Temperature Field Prediction in Additive Manufacturing Process using Machine Learning

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A Machine Learning-based approach for temperature evolution in Additive Manufacturing process is proposed, combining a variational auto-encoder (modelling the process in space) with a recurrent neural network (modelling the process in time within a reduced latent space). This surrogate model is designed to provide a much faster temperature history compared to classical finite element models but still accurate. The proposed approach shows promising results in a simplified AM setting.

I. Introduction

Additive Manufacturing (AM) is a disruptive manufacturing technology that has grown rapidly in the manufacturing industry, attracting much attention for its ability to produce complex parts and its potential of (nearly) zerowaste manufacturing solution. However, despite the progress that has been made in AM over the past decade, there are still significant challenges that need to be addressed before such processes can be widely adopted in industry. AM involves various process parameters to be monitored and controlled to achieve an acceptable level of accuracy. In particular, the mechanical properties and the quality of the manufactured part largely depend on the distribution of temperature fields during the process. Numerical simulations, such as high-fidelity finite element analyses, are commonly used to simulate and analyze the AM process. However, these simulations are usually computationally expensive and their use for real-time or many-query applications (such as sensitivity analysis, uncertainty quantification and process optimization) are prohibitive. In this context, artificial intelligence, and in particular Machine Learning (ML), methods can be applied in several aspects of AM,[1–3] such as process parameter selection, process and performance optimization, design for AM, in-situ process monitoring and control, real-time anomaly detection, etc... In this work, an ML-based approach is proposed for the fast and accurate prediction of the temperature history at the scale of the manufactured part. This represents a first step towards a better AM process control and optimization.

II. ML-based approach for temperature field prediction

The proposed ML-based methodology for the prediction of the temperature field evolution is based on a high-fidelity dataset of 256 simulations generated by a 2D numerical finite element model. A simplified AM setting is considered where the part is a 2D rectangular metallic piece of fixed size, manufactured through a powder bed fusion process. The laser performs several passes, with potentially a break after each pass where the laser is turned off. The main parameters defining the execution of the process are the laser nominal power ($[50 - 250W]$) and the break time ($[0 - 10s]$). Ten layers are added before the laser returns to its initial position, followed by a cooling phase. In each simulation, the target data consists of the simulated temperature, at each time point, at 131 equally spaced points in each layer. At each time point t, the target data is formated as a 2D grid $X_t \in \mathbb{R}^{11\times 131}$ and binary masks are used to identify grid points in layers that are not yet constructed and to deal with the evolving domain. We use a 80%-10%-10% split to divide the 256 simulations into respectively training, validation and test sets. The objective is to provide an ML model able to predict the temporal evolution of the temperature field for any given (unseen) set of process parameters.

The proposed Deep Learning (DL) approach consists of two components:

1. A **variational auto-encoder (VAE)** that projects temperature grids into a latent space. More specifically, the encoder part of the VAE maps a given temperature grid $X \in \mathbb{R}^{11\times131}$ into a normal distribution $q(\mathbf{z}|X;\psi) = \mathcal{N}(\mathbf{z};\boldsymbol{\mu},\boldsymbol{\sigma}^2 I)$ over the latent space, where $\mathbf{z} \in \mathbb{R}^H$ is the latent vector, and $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}^2$ are the outputs of a neural network $\mathrm{NN}_\psi : \mathbb{R}^{11\times131} \to \mathbb{R}^H \times \mathbb{R}^H$ with parameters ψ. The decoder part of the VAE consists of a second neural network $\mathrm{NN}_\theta : \mathbb{R}^H \to \mathbb{R}^{11\times131}$ with parameters θ, that reconstructs the temperature grid from a given latent vector. In our experiments, the latent dimension H is set to 64.

2. A **recurrent neural network (RNN)** that predicts the future latent vector $\mathbf{z}_{t+1}$, given the current latent vector $\mathbf{z}_t$ and some current laser-related features $\mathbf{f}_t$. Note that in addition to the latent vector $\mathbf{z}_t$, the RNN also propagates through time a hidden state $\mathbf{h}_t$, that we initialize with 0's. More formally, the RNN is a parametrized function $\mathrm{RNN}_\phi : \mathbb{R}^H \times \mathbb{R}^F \to \mathbb{R}^H$, where F is the number of laser-related features, and we have $\mathbf{z}_{t+1} = \mathrm{RNN}_\phi(\mathbf{z}_t, \mathbf{f}_t)$, where we have left out the hidden state $\mathbf{h}$ for notation clarity. In our experiments, we use $F = 3$ laser-related features, which are the laser current position in the horizontal axis (x-coordinate), the laser current position in the vertical axis (y-coordinate) and the current laser power.

While the VAE models the process in space, the RNN models the temporal process in the latent space. Given a trained VAE and a trained RNN, the following procedure is used to simulate the evolution of the temperature grid: the initial grid X_1 is set to 20 degrees at all the points and then encoded into an initial latent vector $\mathbf{z}_1 = \mathrm{NN}_\psi(X_1)$. The RNN is then used to predict the future latent vectors $\mathbf{z}_2, \ldots, \mathbf{z}_T$, with $\mathbf{z}_t = \mathrm{RNN}_\phi(\mathbf{z}_{t-1}, \mathbf{f}_{t-1}), t = 2, \ldots, T$, and each of them is transformed back into a temperature grid $X_t = \mathrm{NN}_\theta(\mathbf{z}_t)$. Both models are trained *separately* from each other. Training the whole model on sequences of grids would indeed be very long, while training only the VAE on all the grids can benefit from the GPUs which fasten the training, and the RNN is hence trained on sequences where the sample dimension is much smaller (64 vs 11*131). The training of both the VAE and RNN are performed using the Adam optimizer and learning rate cosine annealing.

III. Results

The predictions of the VAE-RNN model for an unseen simulation are shown for the whole grid at one time point in the left plot of Figure 1 and for one grid point across time in the right plot. One can observe that the highest (relative) errors occur at the borders of the part, where the laser does not pass. We should investigate further whether this is due to the fact that our model does not currently differentiate between points corresponding to melted powder and those corresponding to unmelted powder. High errors are also observed around the position of the laser, corresponding to temperature peaks that are notoriously hard to predict.

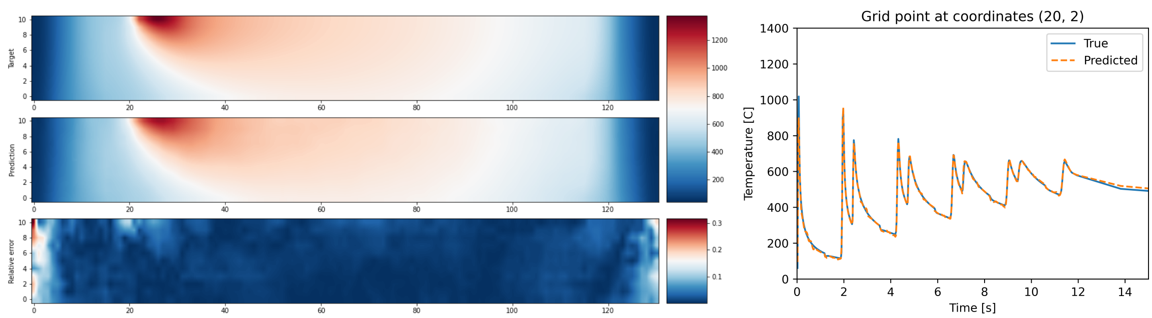

Figure 1. Left: This figures shows, at one time point in one simulation, the true temperature grid (top), the temperature predicted by the VAE-RNN model (middle) and the relative difference between them (bottom) - Right: Time evolution of true versus predicted temperatures, for one grid point in one simulation

Future works will include the extension of the ML-based approach to more complex parts with variable geometries, as well as 3D parts, by investigating graph neural networks which are particularly suited to represent physical fields defined on a complex mesh, such as temperature on a part geometry.

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