# A Feature Selection Method for Machine Tool Wear Diagnosis

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## ABSTRACT

We propose an algorithm for estimating the wear condition of tools. We have previously developed a method for predicting machining dimensions by learning features of waveform shapes such as torque during machining as explanatory variables and measured machining dimensions as objective variables. In this method, the features do not fully explain the machining dimensions because including data other than the machining operation such as tool change. In this paper, we propose a method to improve explanatory power and prediction accuracy by selecting subsequences from the machining waveform that are highly related to machining dimensions as explanatory variables. The effectiveness of the proposed method was confirmed through an evaluation using data of machining product part.

## 1. INTRODUCTION

In factory automation (FA) manufacturing lines, many machine tools are in operation to process workpieces. NC (numerical control) machine tools are machines that use NC machining methods to machine the workpiece. However, due to fluctuations and deterioration in the condition of the machine equipment and tools, as well as fluctuations in the work environment, deviations may occur between the designed dimensions and the actual dimensions of the workpiece. To confirm whether the machined workpiece dimensions are within the tolerance range or not, the dimensions of the workpiece should be inspected after machining, but it is difficult and time-consuming to conduct a full inspection. Therefore, a technology for estimating and predicting machining dimensions has been proposed. Conventionally, there is a technology that extracts feature values from machine tool drive condition information collected in a predefined machining section, and generates a prediction model for predicting machining dimensions from these feature values by multiple regression. Using this prediction model, it is possible to determine the machining quality or to diagnose that the machining was normal, even if the machining dimensions are not measured after machining. However, the conventional method uses the entire waveform during machining as explanatory variables, whereas dimensional measurements are taken only at certain points of the product, making it impossible to explain which of the feature values affect machining quality. Therefore, we developed a method to improve the accuracy of machining dimension prediction [2]. In the developed method, the machining waveform is divided into time series, and intervals with high correlation to the machining dimensions are selected as explanatory variables. We also used a gradient boosting tree, which is less susceptible to multicollinearity, as the prediction model, and improved the prediction accuracy by using features with high importance as explanatory variables. Evaluation using test data confirmed that the prediction accuracy was improved compared to the conventional method.

Section 2 describes the conventional techniques for tool wear diagnosis of machine tools and machine tools, Section 3 describes the proposed algorithm, Section 4 describes the experimental results, and Section 5 provides a summary.

## 2. BACKGROUND AND RELATED WORKS

### 2.1. Machin Tool Wear

In factory automation (FA) manufacturing lines, many machine tools are in operation to process workpieces. Many of these machine tools are automated, and among them, NC (numerical control) machine tools are machine tools that use NC machining methods to process the workpiece. NC machine tools, such as milling machines, lathes, drilling machines, machining centers, and turning centers, can precisely machine metals using tools by executing predefined NC control programs. The tools are, for example, end mills, face mills or drills, taps, and inserts, and the machining is, for example, cutting, abrasive grinding, or cutting.

Figures 1 and 2 show an example of machining on metal. in Figure 1, the machine tool cuts the metal by bringing the tool, an end mill, into contact with it as indicated by the arrow to form a spiral-shaped airfoil. In detail, the machine tool moves the tool in the direction indicated by the right arrow in Figure 2 to form the surface A, indicated by the bold line and then forms surface B, indicated by the dashed line, by moving the tool in the direction indicated by the dashed arrow. The metal processed in this way is used as a component of a scroll compressor. Since the blades of scroll compressors are required to be highly precise, the estimated prediction of the dimensions during such machining must be accurate.

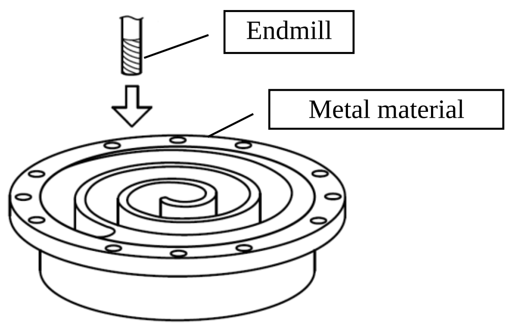


Figure 1. Endmill and Metal material

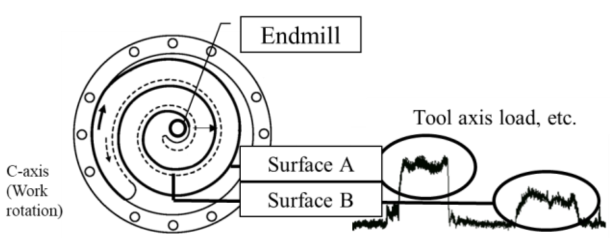


Figure 2. Examples of metal processing

### 2.2. Conventional Method

Machine tools may have deviations between the design dimensions and the actual dimensions of the workpiece to be machined due to fluctuations and deterioration in the condition of the machine equipment and tools, changes in the work environment, and other factors. Therefore, it is necessary to check whether the dimensions of the processed workpiece are within the allowable range or not. Although it is desirable to inspect all the dimensions of the workpiece after machining, this is not realistic due to the time and monetary costs involved. Therefore, there is a need for a technology to estimate and predict machining dimensions. As a conventional technology for predicting machining dimensions, a method has been proposed in which a prediction model such as a multiple regression model is learned in advance using the waveform shape of sensor data such as torque during machining quantified as a feature as the explanatory variable and the actual measured value of machining dimensions as the objective variable. In this method, the learned prediction model is used to predict the machining dimensions for each actual machining operation. This makes it possible to determine the machining quality and diagnose that the machining was normal, even if the machining dimensions are not measured after machining. Furthermore, since the degree of tool wear (number of times the tool has been used) is related to the dimensions of the non-machined workpiece, accurate prediction of the dimensions of the non-machined workpiece can provide a clue to the tool wear condition.

In the conventional method, the feature values are calculated from the sensor data of the entire machining section and learned, while the machining dimensions used in the training data are measured at only one location in the workpiece. However, because the entire machining section includes data other than machining operations (tool movement, tool change, etc.), the feature values do not fully explain the machining at the measurement point. In the case of straight grooving, where the actual cutting tool cut is constant and the groove width formed by cutting is uniform, the error between the predicted machining dimensions and the actual measured dimensions is small. However, in the case of curve machining and partial machining, the amount of cutting is not uniform depending on the cutting tool contact angle to the machining surface and the NC curve interpolation control performance, and the feature values in the machining section do not necessarily provide enough data to fully explain the actual dimensions. Therefore, when a prediction model that predicts machining dimensions from the aforementioned feature values is learned, the error in the machining dimensions predicted by this prediction model may be large. Therefore, there is room for more accurate estimation and prediction of the dimensions of the workpiece machined by the machine tool.

## 3. ALGORITHM

This chapter describes an algorithm that aims to more accurately estimate and predict the dimensions of a workpiece machined by a machine tool from the machining data.

The process flow of the algorithm is shown in Figure 3. First, a data interval selection process is performed to select intervals from the already obtained machining data that have a strong correlation with the machining results contained in the measurement data (weakly correlated intervals = noise portions are removed). Then, feature selection is performed to obtain feature values (statistics such as mean and median values) from the data in the selected intervals. Finally, the contribution to the prediction result (importance) is calculated from the obtained feature values, and the feature values with the highest importance are used as the final feature values to construct a prediction model (LightGBM). By inputting machining data of unknown quality into the constructed prediction model, it is possible to predict the machining workmanship.

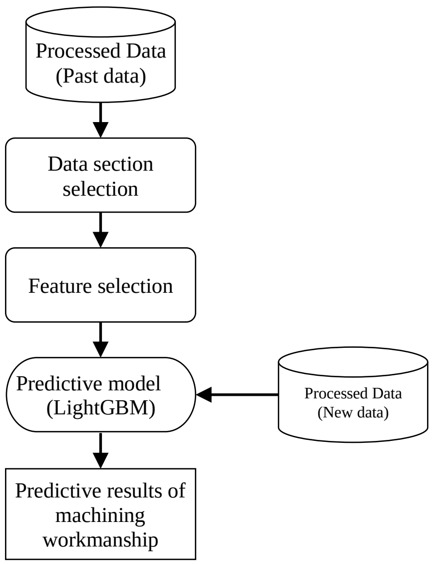


Figure 3. Process flow of the machining workmanship prediction algorithm

### 3.1. Section Selection Method

In addition to the data during excavation, the processing data includes data during the period when the excavator blade is being replaced, and there is a mixture of sections that are related to the processing performance (measurement data) and sections that are not. Since the information in the sections unrelated to the measurement data is noise in predicting the processing quality, we can expect to improve the prediction accuracy by extracting only the sections related to the measurement data from the processing data and cleansing the data. In addition, when calculating the correlation coefficient between the processed data and the measurement data, not only the raw values of the processed data but also various statistics (e.g., average values) are used. Since there are intervals in the processed data that are related to the measurement data and intervals that are not, the processed data are separated by specifying the window width, and the correlation coefficients between the statistics calculated from the separated intervals and the measurement data are calculated. After the correlation coefficient is calculated, the window width is moved, and the correlation coefficient is calculated again at the position where the window width was moved. By repeating this process from the beginning to the end of the processed data, the transition of the correlation coefficient of the window width section in the entire processed data can be calculated. Finally, by extracting only the intervals with high correlation coefficients, i.e., the intervals that are related to the measurement data, the noisy portions can be removed, which is expected to improve the prediction accuracy.

### 3.2. Feature selection method

In the conventional method, the statistic with the highest correlation coefficient was used as the feature, but this time, the statistic with the highest feature importance in the forecast model was selected.

### 3.3. Prediction model

For this development, we chose LightGBM[1] , a type of gradient boosting tree that is computationally inexpensive and has high memory efficiency and prediction accuracy. As explained in 3.2, feature selection is performed using importance.

## 4. PERFORMANCE EVALUATION

### 4.1. Dataset

Data obtained during the machining of scroll compressor parts were used in this evaluation. The data included from several time-series data and included the load and speed of the tool spindle and the load of each of the axes 1/axis 2/axis 3/axis 4 (CH1-6) Figure 4 shows an example of the data.

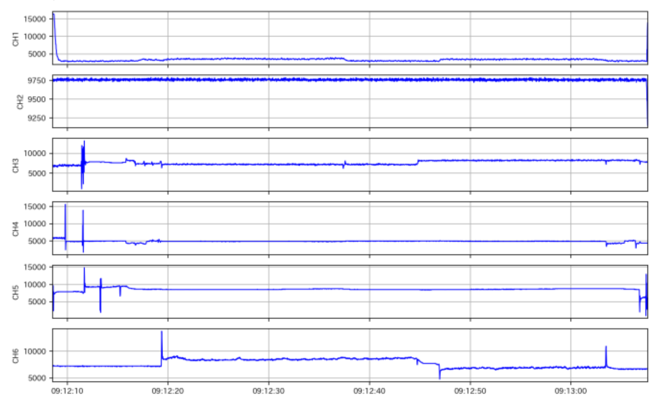

Figure 4. Waveform of processed data (excerpt of one data)

For the measurement data, which is the objective variable, the squareness and straightness of a certain point on the workpiece after cutting were measured with a measuring machine. In this case, straightness, which has the highest correlation with the number of times the tool has been used (degree of wear), was used as the objective variable.

### 4.2. Evaluation of Section Selection Method

Figure 5 shows an example of the correlation coefficient calculation results. The red dashed line is the correlation coefficient between the statistic calculated from the entire processed data and the measurement data. It can be confirmed that the correlation coefficient with the measurement data increases or decreases depending on the section where the statistic is calculated, and that there are sections in the processed data that are related to the measurement data and sections that are not.

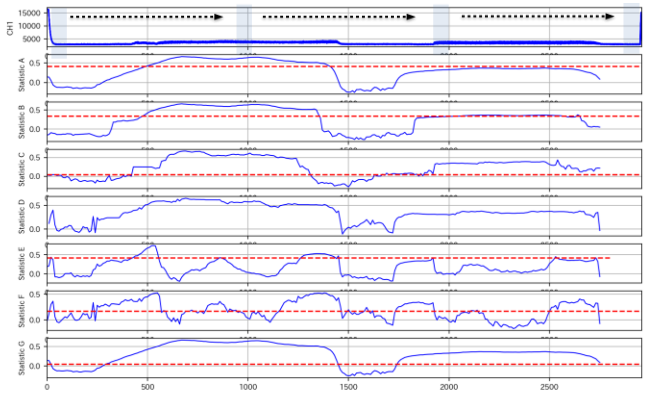

Figure 5. Transition of correlation coefficients (excerpts)

The threshold value of the correlation coefficient for interval selection was set to a value that would not shorten the extraction interval and would leave the part of the data where the metal was actually being processed.

Table 5 summarizes the changes in the correlation coefficients between the processed and measured data after cleansing. The correlation coefficients for all statistics improved after cleansing, and the average correlation coefficient for each statistic improved by 0.292. It is thought that the cleansing process improved the correlation with the measurement data by extracting only the parts of the metal that are actually processed, i.e., the parts that are related to the measurement data.

Table 5. Correlation coefficient before and after cleansing

| | Average of all correlation coefficients |
|---|---|
| Before cleansing | 0.263 |
| After cleansing | 0.555 |

### 4.3. Evaluation of Prediction Accuracy

Next, we discuss the experimental results of the prediction accuracy. As explanatory variables, we used features with a given threshold anomaly in LightGBM importance. The prediction results are shown in Table 6. Absolute mean error (MAE) and absolute mean error rate (MAPE) were used as accuracy indices. With the conventional method, the MAE was 0.000954 mm and the MAPE was 33.6%. With the newly developed method, the MAE was 0.000404 mm and the MAPE was 16.4%, confirming an improvement in accuracy. This may be due to the fact that, as a result of cleansing, data not relevant to processing was removed, improving the correlation coefficient and, consequently, the accuracy.

Table 6. Prediction Results

| | Conventional method | | Proposal method | |
|---|---|---|---|---|
| | MAE | MAPE | MAE | MAPE |
| Target | 0.000954 | 33.6 | 0.000404 | 16.4 |

## 5. CONCLUSION

In this study, we examined an algorithm to analyze machining and measurement data, select intervals, and predict with high accuracy. In order to extract intervals that have a high relationship with machining dimensions, we divided machining data into multiple window lengths and calculated correlation coefficients with machining dimensions by combining window lengths and multiple characteristic quantities (e.g., averages and other statistics). We confirmed that the correlation coefficients actually varied depending on the section. Therefore, this time, intervals with correlation coefficients above a certain level were extracted, and statistics of high importance were extracted as candidates for explanatory variables. In addition, a gradient boosting tree was selected as the forecasting method. As a result of confirming the accuracy of the conventional method and the study method, we confirmed that the use of the study method improved the correlation coefficient by an average of 0.292 and the absolute mean error rate (MAPE) from 33.6% to 16.4%, an improvement of 17.2% in accuracy.

Improving the processing time for interval selection is one of the challenges. By calculating the optimal window width and skip width for searching based on the input data, it is expected to improve processing time without compromising accuracy.

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