Adaptive Data Compression of Ultrasound Data for Long Term Data Acquisition and Trend Evaluation

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Abstract

Data compression technologies such as MP3 have been extensively used for audio technologies. There are two objectives: to maintain the quality of the original sound and two compress the data as much as possible. The degree of compression depends strongly from the signal character. The information of pure harmonic signals can be much better compressed than signals.
The ultrasound produced by various processes in industry has been used for maintenance purposes since some decades. Typical signals have noisy character. Examples are leakage noise, jet noise, the noise of friction in bearings and gears. Signals are generated from (shock) pulses such as bearing faults (cracks or spalled areas) or arcing during electrical discharge.
Traditionally, ultrasound data for maintenance are evaluated by means of narrow band techniques such as heterodyning the ultrasound into the audible range, thereby a reduction of the data rate can achieved. In order to avoid the loss of real physical information, ultrasound broadband technology was introduced in order to consider the complete frequency range leading to a considerably increased data rate. Long-term recording of monitoring data would generate a huge amount of data on short time scales. Furthermore, the broadband technologies require new approaches to make the signal audible. Therefore, a vocoder technique has been modified in order to compress the ultrasound data in real-time to a bandwidth which is compatible to the listening capabilities of testing persons. The spectra of compressed data are also useful for the interpretation of measured data. The degree of loss with respect to the information content has estimated in comparison to the original uncompressed signal. Pattern recognition techniques based on Cellular Neural Networks have been applied to ultrasound data (to original and the compressed audible data).

1. Introduction

1.1 Some Fundamentals of Ultrasound in Condition Monitoring

The increasing importance of maintenance is obvious. Maintenance ensures the availability and reliability of machines and facilities. Different strategies for maintenance have been developed to improve the reliability of predictions. Vibration data (ranging from simple testing tasks to advanced data processing) form the backbone of practical maintenance strategies. In the context of the article, ultrasound frequencies up to approximately 100 kHz are included.

The application of ultrasonic sensors and methods for condition monitoring has been discussed in several papers (1-3). The term *acoustic emission* is often used as special acoustic technology to measure and evaluate transient (high-frequency) signals (4). Acoustic emission is often discussed in a comprehensive sense for all acoustical processes (continuous, transient, stochastic) at higher frequencies. However, the ultrasound methods in maintenance are often used more or less qualitatively by the application of simple techniques and methods (e.g. using rms-values for the recording and evaluation of states and trends). Ultrasound provides early indications of bearing wear and can be used for the predictive analyses of trends in machinery states. Vibration and ultrasound can often be used complementary.The potential of ultrasound methods remains very often unused. Traditional ultrasound (handheld) equipment is used in maintenance for tasks such as leakage detection, testing of steam traps, detection of discharges, checking the state and the quality of lubrication, bearing diagnostics.

From the point of view of signal processing, these applications generate relatively "structure-less" and noisy acoustic data. Consequently, testing handheld equipment with almost no signal processing dominates the market. However, much more demanding applications such as trend analyses, health monitoring, fracture warning and lifetime prognoses and other advanced methods require state-of-the-art computing and signal processing. The value of ultrasound for machinery inspection has been demonstrated by means of several case studies (5). In contrast to the "traditional" hit-counting measurement and data processing of the classical "Acoustic Emission" a continuous signal processing will be applied for many practical situations in maintenance. However, (high-frequency) acoustic emission remains a valuable tool for monitoring of different kind of bearings and other rotating parts in machinery (6, 7). AE is sensitivity to friction and therefore used for control of lubrication and for the prevention of boundary friction. An interesting point is the interaction between different scales of physical phenomena (8). Friction becomes acoustically active on *nm*- to μm-level. This low scale sensitivity is one of the physical reasons for the ability of ultrasound maintenance methods for early predictions.

The advantages of the use of higher frequencies have been recently demonstrated in several publications. Caused by the sensitivity to friction, high frequency vibration has some potential for the monitoring of very low speed of bearing (9). This has been shown also by a complementary research and comparison of the machinery fault detection with traditional vibration methods (10). Analogously, journal bearings are sensitive with respect to acoustic emission. Classical vibration methods often fail (6, 9, 11). However, the extraction of valuable information requires some mathematical effort which is not on board of the standard equipment.

Currently, there is a rapid and successful development on the field of pattern recognition. Prominent examples are image and speech recognition. Despite of a large number of reports in the scientific literature there are only few industrial applications. Cheaper electronics and more performant computing circuit enable new applications of classification and pattern methods (12-14). It can be assumed, that similar methods and algorithms can also be found for ultrasound vibrations which have been successfully developed and applied for the "low frequency vibration" diagnosis.

The most important applications of vibration-based measurement technologies are related to bearings and gear monitoring. Vibration analysis and technical acoustics investigations are predominantly done in the frequency range up to 20 kHz. However, the extension to higher frequencies provides valuable diagnostic information.

Ultrasound inspection exhibits - compared to vibration - some peculiarities. Traditional basic ultrasound instruments for the monitoring of machinery states provide only relatively simple parameters (such as the sound level). Analogous devices are still standard which operate with of narrow-band sensors and electronics. Commonly, the signal is heterodyned (the standard carrier frequency is about 40 kHz caused by the availability of inexpensive transducers). That means that only a narrow frequency band is used to extract information. The frequency content is almost completely lost. Some diagnostic data are derived from the fluctuation of the amplitude of the heterodyned signal. This limits the informative value of ultrasound results since the most physical processes generate ultrasound in a broad frequency range. The heterodyned time signal is in the audio range. However, this cannot be utilized by means of the current analogous ultrasound equipment on the market. More important for the operators, the heterodyne signal can be sent to an audio output (loudspeaker / headphone). Experienced testing operators are able to listen even to "hidden" fault noise and do some kind of "manmade" pattern recognition. But, experience is the prerequisite and the methods remain subjective. This method is not appropriate for long term interpretation in the context of maintenance where objective acquired data and data processing are essential. However, let us keep in mind, that the amount data volume is drastically reduced. The use of the ultrasound high-frequency data would produce much more data volume and require much more computational power.
An approach has been developed for a reconsideration of the use of ultrasound for industrial monitoring (15). The extension of the frequency range has been realized by a consequent digitization of the measurement and signal processing. This results in a broad-band technology for the simultaneous monitoring of processes which cause vibrations up to frequencies of about 200 kHz.
A further important prerequisite for the exploitation of the complete physically-based information (in acoustical broad-band signals) are proper sensors for structural-borne noise. Therefore, sensors have been developed on the basis of new piezo-electric composite material (5, 16) which enables acoustic measurements in a broad frequency range. The sensors have some favourable properties which have been reported elsewhere. Despite of the concentration on ultrasound frequencies within this work, the sensors could be also used for the simultaneous investigation of vibration effects at low frequencies) and for high frequency (friction, cavitation) processes as well. Experimental examples are given for the diagnosis of bearing damage and other applications (5, 16). The advanced sensor principles (5, 16) are part of a new modular and scalable measurement concept which includes data acquisition and treatment, algorithms in real-time and improved calculation and predictions. One consequence is that signal processing gains more significance for the use of ultrasound methods. In some case, a complete revision and revaluation of measurement methods has been proposed.

1.2 Aurelization of Ultrasound Frequencies –and their Use for Data processing

The use of a broader frequency range has consequences for the audio output channel.
Different algorithms have been implemented in evaluation boards and in the destination hardware as well. First of all, heterodyne signal can be extracted "as usual". The carrier frequency can be digitally changed and tuned to the best practical value. When the HF-signal is recorded, all possible carrier frequencies can be recalculated. A pseudo-

broadband spectrum can be provided. The digital version of the heterodyne signal is valuable for an operator who is familiar with the conventional analogous devices.

A further method has been modified and implemented (17) in order to transfer the broadband signal into the audible range. The signal (the audible frequencies are filtered out) is conditioned for listening by means of a real-time Vocoder-procedure. All frequencies are compressed and shifted into the audible range. A compression factor of 32 has been implemented. That means that a frequency of 30 kHz provides a frequency of about 1 kHz and 60 KHz provides about 2 kHz. The temporary fluctuations (signal amplitudes) are still real-time as known from the heterodyne technology. All physically occurring frequencies are simultaneously represented. The audio signals sound different compared to the heterodyne version. In practise, some training seems to be necessary to use the different aurelization versions. As mentioned, the technical ultrasound noise has some stochastic character. Compressed broadband spectra are very similar the original spectra. The use of audio channel for data processing would drastically reduce the data storage space or the requirements for the calculation compressed without a remarkable loss of the physical information. Data reduction would be very valuable for long time recording of maintenance data. Such a recording of compressed audio signal technique would enable the conservation of the complete physical process. The gain for trend evaluation is obvious. In contrast to the traditional recording of “fixed” parameters (rms, $L_{\mu V}$, Crest, Kurtosis), adaptive algorithms can be provided in order to use optimal evaluation procedures in dependence on the actual state of machinery. Even recalculations of fault history with changed algorithms are realistic. An important objective is the improvement of the trend evaluation by means of techniques for pattern recognition such as neural networks.

A third technique has been proposed (17) for further data reduction. The amount of data can be also reduced when 1/n-octave spectra (n~12, 24) are calculated as a representation of the broad-band ultrasound signal. The recorded 1/n-octave spectra do not represent audio spectra in a classical meaning but the resolution is sufficient for many technical problems and even for a rough audio reconstruction. The audio output will be done by the generation of an artificial signal by the superposition of each 1/n-band by means of suitable filter banks. Of course, the data quality gets worse compared to the vocoder technique. However, the acoustic impression and the information content are sufficient for a rough reconstruction in many practical cases.

Ultrasound data exhibit stochastic character. The noise from pressurized air leakage, friction noise between surfaces and fluids (cavitation in pumps, turbulences) cause a relatively unstructured spectral behaviour. The information content is relatively small. The data compression within the aurelization process of the ultrasound data provides a further reduction. On the one hand, it makes no sense (and is not practicable) to record HF-data longer duration. On the other hand, the access to original data opens opportunities for improved maintenance predictions, especially in combination with advanced algorithms and data mining techniques.

Heterodyning selects an unspecific frequency slice from the whole spectrum. In the digital realization, any carrier frequency is possible. The valuable information arises from the amplitude fluctuation. The method works for unstructured broadband spectra (e.g. for the detection of electrical discharge). The vocoder algorithm preserves the principal broadband spectral structure of the original broadband spectrum. The resolution depends on the typical parameters for spectral algorithms and can be adapted. Transient events (such as electrical discharges) need short data blocks (low resolution), for steady state signals a much higher resolution can be achieved.

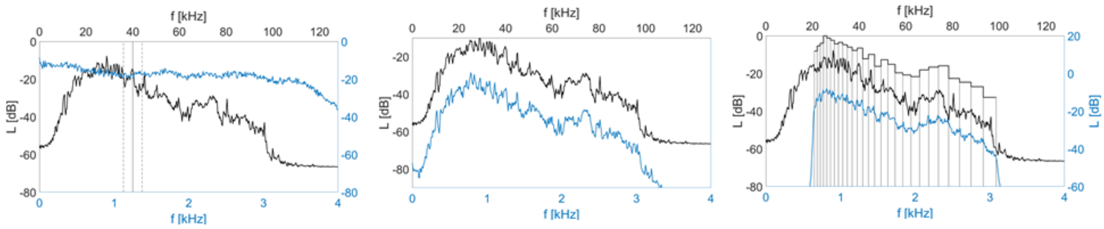

Figure 1. Left: The effect of heterodyning on the selection of frequencies from a broad-band spectrum. The narrow band around 40 kHz generates an unspecific 4 kHz audible band, Middle: Preservation of the spectral shape by the vocoder technique. Right: Data reduction using shifted 1/n-Octaves

2. Experimental and Results

The experiments have been done at some test rigs. The data acquisition has been made under MATLAB (data translation cards from DataTranslation and MATLAB-DAQ). Furthermore, a new digital ultrasound sensor could be directly coupled to a PC. The digital ultrasound system SONAPHONE III has been used for measurements under practical conditions. All sensors had identical transducer components. The calculation of the (audible) audio has been done either with the MATLAB development environment or with the built-in functionality of the SONAPHONE III.
Standard roller bearings have been manipulated by an engraving laser. Five systematically varied faults (Typ SKF E2.6002-2Z/C3, 3 of each fault extension) have been prepared. Including the intact ones, there was an experimental set 18 bearings.

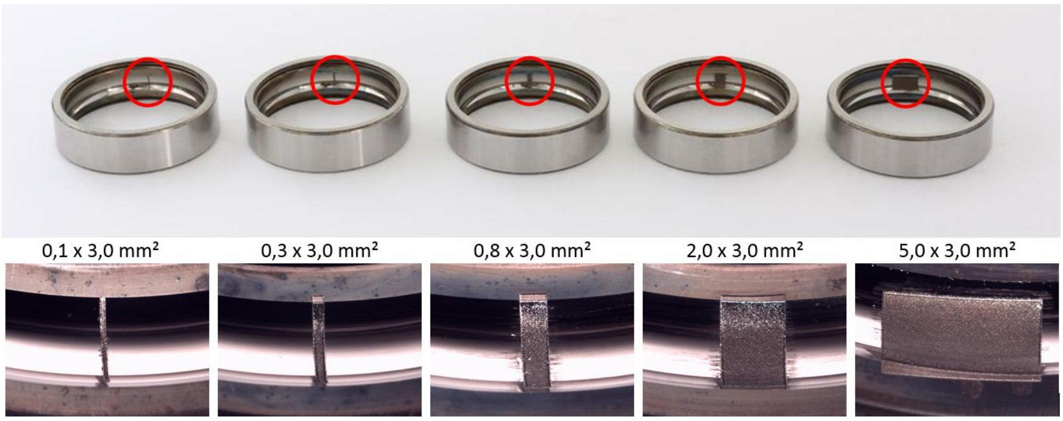

Figure2. Variation of the extension of an outer ring defects (made by LASER engraving). The surface topologies of the defects are comparable.

Typical parameters (for the description of machine condition) have been calculated. However, single parameters do not describe the changes of operational states or different preparations as well. More stability can be achieved by combination of parameters or advanced data processing. The reduction of data (e.g. by using the aurelization data) provides – of course – data loss. The question can be asked: how reliable is the extraction of parameters after data reduction? The ultrasound data are more or less stochastic with some (weak) frequency distribution. The modulation of the amplitude can be highly transient (as for electrical discharge) up to steady-state noise. One procedure to evaluate the signal content is the calculation of a spectral entropy value which stands for the information content of the calculated spectrum. The spectral entropy can be obtained from the power spectrum of the signal. This part of the work is still in progress.

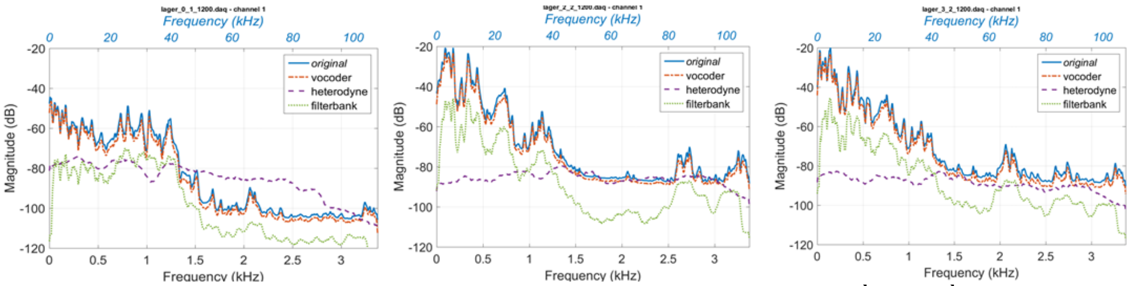

Figure 3. Three typical spectra of a healthy (left), and of faulty bearings (2nd and 3rd in Fig. 2) at the same rotational speed. The aurelization data from the vocoder technique provide the best results.

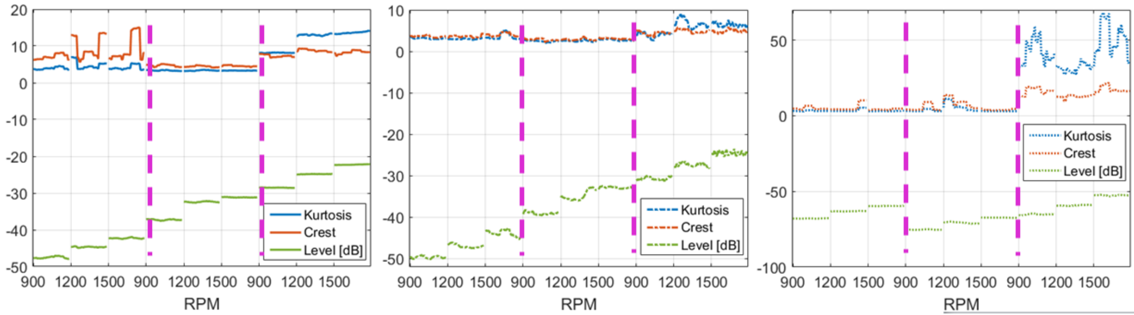

Figure 4. Calculation of diagnostic parameters (rms, crest, kurtosis – over all frequencies) from HF-broadband ultrasound signals for three roller bearings with increasing size of fault. The same type of roller bearing has been modified with notches and defined impact points. Identic revolution speeds have been used for comparison. Calculation of the same parameters has been done from original HF-signal, vocoder technique (1:32) from heterodyne (+/-2kHz around 40 kHz-carrier). The reduction of the dB-Values indicates to a certain degree the "numerical loss"

We used the compressed data sets for the application of neural networks and pattern recognition. The technique has been developed and trained by means of coin tap experiments (18), where several €-coins have been classified based on the tossing ultrasound signals (basing on Fourierspectrum (PSD). Afterwards, the HF-signals has been replaced by reduced data (1:32, Vocoder) as input for calculating the *k* dominant frequencies in the spectral distribution (Figure 5).
Those *k* frequencies are fed into a Multilayer Perceptron (MLP) model with two hidden layers (18) to discriminate between the 1063 different €-coin sounds. For training we used a Stochastic Gradient Descent (SGD) based approach with Momentum to optimise an cross entropy loss and trained with the same set of parameters for duration of 1000 epochs on both datasets. An overview of the algorithm can be seen below (Figure 5).
The trained model achieves an accuracy up to 96% (f1-Score) on the (while training unseen) data for raw signal inputs and up to about 95% for the reduced data (vocoder)
The marginal difference between the two datasets is also present comparing the approximate entropy of the signal (original data: 0.32, vocoder: 0.71) The learning speed of the algorithm is rather similar with being marginaly faster on learning from the reduced data.

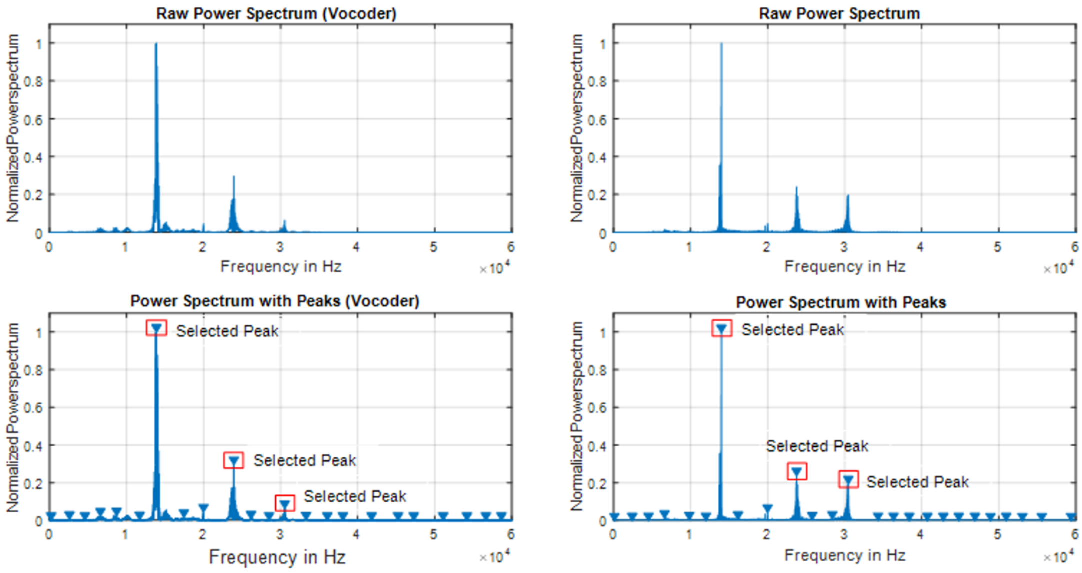

Figure 5. Comparison of power spectral density (top) for raw HF-broadband ultrasound signal (left) and Vocoder-based reduced signal (right) on identical one €-coins toss data with their respectively selected dominant peaks for *k*=3 (bottom)

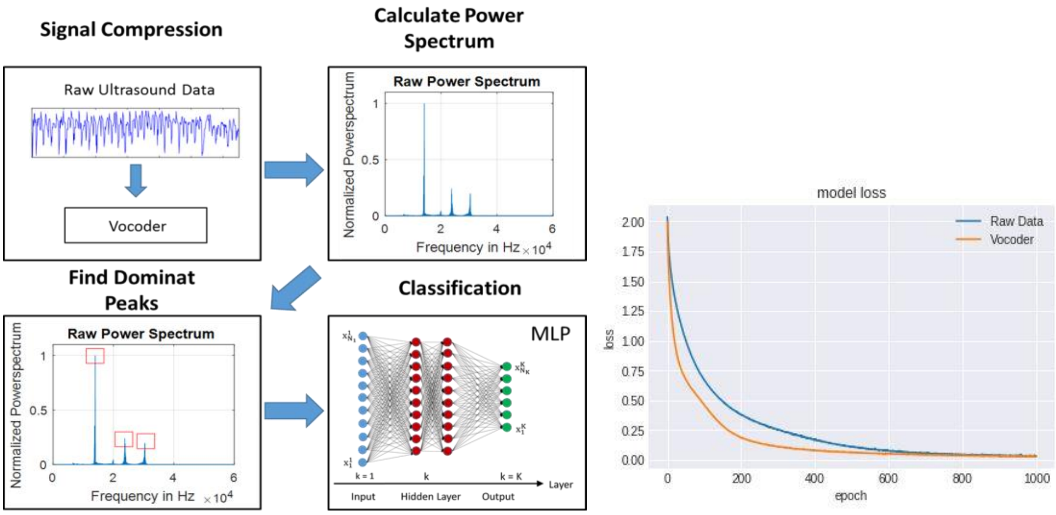

Figure 6. Left: Algorithm flow chart for the classification and,
Right: model loss comparison for raw ultrasound signal (blue line) and vocoder based signal (red line) the corresponding learning curves

3. Conclusions

It could be demonstrated that compressed and audible ultrasound data are valuable for further data processing of maintenance data. Especially for long time recording, the space for recorded data can be drastically reduced. Long-time recording and data evaluation become realistic under practical circumstances. The techniques have been exemplified for roller bearing faults evaluation. At the current stage, the long-time progression of bearing faults is emulated by the preparation of artificial faults. Calculation of typical vibration parameters show that the data of the audible branch are close to the original broadband data. The use of the data for advanced techniques of pattern recognition seems to be very promising when adapted numerical methods are applied.

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