POLITECNICO MILANO 1863

Statistical Process Monitoring of Additive Manufacturing via In-Situ Sensing

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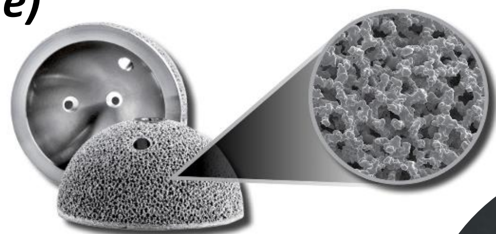
AddMe.Lab

Additive Manufacturing of metals

Additive Manufacturing (AM) allows producing metal parts with innovative characteristics in terms of shape, surface properties, internal structure and overall value chain

Functional surface patterns (e.g., healthcare)

Lima Corporate

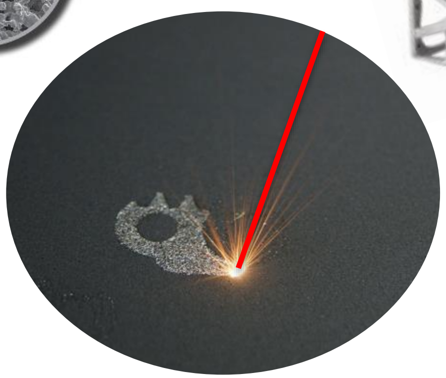


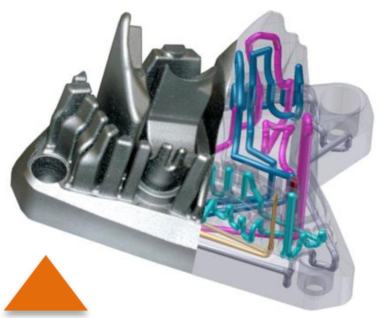
Topologically optimized shapes (e.g., aerospace)

RUAG

GE

Monolithic components (e.g., aerospace)

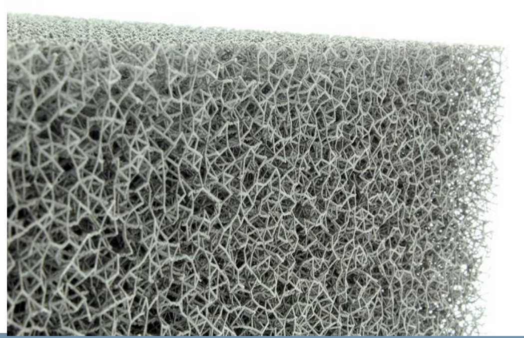




Internal channels & conformal cooling

GE

Lightweight structures (e.g., medical & aerospace)



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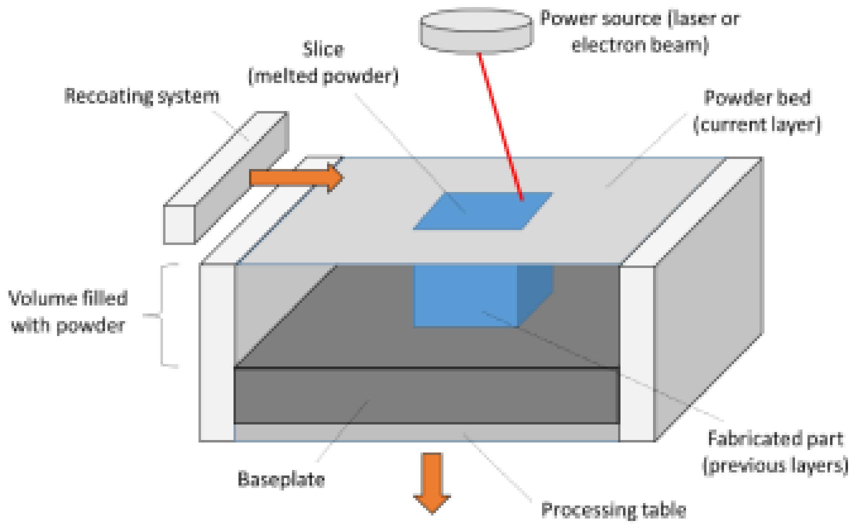
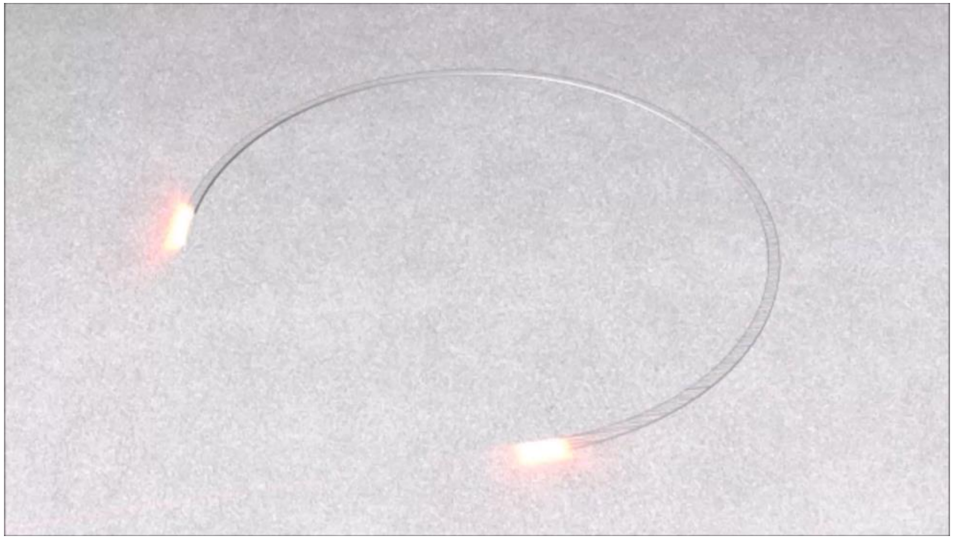
How does it work? The laser powder bed fusion process

Selective Laser Melting (SLM)

A scanner displaces a laser beam along a predefined path to locally melt the metal powder, layer by layer





Courtesy: Lawrence Livermore Laboratory

- Laser beam diameter: 70 µm
- Average powder particle diameter: 35 µm
- Layer thickness: 50 µm

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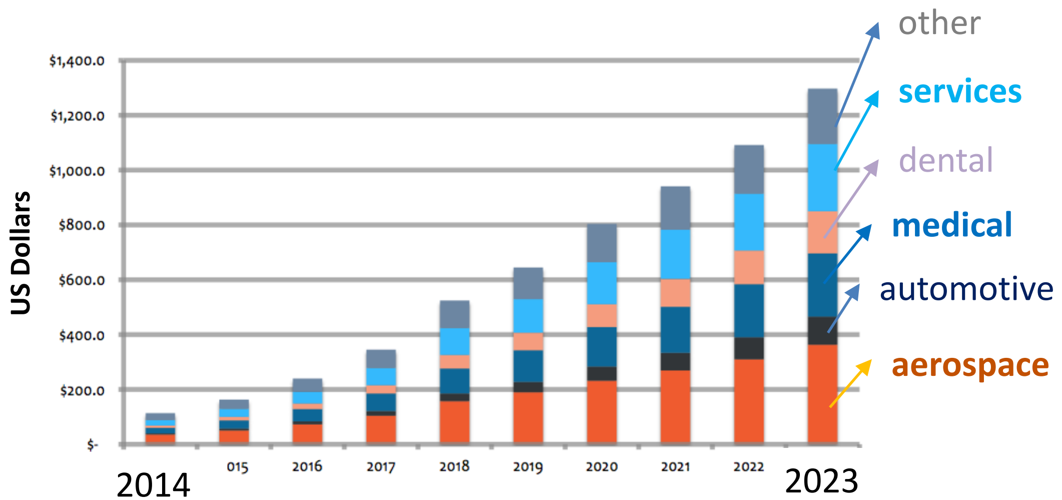
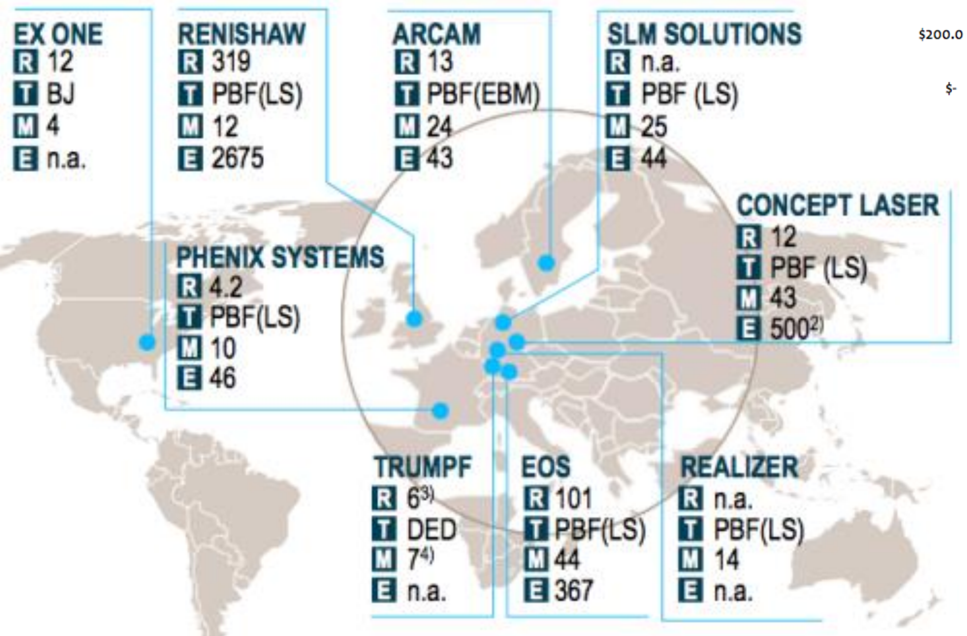
Additive Manufacturing of metals
The market situation and competitive scenario

- **Leading sectors are aerospace and healthcare**
- **They are also the sectors with higher TRL** *(e.g., GE aviation engine components, hip prosthesis, etc.)*





- **Main AM system developers in EU**
- **Merging & acquisitions involving big groups** *(e.g., Concept Laser & Arcam acquired by GE)*
- **Many actors have impressive growth rates** *(e.g., 3D Systems: 52%; Arcam: 43%)*
- **Technological competition mainly involves in-line monitoring and quality control**

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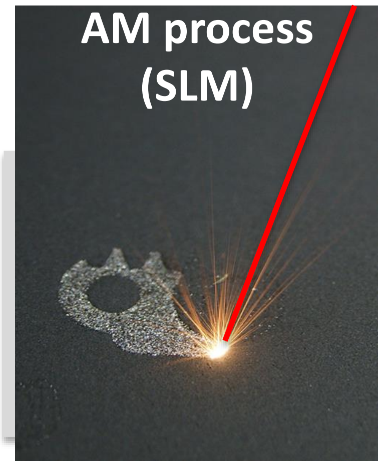
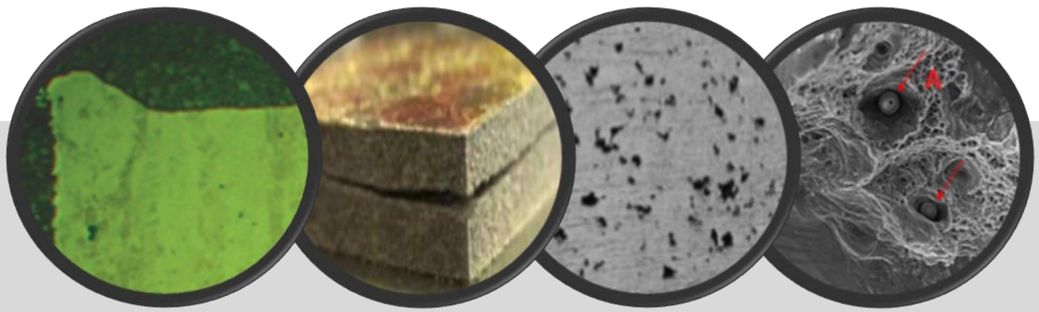
«The limited stability and repeatability of the process still represent a major barrier for the industrial breakthrough of metal AM systems» *(Mani et al., 2015; Tapia and Elwany, 2014; Everton et al., 2016; Spears and Gold, 2016)*





High defective rates (> 5 – 30%)

Current defective rates are not acceptable:

- Expensive materials (e.g., titanium powders > 150€/kg)
- Long processes (e.g., < 10 cm^3/h)
- Long/expensive trial-and-error inflates the time-to-market
- Stringent quality requirements (aerospace & healthcare)

<u>Today, no commercial system is able to automatically detect defects during the process</u>

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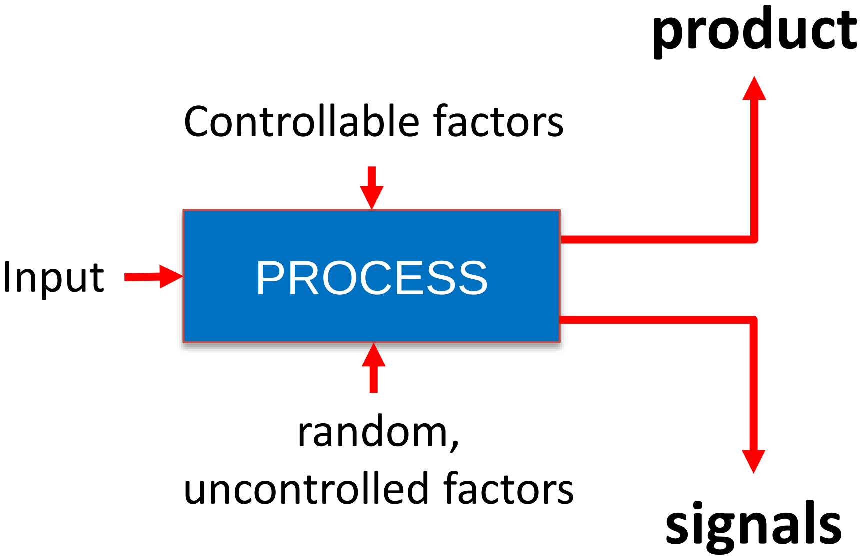
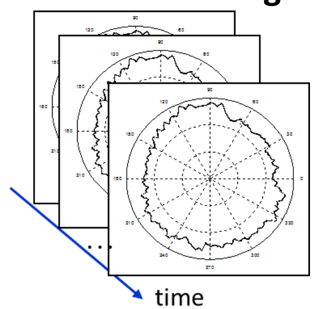
Our background
Statistical monitoring of *product* and *process* data

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

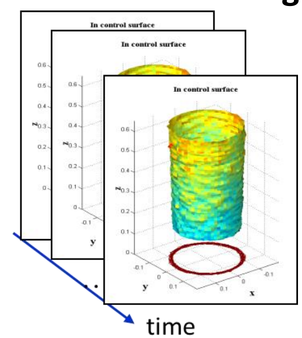


Profile monitoring



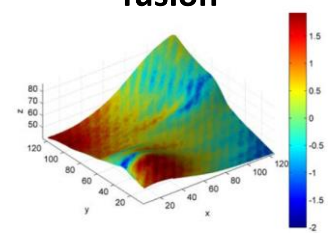
Colosimo et al. (2008), JQT

Surface monitoring



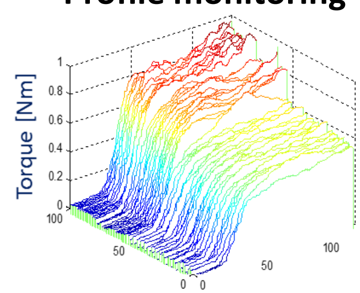
Colosimo et al. (2014), JQT

Multi-fidelity data fusion



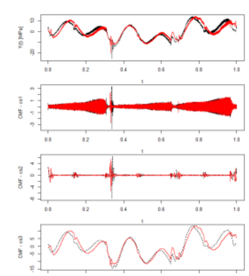
Colosimo et al. (2015), Prec. Eng.

Profile monitoring



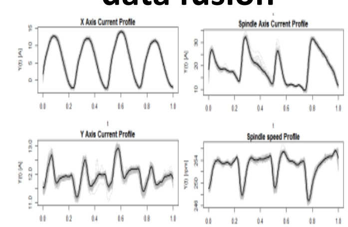
Grasso et al. (2016), JQT

Signal processing



Grasso et al. (2016), MSSP

Multi-sensor data fusion

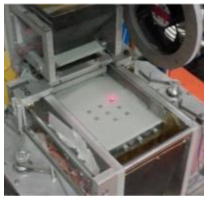


Grasso et al. (2014), IJPR

Our current research in metal Additive Manufacturing
On-line monitoring via *in-situ* sensors

Selective Laser Melting (**SLM**)

Renishaw AM250

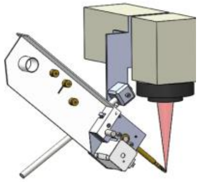


Prototype SLM

Electron Beam Melting (**EBM**)

ARCAM A2

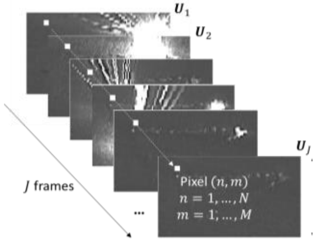
Direct Energy Deposition (**DED**) powder & wire



In-situ process monitoring and control (towards zero-defect metal AM)

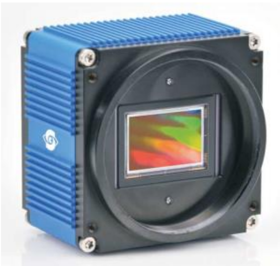
Image-based and multi-sensor statistical methods for on-line detection/localization of defects

High-speed vision

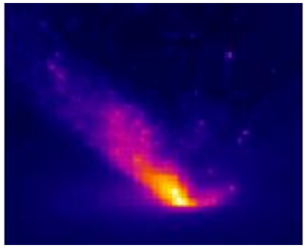


Grasso et al. (2016), Repossini et al. (2017)

High-resolution low-speed vision



Infrared vision



Grasso et al. (2017), RCIM (under review)

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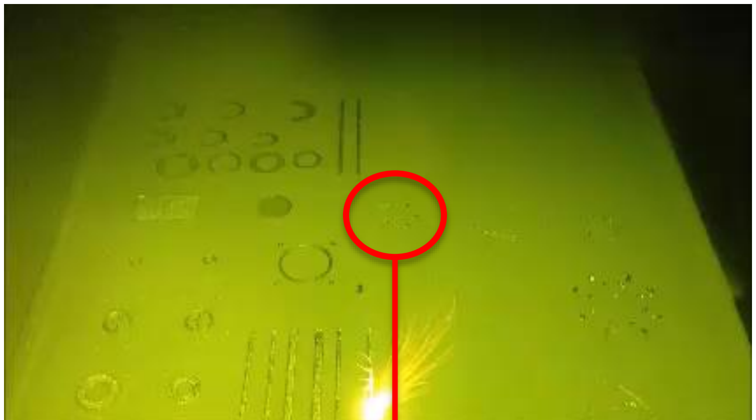
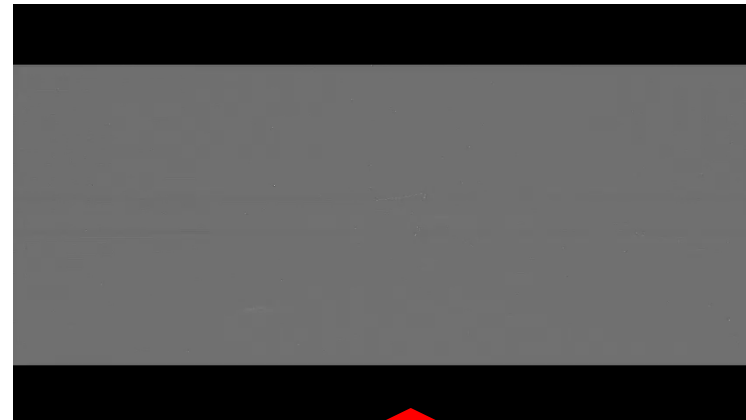
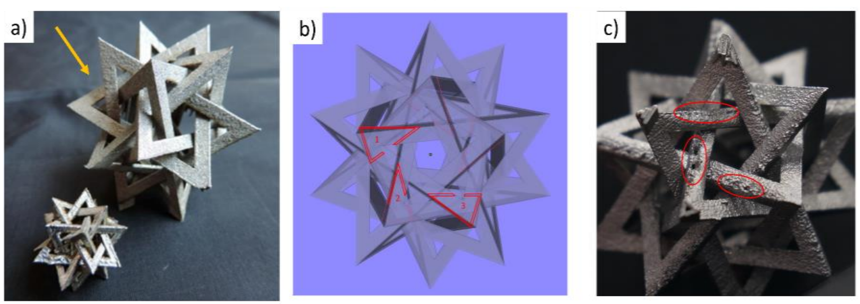
Hot-spot detection and localization in SLM
Case study

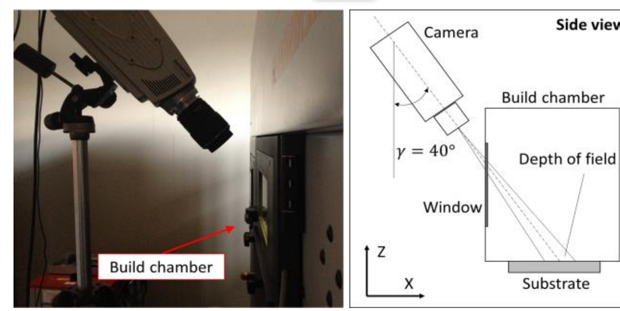
Example of local over-heating in down-facing acute corners (AISI 316L steel)







High-speed image acquisition (300 fps)



Colosimo and Grasso (2017), Journal of Quality Technology (under review)
Grasso et al. (2016), Journal of Manufacturing Science and Engineering

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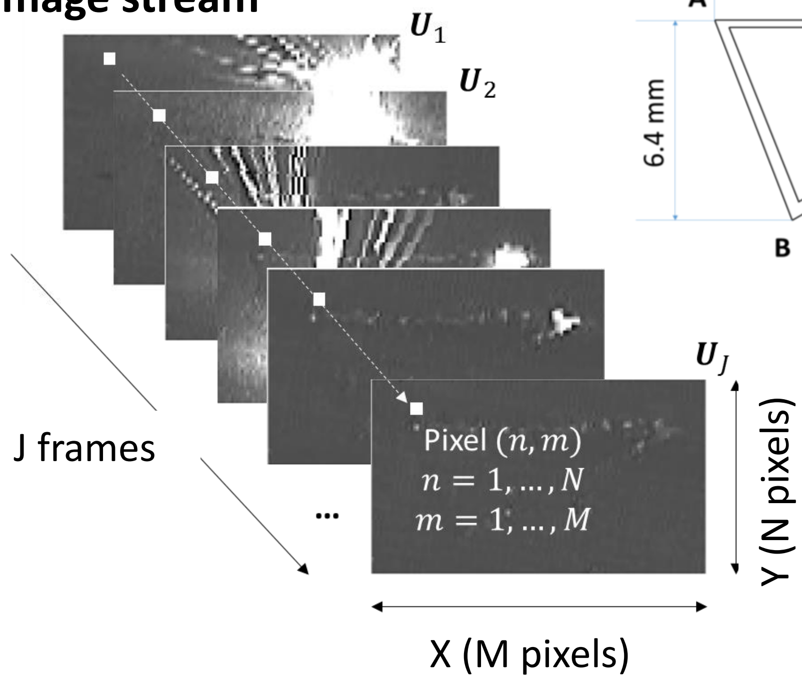
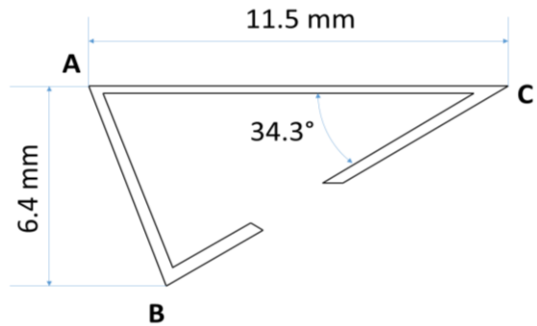
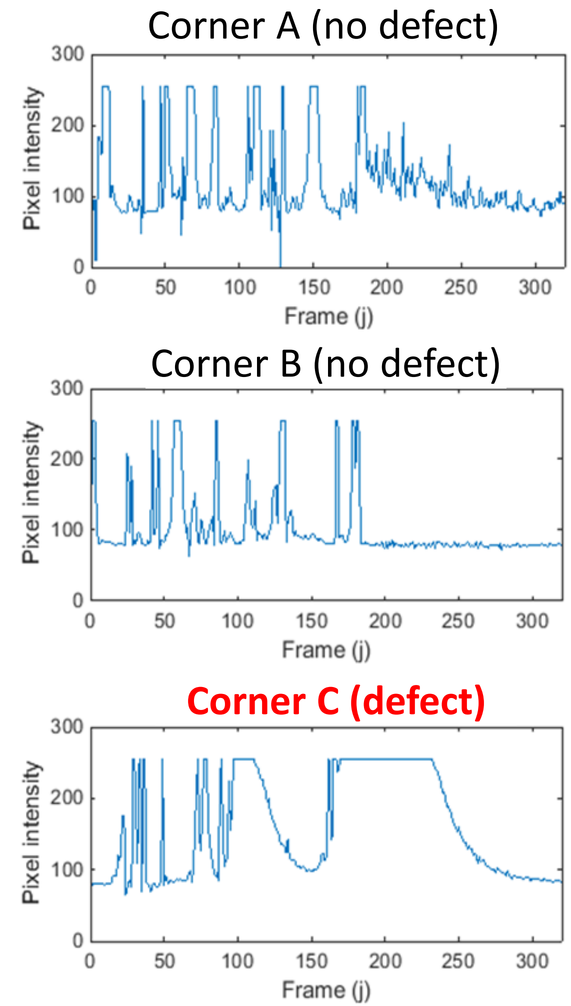
Hot-spot detection and localization in SLM
Proposed approach

Image stream







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

HOT-SPOT

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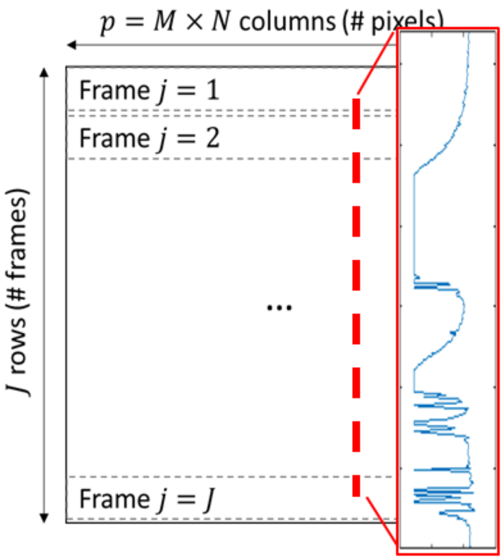
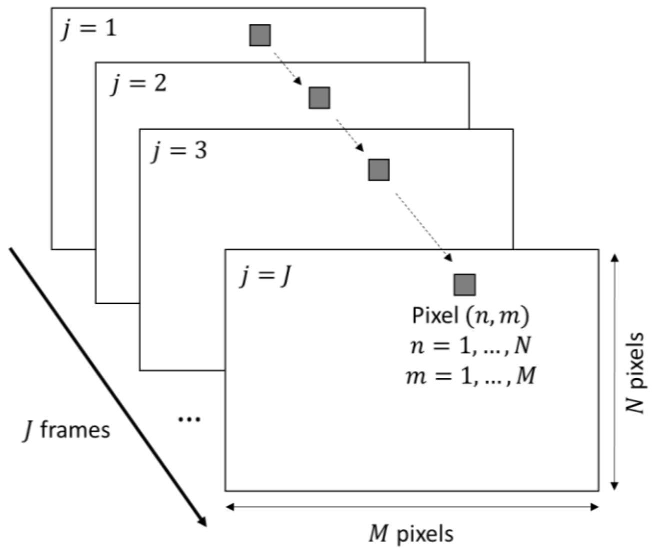
Hot-spot detection and localization in SLM
Proposed approach

Image stream processing

Temporal PCA (S-mode)

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





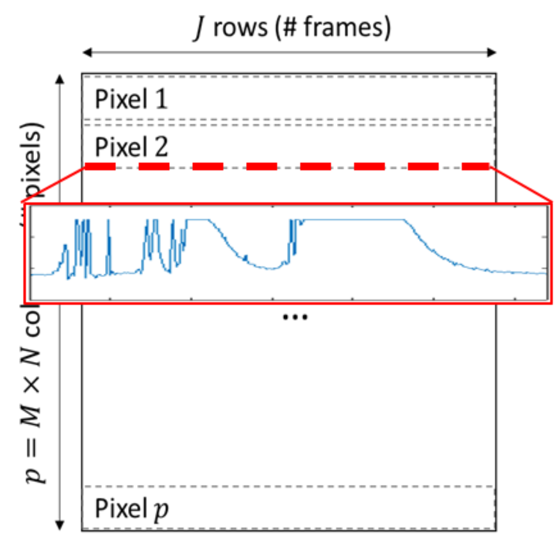
- Principal Component Analysis (PCA) applied to image data
- No segmentation or edge detection operation needed

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

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

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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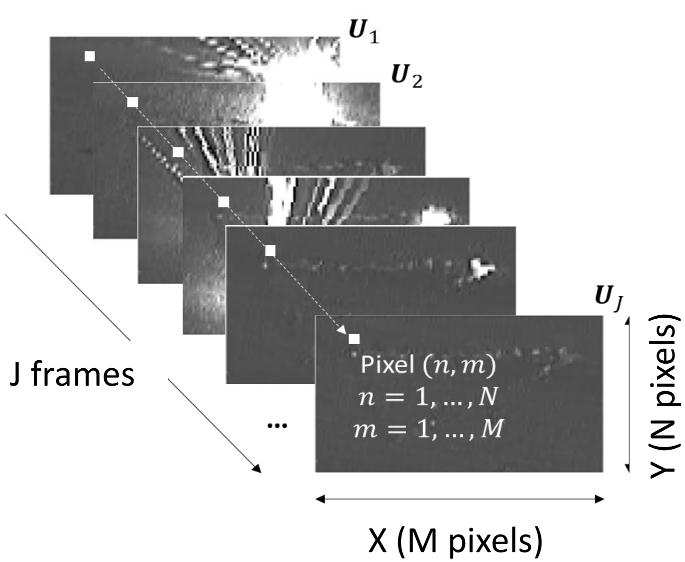
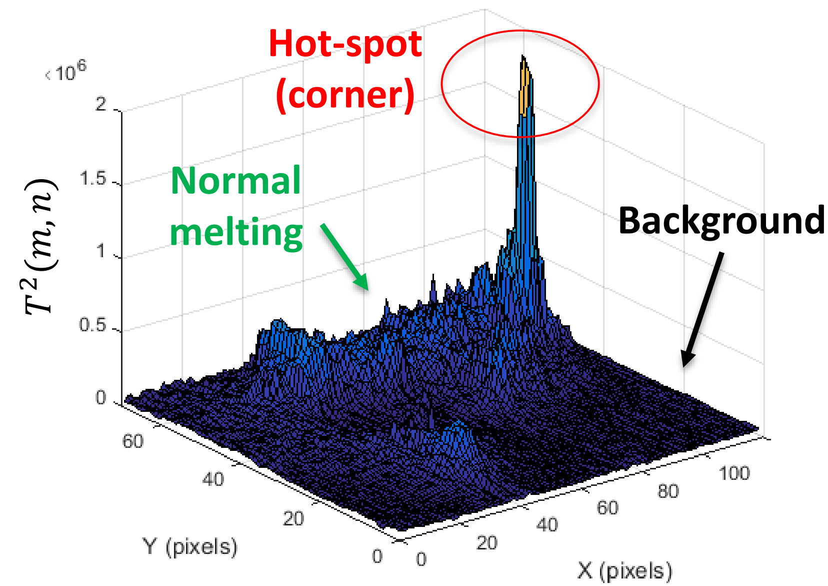
Spatially weighted T-mode PCA (ST-PCA)

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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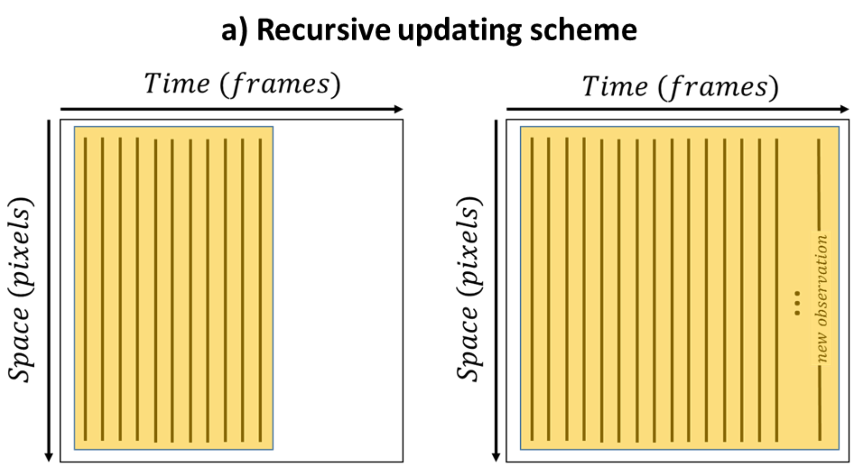
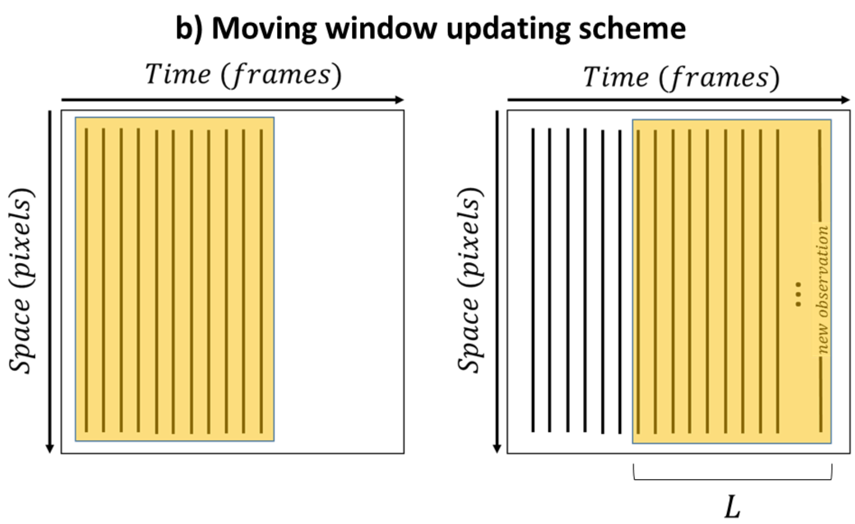
Hot-spot detection and localization in SLM
Proposed approach

Spatially weighted T-mode PCA (ST-PCA)

Two possible ways to iteratively update the ST-PCA as new frames become available





Wold (1994), Gallagher et al. (1997), Li et al. (2000).

Wang et al. (2005); De Ketelaere et al. (2015)

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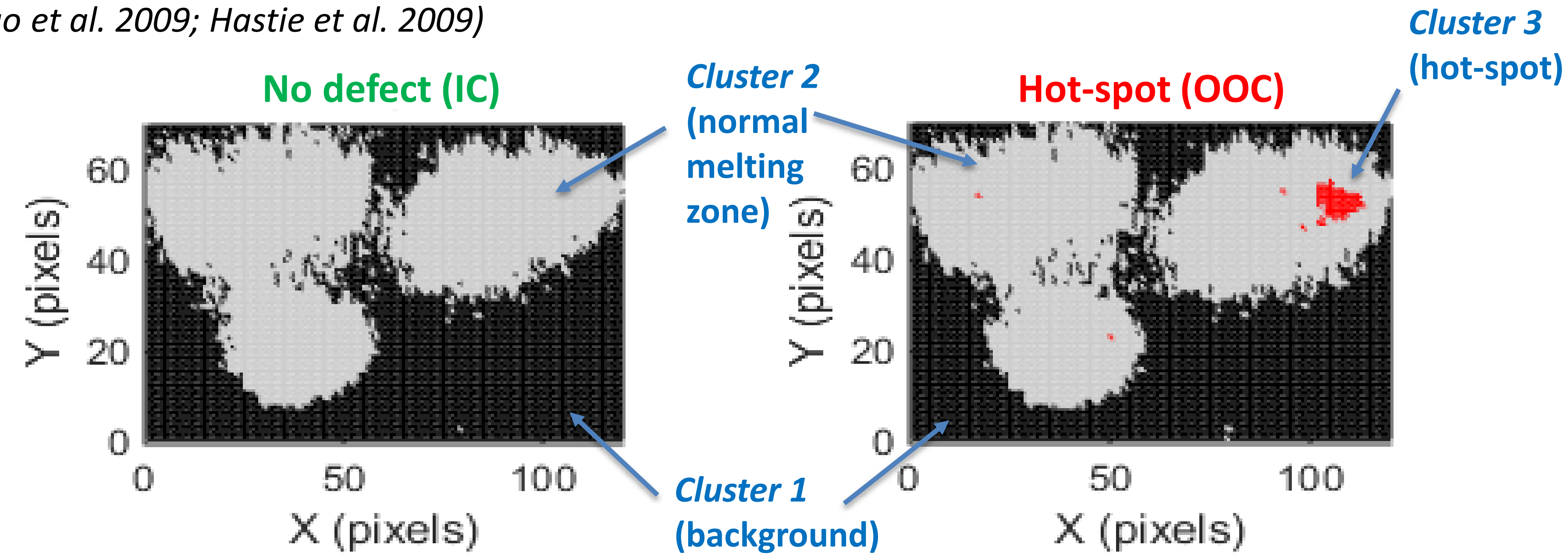
Hot-spot detection and localization in SLM
Proposed approach

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)

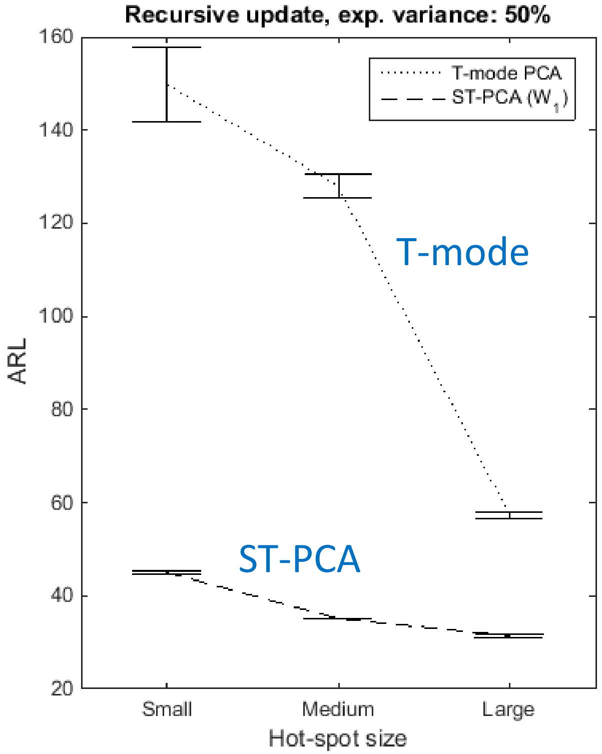
Automated selection of k based on sums of squared within-distances: k>2 → ALARM
(Zhao et al. 2009; Hastie et al. 2009)

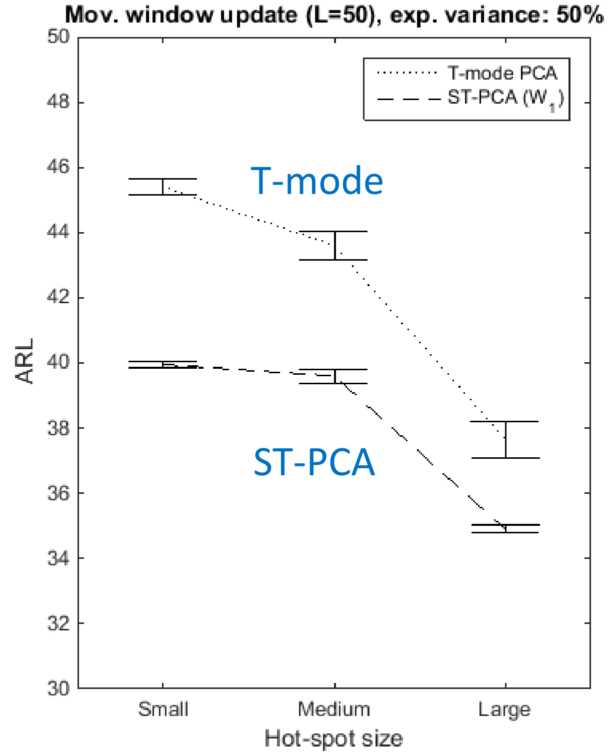


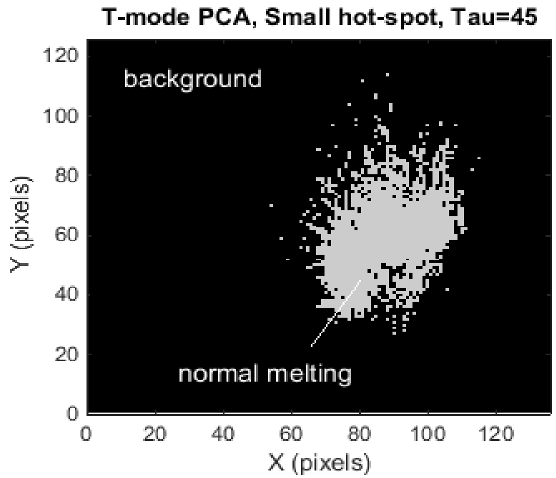
Hot-spot detection and localization in SLM
Results

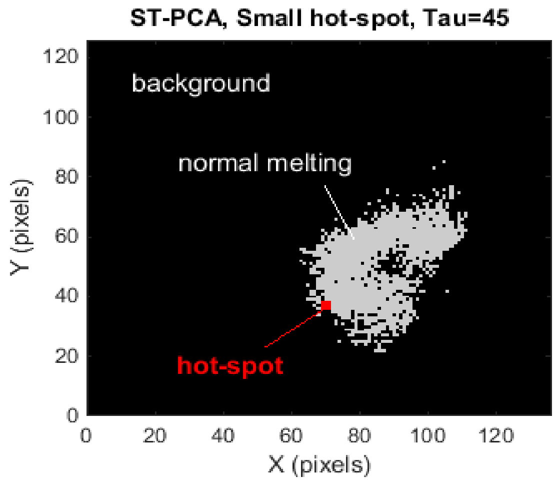
Simulation analysis

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









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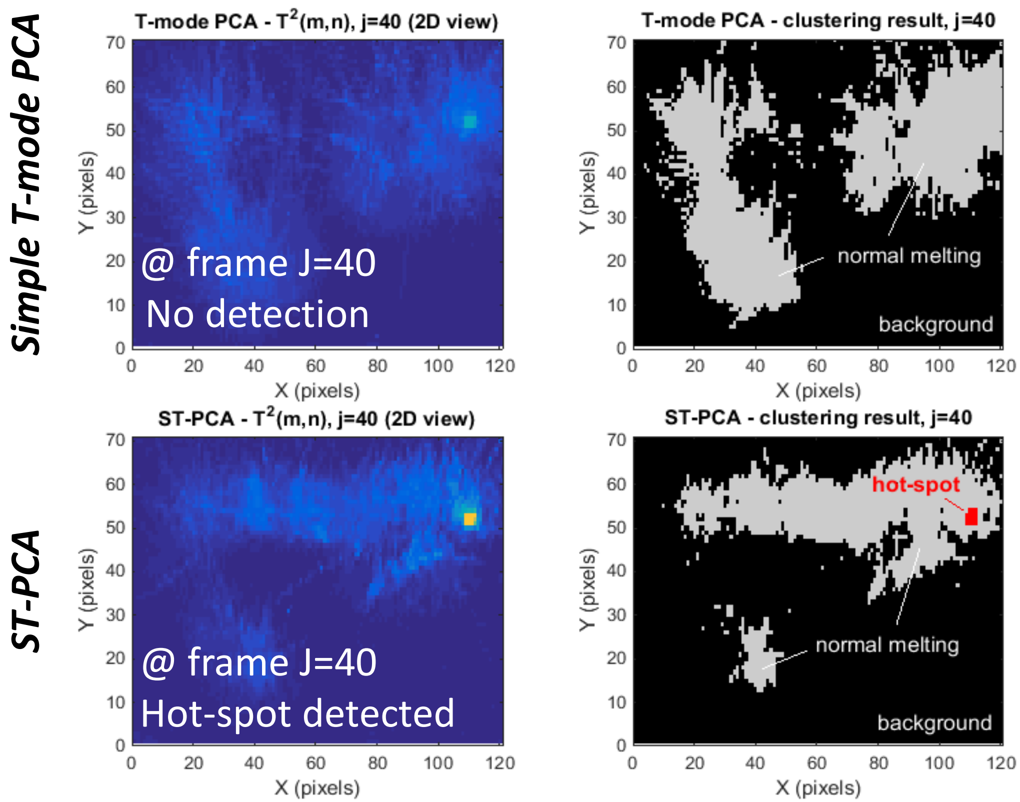
Real case study

Example of T-mode PCA vs 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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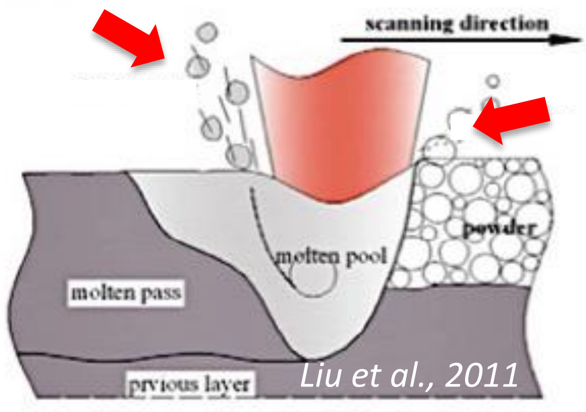
Other research directions
Spatter signature characterization for SLM process monitoring

- Mainstream literature on in-situ monitoring filters out the spatters as nuisance factors
- But spatters may enclose relevant information about the process quality and stability



Goal: spatter signature characterization for SLM process monitoring *(Repossini et al. 2017, Additive Manufacturing)*

Image processing approach

High-speed image acquisition (1000 Hz)

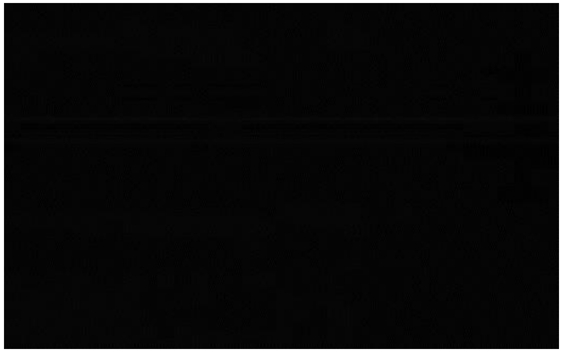
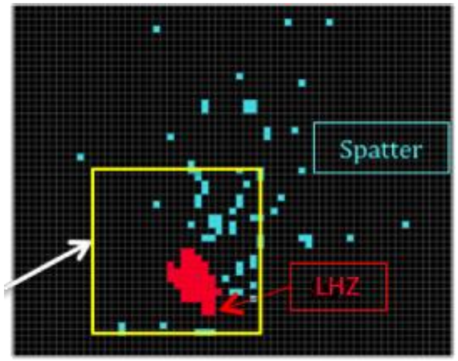


Image segmentation and classification between laser heated zone (LHZ) and spatters



Estimation of statistical descriptors

- *average area*
- *spatial spread*
- *number of spatters*
- *Etc.*

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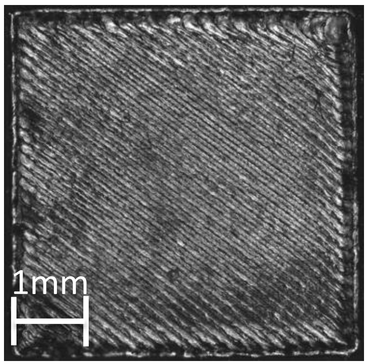
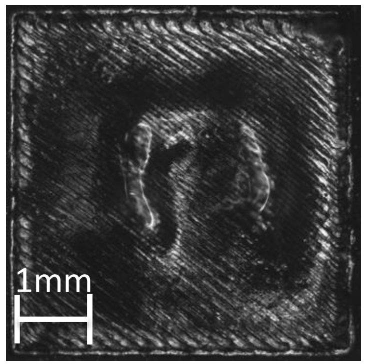
Other research directions
Spatter signature characterization for SLM process monitoring

Real case study

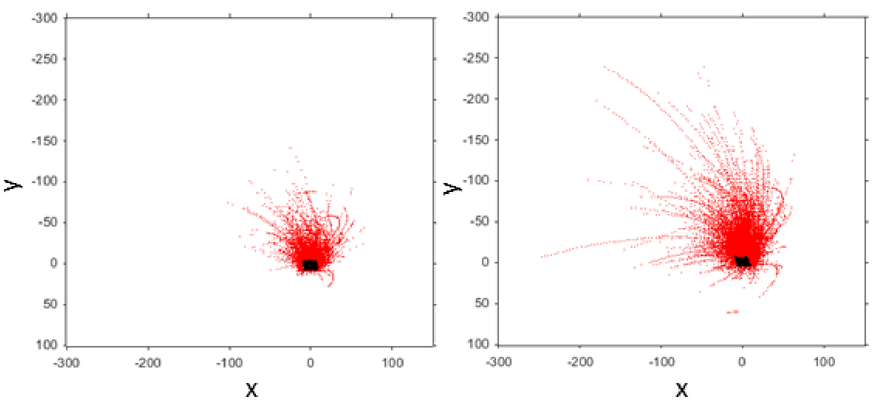
IC energy density (80 kJ/cm³)



OOC energy density (120 kJ/cm³)



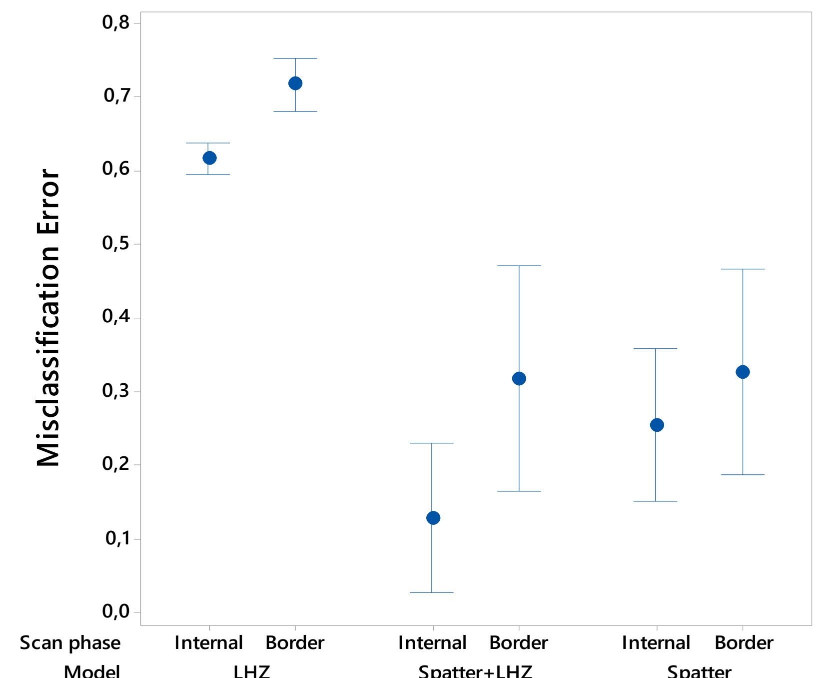
Spatter signature



Comparison of classification models:

- **Model 1:** includes only LHZ area (benchmark)
- **Model 2:** LHZ + spatter descriptors
- **Model 3:** Spatter descriptors alone

95% CI for Mean Misclassification Error (40 um)



Model 1 **Model 2** **Model 3**

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Challenges and future developments

Challenges to face

- ***Computational feasibility***:
  - Hot-spot detection: 0.1s – 0.3s CPU time to process a batch of 1s acquired at 300 Hz (monitored area: 121x71 pixels);
  - <0.1s CPU time to process a batch of 0.5s @ 1000fps
  - Breadboard implementation on real-time platform needed to improve the computational efficiency;
- ***Integration & synchronization*** of image acquisition system with machine controller
- ***Big data stream management*** for continuous process monitoring

Next steps

Study of **multi-sensor data fusion** methods to enhance process monitoring performances

- co-axial + off-axis sensing (process monitoring at multiple levels)
- Evaluation of novel in-situ sensing solutions

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Thank you for your attention

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