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Letters

RLTube: Reinforcement learning based deposition path planner for thin-walled bent tubes with optionally varying diameter manufactured by wire-arc additive manufacturing

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A R T I C L E I N F O

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A B S T R A C T

This study presents RLTube, an algorithm that uses reinforcement learning (RL) to compute the deposition path for thin-walled bent tubes produced by wire-arc additive manufacturing. Rigid mathematical rules are used by state-of-the-art methods and the developed Brute Force Approach (BFA) to achieve this goal. In contrast, RLTube offers greater flexibility, adaptability and efficiency. This RL-based architecture uses 2D images of bent tubes as input, eliminating the need for additional feature extraction steps. As a result, RLTube deposition paths outperform BFA in terms of the developed evaluation criteria reflecting their quality.

1. Introduction

Wire-arc additive manufacturing (WAAM) is an efficient additive manufacturing method that melts a metal wire using an electric arc and deposits it layer by layer on a substrate. WAAM offers customization, cost-effectiveness, and the ability to produce medium to large-sized parts with high deposition rates [1,2]. However, it faces challenges in automated path planning. This study addresses this issue for bent tubes with variable diameters, important in industries like aerospace, marine, oil and gas, and automotive [3,4].

Currently, there are two main methods for deposition path calculation for a bent tube optimizing for different criteria. [5] describe an algorithm where all the layers are perpendicular to its neutral axis. Moreover, [6] develop a solution that tries to minimize the height difference within each layer and demonstrate its suitability for the case of printing a bent tube from plastic material. Finally, [7] deal with bent tubes manufactured using WAAM, but rather than developing a suitable deposition path, the publication focuses on the shrinkage and distortion analysis and their compensation.

The mentioned state-of-the-art methods have a variety of problems. First, they have been tried out only on one simple geometry of a quarter of a torus. Secondly, they are based only on one optimization criterion. Thirdly, the solutions are based on simple mathematical rules, that might work only for a limited number of bent tube geometries and do not represent a robust, widely applicable technique.

Hence, this study aims to find solutions to the above problems and challenges via a reinforcement learning approach by answering the following research questions:

- What is a suitable parameterization of a bent tube with a variable radius for training a reinforcement learning algorithm?
- What parameters should the reward function of the reinforcement learning algorithm contain?
- How to evaluate the quality of the deposition path so that it serves as a reference for further methods?
- How well does the reinforcement learning approach compare to the state-of-the-art?

2. Materials and methods

2.1. RLTube

The general workflow of the developed RLTube together with its parameterisation and agent architecture is visualised in Fig. 1.

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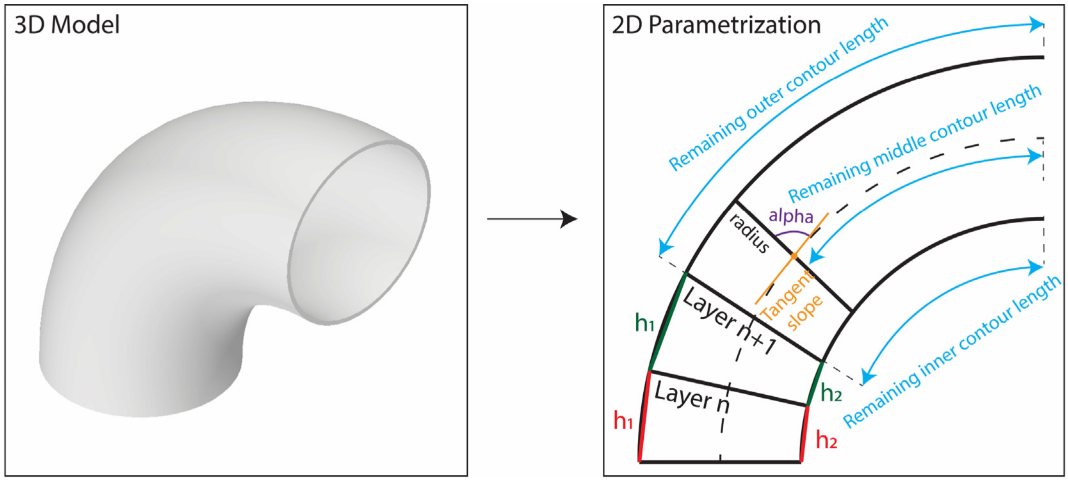
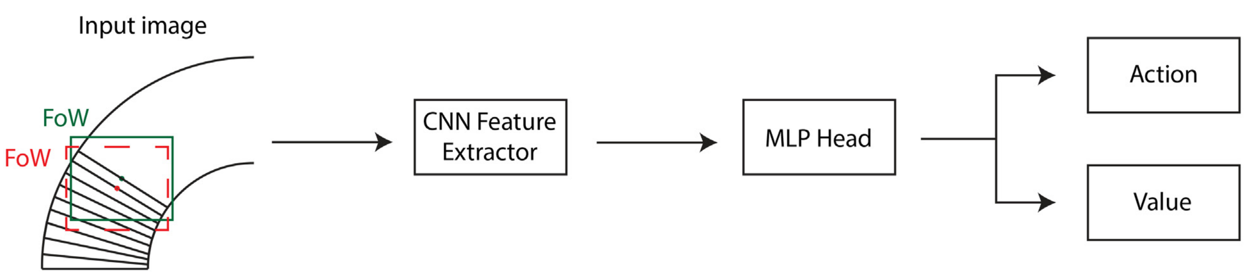
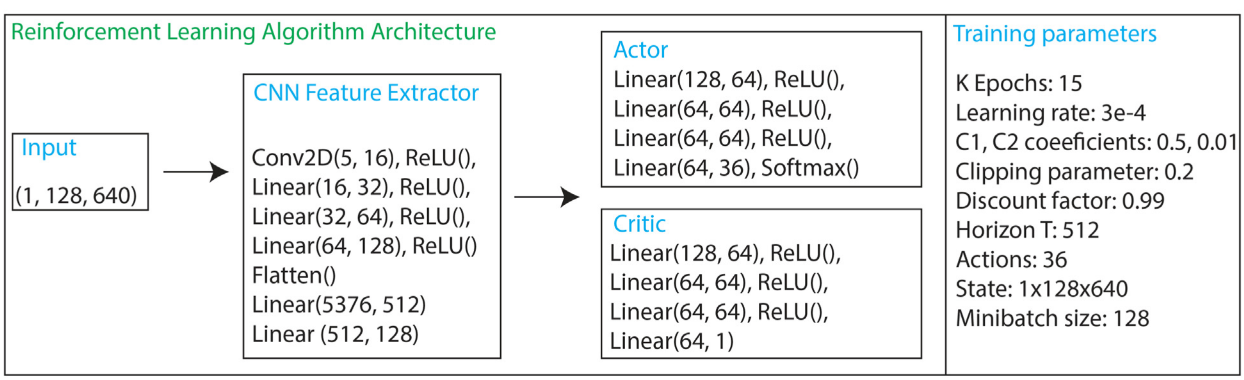


(a) 3D Model and its subsequent parametrization in 2D.



(b) RLTube workflow including the input image, together with the RLTube agent, which outputs the action i.e. the layer heights h_1 and h_2 corresponding to Figure 1(a) as well as the value of the estimated reward achieved by this particular action. Moreover, the layer height between h_1 and h_2 is linearly interpolated. Finally, FoW stands for field of view and was set to 128x128 pixels (the green one is the actual one, while the red one is the previous one).



(c) Architecture of the developed RLTube agent consisting of CNN Feature Extractor and MLP Head (see Figure 1(b)) as well as the training parameters used to train it. The state (1, 128, 640) means that the actual and 4 previous $FoWs$ are taken as concatenated input (5x128=640).

Fig. 1. Visualization of the 3D model and its 2D parametrization together with the RLTube workflow and the architecture of its agent.

The reward function, which the agent tries to maximize is composed as follows:

- Penalization for the difference between the angle of the layer to the tangent of the middle contour (marked as alpha in Fig. 1 and 90 degrees. This is because the layers should be ideally perpendicular to the contours.
- Penalization for difference between h_1 and h_2.
- Reward when there is no difference between layer heights h_1, h_2 in layer n and $n + 1$. The goal is to find a deposition path where the agent does not need to change process parameters frequently.
- Reward when the difference between the normalized distances of the inner and outer contours from the current layer $n + 1$ to the end is smaller than from the previous layer n. This reward is

designed to minimize the difference between the two normalized lengths of the two contours and, in the case of Fig. 1, forces the agent to output a larger h_1 than h_2.
- Reward if the normalized length of the outer contour is greater than the inner contour and at the same time h_1 is greater than h_2. The same applies analogically to the inner contour.

2.2. Deposition path evaluation criteria

Each deposition path is evaluated based on the following criteria:

1. The average difference between the alpha angle and 90 degrees for all proposed layers (the closer to 0 degrees the better).
2. The difference between h_1 and h_2 in one layer averaged over all layers (the lower the better).
3. The number of changes of h_1 and h_2 between two consecutive layers divided by the total number of layers (the lower the better).
4. The average height of one layer (the higher the better).
5. The remaining outer contour length from the last layer to the end of the bent tube (the lower the better).
6. The remaining inner contour length from the last layer to the end of the bent tube (the lower the better).
7. Total number of layers within the proposed deposition path (the lower the better).

2.3. Brute force approach

The brute force approach was programmed to enable RLTube to be compared with another method. This algorithm searches for the optimal h_1 and h_2 by dividing the inner and outer contour into the same number of pieces with a value from 0.5 to 3 mm and a step of 0.5. All these proposals are evaluated based on the above-mentioned criteria and the best value of h_1 and h_2 forming the final deposition path is selected. It is important to highlight that the most important selection criteria are the minimum remaining lengths of the inner and outer contours, because deposition paths with these minimised lengths propose deposition for the largest part of the geometry, which is the basic requirement to be at least theoretically able to print a geometry.

3. Results

Fig. 2 shows the deposition paths proposed by RLTube and BFA for tubes 1 and 2, on which the RLTube was developed and finetuned.

The overall results of the tubes shown in Fig. 2 based on the evaluation criteria are presented in Table 1.

In addition, the fabrication of tubes like the ones shown in Fig. 3 can be accomplished by following the deposition paths proposed by developed and finetuned RLTube. To identify suitable process parameters, specifically welding speed and wire feed rate, based on the layer heights h_1 and h_2 as determined by the RLTube agent, the *Process parameters setter* detailed in [8] can be used.

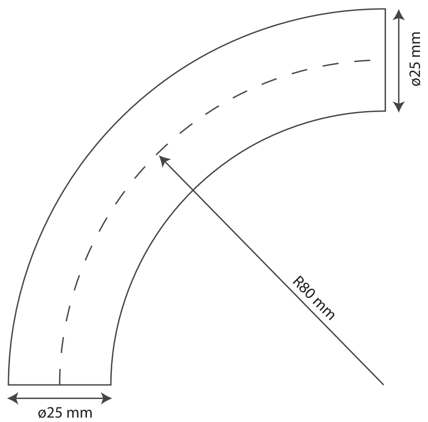
4. Discussion

It was found that the most efficient way to parameterize a bent tube with a potentially varying diameter is to project it into 2D and extract inner and outer contours. This approach saves memory by avoiding the use of a 3D representation in reinforcement learning. However, it is suitable only when 2D projection preserves geometric information. Inner and outer contours can be divided into discrete parts, serving as layer heights, ranging from 0.5 to 3 mm with 0.5 mm increments. This choice offers flexibility to the RLTube agent, balancing speed and deposition paths. Training times are typically one to two hours, ensuring effective results. These training times were influenced by the smaller diameters of the bent tubes (20 to 60 mm). Larger bent tubes are likely to demand longer training times. Importantly, deposition paths for these tubes can be obtained by adding extra deposition layers, positioned between the original inner and outer contour points of neighbouring layers. However, it is crucial to maintain a minimum layer height of 0.5 mm and a maximum of 3 mm.

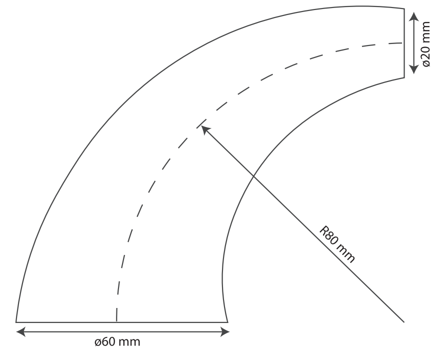
A vital element in the development of the RLTube algorithm is its reward function. This function guides the reinforcement learning agent by rewarding desirable actions and penalising undesirable ones. RLTube's reward function penalises when the layer is not perpendicular to the neutral axis, different heights within one layer, and encourages consistent heights across multiple layers. It also incentivises minimising the difference in the remaining length of the inner and outer contours. Furthermore, it is possible to fine-tune the weighting of various components within the reward function to achieve optimal outcomes in specific geometries of bent tubes. Finally, while this information provides rich feedback for optimisation, it can be confusing due to conflicting incentives and may have limited applicability in some scenarios.

In addition to developing RLTube, this work introduces a comprehensive evaluative scheme, which encompasses multiple criteria: the average deviation of the alpha angle from 90 degrees, emphasizing alignment; the average difference in layer heights to gauge consistency; the frequency of height changes normalized by the total number of layers, favoring smoother paths; the average layer height for deposition speed; remaining lengths of inner and outer contours, indicating coverage; and the total number of layers for efficiency. These criteria collectively form a robust framework for assessing and comparing deposition paths, ultimately leading to improved comparability among different studies dealing with this topic.

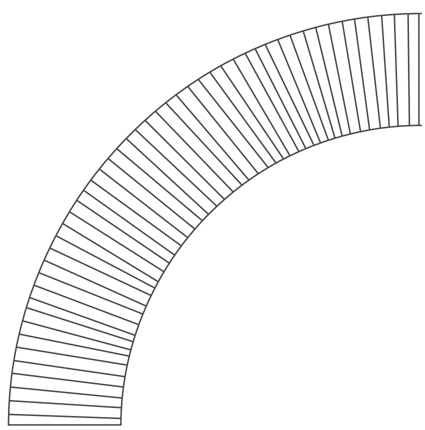
As discussed in the previous paragraph, comparing the RLTube with other methods in the field is challenging due to the lack of a clear evaluation framework and the field's underdevelopment. To establish a baseline, BFA was developed, which is compared with RLTube in Table 1. The comparison of the ultimate geometric and microstructural characteristics of samples produced using RLTube and BFA deposition paths depends on the specific input geometry. For example, RLTube reduces the number of layers by around 30% in the case of Tube 1, potentially leading to quicker build times and higher cost-effectiveness compared to BFA (see Fig. 2(c)). Nonetheless, this increased efficiency may come at the expense of surface smoothness and microstructural uniformity which might be better when the BFA path is followed (see Fig. 2 (e)). Conversely, for Tube 2, both methods propose nearly identical numbers of layers (see Figs. 2(d), 2(f)). However, as seen in Table 1, particularly in the average deviation of the alpha angle from 90 degrees, RLTube demonstrates significantly better performance than BFA. This can lead to better final structural integrity and stress distribution of a fabricated specimen if the RLTube path is followed. Therefore, the choice of deposition path should be made on an individual basis depending on the specific application scenario.



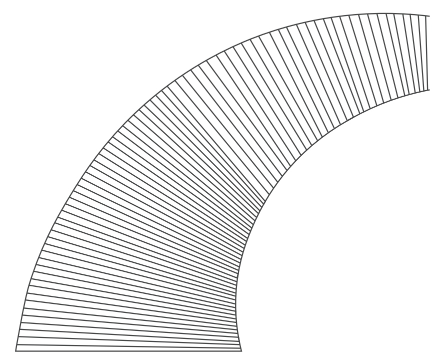
(a) Tube 1 in 2D.



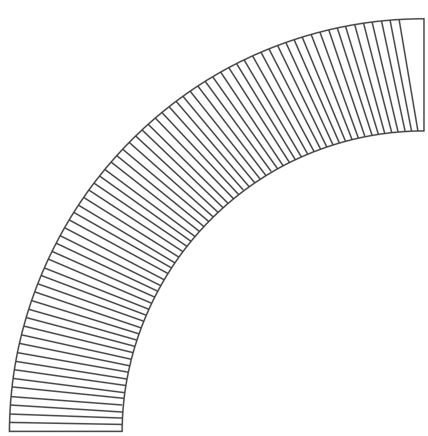
(b) Tube 1 in 2D.



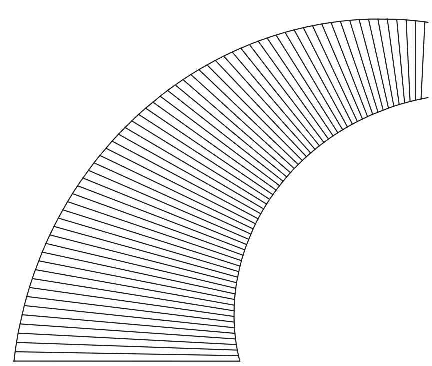
(c) Deposition path for Tube 1 proposed by RLTube.



(d) Deposition path for Tube 2 proposed by RLTube.



(e) Deposition path for Tube 1 proposed by BFA.



(f) Deposition path for Tube 2 proposed by BFA.

Fig. 2. Two bent tubes for which the deposition path was calculated using RLTube and Brute Force Approach (BFA).

Table 1
Evaluation of RLTube based on the evaluation criteria described in SubSection 2.2 and its comparison with the brute force approach (see Section 2.3).

	Tube n. 1		Tube n. 2	
	RLTube	BFA	RLTube	BFA
Crit. 1	**0.5**	3.29	**0.2**	12.2
Crit. 2	0.8	**0.5**	**0.9**	1
Crit. 3	24	**0**	20	**0**
Crit. 4	**2.5**	1.1	1.7	**2**
Crit. 5	0.8	**0.4**	1.3	**0.8**
Crit. 6	**0.5**	1.01	**0.9**	1.9
Crit. 7	**49**	70	**63**	64

(a) 3D model of a printed sample 1 with R=150 mm and ⌀=100 mm.

(b) 3D model of a printed sample 2 with R=314 mm, $\varnothing_1$=100 mm and $\varnothing_2$=50 mm.

(c) Printed sample 1.

(d) Printed sample 2.

Fig. 3. 3D Models as well as the printed samples. Fig. 3(a) shows a bent tube where the radius is 150 mm and the diameter 100 mm. Moreover, the bent tube visualized in Fig. 3(b) has a radius of 314 mm and diameters of 100 and 50 mm [7].

5. Conclusions

This publication introduced RLTube, an innovative reinforcement learning algorithm developed for formulating the deposition path in wire-arc additive manufacturing of bent tubes.

The main contributions of the work are as follows:

- Introduction of a novel method to parameterize bent tubes, which enhances memory efficiency by utilizing a 2D projection.
- Establishment of a detailed set of evaluation criteria for comparing and assessing deposition paths, addressing the existing need for standardized measures in the field of manufacturing research.

- Development of RLTube, an RL-based path planner for bent tubes produced by wire-arc additive manufacturing, with better performance against evaluation criteria compared to a brute-force approach (see Table 1) and bigger flexibility and adaptability than state-of-the-art.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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