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Predicting Surface Roughness in Metallic Additively Manufactured Parts Using Machine Learning

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Abstract

A melt pool geometry-based approach is developed to predict surface roughness in metal additively manufactured parts for a range of processing parameters. It is shown that surface roughness on a particular facet can be estimated by stacking melt pools along the facet, extracting their outer contour and applying the necessary transformations. To be able to predict surface quality of various processing parameters in a reasonable time frame, a machine learning framework is developed. This framework is trained over melt pool data generated by high-fidelity FE simulations.

1. Introduction

Surface roughness plays a key role in fatigue life performance of metallic components. Parts with low surface quality often experience premature fatigue failure and show lower life expectancy. With ever-increasing adoption of additive manufacturing (AM) in aerospace structures, it is of utmost significance to predict surface roughness of metal AM parts and optimize processing parameters to print parts with higher surface quality.

In this work, a numerical approach is introduced in which surface roughness on different surfaces, namely upskin, downskin and flat, is predicted by utilizing melt pool geometry information. It is shown that one can adopt a purely geometric scheme to predict surface roughness by stacking melt pools along the surface of interest and subsequently extracting and transforming outer contour of the melt pools. To expedite the prediction process, melt pool geometry for any given processing parameter is calculated via a machine learning (ML) framework. A high-fidelity FE modeling software is used to generate the training data for the ML framework.

2. Results

In order to calculate surface roughness, we need to know the metl pool geometry. The problem of melt pool geometry estimation based on input process parameters is a good fit to be used in a machine learning (ML) algorithm. ML enables the discovery of hidden links and patterns within a given data-set, and then apply that knowledge to solve a new problem.

To map from the given process parameters to the melt pool depth, we employ a two-layer MLP as the learning model and apply the mean-squared-error as the loss function. The output layer is connected to the last hidden layer and transforms its values to an output. At the beginning of the first forward pass of ANN, the weights and biases are initialized, the inputs are fed into the network, and initial predictions are made. The error function is computed, and a backpropagation algorithm is used to iteratively adjust the weights and biases to minimize the cost function.

We generated the training dataset for ML using finite element method. A high-fidelity parallel FE solver, TDA Additive Suite (TAS), is developed to conduct nonlinear transient thermal analysis and calculate melt pool dimensions as a function of processing parmaters such as laser speed, power and beam spot size. This solver uses implicit time integration and employs a thermal constitutive model with anisotropically-ehanced thermal conductivity factors to yield high-fidelity melt pool geometry results. Figure 2 shows how melt pool geometry evolves as a function of time and reaches the steady-state (i.e. stable melt pool shape) at about 800 μs. The software uses a proprietary algorithm for activating/deactivating elements as the laser beam scans the powder bed, that results in significant savings in computational costs. This is an important feature which makes it suitable for generating a rich training dataset for the machine learning algorithm.

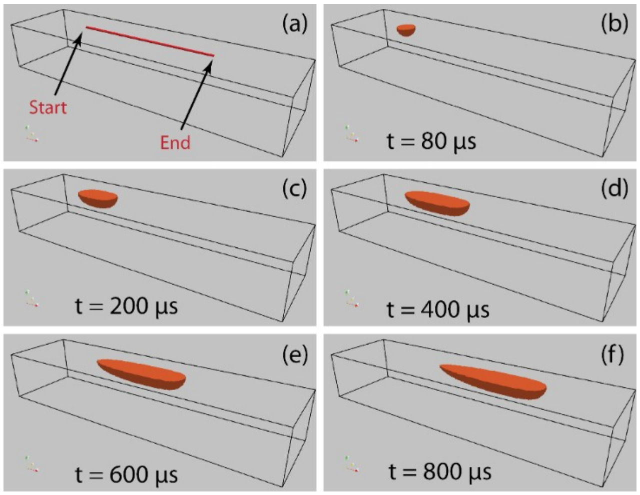

Figure 2.Evolution of melt pool in time

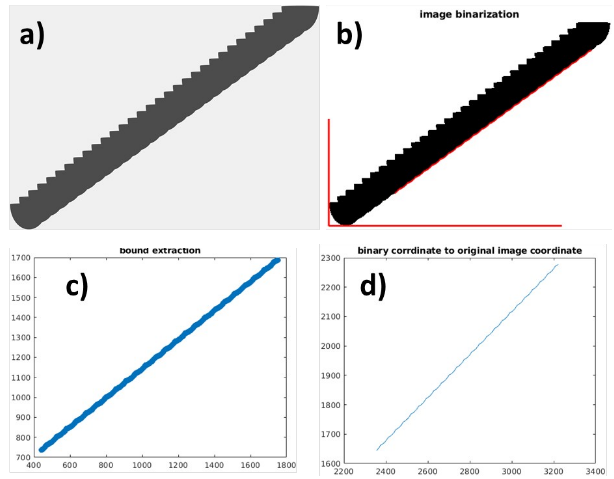

Figure 1.Surface roughness prediction procedure

Knowing the melt pool dimensions, we follow a 5-step procedure to predict surface roughness:
Step 1. Melt pools are planted on the surface of interest (Figure 1a)
Step 2. Image is binarized and the interested melt pool outline is highlighted in red (Figure 1b)
Step 3. The highlighted melt pool outline is extracted and plotted in pixel coordinate (Figure 1c)
Step 4. Dimensions are converted from the pixel to real coordinate system (Figure 1d)
Step 5. The processed image is ready for arithmetic surface roughness Ra characterization.
This algorithm was used to predict the surface roughness for surfaces with different tilt angles in the truncheon part, shown in Figure 3. One can see that the numerical predictions (Ra_p) compare very well with the experimentally measured data (Ra_m).

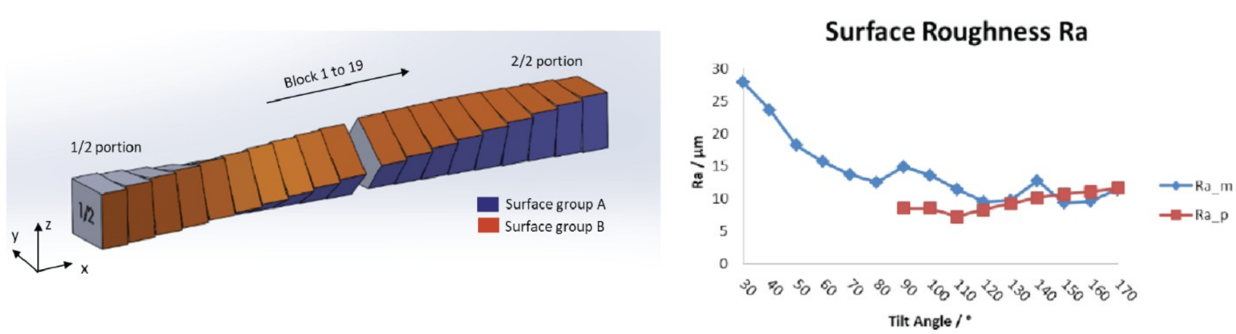

Figure 3.Surface roughness prediction in truncheon part

3. Conclusions

A machine learning framework was developed to calculate melt pool geometry for any given processing parameters. This framework was trained using the data generated by the in-house transient nonlinear thermal FE solver. Using a geometric-based approach, an image file was created where the melt pools were planted on the surface of interest. It was shown that using image processing techniques and simple pixel-to-real transformations and techniques such as detrending, one can extract surface roughness on various surfaces including down- and up-skins and flat surfaces.

Acknowledgements

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