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A new method for in-situ process monitoring of AM cooling rate-related defects

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Abstract

The increasing popularity of additive manufacturing (AM) is pushing the industry to provide new solutions to improve the process stability. In the past, process monitoring and control has proved to be a fundamental tool to enhance the repeatability of many manufacturing processes, however the typical AM fast dynamics require a high spatiotemporal resolution data flow to accurately describe the process and these new types of data are presenting new challenges for standard statistical process monitoring (SPM) techniques.

In this work, the capabilities of a new machine learning (ML) based framework for the detection of cooling rate-related defects in metal additive manufacturing processes via in-situ high-speed cameras are presented and discussed.

Keywords: Image-based process monitoring; In-situ defect detection; Machine Learning; Laser Powder Bed Fusion (L-PBF)

1. Introduction

The high-speed of AM process dynamics have always represented a challenge in terms of process monitoring as it requires a combination of both high spatiotemporal resolution data streams and fast data analysis techniques.

The increased availability of low-cost machine vision systems allowed a more widespread adoption of this new generation of sensors but standard SPM techniques struggle to keep up with the execution speed required for real-time application and to adapt to the new types of dataset which are very often non-normal and highly autocorrelated.

To deal with the new type of dataset, mostly images and high-speed videos, two main strategies have been adopted:

- **Feature extraction via computer vision** [1-6]: which aims at extracting relevant features from the single images and then monitor the trend of the feature along time to detect defects via standard SPM methods.
- **Dimensionality reduction** [7-12]: this set of techniques aims at achieving a lower dimensional description of the complex dataset and to use the new set of low dimensional features for monitoring.

Despite the successful application of some of these methods for anomaly detection in spatiotemporal data streams, they all still show some limitations either in terms of spatiotemporal accuracy or computational speed.

Nomenclature

AM	additive manufacturing
c	cluster index
KM	K-means method
L	data extraction window length
$v_{i,c}$	centroid of cluster c at frame i
x_i	mean brightness at frame i

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The method proposed in this paper aims at combining the simplicity of feature extraction together with the computational efficiency of dimensionality reduction to synthetize the relevant content of the complex dataset into a new, simpler dataset that can be quickly processed using a machine learning technique for anomaly detection.

2. Experimental case study

To test the capabilities of detecting spatiotemporal anomalies in high-speed data streams, the data acquired during a laser powder bed fusion process were employed. The dataset is composed by 3 different high-speed videos, named *Out-of-control (OOC) Scenario 1, 2* and *3*, showing the laser scanning across the powder bed to melt the predefined slice shape of a complex part (see fig. 1). Due to the complex shape and the reduced heat diffusion of certain areas of the slice, i.e. areas mostly surrounded by powder (e.g. overhanging walls, acute corners etc.), a slower, out-of-control cooling behavior can be noticed during all the videos, denoting what is called the hot-spot phenomenon, i.e. a localized heat accumulation that can result in a higher surface roughness, microstructural inhomogeneity and also porosity formation.

Further details on the experimental and monitoring setup are described in the original work published by the owners of the dataset [11].

3. Methodology

The new method presented here exploits the very different cooling behavior of normal (i.e. laser, spatters) and defect-related (i.e. hot spots) bright regions. In fact, even if they are similarly shaped and most often coexist in the same video frame, their brightness temporal evolution is very different, which corresponds to a different cooling behavior. The core idea is to exploit the fast dynamics of normal bright regions to correctly separate them from the defective bright regions, which exhibit much slower cooling history.

To highlight these differences, a new simpler low-dimensional dataset is extracted using computer vision from the high-dimensional data coming from the high-speed camera used for monitoring. The low-dimensional dataset is then fed to a machine learning classifier to detect the position in time and space of the anomalies, i.e. the hot-spots. The sequence of steps is:

1. **Thresholding**: simple binary image thresholding is performed to identify all types of bright regions observed during the process (laser heated zones, spatters and hot-spots). For this step an arbitrary brightness level was set to twice the background gray level (~ 200).
2. **Region isolation**: the pixels inside each individual bright region are isolated
3. **Data extraction**: the mean brightness pixels in the isolated region is extracted from the $L=10$ following frames, as well as the region's centroid position and first frame number.

The resulting dataset is a simple array of time series describing the brightness decay of each bright region (see fig. 2) and the new 1D functional data can then be used for training/testing the machine learning-based classifier used for anomaly detection.

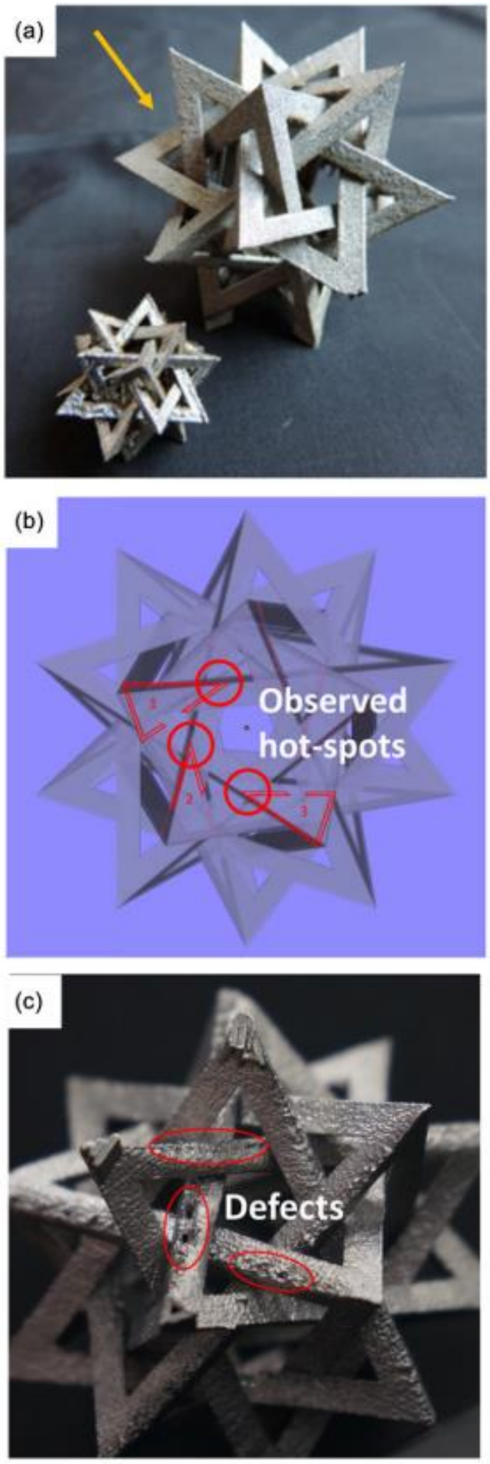

Fig. 1. (a) complex shape; (b) monitored slices position; (c) local defects caused by the hot.spots [11]

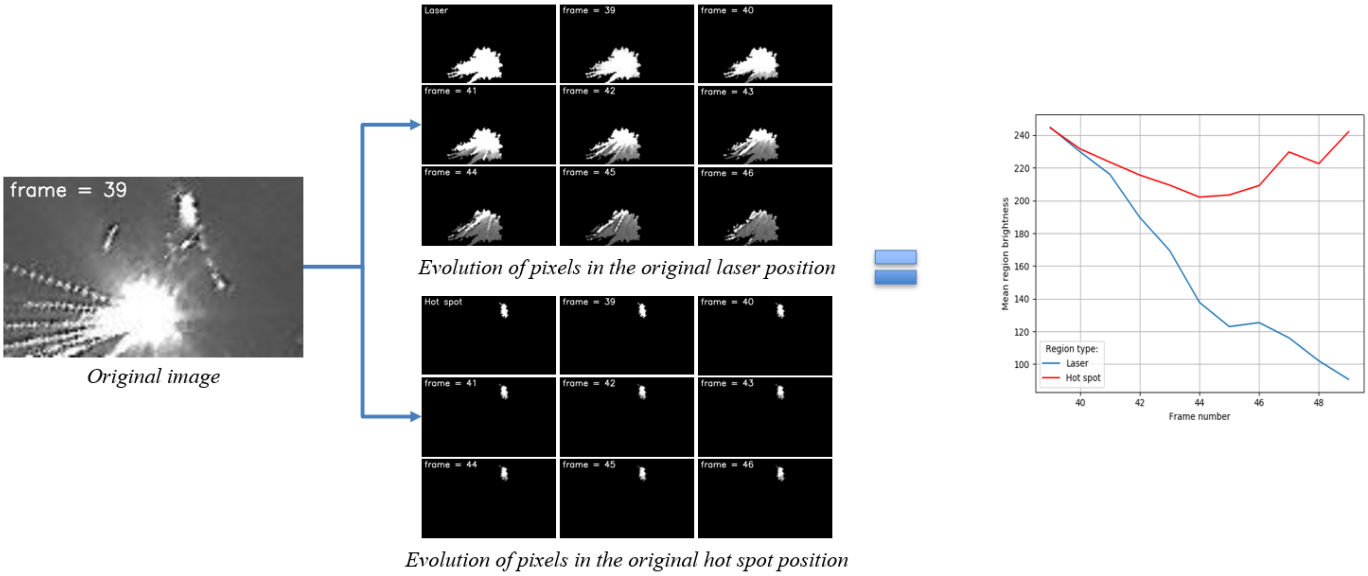

Fig. 2. Representation of the data extraction method

3.1. Machine learning-based defect detection

The machine learning algorithm trained for anomaly detection is the K-means (KM) clustering method. This is the extension to functional data of the popular k-means classification algorithm used in multivariate statistics.

Since the videos contain both normal and defective regions, the number of clusters can be set to 2 in order to separate the hot-spots from the normal process-related bright regions found in the video. Once the 2 functional centroids of the predefined clusters are computed using one of the out-of-control videos, they can be used to set up a simple classifier that compares the distances of a new observed brightness history from each functional cluster to assess if it corresponds to a defective, hot-spot region, by assigning a cluster according to Equation 1:

$$assigned\ cluster = \arg\min_{c} \sum_{i=1}^{L} \left\| x_i - v_{i,c} \right\|^p \tag{1}$$

where x_i is the mean region brightness observed at frame i and $v_{i,c}$ is the centroid of cluster c at frame i.

In this first study, all the time series extracted from *OOC Scenario 1* were used to compute the clusters' functional centroids which have been employed for classification of new observations.

4. Discussion of results

Since a description of hot-spot is not uniquely defined, the position of the detected hot-spots will be compared with the true defect location observed in the final part and, together with time of first signal, it will serve as an indicator performance of the method.

Figure 3 shows the shape of the scanned slice in the three monitored layers and the resulting KM-based classification of all the time series extracted from the original videos. To avoid any human bias, KM predictions were compared with a position-based ground truth that classifies as hot-spot only the bright regions that fall sufficiently close to the real defect location. The comparisons are reported in Tables 1-3.

Table 1. *OOC Scenario 1* confusion matrix.

KM	**Position-based prediction**	
pred.	**Normal**	**Hot-spot**
Normal	298	15
Hot-spot	14	87

Table 2. *OOC Scenario 2* confusion matrix.

KM	**Position-based prediction**	
pred.	**Normal**	**Hot-spot**
Normal	209	7
Hot-spot	16	92

Table 3. *OOC Scenario 3* confusion matrix.

KM	**Position-based prediction**	
pred.	**Normal**	**Hot-spot**
Normal	238	15
Hot-spot	22	92

A considerable number of observations falling in the neighborhood of the real defect are correctly classified as hot-spot, with the first alarm raised in the correct location just after 20 to 40 frames after the start of the video.

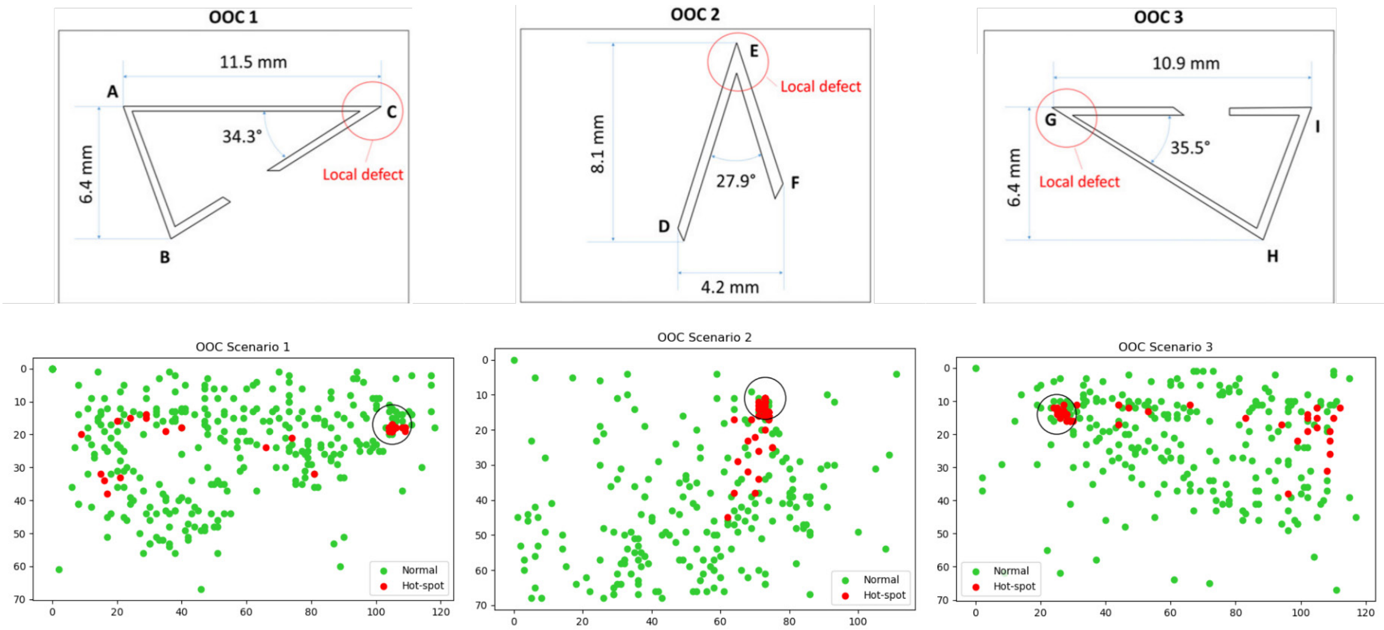

Fig. 3. Top panels: slice shapes and defect location; bottom panels: KM-based classifications

However, in all of the 3 considered OOC scenarios, a few alarms were also raised outside of that region. It should be noted that most of these apparent misclassifications are located near other acute corners of the slice, i.e. in a position where the heat diffusion is poor, thus either revealing other less severe hot-spots that did not result in a final defect on the part, or simply highlighting a slower cool-down dynamics caused by the lower speed of the laser at turn-point. In the latter case, the whole hypothesis of extracting the brightness decay from the video would fall short and either further processing, longer data extraction windows or additional process information (e.g. laser position and speed) shall be needed to improve the prediction accuracy of the method.

4.1. Real-time applicability

High-speed data processing is fundamental to achieve real-time defect detection when monitoring processes characterized by the fast dynamics typical of AM. For this reason, the real-time applicability of the developed method should always be kept into consideration when developing a new monitoring method.

In this preliminary study a first assessment on the real-time applicability was performed considering the computational speed for classifying new time series observation. All tests were performed on a laptop equipped with an Intel i7-8550U CPU and 16GB of RAM. The average classification time of a single time series was found to be below 5 µs, which is 3 orders of magnitude less than the time resolution of the high-speed videos analyzed in this work. This reveals the clear potential of this method for fast and real-time detection of hot-spot phenomena.

5. Conclusion and future work

The new method presented in this work combines feature extraction via computer vision together with an effective dimensionality reduction approach for hot-spot defects detection in AM processes. The performance of the method on a real experimental case study has been discussed, revealing a low error rate and a promising potential for its real-time application.

In future work, additional effort will be put into addressing the questions raised from this preliminary study, studying the sensitivity of the method to its hyperparameters (e.g. length of data extraction window) and to investigate further its performance compared to other existing approaches reported in literature.

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