Title:
GA-CNN-based Tool Wear State Identification Method

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Introduction:
Milling and grinding composite machine tool processing technology is an important advance in modern manufacturing, can complete nearly 80% of the parts of the machining of the mold, especially in aerospace, precision manufacturing and mold processing and other fields with significant applications, as illustrated in Fig. 1. Composite milling and grinding machine tools can perform a variety of machining operations in a relatively short period of time, reducing the frequency of workpiece clamping and tool changes, and greatly reducing machining errors. With the development of technology, milling and grinding composite machine tools in improving the machining quality, shorten the production cycle and reduce the cost of the advantages of more prominent [1-2]. However, milling and grinding composite machine tool machining is also faced with challenges such as tool wear management and equipment maintenance, the state of its tool wear is a key factor in the normal operation of the machine tool, when the tool wear exceeds a certain level, it may lead to a decline in machining accuracy, surface roughness deterioration, and even tool breakage, which will not be able to deal with the poor production quality due to excessive tool wear in the machining process in a timely manner.

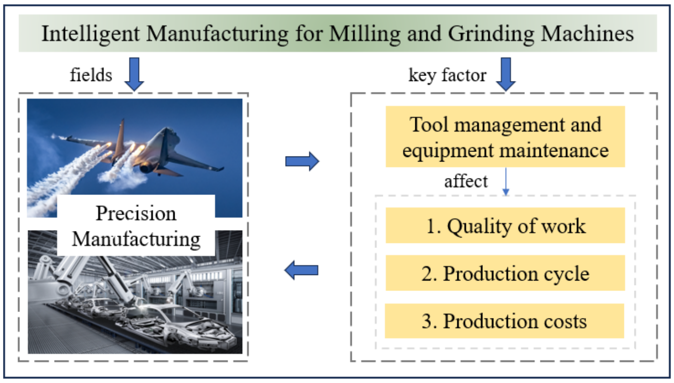

Fig. 1: Intelligent manufacturing for milling and grinding machines.

Traditional methods of tool wear state monitoring are mainly divided into direct and indirect monitoring methods. The direct monitoring method determines the wear state by directly measuring the physical characteristics of the tool (e.g. geometry, surface loss, etc.). The indirect monitoring method indirectly deduces the wear state of the tool by analysing signals related to tool wear (e.g. cutting force, vibration, acoustic emission, spindle current, temperature, etc.). With the progress of science and technology, the data collected by machine tool sensors is becoming more and more abundant, and the traditional methods of tool wear state monitoring can no longer meet the high demands of real-time, accuracy and adaptability in modern intelligent manufacturing. To overcome the limitations of traditional methods, modern tool wear monitoring methods have evolved to be intelligent, integrated and real-time, using a combination of data processing techniques and deep learning. Li et al. [3] proposed a tool wear prediction scheme based on feature transfer learning, where features related to tool wear are screened by GA, features are evaluated for similarity using the maximum mean square discrepancy (MMD) method, and the particle swarm-optimized support vector machine (PSO-SVM) model is applied to predict the tool wear state during machining of a new tool in order to achieve an accurate prediction of the tool wear state. Cheng et al. [4] proposed a new method for tool wear prediction based on Whale Optimisation Algorithm (WOA) optimised Support Vector Machines (SVMs) by extracting multidomain features of cutting force and vibration signals based on time, frequency and time-frequency domains. Cheng et al. [5] obtained the required one-dimensional signals by preprocessing the force and vibration signals, processed the one-dimensional signals into a data matrix using GAF, and ResNext automatically extracted the features of the data matrix to establish a multi-signal tool wear prediction model based on the Gramian Angular Field (GAF) and a deeply aggregated residual transform neural network (ResNext), which is capable of achieving fast and accurate tool wear prediction. Zhang et al. [6] calibrated the tool wear parameters with the help of image detection method and compared the predicted values obtained from the model with the experimental values to establish a milling profile simulation roughness model based on the tool motion trajectory and roughness calculation principle to calculate the tool wear after milling. Sriraamshanjiev Natarajan et al. [7] constructed a balanced virtual instrumentation framework that is perfectly matched to the physical system, where data is collected from the physical system, algorithms based on Machine Learning (ML) classifications are trained, and Probabilistic Neural Networks (PNNs) computed with the help of confusion matrices form the monitoring system of the tool's condition through the DT model. Zhang et al. [8] proposed a new method for identifying tool wear states based on converting force signals into two-dimensional images. CNN model that simultaneously considers both high and low dimensional features of the image is proposed to intelligently and accurately identify the degree of tool wear. Fig. 2 illustrates the common CNN structure.

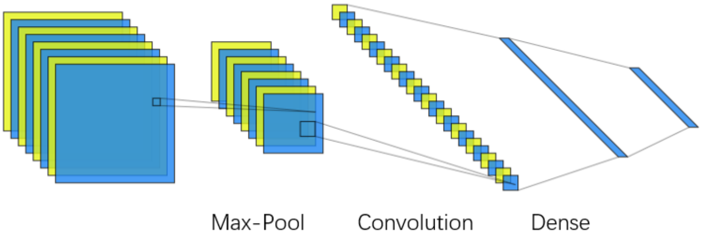

Fig. 2: The common CNN structure.

Main Idea.

This paper explores the training of a tool wear state identification model by collecting tool signals data, as illustrated in Fig. 3. The proposed framework is a CNN combined with GA optimisation for accurate monitoring of the wear state of machine tool and continuous performance enhancement model through integrated smart manufacturing, as illustrated in Fig. 4. The model has three key aspects: data preprocessing, selection of CNN architecture and hyperparameters, and iterative GA updating. During the experimental process of grinding composites on a milling and grinding composite machine, the dynamometer records the grinding force signal in real time, transmits the data to the dynamometer software and applies appropriate data processing methods for processing and analysis to optimise the signal quality. In the initialisation phase of GA optimisation of CNNs, the key hyperparameters in the CNN architecture are used to define population individuals, and a certain number of individuals are generated using a random approach to form an initial population, which improves the likelihood of the GA jumping out of the locally optimal solution in the optimisation process, and evaluates the degree of fitness based on the performance of the CNN model on the validation set. The GA optimises the CNN architecture by iterative optimisation, a process that continues to be iterated until the termination condition is satisfied adaptation converges. The synergy between GA and CNN greatly improves the accuracy and adaptability of tool wear monitoring, while enhancing the optimisation capability of the system. In this framework, GA algorithms are used to optimise the structure and parameters of the CNN to improve the prediction accuracy of tool wear states. CNN, on the other hand, extracts features from the data collected by the sensors and determines the degree of tool wear through deep learning techniques. The GA optimisation process searches for the optimal solution through iteration, effectively reducing the need for hyper-parameter tuning in the CNN training process, and further improving the algorithm's prediction performance and computational efficiency.

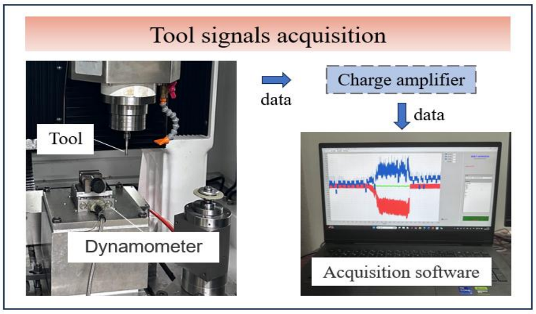

Fig. 3: Tool signals acquisition.

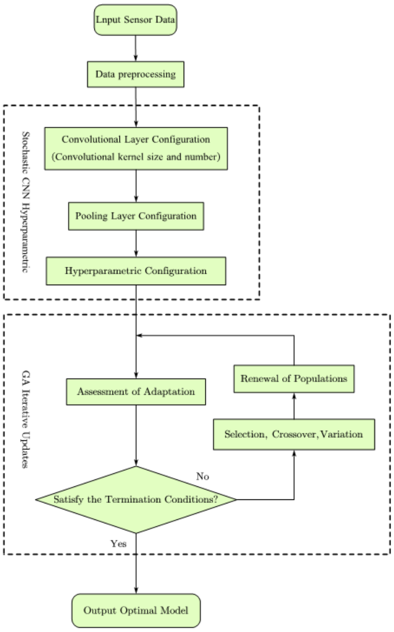

Fig. 4: Flowchart of the GA-CNN model.

In addition, the framework supports iterative updating and dynamic optimisation, and is able to monitor the tool wear status in real time, and through the continuous collection of various types of data from the production process. In the process of data analysis, combining historical wear data and real-time monitoring information, the model is capable of deep learning and pattern recognition, from which the potential patterns and trends of tool wear can be mined. This information not only provides the basis for timely prediction of tool wear, but also helps the system to adapt itself to real-time state when faced with different machining tasks. In the event of abnormal wear and tear, the system can automatically adjust machining parameters to optimise the process, or issue timely maintenance reminders to avoid the impact of equipment failure on production. This continuous iterative updating mechanism provides powerful data support for machine tool machining, helping to optimise tool management and optimisation strategies, avoiding the waste of resources caused by premature tool replacement, and avoiding the impact on production quality due to excessive tool wear, improving overall productivity and reducing maintenance costs.

Conclusions.

The GA-CNN-based tool wear state identification model aims to optimise tool use and management through intelligent analysis methods to improve machine tool productivity and production quality. The framework combines the GA-CNN hyperparameter configuration to improve the model performance, avoid the blindness and time-consuming manual parameter adjustment, and realise efficient data processing and accurate wear prediction in the process of monitoring tool wear state, which reduces the downtime and the risk of equipment failure in the production process.

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