

# Signal-Based Feature Extraction in a Vibration Monitoring Microsystem

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**ABSTRACT:** We describe different signal based feature extraction methods from statistics and signal processing which we are using in a intelligent microsystem for machine vibration monitoring. Each of these methods enables a special view to the machine vibration signal. The statistical methods like the standard deviation, percentiles, kurtosis and skewness are useful for a fast and more global view. Signal processing methods as envelope spectra, fourier transforms, wavelet analysis and time frequency methods are special views to the spectral composition of the vibration signal. With advanced microsystem and microelectronic technologies we have developed a intelligent microsystem for online machine diagnosis which has enough computing power and memory space to integrate powerful statistical and signal processing methods.

**KEYWORDS:** feature extraction, descriptive statistics, envelope spectrum, wavelet analysis, time frequency methods, machine vibration diagnosis, selforganizing neural network, microsystem technology, intelligent microsystem

## 1 INTRODUCTION

Traditional systems for the detection of machine failures are mostly working in two stages. The first stage is the condition monitoring which is directly applied to a sensor on the observed machine and delivers a decision between faulty and healthy machine states. In the most cases condition monitoring uses only one measured signal. On this first stage fast and low level feature extraction and classification algorithms are used. As second stage follows the diagnosis which performs some tasks of more powerful but also more computing power consuming feature extraction and multivariate classification. In contrast to the condition monitoring the diagnosis stage of traditional systems is not located directly in a sensor on the machine and uses in the most cases some different measured signals.

The recent development of microelectronic and microsystem technology delivers the basis for intelligent microsystems with high computing power and large memories. Such technologies open the door to the integration of the condition monitoring and the diagnosis stage in a single online machine diagnosis microsystem. We have used some of the most advanced semiconductor and microsystem technologies for the development of such a intelligent microsystem eg. Jossa, Marschner, Fischer (1999). The housing of our microsystem is nearly 3 cm long and has a diameter of 1,5 cm.

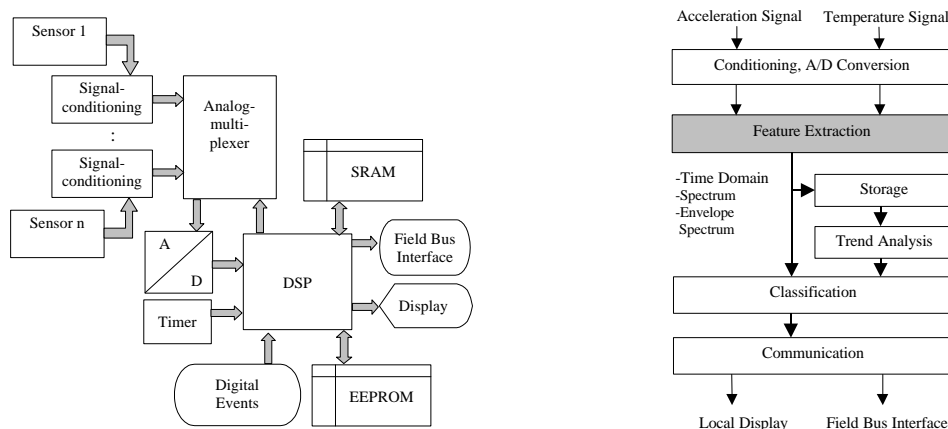


Figure 1: Signal processing architecture and the data flow scheme realized in the vibration monitoring microsystem.

In this small volume a 16 bit DSP with 100MIPS of computing power, 512Kbyte SRAM , 1Mbyte EEPROM, a field bus interface and the vibration sensor are integrated. With this computing power and memory space it is possible to use advanced signal processing and nonlinear methods for feature extraction and classification. The large memory allows a online and autonomous observation of machine vibration signals including long time trend analysis of machine failures which are slowly growing up. Over the field bus interface it is possible that the microsystem communicates with a host computer located in a industrial process control center or in the World Wide Web.

The results of some studies of the IEEE eg. Bell (1985) have shown that the bearing fault is the most probable cause for a motor failure. The Figure 2 shows the results of studies of the IEEE. Due to this results our diagnosis microsystem concentrates on bearing faults. We are using on-line vibration monitoring in addition to the monitoring of the bearing temperature.

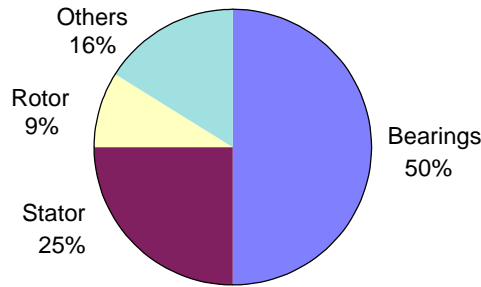


Figure 2: The most probable motor failures as investigated by the IEEE

It is not our goal to find the exakt location of a faulty element in the observed machine. With our feature extraction and also classification methods we are searching for a good estimation of the global machine state. In a first step we have developed a powerful condition monitoring stage which delivers the following three decisions: healthy motor state, changing motor state and faulty motor state. In the healthy state the computed feature values are in ranges far from critical values. The changing state describes the floating and drifting change from the healthy to the faulty state. When the features are becoming critical values the observed machine is in a faulty state.

In the condition monitoring stage we are using fast feature extraction with descriptive statistics and also not so fast but more powerful signal processing methods. Actually we also work on a diagnosis stage and a long time trend analysis as shown by the left side of Figure 1. For the classification of the machine states we are using a self-organizing neural network which uses the computed feature vectors as input.

## 2 DESCRIPTIVE STATISTICS

We use several traditional statistical features in the time domain as median, range, standard deviation, root mean square value (rms), quadratic mean value, kurtosis and percentiles (lower quartile, upper quartile, quartile range). With the rms value a good description of the global machine state is possible. The quadratic mean value represents the energy in the vibration signal. When a machine failure are growing up the energy in the vibration signal becomes also higher values.

A very flexible way for the description of positive and negative peak values in a signal are the so called percentiles. The percentile of a distribution of values is a number  $x$  such that a percentage  $p$  of the population values are less than or

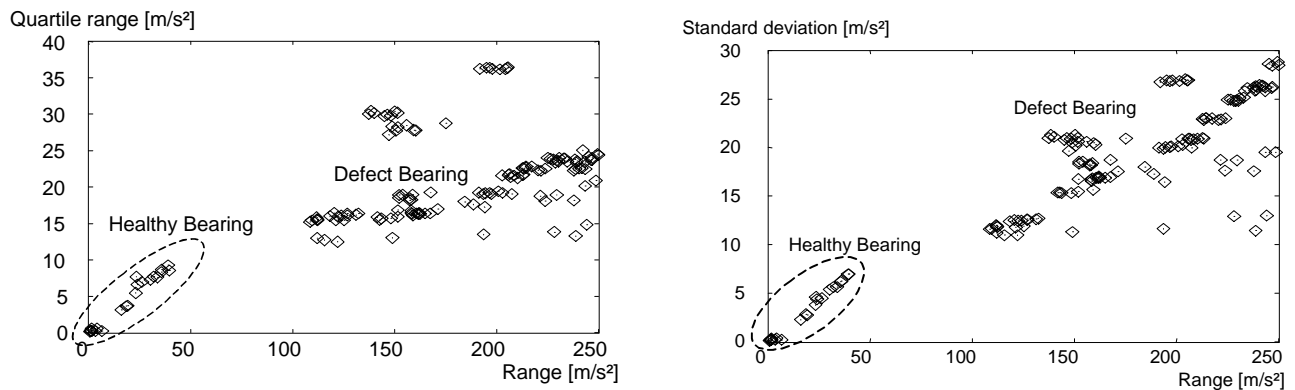


Figure 3: Separation of faulty and healthy bearings by the range, quartile range and standard deviation.

equal to  $x$ . For example, the 25<sup>th</sup> percentile ( also referred as the 0.25 quantile or lower quartile ) of a variable is a value  $x$  such that 25% of all the values of the variable fall below that value. Similarly, the 75<sup>th</sup> percentile ( also referred as the 0.75 quantile or upper quartile ) is a value such that 75% of the values of the variable fall below that value. Figure 3 (left) shows the good separation of the faulty and the healthy motor state by the range and the quartile range of the observed vibration signal magnitudes. The same good separation properties we have found with the standard deviation as shown in Figure 3 (right).

A other way to describe the statistical features of a vibration signal is the usage of so called higher moments of the signal distribution function. In the field of machine vibration monitoring the kurtosis and the skewness are traditional used higher moments. The kurtosis is the fourth moment and measures the peakness or flatness of a distribution in relation to the normal distribution. A pulsating signal produced by a bearing fault has a positive kurtosis which means the distribution of the signal has a strong peakness. For a distribution looks like the normal distribution the kurtosis is zero. The skewness is the third moment and measures the asymmetry of a distribution around its mean. When the skewness becomes a positive value the asymmetric tail of the distribution extending out towards more positive  $x$ . On the other side a negative value signifies a distribution whose tail extends out towards more negative  $x$ . Is the underlying distribution of the measured vibration signal exactly symmetrical the skewness is zero. One of the results of our practical work is that the kurtosis and the skewness are not showing so good separation properties between healthy and faulty bearings as the range, quartile range and standard deviation.

### 3 SIGNAL PROCESSING METHODS

One of the most popular methods for the detection of failures in machine vibration signals is the envelope and it's spectrum. We using different methods for the envelope computing, the hilbert transform, the local maximum method, the rectifier with low pass and the short time root mean square value. Our preferred method in the microsystem is the local maximum method because they needs not so much computing power and realizes a compression. With a window size of 16 we become a compression factor of 16 that means the envelope data are 16 times smaller as the original data set. As next step we computing the spectrum of the envelope. Figure 4 shows the envelope spectra of a healthy (left) and a faulty (right) bearing. The spectrum of the faulty bearing shows typical spectral lines at the failure frequency and its higher harmonics. The magnitude of the spectral lines are much higher as in the spectrum of the healthy bearing.

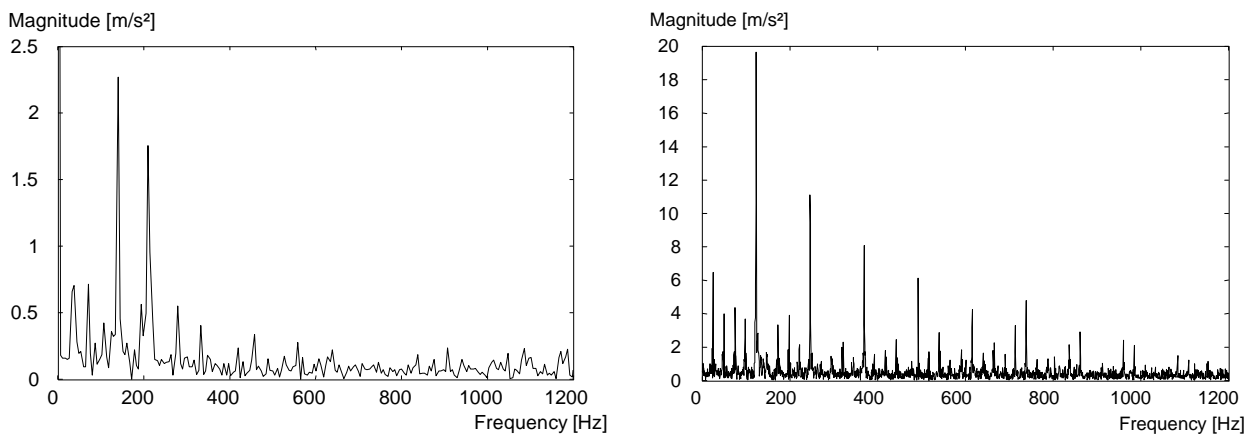


Figure 4: Envelope spectra from the vibration signal of a healthy (left) and a faulty (right) bearing.

We are using a defined magnitude level (for example  $2\text{m/s}^2$ ) for the detection of faulty bearings. This means that we integrate over all the signal parts which are higher than this predefined magnitude level. Becomes this integral a value higher as the so called “faulty value” a bearing fault is detected by this feature.

Actually we are also testing the possibility to use a discrete approach to the Wigner-Ville distribution (WVD) (Figure 5) for feature extraction. A typical fault detection procedure are based on visual observation of the WVD contour plots. Dark zones and curved bands in the contour plot are the main features of an impulse caused by a bearing fault. The progression of a fault can be monitored by observing the changes in the WVD contour plot. Such a visual observation is difficult and needs an great amount of computational power and memory space which is only available on workstations. In fact of this our method differs from the above. We are only using a part of the time frequency plane and to this part we are applying a coarse grained pattern recognition method. For this we are subdividing the time frequency plane (Figure 5) between the frequencies of 0...4KHz in 32 areas. The energy represented by every of this

areas is used as input to a self-organizing neural network. This neural network realizes the pattern classification task whose output is part of the feature vector. After our first experiences with the WVD we are now using the so called Choi-Williams distribution (CWD) which not shows the cross and inference terms as the WVD.

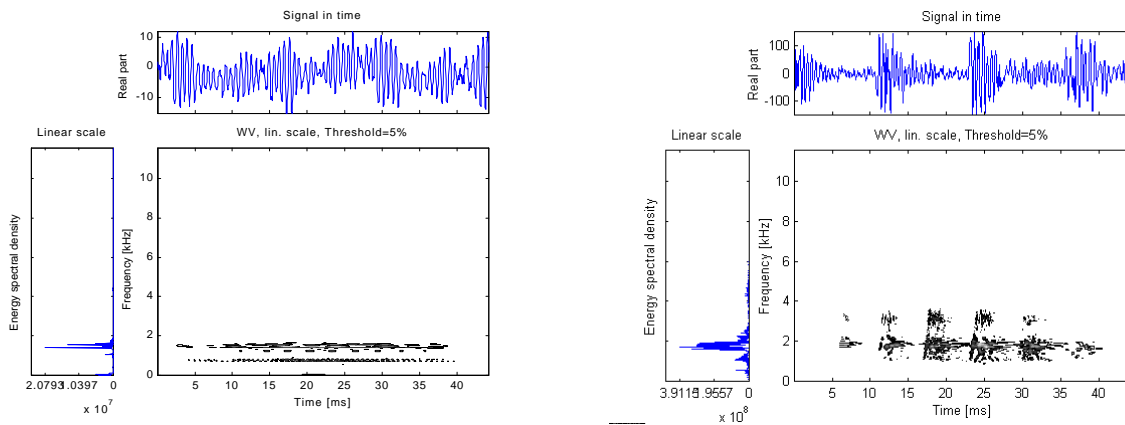


Figure 5: The Wigner-Ville distribution of the vibration signal from a healthy (left) and a faulty (right) bearing.

As other method for the time frequency analysis we are using the wavelet analysis or time-scale analysis. In fact of the strong relation between the contour plots of the WVD and the wavelet analysis we are using the same method for feature extraction. This means that we are subdividing the lower half of the time frequency plane in 32 areas and using the energy represented by every of this areas as input to a self-organizing neural network.

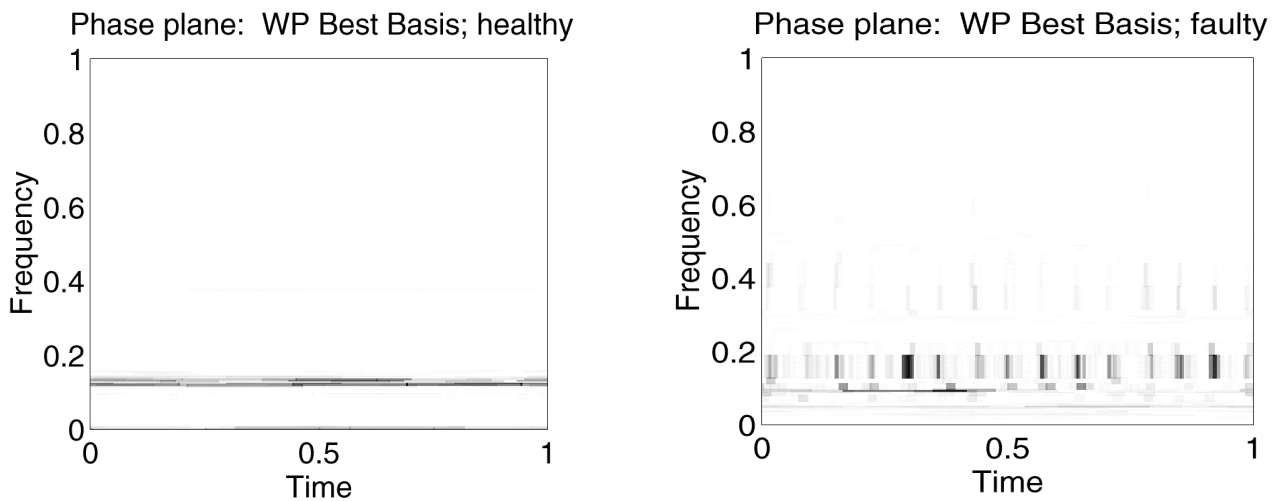


Figure 6: Wavelet representations of the vibration signal from a healthy (left) and a faulty (right) bearing.

Further investigations are being made to the application of methods from the nonlinear time series analysis and chaos theory (phase space methods) and also methods using higher order spectra or higher order statistics.

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