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AI-Assisted CNC Process Planning Using Computer Vision

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Abstract

Computer Numerical Control (CNC) machining is now an essential component of the modern manufacturing process, contributing to the creation of accurate components in various manufacturing sectors such as automotive and consumer electronics. However, traditional CNC programming remains a skill-intensive activity. Engineers are forced to look through engineering drawings, select the appropriate cutting tools, calculate machining operations, and set tool-paths in CAM packages all of which require time and rely heavily on personal experience. The paper is describing an AI-based system that processes the planning of CNC processes directly on the part drawings bypassing human input. It is capable of extracting machining features on its own drawings with the help of computer vision and image processing. Machine learning then intervenes to determine the appropriate operations, recommend appropriate tools, and compile initial toolpaths. All one does is to input a part image with a handful of critical dimensions and the system does the rest. It was prototyped in Python, with OpenCV on the vision side, and Scikit-learn on the machine learning. Experiments on a synthetic dataset provided good results on both feature recognition and tool suggestion, demonstrating that the idea works in practice. This entire framework is aimed at reducing CNC programming time and decreasing reliance on expert knowledge which is exactly in line with Industry 4.0 objectives. The geometries with complexities are yet a bit of a challenge and actual testing in the real world is another step to be considered.

Keywords; CNC machining, computer vision, automated process planning, machine learning Industry 4.0

INTRODUCTION

CNC machining pretty much everywhere now making precise parts for stuff like airplanes, cars, and even medical de-vices. These machines use computer programs to control everything and control it automatically, so you can get complex shapes done right automatically over and over again [1, 2, 3, 28]. But even with all that automation, creating the programs for them still takes a lot of human work and know-how from experienced people [11]. In normal factories, engineers have to look at drawings, figure out what features need machining like holes or slots, pick the right tools and set up parameters in CAM software [10, 24]. It's a bunch of steps where you make decision based on the understanding how machining works and choosing tools smartly [27]. That whole process ends up being slow and depends very much on whomever has the expertise [11, 27].

Things are changing with this Industry 4.0 idea where factory will be brought in with some AI, connected systems and data to make things more efficient and cut down on those manual stuff [4, 22, 23, 26]. The point is to have machines able to make decisions themselves by examining data and changing in real time [12, 13]. AI techniques such as machine learning and computer vision are receiving a lot of

attention to automatically take care of the tasks in manufacturing [29]. The way it would work: computer vision could scan drawings or images of parts and identify geometric things, such as pockets or edges [16, 17, 18]. Then machine learning comes to the rescue to select operations and tools according to sizes and materials [15, 19]. I think that sort of set up makes planning CNC processes so much simpler and less dependent on doing it all by hand.

Some researchers have been done in those systems where CAD models are used to recognize features and tool selection is done automatically [10, 24]. But, a lot of them require well-structured inputs and also still manual tweaks. Plus, those old rule based methods don't change very well and don't respond well when faced with new situations [27]. This paper attempts to correct this by proposing a system for feature recognition using computer vision and decision-making with machine learning [15, 18, 29]. It only needs a part image, along with some basic dimensions, to get started. From there, it finds the features and selects the tools with guesses on the parameters itself. Generating Machining Features from Drawings Toolpath The contributions in this work are as follows: Construct a vision method for pulling machining features from the drawings. Also creating a dataset that has rules imitating real scenarios. Then putting together, a ML model to select tools and predict parameters automatically. And finally showing a prototype that helps with planning using just minimal input from the user.

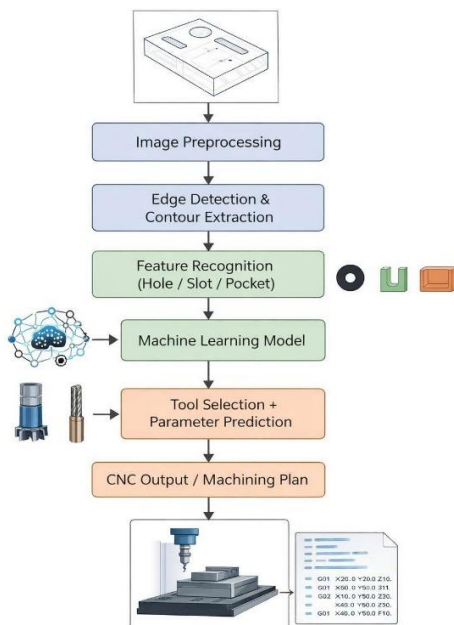


Figure 1: Proposed AI-Assisted CNC Process Planning Architecture

The rest of the paper goes over related work in automated planning and smart manufacturing next. After that, the system setup is described. Dataset making and the math behind it come in the following section. Experiments and results with some visuals are in another part. Limitations and ways to improve get discussed, and it wraps up at the end. It seems like this approach could really cut down on time, though in not totally sure how it handles every possible part yet. Some parts might get messy in practice.

LITERATURE REVIEW

Artificial intelligence is getting integrated into manufacturing systems a lot these days [12, 29]. People have been looking into automated process planning for a while now, mostly to cut down on all that manual programming in operations [11]. I think early work stuck with rule-based expert systems that could pull machining plans right from CAD models, like in some studies from back then [27]. Feature recognition stands out as a big part of this whole automated planning thing. There are algorithms out there for spotting stuff like pockets, slots, or holes in geometric models [10, 24]. For instance, Sun and others came up with geometric reasoning to detect those machining features in CAD [10]. Then Fu's group looked at mixing geometric and topological info to find features that can actually be made [24]. It seems kind of essential, but not always straightforward.

With intelligent manufacturing pushing forward, AI techniques are showing up more in actual machining [29]. Machine learning helps predict tool wear or tweak cutting parameters, and even boosts stability during the process [9, 20]. Random forest models work pretty well for classifying data from manufacturing, at least from what I've read [19]. Computer vision is another area popping up in these environments. Bradski's OpenCV library got big for handling images and detecting objects [18].

Lately, deep learning stuff like YOLO does real-time detection on images for objects and features [15, 17]. Still, using computer vision to read engineering drawings for CNC process planning is not that common yet. A lot of systems just pull features from CAD instead of dealing with images directly [10, 24]. So there is this gap, where we need smarter ways to interpret drawings from pictures and make machining decisions on the fly. This study proposes a framework that tries to fix that by combining computer vision with machine learning for automated CNC planning [15, 18, 29]. It might not cover everything perfectly, but it aims to connect those areas.

PROPOSED METHODOLOGY

The proposed system consists of several modules that work together to automate the CNC process planning workflow. The system architecture includes image preprocessing, feature detection, machine learning-based decision making, and tool selection.

Image Preprocessing

The first stage is the preprocessing of the input image to strengthen the features that are detected in the image. The image is turned to grayscale and noise filtered. Edge detection algorithms are then used to detect boundaries of geometric shapes. Edge detection can be represented by the gradient magnitude equation:

$$G = \sqrt{\{G_x^2 + G_y^2\}} \text{ where,}$$

(G_x) = gradient in the horizontal direction

(G_y) = gradient in the vertical direction

The gradient magnitude helps to bring out the edges in the image and helps the system to identify contours of machining features.

Feature Recognition

After preprocessing, contours in an image are extracted and are classified into geometric shapes. The system identifies the following machining features:

Shape Feature

Circular contour → Hole
Rectangular cavity → Pocket
Elongated rectangle → Slot

These features are typical machining operations in CNC milling and drilling operations [1, 2].

DATASET GENERATION AND MATHEMATICAL MODELLING

To test the proposed framework "a structured dataset was created on the basis of established machining principles and real-world material properties". The machining features, geometric dimension, material type and corresponding machining parameters are included in the dataset.

Feature Diameter–Depth Relationship

Machining depth is related to feature diameter as:

$$\text{Depth} = \alpha \times \text{Feature Diameter}$$

where $0.35 \leq \alpha \leq 0.8$ depending on material properties.

Tool Diameter Selection Tool diameter is selected as:

$$\text{Tool Diameter} = \beta \times \text{Feature Diameter} \text{ where } 0.7 \leq \beta \leq 0.9.$$

This ensures that the cutting tool is slightly smaller than the feature.

Feed Rate Estimation

Feed rate is dependent upon tool diameter:

$$\text{Feed Rate} = k \times \text{Tool Diameter}$$

where (k) is a constant that is determined by machining conditions [1,3].

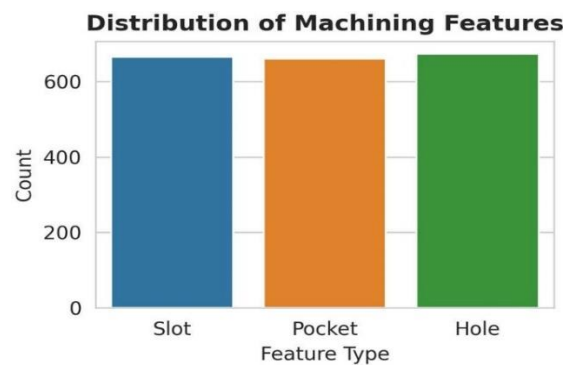


Figure 2. Distribution of machining features in the structured dataset

Experimental results and analysis

The proposed framework was executed with Python libraries such as OpenCV for image processing and Scikit-learn for machine learning [18, 19]. A data set with 2000 machining samples was used for evaluation.

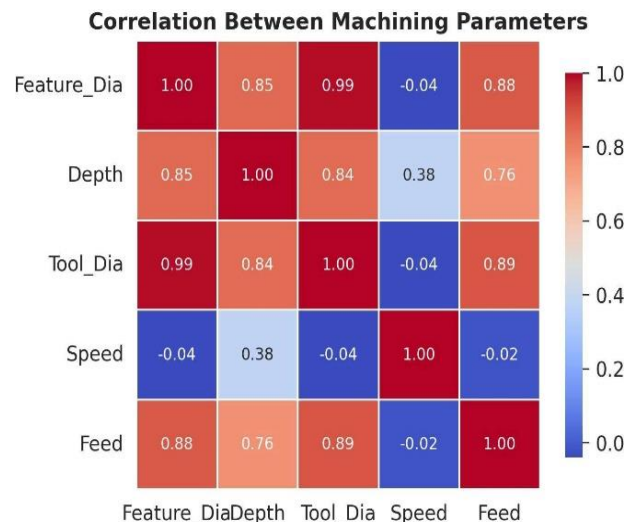


Figure 3. Correlation matrix of feature diameter, tool diameter and feed rate

Explanation: Correlation Matrix

The correlation matrix shows that there exists a high-level correlation between feature diameter, tool diameter and feed rate. A strong correlating (0.99) of feature diameter to tool diameter supports that feature geometry tool selection scales proportionately.

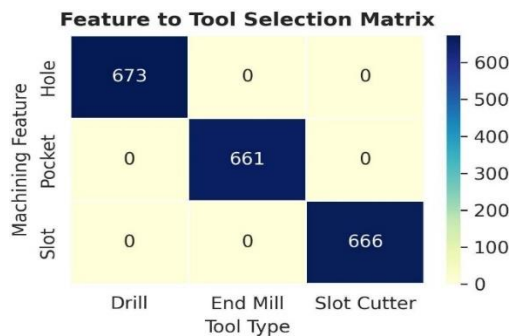


Figure 4. Feature recognition accuracy across hole, pocket and slot categories

CNC Decision Making.

The use of the matrix has shown that hole features are used with drill tools, pocket features with end mills and slot features with slot cutters [2, 3].

DISCUSSION

The experimental results show that the proposed system can well identify machining features and provide suitable cutting tool recommendations [18, 19]. The integration of computer vision and machine learning enables the integration of various steps of planning the CNC process. There are, however, some limitations with the existing prototype [29]. The system at the moment only supports simple machining features and is not yet de-signed to include complex toolpath optimization strategies [28]. Additionally, the dataset used for this study is rule-based and constructed using standard machining formulas, though further validation on real industrial data would strengthen the findings Future research can possibly focus on combining deep learning models for more robust feature recognition, and extending the

system to support complex geometries and multi-axis machining operations [15,16].

CONCLUSION

This paper introduced an artificial intelligence assisted framework for an automated planning process for CNC based on computer vision and machine learning. The proposed system proves that machining features can be

extracted from engineering drawing and applied in generating machining decisions in an automatic fashion. Experimental result show that the system can well identify features, recommend appropriate tools according to geometric parameters. The proposed approach contributes to the development of intelligent manufacturing systems and meets the vision of the industry 4.0.

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- **Funding Statement** -This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
- **Data Availability Statement** - The synthetic dataset generated and used in this study is available from the corresponding author upon reasonable request.

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