

Artificial evolution on EEG signals for the classification of psychophysiological states

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ASTRAL TEAM, Inria and Naval Group joint team **Advanced Statist**ical **infeR**ence **And** **control**

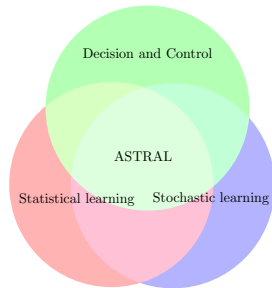
Scientific objectives:

Development of advanced statistical and probabilistic models for the analysis and control of complex systems.

Research activities

Our project is focused on the classical triptych:

- [Statistical/stochastic modeling](#)
- [Estimation/calibration](#)
- [Control/decision](#)



Preliminary comment: Artificial Intelligence (AI): ML, NN, AE...

There is a frequent confusion in the public debate between "artificial intelligence" (AI), machine learning (ML), neural network (NN) and deep learning (DL).

However, these notions are not equivalent, but are intertwined.

And among the techniques contained in the broad spectrum of AI, we also find **artificial evolution**.

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- **Artificial Evolution :** Stochastic optimization which uses mechanisms inspired by the biological evolution, such as reproduction, mutation, selection and survival of the strongest individuals.

Darwinism

"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.

A collection of stochastic techniques

Artificial Darwinism / Evolutionary Algorithms / Artificial Evolution

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)
	...

Common elements

Ingredients

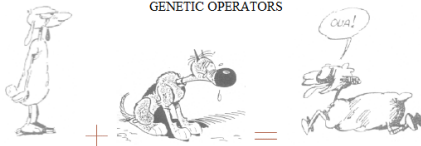
POPULATION



SELECTION

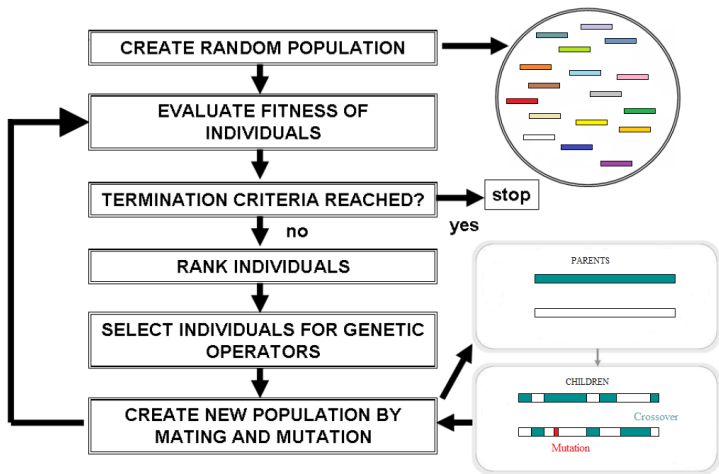


GENETIC OPERATORS



Common elements

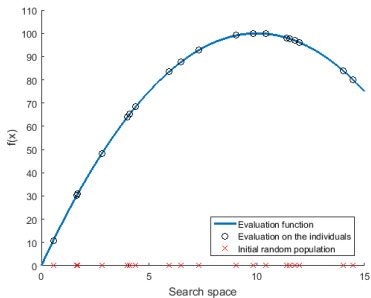
Evolutionary loop



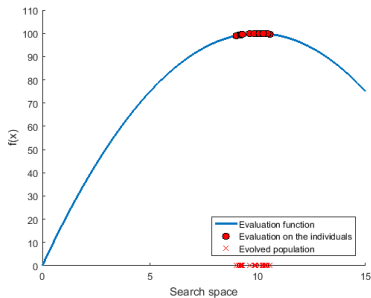
Example

Optimize an "adaptation to the environment"

Potential Solutions = Individuals in a population



Initial random population



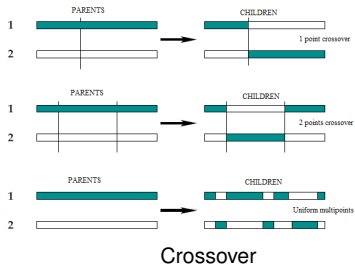
Evolved population

Focus 1

Discrete representation: Genetic Algorithms

Each individual is represented by a binary string.

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



Mutation of the genome

0101101010111111001011100101



Pm

0101101010101111001011100101

Mutation

Focus 2

Continuous representation: Evolution Strategies

Each individual is a vector in R^n .

Hans-Paul Schwefel (1970)

Barycentric crossover

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

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

Gaussian mutation

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

Two parameters P_m and σ .

Application: Evolutionary computation for EEG classification

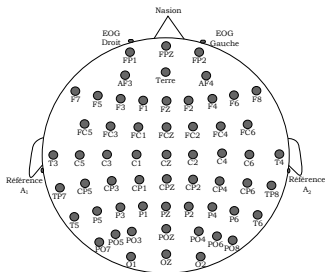
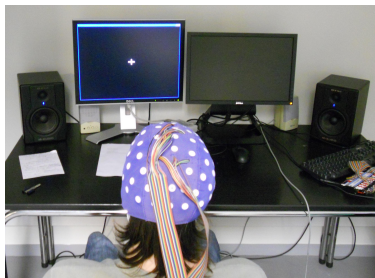
Goal

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

Constraints

- Space-saving and easy to install system.
- Obtaining the results in real time.

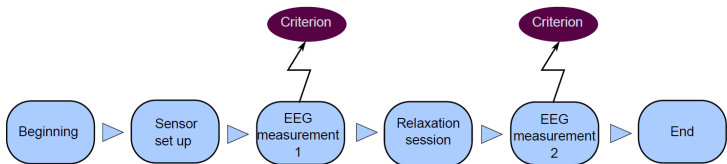
Acquisition Protocole



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

Acquisition Protocole

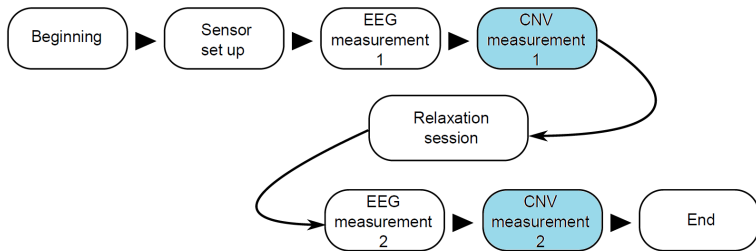
- First EEG recording: subject in a normal state of alertness: "normal"
- Second EEG recording: subject in a state of low vigilance: "relax"



⇒ Is the relaxation session effective?

Acquisition Protocole

Verification of data quality

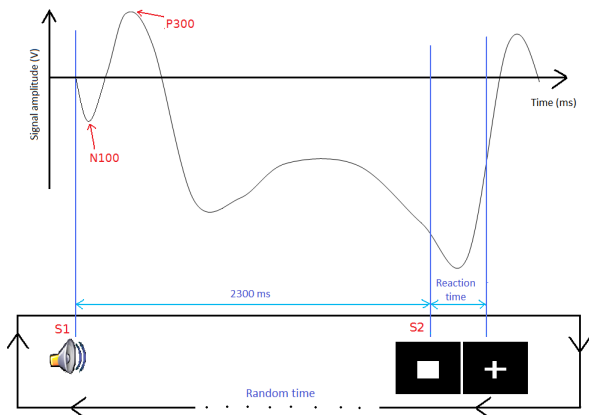


Two steps added to perform a test VCN (Variation Contingence Negative)

Acquisition Protocole

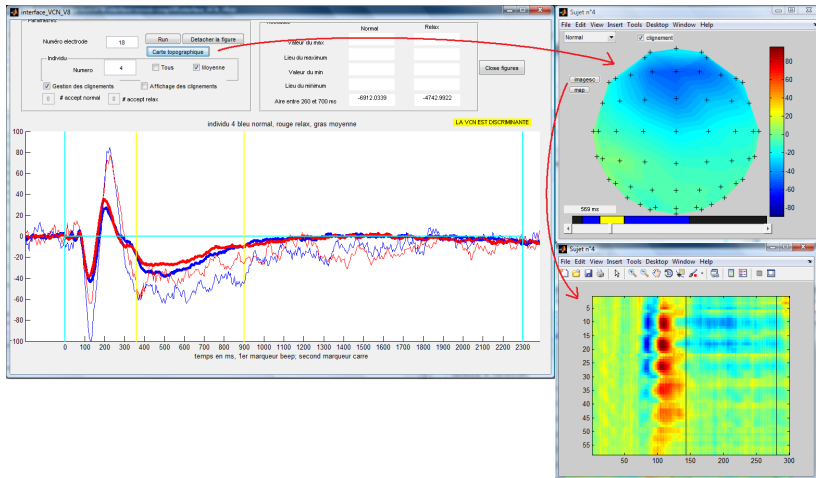
Verification of data quality - CNV measurement

50 occurrences



Acquisition Protocole

Verification of data quality - CNV graphical interface



Campaigns:

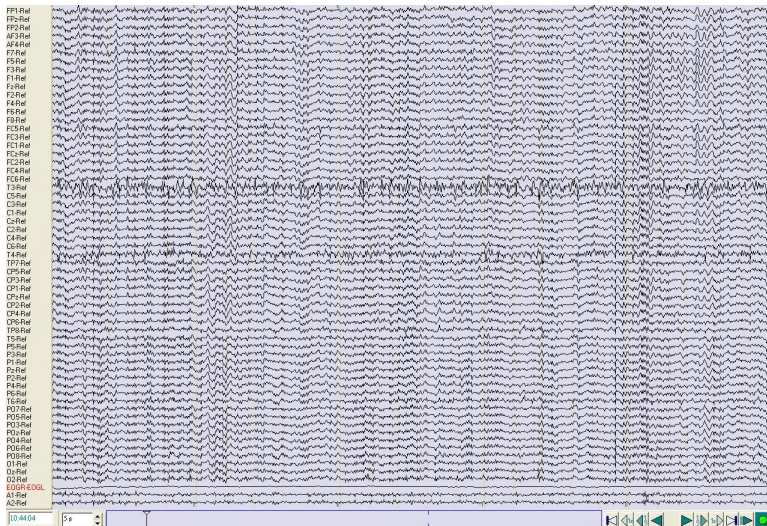
- 58 electrodes renumbered from 1 to 58
- Subjects under 35, right-handed and non-smoker
- 58 subjects ⇒ 16 preserved

Relaxation session

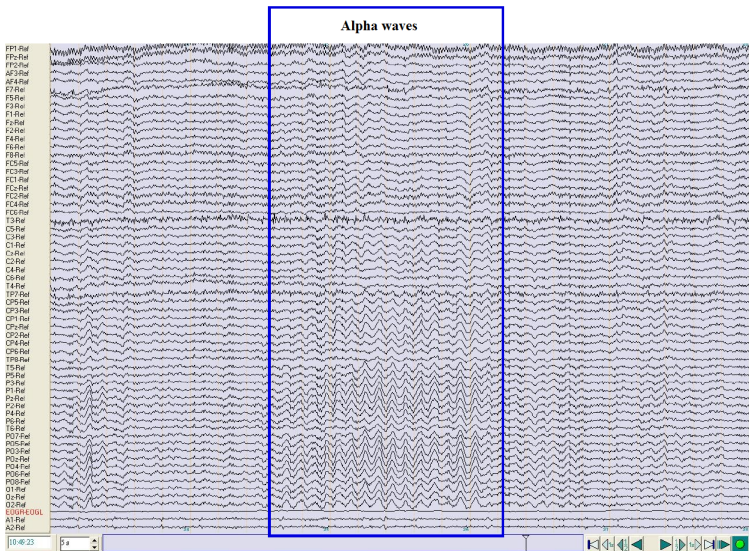
20 minutes with a recorded voice offering 3 exercises:

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

3 minutes of EEG recording **before relaxation**.



3 minutes of EEG recording **after relaxation**.



Feature Extraction: Slope Criterion

Wavelets and energy

A discrete wavelet transform is used in order to calculate the energy of the signal.

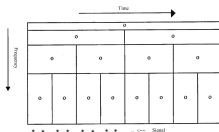
Wavelet coefficient

$C_{j,k}$ denotes the wavelet coefficient at scale j and time k .

$$C_{j,k} = 2^{-\frac{j}{2}} \int_{-\infty}^{\infty} f(t) \psi(2^{-j}t - k) dt$$

Energy at scale j

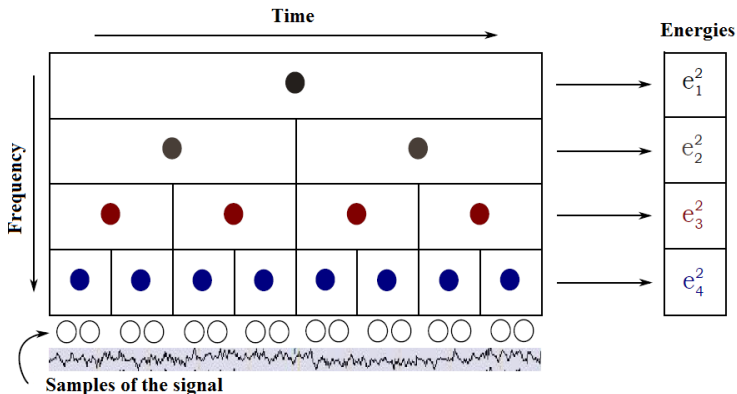
$$E_j^2 = \sum_{k=1}^{2^{j-1}} [C_{j,k}]^2$$



Feature Extraction: Slope Criterion

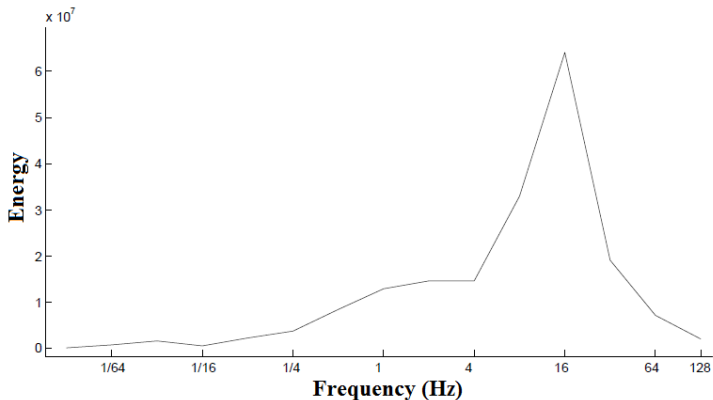
Wavelets and energy

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



Feature Extraction: Slope Criterion

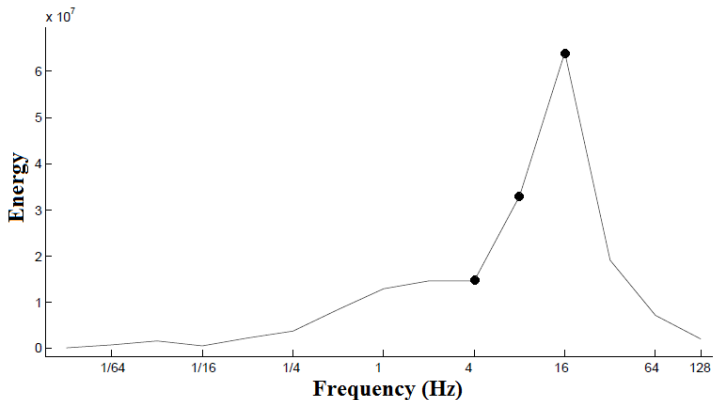
- Alpha: $8 - 12Hz$.
- Waves characteristics of a relaxed state.



Linear regression between 4 and 16 Hz.

Feature Extraction: Slope Criterion

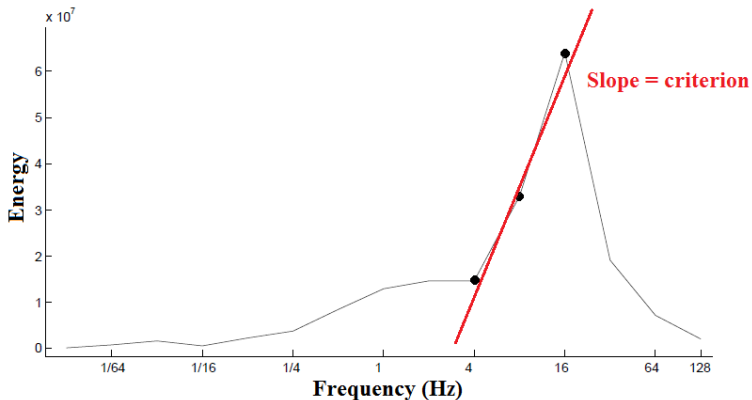
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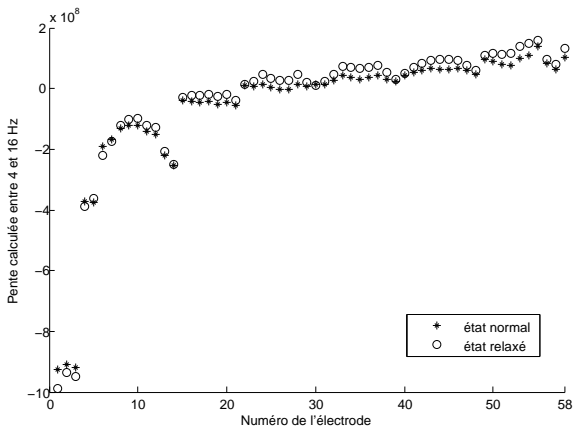
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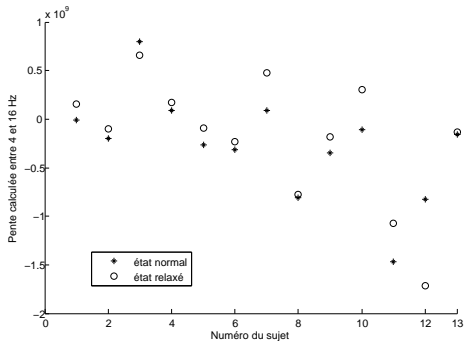
Linear regression between 4 and $16Hz$.

Feature Extraction: Slope Criterion



Slope criterion, sum on subjects for each electrode

Feature Extraction: Slope Criterion



Slope criterion, sum on electrodes for each subjects

⇒ Very strong **inter-subject variability**

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

Feature Extraction: Slope Criterion

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

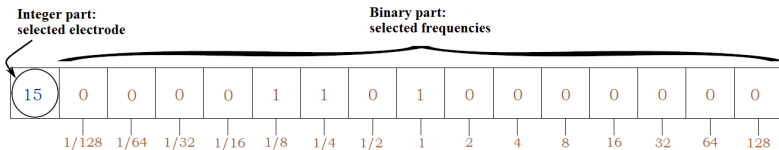
Our contribution: Design a relevant **evolutionary algorithm** to solve this task of classification.

⇒ **Find the relevant electrodes.**

⇒ **Find the relevant frequencies for the calculation of the slope criterion.**

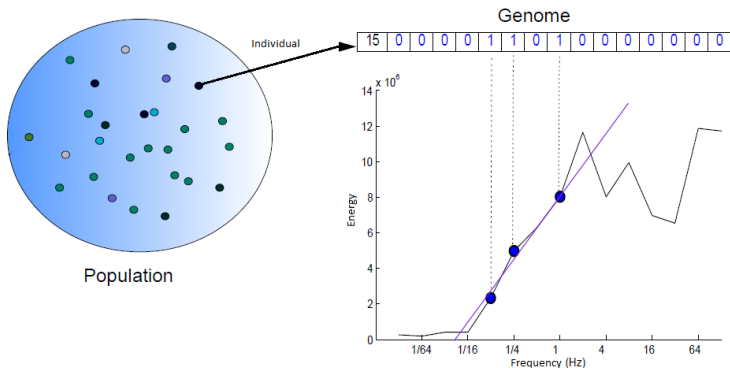
Design

Example of a genome in the evolutionary algorithm



Design

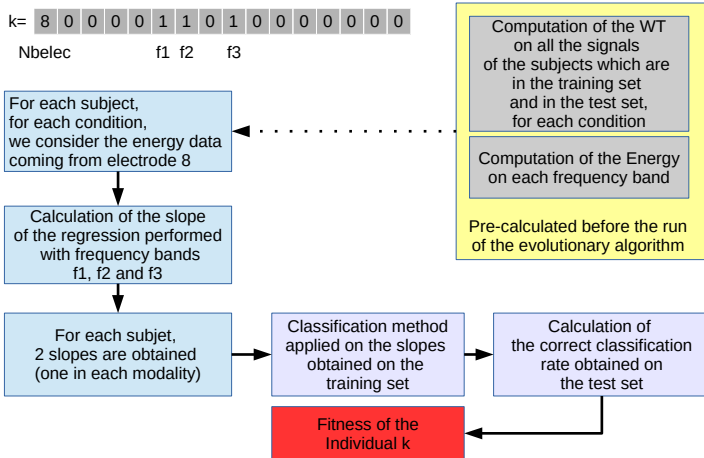
Relationship between the genome and the calculation of the slope criterion



Design

Evaluation of a individual in the evolutionary algorithm

Evaluation of the individual k



Results

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.

Results

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.

**One electrode selected => Quick installation of the acquisition system.
Results obtained in less than a second => Can be used on real application.**

Our contribution

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

⇒ **Find the relevant electrodes.**

⇒ **Find the relevant frequencies for the calculation of the slope criterion.**

Application on similar real applications

For instance: sleeping non sleeping, alertness tunneling of a pilot, etc.

What is needed:

- Data on 2 (or more) conditions
- Use of the same protocol

Warning:

This method cannot be used when the subject is making pronounced movements.

Indeed, the motor activity overwrites the other information contained in the EEG signals.

⇒ **One can use other physiological data (eye tracking, EDA, ECG, etc.) and try the same protocol.**