Project Report

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9. Multimodal Learning Methods for Defect Detection and Prediction in Laser-Based Metal Additive Manufacturing

Abstract

Additive manufacturing enables the creation of materials layer by layer, resulting in complex geometries that require careful control of each layer to prevent manufacturing errors. The outcome is influenced by various factors, including printing parameters, material selection, and design configuration, which requires a series of expensive experiments to determine the optimal parameters. Due to the widespread use of single-shot or small-batch production in the field of additive technologies, researchers often work with limited data. Predicting defects in part creation requires taking into account multiple parameters, such as printing parameters, material properties, part shape, and environmental conditions, which have complex interrelations. Artificial intelligence tools offer a solution to identify these interrelations based on data observations. Multimodal models for defect identification and based on heterogeneous data collected from sensors during printing are applicable to this problem. The effectiveness of the model is enhanced by using different types of data and their combinations. This method allows for the prediction of a wider range of properties in additive manufacturing processes.

StarterPack

Dataset and description
https://nvlpubs.nist.gov/nistpubs/jres/124/jres.124.033.pdf
https://data.nist.gov/od/id/85196AB9232E7202E053245706813DFA2044

Introduction

Laser-based metal additive manufacturing (LAM) has emerged as a transformative technology in the manufacturing sector, enabling the production of complex metallic components that were previously unattainable through conventional methods. By utilizing high-powered lasers to selectively melt and fuse metal powders, LAM facilitates the layer-by-layer construction of intricate geometries, thereby revolutionizing design possibilities and material efficiency.
As industries increasingly adopt LAM, the need for effective defect detection becomes paramount. Defects such as porosity, cracks, and inconsistencies can significantly compromise the mechanical properties and overall integrity of manufactured parts. Traditional inspection methods may not suffice due to the unique challenges posed by the additive manufacturing process. Therefore, integrating machine learning techniques into defect detection presents a promising solution. Machine learning algorithms can analyze vast amounts of data generated during the LAM process, identifying patterns and anomalies that indicate potential defects. By leveraging advanced data analysis techniques, we can enhance the quality assurance processes in LAM, paving the way for its broader application across various industries.

Dataset

This open access dataset [1] introduces the files pertaining to a 3D additive manufacturing build performed on the Additive Manufacturing Metrology Testbed (AMMT) by Ho Yeung on July 8, 2018. The files include the input command files and in-situ process monitoring data, and

metadata. This data is the first of the AMMT Process Monitoring Reference Datasets (https://www.nist.gov/el/ammt-temps/datasets), as part of the Metrology for Real-Time Monitoring of Additive Manufacturing project (https://www.nist.gov/programs-projects/metrology-real-time-monitoring-additive-manufacturing). Dataset consists of In-situ data: layer images and melt pool images; and command data: laser power, scanning speed, coordinates of the laser, plus it calculates aberrations of the laser system.
The main problem is that the data are not synchronized, so we tried to operate them through choosing the right rate (melt pool capturing rate is 2000 frames per second and the commands file has 121 raws in 100 kHz). Also even synchronized data has the mistakes and we see the laser spots on frames without laser power, and we need to consider it.

Methods

Our goal was to predict the next frame melt pool size to avoid the overheating in it. The label is Sum of the pixels brightness. We used the following data for the every condition (frame) description: laser coordinates (X,Y), Laser Power, Frame argmax(X′,Y′), Pixel Sum - label. To train our "TimeSeries" data every five consecutive conditions were merged. The label is the sum of the pixel brightness in the last column.
CatBoostRegressor model was used with automatic validation in it. MSE metric was used to measure the model performance.

Results

CatBoostRegressor predict better when we add the differences between the conditions - the MSE value felt from 0.7298 to 0.024.

Conclusions

Data mining and synchronisation were done successfully. The literature review supported the hypothesis about the relationship between spot size and heating energy risks. The CatBoost model worked well when using the first derivative. It is important to keep all data and to be careful when choosing new data for short-term projects.

Future Plans

In our future plan, we will focus on several key areas to enhance our modeling capabilities and improve outcomes.
First, we will develop a refined score function to enhance the accuracy and reliability of our models. This will involve evaluating existing score functions and experimenting with new scoring metrics to better capture model performance.
Next, we will explore different modeling techniques to identify and implement various algorithms that can improve our results. This will include researching and testing alternative algorithms and comparing performance metrics across different models.
Additionally, we will adopt a multimodal approach by integrating multiple data modalities to enrich our analysis and predictions. We will identify relevant data types, such as text, images, and numerical data, and develop a framework for effectively combining these modalities.
To further enhance our model training, we will focus on label upgrading. This involves reviewing our current labeling processes and implementing strategies for more accurate and informative labels.

We also aim to increase data utilization by maximizing the use of available data to improve model robustness. This will include analyzing underutilized datasets and developing methods for incorporating additional data into our existing models.

Finally, we will conduct a comprehensive search for new datasets to broaden the scope of our analysis. This will involve identifying and acquiring relevant datasets, as well as establishing partnerships or collaborations for data-sharing opportunities.

By following this structured plan, we aim to enhance our modeling capabilities and achieve more accurate and insightful results.

References

1. Lane, Brandon, Yeung, Ho (2019), Process Monitoring Dataset from the Additive Manufacturing Metrology Testbed (AMMT): 3D Scan Strategies, National Institute of Standards and Technology, https://doi.org/10.18434/M32044 (Accessed 2024-08-30)