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ADAPTIVE INTELLIGENT CONTROL OF METAL POWDER BED FUSION VIA TRANSFER LEARNING

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The direct metal laser sintering (DMLS) process is capable of producing complex, dense metallic components, but the parts that are produced can be susceptible to internal porosity caused by insufficient melting of the metallic powders. Advanced in-situ metrology strategies are required to identify such defects that are detrimental to the part quality and mechanical properties. Contact free temperature measurement using infrared (IR) thermography and spectroscopy can be used in defect detection strategies, but it is complicated by the temperature dependent emissivity of the metal powder as it melts and solidifies. Furthermore, the powder condition and oxidation level can also affect the emissivity and resulting temperature readings on the instruments. IR cameras enable full-field temperature measurement, but the emissivity is assumed constant across the entire image.

We propose to develop an experimental methodology for detecting lack-of -fusion porosity defects in DMLS enabled by uncertainty quantification and transfer learning approaches. The methodology will implement in-situ process monitoring through IR camera readings and broadband spectrometer data to enable temperature prediction over a range of material states, material classes, and emissivity variations. An uncertainty analysis will be performed on the experimental results, and the resulting temperature measurements with uncertainty will be used to train a machine learning algorithm to detect powder condition and material state as well as identify regions that are likely to contain defects [1-3]. Then, transfer learning approaches will be implemented to adjust the models for a new material to facilitate defect detection without requiring a complete retraining of the model dataset.

Numerous studies have aimed at analyzing defects for the DMLS process using in-situ monitoring, but most of these strategies have focused on a single material system applied to a single machine. Little work has been done to create a material-resilient methodology that is capable of rapidly identifying process anomalies and defects across machines and materials. Our approach seeks to train machine learning models that can identify lack-of-fusion porosity defects for one material then apply transfer learning techniques combined with limited experimental data to detect defects for a second material. Moreover, we intend to use multiple data streams that combine off-axis IR thermography with optical emission spectroscopy to enable monitoring of the entire powder bed surface while improving measurement accuracy. Off-axis measurements limit the amount of machine modification required to implement this strategy, making it rapidly adaptable to different systems. One of the greatest challenges of implementing thermographic imaging techniques on DMLS machines is the temperature-dependent emissivity of the powder and fused part regions. This work includes developing a methodology for measuring the emissivity of the powder as a function of temperature and material phase to perform uncertainty quantification analyses [4-9] that will inform the transfer learning models. The exploratory aspects of this project include determining how much experimental data is required for the second material before the transfer learning models are able to accurately predict lack-of-fusion porosity and whether these techniques can be applied in an off-axis method.

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