Methods for automatic condition monitoring

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Abstract

Reliable condition monitoring is crucial to successful maintenance operations in many industrial cases but adequate manpower and expertise to conduct proper monitoring is not always available. Suitable signal processing technologies can provide a considerable relief to this matter. Intelligent and adaptive systems can at their best detect the faults or even determine type and severity of the fault. Nowadays high-end technology for automatic monitoring is generally available at reasonable price, but many advanced methods are yet to be put into action. This paper discusses several methods which could relatively easily be built in to modern condition monitoring systems.

Keywords: automatic condition monitoring, feature extraction

1. Introduction

Some type of automatic monitoring is quite commonly used in may fields of industry. At the simplest it can be a question of a regular passenger car warning the driver about some fault in the car or just reminding that the oil change should take place soon. This type of monitoring may in the end be based on something really simple, like the distance driven since the last maintenance, or a sensor indicating an exceptionally high temperature.

In industrial production machinery monitoring is often a bit more complex, but on the other hand still often not very advanced. Quantities like current and temperature are often monitored e.g. in order to conduct an emergency shut down in case of exceeding a set limit. A bit more sophisticated monitoring very often considers vibration, but in this case the degree of automation is often not very high. Automatic systems can usually monitor basic features of vibration, such as RMS value of velocity, but extracting signs of faults which are not yet critical is often not possible this way. In fact, sometimes one is not able to detect fault this way, even if it is a very severe one. More advanced analysis often requires manpower and expertise, which commonly are quite limited resources.

2. Intelligent fault indicators

Feature extraction is a crucial part of condition monitoring. However, proper way of feature extraction is not always the same. Suitable method for fault detection may differ quite a lot depending on the case. Properties of condition monitoring systems are often relatively limited in this respect.

2.1 Advanced signal processing

Filtering is used in signal processing very commonly. In condition monitoring filtering is often used for anti-aliasing, which in case of vibration measurements of is usually a necessity. However, filtering can be used for other purposes as well. Filtering by frequency domain calculations may sound difficult, but as it is shown here it actually is a mere multiplication of numeric data which can be obtained during the procedure, which is traditionally used for spectral analysis. This is to say, that the discrete Fourier transform can be practical for more than it is applied in most of the condition monitoring systems.

Changing the order of derivative e.g. making a velocity signal to be an acceleration signal can be considered filtering. It should be remembered that there is no actual reason to be limited to displacement, velocity and acceleration. Higher orders of derivative, like jerk and snap have shown to be good tools as well, and derivatives of real order can be a useful alternative(1,2). Lahdelma presented in(3) a definition to the α order derivative of function $x = Xe^{i\omega t}$. This definition is:

$$x^{(\alpha)} = \omega^{\alpha} X e^{i(\omega t + \alpha \frac{\pi}{2})}, \tag{1}$$

where X is a constant representing amplitude of a sine, ω is the angular frequency, e is the Napier's constant, i is the imaginary unit and t time variable.

This definition may seem complicated to apply, which it may have been some decades ago, but with modern computers it is quite straightforward. This can be done simply by multiplying the Fourier series elements by power α of their respective angular frequencies. For integration one can simply select $\alpha < 0$. After this sequence of multiplications the time domain signal can be obtained by inverse Fourier transform. Similar technique can be applied for filtering as well. Instead of multiplying spectral components they can be removed by multiplying with zero. This results to a very sharp filter, which is sometimes called an ideal filter.

2.2 Feature extraction

Features of some kind have been applied for condition monitoring for decades. Most common ones are the root mean squared, known as RMS, and the peak value. These features can be useful, but there is no real justification to assume these features are always adequate.

Weighted l_p norms have proven to be very effective tool for detecting different faults, especially when the norms are calculated to a signal of suitable order of derivative.

$$\|x^{(\alpha)}\|_{p,w} = (\sum_{i=1}^{N} w_i |x_i^{(\alpha)}|^p)^{\frac{1}{p}}, \tag{2}$$

where x is displacement, α is order of derivative, p is order of norm, w_i is the weighting factor of the norm and N is number of samples. It is often advisable to select $w_i = \frac{1}{N}$ in order to make features calculated to signals of different length more comparable to each other. Notation of this weighted norm is $\|\overline{x}^{(\alpha)}\|_p$.

MIT index[4] is a tool for expressing relative change in norms discussed above, and is defined as:

$$^{\tau}MIT^{p_1,p_2,\ldots,p_n}_{\alpha_1,\alpha_2,\ldots,\alpha_n} = \frac{1}{n}\sum_{i=1}^{n} b_{\alpha_i} \frac{||\overline{x}^{(\alpha_i)}||_{p_i}}{(||\overline{x}^{(\alpha_i)}||_{p_i})_0}, \tag{3}$$

where b_{α_i} is a weighting factor related to order of derivative α, and $(||\overline{x}^{(\alpha_i)}||_{p_i})_0$ is a norm calculated in a reference situation, which in condition monitoring is often a measurement from a machine in good condition.

The S surface[5] is a figure created by calculating MIT indices using several different orders of derivative and l_p norm, as shown in Equation (2). The S surface is obtained by calculating a set of MIT indices, and then presenting the result as a three dimensional plot. This way it is very simple to state which features show a change. It is quite simple to use this technique for automatic monitoring as well, because it is very straightforward to set warning and alarm limits to an on-line system.

Creating the S surfaces may consume too much computational power at least on low-end systems. In this case, it is possible to select certain order of derivative or norm and calculate a S curve[6]. This needs less calculations and may be easier to interpret, though it requires a bit more knowledge on the case, because one needs to be certain that the selected features are suitable. It may be a good idea to use S surface to determine which features are suitable, and after this reduce the need on computations by replacing the S surface with a S curve or a few of them.

2.3 Spectral features

Spectral analysis is a very common tool in condition monitoring. There are some systems which can perform some automatic spectral monitoring, where for example every frequency has a limit of amplitude in the frequency spectrum, and exceeding any of these limits trigger an alarm. To improve this type of monitoring it is possible to calculate the generalised norms to frequency spectrum as well, as suggested by Karioja and Juuso in[7]. This is in fact quite similar technique as the concept of spectral kurtosis, presented by Dwyer in 1983[8].

3. Example cases

Here are some example cases which show how the methods presented above can be applied. Example cases are from measurements conducted to machinery in laboratory. These examples show, how methodology presented above makes automatic fault detection possible.

3.1 Mechanical looseness and lack of lubrication

In this example the measurements are from a test rig which included an electric motor, a gear and a water pump. The setup of the test rig in shown in Figure 1

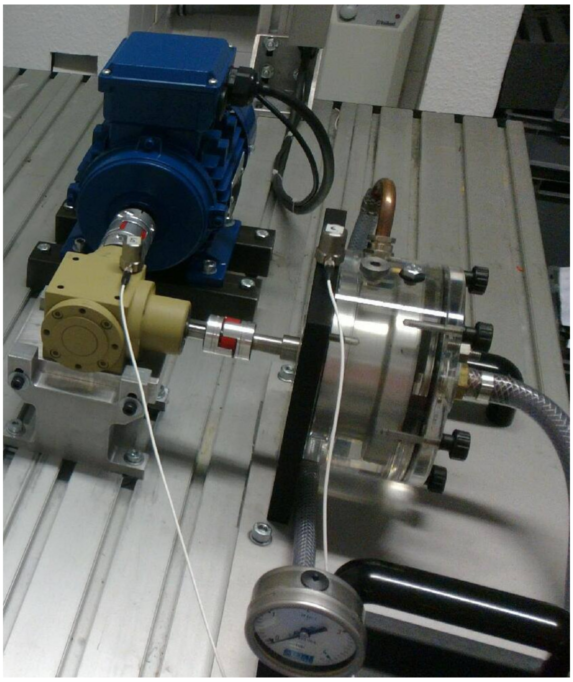

Figure 1. The test rig

In Figure 2 there is a S surface from a situation there is mechanical looseness induced and in the Figure 3 there is a lack of lubricant. The reference used here is a case where no faults are induced to the test equipment. The horizontal planes in these Figures show where value of index exceeds 1.33, which is to say that the value of the feature has increased one third.

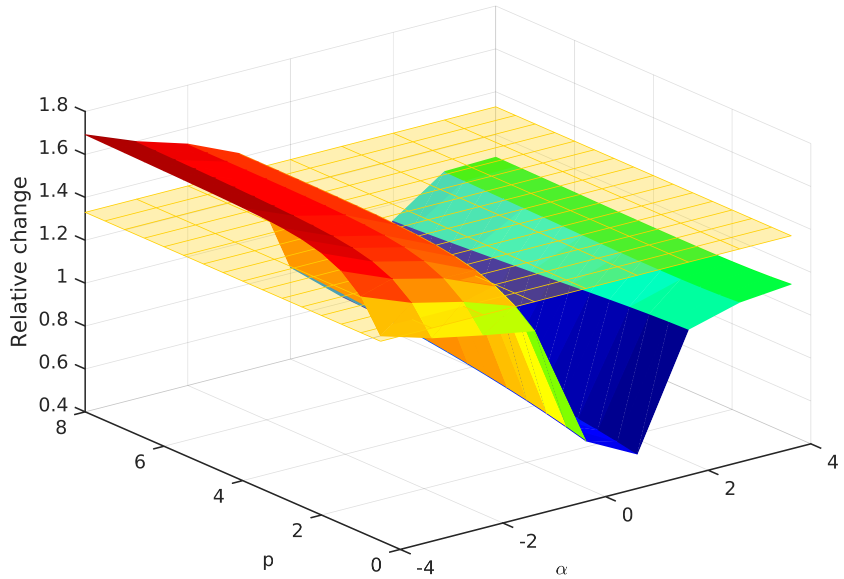

Figure 2. S surface from the situation with mechanical looseness

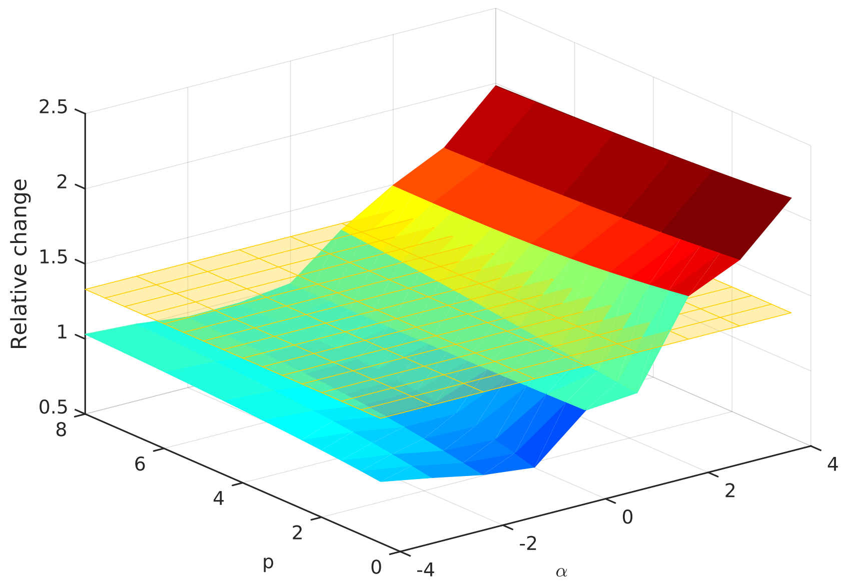

Figure 3. S surface from the situation with lack of lubricant

In Figures 4 and 5 there are S curves from the same situations as in Figures 2 and 3.

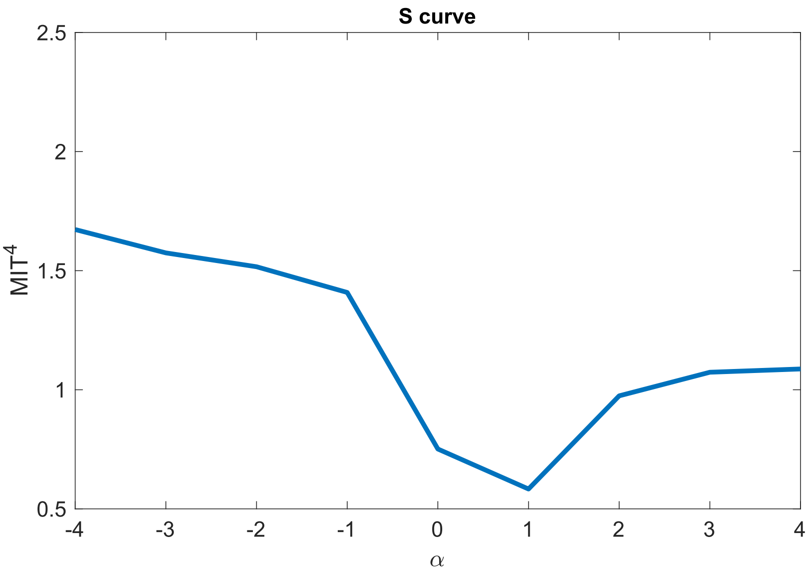

Figure 4. S curve from the situation with mechanical looseness

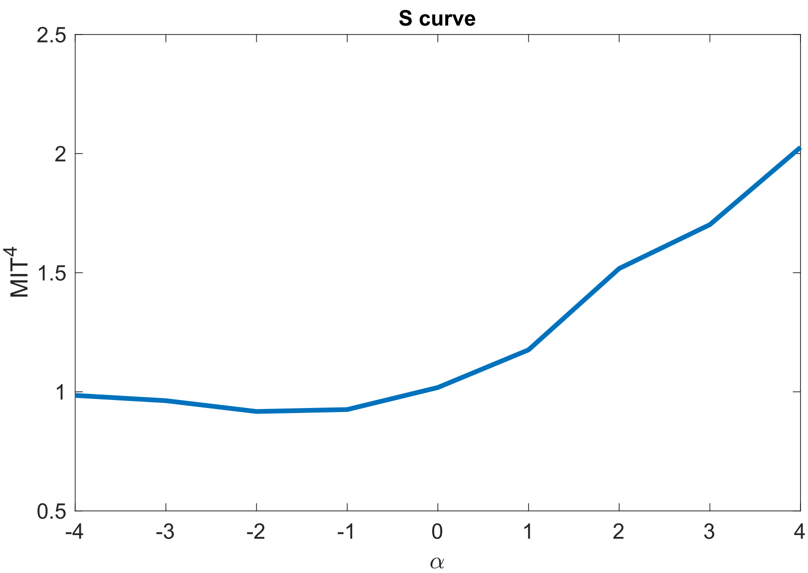

Figure 5. S curve from the situation with lack of lubricant

This shows that we obtain a pretty clear indication of both faults using only l_4 norms. However, it should be noted, that the orders of derivative most commonly used are from 0 to 2 in modern monitoring systems. Figures 2–5 show, that these orders of derivative are not the best choices to detect these faults, which both are relatively common in industrial applications as well.

3.2 Misalignment

High level spectral components at rotational frequency and its harmonics are normally considered a sign of misalignment. This is in fact correct, but instead of traditional spectral analysis more automatic methods can be used. Very good indication of misalignment can be obtained by frequency domain filtering, as shown in[9].

In Figure 6 there are different spectra from measurements to the test rig, where were no faults in the reference situation (Fig. 6a) and then when misalignment was intentionally caused. In Figure 6b is the whole spectrum and in 6c the spectra is filtered using aforementioned frequency domain filtering.

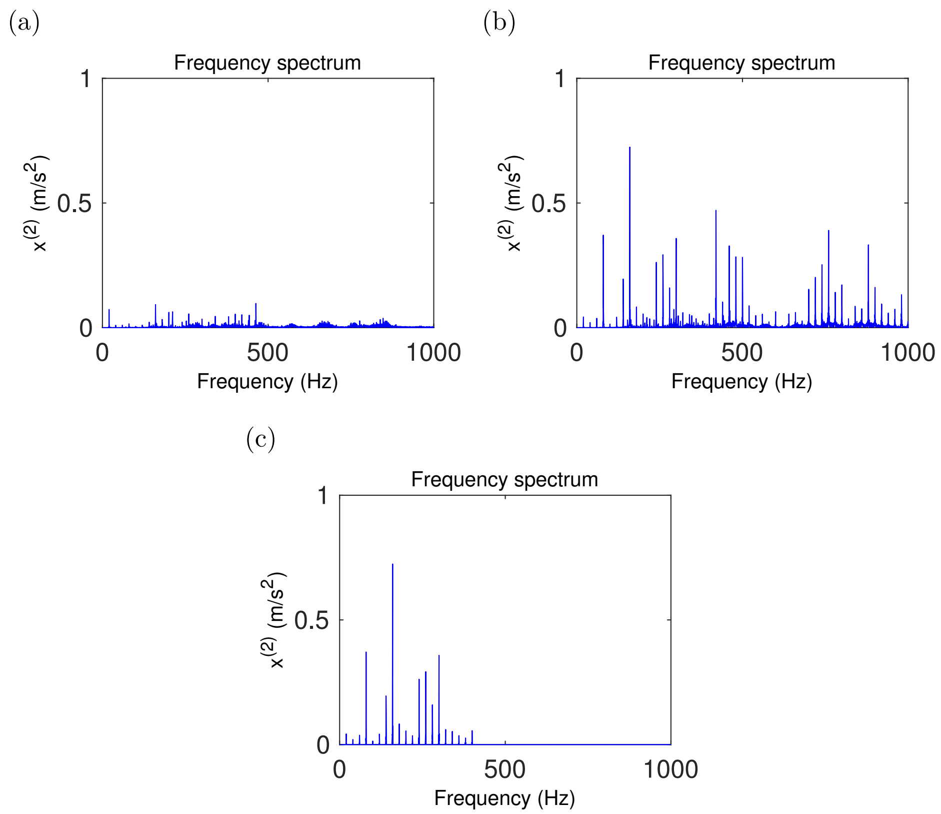

Figure 6. Frequency spectra from three situations a) with no misalignment, b) with misalignment and c) with misalignment after frequency domain filtering

Misalignment can quite clearly be seen in the spectra, but when looking for automatic solutions calculating a feature to filtered signal is a lot less labour intensive.

In this case the filtered signal was $x_{rms}^{(2)}$ of 0.094 m/s^2 before the fault was induced, and it increased to 1.237 m/s^2 when the fault was present. The value may seem low, but one must remember that after filtering most of the frequency content of the signal is removed, and the RMS value is naturally quite low, but the relative change is notable. This method is useful also because of the fact, that this type of feature is very insensitive to other faults, because it is only affected by the rotational frequency and its harmonics. If a condition monitoring system includes measurement of the rotational speed, it is relatively easy to create adaptive indicator, where parameters of the filter are changed depending on the rotational speed.

On the other hand, this type of features can be calculated as spectral features as well. This technique can provide very similar results as the ones discussed above. However, if the calculation of the features is performed on the spectrum, there is no need to perform the inverse Fourier transform. This way there are fewer computations to be done, and a need for computational capacity is reduced. This method could be very easy to include to many systems, because practically all of the condition monitoring systems today perform the Fourier transform, and all the information needed for feature calculations is already available. Calculating features to the spectra should not require any complicated modifications.

4. Discussion

Nowadays, there is a vast amount of different possibilities to process numerical data. Considering the relatively high sampling rates and bit resolutions required in condition monitoring, it is reasonable to expect several gibibytes[10] of data a day. Storing dataset of this size is hardly sensible, and it is simply not possible to analyse it thoroughly. However, if the condition monitoring system can perform an automatic analysis locally, the measurement data can be effectively processed. In this respect, techniques presented here are a lot easier to apply, as they can be carried out even when there is relatively limited computational power available. For more thorough analysis expert work is of course necessary, but for fault detection in on-line systems ones presented here are quite feasible. Some of the methods presented in this paper e.g. monitoring only a narrow frequency range have actually been applied in some applications even in machine diagnostics for decades. Unfortunately, the methodology discussed here is not very commonly applied. It could be highly practical for automatic monitoring and diagnostics often desired, but this resource is far too often wasted. It can be stated, that in this respect the powerful modern computing technology holds a huge untapped potential.

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