Correlation-Based Condition Monitoring of a Roller Chain

Journal:	WCCM 2017
Manuscript ID	CM-MFPT-0145-2017.R1
Topic:	Condition monitoring (CM) methods and technologies
Date Submitted by the Author:	15-Mar-2017
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Keywords:	Condition monitoring, Correlation, Signal processing, Monitoring, Residual

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Condition Monitoring for mechanical systems like bearings or transmissions is often done by analysing frequency spectra obtained from accelerometers mounted to the components under observation. Although this approach gives a high amount on information about the system behaviour the interpretation of the resulting spectra requires expert knowledge, that is, a deep understanding of the effect of condition deterioration on the measured spectra. However, an increasing number of condition monitoring applications demands other representations of the measured signals that can be easily interpreted even by non-experts.

Therefore, the objective of this paper is, to develop an approach for processing measured process data in order to obtain an easy to interpret measure for assessing the component condition. The main idea is, to evaluate the deterioration of a component condition by computing the correlation function of current measurements with past measurements, in order to detect a component condition deterioration from a change in these correlation functions. Besides the simplicity of the obtained measure, this approach opens the opportunity for integrating a model-based approach as well.

The developed method is tested based on a condition monitoring application in a roller chain.

Correlation–Based Condition Monitoring of a Roller Chain

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Abstract

Condition Monitoring for mechanical systems like bearings or transmissions is often done by analysing frequency spectra obtained from accelerometers mounted to the components under observation. Although this approach gives a high amount on information about the system behaviour, the interpretation of the resulting spectra requires expert knowledge, that is, a deep understanding of the effect on condition deterioration on the measured spectra. However, an increasing number of condition monitoring applications demands other representations of the measured signals that can be easily interpreted even by nonexperts. Therefore, the objective of this paper is to develop an approach for processing measured process data in order to obtain an easy to interpret measure for assessing the component condition. The main idea is to evaluate the deterioration of a component condition by computing the correlation function of current measurements with past measurements in order to detect a component condition deterioration from a change in these correlation functions. Besides the simplicity of the obtained measure, this approach opens the opportunity for integrating a model–based approach as well. The developed method is tested based on a condition monitoring application in a roller chain.

1. Introduction

Components of mechanical systems are subject to wearing during their operational lifetime. Therefore, a regular maintenance or replacement is necessary to ensure an adequate operation of these components and to prolong their available lifetime as much as possible. Typically, maintenance or replacement intervals are regularly scheduled based on operational hours or particular information given by the manufacturer. However, these fixed intervals may not be appropriate for a given component under particular operating conditions. As a result, maintenance intervals may be shorter than required leading to higher costs than necessary or maintenance intervals may be too long leading to a component failure. To avoid such situations, condition monitoring and remaining lifetime estimation methods have been developed in recent years. A common condition monitoring technique used in industrial applications for rotating machinery is the analysis of vibration data in time, frequency and time–frequency domain obtained from e.g. accelerometers⁽¹⁾. This technique provides a large amount of data that can be used to identify the condition of the monitored component. However, the interpretation of the resulting data requires a deep understanding of the effect of condition deterioration on the time series or the corresponding spectra and is difficult even for experts.

Therefore, in this paper a method is proposed, that evaluates the condition of a component with an easy to interpret result even by non–experts. The main idea is to determine the component condition by evaluating the similarity between measurement signals in different conditions, e.g. *new* and *worn*, based on correlation techniques using measured process data. The developed method is tested based on a condition monitoring application in a roller chain. Correlation based techniques have been successfully applied in signal and image processing. For condition monitoring approaches the method proposed in⁽²⁾ uses correlation techniques to weak up or to eliminate noises of vibration data. In⁽³⁾ correlations among failure modes are considered to better predict the service life of dam systems. A correlation analysis based approach for feature selection such as mean and standard deviation of signals for reliability estimation or remaining lifetime prediction is given in^(4,5). Optical image correlation was used in⁽⁶⁾ to monitor strain characteristics in electronic systems.

The paper is organized as follows. In section 2 the measurement setup is presented and section 3 explains the wear of roller chains. Then, the problem statement is discussed in section 4. The main idea of this paper and some background on correlation are described in section 5. Analysis of measurement results using the developed method are shown in section 6. Finally, section 7 summarizes the results of this paper.

2. Measurement setup

The method developed in this paper is investigated based on a roller chain drive with one driving sprocket and one driven sprocket as illustrated in figure 1. Roller chains are part of many mechanical systems for power transmission or object transportation. Besides the benefits of roller chains like slip–free power transmission with high efficiency, there are also disadvantages like the polygon effect leading to wear in the chain. The rate of wearing increases strongly depending on operating conditions including speed, stress and lubrication of the chain. Many applications require high chain speeds whereas in other applications only limited lubrication is possible such that the chain lifetime decreases fast.



Figure 1. Roller chain drive test bench

The single roller chain (DIN ISO 606) in the considered test bench has a total of N = 100 links and an undeformed link pitch of l = 9.525 mm. Both, driving and driven sprockets

have z = 20 teeth. Two motors are connected directly to the sprockets, where the left motor acts as driver and the right motor as load to represent the working load. These motors are induction machines with a rated power of $P_{\rm R} = 0.37$ kW, a rated torque $T_{\rm R} = 2.56$ Nm and a rated speed $n_{\rm R} = 1380$ rpm. The driving motor is operated in speed controlled mode with a constant speed of $n_{\rm m} = 400$ rpm such that the chain is moving in anticlockwise direction. For the measurements in this paper no external load torque was applied by the second motor. The chain was operated approximately eight hours a day for a total of 37 days.

In contrast to typical condition monitoring applications no accelerometers are used but all information is extracted from the motor torque available as process data in the frequency inverter that drives the motor. In addition, the angular position is recorded and all measurements are synchronized to a reference position of the motor shaft, given by the zero pulse of the motor encoder system. This synchronization is crucial for obtaining comparable measurements during chain operation.

3. Wear of roller chains

Roller chains suffer from different effects of wear⁽⁷⁾. The main influence of chain wearing are modifications in the joints due to friction between pins, bushes and rollers while the chain is operating^(8–11). This wear leads to abrasion such that the whole chain extends. Furthermore, the stiffness in the joints increases if abrasion and stain are in the joints⁽¹¹⁾ as well as when the lubrication decreases. Figure 2 illustrates the process of chain wear⁽¹⁰⁾.



Figure 2. Process of chain wear

Within the first operating hours $[0, t_{initial}]$ the so called *initial wear*, the wear elongation grows strongly due to adjustments in the joints of the chain. Then, during the *normal wear* interval $[t_{initial}, t_{linear}]$, the wear increases slowly and nearly linear. This stage is followed by the *extreme wear*. During this stage the wear is progressive and the chain should be changed as soon as possible. This trajectory of chain wear was measured by e.g.^(8,9,12). Figure 2 also illustrates two different curves for different lubrication conditions following⁽¹⁰⁾. The dashed line represents a typical curve for a chain lubricated once by the manufacturer without any re–lubrication during operation. In contrast the solid line

illustrates the chain wear when the chain is frequently re-lubricated, resulting in a higher chain lifetime.

4. Problem Statement

Figure 3 shows the measured motor torque T_m and its corresponding spectra for one chain revolution within one day at four different timestamps; start of a day (0h), after 30 minutes (0.5 h), after 2 h and at the end of a day (8h). These data are shown for two chain conditions from day 3 in figure 3a and 3b and day 29 in figure 3c and 3d, respectively.



Figure 3. Measurements within one day for two different chain conditions

From the time series illustrated in figure 3a it is observed that the motor torque decreases during the day. This is due to the fact that the chain temperature increases during the daily operation resulting in a decreasing lubrication viscosity. As the signals given in figure 3c demonstrate, this effect degrades with increasing operation hours due to loss of

lubrication. In the spectra, the mechanical rotation frequency

$$f_{\rm mech} = n_{\rm m}/60 = 6.66\,{\rm Hz}$$

can be seen, where $n_{\rm m} = 400$ rpm is the motor operating speed. In addition, the chain links mesh into the sprockets with the meshing frequency

$$f_{\text{mesh}} = z f_{\text{mech}} = 133.33 \,\text{Hz}$$

The spectra exhibit additional frequencies resulting from the chain dynamics, induction machine harmonics, the bearings but also from harmonics and image frequencies due to limited sampling rate. Although there are notable differences between the spectra in figure 3c and figure 3d a conclusion about the condition of the chain based on these figures is difficult without expert knowledge. Therefore, this paper introduces an approach to determine an easy to interpret condition measure based on correlation techniques.

5. Correlation-based condition monitoring

5.1 Correlation

Correlation in signal processing is used to analyse the degree of similarity of signals. The so called *cross–correlation* of two real–valued signals in continuous time x(t) and y(t) is defined as

$$r_{xy}(\tau) = \int_{-\infty}^{+\infty} x(t)y(t-\tau)dt$$

where τ is the time lag by which y(t) is shifted with respect to x(t). The cross-correlation $r_{xy}(\tau)$ is a measure for the similarity between x(t) and y(t) for every time lag τ . In digital signal processing the signals are sampled at the time instants $t = nT_S$, where T_S is the sampling time. Thus, the discrete cross-correlation of two different real-valued signals x(n) and y(n) in discrete time is defined as

$$r_{xy}(k) = \sum_{n=-\infty}^{+\infty} x(n)y(n-k) , \qquad (1)$$

where k is the time-discrete lag and represents the integer number of sample points by which y(n) is shifted with respect to x(n). As there are no infinite data sets in practice, the summation in (1) will start from n = 0 ending at n = N - 1, where N is the length of the signal buffer for x(n) and y(n). Thus, we have

$$r_{xy}(k) = \sum_{n=0}^{N-1} x(n) y(n-k) , \qquad r_{xx}(k) = \sum_{n=0}^{N-1} x(n) x(n-k) ,$$

for the cross-correlation $r_{xy}(k)$ and the autocorrelation $r_{xx}(k)$. For the evaluation of the similarity between the signals x(t) and y(t) the ratio

$$\rho_{xy}(k) = \frac{r_{xy}(k)}{r_{xx}(k)} \tag{2}$$

can be used. $In^{(13)}$ the similarity is determined from

$$\rho_{xy}(k) = \frac{r_{xy}(k)}{\sqrt{r_{xx}(0)r_{yy}(0)}},$$
(3)

giving a standardized value $|\rho_{xy}(k)| \le 1$. In both cases (2) and (3) a similarity measure *S* can be obtained using the value at zero lag $S = \rho_{xy}(0)$. Furthermore, in⁽¹⁴⁾ the waveform correlation coefficient was proposed:

$$\rho_{xy} = \frac{\max(r_{xy}(k))}{\sqrt{\max(r_{xx}(k))\max(r_{yy}(k))}} \,. \tag{4}$$

As the maximum for any autocorrelation function $r_{aa}(k)$ is obtained for $k = 0^{(13)}$, the denominators in (3) and (4) are equal. So the difference between the two measures is determined by the cross–correlation function $r_{xy}(k)$.

5.2 Main idea

Assume that during the operation of a plant snapshots $X_K = [x_K(0) \dots x_K(N-1)]$ of the process variable x(t) as a sampled data set x(n) are recorded at certain user defined time instants. The index *K* denotes the index of the snapshot. The variable x(t) must be selected such that a deterioration of the component under consideration leads to a change in the behaviour of x(t).

The main idea is to assess the component condition based on the similarity measure of the first snapshot X_1 with the subsequent snapshots X_K , $K \ge 2$. As the condition of the component deteriorates, the similarity between the first snapshot and the subsequent snapshots will gradually decrease resulting in a decrease of the similarity measure. Therefore, the similarity measure S_K of the *K*th snapshot is determined based on (3)

$$S_K = \frac{r_{X_1 X_K}(0)}{\sqrt{r_{X_1 X_1}(0) r_{X_K X_K}(0)}},$$
(5)

where

$$r_{X_1X_K}(0) = \sum_{n=0}^{N-1} X_1(n) X_K(n) , \qquad r_{X_1X_1}(0) = \sum_{n=0}^{N-1} X_1^2(n) , \qquad r_{X_KX_K}(0) = \sum_{n=0}^{N-1} X_K^2(n) .$$

This approach will be illustrated in the following section.

6. Results

For evaluating the performance of the main idea introduced in the previous section the roller chain described in section 2 was operated approximately eight hours a day for a total operation time of 300 hours within 37 days. The chain was lubricated once by the manufacturer. In order to speed up the wear rate, the outer lubrication was removed every eight hours using paper towels which produce additional paper dust stranded in the joints of the chain. The motor rotational speed was constant $n_{\rm m} = 400$ rpm, resulting in a chain speed of $v_{\rm c} = 1.27$ m/s. With an initial chain length of L = 0.9525 m, the duration of one

chain revolution is $t_r = 0.75$ s. Every ten minutes one snapshot X_K of the motor torque was recorded, resulting in a total of 1503 snapshots. The duration of these snapshots was selected such that five chain revolutions with a sampling rate of $f_s = 2$ kHz are included in the data.

At the end of operation, the chain is noticeable stiff in every joint and its elongation is approximately 14mm, which corresponds to 1.5% of the initial chain length. The stiffness is illustrated in figure 4, where the chain links in the slack and tight span do not return into their straight initial position even if the chain is not moving.



(a) New chain



(b) Chain after 300 hours of operation

Figure 4. Roller chain comparison

Furthermore, the chain has brown–red discolourations, shown in figure 5. This is due to fretting corrosion resulting from insufficient lubrication, leading to a strongly increased wear rate⁽¹⁵⁾.



Figure 5. Chain link: New (left) and after 300 hours of operation (right)

The increased stiffness leads to a higher load torque when the chain links bend down while moving along the sprockets. This can be observed in the measured motor torque T_m in figure 6, where the average torque of the worn chain has doubled compared to the new chain and the amplitude of the observed oscillation is about four times higher.

In the sequel, the method described in section 5 is applied to the recorded data and S_K is determined for all snapshots using (5). As the number of snapshots is high, in order to not



Figure 6. Motor torque of the new and worn chain

overload the presentation in figure 7, only the mean values

$$\overline{S}_D = \frac{1}{N_D} \sum_{m \in I_D} S_m \tag{6}$$

are given, where N_D denotes the number of snapshots on day D, D = 1, ..., 37 and I_D is the set of snapshot indices at day D. Note that day zero is used here as a reference value only. This reference value is arbitrarily set to the value 1 and corresponds to the similarity index computed from the very first measurement using

$$\overline{S}_0 := S_1 = \frac{r_{X_1 X_1}(0)}{\sqrt{r_{X_1 X_1}(0)r_{X_1 X_1}(0)}} = 1$$

Within the 37 days of operation, the chain was re-tensed twice at day 30 and 36. As a result the chain dynamics changes as well, resulting in changes in the motor torque $T_{\rm m}$, illustrated in figure 8. Figure 8a displays the motor torque in the last snapshot before the chain was re-tensed and figure 8b immediately after re-tension at day 30.

The trajectories show that vibrations are reduced after re-tensioning while the motor torque increases. This modification of the trajectory of course changes the degree of similarity S_K as well. As this change is not caused by chain wear, it is reasonable to adapt S_K in an appropriate way. This is done by determining the difference

$$\Delta S = S_{K_2} - S_{K_1} , (7)$$

where S_{K_1} and S_{K_2} are the degrees of similarity before and after re-tensioning, respectively with $K_1 = 1126$ and $K_2 = 1168$. As illustrated in figure 9, S_{K_2} corresponds to the degree of similarity of the first snapshot of day 30.

The degree of similarity before re-tensioning S_{K_1} will not be defined as the value of the last snapshot of day 29 due to the effect of heated lubrication, as described in section 4. Instead, S_{K_1} will be defined as the value of the first snapshot of day 29 as shown in figure 9.



Figure 7. Mean of similarity measure per day without adaptations



Figure 8. Motor torque when re-tensioning the chain

By taking the first snapshots for each day, the conditions of operation with respect to the temperature are almost the same. In addition, the chain wear within day 29 is small. Then, ΔS calculated with (7) needs to be subtracted from every following day:

$$S_{\rm K,new} = S_{\rm K,old} - \Delta S$$

where $S_{K,old}$ represents the degree of similarity of every following snapshot and $S_{K,new}$ is the corresponding adapted value. This procedure was repeated for day 36 as well. However, as the chain wear dominates at the previous day 35, S_{K_1} is specified as the value of the last snapshot of day 35. Figure 10 shows the adapted graph of figure 7 with



Figure 9. Adaptation due to re-tensioning

additional errorbars, illustrating how much the degree of similarity S_K varies within each day. In addition, a simple trend line was fitted to the data. It consists of two second order polynomials between the day 1 and 5 and day 25 and 37, respectively and a straight line connecting \overline{S}_5 and \overline{S}_{25} . This trend line illustrates the overall decrease of the degree of similarity during the operating lifetime of the chain indicating the increased chain wear. It resembles the curve illustrated in figure 2 such that in this trend line the stages *initial wear*, *normal wear* and *extreme wear* can be retrieved. In future works, these results will be verified by further chain tests with different chain conditions such as chain speed and chain tension.

7. Conclusion

In this contribution a new approach for evaluating the condition of mechanical systems is proposed. The method is based on the evaluation of the correlation function between measured process data of a new component and of process data acquired during the operational lifetime of the considered component. The result is a similarity index that indicates the deterioration of the component condition.

The method was investigated based on a roller chain system. The process data used in the computations was the motor torque of the motor driving the chain, so that no additional sensors were used. The main result is that the similarity index computed for regularly recorded snapshots of process data decreases with growing operation time. Moreover, the trajectory of the similarity measure resembles the wear curves of roller chains given in the literature and from roller chain manufacturers.

In future work this method will be applied to additional roller chains running under dif-



Figure 10. Mean of similarity measure per day with adaptations

ferent operating conditions in order to generalize and enhance the method. Model based approaches will be investigated as well. Similarly, the method will be applied to other mechanical transmission systems like linear and belt units to enhance the condition monitoring and potentially the residual lifetime prediction capabilities for mechanical components.

Acknowledgement

This work was funded by the Ministerium für Wissenschaft, Forschung und Kunst Baden–Württemberg, Germany.

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