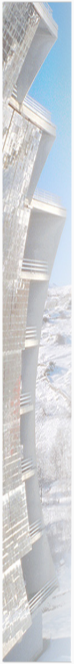

Fast and accurate field reconstruction of Thermal-Large Eddy Simulation (T-LES) by Deep Learning

Société Française de Thermique

PROMES, LISN

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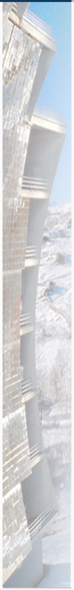
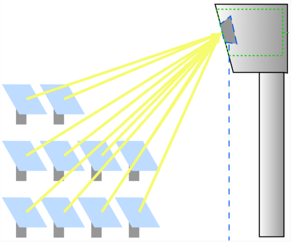
Outline



Context: Issues

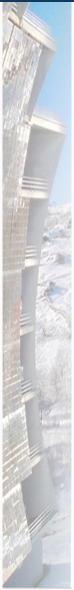


Thémis, Targasonne

Solar receiver

- Only **one side** of the solar receiver is heated
- Implies **high temperature gradient**

Context: Issues



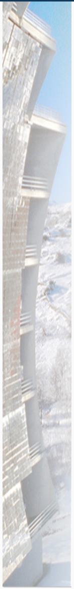
Flows in the receiver

- The flows in the new generation solar receivers are **turbulent** and **anisothermal**
- Thermal exchanges at the **boundary** define the **energy efficiency**

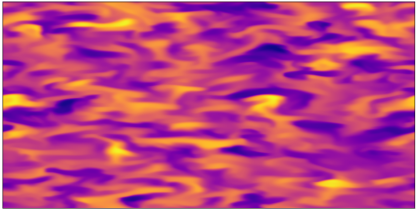
Scientific bottleneck

- Understand the coupling between **velocity** and **temperature** in highly anisothermal flows

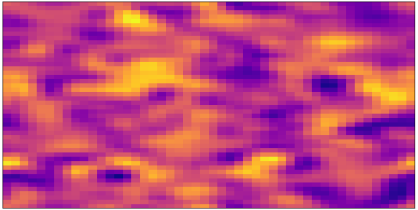
Context: Simulations



DNS

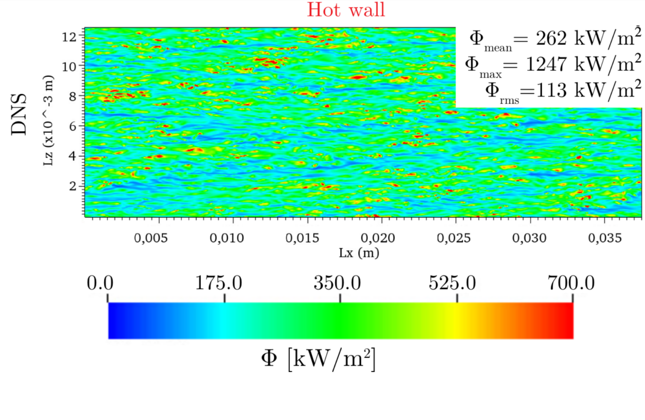


T-LES



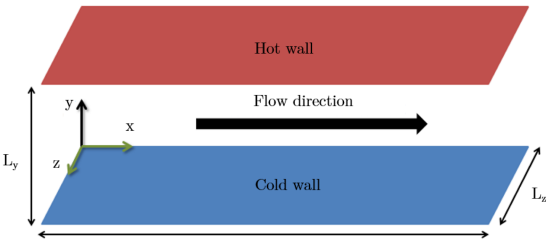
- Modeling of strongly anisothermal turbulence using Thermal Large Eddy Simulation (T-LES)
- T-LES only simulates the large scales, and models the small scales

Hot wall heat flux



- Development of deconvolution techniques to accurately reconstruct fields
  - ⇒ Estimation of RMS temperature for performance of T-LES models against DNS
  - ⇒ Estimation of RMS heat flux for estimation of thermomechanical constraints

Anisothermal bi-periodic plane channel

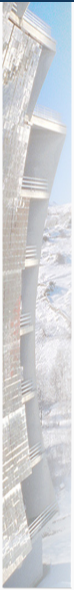


$T_1 = 2T_0$

$T_0 = 293K$

- Hot wall: **concentrated sunlight**, cold wall: **insulated**
- Fluid: **air**
- Regular mesh in the x and z directions
- Hyperbolic tangent mesh in the direction normal to the walls y
- Half height of the channel $h = 15mm$

Outline



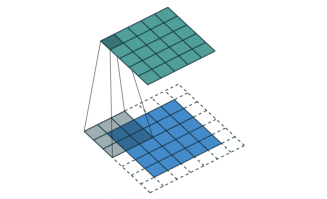
Principles of machine learning

General principles

- Training algorithms to recognize patterns in data and make predictions or decisions based on that data.
- Takes the form of a non-linear optimization problem over labeled data (*i.e.* for each input, there's an expected output)
- Stacking layers with non linearities in between them
- Many applications: Image generation, fraud detection, text translation, artistic tools, etc... .

Convolutional Neural Networks (CNNs)

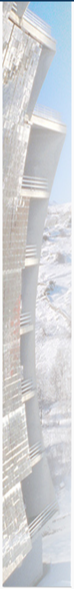
- Type of architecture with a learnable (optimizable) convolutional kernel
- Kernel can be any dimention, we can learn



- Input image
- Convolutional kernel
- Output image

Convolutional neural network layer

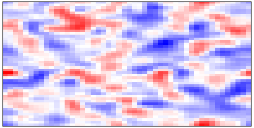
Outline



Super-resolution

- The LES filter is **unknown**
- Learning of an inversion operator for filtering on the temperature field:

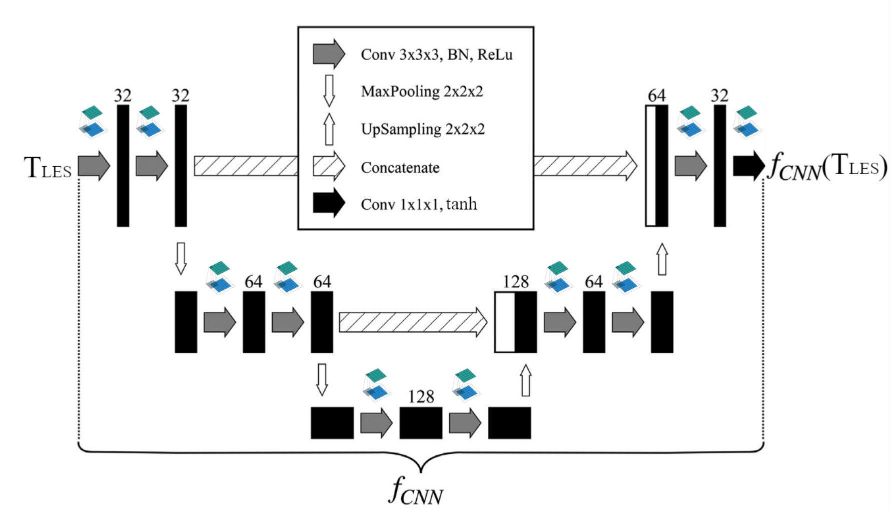
$$T_{\text{DNS}} \approx G^{-1} * T_{\text{LES}}$$



- The neural network learns the correction on the LES field

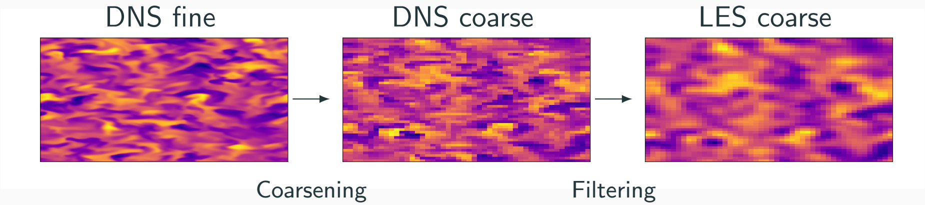
$$T_{\text{pred}} = T_{\text{LES}} + f_{\text{CNN}}(T_{\text{LES}}) \approx T_{\text{DNS}}$$

Proposed architecture in Lapeyre et al. [2019]



Reconstruction of DNS fields from LES fields

Data acquisition step through an image



- Anisothermal **DNS**, mean friction Reynolds number $Re_\tau = 180$, and Prandtl $Pr = 0.76$ after statistical convergence
- 17 DNS snapshots spaced by $\Delta_t^+ = 7.76 \times 10^{-3}$
- Interpolate from a fine mesh of (384, 384, 266) points to (48, 48, 52) points
- Filter using a weighted top-hat filter
- **Filtered DNS** snapshots then serve us as **input** to our network.

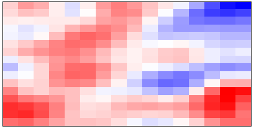
Benchmark

- We compare the performance of our motel to an already existing method developped by Van Cittert The inverse of a convolution filter G assumed invertible, writes

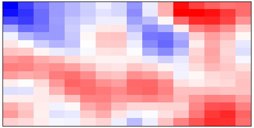
$$
\begin{aligned}
G^{-1} &= (\mathcal{I} - (\mathcal{I} - G))^{-1}, && (1)\\
&= \lim_{p \to \infty} \sum_{i=0}^{p} (\mathcal{I} - G)^{i}. && (2)
\end{aligned}
$$

We take a $p = 6$ approximation to this converging Neumann series (Stolz and Adams [1999] recommend $p = 5$).

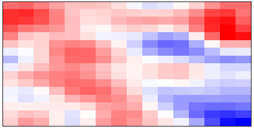
Data management



Original



90° rotation

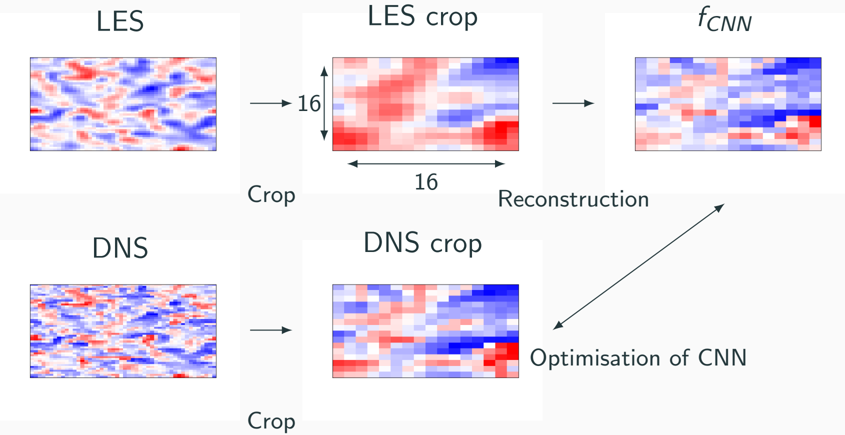


x axis flip

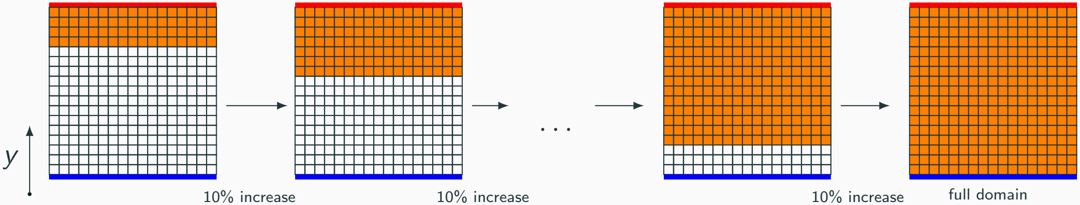
- 17 snapshots are **split** into 13 for **training**, 4 for **validation** and 1 for **test**
- We learn over patches, and increase procedurally the sampling space
- At each fixed height, with patches of size 16, we have the following number of examples

$$\frac{n_x}{16} \times \frac{n_z}{16} \times flip_x \times flip_z \times rotation_{xz} \times n_{train} = 936$$

An illustration of the learning procedure

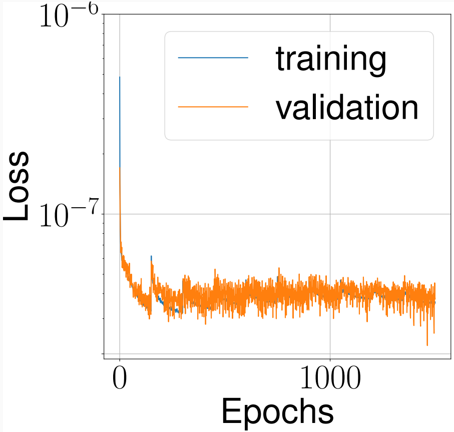


Reconstruction of DNS fields from LES fields



- Previous technique domain increase procedure
- Enables learning harder distributions of flow
- $Re_{\tau\ hot} = 105$, $Re_{\tau\ cold} = 260$

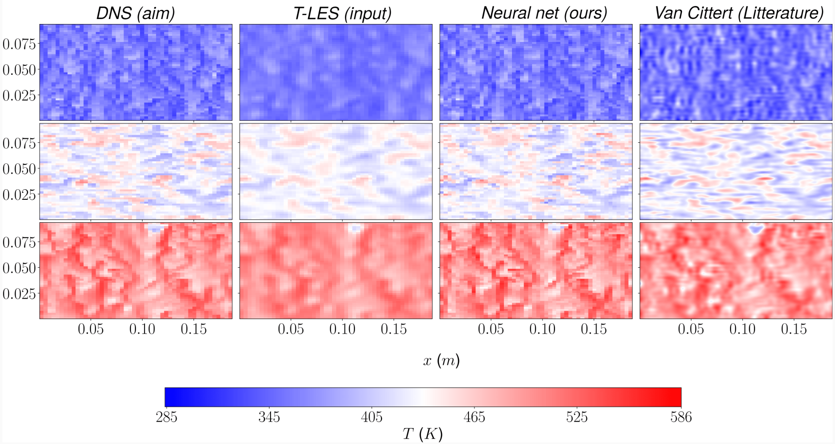
Results: Train loss



- Neural network manages to quickly **learn** and **generalize**
- Jumps are due to **increase** of the learning domain

Reconstruction of DNS fields from LES fields

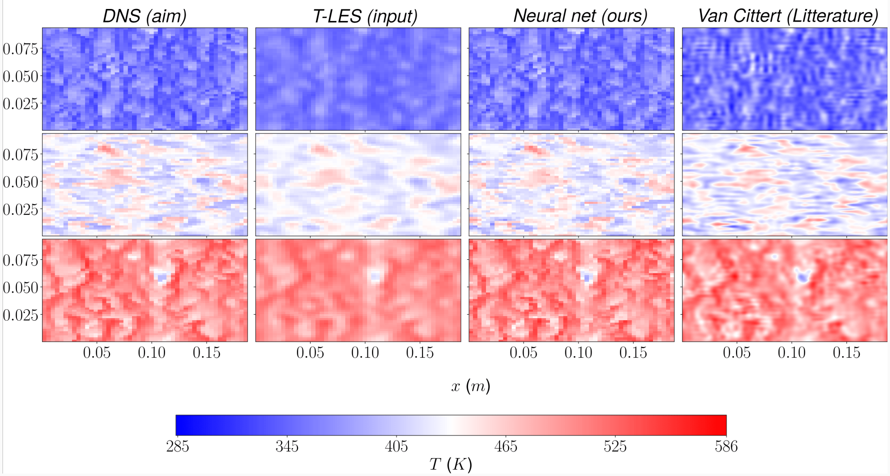
Results: Validation slices, T_{valid_0}



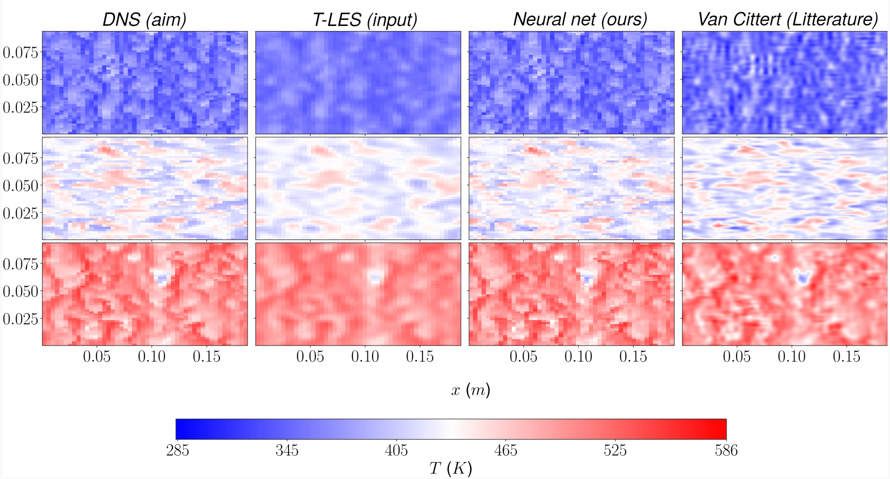
Spacial gradients in our method are **slightly high**

Reconstruction of DNS fields from LES fields

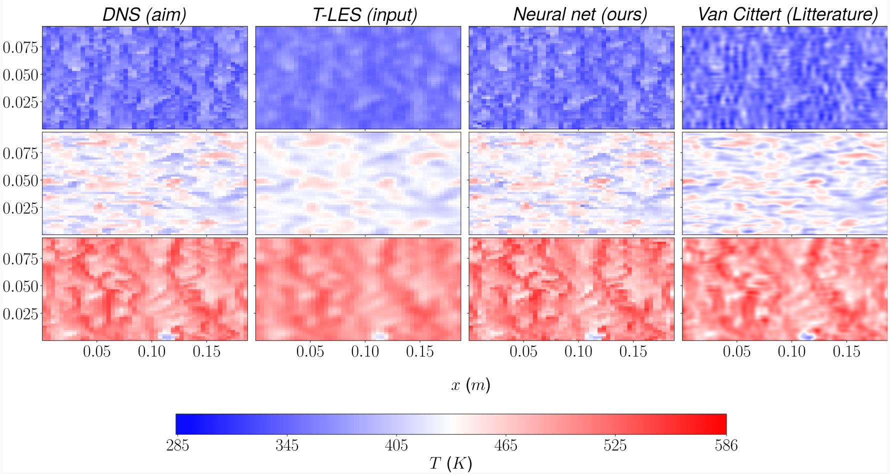
Results: Validation slices, T_{valid_1}



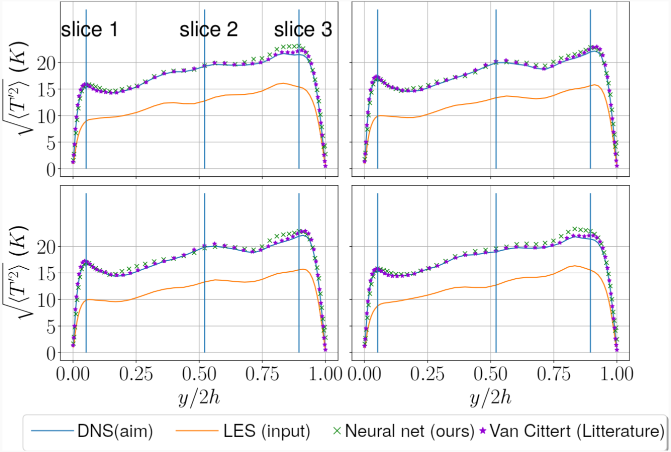
Results: Validation slices, T_{valid_2}



Results: Validation slices, T_{valid_3}



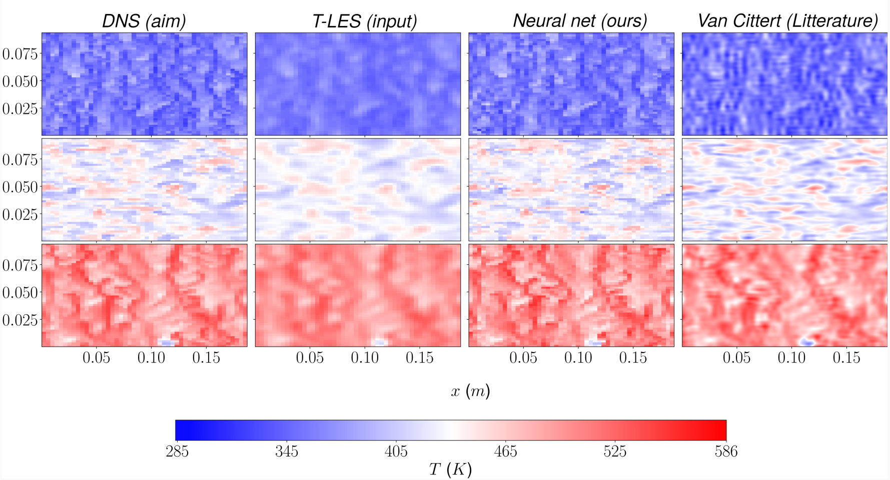
Results: Validation RMS: $\sqrt{\langle T'^2 \rangle} = \langle T^2 \rangle - \langle T \rangle^2$



- Slight overshoot of the RMS on the hot side

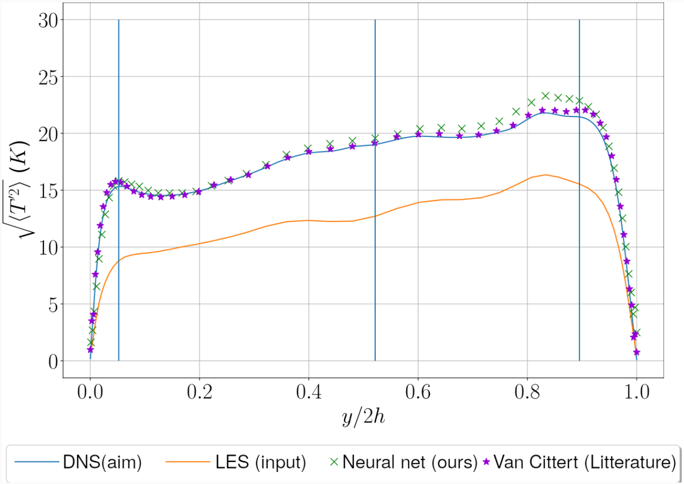
Reconstruction of DNS fields from LES fields

Results: Test slices, T_{test}



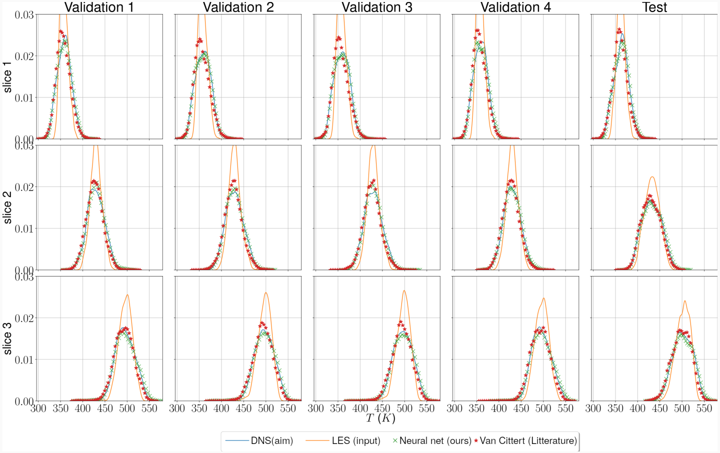
Reconstruction of DNS fields from LES fields

Results: Test RMS



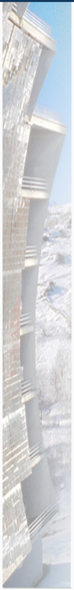
Reconstruction of DNS fields from LES fields

Results: PDF(T) for the 3 above cuts



- Good prediction of the temperature probability distribution

Outline



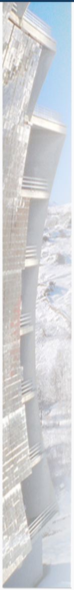
Reconstruction of DNS fields from LES fields

In conclusion

- Our method learns and **generalizes** the small scales reconstruction even for snapshots taken farther in time for RMS, densities and slices
- **Overshot** spacial gradients **can be mitigated** through an additional filtering layer
- Good tool for the study of flows inside **high temperature solar receivers**

Future work

- Learning over **different meshes**
- Learning over **distribution** of data
- **Generalizing** over different Reynolds number flows



Thank you for your attention

Acknowledgement

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- Work done thanks to the **TRUST/TrioCFD software** developped by the **CEA**

C. J. Lapeyre, A. Misdariis, N. Cazard, D. Veynante, and T. Poinsot. Training convolutional neural networks to estimate turbulent sub-grid scale reaction rates. *Combustion and Flame*, 203:255–264, May 2019. doi: 10.1016/j.combustflame.2019.02.019. URL https://hal.archives-ouvertes.fr/hal-02072920.

S. Stolz and N. Adams. An approximate deconvolution procedure for large-eddy simulation. *Phys. Fluids*, 11(7):1699–1701, 1999.