Scattering Transform "Hunting invariants"

A naïve description of the Mallat's team work: https://www.di.ens.fr/data/scattering/

How to statistically characterize 2D structures?

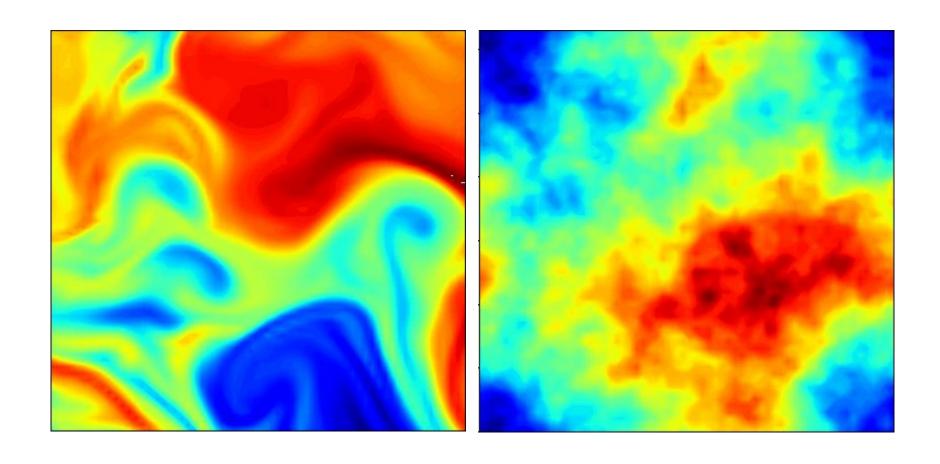
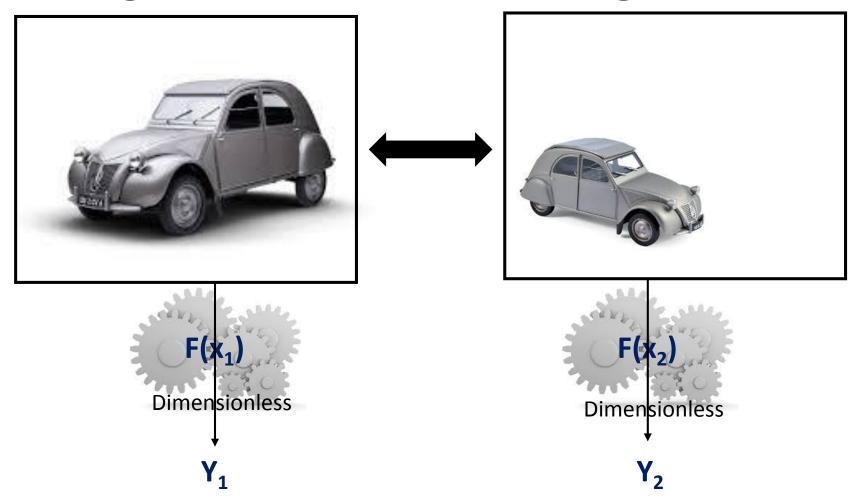
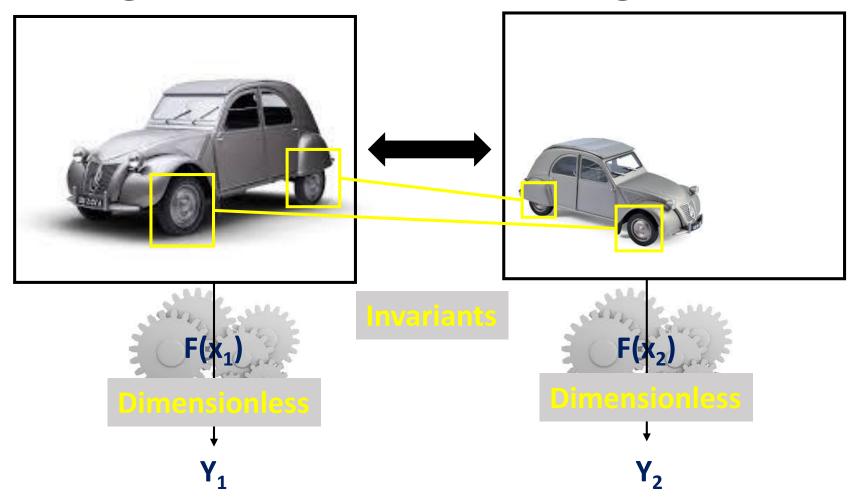


Image classification/recognition



How to a set of invariant rules if x_1 is the same than $x_2 : Y_1 \approx Y_2$

Image classification/recognition



How to a set of invariant rules if x_1 is the same than $x_2 : Y_1 \approx Y_2$

Define Invariants

- Rotation
- Position
- Size
- Deformation
- Colours
- Etc.

Use power spectrum?

- Power spectrum is position invariant thanks to the phase killing, but:
 - No more localisation.
- Wavelet provides frequency/position information but are not at all invariants (e.g. position).

⇒A mathematical transform is needed to make this usable.

Neural Network approach

 Teach the Neural Network with a large training data set to provide the same answer for any elements of the same classe.

⇒Learn "blindly" invariants

- Internal processing is almost unknown.
- ⇒Not usable for the scientific post analysis.

What is scattering transform?

The first three layers of the 2D scattering of an image x are defined by

$$S_0x = \{x \star \phi\}$$

$$S_1x = \{|x \star \psi_{j1,\theta1}| \star \phi\}$$

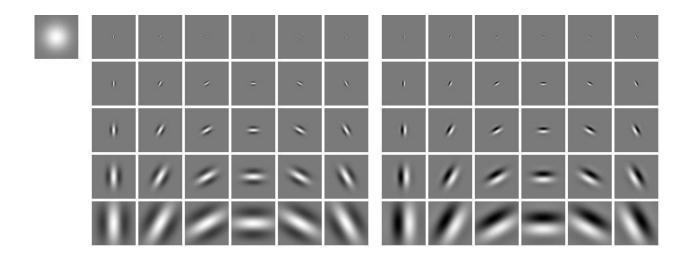
$$S_2x = \{||x \star \psi_{j1,\theta1}| \star \psi_{j2,\theta2}| \star \phi\}$$

where the symbol \star denotes the spatial convolution, ϕ is an averaging window and $\psi_{j,\theta}$ is a wavelet dilated by 2^j and rotated by $\pi(\theta-1)/L.$

The output variable S is a cell array, whose elements are the different layers of the scattering transform : $S\{m+1\}$ corresponds to the m^{th} layer $S_m x$.

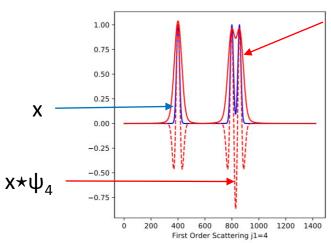
[1] Deep Scattering Spectrum, Andén J. and Mallat. S., Submitted to IEEE Transactions on Signal Processing, 2011.

What is scattering transform?



The top left image corresponds to ϕ . The first left half corresponds to the real parts of $\psi_{j,\theta}$, arranged according scales (rows) and orientations (columns). The right half image corresponds to the imaginary part.

Some plot to understand

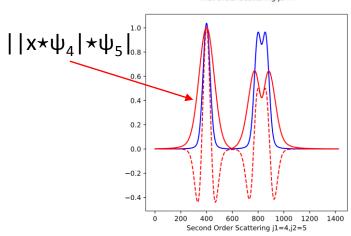


$$|x*\psi_4|$$

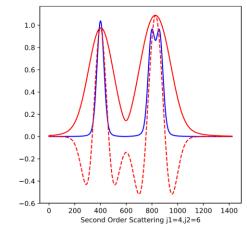
$$S_{1(4)} = \sum_{pixels} |\mathsf{x} \star \psi_4|$$

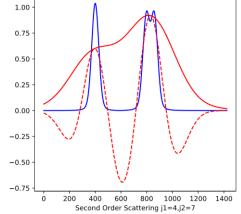
$$S1x=\{|x*\psi_{j1}|\} \\ S_2x=\{||x*\psi_{j1}|*\psi_{j2}|\}$$

⇒Sum makes the position invariants



$$S_{2(4,5)} = \sum_{pixels} ||x * \psi_4| * \psi_5| \qquad S_{2(4,5)} = \sum_{pixels} ||x * \psi_4| * \psi_6| \qquad S_{2(4,5)} = \sum_{pixels} ||x * \psi_4| * \psi_7|$$



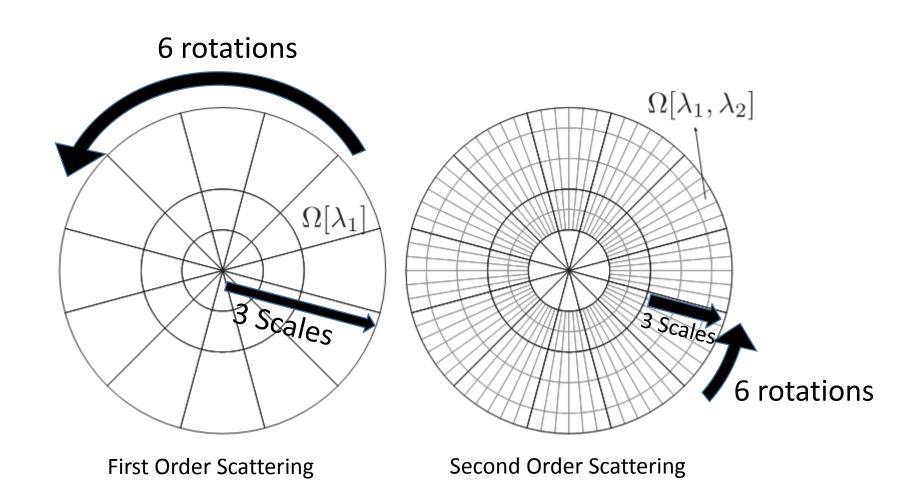


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$$S_{2(4,5)} = \sum_{pixels} ||\mathbf{x} \star \psi_4| \star \psi_7|$$

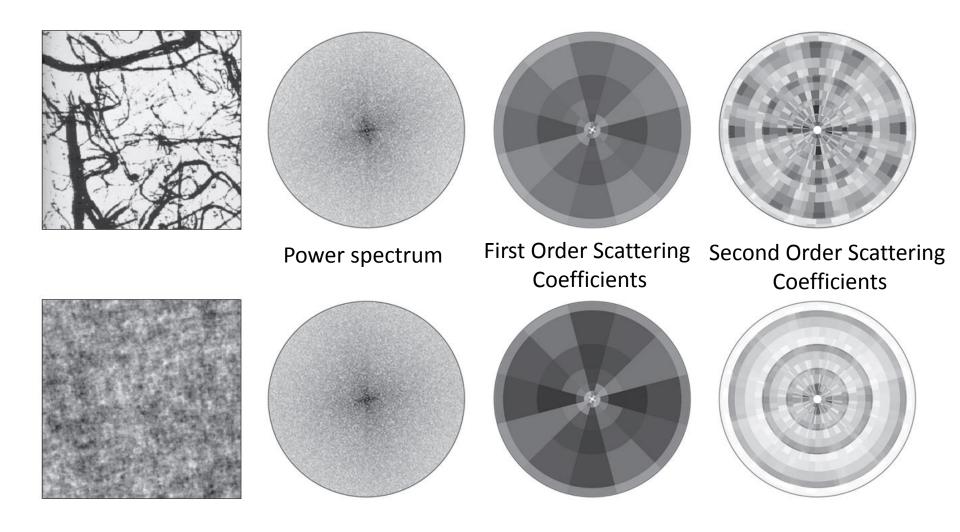
Scattering transform synthetic view

Coefficients

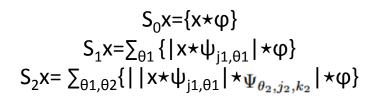


Coefficients

A 2D example



How to manage rotation invariant



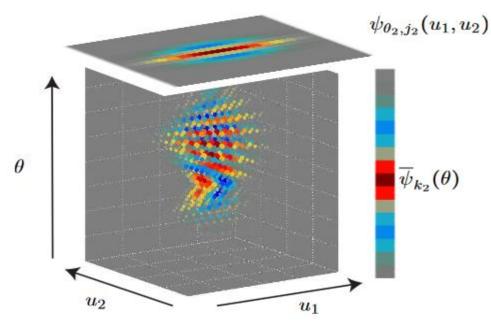
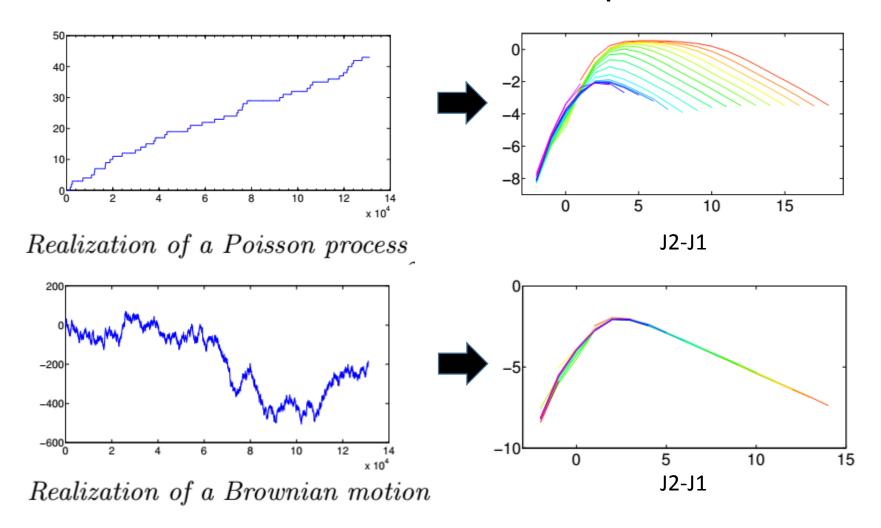


Figure 5: A three dimensional roto-translation convolution with a wavelet $\Psi_{\theta_2,j_2,k_2}(u_1,u_2,\theta)$ can be factorized into a two dimensional convolution with $\psi_{\theta_2,j_2}(u_1,u_2)$ rotated by θ and a one dimensional convolution with $\overline{\psi}_{k_2}(\theta)$.

[1] Rotation, Scaling and Deformation Invariant Scattering for Texture Discrimination, Sifre L. and Mallat S., Proceedings in IEEE CVPR 2013 conference, 2013.

Some theoretical description



And now the T.P.:

Test 1D computation:

testscat_1D.py

Test 2D computation:

testscat_2D.py

More see:

https://www.di.ens.fr/data/scattering/

Short Biblio:

• 1D stats:

Intermittent process analysis with scattering moments; Bruna, J. and Mallat, S. and Bacry, E. and Muzy, J.-F., 2015, arXiv:1311.4104

Scattering Transform reader digest:

Invariant Scattering Convolution Networks; Bruna, J. and Mallat, S., 2013, arXiv:1203.1513v2