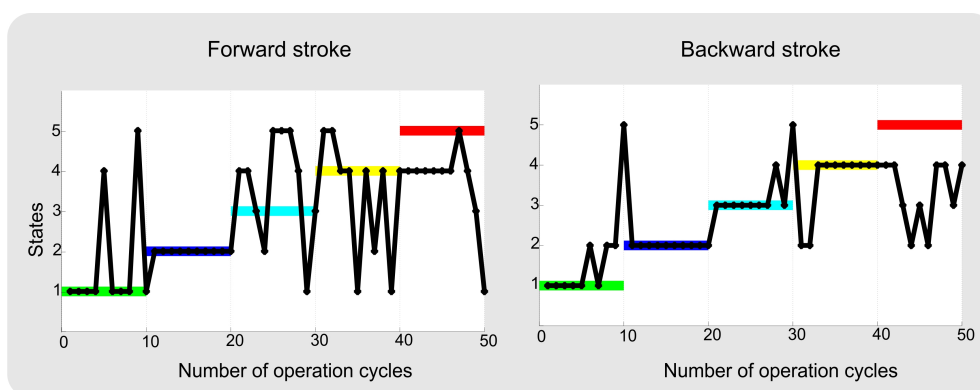


Figure 7 : AFFCA results

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