Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 102 (2021) 270–275

www.elsevier.com/locate/procedia

18th CIRP Conference on Modeling of Machining Operations

Analysis of the impact of data compression on condition monitoring algorithms for ball screws

Reemt Hinrichs[a,*], Alexander Schmidt[b,**], Julian Koslowski[a,b], Benjamin Bergmann[b], Berend Denkena[b], Jörn Ostermann[a]

[a] *Institut für Informationsverarbeitung (TNT), G-30167 Hanover, Germany*
[b] *Institute of Production Engineering and Machine Tools (IFW), Leibniz Universitt Hannover, An der Universitt 2, G-30823 Garbsen, Germany*

Abstract

The overall equipment effectiveness (OEE) is a management ratio to evaluate the added value of machine tools. Unplanned machine downtime reduces the operational availability and therefore, the OEE. Increased machine costs are the consequence. An important cause of unplanned machine downtimes is the total failure of ball screws of the feed axes due to wear. Therefore, monitoring of the condition of ball screws is important. Common concepts rely on high-frequency acceleration sensors from external control systems to detect a change of the condition. For trend and detailed damage analysis, large amounts of data are generated and stored over a long time period (>5 years), resulting in corresponding data storage costs. Additional axes or machine tools increase the data volume further, adding to the total storage costs. To minimize these costs, data compression or source coding has to be applied. To achieve maximum compression ratios, lossy coding algorithms have to be used, which introduce distortion in a signal. In this work, the influence of lossy coding algorithms on a condition monitoring algorithm (CMA) using acceleration signals is investigated. The CMA is based on principal component analysis and uses 17 features such as standard deviation to predict the preload condition of a ball screw. It is shown that bit rate reduction through lossy compression algorithms is possible without affecting the condition monitoring - as long as the compression algorithm is known. In contrast, an unknown compression algorithm reduces the classification accuracy of condition monitoring by about 20 % when coding with a quantizer resolution of 4 bit/sample.

Keywords: machine tools; data compression; differential pulse-code modulation; condition monitoring; health monitoring

1. Introduction

Unplanned failures and thus downtimes of machine tools cause immense costs for companies. On average, 5 minutes in the automotive industry causes follow-up costs of 100.000 € [15]. Therefore, high operational reliability and availability of machine tools must be ensured. However, the availability is limited, for example, by unplanned, wear-related failures of a ball screw [10]. Predictive maintenance and thus condition monitoring of the ball screw is mandatory. Furthermore, extensive data and machine learning methods are required for automated condition monitoring and to be able to trace the causes of failure of complex components, such as ball screws [3, 8, 19]. The costs of data storage are proportional to the amount of data stored and thus to the degree of digitization. The more than 20,000 registered machine tools in the cloud customer portal of the world's largest manufacturer of metal-cutting machine tools in 2019 alone cause theoretical storage costs of more than 2,349,000 € per year - assuming ten applied acceleration sensors (f_S = 10 kHz) with 16 bit/sample and storage device costs of 0.02 €/GB [4, 2]. Backup copies, energy supply etc. increase this amount many times over [2]. Due to these costs, there is a need to compress data or delete non-significant information. However, for maximum compression, lossy compression algorithms are applied which introduce distortions in the signals.

Data compression in the context of condition monitoring of rotating machine elements such as gears and bearings is investigated by [18, 7, 16, 17]. In relation to system identification, the influence of differential pulse code modulation is analyzed in [21]. The work shows the possibility of compressing acceleration signals and further using them for condition monitor-

* Reemt Hinrichs. Tel.: +49-511-762-5055
** Alexander Schmidt. Tel.: +49-511-762-18309
E-mail addresses: hinrichs@tnt.uni-hannover.de (Reemt Hinrichs)., schmidt@ifw.uni-hannover.de (Alexander Schmidt).

2212-8271 © 2021 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2021.09.046

ing. However, there is no knowledge about the impact of coding distortion on condition monitoring of preloaded ball screws. Due to the different geometry of the ball screw compared to a simple stationary rotating bearing, the behavior is expected to be significantly different. In this work, the lossy coding techniques differential pulse-code modulation as well as predictive vector quantization are used to compress data recorded from a acceleration sensor applied on a preloaded ball screw. For the ball screw, four conditions are considered, ranging from high preload to backlash. Signal analytic condition monitoring is applied and the accuracy of the condition monitoring on uncompressed data is compared to the accuracy on coded data.

This manuscript is structured as follows: in section 2, condition monitoring of preloaded ball screws and the measurement setup for the data acquisition are explained. In section 3, details of the applied coding algorithms are described. In section 4, the accuracy of the condition monitoring with coded and uncoded data as well as rate-distortion curves are shown and discussed in section 5. The manuscript concludes in section 6.

2. Condition monitoring of preloaded ball screws

Ball screws are used in machine tools to realize the relative movement between tool and workpiece. Consequently, the machining accuracy is highly dependent on the ball screw assembly. To enhance manufacturing accuracy, ball screws are preloaded in machine tools. For instance, single nuts are filled with oversized balls (some µm). A 4-point contact preload results from the selected ball oversize. The preload causes friction and thus wear. Due to the relative movement between the balls, the spindle and the nut, abrasive wear occurs. As a result, the ball oversize is reduced over the lifetime of the ball screw. This decrease the rigidity and leads to poorer positioning accuracy. The condition of the ball screw is to be considered as total failure as soon as the required manufacturing tolerances cannot longer be met or process vibrations, such as axis chatter, occur. Reliable estimation of the time of failure is not possible in advance [20]. Therefore, the condition of ball screws must be monitored by a condition monitoring system. For this purpose, a differentiation is made between the use of internal and external control signals. While the internal control signals are characterized as cost-effective and robust, the external control signals are usually characterized by a higher accuracy. For example, the external acceleration sensors can be applied very close to the point of impact thus enabling higher damage sensitivity and damage diagnosis. Klein shows approaches to monitor the fatigue damage of ball screws with applied acceleration sensors [10]. Furthermore, Klein presents an approach to monitor insufficient lubrication as a driver for preload loss with accelerometers in the high frequency range 10 - 25 kHz [10]. Further work on condition monitoring is presented in [14, 5, 11]. It should be noted that for condition monitoring of ball screws mainly accelerometers are used, whose sampling rate, taking into account the Nyquist-Shannon sampling theorem, are up to 100 kHz. As a consequence, large datasets are generated and stored.

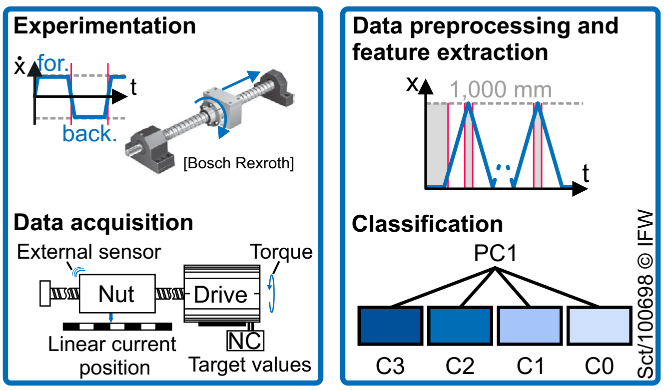

Fig. 1: Implemented approach for preload monitoring

2.1. Method for condition monitoring

Fig. 1 shows the used approach of the implemented condition monitoring. The condition monitoring method is mainly divided into the fields of data acquisition, preprocessing and processing as well as condition classification. In the following, the individual fields are described.

2.2. Measurement setup and data acquisition

A Bosch Rexroth ball screw with single nut 40 x 20 x 6 - 3 (d_0 x P_h x D_w - i) with a screw length of 2,002 mm was used. The ball screw is preloaded with an adaptive 4-point contact preload. Depending on the oversize of the balls, the preload varies between a high preload C3 (5 % of the dynamic load capacity), average preload C2, moderate preload C1 and clearance C0. Internal and external control signals are recorded during the continuous movement from the fixed to the floating bearing and back. The movement cycle is performed 22 times to improve the signal reliability. Whereby the first and last movement cycle were discarded. Thus, 20 similar movement sequences are available. The feed rate was defined for these investigations at 17,000 mm/min. The data of the acceleration sensor KS94B.100 in axial direction from Metra Mess- und Frequenztechnik in Radebeul e. K. with a sampling rate of f_s = 100 kHz is stored by the data acquisition system. Fig. 2 shows the data acquisition system and the positioning of the acceleration sensor.

2.3. Data preprocessing for condition monitoring

The time data is separated into individual repeating sections, know as segments, according to the movement condition. In the

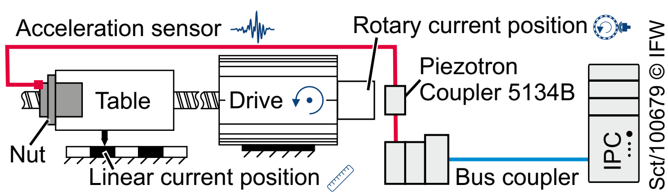

Fig. 2: Implemented data acquisition system and sensor placement

following, the forward and backward movement from fixed to floating bearing without acceleration phases are used as segments. Subsequently, 17 statistic values of position, shape and dispersion, so-called features, are extracted to describe the signal characteristics for each segment [13]. The features are, for example, the mean value, the kurtosis or the standard deviation. Based on these features the preload condition is later determined. To increase the robustness of the approach and to reduce the complexity, only statistically significant features for preload differentiation are selected and subsequently fused with the principal component analysis (PCA) and then reduced to the first and second principle component, see Fig. 3. The figure depicts the raw signal on the left and the extracted and fused information on the right as the principal components for the different preload conditions. In this case, the first two principle components combine > 95 % of the signal variance. Thereby the statistical significance is calculated with the F-statistic F_{stat} according to Backhaus etc. al (Eq. 1) for two conditions [1]. In Eq. 1, G represents the considered preload conditions, here two, K is the number of observations, here 20, $\overline{\mu_{(g)}}$ indicates the overall mean or condition mean. The declared variance, the experimental effect of the preload variation, is set in relation to the non-declared variance. As the F-statistic increases, the statistical significance of the feature distinguishing the preload variation increases. The selection limit for feature fusion (PCA) was defined as $F_{stat} = 50$. The statistical significance was calculated locally between all possible combinations of the preload conditions, six in total. Subsequently, the lowest calculated value was considered as the decisive F-statistic for the automatic feature selection.

$$F_{stat} = \frac{\sum_{g=1}^{G} K \cdot (\overline{\mu}_g - \overline{\mu})^2/(G-1)}{\sum_{g=1}^{G}\sum_{k=1}^{K}(y_{gk} - \overline{\mu}_g)^2/(G\cdot(K-1))} \tag{1}$$

2.4. Condition classification

The extracted and fused information, the principal components, are subsequently used for preload classification using decision tree methods. For this purpose, 100 times randomly 75 % of the measured data are used to train and 25 % of the data are used to test the results of the decision tree. The classification accuracy A is subsequently calculated as the ratio of the correctly classified preload conditions to the total number of trials. Essential is the consideration of a known and unknown change of the trained condition. Therefore, this paper distinguishes whether

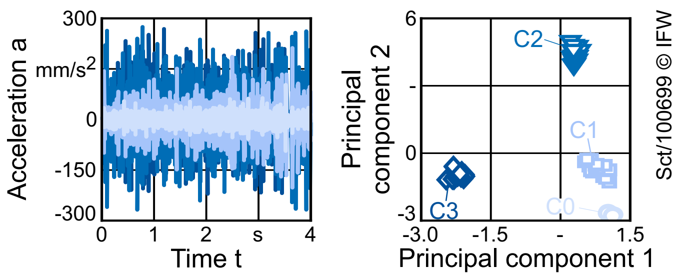

Fig. 3: Raw signal of the acceleration sensor and the first two derived principal components for the four preload conditions Ci

the classifier was trained with the uncompressed or the compressed data. Thus, the following research questions are to be distinguished:

1. Is condition monitoring with compressed data possible in principle?
2. Is condition monitoring with compressed data possible if only uncompressed data are known as reference values?

With answering the first question, it becomes clear whether preload monitoring with extracted features from compressed time series is possible at all. For the second question, it can be concluded whether extracted features from uncompressed data are in general comparable to those of compressed data.

3. Methods for data compression

In this section the applied data compression techniques are explained as well as the evaluation method used to obtain the results of this work.

3.1. Differential Pulse-Code Modulation

Differential pulse-code modulation (DPCM) is a standard algorithm for lossy compression of data [6]. It consists of an encoder, that compresses the data and a decoder, which decompresses the data. The main components are a predictor and a quantizer. The goal is to minimize the variance σ_e^2 of the prediction error $e := x - \hat{x}$, where x is the original signal and $\hat{x}$ is the prediction. This minimization is equivalent to maximizing the so called prediction gain

$$PG := 10 \cdot \log_{10}\left(\frac{\sigma_x^2}{\sigma_e^2}\right), \tag{2}$$

where σ_x^2 is the variance of the original source signal x.

The prediction error e is quantized by a quantizer, which maps intervals to single values and thus introduces irreversible distortion, and the resulting quantization indices, which indicate the mapped values of the quantizer, are transmitted to the decoder.

Maximum compression is achieved, if the quantization indices created by the quantizer are further compressed using lossless compression algorithms. Instead of implementing an actual lossless compression algorithm, in this work, the conditional entropy of context-size two is estimated to obtain the achievable additional lossless compression. Using sufficient sophisticated lossless compression algorithms, the conditional entropy can be achieved to an arbitrary degree.

3.2. Predictive Vector Quantization

In predictive vector quantization (PVQ), the basic coding method is identical to DPCM, but instead of a scalar prediction and scalar quantization, vector prediction and vector quantization are applied [6]. This is achieved by splitting the original signal $x(n)$, where n denotes discrete time, into N subsignals $x_i(N \cdot n + i)$ with $i \in \{0, 1, \cdots, N-1\}$, subsequently creating the vector process $\boldsymbol{X}(n) := (x_0(n), \ldots, x_{N-1}(n))^T$ of dimension N. The vector process $\boldsymbol{X}(n)$ is then predicted using vector prediction and the prediction error is then quantized using vector quantization [6].

3.3. Quantization

Three different scalar quantizers are evaluated in DPCM: uniform quantization, max-lloyd quantization and variance-adaptive quantization. In this work, variance-adaptive quantization is implemented as described in [9]. For the uniform quantizer, the stepsize was initially set according to tabulated optimal values taken from [9] and then, starting from these values, the step size was optimized to minimize the mean-squared quantization error. For PVQ, entropy-constrained vector quantization [6] is used for which the codebook was obtained using the vector quantization design tool of MATLAB.

3.4. Lossless compression

To minimize the mean codeword length, lossless compression has to be applied to compress the quantization indices of the respective coding methods. Fundamentally, lossless compression is achieved by mapping likely quantization indices to short codewords, i.e. bitstrings, and unlikely quantization indices to long codewords. The tight lower bound of the achievable compression, measured by the mean codeword length, is given by the (source) entropy. The (conditional) entropy $H(Y|X)$ of order or context-size D is defined as

$$H(Y|X) = -\sum_{x\in\mathcal{A}^D,\, y\in\mathcal{A}} p_{X,Y}(x,y)\log\frac{p_{X,Y}(x,y)}{p_X(x)}, \quad (3)$$

where $\mathcal{A}$ is the underlying alphabet of the source. Here, $\mathcal{A} = \{0, 1, \ldots, N_R - 1\}$, where N_R is the size of the codebook of the quantizer of the DPCM or PVQ.

In this work, instead of applying an actual lossless compression algorithm, the achievable mean codeword length of such algorithms is estimated by the conditional entropy. Therefore, the acceleration data was compressed by the lossy compression algorithms and the conditional entropy of the quantization indices of the coding algorithms were estimated.

3.4.1. Method

Each recorded acceleration signal was independently coded with each coding algorithm listed in Table 1. For each algorithm, quantizer resolutions of 1 bit/sample up to 4 bit/sample were used. The coding algorithms were individually optimized for each recorded signal, i. e. quantizers and predictor coefficients were newly trained for each recorded signal. The overhead of transmitting or storing the quantizer codebooks and predictor coefficients to the decoder made up less than one promille of the size of the compressed data. For prediction, static linear predictors were used, each specifically trained on the individual signals. Several predictor orders between 1 and 50 were tested. Adaptive least-mean-squared prediction was also tested but did not indicate major improvements. The rate of a coding algorithm in this manuscript is defined as the conditional entropy of order two of the quantization indices of the respective coding algorithms in bit/sample.

Table 1: Overview of the evaluated coding methods together with their labels used throughout the manuscript.

Model Label	Description
DPCM_U	DPCM with uniform quantization
DPCM_M	DPCM with max-lloyd quantization
DPCM_V	DPCM with variance-adaptive quantization
PVQ	PVQ with k-means vector quantization

4. Results

The achieved prediction gain on the acceleration data across preloads of about 6 bit/sample to 7 bit/sample is depicted in Fig. 4. The results suggest an increase of the achievable prediction gain with a decrease of the preload.

The rate-distortion curves, i. e. the rate across mean-squared error (MSE), across the coding algorithms are depicted in Fig. 5 for preload C1, where a predictor order of 50 was used. The MSE was calculated using all of the original, uncompressed acceleration data and all of the corresponding coded data. For the PVQ, a dimension $N = 3$ was used. Generally, the rate of the coding algorithms was 15-30 % smaller than the corresponding quantizer resolution in bit/sample, suggesting a significant benefit of lossless compression of the quantized signal.

The accuracy of the condition monitoring across MSE is depicted for outward journeys in Fig. 6 a) and for inward journeys in Fig. 6 b). The markers denote the performance at the respective quantizer resolution, where quantizer resolutions ranging

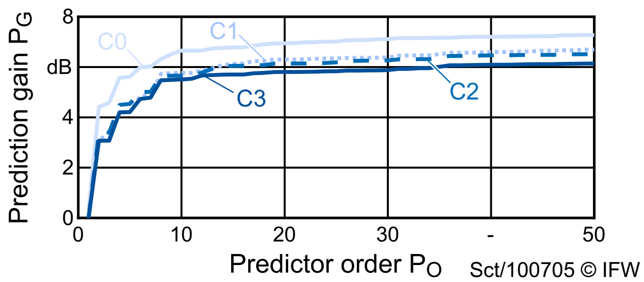

Fig. 4: Resulting prediction gain across preloads Ci for different predictor orders using static predictors optimized for a given acceleration signal.

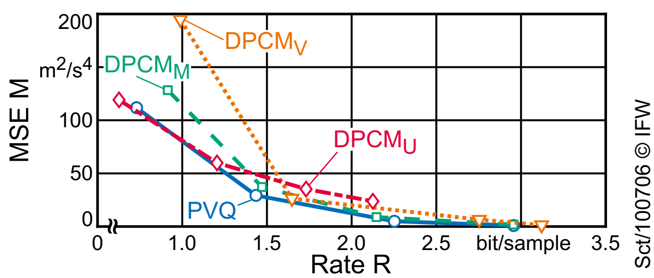

Fig. 5: Rate-distortion of coding algorithms for predictor order of 50 and preload $C1$. Depicted is the mean-squared error MSE M across the rate R.

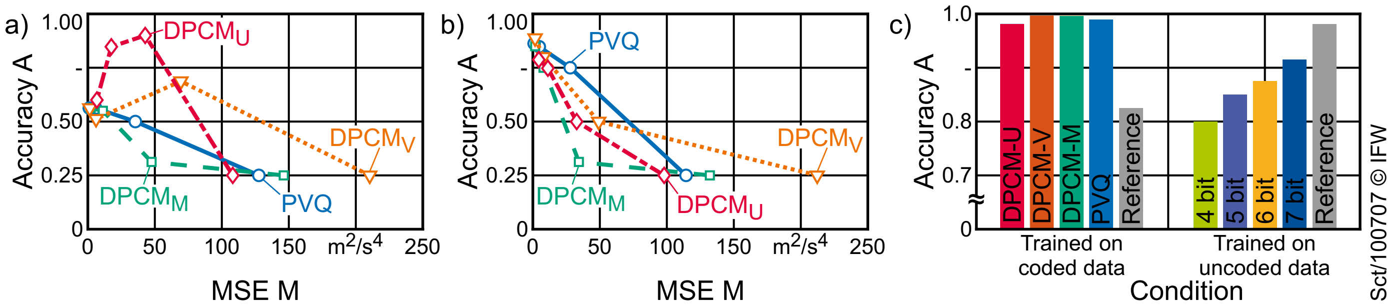

Fig. 6: Accuracy of the condition monitoring across mean-squared error MSE for all investigated coding schemes. Note, that an accuracy of 25 % is chance level. (a) shows the accuracy on outward journeys and (b) shows the accuracy on inward journeys. Depicted are all coding methods with a quantizer resolution of 1 to 4 bit/sample. On the outward journeys, for the DPCM$_G$ and DPCM$_V$ the maximum accuracy is peaking for 2 bit/sample and 3 bit/sample, respectively. (c) (Left) Accuracy of the condition monitoring on coded data of inward journeys at 4 bit/sample. Here, the condition monitoring was trained and tested on the coded data. (Right) Accuracy of the condition monitoring on data coded of inward journeys with DPCM$_M$ at 4 bit/sample up to 7 bit/sample together with the reference accuracy on uncoded data. Here, the condition monitoring was trained on uncoded data and then tested on the coded data. The results (a) and (b) were obtained with a predictor order of 50, whereas (c) was obtained with a predictor order of 10.

from 1 bit/sample to 4 bit/sample are shown. For inward journeys, the accuracy was monotonically increasing with decreasing MSE. However, for outward journeys DPCM$_U$ and DPCM$_V$ achieved maximum accuracy at 2 bit/sample and 3 bit/sample.

Additionally, DPCM$_M$ was tested with quantization resolutions of 4 bit/sample to 7 bit/sample on inward journeys. On the right, Fig. 6 c) depicts the reference accuracy of the condition monitoring on uncompressed data in comparison to the accuracy A of the condition monitoring. Here, the condition monitoring was trained on uncompressed data. Even for 7 bit/sample, the reference accuracy of about 97.5 % was not achieved with an accuracy gap of 6 %. In contrast, as shown on the left in Figure 6 c, when trained on coded data, the accuracy of the condition monitoring was nearly 100 % for all coding methods at 4 bit/sample. At a quantizer resolution of 4 bit/sample, including the lossless compression, the bitrate is reduced by about 81.5 % with respect to the original data resolution of 16 bit/sample. However, the test performance on uncoded data was about 82 % and thus considerably reduced and reduced further with decreasing quantizer resolution.

5. Discussion

The achieved prediction gain of 6 dB to 7 dB is comparatively low considering the high sampling rate of 100 kHz of the acceleration sensors. Interestingly, there seems to be a relationship between the preload and the predicitability, which the prediction gain measures, of the acceleration data. An explanation could be that larger balls, as used to achieve higher preloads, perform a larger amount of work when entering or leaving the contact zone of the ball screw nut. This should result in vibrations of increasing amplitude when the preload increases. These vibrations could be less predictable than the acceleration due to the balls already inside the ball screw and the deacceleration due to friction.

With respect to rate-distortion, PVQ performed the best out of the investigated coding algorithms, aside for a quantization resolution of 1 bit/sample, as shown in Fig. 5. However, a direct comparison is not entirely reasonable, because at a dimension of $N = 3$ and a predictor order of 50, PVQ actually uses the previous 150 time steps to predict the next sample vector. For inward journeys of the ball screw, even at 4 bit/sample, there was a significant drop of the accuracy of about 10 % and more across coding algorithms as shown in Fig. 6 a).

Interestingly, on outward journeys, the accuracy was not monotonically increasing with decreasing mean-squared error (MSE) and the maximum accuracy was attained at 2 bit/sample with DPCM$_U$, where the MSE was about 42.8 m^2/s^4. While it is common practice to consider inward and outward journeys separately, as different behavior is expected, the exact reason for the great difference of the impacts of the coding distortion on the condition monitoring is unknown.

For inward journeys, increasing the quantizer resolution to 7 bit/sample did still not yield the reference accuracy of about 97.5 % that is achieved on uncompressed data. At 7 bit/sample, only very small distortions of the signal peaks are apparent.

However, in principle using the condition monitoring on coded data is feasible at lower quantizer resolutions as shown in Figure 6 c) for 4 bit/sample on the left. Here, the condition monitoring was trained on the coded data. Equally high accuracy is also achieved at lower quantizer resolutions, even down to 1 bit/sample, because the principal components exhibit an increasing clustering tendency with decreasing quantizer resolution. However, because the principal components also perform a rotation with respect to the principal components obtained from uncompressed data, the accuracy when tested on the uncoded, original data is increasingly poor with decreasing quantizer resolution.

The decreased accuracy even at 7 bit/sample on inward journeys suggests that the condition monitoring is very sensitive to distortions of the peaks of the signals. As the signal maximum and the signal energy, which can be greatly affected by signal peaks, are two of the input features of the PCA used by the condition monitoring this is not unreasonable. Considering the difference of the prediction gain, especially of preload class C0, it could be, that using the same quantizer resolution, the distortions of the signals due to quantization are not equal across preload classes. An increase of the prediction gain in general allows to achieve a smaller MSE at the same quantization resolution. Therefore, it is possible that this introduces a "bias" in the classification and decreases the accuracy of the condition monitoring except at very high quantizer resolutions.

On outward journeys of the ball screw, the accuracy of the condition monitoring was found to be not monotonically dependent on the MSE. Similar to other branches of lossy coding, the MSE appears to be a suboptimal measure of the distortion introduced in a signal by a coding algorithm with respect to the condition monitoring. As the applied condition monitoring first calculates a set of features from the data which are then used for classification, it seems evident that using the distortion of these features, perhaps alongside the MSE, should yield a superior measure of signal distortion, in the sense that it could directly measures the impact of signal distortions on the accuracy of the condition monitoring. If the condition monitoring and the coding algorithm are designed and optimized in conjunction, similar to the algorithm optimization in [12], a significant improvement of robustness of the condition monitoring could be achieved as well as a reduction of bitrate of coding algorithm without affecting the accuracy of the condition monitoring.

6. Conclusion

In this work, the influence of lossy coding algorithms on a condition monitoring algorithm (CMA) using acceleration signals is investigated. The CMA is based on principal component analysis and uses 17 features such as standard deviation to classify the preload condition of a ball screw. It is shown that bit rate reduction through lossy compression algorithms is possible without affecting the condition monitoring - as long as the compression algorithm is known. When trained and tested on coded data, the original bitrate can be reduced by around 81.5% without affecting the accuracy of the condition monitoring. In contrast, an unknown compression algorithm reduces the classification accuracy of condition monitoring by about 20 % when coding with a quantizer resolution of 4 bit/sample.

Acknowledgements

The work of "WiZuBe" was supported by the Industrial Community Research program IGF (Industrielle Gemeinschaftsforschung) with the grant no. 19882 N of the Federal Ministry for Economic Affairs and Energy (Bundesministerium fr Wirtschaft und Energie, BMWi).

References

[1] Backhaus, K., Erichson, B., Plinke, W., Weiber, R., 2018. Multivariate Analysemethoden. 15. ed., Springer Gabler, Berlin.

[2] Bhat, W.A., 2018. Long-term Preservation of Big Data: Prospects of Current Storage Technologies in Digital Libraries. Library Hi Tech 36, 539–555. doi:10.1108/LHT-06-2017-0117.

[3] Buczak, A.L., Guven, E., 2016. A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection. IEEE Communications Surveys & Tutorials 18, 1,153–1,176. doi:10.1109/COMST.2015.2494502.

[4] DMG MORI, 2020. Annual Report 2019. URL: https://tinyurl.com/y5upgmnb.

[5] Feng, G.H., Pan, Y.L., 2012. Investigation of Ball Screw Preload Variation based on Dynamic Modeling of a Preload Adjustable Feed-Drive System and Spectrum Analysis of Ball-Nuts Sensed Vibration Signals. International Journal of Machine Tools and Manufacture 52, 85–96. doi:10.1016/j.ijmachtools.2011.09.008.

[6] Gersho, A., Gray, R.M., 1992. Vector Quantization and Signal Compression. Springer US, Boston, MA. doi:10.1007/978-1-4615-3626-0.

[7] Huang, Q., Tang, B., Deng, L., Wang, J., 2015. A Divide-and-Compress Lossless Compression Scheme for Bearing Vibration Signals in Wireless Sensor Networks. Measurement 67, 51–60. doi:10.1016/j.measurement.2015.02.017.

[8] Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L., Muller, P.A., 2019. Deep Learning for Time Series Classification: A Review. Data Mining and Knowledge Discovery 33, 917–963. doi:10.1007/s10618-019-00619-1.

[9] Jayant, N.S., Noll, P., 1984. Digital Coding of Waveforms: Principles and Applications to Speech and Video. Prentice-Hall Signal Processing Series. 5. print ed., Prentice-Hall, Englewood Cliffs, NJ.

[10] Klein, W.H., 2011. Zustandsüberwachung von Rollen-Profilschienenführungen und Kugelgewindetrieben. Dr.-Ing. Dissertation. Rheinisch-Westfälische Technische Hochschule Aachen.

[11] Möhring, H.C., Bertram, O., 2012. Integrated Autonomous Monitoring of Ball Screw drives. CIRP Annals 61, 355–358. doi:10.1016/j.cirp.2012.03.138.

[12] Preihs, S., Wacker, C., Ostermann, J., 2015. Adaptive Pre- and Post-Filtering for a Subband ADPCM-based Low Delay Audio Codec, in: 2015 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics, pp. 1–5. doi:10.1109/WASPAA.2015.7336937.

[13] Rezaei, A., Dadouche, A., Anderson, R., Lipsett, M., 2016. Multi-Sensor-based Framework for Gear Condition Monitoring: Part I. International Journal of Condition Monitoring 6, 17–25. doi:10.1784/204764216819257169.

[14] Schopp, M., 2009. Sensorbasierte Zustandsdiagnose und -prognose von Kugelgewindetrieben. Dr.-Ing. Dissertation. Karlsruher Institut für Technologie.

[15] Schuh, G., Kelzenberg, C., de Lange, J., Busch, M., Stracke, F., Frey, C., 2020. Predictive Maintenance. Final Report. Rheinisch-Westfälische Technische Hochschule Aachen.

[16] Staszewski, W.J., 1997. Vibration Data Compression with Optimal Wavelet Coefficients, in: Genetic Algorithms in Engineering Systems. volume 446, pp. 186–190. doi:10.1049/cp:19971178.

[17] Sun, J., Yan, C., Wen, J., 2018. Intelligent Bearing Fault Diagnosis Method Combining Compressed Data Acquisition and Deep Learning. IEEE Transactions on Instrumentation and Measurement 67, 185–195. doi:10.1109/TIM.2017.2759418.

[18] Tang, X., 2020. Investigation of Data Compression Methods for Intelligent Machine Condition Monitoring. Thesis. University of Huddersfield.

[19] Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., Wrobel, S., 2019. A Review of Machine Learning for the Optimization of Production Processes. The International Journal of Advanced Manufacturing Technology 104, 1,889–1,902. doi:10.1007/s00170-019-03988-5.

[20] Yagmur, T., 2014. Analyse, Verbesserung und Beschreibung des Verschleißverhaltens von Kugelgewindetrieben für Werkzeugmaschinen. Dr.-Ing. Dissertation. Rheinisch-Westfälische Technische Hochschule Aachen.

[21] Zhang, Y., Li, J., 2005. DPCM-based Vibration Sensor Data Compression and its Effect on Structural System Identification. Earthquake Engineering and Engineering Vibration 4, 153–163. doi:10.1007/s11803-005-0033-8.