Data decomposition for unsteady combustion analysis

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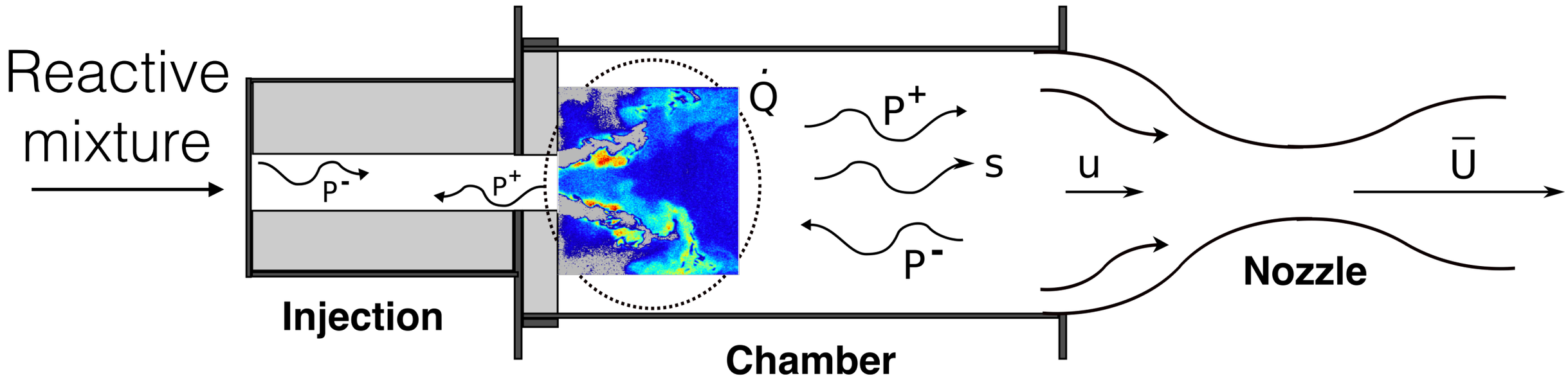
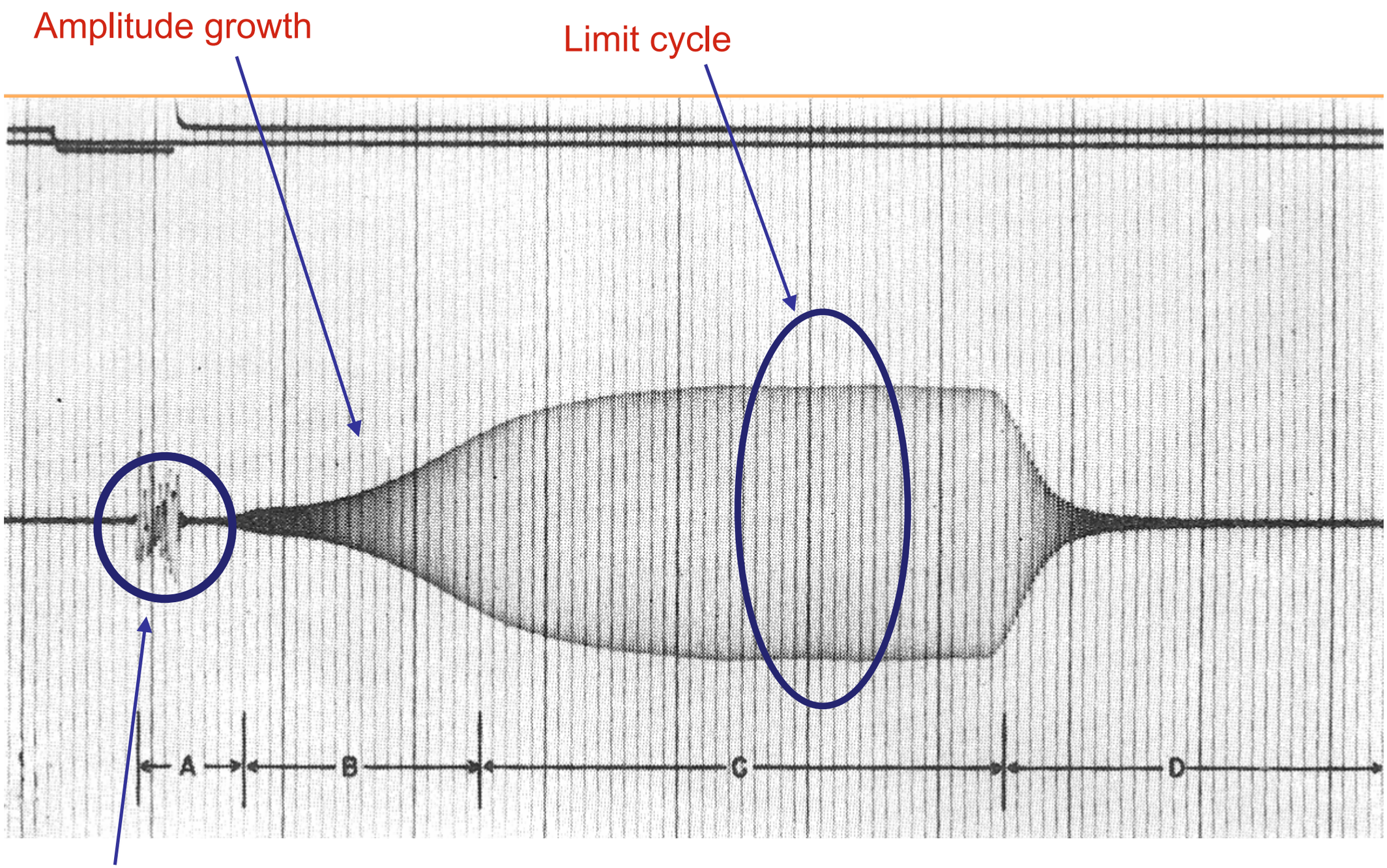
Combustion is based on multi-physics process that interact in a chamber



Turbulent combustion is an unsteady process
that generate interactions between
velocity, pressure and temperature,
in strong interactions with the boundaries of the system.

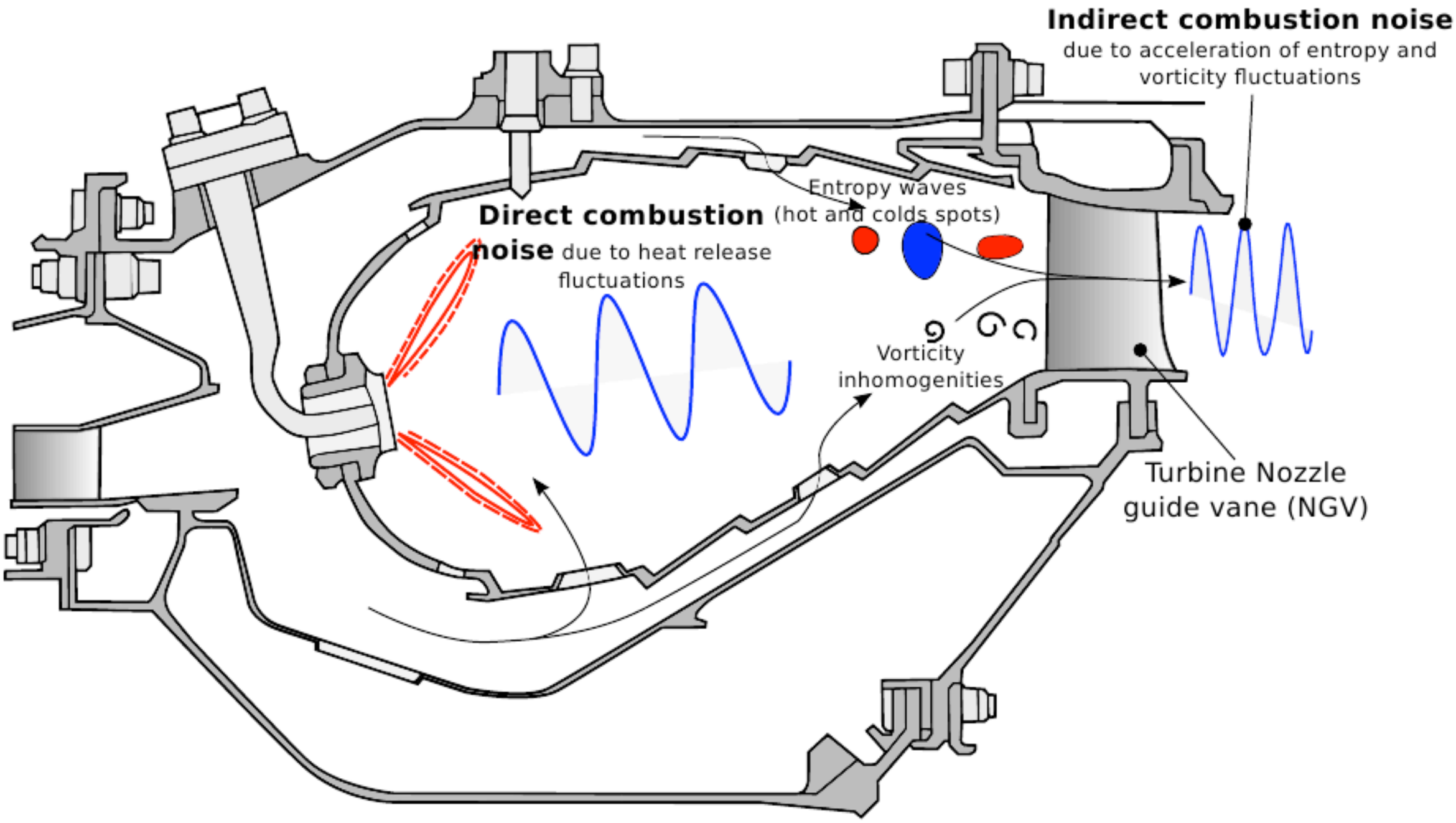
Combustion is based on multi-physics process that interact in a chamber



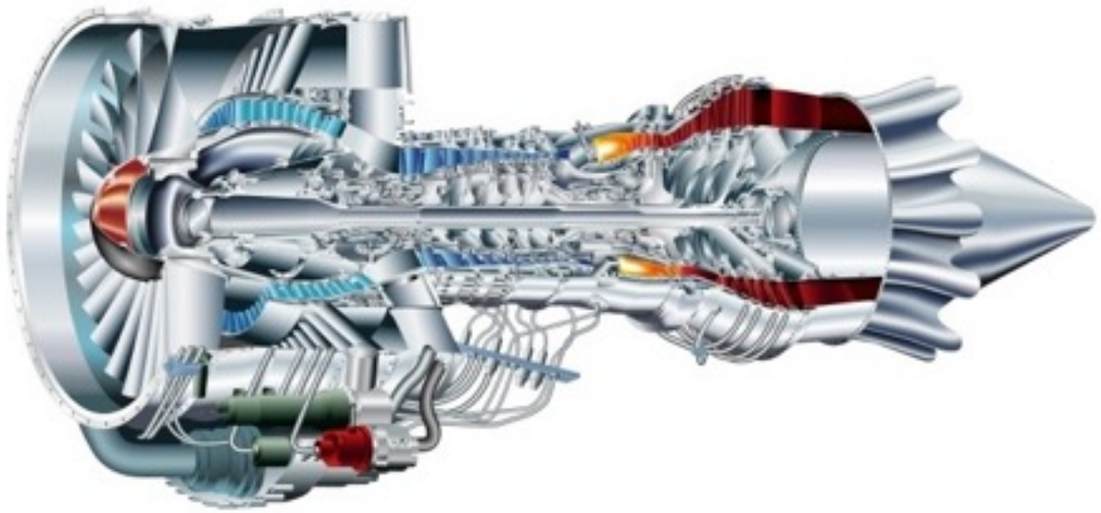
Pressure signal in a burner
(Horton & Price, 1962)

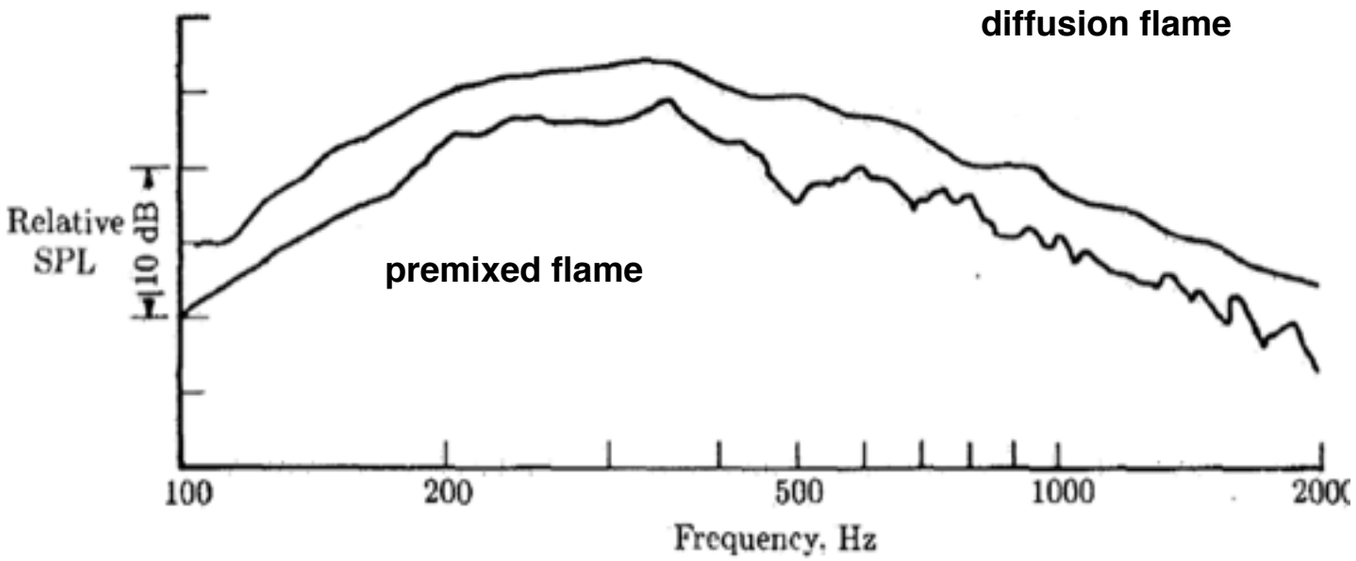
Most of the time, combustion chambers are instable and we try to minimize the amplitude of the limit cycle.

Mastering of the pressure perturbations in the surrounding of the chamber is one the challenges in combustion

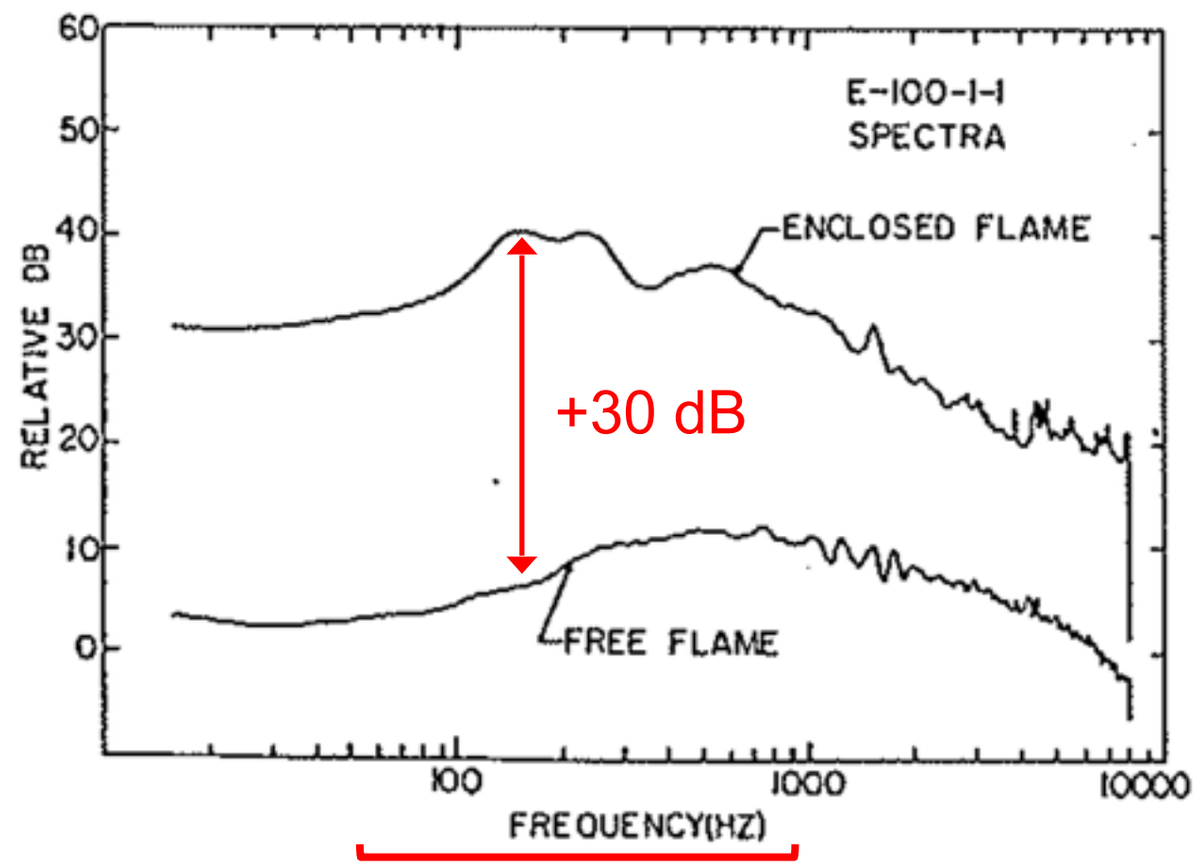


Noise depends on the operating conditions.



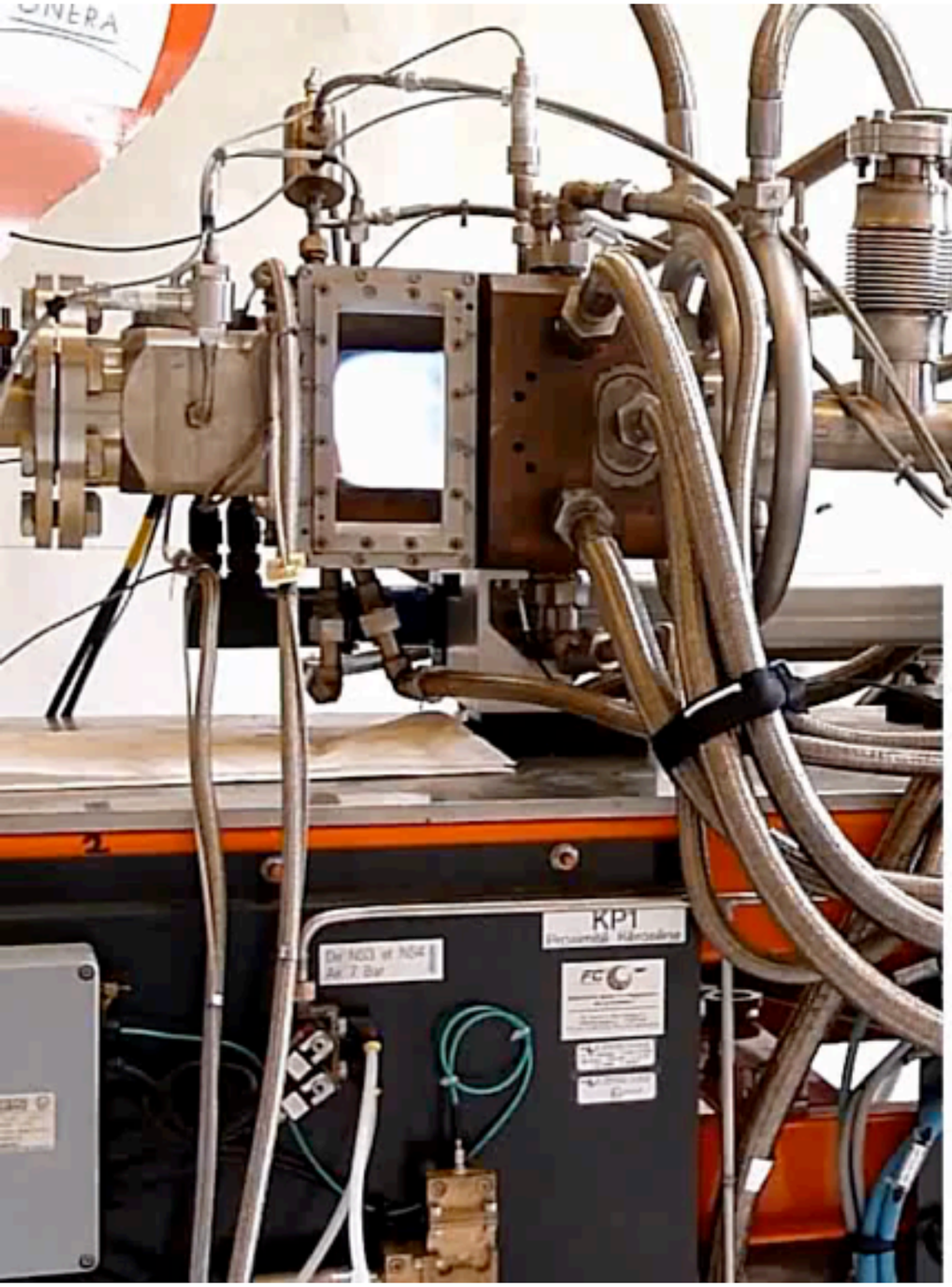


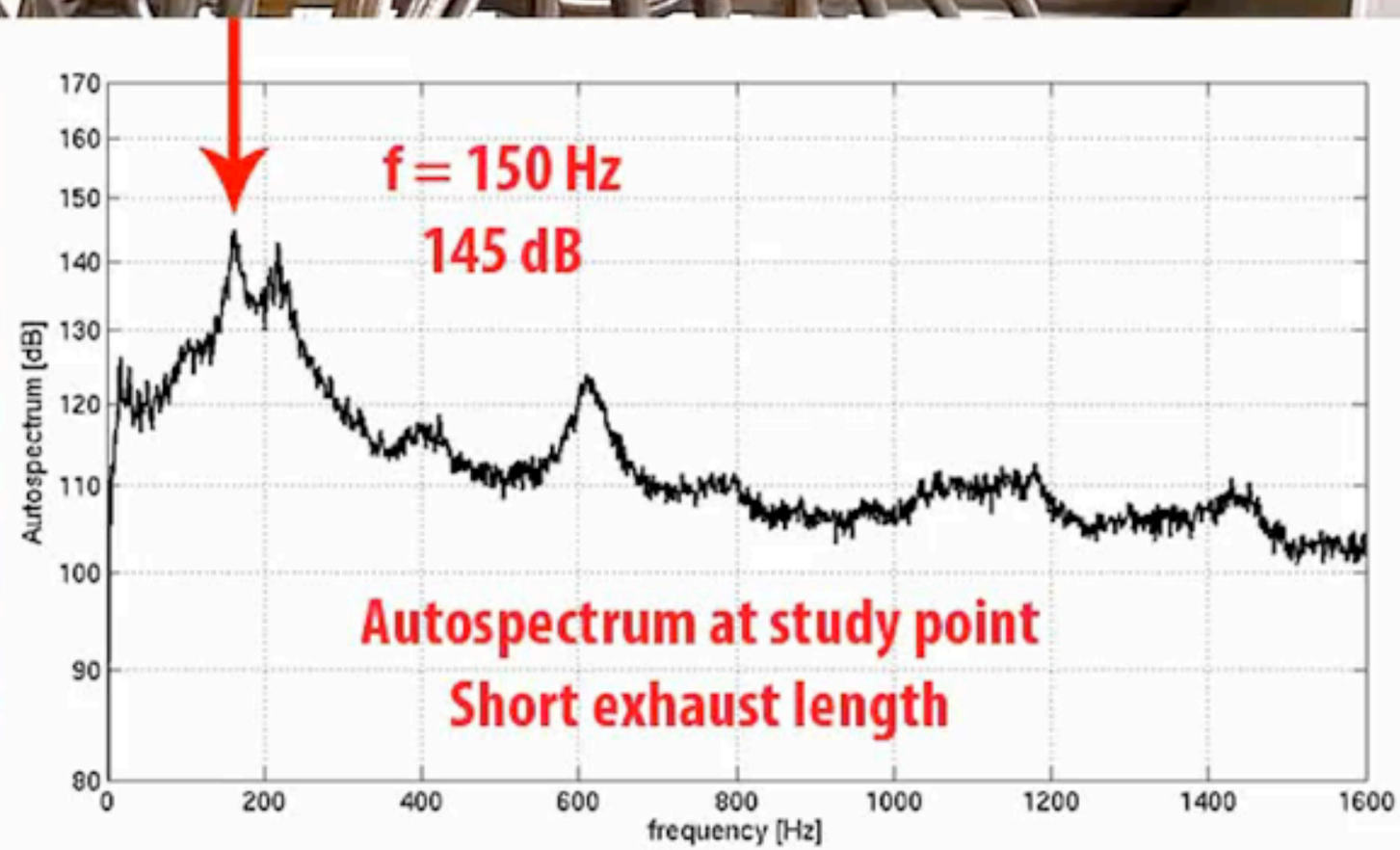
Typical sound pressure level spectra in the far field of unconfined, turbulent, premixed and diffusion flames.
AIAA paper No.73-1023, Oct.1973



Strahle et al., (1975) AIAA Paper 75-127

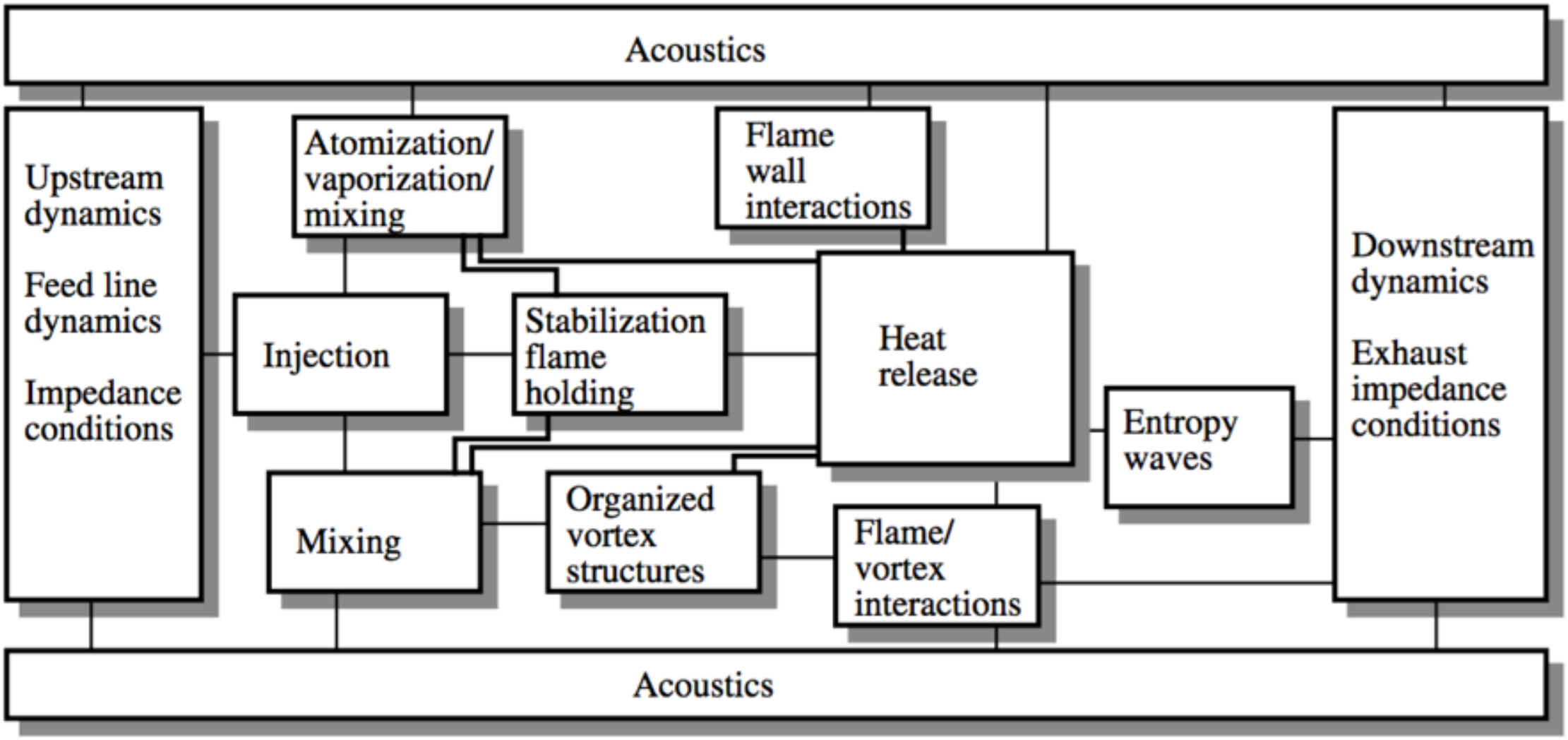
LACOM Bench at ONERA test the influence of outlet conditions on the pressure field.





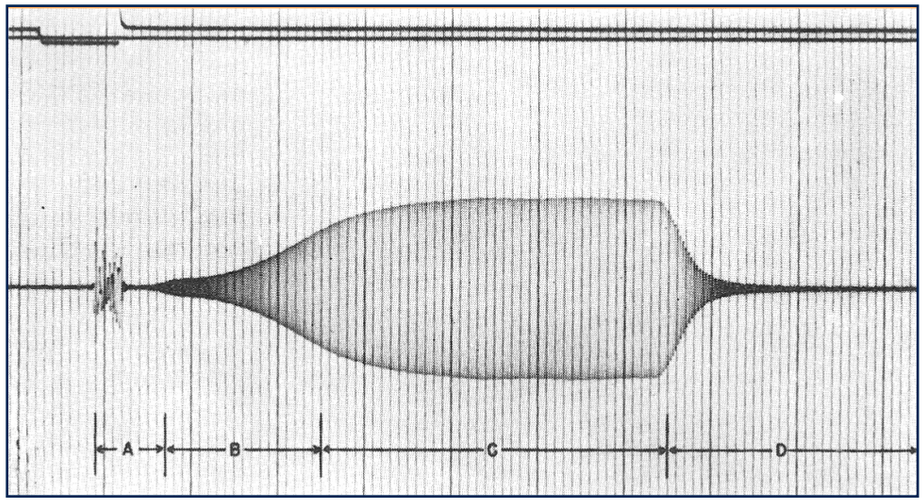
Couplings

Pressure field perturbations are due to numerous couplings that need intense data processing to understand



Candel, 2002

The importance of data decomposition to characterize couplings.



The challenge is to keep pressure amplitudes in a safe domain.

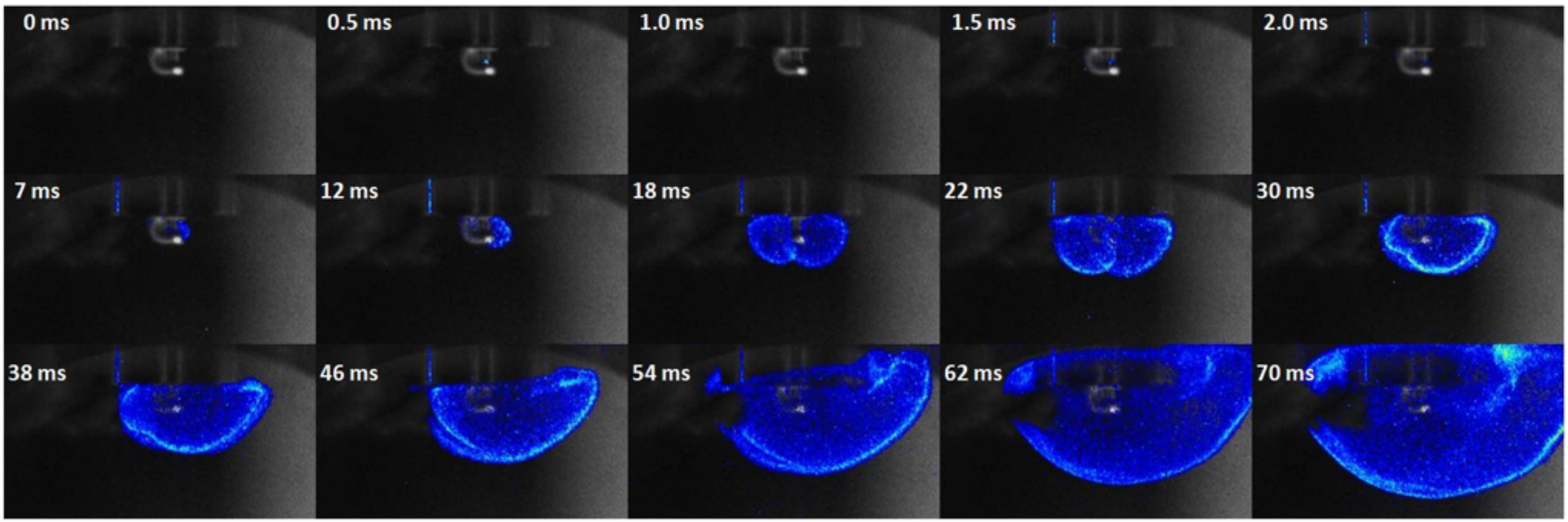
Understand the transient and limit phases.

These amplitudes depend on
- the acoustic sources (jet, combustion, vortex, shear layer…),
- the damping mechanisms (acoustic impedance, damping, turbulence),
- and propagation medium (upstream in fresh gases, downstream in burnt gases…)

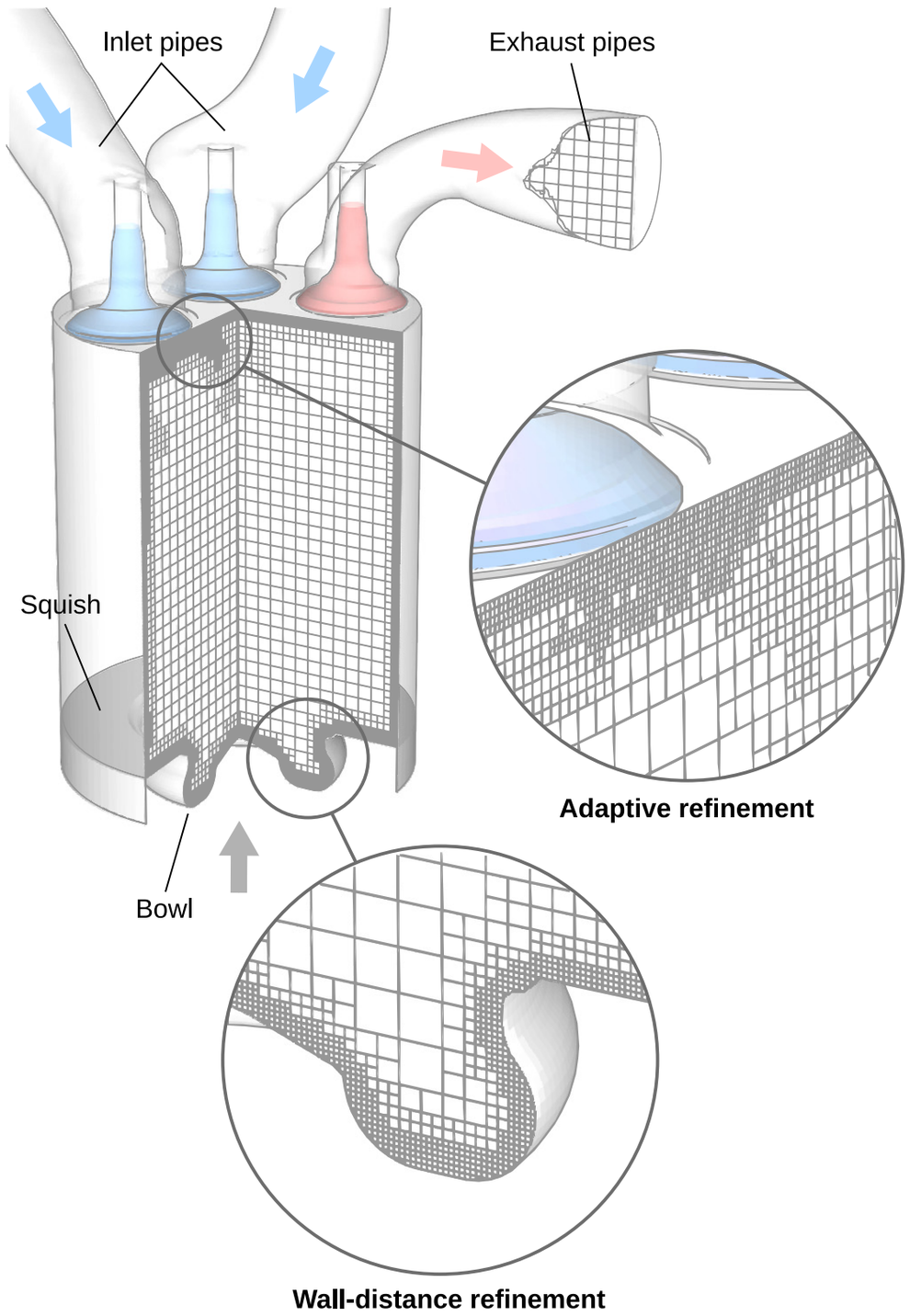
Data decomposition helps in separating time and space scales.

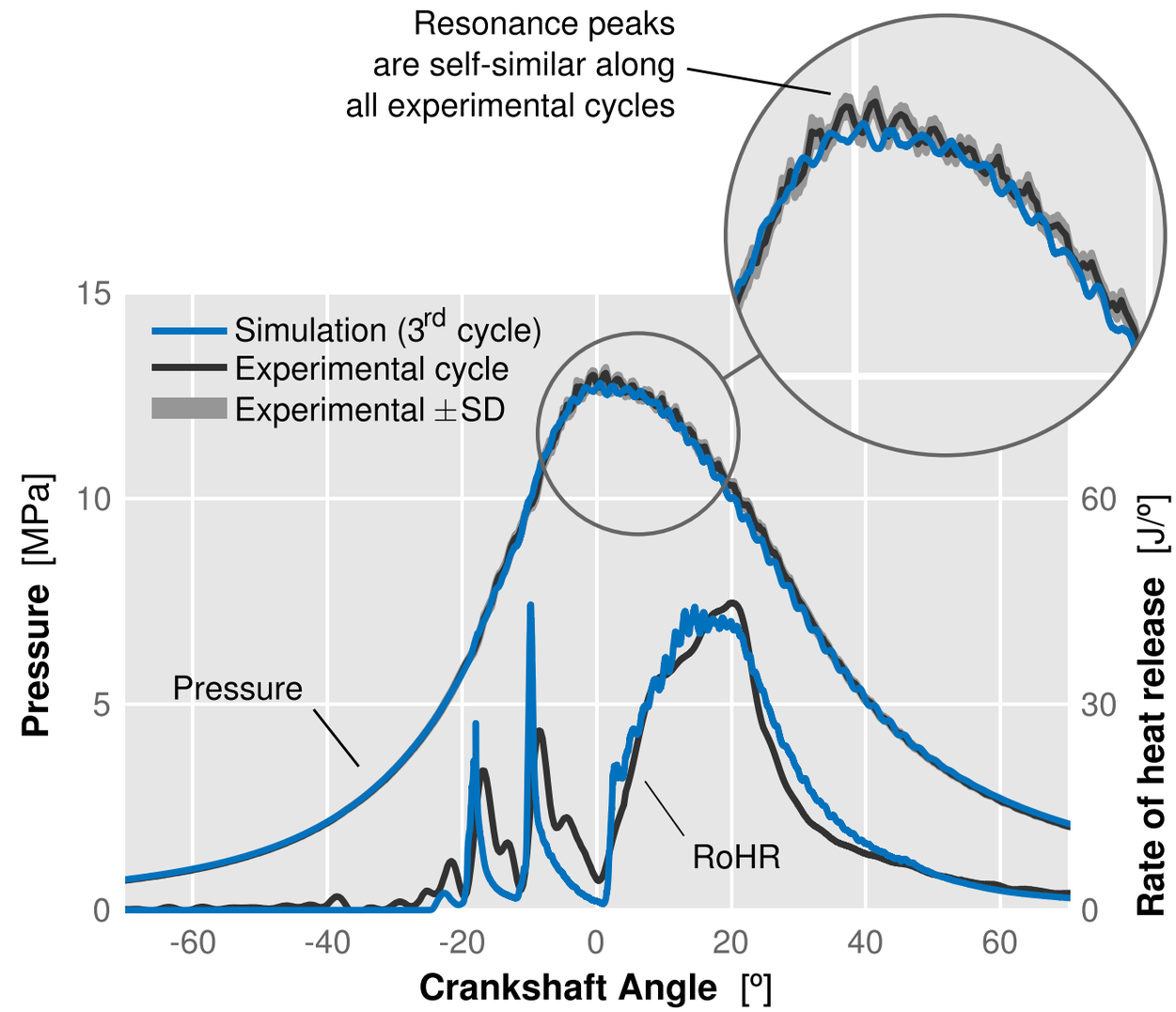
IC Engine Example

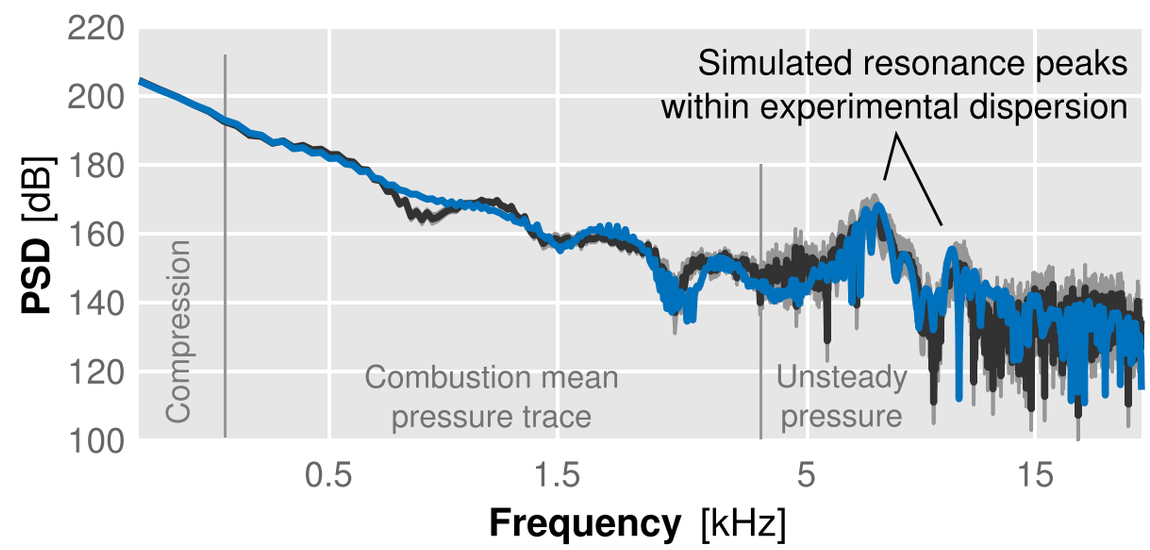
Modal decomposition of the unsteady flow field in compression-ignited combustion chambers
A. Torregrosa, A. Broatch, J. García-Tíscar, J. Gomez-Soriano
Combustion and Flame 188 (2018) 469–482



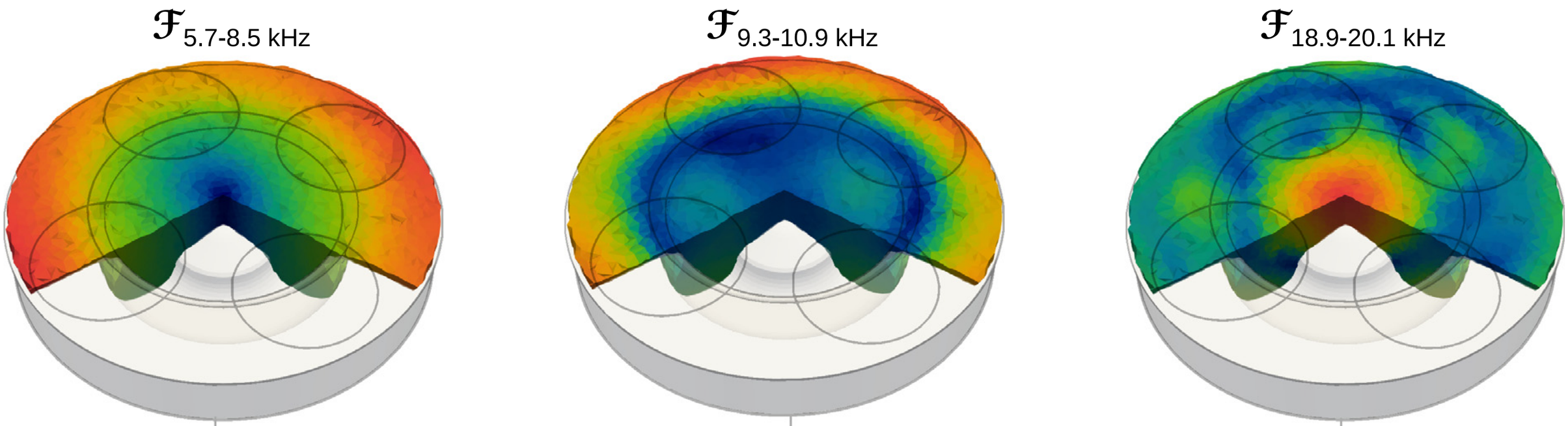
Pressure inside the engine has a broadband frequency content.

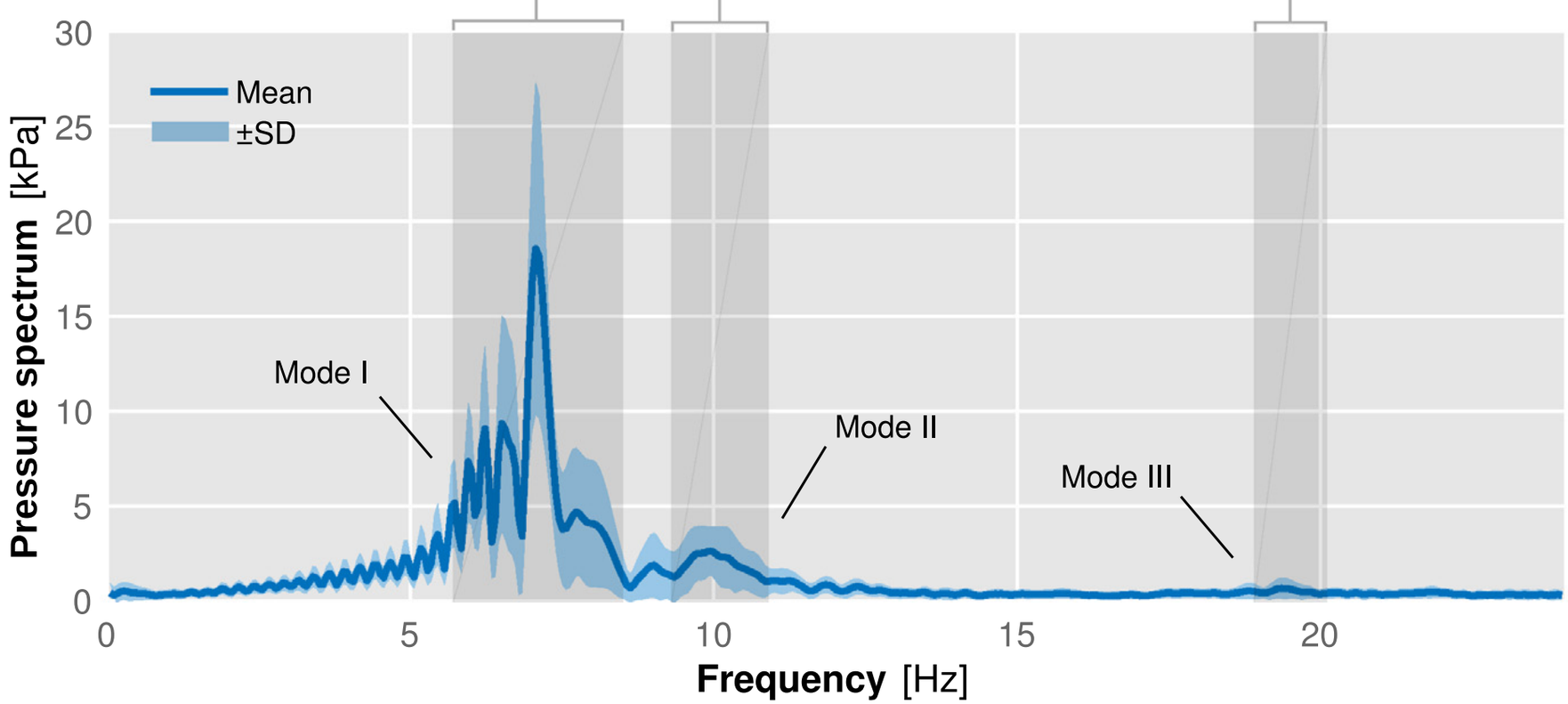






Several Power Density modes have to be collected to describe the spatial pressure evolution

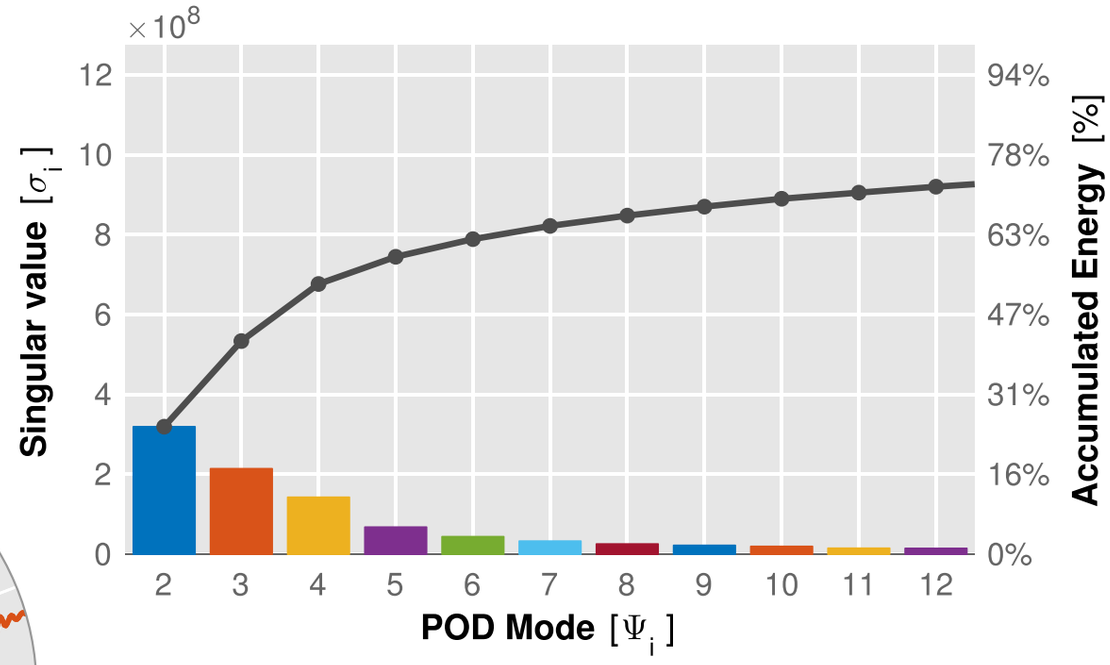


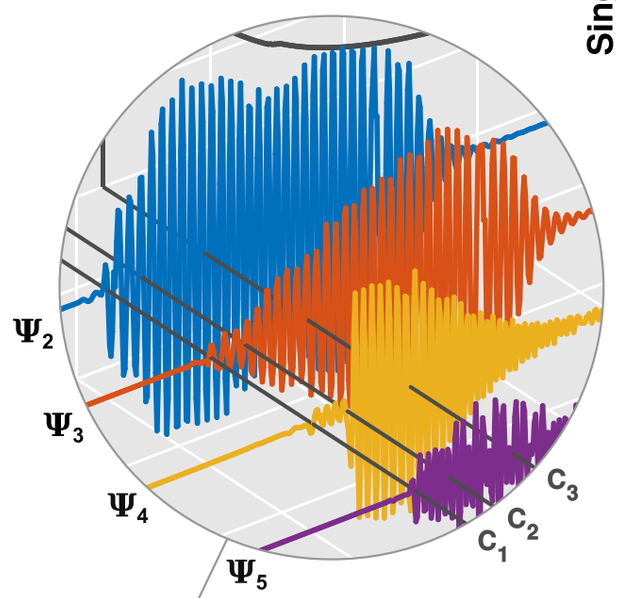


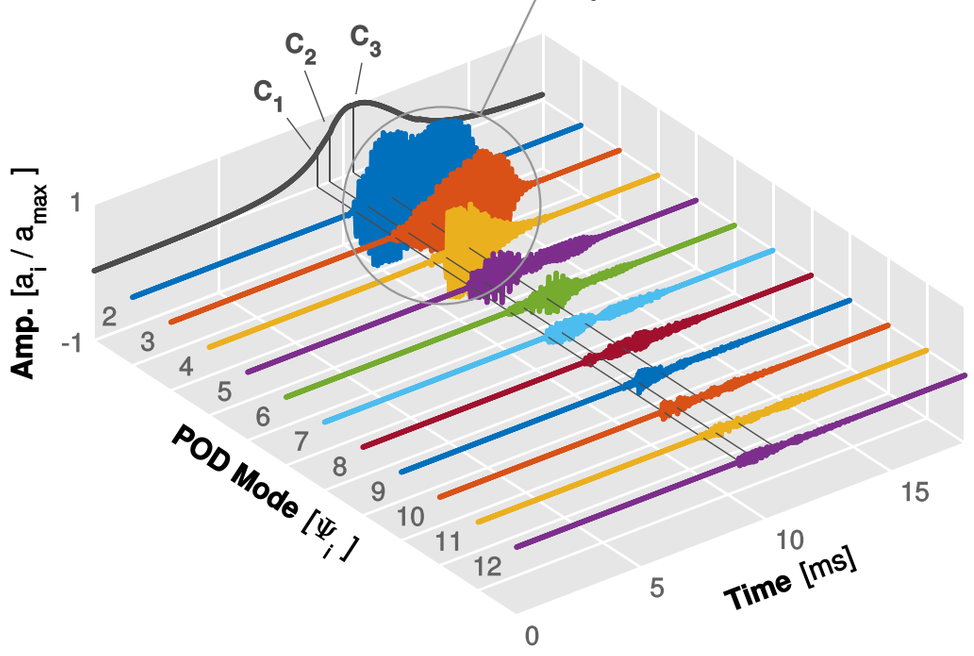
The signal is not periodic.

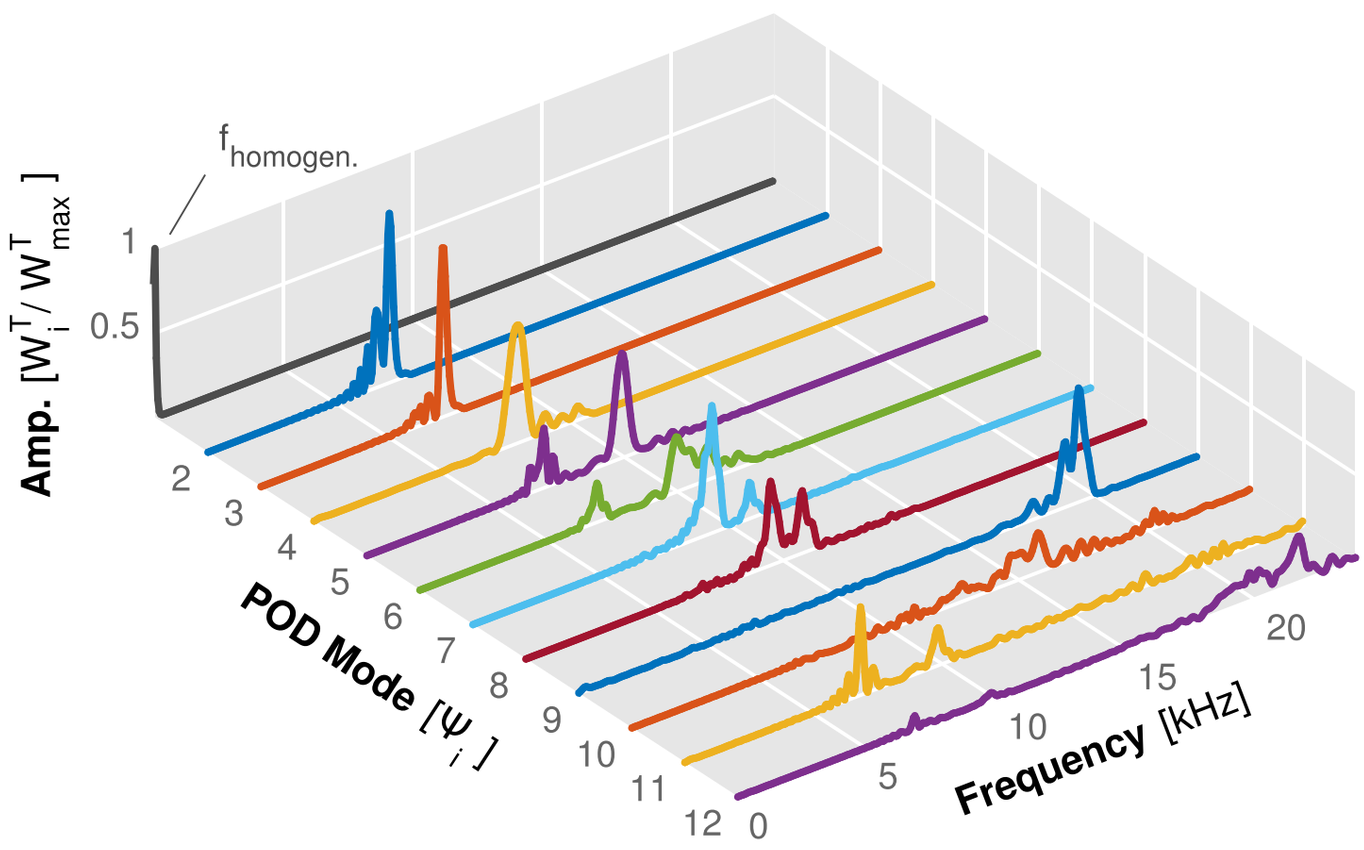
A reduced number of POD modes concentrate most of the energy.

$$\mathbf{V}(\mathbf{x}, t) = \sum_{i=1}^{N} \mathbf{\Psi}_i(\mathbf{x})\, \mathbf{a}_i(t)$$









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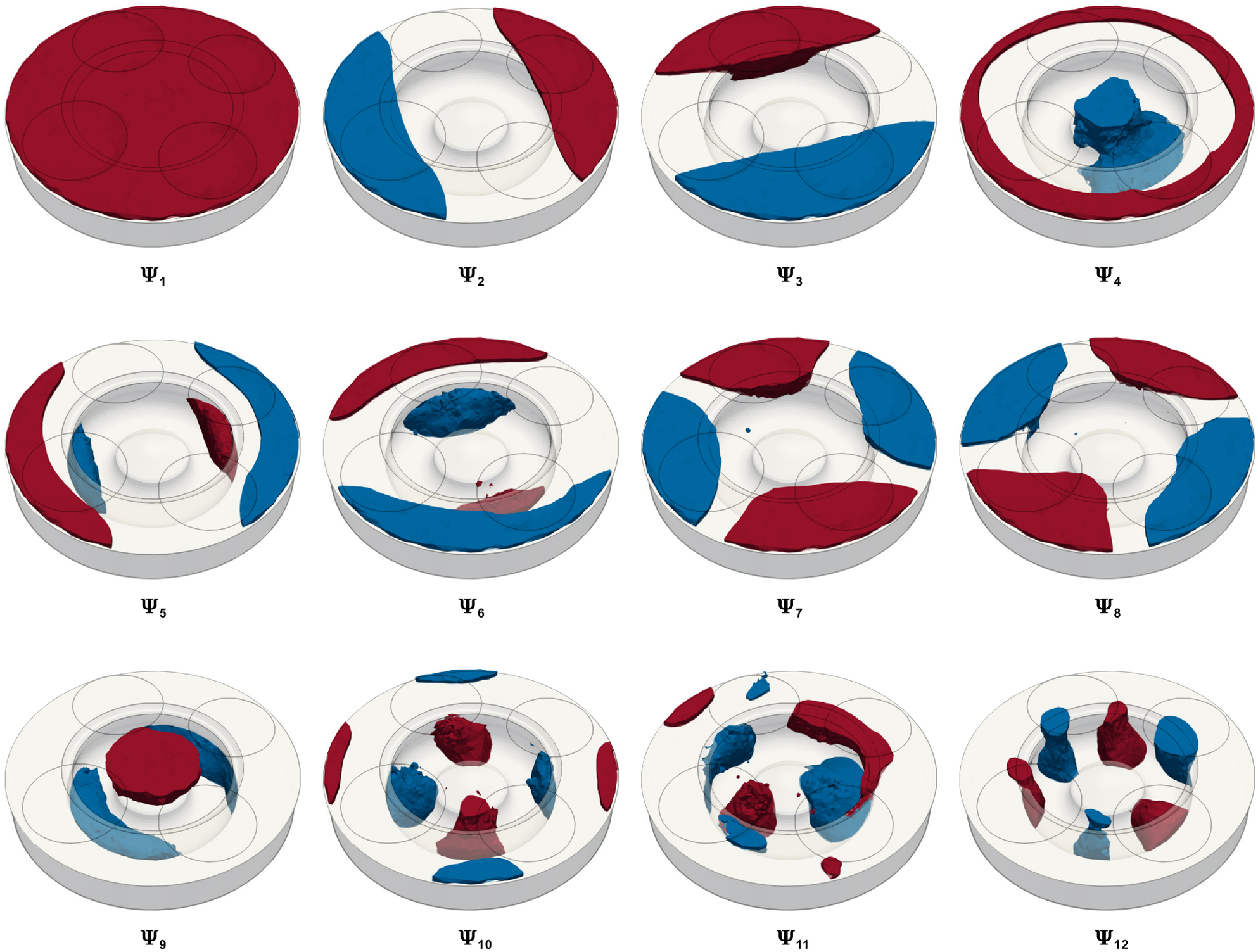
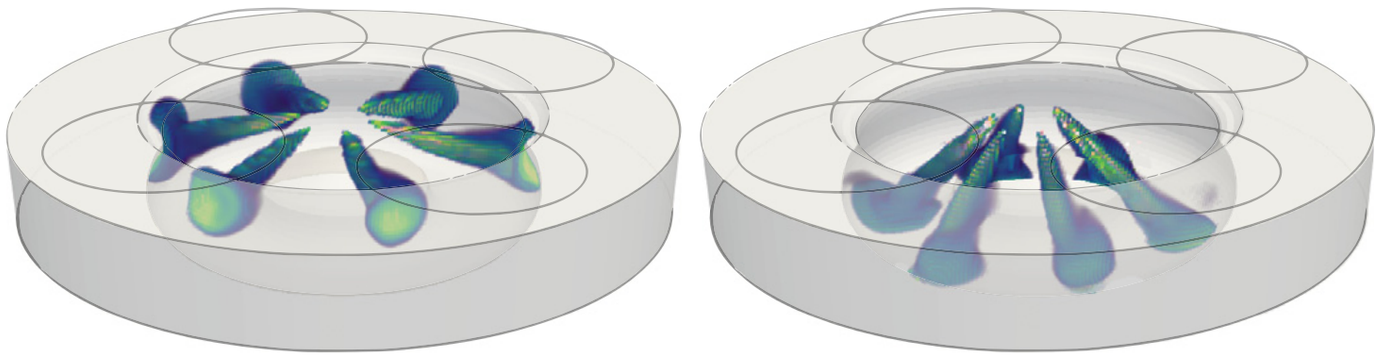
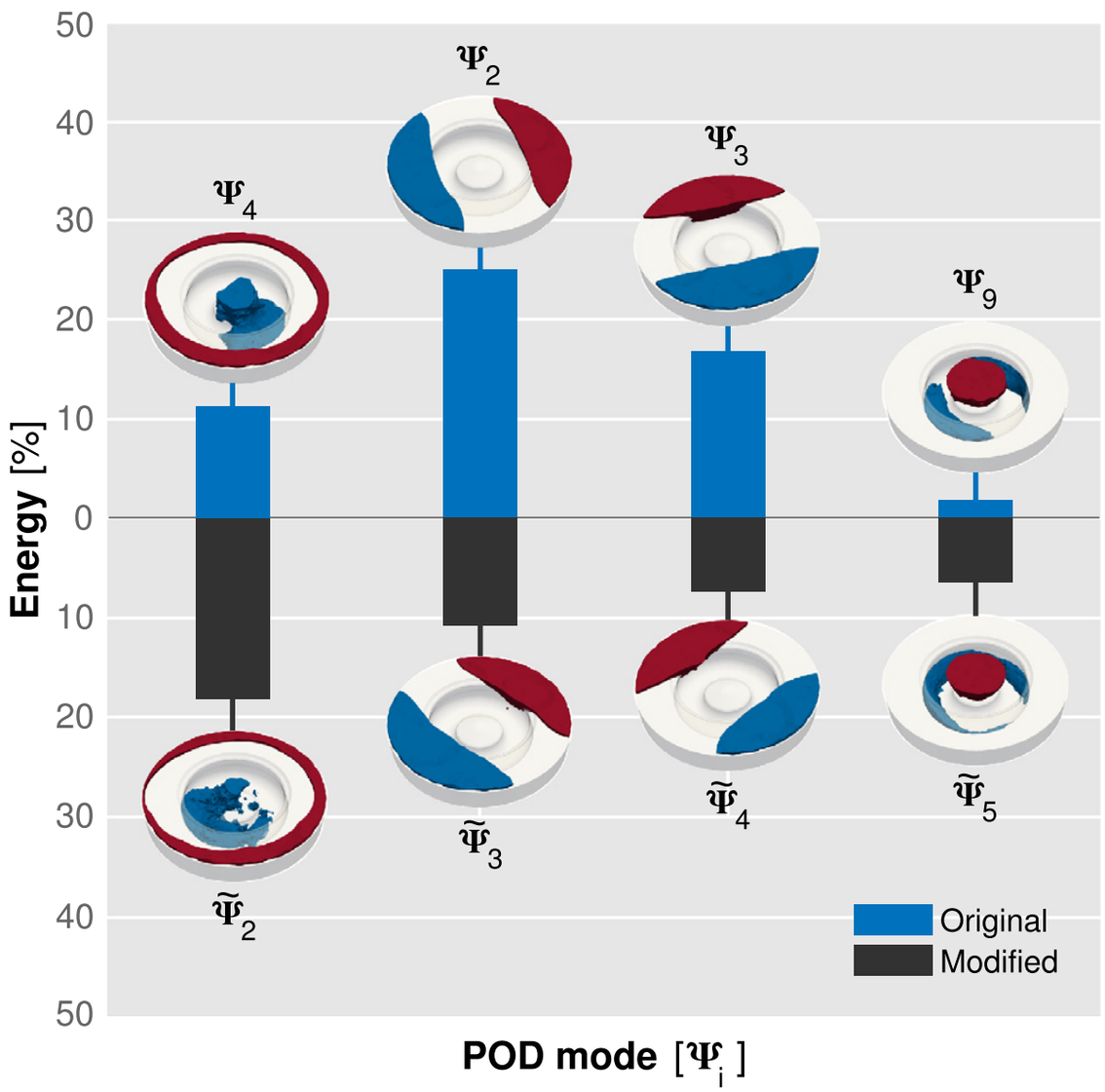
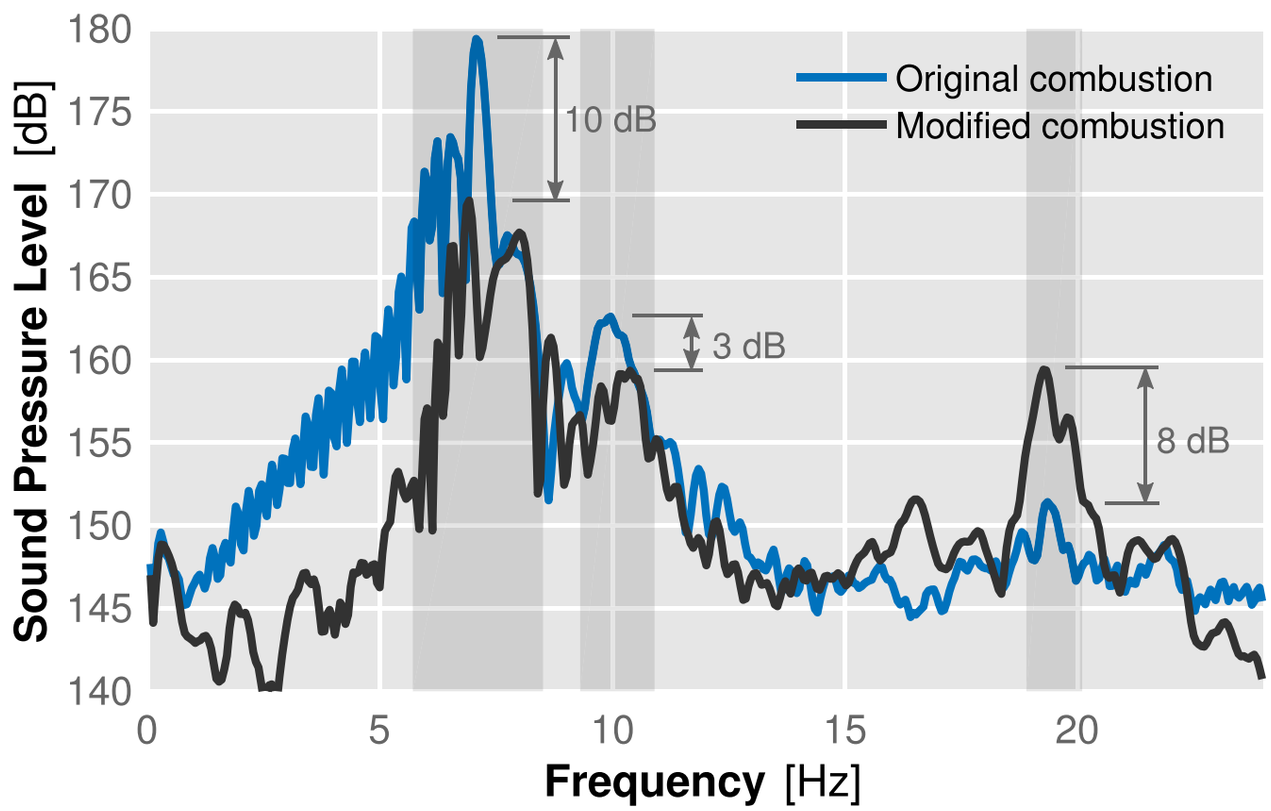


A geometrical modification of the injection reduces the pressure amplitude fluctuations



Original [150º] **Modified** [90º]





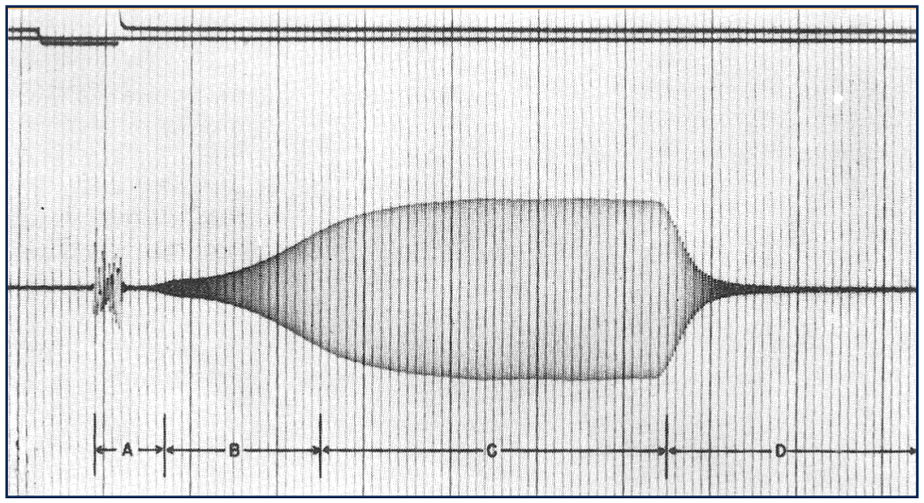
POD used on numerical simulations

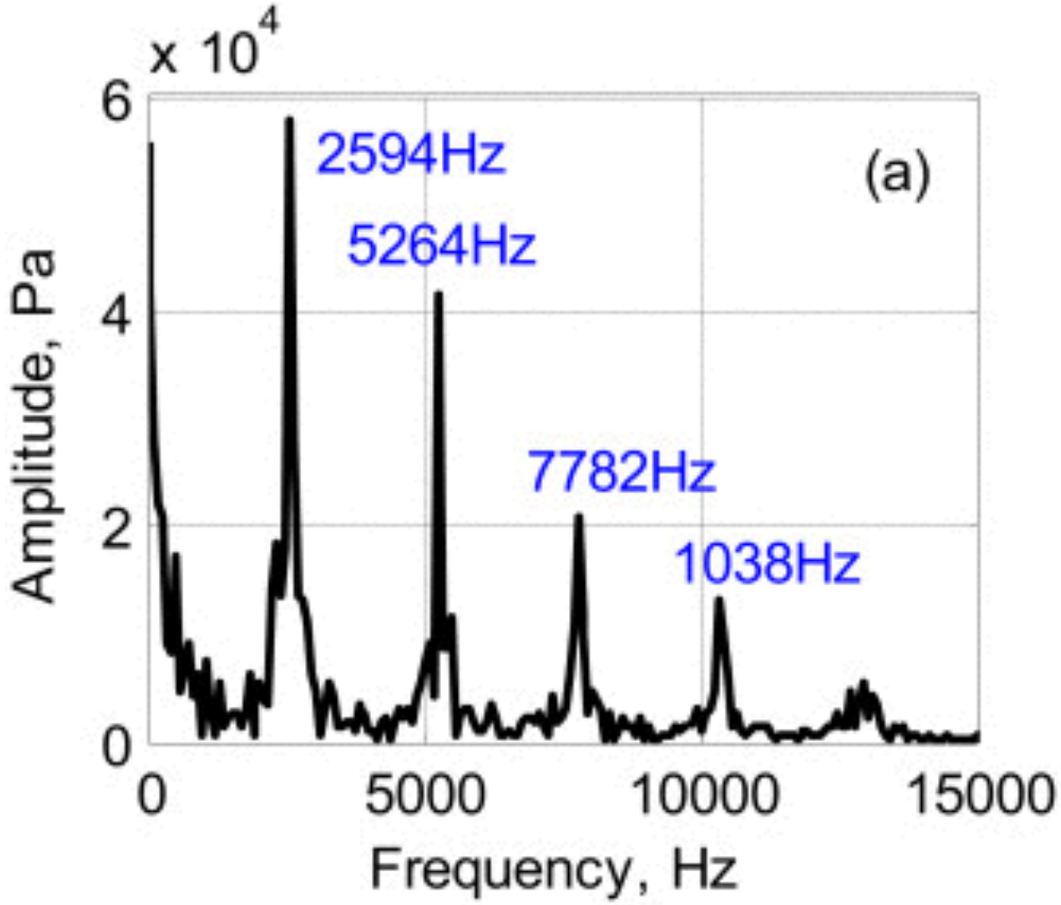
POD is efficient when

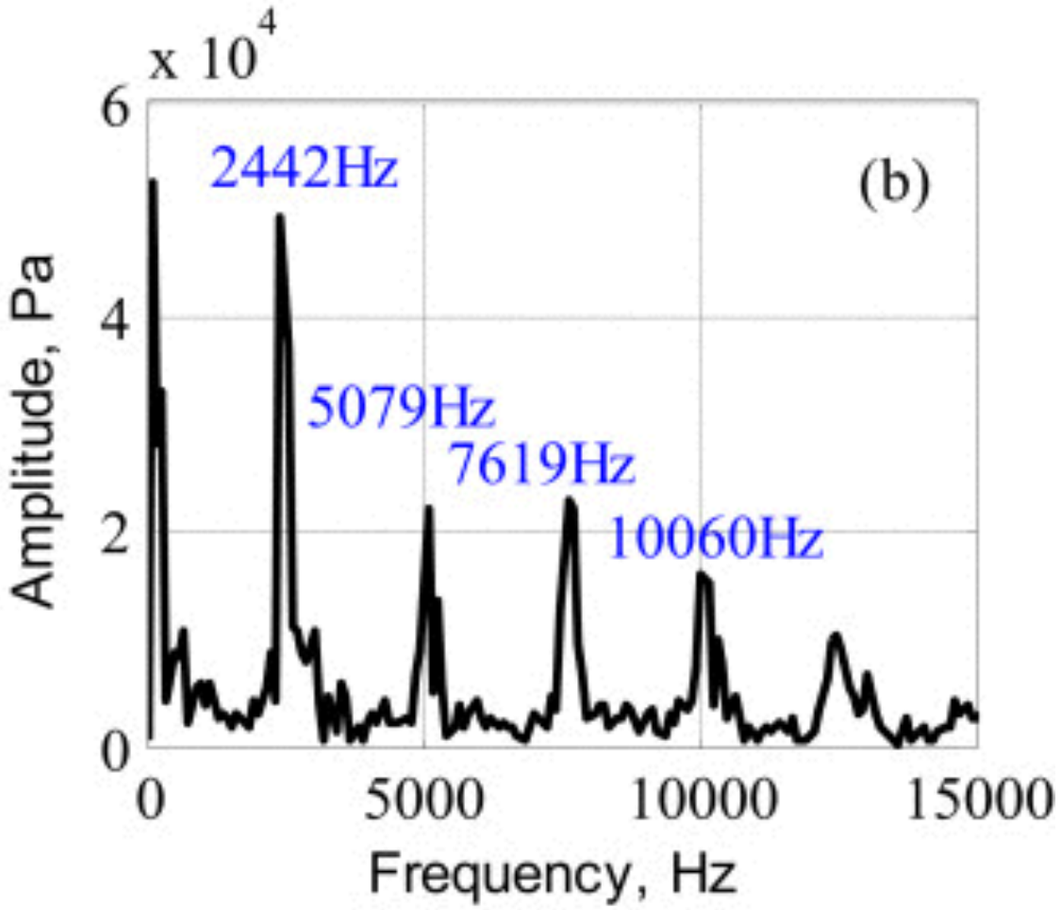
- a few modes concentrate a large amount of energy
- the energy is distributed over a large range of frequencies
- the signal is not periodic
- the time resolution is low

DMD cannot be used to decompose transition signals and require a high time resolution.

Limit cycles observed in combustion chamber feature



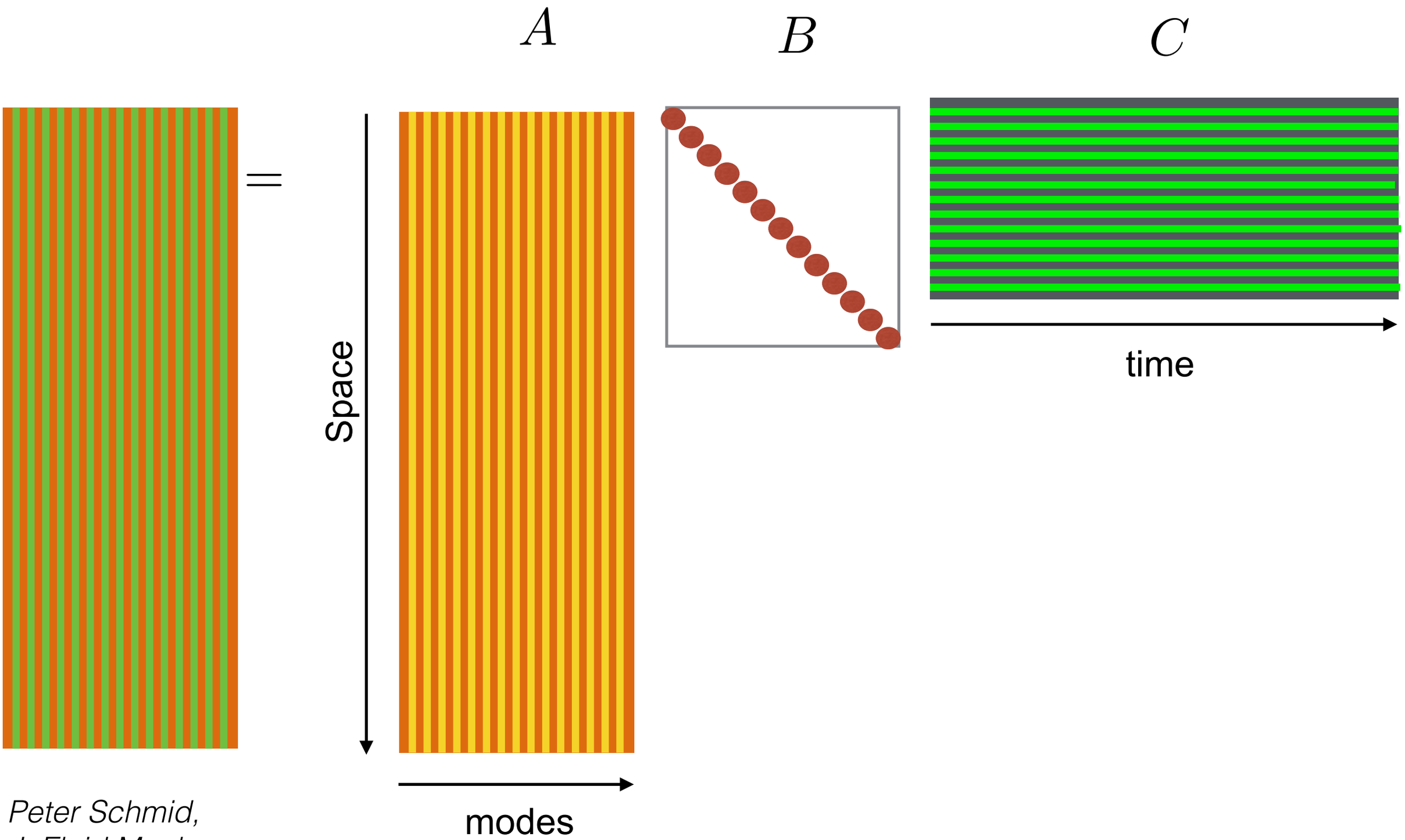




Computational investigation on combustion instabilities in a rocket combustor

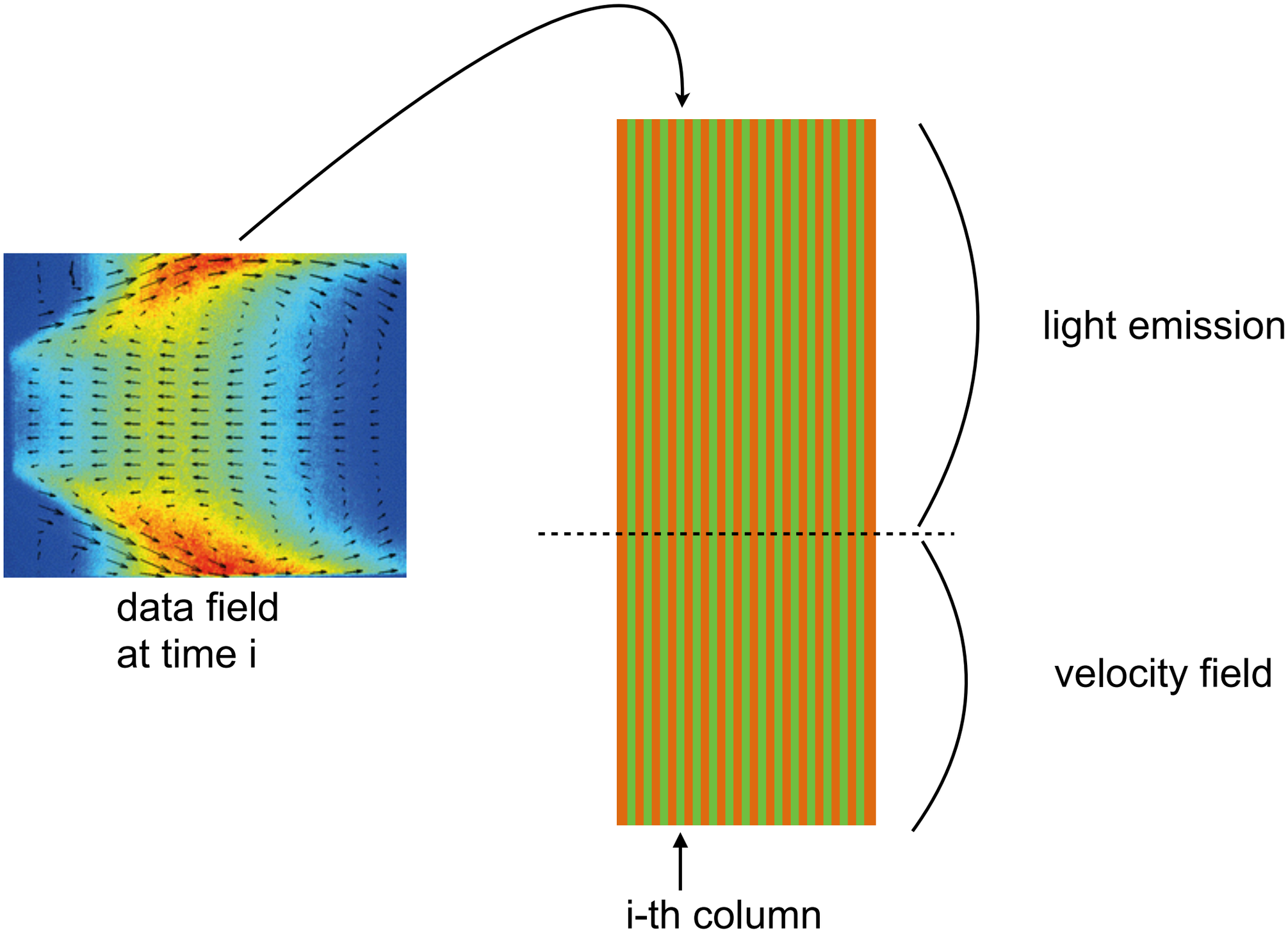
Acta Astronautica
Volume 127, October–November 2016, Pages 634-643
LeiYuan, Chibing Shen

DMD generates a decomposition of the data based on the frequencies.



Peter Schmid, J. Fluid Mech. (2010)

Multi-variables DMD



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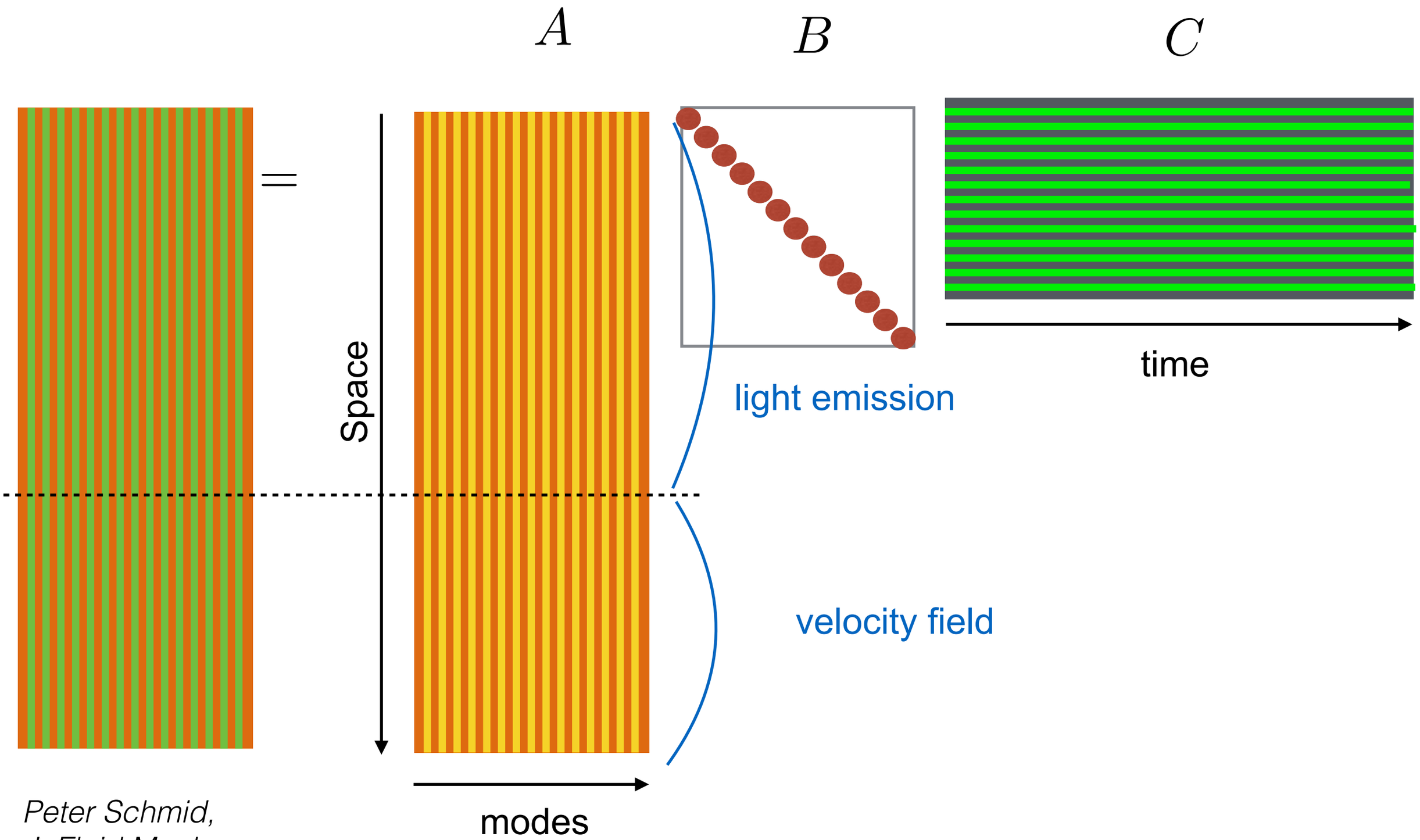
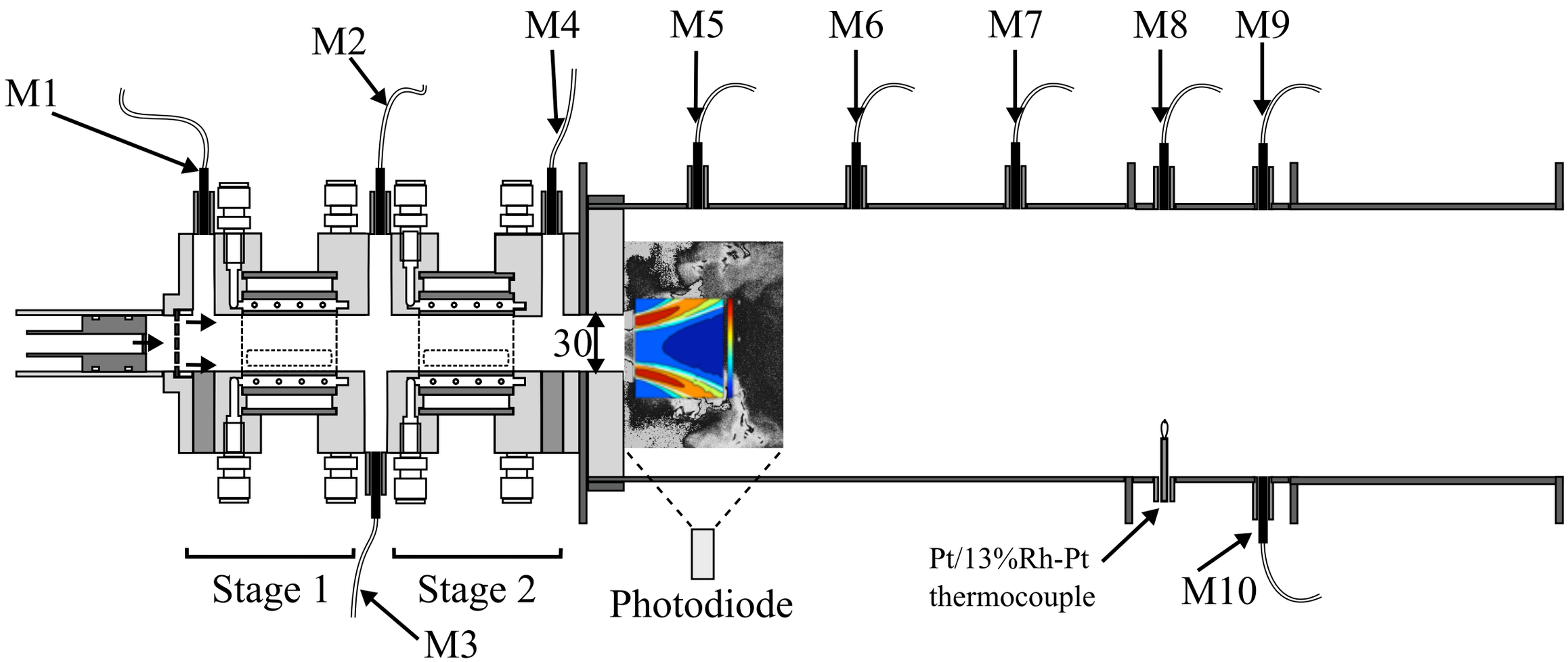
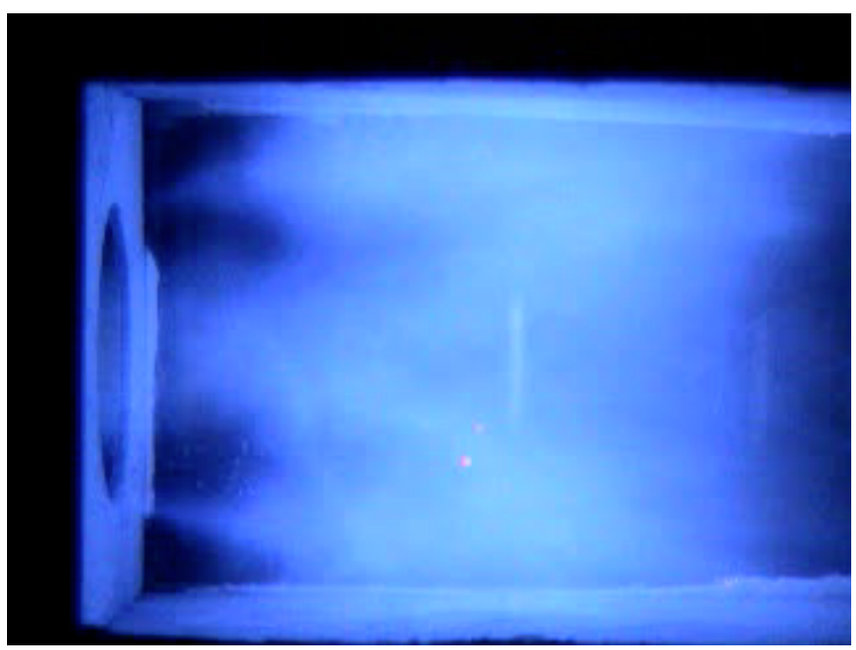
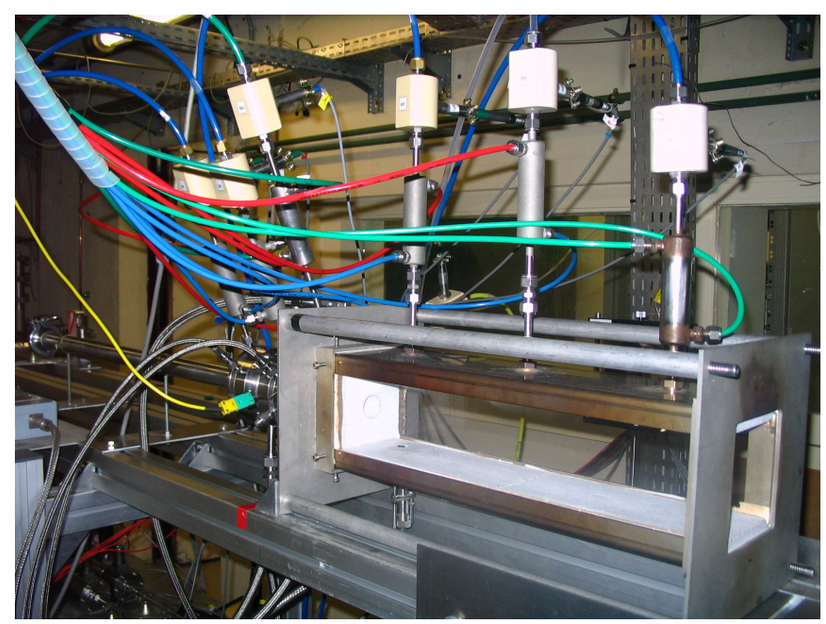


Peter Schmid, J. Fluid Mech. (2010)

CESAM Experimental test bench reproduce most of the coupling phenomena encountered in aeronautical combustion chamber







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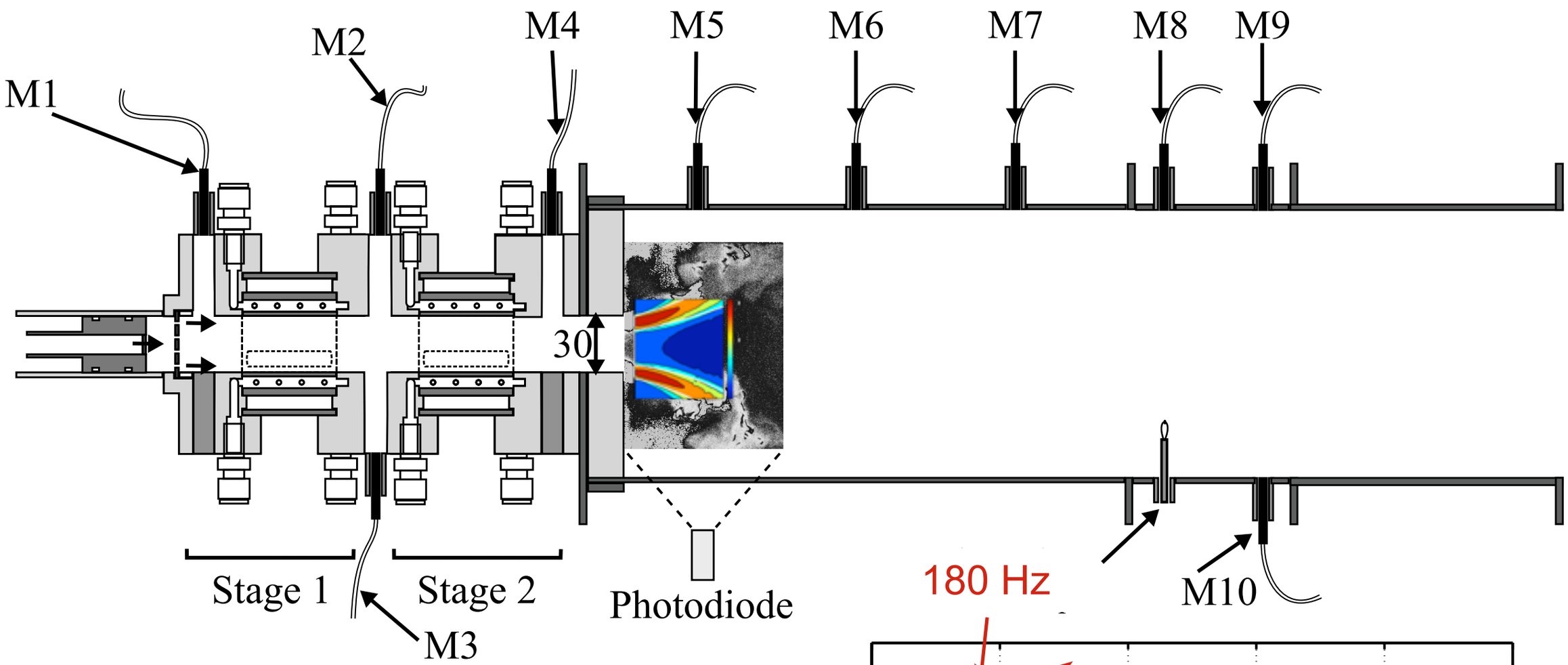
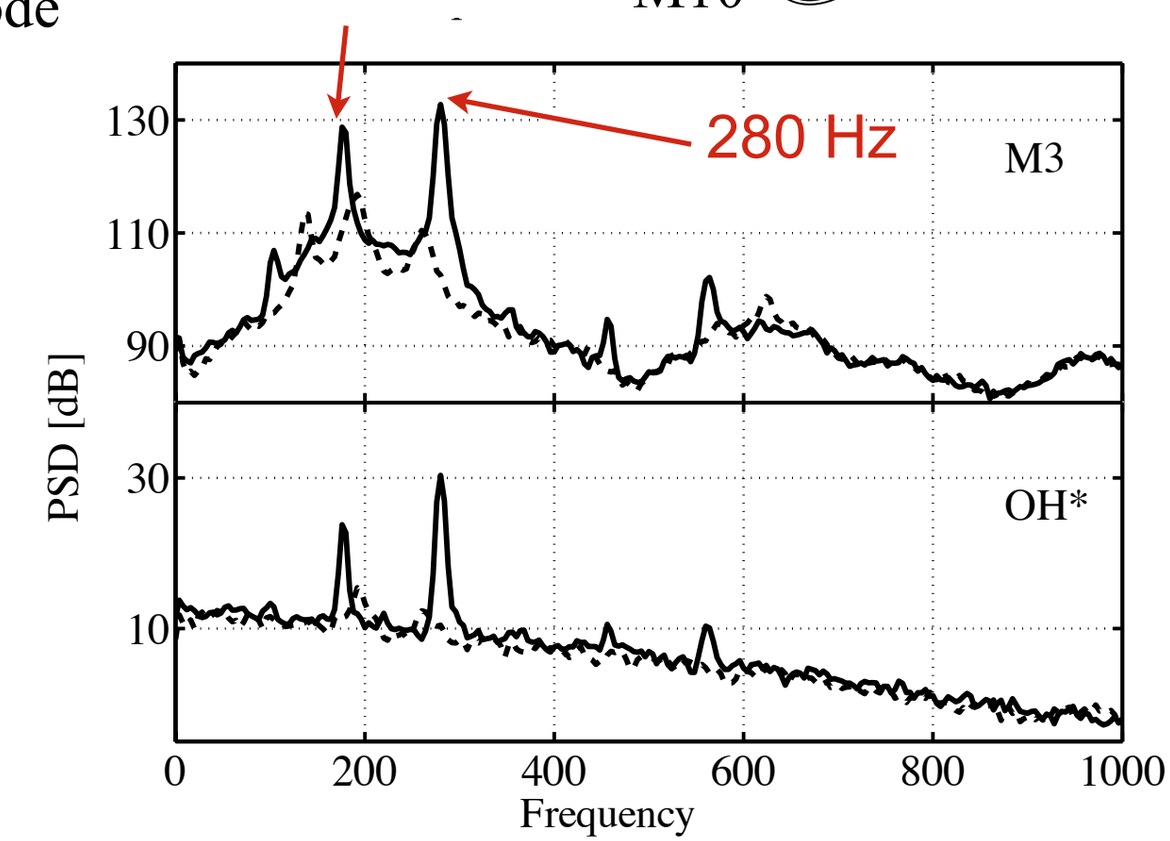




Simultaneous acquisition

- PIV @15kHz
- 10 microphones @16kHz
- OH* et CH* emission @16kHz

Lamraoui, A. et al. *Journal of Engineering for Gas Turbines and Power* 133.1, 011504, p. 011504.

Multi-variable DMD highlights correlation between physical quantities

Two strategies are still available.

1 - Multi-variable DMD

Velocity 1
.
.
.
Velocity M
Pressure 1
.
.
Pressure P

This gives a unique optimal base for all the diagnostics

Values have to be normalized to take into account their volume and their absolute value.

2 - Extended DMD

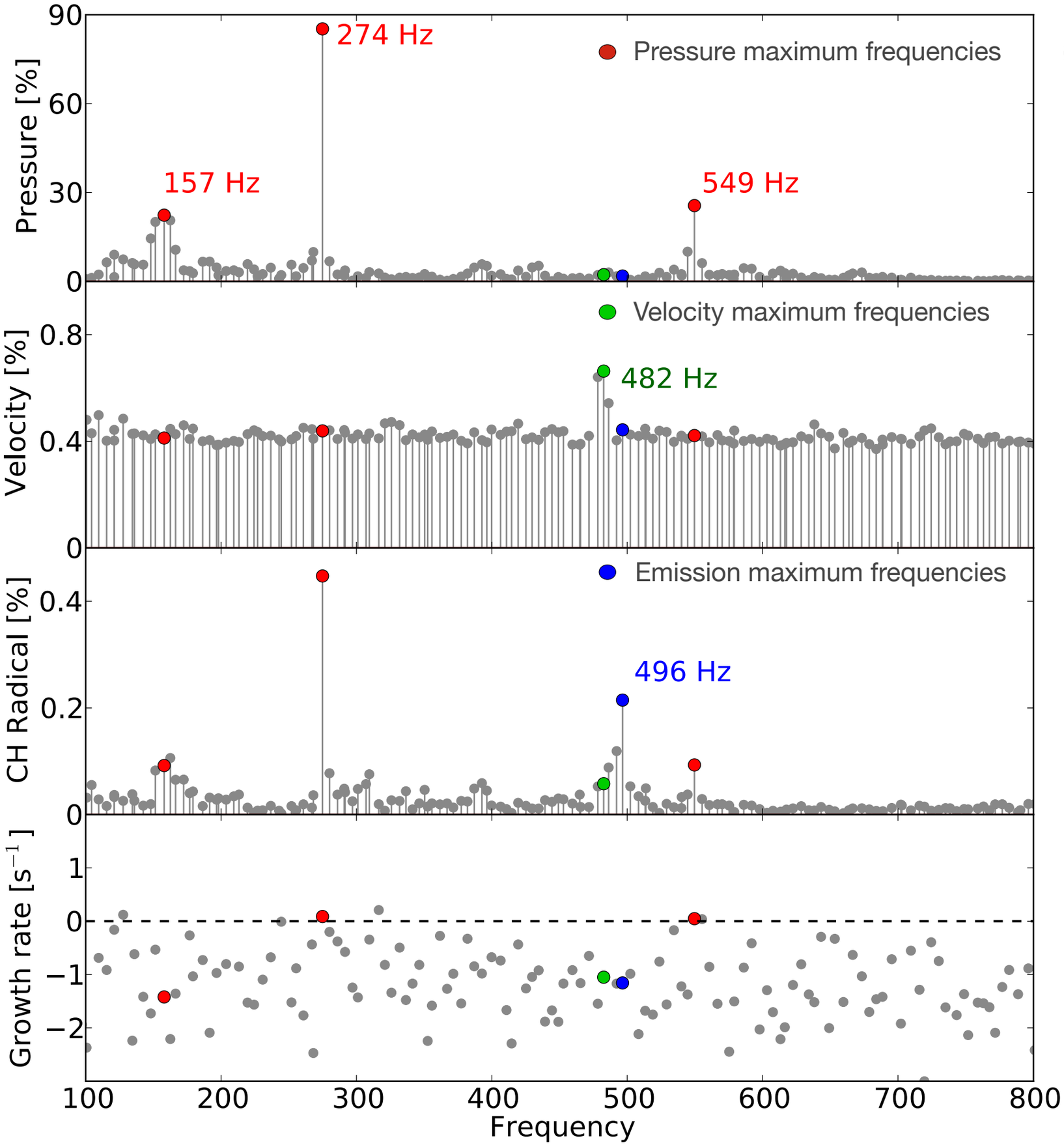
Pressure 1
.
.
Pressure P

Optimal DMD base for pressure

Velocity 1
.
Velocity M

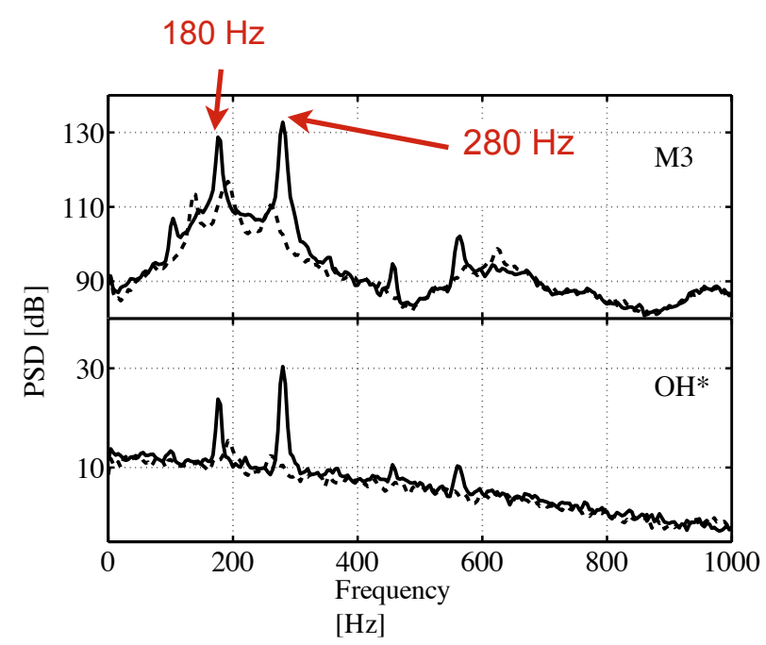
B_i

The amplitude of velocity modes projected on the base B_i highlight the correlation between the two quantities.



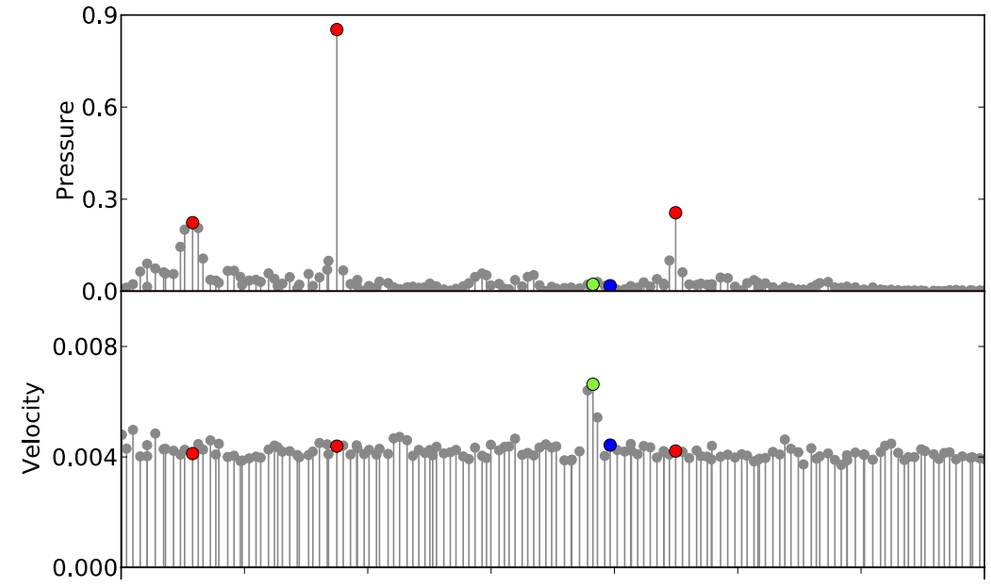
Quantitatives informations

- Velocity has a different dynamic than pressure
- Heat release is sensitive to both the pressure and velocity fluctuations
- Damping strongly depends on the modes

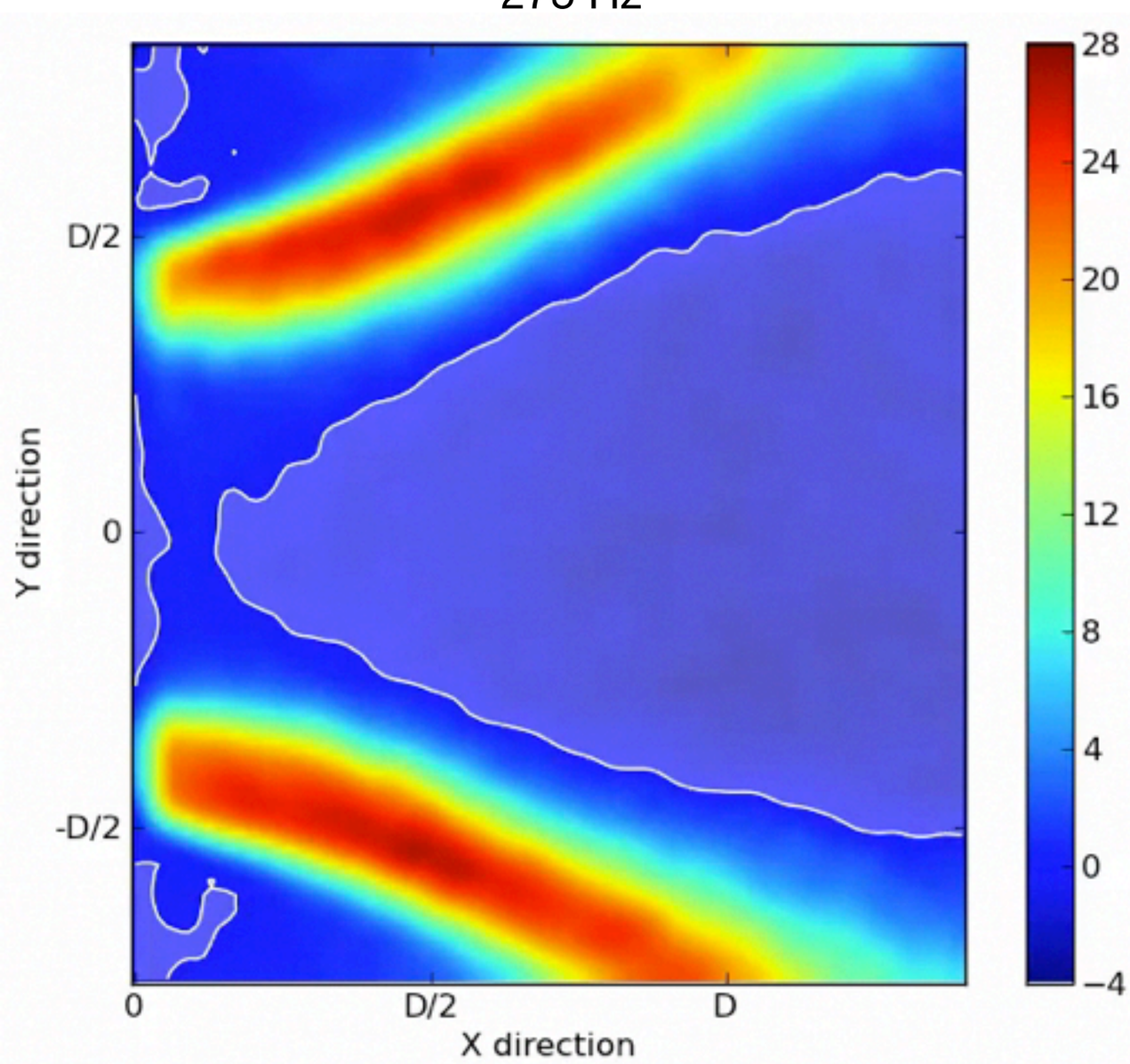


Flow dynamics

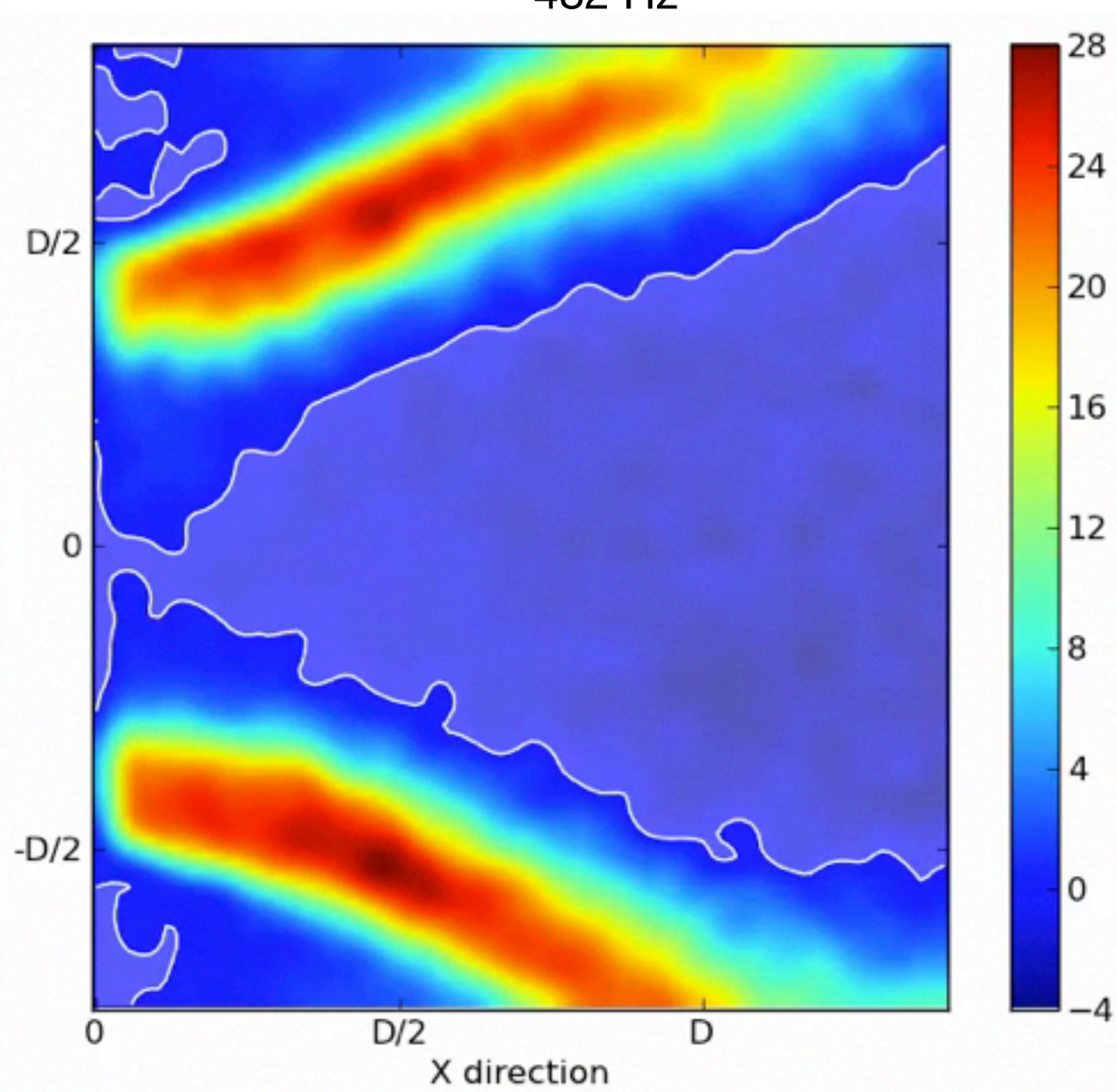
DMD highlight coupling between acoustics and flow.



275 Hz

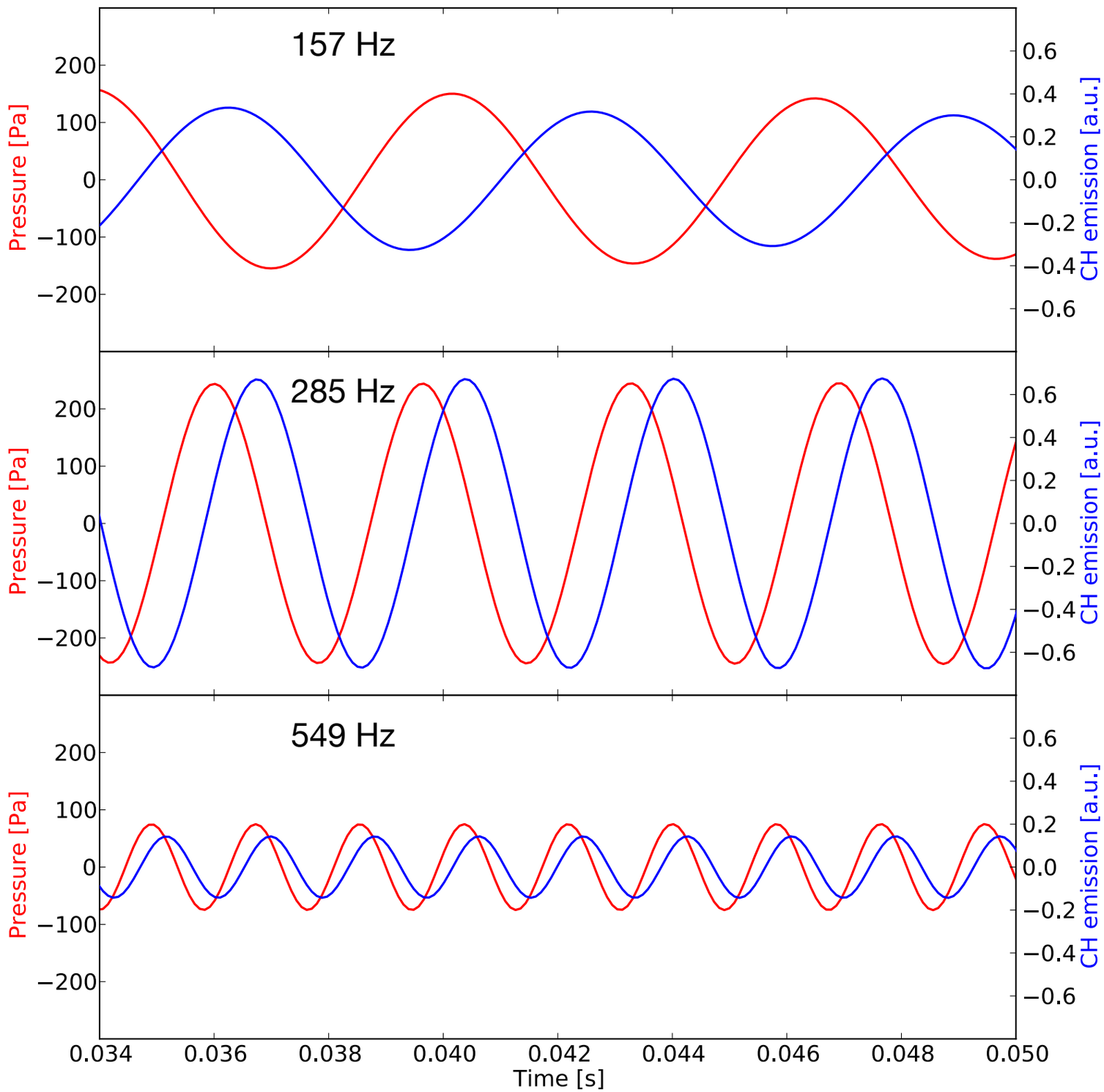


482 Hz



Reconstruction of the acoustic source

The phase between the diagnostics is recovered within the modes.

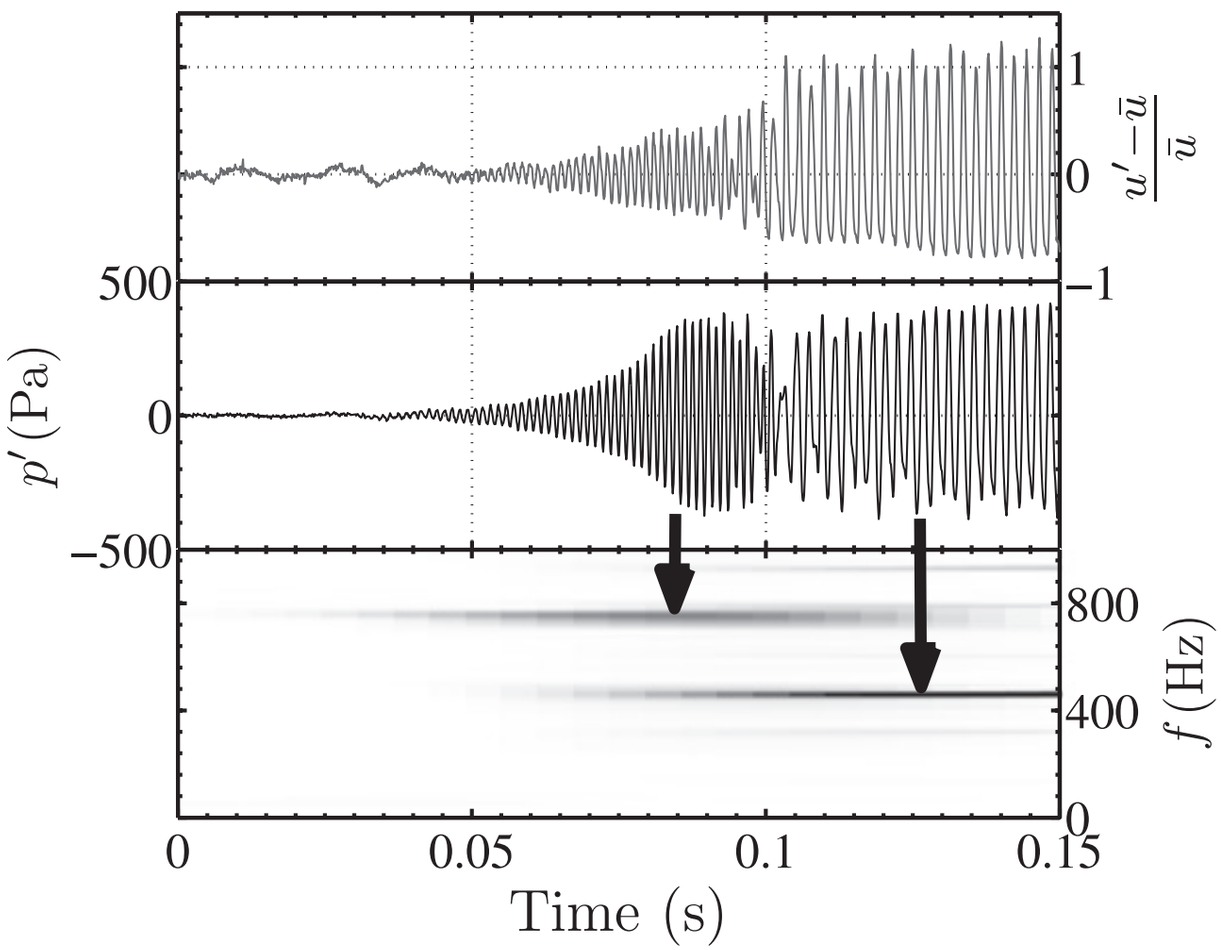


Acoustic energy

$$\frac{\partial e}{\partial t} + \nabla.(p_1 u_1) = \frac{\gamma - 1}{\gamma p_0} p_1 \dot{q}_1$$

Acoustic source term

Data decomposition for model reduction



F. Boudy et al. / Proceedings of the Combustion Institute 33 (2011) 1121–1128

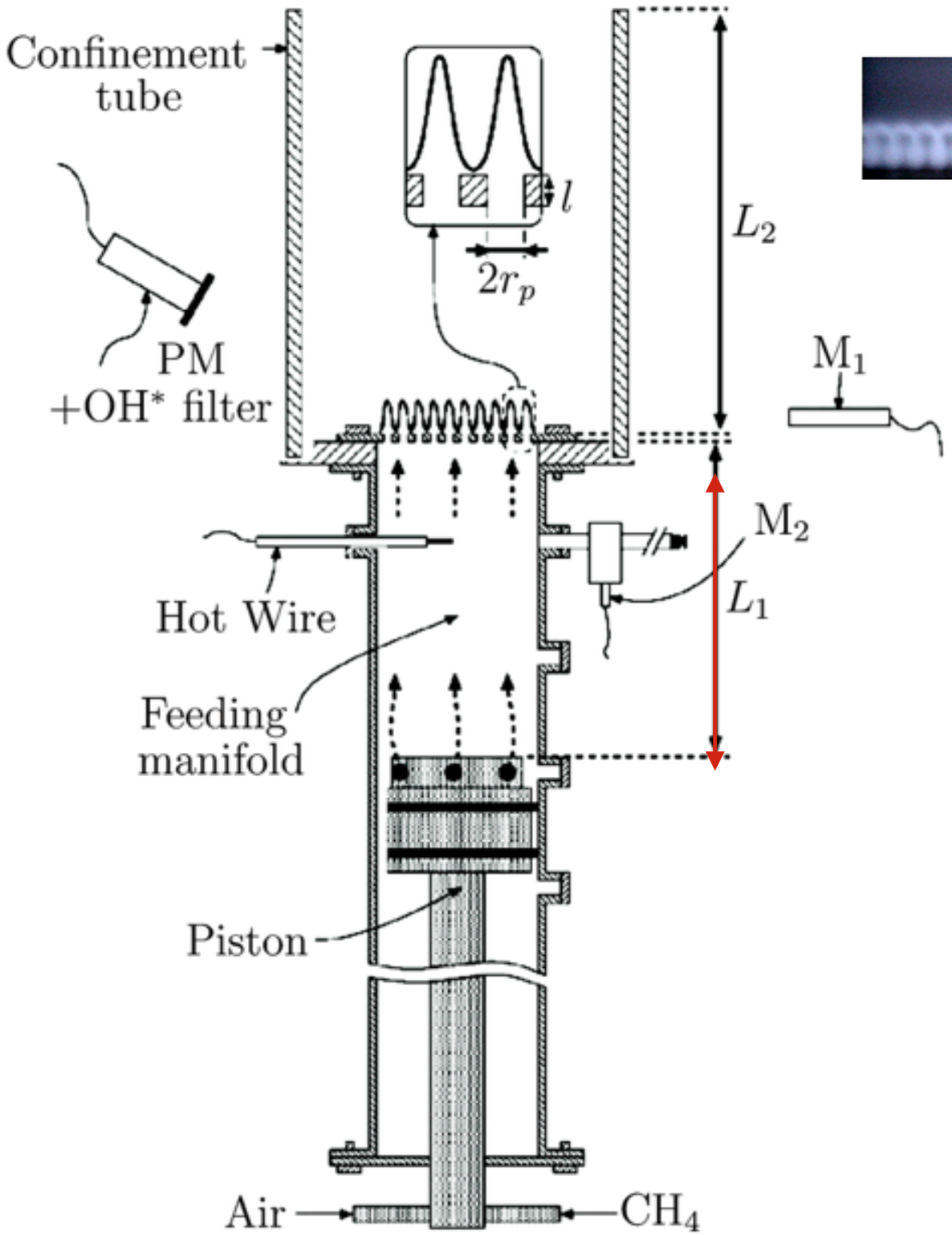
To create models, the strategy is to separate the signal in few modes and amplitudes :

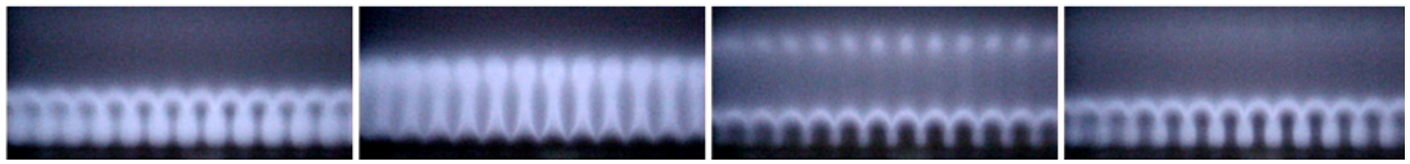
$$p'(t,x) = a_1(t)\Psi_1(x) + ... + a_4(t)\Psi_4(x)$$

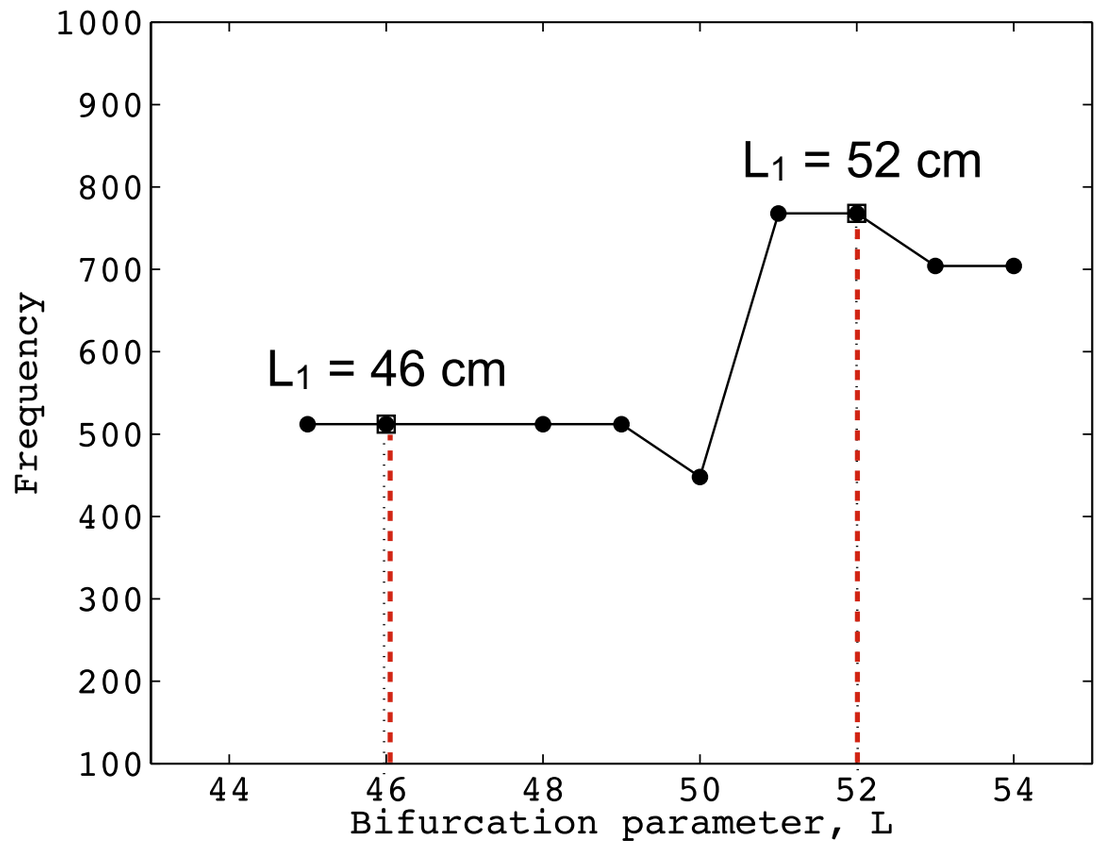
$$\frac{da_i(t)}{dt} = \mathcal{F}(a_i)$$

The problem is to identify the modes that allow to describe the system whatever the operating point.

Combustion systems experience bifurcation that make the modeling complex.



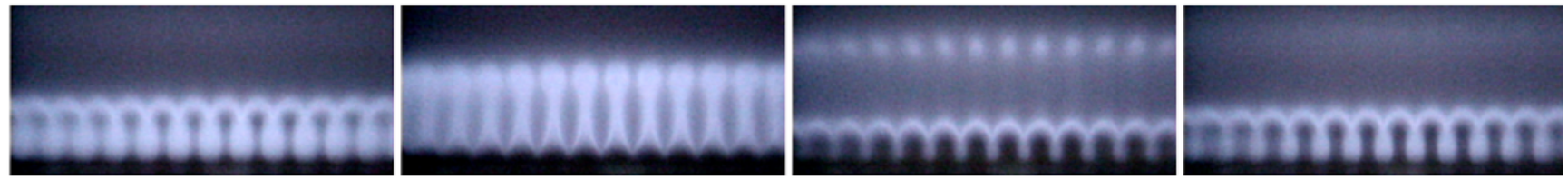




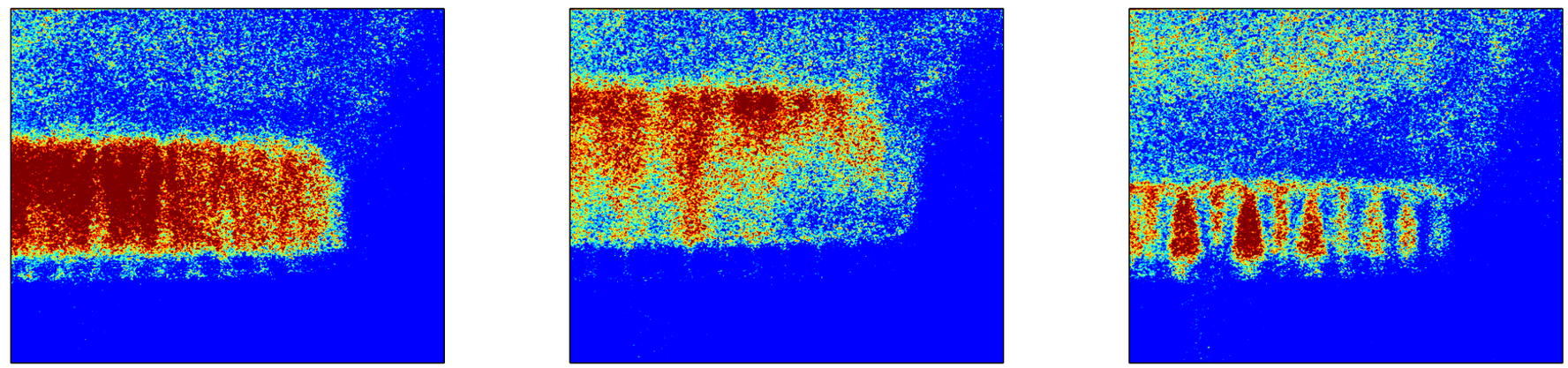
The system experience two kind of dynamics depending on the bifurcation parameter.

Chemiluminescence from flames is recorded for different values of the bifurcation parameter.

80 images, 6 kHz

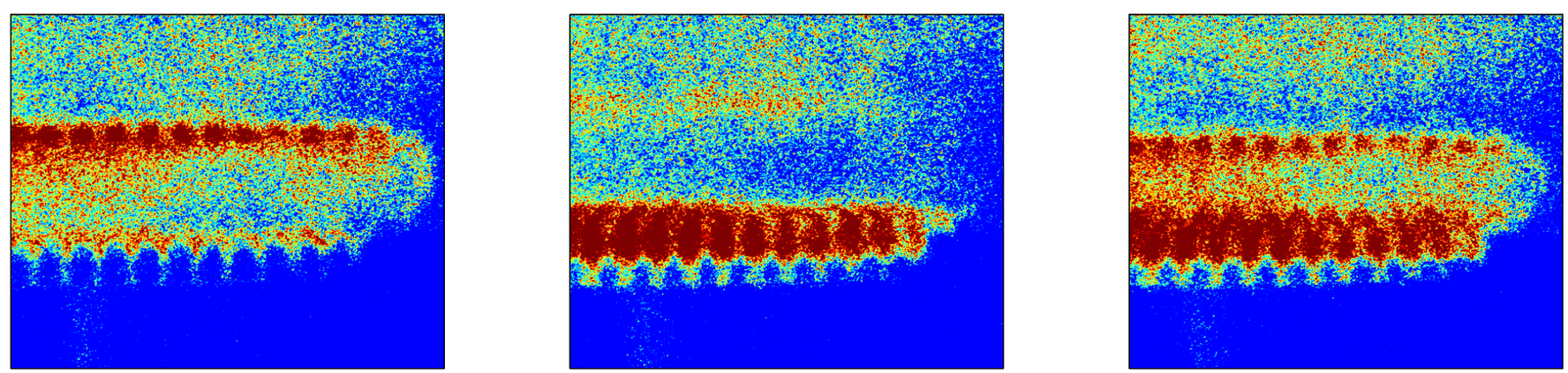


$L_1 = 46$ cm



(a) Case A, t_1 (b) Case A, t_2 (c) Case A, t_3

$L_1 = 52$ cm



(d) Case B, t_1 (e) Case B, t_2 (f) Case B, t_3

The poor quality of the images is due to the high sampling frequency and the low emission level of the flames.

Data processing of the experiments

We saw the multivariable DMD :

$$\begin{pmatrix} u_1^1 & u_1^2 & \text{———} & u_1^t \\ | & | & & | \\ u_n^1 & u_n^2 & \text{———} & u_n^t \\ p_1^1 & p_1^2 & \text{———} & p_1^t \end{pmatrix}$$

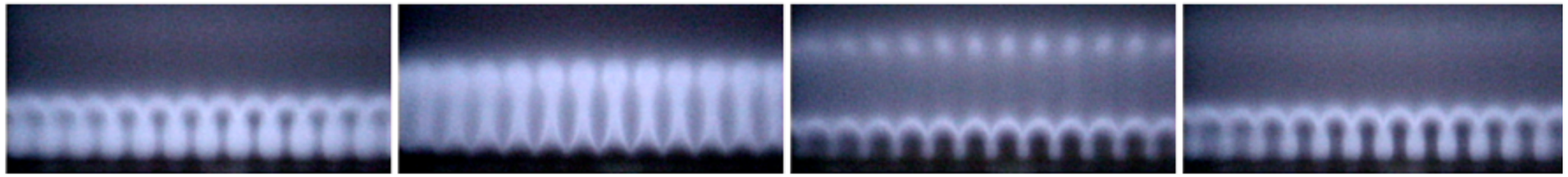
Parametric DMD uses data recorded at different time but with the same sampling rate.

$$\begin{pmatrix} p_{L_1}^1 & \text{———} & p_{L_1}^t \\ p_{L_2}^1 & \text{———} & p_{L_2}^t \\ | & & \\ p_{L_n}^1 & \text{———} & p_{L_n}^t \end{pmatrix}$$

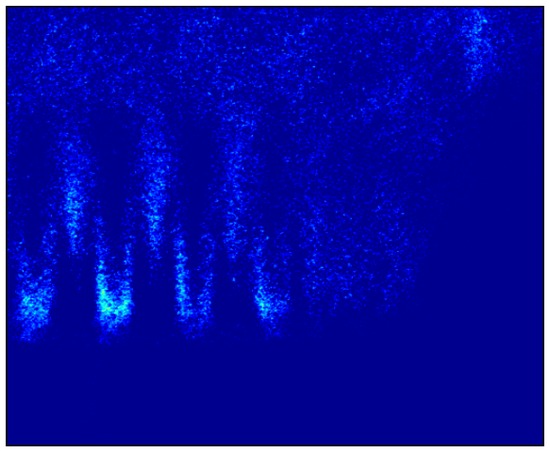
	$L_1 = 46$ cm (case A)	$L_1 = 52$ cm (case B)
Experiment	512 Hz	768 Hz
Parametrized DMD	493 Hz	740 Hz
Dominant mode	mode 3	mode 4

Four dominant modes are identified (1 to 4).

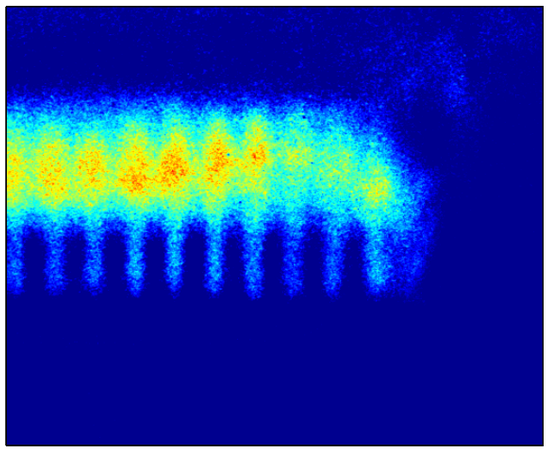
Depending on the bifurcation parameter, the weight of each mode changes.



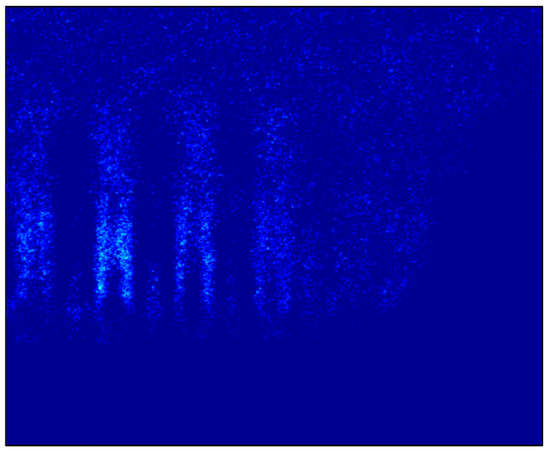
$L_1 = 46$ cm



(a) Case A, mode 2

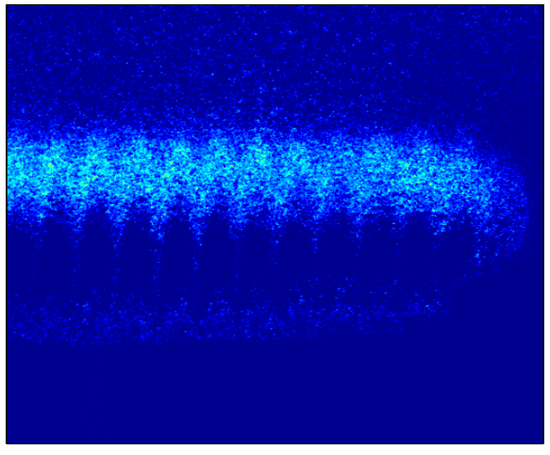


(b) Case A, mode 3

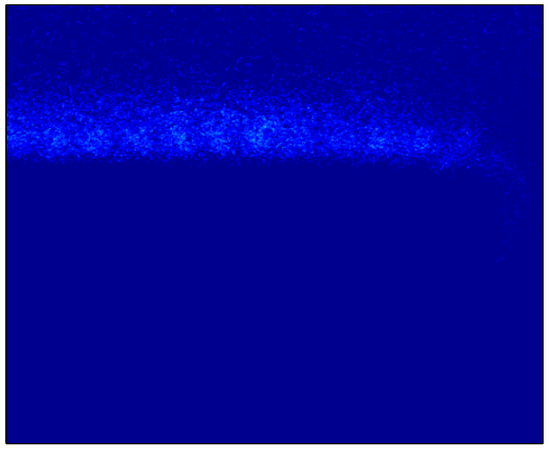


(c) Case A, mode 4

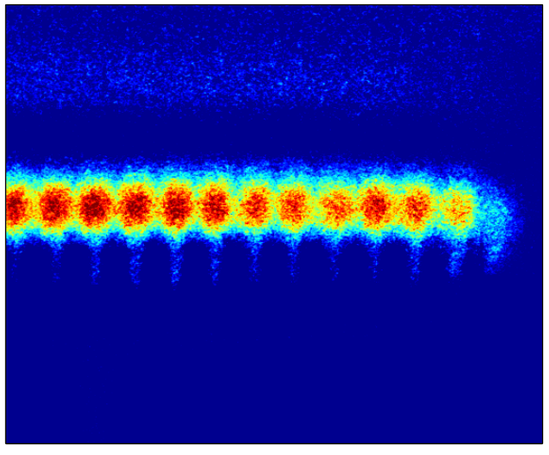
$L_1 = 52$ cm



(d) Case B, mode 2

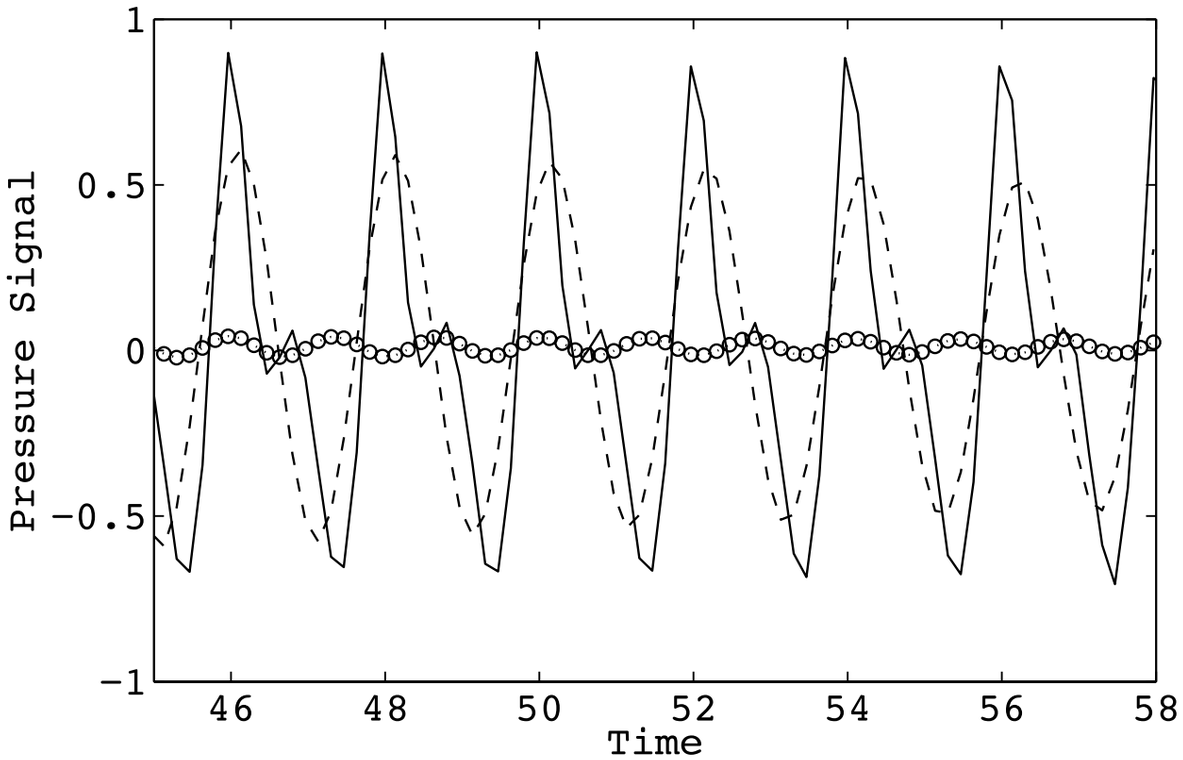


(e) Case B, mode 3



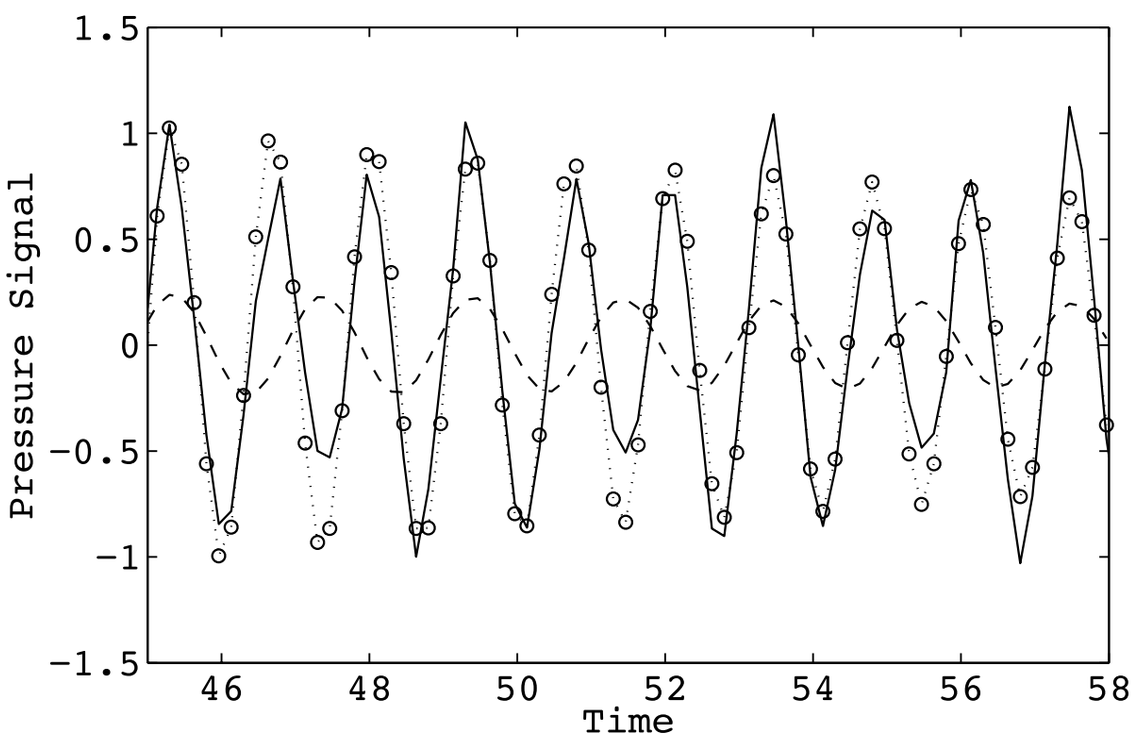
(f) Case B, mode 4

Depending on the bifurcation parameter, the weight of each mode changes.



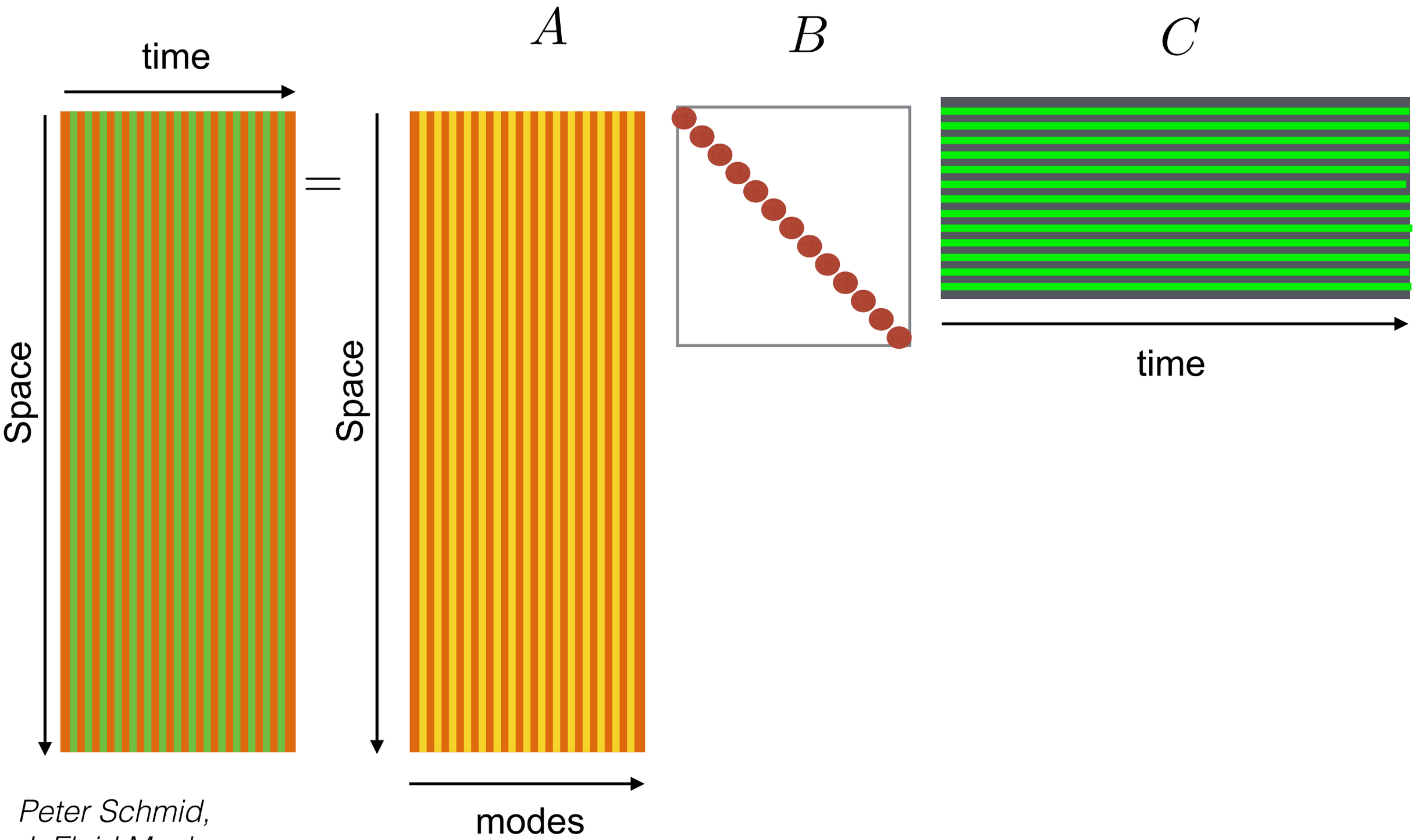
Before bifurcation

— experiment
- - mode 3
o mode 4



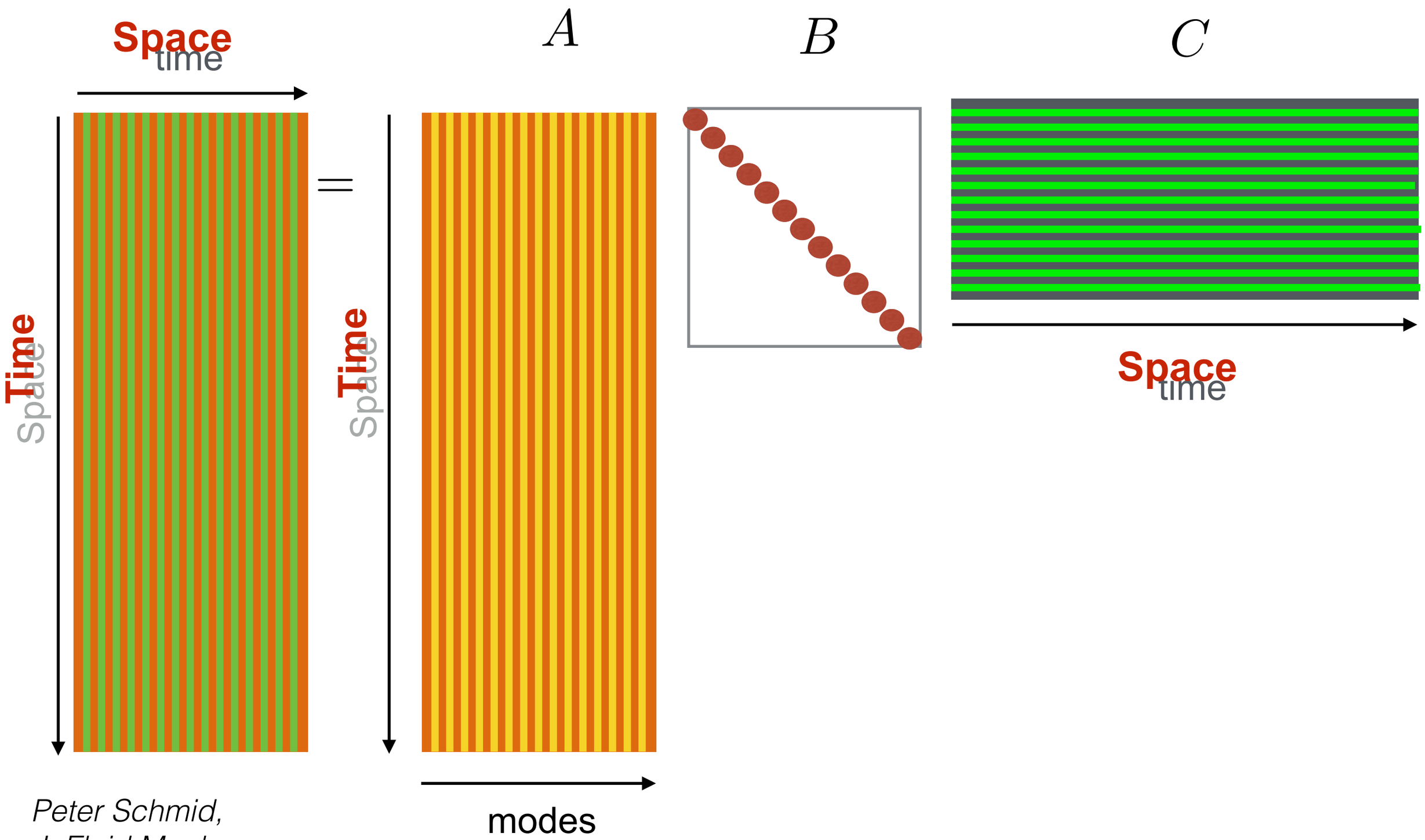
After bifurcation

DMD generates a decomposition of the data based on the frequencies.



Peter Schmid, J. Fluid Mech. (2010)

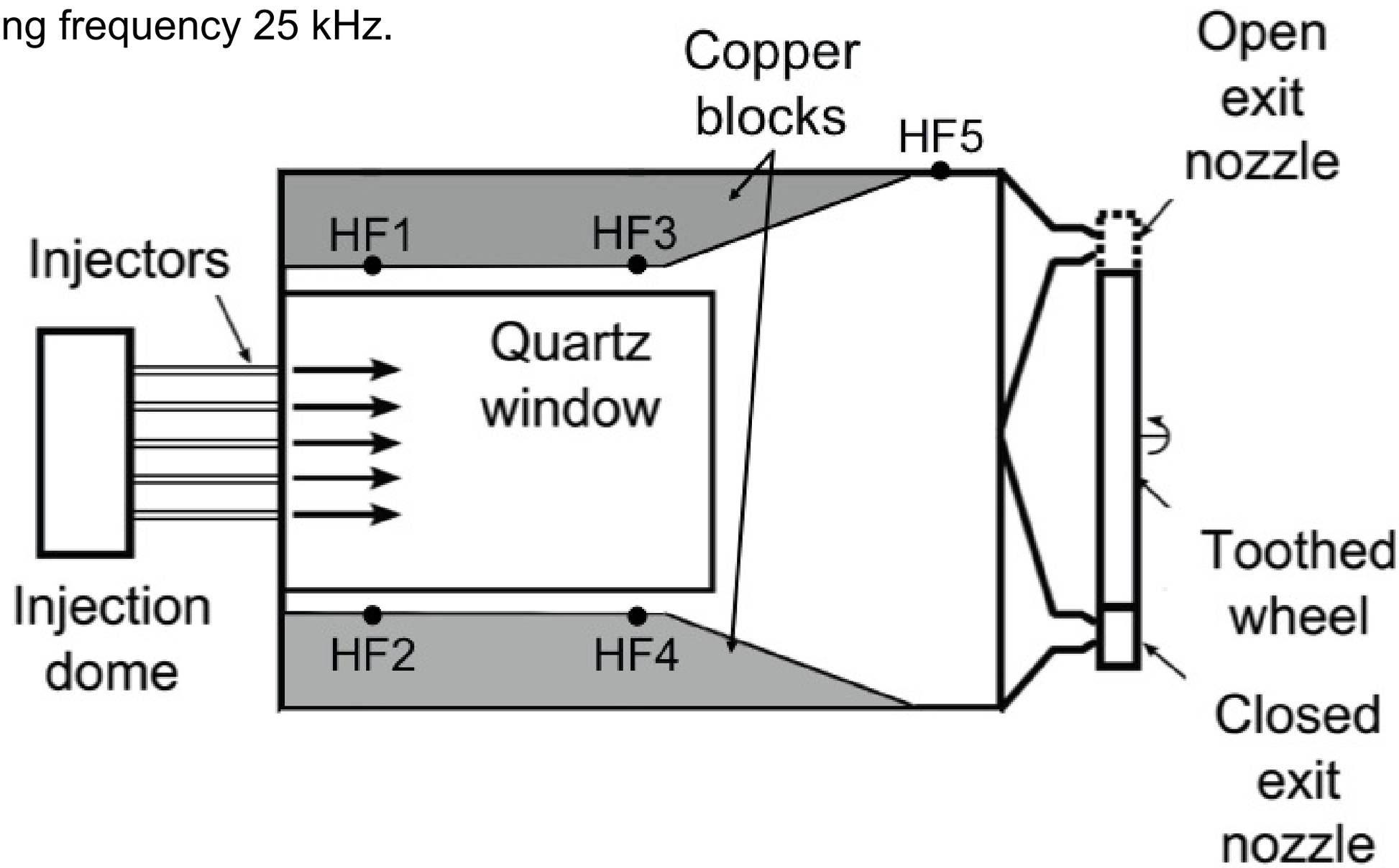
DMD generates a decomposition of the data based on the frequencies.



Peter Schmid, J. Fluid Mech. (2010)

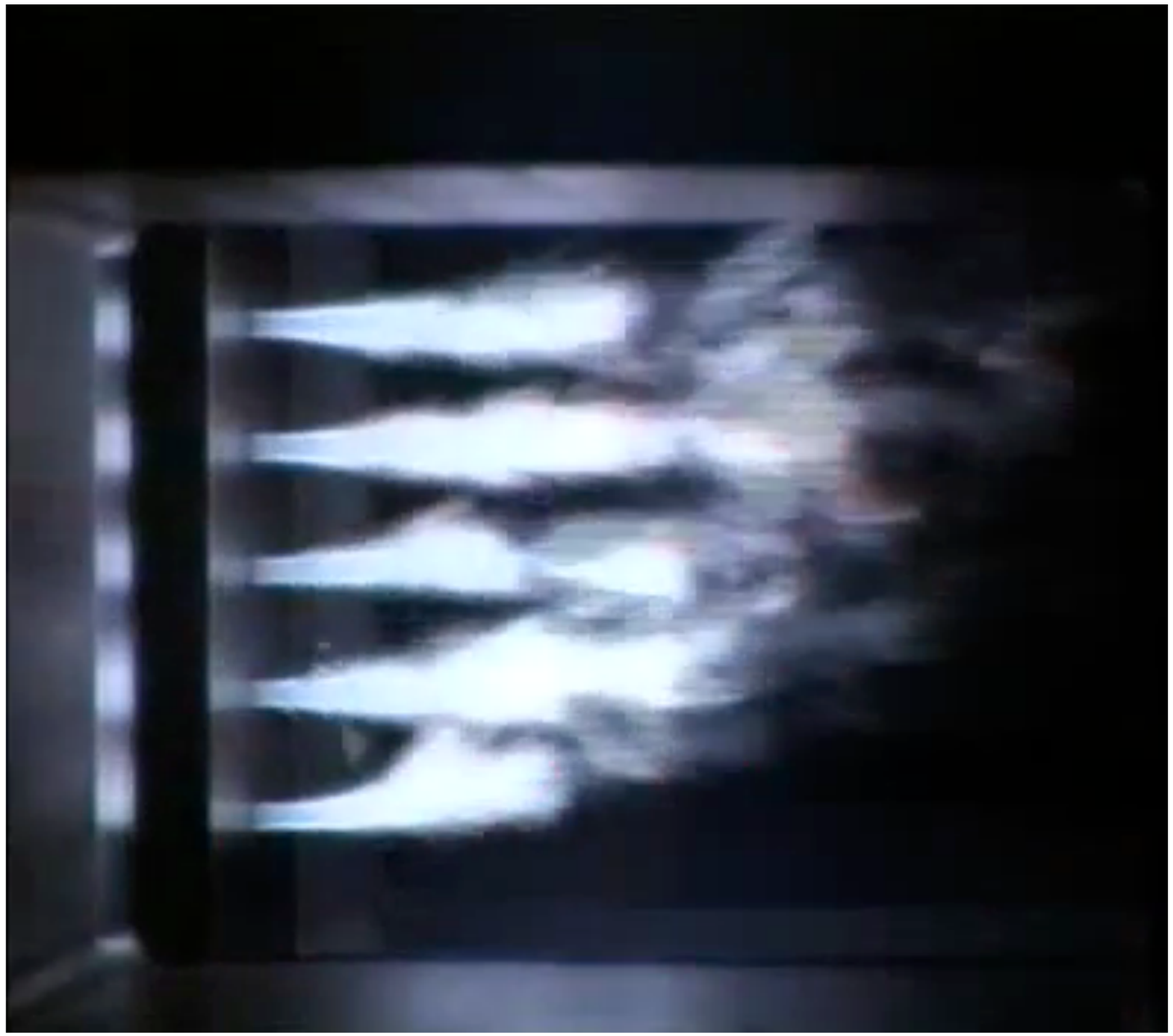
Spatial DMD

- Combustion LOx/LH2 ;
- Chamber pressure 30 bar ;
- External acoustic modulation ;
- Sampling frequency 25 kHz.



MASCOTTE (ONERA, Palaiseau)

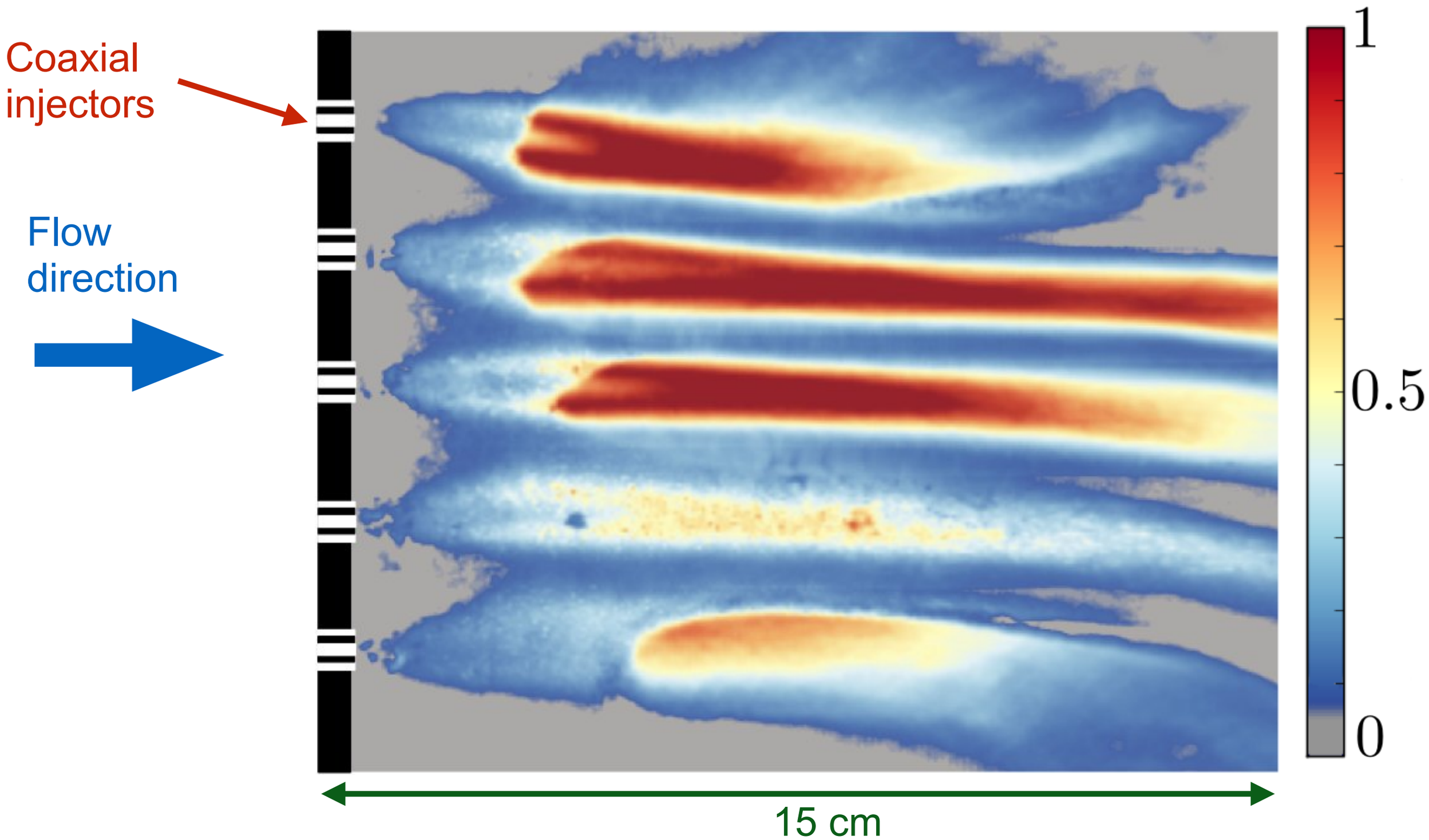
Spatial DMD



MASCOTTE (ONERA, Palaiseau)

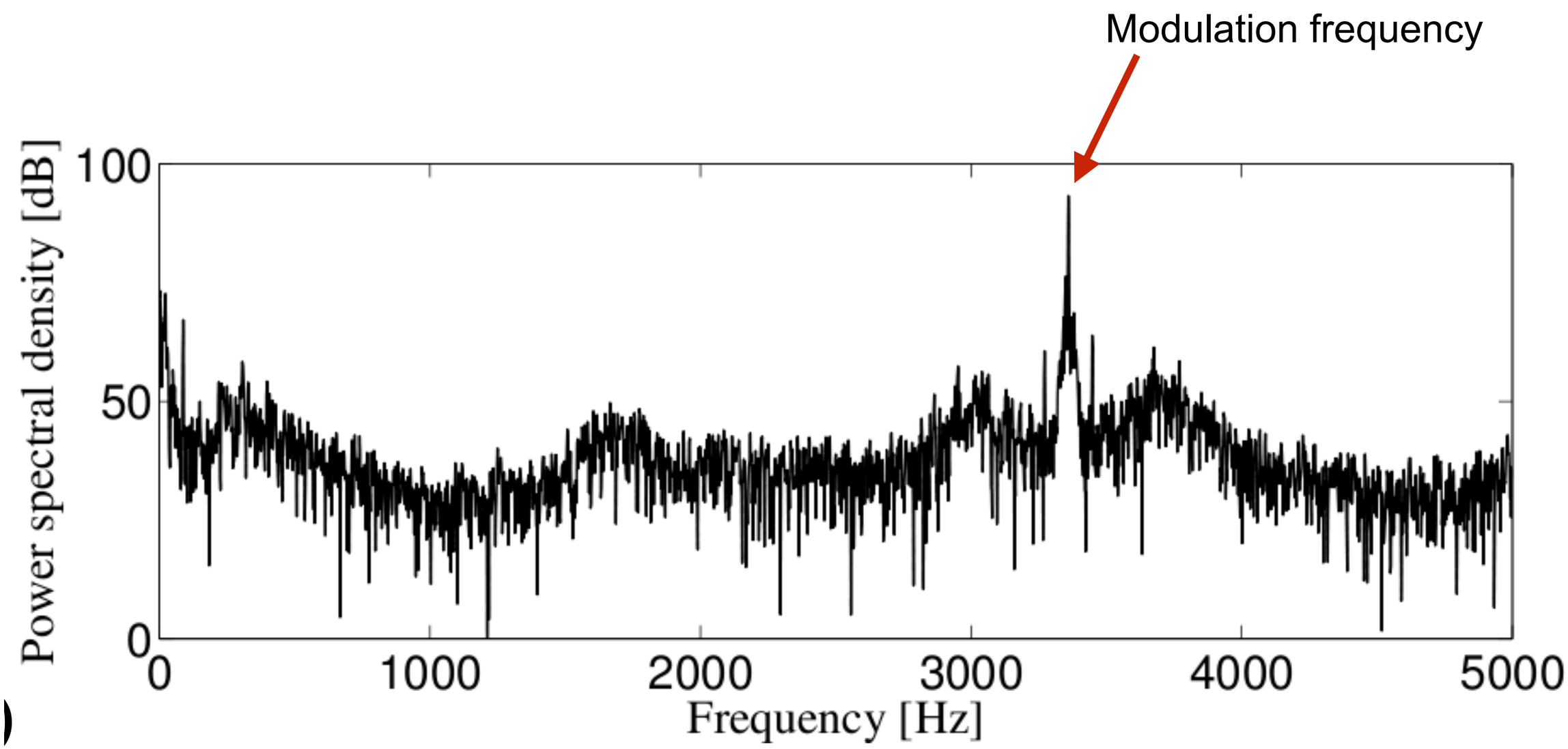
Spatial DMD

Average light emission from the flames



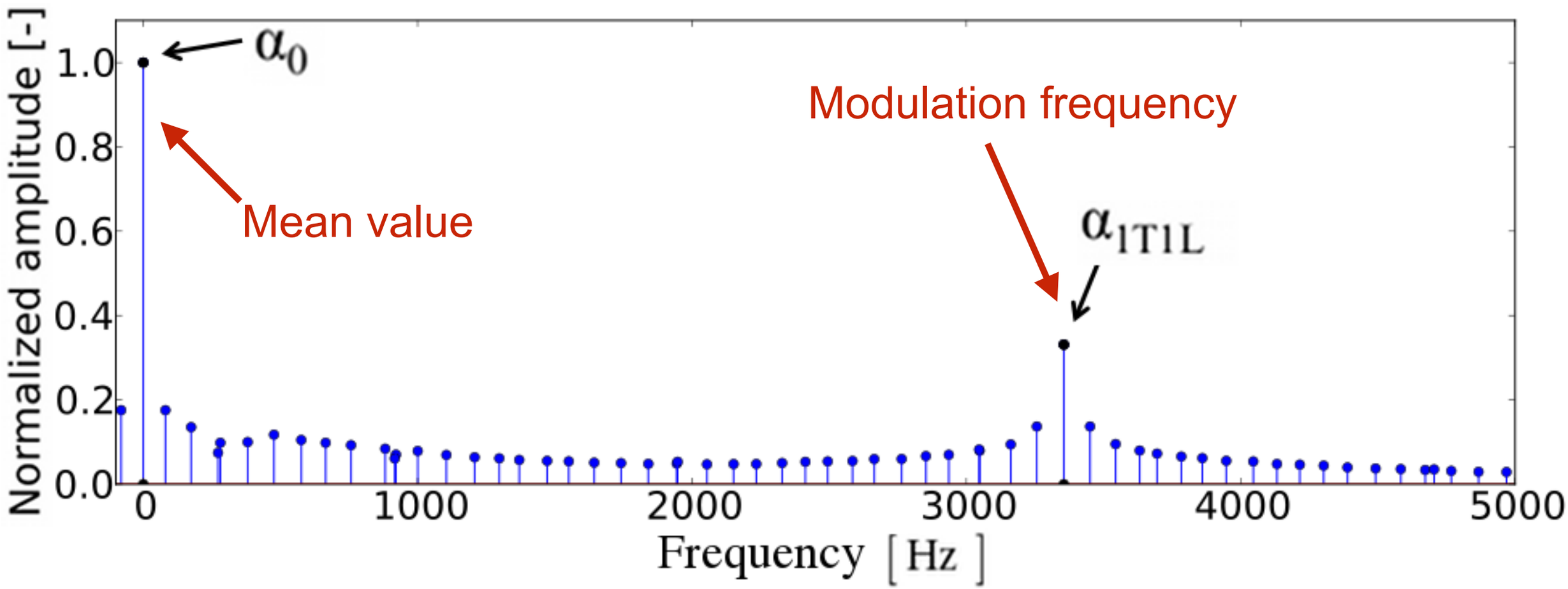
Spatial DMD

Since the flow is acoustically modulated from an external source, pressure sensors detect mainly this frequency



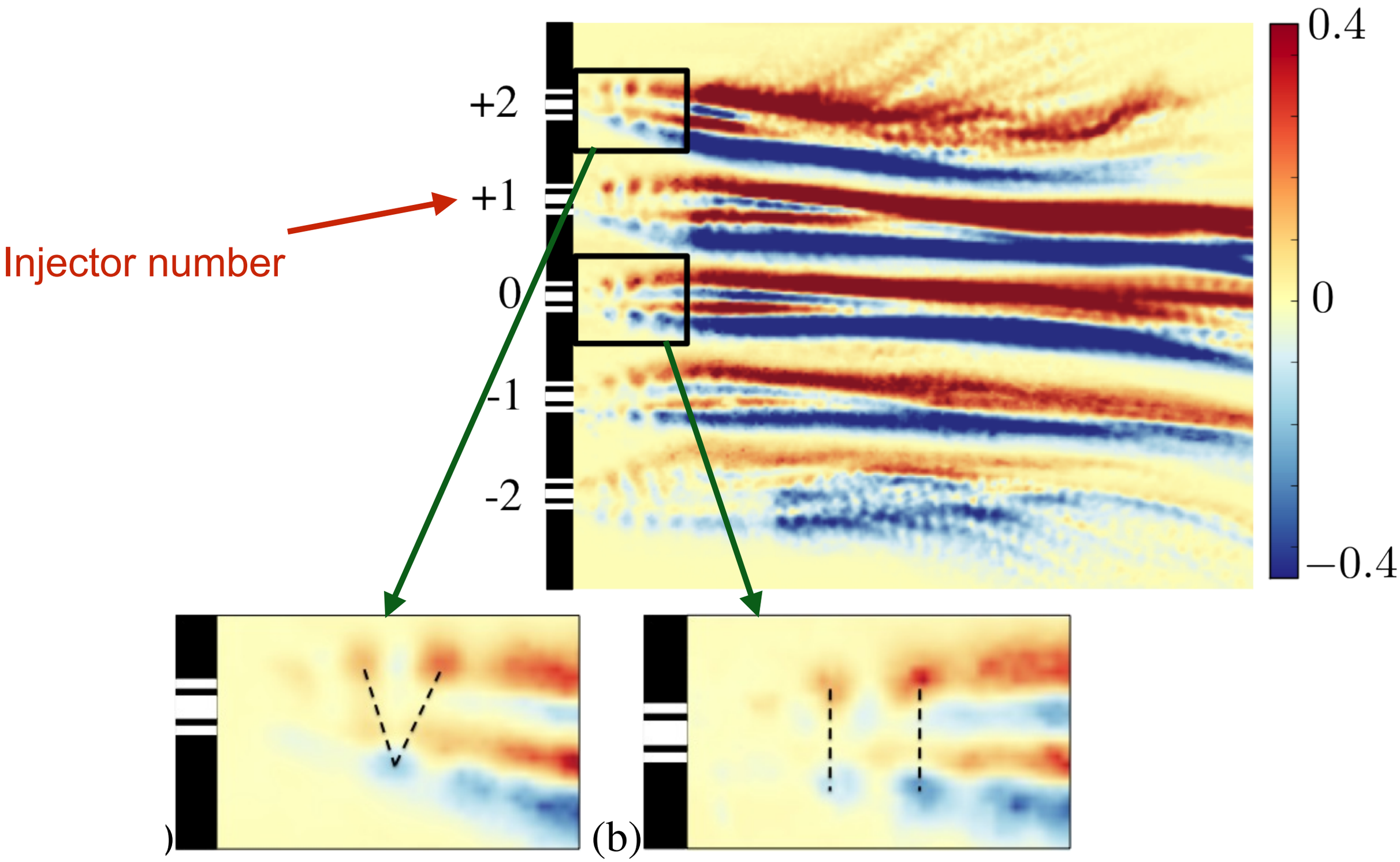
Spatial DMD

A first multi-variable DMD is performed with the pressures and light emission.



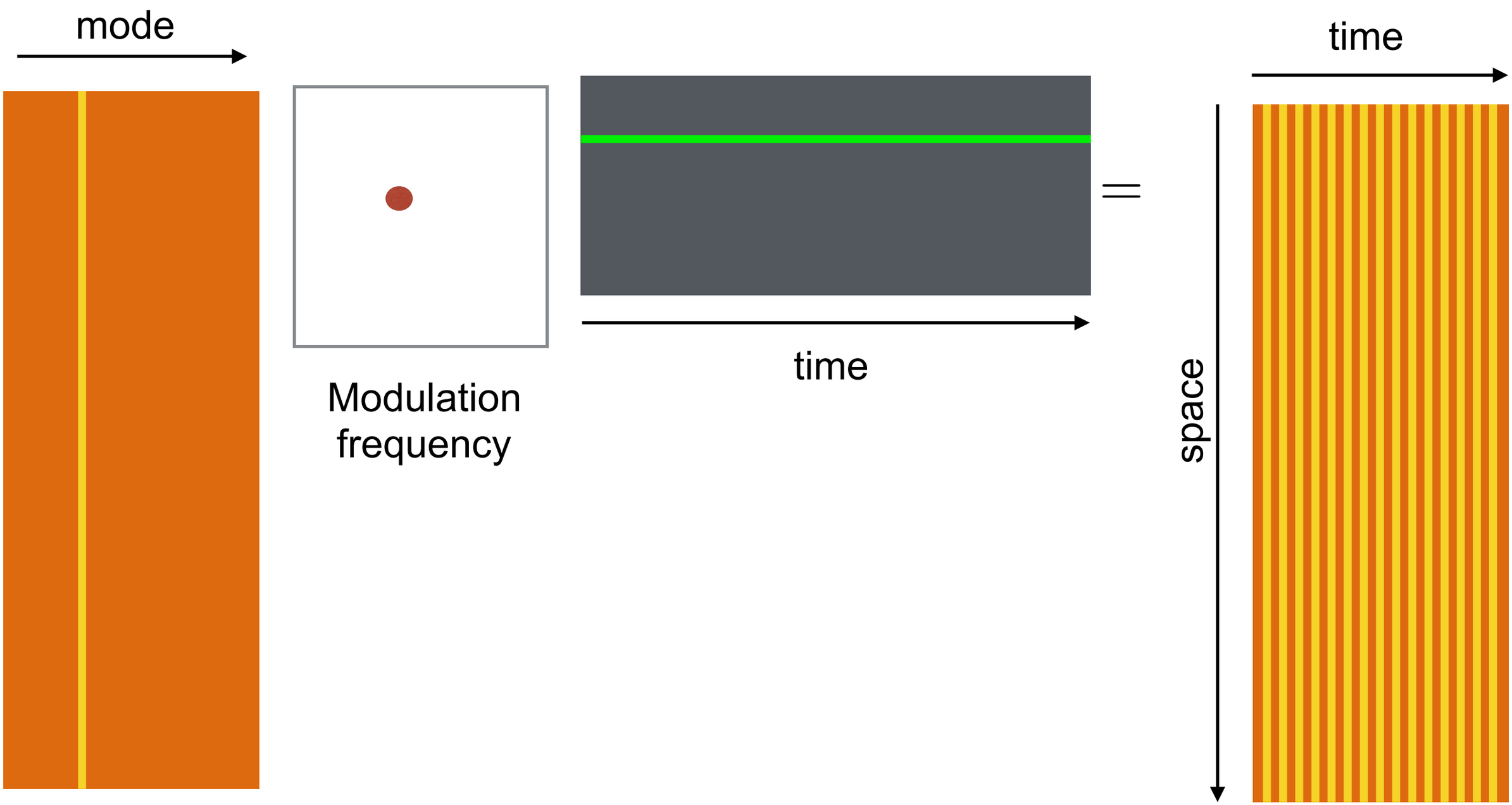
Spatial DMD

All the dynamics is concentrated on one mode.



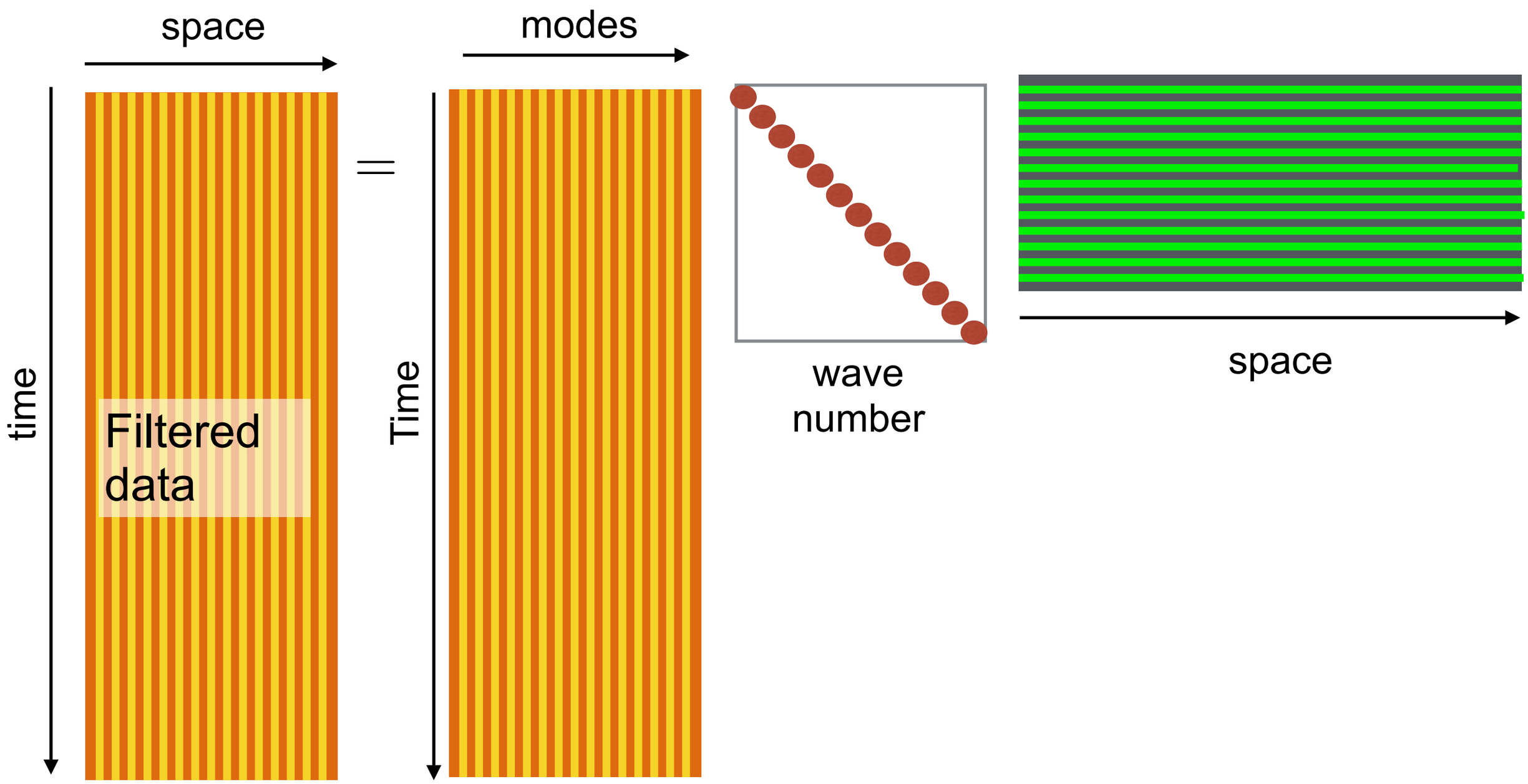
Spatial DMD

DMD is first used to filter the emission field at the modulation frequency.



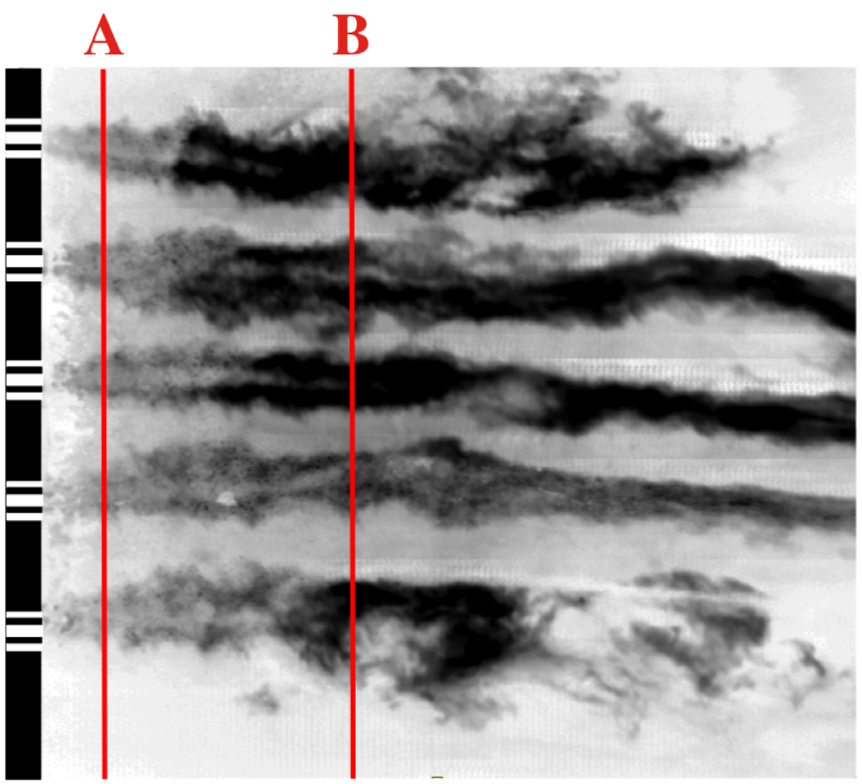
Spatial DMD

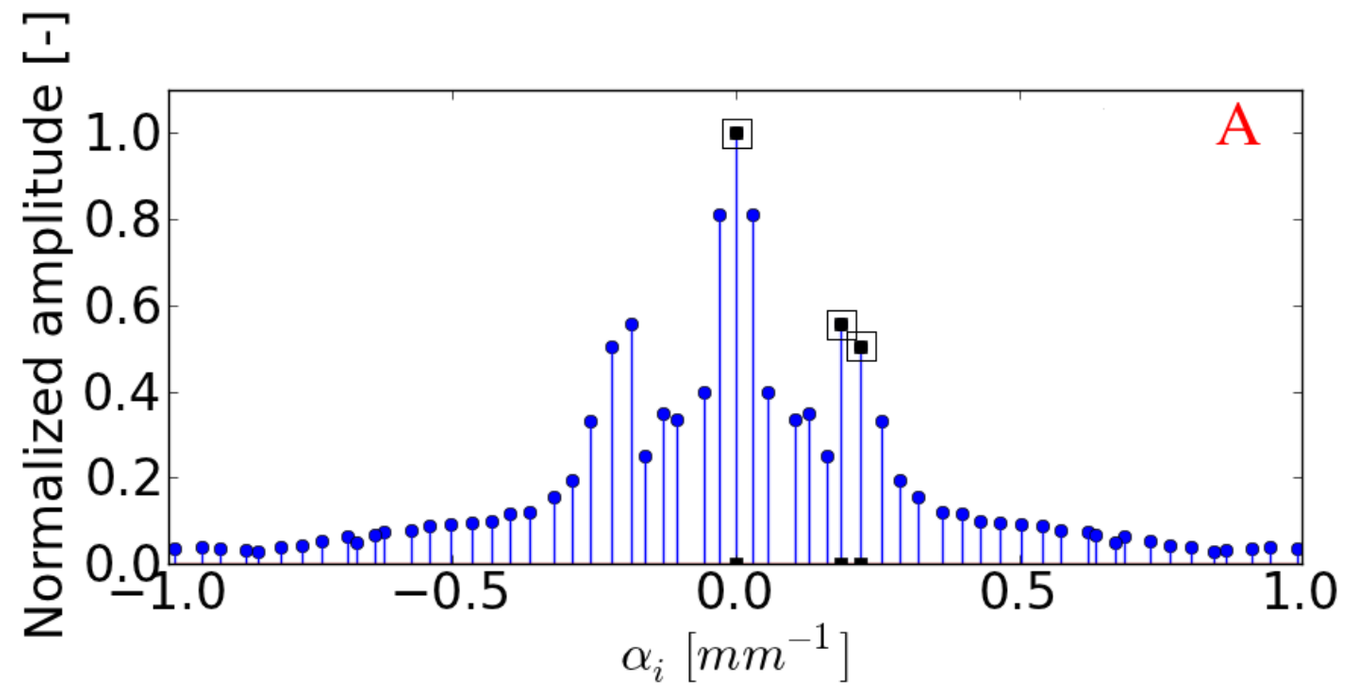
The time evolution of one mode is rebuilt together with the average convective field.

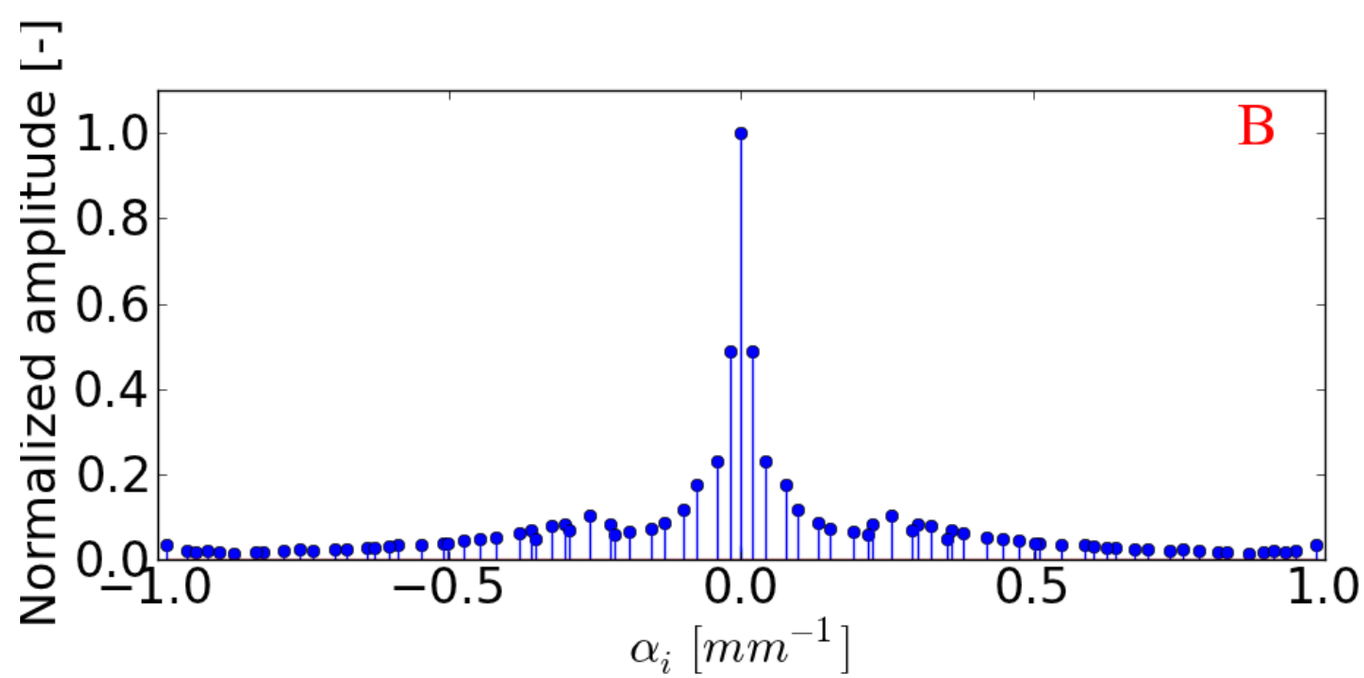


Spatial DMD

Spatial DMD is performed on two subdomains of the chamber.

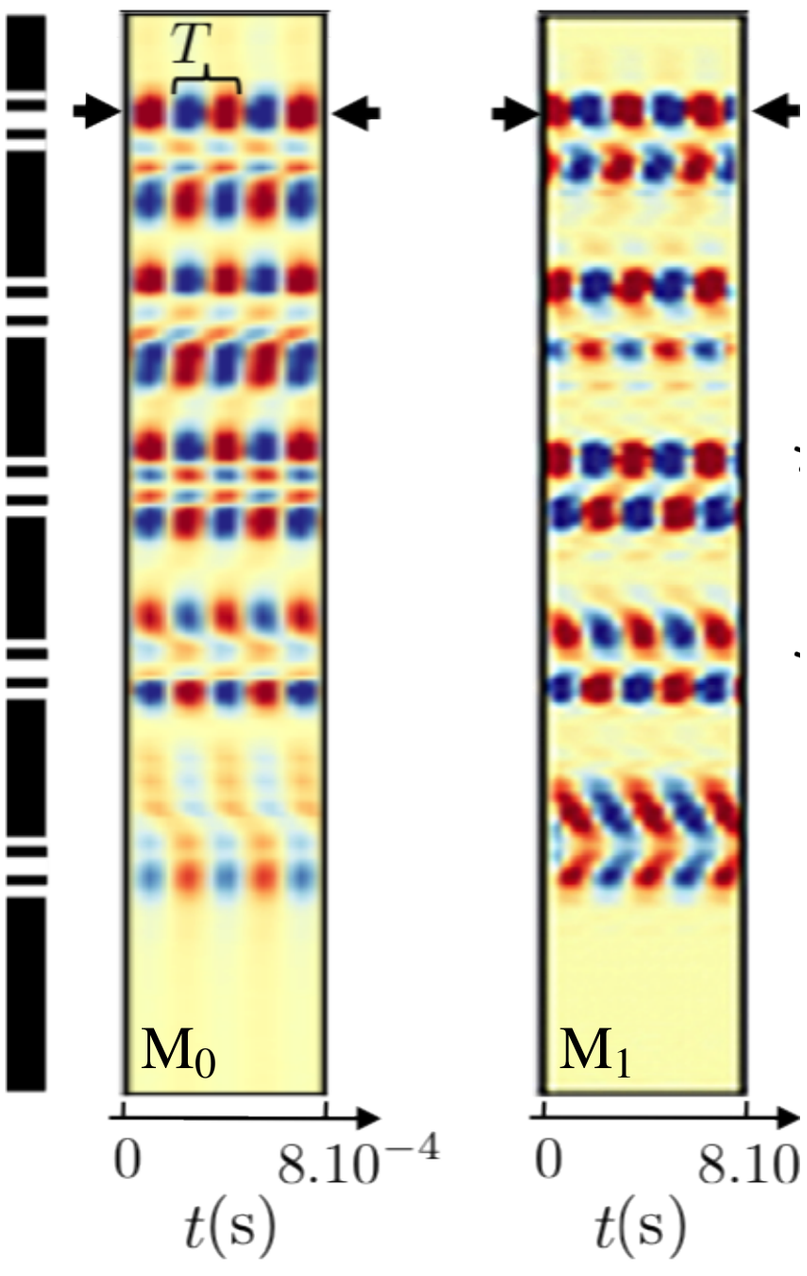


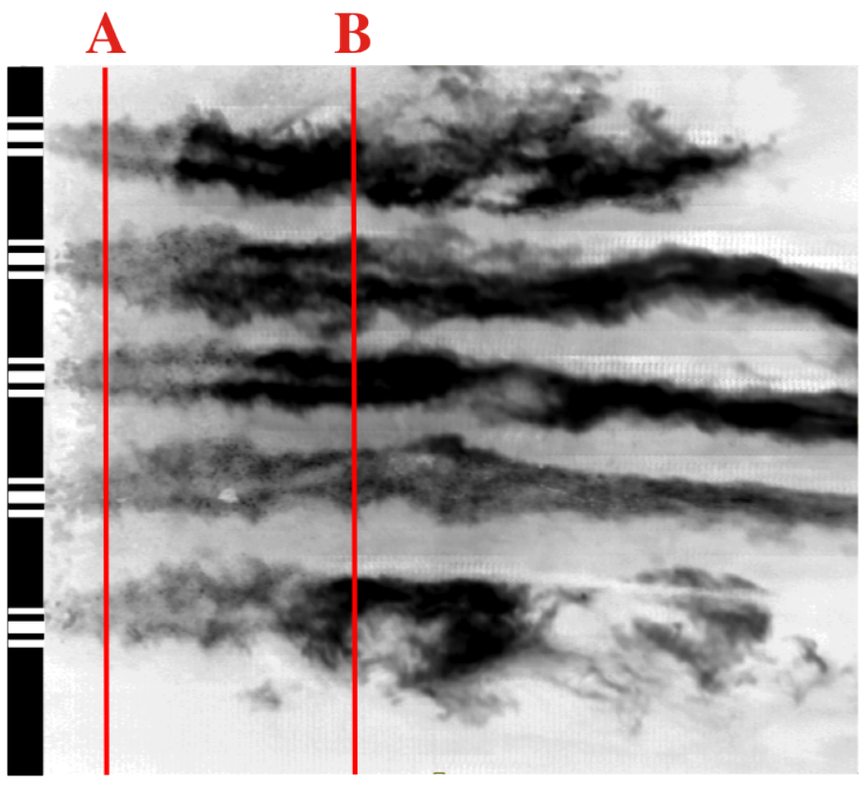


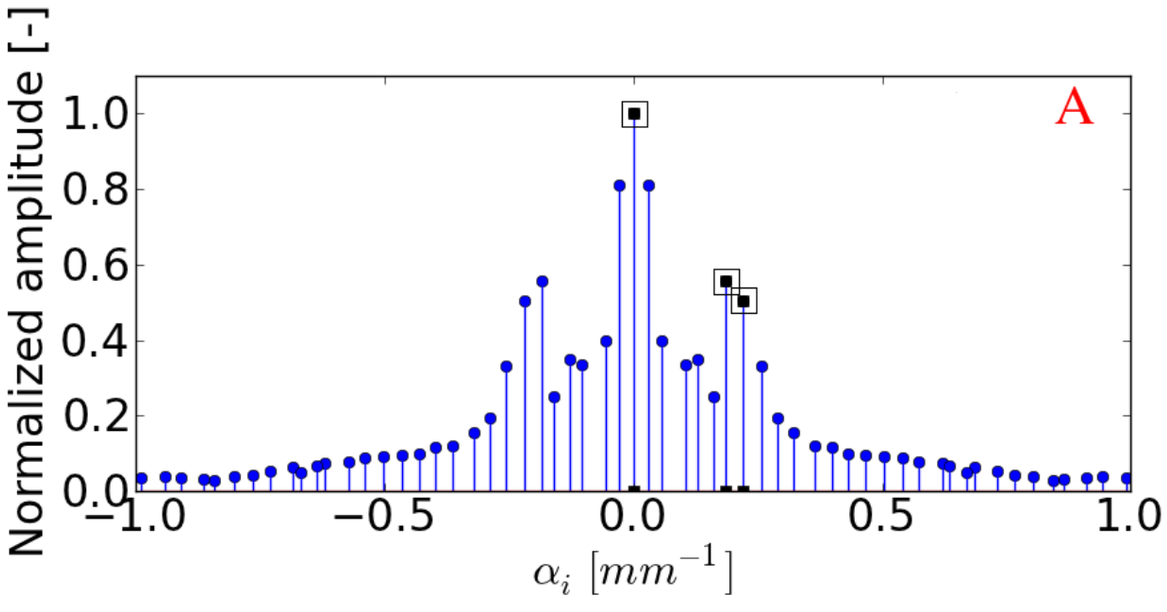


Spatial DMD

Close to the injector (A),
two modes (M0 and M1) evolve at the same frequency but different wavelength.

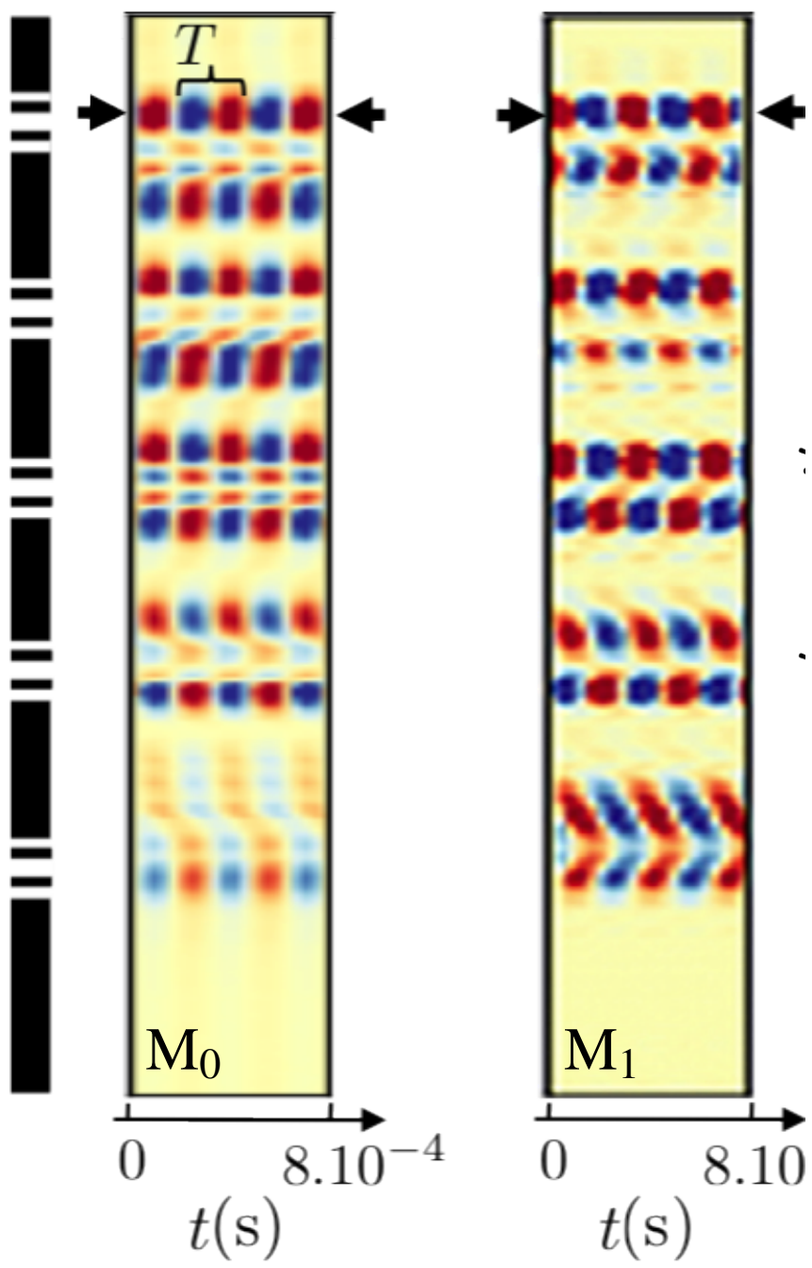






Spatial DMD

One mode is associated to a transverse motion due to the modulation, the other to a longitudinal modulation generated by the injection lines.

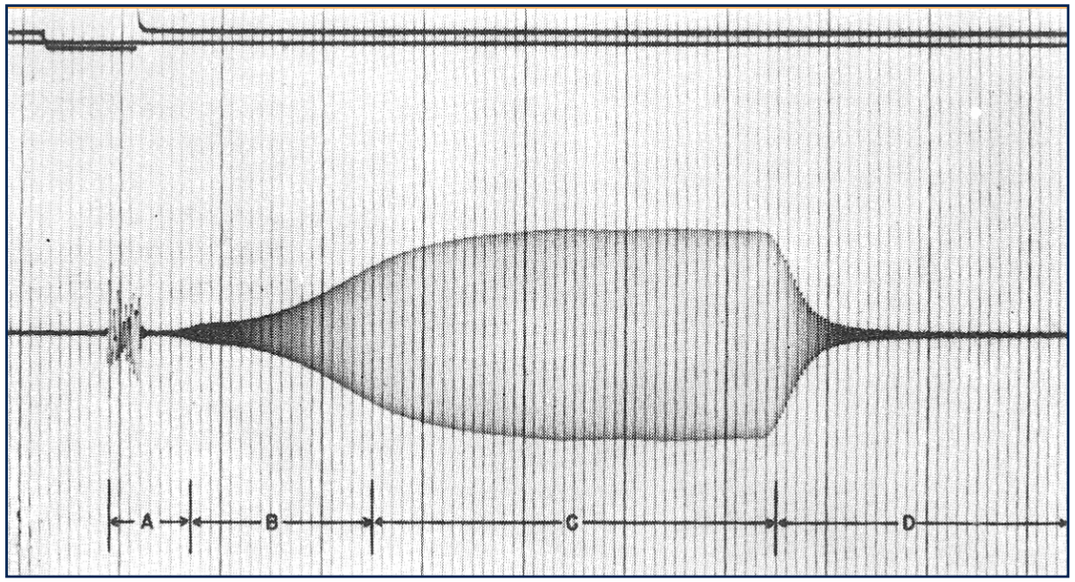


Spatial DMD separated to physical phenomena taking place at the same frequency but with different wavelength.

Conclusion

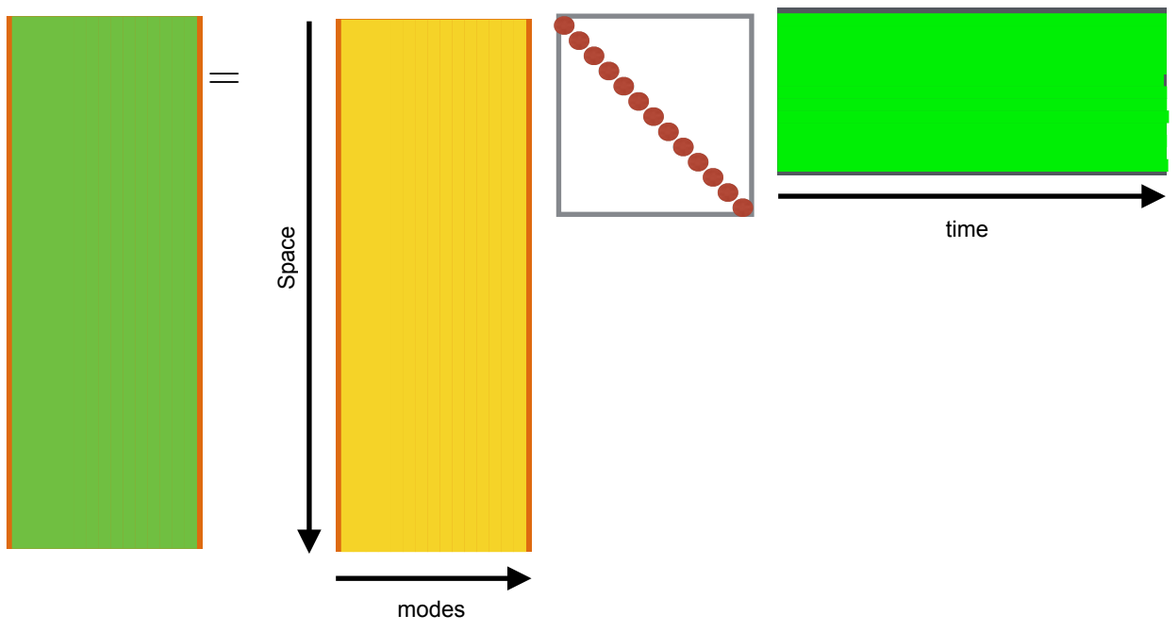
One of the challenge in combustion is to predict the pressure evolution in the chamber.

To reduce low order models, we need to understand the couplings taking place at different time and space scales.



$$p'(t,x) = a_1(t)\Psi_1(x) + ... + a_4(t)\Psi_4(x)$$

$$\frac{da_i(t)}{dt} = \mathcal{F}(a_i)$$



Decomposition methods allow to separate time scales and space scales then simplify the understanding and the modeling.

By adapting the decomposition strategy to the case of study, relevant information can be extracted.