Research Article
Research on Tool Wear Monitoring Method based on Project Pursuit Regression for a CNC Machine Tool

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Abstract: Tool wear is a major contributor to machining errors of a workpiece. Tool wear prediction is an effective way to estimate the wear loss in precision machining. In this study, all kinds of machining conditions are treated as the input variables, the wear loss of the tool is treated as the output variable, and Projection Pursuit Regression (PPR) algorithm is proposed to mapping the tool wear loss. Finally, a real-time prediction device is presented based on the proposed PPR algorithm, and the prediction and measurement results are found to be in satisfied agreement with average error lower than 5%.

Keywords: CNC machine tool, online prediction, project pursuit regression, tool wear monitoring

INTRODUCTION

Tool wear affects the quality of the product and the efficiency of the process, and many studies focus on the area in recent years. Girardin *et al*. (2010) developed a TCM system, and analyzed instantaneous variations in rotational frequency so as to observe milling operation. Ratnam and Shahabi (2008) developed a vision system using high-resolution CCD camera and back-light for the on-line measurement of tool wear. Luo (2004) analyzed the formation mechanism of tool wear and presents a complete solution to calculate wear using a ball end cutter for high-speed cutting.

In order to maintain product quality and process efficiency, machining processes attempt to prevent tool breakage by predicting the tool wear. However, tool wears changes drastically during individual cutting processes. Thus, it often fails to predict the the tool wear. Tool wear can be predicted either out-of-process or in process. The traditional method is moving the tool out of the machine to check the wear under a microscope, or checking the tool wear with other measuring devices, such as a charge-coupled device camera, machining has to be stopped for the out-of-process tool wear monitoring. However, in-process tool wear can be predicted during machining processes. Of the two, out-of-process tool wear monitoring is less promising, in-process tool monitoring leads to optimum process efficiency, but depends on well-selected sensors and prediction algorithm.

Contemporary research on tool wear monitoring is mainly focused on different neural networks. However, most of these studies cannot overcome the undesired local minimum problem of the neural networks. For example, Palanisamy *et al*. (2008) presented An Artificial Neural Network (ANN) models for predicting tool wear. Jacob and Joseph (2005) proposed an Artificial-Neural-Networks-Based In-Process Tool Wear Prediction (ANN-ITWP) system; the system could predict the tool wear online. Quiza *et al*. (2008) presents an investigation into predicting tool wear using neural networks. Dong *et al*. (2006) introduced the application of neural networks based on Bayesian inference, the automatic relevance determination algorithm for selecting relevant features and designing neural estimators for tool wear estimation in face-milling processes. Wang *et al*. (2008) designed a novel but simple neural network-based generalized optimal estimator for CBN tool wear prediction in hard turning. Tae and Dong (1996) introduced an adaptive signal processing scheme that uses a low-order autoregressive time series model to model the cutting force data for tool wear monitoring during face milling.

In this study, a real-time, in-process tool wear prediction system in milling operations is presented, and PPR algorithm is proposed for the prediction of tool wear. As machining parameters and force signals in milling operations are all used for tool wear monitoring, the prediction accuracy of the model is improved.

Experimental setup: Since milling is one of the most complex machining operations, milling process is selected in this study; the tool wear can be formally described by a discrete nonlinear relationship.

Fig. 1: The milling machine used in the experiment

$$T(t) = M(F_x, F_y, F_z, f, D)$$

where,

M = An unknown function to identify,
F_x, F_y, F_z = The cutting force exerted during the removal of metal chips
D = The radial depth of cut
f = The relative feed speed between tool and worktable

In Fig. 1, the experiment was implemented on a high-precision CNC milling machine, which is interfaced with a personal computer by an RS-232 communication link. Both feed speed f and depth of cut D are collected through the CNC control system, and cutting force is collected through two sensors: dynamometer and proximity sensor. The complete experimental setup is shown in Fig. 2 and consists of hardware and software setups.

By monitoring cutting force and controlling cutting conditions, the system can predict tool wear and sense tool change. The dynamometer and the proximity sensor used in the study like an eye to the machine that monitors tool wear by observing the change of the cutting force. With the sensor integrating a PPR tool wear prediction system (PPR TWP System, which is composed of the PPR model and the personal computer) into the experimental system, the machine has the capability of interpreting and reacting to data from the sensors. In addition, the machining parameters are collected from the CNC control system of the milling machine.

The software setup is mainly composed of three modules:

- The NC program, which is uploaded to the CNC control system, is used for the collecting of the milling parameters.
- The VC-based cutting force collecting sub-program, This VC-based program allowed the PPR TWP System to collect the cutting force signals and proximity signals. Figure 3 shows one sample of the cutting force.
- A PPR model sub-program, this program was integrated with the data collection program to reach the purpose of online tool wear monitoring.

During the milling process, the average peak cutting force and the machining parameters are sent to the PPR TWP system, and the tool wear is predicted in-process finally. The structure and the testing procedures of the PPR model will be discussed in the next section.

Tool wears monitoring:
PPR method: The principle thought of PPR method is: with the machining parameters affecting tool wear as input variables and the tool wear as the output variable, the PPR method can be employed to establish the relationship between the input and output variables and thus predict tool wear of the milling machine according to experimental samples.

Based on the above analysis, there are 5 parameters that influence the tool wear. Variables F_x, F_y, F_z, f, D are denoted by the 5 machining parameters, and T is denoted by the tool wear of the milling machine. So PPR model is expressed as:

$$T = \bar{T} + \sum_{j=1}^{m} M_j(\alpha_{j1}F_x + \alpha_{j2}F_y + \alpha_{j3}F_z + \alpha_{j4}f + \alpha_{j5}D) \quad (1)$$

where,
T = The average output variable
m = The number of fitting unit
M = The function of fitting unit
α = The parameter of projection direction

There are many forms to fit the unit function, for example, numerical function and multinomial and so
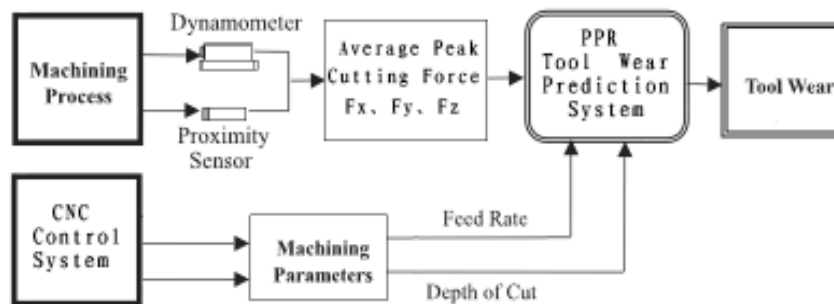

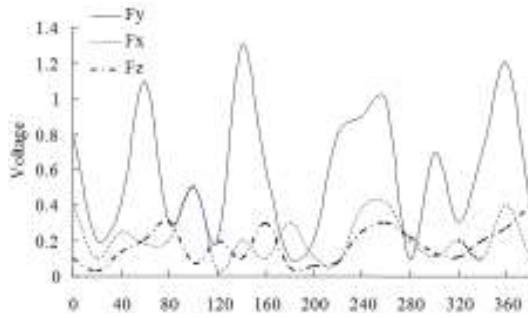Fig. 2: The structure of the experimental setup

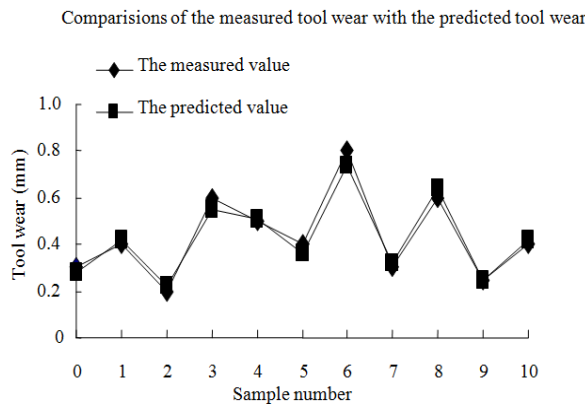Fig. 3: Cutting force history during milling process

Fig. 4: The prediction performance of the PPR model

Table 1: The tool wear results during milling process

Feed rate (in/min)	Depth of cut (in)	Flank wear (0.45 mm) tool wear
6	0.02	0.25
	0.04	0.37
	0.06	0.49
8	0.02	0.39
	0.04	0.53
	0.06	0.69
10	0.02	0.41
	0.04	0.55
	0.06	0.78
12	0.02	0.53
	0.04	0.71
	0.06	0.82

on. Because the numerical function involves in a large matrix, it is difficult to interpolate and extrapolate during prediction. In this study, multinomial form will be used to fit the unit function.

Parameters of the model: In this study, 30 samples are used to train the PPR model. Substituting the 5 machining parameters as input variables and the tool wear as the output variable into Eq. (1) yields optimization and determination of the three parameters of PPR model. The number of unit function and corresponding projection direction parameters will be determined one by one and step-by-step. There are many methods that can realize the above optimization process. In this study, genetic arithmetic is applied to optimize the parameters.

Finally, the parameters are decided, and the parameters in the corresponding projection directions are:

$$\alpha 1 = (3.187, 0.916, 0.140, -0.788, 0.192)$$

$$\alpha 2 = (-0.655, 3.224, -0.246, -0.902, 1.567)$$

where, $\alpha 1$, $\alpha 2$, is the projection direction of the first and the second unit function separately, according to each of which a set of projection variables will be obtained.

Experimental runs. In order to test the performance of the PPR model, one experiment was carried out. During the experiment, the milling machine was set up as the following combination of machining parameters: feed rate at 6, 8, 10, 12 ipm; depth of cut at 0.02, 0.04, 0.06 inch; flank wear at 0.45mm. Finally, the tool wear were measured out-of-process and the results are shown in Table 1. The predicted values of the tool wear were obtained using PPR model. Figure 4 shows the comparison of the measured and the predicted values for the test cut. The results suggest that the proposed PPR TWP system could reasonably predict tool wear in an online real time fashion.

CONCLUSION

In this study, a PPR algorithm was proposed for the prediction of the tool wear on a CNC machine tool. The mapping ability of the presented PPR model is very well. During the performance test, it can be seen that the approximation ability of the model is very well, and the predict error of the model is lower than 5%.

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