Construction of CNC Machining Process Knowledge Base and Intelligent Decision-Making Method

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Abstract: *To address the issues of dispersed process knowledge, strong reliance on tacit experience, and low automation in intelligent decision-making within the field of CNC machining, this paper investigates the construction of a CNC machining process knowledge base and intelligent decision-making methods. By constructing a semantic representation model for process elements, achieving the extraction and cleaning of multi-source heterogeneous data, and completing the standardized description of knowledge based on ontology, this research resolves the problem of structured knowledge representation. Furthermore, a hierarchical and progressive architecture for the process knowledge base is designed, a self-organizing evolution mechanism for knowledge rules is proposed, and an information integration interface with CNC systems is defined, thereby establishing a dynamic and scalable knowledge management infrastructure. Building upon this knowledge base, the generation of process chains based on constraint satisfaction and reasoning is realized, a multi-objective collaborative optimization strategy for process parameters that integrates domain knowledge is proposed, and a simulation verification and confidence assessment system for decision solutions is established, ultimately forming a complete theoretical and methodological framework that spans from knowledge aggregation and organization to the generation of intelligent decisions.*

Keywords: *CNC machining process; knowledge base construction; intelligent decision-making; process knowledge representation; knowledge base architecture*

Introduction

CNC machining process planning heavily relies on the individual experience and tacit knowledge of engineers. This model, based on documentation and experiential transfer, results in low knowledge reuse rates, poor decision-making consistency, and difficulties in meeting the demands for efficient, high-quality machining of complex components. With the explosive growth of manufacturing data, systematically extracting and organizing computable, inferable process knowledge from vast amounts of multi-source heterogeneous data, and subsequently building automated, intelligent process decision-making systems based on this knowledge, has become a critical bottleneck and an urgent requirement for enhancing manufacturing intelligence and achieving closed-loop optimization of process design. This research aims to systematically explore a comprehensive methodology for CNC machining process knowledge, covering the entire chain from low-level representation and mid-level knowledge base construction to high-level intelligent decision-making applications. Its core lies in transforming dispersed, unstructured process information into a structured, semantic knowledge network, designing a knowledge base architecture with self-evolution capabilities, and ultimately supporting the generation of intelligent process decisions that comprehensively consider multiple constraints and objectives. This work provides essential methodological support in knowledge engineering for the evolution from digital manufacturing to intelligent manufacturing.

1. Methods for Representing and Acquiring CNC Machining Process Knowledge

1.1 Semantic Representation Model for Process Elements

The semantic representation model for process elements aims to construct a machine-understandable domain concept system. This model transcends the surface forms of natural language and tabular data to reveal the inherent logical and constraint relationships among process elements. The core of this model lies in adopting formal knowledge representation methods, such as knowledge graphs based on graph theory or frame-based representation languages. It abstracts entities like machine tools, cutting tools, workpiece features, machining operations, and process parameters into nodes. Their rich attributes are defined as attribute-value pairs, while the spatial, temporal, causal, and conditional dependency relationships between entities are modeled as directed edges with explicit semantic labels. This structured representation not only encapsulates static attributes but also dynamically depicts complex process logic, such as "rough milling operations precede finish milling operations" and "vertical milling machines are suitable for planar features"[1].

Through semantic modeling, the heuristic knowledge embedded in engineers' experience can be explicitly encoded and standardized. For example, a "high-speed milling" operation node can be linked to a "carbide ball-end mill" node via the "uses tool" relationship, associated with a "thin-walled cavity" node through the "machines feature" relationship, and connected to the constraint "material is aluminum alloy" via the "applicable condition" relationship. This deep interconnection forms a rich semantic network, enabling computers to perform relationship-based knowledge retrieval, consistency checking, and associative reasoning. It provides a precise, computable knowledge foundation for subsequent logic-based automatic decision generation and represents a crucial step in advancing process intelligence from data processing to semantic understanding.

1.2 Extraction and Cleaning of Multi-Source Heterogeneous Process Data

The sources of process knowledge exhibit significant multiplicity and heterogeneity, making their extraction and cleaning a prerequisite for constructing a reliable knowledge base. For structured data, such as Bill of Materials (BOM) from Enterprise Resource Planning (ERP) systems and equipment status records from Manufacturing Execution Systems (MES), extraction can be performed using predefined structured queries and mapping templates. Semi-structured data, exemplified by Numerical Control (NC) code, requires dependency on lexical-syntactic parsers to deconstruct its command sequences, thereby transforming G-codes, M-codes, and parametric macro programs into actionable and parametric objects with process semantics. Regarding unstructured data, such as process cards and technical reports written in natural language, it is necessary to integrate a Natural Language Processing (NLP) pipeline. This involves using Named Entity Recognition (NER) to locate key process elements and employing dependency syntactic analysis along with relation extraction techniques to construct preliminary element-relationship pairs.

During the data cleaning phase, the focus is on enhancing the quality and consistency of the raw data to construct a credible initial knowledge pool. This process implements the standardized mapping of terminology, establishing a "synonym forest" to unify different expressions such as "CNC milling machine" and "numerical control milling machine." It also performs the normalization of numerical values, ensuring all dimensional, speed, and power parameters adhere to a unified unit baseline. Deeper-level cleaning involves conflict detection and resolution, utilizing rule engines or statistical methods to identify and arbitrate contradictory information within the same context (e.g., conflicting feed rate descriptions for the same operation in two documents)[2]. Furthermore, completeness constraint checks based on ontological concepts can identify and flag instances with missing critical attributes. This phase outputs a standardized set of integrated, corrected, and enhanced process facts, laying a solid data foundation for the structured organization of knowledge.

1.3 Ontology-Based Standardized Description of Process Knowledge

Building upon semantic modeling and data cleaning, the ontology-based standardized description aims to construct a shared, formal domain conceptual model to achieve the unification and interoperability of knowledge at the logical level. Serving as the backbone of domain knowledge, the ontology provides a top-level semantic framework for all process data by defining a rigorous conceptual hierarchy, attribute system, and axiomatic constraints. The conceptual taxonomy clarifies that a "milling operation" is a subclass of "material removal operation," while "end milling" and "peripheral milling" are mutually exclusive subclasses of "milling operation." Object properties define intrinsic relationships between concepts, such as "hasInput" (a machining operation has an input workpiece) and "isPerformedOn" (an operation is performed by a machine tool).

The process of standardized description involves aligning, classifying, and making logical assertions about the previously obtained semantic model instances and the cleaned data, all according to the ontological framework. This ensures that each instance of a "drilling" operation is explicitly categorized under the "DrillingOperation" class and is compelled to satisfy the constraints defined for that class, such as necessarily being associated with a tool of the "drill bit" type. More importantly, ontological axioms endow the knowledge with dynamic reasoning capabilities. For instance, by defining an axiom expressing a value constraint like "tool hardness must be greater than workpiece material hardness," the system can automatically verify the feasibility of a process plan. Consequently, the ontology-based description not only resolves terminological heterogeneity but also weaves discrete knowledge points into a self-consistent semantic network through formal logic. This provides an indispensable logical foundation for the knowledge base's intelligent querying, complex reasoning, and consistency maintenance[3].

2. Architecture and Construction Technology of the Process Knowledge Base

2.1 Design of a Hierarchical and Progressive Process Knowledge Base Architecture

The design of the process knowledge base architecture adheres to the principle of hierarchical progression to achieve effective isolation, organization, and management of knowledge. This architecture typically consists of a data layer, an ontology layer, a rule layer, and an application interface layer. Serving as the physical storage foundation, the data layer is responsible for efficiently managing cleaned raw process instance data, resource parameters, and historical machining records. It may employ a hybrid storage model of relational and graph databases to respectively support transactional queries and complex relationship traversal. Positioned above the data layer, the ontology layer centers on a formalized domain ontology, providing a unified semantic interpretation and conceptual framework for the underlying data. This ensures the consistent meaning of concepts such as "machine tool" and "process step" across different application scenarios. The rule layer further encapsulates constraints inherent in the ontology and engineers' decision logic, manifested as production rules, constraint satisfaction rules, or case-based reasoning templates. This transforms static knowledge into executable reasoning paths.

Interactions between the various layers occur through well-defined interfaces, forming a bottom-up chain of knowledge abstraction. Instances in the data layer are associated with concepts in the ontology layer via mapping rules. The conceptual relationships and attribute constraints within the ontology layer provide the semantic foundation for logical judgments in the rule layer. The rule layer, in turn, directly drives the decision services of the application interface layer. This hierarchical design achieves a progression in knowledge representation from the concrete to the abstract and from data to logic. It not only reduces system coupling, facilitating modular maintenance and updates, but also provides structured support for the progressive expansion of the knowledge base and knowledge retrieval at different levels of granularity through clear layer boundaries.

2.2 Self-Organizing and Evolutionary Mechanism for Process Knowledge Rules

A static knowledge base struggles to adapt to the dynamic introduction of new processes, materials, and equipment in the manufacturing environment. Therefore, it is essential to establish a self-organizing and evolutionary mechanism for process knowledge rules. The core of this mechanism lies in designing a methodology capable of automatically evaluating, revising, and expanding knowledge rules. Its operation is based on the continuous monitoring and analysis of feedback from the knowledge base's application. This includes, for example, recording the execution results of process plans generated by intelligent decisions during actual CNC machining, encompassing machining quality, efficiency, and anomalies. By mining this feedback data, the system can identify deviations between existing rules and successful cases, or discover new optimal solution patterns not covered by the existing rules.

The evolution mechanism is specifically realized through processes such as rule confidence updating, conflict resolution, and case sedimentation. Each process rule is associated with a dynamically adjusted confidence metric. This metric is reinforced based on the frequency with which the rule is successfully validated or triggered, and conversely, it decays otherwise. When newly extracted process patterns or optimized parameter combinations come into logical conflict with existing rules, the system performs automated conflict detection and resolution. This decision—whether to amend, merge, or discard a particular rule—is based on the confidence levels, the sufficiency of data support, and ontological constraints. Furthermore, successful special machining cases can be abstracted and sedimented as new instantiated knowledge. After standardization, they may form new supplementary rules or exception clauses[4]. This bottom-up knowledge evolution process enables the knowledge base to transcend reliance on complete manual maintenance by experts. It endows the system with a degree of autonomous learning and adaptive capability, thereby ensuring its timeliness and practical utility.

2.3 Information Integration Interface Between the Knowledge Base and the CNC System

The ultimate value of the knowledge base is realized through seamless information integration and closed-loop interaction with downstream CNC systems. The information integration interface between the knowledge base and the CNC system defines a bidirectional, standardized data exchange protocol and functional call specification. In the decision generation direction, the application interface layer receives part feature information, material and accuracy requirements from upstream Computer-Aided Design (CAD) or process planning request systems. By invoking the rules and cases within the knowledge base for reasoning, it generates decision results such as structured operation sequences, toolpath planning, and cutting parameter sets. These results must then be transformed through this interface into neutral file formats that the CNC system can directly parse or easily receive, such as the extended STEP-NC standard or specific XML-based process description files.

In the information feedback direction, the integration interface needs to collect, in real-time or asynchronously, the process data generated by the CNC system during machining execution. This includes the actual operating status of the machine tool (such as spindle power, vibration signals), online inspection results, and final machining quality reports. These data serve as crucial input for the knowledge base's rule verification and evolution. The interface design must ensure the timeliness, completeness, and semantic consistency of data acquisition. This typically requires defining unified data models and communication middleware to bridge the heterogeneity of CNC systems from different manufacturers. Through this bidirectional integration interface, the intelligent decision-making capability of the knowledge base is implemented and validated in the physical manufacturing process. Concurrently, the real-world data from the manufacturing process, in turn, feeds back to drive the continuous optimization of the knowledge base, thereby forming a closed-loop intelligent system that spans from intelligent decision-making to physical execution and then to knowledge refinement.

3. Intelligent Process Decision Generation Based on the Knowledge Base

3.1 Constraint Satisfaction and Reasoning Path Planning for Process Chains

The generation of a process chain is a classic constraint satisfaction problem. Its objective is to search for one or more feasible sequences of operations and resource allocation paths within the complex constraint space defined by machine tool capabilities, tooling resources, workpiece geometric features, material properties, and precision requirements. The intelligent decision-making system based on the knowledge base formalizes this problem. Here, the ontology within the process knowledge base defines entity types and basic attribute constraints, while the rule library encodes more complex process logic constraints and experiential heuristics. The reasoning process begins with the semantic parsing and mapping of the input part's manufacturing features. Subsequently, the system performs forward or backward reasoning within the knowledge network[5].

Reasoning path planning involves the selection and optimization of search strategies. The system may employ Rule-Based Reasoning (RBR) to match general process logic, or Case-Based Reasoning (CBR) to retrieve and adapt similar historical process plans. Deeper-level reasoning relies on transforming the constraint satisfaction problem into a computable model, utilizing graph search algorithms (such as the A* algorithm) or logic programming methods to generate preliminary process chains while satisfying all rigid constraints (e.g., collision avoidance, machine tool travel limits). This process emphasizes the completeness and efficiency of reasoning. It necessitates leveraging the hierarchical relationships and constraint relaxation mechanisms within the knowledge base to prune the search space, thereby guiding the reasoning engine to efficiently traverse possible process combinations and ensure the basic feasibility of the generated solutions at both the logical and physical levels.

3.2 Multi-Objective Collaborative Optimization Strategy for Process Parameters

After obtaining a feasible basic process chain, it is necessary to perform refined collaborative optimization of its key process parameters to balance multiple conflicting performance indicators, such as machining time, surface roughness, tool wear, and energy consumption. The knowledge base provides the prior knowledge required for this optimization search, including the initial population, empirical parameter ranges, and the construction of objective functions. The multi-objective optimization problem can be formulated as searching for a Pareto-optimal solution set within the decision space composed of parameters like cutting speed, feed rate, and depth of cut. The core of the strategy lies in integrating intelligent optimization algorithms with domain knowledge guidance mechanisms.

The optimization process can employ population-based metaheuristic algorithms, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) or multi-objective particle swarm optimization algorithms. The involvement of the knowledge base is reflected at multiple levels. During the initialization phase, parameter sets extracted from high-quality historical cases can be injected into the population as high-quality initial solutions to accelerate convergence. Within the evolutionary operations, the process rules from the knowledge base can be transformed into constraints or correction operators to prevent the algorithm from generating invalid solutions that violate process knowledge. Furthermore, surrogate models or fitness functions constructed based on knowledge can partially substitute for time-consuming physical simulations, enabling the rapid evaluation of solutions. This collaborative strategy achieves a combination of global exploration and knowledge-guided local exploitation, ensuring that the optimization process not only pursues the mathematical Pareto front but also guarantees the engineering practicality and reliability of the solution set.

3.3 Simulation Verification and Confidence Assessment of Decision Results

Before being deployed into actual production, the generated intelligent decisions must undergo rigorous virtual verification and quantitative credibility assessment. The simulation verification utilizes digital twin or physics engine technologies to map and execute the planned process chain and parameters within a virtual environment, predicting geometric morphology, mechanical load, thermal deformation, and potential collision interference during the machining process. This process relies on precise machine tool dynamics models, tool models, and material cutting models that are interconnected with the knowledge base. The simulation results are compared with the design objectives to identify potential defects such as overcutting, undercutting, excessive vibration, or unreachable toolpaths. These findings serve as feedback signals to trigger iterative corrections of the process chain or parameters[6].

Confidence assessment, in turn, constitutes a quantitative measure of the overall reliability of a decision solution. It is a multidimensional comprehensive evaluation system comprising the similarity matching value between the solution and historically successful cases, the global average confidence weight of the invoked knowledge rules, the compliance rate of various simulation verification indicators with expected thresholds, and the solution's utilization margin for resource constraint boundaries. By establishing a weighted evaluation function, the system calculates a comprehensive confidence score for each generated decision solution. This score is not only used to rank and recommend multiple Pareto solutions, serving as one of the bases for final solution selection, but is also recorded back into the knowledge base system as a new piece of feedback information. The successful implementation of high-confidence solutions reinforces the rules and cases they depend on, whereas low-confidence outcomes may trigger the knowledge evolution mechanism, thereby forming an enhanced closed loop that spans from decision generation and verification assessment to the self-improvement of the knowledge base.

Conclusion

This paper systematically discusses the methods for constructing a CNC machining process knowledge base and intelligent decision-making. The research establishes a complete pathway for knowledge representation and acquisition, ranging from the semantic representation of process elements and the extraction and cleaning of multi-source heterogeneous data to ontology-based standardized description. This provides a theoretical foundation for making tacit experience explicit and structured. By designing a hierarchical and progressive knowledge base architecture, introducing a self-organizing evolutionary mechanism for the dynamic updating of rule confidence and conflict resolution, and constructing a knowledge base-CNC system integration interface that supports bidirectional data flow, an adaptive ecosystem for process knowledge is established.

Building upon this foundation, the research has realized the generation of process chains that integrate constraint satisfaction and case-based reasoning, achieved the multi-objective collaborative optimization of parameters embedded with domain prior knowledge, and constructed a decision evaluation system integrating digital twin simulation and multi-dimensional confidence quantification. This ultimately forms a complete intelligent closed loop of "data-knowledge-decision-feedback." Future research will focus on the deep integration and automatic acquisition of cross-modal process knowledge, online reinforcement learning algorithms for knowledge bases in small-sample scenarios, and distributed process knowledge service models based on cloud-edge collaborative architectures. These efforts aim to promote the practical application of this methodology in a wider range of manufacturing scenarios.

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