Prediction of Spindle Rotation Error through Vibration Signal based on Bi-LSTM Classification Network

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Abstract. One of the important indexes for high-precision machine tools is spindle rotation error, which is closely related to mechanical processing product quality. However, it’s difficult to directly acquire rotation error in the actual machining process. This literature proposed a novel uncompressed approach to predict spindle rotation error through vibration signal based on Bi-LSTM classification network, and this approach mainly consists of three steps, namely, pretreating original data; training Bi-LSTM classification network; predicting spindle rotation error. This approach adopts an uncompressed vibration signal method, which retains the time characteristic information into the predicted network, to build the relationship between easily collected vibration signal and the spindle rotation error. Finally, the proposed approach is applied in a spindle test rig, which has accomplished over 1700 hours of simulated load abrasion, and collected 170 days’ vibration signal and corresponding rotation error at RPM=1000, 2000, 3000, and 4000 conditions. The results show the proposed approach can effectively predict the spindle rotation error.

1. Introduction

One of the most crucial components for high-precision machine tools is the spindle, which integrates electricity, machinery, liquid of complex facilities [1]. Because of the installation error and complex working conditions, the spindle rotation error becomes larger under long-standing processing time, and it will cause severe vibration, reduction of processing quality, and even industrial accidents [2]. Therefore, it is significantly important to predict spindle rotation error for improving the manufacturing capabilities and productivity of machine tools [3].

Due to the trenchant installation requirements for measuring instruments, it’s difficult to directly obtain the rotating error of spindle in the real machining process, so the existing approach is the prediction of spindle rotation error based on the easily accessible electrical signal [4]. Generally, wearing status and revolving speed closely relate to spindle rotation error [5], and vibration signal includes wearing status and revolving speed information, as well as it can be easily collected [6, 7]. Therefore, there is a great potential to predict rotation error through vibration signals. Additionally, the prediction of spindle rotation error is affiliated as a continuous-time variable, but the continuous prediction can be changed into a discrete classification problem by reasonably processing the rotation error, and common prediction approaches can be divided into two major categories for the mechanical system: conventional data-driven approach and deep learning approach [8].
For the conventional data-driven approach, its step mainly includes feature extraction and identification after accomplished signal collection [9]. Because of the nonlinear and non-stationary characteristics for rotating mechanism’s vibration signal [10], the time-frequency analysis techniques are applied for the feature extraction, and these mainly include Wavelet Transform (WT) [11], Empirical Model Decomposition (EMD) [12,13], Local Mean Decomposition (LMD) [6, 14]. After the vibration signal is decomposed by this time-analysis technique, the decomposed components will be compressed to obtain final feature information, e.g. multi-scale entropy [15], sample entropy [16], multiscale fuzzy entropy [9] and Correntropy [17], etc. After that, the conventional data-driven approaches need to identify the result patterns by artificial neural networks (ANN) [12,15] and support vector machine (SVM) [9,17]. The traditional data-driven methods have been successfully applied to classification and recognition of the existing faults for the mechanical system [18], but the prediction of spindle rotation error belongs to non-fault states, and vibration signal compression leads to the loss of information after all.

For the deep learning approach, which not only can establish a sequential correlation with time characteristic through deep networks, but also don’t need signal compression. In recent years, one framework is a long short time memory network (LSTM) [6], which can directly process sequence signals with memory associated. Since LSTM can’t learn future features, bidirectional LSTM (Bi-LSTM) is proposed and it has been utilized in CNC health monitoring through vibration signal [19]. With the importance of sequence signal, Bi-LSTM has been widely applied in sound recognition, semantic extraction. Additionally, the advantages of softmax and classification layer improve the predicted accuracy and robustness for spindle rotation error. Based on the above discussion, the contributions of this study are listed as follows:

· A novel uncompressed approach for constructing the relationship between easily collected vibration signals and difficultly obtained spindle rotation error. The uncompressed vibration signal not only retains time characteristics of rotation error to improve the predicted ability of Bi-LSTM classification network, but also the predicted steps are simplified.

· The proposed approach is quantitatively validated by experimental data, which have been completed the up to 1700 hours of experimental test, and the spindle rotation error and corresponding vibration signal are collected every 10 hours.

This paper is organized as follows: Section 2 introduces Bi-LSTM classification network. Section 3 describes the proposed approach. Section 4 presents experimental application, which include express experimental processing, pretreatment of experimental data, and analysis of prediction performance. The conclusions are drawn in Section 5.

2. Architecture of Bi-LSTM classification network
In this section, a brief introduction of Bi-LSTM classification network will be presented. Structurally, the Bi-LSTM classification network includes an input layer, a fully connected Bi-LSTM layer, a softmax layer and a classification layer [19], and its final architecture is shown in Fig. 1, where it can be easily observed that the fully connected Bi-LSTM layer consists of two-directional LSTM layers, named as L1 and L2. Moreover, the L1 and L2 are made up of many memory cell units (MC), and the detailed introduction of MC can refer to paper [6]. For the two-directional LSTM layers, the L1 grasps the forward time-series signal, and it’s able to learn the previous feature information; the L2 manages the back time-series signal, and it’s able to learn the future feature information. Therefore,

\[
\begin{align*}
\hat{i}_t &= \sigma_s(W_iX_t + V_i\hat{h}_{t-1} + \hat{b}_i) \\
\hat{f}_t &= \sigma_s(W_fX_t + V_f\hat{h}_{t-1} + \hat{b}_f) \\
\hat{o}_t &= \sigma_s(W_oX_t + V_o\hat{h}_{t-1} + \hat{b}_o) \\
c_t &= \tilde{f}_t \otimes c_{t-1} + \tilde{i}_t \otimes tanh(W_iX_t + V_i\hat{h}_{t-1} + \hat{b}_i) \\
\hat{h}_t &= \tilde{o}_t \otimes tanh(c_t)
\end{align*}
\]  

(1)
the Bi-LSTM network can learn the contextual feature of the exiting signal through two-directional managements, and these advantages are more useful to learn vibration signals with time features. Additionally, for MC, L1, and L2, each of them has independent parameters, and these independences will be an advantage for the Bi-LSTM network to complete learn time sequence at each time step. The parametric learning equation of L1 and L2 are defined as [19].

\[
\begin{align*}
    \hat{t}_i &= \sigma_g (W_{i, X} + V_{i, h_{t-1}} + b_i) \\
    \hat{f}_i &= \sigma_g (W_{f, X} + V_{f, h_{t-1}} + b_f) \\
    \hat{o}_i &= \sigma_g (W_{o, X} + V_{o, h_{t-1}} + b_o) \\
    \hat{c}_i &= f_i \odot c_{t-1} + \hat{i}_i \odot \tanh(W_c X_i + V_c h_{t-1} + b_c) \\
    \hat{h}_i &= o_i \odot \tanh(\hat{c}_i)
\end{align*}
\]  

(2)

Fig. 1. Architecture of Bi-LSTM classification network.

In Eqs. (2) and (3), the \( X_i \), \( \sigma_g \), \( \odot \), \( a_K \) denote input, sigmoid function, Hadamard production and predicted output respectively; \( \hat{t}_i \), \( \hat{f}_i \), \( \hat{o}_i \), \( \hat{c}_i \) and \( \hat{h}_i \) represent the output values of input gate, forgot gate, output gate, cell candidate and for \( L_1 \), respectively; \( W_\cdot \), \( V_\cdot \) and \( b_\cdot \) denote input weight matrices, recurrent weight matrices and corresponding bias matrices for \( L_1 \), respectively. All of variables name are similar to \( L_2 \), only the superscript use ← to distinguish the \( L_1 \) layer.
After the MC, L1, and L2 are fully connected, a softmax layer must follow the fully connected Bi-LSTM network. To increase the recognition rate of classification, an exponential function is used as the activation function, which it can be expressed as

$$y_j(x) = \frac{e^{r_{j}(x)}}{\sum_{j=1}^{K} e^{r_{j}(x)}}$$

where $K$ denotes the number of classes, the $y_j(x)$ ranges from 0 to 1, and $\sum_{j=1}^{K} y_j(x) = 1$.

Finally, a classification layer must follow the softmax layer to realize the prediction of spindle rotation error. In the classification layer, the network uses the output values of the softmax function and assigns each input to one of the $K$ mutually exclusive classes based on the cross-entropy function.

$$\text{loss} = -\sum_{i=1}^{N} \sum_{j=1}^{K} t_{ij} \ln y_{ij}$$

where the $N$ presents the number of samples, and $t_{ij}$ denotes the $i$-th sample belongs to the $j$-th class. The $y_{ij}$ is the output for sample $i$ for class $j$, while in this paper, is the output value of the softmax layer. Therefore, the function of loss is the probability that the network associates the $i$-classified input with class $j$. Based on the description of softmax and classification layers, it’s easy to see that their capabilities are the limitation of previous fully connected Bi-LSTM layer to improve accuracy and robustness for entire predictive network. Due to the feature of the Bi-LSTM classification network, it can realize the predicted network with time information of vibration signal, and this predicted approach will be explained in the next section.

3. Predicted approach

Generally, the prediction of rotation error is a regression problem as discussed in Section 1, but the Bi-LSTM classification network can merely process classified problems; To improve the accuracy of prediction and the convenience of signal collection, the spindle rotation error will be collected long time vibration signal. Since a value spindle rotation error has a lot of sample points, this increases the complexity of the Bi-LSTM classification network. As a consequence, this predicted approach aims to solve problems: (1) To realize the transformation from a regression problem to a classification problem. (2) To effectively deal with long time vibrational sequence to reduce the complexity of the prediction network.

For the first problem, although the rotation error is a continuous-time variable, it is discretized by selecting a smaller unit quantity. If appropriate rotation error resolution is used and combined with the actual acquisition of spindle rotation error value in Section 4.1, this paper set 1um as the minimum unit of interval. Nationally, this continuous prediction of rotation error is transformed into a discrete classification problem.

For the second problem, the vibration signal needs segment processing. According to Section 2, the input layer supports a one-dimensional vector. By segmenting the vibration signal and sorting chronological order, it not only reduces the complexity of the classification network but also the time characteristic of the vibration sequence can be preserved. Additionally, to obtain better fitting combination and prevent training divergence, all of the vibration signals are normalized to zero mean and unit variance by same parameters before segment processing, and the calculation formula is defined as [6]

$$y'(t) = \frac{y(t) - \text{Min}[E(y(t))]}{\text{Max}[D(y(t))]}$$

where $y(t)$ denotes original vibration signal, $y'(t)$ is result of the normalized vibration signal, $\text{Min}[E(y(t))]$ is a minimum mean of the original vibration signal, $\text{Max}[D(y(t))]$ is a maximum variance of the original vibration signal.
Based on the above two problems, the diagram of a predicted approach is shown in Fig.2, in which the original vibration signal and spindle rotation error are pretreated to meet the condition of Bi-LSTM classification network, respectively.

**Fig. 2.** Diagram of proposed prediction approach.

As shown in Fig.2, it easy can be observed that the proposed approach includes three steps, named as pretreatment, training, and prediction, as well as its specific steps, can be defined as

**Step 1:** Discretization of the collected spindle rotation error. Since the rotation error acquainted instrument can achieve the highest resolution of 0.01um, it will cause the complexity of predicted network and decrease predicted accuracy. In this literature, the minimum resolution of the collected rotation error is 1um.

**Step 2:** Rounding off the rotation error. A difference of collected and processed resolution, it will lead to remaining mantissa. In this approach, the mantissa uses round approach to keep a more effective value of rotation error. Suppose all of the collected rotation errors are $Y = [y_1, y_2, y_3, \ldots, y_{170}]$, and then $Y \rightarrow \frac{1}{1000}$ and round off $Y_0$ (notes: the unit of collected rotation error is mm).

**Step 3:** Normalization processing of the vibration signal. Suppose the original vibration signal is $y(t)$, and find out mean ($E(y(t))$) and variance ($D(y(t))$) of all vibration signal segments, and then identify the minimum value $Min[E(y(t))]$ and maximum value $Max[D(y(t))]$ of all same revolving speed, and lastly using Eq. (5) get $y'(t)$ to accomplish normalization.

**Step 4:** Segment of the vibration signal. Because the total vibration signal (200000 samples) is too long with the same spindle rotation error, it needs to be segmented for the vibration signal. In this study, each length of the segment has 500 samples within a cell time unit ($X_m$), and the total segment is 4000 ($m=1, 2, \ldots, 4000$).

**Step 5:** Dividing samples. The collected vibration signal and rotation error would be divided into two parts: training samples and testing samples. In this paper, the 90% vibration signal, corresponding to each value of rotation error in **Step 2**, will be used as training samples, and the rest is testing samples.

**Step 6:** Training network parameters. Basic parameters of the Bi-LSTM classification network are initialized, and then **Step 4**’s vibration signal and corresponding **Step 2**’s rotation error are used as input and output, respectively.

**Step 7:** Prediction rotation error. The network parameters of **Step 6** are used to predict the testing samples and then calculate prediction accuracy.
Therefore, the proposed approach builds a relationship between the vibration signal and spindle rotation error, and this approach will be applied in the next section to demonstrate superior predictive performance for spindle rotation error.

4. Experimental application
Since the accurate prediction of spindle rotation error need too many samples for training model, and the spindle rotation error is acquired by high precision inspection rod, which must be installed in the place of machine tool [20]. However, in the producing spot of CNC machine, it doesn’t get real the value of spindle rotation error, because the place will be replaced as a machine tool for completing the machining work-piece. Due to the harsh environment of mechanical processing, it’s unsuitable for using of a high-precision testing rod to collected spindle rotation error. To address the above problem, the simulated load of the CNC machine is the optimal choice [21, 22]. For this paper, an experimental platform was designed and built, as shown in Fig. 3, to realize simulated load and get the value of spindle rotation error.

![Fig. 3. Platform of spindle testing.](image_url)
Fig. 3 shows the platform of spindle testing includes three parts, namely, pneumatic loading hardware, experimental platform, collection and control system. The pneumatic loading hardware is used to provide variable loading force for the spindle with simulated machining, and it contains an air pump, two reversing valves, and three pneumatic servo-values, one of which is used to achieve axial force loading, and two others are used to complete radial force loading. Considering of radial force has double direction, and the system of hardware only adds two reversing valves. The experimental platform includes a tested spindle, three force sensors, triaxle vibration, and a Lion rotation measuring instrument, which consists of three eddy current sensors and a spend sensor. On the right side in Fig. 3, it can be observed that the inspection robs not only instead of the tool position, but also much close to the eddy current sensor. The task of collection and control system finish speed and load force control for the tested spindle, meanwhile, it needs to collect all sensors signal and corresponding spindle rotation error.

4.1. Experimental processing
For this study, the experiment is mainly divided into two steps, and these two steps loop until the whole experiment ends. The first step is the abrasion process for getting different states of the tested spindle, and the load force is the same as the paper [23] to ensure that more closed as the actual working conditions of spindle change patterns. The second step is acquiring the values of spindle rotation error and the corresponding vibration signal. For the data of this research, 170 days of experiment has been completed and accumulated over 1700 hours of simulated load. In this experiment, vibration signals and corresponding rotation errors under many groups of rotating speed are collected. The RPM (Revolutions Per Minute) value of 1000, 2000, 3000, 4000 are selected to predictive analysis, and the vibration signal comes from sensor (PCB: 256A14) data near the front bearing of the tested spindle.

The vibration signal and corresponding spindle rotation error are continuous variables, which unadapt the proposed approach. To improve predicted precision, the vibration signal and rotation error need to pretreat before they are put into the Bi-LSTM classification network, and these pretreatments of experimental data will be introduced in the next subsection.

4.2. Pretreatment of experimental data
In Section 2, the Bi-LSTM classification network has been used to solve the classified problem. However, the collected rotation error is a continuous variable, which doesn’t suitable for the proposed approach, so it needs the pretreatment of experimental data. For this experiment, the SpindleCheck machine capability tester is utilized, which can realize high precision measurement and minimum resolution is 0.01um. Based on Step 2 of the proposed approach in Section 3, the pretreated spindle rotation is shown in Fig. 4, in which the different color’s waveforms represent the spindle rotation error with different RPM. Moreover, different from the conventional predicted network samples, each of the spindle rotation error is randomly distributed with spindle running status, and it also increases the difficulty for prediction. According to the waveform trend, it can be seen that the rotation error heavily dependent upon the spindle’s RPM, and the values of spindle rotation error also increase with RPM increase, as well as the values of spindle rotation error are dropped in the range of 4-23um.

To better observe the rotation error distribution, the statistics of the occurrence times for each class rotation error are shown in Fig. 5, in which the abscissa axis represents the value of spindle rotation error, and the ordinate axis represents the number of occurrences.
Fig. 4. Distribution of pretreated spindle rotation error under different RPM condition.

Fig. 5. Distribution of spindle rotation errors at different speeds, in which the abscissa axis represents the value of spindle rotation error, and the ordinate axis represents number of occurrences.

Comparison of each distribution at the different RPM conditions, the mostly possibility of spindle rotation error is 7um, 10um, 11um, 11um at RPM=1000, 2000, 3000, and 4000, respectively. When RPM=3000, the classification of rotation error is least than other RPM conditions. Moreover, it can be observed that the higher the rotation speed, the higher probability of a large value for spindle rotation error.
4.3. Predicted performance

According to the proposed approach, the training samples have 3600 segments, and the testing samples have 400 segments, and all of each segment has 500 points. Additionally, the proposed approach has input, fully connected Bi-LSTM, softmax and classification layers, but it mainly needs to set InitialLearnRate (initial learning rate), numHiddenUnits (number of the hidden layer), numClasses (number of the classification layer), maxEpochs (maximum numbers of epochs). Considering the effect of computer random initialization matrix, the InitialLearnRate, numHiddenUnits, maxEpochs are respectively set as 0.0001, 1500, and 4000 for all network parameters. As shown in Fig.5, the numClasses are set as 8, 8, 7, and 10 for corresponding RPM=1000, 2000, 3000, and 4000, respectively. According to these network parameters, all of training accuracy are almost 100% and more than 200 epochs, indicating the predicted network has well fitted the training samples [24], so it’s difficult to obtain higher precision under the existing sample conditions, and final results are shown as in Table 1.

| RPM   | 1000  | 2000  | 3000  | 4000  |
|-------|-------|-------|-------|-------|
| Training accuracy | 99.18% | 99.12% | 100%  | 98.01% |
| Testing accuracy   | 89.59% | 87.65% | 93.53% | 86.47% |

As shown in Table 1, it can be seen that different RPM conditions lead to different training and testing accuracy, but the RPM=3000 owns the highest accuracy than other RPM conditions. Its main reason is that the RPM=3000 only has 7 classes, which makes more samples to learn at the same rotation error condition. Additionally, to better illustrate the predicted results, confuse matrices with different RPM are presented as in Fig. 6. It can be seen that the proposed approach can identify 4, 6, and 8 categorized rotation errors at RPM= 1000, 2000, 3000, and 4000, respectively. Although only 4 categorized rotation errors can be identified at RPM=1000, the accuracy of test samples is already at 89.59% as shown in Table 1.

![Fig. 6](image-url)

In summary, Fig. 6 shows that the proposed approach can accurately predict the most frequent the values of spindle rotation error at each rotation speed, e.g. 7um at RPM=1000, 9um at RPM=2000, 11um at RPM=3000 and 11um at RPM=4000. Moreover, it realizes mostly the prediction of spindle rotation errors under different RPM conditions. Therefore, this study proposes a new approach for the
prediction of spindle rotation error, and it’s very important to improve the machining quality of CNC machine tools.

5. Conclusion and future work
Since the spindle rotation error cannot be directly obtained, this paper proposes an uncompressed prediction approach through the vibration signal based on Bi-LSTM classification network. Pretreatment of the vibration signal and corresponding rotation error, then train the Bi-LSTM classification network, and final realize prediction of spindle rotation error. This proposed approach built the relationship between the easy-collected vibration signal and the difficult-obtained spindle rotation error. Finally, the proposed approach is applied in a spindle testbed to demonstrate outstanding performance for the prediction of spindle rotation error. The results show that the highest predicted accuracy is 93.53%, and it realizes accurate prediction of the high-frequency rotation error under different RPM conditions. This paper not only presents a new approach for the prediction of spindle rotation error, but also a solid foundation for the development of an automatic monitoring rotation error system.

Since the proposed approach can’t accuracy prediction under small sample condition, the future research finds out an improved method to realize all categorized prediction of spindle rotation error.

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