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Prediction of tool wear during linear feed milling using multi-sensorial data fusion

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Abstract
This paper presents a tool wear prediction model based on multi-sensorial data fusion, which integrates both local preserving projection (LPP) and support vector regression machine (SVR). The time-domain features are extracted from spindle current and feed motor torque signals, and the multi-sensorial features are fused by three dimension reduction algorithms of PCA, KPCA and LPP. To compare the fusion effect, SVR model was used to establish the mapping relationship between the fusion feature and the tool flank wear value, and the tool wear value was predicted. The experimental results demonstrate that the effect of feature fusion using LPP method is better than that of PCA and KPCA. In addition, in order to eliminate the motor current fluctuation and unexpected factors in cutting process, wavelet packet transform (WPT) algorithm is used to filter the extracted features to further improve the accuracy of tool wear prediction.

Keywords: multi-sensorial data fusion, tool wear prediction, machine learning

1. Introduction

At present, the goal of the research is to monitor the abnormal conditions in the machine tool processing under the situation of unattended and one worker with multi-machine. With the development of intelligent manufacturing, machine tools have the certain self-perception function. Therefore, monitoring tasks such as tool wear, breakage, chatter and chip load self-adaptive control can be carried out. The target is in line with the industrial 4.0 principle [1].

In the process of NC machining, tool wear will affect the accuracy and surface quality of parts, and damage the machine tool when seriously [2]. In order to avoid it, the tool condition should be monitored during machining.There have been several tool condition monitoring techniques reported in the literature, which can be classified as direct or indirect approaches. In the direct approach, the artificial vision system installed close to the cutting region, such as laser and image sensors on the table with position tracking along the tool path. Milad [3], proposed a method combining PCA and discrete wavelet transform (DWT) with a neural network is used to locate and track cutters in the process of processing infrared and visual cameras. This method has high measurement accuracy, but it is limited by the high cost of laser and the influence of illumination change and environment, which make it difficult to implement this method in industry. Zhu et al. [4] used optical image method to measure tool wear at intervals, but this method needs to interrupt the processing process and affect the processing efficiency.

To solve above problems, the indirect monitoring methods of physical signals such as acoustic emission, vibration, force, temperature and motor current have become the hot pot. Because the model based on artificial intelligence (AI) has made reliable progress in the field of system identification and prediction [5]. In addition, In addition, AI models are widely used in the field of tool condition monitoring to reduce cost, complexity and time [6]. Ghosh et al. [7] used back propagation neural network (BPNN) model to fuse different signals (cutting force, spindle current, vibration and sound) for tool condition monitoring. Yu et al. [8] used a hidden Markov model and combined cutting force, acoustic emission and spindle vibration signals to monitor tool status. Alonso et al. [9] utilized sound and feed motor current to develop the monitoring system to detect the tool wear. The features extracted from sound and feed motor current signals by SSA correlate with tool wear state and were trained by neural network to estimate the tool flank wear. Stavropoulos et al. [10] presented a methodology based on the simultaneous detection of spindle drive current and acceleration sensor signals for tool wear prediction in milling of CGI 450 plates, by utilizing third degree regression models and pattern recognition systems. Balsamo et al. [11] proposed a new methodology based on the acquisition of multiple sensor signals of different nature, including force as well as acoustic emission sensor signals. In [12,13], proposed a methodology for a comprehensive tool condition monitoring, based on the acquisition and processing of multiple sensor signals to acquire a number of sensor signal features relevant for the monitoring of tool wear.

Although the above research has achieved appropriate monitoring results, literature [14] points out that both spindle current and feed motor torque are affected by cutting forces. Wang [15] points out that the features proposed by multi-source information are combined, the dimension of features is highly. Appropriate feature fusion methods should be adopted to reduce the dimension and complexity of the features.

Aiming at the above problem, we use PCA, KPCA and LPP methods to fuse the features of the spindle current and feed motor torque signal of machine tool, reduce the dimension and complexity of features. And then predicts tool wear through SVR model to verify the effectiveness of the fusion method. The experimental results show that the combination method of LPP and SVR enhances the prediction accuracy of the model. In addition, the filtered feature can obtain higher prediction accuracy than the unfiltered feature.

2. Methodology

2.1 PCA and KPCA

The goal of PCA is to map data to a new projection space by an orthogonal transformation. The maps with the largest variance in the new space are the principal elements, while the maps with smaller orthogonal variance are considered noise. It can reduce

the dimensionality of data sets with little information loss. Therefore, PCA can be utilized to feature fusion.

However, PCA algorithm cannot get satisfactory results in solving the reduction problem of non-linear data sets. The principal kernel component analysis (KPCA) algorithm, which maps low-dimensional input data space to high-dimensional with the help of the kernel function, and uses PCA in high-dimensional space, thus effectively solving the problem of reduction of non-linear data sets, and improves the efficiency of calculation.

2.2 Proposed method

LPP [16] is a type of mapping which uses neighbor graph to establish mapping. Compared with PCA method, LPP is a popular learning algorithm. By using the local symmetry of linear reconstruction, the potential non-linear structure of high-dimensional data can be found, so the essential features of non-linear data can be retained. Compared with KPCA method, LPP mapping matrix needs less computation, and retains the advantages of linear method which is simple and intuitive.

Taking n-dimensional data sample $X = \{x_1, x_2 \ldots x_m\}$, which containing cutting process quantity is m as an example *(n<<m)*. Using LPP algorithm to find a projection matrix *W* to map data sample *X* to low-dimensional space *R (l<<n)* so $Y = W^T X$. The optimal projection matrix *W* can be obtained by minimizing the problem, as shown in (1):

$$W_{ij} = \underset{W}{\operatorname{argmin}} \sum_{i,j=1}^{n} (y_i - y_j)^2 S_{ij} \tag{1}$$

Among them, the weight matrix S_{ij} is constructed by the proximity graph. Its size describes the proximity degree (similarity) between x_i and x_j. When x_i and x_j are near neighbors($\|x_i - x_j\|^2 < \varepsilon, S_{ij} = \exp(-\|x_i - x_j\|^2 / t$). Otherwise $S_{ij} = 0$. Besides $y_i = w^T x_i$. Thus:

$$\begin{aligned} \frac{1}{2}\sum_{i,j=1}^{n}(y_i - y_j)^2 S_{ij} &= \frac{1}{2}\sum_{i,j=1}^{n}(w^T x_i - w^T x_j)^2 S_{ij} \\ &= W^T X(D-S)X^T W \\ &= W^T XLX^T W \end{aligned} \tag{2}$$

Equation (1), $D_{ij} = \sum_{j=1}^{n} S_{ij}$ (*D* is a diagonal matrix) and $L = D - S$ is a Laplacian matrix. Additional constraints are:

$$y^T Dy = 1 \Rightarrow W^T XDX^T W = 1 \tag{3}$$

Finally, the optimization objective function in (1) can be modified as follows:

$$\begin{cases} W_{ept} = \underset{W}{\operatorname{argmin}} W^T XLX^T W \\ s.t. W^T XDX^T W = 1 \end{cases} \tag{4}$$

The optimization problem can be transformed into solving eigenvalue equation.

$$XLX^T w = \lambda XDX^T w \tag{5}$$

By selecting the first *l* eigenvectors from $W(l \square n)$, the following mappings can be obtained:

$$y_i = W^T x_i, W^T = [w_1, w_2 \ldots w_l] \tag{6}$$

Therefore, *W* is $l \times m$ matrix, the data dimension is reduced from *n* to *l* dimensional. Besides the structure between neighboring data points of the original data remains unchanged.

3. Experimental setup

The TC4 material is used in this experiment with size of 190mm×140mm×60mm. The cutting tool diameter is equal to 50mm. Two carbide inserts are installed. The installation of the workpiece and cutting tool is shown in Figure 1. Dry cuttings are carried out in the experimental process. The cutting parameter is indicated in Table 1.

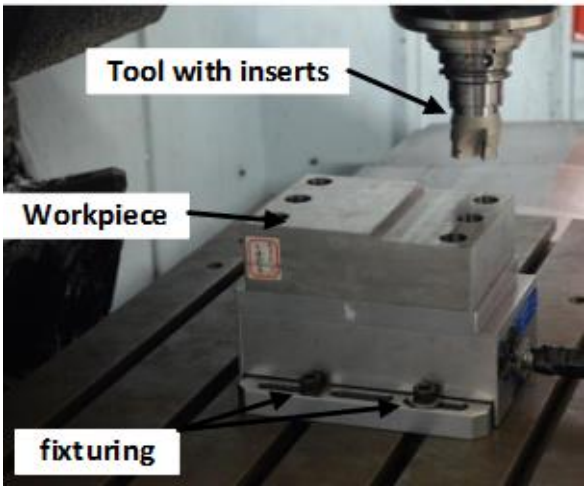


Figure 1. Cutting tool and wrokpiece mounting

Table 1 Cutting Parameters

Parameter	Value
Y Depth of Cut	2 mm
Z Depth of Cut	2 mm
Spindle Speed	1500 rpm
Feed Rate	150 mm/min
Milling Method	Down milling

As showed in Figure 2, the HIOKI 3283 current clamp is installed at the output end of X, Y, Z and spindle servo drive. The sampling frequency of each channel is 2 KHz. The signal acquisition is done through the DAQ acquisition card.

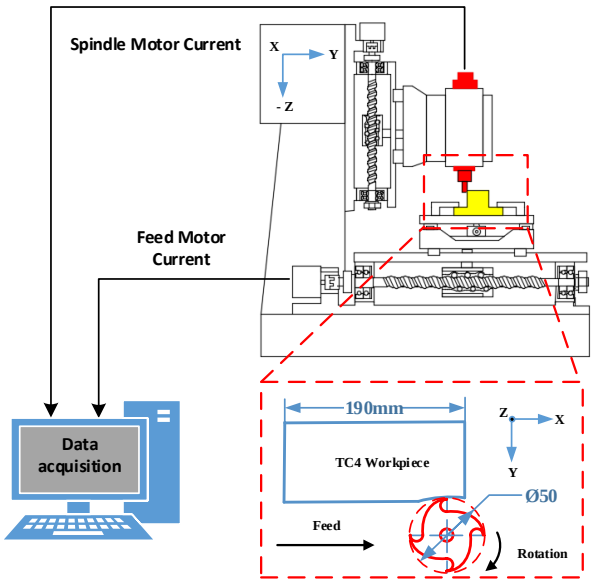


Figure 2. Schematic diagram of cutting process

In addition, after each cutting, the blade is removed to observe the wear of the tool flank (VB) through the INSIZE magnifier, and the worn value of the tool flank is measured. As it is non-uniform wear, take the mean value of VB value in different areas.The wear of tool flank is shown in Fig. 3.

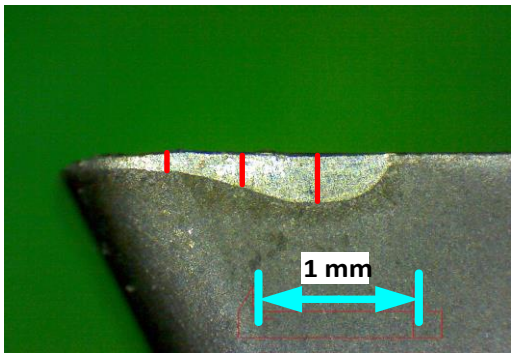
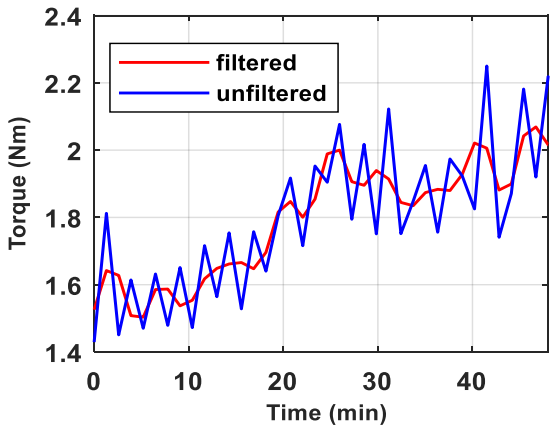
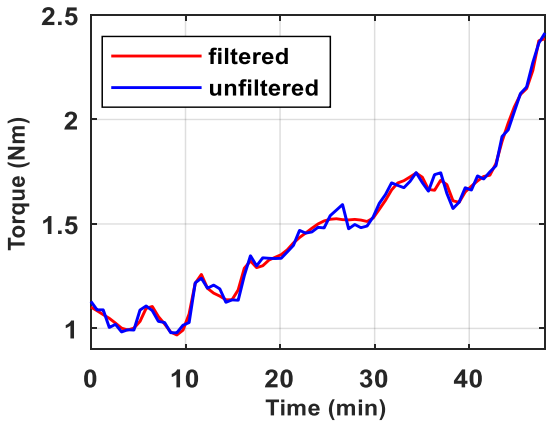


Figure 3. Schematic diagram of tool wear value measurement



(a) Torque of X axis



(b) Torque of Y axis

Figure 4. Contact before and after feature filtering

4. Signal processing

4.1 Feature extraction

The traditional features according to the characteristics of the response are chosen, as showed in Table 2. Two features were extracted from the response of one channel, and in this experiment we use 4 channels, so the number of the feature set is 8.

4.2 Signal filter

Although the collected data are an incremental process caused by tool wear, there will be many disturbances (such as friction, high frequency vibration, etc.) due to the distance between the collected signal and the cutting area, resulting in the oscillation phenomenon in the extracted feature trend. The extracted features cannot directly reflect the trend of tool wear. To avoid this problem, WPT is used to filter the RMS feature of tool wear tendency. The results are shown in Figure 4.

Table 2 Extracted Features and Feature Description

Feature	Formula
RMS	$x_{rms} = \sqrt{\frac{1}{w}\sum_{i=t-w+1}^{w} x_i^2}$
Kurtosis	$K = \sum_{i=1}^{n} x_i^4 / nX_{rms}$

5. Comparison Results

5.1 Feature Fusion

Two feature reduction techniques were chosen to fuse features and compare with the proposed hybrid approach by averaging the results of 100 tests. Therefore, in the case of PCA and KPCA and LPP are implemented to find the best features for each regression respectively. Same SVR model is used in this section.

The comparison of different feature reduction methods is given in Table 3. Figure 5 shows the relation curve of meaning accuracy with the number of features. The accuracy curve of the proposed method reached a peak at 8.7 (MSE), where the number of selected features is for two. Then the accuracy curve gradually declined and stabilized at 13.4. PCA algorithm worked well, while KPCA performed worst in this tool wear regression task. Specific information about selecting features is listed in Table 3.

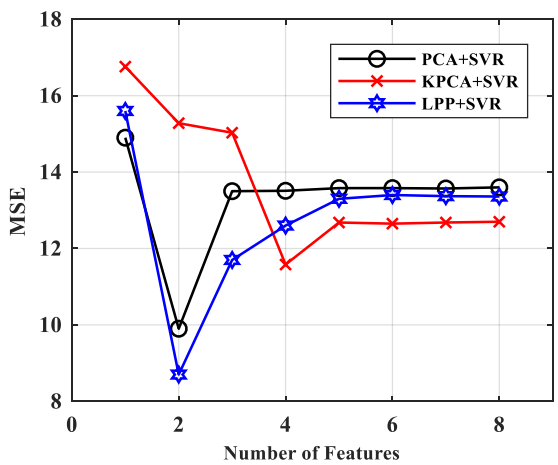


Figure 5. Relation curves of means accuracy with number of selected features in 100 tests

Table 3 Comparison of different feature reduction methods

Method	Number of selected features	Number of total features	MSE
PCA+SVR	2	8	9.9
KPCA+SVR	4	8	11.6
LPP+SVR	2	8	8.7

5.2 Regression

The proposed hybrid approach compares with other data fusion methods for averaging the results of 100 tests. Nine tens (9/10) of the input data were used only for model development (training). The remainder (1/10) of the input data was used for

model validation (testing). Figure 6~7 shows the predicted against observed tool wear values using the experimental data set. Besides, the comparison result is shown in table 4.

Table 4 Comparison of different algorithms for tool wear prediction

Method	Prediction results			
	Filtered		Unfiltered	
	MSE	Error_avg/μm	MSE	Error_avg/μm
SVM	12.7	25	13.1	27
PCA+SVR	9.9	17	10.7	19
KPCA+SVR	11.6	22	12.8	25
LPP+SVR	8.7	11	9.9	17

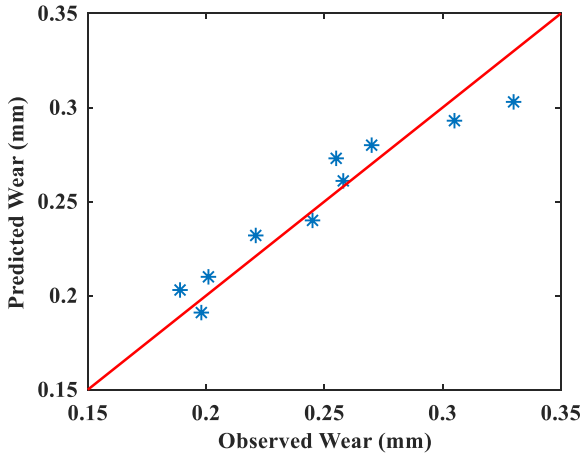


Figure 6. LPP-SVR; filtered; maxmum error: 27μm and minmum error: 3μm and avg error: 11μm

The proposed method gets the highest average regression accuracy while comparing with other algorithms. The accuracy derives from two aspects. (a) when the feature numbers were set to two. The accuracy represents the performance of SVR model. Depending on Table 4, LPP is more precise than PCA in our experiment. (b) by filtering the extracted features, the prediction accuracy of the model can be also improved.

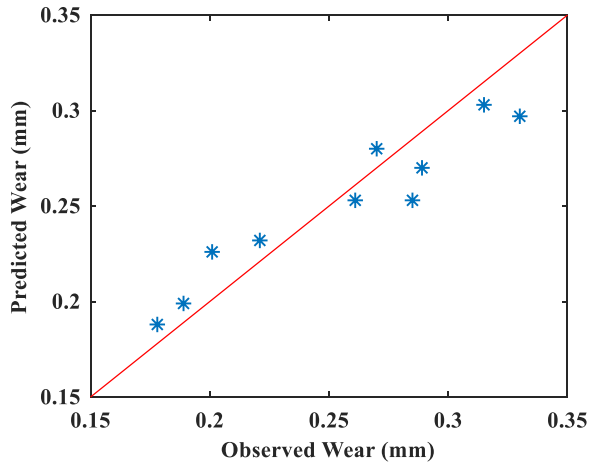


Figure 7. LPP-SVR; unfiltered; maxmum error: 33μm and minmum error: 8μm and avg error: 17μm

6. Conclusion

In this paper, time domain features of RMS and Kurtosis are extracted from the spindle current and feed motor torque signals, and the multi-sensorial features are fused by three dimension reduction methods of PCA, KPCA and LPP. Finally, the mapping relationship between the fused features and tool flank wear (VB) value is established by SVR model. The results of three dimension reduction methods were compared by the index of average wear value and MSE. The experimental results show that the index of LPP + SVR method proposed in this paper is higher than that of other two methods, which solve the problem of high dimension of multi-sensorial features in tool wear monitoring process. In addition, the prediction accuracy of the model can be well improved by filtering the proposed features.

The future work is to combine the mechanism model with the data model to predict the tool wear. In order to eliminate the influence of cutting parameters on the response signal.

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