# Parallelized Machine Learning for the Analysis of Hybrid Rocket Combustion Data

14th World Congress on Computational Mechanics (WCCM)
ECCOMAS Congress 2020
January 11th – 15th 2021

Alexander Rüttgers (SC-HPC)
Institute for Software Technology
German Aerospace Center (DLR)

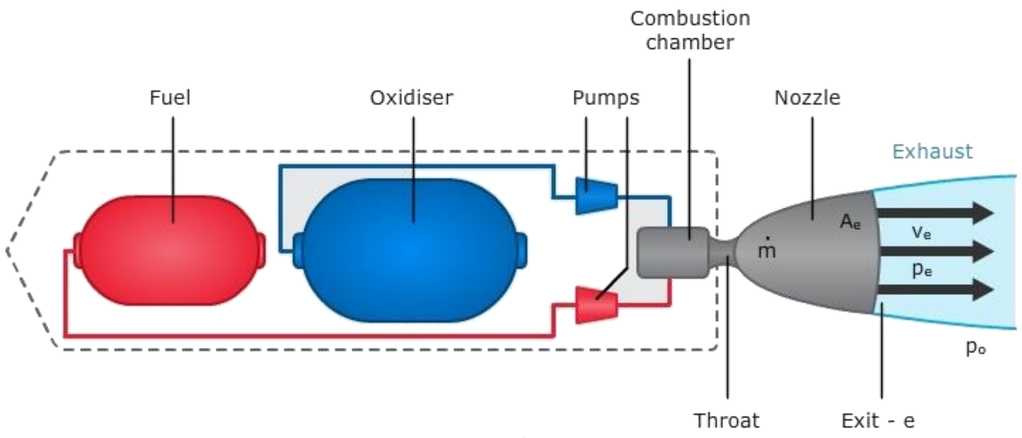
Joint work with Anna Petrarolo, Mario Kobald,
Martin Siggel (all DLR) and Charlotte Debus (KIT)

# Outline

1. Rocket engine combustion analysis at DLR
2. Helmholtz Analytics Toolkit (HeAT) for distributed ML
3. Results
   a) Spectral Clustering
   b) Anomaly Detection

# Rocket engine combustion analysis

- **Aim:** Cost reduction of rocket engines, be competitive with e.g. Space-X

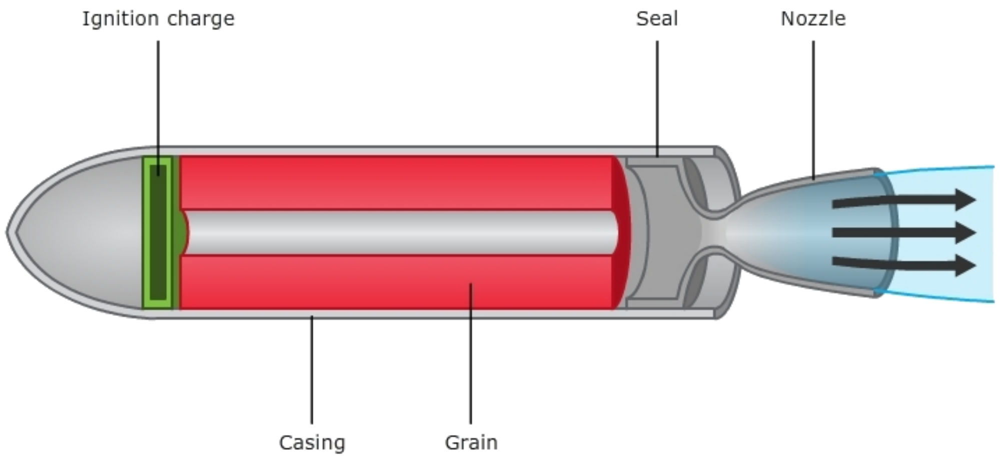



**Traditional liquid rocket engine:**

- 2 pumps transporting fluid fuel and oxidizer at very high pressure and flow
- Advantages
  - Burning rate can be controlled precisely
- Disadvantages
  - Pumps are mechanically very complex
  - Expensive

# Rocket engine combustion analysis

- **Aim:** Cost reduction of rocket engines, be competitive with e.g. Space-X

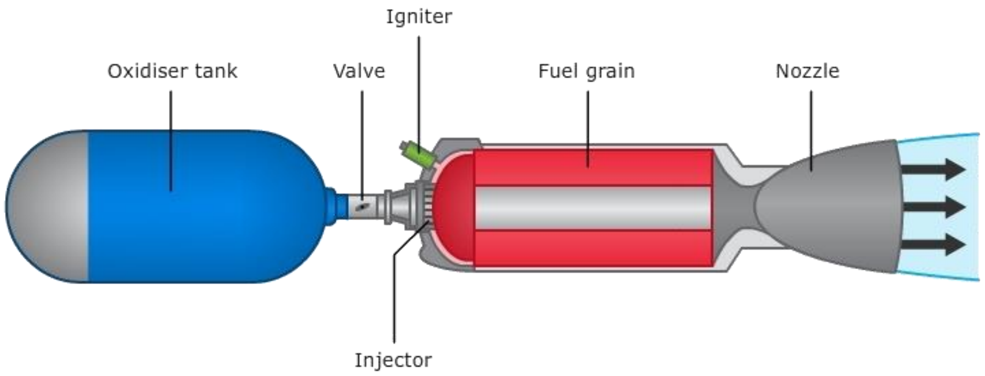



**Solid propellant rocket engine**

- Fuel and oxidizer are mixed in solid form
- Advantage
  - Cheap
- Disadvantage
  - Burning rate can not be varied during flight

# Rocket engine combustion analysis

- **Aim:** Cost reduction of rocket engines, be competitive with e.g. Space-X




**Hybrid rocket engine**

- Pressurized fluid oxidizer
- Solid fuel
- A valve controls, how much oxidizer gets into the combustion chamber
- Advantages
  - Cheap
  - Controllable

# Experiments on new hybrid rocket fuels at DLR

- DLR investigates new hybrid rocket fuels on a paraffin basis at Institute of Space Propulsion in Lampoldshausen.
- About 300 combustion tests were performed with single-slab paraffin-based fuel with 20° forward facing ramp angle + gaseous oxygen.
- Combustion is captured with high-speed video camera with 10 000 frames / second

**Fig. 1:** Fuel slap configuration before (top) and after (bottom) combustion test.

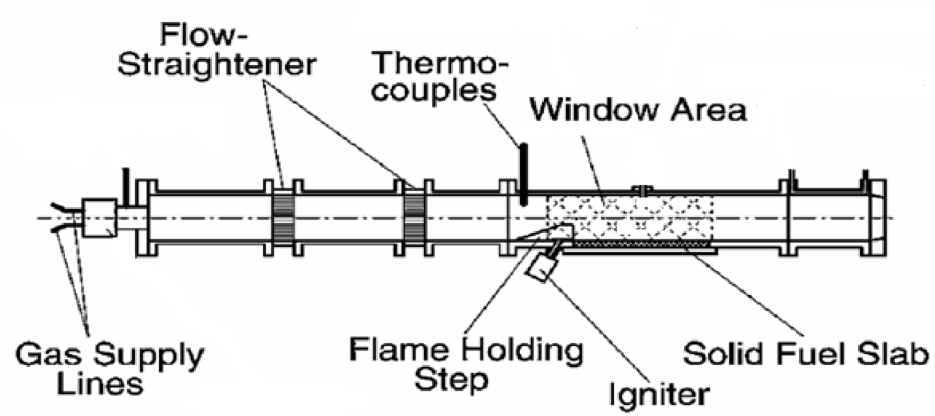



**Fig. 2:** Side view of combustion chamber


| Video extract of test 284 | fuel | oxidizer mass flow | CH*-filter | duration |
|---|---|---|---|---|
| Ignition, steady combustion, extinction | pure paraffin 6805 | 50 *g*/*s*, | yes, i.e. only wavelengths emitted from CH* are filmed | 3 s = 30 000 frames / 8GB raw data per test |

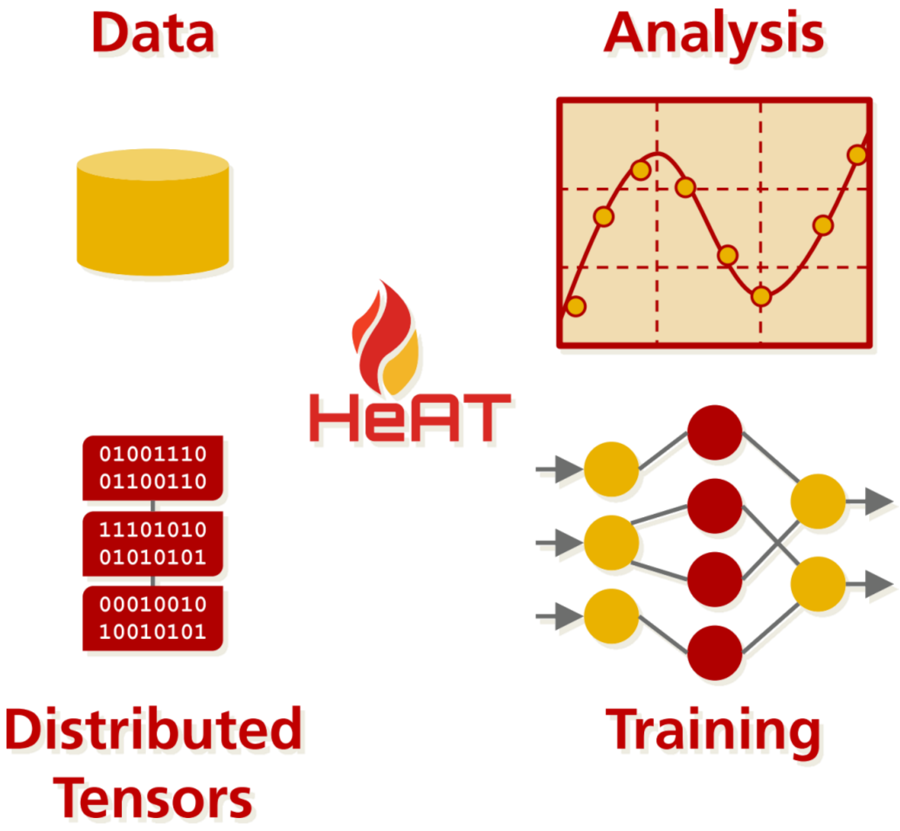
# Outline

1. Rocket engine combustion analysis at DLR
2. Helmholtz Analytics Toolkit (HeAT) for distributed ML
3. Results
   a) Spectral Clustering
   b) Anomaly Detection

# HeAT

- HeAT = Helmholtz Analytics Toolkit
- Python framework for **parallel**, **distributed** data analytics and machine learning
- Developed within the Helmholtz Analytics Framework Project since 2018
- **Aim:** Bridge data analytics and **high-performance computing**
- Open Source licensed, MIT

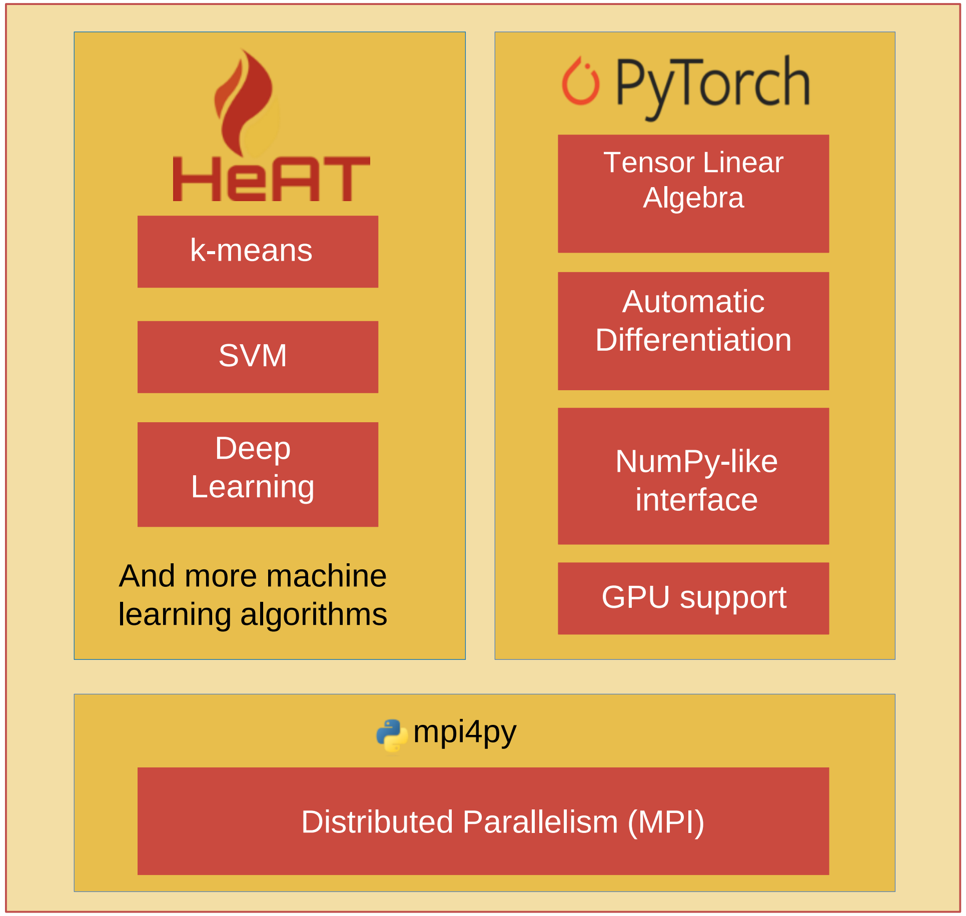
[helmholtz-analytics/heat](helmholtz-analytics/heat)



# Scope

- Facilitating analysis of Helmholtz applications
- Bringing HPC and Machine Learning / Data Analytics closer together
- Ease of use

# Design



# Data Distribution

HeAT Tensor

| Server#1 PyTorch Tensor#1 | Server#2 PyTorch Tensor#2 | Server#3 PyTorch Tensor#3 |
|---|---|---|

split=1

Server#1 PyTorch Tensor#1
Server#2 PyTorch Tensor#2
Server#3 PyTorch Tensor#3

HeAT Tensor

split=0

Example:

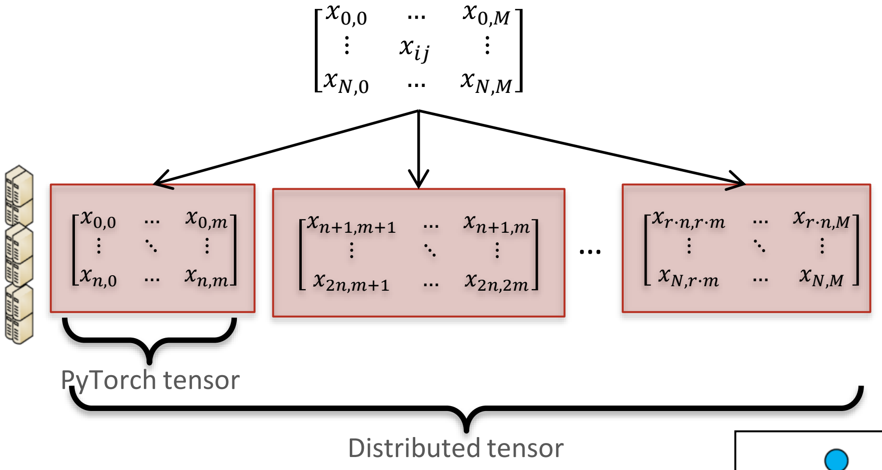
```
import heat as ht
# construct a range tensor
>>> range_data = ht.arange(6, split=1)
```

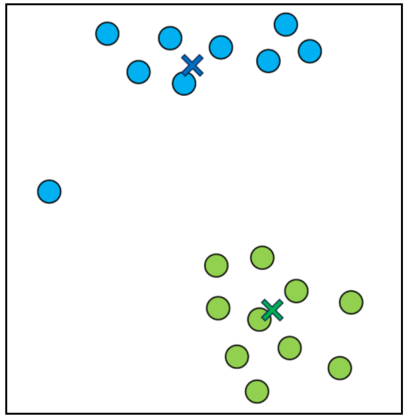
| Server#1 [0, 1] | Server#2 [2, 3] | Server#3 [4, 5] |
|---|---|---|

```
>>> range_data.mean()
2.5
>>> range_data.argmax()
5
```

# What has been done so far?

- The core technology has been identified
- Implementation of a distributed parallel tensor core framework
- NumPy-compatible core functionality
- Some linear algebra routines
- Parallel data I/O via HDF 5 and NETCDF
- K-means and spectral clustering algorithms are available



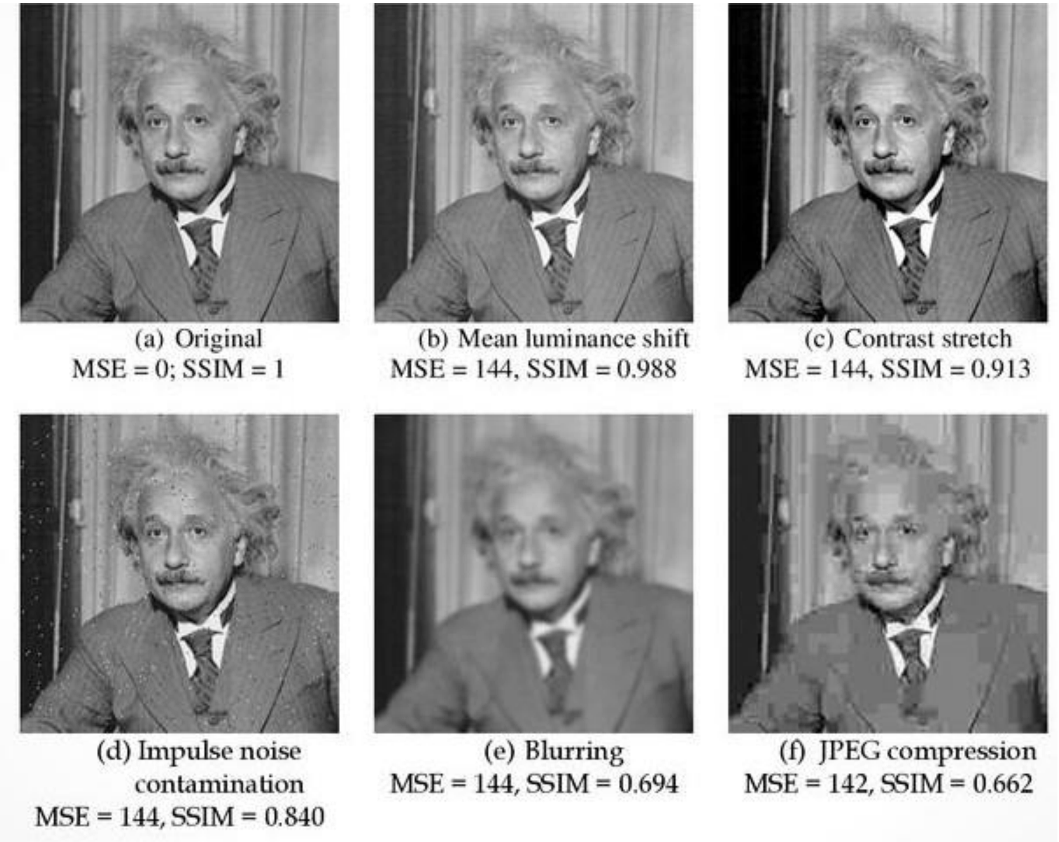



# Outline

1. Rocket engine combustion analysis at DLR
2. Helmholtz Analytics Toolkit (HeAT) for distributed ML
3. Results
    a) Spectral Clustering
    b) Anomaly Detection

# Dissimilarity measure for image data

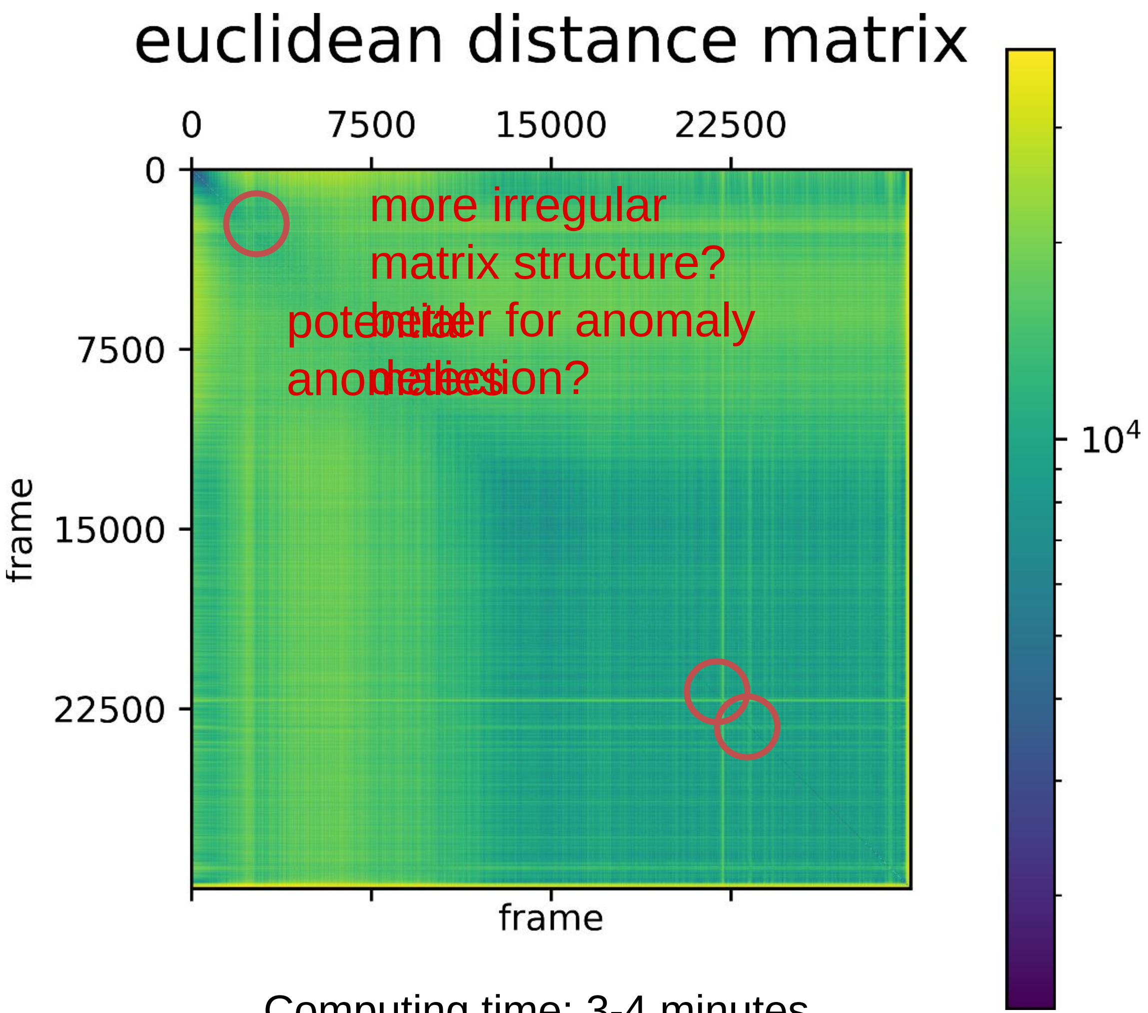
- Algorithms often require pairwise dissimilarity of images (matrix of size nr_of_images x nr_of_images).
- Standard approaches such as mean squared error (MSE) / discrete $L^2$-norm often differ from human recognition.
- Advanced dissimilarity measures such as structural similarity (SSIM) often perform better (considers luminance, contrast and structure) but are much more expensive.
- Structural similarity (SSIM)/ structural dissimilarity (DSSIM) is not a distance metric.



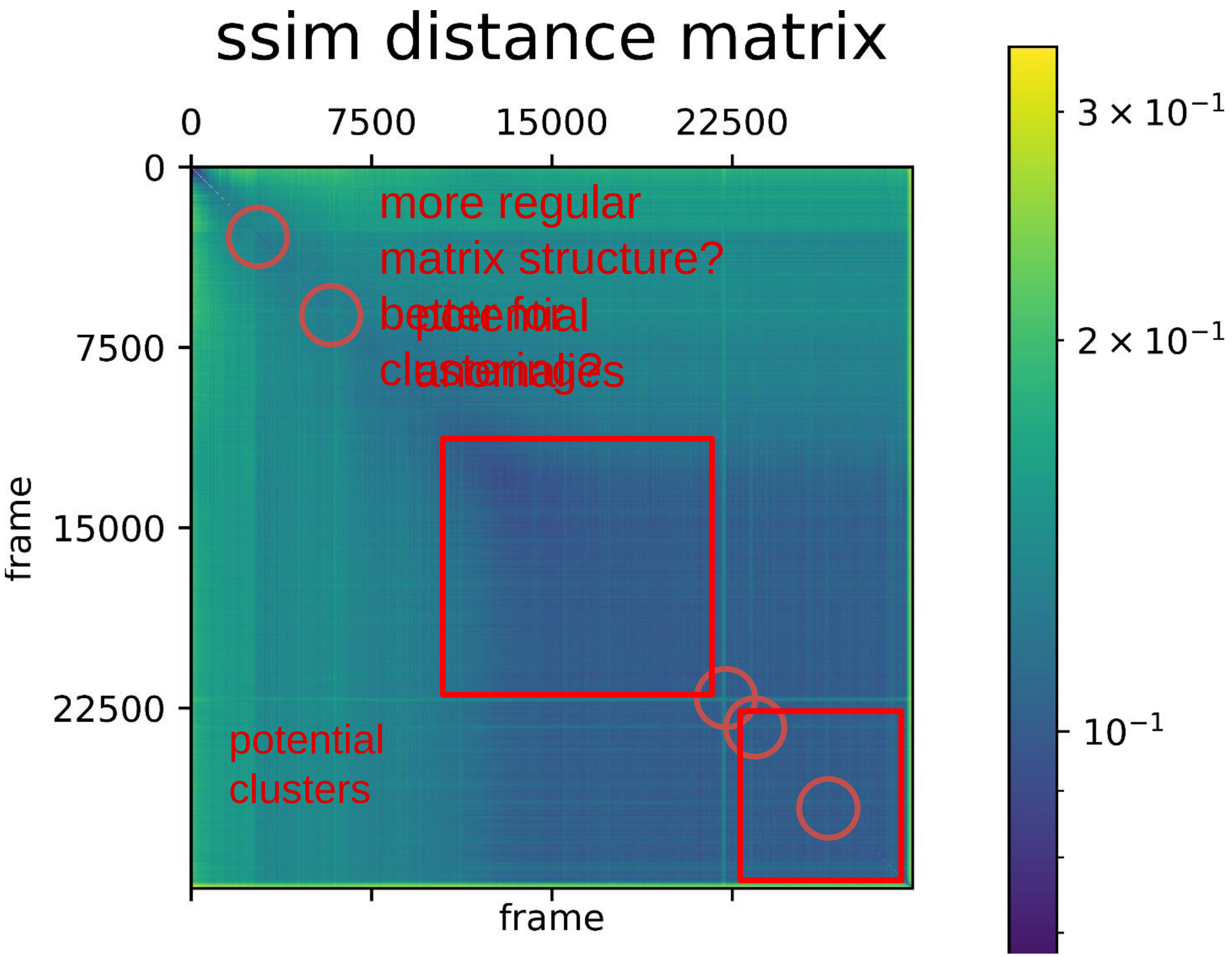

Example: (b)-(f) with same MSE, SSIM decreases*

*https://nsf.gov/news/mmg/mmg_disp.jsp?med_id=79419&from=

# Pairwise distance matrices for test 284

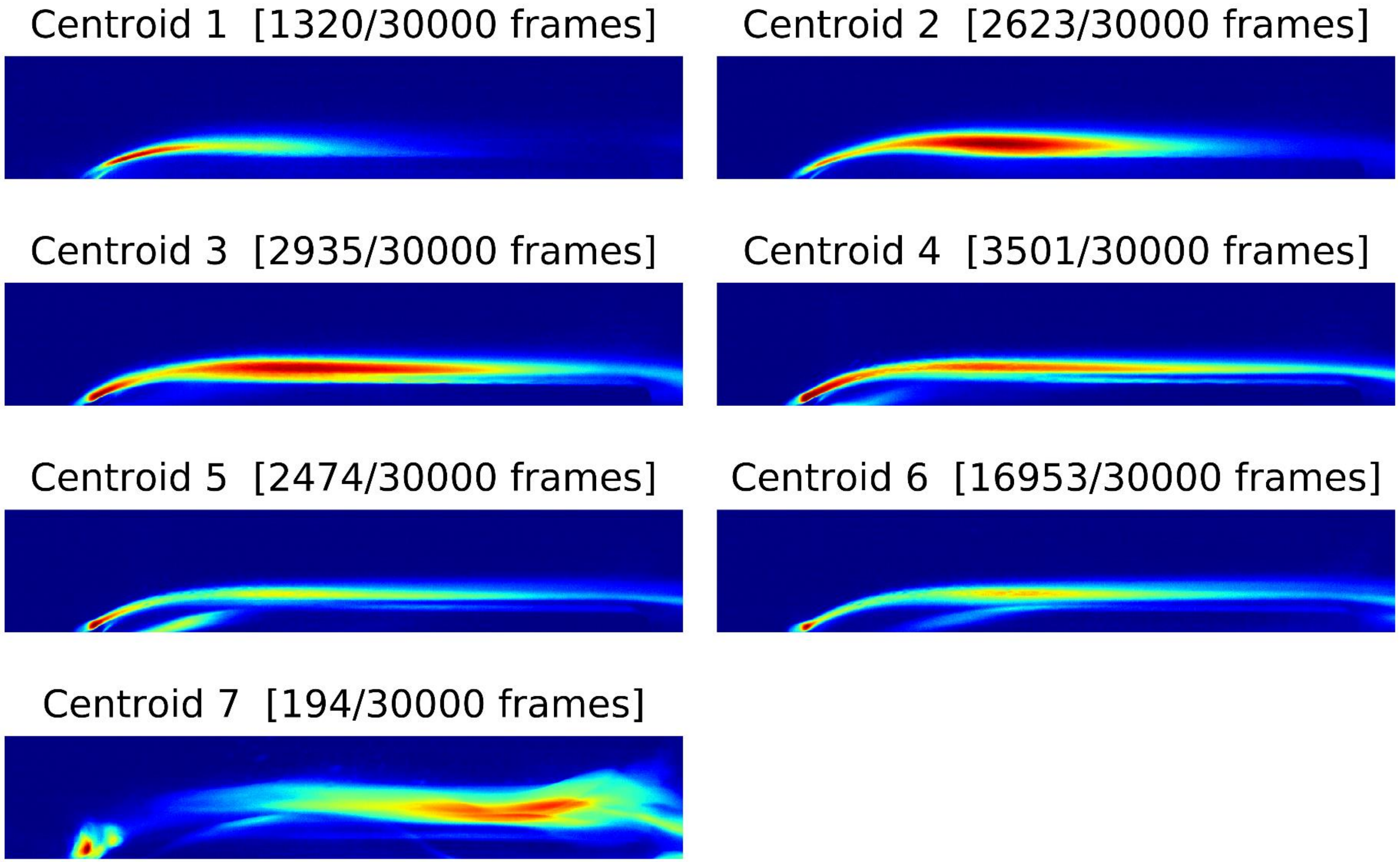



Computing time: 3-4 minutes




Computing time: 5 days (OpenMP parallel, 56 cores)
one comparison ≈ 0.1 s (scikit-image)

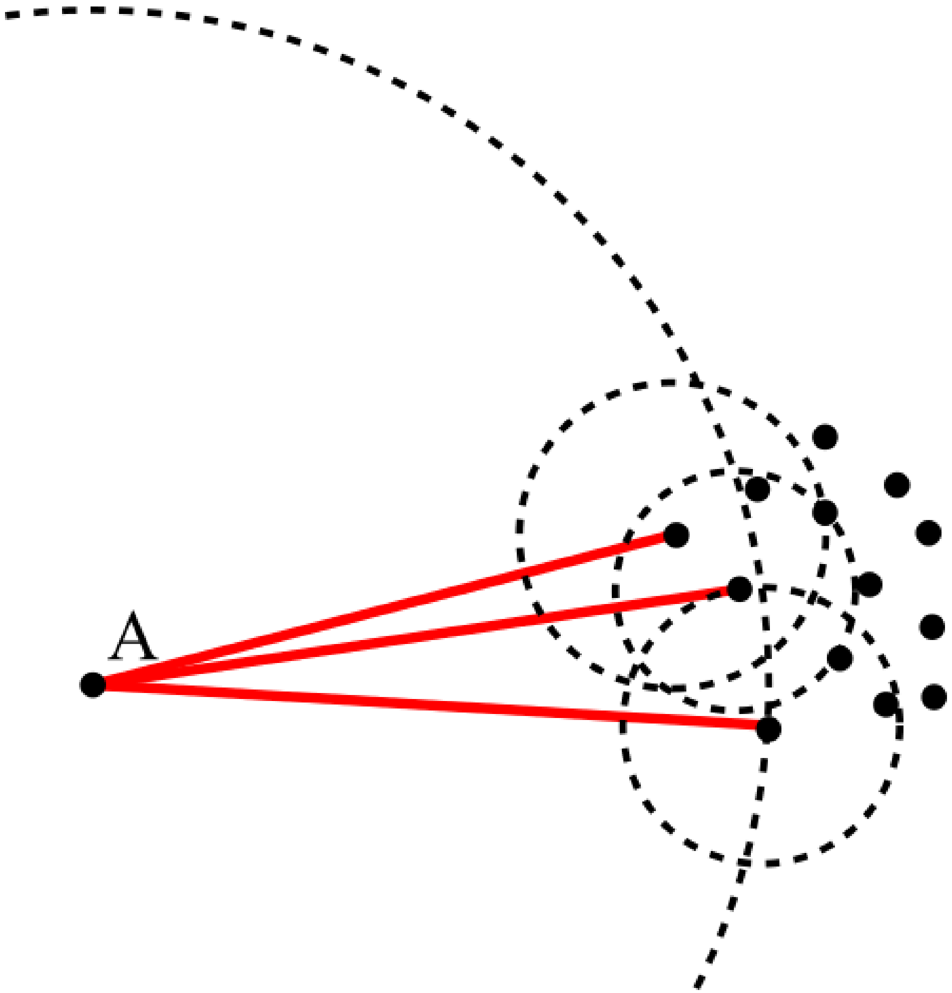
# Spectral Clustering of test 284



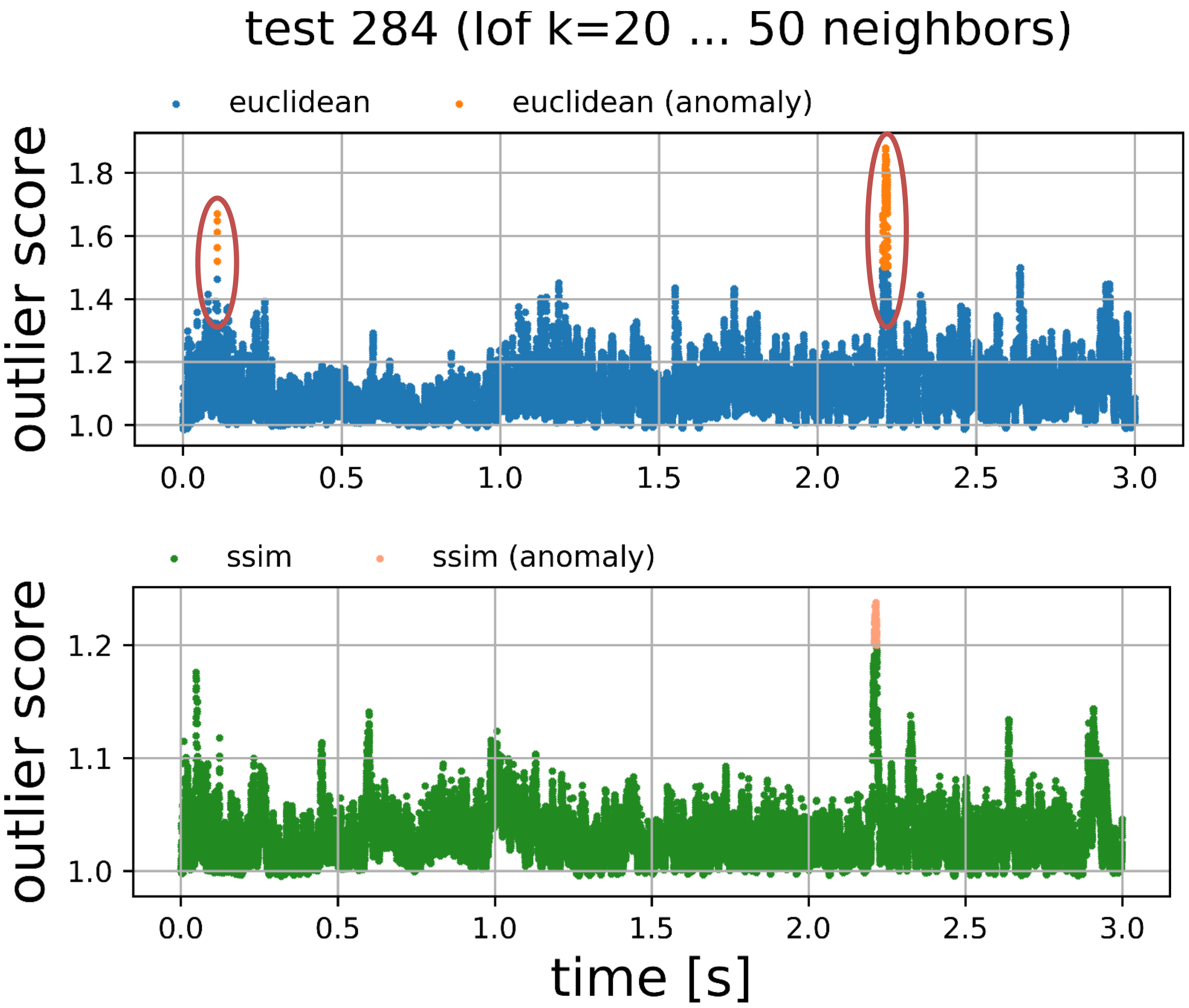

- **Fig. 1**: Results of spectral clustering with ssim affinity matrix.
- Using an Euclidean affinity matrix leads to a separation of the extinction phase into various clusters.
- Note that the number of clusters *k* is a hyperparameter of the clustering algorithm.

# Anomaly Detection: Local Outlier Factor (LOF)

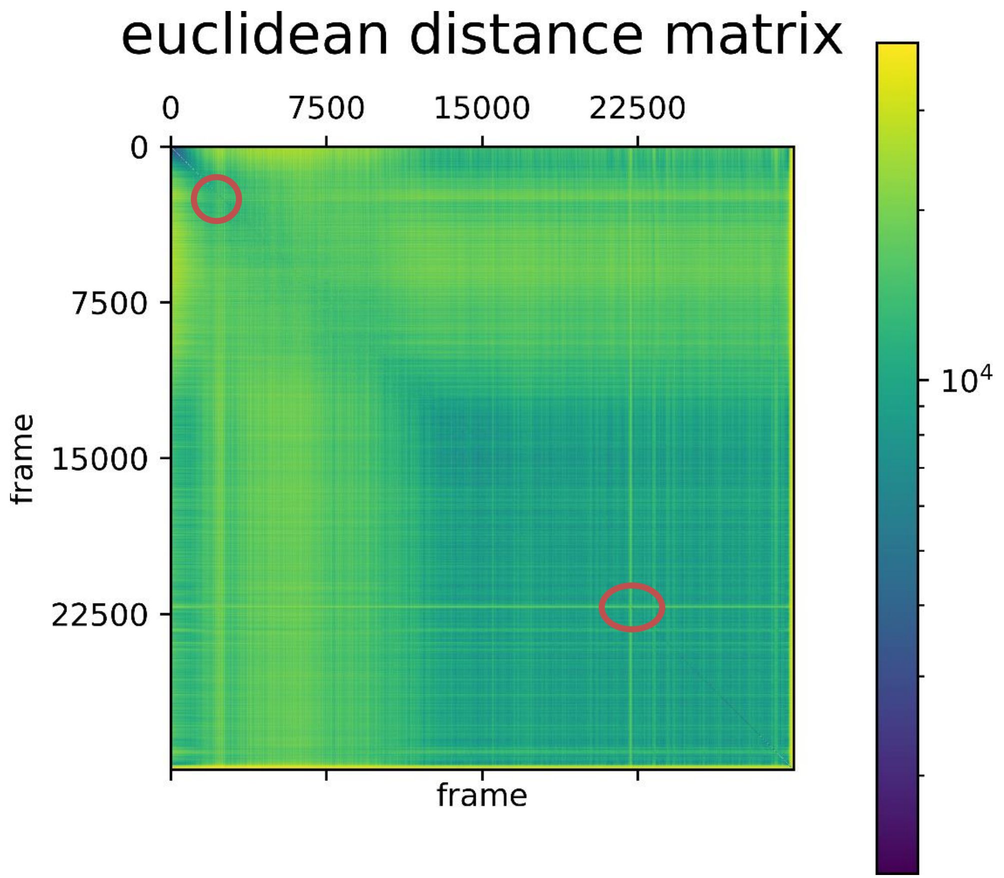
- Algorithm that bases on local density of data points.
- Shares some concepts with clustering algorithms such as DBSCAN and OPTICS.
- Does not show a decision boundary, i.e. cannot directly be used on new data (not necessary here).
- **Core idea:** Compare local density of an object to the local densities of its neighbors.
- Ratio „Density of neighbors / local density of an objects"
  - ≈ 1.0 means similar density as neighbors
  - > 1.0 means lower density than neighbors (outlier candidate)



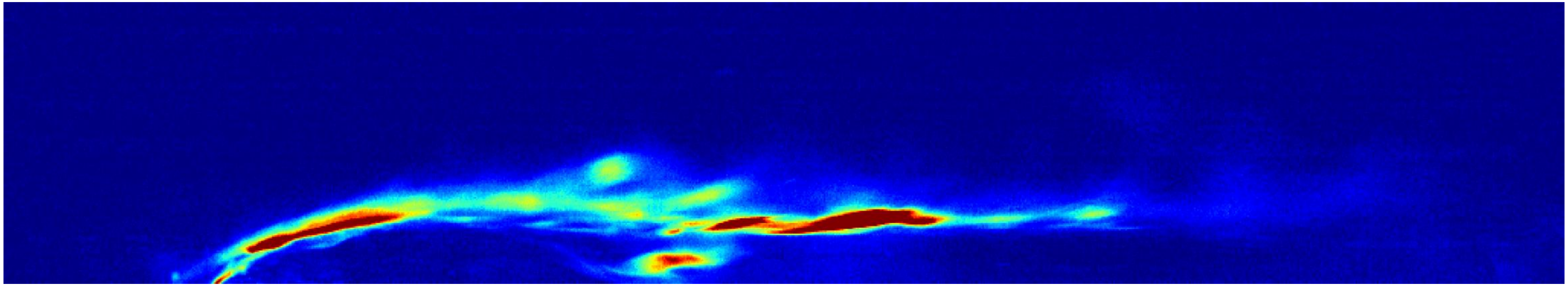

Point density with respect to *k*=3 closest neighbors



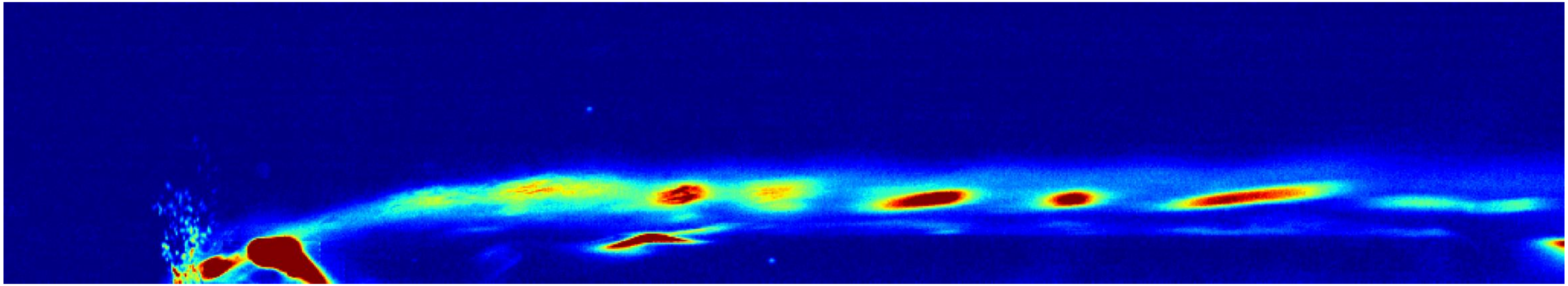

- Euclidean distance norm returns larger outlier score values (due to irregular matrix?).
- SSIM and Euclidean distance share some anomalies but there are differences.



# Peak outliers of Euclidean metric (test 284)

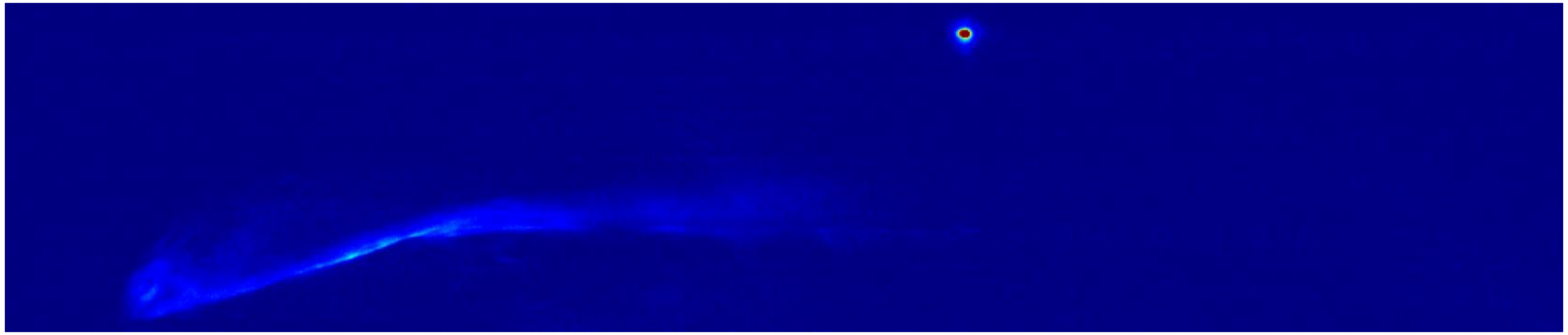


Flame fluctuations in ignition phase at $t$ = 0.1078 $s$



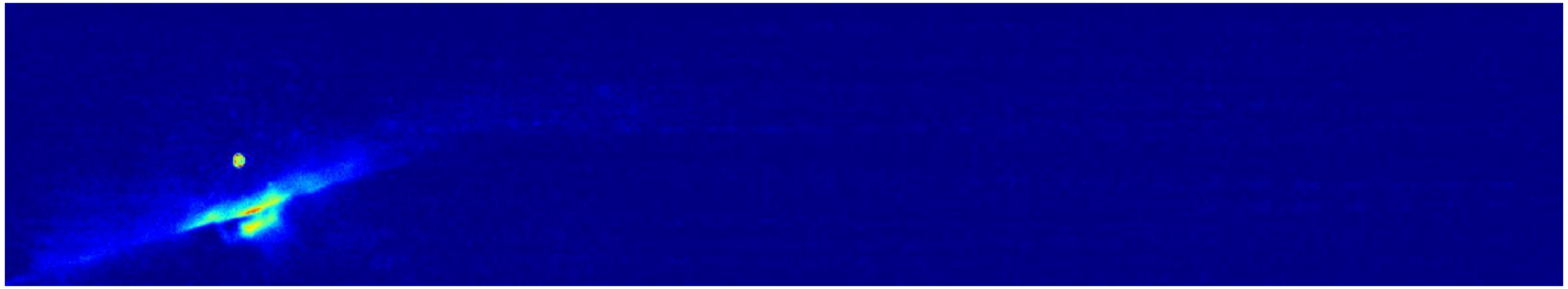
Droplet detection towards end of combustion at $t$ = 2.2055 $s$

# Some outliers found in other combustion tests



Test 291:
satellite droplet at $t$ = 0.0253 $s$

Test 296:
satellite droplet at $t$ = 0.0017 $s$



Test 296:
satellite droplet at $t$ = 0.0223 $s$

# Conclusion and outlook

- Clustering and anomaly detection in rocket combustion image data is possible provided that distance measure is adequate.

- Further insights are possible if datasets are combined (e.g. anomaly detection in spectral and image data).

- Future work is spent on distance measures that are more adapted to the „interesting anomalies“.

Thank you for your attention!