EVALUATING SIGNAL PROCESSING METHODS FOR USE IN GEARBOX CONDITION MONITORING

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Intelligent machinery condition monitoring and damage diagnostics is becoming increasingly important: Meeting low maintenance budgets is of key importance in a more and more globalized and competitive market environment. Being able to detect gearbox damage early and in an automated way allows for extended service intervals, less standstill and decreased total cost. One of the know mechanisms of gear failure is the occurrence of pitting on gear teeth flanks. Advancing pitting damage leads to a shift in the noise excitation behaviour of a gear pair. Common gearbox condition monitoring solution often rely on acceleration measurements on the gearbox case. As a means of excitation behaviour examination, angular position encoders are able to provide high quality data on the gear pair transmission error. These angular encoders work preferably at low rotational speeds. Transmission error is widely used to characterize the tooth flank form and quality relating to noise excitation. Recording and processing high-frequency and high-precision angular shaft positions to utilize them in subsequent flank damage detection at high rotational speeds poses a challenge. An FZG standard gear test rig was equipped with angular position encoders, acceleration sensors and the corresponding data acquisition units. This sensorial equipment is capable of performing synchronous, high-frequency combined measurements of angular positions of the shafts and acceleration signals on the gear housing. A detailed evaluation shows that an early damage detection with position encoder signals is possible. Different digital signal processing methods were examined and compared regarding their appropriateness for pitting damage detection.

Keywords: Condition Monitoring, Gears, Noise Excitation, Acceleration Sensors, Digital Signal Processing

1. Introduction

Transmissions often form a central part of machines and are common in many different technological products. They have e.g. automotive, aviation, energy sector, food technology, agricultural and construction engineering appliances. Gears are counted amongst the most common elements in transmissions, at the same time being functionally critical. Gears are often dimensioned in such a way that neither too much of material and space is used nor the load capacity design target is missed.

Gears can show various damage patterns, depending on e.g. gear material, gear geometry, gear load spectrum or lubrication condition. Some of these occur on or below the gear tooth flank surface, others occur in the tooth root region. Fig. 1 shows exemplary occurrances of three kinds of gear flank damage: pitting, wear and micropitting.

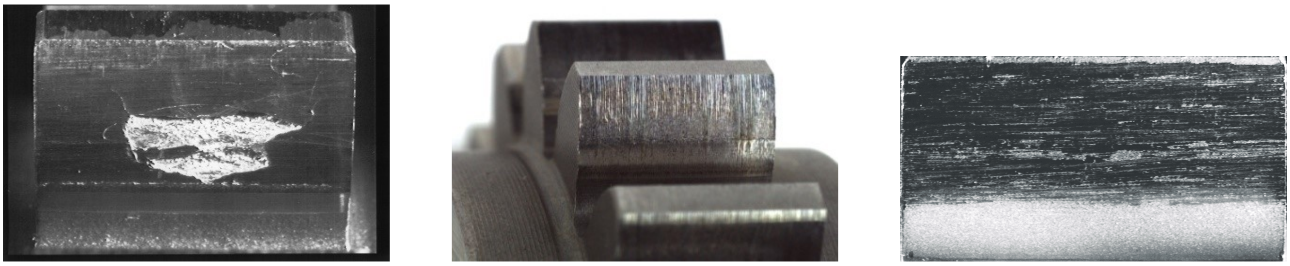

Figure 1: Samples of gear flank damage, left to right: pitting, wear, micropitting

Progressing gear damage can lead to increasing noise excitation levels and ultimately to a complete failure of the machine. Numerous research projects as well as commercial developments have been conducted in order to perform early detection of emerging gear flank form modifications.

Being able to reliably detect gear damage can allow for an overall reduction of noise and vibration levels as well as longer maintenance intervals (up to condition based maintenance), less downtimes and ultimately less total cost of ownership.

A selection of experimental set-ups as well as commonly used signal processing methods shall be given below.

2. Gear condition monitoring and excitation behaviour evaluation in practice

Commercial and research equipment for gear condition monitoring often relies on acceleration sensors in combination with tachometers. The acceleration sensors are often fixed to the transmission housing of the machine or test rig that is to be monitored. The tachometer signals are usually acquired from the gear shafts of the gears that shall be observed. Time-invariant auxiliary numbers such as the gear tooth count often serve as additional input parameters for the subsequent signal processing.

Alternatively, the loaded transmission error (LTE) can serve as a criterion for evaluating the noise excitation behaviour of a gear mesh. It can be obtained by measuring the angular positions of both shafts of one gear stage while it is revolving under torque load. The LTE can be defined as the difference between the actual angular position of the driven gear and the theoretical position it would occupy if the system were ideally stiff and both gears perfectly conjugate. It is often measured at slow, quasi-static rotational shaft speeds.

2.1 LTE and gear condition monitoring in research

Remond[1] explored how angular encoders can be used for high-speed LTE measurements. For reaching high angular speeds, incremental angular encoders with small numbers of increments were used. For acquiring absolute angular positions with incremental encoders, the increments have to be reliably tracked and counted. For increased angular resolution, the temporal extent of each increment was measured by high-frequency sampling (in addition to counting the increments). For this enhancement of accuracy, a constant angular shaft speed during the extent of one encoder increment was assumed.

This assumption has to be re-evaluated if highly dynamic LTEs - as they can occur if damaged, discontinuous gear flank areas are rolled over - are to be measured.

Henriksson[2] investigated the correlation between the LTE at full speed (dynamic transmission error, DTE), the structure-borne vibration and the noise emission using the example of a lorry gearbox. To capture these three measurands, angular encoders, acceleration sensors and microphones were used. Correlation between DTE and airborne noise could be shown. Additionally, static LTEs were calculated and compared to the measured air-borne sound levels. In some operating ranges, divergent behaviour could be observed. Henriksson[2] attributes this to non-linear effects such as shaft resonance. A commercial measurement system was used for this research. It allowed for acquisition of the three measurands using one common time axis. The highest shaft speed in this research was 2000 /min.

Singh[3] evaluated the suitability of acoustic emission (AE) sensors for pitting damage detection. AE sensors are acceleration sensors specially designed to detect elastic waves in solid bodies as they produced from e.g. cracking events. Depending on their design, they are capable of detecting high frequency events. The can be designed to be intentionally operated above their own main resonance frequency (i.e. supercritical). Singh[3] mounted AE sensors and conventional acceleration sensors onto the casing of a test gearbox. He conducted experiments with artificial dimples as well as with gears bearing natural pitting damage. The acceleration signals were averaged per-revolution using an additional tachometer signal. Singh[3] concludes that AE sensors show a significant signal influence of pitting earlier than conventional sensors, having a higher signal/noise ratio.

Weinberger[4] calculated the total transmission error of complex gearboxes.

2.1.1 Signal processing methods

For processing the obtained signals with the target of detecting gear damage, numerous methods are documented and have been practically applied. This section shall give a brief overview.

Time-domain methods

These methods analyze signals without transforming them. They are basic, and have often been replaced by more complex methods, enabled by increased computing capacities.

Aherwar[5] and Forrester[6] have shown that some criteria of this category - such as the root mean square (RMS), evaluation of signal extreme values, the crest factor, signal skewness - are suitable only for detecting major damage occurances.

Other time-domain processing methods are actively employed in condition monitoring, either as signal preprocessing method (such as time-synchronized signal averaging) or as direct criterion (e.g. kurtosis; According to Pachaud[7] kurtosis is susceptible to noise and often requires filtering. On the other hand - according to Townsend[8] - a time-synchronously averaged signal can serve for condition monitoring purposes using kurtosis as criterion).

Frequency-domain methods

Frequency-domain methods in digital signal processing in general rely on the discrete Fourier transform (DFT) - or rather the fast Fourier transform (FFT) in practical implementations. The FFT serves as foundation for a variety of condition monitoring approaches. Among mentionable are:

- Spectrum comparison
  This is the most basic form of frequency-domain condition monitoring approaches. Amplitudes of spectra of a running machine are compared to one or more spectra from a machine state know as not faulty. Randall[9] considers an amplitude increase of more than 6 dB in acceleration signal spectra as 'significant', an increase of more than 20 dB as 'serious'.
- Spectrum comparison using spectral masks
  This technique is an extension of the aforementioned spectrum comparison. Before being utilized for comparison, the non-faulty spectra are broadened in frequency direction. This envelope spectrum leaves room for small amounts of frequency shifts as they can occur with e.g. slightly inconstant rotational speeds of a machine drive unit. If the spectral mask is well-formed for the designated purpose, this can lead to less false positives while retaining the ability to detect damage.
- Sideband analysis
  For the sideband analysis, sideband structures forming around defined reference frequencies (e.g. gear mesh frequency of a gear stage) are analysed. Sideband analysis can allow for

classifying condition monitoring signals in terms of damage type.

Time-frequency-domain methods
These methods provide time variant spectral representations. They are highly heterogeneous; Feng[10] categorizes them into linear, bilinear, higher-order and adaptive methods. Selected examples:

- Short-time Fourier transform (STFT)
  The STFT has been the first method of the time-frequency domain category. This linear method uses a moving window in order to cut a time signal into shorter partial signals. Those partial signal are assumed quasi-stationary and individually processed by means of FFT. STFT applications often use a fixed window size and as such have a fixed ratio of time-domain to frequency-domain resolution. The nature of the FFT leads to problems when using STFT to analyse highly transient signals.
- Wavelet transform
  Instead of stationary sine functions as in the FFT, the linear wavelet transform uses special wavelet functions as transformation base. These wavelet functions hold finite signal energy and therefore can be located along the time axis. This leads to a better suitability for transient time signals than e.g. the STFT.
- Wigner-Ville transform (WVT)
  This bilinear transform[11] often serves as a basis for other methods of the bilinear class. In general it offers a better time-frequency resolution than the STFT, especially when applied to highly transient signals. Because of the quadratic nature of the WVT, signals composed of more than one component produce interference terms. For example, the WVT of a signal consisting of two components equals the sum of the WVT of the two individual components plus an interference term. Approaches for separating these interference terms have been proposed[12].
- Hilbert-Huang transform (HHT)
  This adaptive, non-parametric transform iteratively separates a multi-component time signal into separate functions ("intrinsic mode functions", IMFs) for each signal component until the signal is decomposed into a number of IMFs and a monotonic residuum (the difference of the original singal and each IMF). Knowing the mode functions of each components, the HHT of the original signal can then be displayed as the linear superposition of each single IMF's time-frequency distribution. This avoids interference terms as they occur in higher-order methods as the WVT. It has been proposed by Huang et al.[13], its derivation and various applications being subsequently commented by Huang et al. in numerous publications[14][15] and books[16].

3. Per-tooth gear condition monitoring

The approaches used in industrial practice and in research usually do not evaluate gear condition monitoring signals on a per-tooth basis. A per-tooth approach for gear condition monitoring has been tested, based on earlier work[17]. The utilized test rig set-up, details on the signal processing chain as well as a first comparison to existing methods shall be given in the following sections.

3.1 Gear test rig

For exploring per-tooth gear condition monitoring, an FZG gear test rig was used. Fig. 2 shows a perspective sketch and the corresponding schematic diagram of this test rig type.

This test rig consists of two gear stages, each formed by two cylindrical, involute gears. One stage serves as test stage (B and C in fig. 2) and is designed to produce pitting damage after a finite number of load cycles. The other stage (D in fig. 2) serves as retransmission; both stages and their shafts form a power loop. Torque can be inserted into this loop by means of a loading clutch (A in fig. 2). For this, the clutch is opened at standstill. Then the clutch halves are twisted relative to each other by a defined amount. Afterwards, the clutch is closed again. As both gear stages are arranged in a loop, the electric motor (F in fig. 2) has to insert just the dissipating power into the system. To monitor the torque in the loop, some kind of torque indicator or sensor is used (E in fig. 2).

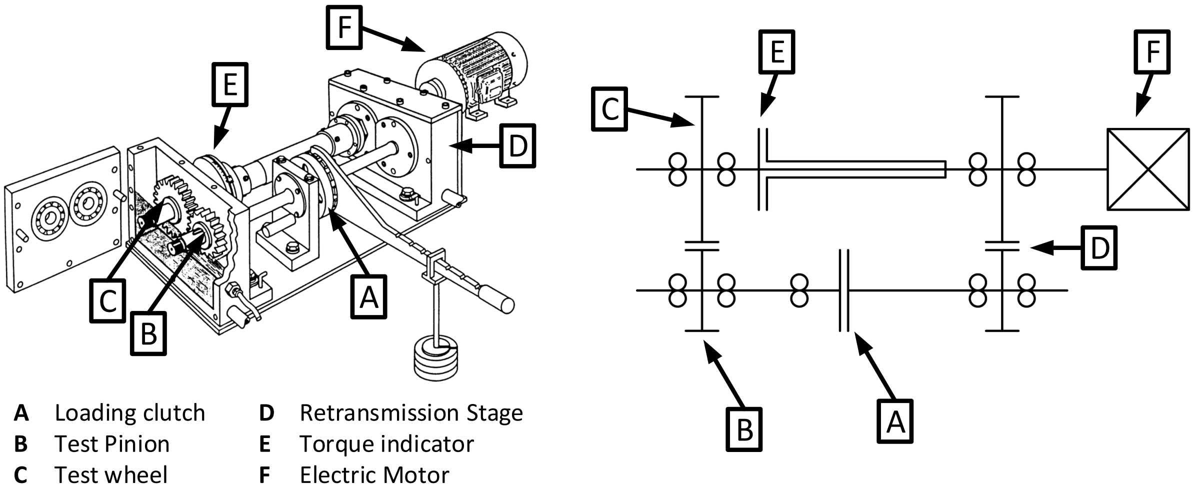

Figure 2: FZG gear test rig

3.2 Enhancing the test rig sensor equipment

In order to allow for a tooth specific acceleration signal processing, the gear test rig sensor equipment has been enhanced, based on earlier research[17]. In addition to piezoelectric acceleration sensors mounted to the case of the test gear stage, absolute angular encoders were attached to the two test rig shafts. They were placed as close to the test gears as physically possible - because of the optical nature of angular measurement, mounting them inside the case has not been possible. These absolute angular encoders provide a way out of the incremental encoders' dilemma: Their increment-counting method of data acquisition makes it difficult for both shaft rotational speed and measurement accuracy to be maximised at the same time.

Absolute angular encoders offer fixed measurement frequencies at high accuracy, and - depending mainly on the shaft diameter - are usable on shafts with rotational speeds up to tens of thousands of revolutions per minute. The specification of the selected absolute angular encoder are listed in table 1.

Table 1: Specification of used angular encoder [18]

Property	Value
type	optical, absolute
max. operating temperature	80 °C
system accuracy (angular seconds)	$\pm$ 3.82 $''$
max. shaft speed	25 000 min^{-1}
max. measurement frequency	ca. 25 kHz
outer diameter	75 mm
electric signal	5V TTL
data protocol	BiSS

3.3 Comparison of per-tooth evaluation and total signal evaluation

For a first assessment of the suitability for condition monitoring, a standardized pitting test has been monitored. This test consists of a run-in phase after which the test rig is operated in blocks of

$1.8 \cdot 10^6$ load cycles. Every ten minutes, a combined measurement of angular shaft positions an gear case acceleration was acquired. Each measurement lasted for five seconds.

Using the angular signal, acceleration signals were split and then assigned to each of the 17 teeth of the test pinion. For each tooth, the split signals were recomposed into per-tooth acceleration signals (with discontinuities). The assumption was made that a damaged tooth generated more vibration power than a not damaged tooth when being rolled over. Thus, a relative, mean signal power L_s according to Ohm [19] was calculated from the per-tooth acceleration signals, and its change along the course of measurments has been observed. Signal power L_s is calculated acc. to equation (1) ($s(t)$ being the signal value at the time t).

$$L_s = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} |s(t)|^2 \mathrm{d}t \qquad (1)$$

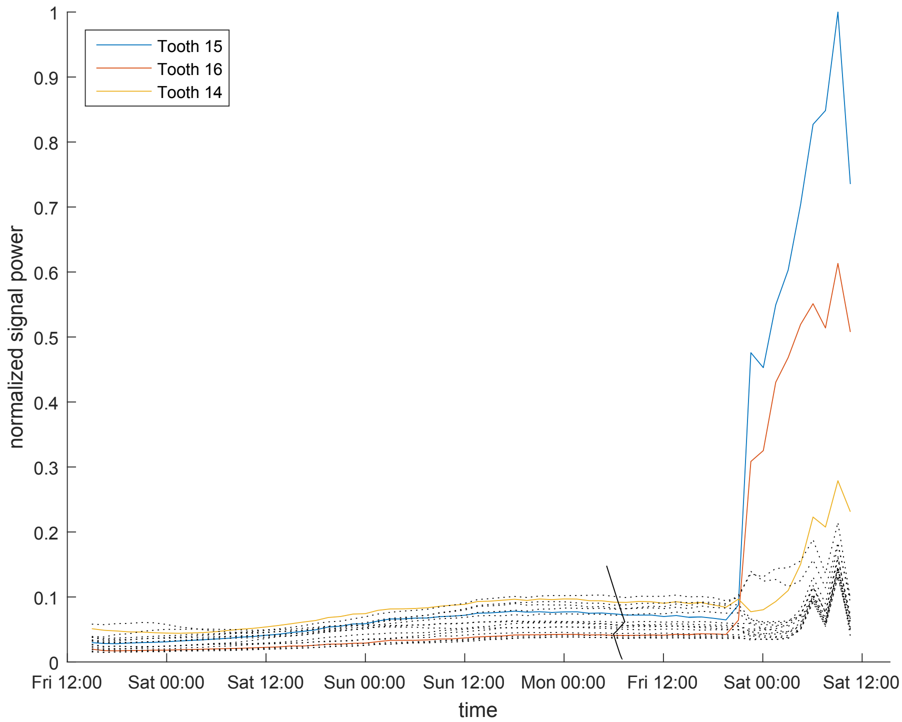

Figure 3: per-tooth signal power for sample experiment

In fig. 3 the per-tooth signal power graphs (normalized to the maximum value) are shown. A mapping of actual gear teeth to the tooth-specific acceleration signals has not been made, but in measurement as well as at the real test pinion the three most notable teeth are in a sequence. At peak, per-tooth signal 15 rises above the non-damaged signal levels by a factor of about 10. Per-teeth signal levels are significantly increased at about six hours before the experiment has been ended by an external vibration monitor (pre-loaded leaf spring principle) connected to the test rig's PLC.

For comparison purposes, a non tooth-specific approach for condition monitoring has additionally been implemented. For this, a common condition monitoring sensor equipment consisting of acceleration sensors and a tachometer signal is sufficient. The algorithm:

1. Shaft-synchronized acceleration signal averaging (eliminates disturbances that are not periodic with multiples of shaft frequency)
2. FFT of the averaged acceleration signal
3. First few measurements (gears assumed to be intact) are used for spectral mask generation:
   (a) Generation of spectral mask by broadening the acceleration spectra, increasing the mask amplitudes over the original spectrum amplitudes by 10% and ensuring a maximum dy-

namic range of about 40dB (this accounts for data acquisition system limitation of dynamic range, see Randall[9]).

(b) Averaging the masks of the first few measurements. This helps reducing false positives by non-damage processes such as running-in, build-up of heat etc.

4. Each measured spectrum is being compared to the spectral mask. The sum of all amplitude values that exceeded the mask is calculated and serves as a gear condition criterion.

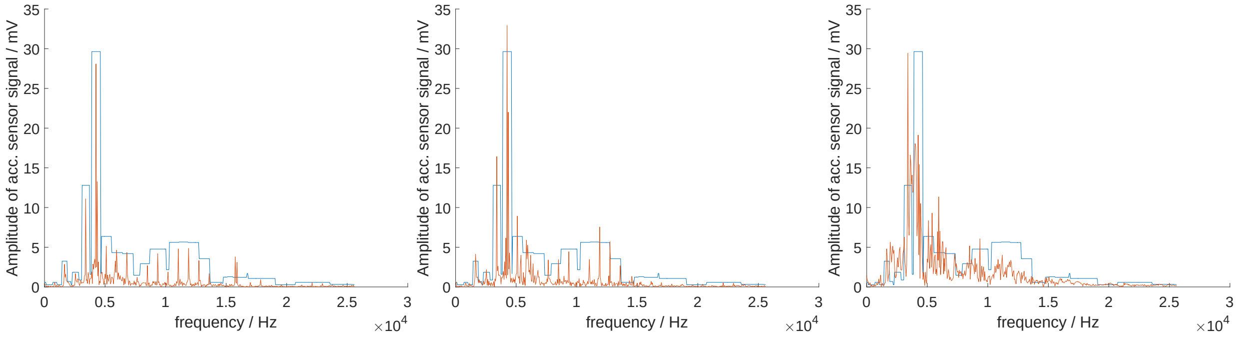

Figure 4: signal spectra at the beginning, in the midst and at the end of the pitting test (left to right), with mask

Fig. 4 shows three acceleration signal spectra from the beginning, in the midst and at the end of the pitting test. In addition, the mask generated from the first few measurements is shown (graph composed from rectangles) - it is constant throughout each pitting test.

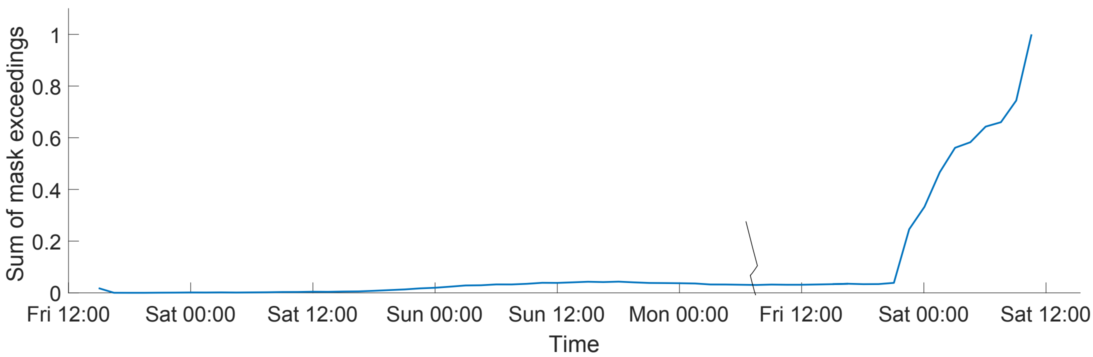

Figure 5: normalized sum of mask exceeding amplitude values

Fig. 5 shows the corresponding sum of all mask exceeding amplitudes of each measurements over the course of the pitting test. This kind of evaluation shows an even higher ratio (value being ca. 30) between the damaged and non-damaged signal levels. The signal level rises significantly at about six hours before the end of the experiment - this is similar to the per-tooth evaluation.

4. Conclusion

At an FZG gear test rig acceleration sensors were mounted on the test gear case, absolute angular encoders were attached to the test rig shafts. A test was conducted that produced pitting damage on the test pinion, this test hast been accompanied by measurements.

In order to evaluate the feasibility of per-tooth condition monitoring, tooth based signal splitting was done and signal power values were calculated for the course of the test. The per-tooth signal characteristics showed a general suitability for monitoring single teeth.

For comparison purposes, a spectral mask analysis of the non-split signal has been done, as it is possible using just acceleration sensors and tachometer signals. This showed an even better signal to noise ratio, but needed more parametrisation than the per-tooth analysis: a non-damaged state has to be defined in order to generate a spectral mask, whereas the per-tooth approach allows comparison between teeth without having to know an initial state. This makes the per-tooth approach applicable for e.g. end-of-line machine tests even for small batches.

Further theoretical and experimental investigation is planned for the per-tooth approach in order to achieve a better signal to noise ratio, e.g. by applying shaft-synchronized averaging to the per-tooth approach or by evaluating results for longer measurements.

Also, additional comparisons to latest signal processing and condition monitoring approaches are planned.

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