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Hybrid Reinforcement Learning and Neural Network Framework for Optimizing Deposition Paths and Thermal Profiles in Solid Freeform Fabrication of Functionally Graded Materials Using Maxel (Material Voxel) Framework

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Abstract

Solid Freeform Fabrication enables the production of functionally graded materials by allowing control over material composition within internal volume. However, the material deposition is often constrained by geometry of the path vs desired material distribution presenting many process-related inefficiencies. To address this we are using a field-based approach to develop path geometry; additionally, remelting and remixing is employed to facilitate smoother transitions.

This research introduces an AI-agent-based framework utilizing a maxel (material voxel) representation to optimize deposition paths. Furthermore, we investigate the impact of substrate heat dissipation. The framework employs a hybrid agent combining Reinforcement Learning (RL) and Neural Networks (NN) to learn optimal deposition strategies. By simulating discrepancies between intended and actual material fields, we quantify deposition errors and analyze their propagation throughout the build process. Employing the shape factor as a parameter, our AI-agent framework predicts and adjusts thermal profiles to improve material properties.

Introduction

Functionally graded materials are characterized by inherent material composition tailored for attributes such as mechanical, thermal, and chemical properties[1,2]. Additive manufacturing, particularly Solid Freeform Fabrication, enables manufacturing of Functionally Graded Materials by delivering different materials at specific locations within the build volume [3-7].

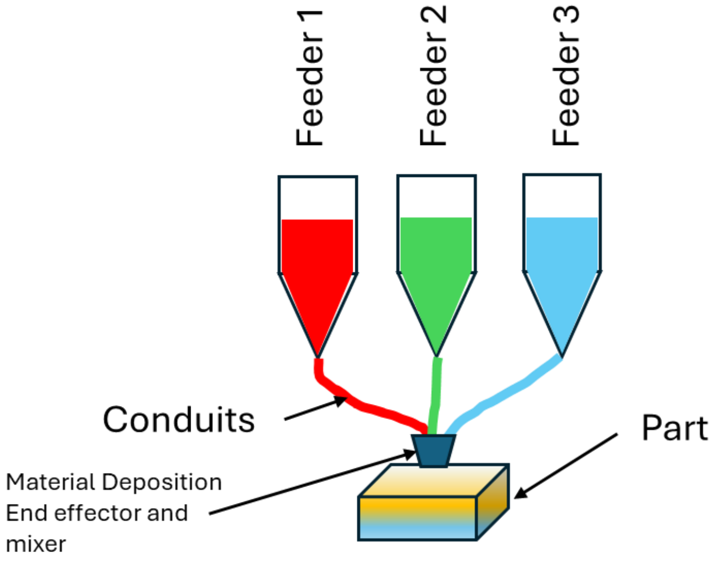

Figure 1: Schematic for Fabrication of Functionally graded material using SFF

Solid Freeform Fabrication (SFF) allows precise control over both geometry and internal composition of parts, particularly for functionally graded materials (FGMs). Typical SFF systems build parts layer by layer with two-dimensional toolpaths that often ignore part morphology. While this approach suffices for most geometries, depositing material in discrete amounts limits shape fidelity. As described in Figure 1, a generic SFF FGM system includes material feeders, a mixer, a spatial manipulator, a deposition head, and a controller to coordinate material blending and placement.

Typically for any SFF system the material addition for each layer is done by material deposition end effector following a zig zag path. The toolpath for each layer is independent of part morphology and follows a zigzag or similar trajectory. As described in *Figure 2*, while layered deposition simplifies process planning, it fails to align with the direction of least composition gradient, causing frequent changes in composition and requiring additional time for material mixing and purging[6].

Removing leftover material during composition changes imposes further constraints. Dwivedi et. al [2] noted that varying composition with a zigzag path leads to process inefficiencies because the deposition head delivers material in discrete amounts and suffers from time delays between requested and actual composition. Subsequent work introduced a “maxel” representation that discretizes composition into “material voxels” and proposed linking points of equal composition into iso-composition curves to guide the deposition head[6,8].

Despite these advances, path planning remains a challenge when complex geometries require tight coupling between geometry, composition, and heat dissipation. The maxel-based process planning method optimizes material addition by scheduling paths that minimize composition changes and determine purge times.

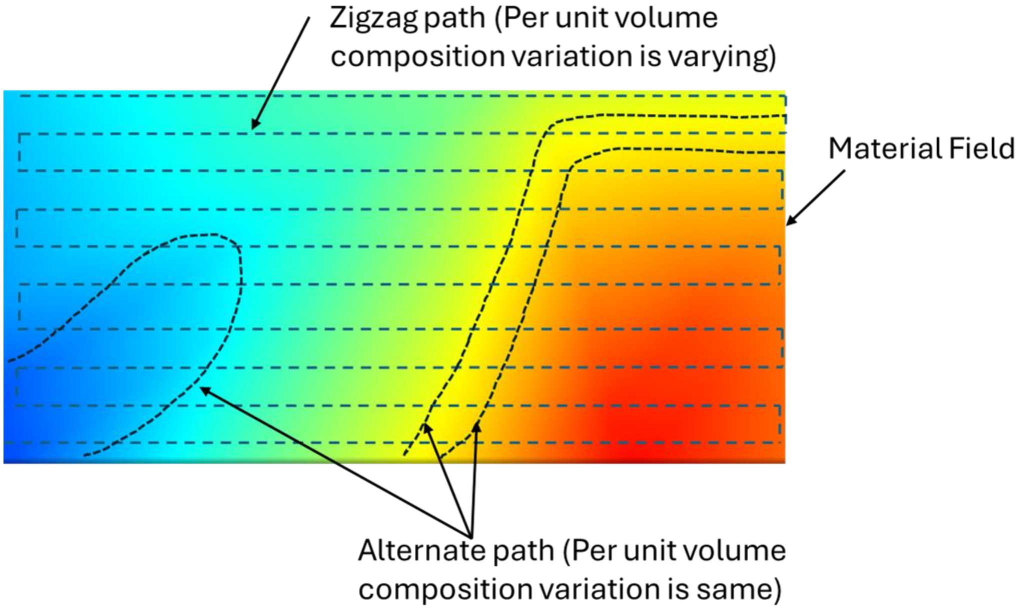

Figure 2: Material distribution and zigzag path limitation

Until recently, the field feature detection and subsequent process planning have been rule-based geometric heuristics. Once the CAD model is sliced for 2-½ axis deposition the process planner generates deposition paths by connecting points with the same material composition, producing a set of iso-composition curves. The path is generated by identifying the curves such that the distance between successive paths is set by the bead width and required overlap to maintain uniform material volume and smooth surfaces. This rule-based method works when iso-composition contours are nearly parallel, but it struggles with complex material fields. When the radial distance between adjacent iso-composition contours exceeds the allowable bead spacing, new curves are inserted using interpolation. Although linear interpolation ensures that composition variation in the added segment is small, regions with sharp curvature or steep composition gradients still cause discontinuities, significant deviation from the desired material composition and demand frequent composition changes, making the approach inefficient.

In this research we are employing machine-learning agents to address these limitations. This paper proposes an AI-agent framework that integrates a field-based path-planning strategy with RL-based decision making. The goal is to align the deposition trajectory with the desired material field while adapting to heat dissipation and composition delays. The proposed framework is validated using pilot experiments on a custom multi-material printer dispensing plain nylon and steel-fiber-reinforced nylon. A stepper-motor-driven feeder on a modified Fused Deposition Modeling (FDM) machine serves as a proof-of-concept for this framework.

We are also investigating path planning adapted for thermal management. The experimental validation of path planning optimization for thermal dissipation is very limited, we however share the simulation results.

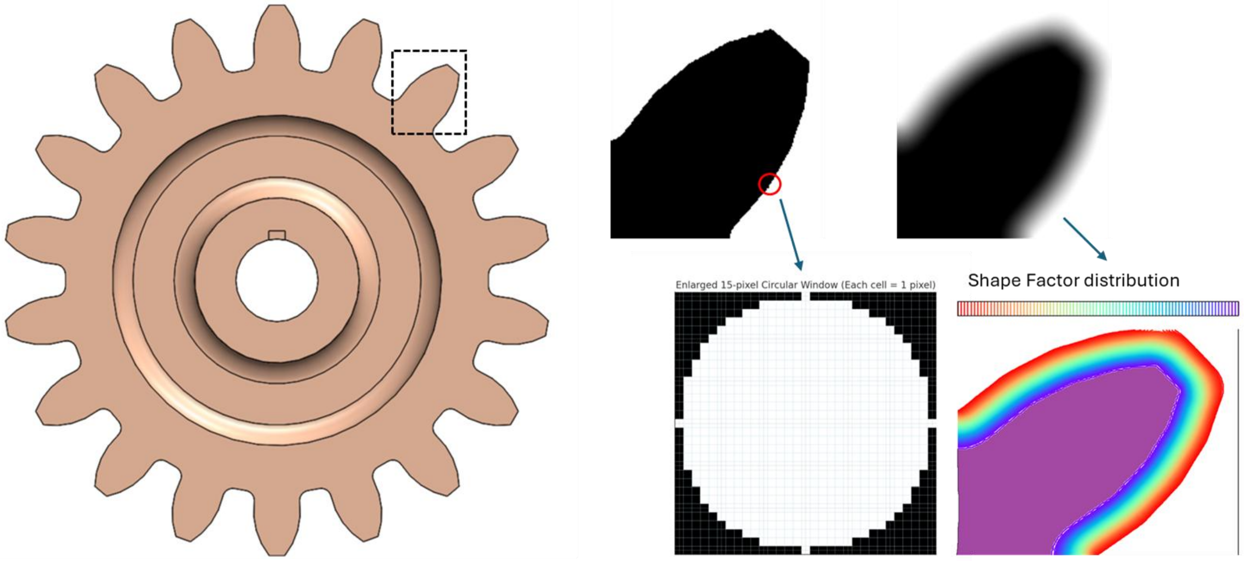

Figure 3: Determining the shape factor for a geometry

As a reference excessive heat leads to uncontrolled melting of filament and distortion, while insufficient heat results in incomplete fusion. We are using shape factor, defined as the ratio of the instantaneous molten pool volume to that of a perfect semi-infinite geometry, to quantify the effect of part geometry on heat sink capacity [9]. For a perfect semi-infinite body the molten pool is hemispherical; in real geometries the intersection between the unit sphere and the solid volume determines the shape factor. Heat transfer modeling uses the shape factor to adjust process parameters; if the shape factor is small (thin features), the substrate dissipates heat quickly and higher power or slower travel speed, in conjunction with the controlled material feeding may be needed. As described in the Figure 3, our calculation of the figure shape factor is based on a 15 pixel moving window. Each section is scaled to appropriate scale and then a 15 pixel moving window is used to estimate the shape factor per following:

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shape_factor = (sum of all 15 pixel values in the window) / 15
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Machine learning has been applied to various aspects of additive manufacturing, from defect detection to process parameter optimization. The framework is based on perception of composition and thermal fields, multi-physics informed rewards leading to adaptive approach. The adaptive approach provides a path generation for material composition requirements and maintain thermal uniformity.

3 AI-Agent-Based Process Planning Framework

The proposed framework combines a field-based path generator with a hybrid RL-NN agent to optimize deposition for FGMs. The process begins with a maxel representation of the part. The continuous material field M(x,y,z,t) is sampled to produce a grid of maxels with specified composition vectors. For each layer the system performs the following steps executed through representative agents that constitute the framework:

1. **Iso-composition curve extraction:** The Perception agent utilizes field feature detection in executing segmentation of the slice into regions of similar composition. Consecutive contour points are plotted via the Manipulation agent across corresponding regions of similar material composition where the Path-Optimization agent then generates iso-composition curves to connect the contour points with the identical material vectors.
2. **Curve interpolation:** If the distance between adjacent iso-composition curves exceeds the maximum deposition spacing, the Path-Optimization agent generates intermediate curves via interpolation to secure high-order continuity of material vectors.
3. **Order optimization:** The order of traversing iso-composition curves is arranged by the Path-Optimization agent to minimize compositional changes and mixing delays, taking into account the travel distance and required purge times for material feeders.
4. **Agent-based adaptation:** A hybrid RL-NN agent evaluates candidate path segments using a reward function that balances composition fidelity, travel efficiency and thermal considerations. The state includes the current position, composition vector, residual material in the mixing chamber and a thermal field predicted via finite differences. Actions correspond to selecting the next path segment and deposition speed. The agent is trained through simulations where discrepancies between intended and actual material fields are introduced by modeling mixing delays and heat accumulation. Neural networks approximate the value function and policy, while RL updates the weights based on the observed reward.
5. **Thermal adjustment:** The Thermal Regulator agent employs shape factor estimates to adjust extrusion rate. Regions with a small shape factor dissipate heat quickly and require higher power, whereas regions with a larger shape factor maintain heat longer and may necessitate lower power to prevent over-melting.

Reward Function and Learning Strategy

The reward function integrates three components: (i) **material fidelity**, which penalizes deviation between the deposited composition and the target composition; (ii) **path efficiency**, which encourages shorter travel distances and fewer changes in direction; and (iii) **thermal stability**, which penalizes excessive heat accumulation or insufficient fusion. To evaluate thermal stability, the shape factor is computed for the local geometry and used to predict temperature gradients.

Experimental setup

Experiments are conducted on a custom fused-filament fabrication printer equipped with four stepper-motor-driven feeders. The feeders dispense either plain nylon or steel-fiber-reinforced nylon; mixing occurs in a small chamber before extrusion. The shape factor is estimated based on the local geometry and used to adjust the heater power.

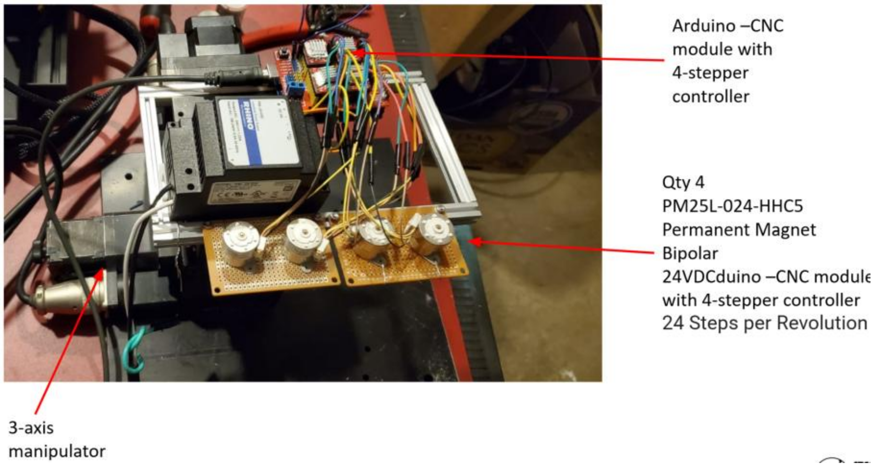

Figure 3: Experimental setup for multi material deposition end effector

The experimental setup used 1.75 mm PLA filament through extruders with 0.4 mm orifices. Each extruder was driven by a PM25L-024-HHC5 high-torque bipolar stepper motor, chosen for their compactness and ability to deliver a steady material flow. The motors were controlled by an open-source Arduino CNC controller and operated at up to 18 rpm. At full speed, the combined extrusion rate was about 16 mm³ per second. The motion platform was a repurposed Suruga-Seiki K332 3-axis goniometer with 10 µm positioning accuracy and 10 mm/s travel speed.

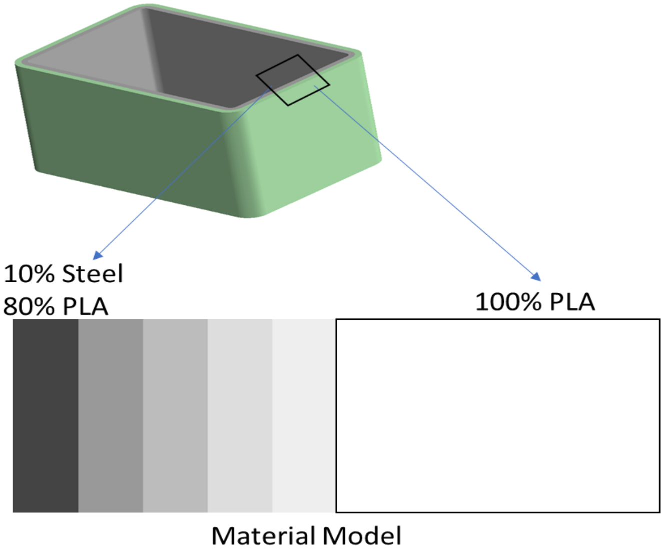

Figure 4: Desired material composition distribution for EMI protection

We used the experimental setup to manufacture the EMI protection casing for a remote controlled robotic motor power module. The protective shell was fabricated consisting of an outer layer of steel-fiber-reinforced nylon with the composition gradually changing to pure nylon. Plastic shell with powdered steel blended 0% to 20% . Successful layered segmentation of the part provided precise iso-composition contours and material field features for effective curve interpolation.

CAD Model

Manufacturing Setup and manufactured Part

Figure 5: Side-by-side shell display of CAD visualization (left) and printing end result (right)

Conclusions and Future Work

This paper introduced an AI-agent-driven process planning framework for functionally graded materials in Solid Freeform Fabrication. By leveraging a maxel representation and field-based path planning, the framework aligns deposition trajectories with material gradients and interpolates intermediate curves when necessary. A hybrid reinforcement learning–neural network agent optimizes the order and spacing of path segments while adjusting thermal profiles based on a shape-factor-based model. Simulations and experiments on a custom multi-material printer demonstrate that the proposed approach reduces composition errors, shortens build time and improves thermal uniformity. Future work will focus on scaling the framework to more complex geometries, incorporating additional materials, and integrating online learning to adapt to process variations. Improved thermal models and real-time sensing will further enhance the agent’s ability to manage heat dissipation and ensure part quality.

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