

Intelligent Application of Software in Aerospace

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Abstract. In the context of the continuous development of the global manufacturing industry, milling has become a key means to meet the needs of precision or ultra-precision machining, and intelligent milling technology has gradually become the core of high-quality and efficient processing. This paper systematically reviews the relevant technologies, application scenarios, and future challenges of the intelligent application of milling software, and shows that the interactive integration of an intelligent milling system and hardware can effectively improve the machining accuracy and efficiency. However, in actual production, there are still data barriers and real-time computing bottlenecks that restrict large-scale and group application production. The future for intelligent milling needs to focus on multi-sensor fusion (cross-device knowledge transfer) to promote the transition of intelligent milling from 'simple intelligence' to 'industrial intelligence'. This paper provides the theoretical framework and technical route guidance for the intelligent transformation of milling manufacturing.

Keywords: milling, intelligence monitoring, monitoring sensor, monitoring software

1. Introduction

With the deep integration of Industry 4.0 and intelligent manufacturing, milling processing, as the basic process of manufacturing, is undergoing a change from traditional experience-driven to data-driven. As the core processing means for the production of complex surfaces and high-value-added parts, the quality and efficiency of the milling process will directly affect the performance, cost, and market competitiveness of the product. However, the traditional experience-driven milling process relies too much on manual experience to set process parameters and monitor machining status, which is difficult to deal with real-time dynamic interference (tool wear, chatter, thermal deformation), resulting in poor machining accuracy and efficiency [1]. According to statistics, the direct economic losses caused by processing anomalies in the global manufacturing industry exceed \$50 billion per year [2]. In this context, through the intelligent milling upgrade of software, monitoring, and other aspects, it can break through the current manufacturing bottleneck faced by milling processing, and pave the way for subsequent high-reliability production.

2. The development history of intelligent milling

2.1. From 1950s to 1970s

NC Technology (Software) MIT vacuum tube circuit and punching paper bag programming technology developed the first milling machine programming language. The disadvantage is high cost, lack of a real-time feedback mechanism, and the process parameters require manual intervention. Lay the technical foundation for the follow-up study [3].

2.2. From 1980s to 1990s

The CNC system replaces the traditional NC system, and the intel-8086 chip further improves the machining accuracy to $\pm 0.05\text{mm}$ while making multi-axis linkage possible. The Boeing company used CNC to reduce the machining cycle time of B-747 aircraft by 40% [4]. However, at this stage, the data is still in an isolated state, the integration between systems and sensors is still not significant, and the intelligent decision-making ability has not yet formed.

2.3. From 2000s to 2010s

Multi-sensor technology promotes the refinement of milling monitoring. Through wavelet transform and empirical mode decomposition, dynamic disturbance features such as tool wear and flutter can be extracted. This technology is used in the machining of titanium alloy parts by Boeing and Airbus to reduce tool damage and improve cutting efficiency. However, the algorithm at this stage still relies on empirical models, sensor fusion is still imperfect, machine learning is not yet popular, and the data processing delay is still as high as hundreds of milliseconds, which makes it difficult to meet the actual processing needs.

2.4. 2010-present

Data-driven decision making is the core. Through deep learning CNN, LSTM, reinforcement learning RL, tool wear prediction GRU, and digital twins realize virtual real-time mapping of objects is realized to increase efficiency. The milling machine RFM760 produced by Rödgers Tech, through a new method, Bayesian optimization algorithm (BO), the MAE is reduced by 14.8% [5]. However, the technical generalization is insufficient, and the problem of algorithm black box is still a challenge.

3. Future tendency

Three development directions:

1. Achieve distributed knowledge sharing and reduce data annotation dependency through technical support.
2. Augmented reality, language interaction, and other means to build a human-machine combined intelligent system, aiming to achieve a "experience and AI" combination of collaborative decision-making.
3. Reduce carbon emissions, reduce wastage and waste.

Although there is a lot of research on milling monitoring and milling technology upgrading, there is still a lack of in-depth research on intelligent milling. This paper systematically describes the

application scenario, use method, and stage effect of intelligent milling in detail. The core contributions mainly include:

(1) The technology chain of intelligent milling is analyzed from the direction of software or monitoring, and the application scenarios and limitations of different methods are compared.

(2) The economic benefits of intelligent milling in aerospace are summarized across scales.

In the process of milling manufacturing, it is usually possible to realize the intelligent milling process in the following ways:

(1) Reduce the processing time and improve the processing efficiency by optimizing the parameters of the processing path;

(2) By using algorithmic tool compensation technology, the tool life is improved;

(3) Reduce the vibration of parts and improve the machining accuracy by using reasonable trajectory planning;

(4) Improve equipment utilization by dynamically adjusting tool paths and using anti-collision strategies.

The above aspects can provide further ideas for intelligent milling. Next, we will discuss in detail the several ways mentioned:

During the operation of the machine tool, the appropriate processing path can effectively improve the processing efficiency. The reinforcement learning method can adapt to complex processing conditions, avoid excessive idling and other situations, and reduce the empty tool to improve efficiency.

In the process of machining complex parts, optimizing the tool path can significantly improve the machining efficiency and reduce the non-cutting time. A reinforcement learning algorithm can dynamically adapt to different processing environments and realize path self-optimization, as shown in Figure 1 [6]. A study used deep reinforcement learning to optimize the path, which increased the processing efficiency by 44.87% and reduced the idling time [7]. Another study combined genetic algorithm and reinforcement learning to optimize the five-axis machining path of aluminum alloy parts, increasing efficiency by 18% while reducing spindle load fluctuation [8].

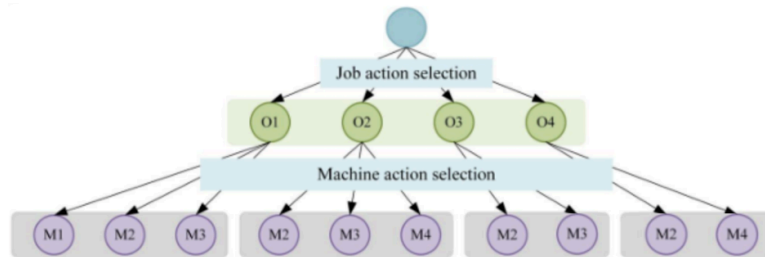


Figure 1. Hierarchical action space structure diagram of FJSP [6]

In order to meet the machining requirements of complex surfaces such as aero-engine blades and titanium alloy structural parts, NURBS curve interpolation and multi-axis linkage control technology, combined with flutter suppression algorithm (such as frequency domain feature recognition and active damping regulation), the surface roughness (R_a) of 50% of the machines is controlled below $0.45\mu\text{m}$, the processing cycle is shortened, and the tool life is extended [9].

In the machining process of high-precision parts, tool compensation technology can effectively improve the surface quality and extend the tool life. Combined with NURBS curve interpolation and flutter suppression algorithm (such as adaptive filtering and dynamic damping regulation), vibration influence can be reduced during machining, and machining stability can be improved. Another study uses intelligent error compensation technology to predict tool wear and adjust the compensation

amount in real time through machine learning to achieve high-precision machining of complex surfaces, while extending tool life. For the machining process of high-precision and high-yield aerospace parts, reasonable milling trajectory planning helps to suppress the vibration of the workpiece, and the stability of the system can be effectively improved through the use of a mirror milling system and machine learning. The difference between the predicted value and the expected value simulated by the finite difference method (FDM) and artificial neural network (ANN) is less than 2.5%. Greatly reduce local and global deformation and vibration [10].

Five-axis machining technology is widely used in the aerospace industry, which can process complex and fine parts. Traditional methods rely on CAD/CAM systems for off-line calculations, but these systems ignore the movement of parts during machine operation. In order to avoid this problem, real-time monitoring by cameras can be used to optimize the machining process of the machine using a combination of simulation technology and path generation algorithms. Combined with the actual test, it is concluded that this algorithm enables 76% of the driving points to have a collision-free working attitude, as shown in Figure 2, which can reduce the probability of machine tool damage due to collision [11].

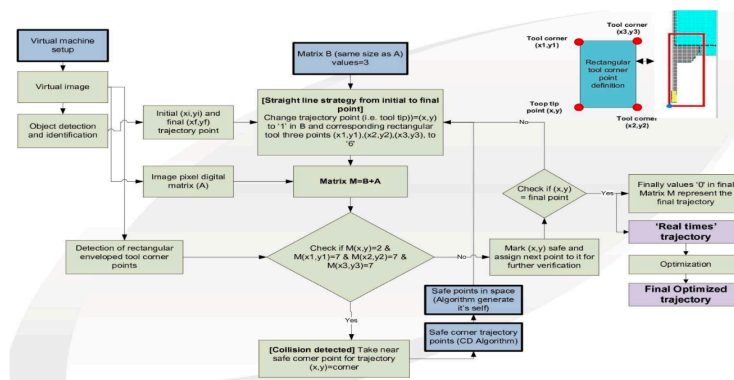


Figure 2. Tool collision avoidance [11]

Five-axis machining technology is widely used in the aerospace field. In order to avoid tool collision caused by component movement during machine tool operation, using the hull modeling idea, the hull model is formed through correct modeling, and the collision model is calculated in real time through the axis data (obtained through Profibus), and whether the collision is determined. Modern computer configurations (4-core CPU, 8GB RAM, any graphics card) can handle 107k to 137k vertices and 215k to 268k triangles in 3 to 6 milliseconds and make instant judgments to avoid collisions [12]. Another study, based on Digital Twin technology and a self-learning model, optimized the tool motion path through multiple data virtual simulations and real-time data fusion, and the initial error prediction was 8.69%, which improved surface quality and reduced collision probability [13].

Through the software intelligent transformation of the milling process, the machining cost can be effectively reduced, and unnecessary collision or wear of the spindle or tool can be avoided in the machining process. On the basis of software intelligence, combined with the Internet of Things or 5G networks, further leaps in processing efficiency can be achieved.

4. Conclusion

Intelligent milling technology, through the application of multi-modal sensing (sensors) or deep learning (algorithms), has achieved a 30% reduction in tool wear and a compression of response

time to less than 50ms. On this basis, by combining with reinforcement learning or fusion with multiple sensors, the machining surface accuracy reaches $\pm 2\mu\text{m}$, and the efficiency is increased to 1.5 times that of the traditional method. The industry has proved that monitoring/software intelligence has a high economic value through relevant practical cases, such as an aviation manufacturing company through an intelligent monitoring system to reduce production costs by 20%, while the product pass rate increased to 99.5%.

However, problems such as data barriers and calculation delays still limit the scale application of intelligent milling. In the future, with the help of knowledge transfer, 5G, edge computing, and other technologies, it is expected to achieve a breakthrough in milling. Intelligent milling is promoting the manufacturing industry to the goal of "zero defects, zero emissions", and its success depends on the collaborative innovation of multi-disciplines, multi-goals, and multi-modes.

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