Statistical process monitoring of Powder Bed Fusion processes via in-situ video imaging

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AddMe.Lab

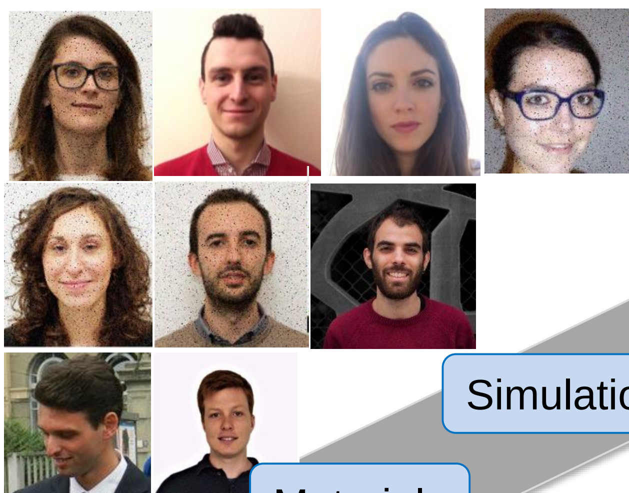
AddMe.Lab – Additive Manufacturing lab @ Department of Mechanical Engineering (Politecnico di Milano)

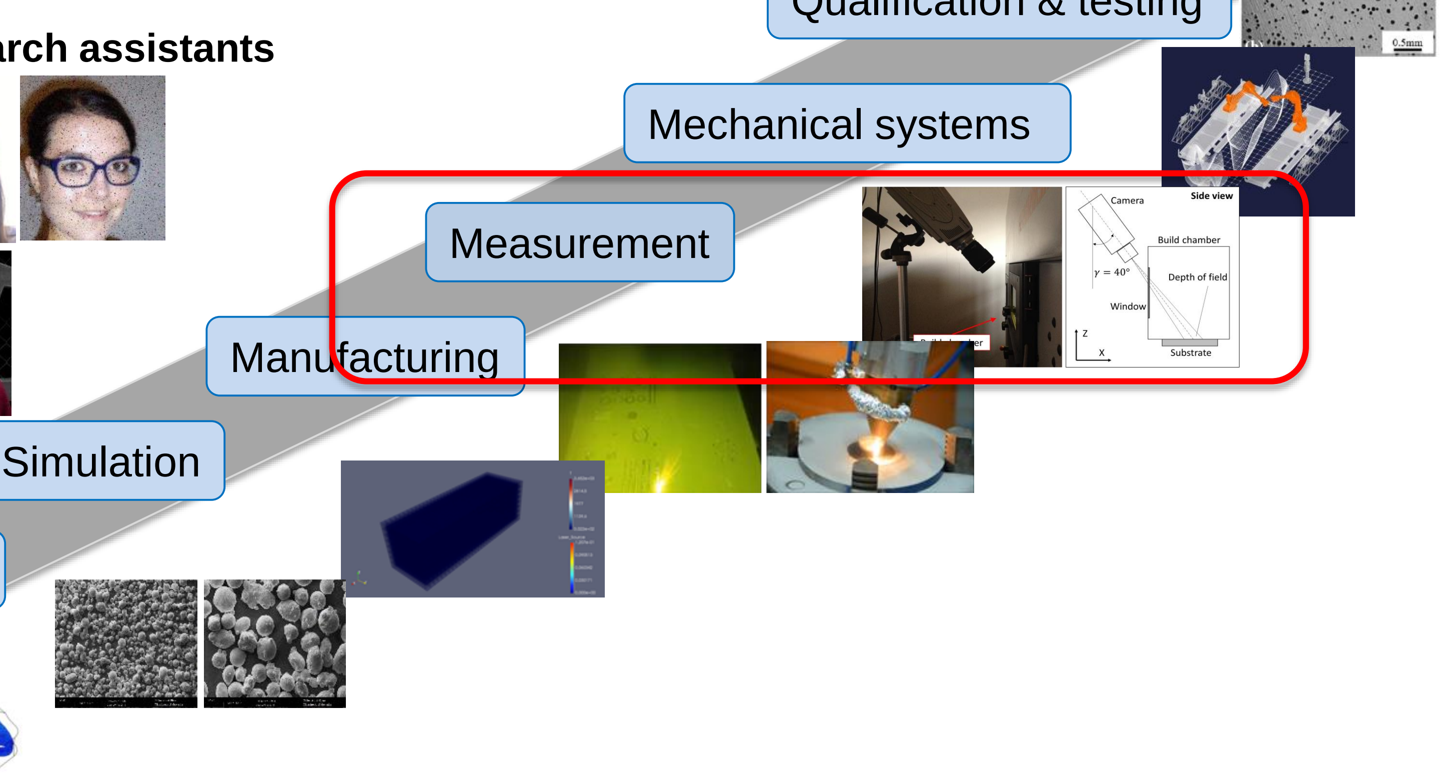
Who we are

Three full professors

Two assistant professors

9 PhD students & research assistants





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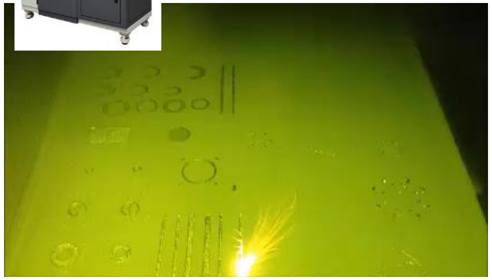
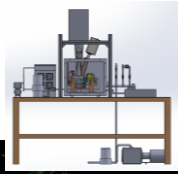
Who we are

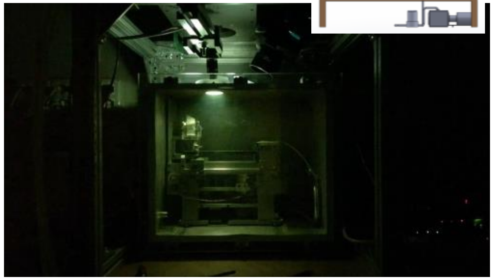
Laser Powder Bed Fusion

Renishaw AM250

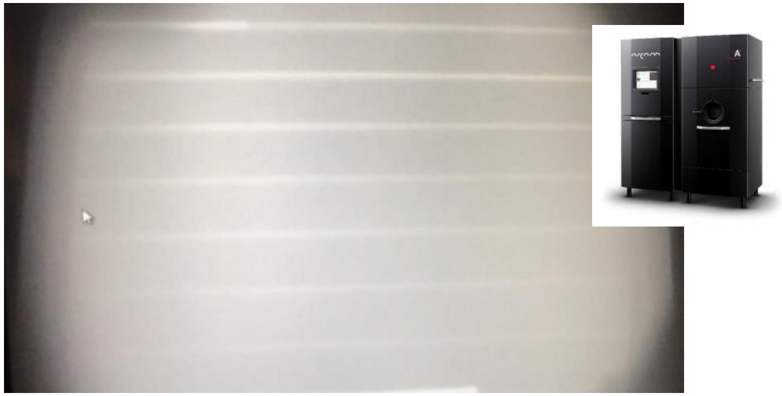


SLM Prototypes



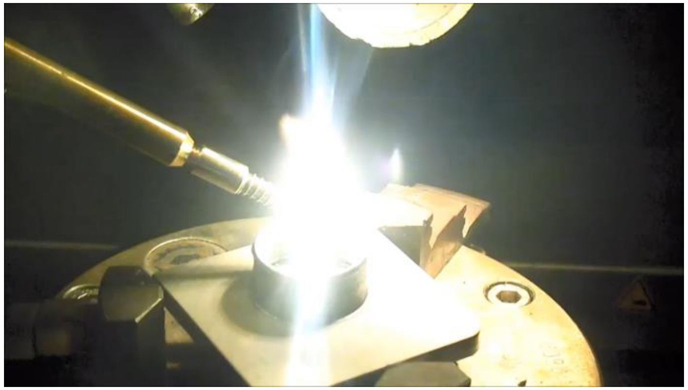


Electron Beam Powder Bed Fusion



Direct Energy Deposition (DED) - powder

Direct Energy Deposition (DED) - wire



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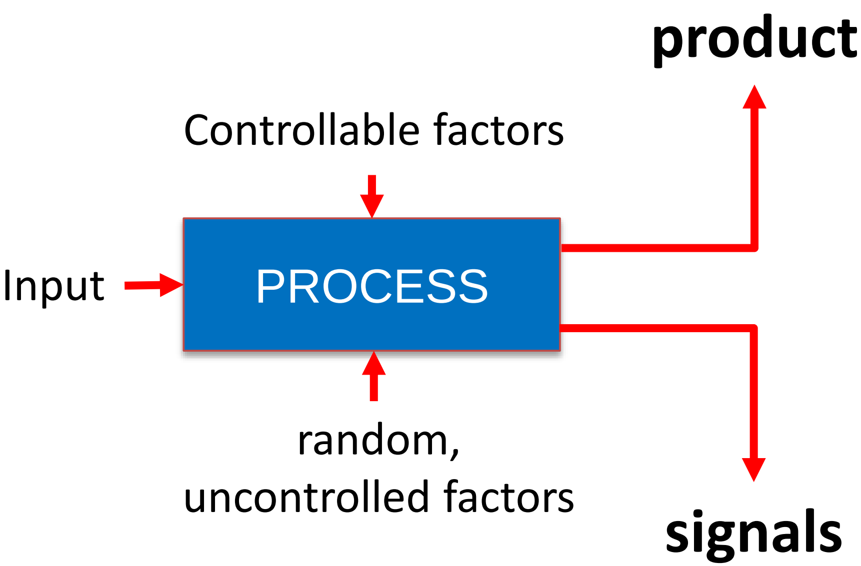
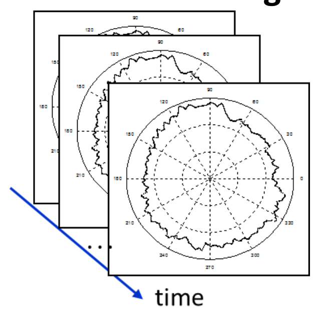
Our background
Statistical monitoring of *product* and *process* data

Statistical monitoring of industrial processes for quick and reliable detection of out-of-control states and defects based on product and process data.

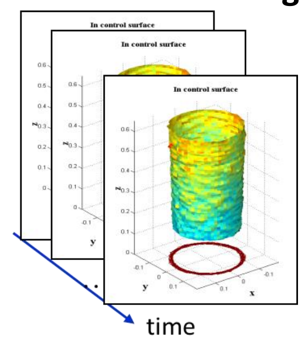


Profile monitoring



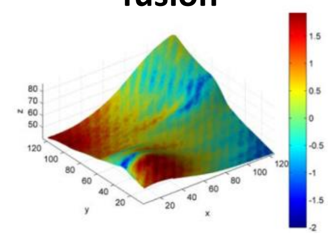
Colosimo et al. (2008), JQT

Surface monitoring



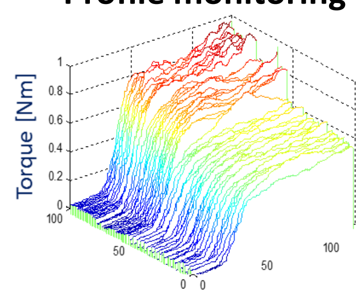
Colosimo et al. (2014), JQT

Multi-fidelity data fusion



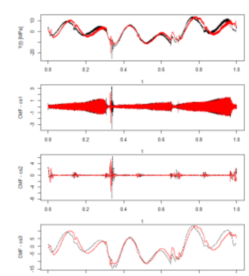
Colosimo et al. (2015), Prec. Eng.

Profile monitoring



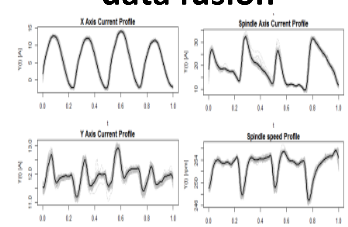
Grasso et al. (2016), JQT

Signal processing



Grasso et al. (2016), MSSP

Multi-sensor data fusion



Grasso et al. (2014), IJPR

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The new intelligent machine

«The limited stability and repeatability of the process still represent a major barrier for the industrial breakthrough of metal AM systems»

(Mani et al., 2015; Tapia and Elwany, 2014; Everton et al., 2016; Spears and Gold, 2016)

AM in the I4.0 framework

MACHINE AS A SENSOR
INTELLIGENT MACHINE

Current defective rates are an industrial barrier:

- Expensive materials
- Long processes (e.g., < 10 cm^3/h)
- Long/expensive trial-and-error inflates the time-to-market
- Stringent quality requirements (aerospace & healthcare)

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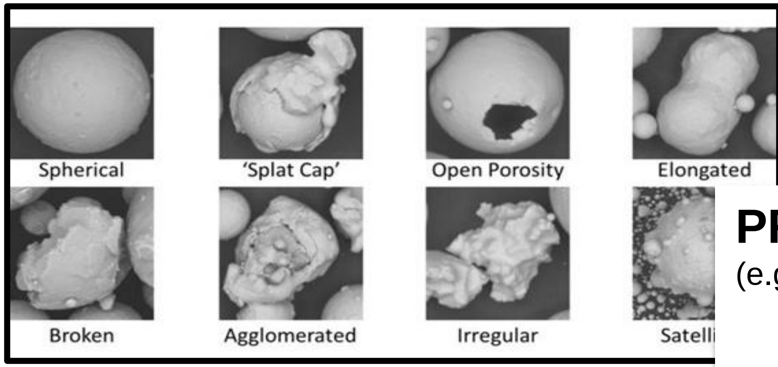
Sources of defects in laser-based powder bed fusion (LPBF)

FEEDSTOCK MATERIAL
(e.g., composition, morphology, porosity, contaminations)

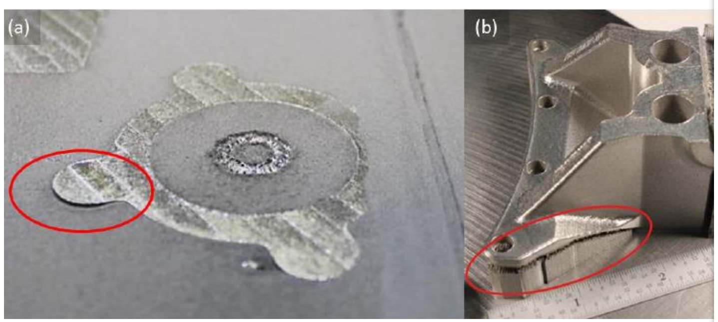


http://www.additivemanufacturing.r

EQUIPMENT
(e.g., powder recoating, chamber environment, beam deflection)

Example from Foster et al., 2015

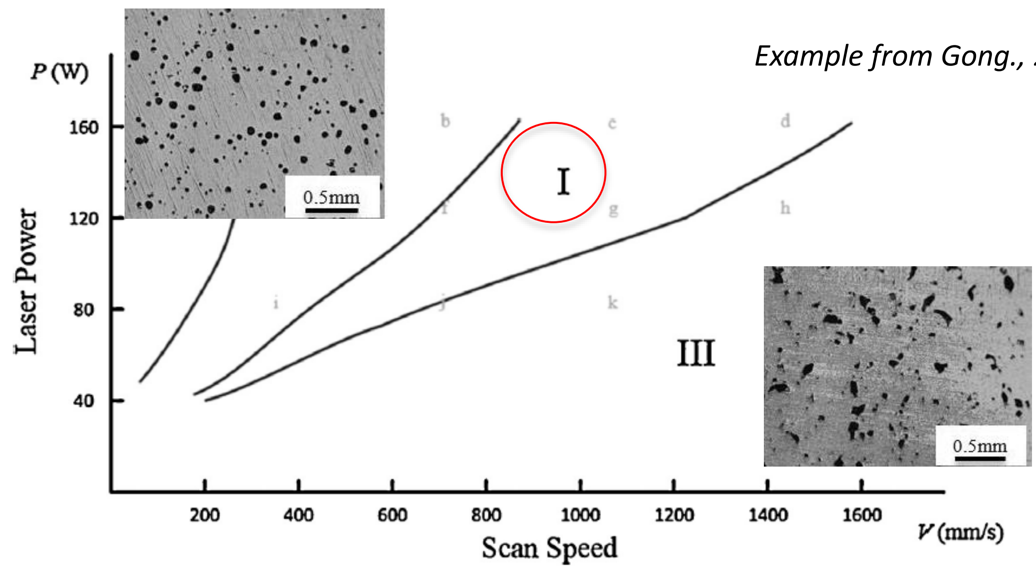
DESIGN CHOICES
(e.g., supports, part orientation)



Foster et al., 2

PROCESS
(e.g., parameters and scan strategy, material ejections)

Example from Gong., 2014



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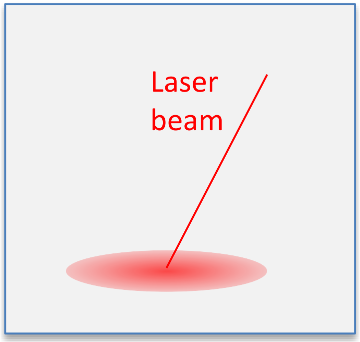
Sources of defects in laser-based powder bed fusion (LPBF)

Source: *Grasso & Colosimo, Measurement Science & Technology, 2017*

Sources of defects		Porosity	Balling	Geometric defects	Surface defects	Residual stresses, cracks & delamination	Microstructural inhomog. & impurity
		Categories of defects					
Equipment	Beam scanning/ deflection	Foster et al., 2015		Moylan et al., 2014b; Foster et al., 2015			
Equipment	Build chamber environment	Ferrar et al., 2012; Spears and Gold, 2016	Li et al., 2012			Edwards et al., 2013; Chlebus et al., 2011; Buchbinder et al., 2014; Kempen et al., 2013	Spears and Gold, 2016
Equipment	Powder handling & deposition	Foster et al., 2015		Foster et al., 2015; Kleszczynski et al., 2012	Foster et al., 2015; Kleszczynski et al., 2012		Foster et al., 2015
Equipment	Baseplate			Prabhakar et al., 2015		Prabhakar et al., 2015	
Process	Parameters and scan strategy	Matthews et al., 2016; Yasa et al., 2009; Attar, 2011; Gong, 2013; Read et al., 2015; Kruth et al., 2004; Weingarten et al., 2015; Thijs et al., 2010; Scharowsky et al., 2015; Puebla et al., 2012; Tammas-Williams et al., 2015; Biamino et al., 2011; Zeng, 2015	Li et al., 2012; Kruth et al., 2004; Tolochko et al., 2004; Zhou et al., 2015; Attar, 2011; Gong, 2013	Yasa et al., 2009; Mousa, 2016; Kleszczynski et al., 2012; Thomas, 2009	Li et al., 2012; Kruth et al., 2004; Matthews et al., 2016; Attar, 2011; Gong, 2013; Zaeh and Kanhert, 2009; Delgado et al., 2012;	Mercelis and Kruth, 2006; Parry et al., 2016; Cheng et al., 2016; Van Belle et al., 2013; Casavola et al., 2008; Zah and Lutzmann, 2010; Zaeh and Branner, 2010; Kempen et al., 2013; Kruth et al., 2004; Carter et al., 2012 - 2014	Carter et al., 2012 - 2014; Arisoy et al., 2016; Niu and Chang, 1999; Huang et al., 2016; Thijs et al., 2010; Scharowsky et al., 2015; Puebla et al., 2012; Biamino et al., 2011
Process	Byproducts and material ejections	Liu et al., 2015; Khairallah et al., 2016;					Liu et al., 2015; Khairallah et al., 2016;
Design choices	Supports			Foster et al., 2015; Kleszczynski et al., 2012; Zeng, 2015	Foster et al., 2015; Kleszczynski et al., 2012; Zeng, 2015	Foster et al., 2015; Kleszczynski et al., 2012; Zeng, 2015	
Design choices	Orientation		Li et al., 2012; Strano et al., 2013;	Delgado et al., 2012	Delgado et al., 2012; Fox et al., 2016; Strano et al., 2013		Meier and Haberland, 2008
Feedstock material (powder)		Liu et al., 2015; Van Elsen, 2007; Das, 2003		Das, 2003	Seyda et al., 2012		Das, 2003; Niu and Chang, 1999; Huang et al., 2016

Process signatures and sensing methods

Source: *Grasso & Colosimo, Measurement Science & Technology, 2017*

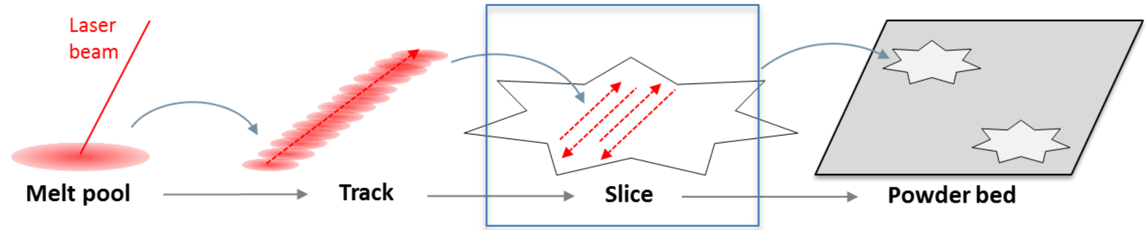


Monitored signature		In-situ sensing (main categories)		
		Pyrometry	**Imaging (visible to NIR)**	**Thermal imaging (NIR to LWIR)**
Melt pool	**Size**	*Clijsters et al., 2014; Craeghs et al., 2010 - 2011;*	*Craeghs et al., 2010 - 2012; Clijsters et al., 2014; Berumen et al., 2010; Kruth et al., 2007; Van Gestel, 2015*	
	Shape		*Craeghs et al., 2011; Berumen et al., 2010; Van Gestel, 2015; Kruth et al., 2007*	Doubenskaia et al., 2015
	Temperature intensity	*Craeghs et al., 2011; Berumen et al., 2010; Chivel, 2013; Clijsters et al., 2014; Doubenskaia et al., 2012; Pavlov et al., 2010; Thombansen et al., 2015;*	*Berumen et al., 2010; Van Gestel, 2015; Yadroitsev et al., 2014; Chivel, 2013;*	
	Temperature profile		*Doubenskaia et al., 2012;*	Gong et al., 2013b; Price et al., 2012

Co-axial monitoring

In-situ monitoring of LPBF processes
GEOMETRICAL ERRORS

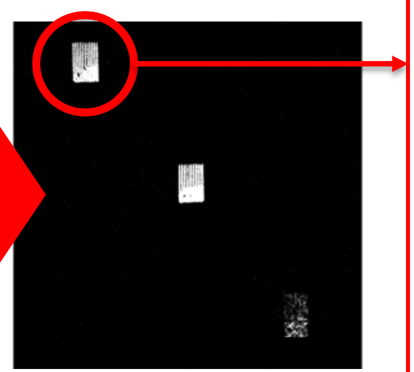
In-situ detection of geometrical errors via high-spatial resolution imaging



- One image per layer (<100µm/pixel)
- Difference between pre-scan and post scan images
- Image segmentation and edge detection
- Reconstruction of the actual layer geometry and comparison with the nominal one

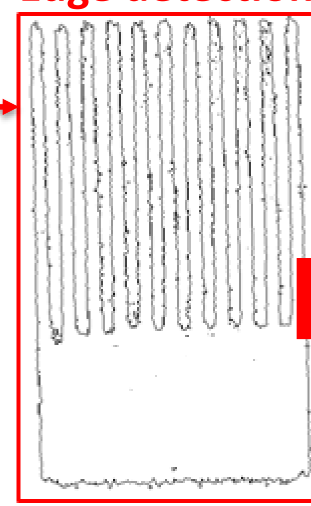
PRE scan

POST scan

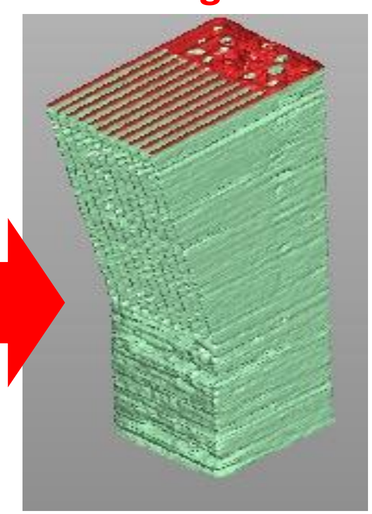


Thresholded POST-SCAN

Edge detection



3D reconstruction Based on in-situ images



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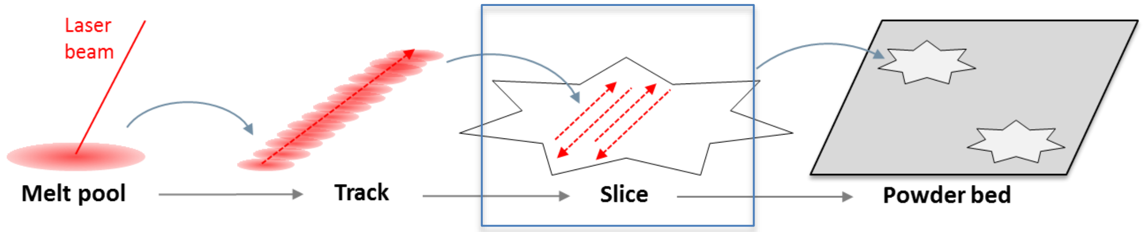
In-situ monitoring of LPBF processes
GEOMETRICAL ERRORS

In-situ detection of geometrical errors via high-spatial resolution imaging



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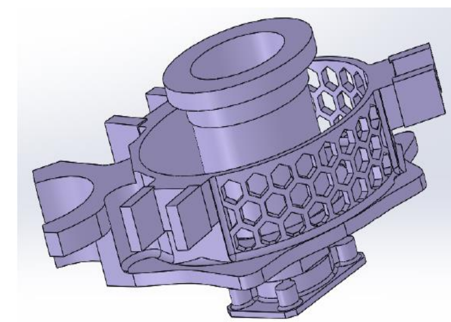
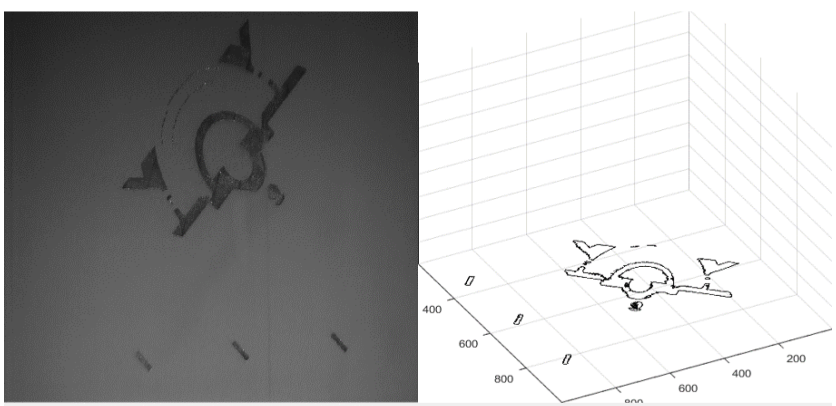
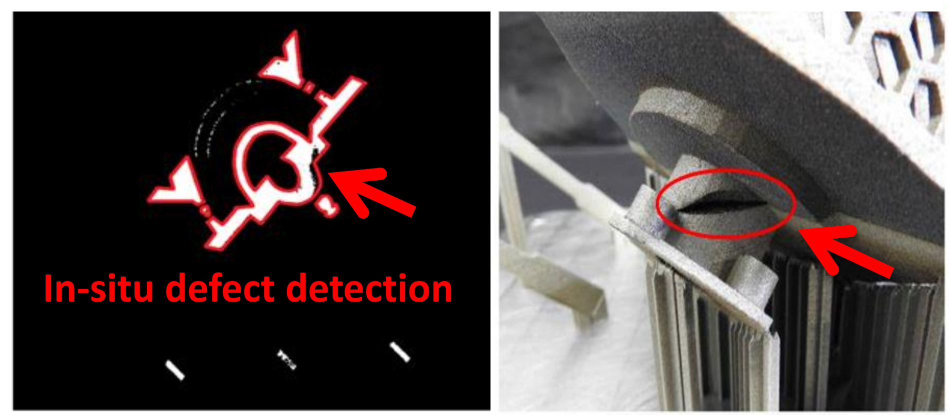


Example of 3D image-based reconstruction



Example of error detection



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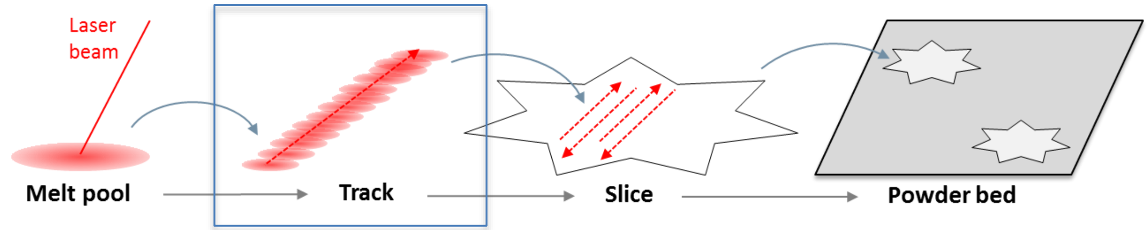
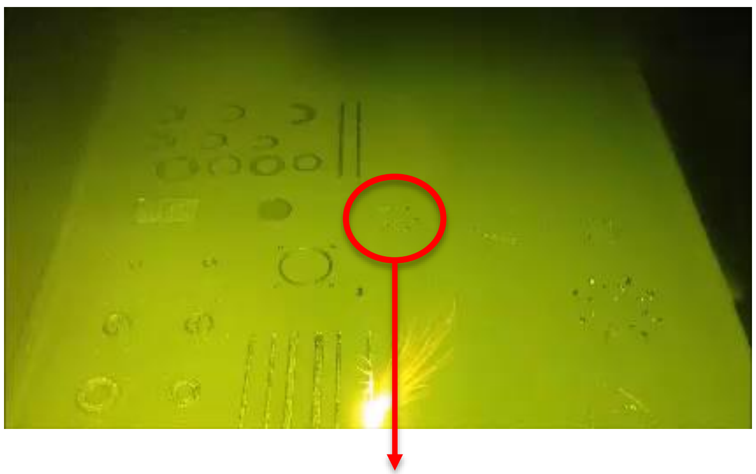
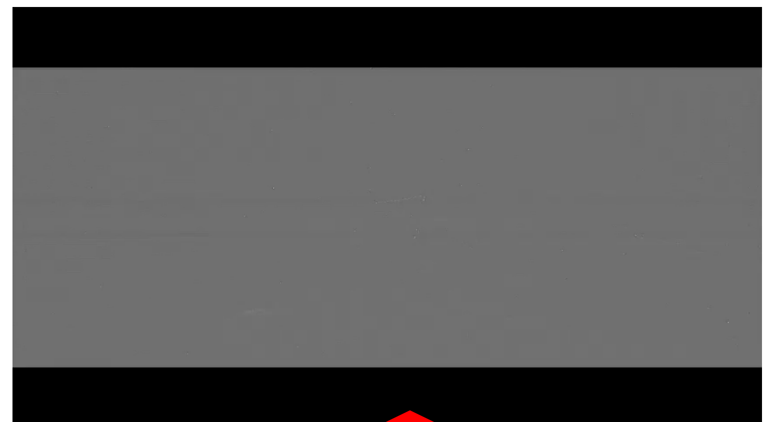
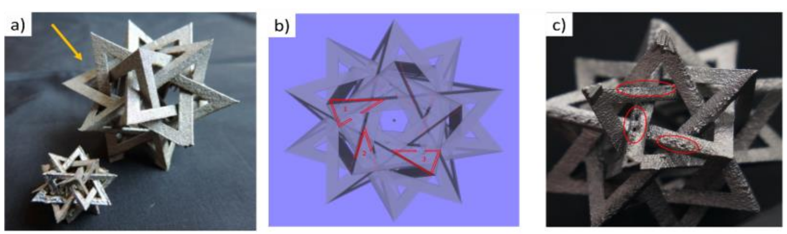
Grasso et al., Journal of Manufacturing Science & Technology, 2016
Colosimo and Grasso, Journal of Quality Technology, 2018

Hot-spot detection and localization via spatio-temporal statistical methods

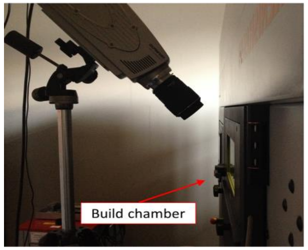


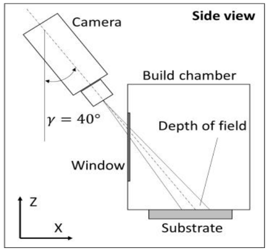






High-speed image acquisition (off-axis)
Olympus i-speed 3





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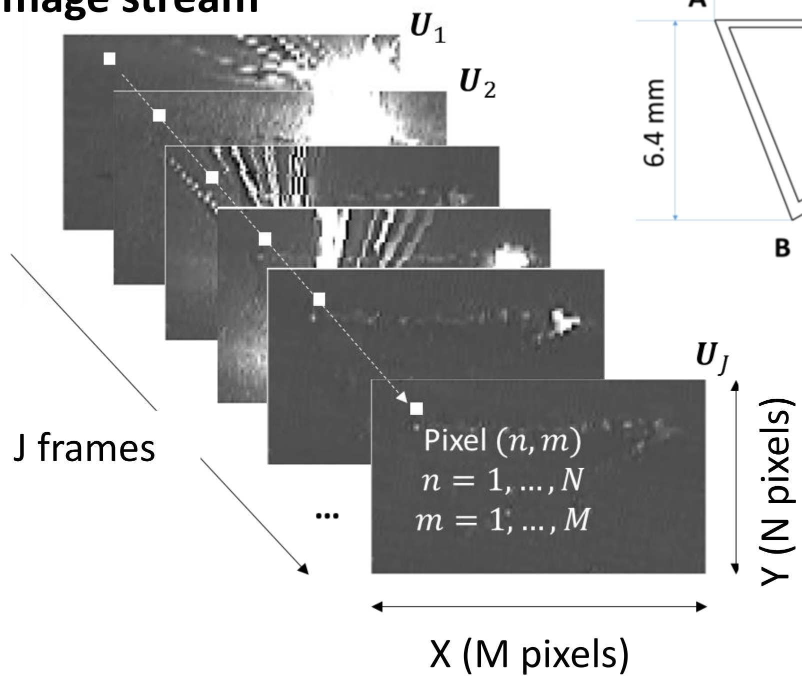
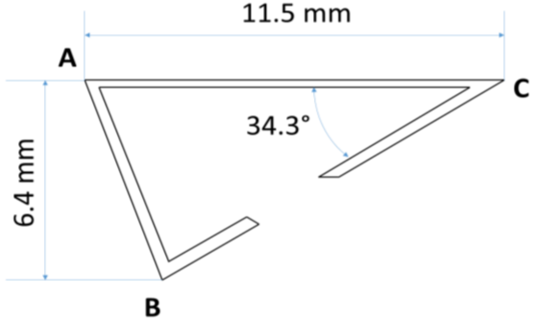
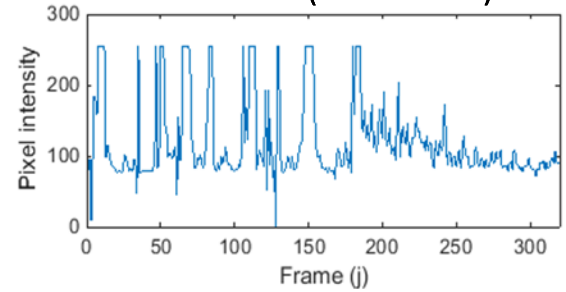
In-situ monitoring of LPBF processes
HOT SPOT

Image stream

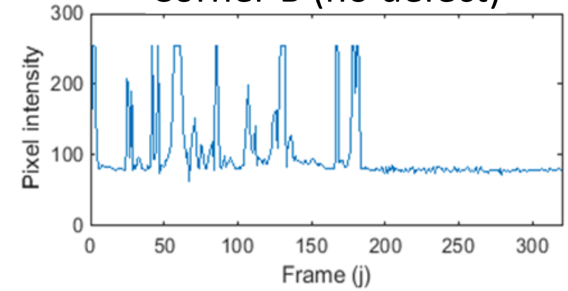




Corner A (no defect)

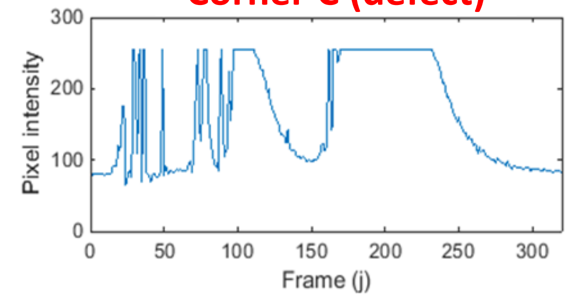


Corner B (no defect)



Corner C (defect)

HOT-SPOT



350 frames of size 121 × 71
Intensity profiles over time
(8bpp – scale: 0-255)

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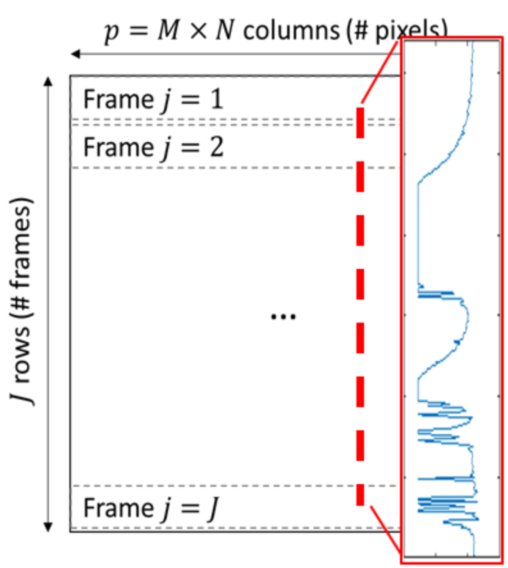
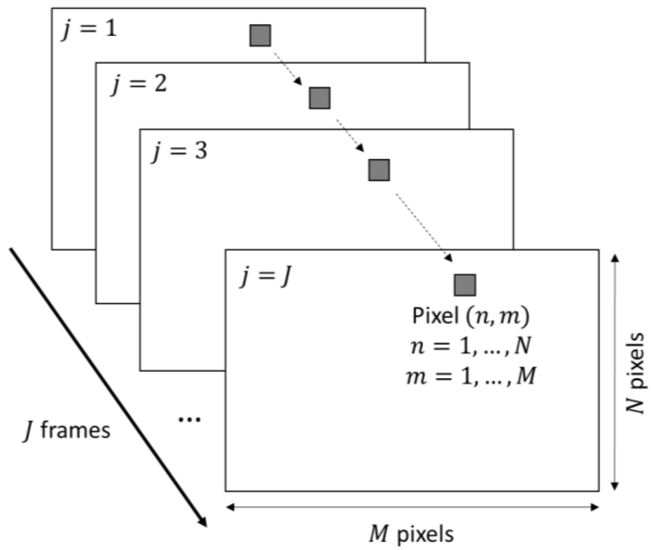
Image stream processing

Temporal PCA
(S-mode)

$$\mathbf{X} \in \mathbb{R}^{J\times(M*N)}$$





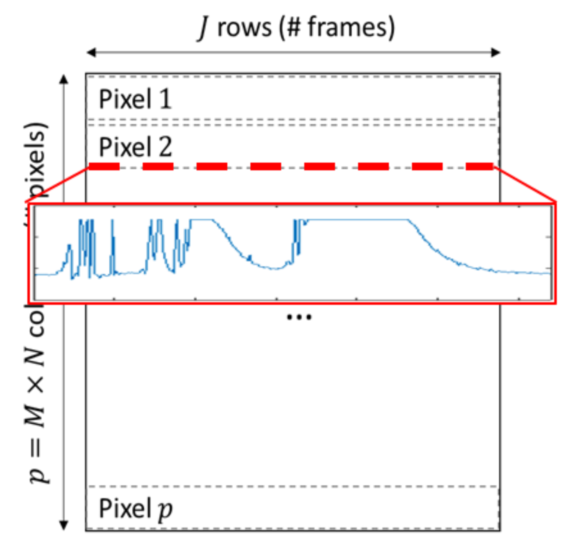
- Principal Component Analysis (PCA) applied to image data
- No segmentation or edge detection operation needed

$$\mathcal{U} \in \mathbb{R}^{J\times M\times N}$$

$$\mathcal{U} = \{\boldsymbol{U}_1, \boldsymbol{U}_2, \ldots, \boldsymbol{U}_J\}$$

Spatial PCA
(T-mode)

$$\mathbf{X} \in \mathbb{R}^{(M*N)\times J}$$



Geospatial statistics & atmospheric science

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Spatially weighted T-mode PCA (ST-PCA)

Underlying idea: incorporating pixel spatial correlation into the projection entailed by the T-mode PCA to preserve the spatial depency and enhance the identification of local defects

Weighted sample variance –covariance matrix:

$$\mathbf{S} = \frac{1}{p-1}(\mathbf{X} - 1\bar{\mathbf{x}})^T \mathbf{W}(\mathbf{X} - 1\bar{\mathbf{x}})$$

$\mathbf{X} \in \mathbb{R}^{p \times J}$ is the data matrix (p=MxN pixels by J frames)

$\bar{\mathbf{x}} \in \mathbb{R}^{1 \times J}$ is the sample mean vector

$\mathbf{1}$ is a $p \times 1$ vector of ones

$\mathbf{W} \in \mathbb{R}^{p \times p}$ is the **spatial weight matrix**

The (k, h)-th element of the matrix, $w_{k,h}$, quantifies the spatial dependency between the k-th and h-th pixels

The matrix $\mathbf{S}$ is a quadratic form whose decomposition into orthogonal components via eigenvector analysis has a closed analytical solution, being $\mathbf{W}$ a symmetric weighting matrix

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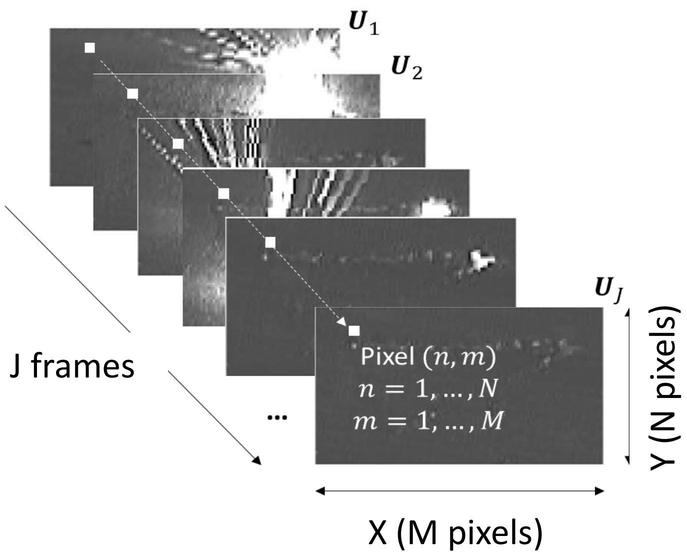
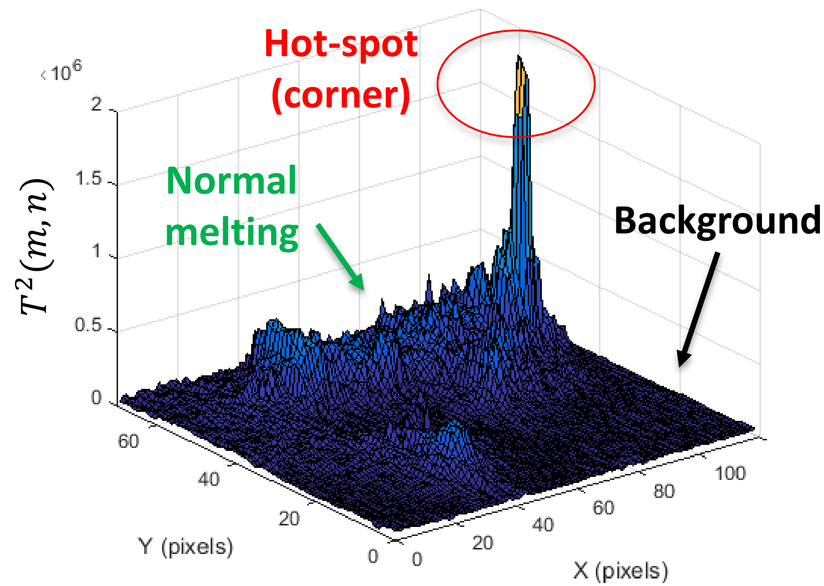
Spatially weighted T-mode PCA (ST-PCA)

Use of Hotelling's T^2 as a **synthetic index** to describe the information content along the most relevant components of the video image data within J observed frames

$$T^2(m,n) = \sum_{l=1}^{q} \frac{z_{l,i}^2}{\lambda_l},$$

where λ_j is the *l*-th eigenvalue, (m,n) are the pixel coordinates $(m = 1,\dots,M, n = 1,\dots,N)$ and q is the number of retained PCs





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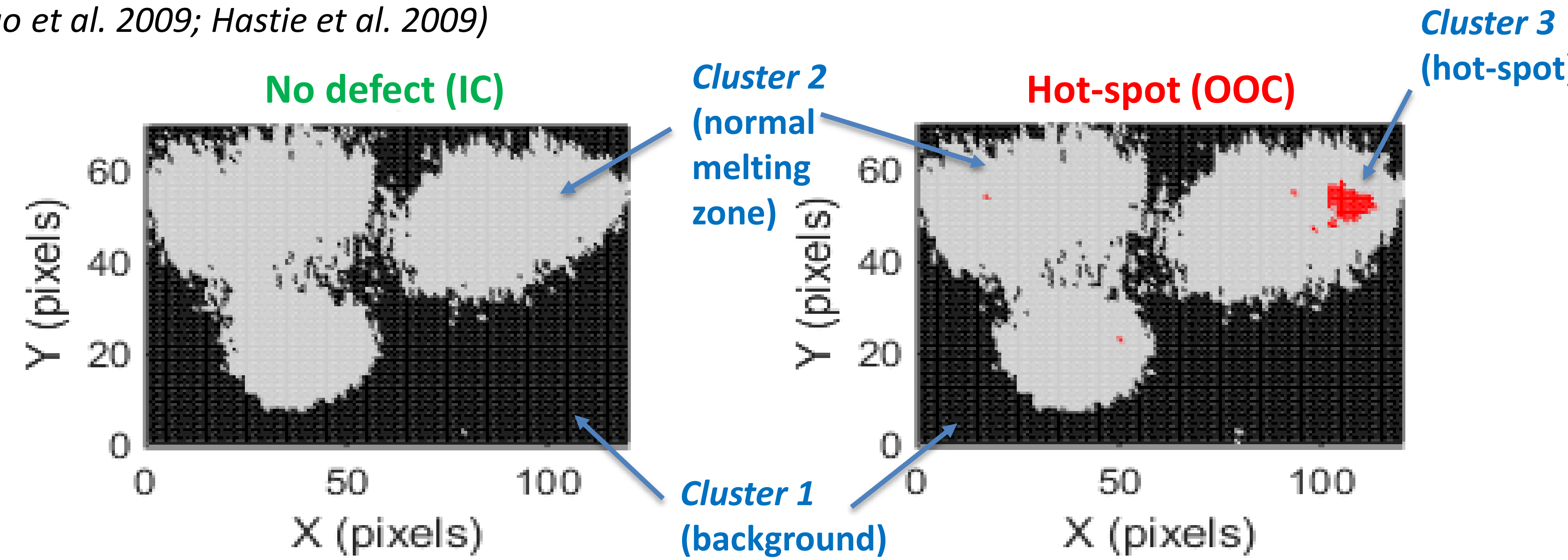
Spatially weighted T-mode PCA (ST-PCA)

Alarm rule based on *k*-means clustering of $T^2(m,n)$

- When process is IC : $k=2$ clusters are expected (background + normal melting)
- When process is OOC : additional clusters correspond to defective areas (hot-spots)

Automated selection of *k* based on sums of squared within-distances: *k*>2 → ALARM

(Zhao et al. 2009; Hastie et al. 2009)



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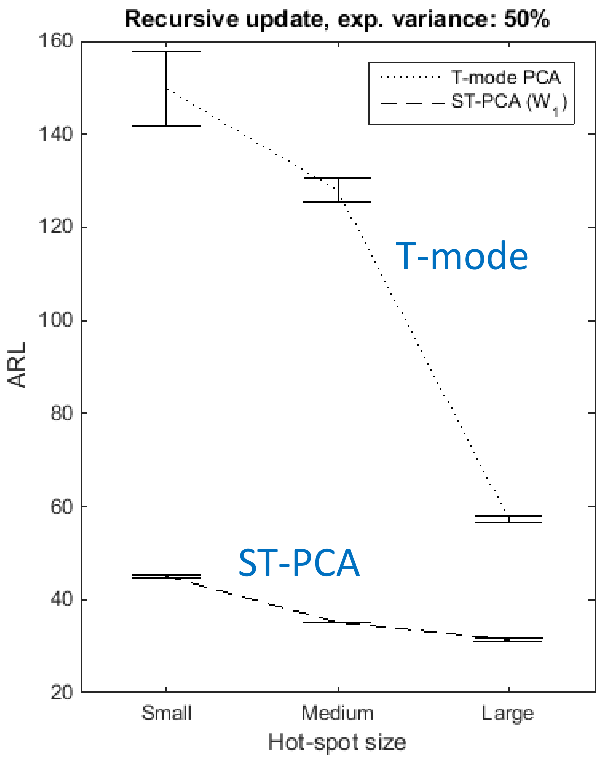
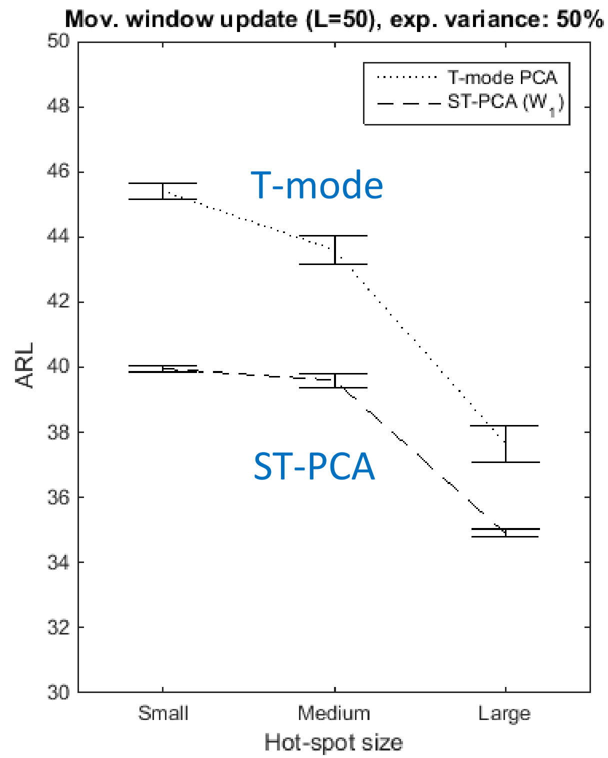
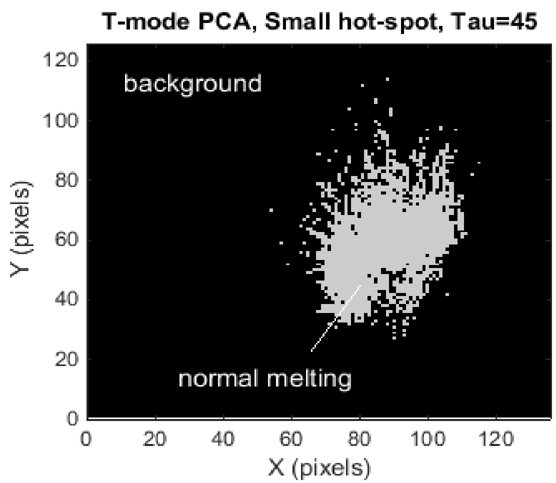
In-situ monitoring of LPBF processes
HOT SPOT

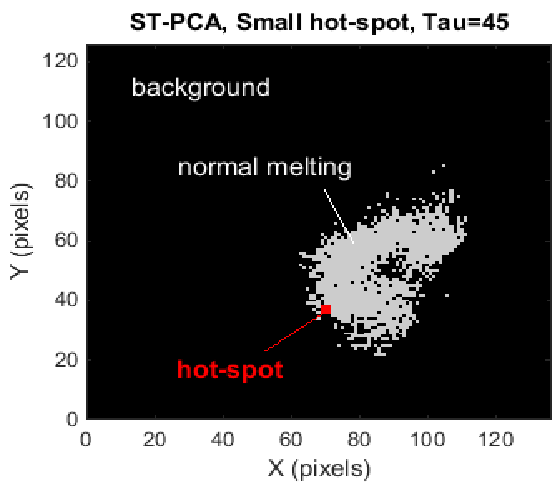
Simulation analysis

Simple T-mode PCA vs ST-PCA (Average Run Length – ARL)









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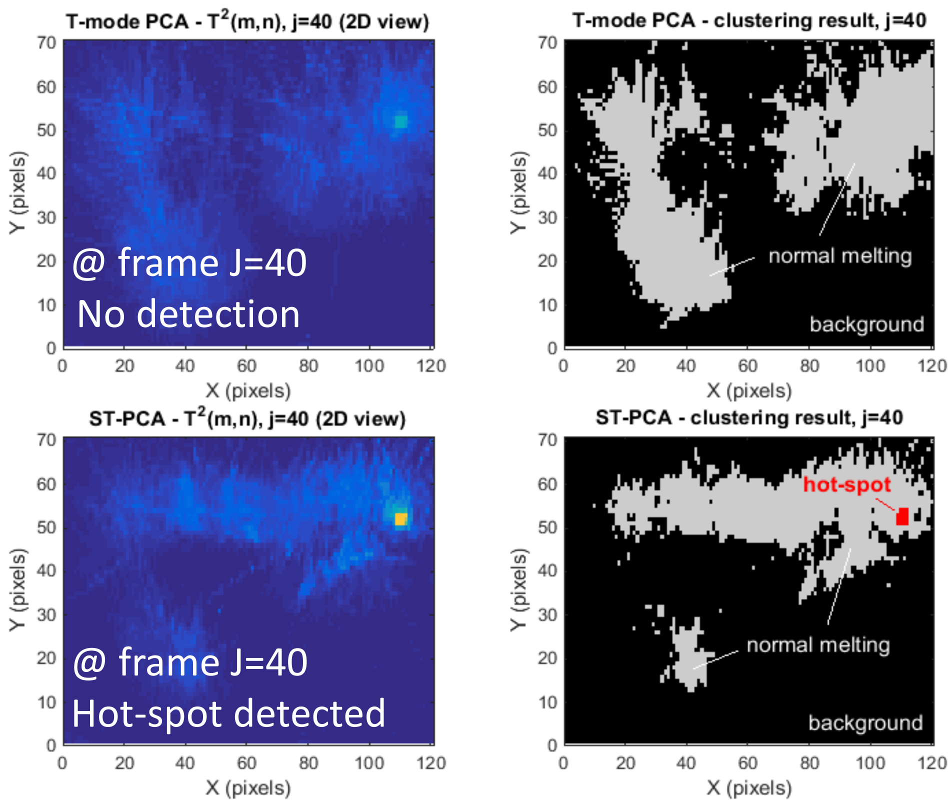
In-situ monitoring of LPBF processes
HOT SPOT

Real case study

Example of T-mode PCA vs ST-PCA

Simple T-mode PCA

ST-PCA



Approach		Time of first signal (frame index)
OOC Scenario 1		
Average intensity	Recursive	*No detection*
	Mov. window	*No detection*
T-mode PCA	Recursive	$j = 201$
	Mov. window	$j = 198$
ST-PCA	Recursive	$\boldsymbol{j = 40}$
	Mov. window	$\boldsymbol{j = 40}$
OOC Scenario 2		
Average intensity	Recursive	$j = 144$
	Mov. window	*No detection*
T-mode PCA	Recursive	$j = 95$
	Mov. window	*No detection*
ST-PCA	Recursive	$j = 94$
	Mov. window	$\boldsymbol{j = 92}$
OOC Scenario 3		
Average intensity	Recursive	*No detection*
	Mov. window	$j = 173$
T-mode PCA	Recursive	$j = 169$
	Mov. window	$j = 168$
ST-PCA	Recursive	$j = 164$
	Mov. window	$\boldsymbol{j = 153}$

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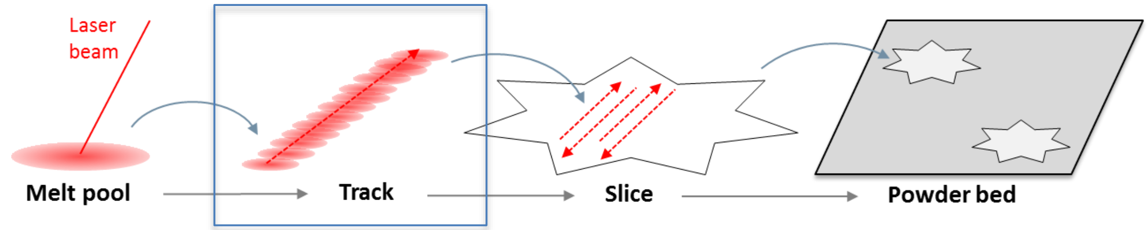
In-situ monitoring of LPBF processes

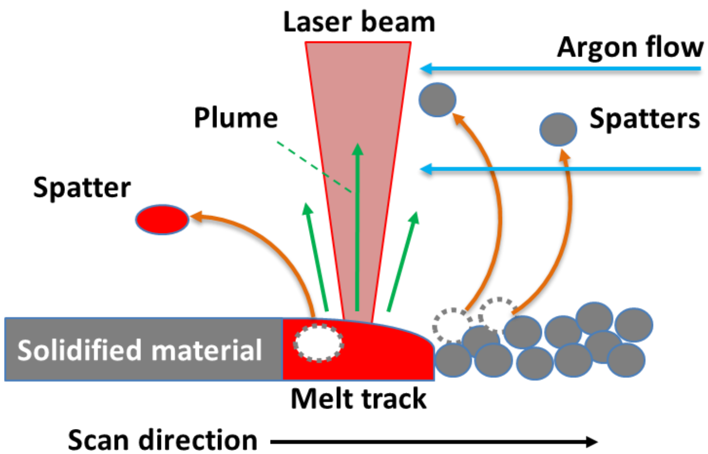
Repossini et al., Additive Manufacturing, 2017
Grasso et al., Robotic and Computer-Integrated Manufacturing, 2018

Study of process by-products signatures for process monitoring and optimization

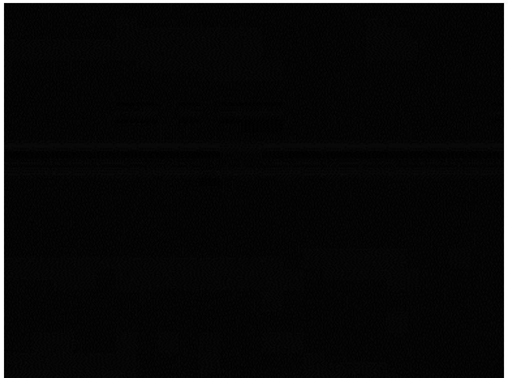


- Mainstream literature on in-situ monitoring focuses on melt pool and track
- Process by-products filtererd out as nuisance factors
- But by-products may enclose relevant information about the process quality and stability

By-product generation in LPBF



Spatters


Visible range, 1000fps

Plume


Infrared range, 50fps

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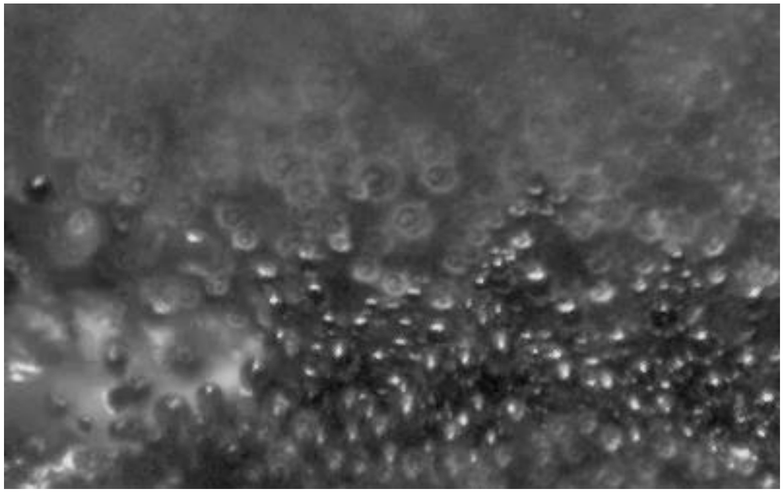
SPATTERS

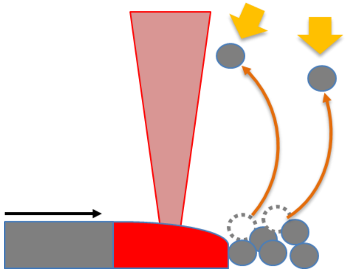
What type of spatters and why do they originate?



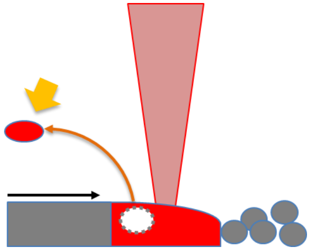
Example: Ti6Al4V particle dynamics

Ly et al. 2017 available at http://rdcu.be/tC7W (100 KHz)

- **Powder spatters**: non-melted powder particles blown away as a result of the impact with the metallic vapour



- **Droplet spatters:** caused by the convective transport of liquid or vapourized metal out of the melt pool



Research goals

- Characterize **spatter behaviour** under different energy density conditions (synthetic descriptors)
- Can spatter-related information be a suitable driver for **in-situ process monitoring**?
- Can spatter-related information be a suitable driver for **process optimization**?

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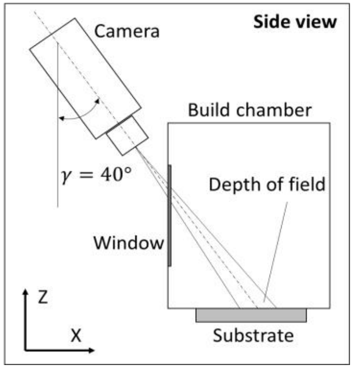
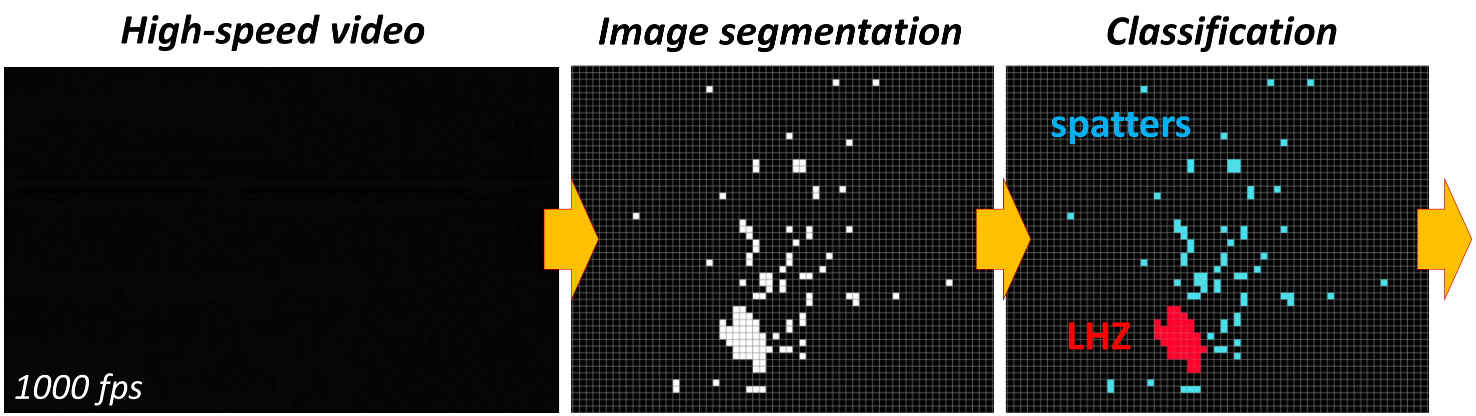
In-situ monitoring of LPBF processes
SPATTERS

Repossini et al., Additive Manufacturing, 2017

Proposed approach

Off-axis high speed video acquisition
- 1000 frames per second
- Visible range
- Spatial resolution: ~250μm/pixel
- Field of view: about 120x120 mm





Descriptors
- *LHZ area*
- *average spatter area*
- *spatter spatial spread*
- *n° of spatters*

LHZ = Laser Heated Zone

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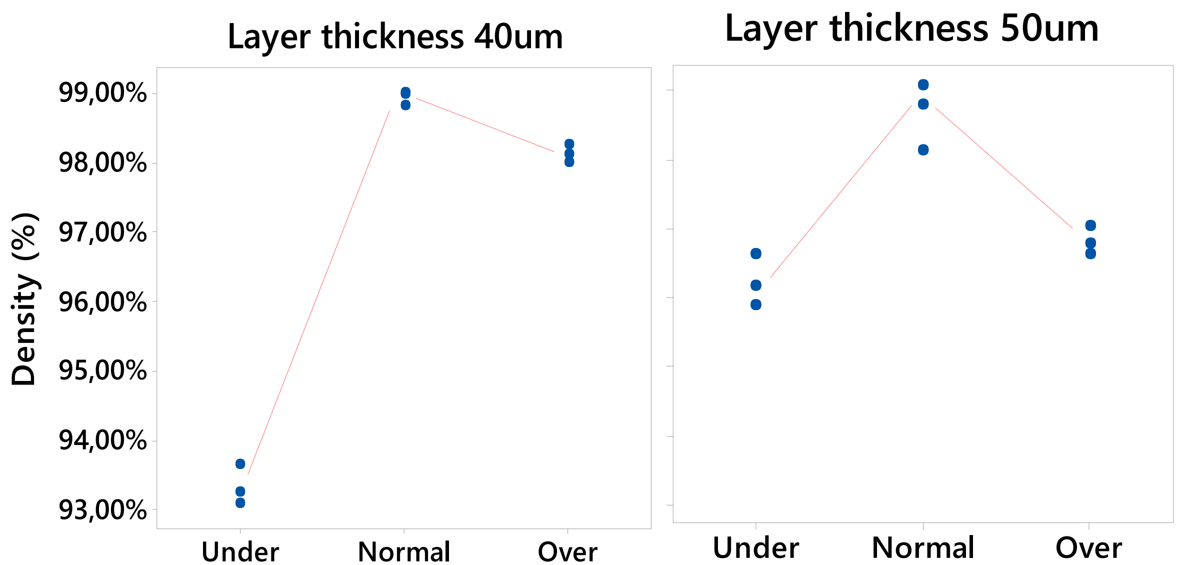
Repossini et al., Additive Manufacturing, 2017

Experimentation

Build	Energy density level	t [μs]	z [μm]	F [J/cm^3]
Build 1 ($z = 40\ \mu m$)	Lack-of-fusion	42	40	40000
	Normal-melted	83	40	80000
	Over-melted	125	40	120000
Build 2 ($z = 50\ \mu m$)	Lack-of-fusion	52	50	40000
	Normal-melted	104	50	80000
	Over-melted	156	50	120000

- Maraging steel specimens (av. particle size 35 µm)
- 3 levels of energy density:
  - ✓ under-melting
  - ✓ normal melting
  - ✓ over-melting
- Two layer thickness levels: (40 µm and 50 µm)



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Comparison of logistic regression classification models (response = energy density level):

- **Model A:** includes only LHZ area (benchmark)
- **Model B:** Spatter descriptors only: n° of spatters, average area, spatial spread (convex hull)
- **Model C:** LHZ + spatter descriptors

➢ ***Misclassification analysis***

- Percentage of wrongly classified energy density levels (estimation based on leave-one-out cross-validation)

Model	Predictors	Misclassif. error (Build 1)	Misclassif. error (Build 2)
Model A	LHZ area	66.7%	53.42%
Model B	Spatter descriptors	29.0%	20.7%
Model C	All	**22.3%**	**20.5%**

➢ The inclusion of spatter descriptors as classifier predictors enhances the goodness-of-fit and reduces the misclassification error

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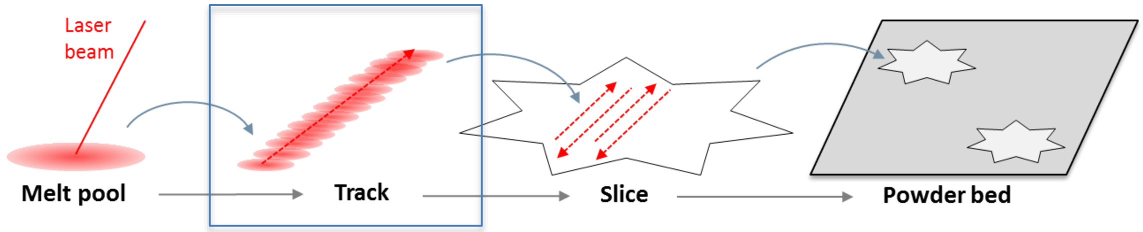
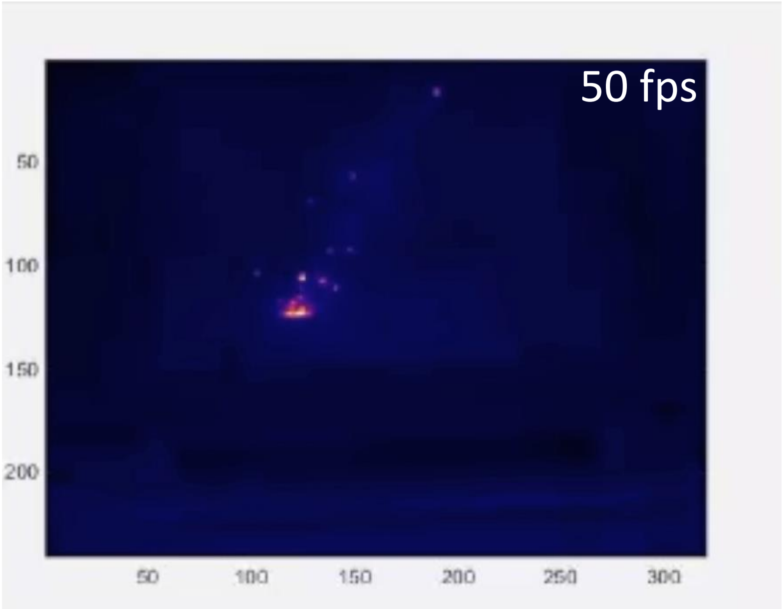
In-situ monitoring of LPBF processes
PLUME

Grasso, Demir, Previtali, Colosimo (2017), RCIM

Study of process by-products signatures for process monitoring and optimization





Example of plume generation during SLM of pure zinc

- Zinc and its alloys - biodegradable metals (cardiovascular stents).
- Difficult to print by LPBF - very low melting and vaporization points – plume (ionized gas and metallic vapor)
- Plume absorbs/reflects laser radiation – possible bursts and modification of local energy density

Main idea: use the plume as process signature to detect process instability via in-situ IR video imaging

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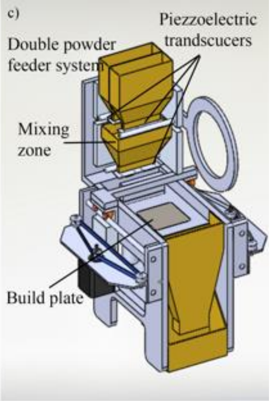
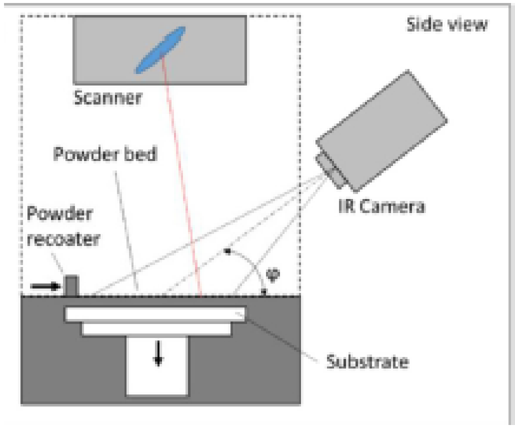
In-situ monitoring of LPBF processes
PLUME

Grasso, Demir, Previtali, Colosimo (2017), RCIM

In-situ IR monitoring on LPBF system prototype (Powderful)

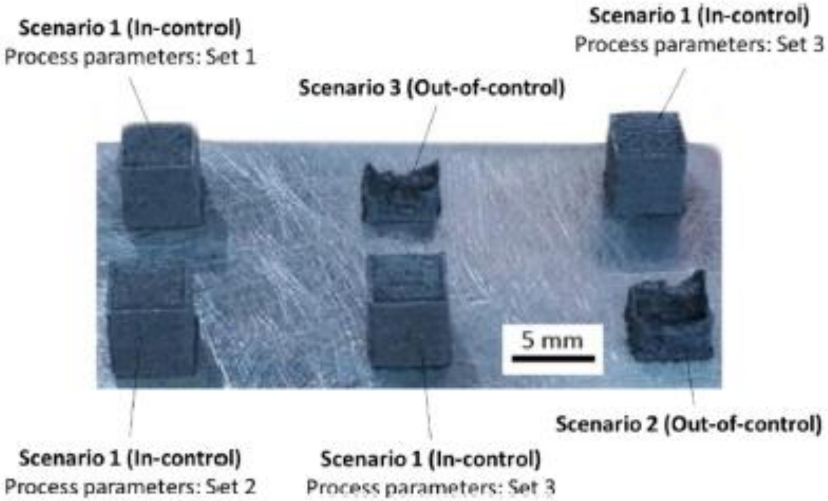
- FLIR SC3000
- Spectral range: 8-9 µm
- 320 x 240 pixels
- Temp. range: 100 – 500 °C





Experimental activity

- Scenario 1 – stable process (optimal process parameters)
- Scenarios 2 and 3 (over-melting) - unstable process conditions that yielded part disintegration



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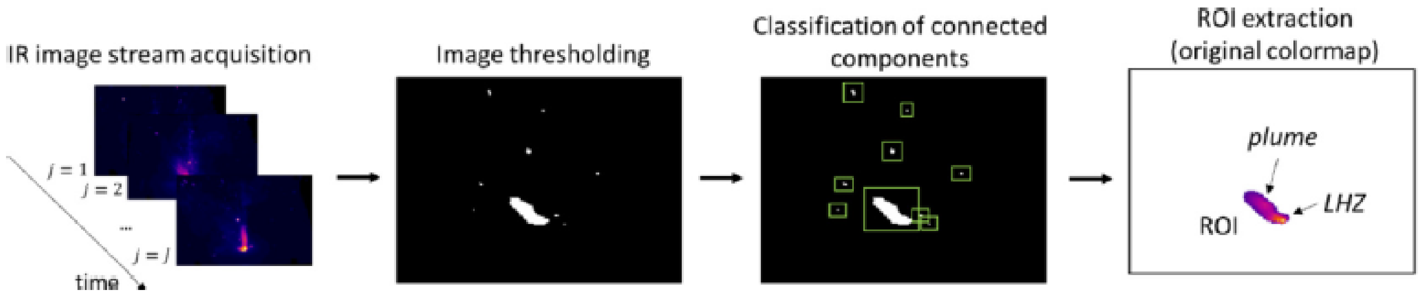
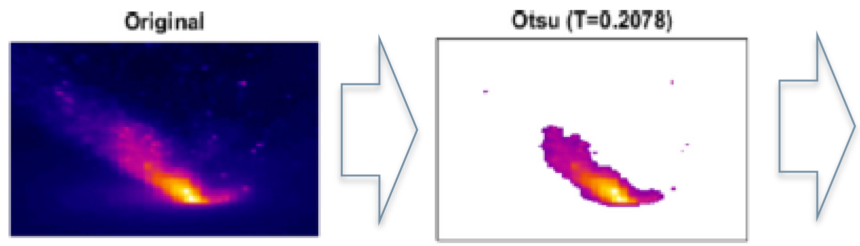
In-situ monitoring of LPBF processes
PLUME

Grasso, Demir, Previtali, Colosimo (2017), RCIM

Image processing

Analysis of the region of interest (ROI) that includes the plume and the laser heated zone





Multivariate Control chart:

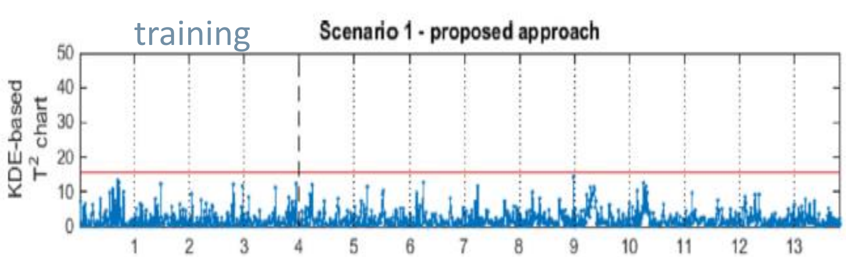
- *Area*
- *Average Intensity*

Control charts

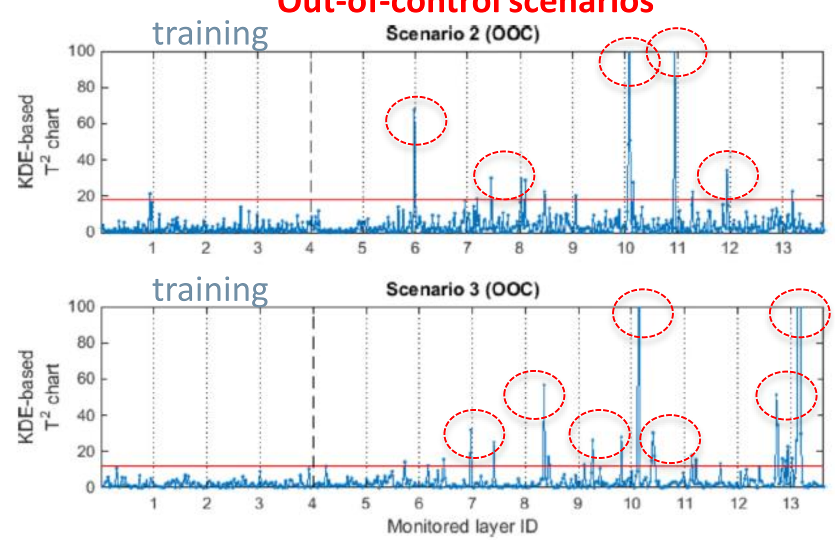
Training of first few layers (assumed in-control)

Monitoring of following layers

In-control scenario



Out-of-control scenarios



What's next? Towards multi-sensor fusion…

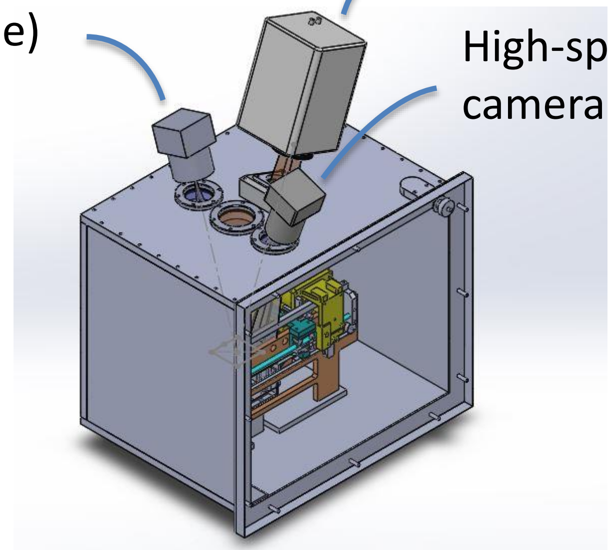
Laser PBF

Prototype systems equipped with different in-situ sensors (either co-axial and off-axis)

IR camera

High-speed camera (visible)

High-spatial res camera (visible)

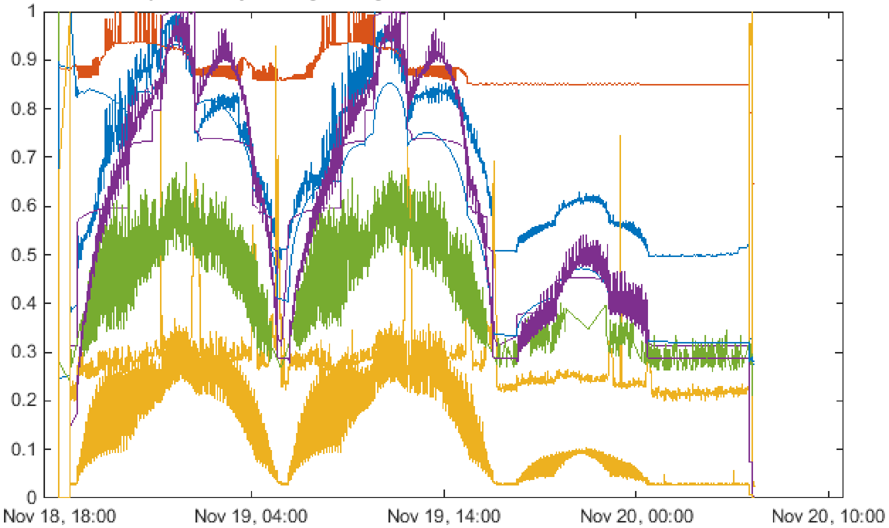


+ integrated co-axial sensing (photodiodes and cameras)

Electron beam PBF

Multiple sources of information from embedded and external sensors

Example of log signals



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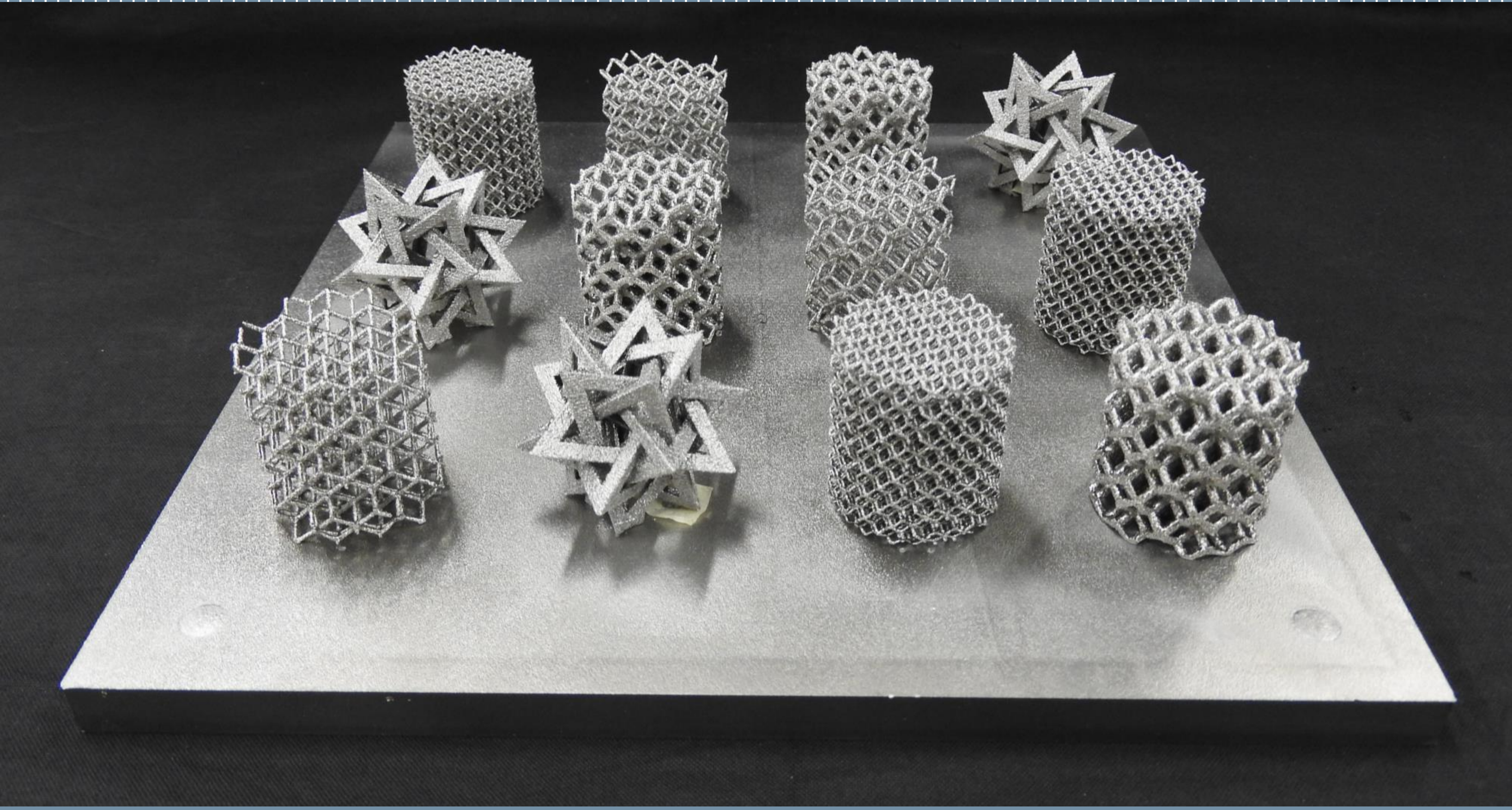
Thank you for your attention



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