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Degradation monitoring of machine tool ballscrew using deep convolution neural network

Nurudeen Alegeh [1], Abubakar Shagluf [1], Andrew Longstaff [1], Simon Fletcher [1]

[1]*Centre for precision Technologies, University of Huddersfield*

Nurudeen.Alegeh@hud.ac.uk

Abstract

High-value manufacturing often requires a high level of accuracy. While this may be an achievable aim, the demands of consumers and end-users are also for the often competing targets of lower cost, greater efficiency and resource-lean products. Notwithstanding the ambition for higher accuracy, increased availability of production machines is a fundamental requirement to maintain competitiveness in the manufacturing industry. Ballscrews are a fundamental part of the transmission system for most high-value machine tools. They are therefore integral to the positional accuracy and performance of the machine and also represent a weak-link in terms availability. Hence, the state of the ballscrew is essential in determining machine accuracy and availability.

This work proposes a deep learning approach for ballscrew performance monitoring. The technique works such that remedial activities can be scheduled and carried out when degradation is detected before breakdown occurs. The deep learning algorithm uses convolution to distinguish between a worn and good ballscrew in a machine tool. The technique was tested on a five-axis gantry-type machine tool with two parallel axis ballscrew. The results from the test carried out indicates that an overall accuracy of 94 % can be achieved with this technique.

Ballscrew, condition monitoring, machine learning, deep learning.

1. Introduction

Computer Numerical Control (CNC) machine tools used for production are required to operate within certain acceptable limits of tolerance, which become ever tighter with the availability of new enabling technology and greater customer drive. As industrial competition grows, more emphasis is increasingly being placed on both diagnosis and failure prevention, whilst predicting reliability and availability for manufacturing machines [1, 2]. This is due to an ever-growing need for tighter tolerances on manufactured components and on machine tools that can more reliably produce them [3].

No part is ever made perfectly and no measurement is exactly correct. Therefore, achieving tolerances on manufactured components is only assured if the sum of all sources of inaccuracies does not exceed the total tolerance. This in itself contributes to the discussion of machine accuracy, since it represents only one component of the total error budget for a manufactured product and solutions are often found by making compensating adjustments in other areas [4]. Herein lies the main argument against regular maintenance of the machine to preserve accuracy; a machine can continue to produce parts by adapting the process to suit changing conditions [5].

There is therefore often a reluctance to spend time understanding the error budget at a granular level if the overall statistical process control (SPC) results show good consistency [5]. However, such an approach is only viable where the same product is produced in sufficient quantity on a given machine to allow the process to be modified, based upon errors found on previous parts. Machines producing small numbers of differing product down to "batch size one" require right-first-time-every-time.

This paper does not seek to provide a universal answer to the question of "the best" strategy but rather proposes a predictive method to detect ballscrews unforeseen failures. It exploits the already established framework of the bottom-up modelling solution for data-driven machine health monitoring systems [6].

The majority of machine tools are comprised of a number of linear axes, sometimes with the addition of rotary axes to increase flexibility and functionality. This paper focuses on the motion of linear axes, though the principles developed could easily be extended to other motion systems.

The translational motion for a machine tool linear axis can be achieved in several ways such as ballscrew and ballnut, rack and pinion, leadscrew, belt drive etc. However, ballscrews are most widely used in high-precision machines because of their high accuracy in converting rotary to linear motion [7] and low friction, leading to better dynamic performance and reduced backlash. They are also well suited to other precise position control and levelling systems, such as aircraft wings [8]. Ballscrews found in high-speed drive systems such as machine tools suffer from wear in the raceway and the ball-bearings and can generate excessive heat due to friction, thereby causing geometric and thermal deformation. These deformations adversely affect the machine tool accuracy [9]. Typically, ballscrew deterioration occurs due to wear under unbalanced operation, improper lubrication, or installation errors. At present, major ballscrew deterioration detection systems are either based on vibration or Acoustic Emission (AE) signatures as there is a direct link between vibration and noise levels associated with increased bearing deterioration [10].

The rest of this paper is arranged as follows; section 2 machine learning and its application to ballscrew monitoring. Section 3 discusses convolution neural network as it is applied in deep learning. Section 4 and section 5 deals with the experiment set up and results obtained respectively. And finally, the conclusion is outlined in section 6.

2. Machine learning applied to ballscrew monitoring

The functional complexity of the ballscrew system makes machine learning algorithms a viable candidate to accurately model the non-linear characteristics of the ball screw degradation [11]. Machine learning is a data-driven method of modelling non-linear systems and it involves feature extraction and pattern recognition [12]. One of the most commonly used machine learning algorithms for monitoring the health condition of a ballscrew is the artificial neural network (ANN) [11]. Although, many researchers have used ANNs for condition monitoring and fault diagnosis with good results [13], their accuracy is greatly dependant on the feature extraction method employed. Hence, in order to effectively use neural network or more generally machine learning for that matter, good knowledge of signal processing techniques and fault diagnosis is mandatory. Applying good domain knowledge requires expertise that can deterministically identify and monitor every failure mode for every component on a machine tool, thus creating a potential source of error in the model.

This research seeks to establish methods that can be applied more efficiently to keep pace with rapid developments in mechanical, sensor and control technology. As such, a concept of deep learning first proposed in 2006 by Hinton and Salakhutdinov [13] has been investigated to overcome this deficiency. Many researchers have used deep learning for various diverse studies [14, 15]. Showing how effective and accurate deep learning can be in a wide variety of complex applications. This has led to the adoption of these techniques for fault diagnosis and condition monitoring [16]. In the field of predictive maintenance, deep learning has been used in several ways; scalable and unsupervised feature engineering method that uses vibration imaging and deep learning [16], a multi-objective deep belief networks ensemble for remaining useful life estimation in prognostics [17] and a deep learning approach for fault diagnosis of induction motors in manufacturing [18]. All of these research focus on induction motors, probably due to their prevalence in many sectors. However, very little research exists on the use of deep learning for the condition monitoring of ballscrew/ballnut assemblies [11].

A major advantage that deep learning offers over traditional machine learning, is the ability to perform feature extraction directly from the input data within the model. Hence, prior domain knowledge or expertise on the side of the algorithm designer is not required. A similar approach to the one proposed in this research has been used in the field of remote sensing [15], however, this implementation remains limited as only a single layer of feature extraction is used. Similar methods have also been used to develop a deep learning strategy for earth observation classification [19] (improving overall prediction accuracy from 83.1 % to 92.4 %) and for object classification [20]. Even with the success of such methods, there are very few relevant studies found addressing the CNC machine tool domain.

3. Deep Convolution neural (DCNN)

The advent of DCNN and the emergence of large natural image database for vision-related classifications such as ImageNet [21] sets the stage for efficient image-based classifications. ImageNet is a pre-trained convolution neural network originally designed by training about 15 million labelled images divided into about 22 thousand classes, which allows the DCNN to offer a rich and varied feature description from broad-spectrum images [21]. The condensed descriptions contained within these feature description works well for a set of diverse image classification tasks and performs better than typical classification methods. These outcomes give sustenance to the idea that the descriptions from the DCNN are universal and aids transfer learning between different domains, especially where the amount of available data is limited [19].

In this paper, the DCNN used is derived from the ImageNet pre-trained networks. It is a deep learning neural network with ten layers; the first layer is the input layer, the last layer forms the output layer and the rest forms the hidden layers. Table 1 shows the DCNN architecture.

Table 1. The DCNN architecture

Layer	Description	Neurons	Dimension
1	Input	2	227X227X3
2	Convolution 1	96	11x11x3
3	Convolution 2	256	5x5x48
4	Convolution 3	384	3x3x256
5	Convolution 4	384	3x3x192
6	Convolution 5	256	3x3x192
7	Fully connected 1	4096	-
8	Fully connected 2	4096	-
9	Fully connected 3	2	-
10	Output	2	

In the DCNN algorithm, the feature extraction is done internally within the algorithm by the convolution and the fully connected layers. It is initiated in layer 2, which corresponds to the convolution layer, with edge and colour detection at different angles.

The following is a description of the different layers of the model:

The input layer – the input to the network is a coloured image file of size 227x227x3 with zero-centre normalization. The number of input neurons is determined by the number of classes to predict, in this case – there are two classes, which are the “good” and “worn” states of the ballscrew/ballnut. The network is presented with raw data files of acoustic emission obtained from ballscrews during operation (one worn and the other in good condition).

The hidden layer – the hidden layer performs the feature extraction and classification activities. The feature extraction is done by five convolution layers, while the classification is achieved by three fully connected layers.

Each of the hidden layers has a Rectified Linear Unit (ReLU), except for layer 9. The ReLU is a non-saturating non linearity function f(x) [20].

$$f(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)$$

The ReLU performs a threshold operation to each element of the input such that any value less than zero is set to zero. DCNNs with ReLU trains six times faster than their equivalents without ReLU [20]. In layer 2 and layer 3, local response normalization is performed on the data via channel-wise normalization. This is typically required before ReLU nonlinearity to aid data generalization.

Data down-sampling is achieved in layer 2, layer 3 and layer 6 by dividing the input into rectangular pooling regions and calculating the maximum of each region. This process is known as maximum pooling and it is observed that overlapping pooling helps reduce overfitting in models [22].

The fully connected layer performs the supervised learning on the extracted features received from the convolution layer based on the known classes. The first two layers have 4096 neurons each and perform random dropouts by setting to zero any input elements with a probability of less than half. The technique of performing dropouts reduces overfitting of data thereby improving the neural network [22]. This is done by randomly breaking up the co-adaptations that would normally develop in standard backpropagation supervised learning. However, the use of dropout will lead to an increase in training time as the model without dropouts takes a longer time to converge.

The output layer – the output presents the final classification according to the accuracy of the developed model. The number of neurons in the output will typically be equal to the number of classes required. This layer assigns each input to each of the two neurons (one for each class). The error function E(θ) used is the cross-entropy function for a 1-of-2 coding scheme [23], given by

$$E(\theta) = -\sum_{i=1}^{n}\sum_{j=1}^{2} t_{ij} \ln y_j(x_i, \theta) \qquad 2$$

Where t_{ij} indicates that the ith sample belongs to the jth class, $y_j(x_i,\vartheta)$ is the output for sample i, n the number of observations and ϑ is the parameter vector. The output $y_j(x_i,\vartheta)$ is the probability that the network associates the ith input with jth class, which is interpreted as $P(t_j = 1|x_i)$. Also, the output unit activation function is given by a softmax function which satisfies the conditions $0 \le y_j \le 1$ and $\sum_j y_j = 1$.

$$y_j(x, \theta) = \frac{exp\left(a_j(x, \theta)\right)}{\sum_p exp\left(a_p(x, \theta)\right)} \qquad 3$$

Note that the $y_j(x,\theta)$ will remain unchanged with the addition of a constant term to all value of $a_j(x,\theta)$, hence the error is the same in some directions in weight space [23].

4. Experiment set-up

The experiments were conducted in a workshop environment on a five-axis CNC milling machine. The machine was chosen because the gantry is comprised of two ballscrews, one of which is in a good state of health and the other is worn. The AE sensor setup on the (good/worn) ballscrew of the CNC machine is shown in figure 1. The AE sensor used is a piezoelectric type with an integrated amplifier. The frequency response range is 100 000 Hz to 450 000 Hz and the normal operating temperature is between - 40 °C and 85 °C.

The AE sensor was positioned as close as physically possible to the ballscrew nut. The experiment was designed such that the AE sensor continuously acquires data from the ballnut as the ballscrew axis moves. Testing was under a controlled motion from one end of the axis to the other, a distance of 2 200 mm. Figure 1 shows the diagram of the machine tool with the AE sensor attached. Data were collected while this movement is repeated at different speeds, from low through moderate to high speed, within the normal operating speed in manufacturing. The speed/mm min^{-1} of movement included 1 000, 2 500, 3 000, 5 000, 7 500, 9 000 and 10 000. Thirty data set was collected for each of the seven different speeds for both ballscrew. Figure 2 shows the Fast Fourier Transform (FFT) of the signal captured at 1 000 mm min^{-1} for the good and worn ballscrew. The good ballscrew shows more prominent frequency content at a higher amplitude compared to the worn one.

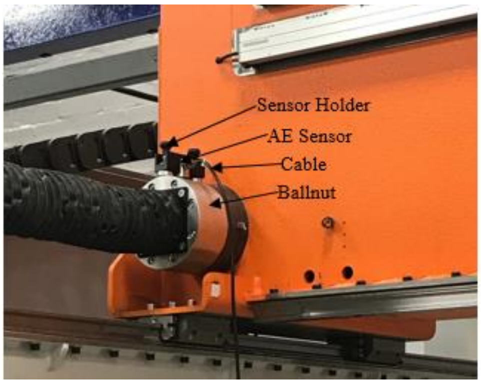

Figure 1. AE sensor on the healthy ballscrew nut

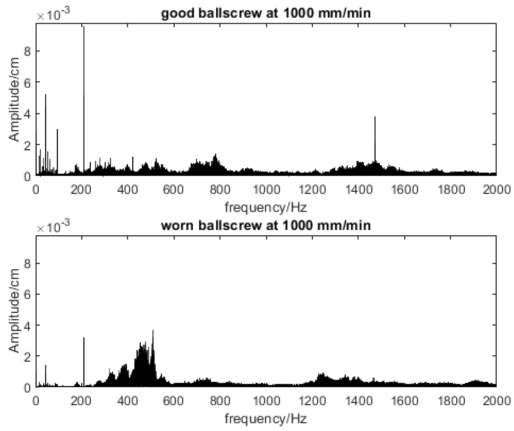

Figure 2. FFT of captured AE data for good and worn ballscrew

5. Results

The input to the DCNN is an image file, so in order to perform the DCNN analysis on the AE data obtained from the experiment, the input data is organised as a two-dimensional array of pixel values. The first convolution layer initialises the process of feature extraction by applying sliding filters to the input image such that it can learn from various features of the input data irrespective of their absolute location on the image. This is done by moving the filter along the vertical and horizontal coordinate of the input and performing the dot product of the learned weight and input and then adding a bias term [23]. Subsequent convolution layers and the fully connected layers perform high-level combinations of the features learned in the previous layers. The third fully connected layer is the final feature extraction stage that is used for classification.

The goal of the experiment is to show the effectiveness of DCNN to accurately predict the state of a ballscrew. For this purpose, the collected data was analysed using DCNN method and compared to Long Short Term Memory (LSTM) and various other machine learning algorithms namely: decision tree, support vector machine (SVM), K-nearest neighbour (KNN) and artificial neural network (ANN).

For the machine learning algorithms, feature extraction was performed before classification is done based on the extracted features. The extracted features are the mean value, root mean square (RMS), skewness, kurtosis, single value decomposition (svd), and standard deviation (std). The extracted features consist of 420 observations. Using 80 % of the data for training and 20 % for validation to reduce the risk of overfitting. The result is shown in table 2, and It can be observed that the decision tree algorithm is the best performer at 87 %.

Table 2. Validation results

Model type	Accuracy/%
Decision tree	87
SVM	84
KNN	77
Neural network	75
LSTM	51
DCNN	94

At the classification stage, the DCNN is able to achieve an accuracy of 94 % from 420 observations and 20 % hold out validation.

6. Conclusion

In this research paper, we have applied the deep convolution neural network (DCNN) for monitoring and detecting ballscrew degradation. The motivation for this work is to reduce the burden of explicit domain knowledge required to implement machine learning techniques. Such knowledge is difficult and expensive to apply and oversights can lead to errors in the model, missing potential sources of degradation. We showed that by formatting the input data as images, we are able to use DCNN to analyse and classify ballscrew health state. We were able to achieve a high rate of classification accuracy of 94 %. The main characteristic of this method is that it requires minimal data processing and still achieves a high rate of accuracy. We then compared the proposed algorithm with five other machine learning algorithms: decision tree, SVM, KNN, feed-forward neural network and LSTM recurrent neural network. The results obtained showed that the DCNN was able to improve the accuracy of the next best classifier (decision tree) by 7 %.

This work is focussed on the degradation of ballscrews in CNC machines for high-value manufacturing, where their condition can fundamentally affect the availability, performance and quality of the machine. Precision ballscrews are prevalent in many different applications, such as in aircraft, automotive brakes, robotics, etc. The proposed methodology is extensible to these applications.

The presented technique has shown the applicability of the method for the chosen problem domain. Future work will increase the granularity of classification to take into account the progressive stages of degradation which would make predictive maintenance more effective.

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