Title:
Development of Quantification Measures to Compare Mechanical and Physical Properties' Patterns from Additive Manufacturing Simulations

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Introduction:
Additive manufacturing (AM) layer-based fabrication techniques have been developed for several technologies and systems. Understanding the impact of the discrete heating and cooling cycles due to the side-by-side scan paths or deposition tool paths, and the layer build approach on the physical and mechanical properties for a build strategy is a significant research challenge that is being investigated for several AM process types. For metal powder bed processes (e.g., Powder Bed Fusion (PBF) [12]), the pre-placed powder is joined 'point by point' using an energy source that travels in a scanning pattern, typically a laser beam or an electron beam. With the Directed Energy Deposition (DED) [1]). processes, powder or wire is melted by a heat source (e.g., laser, electron beam) and deposited onto a substrate or previous layers. DED processes lend themselves to repair and coating applications as well as component fabrication. The problem definition and boundary conditions vary for powder-based systems and bead-based deposition systems; consequently, process specific simulation strategies are being developed. With properly defining the governing equations, the variable heat inputs, and the numerical analysis strategy (an active area of research), insights into the heat product behaviors during and after the build process can be determined. However, typical post-processing analysis of the simulation results tends to focus on identifying maximum and minimum values for the selected mechanical and physical properties in specific regions, not on the intermediate regions or the resulting patterns that occur. There is much data that is not being evaluated, which can provide insights for artificial intelligence predictive models [5] or for determining optimal build solutions, which is the long-term goal. A more comprehensive and quantifiable strategy for comparing build scenario results that assesses the results and the pattern variations between different simulation scenarios needs to be developed. The solution data needs to be transformed into usable knowledge.

Preliminary research has been performed where finite element (FE) simulation results, derived using SYSWELD [9] for a laser-based DED process, were transformed into discrete data sets for preliminary comparison analyses. A semi-automated process had been developed using CAD tools, generating an (x, y, z) data set where x, y are points within the image and z corresponds to a color/property classifier. With this methodology, data is collected between the nodes. An example of an FE result for a DED simulation [11] and the geometry interpretation complete with points is shown in Fig. 1.

The FE results (e.g., hardness or residual stress) are essentially binned in a manner that allows for more systematic and comprehensive downstream post-processing analyses. This is a standardized platform-independent method for generating data sets from FE simulation results. An example is presented in Fig. 2. for three parallel beads deposited using different process settings.

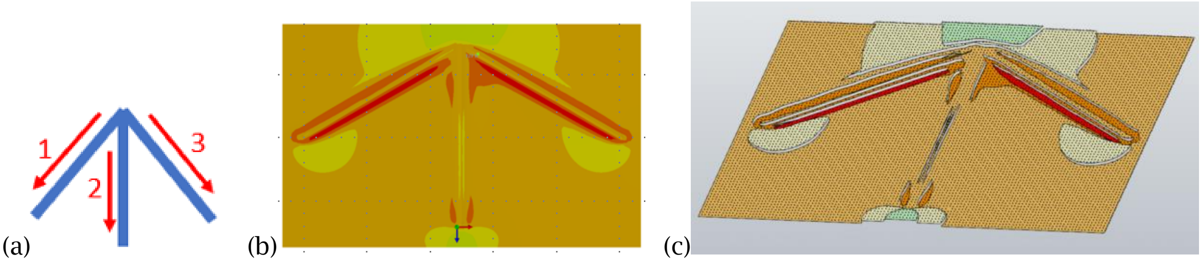
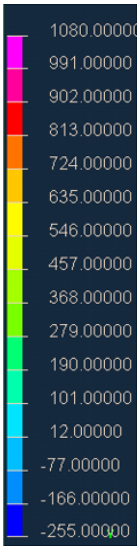
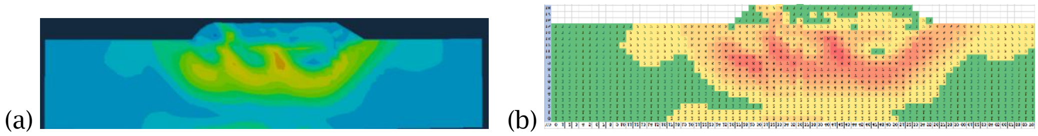


Fig. 1: (a) Deposited DED bead set and the deposition order, radiating out from the junction, (b) the FE simulation results for the plate top for the *xx* residual stresses, and (c) CAD model with layers at different z heights which correspond to a *xx* residual stress range, and points for each color-region.

Ideally, the data collection approach extracts the point cloud data directly from the FEA images without introducing intermediary CAD geometry. Limited 'heat map' based comparison analyses had been performed; however, no quantification metrics were developed, only a presentation of residual stress gradients and simple histogram comparisons (Fig. 3). Quantification metrics are required to effectively compare different build solutions. The solution approach must be scalable and extendable.

Powder feed rate (g/min)	20
Laser power (KW)	2.5
Focal length of lens (mm)	400
Laser speed (mm/s)	10





Powder feed rate (g/min)	20
Laser power (KW)	2
Focal length of lens (mm)	400
Laser speed (mm/s)	12

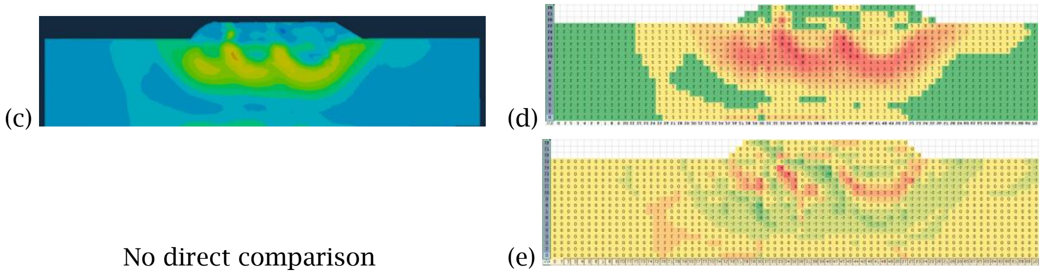


Fig. 2: (a) & (c) Residual stress results for 40% overlap for the presented process setting (b & (d), the heat map, and (e), the difference map for the two FE simulations, adapted from [11].

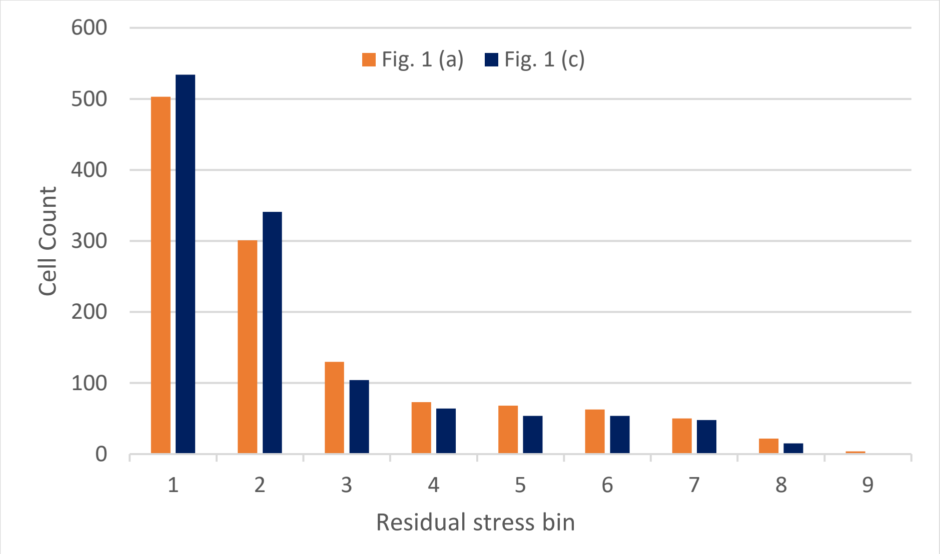


Fig. 3: Residual stress bins data for the two simulation scenarios presented in Fig. 1. Note that the build conditions in Fig. 1 (a) have less compressive stress cells (503 vs 534) and more high tensile stress cells (4 vs 0).

Main Idea:
There are identifiable patterns that are generated as results for an FE simulation. Pattern analysis or similarity measures should be introduced to quantify characteristics or provide baseline classification information for a given result set to allow researchers to compare results systematically. For this research, only 2D comparison approaches are being explored for curves and images. DED process simulation results are used for the case studies for the predicted *xx*, *yy*, and *zz* residual stresses, and Von Mises stresses.

For the curve comparisons, the nearest neighbor and Hausdorff distances are determined along with a repurposed Kolmogorov-Smirnov test. A logic test related to offset curves based and a user defined range is proposed. CAD tools (Rhino® and Mastercam®) are employed to create the offset curves.

CAD tools (Rhino® and Grasshopper® with VBA) and Excel tools are used for quantifying the patterns. From the FEA data, the sizes, shapes, and locations of the regions are quantified to be able to compare results for different regions within one layer-deposition scenario and from multiple virtual test scenarios. Unlike shape similarity assessment strategies used for object localization [5], algorithms to match and recognize 2D objects [2], or strategies to analyze cell populations [8], the user is to define the regions of interest for analysis, and the baseline shape sets for comparisons. An example of the image comparisons is shown in Fig. 4, where layers 2, 3, and 4 are analyzed and the residual stresses are compared between layers, and for different deposition patterns. This case study is selected due to its shape symmetry. In Fig. 4 (c), there is a noticeable the shift in the Heat Affected Zone (HAZ) influence regions between the top of the substrate and 2 mm into the substrate. The high stress region pulled 'in' towards the center.

Basic CAD tools are utilized to perform shape analyses that are based on geometric descriptors, such as the contour perimeter, the area, and centroid. Understanding the shifts in centroid positions, and size variations for the residual stress patterns from one layer to another or one deposition scenario to another will provide insights for predictive modeling. A selection of spatial similarity indices and spatial statistics are explored. Shape similarity measurements are usually used for shape matching and indexing for databases, transmitting geospatial data [10], and for psychological cognition [6]. There is significant potential for translating or expanding these techniques for FE simulation results interpretation.

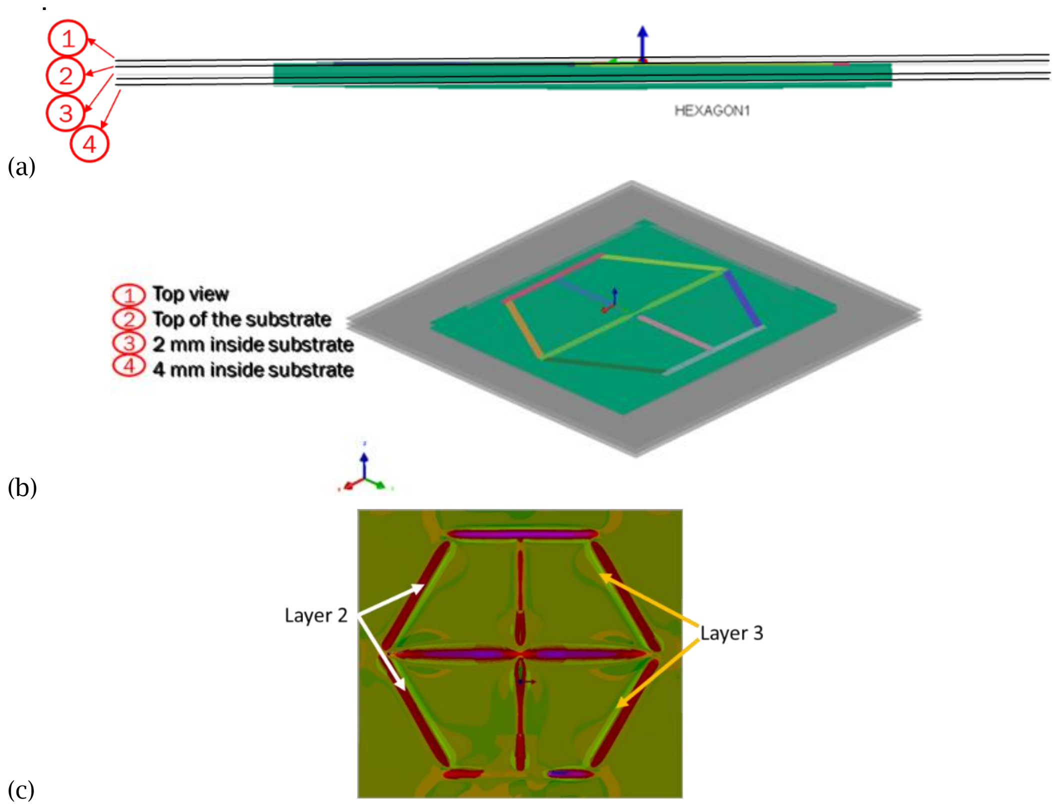
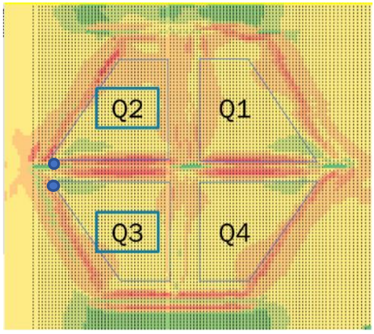


Fig. 4: (a) and (b) A hexagon case study, illustrating the reference positions where the images are collected. Note: The Layer 1 top view includes data related to the top of the beads, (c) a comparison of layers 2 and 3 using the GIMP [3] grain extract feature (the red tones represent Layer 2).

Bar charts can interpret fill regions within a defined pattern by enumerating the properties with respect to a common position baseline within a bounded region. Absolute and normalized data analyses can be presented to reflect the characteristic impact zones for the properties being assessed, and statistical analyses can be performed. An example is shown in Fig. 5, where the blue dot represents position 1 for the 4-sided polygon defining the regions of interest (Fig. 5 (a)). The orange cells (identifying low to no stress regions) are counted in the vertical direction. The low or zero stress regions vary significantly between quadrants Q2 and Q3. It is evident visually, but the Fig. 5 (b) graph quantified these differences.

Conclusions:

There are many research questions to be addressed for the AM processes. As experimentation is costly and typically only provides localized discrete data, simulations can provide insights into the thermal-mechanical-metallurgical behaviors that experimental approaches cannot determine. The goal of this research is to interpret the result patterns beyond determining maximum and minimum points, or querying the properties at specific nodes. Much data is not assessed, and as the long-term goal is to determine optimal build solutions for functional components, this data should not be ignored. Converting FE result images into CAD geometry, and introducing discrete classifications via geometry manipulation tools allows researchers to extract data that will allow for extended analyses to be performed. Results for different quantification measures will be presented in the paper for the 3-bead junction and hexagon case studies.

(a) 

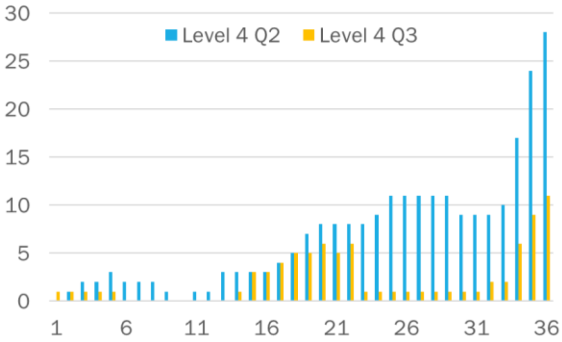
(b) 

Fig. 5: (a) Trapezoid base shapes identifying the regions to be assessed, (b) a comparison of the number of 'orange' cells along the horizontal axis with residual stress level 4 (-99 to 6 MPa).

The techniques discussed here have potential beyond the AM-DED simulation environment, and can be extended to a general FE post-processing module. However, more research is required for to develop a robust automated FE image to CAD data converter and to develop the pattern-based quantification measures.

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