AI accelerates process design for 3D printing metal alloys

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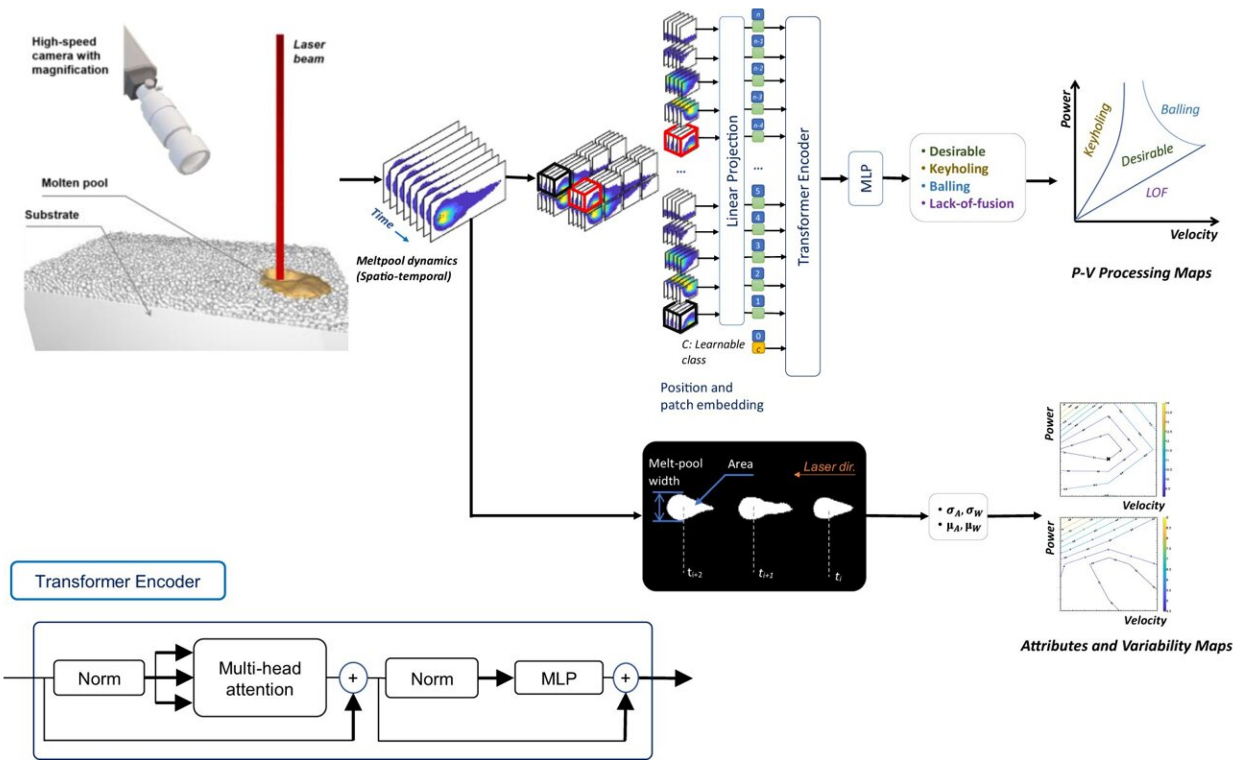

Pipeline of the proposed in situ process development approach. A high-speed imaging setup is used to monitor the dynamic changes in the molten pool, and the spatio-temporal data is used to classify the process into different types of defects and printing regimes using video vision transformers. The variability in the morphological attributes of the molten pool is captured from the imaging data and processing maps of variability, represented by the standard deviations, are constructed indicating the processing parameters that can result in a more stable process. Credit: *Nature Communications* (2024). DOI: 10.1038/s41467-024-44783-5

In order to successfully 3D-print a metal part to the exacting specifications that many in industry demand, process parameters—including printing speed, laser power, and layer thickness of the deposited material—must all be optimized.

But to develop additive manufacturing process maps that ensure those optimal results, researchers have had to rely upon conventional methods—lab experiments that use ex situ materials characterization to test parts that have been printed using various parameters. Testing so many combinations of parameters in order to develop the optimal process can be both time-consuming and expensive, especially considering the wide range of metals and alloys that can be used in additive manufacturing.

David Guirguis, Jack Beuth, and Conrad Tucker of Carnegie Mellon University Mechanical Engineering have developed a system using ultra high-speed in-situ imaging and vision transformers that can not only optimize those process parameters, but is also generalizable so that it can be applied to various metal alloys.

Their work is published in the journal *Nature Communications*.

Vision transformers are a form of machine learning that apply neural network architectures originally developed for natural language processing tasks to computer vision tasks such as image classification. The video vision transformers take that a step further by using video sequences instead of still images to capture both spatial and temporal relationships that enable the model to learn complex patterns and dependencies in video data.

The self-attention mechanism, which allows natural language processing models to weigh the importance of different words in a sequence, allows the model Guirguis created to weigh the importance of different parts of the input sequence for making predictions about the occurrence of defects.

"We needed to automate the process, but it can't be done with computer programming alone," explained Guirguis, a postdoctoral associate in mechanical engineering. "In order to capture the patterns, we need to apply machine learning."

"We are excited to have developed an AI method that leverages temporal features in AM imaging data to detect different types of defects. Demonstrating the generalizability of the AI method using different AM metals is groundbreaking and reveals that the same trained AI model can be employed without costly retraining using additional data," remarked Tucker, a professor of mechanical engineering.

Guirguis says he is fortunate to have had such strong training in machine learning at Carnegie Mellon because it is more important than ever that mechanical engineers know how to apply both experimental and computational solutions to the problems they solve.

In this case, Guirguis was trying to overcome the primary limitation of in-situ imaging of the laser powder bed fusion (LPBF) additive manufacturing process. The technology uses a high-power laser as an energy source to melt and fuse powders in specific locations to form certain shapes, a re-coater then spreads a new layer of powder, and the process repeats until 3D objects are formed.

But the molten metal seen by a camera during the printing process is saturated, so it's not possible to see its physical features, which can identify possible defects that can deteriorate the mechanical properties and reduce fatigue life of the printed part.

Guirguis developed a high-speed imaging setup to capture clear features of the molten pool and a machine learning model that could see the patterns associated with the defects they were trying to detect and prevent.

He incorporated the temporal features of molten metal as it changed over time by using high-speed imaging and video vision transformers.

By using the vision transformers to classify the different types of defects that can occur during the 3D printing process, Guirguis enhanced the algorithmic accuracy to greater than 90% depending on the material.

"In additive manufacturing processing of a new alloy, the first goal is to find a 'window' of process variables yielding flaw-free parts," explained Beuth, a professor of mechanical engineering. "Dave's use of vision transformers to relate the variability in high-speed melt pool images to flaw formation can greatly reduce the time needed to find that window. It is a huge step forward."

The researchers developed an off-axial imaging setup using a high-speed video camera and magnification lens to capture the high-frequency oscillation in the melt-pool shape with video recorded with extremely high temporal resolution of over 50,000 frames per second. The videos were then classified into four categories: a desirable regime and printing regimes of the three different types of defects (keyholing, balling, and lack-of-fusion).

Keyholing defects, which are characterized by unstable, deep, and narrow penetration, can lead to enclosed pores inside the printed parts and result in cracks that can degrade the fatigue life of the parts. The keyhole regime is typically characterized by fluctuations in the width and depth of the keyhole.

With balling defects, known as humping in welding, the melted tracks exhibit a rough surface with a periodic ball cross-section shape and are associated with undercuts at the corners. In the balling regime, the molten pool elongates and disconnects, leaving behind peaks in the track.

Lack-of-fusion defects, where the energy density is not sufficient to fully melt the powder, cause unmelted powder and irregular gaps between the melted tracks. Melt pools captured in the lack-of-fusion regime are very small with a low length-to-width ratio, as the energy density is very low, and the laser beam does not penetrate deeply into the material.

To explore the generalizability of the method, they conducted single-bead experiments with different P-V combinations, covering the four printing regimes on stainless steel SS316L, titanium alloy Ti-6AL-4V, and Inconel alloy IN718. They performed a cross-dataset evaluation, where the model was trained on the recorded videos of one alloy and tested on the videos while the hyperparameters were kept unchanged.

Their findings show that video vision transformers with temporal embedding can enable in situ detection of melt-pool defects with a simple off-axial imaging setup and generate process maps that can potentially accelerate the qualification of printability and process development for newly developed 3D printed alloys.

More information: David Guirguis et al, Accelerating process development for 3D printing of new metal alloys, *Nature Communications* (2024). DOI: 10.1038/s41467-024-44783-5. www.nature.com/articles/s41467-024-44783-5

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