

FEW-SHOT GAUSSIAN MIXTURE MODELS FOR UNCERTAINTY-AWARE PROCESS WINDOW IDENTIFICATION IN LASER-BASED ADDITIVE MANUFACTURING

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ABSTRACT

Laser-based additive manufacturing (AM) enables the production of complex and customized designs with highly-optimized geometries. Although the technology has transformed modern manufacturing, there are still multiple challenges and open questions. Particularly, the wide range of significantly different machine designs with the same nominal name, e.g. powder bed fusion (PBF) or directed energy deposition (DED), is known to hinder machine-to-machine comparability of part quality data, and consequently makes high-quality labeled experimental data an important bottleneck in AM processes [1]. These restrictions impact in the applicability of machine learning (ML) models. Since data is often noisy, scarce and imbalanced [2]. In addition, exhaustive process window identification is especially challenging in AM, as labeling anomalies/defects is costly. Intentionally producing controlled defective samples to enlarge the number of observations is expensive and difficult to replicate, which also negatively impacts the reliability of ML models. In this study, we address this common scenario of handling a limited number of laser-based AM samples, where the dataset is imbalanced, the target is binary (defective and defect-free samples), and several unlabeled samples exist. We apply a soft-classification approach using physics-informed Gaussian Mixture Models (GMMs) for process window identification, and integrate few-shot learning concepts into the Expectation Algorithm used for optimizing the GMM [3]. We obtain data representatives in a feature map, and we compute similarity analysis to compute distance to class prototypes, which define the soft discriminative embeddings. The methodology is first implemented on IN625 processed by DED, and later the performance is also analysed with a public dataset for PBF. The results are promising and offer a potential new workflow for reducing labeling costs for AM parts and improving the robustness of GMMs when modeling data with uncertain and noisy labels [2].

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