Condition monitoring for reciprocating devices

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Subject: 23. CONDITION MONITORING (Zustandsüberwachung)

Abstract: Condition monitoring is a field of rising importance and interest both in science and industry. A very powerful tool for this task is vibration analysis. Nowadays mainly large and expensive machines like generators, engines or circuit breakers of power delivery systems are monitored to detect failures before serious damage can happen [1-2]. With rising automation in industry a lot of new machines and mechatronic systems were developed and installed in the last decades. In these systems reciprocating devices like valves and relays play a vital role. So it seems useful and necessary to monitor the condition of these devices online during their lifetime.

The aim of this research is to develop a condition monitoring system for relays and valves. During the work it was seen, that a deeper understanding of the vibration signals can lead to a reliable and more straightforward classifier. In this paper some new knowledge about the signals in the time- and frequency domain was presented. By sophisticated segmentation of the signals in both domains a relationship between the resulting segments and the mechanical operation of the device could be found. This relationship gives the possibility to interpret the electrical signals in a mechanical sense and to find more easily powerful features for certain failures in the vibration signal. The monitored signals are highly non-stationary and it is necessary for the processing of non-stationary signals to find appropriate algorithms [3-4]. The presented approach is capable to isolate segments in the signal with a higher stationarity and to increase the reliability of the condition monitoring system [5].

The segmentation was performed by applying new unsymmetrical windows and filters to the signal. Algorithms for the adaptive parameterization of the windows and filters are presented.

The results of the segmentation are promising: four different operations in the time domain could be isolated (the lifting of the movable part, the movement itself, the impact and the vibration of the whole device caused by the impact). In the frequency domain it was possible to separate random sources like flow induced noise and more deterministic sources like the natural frequencies of the device. A straightforward linear classifier which was used to separate between faulty and unfaulty devices reached an accuracy above 95%.

1. Introduction

Electromagnetically operated switching devices in automation and control like valves and relays have a reciprocating characteristic in their movement. These devices are often rather small and cheap but play a vital role for the overall system (machine or plant). If these devices break down or if their technical parameters deteriorate seriously an severe damage can happen for the technical system or humans. Thus it seems sensible and desirable to replace these devices when deterioration exceeds some limits and becomes serious. To achieve this goal it is necessary to monitor the state of the device of interest by some suitable means. Possible quantities for supervision are electrical current and voltage of the coil (Kryter 1989 and Blakeman 1997), the actuation time (Perreault 1970 and Yamashina 1990), process parameters like the flow through a valve (Gallier 1997) or the vibration of the switching event (Park et al. 1990; Aurud et al. 1991; Runde et al. 1996).

In this research project vibration analysis is used for condition based maintenance. The aim is to detect mechanical failures in the device before the damage caused by the failure becomes unacceptable.

2. Classification

2.1 Introduction

Classification is the task of mapping a set of objects which are represented by several variables to a smaller number of groups (or classes, or clusters) in a way that the structure within the of objects is preserved in the new mapping. That is the within-group-scatter should be smaller for similar objects than the between-group-scatter (Gordon 1981; Li 1995). The training of a classifier may be supervised or unsupervised. Unsupervised training (e.g. clustering) is based on the possibility of the data to self-organise into a number of groups. Supervised training is performed if a labelled set of training data is used for the learning process. Further objects from the test data set are assigned to the class with the highest similarity (Darrell 1998)

Sometimes it is difficult to generate the data which covers all uncertainties and differences within one class or group in an experimental programme. It is also often not known if examples of every possible class can be simulated at a reasonable level of accuracy, either numerically or experimentally. These are the reasons to choose sometimes an unsupervised classification strategy (Skitt 1993). Unsupervised classification is a task were the number of classes is not known before classification and there are no labeled training data available. Thus the classifier itself has to be capable of exploring the number of classes which is optimal in a certain sense.

Classification of patterns to distinct classes can be seen as a process of three steps:

1) Data acquisition
2) Feature extraction or feature selection
3) Classification

These three steps represent the information about the objects (e.g. a time-series) in different vector-spaces. The dimension of the spaces is reduced from one step to another. When the data are gathered from a set of sensors the dimensionality is determined by the sampling rate, the number of channels (that is usually the number of sensors) and the sampling time. Usually the dimension is rather high (many hundreds or thousands of data points are common for one object) and a classification in the signal space is difficult or impossible because the parameters with high discriminative power are often hidden in the overall signal.
This is the reason why the signal is transformed to the lower dimensional feature space (Lai 1988). A large variety of methods and algorithms are available for this step. An important difference is made between feature extraction and feature selection (Webb 1999). Feature selection is the process when a smaller subset of the original sequence is used as a set of features for further classification. Feature extraction is the term used when new variables are generated from the original sequence (Basak 1998). In the last step the classification is performed and the features are mapped to discrete set of classes. The higher the discriminative power of the features the easier the classifier can be realised.

2.2 Feature extraction from transient vibration signals

The vibration signals of switching valves and relays are transient signals which correspond to different processes of movement inside the device. In Fig. 1 a typical vibration signal (solid line) was shown together with the electrical current (dashed line) over the coil. It can be seen that the vibration signal vanishes at the beginning and the end of the switching process. During the switching event several processes happen in a temporal sequence (see Fig. 2).

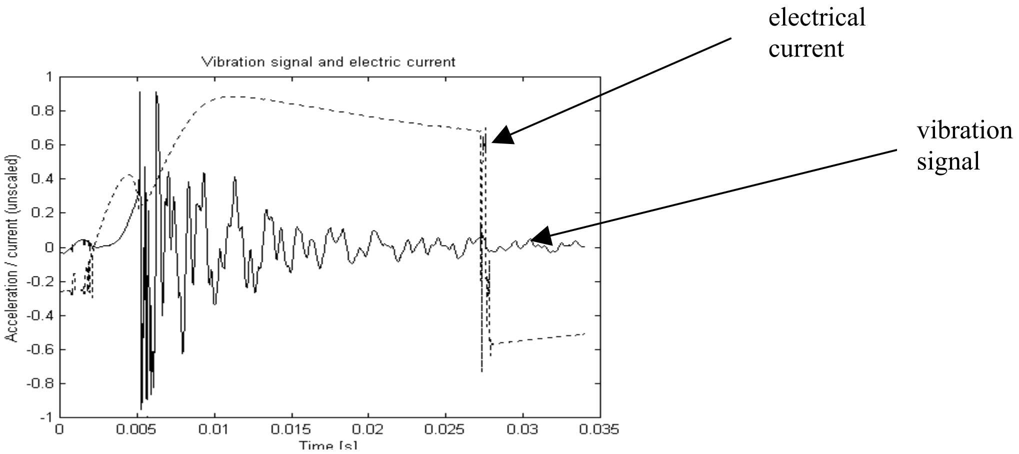

Figure 1: Vibration signal and electrical current

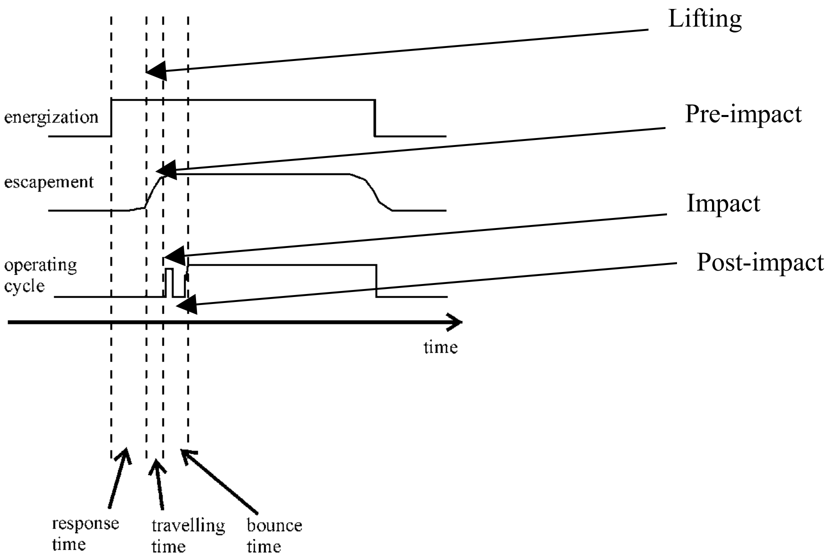

Figure 2: Temporal operation of a switching event

In Table 1 the different sections of the movement and the mechanical interpretation of the vibration signal are listed. The interpretablility is an important advantage of segmentation in the time domain. The different segments of vibration coincide with available expert knowledge and experience.

No	Section	Interpretation / included Information
1	Lifting	Change from static to sliding friction
2	Pre-impact	• Friction during the motion • Travelling time of the movable part
3	Impact	• Energy of the impact • Condition of the movable part
4	Post-impact	• Condition of the whole vibrating device • Bouncing of the movable part in the device can be detected in this segment

Table 1: Sections of the movement

3. Segmentation in the time-domain

The different origins of the four sections cause that the overall signal is non-stationary and that it is not reasonable to analyse the entire signal as a whole. To segment the vibration signal into the four sections (i=1..4) a new window method is proposed.

The four windows are not of equal length and shape as the windows usually used for time-frequency-distributions (Sun 2000) like the short-time Fourier transform (STFT). In eq. 10 the window is described.

$$W_i(t)=\begin{cases}0, & t \le b1_i \\ \frac{1}{2}\left[1-\mathbf{cos}\left(2\cdot\pi\cdot(t-b1_i)/(2\cdot b2_i)\right)\right] & b1_i < t \le b1_i + b2_i \\ 1, & b1_i + b2_i < t \le b1_i + b2_i + b3_i \\ \frac{1}{2}\left[1-\mathbf{cos}\left(2\cdot\pi\cdot\left(b1_i+b2_i+b3_i+b4_i-t\right)/(2\cdot b4_i)\right)\right], & b1_i + b2_i + b3_i < t \le b1_i + b2_i + b3_i + b4_i \\ 0, & b1_i + b2_i + b3_i + b4_i < t \le b1_i + b2_i + b3_i + b4_i + b5_i \end{cases} \qquad (1)$$

Five sections (j=1..5) with arbitrary length ($b1_i..b5_i$) are used to describe the i^{th} window. For sampled time signals with equidistant sampling intervals the parameters $b1_i$ – $b5_i$ are the number of data points for each section. The first section is a zero-valued part of length $b1_i$ and is used to suppress the part of the original time signal before the section of interest. The second part is a rising edge with Hanning characteristic (Oppenheim 1989). The next part is the identity function to separate a section of the original time signal with an arbitrary length without perturbation. A decaying Hanning edge is the next section and at last the window equals zero again to suppress the right part of the original time signal.

4. Segmentation in the frequency-domain

In the frequency domain the original signal was separated in two parts by two filters. The higher frequency part corresponds to more random parts of the vibration and in the lower frequency segment the ringing of the natural frequencies can be found (Ellwein 2000b). The cut-off frequency for both filters is determined by the Multi-ACF-algorithm. The advantage of this new algorithm over fixed cut-off frequencies is the increased fitting of the cut-off frequency in the raw-data. In the literature a fixed frequency threshold was proposed in (Alguindigue 1993, Kiesbauer 2000). This new algorithm is an iterative application of the autocorrelation function to the data. After the first pass, the result of the last ACF is used as new input for the next iteration (see Fig. 3).

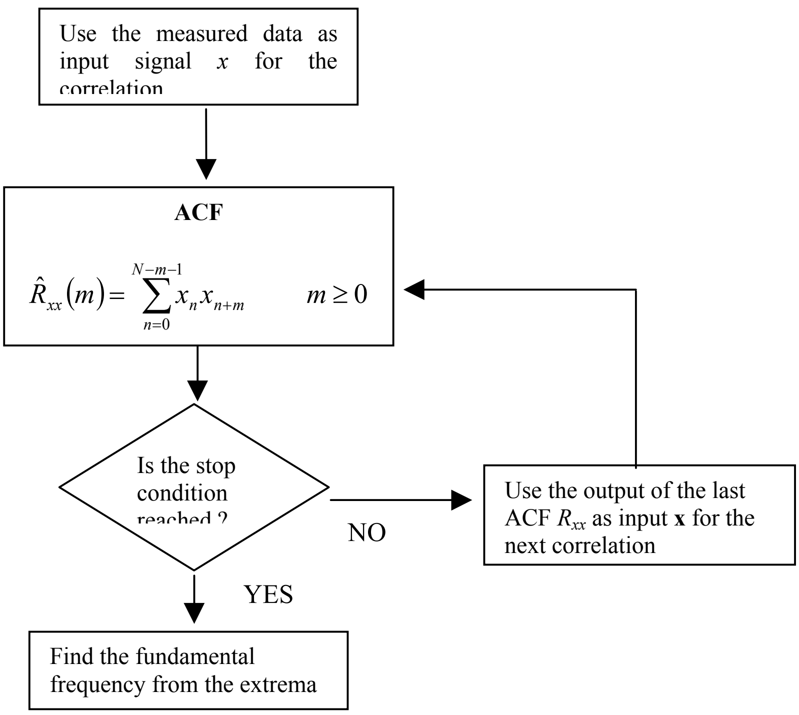

Figure 3: The Multi-ACF-algorithm

The period of the non-random part of **x** can be detected by measuring the distance between the minima and / or maxima. The extrema in a discrete signal can be found by Equation

$$m(t) = \frac{1}{2} \cdot \left| \frac{\Delta\left(sign\left(\frac{\Delta x(t)}{\Delta t} \right) \right)}{\Delta t} \right| \tag{7}$$

All extrema in $x(t)$ are represented by a peak of value one in $m(t)$. The fundamental frequency of the periodic part can be found by computing the inverse of the distance between to peaks in $m(t)$.

$$f_{fund} = \frac{1}{m(t_2) - m(t_1)} \quad t_2 > t_1 \text{ and } m(t_1), m(t_2) = 1 \tag{8}$$

Because the random parts of $x(t)$ vanish not completely the fundamental frequency is scattering for different pairs (t_n, t_{n+1}). Especially for short data segments **x** the random parts of **x** are often not suppressed properly. This drawback can be reduced by applying the Multi-ACF-algorithm. The ACF as defined in Eq. 2 is biased and linearly damped. This damping of each ACF will also influence the periodic part of **x** in the Multi-ACF-algorithm. Thus it is important to find the right number of iterations for the Multi-ACF-algorithm, that is to define a suitable stop-condition (Fig 2) . If the number is to small the influence of the random parts of **x** will result a high scatter in the fundamental frequency. On the other hand, if there are to many iterations the periodic parts of **x** are also damped to much and the ACF is vanishing completely.

A suitable stop-criterion was found in the standard deviation of the fundamental frequency calculated over all pairs $(t_n, t_{n+1} | m(t_n), m(t_{n+1}) = 1)$ of $m(t)$. If the standard deviation is computed for each iteration there will be a minimum when the influence of the linear damping is minimal with respect to the influence of the random parts of **x**. The iteration when the minimum is reached is optimal in this sense for the Multi-ACF-algorithm.

5. Results

5.1 Data acquisition

The vibration data were acquired with an capacitive micromachined accelerometer type ADXL105 from Analog Devices. This IC is a single-axis sensor with 20kHz resonance frequency, ±5*g* full-scale range and up to 1.5V/*g* programmable output scale factor. Three piecoelectric sensors were used for reference measurements (Kistler accelerometers type 8636C10, 8636C50 and 8730AE500). The ADXL105 is mounted with a two-sided sticky tape as recommended in literature (PCB Piezotronics 1999) at the cable head of the valve. To damp the vibration for the measurement range of the sensor a piece of rubber (perbunan) with 0.196 inch (=5mm) thickness was mounted between the transducer and the cable head. The sensor output was sampled with a sound-card (SoundBlaster-16pnp) (Ellwein 2000a). The sampling rate for the data acquisition was 44,1kHz and the accuracy 16bits. Vibration signals of 40 different valves type 6011 About 8000 switching events were recorded in total. The internal leakage of the valves with fault 4 was between 0.1 l/min and 10.5 l/min. In the valves with fault 5 small chips of iron (0.1g/valve) or small chips of polyamide (0.03g/valve) were added in the valves. The valves were connected to compressed air with different pressures (0, 7.25, 72.5 and 145 psi).

5.2 Test for stationarity

The stationarity of the original signal and the segments was tested as described in [Bendat 1986] with the run-test. In Fig. 4 – 7 the results are shown. The signal is stationary if the number of the runs lies within the borders of the run-test (solid lines in the Figures). The unsegmented original signal is represented by the circles and the crosses represent the segment. Each circle or cross is the test of a certain switching event with or without segmentation. The segments are nearly stationary except the post-impact signal (Fig. 7). But also the post-impact signal is more suitable for further processing because it contains mainly the influence of the ringing natural frequencies which are damped sinoids. Thus the dregree of stationarity was increased strong by the segmentation in the frequency- and time-domain.

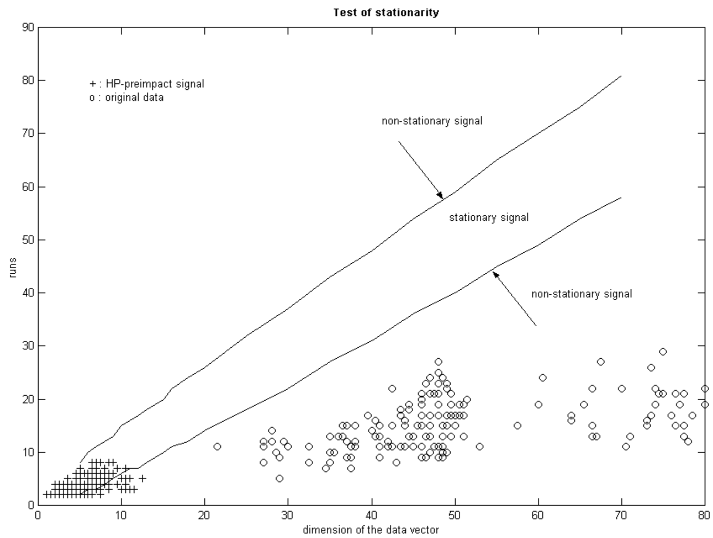

Fig. 4: Test for stationarity of the HP-preimpact signal

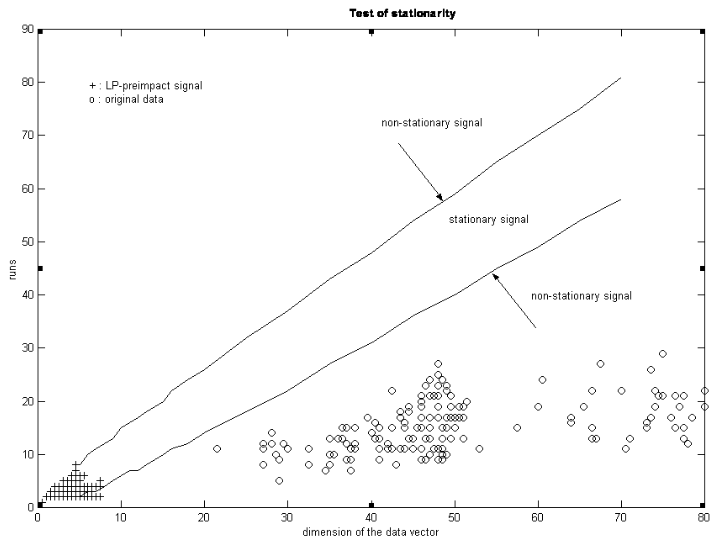

Fig. 5: Test for stationarity of the LP-preimpact signal

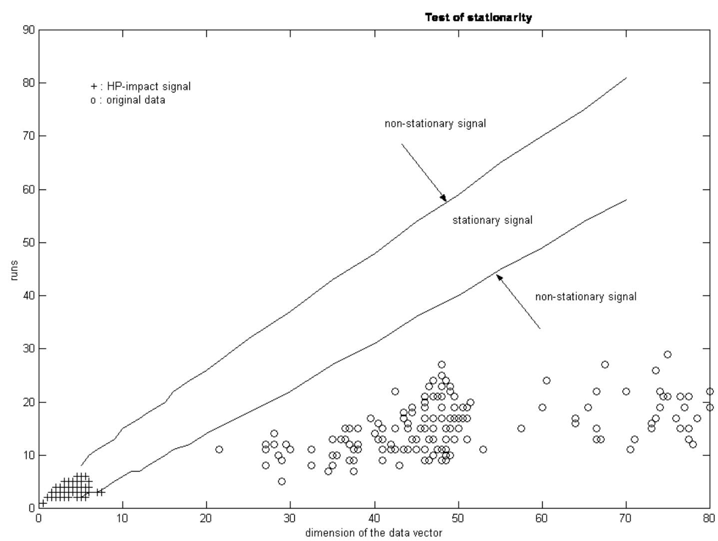

Fig. 6: Test for stationarity of the HP-impact signal

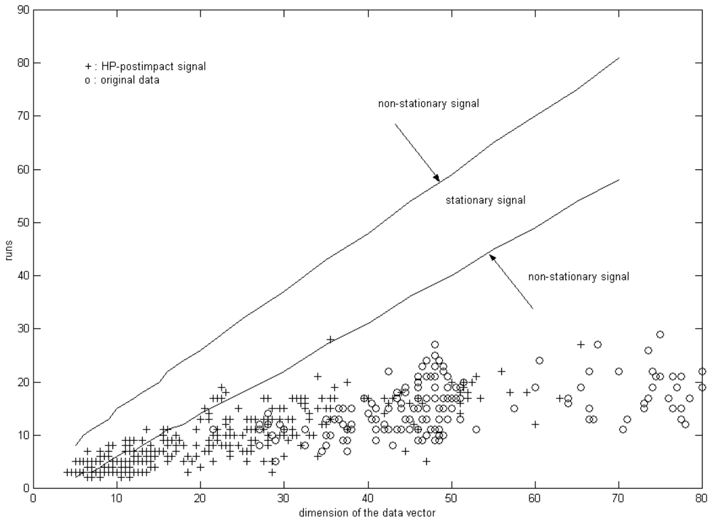

Fig. 7: Test for stationarity of the HP-postimpact signal

6. Literature

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