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AI Agent Framework-Driven Process Planning for Multi-material and Multi-DOF Manipulator-Based Support-Free Additive Manufacturing

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Abstract:

Multi-degree-of-freedom (DOF) manipulators offer a transformative approach by allowing substrate reorientation in conjunction with material deposition, thereby eliminating the need for support structures. This paper presents an AI-driven framework for process planning that effectively replicates material addition intent using a spatial manipulator with multiple DOFs.

When manufacturing a complex geometry that may have different regions a critical limitation is the finite size of the deposition end-effector, which constrains feature resolution and process scalability. Our proposed framework leverages AI-based optimization to dynamically adapt toolpath planning and deposition strategies, ensuring high-fidelity replication of desired geometries while maximizing process efficiency. As a proof of concept, we demonstrate the effectiveness of our AI-driven process planning through a pilot test case where we manufacture a complex slender structure that will need support.

The proposed approach enables flexible, support-free fabrication and enhances material versatility. By reducing material waste, optimizing deposition strategies, and enabling complex multi-directional structures.

Keywords:

Additive Manufacturing, Multi-DOF Manipulator, AI-Based Process Planning, Multi-Material Deposition, Functionally Graded Materials.

Introduction:

Many Engineering domains are benefitting by shifting from limited rule-based solutions to adaptive data-driven frameworks. The inherent ability to use machine learning agent enables the possibility for exhaustive scenarios that otherwise would be limited with a rule-based system. Rule-based systems quite often are limited in their ability to address edge cases; whereas the ML based framework when presented with ample learning cases can adapt for edge cases. Solid freeform fabrication is one of many fields that is benefitting significantly from ML. Some reported applications include process control, defect detection, root causing and corrective actions[1,2]. Additionally core manipulations improve aspects such as autonomously planning and realizing printing tasks, e.g. building structures, block stacking, and adapting to sensor feedback[3,4] reinforcement learning algorithms based on deep Q-learning for dry stacking [5] have been suggested. Traditional rule-based expert systems[6-8] are constrained by their reliance on static, predefined logic structures. They typically use geometry-based reasoning, first-order logic, and a sequential forward-chaining approach to process rules. While effective for well-understood and predictable problems, these systems operate on fixed "if–then" rule sets, limiting their ability to adapt or optimize for complex geometries. The lack of ability to learn and adapt means they cannot respond to scenarios that are not included in the "if-then" lookup catalog. Moreover, these systems do not support adaptive learning or self-improvement over time, nor can they perform backward reasoning to identify root causes of errors or revise previous steps based on new information. As a result, they struggle to handle complexity, uncertainty, or failure recovery.

This research applies the slender structure and skeletal framework and uses a machine learning based agentic tool to expand the framework to complex geometries. The agentic tools overcome the limitations of rule-based expert systems for process planning and adapt to a wide range of geometry. Additionally it adapts to real-time process variations for autonomous planning, and optimization.

In the following section we introduce some key attributes of the Agentic framework that make them suitable for free form additive manufacturing of complex geometries. We then present our implementation and the architecture of the agentic framework used for process planning. We present two unique examples; the first example suggests a multidirectional slender structure with linear segments, while the second example is based on a 3D spatial curve. In addition to the process planning for slender structures, we also present process planning that accounts for material deposition sequence that takes into account finite size of material deposition end effector so as to prevent interferences. We then test the manufacturing process using a customized 3D printer.

Attributes of AI Agent Framework:

An AI-based agentic framework is a type of computational architecture wherein autonomous agents perceive, reason, learn, and act within dynamic environments to achieve specified goals. Each agent typically comprises four key components: a **perception module** to interpret inputs, a **reasoning engine** to evaluate states and make decisions, a **learning module** (e.g., reinforcement or supervised learning) to adapt from experience, and an **action module** to execute responses or influence the environment. These agents operate in closed-loop systems, continuously updating their internal models based on processing and environmental feedback. Learning enables the agent to refine actions over time, while reasoning allows goal-oriented behavior, error correction, and planning. Adaptation occurs as the agent generalizes from past data to handle new tasks or perturbations, making such frameworks highly effective for complex, uncertain domains like additive manufacturing.

The deposition process is based on a geometry-aware, adaptive strategy for material deposition in 3D printing. The 3D model of the part is an input. The model is then analyzed to identify overhanging regions. Based on the overhang, a part is broken into different sub-volumes. For each sub-volume a morphological skeleton vector is created. Sub-volume is then sliced along planes normal to its local skeleton vector, allowing directional control of deposition paths.

A configuration space (C-space) analysis is employed to detect possible collisions between the deposition head and previously built structures. To resolve such conflicts, the system may reorient the part, modify deposition vectors, or resequence the layer order. These strategies are chosen based on the complexity of the geometry: simple parts may only need reorientation, while more complex shapes require a combination of orientation adjustment and layer sequencing.

This method enables support-free fabrication by aligning deposition paths with optimal growth vectors and avoiding obstructed regions. For areas with limited accessibility or interference risk, the approach allows a hybrid of sequential and parallel deposition to ensure complete coverage.

In order to accomplish the process planing the agentic frame work will be distributed into following :

- **GeometryAgent**: Extracts features and skeletons from 3D model.
- **SlicingAgent**: Determines optimal slicing orientation using skeleton vector.
- **InterferenceAgent**: Uses C-space mapping to detect possible collisions.
- **PlannerAgent**: determines order deposition steps.
- **ErrorAgent***: Predicts or adapts based on estimated deviations (e.g., thermal distortion).
- **FeedbackAgent***: Monitors deposition process in real-time and prompts replanning.

*Above framework suggest desired complete solution. However, the highlighted components will be included in future. They are not included in the current research.

Sample Agent Flow

1. Input: CAD file → GeometryAgent → Region/Slice info

2. Slice info → SlicingAgent → Orientation & sequence

3. C-space + slice → InterferenceAgent → Identify conflicts

4. Interference info → PlannerAgent → Reorder deposition

5. Plan → SimulationAgent → Check feasibility

6. Feedback → ErrorAgent → Adjust if needed

7. Final Plan → ExecutionAgent → Output machine inputs

2. Agent Flow

2.1 Geometry Agent

The geometric agent converts the CAD model (typically in STL format) into a morphological skeleton. A morphological skeleton preserves the topology and branching characteristics of the original structure and makes the connections among surface points. Skeleton points are extracted from the points along the surface and the resulting point set is fitted with a continuous curve or branching network. Each segment's tangent vector defines the local build direction; these vectors drive a multi-axis manipulator that rotates the workpiece so the print head's deposition direction remains perpendicular to the substrate surface. The skeleton also predicts build directions and subsequently reorient supporting platform allowing the process plan to eliminate dedicated support structure . *Fig. 1* describes the morphological skeleton created from a uniform cross section spiral. The figure also describes the tilt vectors. *Fig. 2* describes the morphological skeleton for a branched structure.

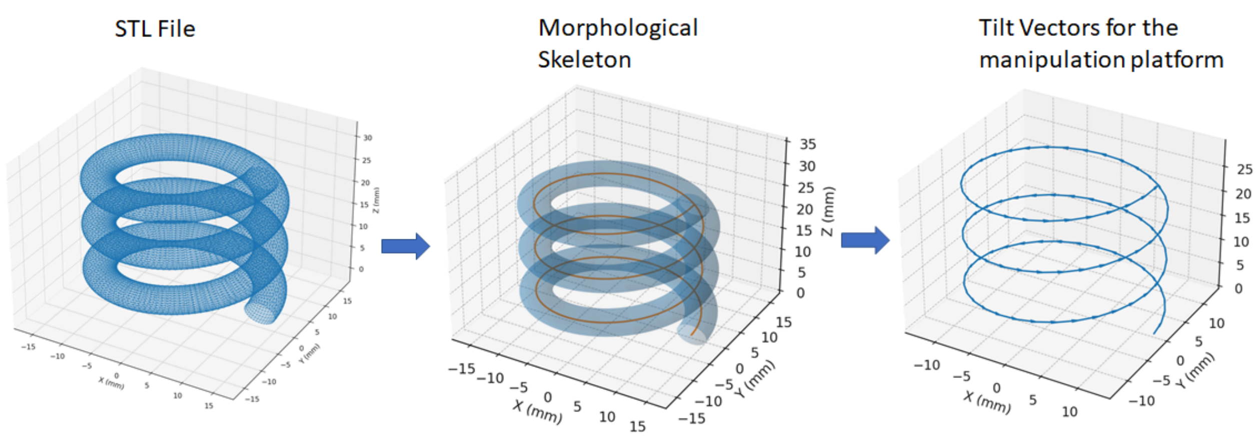

Figure 1: Using Geometry Agent to Create Skeleton

2.2 Slicing Agent

The Slicing Agent takes the skeleton produced by the Geometry Agent and converts it into a structured set of deposition layers. Unlike traditional slicing, which cuts a model along fixed planes, the agent aligns slices with the geometry itself by using the tangent vectors of the skeleton. This ensures that each layer follows the natural direction of the part, causing each layer to be printed on previously deposited material, hence removing the need for supports. By aligning the deposition head along with the vector for the region, support requirement is eliminated. To define the layers, the Slicing Agent samples points along the skeleton at regular intervals, with the spacing between points determining the layer height. This creates a consistent framework for deposition while maintaining flexibility. The resulting layers form the foundation for further planning and sequencing by the Planner Agent.

2.3 Interference Agent

The Interference Agent ensures that all deposition paths can be carried out without collisions or conflicts. The multi-axis additive manufacturing may lead to the material deposition end effector colliding with previously deposited layers or the machine datum. To prevent this, the agent uses geometric reasoning methods such as configuration-space (C-space) analysis to model the volume that the tool and part occupy during motion. This allows it to predict when paths are infeasible or when the tool lacks sufficient clearance to operate safely. When potential conflicts are detected, the Interference reorders the deposition steps. *Fig. 2* describes a sequence for reorienting and manufacturing for a 4 branched structure.

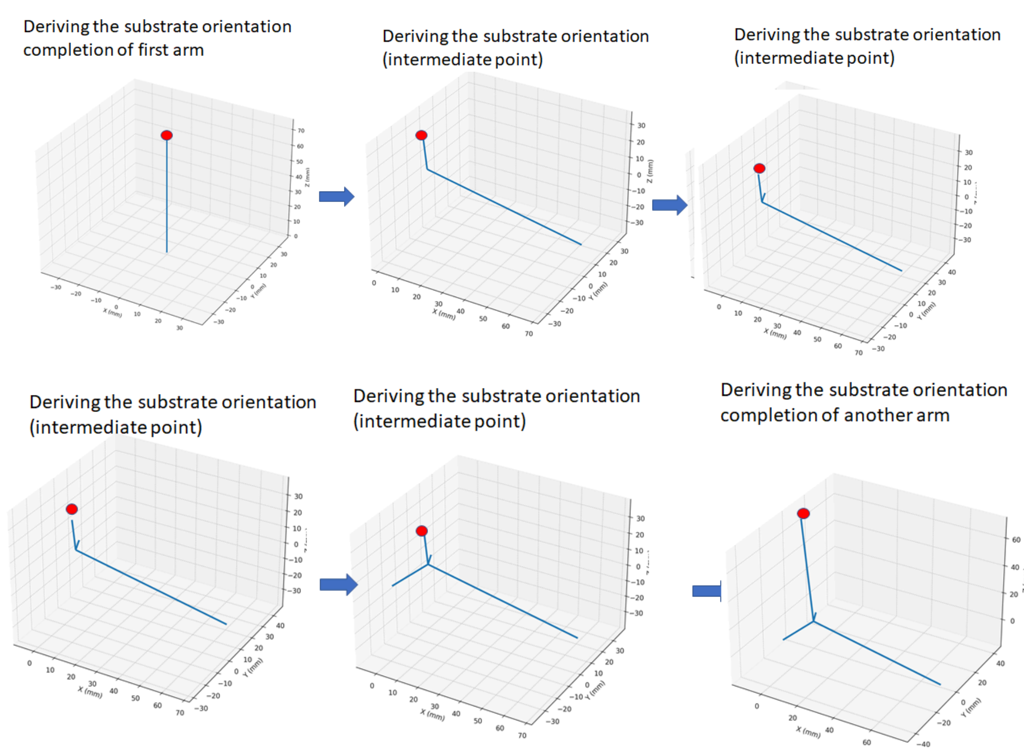

Figure 2: Using Planner Agent to decide the order of printing the slices

The 2D flowchart shows the logic behind selecting and processing printable points from an input geometry. The workflow begins when a user supplies a 2D image of the target part. The program preprocesses this image, labeling each pixel or point according to its position in the geometry into one of three lists: buildplate, previously deposited layers, and next possible layers. Using breadth-first search (BFS), the system identifies which points are valid for deposition at a given stage. One large constraint is that any new material must remain adjacent to already-deposited material for it to print correctly. The resulting set of candidate coordinates is then divided into adjacent groups, which represent possible clusters of points that could be printed together. This grouping step simplifies the planning problem by reducing a large number of possible coordinates into manageable, connected subsets.

The grouped coordinates are passed into a large language model (LLM) for decision-making. Along with the coordinate data, the LLM receives a scaled-up image of the part as well as the history of all previous deposition steps, providing full context for its evaluation. The LLM selects one group to be printed at that stage, and a secondary LLM validates this choice to reduce the likelihood of errors or impractical selections. This dual-LLM setup introduces redundancy and strengthens the reliability of the decision-making process. Once validated, the selected group is sent to the printing module for execution. The program then checks whether additional unprocessed points remain in the geometry. If so, the updated state of the part is re-encoded, and the cycle repeats, with the LLM making a new decision on the next deposition group. This loop continues until no unprocessed points remain, at which point the process concludes, and the final printed structure is complete.

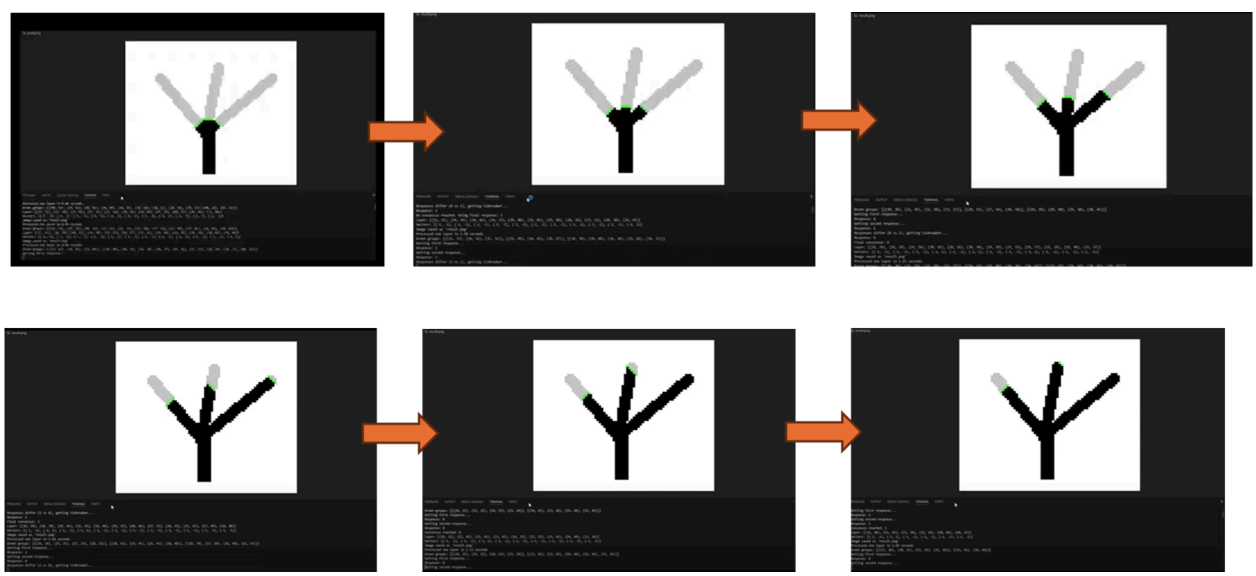

Figure 3: Process planning and sequencing the slices

3. Approach for Solving Multi Branch structure

As described in Figure 3, our approach begins with a breadth-first search (BFS) of the part geometry, initiated from the build plate. The BFS systematically explores the structure by identifying all possible points that can be printed next. At each step, a new point is only considered viable if it is adjacent to already deposited material, ensuring that the printed structure remains physically supported. When the part branches—for instance, in a Y-shaped geometry—the BFS naturally partitions the frontier into separate groups of candidate points, each corresponding to a different branch of the part.

Once candidate points are identified, the algorithm computes the optimal deposition vector for each one. Rather than operating directly in the tool head's coordinate frame, all calculations are carried out in the reference frame of the build plate. For every new point, the orientation of the tool head is derived by finding the angle that maximizes its resting area on the existing material. This ensures mechanical stability during deposition while also reducing the likelihood of overhang-related failures.

In cases where branch selection is necessary, we explored the use of a large language model (LLM) as a decision-making layer. The LLM receives the current part state—represented as a scaled image of the geometry—along with the set of possible next branches. It then outputs the index of the branch to pursue. While this process can be computationally intensive due to repeated calls at each layer, it provides a proof of concept for integrating AI-driven decision-making into path planning.

To make the decisions on which branch to extend and print, we used a Vision based LLM (minicpm-v:8b) running with Ollama. We chose to use a local LLM because each layer that is printed requires a call to the LLM, so utilizing a closed source LLM with an API would result in hundreds of requests even for simple parts, resulting in hitting the rate limits. By using a local model, we can run the LLM hundreds of times quickly, resulting in a cost effective way of process planning.

In order to preserve the history of what choices are made, we make sure to save every decision the LLM makes into the conversation history. This allows it to make a plan for how to move forward in the future, as well as ensuring that quality results are returned. By giving the entire history of decisions to the LLM for each step, we allow the agent to better reason forward.

To pass the current part into the LLM, we simply scale up the image so that small pixel differences are amplified. The current 2D part is saved as a PNG image, so it is straightforward to scale up the image and give it to Ollama for processing.

To improve response quality, we run the same process twice. If the results from the two models disagree, we use a tiebreaker to decide which path should be taken.

4. Experimental Setup and Results

The proposed framework was implemented on a 4-degree-of-freedom system. We developed a 4-DOF 3D printing system by adding a rotary axis to a Creality Ender 3 Cartesian-based printer. The fourth axis is built on a rotary table powered by a NEMA 23 stepper motor, providing enhanced flexibility for part orientation during printing. An Arduino Uno serves as the dedicated controller for the rotary platform, enabling synchronized operation with the printer. We use a 1.75mm PLA filament to manufacture a quarter rotation section of a spiral.

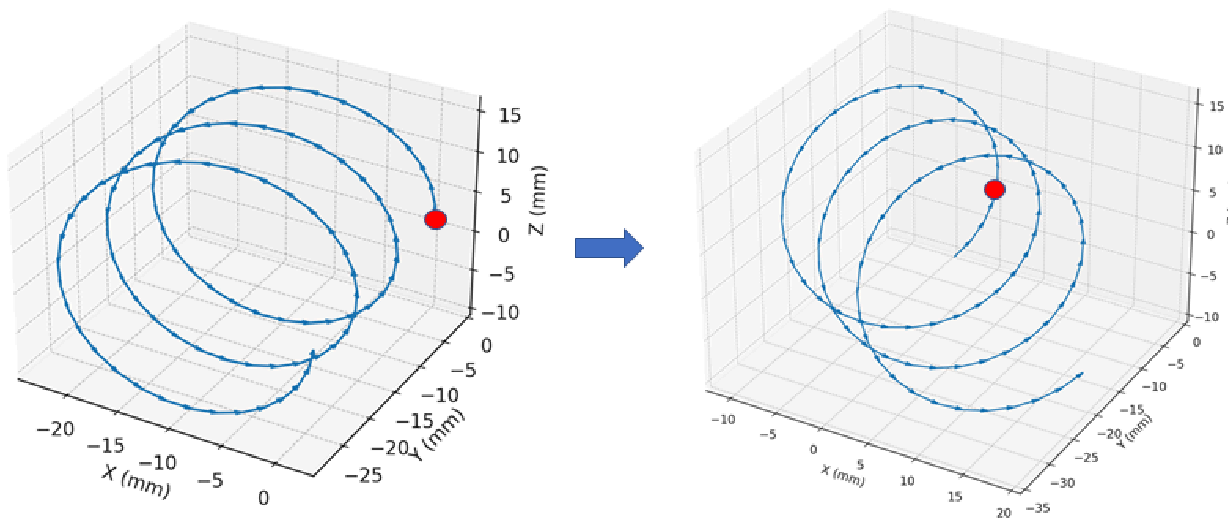

Figure 4: Using Slicing Agent to separate skeleton into layers

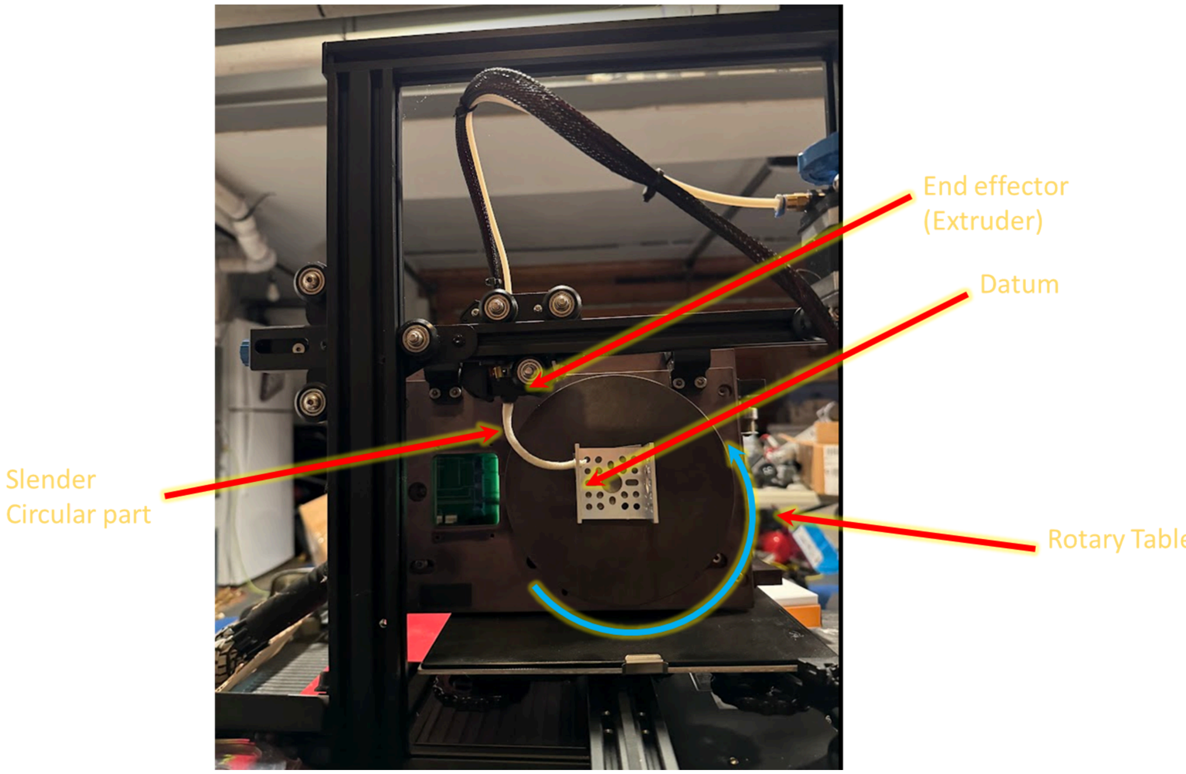

Figure 5: Experimental setup created by adding a 4th Rotary axis

5. Conclusion and Future Work

The proposed AI agent-based framework enhances process planning for slender and complex geometries by introducing adaptive learning, and path optimization. Experimental results demonstrate significant improvements over traditional rule-based expert systems. Future work includes:

- Expanding reinforcement learning models for multi-objective optimization.
- Integrating computer vision-based real-time monitoring for enhanced process control.
- Extending the framework to hybrid additive-subtractive manufacturing.

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