

Path-resolved melt-track width enables relative spatial-stability characterization and velocity-orientation mapping in laser powder bed fusion

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Abstract: In laser powder bed fusion (LPBF), melt-track width is often compressed into a condition-level mean, but this representation loses local narrowing, sustained drift and clustered fluctuation along the scan path. Here, path-resolved melt-track width, $\text{Width}(x)$, was used as the response variable for 72 velocity–orientation conditions at a fixed laser power of 370 W to establish a width-trajectory-based relative spatial-stability analysis. $\text{Width}(x)$ records the processed melt-track width as a function of path position rather than a real-time liquid melt-pool width. Seven spatial signatures were extracted and combined into S_{spatial} , an empirical composite index for relative ranking and review prioritization within the fixed-power, observed-orientation set. Mean Width and Width CV were moderately negatively correlated (Pearson $r = -0.48$), indicating that average width cannot replace local within-path fluctuation. Under LOVO, the random forest achieved Spearman $\rho = 0.811$ and MAE = 0.086; under LOOO, precision for the highest 20% of high-instability conditions decreased to 0.143, indicating good recoverability along the speed dimension but a clear orientation-extrapolation boundary. The index organizes relative path stability as defined by $\text{Width}(x)$ and is not equivalent to defect probability, quality certification or a general process window.

Keywords: laser powder bed fusion, melt-track width, path-resolved signal, relative spatial stability, process map

1. Introduction

Laser powder bed fusion (LPBF) uses a focused laser to melt and solidify metal powder layer by layer, enabling the fabrication of complex metallic components. The process involves coupled laser-energy absorption, melt-pool flow, vapour recoil pressure, spatter, powder denudation and rapid solidification, which together determine melt-pool size, morphology and stability. The measured quantity in this study is processed melt-track width and its variation with path position. The analysis therefore focuses on path geometry and spatial organization rather than treating the measurement as a real-time liquid melt-pool width.

Path-resolved measurements have shown that melt-track geometry is not adequately represented by a single forming outcome, because local width can vary with scan position. For the present study, the measured Width(x) profile is a processed-track width record rather than a real-time liquid-melt-pool signal. The analysis therefore focuses on geometry, path order, local lows and spatial persistence, while keeping mechanistic claims about melt-pool dynamics outside the evidence directly available in the dataset.

Existing process-window studies commonly analyse relationships among laser power, scan speed and track geometry using cross-sectional metallography, single-track tests and other measurements. Condition-level statistics such as Mean Width are widely used because they are intuitive and comparable[2]. However, compressing the full width trajectory into a single mean weakens local variations along the scan path. Even when laser power and scan speed remain fixed, a retained path can contain leading-segment fluctuation, a relatively stable middle region, end contraction, local narrowing and stage-wise drift[4]. These changes cannot be fully represented by Mean Width.

Local path variability can be relevant to later geometric and performance outcomes, but the present dataset does not contain defect, porosity or fatigue labels. The amplitude, persistence and spatial clustering of Width(x) variation are therefore treated here as measurable path-geometry responses, not as direct evidence of defect probability or part quality.

The central methodological opportunity is to retain the spatial order of a width profile instead of collapsing it to a condition-level mean. Compared with Mean Width, Width(x) preserves sequence, persistence distance and local clustering of width variations, making it suitable for

identifying short-duration narrowing, sustained drift, fluctuation bursts and frequency organization. This path-resolved representation is the basis of the present relative-stability analysis.

Despite progress in melt-pool mechanism studies and process monitoring, three limitations remain. First, many process-window studies use condition-level metrics such as Mean Width, melt-pool depth or depth-to-width ratio and do not retain the spatial order and persistence scale of width variations[2,4]. Second, width variability is often reported as a single dispersion value rather than an integrated path-level representation[6,23,26]. Third, process maps mainly focus on laser power and scan speed and less often treat scan orientation and its interaction with speed as explicit dimensions[28,31].

On this basis, $Width(x)$ was used as the direct response variable to characterize relative stability in the scan-speed and scan-orientation space under fixed laser power. The study used 72 velocity–orientation conditions and their complete $Width(x)$ trajectories obtained on an EOS M290 system at a fixed power of 370 W. The fixed-power design reduces confounding from power variation, allowing speed, orientation and their interaction to be compared within the same power boundary.

The overall analysis contains four levels: trajectory representation, score construction, blocked validation and map output. First, seven spatial signatures were extracted from $Width(x)$, covering full-path fluctuation, leading-segment fluctuation, remaining-path fluctuation, the low-width tail, spatial memory and frequency organization. The signatures were normalized in a direction-consistent manner and integrated into $S_{spatial}$, a width-path-based relative ranking index across the 72 conditions. $S_{spatial}$ is an empirical composite index for relative comparison among the 72 observed conditions and is not treated as an externally calibrated physical quantity. Leave-one-velocity-out (LOVO) and leave-one-orientation-out (LOOO) validation then tested recoverability along speed and the extrapolation boundary along orientation. Finally, observed scores, predictions, residuals and Top 20% high-instability candidates were mapped into velocity–orientation space. The resulting $Width(x)$ -only map is used for review prioritization within its stated scope.

The main contribution is to extend measured track width from a condition-level mean into a path-resolved spatial response and to establish a comparable, testable and explicitly bounded relative-stability index without posterior defect labels. The map reflects stability as defined by

Width(x), rather than defect probability, part-quality certification or a cross-power general process window.

2. Spatial-stability characterization using path-resolved melt-track width

2.1 Mean-width boundary in the fixed-power process space

Mean Width is a primary metric for describing the average lateral scale of the processed melt track[2], but it cannot fully describe path stability. A condition may have an apparently stable mean while still containing local narrowing, clustered fluctuation or long-range drift[4]. The initial analysis therefore tests whether Mean Width and Width CV describe the same response or reveal different path-geometry dimensions in the fixed-power process space.

The path-resolved single-track melt-track width measurements analysed here were taken from the public dataset “Dataset of Melt Pool Variability Measurements for Powder Bed Fusion–Laser Beam of Ti-6Al-4V”, specifically the StWidths.csv file. The file records scan position, scan speed, scan orientation, laser power and the corresponding processed melt-track width. The underlying experiments were conducted on an EOS M290 system using Ti-6Al-4V alloy powder, with a substrate preheating temperature of 200 °C, a layer thickness of 30 µm and a single-track scan length of 10 mm. Laser power was fixed at 370 W, scan speed ranged from 1300 to 1700 mm/s in 50 mm/s increments, and scan orientation ranged from 0° to 315° in 45° increments, yielding 72 velocity–orientation conditions. The present analysis used StWidths.csv for path-width analysis and did not use defect, porosity or fatigue-life labels.

The path-resolved data contained approximately 2,160,000 width sampling points, but the statistical unit in this study was the velocity–orientation condition rather than an individual sampling point. Point-level samples were used to reconstruct each Width(x) curve while preserving spatial order. Sspatial, state labels and process-input predictions were calculated at the condition level, thereby avoiding pseudoreplication caused by adjacent path points.

Two condition-level quantities were first calculated for each Width(x) curve. Mean Width is the arithmetic mean of all width samples and describes average processed-track width. Width CV is the ratio between width standard deviation and Mean Width and describes relative path fluctuation. Both quantities are derived from the same curve, but Mean Width retains the average level whereas Width CV retains variation around that level.

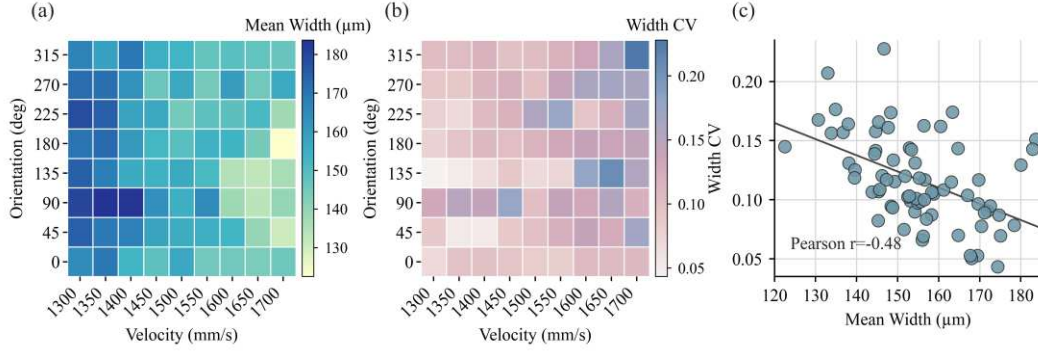


Fig. 1 Mean Width and path-resolved Width CV capture different width responses. (a) Mean Width map across nine velocity levels and eight scan orientations. (b) Width CV map computed from the same Width(x) traces. (c) Condition-level relationship between Mean Width and Width CV, with each point representing one velocity–orientation condition and Pearson $r = -0.48$.

Condition-level Pearson correlation further quantifies this separation. Mean Width and Width CV show a moderate negative correlation, with $r = -0.48$, showing that conditions with larger average width generally have lower relative fluctuation, although the scatter remains broad, as shown in Fig. 1(c). Average geometry therefore explains only part of the Width(x) fluctuation response.

The residual dispersion between Mean Width and Width CV motivates subsequent feature construction. Local narrowing, sustained fluctuation, stage-wise drift and spatial organization are compressed during mean aggregation. Mean Width is suitable for preliminary process-window comparison[2], but Width(x) stability still requires additional signatures that represent amplitude, the low-width tail, spatial memory and frequency organization.

2.2 Width(x) spatial signatures and stability score

Width(x) preserves continuous spatial variation of melt-track width along the scan path, but the complete curve is not suitable for direct comparison among conditions. Each velocity–orientation condition contains approximately 30,000 path sampling points, and curve differences involve overall fluctuation, local narrowing, stage-wise drift, spatial persistence and frequency organization. Direct comparison of raw curves is easily affected by high-dimensional noise and the position of local events. Compressing the curve back into Mean Width would again lose the within-path fluctuation information revealed by the Mean Width and Width CV boundary analysis. Width(x) needs to be converted into a low-dimensional, interpretable and condition-level set of spatial signatures that can be compared consistently across the 72 conditions.

Spatial-signature selection followed three constraints. First, the signatures needed to cover different stability dimensions rather than repeat the same amplitude statistic. Second, each signature had to be computed robustly from every Width(x) curve and could not be dominated by a single isolated sampling point. Third, the signatures needed to be summarized into condition-level responses to support state partitioning, blocked validation and process-map construction.

For condition i , the path-width sequence was denoted as $w_i(x_j)$, where $j = 1, 2, \dots, N_i$. The path mean μ_i and standard deviation σ_i of this condition were calculated using Eq. (1) and Eq. (2), respectively, and were used to establish a common statistical baseline for all subsequent relative-fluctuation metrics.

$$\mu_i = \frac{1}{N_i} \sum_{j=1}^{N_i} w_i(x_j)$$

$$\sigma_i = \left[\frac{1}{N_i - 1} \sum_{j=1}^{N_i} (w_i(x_j) - \mu_i)^2 \right]^{\frac{1}{2}}$$

Width CV was defined as σ_i/μ_i and used to describe relative fluctuation intensity over the entire retained path. Leading-segment CV and Remaining-path CV describe the fluctuation levels in the first 10% and remaining 90% of the retained path, respectively. This split is a path-position convention for the available width trajectory and does not represent laser start-up or melt-pool establishment. The former describes fluctuation in the retained leading segment, whereas the latter describes fluctuation over the remainder of the processed path.

Width P5 was defined as the 5th percentile of the Width(x) distribution within the same condition. Compared with the minimum width, P5 is less sensitive to a single outlier and is more suitable for describing the persistent low-width tail. A lower Width P5 indicates that the condition is more likely to contain local narrowing regions[4], and it enters the stability score in an inverse form. In other words, the lower the P5 value, the higher its contribution to path instability.

Spatial memory was described by the normalized autocorrelation function (ACF). After mean removal, the autocorrelation function $R_i(\ell)$ was calculated for each Width(x) curve, where ℓ denotes spatial lag. Its calculation is given in Eq. (3). ACF correlation length was defined as the lag distance at which $R_i(\ell)$ first decays to e^{-1} .

$$L_{ACF,i} = \min\{\ell \mid R_i(\ell) \leq e^{-1}\}$$

A longer ACF correlation length indicates that width disturbances remain correlated over a longer path distance, reflecting stronger spatial persistence. This metric complements Width CV

because two conditions with similar fluctuation amplitudes can still have different spatial memory lengths.

Frequency-domain organization was calculated from the power spectrum obtained by fast Fourier transform (FFT). Let P_{ik} be the power-spectrum value of condition i at frequency k , and let p_{ik} be the normalized power spectrum. The calculation of p_{ik} is given in Eq. (4). Spectral entropy was defined as the information entropy of the normalized power spectrum and was calculated using Eq. (5).

$$p_{ik} = \frac{P_{ik}}{\sum_k P_{ik}}$$

$$H_i = -\frac{\sum_k p_{ik} \log(p_{ik})}{\log K}$$

Here, K denotes the number of frequency components. Spectral entropy describes the dispersion of spectral energy across frequency space. The high-frequency energy fraction (EHF) was defined as the proportion of power-spectrum energy above 0.2 times the Nyquist frequency relative to total energy, as calculated using Eq. (6).

$$EHF_i = \frac{\sum_{f_k > 0.2 f_{N_{yq}}} P_{ik}}{\sum_k P_{ik}}$$

Spectral entropy and EHF jointly describe the frequency organization of $\text{Width}(x)$. The former reflects whether energy is concentrated in a small number of frequency components, whereas the latter reflects the share of short-scale high-frequency disturbances in the total energy. Neither metric independently determines the stability state. Instead, both enter the integrated score as supplementary frequency-domain information.

To compare the response differences of the seven spatial signatures in the fixed-power process space, each metric was mapped to the velocity–orientation matrix formed by nine scan speeds and eight scan orientations, as shown in Fig. 2(a)–2(h). Width CV, Leading-segment CV and Remaining-path CV all use relative-fluctuation forms, but their high-value regions do not fully overlap. Width CV and Remaining-path CV show similar patterns in parts of the process space, whereas high Leading-segment CV values are more concentrated in specific speed-orientation combinations. This result is interpreted as retained path-position dependence; the available $\text{Width}(x)$ record does not support a device-startup explanation or any mechanism beyond the observed path-position response.

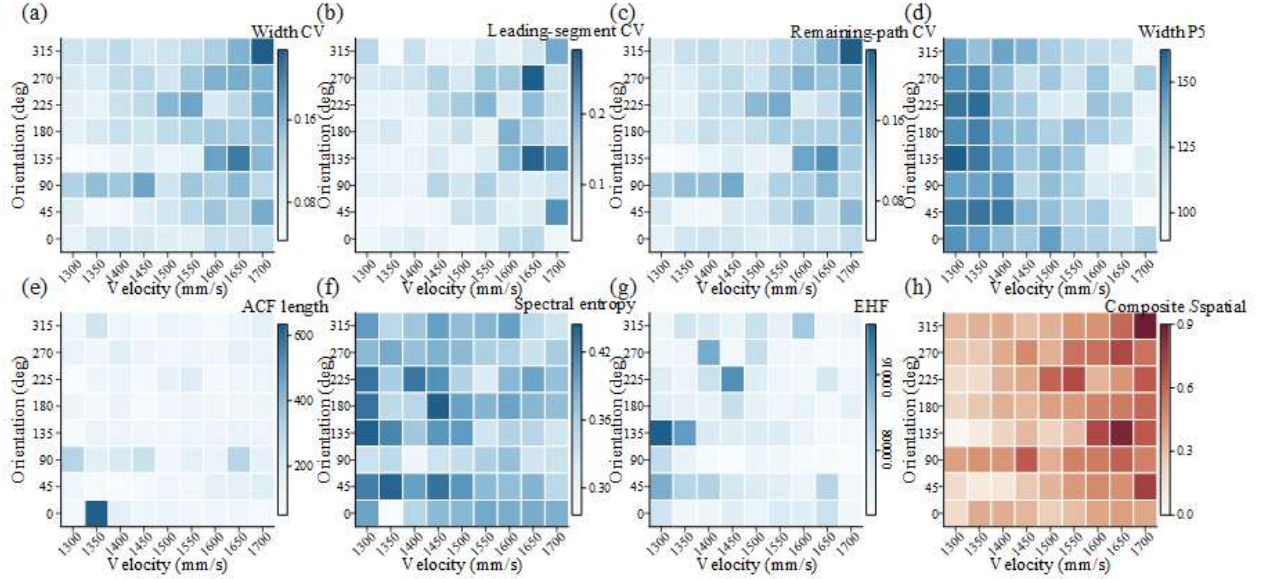


Fig. 2 Seven spatial signatures convert Width(x) into interpretable relative-instability dimensions. (a) Width CV. (b) Leading-segment CV. (c) Remaining-path CV. (d) Width P5 after direction-consistent interpretation of low-width tails. (e) ACF correlation length. (f) Spectral entropy. (g) High-frequency energy fraction. (h) Composite Sspatial score. The atlas shows that fluctuation amplitude, low-width tails, spatial memory, frequency organization and their empirical composite ranking occupy related but non-identical regions of the process space.

The process-space distribution of Width P5 is not consistent with the three CV metrics, as shown in Fig. 2(d). This shows that the low-width tail and overall fluctuation amplitude are not the same statistical dimension. Some conditions can show pronounced local narrowing even when overall fluctuation is not prominent. Conversely, a higher Width CV does not necessarily correspond to a lower Width P5.

High values of ACF correlation length are concentrated in a small number of conditions and do not fully correspond to the high-value regions of Width CV or Remaining-path CV, as shown in Fig. 2(e). This shows that fluctuation amplitude and the spatial persistence distance of disturbances can be separated. Conditions with similar overall fluctuation intensity can still show different spatial-memory characteristics.

The process-space distributions of Spectral entropy and EHF are shown in Fig. 2(f) and Fig. 2(g), respectively. Their speed and orientation gradients and local extrema differ from those of CV, Width P5 and ACF correlation length. This shows that spectral-energy dispersion and high-frequency energy fraction provide information complementary to amplitude statistics and spatial correlation.

The seven spatial signatures show different but partly correlated distribution structures across the 72 conditions. This result shows that path stability in Width(x) is not determined by a single statistic. Instead, it is a multidimensional response jointly formed by overall fluctuation, leading-

segment fluctuation, sustained fluctuation, the low-width tail, spatial memory and frequency-domain organization. Accordingly, using any single signature alone may miss information carried by other path-behaviour dimensions, making an integrated score necessary.

Because the seven signatures have different dimensions and numerical ranges, each metric was first min-max normalized across the 72 conditions. For any signature s , the normalized value $z_{s,i}$ was calculated using Eq. (7).

$$z_{s,i} = \frac{s_i - \min(s)}{\max(s) - \min(s)}$$

For signatures in which larger values indicate greater instability, $z_{s,i}$ was used directly. For signatures such as Width P5, in which smaller values indicate greater instability, $1 - z_{s,i}$ was used for direction-consistent transformation. The transformed terms were denoted as d , and all represented relative instability contributions along the corresponding dimensions. Eq. (7) only performs scale normalization, whereas direction-consistent transformation ensures that all d terms point toward higher instability.

After direction-consistent transformation, $S_{spatial}$ was calculated as the weighted sum of the seven normalized signatures. The seven weights sum to 1, and the specific form is given in Eq. (8).

$$S_{spatial,i} = 0.2d_{CV,i} + 0.1d_{TCV,i} + 0.2d_{SCV,i} + 0.2d_{P5,i} + 0.1d_{ACF,i} + 0.1d_{H,i} + 0.1d_{EHF,i}$$

Width CV, Remaining-path CV and Width P5 were assigned a high-contribution weight of 0.20, whereas Leading-segment CV, ACF correlation length, Spectral entropy and EHF were assigned supplementary weights of 0.10. The terms d_{CV} , d_{Lseg} , d_{Rpath} , d_{P5} , d_{ACF} , d_H and d_{EHF} correspond to the direction-consistent normalized contributions of width variability, leading-segment variability, remaining-path variability, the low-width tail, spatial memory, spectral entropy and high-frequency energy fraction, respectively. A higher $S_{spatial}$ indicates higher relative instability across multiple path-stability dimensions. The weights in Eq. (8) are not fitted coefficients and do not represent unique physical constants. Instead, they express the empirical proximity between different signatures and instability in the original Width(x) traces.

The empirical basis and robustness of the weights are further audited in Section 2.4 using Width(x)-based reference metrics excluded from score construction, information-domain deletion and weight perturbation. At this stage, Eq. (8) defines only a sortable composite response. The reasonableness of the weights is evaluated by the subsequent audit, avoiding self-validation during score construction.

2.3 Path morphology, spatial memory and frequency organization

Representative conditions were selected from the relatively Stable, Transition and Unstable states, and their complete Width(x) curves and rolling width coefficient of variation, abbreviated as rolling CV, were compared. The three representative conditions were velocity = 1300 mm/s and orientation = 135°, velocity = 1500 mm/s and orientation = 45°, and velocity = 1700 mm/s and orientation = 315°. Rolling CV was calculated as the ratio between the width standard deviation and local mean within a sliding window, and was used to describe how local relative fluctuation changed with scan position. The representative Width(x) traces and corresponding local fluctuations are shown in Fig. 3. The path width of the Stable condition varied only slightly around its condition-level mean. Although local undulations were present, the curve showed no sustained deep narrowing or pronounced stage-wise drift. Its rolling CV remained low over most of the path and increased briefly at only a few locations, as shown in Fig. 3(b). This indicates that local disturbances in this condition were limited in amplitude and persistence and did not form a continuous unstable segment over a longer path distance.

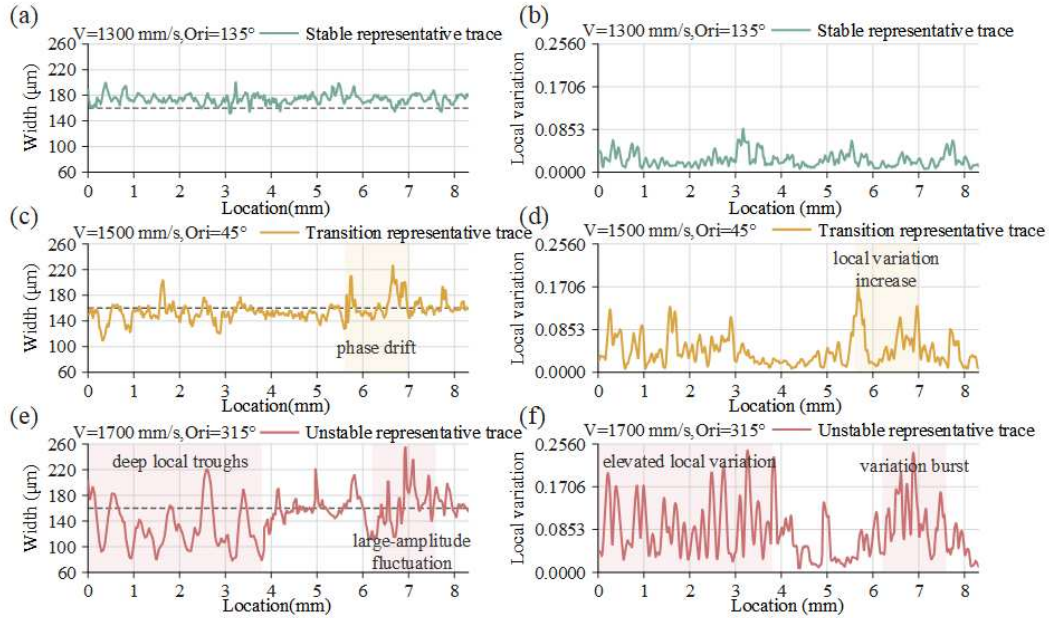


Fig. 3 Representative Width(x) traces and rolling variation reveal state-dependent path morphologies. (a,b) Stable condition showing low-amplitude width variation and limited rolling-CV excursions. (c,d) Transition condition showing alternating stable and locally unstable path segments. (e,f) Unstable condition showing deep local narrowing, persistent high rolling CV and clustered fluctuation events.

By contrast, the Unstable representative condition shows deeper local valleys, larger-amplitude undulations and fluctuation bursts in Width(x), as shown in Fig. 3(e). Its rolling CV remains high over several continuous path intervals and exhibits clear local clustering, as shown in

Fig. 3(f). This shows that unstable events do not appear as isolated abnormal points. Instead, they form persistent or clustered high-fluctuation segments over finite spatial ranges.

Path morphology and rolling CV jointly show that the differences among the three relative states are not limited to full-path fluctuation amplitude. They also involve the spatial location, persistence range and clustering mode of local anomalies. These features are path information that condition-level Mean Width cannot retain, and they provide the raw-signal basis for constructing Width CV, Leading-segment CV, Remaining-path CV and Width P5.

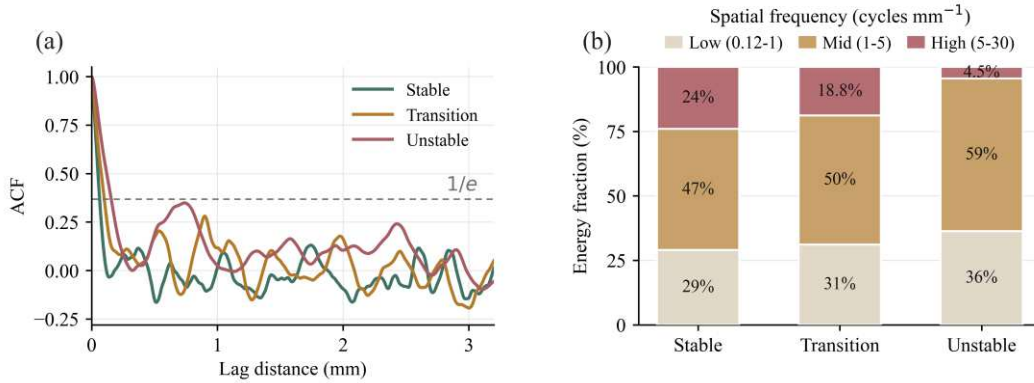


Fig. 4 ACF and FFT quantify spatial memory and frequency organization of Width(x). (a) Normalized autocorrelation functions for representative Stable, Transition and Unstable conditions. (b) Low-, mid- and high-frequency energy fractions for the three representative conditions. State-wise distributions of spectral entropy and EHF are shown in Fig. 7(f,g).

To further characterize the spatial persistence and frequency-scale composition of Width(x) disturbances across stability states, we compared normalized ACFs and sub-band energy fractions for the three representative conditions and summarized the Spectral entropy and EHF distributions across all 72 conditions, as shown in Fig. 4. The normalized ACFs of the three representative conditions are shown in Fig. 4(a). All three curves decayed rapidly over short lag distances, but their post-decay correlation structures differed markedly. The ACF of the Stable condition subsequently oscillated around zero with low amplitude, indicating predominantly short-range correlation in its width disturbances. The Transition and Unstable conditions retained more pronounced secondary correlation peaks at longer lags, with the Unstable condition showing the strongest subsequent structure. This pattern is consistent with the stage-wise shifts and continuous fluctuation segments observed in Fig. 3, indicating that higher relative instability involves not only larger fluctuation amplitude but also stronger spatial organization and persistence.

The spatial-frequency energy compositions of the three states are shown in Fig. 4(b). In the Stable, Transition and Unstable states, low-, mid- and high-frequency energy accounted for 29.0%,

47.0% and 24.0%; 31.2%, 50.0% and 18.8%; and 36.4%, 59.1% and 4.5%, respectively. As the state changed from Stable to Unstable, the high-frequency fraction decreased continuously, whereas the mid- and low-frequency fractions increased. Thus, the dominant fluctuations in unstable paths were more strongly expressed as persistent changes and slow drift over longer spatial scales, rather than as many independent short-scale rapid disturbances.

Spectral entropy generally decreased from Stable to Transition and Unstable, and EHF also declined; their state-wise distributions are shown in Fig. 7(f,g).

Path morphology, local fluctuation, spatial memory and frequency composition jointly support the signal-level interpretation of Sspatial. Sspatial remains an empirical composite index for relative comparison among the 72 observed conditions; it is not an absolute stability measure, physical ground truth or externally calibrated quality quantity.

2.4 Score robustness, state partitioning and process-interaction constraints

Sspatial combines the seven direction-consistent spatial signatures into a condition-level instability ranking for the 72 velocity–orientation conditions. This ranking is then used for state partitioning and process-input prediction, so two reliability questions must first be addressed. First, is the high-, medium- and low-contribution hierarchy supported by evidence from the original Width(x) traces? Second, are the score-derived relative states stable to changes in the leading-segment window, removal of individual signatures and perturbation of the weights?

To avoid using score components to validate the composite score directly, four Width(x)-based reference metrics excluded from score construction were calculated from the raw curves: the proportion of anomalously narrow width points, the longest continuous low-width segment, the proportion of high rolling-CV segments and the segment-wise mean-drift burden.

The seven direction-consistent spatial signatures formed a tiered correlation structure with the four Width(x)-based reference metrics, as shown in Fig. 5(b). Width CV and Remaining-path CV showed the highest mean Spearman correlations with the Width(x)-based reference metrics, with mean ρ values of 0.636 and 0.606, respectively. Leading-segment CV and the low-width tail showed intermediate correlations, with mean ρ values of 0.533 and 0.509, respectively. By contrast, inverse EHF, inverse spectral entropy and ACF correlation length showed lower mean correlations of 0.405, 0.394 and 0.343, respectively. Amplitude fluctuation and the low-width tail therefore

corresponded more directly to unstable events in the original paths, whereas spatial memory and frequency organization provided complementary structural information.

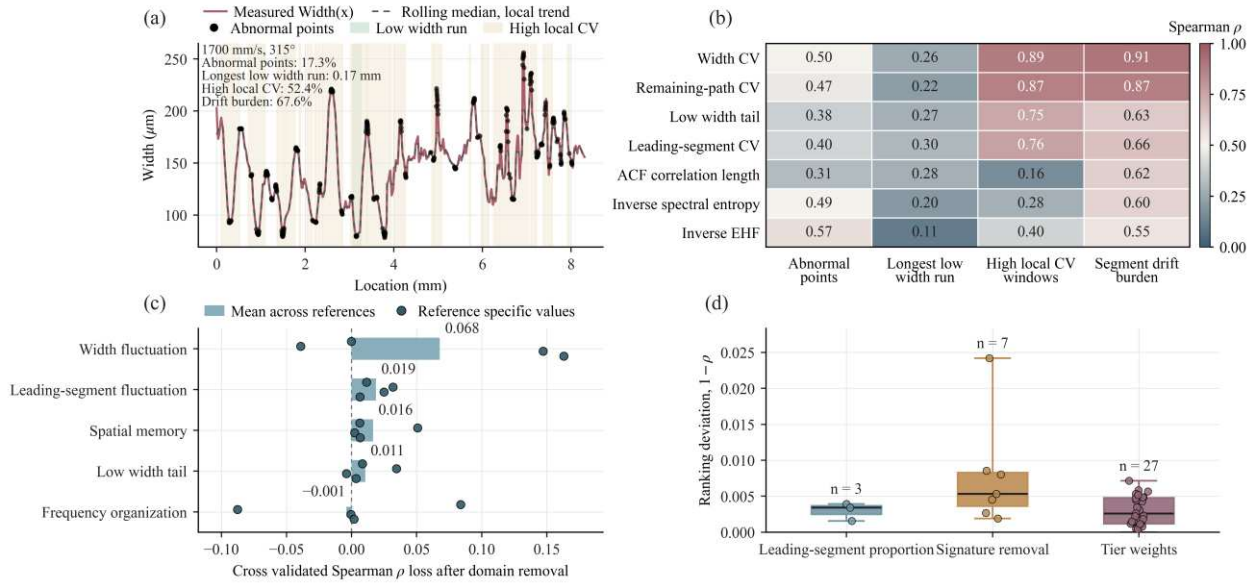


Fig. 5 Empirical basis and robustness of the tiered relative spatial-stability weighting. (a) Width(x)-based reference metrics excluded from score construction. (b) Hierarchical correlations between the seven direction-consistent spatial signatures and the four Width(x)-based reference metrics. (c) Cross-validated performance after information-domain deletion. (d) Rank stability under leading-segment-window, signature-deletion and weight-perturbation audits.

Information-domain analysis further separated single-variable correlation from contribution after redundancy control. The seven signatures were grouped into five information domains: fluctuation, low-width tail, leading-segment behaviour, spatial memory and frequency organization. Cross-validated results after deleting each domain are shown in Fig. 5(c). “Leading-segment behaviour” refers only to the first 10% of the retained Width(x) path and does not denote equipment start-up or melt-pool establishment.

The purpose of weight tiering was not to fit a unique set of optimal continuous coefficients, but to express the empirical proximity between different signatures and path instability using ordered levels. Three robustness tests show that the exact numerical setting does not dominate the Sspatial ranking, as shown in Fig. 5(d). When the leading-segment proportion was varied among 5%, 10%, 15% and 20%, the lowest Spearman ρ relative to the default setting was 0.9961, with a median of 0.9975. After each of the seven signatures was removed in turn, the lowest Spearman ρ was 0.9758, with a median of 0.9947. When the high-, medium- and low-tier weights were perturbed while preserving their order, the lowest Spearman ρ was 0.9929, with a median of 0.9974. Kendall τ also remained highly consistent, with minimum values of 0.9609, 0.8748 and 0.9484 in the three tests. The Sspatial ranking mainly reflects the relative instability jointly formed by the

seven signatures, rather than being determined by one leading-segment proportion, one individual signature or one precise set of decimal weights.

After the weight tiering and ranking robustness were constrained, the 72 velocity–orientation conditions were organized into Stable, Transition and Unstable classes according to S_{spatial} tertiles, with 24 conditions in each class. The three labels denote score-tertile groups for descriptive convenience and should not be interpreted as three naturally discrete or externally certified process states. They organize the continuous Width(x)-based relative response into three intervals within the fixed-power process space.

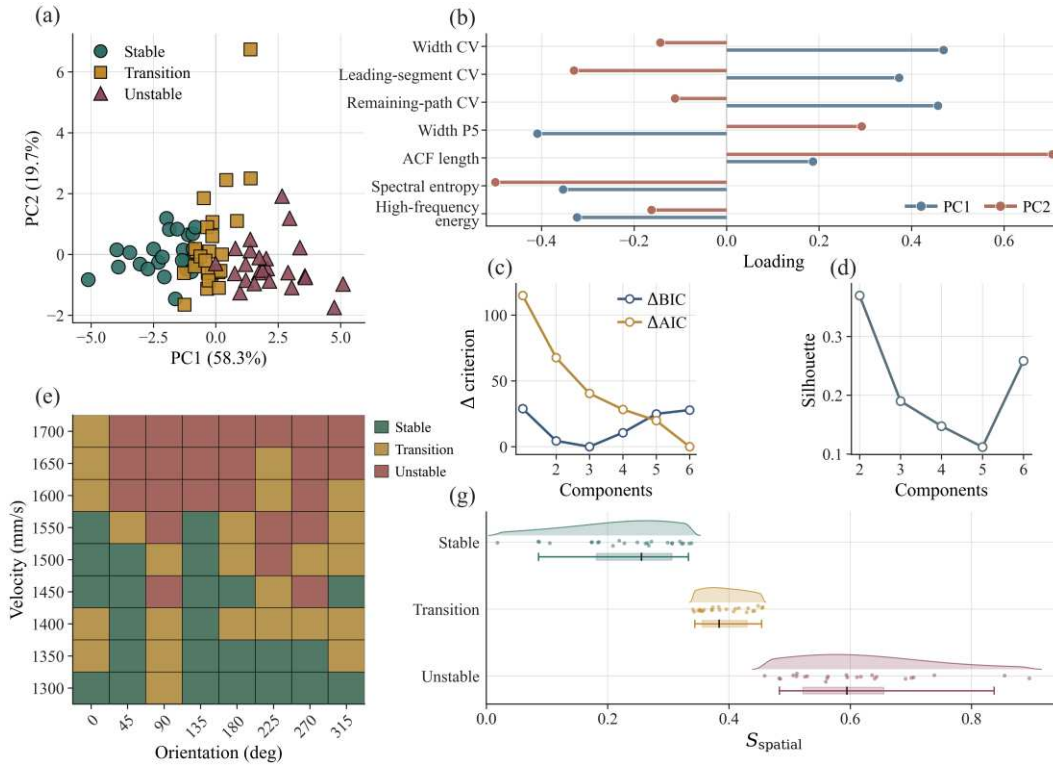


Fig. 6 PCA/GMM audit of score-defined stability states. (a) PCA projection of 72 velocity–orientation conditions in the seven-signature space. (b) PC1 and PC2 loading structure of the seven spatial signatures. (c) GMM BIC/AIC audit across component numbers. (d) Silhouette score across component numbers. (e) Tertile state map in the velocity–orientation process space. (f) S_{spatial} map in the same process space. (g) Raincloud distribution of S_{spatial} across Stable, Transition and Unstable states.

Principal component analysis (PCA) and Gaussian mixture modelling (GMM) were used to audit whether the three-state partition was consistent with the internal structure of the seven-dimensional signature space, rather than to generate the state labels. The first two PCA components explained 78.0% of the signature variance, with PC1 explaining 58.3% and PC2 explaining 19.7%, as shown in Fig. 6(a,b). In the GMM audit, the Bayesian information criterion, abbreviated as BIC, reached its lowest value of 717.4 at $k = 3$, as shown in Fig. 6(c). The silhouette score was 0.370 at $k = 2$, higher than the value of 0.190 at $k = 3$, as shown in Fig. 6(d). This result shows that the three

states are better interpreted as relative segments along a continuous stability spectrum than as fully separated natural clusters. The projection of state labels and S_{spatial} in the velocity–orientation process space further shows that state boundaries form continuous transitions rather than abrupt separations, as shown in Fig. 6(e,f). The mean S_{spatial} values of the Stable, Transition and Unstable states are 0.231, 0.393 and 0.609, respectively, as shown in Fig. 6(g).

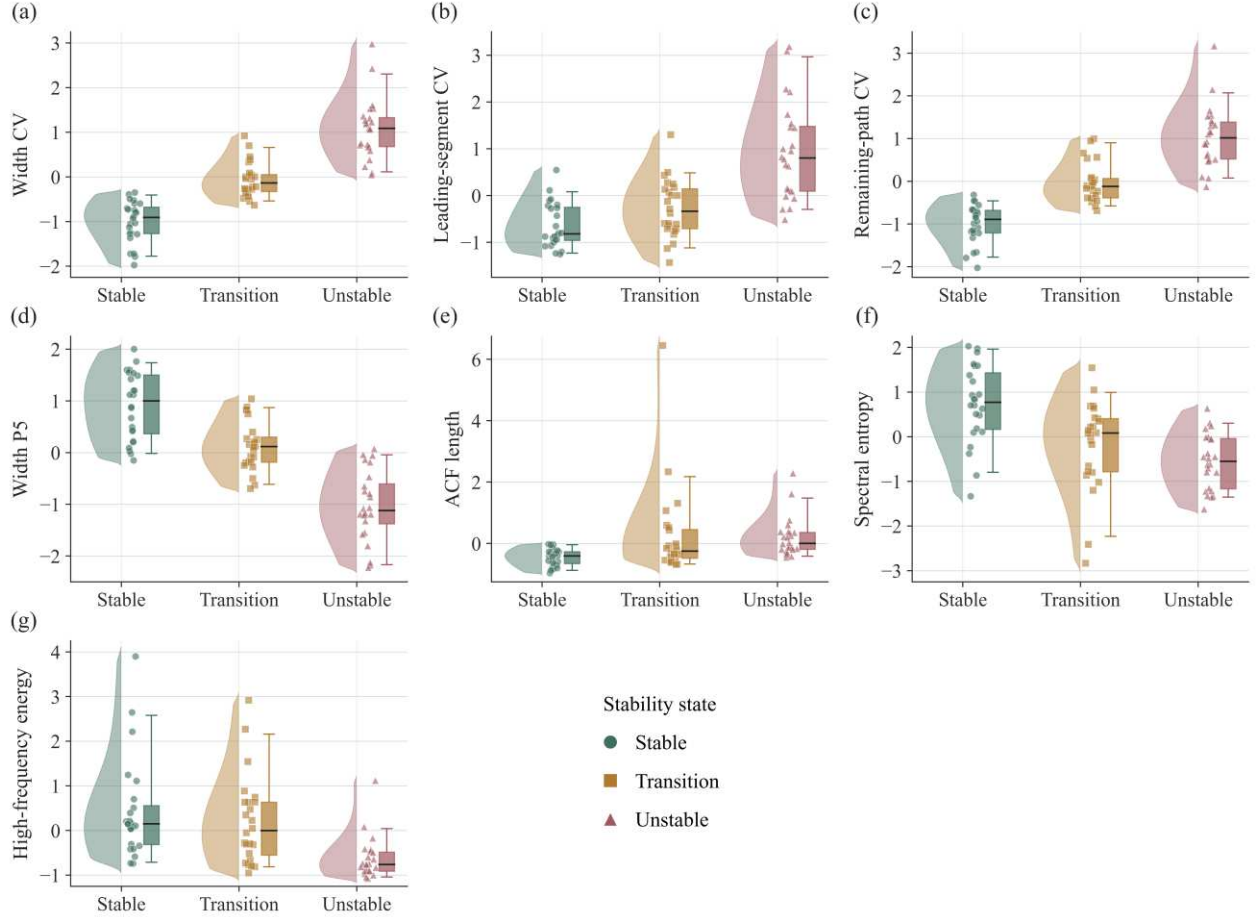


Fig. 7 State-wise spatial-signature distributions reveal coordinated multi-signature shifts. (a) Width CV. (b) Leading-segment CV. (c) Remaining-path CV. (d) Width P5. (e) ACF correlation length. (f) Spectral entropy. (g) High-frequency energy fraction. The seven panels show state-wise distributions and overlap across Stable, Transition and Unstable conditions; the labels describe relative positions along a continuous score spectrum.

The differences among the three states appear not only in S_{spatial} itself, but also in coordinated changes among the seven spatial signatures. The Stable state has lower Width CV, Leading-segment CV and Remaining-path CV, whereas the Unstable state shows overall increases in these fluctuation signatures, as shown in Fig. 7(a). Width P5 decreases in the Unstable state, showing that the low-width tail has an independent role in state separation. The change directions of ACF length, spectral entropy and high-frequency energy indicate that unstable paths are not simply stronger short-scale random disturbances. They also involve longer-scale sustained

variation and more concentrated frequency-domain organization. Although the signatures overlap among the three states, their overall migration direction is consistent, as shown in Fig. 7(b). The three states are therefore not driven by a single threshold, but are jointly shaped by amplitude, tail behaviour, leading-segment behaviour, spatial memory and frequency-domain organization.

The effect of process parameters on path stability was further constrained using segment-level analysis and orientation-pair comparison. Each condition was divided into 30 path segments, yielding 2160 segment-level observations. A two-way ANOVA used segment-level CV as the response and velocity, orientation and their interaction as predictors. The η^2 values were 0.09 for the velocity main effect, 0.03 for the orientation main effect and 0.07 for the velocity–orientation interaction, with $F(56, 2088) = 3.38$ and $p = 1.78 \times 10^{-15}$ for the interaction. The interaction term is of the same order as the velocity main effect, showing that path fluctuation cannot be simplified as independent additive effects. Across the existing 36 orientation-pair comparisons, the mean absolute difference was 0.129, the maximum difference was 0.301, and 21 pairs exceeded 0.1. Because Width(x) alone cannot distinguish contributions from the melt-pool tail, thermal history, imaging-direction sensitivity or coordinate/segmentation effects, this pattern is treated as orientation-dependent condition specificity rather than a final mechanistic attribution.

After the weight audit, subsequent modelling used only the Sspatial response constrained by the three lines of evidence. The Width(x)-based reference metrics excluded from score construction showed that the weight hierarchy was consistent with the original unstable events. Perturbation tests showed that the ranking remained stable to changes in the leading-segment window, removal of individual signatures and small weight adjustments, as documented in Fig. 5. The PCA and GMM audits indicated that the three-state labels were compatible with the seven-signature space but were better understood as relative segments of a continuum, as shown in Fig. 6. State-wise signature distributions further showed that Stable, Transition and Unstable reflected coordinated shifts across multiple signatures rather than a single threshold, as shown in Fig. 7. Segment-level interactions and orientation-pair asymmetry therefore motivated the inclusion of velocity, orientation and their interaction terms in the process-input model.

3. Process-input analysis of spatial stability

3.1 *Velocity–orientation input features and blocked generalization validation*

Process-input prediction was used to test whether the stability score could be recovered from process variables known before measurement. The response was represented at two levels. The continuous response was S_{spatial} , preserving the relative ranking of the 72 velocity–orientation conditions. The categorical response was the Stable, Transition and Unstable label derived from S_{spatial} tertiles. Input features were restricted to velocity, linear energy, periodic orientation terms and their interactions, so the model could not reuse $\text{Width}(x)$ -derived signatures or post hoc state labels as predictors.

The input design addressed three related but distinct issues. Linear energy was calculated as P/v under fixed power [2,28] and is therefore deterministically coupled to velocity; it was not interpreted as an independent physical driver. Orientation was encoded using $\sin \theta$, $\cos \theta$ and higher-order periodic terms to remove the artificial discontinuity between 315° and 0° . Interaction terms multiplied velocity- or linear-energy-related quantities by periodic orientation terms, allowing the same speed to produce different S_{spatial} responses at different scan orientations.

The validation scheme used blocked partitioning. Random six-fold validation measured whether the model could fit the observed process space, but the training and test sets could share neighbouring speeds or neighbouring orientations. LOVO removed all orientation conditions at one speed in each fold and was used to test speed-level interpolation or mild extrapolation within the observed orientation set. LOOO removed all speed conditions at one orientation in each fold and was used to test whether periodic orientation encoding could predict an unobserved orientation. Together, the three partitions separate local fitting, speed generalization and orientation extrapolation.

The evaluation metrics matched the response types. Spearman ρ was used to evaluate the consistency between predicted and observed S_{spatial} rankings, because the main purpose of the score is relative instability ranking. Mean absolute error, abbreviated as MAE, was used to measure continuous-score error. Balanced accuracy and macro F1 were used to evaluate three-state classification and to avoid dominance by one state. Top 20% precision was used to measure whether the model could retrieve the most unstable candidate conditions, and was therefore more directly aligned with the screening target than average error.

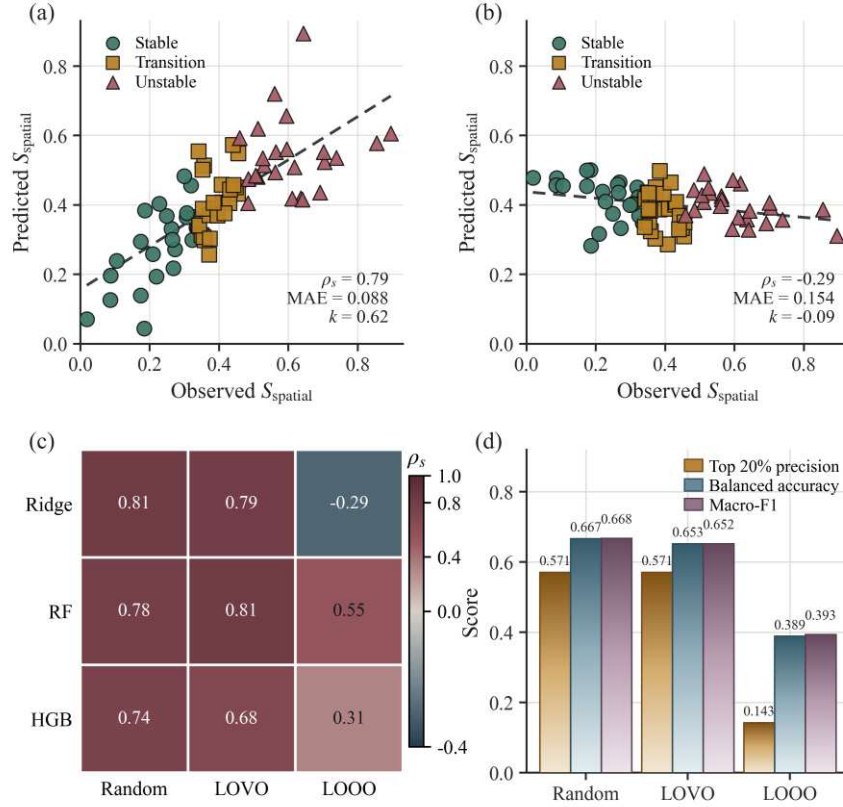


Fig. 8 Blocked validation of process-input prediction. (a) Leave-one-velocity-out prediction of S_{spatial} obtained using Ridge polynomial regression. (b) Leave-one-orientation-out predictions obtained using the same model. (c) Spearman rank correlations of Ridge polynomial regression, Random forest and histogram gradient boosting under random, LOVO and LOOO validation. (d) Top 20% retrieval precision obtained using Ridge polynomial regression, together with balanced accuracy and macro-F1 obtained using multinomial logistic regression. The results show stronger speed-level generalization than orientation-level extrapolation.

Three regression models served complementary testing roles. Ridge polynomial regression provided a low-complexity smooth nonlinear baseline. Random forest captured local nonlinearity and feature interactions. Histogram gradient boosting provided a second tree-ensemble baseline. The three models were used to test whether conclusions remained consistent across different levels of model complexity.

LOVO results showed that process inputs recovered the main speed-related stability ranking. Among the three regression models, Random forest achieved the highest Spearman ρ and the lowest MAE, with values of 0.811 and 0.086, respectively; Ridge polynomial regression achieved $\rho = 0.795$ and MAE = 0.088, and Hist gradient boosting achieved $\rho = 0.680$, as shown in Fig. 8(a,c). As a low-complexity comparison, the velocity-only linear baseline achieved $\rho = 0.746$ and MAE = 0.095 under LOVO; adding periodic orientation terms yielded $\rho = 0.756$ and MAE = 0.093. These baseline results showed that simple models recovered the main speed trend but did not remove the orientation-extrapolation boundary. Fold-wise LOVO results varied across held-out speeds, with

Random forest ρ ranging from -0.095 to 0.810 and MAE from 0.060 to 0.135 ; these values were condition-level diagnostics of the speed boundary. On the 0–1 Sspatial scale, an MAE of 0.086 – 0.088 was close to one tenth of the score range. Together with rank correlations of 0.795 – 0.811 , this indicated that velocity-related inputs retained most of the relative-instability order within the fixed-power and observed-orientation range.

LOOO results exposed the quantitative boundary of orientation extrapolation. Ridge polynomial regression reached Spearman $\rho = -0.295$ and MAE = 0.154 for unobserved orientations; Random forest reached $\rho = 0.554$, a decrease of 0.257 from its LOVO value of 0.811 ; and Hist gradient boosting decreased from 0.680 to 0.314 , as shown in Fig. 8(b,c). Across the eight held-out orientations, fold-wise Random forest results ranged from $\rho = 0.650$ to 0.933 and MAE = 0.063 – 0.202 . This range describes differences in predictive performance across held-out orientations and is not used to estimate repeated-experiment variation. Simple baselines retained the same boundary: the velocity-only linear model reached $\rho = 0.691$ under LOOO, whereas adding periodic orientation terms and velocity–orientation interactions yielded $\rho = 0.455$ and 0.347 , respectively. Even the best LOOO model therefore retained only a limited positive ranking, and periodic encoding could not turn unobserved orientations into a reliable interpolation problem.

Classification and high-instability retrieval metrics provided discrete evidence for the same boundary. Multinomial logistic regression achieved balanced accuracies of 0.667 , 0.653 and 0.389 under random six-fold, LOVO and LOOO validation, respectively, with corresponding macro F1 values of 0.668 , 0.652 and 0.393 , as shown in Fig. 8(d). Bootstrap resampling of the out-of-fold predictions from the 72 conditions yielded LOVO intervals of 0.545 – 0.757 for balanced accuracy and 0.541 – 0.755 for macro F1, compared with 0.276 – 0.504 and 0.278 – 0.506 under LOOO. These intervals reflect uncertainty in condition-level predictions and do not represent repeated-experiment variation. Ridge polynomial regression retrieved the highest 20% high-instability conditions with a precision of 0.571 under both random six-fold validation and LOVO, but only 0.143 under LOOO. The simultaneous decline in continuous ranking, three-state classification and high-instability retrieval indicates that orientation extrapolation is a consistent generalization boundary across evaluation targets rather than an isolated failure of one metric.

These values convert the process-input modelling result from a qualitative pattern into a testable boundary. Velocity-related inputs produced rank correlations of 0.795 – 0.811 and MAE below 0.09 under LOVO, indicating that the speed dimension was predictable within the observed

orientation set. Orientation limited the best LOOO Spearman ρ to 0.554 and reduced high-instability retrieval precision to 0.143, indicating stronger condition specificity along the orientation dimension. Subsequent attribution was therefore restricted to the LOVO-supported speed-prediction range and was not extrapolated to unobserved orientations.

3.2 Process attribution and interaction effects of the stability response

Prediction accuracy alone cannot explain how input variables shape the S_{spatial} response. SHAP, or SHapley Additive exPlanations, is an interpretation method that decomposes model predictions into feature contributions [25]. Here, it was used to decompose Random forest predictions within the LOVO-supported range. The interpretation was restricted to that range because LOOO showed that unobserved orientations could not be recovered reliably. This restriction avoids interpreting feature importance as a general physical law across orientations.

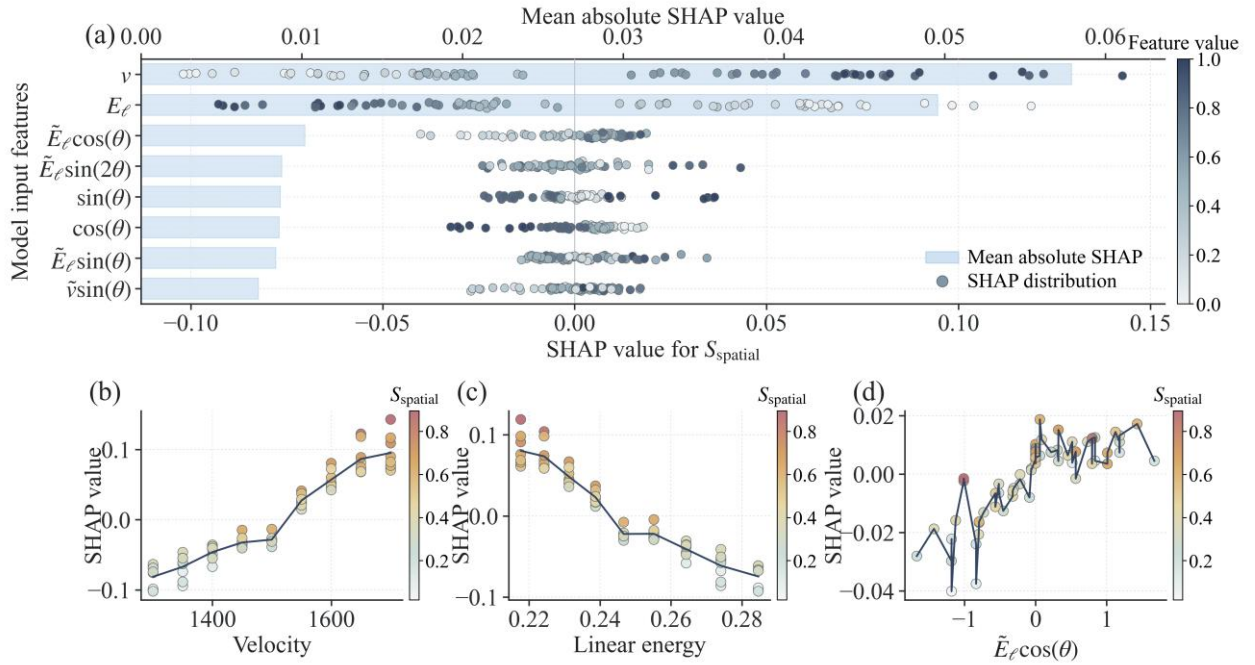


Fig. 9 SHAP interpretation of process-input contributions within the LOVO-supported regime. (a) SHAP summary of leading process-input features for S_{spatial} prediction. (b) SHAP dependence on velocity. (c) SHAP dependence on linear energy. (d) Dependence of the leading direction–energy interaction feature, showing orientation-related modulation of speed–energy responses. Grouped contributions were calculated by summing the mean absolute SHAP values within the coupled speed–energy, pure-orientation and interaction feature families.

SHAP variables were grouped by process meaning rather than interpreted individually. Velocity denotes scan speed; linear energy denotes P/v under fixed power and should be interpreted jointly with velocity as one coupled speed–energy process dimension; orientation contains periodic orientation terms; and interaction contains products of velocity- or linear-energy-related terms with

periodic orientation terms. SHAP is a model-attribution method rather than a causal-identification method, so 57.5% represents model contribution and not physical-mechanism contribution.

The global contribution pattern was dominated by speed-related inputs. Velocity accounted for 31.0% of grouped mean |SHAP| and linear energy for 26.5%, giving 57.5% in total. Because linear energy is P/v under fixed power, these two values represented model contribution from one coupled speed–energy process dimension rather than two independent physical mechanisms.

Orientation contributed mainly through interaction terms. Pure orientation terms accounted for 14.1% of the grouped contribution, whereas interaction terms accounted for 28.3%. The difference was 14.2 percentage points, and the interaction contribution was nearly twice the pure-orientation contribution, as summarized by the feature-family values in Fig. 9(a). The interaction contribution was only 1.8 percentage points higher than the linear-energy contribution of 26.5%, indicating that the main orientation-related information had a magnitude close to that of a single important component on the speed–energy axis. This proportional relationship was consistent with the segment-level ANOVA results, in which the velocity–orientation interaction had $\eta^2 = 0.07$, the velocity main effect had $\eta^2 = 0.09$ and the orientation main effect had $\eta^2 = 0.03$. Orientation changed the local form of the speed and linear-energy response rather than providing a uniform orientation bias.

The velocity-dependence curve identified the main response-transition region. As speed increased, velocity SHAP values changed from negative to positive, with the sign change concentrated near 1500–1550 mm/s, as shown in Fig. 9(b). The transition width was approximately 50 mm/s, corresponding to 12.5% of the full 1300–1700 mm/s speed range and lying in the middle-to-high part of the discrete speed sequence. Below this range, the velocity contribution generally decreased predicted S_{spatial} ; above it, the contribution increased predicted S_{spatial} . This transition represents an internal Width(x)-stability response range in the present dataset, not a universal defect threshold.

The linear-energy dependence provided the reciprocal view of the same boundary. At a fixed power of 370 W, P/v decreased from approximately 0.285 J/mm at 1300 mm/s to approximately 0.218 J/mm at 1700 mm/s. The 1500–1550 mm/s speed-transition range corresponded to a linear-energy range of approximately 0.247–0.239 J/mm, as shown in Fig. 9(c). As speed increased, P/v decreased accordingly, so the linear-energy dependence had the opposite direction to the velocity

dependence. This mirrored structure further indicated that speed and linear energy formed one coupled process dimension under fixed power, rather than two independent physical causes.

The leading interaction dependence showed that orientation could not be removed from the model. At similar speed or linear-energy levels, orientation-related interaction terms moved the prediction into different Sspatial contribution ranges, as shown in Fig. 9(d). Orientation effects could reflect actual thermal history, melt-pool-tail geometry, imaging-direction sensitivity, coordinate conventions or segmentation sensitivity, and the present Width(x) data could not distinguish among these sources. Orientation was therefore interpreted only as condition-specific modulation related to orientation within the observed data, without assigning a single mechanism or causal effect.

Feature attribution converted the blocked-validation results into a quantitative process-input structure. Velocity and linear energy contributed 57.5% in total and defined the main ranking gradient. Interaction contributed 28.3%, showing that orientation reshaped this gradient through interaction terms. Pure orientation contributed 14.1%, indicating a limited independent contribution from orientation itself. This proportional structure was jointly constrained by the LOOO Spearman ρ decrease, which ranged from 0.257 to 1.090, and by the decrease in Top 20% precision from 0.571 to 0.143. SHAP values were not interpreted as causal effects, and the 1500–1550 mm/s transition range was not interpreted as a quality-acceptance boundary.

3.3 Width(x)-based stability map and application boundary

The process map converted the modelling results into an inspectable and usable process-space object. The observed Sspatial provided the Width(x) response for each condition. The LOVO-predicted Sspatial showed the response component recoverable from process inputs. Residuals located departures from the observed response. The Top 20% candidate map converted the continuous score into screening priority. The map integrated measurement, prediction, error structure and use boundary without redefining stability.

Fig. 10 comprised six interrelated results: the observed Sspatial map described the empirical stability landscape of the 72 conditions; the LOVO-predicted map tested recovery of the main landscape from process inputs; the residual map located local prediction departures; grouped MAE compared errors across held-out speeds and orientations; the Top 20% candidate map distinguished

retrieved, missed and false-alarm conditions; and the cumulative retrieval curve evaluated model efficiency for high-instability screening.

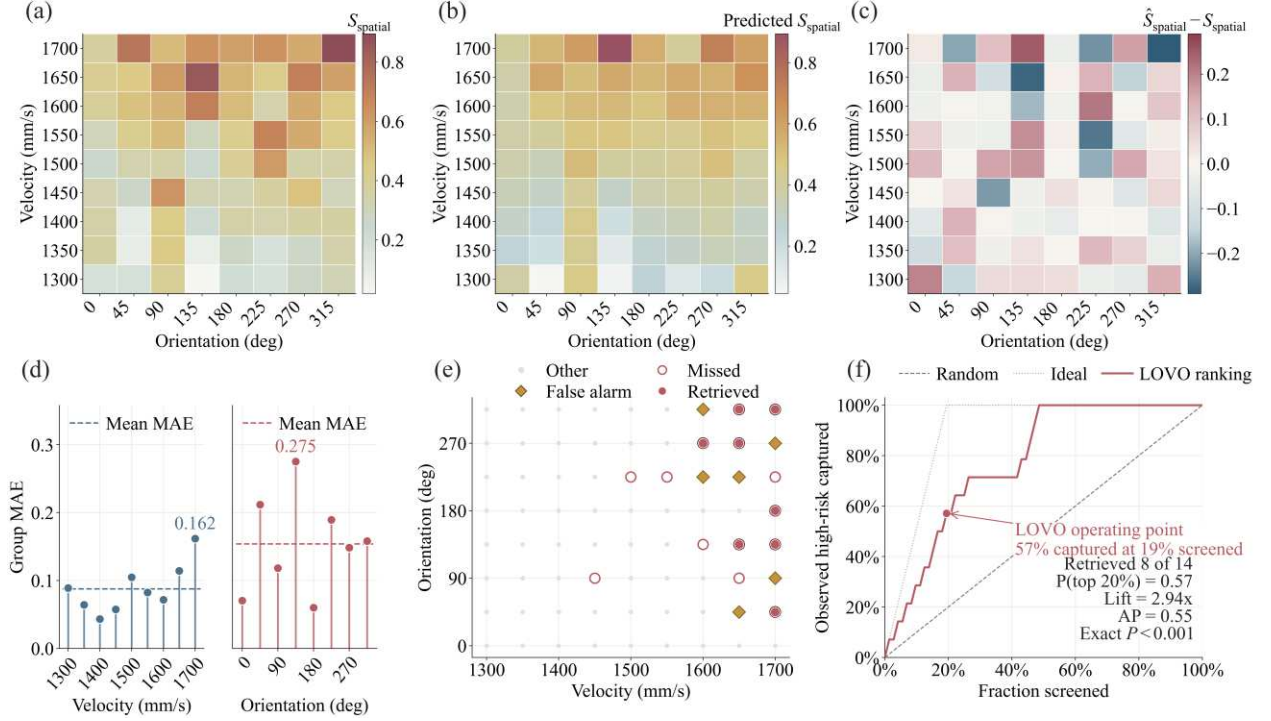


Fig. 10 Width(x)-only process stability map and validation boundary. (a) Observed S_{spatial} map across velocity and orientation. (b) LOVO-predicted S_{spatial} map. (c) Prediction residual map. (d) Group-wise MAE for held-out velocities and orientations. (e) Retrieved, missed and false-alarm Top 20% candidates. (f) Cumulative high-instability retrieval curve and LOVO operating point.

The observed S_{spatial} showed a clear speed gradient across the 72-condition space, as shown in Fig. 10(a). The 1300–1400 mm/s range was closer to low S_{spatial} across most orientations, whereas speeds of 1600 mm/s and above contained multiple high- S_{spatial} conditions. All five highest-ranked high-instability candidates were located at 1600 mm/s or above, and four were at 1650 mm/s or above. This distribution was consistent with the velocity and linear-energy SHAP dependences, both of which identified a speed-related transition near 1500–1550 mm/s. The map therefore showed not only a speed gradient but also the quantitative clustering of high- S_{spatial} conditions at the high-speed end.

Orientation superimposed local structure on this speed gradient. Different orientations at the same speed did not always have similar S_{spatial} values, and orientation-sensitive differences also appeared in the intermediate-speed region. Orientation-pair comparisons provided quantitative evidence: the mean absolute difference across 36 pairs was 0.129, the maximum difference was 0.301 and 21 pairs differed by more than 0.1. The observed map, SHAP interaction dependence and decline in LOOO performance all pointed to the same conclusion. Orientation must remain an

explicit process dimension, and unmeasured orientations cannot be filled in solely by periodic encoding.

The predicted map preserved the broad speed trend but retained local residuals, as shown in Fig. 10(b,c). This residual structure must be interpreted together with validation error. Ridge polynomial regression MAE increased from 0.088 under LOVO to 0.154 under LOOO, an increase of 0.066. Random forest Spearman ρ decreased from 0.811 under LOVO to 0.554 under LOOO, a decrease of 0.257. The residual map should prioritize not all prediction errors but local departures that exceeded the velocity-blocked mean-error scale and were associated with orientation combinations. Such conditions have experimental value because they indicate a need for denser orientation sampling, direct imaging review [5,26,27] or additional physical descriptors.

Retrieval of the highest 20% candidate conditions is shown in Fig. 10(e), and cumulative capture performance is shown in Fig. 10(f). The highest-ranked conditions included 1700/315, 1650/135, 1700/45, 1600/135 and 1650/270. The S_{spatial} values of 1700/315 and 1650/135 were 0.895 and 0.855, respectively, with a difference of 0.040. Relative to the mean S_{spatial} of the Unstable state, 0.609, these two candidates were higher by 0.286 and 0.246, respectively. All five highest-ranked candidates were located at 1600 mm/s or above, indicating that high-instability priority was concentrated at the high-speed end rather than uniformly distributed across the process space. These candidates were not interpreted as forming-quality decisions but as high-instability conditions defined by $\text{Width}(x)$.

High-instability candidate-screening performance is shown in Fig. 10(f), and error differences across held-out speeds and orientations are shown in Fig. 10(d); the orientation-extrapolation boundary should be interpreted together with the LOOO results in Fig. 8. LOVO supported relative-stability navigation along the speed dimension within the observed orientation set, with representative Spearman $\rho = 0.811$ and MAE = 0.086. LOOO indicated that orientation details require direct observation or denser orientation sampling, with three-state balanced accuracy of 0.389, macro F1 of 0.393 and Top 20% precision of 0.143. The map applies only to the 370 W fixed-power setting and the 72 observed velocity–orientation conditions. It is not a general process window, cross-power quality classifier or post hoc quality-decision model.

In practical use, the map provides a priority ranking rather than a final decision. High- S_{spatial} regions correspond to the highest 20% of candidates and are suitable priorities for repeat experiments, denser orientation sampling or raw-image review. Conditions near state boundaries

correspond to the transition region defined by score tertiles and can be used to test whether small parameter perturbations change the stability classification. Large-residual regions should be assessed against the LOVO MAE of 0.086 and the LOOO MAE of 0.154 before deciding whether to add orientation sampling or inspect orientation-sensitive imaging effects. The Width(x)-only map should be treated as a fixed-power stability layer. Its quantitative role is to organize the 72 conditions by Sspatial, prediction error and high-instability priority, not to serve as a final physical model beyond the evidence provided by Width(x).

4. Conclusions

Using path-resolved melt-track width Width(x) from 72 velocity–orientation conditions at a fixed power of 370 W, this study established Sspatial, an empirical composite index combining path geometry, spatial memory and frequency organization for relative comparison among conditions. The Pearson correlation between Mean Width and Width CV was $r = -0.48$, indicating that average width cannot replace local within-path fluctuation information.

Blocked validation defined the applicability boundary: within the observed orientation set, Random forest achieved Spearman $\rho = 0.811$ and MAE = 0.086 under LOVO, whereas ranking and Top 20% retrieval declined substantially when orientations were held out. In SHAP attribution, velocity and linear energy jointly represented one coupled speed–energy process dimension under fixed power, whereas orientation effects were interpreted only as condition-specific modulation within the observed data and not as a causal mechanism.

Accordingly, the map is a fixed-power, Width(x)-only tool for relative ranking and review prioritization of the 72 observed conditions. It is not an absolute stability measure, defect-probability model, quality certificate or cross-power process window. Unobserved orientations, other powers, material systems and independent defect labels require additional data for validation.

References

- [1] Saad A. Khairallah, Andrew T. Anderson, Alexander Rubenchik et al. Laser powder-bed fusion additive manufacturing: Physics of complex melt flow and formation mechanisms of pores, spatter, and denudation zones. *Acta Materialia* 108, 36-45 (2016). 10.1016/j.actamat.2016.02.014
- [2] Jincheng Wang, Rui Zhu, Yujing Liu et al. Understanding melt pool characteristics in laser powder bed fusion: An overview of single- and multi-track melt pools for process optimization. *Advanced Powder Materials* 2(4), 100137 (2023). 10.1016/j.apmate.2023.100137

- [3] Justin P. Miner, Austin Ngo, Christian Gobert et al. Impact of melt pool geometry variability on lack-of-fusion porosity and fatigue life in powder bed fusion-laser beam Ti–6Al–4V. *Additive Manufacturing* 95, 104506 (2024). 10.1016/j.addma.2024.104506
- [4] Luke Scime, Jack Beuth. Melt pool geometry and morphology variability for the Inconel 718 alloy in a laser powder bed fusion additive manufacturing process. *Additive Manufacturing* 29, 100830 (2019). 10.1016/j.addma.2019.100830
- [5] Brian J. Simonds, Jack Tanner, Alexandra Artusio-Glimpse et al. The causal relationship between melt pool geometry and energy absorption measured in real time during laser-based manufacturing. *Applied Materials Today* 23, 101049 (2021). 10.1016/j.apmt.2021.101049
- [6] M Grasso, A Remani, A Dickins et al. In-situ measurement and monitoring methods for metal powder bed fusion: an updated review. *Measurement Science and Technology* 32(11), 112001 (2021). 10.1088/1361-6501/ac0b6b
- [7] Chu Lun Alex Leung, Sebastian Marussi, Robert C. Atwood et al. In situ X-ray imaging of defect and molten pool dynamics in laser additive manufacturing. *Nature Communications* 9(1), 1355 (2018). 10.1038/s41467-018-03734-7
- [8] Aiden A. Martin, Nicholas P. Calta, Saad A. Khairallah et al. Dynamics of pore formation during laser powder bed fusion additive manufacturing. *Nature Communications* 10(1), 1987 (2019). 10.1038/s41467-019-10009-2
- [9] Yuze Huang, Tristan G. Fleming, Samuel J. Clark et al. Keyhole fluctuation and pore formation mechanisms during laser powder bed fusion additive manufacturing. *Nature Communications* 13(1), 1170 (2022). 10.1038/s41467-022-28694-x
- [10] I. Bitharas, N. Parab, C. Zhao et al. The interplay between vapour, liquid, and solid phases in laser powder bed fusion. *Nature Communications* 13(1), 2959 (2022). 10.1038/s41467-022-30667-z
- [11] Lu Wang, Yanming Zhang, Hou Yi Chia et al. Mechanism of keyhole pore formation in metal additive manufacturing. *npj Computational Materials* 8(1), 22 (2022). 10.1038/s41524-022-00699-6
- [12] Minglei Qu, Qilin Guo, Luis I. Escano et al. Controlling process instability for defect lean metal additive manufacturing. *Nature Communications* 13(1), 1079 (2022). 10.1038/s41467-022-28649-2
- [13] Zhongshu Ren, Lin Gao, Samuel J. Clark et al. Machine learning–aided real-time detection of keyhole pore generation in laser powder bed fusion. *Science* 379(6627), 89-94 (2023). 10.1126/science.add4667
- [14] Zackary Snow, Luke Scime, Amirkoushyar Ziabari et al. Observation of spatter-induced stochastic lack-of-fusion in laser powder bed fusion using in situ process monitoring. *Additive Manufacturing* 61, 103298 (2023). 10.1016/j.addma.2022.103298
- [15] Qilin Guo, Cang Zhao, Luis I. Escano et al. Transient dynamics of powder spattering in laser powder bed fusion additive manufacturing process revealed by in-situ high-speed high-energy x-ray imaging. *Acta Materialia* 151, 169-180 (2018). 10.1016/j.actamat.2018.03.036
- [16] S. Mohammad H. Hojjatzadeh, Niranjana D. Parab, Wentao Yan et al. Pore elimination mechanisms during 3D printing of metals. *Nature Communications* 10(1), 3088 (2019). 10.1038/s41467-019-10973-9
- [17] Ziyad Smoqi, Aniruddha Gaikwad, Benjamin Bevans et al. Monitoring and prediction of porosity in laser powder bed fusion using physics-informed meltpool signatures and machine learning. *Journal of Materials Processing Technology* 304, 117550 (2022). 10.1016/j.jmatprotec.2022.117550
- [18] Aniruddha Gaikwad, Richard J. Williams, Harry de Winton et al. Multi phenomena melt pool sensor data fusion for enhanced process monitoring of laser powder bed fusion additive manufacturing. *Materials & Design* 221, 110919 (2022). 10.1016/j.matdes.2022.110919
- [19] Sina Malakpour Estalaki, Cody S. Lough, Robert G. Landers et al. Predicting defects in laser powder bed fusion using in-situ thermal imaging data and machine learning. *Additive Manufacturing* 58, 103008 (2022). 10.1016/j.addma.2022.103008
- [20] Vigneashwara Pandiyan, Giulio Masinelli, Navarre Claire et al. Deep learning-based monitoring of laser powder bed fusion process on variable time-scales using heterogeneous sensing and operando X-ray radiography guidance. *Additive Manufacturing* 58, 103007 (2022). 10.1016/j.addma.2022.103007
- [21] Sanam Gorgannejad, Aiden A. Martin, Jenny W. Nicolino et al. Localized keyhole pore prediction during laser powder bed fusion via multimodal process monitoring and X-ray radiography. *Additive Manufacturing* 78, 103810 (2023). 10.1016/j.addma.2023.103810

- [22] Benjamin Bevens, Christopher Barrett, Thomas Spears et al. Heterogeneous sensor data fusion for multiscale, shape agnostic flaw detection in laser powder bed fusion additive manufacturing. *Virtual and Physical Prototyping* 18(1), e2196266 (2023). 10.1080/17452759.2023.2196266
- [23] Mandaná Moshiri, David Bue Pedersen, Guido Tosello et al. Performance evaluation of in-situ near-infrared melt pool monitoring during laser powder bed fusion. *Virtual and Physical Prototyping* 18(1), e2205387 (2023). 10.1080/17452759.2023.2205387
- [24] Rita Drissi-Daoudi, Vigneashwara Pandiyan, Roland Logé et al. Differentiation of materials and laser powder bed fusion processing regimes from airborne acoustic emission combined with machine learning. *Virtual and Physical Prototyping* 17(2), 181-204 (2022). 10.1080/17452759.2022.2028380
- [25] Vigneashwara Pandiyan, Rafał Wróbel, Christian Leinenbach et al. Optimizing in-situ monitoring for laser powder bed fusion process: Deciphering acoustic emission and sensor sensitivity with explainable machine learning. *Journal of Materials Processing Technology* 321, 118144 (2023). 10.1016/j.jmatprotec.2023.118144
- [26] Rongxuan Wang, David Garcia, Rakesh R. Kamath et al. In situ melt pool measurements for laser powder bed fusion using multi sensing and correlation analysis. *Scientific Reports* 12(1), 13716 (2022). 10.1038/s41598-022-18096-w
- [27] Chaitanya Krishna Prasad Vallabh, Xiayun Zhao. Melt pool temperature measurement and monitoring during laser powder bed fusion based additive manufacturing via single-camera two-wavelength imaging pyrometry (STWIP). *Journal of Manufacturing Processes* 79, 486-500 (2022). 10.1016/j.jmapro.2022.04.058
- [28] Alex Riensche, Benjamin D. Bevens, Ziyad Smoqi et al. Feedforward control of thermal history in laser powder bed fusion: Toward physics-based optimization of processing parameters. *Materials & Design* 224, 111351 (2022). 10.1016/j.matdes.2022.111351
- [29] Vigneashwara Pandiyan, Rita Drissi-Daoudi, Sergey Shevchik et al. Deep transfer learning of additive manufacturing mechanisms across materials in metal-based laser powder bed fusion process. *Journal of Materials Processing Technology* 303, 117531 (2022). 10.1016/j.jmatprotec.2022.117531
- [30] S. Lapointe, G. Guss, Z. Reese et al. Photodiode-based machine learning for optimization of laser powder bed fusion parameters in complex geometries. *Additive Manufacturing* 53, 102687 (2022). 10.1016/j.addma.2022.102687
- [31] Rita Drissi-Daoudi, Giulio Masinelli, Charlotte de Formanoir et al. Acoustic emission for the prediction of processing regimes in Laser Powder Bed Fusion, and the generation of processing maps. *Additive Manufacturing* 67, 103484 (2023). 10.1016/j.addma.2023.103484
- [32] Alisha Bhatt, Yuze Huang, Chu Lun Alex Leung et al. In situ characterisation of surface roughness and its amplification during multilayer single-track laser powder bed fusion additive manufacturing. *Additive Manufacturing* 77, 103809 (2023). 10.1016/j.addma.2023.103809
- [33] Ming Chen, Marco Simonelli, Steven Van Petegem et al. A quantitative study of thermal cycling along the build direction of Ti-6Al-4V produced by laser powder bed fusion. *Materials & Design* 225, 111458 (2023). 10.1016/j.matdes.2022.111458
- [34] M. Strantza, R.K. Ganeriwala, B. Clausen et al. Effect of the scanning strategy on the formation of residual stresses in additively manufactured Ti-6Al-4V. *Additive Manufacturing* 45, 102003 (2021). 10.1016/j.addma.2021.102003
- [35] Ozkan Gokcekaya, Takuya Ishimoto, Shinya Hibino et al. Unique crystallographic texture formation in Inconel 718 by laser powder bed fusion and its effect on mechanical anisotropy. *Acta Materialia* 212, 116876 (2021). 10.1016/j.actamat.2021.116876
- [36] Jinghao Xu, Paraskevas Kontis, Ru Lin Peng et al. Modelling of additive manufacturability of nickel-based superalloys for laser powder bed fusion. *Acta Materialia* 240, 118307 (2022). 10.1016/j.actamat.2022.118307
- [37] Yaasin A. Mayi, Morgan Dal, Patrice Peyre et al. Physical mechanisms of conduction-to-keyhole transition in laser welding and additive manufacturing processes. *Optics & Laser Technology* 158, 108811 (2023). 10.1016/j.optlastec.2022.108811
- [38] Liping Guo, Hongze Wang, Hanjie Liu et al. Understanding keyhole induced-porosities in laser powder bed fusion of aluminum and elimination strategy. *International Journal of Machine Tools and Manufacture* 184, 103977 (2023). 10.1016/j.ijmachtools.2022.103977

- [39] Jiandong Yuan, Qilin Guo, Samuel J. Clark et al. Revealing mechanisms of processing defect mitigation in laser powder bed fusion via shaped beams using high-speed X-ray imaging. *International Journal of Machine Tools and Manufacture* 204, 104232 (2025). 10.1016/j.ijmachtools.2024.104232
- [40] Yanming Zhang, Shiwei Wu, Zixu Guo et al. Defects caused by powder spattering and entrainment in laser powder bed fusion process: High-fidelity modeling of gas, melt pool and powder dynamics. *Acta Materialia* 288, 120816 (2025). 10.1016/j.actamat.2025.120816