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DEVELOPMENT OF A DEVIATION-DRIVEN FRAMEWORK FOR SELECTIVE MESH CORRECTION IN ADDITIVE MANUFACTURING

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Abstract: Additive manufacturing has gained prominence for producing complex geometries with minimal lead time, yet systematic geometric deviations remain a persistent challenge. The current study presents a framework for targeted mesh morphing based on consistent deviation mapping to selectively compensate for systematic geometric errors. The framework uses stereoscopic scanner data to precisely determine surface deviations. Surface deviations are quantified by comparing multiple parts printed under similar conditions to the original CAD model. Deviation vectors are computed for each vertex in two sections, across multiple parts and systematic errors are identified by analyzing the statistical distribution of deviations. Only vertices exhibiting consistent deviations, defined as those with a standard deviation below a defined threshold and a mean deviation exceeding a minimum magnitude, are selected for compensation. Targeted morphing is done by applying corrective adjustments exclusively to the selected regions. This prevents over-compensation while minimizing computational overhead. A validation module re-scans the compensated part to assess the reduction in deviation magnitude, forming a feedback loop to refine morphing parameters. This approach has the potential to enhance precision targeting of systematic errors, reduce computational complexity, and adaptive parameter optimization. It can improve geometric accuracy and preserve surface integrity, which makes it a cost-effective solution for enhancing dimensional fidelity in additive manufacturing processes.

Key words: Additive manufacturing, Surface deviation mapping, Mesh corrections, Optical 3D metrology

1. INTRODUCTION

Additive manufacturing (AM) technologies, notably fused filament fabrication (FFF), selective laser sintering (SLS), and stereolithography (SLA), are increasingly employed for the fabrication of complex geometries with high levels of customization. However, achieving geometric fidelity remains challenging due to systematic and random deviations introduced across various stages of the digital-physical workflow. Surface deviations in AM are typically quantified by comparing scanned models of final printed components to their originating CAD sources, using high-precision 3D metrology systems such as structured light or stereoscopic scanning. Through these comparisons, both mean and standard deviation of deviation vectors at discrete mesh vertices may be computed, enabling decomposition of errors into systematic and stochastic components [1], [2], [3].

Multiple studies have emphasized the impact of material choice, print orientation, and process parameters on observed deviations [1]. For example, analyses demonstrate that FDM-printed parts exhibit characteristic warping and layer-induced artifacts, leading to deviations on the order of several percent from nominal dimensions, with surface roughness and waviness profiles strongly dependent on filament material and layer height [2]. Similarly, research into SLA-based and SLS-based components highlights that resin type, resolution, and alignment can significantly affect both the magnitude and distribution of surface errors [3]. Advanced quantitative analyses, such as decomposition of root mean square error and higher moment statistics (skewness, kurtosis), further allow for a detailed statistical description of surface quality across different AM platforms [2].

Additive Manufacturing (AM) processes often exhibit deviations between the printed part

and its nominal CAD geometry. These deviations can be categorized into systematic errors (repeatable, directional biases) and stochastic errors (random variability) [4]. Systematic deviations appear from identifiable causes like material shrinkage, residual stress deformation, or machine calibration offsets, and tend to affect every part in a similar way (e.g. consistent shrinkage in certain directions) [5]. In contrast, stochastic errors come from fluctuating conditions (temperature drift, material inconsistencies, etc.) and cannot be completely eliminated [4]. A prerequisite for compensating geometric inaccuracies is to separate the repeatable systematic component from the noise. Researchers [4] stress that multiple measurements (or builds) are needed to reliably discern systematic error patterns from one-off variation. By analyzing several identical parts, one can statistically map where the printed geometry consistently deviates from the design. These deviation maps inform correction strategies that specifically target systematic errors while avoiding “chasing” random outliers.

2. LITERATURE REVIEW

State-of-the-art correction frameworks for AM components increasingly incorporate statistical mapping of deviations accumulated over multiple sacrificial prints. By printing several nominally identical parts and registering each scan to the reference CAD, researchers can average vertex-wise deviation vectors and apply statistical filtering (e.g., thresholding based on standard deviation) to distinguish consistent systematic errors from randomness. This procedure not only allows the localization of regions susceptible to recurrent error but also informs targeted compensation strategies [5].

Studies emphasize the necessity to filter out the influence of random, process-specific noise before using deviation data for digital model compensation. As such, only mesh regions where the mean deviation exceeds a prescribed minimum magnitude and the standard deviation remains below a critical threshold are deemed suitable for corrective treatment. This process avoids over-compensating regions where stochastic effects dominate, thus preserving surface integrity and minimizing the

introduction of new inaccuracies during correction [5], [6]].

A straightforward approach to error compensation in AM is often termed “scan-and-morph”, where the original CAD mesh is modified (morphed) based on measured deviation vectors. Jadayel and Khameneifar (2020) [5] demonstrated a representative workflow: fabricate multiple sacrificial parts under identical conditions, 3D scan each part, and compute the deviation of each point on the surface from the CAD model. By averaging the deviation vectors across, say, 5 parts, they obtained an average deviation field capturing the systematic error at each mesh vertex. They then morph the original surface mesh by the inverse of this averaged deviation field, pre-distorting the CAD model in the opposite direction of the systematic error. This targeted mesh morphing eliminates the consistent biases in the next print. Random noise is filtered out via averaging and smoothing so that only persistent errors drive the compensation. In case studies on a Fused Filament Fabrication (FFF/FDM) part, printing the compensated mesh (based on the average of five scans) yielded final deviations about three times smaller than those of an uncompensated print. Notably, using the multi-part average outperformed a single-part compensation. The deviations on the part compensated with one sample were about double those of the part compensated with five-sample averaging. This shows the value of focusing on consistent error patterns and averaging out the rest.

Hartmann et al. (2019) [4] similarly proposed a purely geometrical compensation concept for AM, adapting ideas from metal forming technology. Their approach applies non-rigid transformations to the CAD model based on measured shape deviations from a “calibration” build. In their study, a fin-shaped test part was printed and scanned, then the CAD geometry was incrementally adjusted to counteract the observed errors. They iterated this process over three build-and-scan cycles and demonstrated convergence to a more accurate shape. Hartmann’s results underscored that compensation must account for only the systematic portion of error – the repeatable deformation modes attributable to process physics or machine offsets. They emphasize that

stochastic deviations (e.g. due to random thermal fluctuations or machine noise) should not be naively “compensated,” as this could over-correct and even worsen variability. Instead, one should use strategies (like averaging multiple samples or applying statistical filters) to ensure that only consistent, statistically significant deviation vectors inform the mesh morphing. This philosophy aligns well with the proposed selective morphing in the proposed framework. By defining consistency criteria (e.g. a deviation mean above a threshold and low standard deviation), one can isolate the vertices or regions that show true systematic error and apply corrections there, avoiding areas where the deviations behave randomly. Jadayel et al. explicitly note the necessity of filtering out random deviations from scan data before applying any compensation, which is effectively achieved in their work by Laplacian smoothing and cross-part averaging of the deviation field.

Another notable study is by Afazov et al. (2021) [7], who tackled distortion compensation in metal powder bed fusion using optical scan data. They presented an improved distortion compensation loop where an initial part is printed and 3D scanned, then the point cloud is registered to the nominal model to compute error vectors, and the design is updated accordingly for the next build. Through this iterative scan-and-morph process (demonstrated on a complex thin-walled geometry), they achieved “right-first-time” manufacturing of parts with much lower distortion. Afazov’s work reinforces the effectiveness of using high-resolution scan feedback to drive geometric corrections in AM. It also illustrates that mesh morphing compensation is applicable beyond polymers. Similar principles improve accuracy in metal AM, where thermal stresses cause significant systematic deformation.

Recently, machine learning-based strategies have entered the field, utilizing neural networks trained on mesh and scan data to predict, and then compensate for, geometric deviations in an automated fashion. This approach enhances generalizability and enables rapid adaptation to new geometries and AM modalities, as demonstrated in studies utilizing convolutional neural networks for predicting per-vertex

deviation and subsequent mesh morphing [6], [8].

Although prior research has demonstrated effective methodologies for mapping and compensating systematic deviations in additively manufactured parts, most existing frameworks either apply full-field mesh morphing or rely on data-intensive machine learning models, with limited attention to lightweight, vertex-specific approaches that are both statistically robust and computationally efficient. Furthermore, the literature predominantly addresses single-machine scenarios, overlooking the potential of cross-printer, cross-section analyses to reveal platform-specific deviation signatures that could inform targeted compensation strategies. Few studies explicitly integrate percentile-based statistical thresholding of mean and standard deviation values to isolate stable, significant deviations for correction, particularly in contexts where rapid iteration and minimal sacrificial prints are required. This study addresses these gaps by implementing and validating a reproducible, data-driven framework for systematic deviation detection at the vertex level, enabling printer-specific deviation profiling and precision-targeted morphing that balances geometric accuracy with computational efficiency.

3. METHODOLOGY

In response to the limitations identified in prior research, this study develops and applies a percentile-based, data-driven framework to isolate and characterize systematic deviations with high spatial specificity. The methodology was designed to enable printer-specific deviation mapping and targeted morphing in a computationally efficient manner, while retaining adaptability for iterative, feedback-driven refinement.

The process began with the acquisition of coordinate and deviation data from optical scans of nominally identical parts manufactured on two distinct fused filament fabrication (FFF) platforms: a Prusa i3-based system and a Bambu Lab X1 platform. For each printer, parts were printed under identical design and process conditions, and deviations were measured at two

distinct cross-sections ($Z = 6.50$ mm and $Z = 9.50$ mm) using a stereoscopic scanner as shown in figure 1. The scan data was exported in GOM XML format, from which the relevant “picker” point coordinates and deviation values were programmatically extracted into a structured CSV dataset.

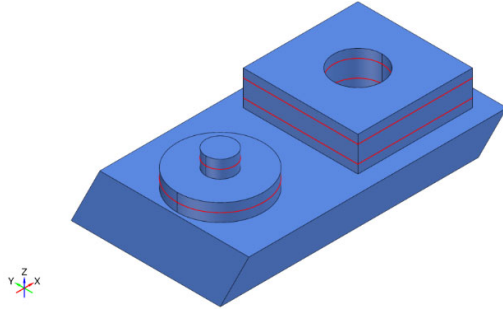


Fig. 1. Cross-sections of analyzed part

To ensure analytical consistency, all non-numeric entries, including measurements marked as “invalid,” were treated as null values and excluded from further analysis. The cleaned dataset was then grouped by nominal coordinates, rounded to four decimal places in X and Y and two decimal places in Z to ensure consistent vertex identification across repeated measurements.

For each unique vertex, descriptive statistics were computed, including the mean deviation (μ), standard deviation (σ), and the count of valid observations. These metrics were then subjected to distributional analysis to determine empirical stability and magnitude thresholds. The stability threshold, $\sigma_{\max}$, was defined as the 90th percentile of the per-vertex σ distribution, thereby excluding the most variable 10% of points from systematic classification. The magnitude threshold, $\mu_{\min}$, was defined as the 50th percentile of the absolute μ distribution, ensuring that only deviations of at least median magnitude were considered for compensation. These thresholds were derived independently for the dataset at hand, enabling the framework to adapt dynamically to different printing scenarios without relying on fixed, heuristic values.

Vertices were classified as systematic if they satisfied both $\sigma \leq \sigma_{\max}$ and $|\mu| \geq \mu_{\min}$. This binary classification generated a systematic deviation mask, which isolates the regions of the geometry most susceptible to consistent, printer-specific bias. Coordinate-true heatmaps were generated for each printer and section, visualizing the spatial distribution of deviations

with a symmetric color scale to preserve comparability. Additional binary visualizations highlighted systematic points in red and non-systematic points in gray, providing an immediate visual cue of the regions targeted for potential morphing.

Percentile-based statistical filtering was combined with spatially accurate visualization, to enable the identification of printer-specific, section-specific systematic deviations in a form that can be directly integrated into targeted mesh morphing workflows. The approach retains the adaptability required for iterative refinement in feedback-driven compensation loops, and at the same time minimize computational overhead compared to full-field morphing or data-intensive machine learning models.

4. RESULTS

The application of the proposed percentile-based framework to the multi-printer dataset yielded quantitative insights into the magnitude, stability, and spatial distribution of deviations for both the Prusa and Bambu platforms. The cleaned dataset contained 500 valid measurement points across the two Z-sections (6.50 mm and 9.50 mm), with each coordinate represented by multiple observations due to repeated measurements across printers. In total, 50 unique vertices were identified after spatial rounding and grouping.

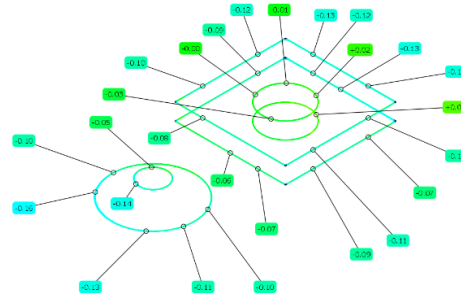


Fig. 2. Visual representation of surface deviation data with labels

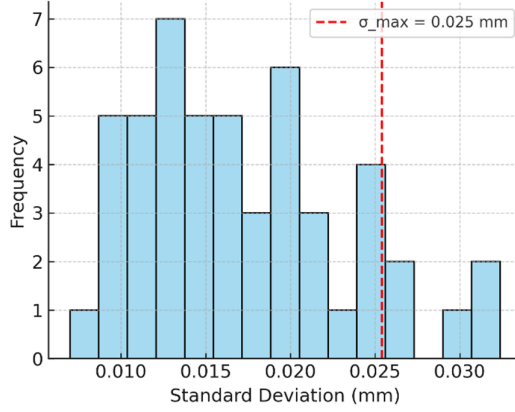
4.1 Statistical Characterization of Deviations

The per-vertex aggregation revealed distinct statistical profiles for the deviations in the dataset. The distribution of standard deviations (σ) exhibited a right-skewed form, with the majority of vertices exhibiting low variability but a small proportion showing pronounced dispersion. The distribution of absolute mean deviations ($|\mu|$) was more symmetric, indicating

that systematic bias was not concentrated in a small number of extreme outliers but rather distributed more evenly across the measured surface.

From these distributions, the empirically derived thresholds for systematic deviation detection were determined as:

- Stability threshold: $\sigma_{\max} = 0.025$ mm (90th percentile of σ distribution)



- Magnitude threshold: $\mu_{\min} = 0.090$ mm (50th percentile of $|\mu|$ distribution)

These thresholds are illustrated in Figure 1, which presents histograms of σ and $|\mu|$ with vertical dashed lines marking the threshold cut-offs. This adaptive, dataset-specific derivation of thresholds ensures the methodology remains transferable across different printing conditions without reliance on arbitrary constants.

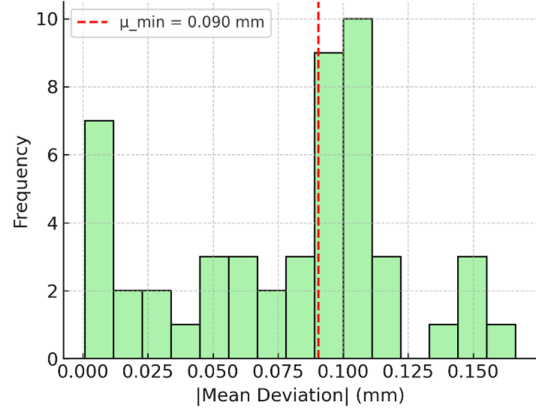


Fig. 1. Histograms of standard deviation and absolute mean deviation per vertex with threshold markers

4.2 Spatial Mapping of Deviations

Coordinate-true heatmaps for each printer and section (Figures 2) revealed clear differences in the magnitude and spatial patterning of deviations between the two platforms. The Bambu-produced parts generally exhibited more spatially uniform deviations with lower peak magnitudes, whereas the Prusa parts

displayed localized regions of higher bias, particularly in certain peripheral zones. This distinction suggests differences in machine calibration, extrusion stability, or mechanical alignment, consistent with observations from prior comparative AM studies.

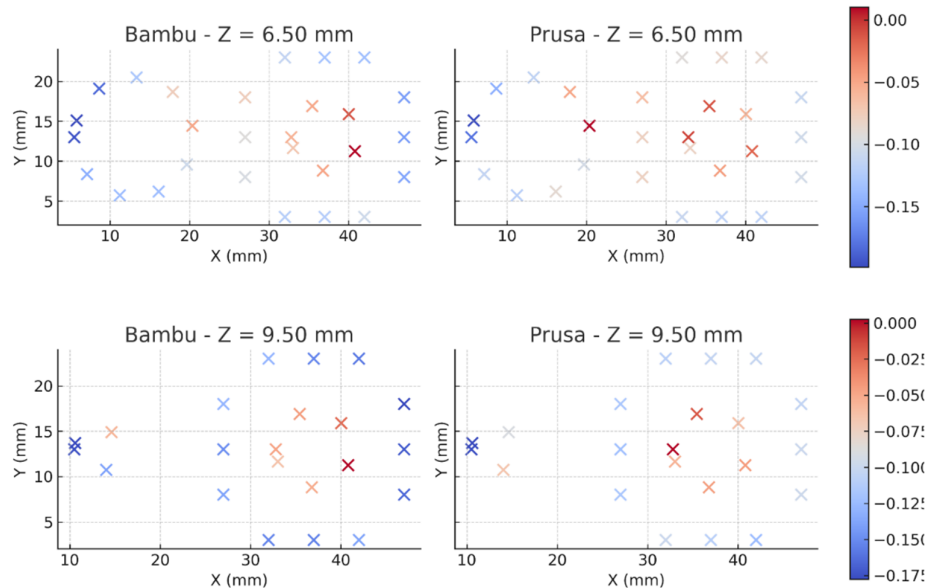


Fig. 2. Coordinate-true deviation heatmaps for Bambu and Prusa at $Z = 6.50$ mm and $Z = 9.50$ mm

4.3 Identification of Systematic Deviations

Applying the dual-threshold filter ($\sigma \leq \sigma_{\text{max}}$ and $|\mu| \geq \mu_{\text{min}}$) resulted in the classification of 25 out of 50 vertices (50.0%) as exhibiting systematic deviation. The binary spatial maps in Figure 3 visualize these classifications, with systematic points shown in red and non-

systematic points in gray. The resulting systematic masks highlight contiguous surface regions where correction efforts could be targeted without risk of overcompensating random variation.

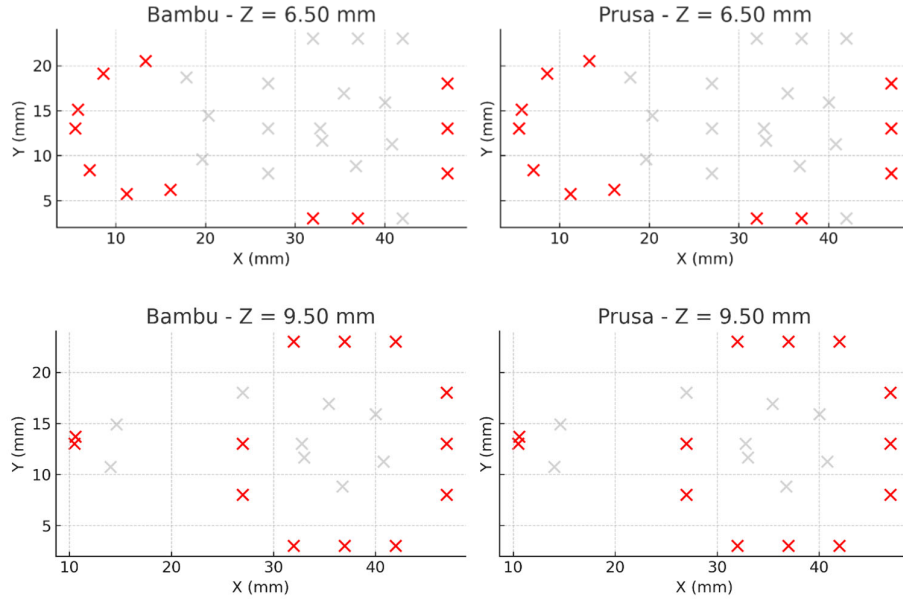


Fig. 3. Binary maps showing systematic (red) vs non-systematic (gray) points for each section

4.4. Cross-Printer Comparative Analysis

To further contextualize these findings, a direct pointwise comparison between Prusa and Bambu deviations was conducted. The difference maps (Prusa – Bambu), presented in **Figure 4**, revealed systematic polarity in certain regions, indicating consistent over- or under-

deviation by one platform relative to the other. This comparative view not only reinforces the presence of printer-specific error signatures but also provides actionable input for machine-calibrated morphing strategies, where corrective offsets could be tuned per platform.

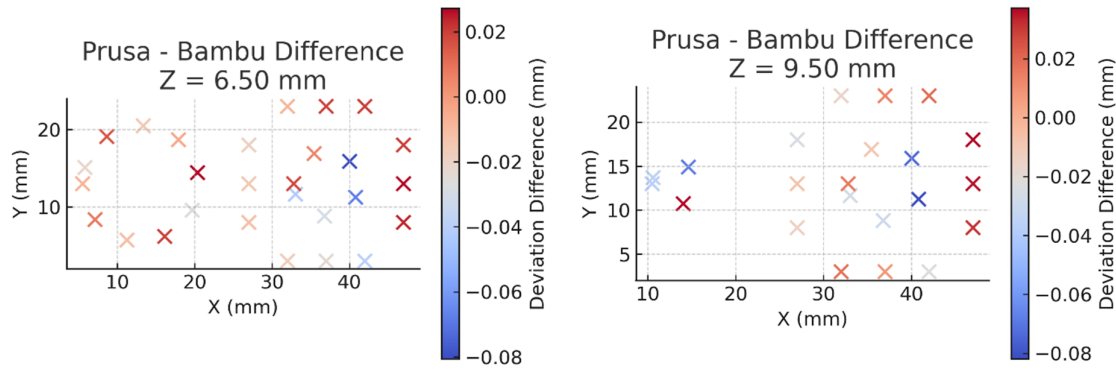


Fig. 4. Prusa – Bambu difference heatmaps for Z = 6.50 mm and Z = 9.50 mm.

5. DISCUSSION

The results confirm that the proposed percentile-based, vertex-level classification framework (Figure 5) is effective in isolating systematic deviations in a multi-printer context. By avoiding full-field morphing and focusing only on statistically stable, high-magnitude deviations, the framework achieves a balance between geometric accuracy and computational efficiency. Importantly, the identification of printer-specific deviation patterns supports the feasibility of a calibration-aware correction pipeline, where morphing strategies are tailored to the bias characteristics of each machine.

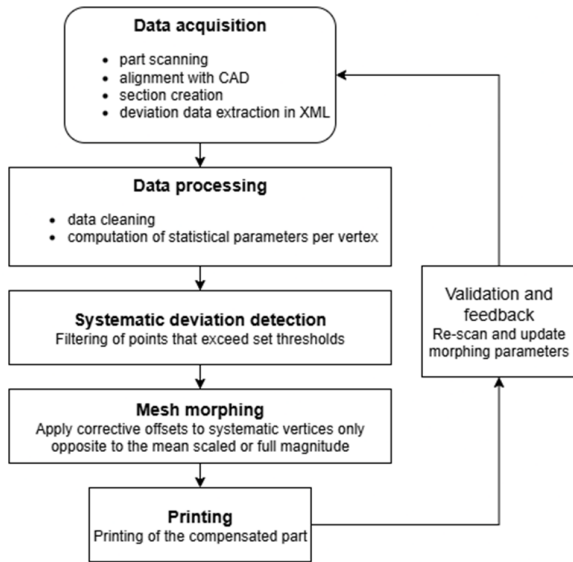


Fig. 5. Framework for selective morphing of 3D printed parts

Furthermore, the ability to generate consistent, interpretable outputs from a relatively small dataset demonstrates that the approach can be applied in industrial scenarios with limited sacrificial prints. Compared to prior work, which often depends on larger sample sizes or high-complexity models, the present framework retains adaptability while lowering the data and processing overhead. In doing so, it addresses both the practical constraints and precision requirements highlighted in the literature review.

6. CONCLUSION

This study presented a percentile-based, vertex-level framework for detecting and characterizing systematic deviations in

additively manufactured parts, with a specific focus on cross-printer comparative analysis. By applying a statistically adaptive thresholding approach to stereoscopic scan data from two distinct fused filament fabrication platforms, we demonstrated that systematic deviations can be reliably isolated from stochastic variation, even when the available dataset is relatively small.

The empirical results showed that half of the measured vertices (50.0%) exhibited systematic deviation, defined by a standard deviation below 0.025 mm and a mean absolute deviation exceeding 0.090 mm. Coordinate-true heatmaps and binary classification masks revealed that deviation patterns were not only spatially heterogeneous but also printer-specific, with the Prusa and Bambu systems showing distinct bias signatures. This reinforces the potential value of machine-specific calibration and morphing strategies that are informed by statistical stability and deviation magnitude, rather than indiscriminate full-field compensation.

Importantly, the framework’s reliance on adaptive, dataset-derived thresholds ensures its applicability across varied printing scenarios without the need for extensive empirical tuning. The approach also minimizes computational overhead, making it suitable for integration into iterative, feedback-driven compensation pipelines where time and resource constraints are critical.

By addressing the research gap identified in the literature, this work contributes a flexible and scalable methodology that can be extended to other additive manufacturing technologies and measurement systems. Future research will focus on embedding this detection stage directly into CAD/CAM workflows, enabling automated morphing of only those surface regions where systematic deviations are statistically significant, thereby further improving the geometric fidelity of additively manufactured parts.

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Dezvoltarea unui framework bazat pe deviații de suprafață pentru corectarea selectivă a mesh-urilor în fabricația aditivă

Fabricarea aditivă a devenit importantă pentru producerea de geometrii complexe cu un timp de execuție minim, însă abaterile geometrice sistematice rămân o provocare persistentă. Studiul actual prezintă un cadru pentru transformarea țintită a rețelei pe baza mapării consecutive a abaterilor pentru a compensa selectiv erorile geometrice sistematice. Cadrul utilizează date de scanare stereoscopică pentru a determina cu precizie abaterile de suprafață. Abaterile de suprafață sunt cuantificate prin compararea mai multor piese imprimate în condiții similare cu modelul CAD original. Vectorii de abatere sunt calculați pentru fiecare punct în două secțiuni, pe mai multe piese, iar erorile sistematice sunt identificate prin analiza distribuției statistice a abaterilor. Numai punctele care prezintă abateri consistente, definite ca fiind cele cu o abatere standard sub un prag definit și o abatere medie care depășește o magnitudine minimă, sunt selectate pentru compensare. Modificarea geometrică țintită se realizează prin aplicarea ajustărilor corective exclusiv regiunilor selectate. Acest lucru previne supracompensarea, minimizând în același timp sarcina de calcul. Un modul de validare rescansează piesa compensată pentru a evalua reducerea magnitudinii deviației, formând o buclă de feedback pentru a rafina parametrii de modificare geometrică. Această abordare are potențialul de a îmbunătăți precizia identificării erorilor sistematice, de a reduce complexitatea calculului și de a optimiza parametrii adaptivi. Poate îmbunătăți precizia geometrică și păstra integritatea suprafeței, ceea ce o face o soluție rentabilă pentru îmbunătățirea fidelității dimensionale în procesele de fabricație aditivă.

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