

GENETIC ALGORITHM-BASED OPTIMIZATION OF THE LASER-BEAM PATH IN ADDITIVE MANUFACTURING

OPTIMIZACIJA POTI LASERSKEGA ŽARKA Z GENETSKIM ALGORITMOM V PROIZVODNJI Z DODAJALNO TEHNOLOGIJO

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This study presents a methodology of genetic-algorithm-based optimization of the laser-beam path for improving laser-based additive manufacturing (AM). A simple thermal model was developed to simulate the effects of laser-induced heat input on the temperature distribution within the substrate during the fabrication of one layer. The optimization approach aims to find solutions with more homogeneous temperature properties that minimize the thermal gradient on the substrate caused by laser-based AM. The laser beam, i.e., the tool-path planning, is formulated as the search for the optimal sequence of cell depositions that minimize the fitness function, which is composed of two components, i.e., the thermal fitness and process fitness. The thermal fitness is expressed as the average thermal gradient, and the process fitness regulates the suitability of the proposed tool path for the implementation of the AM process. Various tool-path generators are proposed to initialize the initial population of tool-path solutions. Genetic-algorithm-based tool-path optimization is proposed, where custom initialization, crossover and mutation operators are developed for application in laser-based AM. Simulation studies demonstrate the effectiveness of the genetic-algorithm-based optimization in finding solutions that minimize the fitness function and therefore provide both thermally and, for the AM process implementation, more suitable laser-beam-path solutions.

Keywords: additive manufacturing, laser beam path, genetic algorithm, optimization

Raziskava predstavlja metodologijo optimizacije poti laserskega žarka na podlagi genetskega algoritma za izboljšanje proizvodnje z lasersko dodajalno tehnologijo (AM; angl.: additive manufacturing). Razvit je bil preprost toplotni model za simulacijo učinkov lasersko povzročene toplote na porazdelitev temperature znotraj substrata (podlage) med postopkom nanašanja ene plasti. Cilj optimizacijskega pristopa je poiskati rešitve z bolj homogenimi temperaturnimi lastnostmi za zmanjšanje toplotnega gradienta na substratu, ki ga povzroča dodajalna tehnologija na osnovi laserja. Načrtovanje poti laserskega žarka, to je poti orodja, je formulirano kot iskanje optimalnega zaporedja nanosov celic, ki minimizirajo kriterijsko funkcijo, sestavljeno iz dveh komponent; toplotnega kriterija in kriterija procesa. Toplotna ustreznost je izražena kot povprečni toplotni gradient, procesni kriterij pa izraža primernost predlagane poti orodja za izvajanje procesa AM. Za inicializacijo začetne populacije rešitev poti orodja so predlagani različni generatorji poti orodja. Predlagana je optimizacija poti orodja na podlagi genetskega algoritma, pri čemer so za uporabo v laserskem AM procesu razviti prilagojeni operatorji inicializacije, križanja in mutacije. Simulacijske študije kažejo učinkovitost optimizacije na podlagi genetskega algoritma pri iskanju rešitev, ki minimizirajo kriterijsko funkcijo in tako zagotavljajo toplotno ustreznost ter za izvajanje procesa AM primernejše rešitve poti laserskega žarka.

Ključne besede: aditivna proizvodnja, pot laserskega žarka, genetski algoritem, optimizacija

1 INTRODUCTION

Additive manufacturing (AM) is one of the fastest-growing industrial techniques, bringing many innovative solutions and applications to different industries.^{1,2} Laser-based AM has gained a lot of attention due to its ability to process a wide range of materials. In particular, selective laser melting and direct laser deposition are widely adopted AM processes that involve the selective melting and deposition of material layers to build up a three-dimensional (3D) part.^{3,4} However, achieving the desired quality, accuracy, and mechanical properties in laser-based AM remains a challenge, primarily due to the complex interplay of process parameters, part geometry and material characteristics. Consequently, various new

machine-learning-based approaches have been proposed to address these challenges.^{5,6}

One of the key challenges in laser-based AM is the control of the temperature distribution in the fabricated part during the deposition. The laser-induced heat input can lead to non-uniform temperature distributions within the build part, resulting in undesirable effects such as residual stresses, deformation, and deterioration of the mechanical properties of the 3D printed part.^{7,8} Achieving a more homogeneous temperature distribution during the deposition process is critical for improving the quality and accuracy of 3D metal printing. Various tool-path planning approaches have been proposed to optimize the temperature properties of the AM process,⁹⁻¹¹ to predict the temperatures with an artificial neural network,¹² and to introduce the optimized tool path to the AM process.¹³⁻¹⁵

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This study presents a novel methodology for optimizing the laser-beam path in laser-based AM using a customized genetic algorithm (GA) approach, which resembles and builds upon previous study using an evolutionary method in wire-arc additive manufacturing.¹⁶ The approach proposed in this study includes a simple thermal model to simulate the effects of laser-induced heat input on the temperature distribution within the substrate during the deposition of a single layer. By using genetic algorithms for optimization, the limitations of traditional time-consuming trial-and-error tool-path formulations are overcome. The proposed approach provides an automated and efficient solution for finding an optimal laser-beam path, leading to an improved temperature distribution and increased suitability for the implementation of the AM process.

2 METHODS

2.1 Overview of the methods and optimization approach

This research is focused on 3D metal printing using a direct laser deposition process. The basic simulation setup includes a substrate of various dimensions, on which a layer of the desired design is deposited. Due to the effects of laser-induced heat input, the substrate may be subject to undesirable deformation. Therefore, the focus of this research is to combine the simulation of a thermal model with an evolutionary optimization approach to find solutions with thermally more homogeneous properties, which in turn presumably result in products with less deformation of the desired geometry. The fitness function is designed to minimize the average thermal gradient on the substrate during the laser-deposition process while regulating the suitability of the tool path for the implementation of the AM process.

2.2 Tool-path formulation

The substrate for the laser-based deposition is designed as a grid of $N_s \times N_s$ cells, where each cell represents a small unit as a sub-grid of $N_c \times N_c$ sub-cells. The physical dimensions of the cells are determined by the parameters of the direct laser-deposition technology used, e.g., in the case of using the selective laser melting method, each sub-cell in the $N_c \times N_c$ sub-grid has dimensions of approximately 0.1 mm \times 0.1 mm. The individual cells are covered by one of the standard path-generating methods (e.g., raster or zigzag). By keeping the dimension of intra-cell topology small, the optimization problem can be formulated as the search for the optimal sequence of cell depositions that minimizes the fitness function. To provide the methodology for arbitrary design shapes, this study also introduces the "mask" operator that defines which cells are to be covered by the direct laser deposition and which cells remain uncovered.

Path representation

The basic format of the tool-path representation is a matrix of the same size as the substrate ($N_s \times N_s$) with the cells of the matrix containing the numbers of subsequent steps of the tool. Eq. 1 presents an example for $N_s = 3$ of a path p_1 represented by the matrix. However, for the manipulation of the paths in the genetic algorithm, the paths must be represented as strings, so the path p_1 can also be represented as a string s_1 defining the sequence of locations of sequentially visited cells (according to the predefined cell order) (Eq. 2).

$$p_1 = \begin{bmatrix} 1 & 2 & 3 \\ 8 & 9 & 4 \\ 7 & 6 & 5 \end{bmatrix} \quad (1)$$

$$s_1 = [1 \ 2 \ 3 \ 6 \ 9 \ 8 \ 7 \ 4 \ 5] \quad (2)$$

The string representation of a path is then applied in the genetic-algorithm-based operators. Nevertheless, both formats, matrix, and strings, are equal and can be converted from one to the other.

2.3 Thermal model

To determine the thermal response of the substrate and the corresponding thermal fitness for the generated tool paths, a two-dimensional, finite-volume thermal conduction model of the substrate was formulated. The volume of the substrate was divided into $N_s \times N_s$ control volumes. In each control volume, the conservation of energy was satisfied:

$$\rho c \frac{dT}{dt} = \frac{\partial}{\partial x} \left(k \frac{\partial T}{\partial x} \right) + \frac{\partial}{\partial y} \left(k \frac{\partial T}{\partial y} \right) + S \quad (3)$$

To keep the model simple, adiabatic boundary conditions, uniform temperature T in the z direction, and constant properties of the AISI 304 substrate were assumed: density $\rho = 7900$ kg/m³, specific heat $c = 480$ J/(kg K) and thermal conductivity $k = 15$ W/(m K).¹⁷ To simulate the direct laser-deposition process without material addition, a uniform volumetric heat source S was applied to the control volumes according to the tool path s_1 . The model was solved numerically using a tri-diagonal matrix algorithm¹⁸ with a fully implicit time scheme resulting in a time-dependent temperature field $T(x,y,t)$.

2.4 Genetic algorithm

The genetic algorithm (GA) provides a global optimization solver for smooth or non-smooth optimization problems with any type of constraint. The customized functions of the GA for tool-path optimization are proposed in this paper.

Initialization

For the initial population of tool-path solutions, we propose a set of generators that are designed to implement standardized tool-path generators (raster, zigzag,

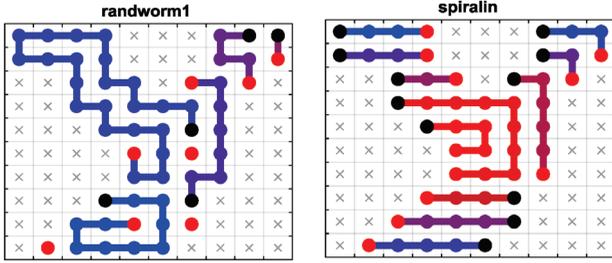


Figure 1: Examples of the initial population for the substrate of $N_s = 10$

spiral, etc.), a specialized stochastic-based search generator, denoted as 'randworm', and two temperature-optimized generators. Examples of two members of the initial population for the substrate of $N_s = 10$ with a non-symmetrical design mask "Y" are shown in **Figure 1**.

Fitness function

The fitness function (J) in this study is composed of two components:

1. thermal fitness (J_{thermal}),
2. process fitness (J_{process}).

The first component denotes the quality of the thermal distribution, which is expressed as an average temperature gradient across the workpiece and averaged across the deposition time frame:

$$J_{\text{thermal}} = \text{mean}(\text{grad}(T)) \quad (4)$$

The second component of the fitness function evaluates the properties of the tool-path solutions with respect to technological and process features and constraints. Usually, the following properties are desirable: a small number of laser stops N_{up} , a small number of single drops N_{singles} , and long deposition segments (expressed through

the length of the shortest segment L_{minSeg} and the average length of segments L_{meanSeg}):

$$J_{\text{process}} = (N_{\text{up}} + N_{\text{singles}}) / (L_{\text{minSeg}} + L_{\text{meanSeg}}) \quad (5)$$

Finally, the fitness function is completed as a combination of the thermal and process fitness with weight α denoting the ratio between the thermal and process fitness (in our study set to $\alpha = 1$):

$$J = J_{\text{thermal}} + \alpha J_{\text{process}} \quad (6)$$

Crossover operator

The crossover function performs a crossover operation between two parents, represented as tool-path strings s_1 and s_2 , to generate a new offspring s_3 . The crossover operation involves the following steps:

Splitting the tool-path strings s_1 and s_2 at the random crossover point N_{cross} to generate two sub-strings.

Composing the initial offspring s_3 from the two sub-strings.

Removing the overlapping cells from s_3 and filling removed elements by one of the available tool-path generators.

Figure 2 shows an example of the crossover operation between two paths. The first row presents the original parents (s_1 and s_2), and the second row shows the crossover child, which is composed of both parent segments, and the final filled child (s_3), which has all the missing cells filled by using a randomly assigned one of the available generators.

Mutation operator

The mutation operator in this study creates a new offspring from a parent by removing a randomly chosen deposition sequence from the parent and filling removed cells with one of the available tool-path generators. An example of the mutation operation is shown in **Figure 3**.

3 SIMULATION AND RESULTS

Simulations were performed with various symmetric and non-symmetric mask designs, and with various substrate dimensions N_s . A simulation example is described below, namely the 'Y' mask on a substrate size $N_s = 10$, based on the following thermal model configuration:

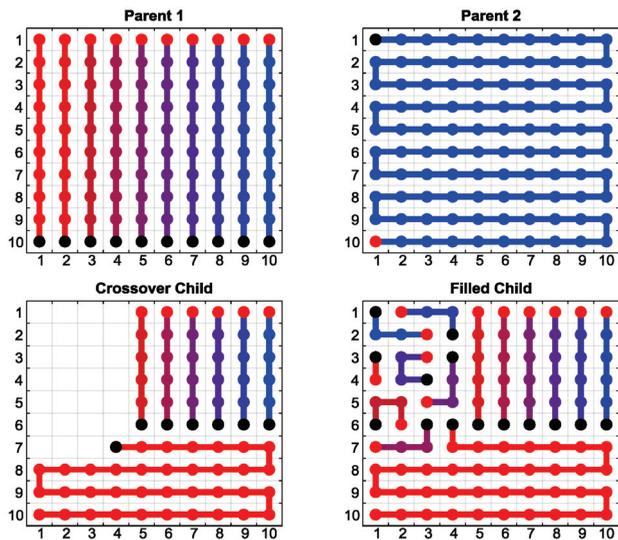


Figure 2: Crossover operation; the segments of the parents are combined by crossover into a child

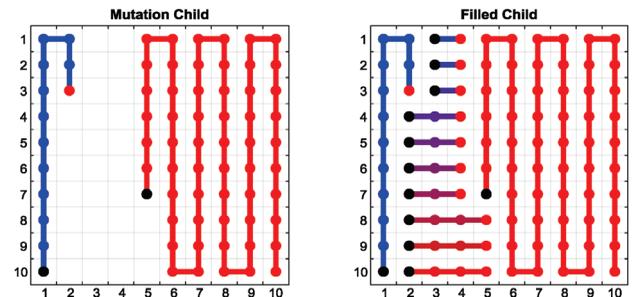


Figure 3: A mutation operation is applied to a parent to obtain the mutated child

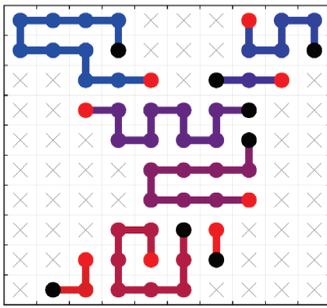


Figure 4: Simulation result of optimizing the tool path for the 'Y' mask on a substrate $N_s = 10$

substrate dimensions 50 mm × 50 mm, substrate thickness 3 mm, laser power 200 W, and time for one cell deposition 0.5 s. The GA-based optimization included 500 generations. The result of the simulated evolution is shown in **Figure 4**. The resulting path improves the overall fitness, which in this case amounts to $J = 30.3$. The fitness evaluations for a complete initial population and the optimized result are shown in **Figure 5**.

4 CONCLUSIONS

A novel methodology of the genetic-algorithm-based optimization of tool paths for laser-based additive manufacturing is described. The method includes custom GA operators (initialization, crossover, mutation) and can be applied to various laser-based AM processes. The study provides a simulated result that demonstrates the possi-

bilities of this approach to optimize the composite fitness function, thus finding the best ratio between the optimal thermal properties and the suitability for the implementation of the AM process. The fitness function can be arbitrarily modified for different laser-based AM processes. Therefore, this study provides a general GA-based optimization framework suitable for further research of optimal tool-path methods for additive manufacturing. By offering an automated and efficient approach to optimizing laser-beam paths, this research contributes to the advancement of laser-based additive manufacturing and its applications in diverse industrial sectors.

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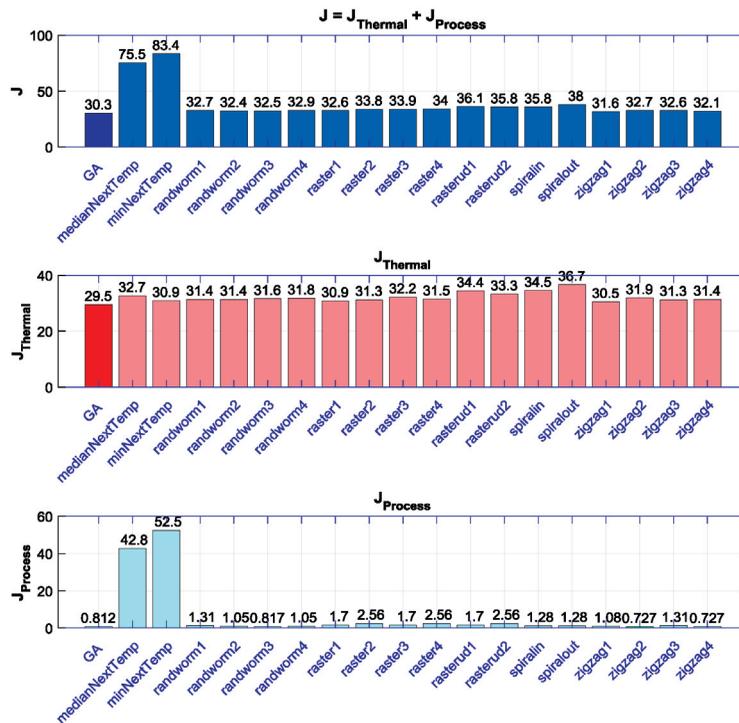


Figure 5: Fitness evaluations ('Y' mask on a substrate $N_s = 10$) for a complete initial population and the simulation result (GA), including the overall fitness (J), thermal fitness ($J_{thermal}$) and process fitness ($J_{process}$)

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