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AdditiveFOAM: A Continuum Multiphysics Code for Additive Manufacturing

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Summary

AdditiveFOAM is a computational framework that simulates transport phenomena in Additive Manufacturing (AM) processes. It is built on OpenFOAM (Weller et al., 1998), the leading free, open-source software package for computational fluid dynamics (CFD). OpenFOAM offers an extensible platform for solving complex multiphysics problems using state-of-the-art finite volume methods. AdditiveFOAM leverages these capabilities to develop specialized tools aimed at addressing challenges in AM processing.

Metal additive manufacturing, also known as metal 3D printing, is an advanced manufacturing technique that creates physical parts from a three-dimensional (3D) digital model by melting metal powder or wire feedstock. A significant area of research in metal AM focuses on process planning to mitigate anomalous features during printing that are deleterious to part performance (e.g., porosity and cracking), as well as controlling localized microstructure and material properties. Given the high costs and substantial time requirements associated with experimental methods for qualifying new materials and processes, there is a compelling incentive for researchers to utilize advanced computational simulations. In this context, AdditiveFOAM offers a simulation framework to better understand undesirable features in printing, thereby enhancing process planning and reducing the reliance on labor-intensive experimental campaigns.

Statement of need

Numerical models for AM traditionally seek to represent physics at a single length scale depending on the target question. Two main categories of models with available software solutions are distinguished: 1) high-fidelity melt pool-scale models, and 2) part-scale heat transfer models.

The first category contains models that seek to resolve all relevant physics within the melt pool. These models can produce excellent agreement with experiments and offer insights into the underlying causes of anomalous features during processing, but are generally expensive to run, limiting the scan length that can be simulated to a few millimeters with current computational resources (Yan et al., 2020). Due to their computational expense, these models are well-suited for use at specialized research institutions with large HPC infrastructure to answer target questions about melt pool scale physical phenomena. For example, ALE3D (Noble et al., 2017) is a versatile multiphysics simulation tool that uses the Arbitrary Lagrangian-Eulerian approach and has been used for powder-resolved simulations of laser-material interactions in AM. However, ALE3D is a limited access code for use by United States Department of Defense/Energy laboratories and their contractors, while ALE3D4I is available for U.S. companies and academics through individual use agreements. Alternatively, FLOW-3D (Flow Science, 2023) is a commercial CFD software known for its capabilities in simulating complex free-surface problems, and it has several specialized models for AM. However, FLOW-3D is proprietary, meaning its source code is not available for public inspection or modification, and users must purchase a license to use the software.

The second category contains models that simplify melt pool physics to rapidly simulate heat transport, residual stress, and distortion across an entire part. Commercial finite element thermomechanics software solutions built on Abaqus (Dassault Systèmes Simulia Corp., 2024) and Ansys (ANSYS Inc., 2024) are available; however, these software packages are not open and free to use and develop upon. Alternatively, Adamantine (Turcksin & DeWitt, 2024) is a thermomechanics simulation tool built on the open-source deal.II finite element software package (Arndt et al., 2023) designed for high-performance computing across architectures, providing an alternative to proprietary software solutions.

There is an established need for intermediate frameworks that accurately predict melt pool shape, thermal gradients, and other meso-scale quantities across an entire part (DebRoy et al., 2018). These models can inform process design decisions through heuristic estimations of anomalous printing features (e.g., keyhole formation and lack-of-fusion) and predict the final microstructure and material properties of AM components (Wei et al., 2021). AdditiveFOAM addresses these challenges, featuring a volumetric source term in the energy equation for multiple heat sources, optional Marangoni-driven fluid flow, and a scheme for implementing tabulated thermodynamic pathways for metal alloys.

Software Features

The main feature of AdditiveFOAM is a transient, multiphysics application that solves conservation equations for mass, momentum, and energy during AM processing, built upon the OpenFOAM finite volume software package (Weller et al., 1998). This solver includes a novel thermodynamic algorithm enabling variable-order time integration for tabulated thermodynamic pathways. The available time integration schemes are explicit forward Euler, implicit backward Euler, backward differentiation formula (BDF-2), and Crank-Nicolson. An adaptive time integration and time-stepping method automatically switches between implicit and explicit schemes to balance computational cost and solution accuracy depending on the problem state and user-defined tolerances. Additionally, AdditiveFOAM features boundary conditions for Marangoni-driven fluid flow in the melt pool, as well as convective and radiative heat transfer. Another feature of AdditiveFOAM is the volumetric heat source library that supports any number of independently moving sources with distinct energy profiles that have been validated for several AM processes, including laser powder bed fusion (LPBF), directed energy deposition (DED), and electron beam melting (EBM). Finally, AdditiveFOAM leverages existing OpenFOAM libraries to sample thermal data needed for microstructure predictions with a specific library for coupling to the grain structure prediction software ExaCA (Rolchigo et al., 2022). Future releases of AdditiveFOAM will focus on resource-optimized adaptive mesh refinement (AMR), dynamic load-balancing using the Zoltan (Devine et al., 2009) library, and the integration of next-generation laser profiles (e.g., nLight AFX series) into the volumetric heat source library.

AdditiveFOAM was designed to be used openly by researchers, industry, and academics. It has already been used in several scientific publications primarily focused on studying how AM process planning influences the development of local microstructural features in a part. Select publications that demonstrate AdditiveFOAM's usage towards understanding the connection between process planning and microstructure evolution in metal AM include:

- Knapp et al. (Knapp et al., 2023) developed an automated framework for statistical calibration of the gaussian heat source parameters available in AdditiveFOAM to accurately predict the melt pool shape, solidification conditions, and solidification grain structure for single track welds on IN625 plate.

- Rolchigo et al. (Rolchigo et al., 2022, 2024) used AdditiveFOAM to generate thermal data for solidification grain structure predictions is laser powder bed fusion, validated against the NIST 2018 AM-Bench dataset (Levine et al., 2020).
- Haines et al. used AdditiveFOAM to confirm experimentally observed phase transformation pathways in 17–4 PH stainless steel during the laser powder bed fusion (L-PBF) process (M. P. Haines et al., 2023), and investigated the role of scan strategy on recrystallization and grain growth in Fe-Si steel made by L-PBF with a pulsed laser (M. Haines et al., 2022).
- Plotkowski et al. (Plotkowski et al., 2024) used AdditiveFOAM to confirm experimentally observed grain growth in Fe-Si steel during the Laser Engineered Net Shaping (LENS) process.

The free, open-source nature of AdditiveFOAM will continue to enable scientific explorations in AM processing. Documentation for AdditiveFOAM is hosted on GitHub Pages.

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