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Tool condition monitoring of titanium alloy end mill process based on artificial intelligence model using transfer learning

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Abstract

Titanium alloy has low thermal conductivity during cutting, so a lot of heat is generated, which leads to a short tool life and difficult tool management. When machining titanium alloy, it is important to detect the condition of the tool and determine the appropriate replacement time when a large amount of machining is required. Therefore, an AI-based analysis model was applied to monitor the end mill machining process status of titanium alloy. Many cases have been reported in which AI models combining CNN and LSTM directly applied time series data to design AI models with high accuracy and reliability. But AI models learned through deep learning have a limitation in that the accuracy for input values that deviate from the learned conditions are low. To overcome this, it is necessary to build data for all possible conditions and learn through deep learning, but this is realistically difficult. Recently, efforts have been made to solve the problems of data shortage or increased learning time by methods such as transfer learning or hyperparameter tuning that maintain the weights of existing AI models and change some layers.

To obtain acceleration sensor data required for deep learning, we performed a machining experiment on titanium alloy using an end mill tool. To identify the relationship between the sensor signal and the tool condition, we periodically measured tool wear using an optical microscope. Based on the acquired dataset, we developed an AI model suitable for tool monitoring that classifies the tool condition according to the machining signal using deep learning combining CNN and LSTM. In addition, we applied and reviewed a method to improve the classification accuracy of the tool condition according to new machining conditions using transfer learning based on this. Through this, we understood transfer learning and reviewed solutions for solving the problem.

End mill, Titanium alloy, Tool monitoring, Artificial intelligence model, Transfer learning

1. Introduction

In general, indirect methods are mainly used to monitor the tool status of machine tools, which requires measuring the machine tool signal and finding a way to identify the relationship between the tool status and the machining signal during machining [1, 2]. For this purpose, it is useful to apply an AI-based analysis model.

Titanium alloy, a typical difficult-to-cut material, has low thermal conductivity during cutting, so a lot of heat is generated, which leads to a short tool life and difficult tool management. When machining titanium alloy, it is important to detect the condition of the tool and determine the appropriate replacement time when machining a long time with one tool or when a large amount of machining is required. Therefore, an AI-based analysis model was applied to monitor the end mill machining process status of titanium alloy.

In this paper, we developed an AI model suitable for tool monitoring that classifies the tool condition according to the machining signal using deep learning that combines CNN and LSTM and applied and reviewed a method to improve the classification accuracy of the tool condition according to new machining conditions using transfer learning based on this. Through this, we understood the transfer learning method and examined ways to overcome its limitations.

2. Experiments

The machining experiment of titanium alloy (Ti-6Al-4V) was conducted using an end mill tool with a diameter of 16mm to obtain the necessary data, and a monitoring system was created by attaching an acceleration sensor (Kistler 8688A10) to the spindle of the machining equipment as shown in Figure 1. Figure

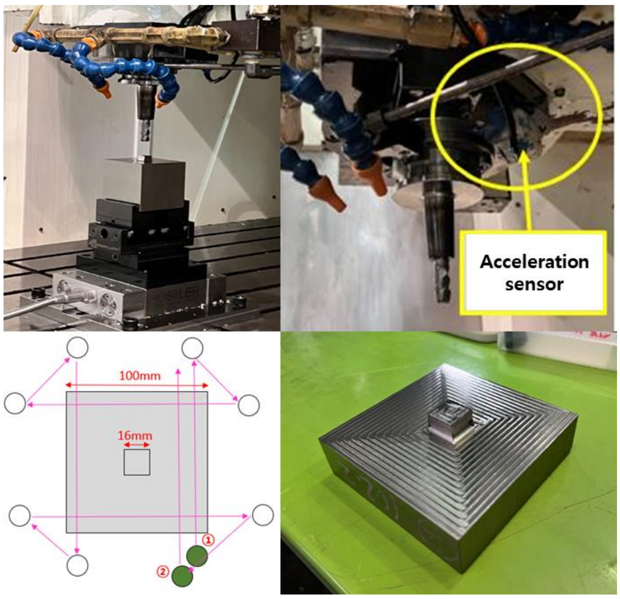

Figure 1. Experimental set-up, installation of acceleration sensor, cutting path and workpiece after cutting

1 also show the side milling and the state of the workpiece after processing. Additionally, as shown in Figure 2, tool wear was periodically measured using an optical microscope and used for tool condition analysis according to machining signals.

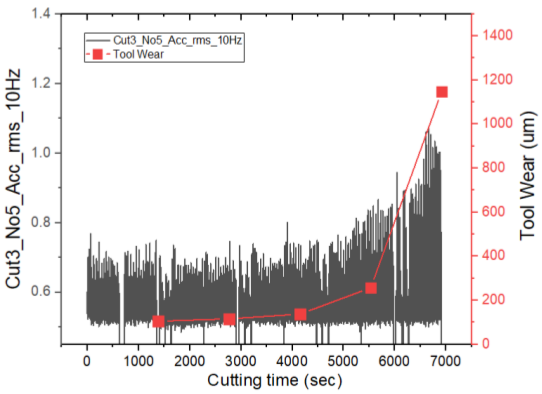

Figure 2. Data comparison between the signal of acceleration sensor and tool wear

3. Transfer learning

Deep learning techniques perform learning on a given data set, so it is difficult if there is not enough training data required for a given task. Transfer learning aims to solve a new, related task by utilizing the knowledge acquired in one task[3].

3.1. Pre-trained model

The artificial intelligence model used for pre-training is shown in Figure 3 and consists of CNN, LSTM, and DNN. Learning of end-milling data was conducted based on data acquired through experiments, and learning was performed by configuring a pre-learning data set. In order to use the pre-trained model for transfer learning, the parameters were fixed and stored.

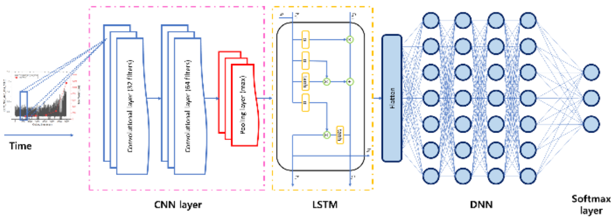

Figure 3. Architecture of CNN LSTM MLP for deep learning

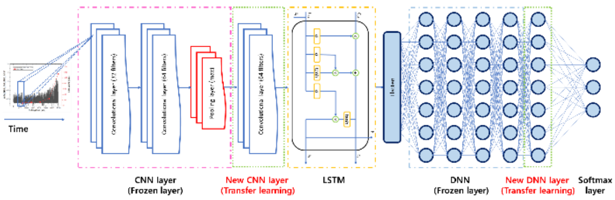

Figure 4. Architecture of CNN LSTM MLP for transfer learning

3.2. Transfer learned model

For transfer learning, a new 1D CNN one layer and DNN one layer were added to the model pre-trained using end-milling data, as shown in Figure 4. To compare the performance of transfer learning, classification performance was confirmed using a model with fixed parameters so that learning was impossible. The test data was the same data set used for transfer learning.

4. Results

As a result of pre-learning end-milling data using an AI model consisting of a combination of CNN, LSTM, and DNN, the classification accuracy of tool condition was very high, and detailed accuracy is shown in Table 1. Figure 5, Figure 6 show the training scores and confusion matrix results for pre-trained model, transfer learned model. As a result of performing transfer learning using end-milling data different from pre-learning, the classification accuracy was high at about 94%. However, when the classification performance of the model with fixed parameters was checked using the same end-milling data as transfer learning, the accuracy was quite low at about 52%. This shows that in the case of deep learning, there is a limit to lower accuracy if there is not enough data.

Table 1 Evaluation metrics of the confusion matrix for each AI model

Endmilling data	Pre-trained model	Transfer learned model	Model with fixed parameters
Accuracy (%)	99.4	94.7	52.1

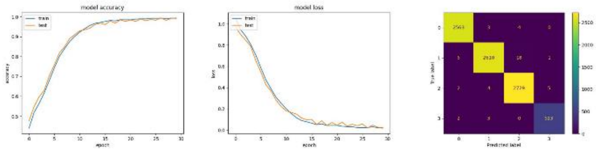

Figure 5. Training score, model loss and confusion matrix (pre-trained AI model)

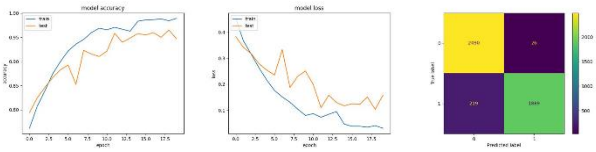

Figure 6. Training score, model loss and confusion matrix (transfer learned AI model)

5. Conclusion

In this study, we applied and reviewed a method to increase classification accuracy using transfer learning. Through this, we were able to gain consideration and understanding of transfer learning methods and overcoming limitations. We created a transfer learning model that added a new learning layer using an artificial intelligence model pre-trained on end-milling data. As a result of performing transfer learning using end-milling data different from the pre-learning data, the prediction accuracy was similar to that of the existing pre-learning model. It showed very high prediction accuracy. On the other hand, in order to compare the performance of transfer learning, the classification performance was checked using a model with fixed parameters, and the results showed relatively lower prediction accuracy than the transfer learning model. Through this, it was found that deep learning has a limitation in that accuracy decreases if there is not enough data. In order to optimize the AI model in the future, we plan to secure additional experimental data and conduct research on improving reliability through transfer learning.

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References

[1] Kurada S and Bradley C 1997 Computer in Industry 34(1) 55-72
[2] Zhu K and Yu X 2017 Mechanical Systems and Signal Processing 93 80-91
[3] Torrey L and Shavlik J 2009 Transfer Learning IGI Global