Artificial evolution and applications

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PART 1: Artificial Evolution

PART 2: Applications

- Evolutionary computation for EEG classification
- Regularity estimation with Genetic Programming

PART 1: Artificial Evolution

Darwinism

Artificial Darwinism

- A set of techniques grouped under a generic term
- Ingredients
- Evolutionary loop
- Example

Genetic Algorithms

- Discrete representation: Genetic Algorithms

Evolution strategies

- Continuous representation: Evolution Strategies

Genetic Programming

- Functional representation: Genetic programming
- Example: Using GP for regression

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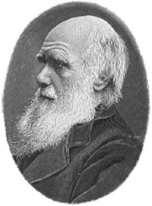
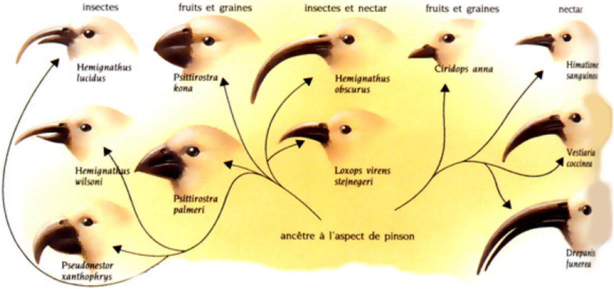
Darwinism, evolutionism

Charles Robert Darwin (1809-1882).
1831 - 5 years on the HMS Beagle to Galapagos Islands.
November 1859, book "On the origin of species".



The Darwin Finch

"We can say, by metaphor, that natural selection seeks, at every moment and worldwide, the slightest variations; it repels those that are harmful, it preserves and accumulates those that are useful; she works in silence, imperceptibly, everywhere and always, as soon as the opportunity arises, to improve all organized beings relative to their organic and inorganic living conditions" (Darwin, 1859).



Simple mecanisms

1. Variations, macroscopic and microscopic, within species.
2. Fight for survival.
3. Natural selection: triumph of the lineage that has a useful variation in its environment.

Artificial Darwinism

Stochastic optimization which uses mechanisms inspired by the biological evolution, such as:

- reproduction,
- mutation,
- selection and
- survival of the strongest individuals

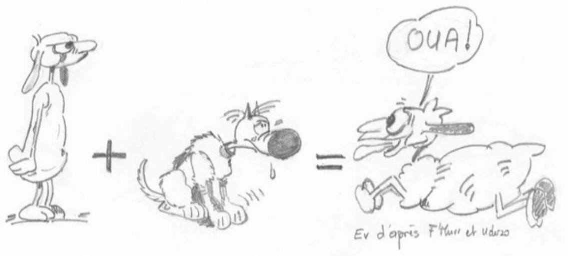
A set of techniques grouped under a generic term

Evolutionary Algorithms	Genetic Algorithms (GA)
	Evolution Strategies (ES)
	Genetic Programming (GP)
	...

Ingredients

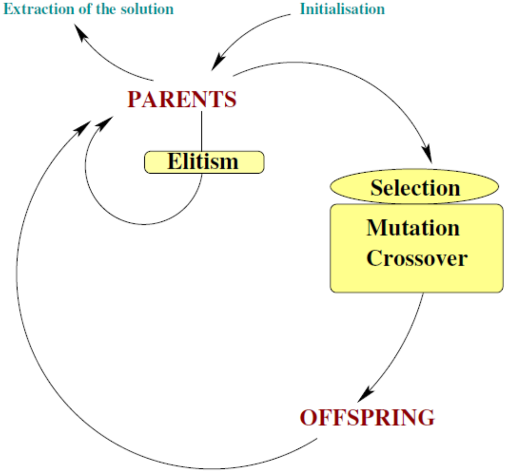
Selection

Population



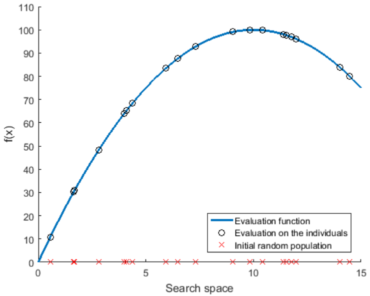
Genetic Operators

Evolutionary loop

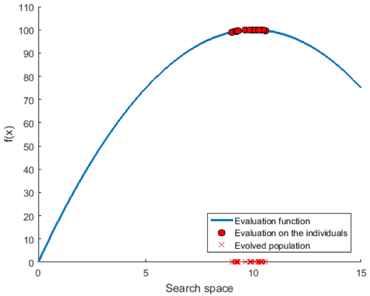


Example

Potential Solutions = Individuals in a population



Initial random population

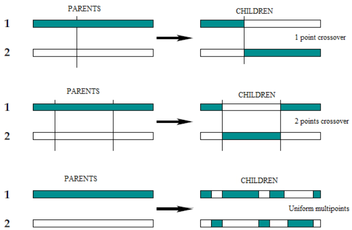


Evolved population

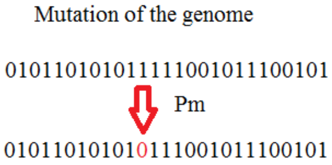
Discrete representation: Genetic Algorithms

Each individual is represented by a binary string.

John H. Holland (1960, 1975), David Goldberg (1989)



Crossover



Mutation

Each individual is a vector in R^n.

Hans-Paul Schwefel (1970)

Barycentric crossover

$\forall i \in \{1, .., n\}, x_i^{children} = \alpha x_i^{father} + (1-\alpha) x_i^{mother}$

α random value in $[-\epsilon, 1+\epsilon]$.

Gaussian mutation

$\forall i \in \{1, .., n\}, x_i^{children} = x_i^{children} + N(0, \sigma)$

Two parameters P_m and σ.

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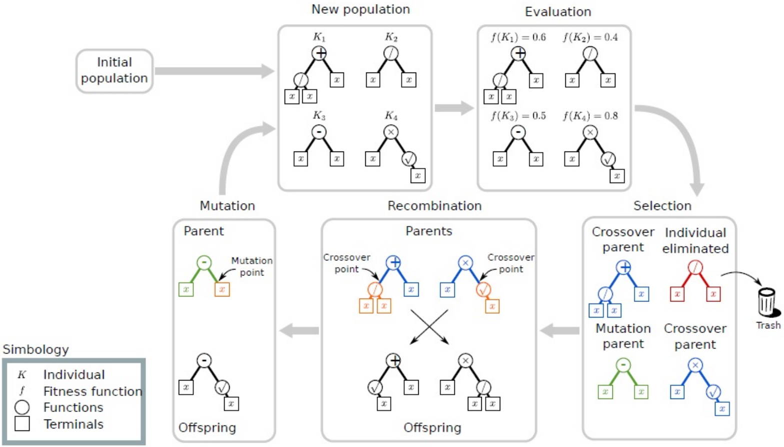
Demo

Definition

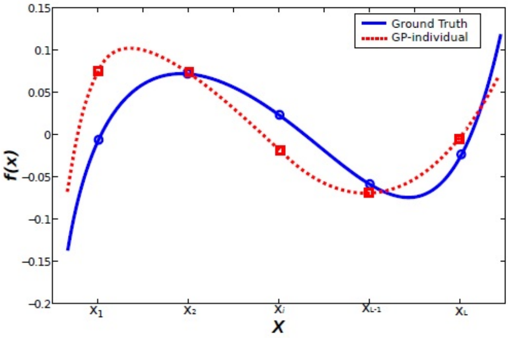
Genetic programming (GP) is an evolutionary computation (EC) technique that automatically solves problems without requiring the user to know or specify the form or structure of the solution in advance [Koza, 1992].



Symbolic Regression

Given a set of input data X and a set of desired outputs Y, find a function f such that:
$f(X_i) = Y_i \quad \forall i \in \{1, N\}$

	X	Y
1	0.2	0.00
2	0.4	0.06
..	...	...
N	0.9	-0.03



PART 2: Applications

Evolutionary computation for EEG classification

This work is related to the PhD thesis of Laurent Vezard and developed in the context of the PSI Region Project and the ACOBSEC European project. A slightly different version has been published in a book chapter. Eduardo Miranda; Julien Castet; Benjamin Knapp. Guide to Brain-Computer Music Interfacing, Springer, 2014. Work carried out with Laurent Vézard, Marie Chavent, Frédérique Faïta-Aïnseba.

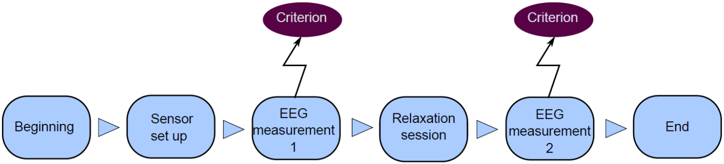
Goal

- **Characterize the state of alertness of a person from his electroencephalogram (EEG).**

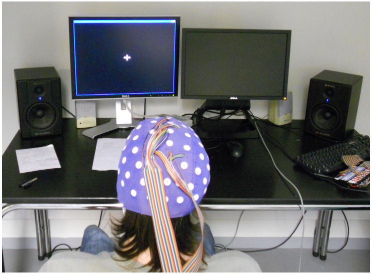
- EEG data Acquisition
  - Acquisition Protocole
- Feature Extraction
  - Slope Criterion
- Evolutionary Algorithm
  - Design
  - Results

Acquisition Protocole

- First EEG recording: subject in a normal state of alertness: "normal"
- Second EEG recording: subject in a state of low vigilance: "relax"



Acquisition Protocole



- EEG headset installation time: 45 minuts.
- Subject with open eyes.
- Sampling frequency: 256Hz.
- Recording time: 3 minuts (46000 sample points).

Acquisition Protocole

Campaigns:

- 58 electrodes renumbered from 1 to 58
- Subjects under 35, right-handed and non-smoker
- 58 subjects $\Rightarrow$ 16 preserved

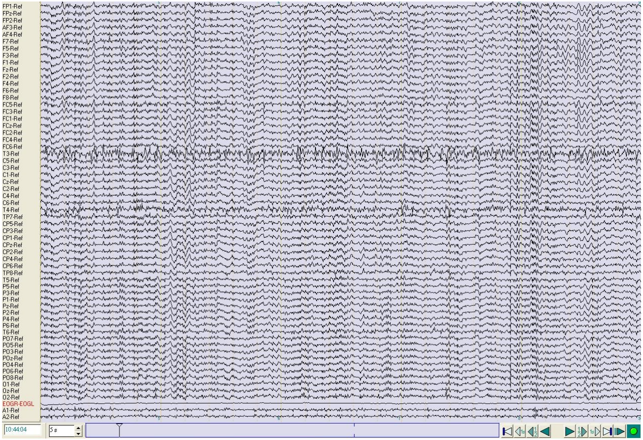
Relaxation session

20 minutes with a recorded voice offering 3 exercises:

- Autogenic training [Schultz1958]: repetition of sentences, self-hypnosis.
- Progressive muscle relaxation [Jacobson1974].
- Mental visualization (familiar places, smells, noises).

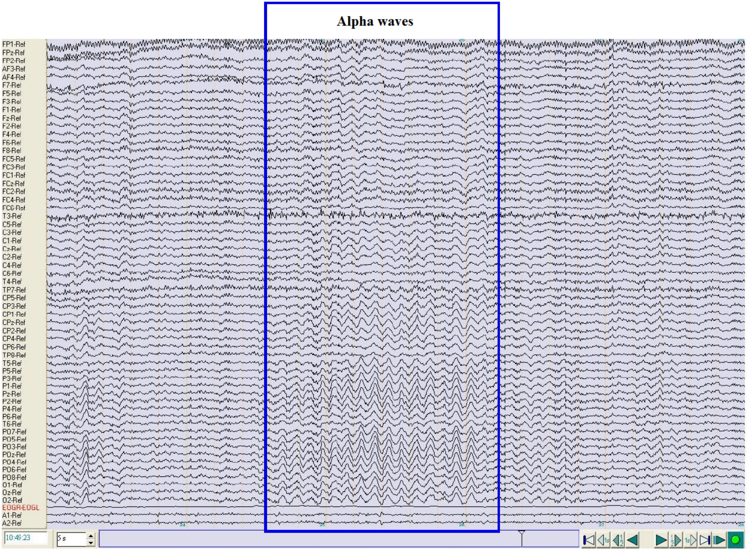
Acquisition Protocole

3 minutes of EEG recording before relaxation.

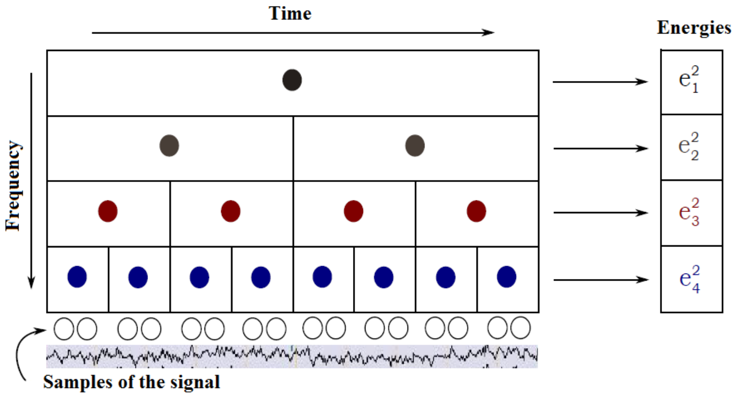


Acquisition Protocole

3 minutes of EEG recording after relaxation.

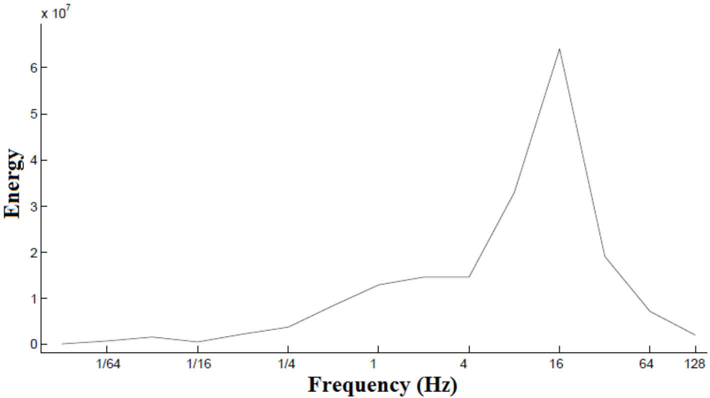


The dyadic grid gives a spatio-frequential representation of the discrete dyadic wavelet decomposition



Slope Criterion

- Alpha: $8 - 12Hz$.
- Waves characteristics of a relaxed state.



Linear regression between 4 and $16Hz$.

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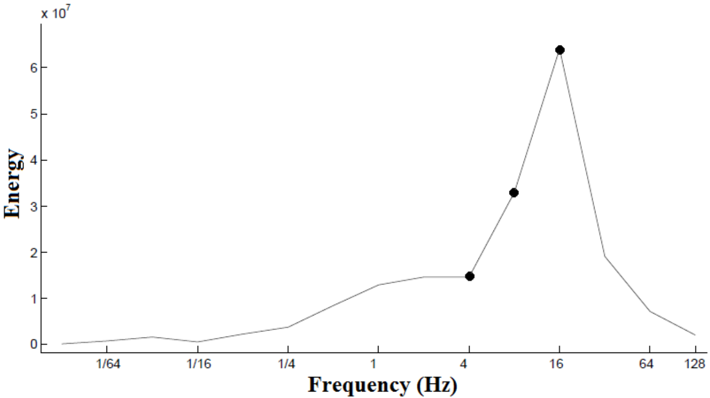

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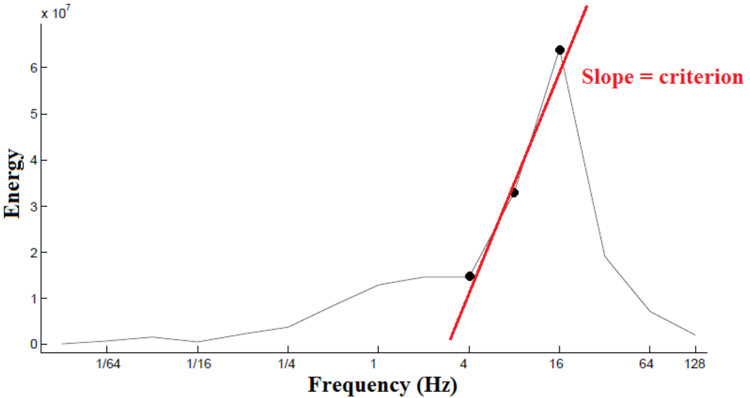

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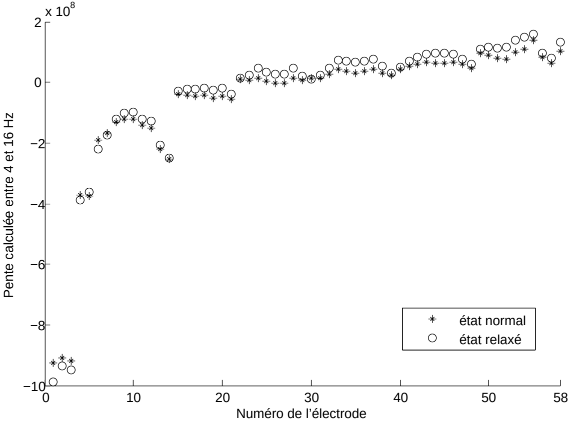
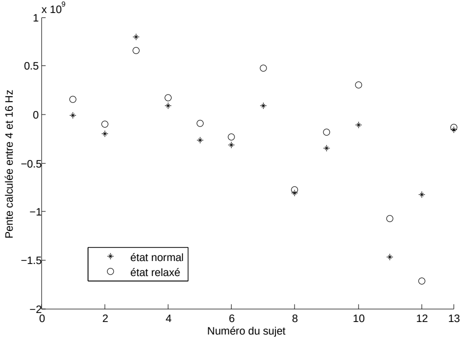


Slope criterion, sum on subjects for each electrode

Slope Criterion



Slope criterion, sum on electrodes for each subjects

⇒ Very strong inter-subject variability

⇒ This criterion that does not allow to build a powerful classifier for different subjects.

Classification: Usual methods

	K nearest neighbors	Binary decision trees	Random forests	Discriminant PLS	Sparse Discriminant PLS
Mean	37.28	33.98	32.03	40.63	36.25
Standard Deviation	10.47	5.15	6.46	8.55	7.96

Mean and standard deviations of Correct Classification Rates for different classification methods applied on slope criterion.

This approach is not efficient

Our contribution: Design a relevant **evolutionary algorithm** to solve this task of classification.

$\Rightarrow$ **Find the relevant electrodes.**

$\Rightarrow$ **Find the relevant frequencies for the calculation of the slope criterion.**

EEG data Acquisition

- Acquisition Protocole

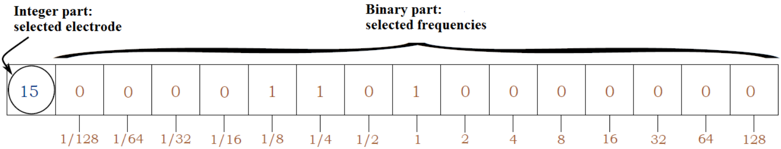
Feature Extraction

- Slope Criterion

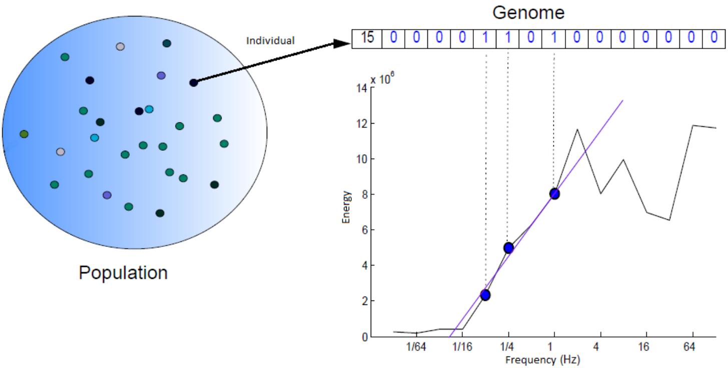
Evolutionary Algorithm

- Design
- Results

Example of a genome in the evolutionary algorithm



Relationship between the genome and the calculation of the slope criterion



Average correct classification rate

Evaluation Method	CCR	
	Mean	Standard deviation
CART	86.68	1.87
SVC	83.49	2.37

Average and standard deviations of the correct classification rates obtained for the 100 runs of the evolutionary algorithm and for two methods of evaluation.

Best genome

Evaluation method	BEST genome		
	Selected electrode	Selected frequency (Hz)	Correct classification rates
CART	F4	$1/8, 1/4, 2, 4$ et 64	$89, 33\%$
SVC	F2	$1/32, 1/16, 2, 4, 8, 64$ et 128	$89, 33\%$

Table summarizing the two best genomes found during the 100 runs of the genetic algorithm with two methods of evaluation.

Regularity estimation with Genetic Programming

Joint work with Leonardo Trujillo, Gustavo Olague and Jacques Levy-Vehel. *Evolving estimators of the pointwise Hölder exponent with Genetic Programming. Information Sciences 209 (Nov. 2012), 61-79*.

Hölderian Regularity

Contribution

- Training set

Results

Hölderian Regularity

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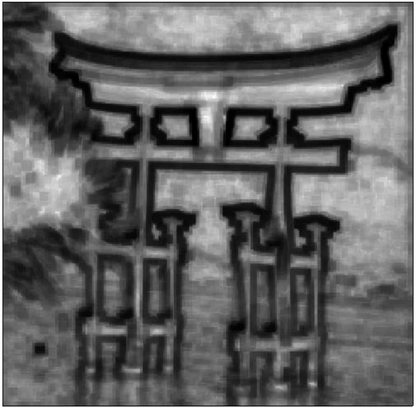
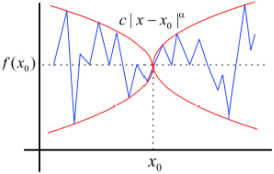
Hölder exponent

Mathematical tool that measures the regularity of a signal around each point.



General motivation

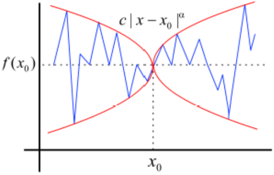


Hölderian envelope of signal f at point x_0

$$\alpha_p(x_0) = \liminf_{h \to 0} \frac{\log |f(x_0+h) - f(x_0)|}{\log |h|}$$

- For real-world signals the Hölder exponent must be **estimated** for each point.

General motivation



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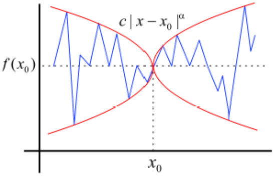

$$\alpha_p(x_0) = \liminf_{h \to 0} \frac{\log |f(x_0 + h) - f(x_0)|}{\log |h|}$$

Hölderian envelope of signal f at point x_0

- For real-world signals the Hölder exponent must be **estimated** for each point.
- Several estimation methods exist, but most methods are **slow** or **highly parameterized**;
- **Therefore there use is not common** (particularly in applications where speed can be of importance)

Hölderian Regularity

Contribution

Training set

Results

Contribution

- Evolve estimators of the pointwise Hölder exponent for 2D signals with Genetic Programming.

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Awards

- Best Paper Award in the track Genetic Programming, GECCO 2010, Portland, Oregon.
- Humies Award Finalist, GECCO 2013, Amsterdam, The Netherland.

Training set

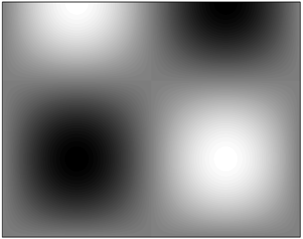
We generate three groups of images with **FracLab**, using three different functions that take as input the point coordinates (x, y) of an image and provide as output the desired regularity; these functions are:

1. a *Polynomial* $p_1(x, y) = 0.1 + 0.8xy$;
2. a *Sine* $p_2(x, y) = 0.5 + 0.2(sin(2\pi x))(cos(\frac{3}{2}\pi y))$;
3. an *Exponential* $p_3(x, y) = 0.3 + \frac{0.3}{1+e^{-100(x-0.7)}}$.

These functions provide the prescribed regularity needed to build the synthetic images used for training and testing of our evolved operators.

Training set

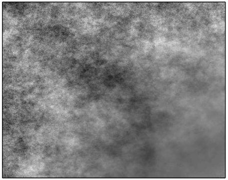
(a) Polynomial p_1



(b) Sine p_2

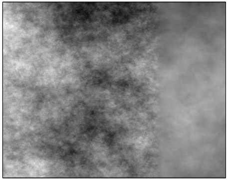
(c) Exponential p_3

Training set

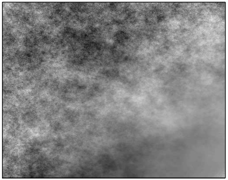


(a) Polynomial

(b) Sine

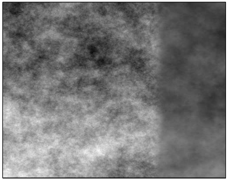


(c) Exponential



(d) Polynomial

(e) Sine



(f) Exponential

These images have a prescribed regularity given by functions p_1 (Polynomial), p_2 (Sine) and p_3 (Exponential).

Hölderian Regularity

Contribution
- Training set

Results

Results: Real Images

Original Image

Traditional Method

GP-Estimator

GP-Estimator