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Longitudinal Segmentation and Terminal Classification of WAAM Single Beads from 3D Point Clouds

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Abstract

Longitudinal averaging can conceal transient geometric behaviour at the initiation and termination of wire arc additive manufacturing (WAAM) deposition paths. This study presents an expert-informed and geometry-driven point-cloud based workflow for separating and characterising the START, MID, and END regions of 50 single beads deposited on three physical substrate plates and represented by six partially overlapping point-cloud scans. Before development of the automatic procedure, an expert-informed reference segmentation was established through visual assessment with computational support. Analysis of these reference regions showed systematic nonlinear evolution in START and END and an approximately linear, low-variation MID, providing the empirical basis for a quadratic–linear–quadratic (Q–L–Q) formulation. The automatic Q–L–Q algorithm subsequently determined operational transition coordinates directly from longitudinal width, height, and cross-sectional-area profiles. In the automatic regions, mean area coefficients of variation were 0.346, 0.054, and 0.437 for START, MID, and END, respectively, with MID having the lowest value in all 50 beads. Automatic and expert-transition coordinates showed a combined mean absolute boundary difference of 3.49 mm, reflecting distinct operational definitions rather than absolute segmentation error. After matched-length extraction, START and END remained distinguishable with accuracies of 0.94 under nested leave-one-bead-out validation and 0.96 under leave-one-plate-out validation. The workflow preserves regional geometric information that is obscured by whole-bead averaging. Because development and assessment used the same experimental campaign, the results represent internal rather than external validation.

Keywords: wire arc additive manufacturing; three-dimensional point cloud; longitudinal segmentation; quadratic–linear–quadratic model; bead geometry; terminal classification

1. Introduction

Wire arc additive manufacturing (WAAM) is increasingly used for medium- and large-scale metallic components because it combines high deposition rates with comparatively low equipment cost and efficient material use [1-3]. Reliable process planning nevertheless depends on controlling deposited geometry, since bead width, height, and cross-sectional area influence layer height, overlap, dimensional accuracy, and the stability of subsequent deposition steps [4-6].

Most process–geometry studies summarize a bead using global descriptors or a small number of cross sections, typically relating process parameters to representative bead width, height, or cross-sectional area [4,5,7]. Such descriptors are useful for comparing process settings but can suppress the longitudinal structure of an individual deposition path. WAAM deposition can exhibit transient geometric behaviour outside quasi-steady operating conditions, and local bead geometry may vary substantially along the deposition trajectory. Three-dimensional reconstruction under transient deposition conditions has shown that simplified bead representations may not adequately describe locally varying bead geometry [8]. Temperature evolution and substrate conditions have likewise been shown to affect the geometry of individual deposited beads [6]. The beginning and termination of a bead may therefore contain transient geometric development that is obscured when the complete deposition path is represented by a single global response.

Dense three-dimensional measurements provide a means of preserving this spatial information instead of reducing a complete bead to a small set of representative cross sections. Three-dimensional reconstruction has already been used to describe spatially varying WAAM bead geometry under nonuniform deposition conditions [8]. For longitudinal regional analysis, however, substrate tilt, bead orientation, spatially disconnected measurements, and nonuniform terminal geometry must be handled consistently. Together, these requirements motivate a reproducible operational definition of the gradual START–MID–END transitions that can be applied across specimens and determined from their measured longitudinal geometry.

Existing WAAM studies have established extensive relationships between process parameters and bead geometry and have developed analytical, statistical, and data-driven models for predicting geometric responses [9,10,7]. Other studies have demonstrated relationships among thermal conditions, molten-pool behaviour, deposition conditions, and resulting geometry [6,11]. Nevertheless, bead geometry is still commonly represented by global responses or sparsely sampled cross sections. Comparatively less attention has been given to identifying directly from dense post-process geometry the longitudinal transition from deposition initiation, through a quasi-stationary interval, to termination. Consequently, terminal transients can be averaged together with the central deposition regime, reducing both physical interpretability and the consistency of geometry-based process models.

In this study, START, MID, and END denote functional phases of deposition whose gradual transitions are expressed in the longitudinal bead geometry. The methodology was developed sequentially. A domain expert first established an expert-informed START–MID–END reference structure. Statistical analysis of these regions showed nonlinear geometric evolution in START and END that was better represented by quadratic functions, whereas MID exhibited comparatively stable and approximately linear behaviour. These findings motivated a quadratic–linear–quadratic (Q–L–Q) representation of longitudinal bead geometry. The resulting geometry-driven Q–L–Q algorithm estimates the two internal transition coordinates directly from longitudinal width, height, and cross-sectional-area profiles.

Accordingly, the study addressed four research questions: (i) whether longitudinal bead geometry supports distinct START, MID, and END regimes; (ii) whether regional model comparisons provide an empirical basis for the Q–L–Q formulation; (iii) whether a geometry-driven procedure can produce coherent and robust operational segmentation; and (iv) whether START and END can be distinguished based on their geometric descriptors.

2. Materials and Methods

2.1 Experimental data and point-cloud preprocessing

The dataset was obtained from previous WAAM experiments performed on S355 structural-steel plates measuring 250 mm × 120 mm [7,12]. Single beads with a programmed length of 40 mm were deposited using a 1.2 mm VAC 60 copper-coated welding wire in a Daihen NV8L-NEFC robotic cell. Welding current was varied from 65 to 155 A in 10 A increments and robot travel speed from 20 to 40 cm/min in 5 cm/min increments, forming a 10 × 5 full-factorial design with 50 beads. The specimens were measured after deposition with a Wenglor MLWL 132 laser-profile scanner mounted on a servo-driven linear guide. Successive transverse profiles were acquired at nominal 0.5 mm increments and assembled into six plate-level point clouds. The 50 beads were deposited on three physical substrate plates. Because the scanner field of view did not cover the complete width of each plate, each physical plate was acquired in two partially overlapping scans, yielding six point-cloud datasets in total. The physical plate, rather than the individual scan, was therefore treated as the highest-level experimental grouping factor in plate-clustered analyses. The experimental setup, line-scanner acquisition, deposition order, and division of the three plates into six point-cloud scans are summarised in Figure 1.

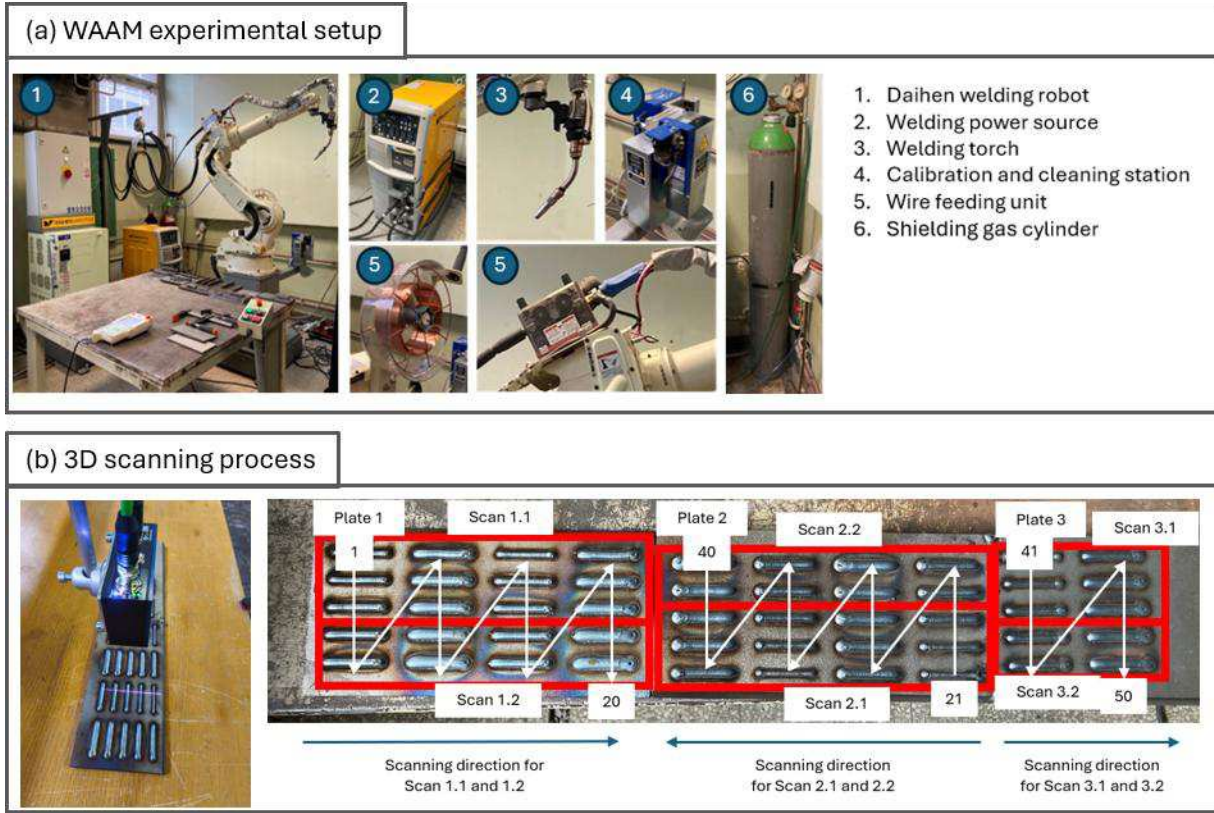


Figure 1. Experimental and data-acquisition setup: (a) WAAM deposition system and its components; and (b) line-scanner acquisition along the Y-axis (left) and the arrangement of 50 sequentially deposited single beads on three plates divided into six point-cloud scans (right). White arrows indicate the deposition order according to the design of experiments (DOE), blue arrows indicate the scanner travel direction, and red rectangles indicate the spatial coverage of the individual scans.

For each bead, manually selected spatial regions defining the analysis area, substrate-plane reference, and bead vicinity were recorded together with the corresponding process-condition metadata. These bead-level spatial ROI definitions, process-condition metadata, and point-cloud acquisition groups are provided in Online Resource 1 (Supplementary Data S1).

A local substrate plane was estimated from points outside the bead using iterative singular-value-decomposition fitting and robust residual rejection. The point cloud was rigidly transformed so that the fitted substrate normal coincided with the vertical axis. Candidate bead points were selected below the corrected plate threshold and inside the manually defined analysis region of interest (ROI). An adaptive longitudinal corridor tracked the continuous bead cluster and rejected disconnected measurements. The adaptive corridor was used to identify the continuous bead path and determine its orientation and longitudinal extent. Final regional metrics were then calculated from the original bead-mask points assigned to the respective START, MID, and END regions.

Principal-component analysis defined a local longitudinal coordinate u and transverse coordinate v . The scanning orientation was fixed across the experiment, and the actual bead initiation was consistently located at the lower transformed Y coordinate. The sign of the first principal axis was therefore constrained so that increasing u corresponded to increasing transformed Y: START occupied the lower- u terminal and END the higher- u terminal. The valid bead was divided into nominally 1 mm intervals along the longitudinal coordinate u . Within each interval, bead width was calculated as the difference between the 99th and 1st percentiles of the transverse coordinate v , reducing sensitivity to isolated edge points. Bead height was determined relative to the corrected substrate-plane reference using the 1st percentile of the measured surface in the scanner orientation. To estimate cross-sectional area, the transverse span

was subdivided into 30 bins. Within each bin, the local depth relative to the substrate reference was estimated from the 5th percentile of the measured surface, and the resulting transverse depth profile was numerically integrated using the trapezoidal rule.

2.2 Expert-informed regional structure

2.2.1 Expert-informed segmentation procedure

Before development of the Q–L–Q algorithm, a domain expert established the reference START–MID–END structure by inspecting the 50 beads within the six point-cloud scans. For each bead, the expert first specified a spatial region of interest enclosing the complete bead and defined the position and dimensions of an initial MID interval. A supporting geometric routine then positioned START and END on either side of MID using standardized rules for regional length, overlap, and sampling-line balancing. The expert reviewed the resulting segmentation against the point-cloud geometry and, where necessary, revised the ROI or MID definition before repeating the procedure. The three regions were finalized after expert acceptance.

This expert-guided process produced consistent regional definitions while retaining human judgement in the final boundary selection. The complete procedure was performed before formulation of the Q–L–Q objective function. Throughout the manuscript, the resulting boundaries are termed the expert-informed reference. They provide an operational interpretation of the gradual START–MID–END process phases and serve as the basis for the initial regional analysis and subsequent comparison with the automatic segmentation.

2.2.2 Analysis of the expert-informed regions

The expert-informed regions were analysed in four stages: regional geometric characterisation, assessment of MID quasi-stationarity, comparison of linear and quadratic models in START and END, and sensitivity to the supporting segmentation settings. This sequence was used to establish the regional geometric pattern before formulation of the automatic Q–L–Q method.

Regional geometric characterisation. For each expert-informed START, MID, and END region, the mean, median, and sample standard deviation were calculated for longitudinal width $W(u)$, height $H(u)$, and cross-sectional area $A(u)$. The corresponding coefficients of variation were used to describe within-region longitudinal variation relative to the mean value of each descriptor.

Assessment of MID quasi-stationarity. The stability of MID was assessed using the slope of a linear model and the relative residual root-mean-square error. For descriptor $X \in \{W, H, A\}$, relative residual RMSE was defined as:

$$\text{rRMSE}_X = \frac{\text{RMSE}_X}{|\bar{X}|},$$

where $\bar{X}$ is the mean unsmoothed slice-level value of descriptor X within MID. Lower rRMSE_X indicates that less variation remains after fitting the linear regional trend.

A MID slope was classified descriptively as near zero when:

$$|b_{M,X}| \leq \tau_X.$$

where $b_{M,X}$ is the slope coefficient of the linear model fitted to descriptor X within the expert-informed MID region. The descriptor-specific thresholds were $\tau_W = 0.02$ mm/mm, $\tau_H = 0.01$ mm/mm, and $\tau_A = 0.10$ mm²/mm. These thresholds provided practical criteria for identifying a near-horizontal MID profile while accounting for the different numerical scales of the three descriptors. Over the mean MID length of approximately 26 mm, they correspond to maximum linear changes of approximately 0.52 mm in width, 0.26 mm in height, and 2.6 mm² in cross-sectional area.

Linear–quadratic model comparison in START and END. Linear and quadratic models were fitted separately to $W(u)$, $H(u)$, and $A(u)$ within each expert-informed terminal region. Model performance was compared using adjusted R^2 , RMSE, and the small-sample corrected Akaike information criterion (AICc). The improvement in adjusted R^2 was calculated as:

$$\Delta R_{\text{adj}}^2 = R_{\text{adj,quadratic}}^2 - R_{\text{adj,linear}}^2,$$

and the relative reduction in RMSE as:

$$\text{RMSE}_{\text{reduction}}(\%) = 100 \left(1 - \frac{\text{RMSE}_{\text{quadratic}}}{\text{RMSE}_{\text{linear}}} \right).$$

AICc was calculated as:

$$\text{AICc} = n \ln \left(\frac{\text{RSS}}{n} \right) + 2k + \frac{2k(k+1)}{n-k-1},$$

where $\text{RSS} = \sum_{i=1}^n (X_i - \hat{X}_i)^2$ is the residual sum of squares, X_i is the measured descriptor value, $\hat{X}_i$ is the corresponding value predicted by the fitted model, n is the number of observations in the analysed region, and k is the number of fitted regression coefficients ($k = 2$ for the linear model and $k = 3$ for the quadratic model).

Model preference was summarized as:

$$\Delta \text{AICc} = \text{AICc}_{\text{linear}} - \text{AICc}_{\text{quadratic}}$$

Positive values of ΔR_{adj}^2 , RMSE reduction, and ΔAICc indicate preference for the quadratic model.

Sensitivity of the expert-informed regional structure. The robustness of the regional pattern was additionally evaluated across nine supporting segmentation configurations. These configurations varied the central and terminal lengths, intrusion distances, and sampling-line balancing. For each configuration, the regional ordering of within-region longitudinal variation was recalculated to assess its consistency across plausible variations of the supporting segmentation geometry.

The combined evidence of nonlinear terminal evolution and comparatively stable, approximately linear MID behaviour provided the empirical basis for selecting the quadratic–linear–quadratic structure subsequently implemented in the automatic segmentation method.

2.3 Automatic Q–L–Q segmentation

2.3.1 Q–L–Q algorithm

The automatic method retained the valid outer bead extent established by the expert-informed reference. Within this extent, the two internal transition coordinates were estimated independently by evaluating all admissible START–MID–END partitions using an objective function that combines regional model fit, continuity at the transitions, and a penalty for an excessively short MID region. For transition-coordinate estimation, the longitudinal width $W(u)$, height $H(u)$, and cross-sectional-area $A(u)$ profiles were smoothed using a three-slice moving median. All reported regional characteristics were calculated from the original unsmoothed slice values. The unsmoothed slice-level width, height, and cross-sectional-area profiles, the corresponding moving-median profiles used for transition-coordinate estimation, and the automatic START–MID–END assignments are provided in Online Resource 2 (Supplementary Data S2). For each admissible transition-coordinate pair $u_1 < u_2$, each descriptor $X \in \{W, H, A\}$ was represented by a quadratic polynomial in START, a linear polynomial in MID, and a quadratic polynomial in END:

$$\begin{aligned} X_S(u) &= a_S + b_S u + c_S u^2, \\ X_M(u) &= a_M + b_M u, \end{aligned} \tag{1}$$

$$X_E(u) = a_E + b_E u + c_E u^2.$$

For the *regional model-fit term*, the coefficients of the Q–L–Q model in Eq. (1) were estimated independently by least squares. For descriptor X , the residual contribution was obtained by summing the residual sums of squares across the three regions and normalizing the result by the number n of valid slices and the robust scale s_X^2 :

$$\text{RSS}_X = \text{RSS}_{X,S} + \text{RSS}_{X,M} + \text{RSS}_{X,E},$$

$$J_X = \frac{\text{RSS}_X}{n s_X^2},$$

$$s_X = 1.4826 \text{ median}(|X - \text{median}(X)|).$$

Here, s_X is the scaled median absolute deviation of the smoothed descriptor profile. The factor 1.4826 provides consistency with the standard deviation under a normal distribution. If s_X was numerically degenerate, the sample standard deviation of X was used. The combined model-fit term emphasized height and cross-sectional area while retaining width as a complementary descriptor:

$$J_{\text{fit}} = 0.20J_W + 1.00J_H + 1.00J_A$$

The weights assigned to width, height, and cross-sectional area were 0.20, 1.00, and 1.00, respectively. The contribution of each geometric descriptor to transition-coordinate estimation was examined using leave-one-descriptor-out ablation. Each descriptor was omitted in turn, the transition coordinates were re-estimated, and the resulting solution was evaluated using the complete three-descriptor objective function.

The *transition-continuity term* promoted agreement between the fitted values of adjacent regional models at u_1 and u_2 , while allowing their slopes to differ. For descriptor X , the normalized fitted-value mismatches were defined as:

$$d_{X,1} = \frac{\hat{X}_S(u_1) - \hat{X}_M(u_1)}{s_X},$$

$$d_{X,2} = \frac{\hat{X}_M(u_2) - \hat{X}_E(u_2)}{s_X}.$$

Here, $\hat{X}_S(u)$, $\hat{X}_M(u)$, and $\hat{X}_E(u)$ denote the values predicted by the fitted START, MID, and END models, respectively. The descriptor-specific continuity contribution was:

$$C_X = d_{X,1}^2 + d_{X,2}^2.$$

The contributions of the three descriptors were combined using the same relative weights as the regional model-fit term:

$$J_{\text{continuity}} = 0.20C_W + 1.00C_H + 1.00C_A.$$

The *short-MID penalty* favored partitions containing a sufficiently developed central region. Admissible transition-coordinate pairs were required to retain at least five slices in START, ten slices in MID, and five slices in END. Let f_M denote the fraction of the analysed bead extent assigned to MID. To discourage solutions in which MID remained close to its minimum admissible length, a gradually increasing penalty was applied when $f_M < 0.25$:

$$J_{\text{length}} = \begin{cases} (0.25 - f_M)^2, & f_M < 0.25, \\ 0, & f_M \geq 0.25. \end{cases}$$

The complete objective function combined regional fit, fitted-value continuity, and the short-MID penalty:

$$J(u_1, u_2) = J_{\text{fit}} + 0.20J_{\text{continuity}} + 0.10J_{\text{length}} \quad (2)$$

The coefficients 0.20 and 0.10 were selected as regularization weights to preserve regional model fit as the primary criterion, while assigning secondary influence on fitted-value continuity and a weaker influence on MID length. Their influence was subsequently assessed by varying the continuity weight and removing the short-MID penalty in the sensitivity analysis.

The selected operational transition coordinates u_1^* , u_2^* were the admissible pair that minimized the complete objective function in Eq. (2):

$$(u_1^*, u_2^*) = \arg \min_{(u_1, u_2) \in \Omega} J(u_1, u_2) \quad (3)$$

In Eq. (3), Ω denotes the set of all admissible transition-coordinate pairs satisfying $u_1 < u_2$, the minimum regional slice-count requirements, and the requirement that both transition coordinates coincide with discrete slice-centre positions. Every pair in Ω was evaluated by exhaustive search, and the pair with the lowest objective-function value defined the final START, MID, and END assignment.

Figure 2 illustrates a representative automatic segmentation together with the corresponding expert-informed reference boundaries.

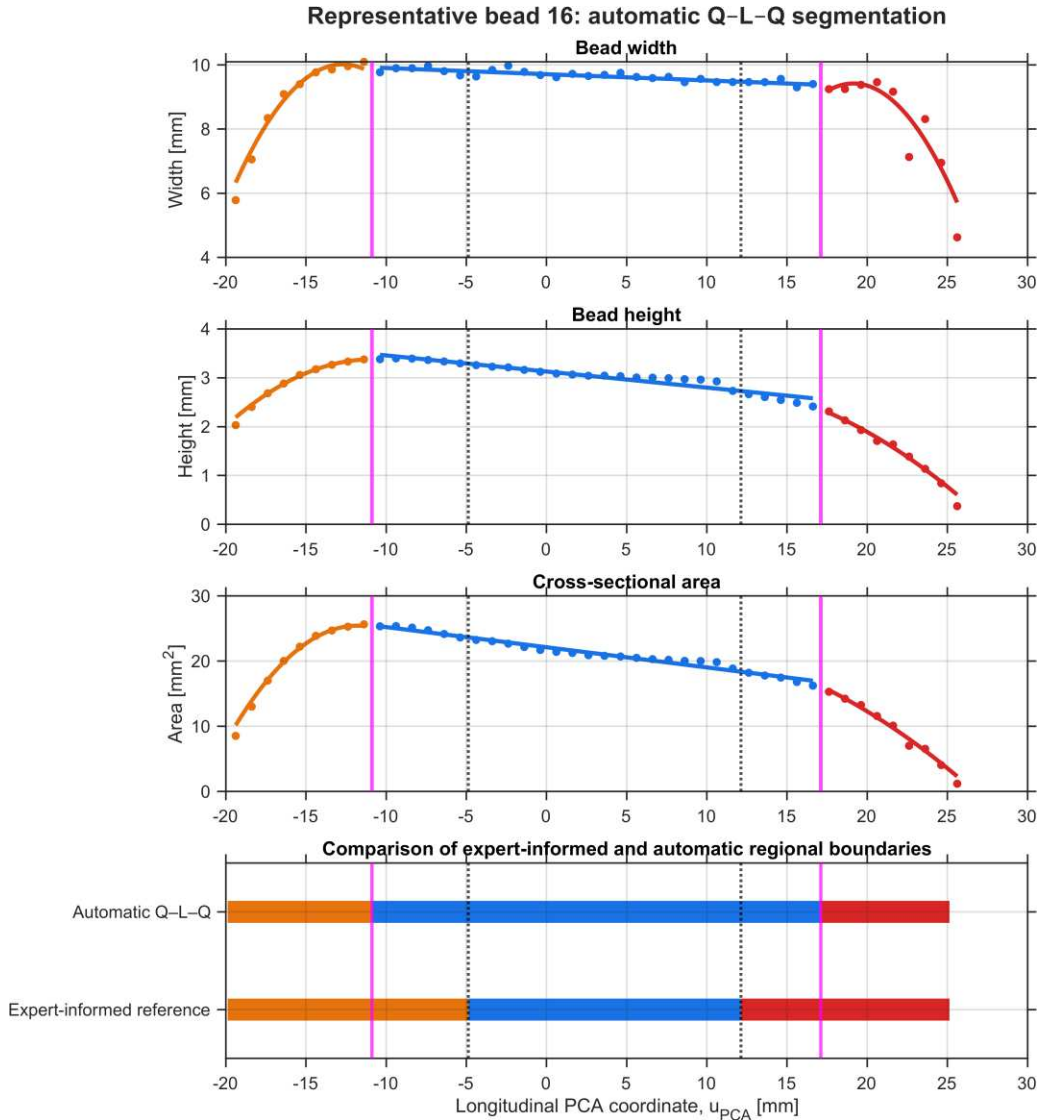


Figure 2. Representative automatic Q-L-Q segmentation of bead 16 based on longitudinal width, height, and cross-sectional-area profiles. Points show slice-wise measurements, while coloured curves show the fitted

quadratic START, linear MID, and quadratic END models. Magenta vertical lines indicate the automatically determined boundaries, and black dotted lines indicate the expert-informed reference boundaries. The lower panel compares the corresponding regional definitions over the same valid global bead extent.

2.3.2 Evaluation of automatic Q–L–Q segmentation

Automatic Q–L–Q segmentation was evaluated from four complementary perspectives: regional geometric coherence, paired regional differences, correspondence with the expert-informed transition coordinates, and sensitivity to algorithm settings. These analyses assessed, respectively, the geometric structure of the identified regions, the statistical contrast between MID and the terminal regions, the correspondence between the two operational transition definitions, and the robustness of the segmentation to changes in algorithm parameters.

Regional geometric coherence analysis examined whether the automatically identified regions exhibited a comparatively stable MID interval between two longitudinally evolving terminal regions. For each region, the mean, median, and sample standard deviation were calculated for width, height, and cross-sectional area using the original unsmoothed slice-level values. The coefficient of variation of cross-sectional area, CV_A , was used as the primary measure of within-region longitudinal variation:

$$CV_A = \frac{s_A}{\bar{A}},$$

where $\bar{A}$ and s_A are the mean and sample standard deviation, respectively, of the cross-sectional-area values within the region. Because CV_A was calculated from the original slice-level values, it captures both systematic longitudinal evolution and local geometric fluctuations. Relative residual RMSE was additionally used to describe the variation remaining after fitting the corresponding regional trend model. Regional mean width, height, and cross-sectional area were treated as secondary geometric outcomes.

Paired regional comparisons analysis quantified whether within-region longitudinal area variation differed systematically between MID and each terminal region across the 50 beads. For bead i and terminal region $R \in \{\text{START}, \text{END}\}$, the paired difference was defined as:

$$d_{i,R} = CV_{A,R,i} - CV_{A,MID,i}.$$

Positive values therefore indicate greater longitudinal area variation in the terminal region than in MID. Each comparison was summarized using the mean paired difference $\bar{d}_R$, a 10,000-resample paired-bootstrap confidence interval, an exact two-sided sign test, and the standardized paired effect size Cohen's $d_z = \bar{d}_R / s_{d,R}$, where $s_{d,R}$ is the sample standard deviation of the bead-level paired differences. Holm correction was applied to the START–MID and END–MID comparisons.

Because multiple beads were deposited sequentially on the same physical substrate plate, the paired regional comparisons were additionally assessed using a physical-plate cluster bootstrap. The three plates were resampled with replacement, with all beads from each selected plate retained as a single cluster. This analysis assessed the robustness of the regional differences to within-plate dependence and was interpreted as a sensitivity analysis because three physical plates were available.

Comparison with the expert-informed transition coordinates analysis quantified the correspondence between the automatic and expert-informed operational definitions of the gradual regional transitions. For bead i and transition j , the signed coordinate difference was defined as:

$$\Delta u_{i,j} = u_{i,j}^{\text{auto}} - u_{i,j}^{\text{ref}},$$

where $j = 1$ denotes the START–MID transition and $j = 2$ the MID–END transition. Positive values indicate displacement of the automatic transition estimate towards increasing u . The mean absolute boundary difference (MABD), defined in Eq. (4), was calculated across both transition coordinates of all N beads:

$$\text{MABD} = \frac{1}{2N} \sum_{i=1}^N \sum_{j=1}^2 |\Delta u_{i,j}|. \quad (4)$$

The corresponding root-mean-square boundary difference (RMSBD), defined in Eq. (5), was calculated as:

$$\text{RMSBD} = \sqrt{\frac{1}{2N} \sum_{i=1}^N \sum_{j=1}^2 (\Delta u_{i,j})^2}. \quad (5)$$

Tolerance-based agreement was defined as the number of beads for which both automatic transition estimates were within a specified distance of the corresponding expert-informed coordinates. Together, the signed differences, MABD, RMSBD, and tolerance-based agreement describe the correspondence between the two operational transition definitions.

Sensitivity to algorithm settings. This analysis assessed the stability of the automatic transition estimates and the resulting regional structure when selected algorithm settings were varied. A one-factor-at-a-time design was used to examine minimum terminal length, minimum MID length, the continuity weight, the short-MID penalty, and the moving-median window. For smoothing, the default three-slice window was compared with no smoothing and a five-slice window.

For each configuration, four outcomes were recorded: the proportion of beads producing an admissible solution, the absolute displacement of each transition coordinate relative to the default configuration, the mean MID length, and the fraction of beads in which MID retained the lowest CV_A . For bead i and transition j , the absolute displacement was defined as:

$$\delta_{i,j} = |u_{i,j}^{\text{test}} - u_{i,j}^{\text{default}}|,$$

where $j = 1$ denotes the START–MID transition and $j = 2$ the MID–END transition. Together, these outcomes evaluated computational feasibility, boundary stability, stability of the resulting MID extent, and preservation of the regional variation pattern.

2.4 Position-independent START–END classification

START–END classification was developed to determine whether the automatically identified terminal regions could be distinguished from their geometric characteristics without using positional information. The procedure comprised two parts: development and validation of a paired classification model, followed by statistical and diagnostic analyses of the resulting discrimination.

2.4.1 Paired classification model and validation

Terminal candidates and predictors. Each bead contributed two terminal candidates located at opposite ends of its longitudinal axis. The experimentally verified deposition direction identified the terminal at the lower longitudinal coordinate u as START and the opposite terminal as END. This information was used to assign the reference labels.

Each candidate was represented by the mean, median, sample standard deviation, and coefficient of variation of width, height, and cross-sectional area, yielding 12 geometric predictors. Classification was based on the paired predictor difference:

$$D_i = X_{\text{START},i} - X_{\text{END},i},$$

where $X_{\text{START},i}$ and $X_{\text{END},i}$ contain the 12 predictor values for bead i . This paired formulation directly describes the geometric contrast between the two terminals of the same bead.

Classification model. A logistic regression model with L2 ridge regularization was fitted to the paired geometric differences. Each training difference D_i was included together with its sign-reversed counterpart $-D_i$ and the corresponding opposite label. This symmetric construction made the model independent of the order in which the two candidates were presented.

Within every training fold, missing predictor values were replaced by training-set medians and the predictors were standardized using training-set means and standard deviations. The ridge parameter λ was selected from 17 logarithmically spaced values between 10^{-4} and 10^4 . Selection was performed in an inner validation loop using logistic loss. Model coefficients were estimated by Newton iteration. Ridge regularization was used to stabilize the coefficients in the presence of correlated geometric predictors and the available sample size.

Validation. Two outer validation schemes were used. Nested leave-one-bead-out (LOBO) validation held out both terminal candidates of one bead, selected λ using the remaining beads, fitted the model, and then classified the held-out pair. This procedure was repeated until every bead had served once as the test observation.

Leave-one-plate-out validation held out all beads deposited on one of the three physical plates and fitted the model using beads from the remaining plates. This evaluation tested whether the learned geometric distinction transferred to a physical substrate plate excluded from model training. In both validation schemes, pair accuracy was defined as the proportion of beads for which START and END were both assigned correctly. Wilson 95% confidence intervals were calculated for pair accuracy.

2.4.2 Statistical and diagnostic evaluation

Classification performance was further examined using four complementary analyses: permutation testing, feature-family ablation, a region-size control, and a matched-length control. These analyses evaluated statistical evidence, the contribution of individual descriptor families, the information contained in unequal terminal sizes, and geometric discrimination over equal physical lengths.

Permutation testing. A paired permutation test assessed whether the observed classification accuracy exceeded the accuracy expected under random START–END assignment. In each of 2,000 permutations, the START and END labels were randomly retained or exchanged within every bead pair. The geometric data therefore remained unchanged while their association with terminal orientation was randomized. LOBO classification was repeated for every permutation. For each analysis – original-length or matched-length – a fixed ridge parameter selected from the corresponding non-permuted dataset was used for both the observed and permuted classification statistics. The permutation p -value was calculated as the proportion of permutations producing an accuracy equal to or greater than the observed accuracy.

Feature-family ablation. Nested LOBO validation was repeated using width, height, cross-sectional area, and all combinations of these descriptor families. Training-fold imputation, standardization, and selection of λ were repeated for every feature set. Comparing the resulting accuracies showed which geometric descriptor families contributed most strongly to START–END discrimination.

Region-size control. A separate diagnostic model used only the difference in the number of slices between the two terminal regions. This analysis measured how much START–END information was contained in unequal region sizes. Its result motivated the matched-length analysis, in which both candidates were evaluated over the same physical span.

Matched-length control. For each bead, the START and END profiles were oriented from their respective outer bead edges towards MID. The common range of slice-centre distances covered by both candidates was retained, providing equal physical spans for the two terminals. Width, height, and cross-sectional area were linearly interpolated at 20 equally spaced positions within this common span. The same 12

geometric predictors were then recalculated from the interpolated profiles, while the matched span itself was excluded from the predictor set.

The matched-length dataset was evaluated using nested LOBO and leave-one-plate-out validation. Permutation testing and feature-family ablation were repeated using the same procedures as for the complete terminal regions. The calculation was additionally performed using 10 and 30 interpolation points. This sensitivity analysis examined whether the classification result depended on interpolation-grid density. Together, these controls tested whether START and END remained geometrically distinguishable after the influence of unequal terminal length had been removed.

2.5 Use of generative AI-assisted tools

ChatGPT (OpenAI) was used during manuscript preparation for language editing, refinement of manuscript structure and wording, and assistance with code development and debugging. All AI-assisted outputs were reviewed and verified by the authors, who take full responsibility for the content of the manuscript.

3. Results

3.1 Geometric evidence from the expert-informed regions

The expert-informed regional structure was evaluated through regional geometric characterisation, assessment of MID quasi-stationarity, linear–quadratic model comparison in START and END, and sensitivity to the supporting segmentation settings.

Regional geometric characterisation. MID had the lowest cross-sectional-area coefficient of variation in all 50 beads. Its mean CV_A was 0.040 (median 0.030), compared with 0.319 in START and 0.369 in END. The mean paired differences relative to MID were 0.279 for START and 0.329 for END.

Assessment of MID quasi-stationarity. Linear fits within the expert-informed MID showed low residual errors and small longitudinal slopes. Mean rRMSE values were 0.0191 for width, 0.0196 for height, and 0.0269 for cross-sectional area, corresponding to 1.91%, 1.96%, and 2.69%, respectively. Mean absolute slopes were 0.0110 mm mm⁻¹ for width, 0.0063 mm mm⁻¹ for height, and 0.0501 mm² mm⁻¹ for cross-sectional area. The descriptor-specific near-zero-slope criterion was satisfied by 42/50 beads (0.84) for width, 39/50 (0.78) for height, and 43/50 (0.86) for cross-sectional area. Mean linear R^2 values were 0.231, 0.342, and 0.392, respectively. The low CV_A , small slopes, and low residual errors consistently characterised MID as a comparatively stable and approximately linear region.

Linear–quadratic model comparison in START and END. Quadratic models improved the representation of longitudinal geometry in both terminal regions. Improvements were observed in adjusted R^2 , relative RMSE, and AICc, with the strongest and most consistent gains for height and cross-sectional area. The descriptor-specific results are summarised in Table 1.

Table 1. Improvement of quadratic over linear models in the expert-informed terminal regions.

Region / descriptor	Mean ΔR^2_{adj}	Mean RMSE reduction (%)	$\Delta R^2_{\text{adj}} > 0, n/50$	Median ΔAICc
START width	0.416	38.0 %	49/50	10.57
START height	0.538	63.0 %	50/50	26.14
START area	0.595	61.9 %	50/50	25.05

Region / descriptor	Mean ΔR^2_{adj}	Mean RMSE reduction (%)	$\Delta R^2_{\text{adj}} > 0, n/50$	Median ΔAICc
END width	0.360	27.7 %	46/50	3.70
END height	0.397	55.7 %	50/50	17.75
END area	0.433	53.7 %	50/50	17.98

The $\Delta R^2_{\text{adj}} > 0$ column reports the number of beads for which the quadratic model achieved a higher adjusted R^2 than the linear model. Positive ΔAICc values indicate preference for the quadratic model, while RMSE reduction is expressed relative to the linear-model RMSE. Adjusted R^2 favoured the quadratic model for height and cross-sectional area in every bead. Width also showed a systematic nonlinear pattern, although the evidence was weaker, particularly in END.

Median ΔAICc values were 10.57, 26.14, and 25.05 for START width, height, and cross-sectional area, respectively. The corresponding values for END were 3.70, 17.75, and 17.98. Together, the adjusted R^2 , RMSE, and AICc results demonstrate systematic terminal curvature and provide the empirical basis for the Q–L–Q formulation. The bead-level improvements in adjusted R^2 and relative RMSE are shown in Figure 3.

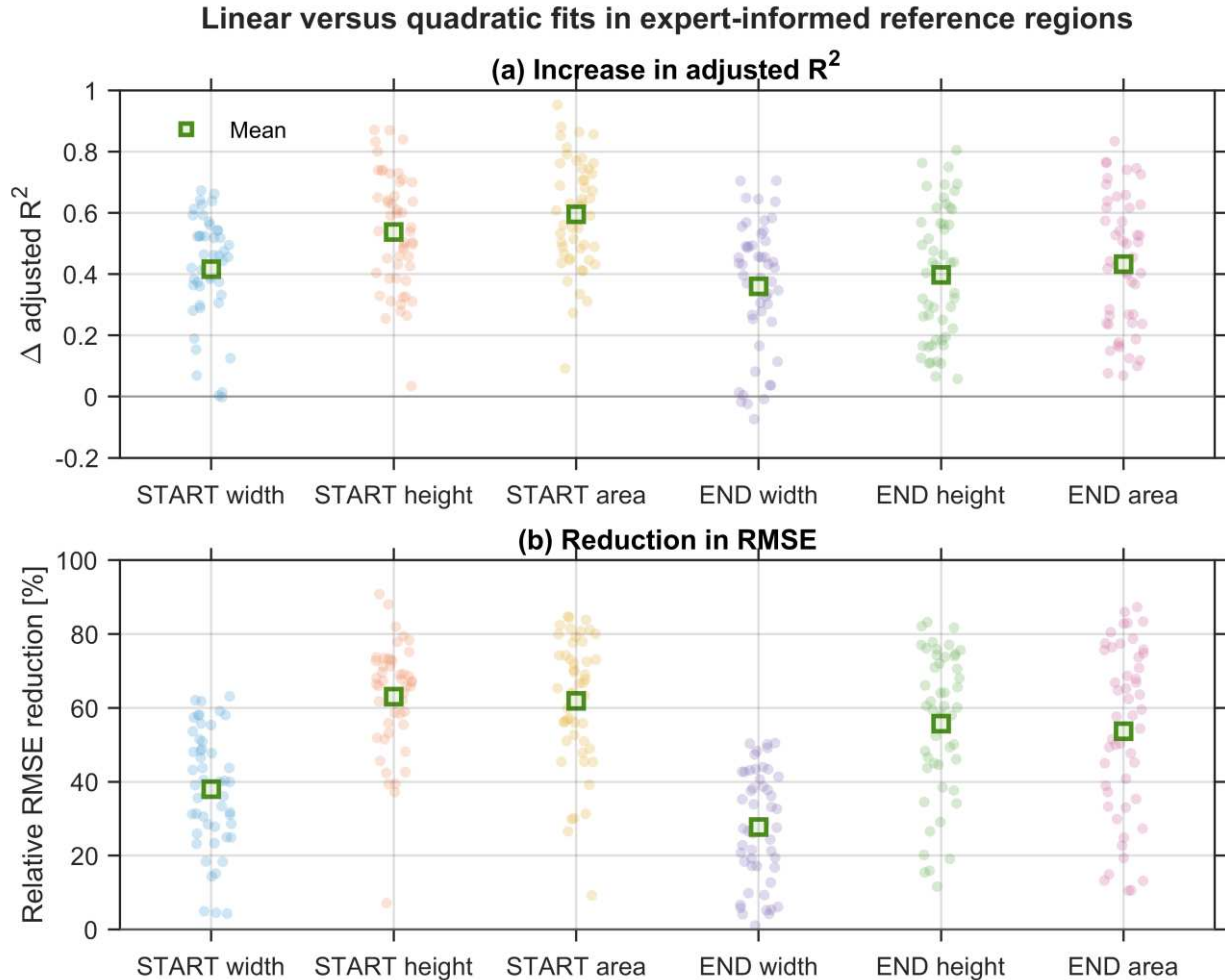


Figure 3. Comparison of linear and quadratic longitudinal models within the expert-informed START and END reference regions. Individual points represent the 50 beads, and green squares indicate group means. Panel (a) shows the increase in adjusted R^2 obtained with the quadratic model, and panel (b) shows the corresponding relative reduction in RMSE. Positive values favour the quadratic model.

Sensitivity of the expert-informed regional structure. The regional variation pattern remained consistent across all nine supporting segmentation configurations. Mean MID CV_A ranged from 0.031 to 0.077, compared with 0.298–0.401 in START and 0.332–0.416 in END. MID retained the lowest mean CV_A in every configuration. The finding of lower longitudinal area variation in MID was therefore consistent across the tested central and terminal lengths, intrusion distances, and sampling-line-balancing settings.

3.2 Evaluation of the automatic Q–L–Q segmentation

The automatic Q–L–Q segmentation was evaluated through regional geometric coherence, paired regional comparisons, correspondence with the expert-informed transition coordinates, descriptor ablation, and sensitivity to algorithm settings.

Regional geometric coherence. The exhaustive search returned an admissible START–MID–END segmentation for all 50 beads. The regional geometric descriptors calculated from the original unsmoothed slice values are summarised in Table 2.

Table 2. Regional geometric descriptors from automatic Q–L–Q segmentation (n = 50 beads).

Region	Mean width (mm)	Mean height (mm)	Mean area (mm ²)	Mean CV_A
START	5.644	2.016	9.059	0.346
MID	5.899	2.023	9.010	0.054
END	5.923	1.745	7.785	0.437

MID had the lowest cross-sectional-area coefficient of variation CV_A in every bead. Its profiles also showed small residual errors and predominantly near-zero longitudinal slopes. The near-zero-slope criterion was satisfied by 46/50 beads (0.92) for width, 39/50 (0.78) for height, and 43/50 (0.86) for cross-sectional area. Mean rRMSE values were 0.019, 0.029, and 0.036 for width, height, and cross-sectional area, respectively. The regional distributions of mean width, mean height, mean cross-sectional area, and CV_A are shown in Figure 4.

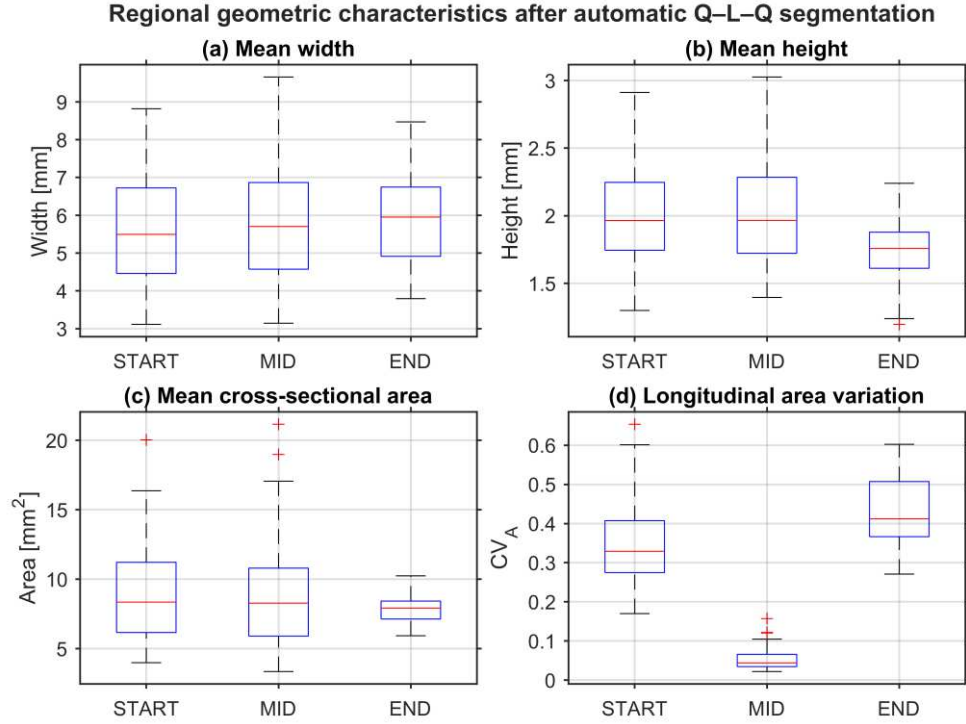


Figure 4. Regional geometric characteristics obtained using automatic Q–L–Q segmentation: (a) mean width, (b) mean height, (c) mean cross-sectional area, and (d) within-region longitudinal area variation expressed by CV_A . Each boxplot summarises the corresponding bead-level regional values for 50 beads. Red lines indicate medians, boxes represent the interquartile range, whiskers show the non-outlier range, and crosses denote outliers.

Paired regional comparisons. The mean paired START–MID difference in CV_A was 0.292, with a 95% bead-level bootstrap confidence interval of [0.270, 0.315] and Cohen's $d_z = 3.52$. The corresponding END–MID difference was 0.383, with a 95% confidence interval of [0.361, 0.406] and $d_z = 4.65$. The exact two-sided sign-test p -value was 1.78×10^{-15} for both comparisons, and both remained significant after Holm correction. Median CV_A ratios were 6.89 for START/MID and 8.92 for END/MID.

The physical-plate cluster bootstrap produced the same regional ordering. For the START–MID comparison, the observed mean paired difference was 0.292, and the cluster-bootstrap 95% confidence interval was [0.277, 0.321]. For the END–MID comparison, the corresponding values were 0.383 and [0.337, 0.426]. Both contrasts were positive on each of the three physical plates and in all cluster-bootstrap resamples. The lower longitudinal area variation in MID was therefore retained when physical plates were used as the resampling units.

Correspondence with the expert-informed transition coordinates. Relative to the expert-informed reference, the automatic START–MID transition showed a mean signed displacement of -2.63 mm towards decreasing u . The automatic MID–END transition showed a mean signed displacement of $+3.98$ mm towards increasing u . Across both transition coordinates and all 50 beads, MABD was 3.49 mm and RMSBD was 4.04 mm. Both automatic transition coordinates were within ± 2 mm of their corresponding expert-informed coordinates in 2/50 beads.

Descriptor contribution. Leave-one-descriptor-out ablation identified cross-sectional area as the strongest contributor to transition-coordinate estimation. Removing cross-sectional area increased the complete objective function by a mean of 0.706 and shifted the two transition coordinates by a mean of 1.47 mm. Cross-sectional area produced a positive contribution in 37/50 beads and accounted for 55.4% of the total mean ablation contribution.

Removing height increased the complete objective function by a mean of 0.306 and produced a mean boundary shift of 0.70 mm. Height contributed positively in 30/50 beads and accounted for 24.0% of the total mean contribution. Removing width increased the complete objective function by a mean of 0.263 and produced a mean boundary shift of 1.11 mm. Width contributed positively in 27/50 beads and accounted for 20.6% of the total mean contribution. Cross-sectional area showed the clearest overall contribution, while width and height showed smaller and more similar effects.

Sensitivity to algorithm settings. All ten tested Q–L–Q configurations produced admissible solutions for all 50 beads, and MID retained the lowest CV_A in every configuration. Changes in minimum regional lengths, continuity weight, and the short-MID penalty produced few or no changes in the selected transition coordinates. Alternative smoothing settings had the greatest influence on exact boundary position.

Relative to the default three-slice moving median, removing smoothing changed at least one transition coordinate in 44/50 beads, while the five-slice window changed at least one coordinate in 47/50 beads. The median absolute boundary displacement was 1 mm for both alternative settings. Without smoothing, the maximum displacement was 8 mm; 9/50 beads exceeded 2 mm, 4/50 exceeded 5 mm, and none exceeded 10 mm. With the five-slice window, the maximum displacement was 20 mm; 5/50 beads exceeded 2 mm, 3/50 exceeded 5 mm, and 2/50 exceeded 10 mm. The boundary-displacement distributions and the corresponding MID outcomes are shown in Figure 5.

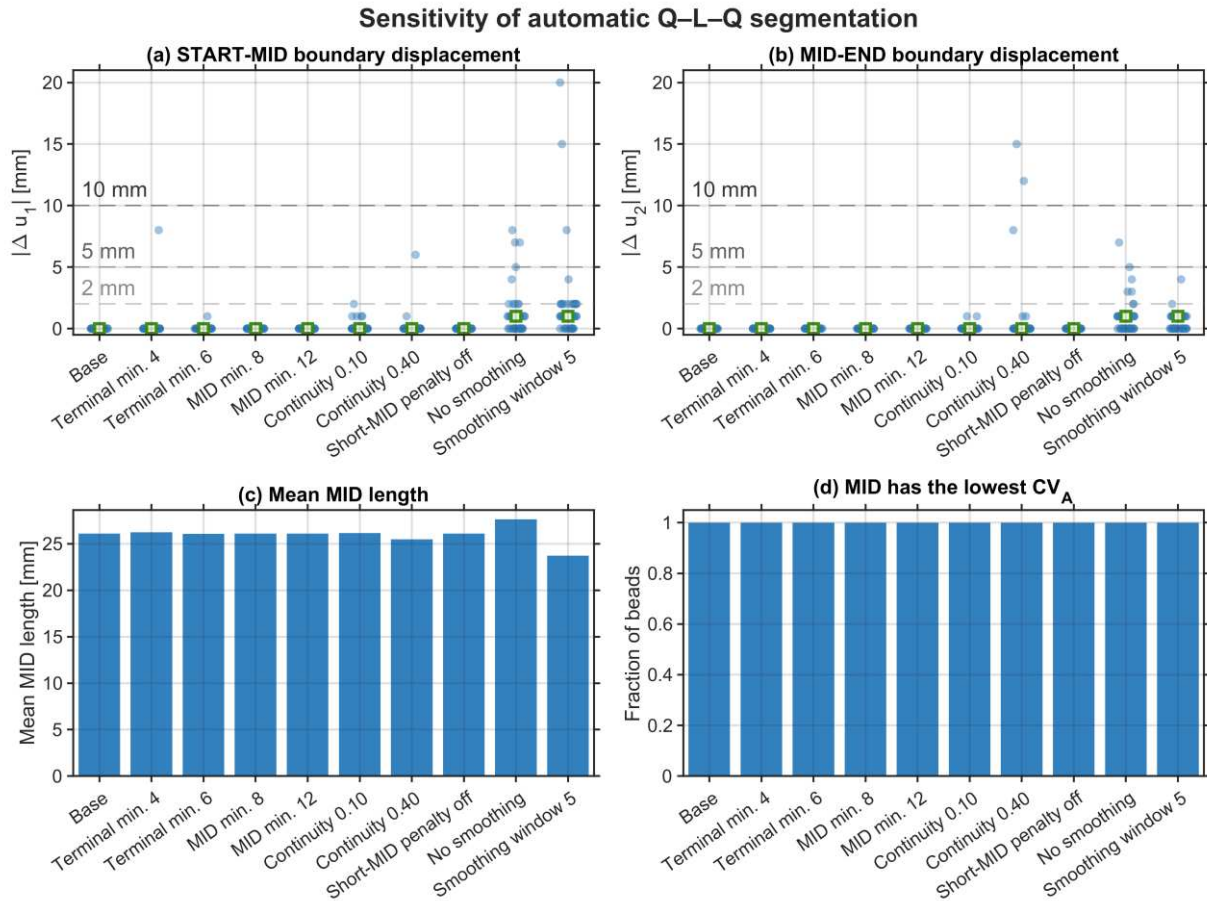


Figure 5. One-factor-at-a-time sensitivity of automatic Q–L–Q segmentation within the tested parameter ranges. Panels (a) and (b) show absolute START–MID and MID–END boundary displacements relative to the default configuration for individual beads; green squares indicate medians, and dashed lines denote displacement thresholds of 2, 5, and 10 mm. Panel (c) shows the mean MID length, and panel (d) shows the fraction of beads for which MID retained the lowest CV_A . Exact boundaries changed most frequently under alternative smoothing

settings, whereas large displacements occurred only in a limited subset and MID retained the lowest CV_A in every tested configuration.

3.3 Geometric discrimination between START and END

START–END classification was evaluated through overall classification performance, permutation testing, descriptor-family ablation, a region-size control, and a matched-length control.

Classification performance. Classification results for the original and matched-length terminal regions are summarised in Table 3.

Table 3. Pairwise START–END classification performance.

Analysis	Nested LOBO accuracy	Leave-one-plate-out accuracy	Permutation p -value
Original unequal-length regions	1.00	1.00	0.0005
Matched-length regions	0.94	0.96	0.0005

LOBO denotes leave-one-bead-out validation. Accuracy represents the proportion of bead pairs for which both terminal labels were assigned correctly. Leave-one-plate-out validation held out all bead pairs deposited on one of the three physical plates.

Using the original unequal-length terminal regions, nested LOBO and leave-one-plate-out validation both classified all 50 bead pairs correctly. Both validation schemes therefore achieved an accuracy of 1.00 (50/50; Wilson 95% CI [0.929, 1.000]).

Permutation testing. The paired permutation test yielded $p = 0.0005$ for the original unequal-length terminal regions. The matched-length analysis also yielded $p = 0.0005$. In both analyses, the observed classification accuracy exceeded the accuracies obtained after random within-pair exchanges of the START and END labels.

Descriptor-family ablation. For the original terminal regions, nested LOBO accuracy was 0.82 using width descriptors alone, 0.86 using height alone, and 0.78 using cross-sectional area alone. Width combined with height and width combined with cross-sectional area both achieved an accuracy of 1.00. Height combined with cross-sectional area achieved 0.94.

For the matched-length terminal regions, width descriptors alone achieved a nested LOBO accuracy of 0.94 (47/50). Width combined with cross-sectional area produced the highest accuracy of 0.96 (48/50). Height alone achieved 0.68 (34/50), cross-sectional area alone achieved 0.72 (36/50), and the complete 12-predictor model achieved 0.94 (47/50). The matched-length results show that the statistical descriptors of width, supplemented by those of cross-sectional area, provided most of the information used to distinguish START from END.

Region-size control. Classification using terminal region size alone achieved an accuracy of 0.84 (42/50). Differences in terminal slice counts therefore contained substantial information about the START–END labels, although slice count and region length were excluded from the geometric classifier.

Matched-length control. After equal physical spans had been extracted from both terminal candidates and all geometric predictors had been recalculated, nested LOBO accuracy was 0.94 (47/50; Wilson 95% CI [0.838, 0.979]). Leave-one-plate-out accuracy was 0.96 (48/50; Wilson 95% CI [0.865, 0.989]). START and END therefore remained distinguishable from their geometric characteristics after the analysed terminal lengths had been equalised.

Interpolation-grid sensitivity. Classification accuracy remained between 0.94 and 0.96 when the matched terminal profiles were interpolated using 10, 20, and 30 points. Classification performance was therefore consistent across the tested interpolation-grid densities.

4. Discussion

4.1 Interpretation of the expert-informed regional structure

The expert-informed analysis established the geometric basis for the START–MID–END representation before formulation of the automatic Q–L–Q procedure. START and END showed systematic nonlinear longitudinal evolution, whereas MID exhibited lower total variation, small slopes, and low residual errors around a linear trend. Identifying this pattern before defining the Q–L–Q objective provided an empirical basis for selecting quadratic terminal models and a linear central model.

The comparison of linear and quadratic models further supported this structure. Quadratic models improved adjusted R^2 , RMSE, and AICc in both terminal regions, with the strongest and most consistent improvements for height and cross-sectional area. Width showed weaker terminal curvature, particularly in END, but still contributed evidence of nonlinear longitudinal development. These results indicate that the Q–L–Q formulation represents a recurring geometric pattern observed across the analysed beads.

The relatively modest R^2 values obtained for linear models within MID are consistent with the small slopes and narrow response ranges in this region. Under these conditions, small residual deviations can account for a comparatively large proportion of the limited total variation. Absolute slope and relative residual RMSE therefore provide more direct measures of MID quasi-stationarity. In the terminal regions, higher adjusted R^2 values reflect the ability of the quadratic models to describe pronounced systematic geometric evolution.

Sensitivity analysis across nine expert-informed segmentation configurations retained the same regional ordering, with MID showing the lowest mean CV_A in every configuration. The central finding therefore remained consistent across the tested variations in regional lengths, intrusion distances, and sampling-line balancing. This consistency supports the interpretation of the expert-informed START–MID–END structure as a reproducible longitudinal geometric pattern within the present dataset.

4.2 Interpretation of the automatic Q–L–Q segmentation

The automatic Q–L–Q procedure reproduced the principal regional pattern identified in the expert-informed analysis. MID had the lowest CV_A in every bead and retained small residual errors around the fitted linear trend. The paired START–MID and END–MID differences were large and consistent across beads. Their direction was also preserved when physical substrate plates were used as the resampling units. These findings indicate that minimisation of the combined regional-fit, transition-continuity, and short-MID terms produced geometrically coherent START–MID–END segmentations.

The automatic and expert-informed transition coordinates represent two operational interpretations of gradual geometric transitions. The expert-informed coordinates were established through visual assessment with computational support, while the automatic procedure located the coordinates that minimised the Q–L–Q objective. The observed MABD of 3.49 mm and RMSBD of 4.04 mm quantify the separation between these definitions. The mean signed displacements show that the automatic procedure generally produced a longer MID region, extending its START–MID boundary towards decreasing u and its MID–END boundary towards increasing u . Regional geometric coherence and stability under changes in algorithm settings therefore provide essential context for interpreting coordinate-level agreement.

Leave-one-descriptor-out ablation showed that cross-sectional area made the strongest overall contribution to transition-coordinate estimation, accounting for 55.4% of the total mean ablation

contribution. Height and width contributed 24.0% and 20.6%, respectively. Removing cross-sectional area also produced the largest mean boundary displacement. Width produced a larger mean boundary displacement than height despite its smaller contribution to the complete objective function. The descriptors therefore contributed in complementary ways: cross-sectional area most strongly supported the overall Q–L–Q fit, while width also influenced the exact placement of the transition coordinates.

Sensitivity analysis showed that minimum regional lengths, continuity weight, and the short-MID penalty had little influence on the selected transition coordinates within the tested ranges. Smoothing had a greater effect on their exact positions. Removing smoothing or increasing the moving-median window changed at least one coordinate in most beads, although the median absolute displacement remained 1 mm under both alternative settings. Larger displacements occurred in a limited subset of beads, particularly with the five-slice window. This wider window spans the minimum permitted terminal-region length and can smooth short terminal developments more strongly.

All regional characteristics were calculated from the original unsmoothed slice values, and MID retained the lowest CV_A under every tested algorithm configuration. The results therefore distinguish two aspects of sensitivity: smoothing affected the precise operational placement of individual transition coordinates, while the resulting regional variation pattern remained consistent throughout the tested parameter range.

4.3 Interpretation of START–END geometric discrimination

Perfect classification of the original terminal regions showed that START and END contained strongly distinguishable information. The region-size-only control achieved an accuracy of 0.84, demonstrating that systematic differences in terminal length contributed substantially to this distinction. The matched-length analysis removed this source of information by evaluating equal physical spans from both terminal candidates.

After length matching, accuracy remained 0.94 under nested LOBO validation and 0.96 under leave-one-plate-out validation. The paired permutation test yielded $p = 0.0005$, providing evidence that the observed discrimination exceeded the level produced by random START–END label assignments. START and END therefore remained distinguishable through their geometric characteristics after equalising the analysed terminal lengths.

Descriptor-family ablation clarified which geometric measurements supported this distinction. Width descriptors alone achieved the same nested LOBO accuracy as the complete 12-predictor model, whereas the combination of width and cross-sectional-area descriptors achieved the highest matched-length accuracy of 0.96. This difference represents one additional correctly classified bead pair and is best interpreted as evidence of complementary information from cross-sectional area. The statistical descriptors of width, supplemented by those of cross-sectional area, captured most of the geometric distinction between deposition initiation and termination.

The classification descriptors represent the magnitude and dispersion of width, height, and cross-sectional area within each terminal region. They do not explicitly encode longitudinal position or the direction of geometric development along the bead. The strong matched-length classification performance therefore indicates that START and END differ in their regional geometric distributions, in addition to their different locations and lengths.

Nested LOBO validation assessed discrimination across individual beads, while leave-one-plate-out validation assessed its transfer to a physical substrate plate excluded from model training. Both procedures kept the paired terminal candidates from each bead together. The resulting accuracies demonstrate consistent internal and plate-grouped discrimination within the investigated experimental campaign.

4.4 Implications for WAAM analysis

Previous WAAM studies have primarily related process parameters, thermal conditions, and metal-transfer behaviour to global or representative bead-geometry responses [6,10,7]. The present findings extend this perspective by demonstrating that a single bead contains longitudinally distinct geometric regions. Combining these regions into one whole-bead response can obscure the comparatively stable geometry of MID and the systematic evolution occurring near deposition initiation and termination.

The observed START–MID–END pattern is consistent with the transient nature of arc-based deposition. Arc initiation, development of the molten pool and thermal field, quasi-stationary deposition, and process termination can each produce characteristic longitudinal changes in bead geometry. Previous research has also connected molten-pool behaviour with the resulting WAAM geometry using in-process thermal monitoring [11]. In the present study, the physical interpretation is based on post-process geometry and established WAAM process behaviour. Future measurements combining geometry with synchronised arc, thermal, or molten-pool signals could establish the physical relationship between the estimated transition coordinates and changes in the deposition process.

Automatic identification of a quasi-stationary MID region provides a consistent basis for process–geometry modelling when the aim is to characterise stable deposition behaviour. START and END can be analysed separately as transient responses associated with process initiation and termination. This regional approach can support modelling of stable bead geometry, comparison of start and stop strategies, and development of location-dependent toolpath compensation.

Real-time geometry sensing and feedback control have already been demonstrated in WAAM-related processes. Xia et al. combined vision-based layer-width measurement with model predictive control [13], while Xiong et al. used vision-based molten-pool-width sensing and closed-loop adjustment of arc current in gas metal arc additive manufacturing [14]. The proposed Q–L–Q method provides a complementary post-process framework for identifying regions that may require different modelling, monitoring, or compensation strategies. Its operational regional definitions could subsequently support the development and evaluation of region-specific sensing and control approaches.

4.5 Limitations and generalisability

Several limitations define the scope of the present findings. First, the expert-informed reference was established by one evaluator. Inter-rater and intra-rater agreement remain to be examined in future studies. The reference boundaries therefore represent one reproducible expert-informed operational definition of the gradual START–MID–END transitions.

Second, the regional pattern, Q–L–Q formulation, descriptor weights, and automatic procedure were developed and evaluated using the same experimental campaign. The classification results likewise represent internal and plate-grouped validation within this dataset. Evaluation using independent datasets is required to establish transferability across materials, deposition systems, bead geometries, and process windows.

Third, manually selected outer regions of interest were used to initialise bead extraction and define the valid longitudinal bead extent. Within this extent, the two internal Q–L–Q transition coordinates were determined automatically. Further development could extend the workflow to automatic identification of the complete bead extent and thereby reduce the remaining manual input.

Fourth, the descriptor and penalty weights were selected empirically. Leave-one-descriptor-out ablation quantified the contribution of width, height, and cross-sectional area under the selected weighting, while the one-factor-at-a-time sensitivity analysis examined individual algorithm settings over predefined ranges. A broader multivariable sensitivity analysis could examine interactions among descriptor weights, penalty weights, regional constraints, and smoothing settings.

Fifth, the estimated transition coordinates were derived from post-process bead geometry. Synchronised arc, thermal, or molten-pool measurements would be required to relate these operational geometric coordinates directly to specific physical events during deposition.

Sixth, alternative smoothing settings changed at least one transition coordinate in most beads. Typical displacements were small, and MID retained the lowest CV_A in every tested configuration, but larger displacements occurred in a limited subset. These cases indicate that the exact boundary positions remain sensitive to local profile characteristics and the selected smoothing scale.

Finally, dependence among beads deposited on the same substrate was examined using a physical-plate cluster bootstrap and leave-one-plate-out classification. Only three independent physical substrate plates were available, which limits cluster-level inference. Additional plates would allow a stronger assessment of between-plate variability and external transfer.

Within these limits, the analyses consistently support a low-longitudinal-variation MID region, nonlinear terminal evolution, reproducible geometry-driven Q–L–Q segmentation, and geometric discrimination between START and END. Broader generalisation requires confirmation across independent experimental conditions and deposition systems.

5. Conclusions

This study developed and evaluated an expert-informed, geometry-driven workflow for longitudinal segmentation and terminal-region classification of WAAM single beads from three-dimensional point clouds. The main conclusions are as follows:

- Expert-informed regional analysis established the geometric basis of the START–MID–END structure before development of the automatic procedure. START and END showed systematic nonlinear longitudinal evolution, while MID exhibited comparatively low total and residual variation and an approximately linear longitudinal profile.
- Linear–quadratic model comparisons supported the Q–L–Q formulation. Quadratic models consistently improved the representation of START and END, with the strongest improvements observed for height and cross-sectional area. The expert-informed regional ordering remained consistent across all nine tested supporting segmentation configurations.
- The automatic Q–L–Q procedure produced admissible START–MID–END segmentations for all 50 beads. MID had the lowest cross-sectional-area coefficient of variation in every bead. This regional ordering was preserved across the tested algorithm settings and in the physical-plate cluster-bootstrap analysis.
- The automatic and expert-informed transition coordinates represented related operational definitions of gradual geometric transitions. Their combined MABD was 3.49 mm and RMSBD was 4.04 mm. The automatic procedure generally identified a longer MID region, with a mean START–MID displacement of -2.63 mm and a mean MID–END displacement of $+3.98$ mm relative to the expert-informed coordinates.
- Leave-one-descriptor-out ablation identified cross-sectional area as the strongest overall contributor to Q–L–Q transition-coordinate estimation. Cross-sectional area accounted for 55.4% of the total mean ablation contribution, while height and width accounted for 24.0% and 20.6%, respectively.
- START and END remained geometrically distinguishable after equal physical terminal spans had been extracted. Matched-length accuracy was 0.94 under nested LOBO validation and 0.96 under leave-one-plate-out validation. Statistical width descriptors provided most of the classification information, with an additional contribution from cross-sectional-area descriptors.

Overall, the proposed workflow preserves longitudinal geometric information that is obscured by whole-bead averaging and separates quasi-stationary and transient bead regions using reproducible operational definitions. The findings provide a basis for region-specific process–geometry modelling and future integration with synchronised process monitoring. Validation across additional materials, process windows, deposition systems, and physical substrate plates will determine the broader transferability of the approach.

Supplementary information

Online Resource 1 (Supplementary Data S1) contains the bead-level spatial ROI definitions, process-condition metadata, and point-cloud acquisition groups for all 50 beads. Online Resource 2 (Supplementary Data S2) contains the unsmoothed longitudinal width, height, and cross-sectional-area profiles, the corresponding moving-median profiles used for transition-coordinate estimation, and the automatic Q–L–Q regional assignments. Online Resource 3 provides a README defining the variables, units, and structure of the supplementary datasets.

Statements and Declarations

Author contributions

Janez Gotlih: Conceptualization, methodology, software, validation, formal analysis, investigation, data curation, visualization, and writing – original draft.

Kristijan Šket: Software and data curation.

Rok Belšak: Methodology, formal analysis, and investigation.

Timi Karner: Conceptualization, methodology, software, validation, formal analysis, investigation, data curation.

All authors read and approved the final manuscript.

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Data availability

The bead-level spatial ROI definitions, process-condition metadata, and longitudinal slice-level profiles underlying the reported analyses are provided in Online Resources 1 and 2. The source point clouds are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Supplementary Files

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