Sensors and Materials, Vol. 34, No. 8 (2022) 3241–3253
MYU Tokyo

S & M 3038

Intelligent Performance Prediction of Flank Milling of Ti6Al4V Using Sensory Tool Holder

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(Received February 25, 2022; accepted July 13, 2022)

Keywords: convolutional neural network, sensory tool holder, surface roughness, machining accuracy

In this study, we explore the process performance of flank-end milling of Ti-6Al-4V titanium alloy. Experiments and convolutional neural networks are used to establish a predictive model of machining quality. Sensory tool holders are used to capture the cutting force signals during machining and to perform feature extraction. The neural network model utilizes feature data as input with surface roughness and dimensional accuracy as outputs. The experimental framework can be divided into several stages: machining, cutting data collection, surface roughness and machining accuracy measurement, and neural network parameter setting. The experimental parameters consisted of cutting speed, feed per tooth, axial cutting depth, and radial cutting depth. Each parameter has three levels. Therefore, for a full-factor experiment, 81 sets of experimental data are obtained. Furthermore, 162 sets of data are obtained by performing each experiment twice. In the neural network prediction results, the minimum average percentage for surface roughness prediction error is below 10% when grouping the feed per tooth. This result was considered favorable compared with the error percentage of 18% obtained from predictions through training with all data. On the other hand, the machining accuracy prediction results were better when training with all data, with the error percentage being approximately 20%.

1. Introduction

Titanium alloys have low weight, high strength, good corrosion resistance, and good heat resistance. Moreover, they maintain good strength and stability in working environments with a temperature of approximately 500 °C. Therefore, they are widely used in the aerospace industry. However, their physical and chemical properties create problems during machining, such as poor thermal conductivity, easy accumulation of heat, high chemical affinity, and easy sticking of chips. These result in rapid tool wear, which in turn affects workpiece quality. In a cutting process, surface roughness and machining accuracy are two important indicators of the quality of a finished product; they are affected by machining parameters such as the spindle speed, feed rate, cutting depth, and step over. Because of the complexity of cutting behavior and operating conditions, the relationship between input parameters and cutting results is often nonlinear. We have aimed to

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https://doi.org/10.18494/SAM3876

ISSN 0914-4935

establish a mathematical model that can predict production quality according to operating conditions. Such a systematic model can predict the effectiveness of given machining parameters for the machining result, without the need for determining machining parameters based on the experience of the operator.

Neural networks are often used to establish mathematical cutting models. In previous studies, the cutting force was used as the output result because the cutting force data could be obtained through online measurements and could be verified.(1–6) Alique *et al.* developed a versatile neural network model to predict the mean cutting force under commonly encountered conditions during online operation.(2) This model could describe the resultant mean cutting force with changes in plant inputs such as the feed rate and cutting depth. Cus *et al.* used an artificial neural network (ANN) to predict the cutting forces in ball-end milling operations.(3) Comparisons of the neural network predictions with experiments revealed a 4% error in the prediction of three cutting force components. Kadirgama and Abou-El-Hossein used a neural network method to predict the cutting force for milling 618 stainless steel.(4) The cutting speed, feed rate, axial depth, and radial depth were used as inputs, and the cutting force was provided as the output. The neural network prediction result showed an acceptable error.

The cutting force is easy to measure and can be used to analyze the cutting results. However, it cannot be directly used to determine machining quality. A finished product after machining should have good dimensional accuracy and surface roughness to achieve suitable matching properties, wear resistance, contact stiffness, and vibration characteristics and to satisfy other assembly and functional requirements. However, the direct measurement of machining quality requires the use of special devices or machining quality can be determined through offline measurements. The measurement efficiency is low and the cost is high. In recent years, with improvements in sensing capabilities and advancements in networking technology, wireless sensory tools have often been used to collect cutting process data such as vibration, current, acceleration, and cutting force. These tools are widely used for monitoring the machining of machine tools and for realizing effective online monitoring systems. Ye proposed multiaxis machining technology for manufacturing turbine blades.(7) He used a sensory tool holder system for analysis during the rough machining of turbine blades; it improved process planning and shortened the processing time. Chen *et al.* used a sensory tool holder to measure the cutting forces during thin-wall milling and established data coordinate transformation between the tool and the workpiece.(8) They established modified tool paths to compensate for volumetric errors according to deformation data. This method successfully improved machining precision and processing efficiency. By collecting signals using sensors, an effective prediction model for machining quality can be established, reducing production costs and improving processing efficiency.

Early studies often used the cutting conditions as the input variables of an ANN for establishing the cutting model. The amount of training data, the number of hidden layers, and the model structure were all small. In recent years, with improvements in computing capabilities, deep learning algorithms have been developed to perform the inductive analysis of big data. In the past, real-time processing signals collected using sensors were used to monitor abnormal process conditions. However, owing to the large amount of data, their use to determine or predict machining results was impractical. Presently, such data can be captured, used as neural network input information, and analyzed to generate real-time predictive models. Lu *et al.* used a wireless sensory tool holder to collect machining process signals and then extract the features of data.(9) They adopted the deep forest algorithm to determine surface quality. The results could be applied to ensure surface quality and improve machining efficiency. Huang *et al.* predicted tool wear by using a holistic-local long short-term memory (LSTM) model. With rapid developments in deep learning methods, data features can be captured effectively.(10)

In this study, a sensory tool holder was used to collect the cutting force signals during machining, fast Fourier transform (FFT) was performed to extract the features, and finally, the feature information was imported into a convolutional neural network (CNN) model for training. Dimensional accuracy and surface roughness were chosen as output results. It is expected that an effective prediction model can be developed.

2. Materials and Methods

2.1 Materials

The material tested in this study was Ti-6Al-4V titanium alloy. This alloy has excellent mechanical properties and corrosion resistance, low weight, high temperature resistance, high fatigue strength, and low thermal expansion coefficient. It is also nonmagnetic. Moreover, because of its high melting point, it has low thermal conductivity and high chemical affinity. After processing, chips can very easily adhere to the cutting tool and workpiece surface, which accelerates the wear of the milling tool.(11) Owing to the low thermal conductivity of Ti-6Al-4V, this problem is more severe. Table 1 shows the mechanical properties of the Ti-6Al-4V alloy. These data are provided by the material supplier S-Tech Corp.(12)

2.2 Neural network

1) ANN

Recently, machine learning has emerged as a useful artificial intelligence approach for achieving effective knowledge discovery from a database (i.e., data mining). ANNs are used in machine learning. They can imitate the human neural network and use multilayer nonlinearity to learn the features of data. They have a parallel structure and high calculation speed, and they can be used to establish models without mathematical formulas; therefore, useful results can be obtained from a large amount of training data. Moreover, because the parameters are independent, changing the

Table 1
Mechanical properties of Ti-6Al-4V alloy.

Density (g/cm^3)	4.43
Poisson's Ratio	0.34
Young's Modulus (GPa)	113.8
Ultimate Stress (MPa)	993
Yield Stress (MPa)	924
Elongation (%)	14
Hardness (Rockwell)	HRC36

cutting conditions does not affect the analysis results. For a model that analyzes the processing signals collected using a sensor, various working conditions can be examined without modifying the model structure.

Various types of ANNs have been developed for applications in different fields, such as deep neural network, recurrent neural network, CNN, and LSTM. Among these, the CNN has a local weight shared special structure that affords unique advantages for image and pattern recognition.(13)

2) CNN

The CNN structure mainly includes the convolutional layer, pooling layer, and fully connected network; the convolutional and pooling layers can be alternately repeated many times. A complete CNN structure is formed by stacking these layers.

The convolutional layer is the core of the CNN. It mainly comprises different convolution kernels that perform convolution operations on the input data, and a filter is used to move on the data and to continue to calculate a matrix dot product. The information obtained after performing convolutions is called a feature map. Usually, a pooling layer is inserted between the convolutional layers to reduce the spatial size of the data. This can reduce the number of parameters in the network, reduce the consumption of computing resources, and effectively control overfitting. Commonly used pooling methods include max pooling and average pooling. Each depth slice of the input data is processed separately to reduce its spatial size. The fully connected layer has the same structure as the general neural network.

2.3 Experiment procedure

In this study, we used NX software to plan the tool path and Tongtai CT-350 with a Siemens Sinumerik 840D sl controller B-Type five-axis machine tool for milling experiments.(14) The cutting tool used was a four-flute carbide end mill with a diameter of 10 mm. A Pro-micron GmbH & Co. KG sensory tool holder was used to collect the cutting force signals during machining. Table 2 shows the specifications of the sensory tool holder. The axial force, torque, and bending moment in the XY direction were measured during machining, and these data were wirelessly transmitted to the computer. The bending moment coordinate graph in the XY direction was used to observe the real-time blade force. The neural network program was written using Python. It extracted data features and imported them into the neural network for model training and prediction.

The cutting workpiece was a Ti-6Al-4V alloy cube with dimensions of $80 \times 80 \times 80$ mm^3. The machining parameters included the cutting speed, feed per tooth, axial cutting depth, and radial

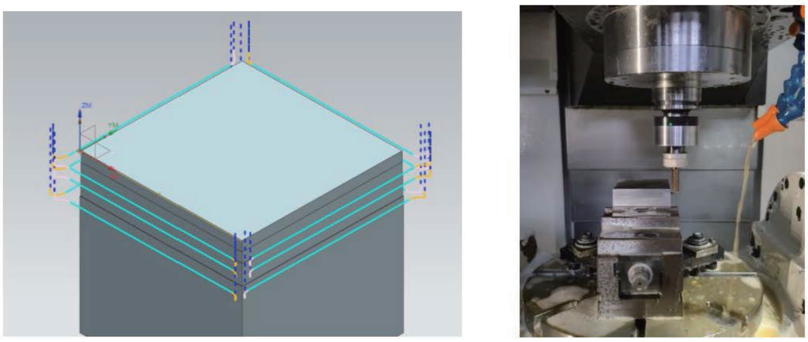
Table 2
Specifications of sensory tool holder.

Measuring frequency (Hz)	2500
Maximum allowable speed (rpm)	18000
Operating temperature (°C)	0–50
Collet size	ER20
Spindle taper	HSK63A
Diameter (mm)	34
Total length (mm)	100

cutting depth, and each parameter was set to three levels, as shown in Table 3. These combinations of processing parameters required 81 sets of experiments for performing a full-factorial experiment of flank-end milling, and 162 sets of data were obtained because cutting was performed twice. Before machining, the face milling cutter was used for reference surface milling, and then machining was performed side-by-side according to the machining parameters.[15] The machining results were measured after the completion of machining. Figure 1 shows the cutting path and the actual cutting screen. To control tool wear, different tools were used for each axial depth of cut. To verify the machining results, a TESA-hite Magna 400 height gauge was used to measure the finished and reference surfaces of the workpiece. We measured the three points on the two surfaces and took the average to calculate the dimensional error between the two surfaces, as shown in Fig. 2. A Hommel-Etamic T8000 measuring instrument was used to measure surface roughness. We measured each surface thrice and took the average, as shown in Fig. 3.

Table 3
Machining parameters.

	Cutting speed (m/min)	Feed per tooth (mm/tooth)	Axial depth of cut (mm)	Radial depth of cut (mm)
1	40	0.03	5	0.05
2	70	0.06	10	0.1
3	100	0.1	20	0.2



(a) (b)

Fig. 1. (Color online) (a) Processing path and (b) machining.

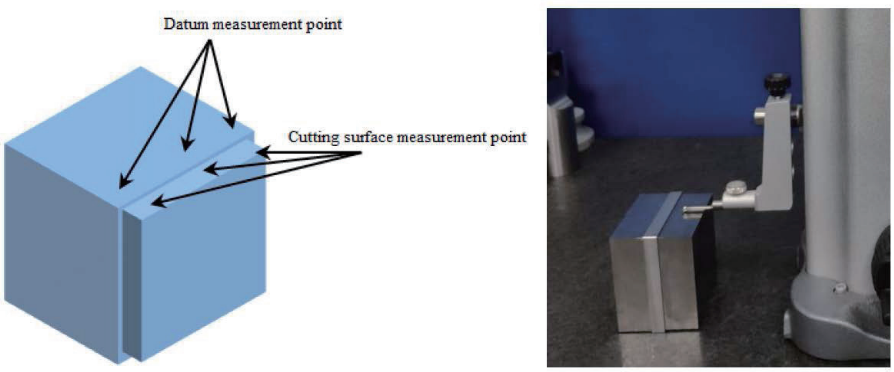


Fig. 2. (Color online) Dimension measurement (TESA-hite Magna 400).

2.4 Signal preprocessing

The data obtained from the experiment comprised cutting force signals, as shown in Fig. 4, with the tension, torque, and bending moment from top to bottom. In each experiment, 10000 sets of bending moment data were captured during a 4 s period and used as input information. Signal features were extracted before being imported into the neural network for training. Feature extraction was performed to obtain meaningful features from the original data and to improve the efficiency of the analysis of a large amount of data. FFT was used to convert a cutting force signal into the frequency domain. Because the sampling frequency of the sensory tool holder was 2500 Hz, the bandwidth after FFT was 1250 Hz. Figure 5 shows the frequency spectrum under idling with a spindle speed of 3000 rpm. We saw a peak corresponding to the spindle speed with 50 Hz. Figure 6 shows the frequency spectrum during cutting. We observed peaks corresponding to the spindle speed and its harmonic frequencies.

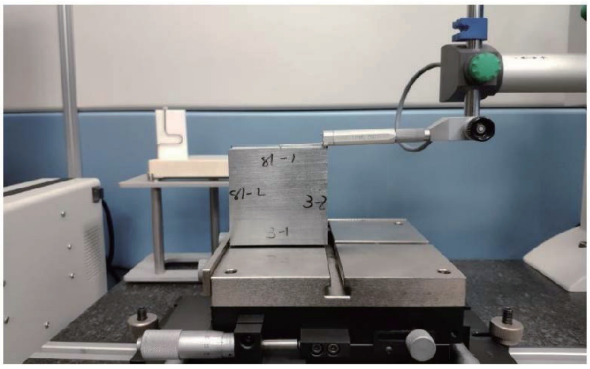


Fig. 3. (Color online) Roughness measurement (Hommel-Etamic T8000).

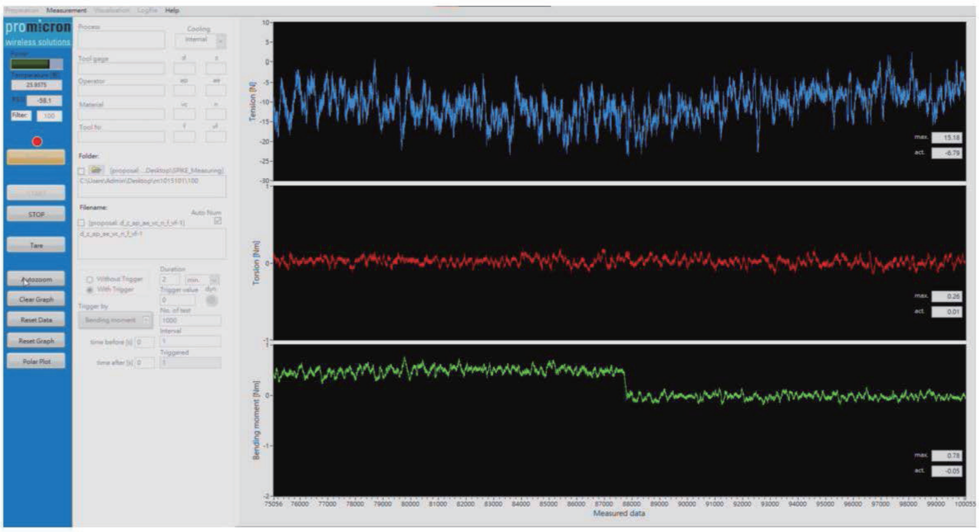


Fig. 4. (Color online) Cutting force signals.

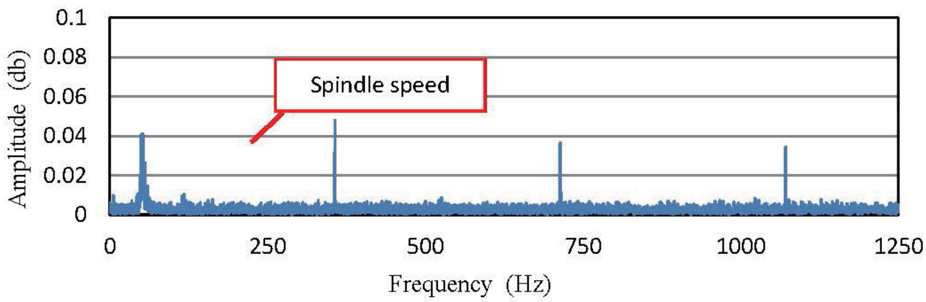


Fig. 5. (Color online) Bending moment spectrum under idling (spindle speed: 3000 rpm).

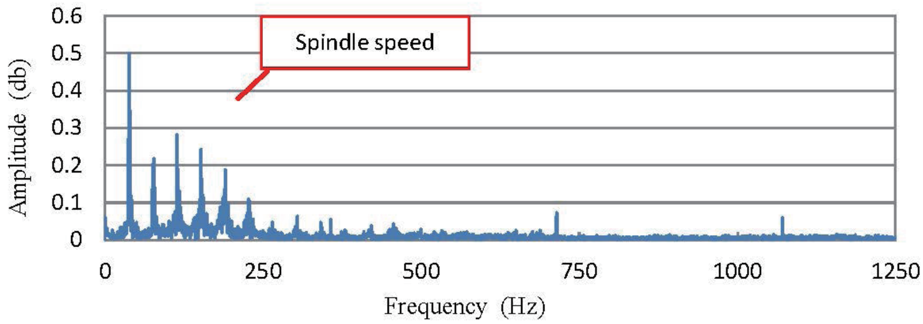


Fig. 6. (Color online) Bending moment spectrum during cutting.

2.5 Modeling setup

In this study, we used the Google Colab online Python compiler importing PyTorch to edit and run the Python code. PyTorch is an optimized tensor library primarily used for deep learning. We used PyTorch to build a kernel module of the CNN model. The input data of this study is the bending moment spectrum after FFT, and the format is a one-dimensional matrix. Thus, the CNN model set the number of input channels to one. The model was a single hidden layer CNN architecture and contained a convolutional layer, a pooling layer, and a fully connected layer. Table 4 shows the parameter settings for the CNN model.

There are 162 sets of experimental data in this experiment, which were grouped according to feed per tooth into Fz0.03, Fz0.06, and Fz0.1. Each group contained 54 sets of data. Fifty sets were randomly selected for training and the other four sets for prediction. For comparisons, ungrouped data training was also performed.

After repeated training, the number of trainings for neural network was set to 1000, and the training results were verified every 10 trainings. Performing training an excessive number of times will cause over-training, leading to a waste of time. The mean squared error (*MSE*) was used as the Train AVG Loss function to evaluate the modeling results, as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2. \tag{1}$$

Table 4
Parameters of CNN.

Number of input channels	1
Number of output channels	16
Kernel size	500
Stride	300
Padding	200
Pooling size	3 (stride = 2)
Activation function	ReLU

Table 5
Final training parameters and convergence conditions

	Learning rate	Training times	Batch size	Convergence criteria
Fz 0.03	0.0015	1000	25	0.02
Fz 0.06	0.0015	1000	25	0.05
Fz 0.1	0.0015	1000	25	0.1
All	0.0015	1000	75	0.15

Train AVG loss is mainly used to evaluate the convergence of the model. If the trained model has been trained to a stable stage, train AVG loss will also be stable.

The loss function was used to estimate inconsistency between the predicted value obtained using the model and the true value. The smaller the loss function, the better was the robustness of the model. The root mean squared error (*RMSE*) was set as the model convergence criterion, as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2} \quad . \tag{2}$$

According to the feed per tooth grouping and training with all data, different training parameters and convergence criteria (*RMSE*s) were given. After convergence test analysis, the final training parameters and convergence conditions were set as shown in Table 5.

3. Results and Discussion

3.1 Surface roughness

The 162 sets of roughness values were measured using the surface roughness meter and arranged in order from small to large. Figure 7 shows the surface roughness distribution. The roughness values were divided into three groups corresponding to different feeds per tooth, which is an important factor that affects surface roughness in straight side edge end milling. When training was completed, four sets of test data were randomly selected to compare the results. The tests were performed thrice, and all *RMSE*s reached the convergence criteria. The individual and average percent errors were calculated. Table 6 shows the roughness prediction results according to the feed per tooth grouping; the average error percentage was within 10%. However, the minimum average error percentage was approximately 18% for the full data training results, as shown in Fig. 8.

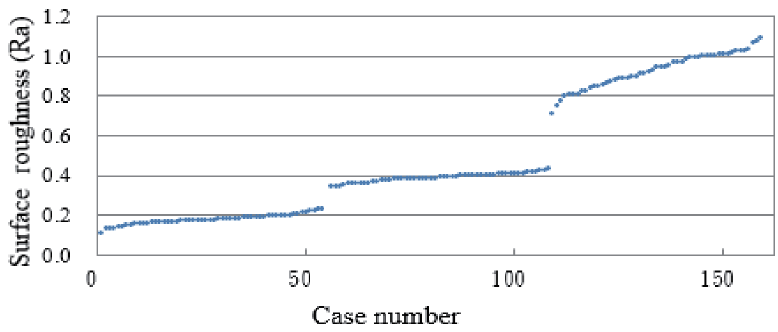


Fig. 7. (Color online) Surface roughness distribution.

Table 6
Roughness prediction results.

	Convergence criteria		*RMSE*	Error of test data 1st (%)	2nd (%)	3rd (%)	4th (%)	Average (%)
FZ 0.03	0.02	1st	0.0109	8.79	9.60	2.20	1.24	5.46
		2nd	0.01181	8.48	5.90	7.81	1.23	5.86
		3rd	0.01495	7.68	6.99	9.78	6.26	7.68
FZ 0.06	0.05	1st	0.03646	3.86	5.87	13.59	9.09	8.10
		2nd	0.01676	1.86	4.22	3.70	6.54	4.08
		3rd	0.03113	9.11	8.98	7.08	5.47	7.66
FZ 0.1	0.1	1st	0.07522	4.72	11.52	7.19	7.38	7.70
		2nd	0.06669	9.46	7.18	5.68	4.60	6.73
		3rd	0.089	1.72	12.31	15.58	2.63	8.06
ALL	0.15	1st	0.13974	25.09	68.90	28.52	8.32	32.71
		2nd	0.07989	33.29	15.88	16.39	7.34	18.23
		3rd	0.11842	40.35	16.33	24.33	1.96	20.74

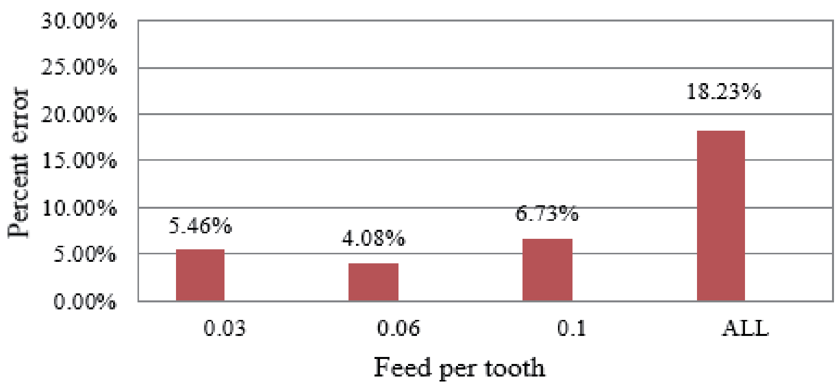


Fig. 8. (Color online) Minimum error of roughness prediction.

3.2 Dimensional accuracy

The 162-dimensional accuracy error values were arranged in order from small to large. Figure 9 illustrates the dimensional accuracy distribution. The distribution indicated a gouging or excess phenomenon, and it had no cluster correlation with the four main parameters of the experimental plan (i.e., cutting speed, feed per tooth, axial cutting depth, and radial cutting depth). We grouped the training data in a manner similar to roughness training. After the convergence test analysis, the final training parameters and convergence conditions were obtained. Training with all data showed the best prediction results, with the minimum average error being less than 20%, as shown in Table 7 and Fig. 10. Group training with feed per tooth showed worse results than training with all data. The results of group training with the other parameters were also poorer. Given these results, it is speculated that the parameters are not the main factor affecting the outcome. Furthermore, the number of samples in group training was very small, resulting in poor training results and an inability to generate good prediction models.

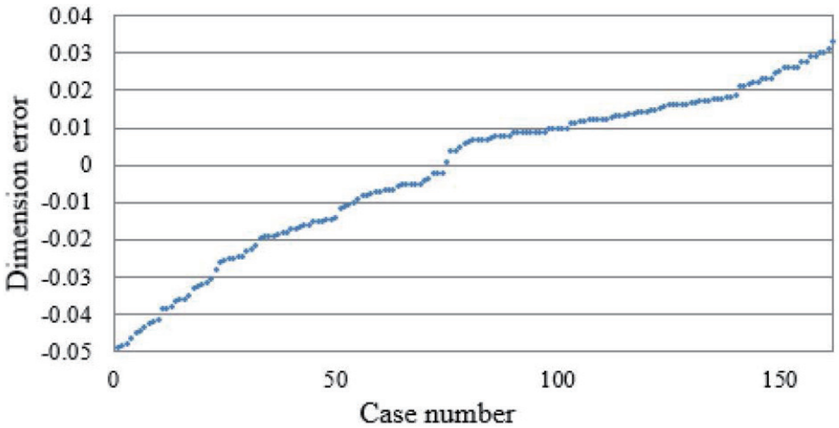


Fig. 9. (Color online) Dimensional accuracy distribution.

Table 7
Dimensional accuracy prediction results.

	Convergence criterial		*RMSE*	Error of test data 1st (%)	2nd (%)	3rd (%)	4th (%)	Average (%)
FZ 0.03	0.01	1st	0.0043963	28.39	55.37	30.70	1.90	29.09
		2nd	0.0087497	17.70	81.48	40.28	16.25	38.93
		3rd	0.0053993	28.49	22.37	74.64	6.79	33.07
FZ 0.06	0.01	1st	0.0049806	23.49	45.72	10.75	84.17	41.03
		2nd	0.0098533	13.11	36.60	29.66	50.46	32.46
		3rd	0.0067884	18.76	89.21	80.55	11.24	49.94
FZ 0.1	0.01	1st	0.0082456	104.51	27.17	18.65	141.32	72.91
		2nd	0.0046378	12.70	57.10	43.97	128.54	60.58
		3rd	0.0059726	29.61	23.73	72.83	98.51	56.17
ALL	0.01	1st	0.0048844	22.25	93.58	19.45	21.68	39.24
		2nd	0.0065582	4.32	51.13	52.59	0.90	27.24
		3rd	0.0071992	5.03	11.00	30.29	31.16	19.37

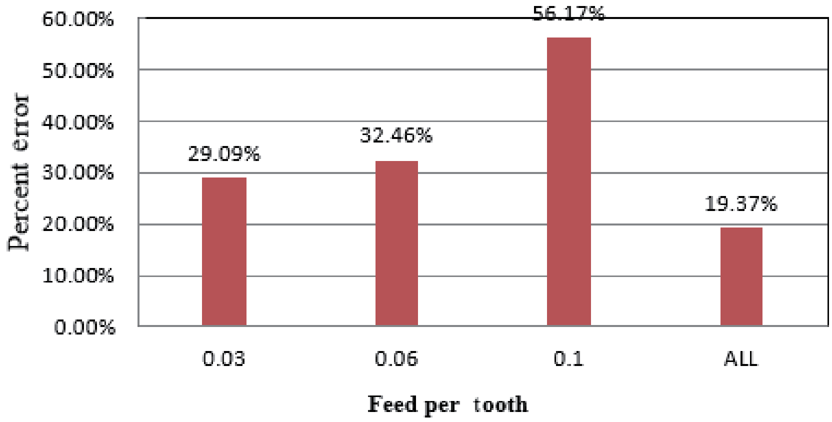


Fig. 10. (Color online) Minimum error of dimensional accuracy prediction.

4. Conclusions

In this study, we used sensory tool holders to collect machining data and to perform signal processing. The CNN model was written in Python and the processed data were imported into a neural network for training in order to predict machining accuracy and surface roughness. The following conclusions were obtained from this study.

(1) When predicting surface roughness based on the feed per tooth grouping, the minimum average error percentage of the prediction was less than 10%. Therefore, the obtained prediction results were accurate and better than those obtained by training with all data.
(2) For titanium alloy machining accuracy prediction, the results of training with all data were better than those of training using groups. The feed per tooth was clearly not the factor that most affected machining accuracy. The error percentage of the predicted results was as large as 20%. This is speculated to be the result of an insufficient number of training groups. In the future, the number of training groups will be increased to improve the model.
(3) Gouging or excess may occur in titanium alloy machining. The present model cannot accurately predict these phenomena. In the future, in addition to increasing the number of training groups, the tool wear data will be considered to improve dimensional accuracy error prediction.

Acknowledgments

The authors would like to thank all colleagues and students who contributed to this study. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. This manuscript was edited by Wallace Academic Editing.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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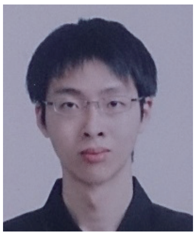
About the Authors



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