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Comparison and validation of segmentation methods for feature-based characterisation of metal powder bed fusion surfaces

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Abstract
Feature-based characterisation approaches, based on assessment of individual topographic formations (features), are increasingly being applied to characterise complex surfaces. Feature-based characterisation consists of segmenting (partitioning) a topography in order to isolate interesting regions (features) that can then be assessed via dedicated procedures, for example via dimensional characterisation. Segmentation, and its ability to isolate the feature of interest, are at the core of any feature-based characterisation approach. In this work, three segmentation approaches are compared and validated as they are applied to the isolation of particles and spatter on various powder bed fusion surfaces. The investigated segmentation approaches are morphological segmentation on edges, contour stability analysis and active contours. A manual segmentation is performed to generate a reference result to assess the performance of the investigated segmentation methods. The methods are assessed based on identification of performance (capability of detecting the features) and accuracy of feature boundary detection (capability of identifying the correct feature boundaries). The assessment is based on computing a series of custom performance indicators developed for the purpose of the comparison and derived from the theory of binary classifiers. The proposed comparison method allows for the qualification and quantification of segmentation methods used for feature-based characterisation and can help determine the efficacy of a segmentation approach when applied to a certain test case. In future, it may be possible to use this methodology to investigate and compare how changing parameters for feature-based segmentation algorithms can result in more effective segmentation.

Feature-based characterisation, topography segmentation, surface metrology, additive manufacturing

1. Introduction

Feature-based characterisation, i.e. the characterisation of surface topography based on the isolation of relevant topographic formations (features) and their dimensional assessment, is a developing field of surface texture metrology [1]. Used alongside ISO 25178-2 surface texture parameters [2], feature-based approaches provide dimensional assessments of individual features (area, width, height, etc.) as well as statistical properties of feature aggregates (e.g. mean, standard deviation), which may be related to functionality [1]. For powder bed fusion (PBF) surfaces, a commonly investigated feature of interest is the particles or spatter present on the surface [3–5]. For example, assessing particle/spatter coverage as a percentage of the measured surface may be of interest to understand the requirements for surface finishing operations. In this work, we investigate segmentation, a necessary step of feature-based characterisation, where the measured surface topography is spatially partitioned into regions to isolate the targeted features from their surroundings. Understanding segmentation performance is fundamental to understanding how the whole feature-based characterisation pipeline will perform. Segmentation affects the ability to identify features (by generating partitions that are effective at separating each feature from its surroundings). Segmentation also affects the capability to correctly characterise the geometry of the isolated features (by generating partition boundaries which may or may not accurately correspond to the correct feature boundaries). In this work, three segmentation methods are compared, applied to the identification of particles and spatter in areal topography data obtained by measurement from powder bed fusion surfaces (Figure 1).

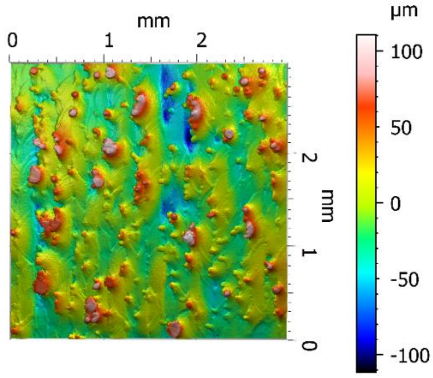

Figure 1: Test case surface, an electron beam powder bed fusion angled surface

2. Methodology

2.1. Test case surfaces

Three topography segmentation methods were investigated: contour stability analysis [4], morphological segmentation [6] and active contours [7]. To perform the comparison, three PBF surfaces obtained at differing build orientations (laser PBF top (0°) surface, electron beam PBF (EBPBF) angled (30°) surface and EBPBF side (90°) surface) were measured using focus variation microscopy and subjected to the segmentation approaches optimised to isolate particles and spatter on the surface [8]. Figure 1 shows the EBPBF angled surface; this surface contains individual and agglomerated particles, and spatter formations.

2.2. Segmentation approaches

Morphological segmentation on edges

This segmentation method is a variation of that defined in ISO 25178-2 [6,9]. The method performs a partitioning into dales working on the unsigned gradient map obtained from the original surface topography. The segmentation map can be pruned, i.e. simplified by merging smaller segments into larger ones, by grouping the dales that correspond to particles and spatter by applying a threshold of heights on the surface.

Contour Stability

The topography is sliced by height and the sliced contours are tracked as their shape changes moving down through the sequence of slicing planes [4]. Those contours that change minimally (within a threshold), are defined as stable and are representative of steep feature boundaries. They are used as edges to delimit the regions that form the segmentation result.

Active contours

Active contours is a method that, starting from an initial guess, based on a threshold of heights, iteratively refines the position of a closed contour [10,11]. The contour iteratively moves towards its most stable position based on energy minimisation. The final stable position is assumed as the boundary of the feature being isolated**.**

2.3. Comparison of segmentation methods

Similar to the methodology outlined in [7], the comparison of the segmentation methods focused on two performance indicators: performance in feature identification (i.e. the capability of correctly detecting the presence of the target features: particles or spatter) and performance in feature boundary determination (i.e. the capability of correctly tracing the boundaries of each feature). Without a reference method to validate the selected segmentation methods against, a hand-drawn segmentation result was created for each test surface.

The performance in feature identification is assessed using **Error! Reference source not found.**

$$\text{Identification performance} = \frac{\text{no. identified features}}{\text{no. total features}} \qquad (1)$$

A feature is not identified if there is no segment that at least partially covers it. The ratio between the number of identified features and the total number of features present in the reference map defines identification performance. A value of 1 corresponds to 100% identification (i.e. all features have been found).

Figure 2 shows the procedure for assessing performance of feature boundary determination. The procedure is applied individually to each feature that has been positively identified (i.e. there is a segment which at least partially overlaps to where the feature is located).

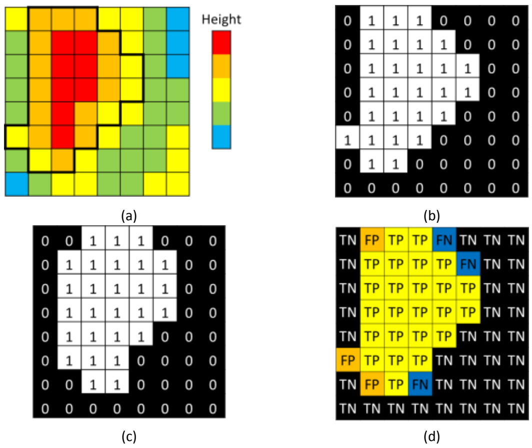

Figure 2: Pre-processing for the quantitative performance indicators for individual feature assessment showing (a) portion of surface topography (height map) where a feature instance is visible, highlighted by the thick black contour (b) ideal segmentation result drawn by hand; (c) result of one of the segmentation algorithms; (d) classification of the individual cells from comparing the segmentation result with the reference, ideal one.

Class	**description**	**short name (feature-centric)**
TP (true positive)	1-valued segmentation pixel overlaid to a feature pixel in the height map	feature pixel
FP (false positive)	1-valued segmentation pixel overlaid to a background pixel in the height map	excess (feature) pixel
TN (true negative)	0-valued segmentation pixel overlaid to a background pixel	background pixel
FN (false negative)	0-valued segmentation pixel overlaid to a feature pixel	missing (feature) pixel

Table 1: Table of classification descriptions for the classes in the binary classification test

The individual pixels of the segmentation result are classified based on agreement with the pixels in the reference result. The classification leads to the states described in Table 1. From such states, a series of performance indicators can be derived, following the theory of binary classifiers:

- Precision – positive predictive value, PPV:

$$\text{PPV} = \frac{TP}{TP+FP} = \frac{\text{no. feature pixels}}{\text{no. feature pixels +no. excess pixels}} \qquad (2)$$

- Recall – sensitivity, true positive rate (TPR):

$$TPR = \frac{TP}{TP+FN} = \frac{\text{no. feature pixels}}{\text{no. feature pixels + no. missing pixels}} \qquad (3)$$

- Specificity – selectivity, true negative rate (TNR):

$$TNR = \frac{TP}{TP+FP} = \frac{\text{no. background pixels}}{\text{no. background pixels + no. excess pixels}} \qquad (4)$$

- Balanced accuracy

$$\text{Balanced accuracy} = \frac{TPR+TNR}{2} = \text{arithmetic average of recall and specificity} \qquad (5)$$

The performance indicators can be calculated on the individual features, but also on the whole segmentation map to provide a further summary of performance.

3. Results

Results for the EBPBF angled surface are shown in Figure 3. Morphological segmentation on edges (a) resulted in an identification performance of 0.574 (about 57% identified features). Contour stability (b) resulted in an identification performance of 0.465. Active contours resulted in the highest identification performance (c) with a score of 0.929.

Figure 4 shows boxplots for the values of the performance indicators related to boundary delimitation accuracy, computed on the individual features. The results are again for the EBPBF angled surface. For the morphological segmentation on edges, the boxplots were calculated for the 73 matched features from the reference image. The boxplots for the contour stability were calculated on the 59 matching features and the active contours was calculated on the 118 matching features from the reference.

As shown in Figure 4, there is a significantly high dispersion for all scores for active contours and contour stability, with contour stability showing a very large spread of scores for specificity, likely due to the difficulty in defining contours on agglomerated particles that have low gradients on some edges. Morphological segmentation on edges results in a lower dispersion than the

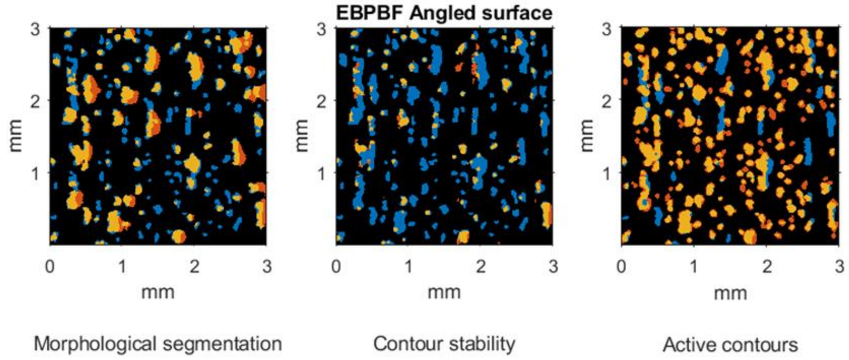

Figure 3: Segmentation results overlaid to the reference map for the EBPBF angle surface. Yellow denotes matching pixels; orange represents excess pixels and blue denotes missing pixels.

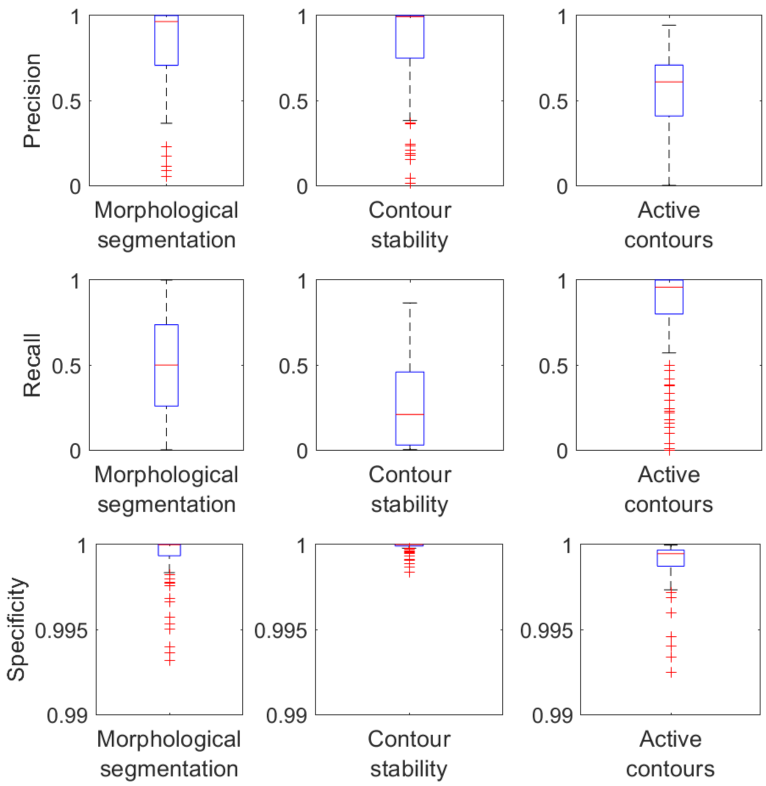

Figure 4: Error determination metrics for matched features on the EBPBF angled surface

EBPBF angled surface			
	Morphological segmentation	Contour stability	Active contours
Balanced accuracy	0.838	0.698	0.852
Precision	0.796	0.848	0.705
Recall	0.764	0.419	0.904
Specificity	0.911	0.976	0.800

Table 2: Performance parameters calculated over the whole datasets for the EBPBF angled surface

other approaches for all performance metrics; it has the highest scores for precision and specificity but much lower scores for recall. Active contours result in the highest scores and lowest dispersion for recall with the values covering the interquartile range (IQR) all above 0.8.

In general, there appears to be a trade-off between recall and specificity between the methods. Active contours are generally a good approach with high recall but low precision and specificity, able to identify most of the features from the reference. On the contrary, morphological segmentation on edges, whilst leading to lower recall, possesses higher values of precision and specificity. Essentially, active contours will find all objects found in the reference, but at the cost of oversizing and over-estimation, whilst morphological segmentation on edges may struggle to identify all features in the reference but will more accurately track the edges of the feature boundaries. The performance of contour stability falls in-between the other methods but is often unable to identify agglomerated particles, resulting in lower values of recall on surfaces where these features are present in more abundance, such as seen in Figure 3.

4. Discussion

A limitation of the performance assessment method is its reliance on a hand-drawn segmentation result. Operator-driven segmentation has lower reproducibility with increasing complexity of the topography and lower repeatability with increasing numerosity of features. The reasoning process for feature determination is subjective and difficult to repeat between operators. However, using a hand-drawn segmentation is so far the only method available to produce a reference map for comparison (to the knowledge of the authors).

Morphological segmentation on edges will often result in over segmentation requiring some pruning. Optimal pruning parameters are often difficult to determine. As seen in the results, morphological segmentation on edges performs well on the test case, with high scores for precision and specificity, however, recall is often lowest.

Contour stability was designed for steep edges only, so it is understandable that its performance is rather weak when applied on smoother feature boundaries as sometimes found where agglomerated particles and spatter formations connect to the underlying weld tracks.

Active contours require additional preparation steps, if compared to the other methods, as an initial "guess" for the contours must be available. Moreover, in the test cases, active contours consistently ‘overgrew’ outside of the feature boundaries, leading to lower precision and specificity results.

For all the test cases and all the methods investigated, filtering is required to remove larger-scale formations which can confuse the segmentation process. Though this aspect has not been covered in detail in this paper, the identification of optimal filtering parameters is often challenging and still subjected to trial and error.

In general, all feature-based approaches require significant effort for the initial set up. Features can be difficult to define, and to ensure a meaningful segmentation can be achieved, it is essential that a robust definition is found of the target features that must be identified. This challenge is evident for the test case, where even to the human eye, individual and agglomerated particles and spatter are sometimes difficult to discern.

5. Conclusions and future work

Feature based characterisation offers a way to assess surface topographies in a complementary way to texture parameters, and in some cases may provide richer information content, as features can be defined that more closely match the subject of interest in any specific surface investigation scenario.

Segmentation performance is fundamental in determining success of the entire feature-based characterisation approach. The method proposed in this work allows for the comparative assessment of performance of various segmentation methods applied to the same test case and can be used to design/optimise a feature-based characterisation pipeline.

Acknowledgements

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