

Additive manufacturing (AM) process planning relies on experimentally learned relationships between process settings and printing quality. However, collecting compensation data for every slicing pattern and multi-layer printing condition is costly. This thesis proposes a probabilistic framework that extends single-layer compensation predictions to multi-layer printing through a calibration term. First, local spacing-pattern features and single-layer quality observations are used to identify defect-prone regions and train a Bayesian logistic regression model that estimates the probability of successful compensation. This relationship supports compensation predictions for unseen slicing patterns using features extracted from their G-code. Second, sparse multi-layer observations are compared with the corresponding single-layer predictions to calculate calibration discrepancies. A multi-output Gaussian process models these discrepancies using slicing-pattern descriptors and base printing speed. The model estimates calibration discrepancies through interpolation within the observed calibration domain and provides more uncertain estimates when extrapolating beyond it. Rather than transferring an entire compensation strategy from another pattern, the framework adjusts the target pattern's single-layer prediction using the estimated calibration term. The resulting compensation strategy can then be evaluated through printing-time optimization, subject to quality constraints. The Benchy case study involving Layers 2 and 19 demonstrates geometric characterization and region-specific single-layer compensation prediction. These preliminary computational results illustrate the proposed approach, while experimental validation of multi-layer calibration discrepancies, predictive uncertainty, and printing-time savings remains for future work. Overall, this framework provides a structured approach to extending single-layer compensation to multi-layer printing when experimental data are limited.