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Crossing Borders: My Research Journey from Theory to Applications in Biomedical Signal Processing

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University of Vic – Central University of Catalonia

21 February 2025


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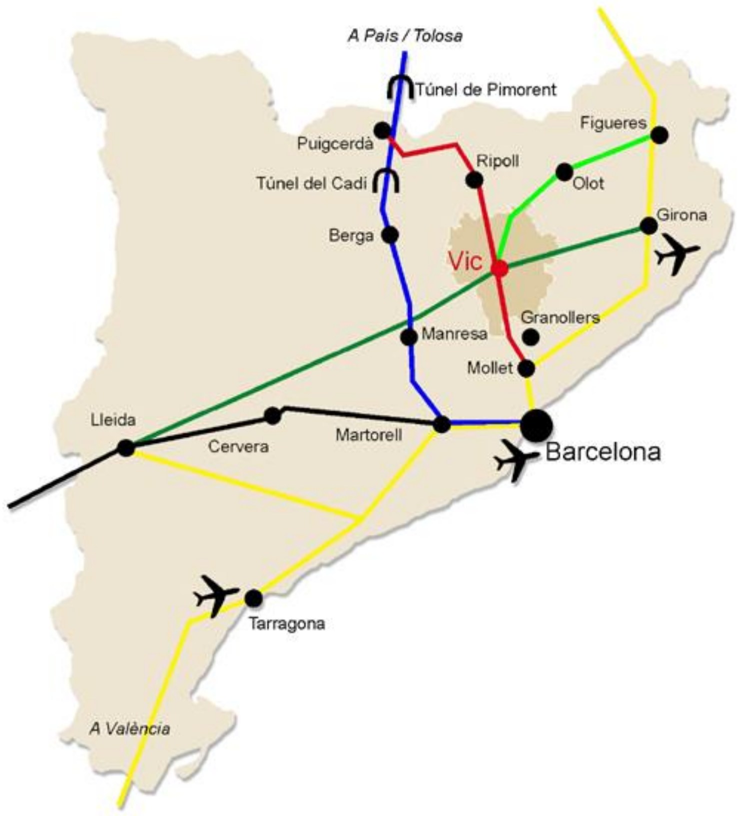
The University of Vic – Central University of Catalonia and the Data and Signal Processing (DSP) research group



- **UVic-UCC** is located in the city of Vic, a town of 40,000 inhabitants in the heart of **Catalonia**. Currently the number of students is about 12,000.
- UVic-UCC has 5 Faculties:
- **Faculty of Science, Technology and Engineering**
- Faculty of Education, Humanities and Translation
- Faculty of Business and Communication
- Faculty of Health and Welfare
- Faculty of Medicine

The University of Vic – Central University of Catalonia and the Data and Signal Processing (DSP) research group

- The Data and Signal Processing research group is recognised as a consolidated research group by the Government of Catalonia.
- Interested in data and signal processing, machine learning / deep learning, gamification and apps.
- The group has 6 senior (PhD) members, 7 PhD students, 2 PhD student visitors and some undergraduate students.
- You can follow us on X (Twitter): @uvic_DSP

Overview

1 – First steps: my PhD work between Vic and Grenoble

2 – Japan, the Asian adventure

3 – Cambridge, closing the circle

4 – And then… China!

5 – From my experience…

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First steps: my PhD work between Vic and Grenoble

First steps: my PhD work between Vic and Grenoble

- I started my PhD while working as teaching assistant at the University of Vic (October 1994).
- I went to Grenoble for one month (1998), with:
  - No knowledge of French language
  - Limited English knowledge
  - By train
  - No grants… but then I got one!

First steps: my PhD work between Vic and Grenoble

- Then, I repeated a one-month stay in Grenoble, two more times
  - Developing my PhD work
  - By car
  - With research grants!
- I defended my thesis and obtained my PhD degree in October 2000
- I continued to visit Grenoble regularly for about 10 more years

First steps: my PhD work between Vic and Grenoble

- What happened in between?

To understand how the vertebrate brain is able to encode/decode its own movements, Christian Jutten, together with Professor Jeanny Hérault and Dr. Bernard Ans, developed the concept of blind source separation and contributed to its theoretical foundation (1985).

Christian Jutten, *father* of BSS/ICA

First steps: my PhD work between Vic and Grenoble

- What happened in between?

DIXIEME COLLOQUE SUR LE TRAITEMENT DU
SIGNAL ET SES APPLICATIONS

NICE du 20 au 24 MAI 1985

DETECTION DE GRANDEURS PRIMITIVES DANS UN MESSAGE COMPOSITE PAR UNE
ARCHITECTURE DE CALCUL NEUROMIMETIQUE EN APPRENTISSAGE NON SUPERVISE

J. HERAULT, C. JUTTEN, B. ANS*

Laboratoire de Traitement d'Images et Reconnaissance de Formes
INP-ENSER, 46 avenue Félix Viallet 38031 - GRENOBLE-CEDEX (France)

Christian Jutten, *father* of BSS/ICA

First steps: my PhD work between Vic and Grenoble

Christian Jutten

Anisse Taleb

Shahram Hosseini

Massoud Babaie-Zadeh

Jeanny Hérault.

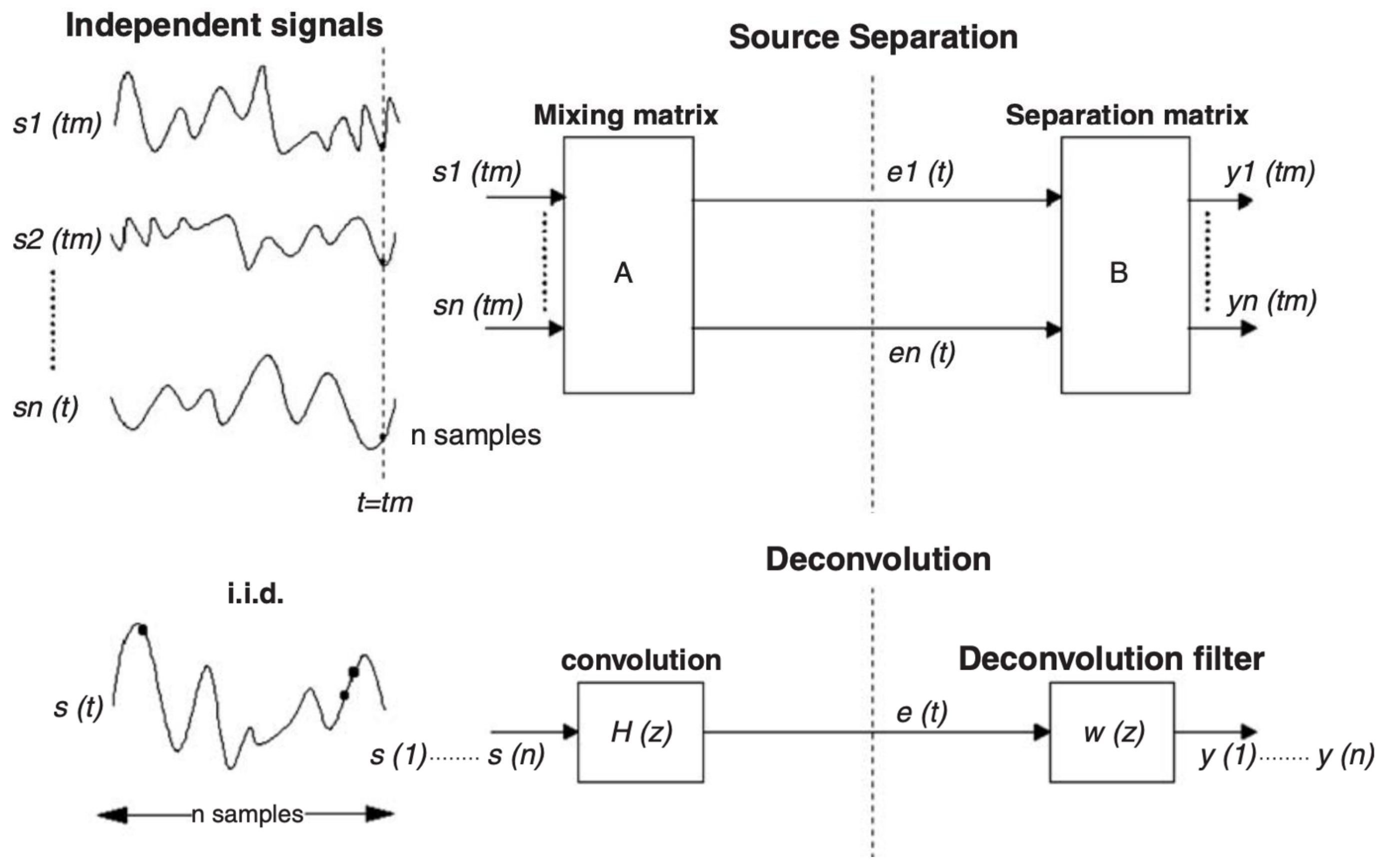
Sophie Achard

Vincent Vigneron

Marco Congedo

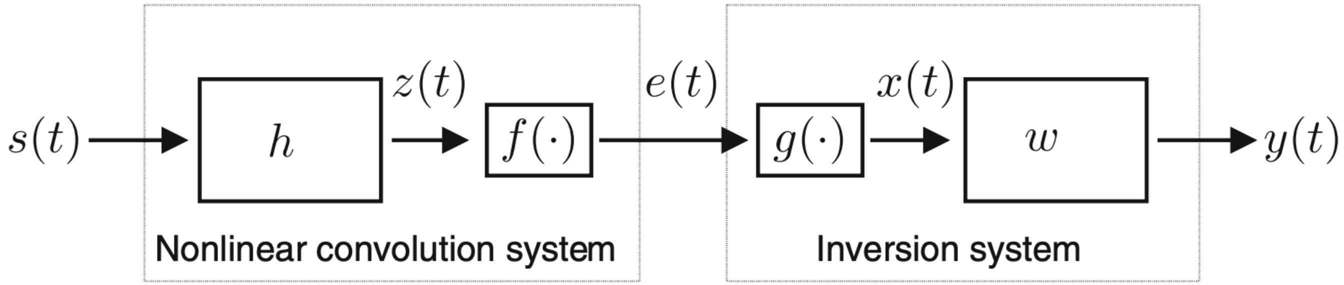
Scientific contributions from my research in Grenoble

1. Blind inversion of Wiener systems



Scientific contributions from my research in Grenoble

1. Blind inversion of Wiener systems



Linear part

$$I(\mathcal{Y}) = H(y(\tau)) - \frac{1}{2\pi} \cdot \int_0^{2\pi} \log\left|\sum_{t=-\infty}^{+\infty} w(t)e^{-jt\theta}\right| d\theta - E[\log g'(e(\tau))] - H(\mathcal{E}).$$

$$w \leftarrow w + \mu\left\{\gamma_{y,\,\psi_y(y)} + \delta\right\} * w$$

Nonlinear part

Nonparametric approach

$$g \leftarrow g + \mu\{Q \circledast J\} \circ g$$

$$\underbrace{E[\psi_y(y(\tau))\{w * \delta(x - v)\}(\tau) + \delta'(x(\tau) - v)]}_{J(v)}$$

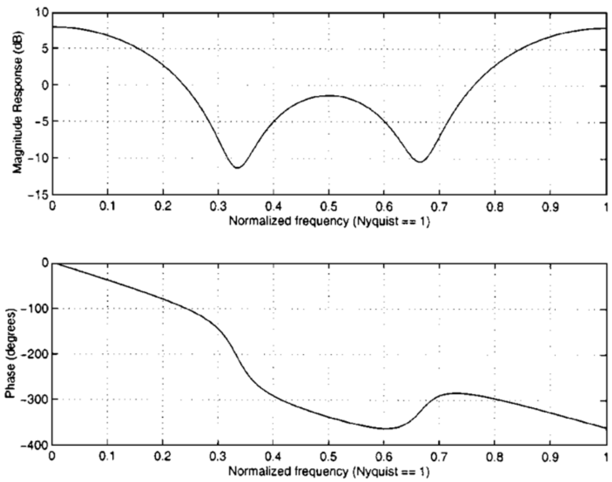
$$\int_{\mathbb{R}} J(v) Q \circledast J(v)\, dv \geq 0$$

https://doi.org/10.1109/78.917796

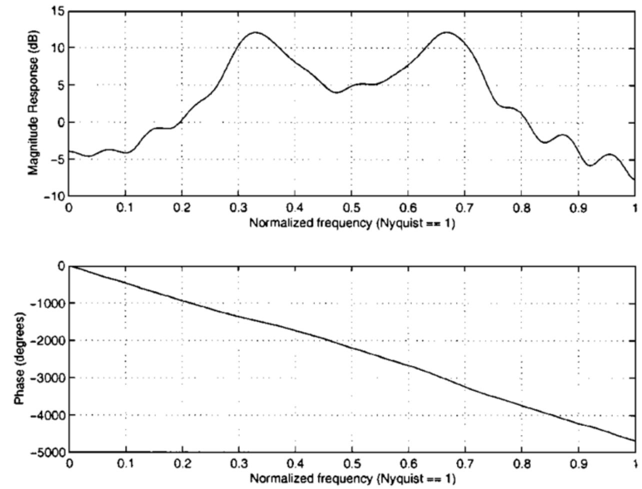
Scientific contributions from my research in Grenoble

1. Blind inversion of Wiener systems

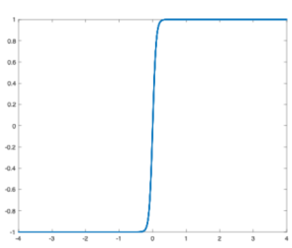
Filter



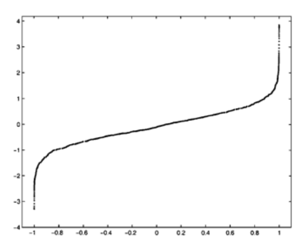
Inverse filter



Distortion $f(u) = \tanh(10u)$

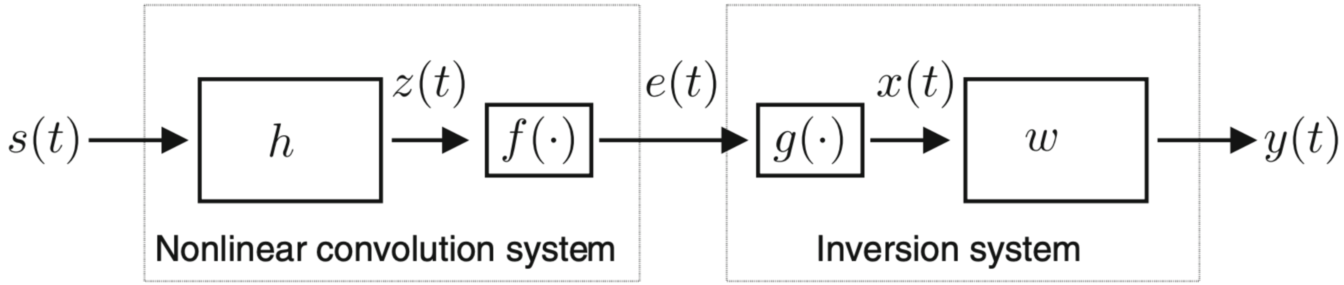


Inverse distortion



Scientific contributions from my research in Grenoble

1. Blind inversion of Wiener systems



Linear part

$$I(\mathcal{Y}) = H(y(\tau)) - \frac{1}{2\pi} \cdot \int_0^{2\pi} \log \left| \sum_{t=-\infty}^{+\infty} w(t) e^{-jt\theta} \right| d\theta - E[\log g'(e(\tau))] - H(\mathcal{E}).$$

$$w \leftarrow w + \mu \left\{ \gamma_{y,\psi_y(y)} + \delta \right\} * w$$

Nonlinear part

Parametric approach, using polynomials:

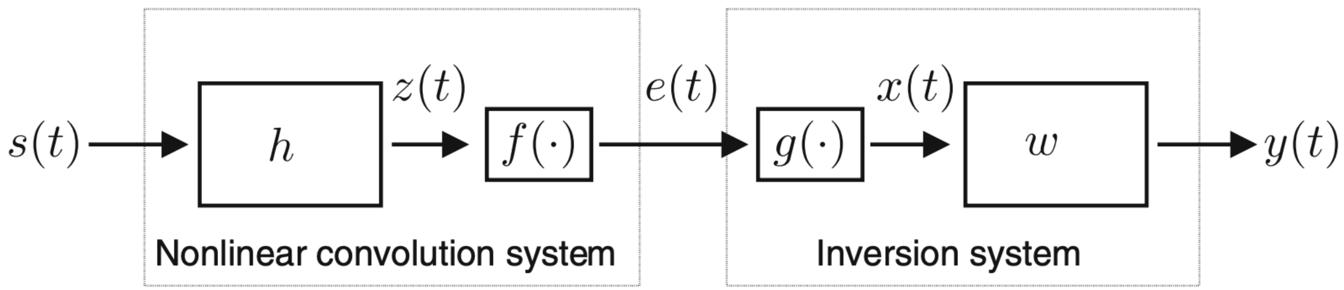
$$g(t) = \sum_{n=1}^{N+1} a_n t^{n-1}.$$

$$\frac{\partial I(Y)}{\partial a_p} = -E\left[\psi_Y(y(\tau)) \sum_{t=-\infty}^{+\infty} w(t) e(\tau - t)^{p-1} \right] - E\left[\left(\sum_{n=1}^{N+1} a_n (n-1) e(\tau)^{n-2} \right)^{-1} (p-1) e(\tau)^{p-2} \right]$$

https://doi.org/10.1016/S0925-2312(01)00651-8

Scientific contributions from my research in Grenoble

1. Blind inversion of Wiener systems



Linear part

$$I(\mathcal{Y}) = H(y(\tau)) - \frac{1}{2\pi} \cdot \int_0^{2\pi} \log \left| \sum_{t=-\infty}^{+\infty} w(t) e^{-jt\theta} \right| d\theta - E[\log g'(e(\tau))] - H(\mathcal{E}).$$

$$w \leftarrow w + \mu \left\{ \gamma_{y,\, \psi_y(y)} + \delta \right\} * w$$

Nonlinear part

Parametric approach, using NN:

$$g[\mathbf{a}, \mathbf{c}, \mathbf{b}, u] = \sum_{i=1}^{N} a_i \sigma(c_i u - b_i)$$

$$a \leftarrow a - \mu_a \frac{\partial I(Y)}{\partial a}, \quad c \leftarrow c - \mu_c \frac{\partial I(Y)}{\partial c}, \quad b \leftarrow b - \mu_b \frac{\partial I(Y)}{\partial b}.$$

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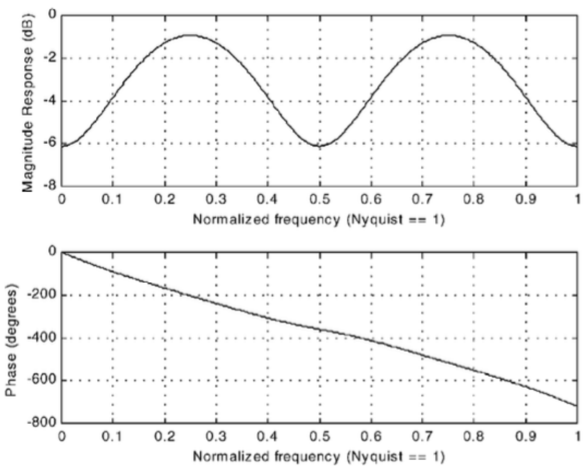
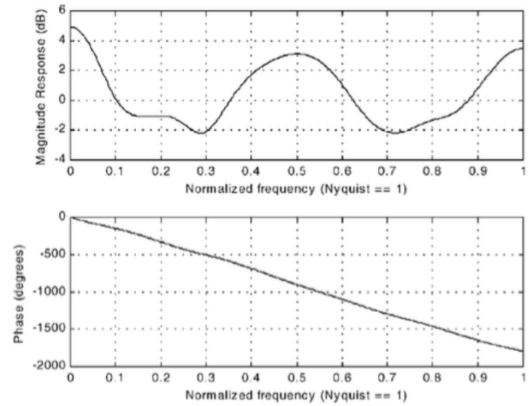
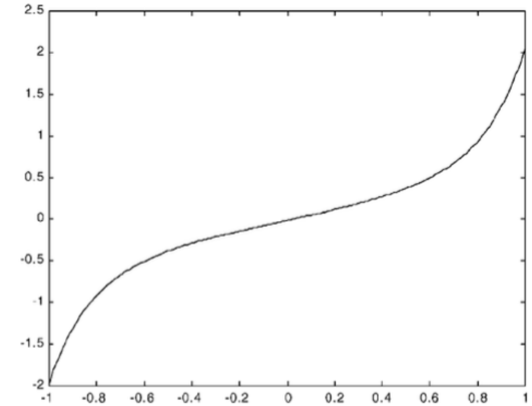
Filter



Inverse filter

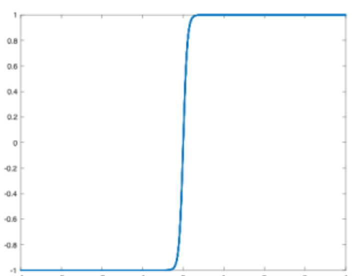


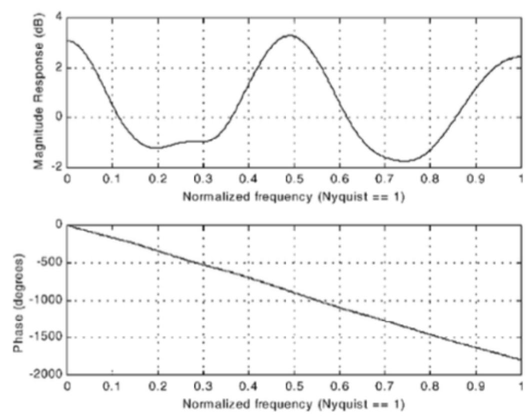
Inverse distortion

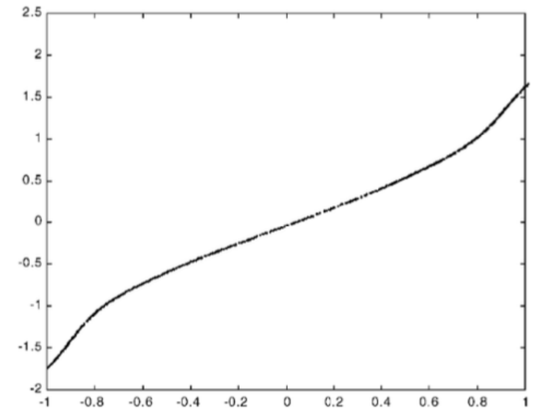


Distortion

$$f(u) = \tanh(10u)$$

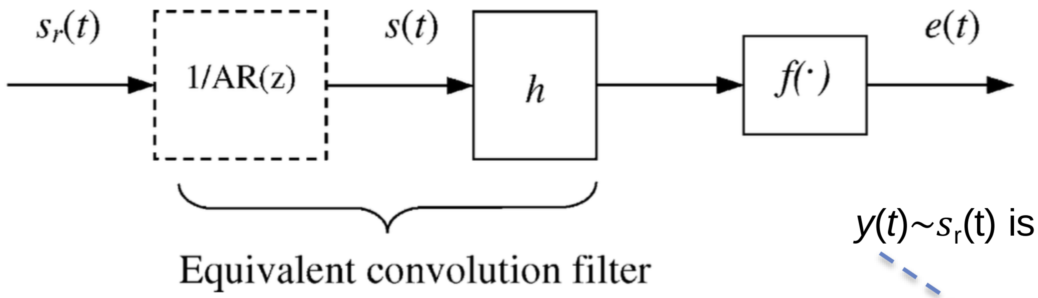




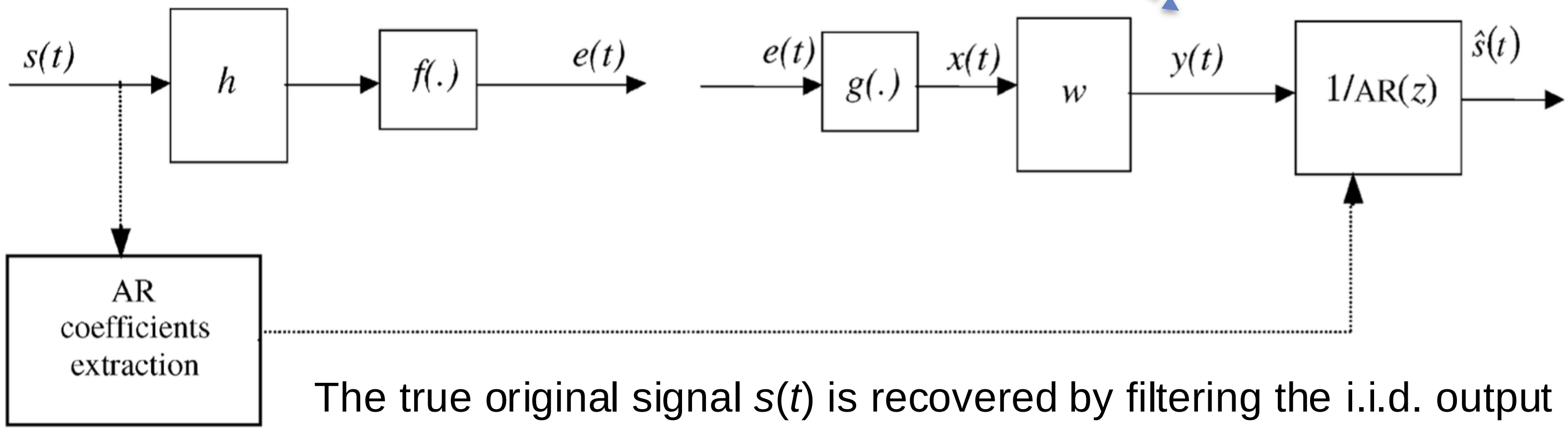


Scientific contributions from my research in Grenoble

What if the input signal *s*(t) is not i.i.d.?



$y(t) \sim s_r(t)$ is a whitened version of $s(t)$



The true original signal $s(t)$ is recovered by filtering the i.i.d. output $y(t)$ with the AR filter, which requires prior information on the signal.

Scientific contributions from my research in Grenoble

2. Fast gradient approximation

The score function (non-linear blind deconvolution case) or the perturbation function (PNL case) must be evaluated in all the sample points. The complexity is $O(T^2)$ (T = number of samples).

$$\widehat{\psi}_y(y) = \frac{\sum_{\tau=1}^{T} K'\left(\frac{y-y(\tau)}{B}\right)}{\sum_{\tau=1}^{T} K\left(\frac{y-y(\tau)}{B}\right)},$$

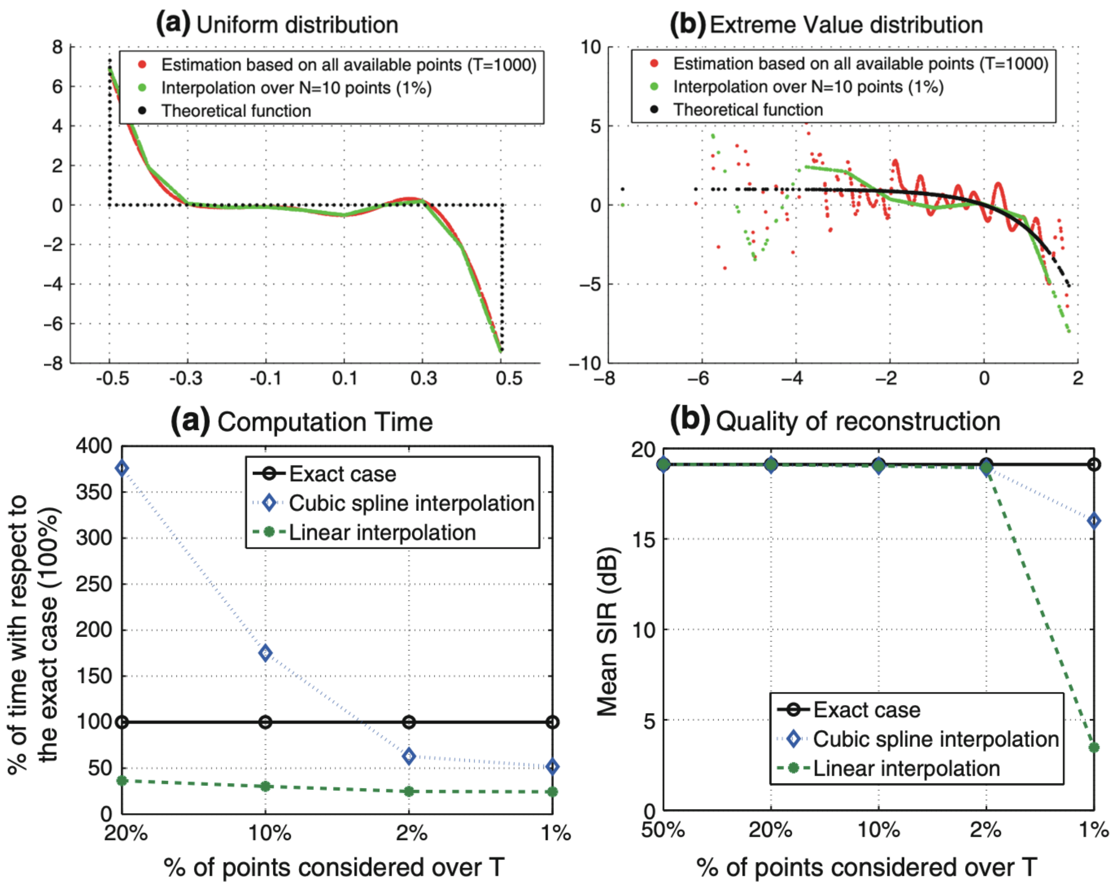
$$\varepsilon(x(t)) \approx \frac{1}{T}\sum_{\tau=1}^{T}\Big[\widehat{\psi}_y(y(\tau))(w * r(x - x(t)))(\tau) + r'(x - x(t))(\tau)\Big],$$

We propose to create a grid of N amplitude values covering the ranges of the variables by using evenly spaced points (quantization) which give us complexity $O(N \cdot T)$, and then linearly interpolate these values.

https://doi.org/10.1007/s12559-012-9192-x

Scientific contributions from my research in Grenoble

2. Fast gradient approximation



Scientific contributions from my research in Grenoble

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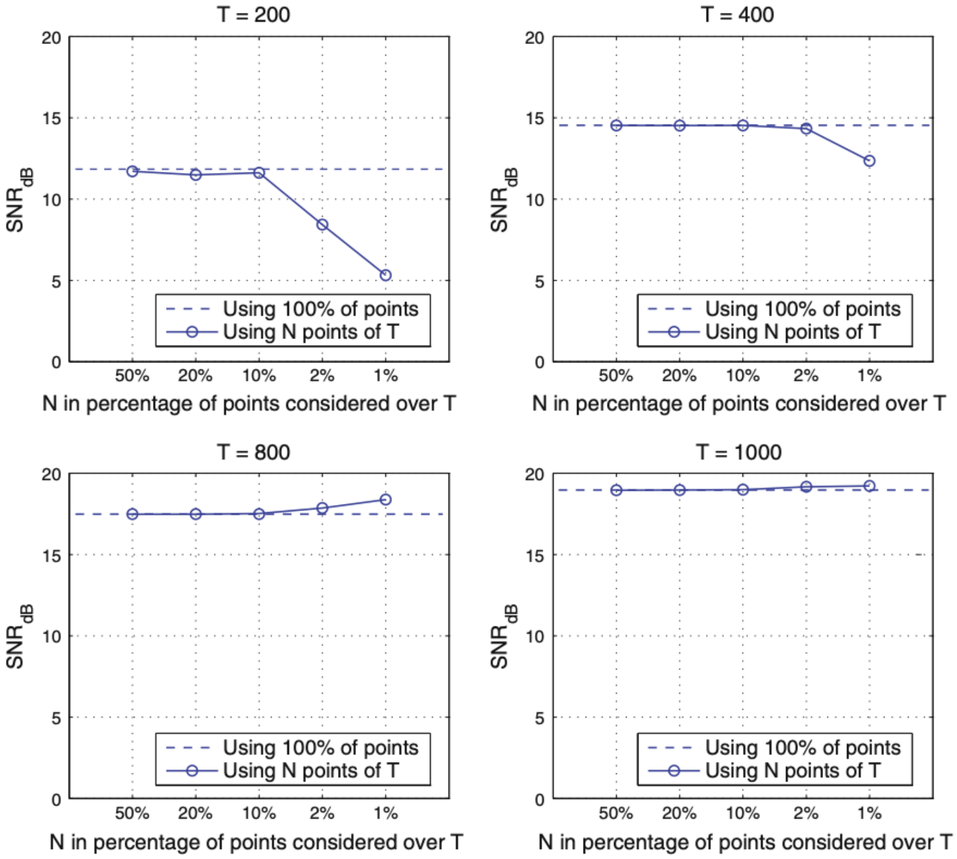
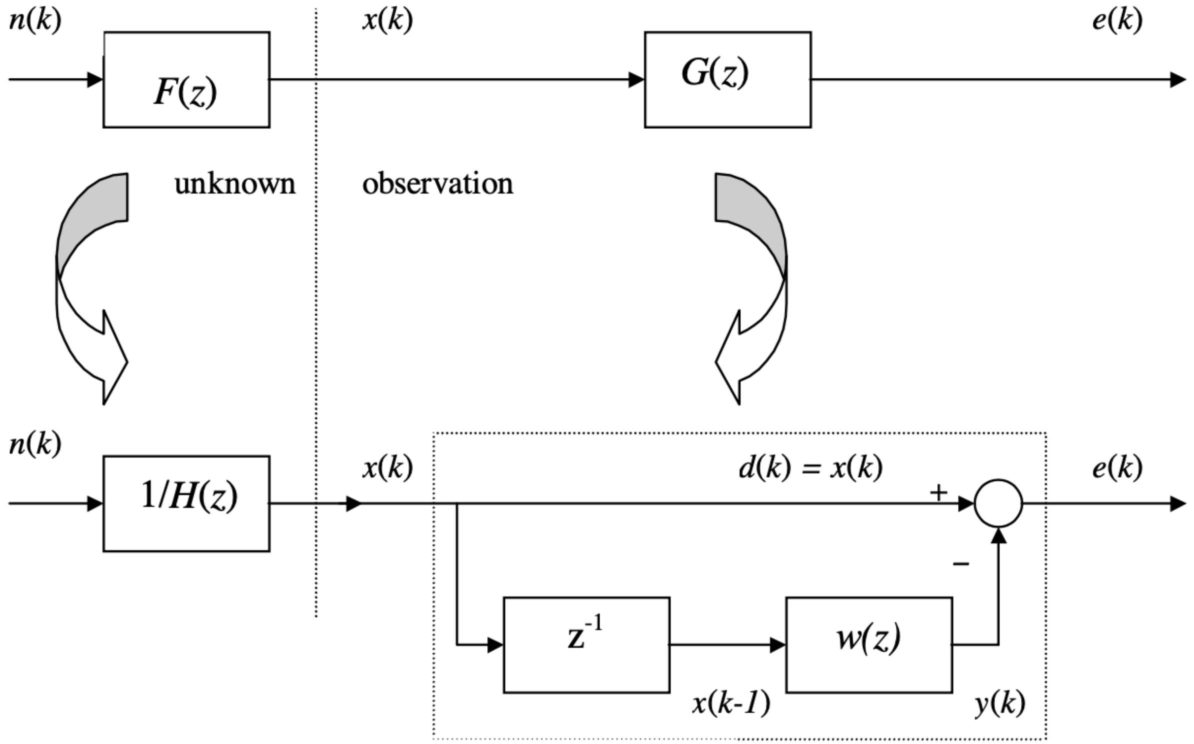


Scientific contributions from my research in Grenoble

3. Source separation techniques applied to linear prediction



LPC viewed as a deconvolution problem: $1/H(z)$ is the unknown filter and the dashed block its inverse, to be estimated to recover $e(k) = n(k)$.

Scientific contributions from my research in Grenoble

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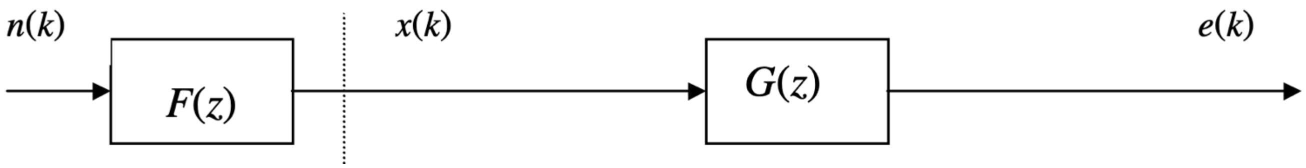
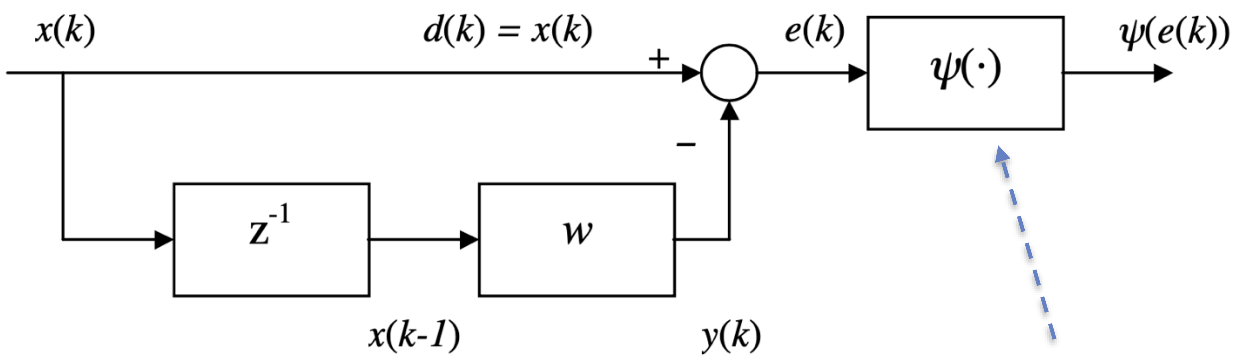


If $n(k)$ is Gaussian, classical LPC and second order deconvolution are equivalent, because the optimal filter must provide Gaussian residue $e(k)$.



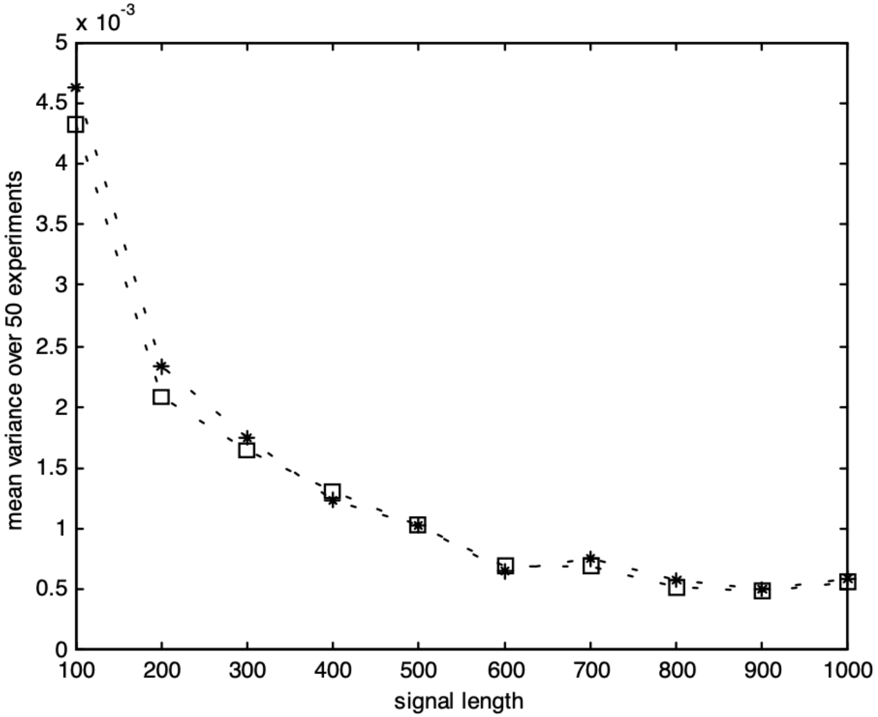
if $n(k)$ is not Gaussian, the error residue can not be Gaussian

Estimated score function

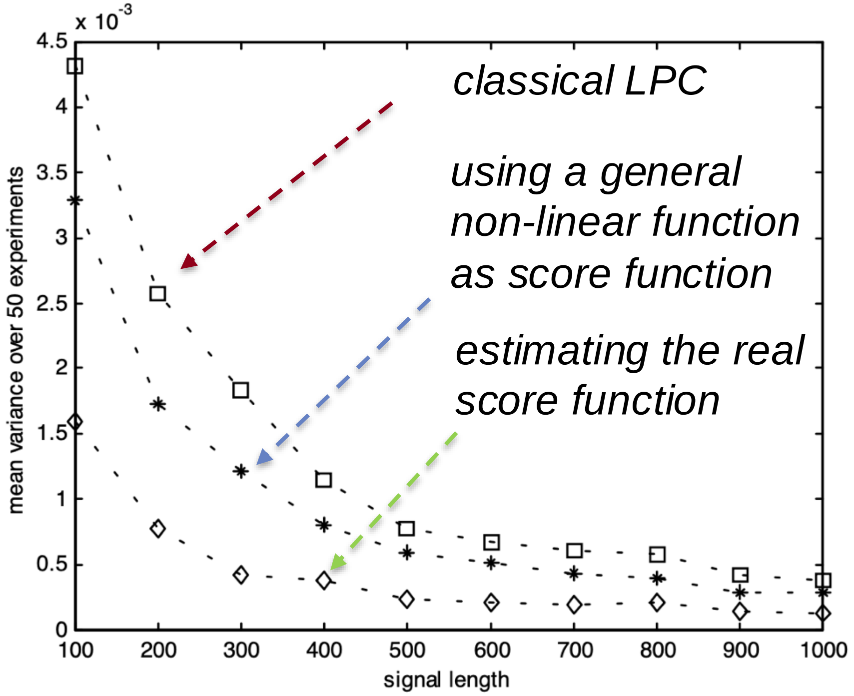
$$E\left[\psi_E(e(k))\,x(k-j-1)\right]=0,\quad j=0,\cdots,K$$

Scientific contributions from my research in Grenoble

3. Source separation techniques applied to linear prediction



Gaussian case

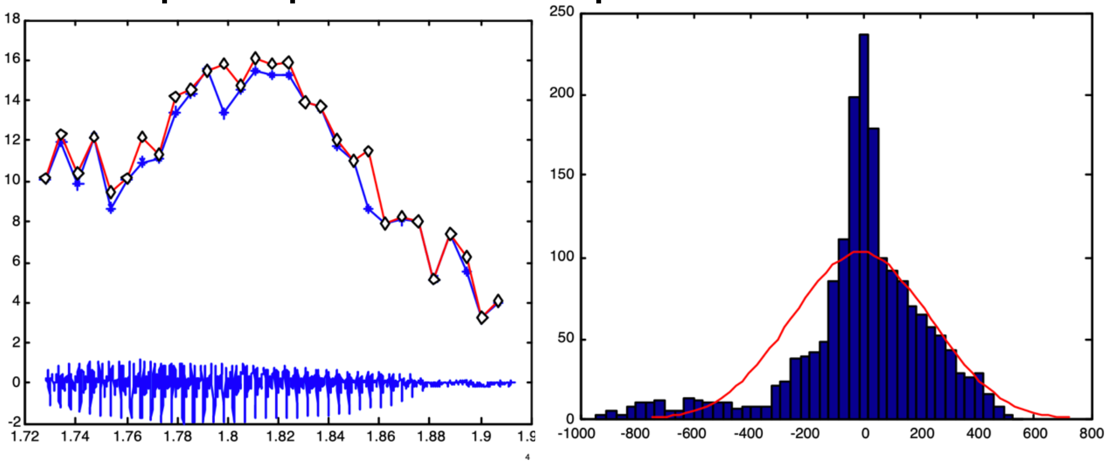


Non-Gaussian case

Scientific contributions from my research in Grenoble

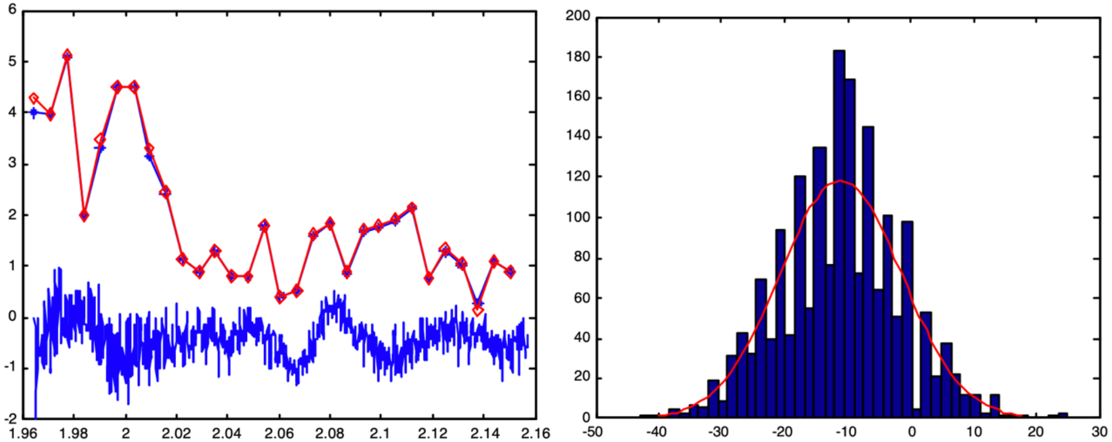
Example: speech linear prediction

prediction gain : $Gp(dB) = 10\log\left(\frac{E\left[x^2(n)\right]}{E\left[e^2(n)\right]}\right)$



30 frames of the input signal, with the prediction gain obtained for classical method (line with stars) and quasi-optimal method (line with diamonds).
We observe that the signal distribution is *not centred and non-Gaussian*.

The mean gain for this experiment is about 4.16 %.

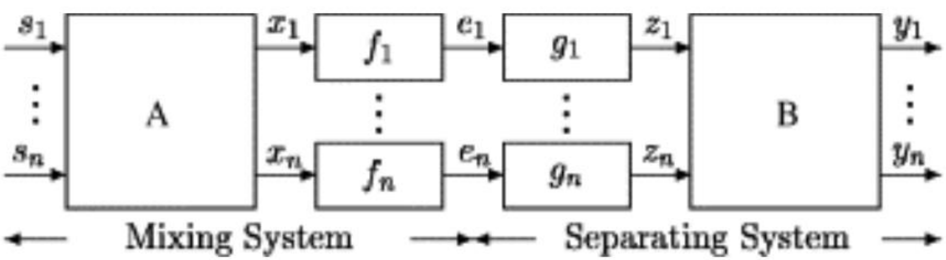


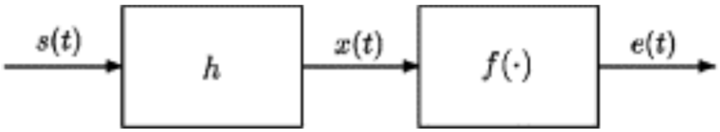
30 consecutive frames of a silence part of the input signal, with the prediction gain obtained for classical method (line with stars) and quasi-optimal method (line with diamonds). We observe that the signal distribution *fits a Gaussian distribution*

Scientific contributions from my research in Grenoble

4. Fast approximation of nonlinearities

- According to the Central Limit Theorem, X_i tends toward a Gaussian random variable. The nonlinear mapping f_i changes the distribution, and consequently we can assume that the random variable $E_i=f_i(X_i)$ is more distant of a Gaussian than X_i.
- The algorithm estimates the inverse of f_i, as the nonlinear mapping g_i which enforces the random variable $Z_i=g_i(E_i)$ to be Gaussian

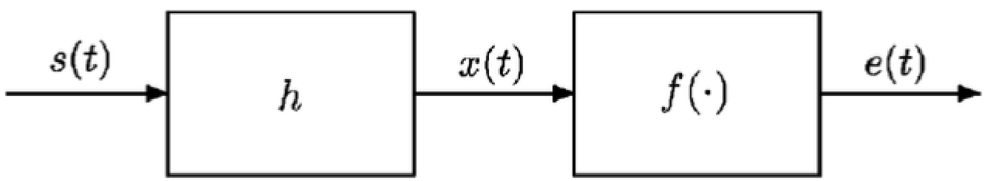


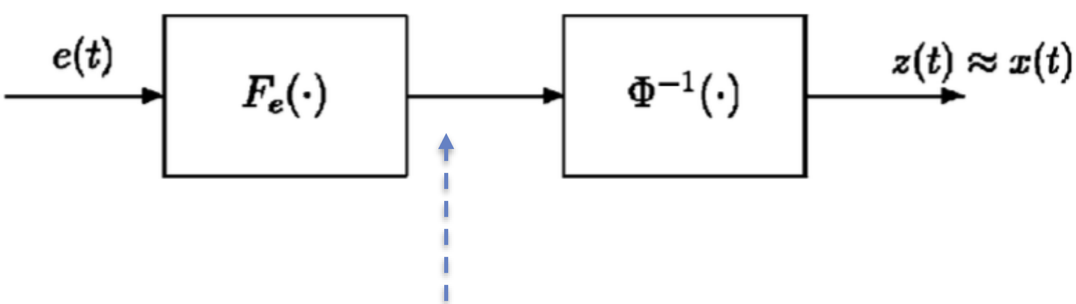


https://doi.org/10.1016/j.sigpro.2004.11.030

Scientific contributions from my research in Grenoble

4. Fast approximation of nonlinearities





The random variable *U* is uniformly distributed in [0,1]

Analytical solution, no iterations:

$$\hat{g} = \Phi^{-1} \circ F_E.$$

$F_E(u) = \Pr(E < u)$ is the cumulative density function of *E*

$\Phi(u)$ is the Gaussian cdf,

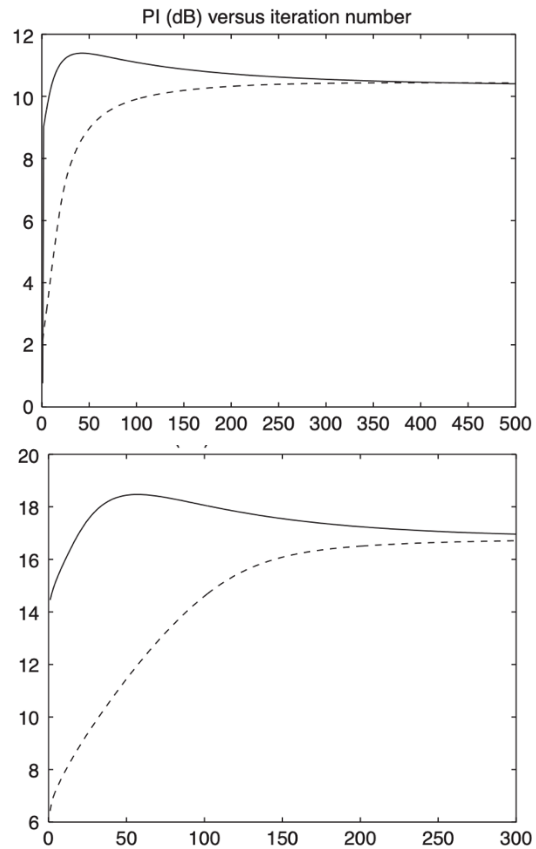
which transforms a unit variance Gaussian variable into a uniform random variable in [0, 1]

$\Phi^{-1}(U)$ is a unit variance Gaussian random variable

https://doi.org/10.1016/j.sigpro.2004.11.030

Scientific contributions from my research in Grenoble

4. Fast approximation of nonlinearities



Performance index (PI) and convergence speed (CS) for PNL mixtures, with or without nonlinear initialization (RENL algorithm)

	Average	SD	Min	Max
PI with RENL algorithm (dB)	16.1	3.2	10.5	20
PI without RENL algorithm (dB)	15.6	3.6	9.7	20.2
CS with initialization	12.0	9.4	2	30
CS without RENL algorithm	35.5	18.2	11	78

$$\mathrm{PI} = 10\log(E[s_i^2]/E[(y_i - s_i)^2])$$

CS: convergence speed

RENL: rough estimation of nonlinearities

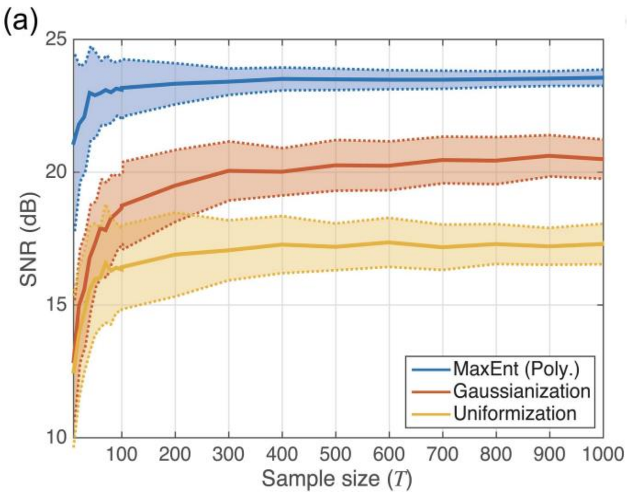
PI (dB) versus iterations for separating PNL (up) [or inverting Wiener system (bottom)] without (dashed) or with (solid) nonlinear initialization.

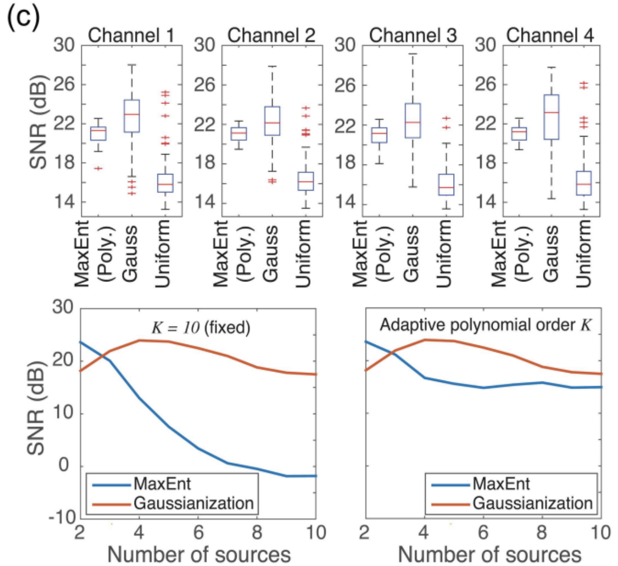
https://doi.org/10.1016/j.sigpro.2004.11.030

Scientific contributions from my research in Grenoble

5. Entropy maximization for estimating nonlinearities

Experimental results with MaxEnt algorithm with polynomial parameterization, Gaussianization and Uniformization methods, for different scenarios over a set of 100 experiments.





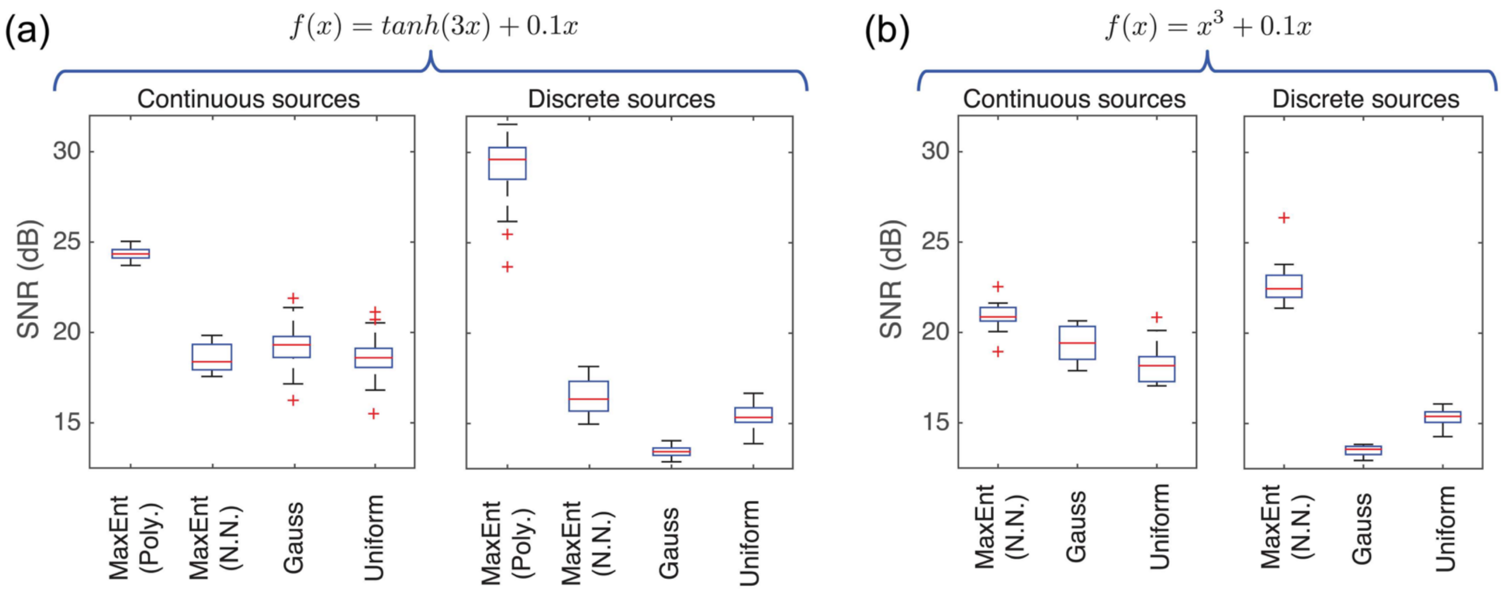
(a) Mean ± std SNR evolution (channel 1) when the number of samples T changes from 10 to 1000 for a fixed random matrix A.

(c) Top: Boxplot of SNR for each channel with a fixed 4 × 4 random mixing matrix. Bottom: SNR as a function of the number of mixing sources for a fixed polynomial order K = 10 (left) and for adaptively chosen polynomial order K.

https://doi.org/10.1371/journal.pone.0165288

Scientific contributions from my research in Grenoble

5. Entropy maximization for estimating nonlinearities



SNR (dB) boxplots obtained in channel 1 for MaxEnt algorithm with polynomial (Poly.) and neural network (N.N.) parameterizations, Gaussianization and Uniformization methods, for continuous (uniformly distributed) and (3-level) discrete sources (–0.4, 0, +0.4).

(a) Results for the nonlinearity f(x) = tanh(3x) + 0.1x.

(b) Results for the nonlinearity f(x) = x^3 + 0.1x

Scientific contributions from my research in Grenoble

- Starting conditions:
  - Scared
  - Knowing nobody
  - No good knowledge about the topic of my research
  - No knowledge about French language and culture

Scientific contributions from my research in Grenoble

- Final conditions:
  - Happy
  - With a lot of friends
  - At the forefront of knowledge on my research topic
  - Proficient on French language and loving French cuisine and patisserie

Japan, the Asian adventure

- Why Japan? I when to a conference

2n International Workshop on INDEPENDENT COMPONENT ANALYSIS and BLIND SIGNAL SEPARATION, 19-22 June 2000, Helsinki, Finland

SOURCE SEPARATION TECHNIQUES APPLIED TO LINEAR PREDICTION

Jordi Solé i Casals (1), Christian Jutten(2), Anisse Taleb (2)

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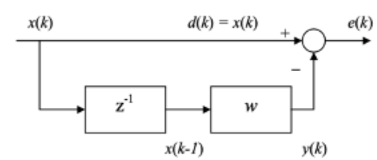
University of Vic, Sagrada Família 7, 08500, Vic (Catalunya, Spain)
(2)INPG-LIS, 46 Av. Félix Viallet, 38031, Grenoble Cedex, France

ABSTRACT

The prediction filters are well known models for signal estimation, in communications, control and many others areas. The classical method for deriving linear prediction coding (LPC) filters is often based on the minimization of a mean square error (MSE). Consequently, second order statistics are only required, but the estimation is only optimal if the residue is independent and identically distributed (iid) Gaussian. In this paper, we derive the ML estimate of the prediction filter. Relationships with robust estimation of auto-regressive (AR) processes, with blind deconvolution and with source separation based on mutual information minimization are then detailed. The algorithm, based on the minimization of a high-order statistics criterion, uses on-line estimation of the residue statistics. Experimental results emphasize on the interest of this approach.

This paper is organized as follows. In Section 2, we derive the maximum likelihood (ML) estimate of LPC and show that it only coincides to the classical method in the Gaussian case. In Section 3, we compute the ML estimate in the general case, which clearly involves the score functions. In section 4, we show the relationships with blind deconvolution and recent advances in source separation, which inspire a new, quasi-optimal LPC algorithm. Section 5 is devoted to experiments and comparisons between the new and classical LPC algorithms. Finally, the major results and outline of future works are summarized in the conclusion.



The Chairman of my session was Prof. Andrzej Cichocki

Japan, the Asian adventure

- The Chairman of my session was Prof. Andrzej Cichocki

Japan, the Asian adventure

- He liked my talk
- He invited me to visit his lab:

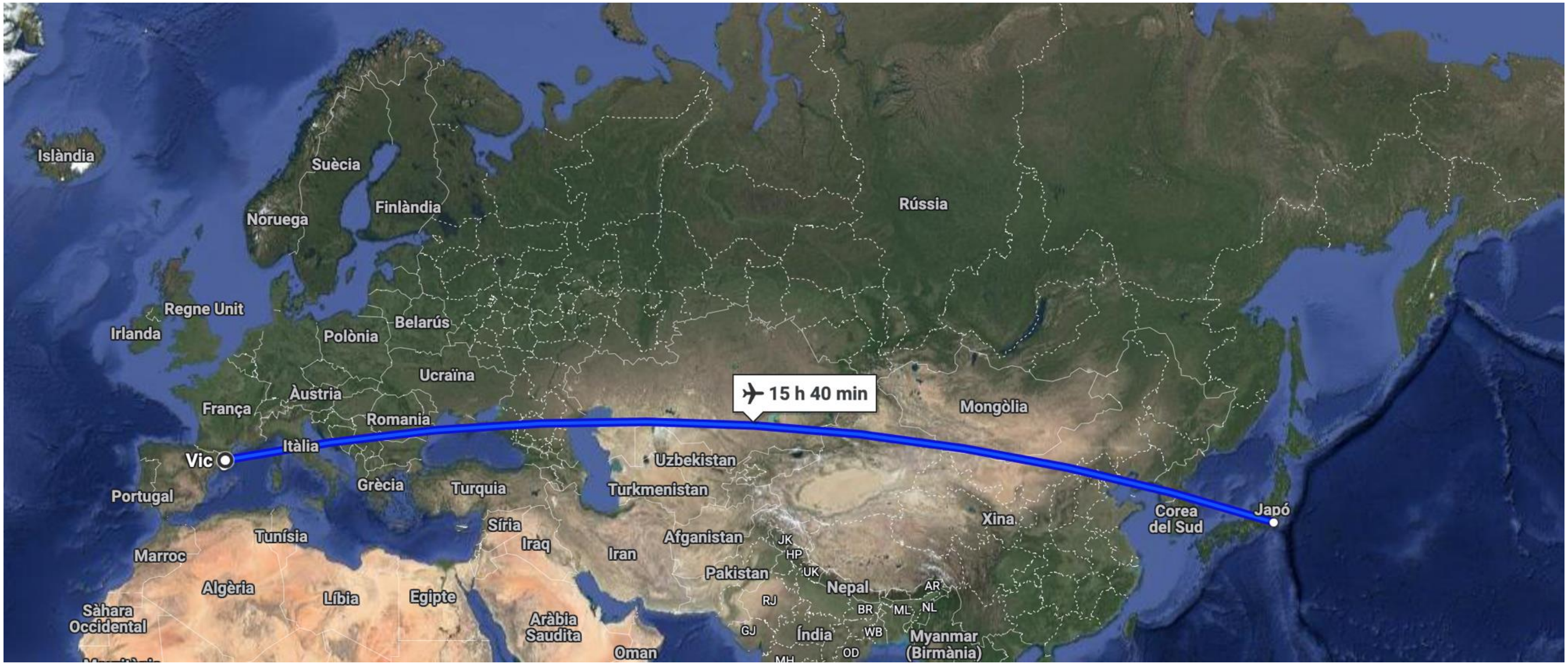
  Advanced Brain Signal Processing Laboratory,

  RIKEN (Tokyo, Japan)
- I applied for a grant, and I went to Japan for 5 weeks
- This time, by plane with my family: my wife and two babies: 2 years old boy, 8 months old girl.
- Again, I was scared!

Japan, the Asian adventure

- Scared… but why?
  - Far away, unknown country, knowing no one.
  - No tourism in Japan at that time (2003)
  - No knowledge of Japanese culture and language
  - Impressed by the lab scientific work
- What I did?
  - Basically, working on my own projects, but… talking a lot with all the members of the lab, to understand their research topics. Specially, with Toshihisa Tanaka.
- Since then, I have continued visiting Japan...

Japan, the Asian adventure



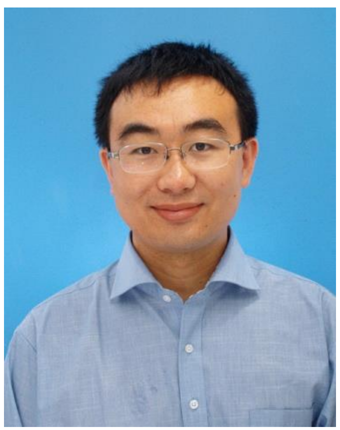
Japan, the Asian adventure

Andrzej Cichocki

Toshihisa Tanaka

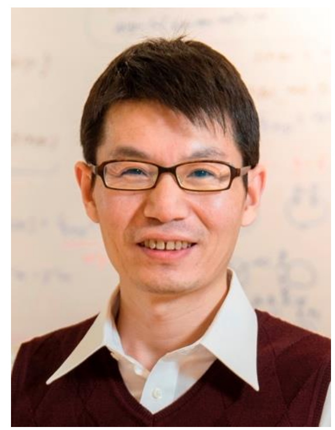
François Vialatte

Tomek Rutkowski



Zhe Sun

Cesar Caiafa



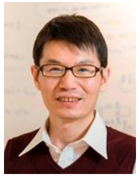
Qibin Zhao.

Ruggero Micheletto

From my experience…

Grenoble
(France)

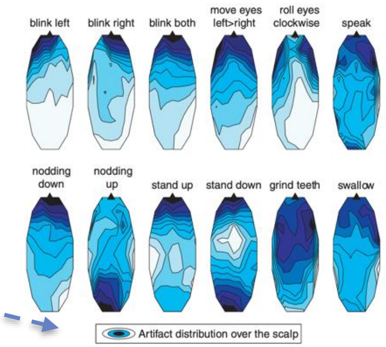
Tokyo
(Japan)

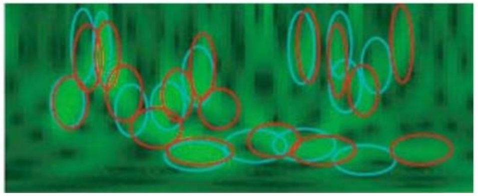


Scientific contributions from my research in Japan

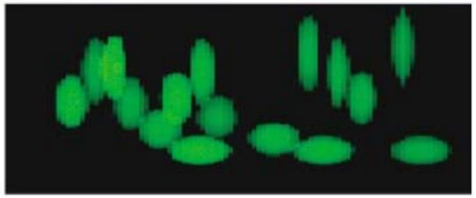
1. EEG denoising, artifact detection

- The laboratory was focused on brain signal processing, therefore artifact detection and denoising was a hot topic:
  - Wavelet-based methods ICASSP 2007
    2008 *Physiol. Meas.* **29** 1435
  - ICA-based methods Biosignals 2008
  - Bump time frequency modelling ICONIP 2008
    2009 *BMC Neuroscience* **10**

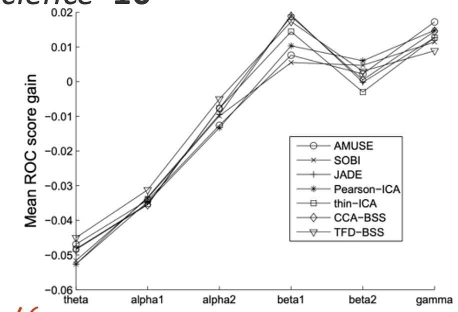




Wavelet representation



Sparse bump model



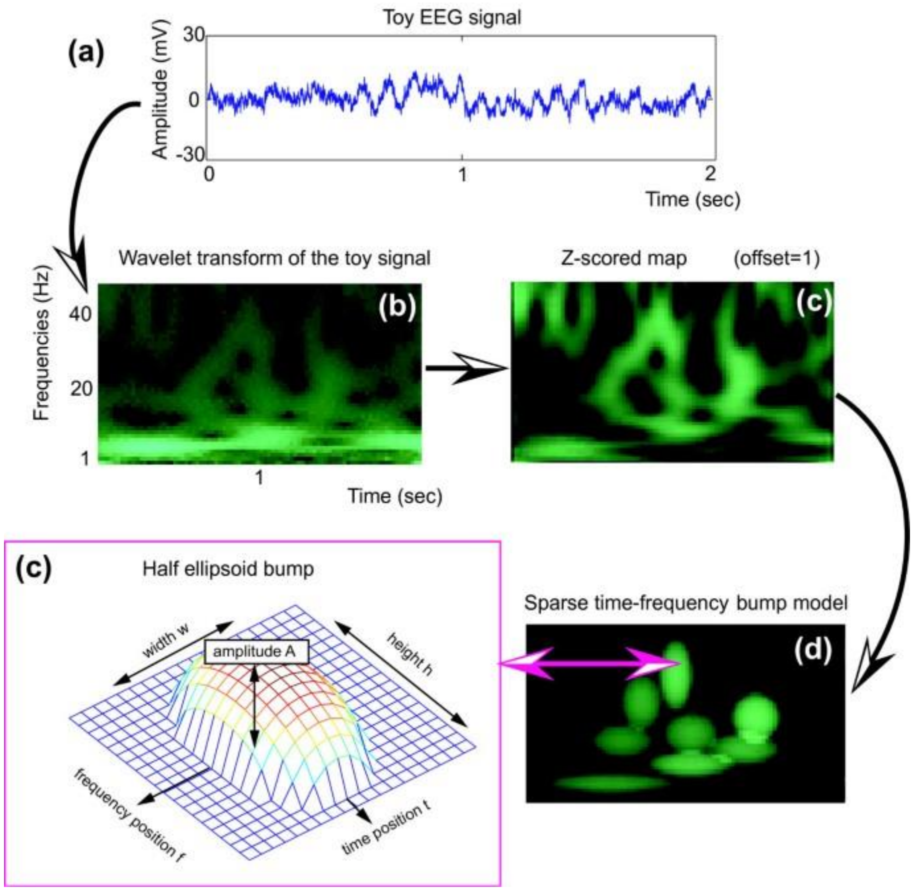
https://doi.org/10.1109/ICASSP.2007.367281 https://doi.org/10.1088/0967-3334/29/12/007 https://doi.org/10.1186/1471-2202-10-46

Scientific contributions from my research in Japan

1. EEG denoising, artifact detection

(a) The EEG signal, recorded in rest condition with eyes closed, is first (b) transformed using complex Morlet wavelets, then (c) the map is z-scored.

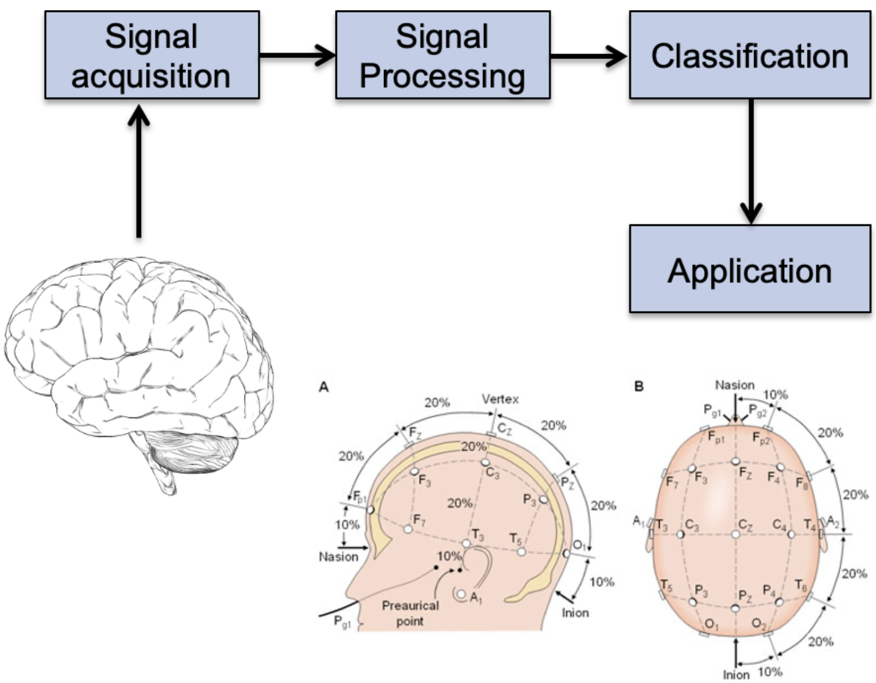
Sparse time-frequency bump modelling decomposes the z-scored map into a sum (d) of half ellipsoid (c) parametric functions (pruned to the 8 first bumps).



https://doi.org/10.1186/1471-2202-10-46

Scientific contributions from my research in Japan

2. Early detection of Alzheimer’s Disease



a) Parameterize the EEG signals with different measures:
- Power measure
- Synchrony measures

Select the best frequency range

b) Use these features to build a classifier:
- Each measure Individually
- Selecting the best measures and frequency ranges

c) Help medical doctors to improve Alzheimer’s Disease diagnosis

https://doi.org/10.1088/1741-2560/12/1/016018

Scientific contributions from my research in Japan

2. Early detection of Alzheimer's Disease

Power Measure: Relative Power

$$RP_i\,(f_1,f_2)=\frac{P_i(f_1,f_2)}{P_i(f_{min},f_{max})}$$

Synchrony Measures

- Bivariate Measures

  Correlation

$$r=\frac{1}{N}\sum_{k=1}^{N}\frac{(x(k)-\tilde{x})}{\sigma_x}\frac{(y(k)-\tilde{y})}{\sigma_y}$$

  Coherence

$$c^2(f)=\frac{|\langle X(f)Y^*(f)\rangle|^2}{|\langle X(f)\rangle||\langle Y(f)\rangle|}$$

  Phase Synchrony

$$\gamma=\left|\langle e^{i(n\phi_x-m\phi_y)}\rangle\right|$$

- Multivariate Measures

  Granger Causality

  Omega Complexity

$$\Omega=\exp\left(-\sum_{i=1}^{n}\lambda_i\log\lambda_i\right)$$

https://doi.org/10.1088/1741-2560/12/1/016018

Scientific contributions from my research in Japan

2. Early detection of Alzheimer's Disease

Granger Coherence: $$K_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)}\sqrt{S_{ij}(f)}}$$

Partial Coherence: $$C_{ij}(f) = \frac{M_{ij}(f)}{\sqrt{M_{ii}(f)}\sqrt{M_{ij}(f)}}$$

Directed Transfer Function: $$\gamma_{ij}^2(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{j=1}^{m}\left|H_{ij}(f)\right|^2}$$

Full Frequency Directed Transfer Function: $$F_{ij}^2(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_f \sum_{j=1}^{m}\left|H_{ij}(f)\right|^2}$$

Partial Directed Coherence: $$P_{ij}(f) = \frac{\tilde{A}_{ij}(f)}{\sqrt{\sum_{i=1}^{m}\left|\tilde{A}_{ij}(f)\right|^2}}$$

Direct Directed Transfer Function: $$\chi_{ij}^2(f) = F_{ij}^2(f)C_{ij}^2(f)$$

https://doi.org/10.1088/1741-2560/12/1/016018

Scientific contributions from my research in Japan

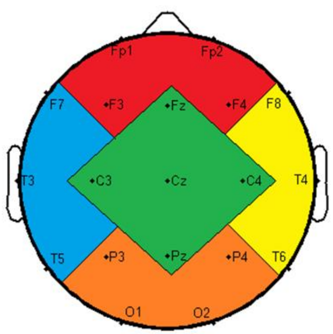
2. Early detection of Alzheimer’s Disease

All the 11 measures are calculated in the following 435 different frequency ranges (from F to F+W):

$$W \in \mathbb{N}[1{,}29] \quad \begin{bmatrix} 1-2 & & & & & \\ 1-3 & 2-3 & & & & \\ 1-4 & 2-4 & 3-4 & & & \\ \vdots & \vdots & \vdots & \ddots & & \\ 1-29 & 2-29 & 3-29 & & 28-29 & \\ 1-30 & 2-30 & 3-30 & \cdots & 28-30 & 29-30 \end{bmatrix}$$

$$F \in \mathbb{N}[1{,}29]$$

- 5 Regions were defined.
- Local synchrony was computed between electrodes of the same region.
- Global synchrony was computed averaging the local synchrony.



MCI data set

Measure Number	Measure	Frequency Range (Hz)
1	Relative Power	2 – 8
2	Correlation	3 – 8
3	Coherence	1 – 6
4	PDC	1 – 3

CR: 81,67 %

Mild AD data set

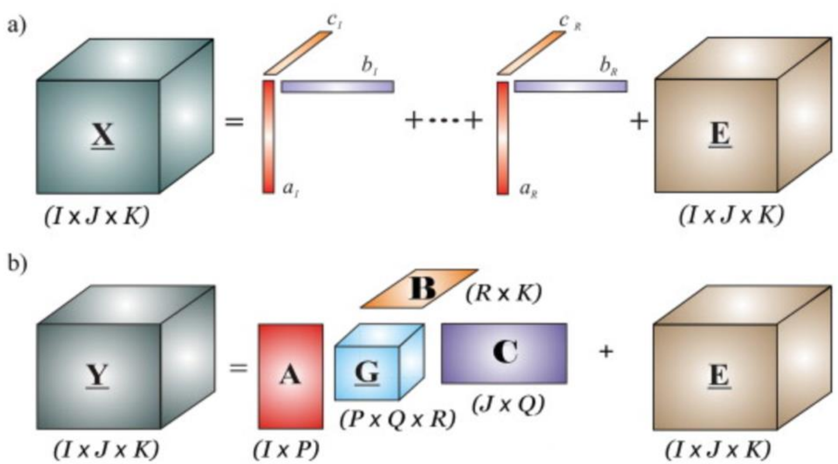
Measure Number	Measure	Frequency Range (Hz)
1	Relative Power	4 – 7
2	Granger Coherence	1 – 2
3	Correlation	9 – 10
4	Phase Synchrony	25 – 26
5	Partial Coherence	13 – 14

CR: 100 %

https://doi.org/10.1088/1741-2560/12/1/016018

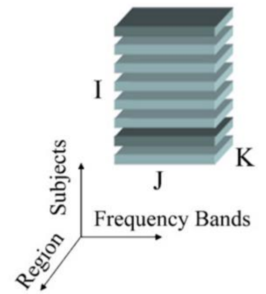
Scientific contributions from my research in Japan

3. Tensor (multi-array) decomposition of EEG



(a) Candecom/PARAFAC decomposition assumes that the data is composed of a few basic patterns that combine linearly
(b) NTD (Non-negative Tensor Decomposition) allows for non-linear interactions

Each subject's EEG is stored as a matrix of frequency band powers across brain regions. Multiple subjects together form a 3D tensor:



EEG Tensor =
(Subjects × Frequency Bands × Brain Regions)

- Subjects = Each person's EEG recording.
- Frequency Bands = Power in different EEG frequency ranges (5)
- Brain Regions = EEG power from different brain areas (5).

https://doi.org/10.1016/j.jneumeth.2012.03.005

Scientific contributions from my research in Japan

3. Tensor (multi-array) decomposition of EEG

The encoding variable matrix is obtained from Database A. Using the features extracted from Database A, we train MLPs and selected the best model

SSF on ICA processed data	Training Validation	97.4% **87.8%**
PARAFAC	Training Validation	97.6% **92.7%**
Tucker3	Training Validation	97.6% **92.7%**
NTD	Training Validation	97.6% **97.6%**

Using the features extracted from Database B, we regularize the best MLP and the best MLP is selected.

The regularized MLP is finally test using the features extracted from the Database C.

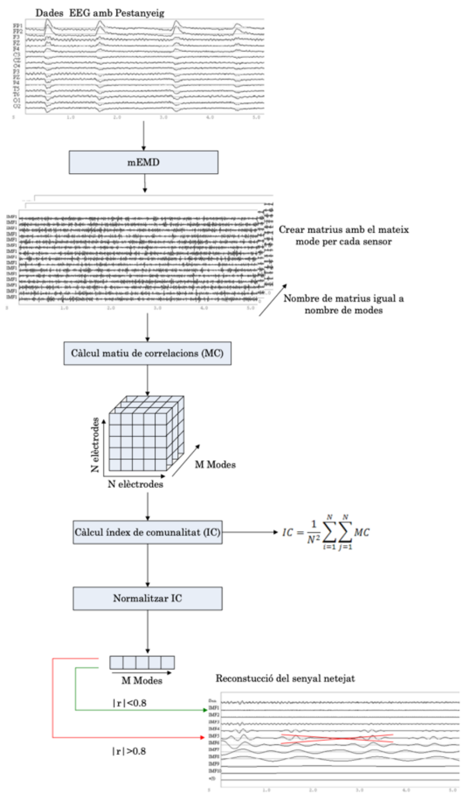
	Database A		Database B	Database C
	Training	Validation	Regulation	Test
SSF				
Accuracy (%)	97.4%	87.8%	90.0%	100%
RMSE	0.16	0.30	0.31	0.19
PARAFAC				
Accuracy (%)	**97.6%**	**92.7%**	**90.0%**	**100%**
RMSE	**0.15**	**0.30**	**0.30**	**0.11**
Tucker3				
Accuracy (%)	97.4%	92.7%	**90.0%**	100%
RMSE	0.16	0.30	**0.27**	0.20
NTD				
Accuracy (%)	**97.6%**	**97.6%**	90.0%	**100%**
RMSE	**0.16**	**0.20**	0.31	**0.13**

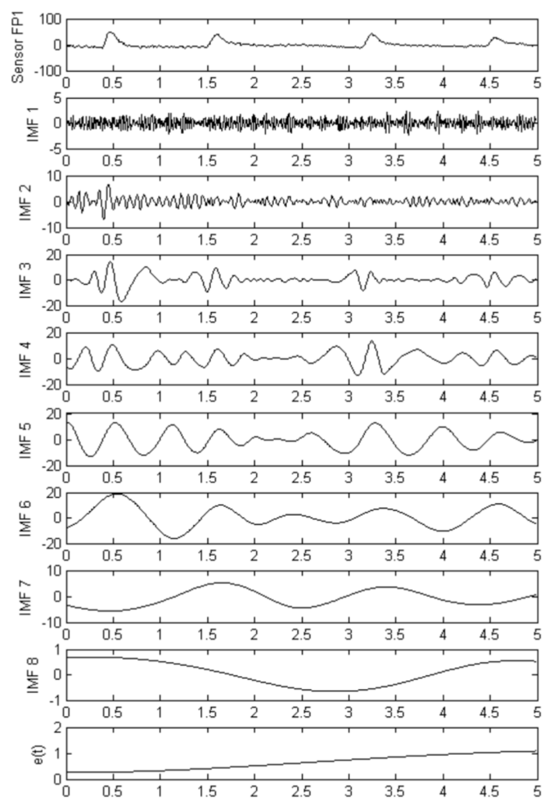
https://doi.org/10.1016/j.jneumeth.2012.03.005

Scientific contributions from my research in Japan

4. EMD decomposition and its applications: artifact detection

$$x(t) = \sum_{k=1}^{M} \mathrm{IMF}_k(t) + \varepsilon_n(t)$$





Classification Rates:

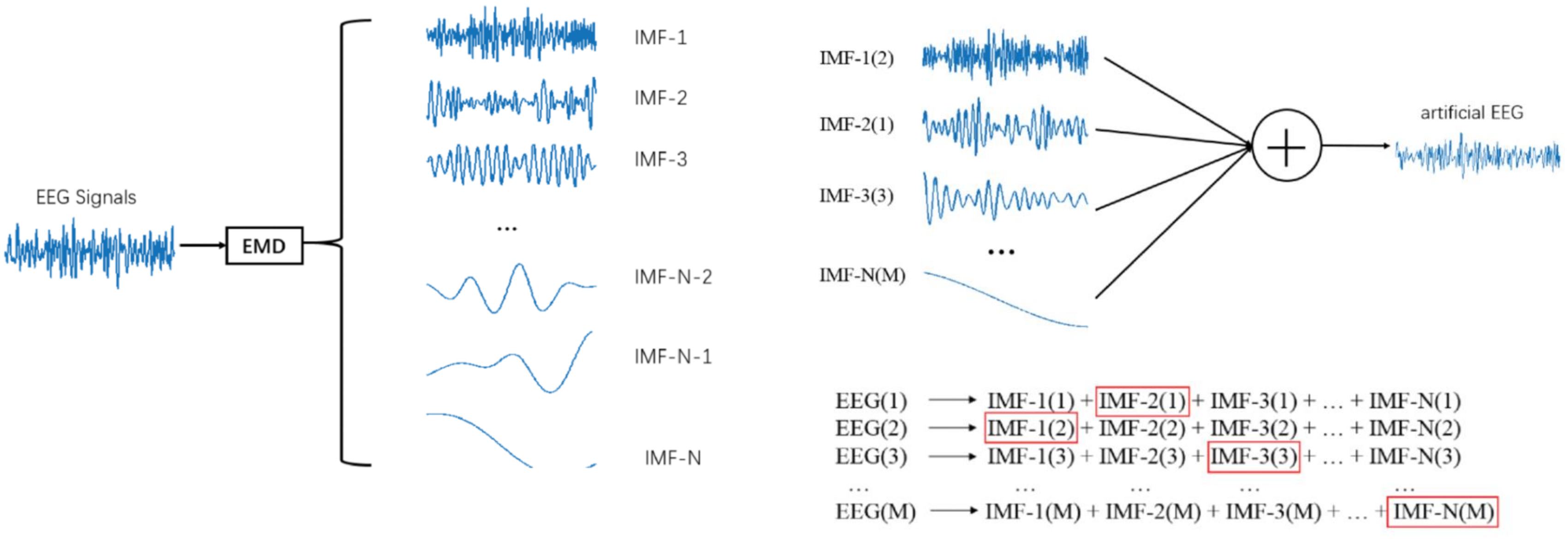
- LDA:
  Raw data 56.67%
  cleaned data 76.67%

- NN:
  Raw data: 58.89%
  Clean data: 80%

Improvement of 20% (LDA) and 21.11% (NN).

Scientific contributions from my research in Japan

4. EMD decomposition and its applications: data augmentation



https://doi.org/10.3389/fnins.2018.00308 https://doi.org/10.1109/ACCESS.2019.2895133

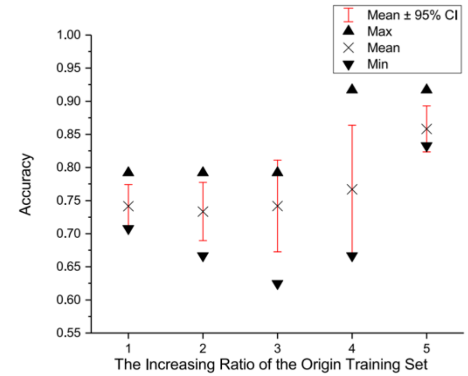
Scientific contributions from my research in Japan

4. EMD decomposition and its applications: data augmentation

	S01		S02		S03		S04		S05		S06		S07	
AF[1]	R[2]	L[3]	R	L	R	L	R	L	R	L	R	L	R	L
2.5	0.12	0.67	0.22	0.64	0.58	1.27	0.32	0.31	0.32	0.27	0.33	0.64	0.34	0.69
5.0	0.05	1.03	0.82	0.56	1.11	1.02	0.46	0.45	0.18	0.35	0.47	0.83	0.01	0.63
7.5	0.29	0.88	1.03	0.07	1.06	1.51	0.51	0.51	0.00	0.02	1.17	1.49	0.46	0.62
10.0	0.37	1.13	0.99	0.11	1.19	1.75	0.80	0.46	0.38	0.08	1.04	1.66	0.49	0.84
12.5	0.24	0.94	1.42	0.04	1.89	1.86	1.00	0.44	0.46	0.27	0.87	1.52	0.40	0.85
25.0	0.09	1.44	2.79	0.44	2.13	1.94	1.28	0.61	0.96	0.78	0.71	2.09	0.51	1.28
37.5	0.11	1.55	3.12	0.41	1.97	2.01	1.20	0.69	1.07	1.18	0.57	2.66	0.73	1.92
50.0	0.15	1.45	2.86	1.00	2.18	2.68	1.27	1.06	1.42	1.23	0.62	2.76	0.73	1.86

[1] AF: % of artificial frames in the classifier
[2] R: R proportion for the right side
[3] L: R proportion for the left side

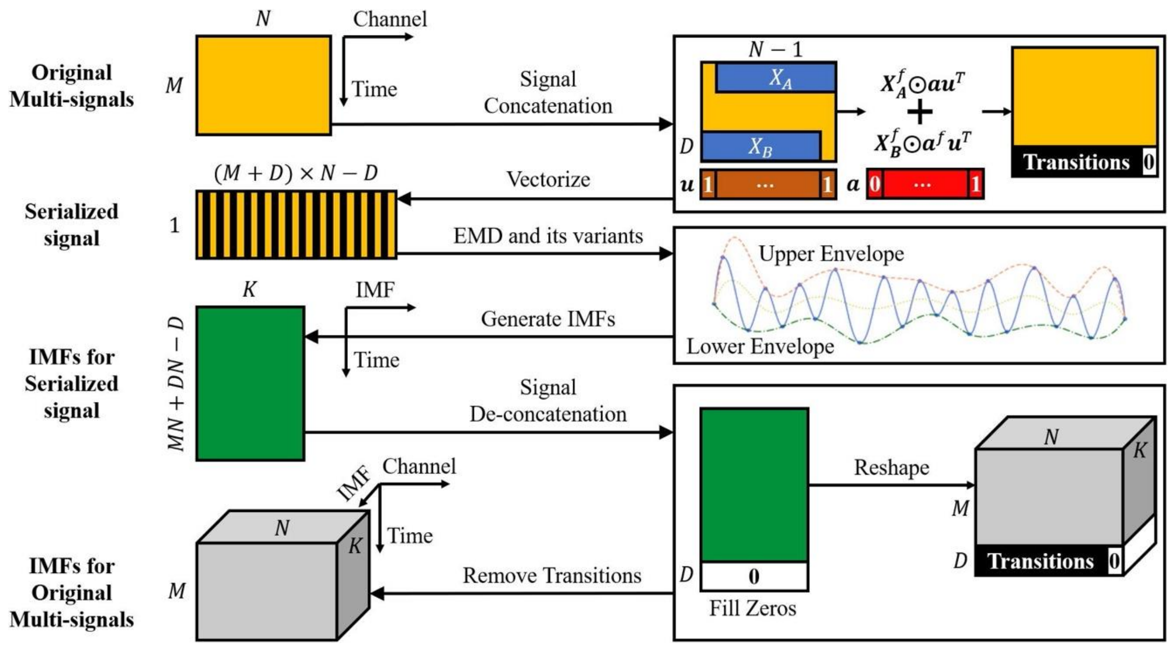
R: measure of dispersion

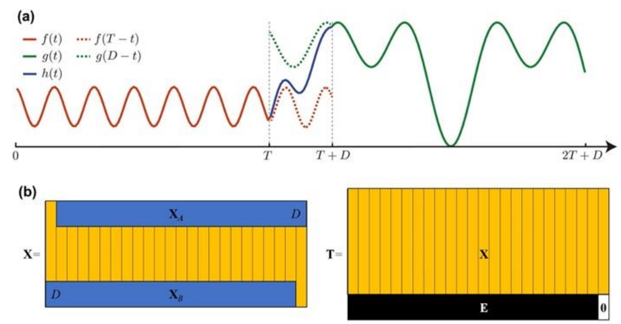


https://doi.org/10.3389/fnins.2018.00308 https://doi.org/10.1109/ACCESS.2019.2895133

Scientific contributions from my research in Japan

4. EMD decomposition and its applications: fast decomposition by serialisation





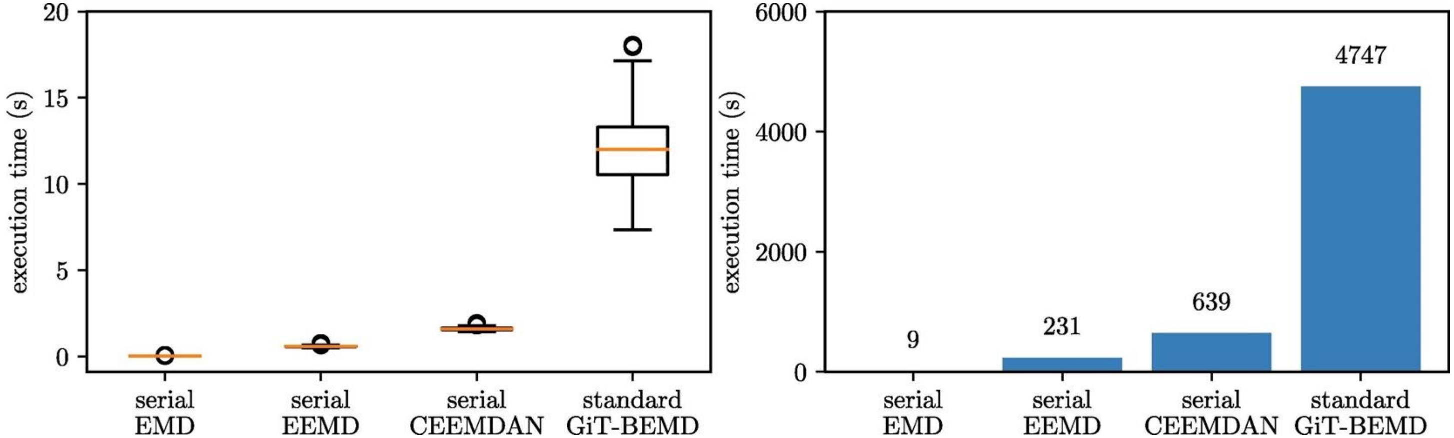
$$s(t) = \begin{cases} f(t) & t \in [0, T] \\ h(t-T) & t \in [T, T+D] \\ g(t-T-D) & t \in [T+D, 2T+D] \end{cases}$$

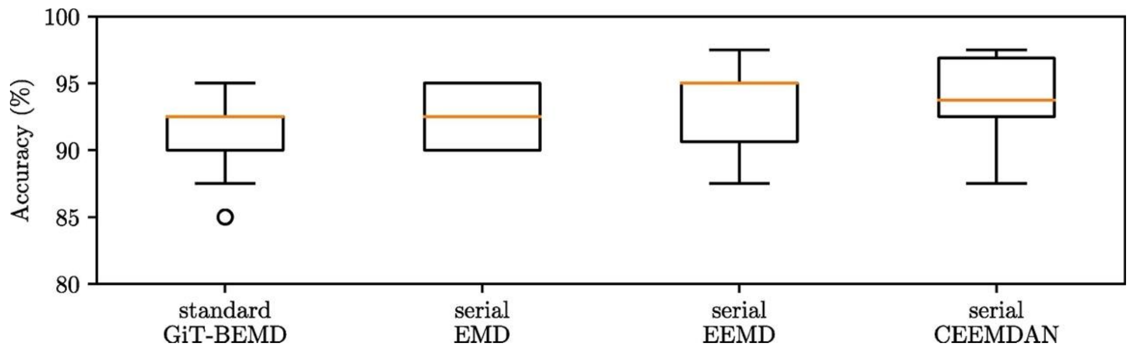
$$h(t) = \left(1 - \tfrac{t}{D}\right) f(T-t) + \tfrac{t}{D} g(D-t)$$

https://doi.org/10.1016/j.ins.2021.09.033

Scientific contributions from my research in Japan

4. EMD decomposition and its applications: fast decomposition by serialisation

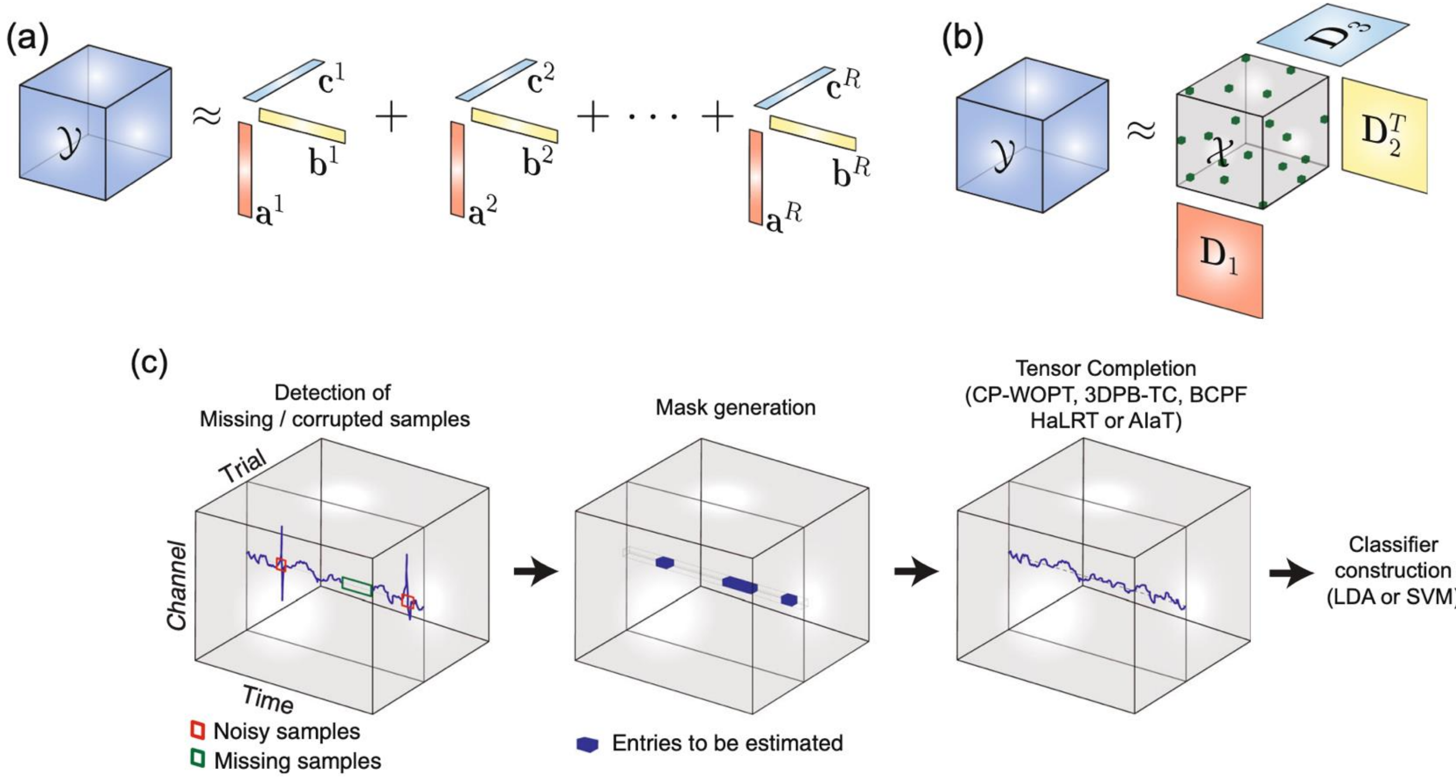




https://doi.org/10.1016/j.ins.2021.09.033

Scientific contributions from my research in Japan

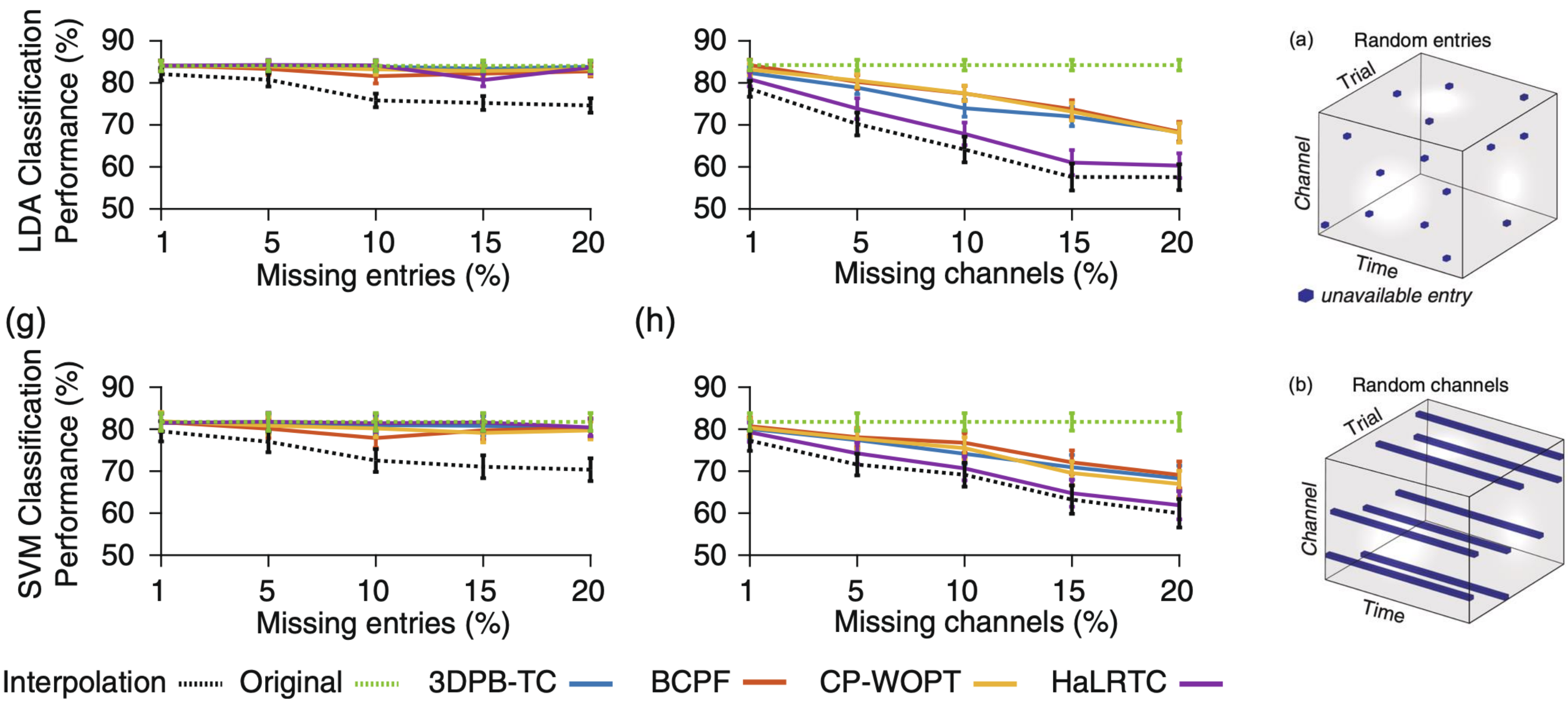
5. Tensor completion



https://doi.org/10.1007/s12559-018-9574-9

Scientific contributions from my research in Japan

5. Tensor completion

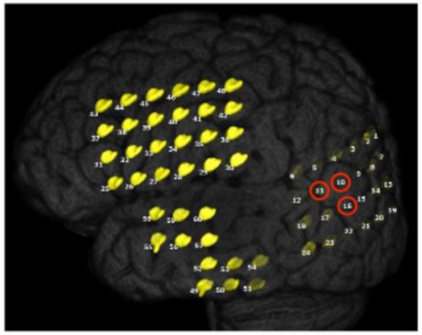


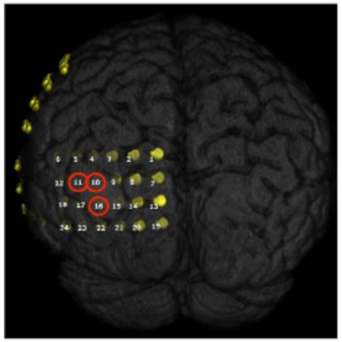
https://doi.org/10.1007/s12559-018-9574-9

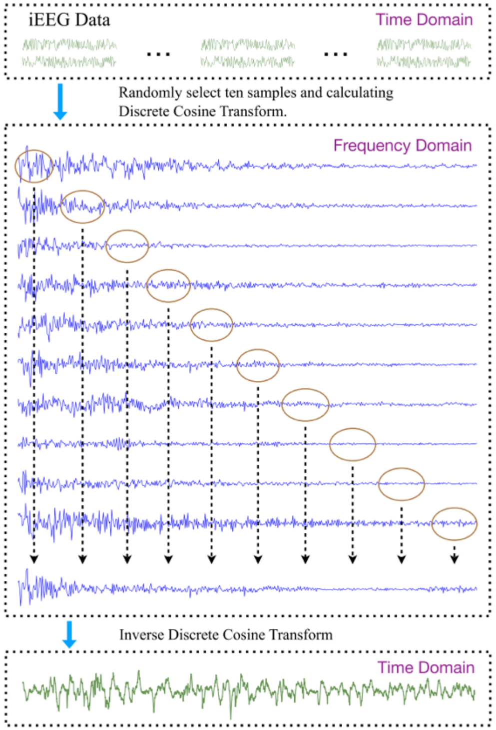
Scientific contributions from my research in Japan

6. Epilepsy

After we met in 2003, I resumed my collaboration with Dr Toshihisa Tanaka in 2019, working on iEEG and EEG data for epilepsy detection:





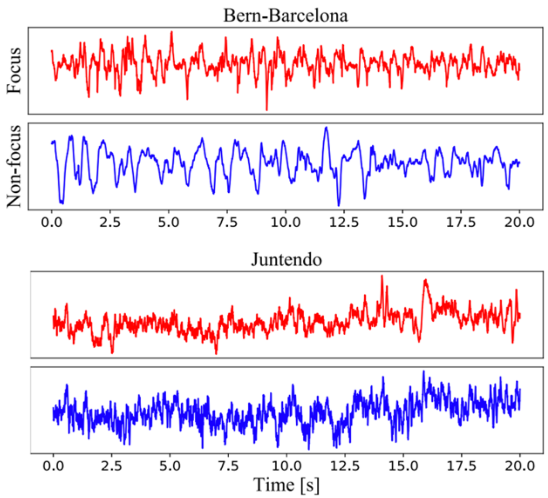


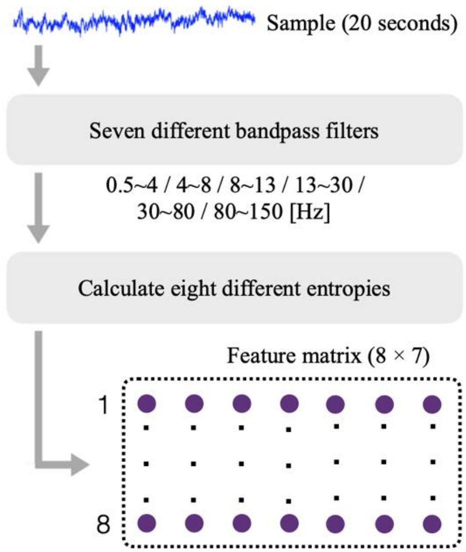
	Augmentation methods	Loss functions	Acc
P1	No Use	CB-Focal	97.32
	EEGAug	CE	97.55
	SMOTE	CE	95.75
	ADASYN	CE	96.16
P2	No Use	CB-Focal	83.50
	EEGAug	CE	87.61
	SMOTE	CE	83.80
	ADASYN	CE	81.07
P3	No Use	CB-Focal	89.95
	EEGAug	CE	86.97
	SMOTE	CE	80.43
	ADASYN	CE	81.56
P4	No Use	CB-Focal	95.51
	EEGAug	CE	93.96
	SMOTE	CE	83.02
	ADASYN	CE	88.88
P5	No Use	CB-Focal	91.56
	EEGAug	CE	93.04
	SMOTE	CE	84.65
	ADASYN	CE	86.22
P6	No Use	CB-Focal	74.89
	EEGAug	CE	68.90
	SMOTE	CE	54.83
	ADASYN	CE	59.54

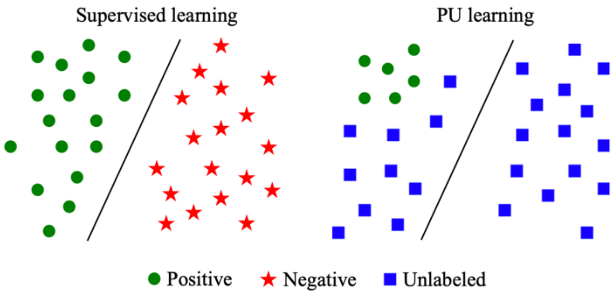
https://doi.org/10.1088/1741-2552/aca04f

Scientific contributions from my research in Japan

6. Epilepsy







positive unlabeled (PU) learning

Reference	Method	Annotation Ratio (%)	Avoids Hard Sample	Accuracy (%)
Acharya et al. (2019)	Bispectrum, LS-SVM	100	✗	87.93
Borowska (2021)	Lempel-Ziv, LS-SVM	100	✗	86
Gupta and Pachori (2019)	EMD, LS-SVM	100	✗	83.12
Proposed	STFT, CNN	100	✗	88.14
	Entropy, FCNN	100	✗	80.06
	Entropy, FCNN & PU	15.87	✓	76.91

https://doi.org/10.1007/s11571-022-09857-4

Scientific contributions from my research in Japan

- Starting conditions:
  - Scared (again)
  - Knowing nobody (again)
  - No precise idea of what I would do
  - No knowledge about Japanese language and culture
  - … But excited for this opportunity!

Scientific contributions from my research in Japan

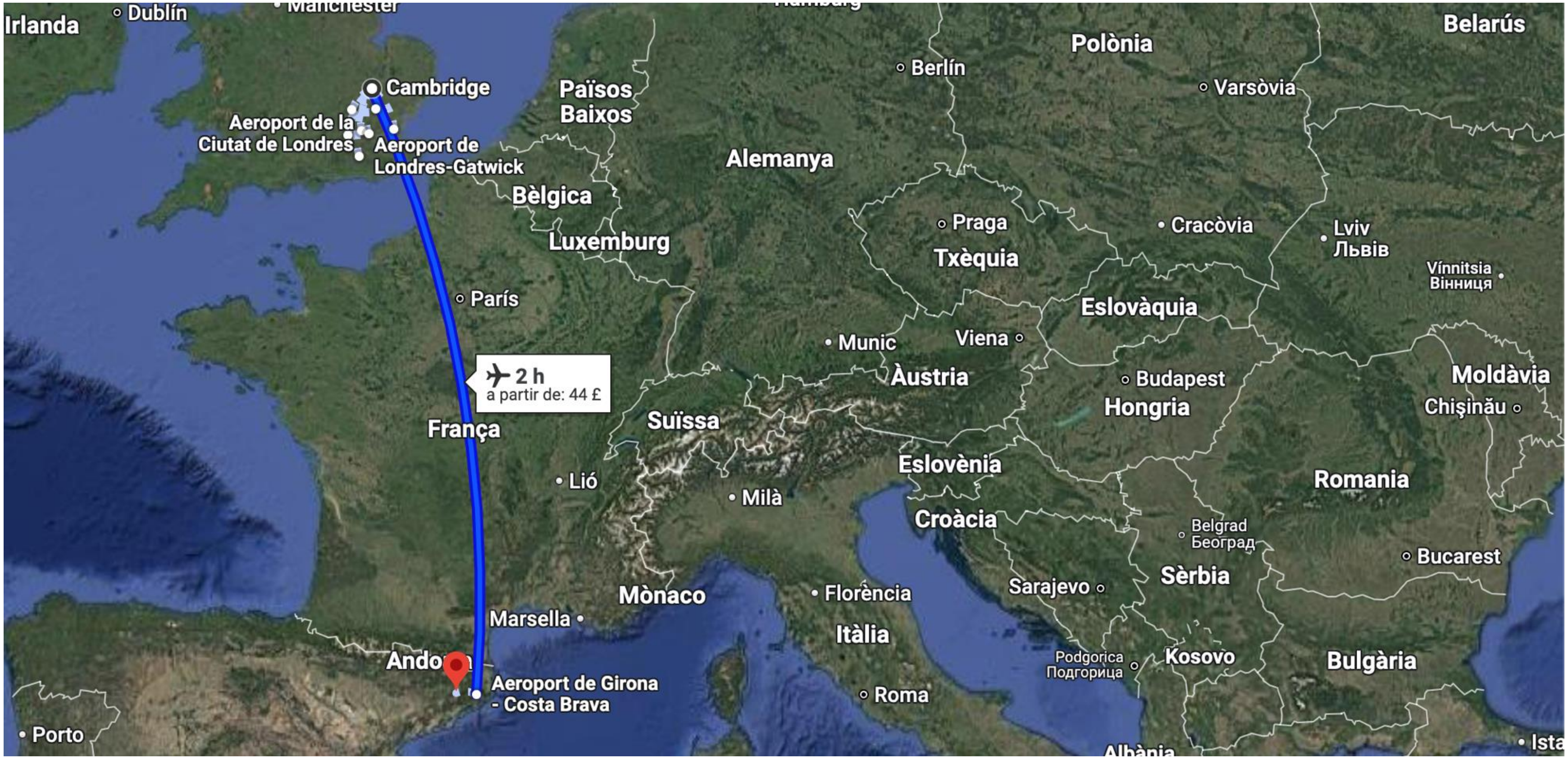
- Final conditions:
  - Happy
  - With a lot of friends
  - With the clear idea that applied science is what I like
  - But still no idea of Japanese language!
  - ... and still visiting Japan

Cambridge, closing the circle

- Dr Sophie Achard (Grenoble) invited me to visit the Brain Mapping Unit (BMU) at the Department of Psychiatry of the University of Cambridge (UK), while she was a postdoc there:
  - I applied for grants
  - We visited Cambridge for a 5 weeks stay (2009)
  - Then, we repeated for a 3 months stay (2014)
  - Finally, for 7 months (2016)
  - …And we are still visiting it regularly!

- Here I started to work on connectivity analysis with MRI/fMRI.
- Then, I also used this knowledge to reanalyse EEG data.

Cambridge, closing the circle



Cambridge, closing the circle

Ed Bullmore

Sophie Achard

B M U

Rafa Romero

Javier Bernacer

Cambridge, closing the circle

Ed Bullmore

Sophie Achard

B M U

Rafa Romero

Javier Bernacer

Cambridge, closing the circle

Ed Bullmore

Sophie Achard

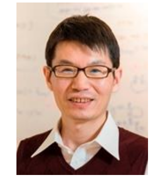
B M U

Rafa Romero

Javier Bernacer

From my experience…

Grenoble
(France)



Tokyo
(Japan)

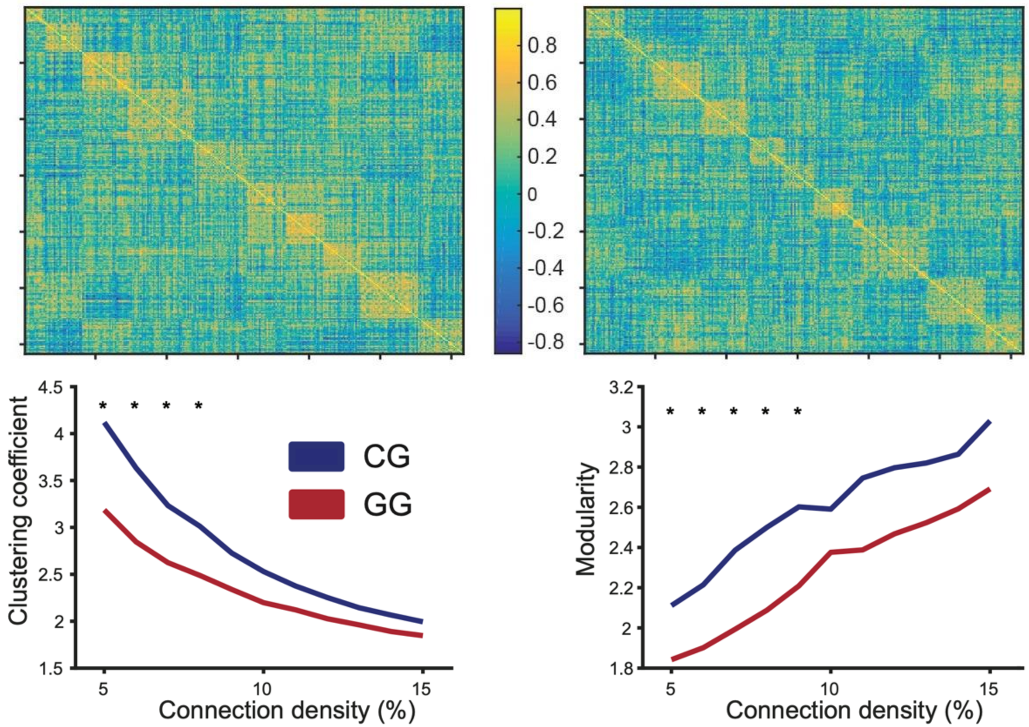
Cambridge
(United Kingdom)

Sevilla, Pamplona
(Spain)

Scientific contributions from my research in Cambridge

1. Structural covariance analysis of MRI

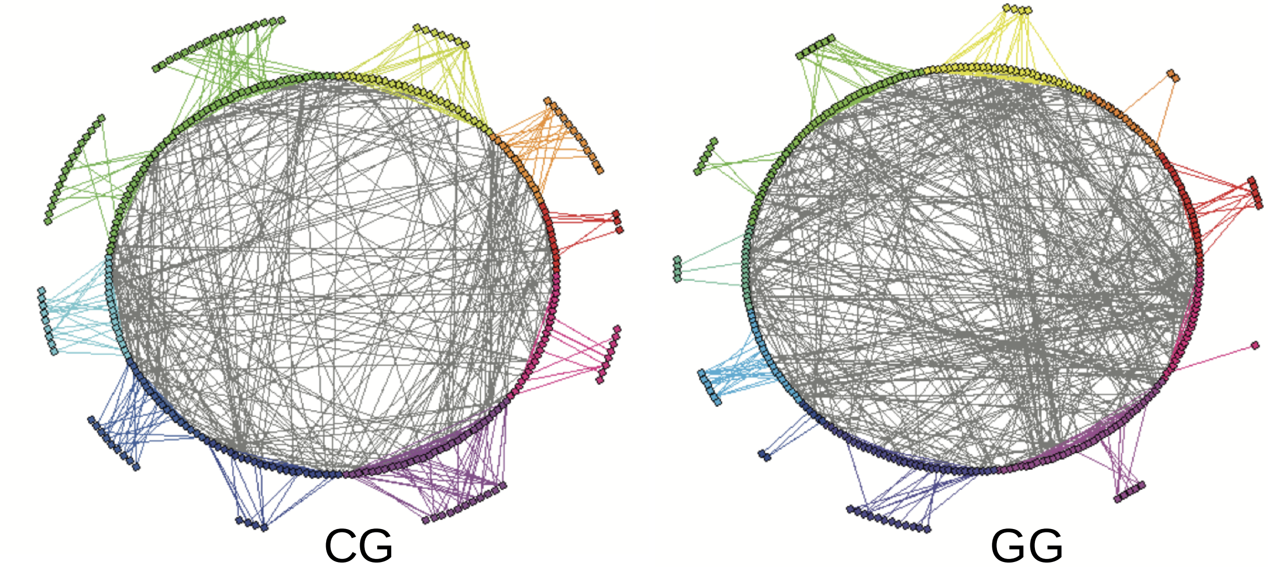
- Control Group (CG): n=14, age=12.53 ±0.77, IQ=122.71 ±3.89
- Gifted Group (GG): n=15, age=12.03 ±0.54, IQ=148.80 ±2.93
- Mean cortical thickness was used to compute the structural covariance matrices.

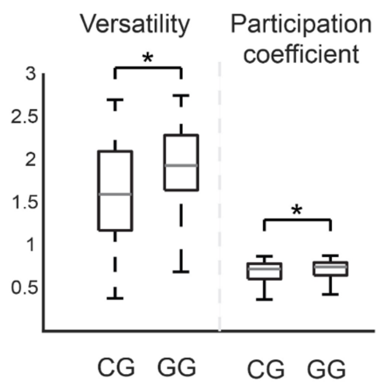


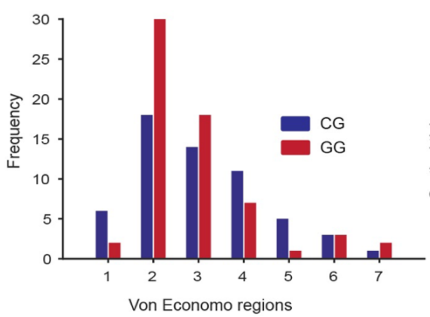
(A) Clustering coefficient (B) Modularity

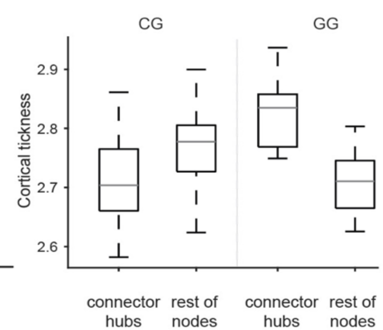
https://doi.org/10.1007/s00429-019-01914-9

Scientific contributions from my research in Cambridge







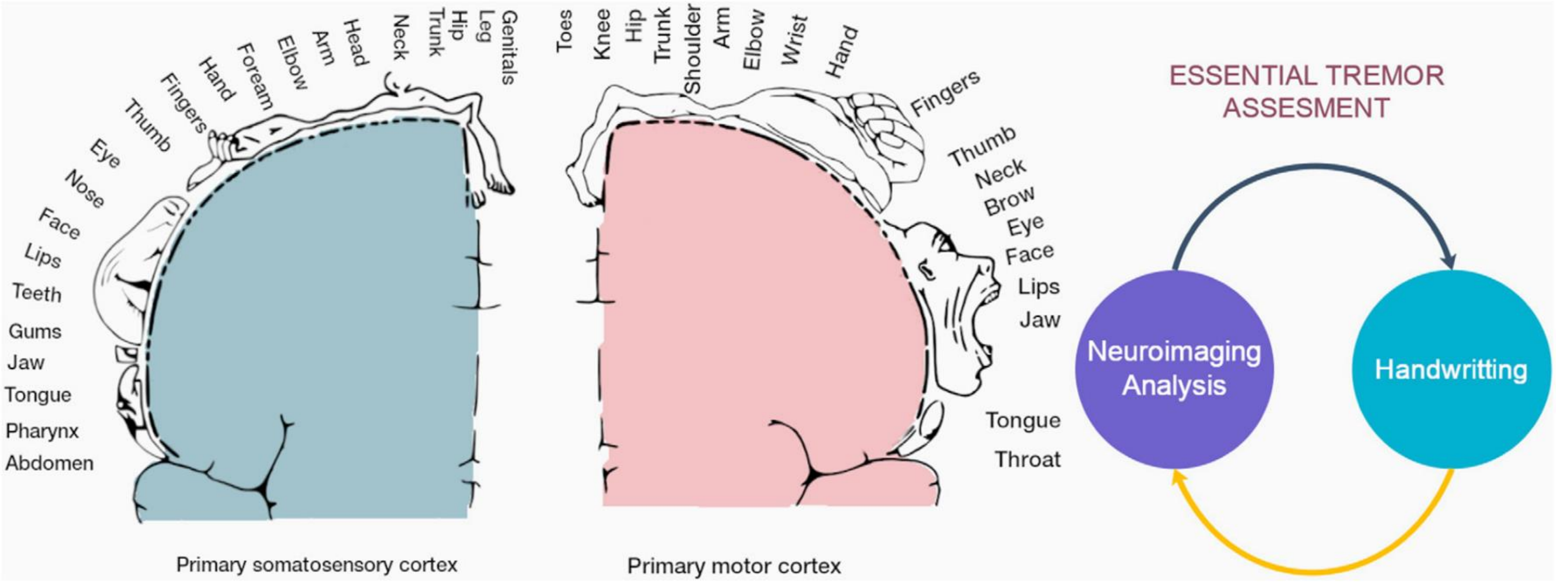


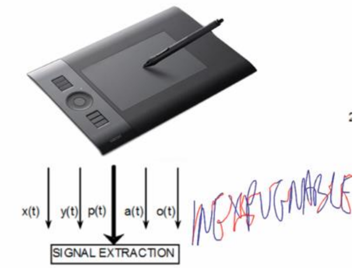
- We found that the gifted group network was more integrated (and less segregated) than the control group network.
- Connector hubs of the networks of both groups were located mainly in association with neocortical areas.
- In the group of gifted children, a larger proportion of connector hubs were located in association cortex.
- In conclusion, gifted children have a more integrated and versatile brain network topology.

https://doi.org/10.1007/s00429-019-01914-9

Scientific contributions from my research in Cambridge

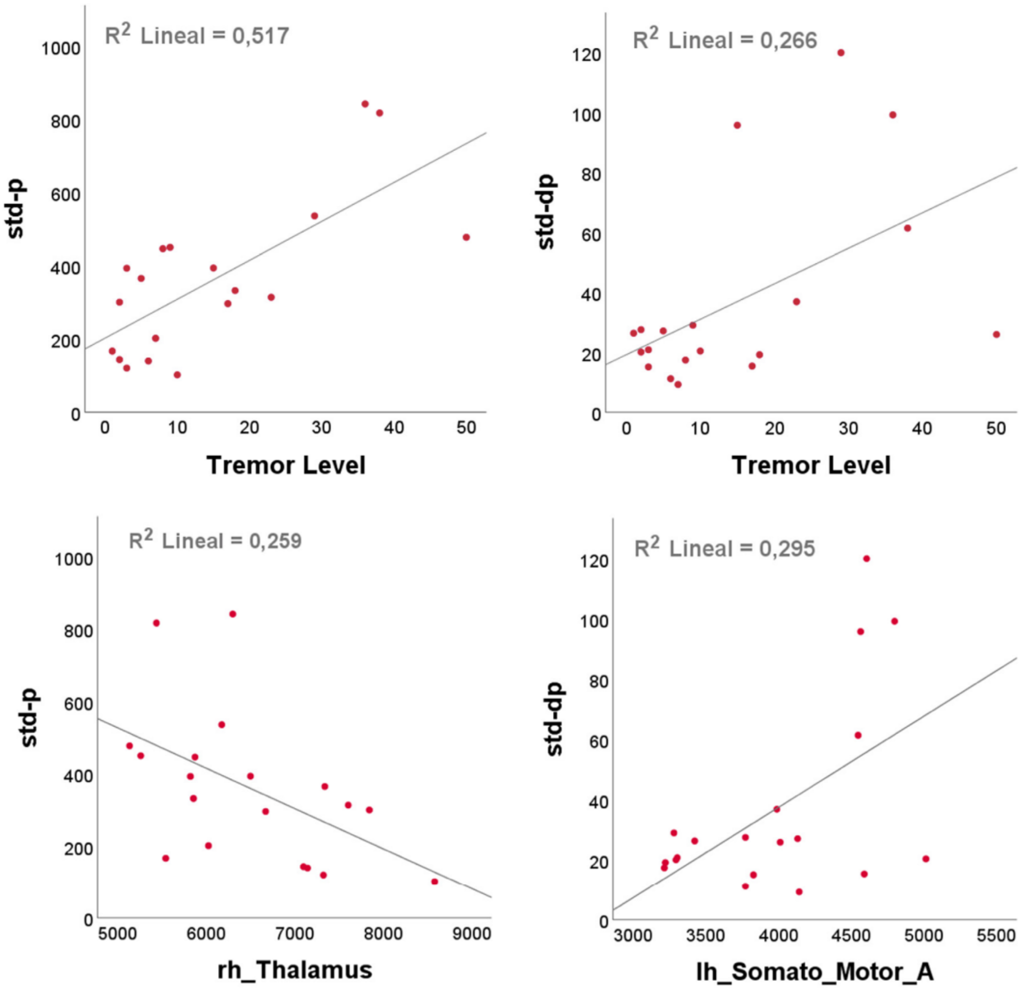
2. Analysis of fine motor skills in essential tremor (ET)





https://doi.org/10.3389/fnhum.2021.648573

Scientific contributions from my research in Cambridge



Our study showed:

(i) Association between tremor level with pressure and its variations;

(ii) Correlation of tremor level to brain structure in several areas of the motor cortex (specifically, differences in cortical volume and cortical thickness);

(iii) Correlation among fine movement skills, pressure, and variations to subcortical areas, thalamus, ganglia, and cerebellum

Scientific contributions from my research in Cambridge

- Starting conditions:
  - Confident
  - Knowing Sophie
  - With a clear idea of what to do
  - Sufficient knowledge of English language
  - And, again, excited for this opportunity!

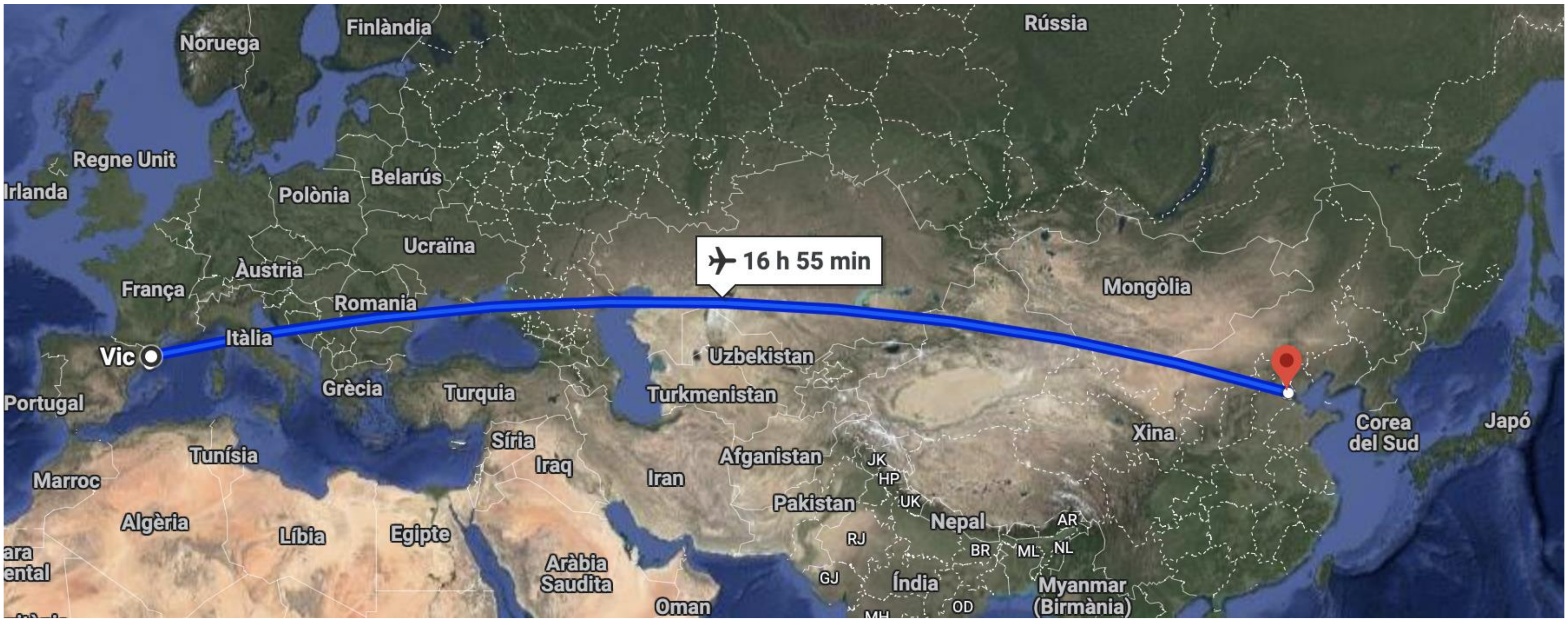
Scientific contributions from my research in Cambridge

- Final conditions:
  - Happy
  - With a lot of friends
  - With new knowledge to analyse brain data
  - With a Visiting Researcher position since 2016
  - ... and still visiting Cambridge

And then… China!

- Dr Sun Zhe (Japan) put me in contact with Prof. Duan Feng, from Nankai University, in Tianjin (China).
- I visited Nankai University for the first time in 2019.
- Since then, we have collaborated trough PhD students.
- I have co-supervised 1 PhD student from Nankai University, together with Dr Sun Zhe and Dr Cesar Caiafa, and 2 more are in progress.
- I currently have two visiting PhD students from Nankai University in my group.
- We plan to continue our collaboration in the future.

And then… China!



And then… China!

Duan Feng

Yang Zhenglu

Toshi Sun

Zhang Jin

Jia Hao

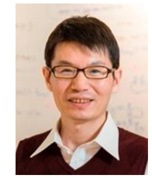
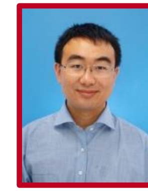
Yong Liu

From my experience…


Grenoble
(France)

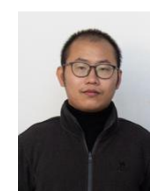
Tokyo
(Japan)



Tianjin
(China)



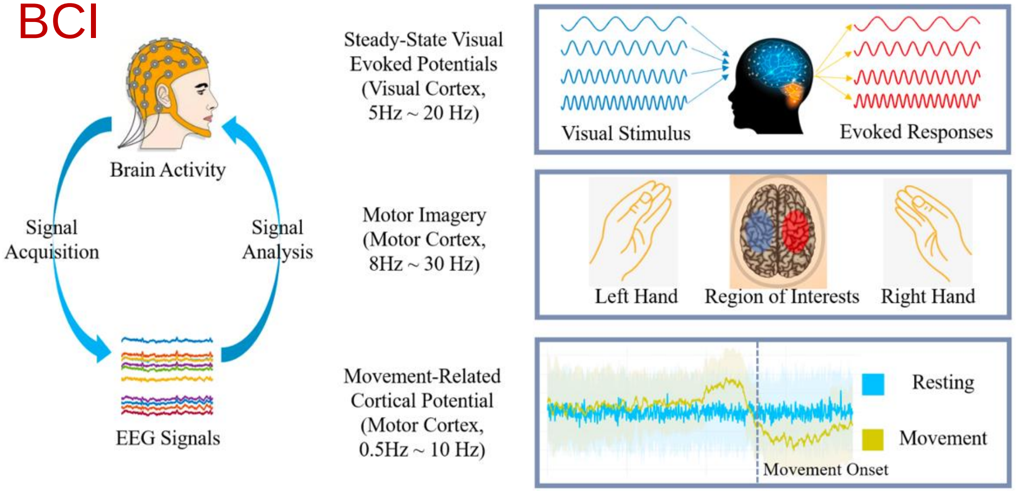


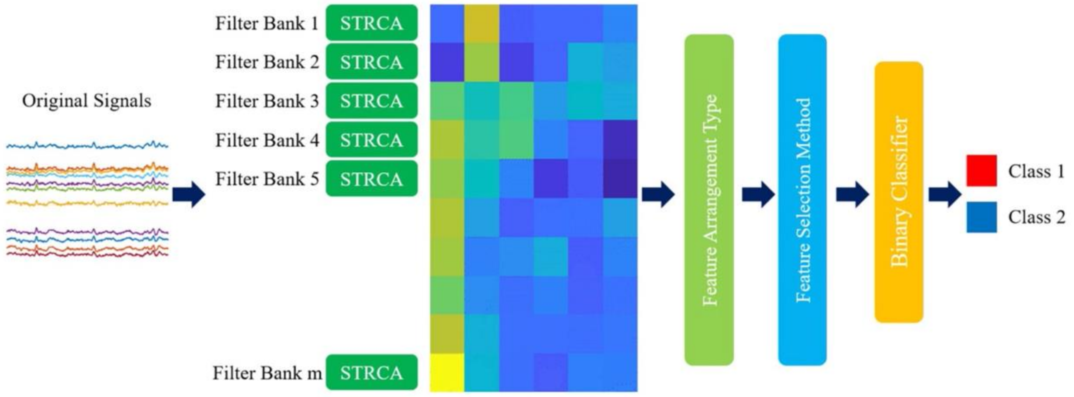
Cambridge
(United Kingdom)

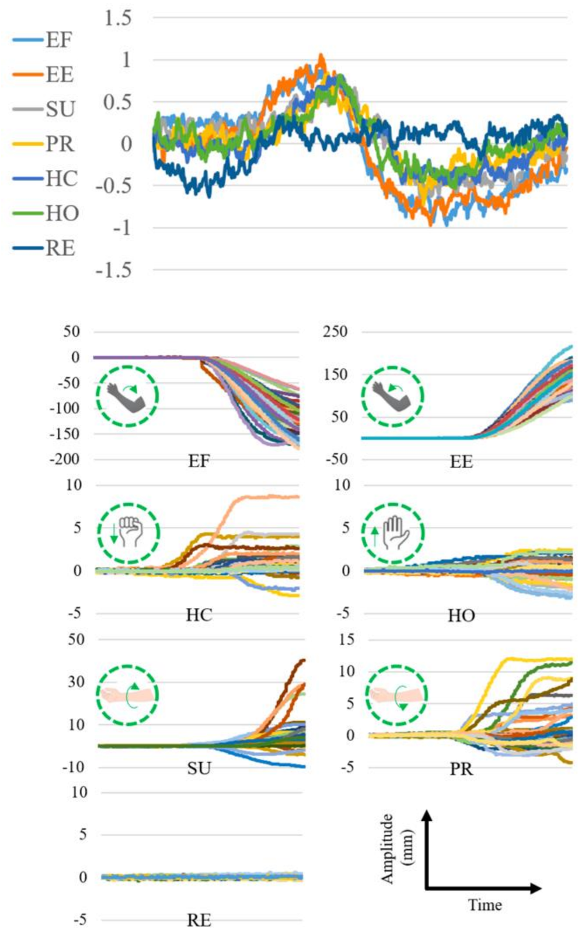

Sevilla, Pamplona
(Spain)

Scientific contributions from my research in China

BCI







https://doi.org/10.1109/JBHI.2023.3278747 https://doi.org/10.1007/s00429-019-01914-9 https://doi.org/10.1016/j.engappai.2024.108473

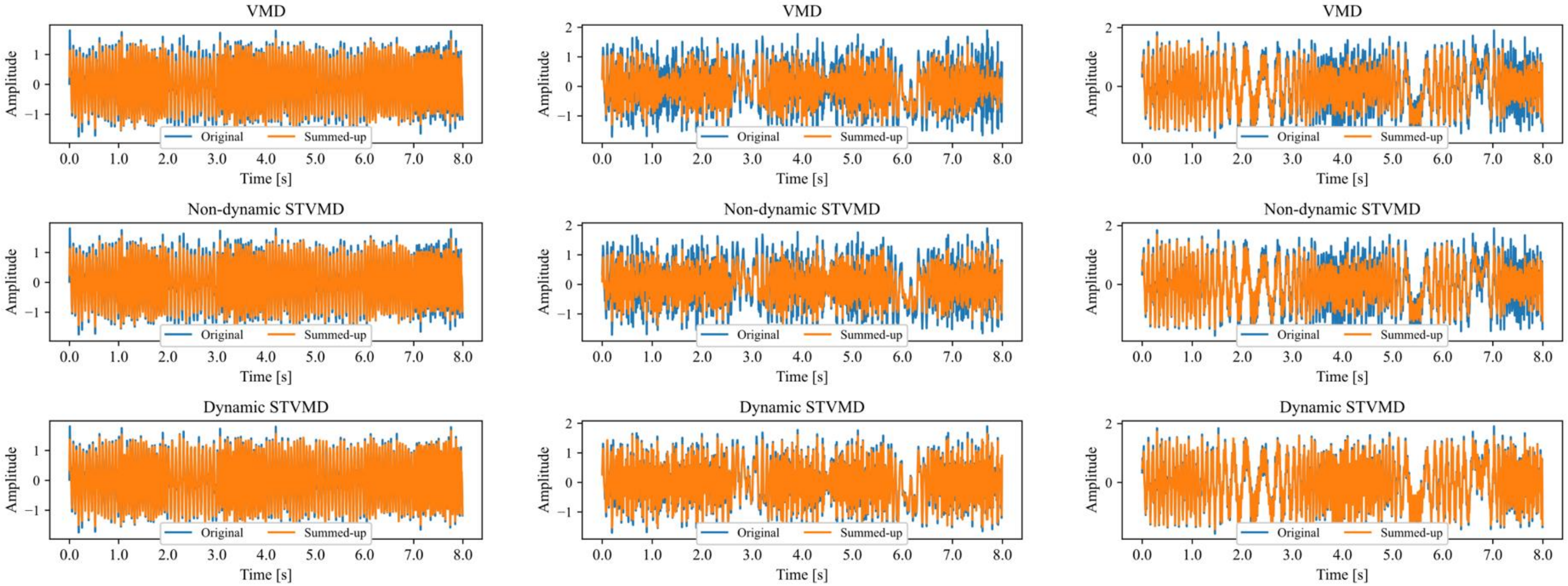
Scientific contributions from my research in China

Short-Time Variational Mode Decomposition

Table II
Root Mean Square Error between Original and Recovered Signal

Simulated Signal	1	2	3	Average
VMD [4]	0.1239	0.2982	0.2227	0.2149
Non-dynamic STVMD	0.1220	0.2691	0.2236	0.2049
Dynamic STVMD	**0.0950**	**0.1058**	**0.0886**	**0.0965**

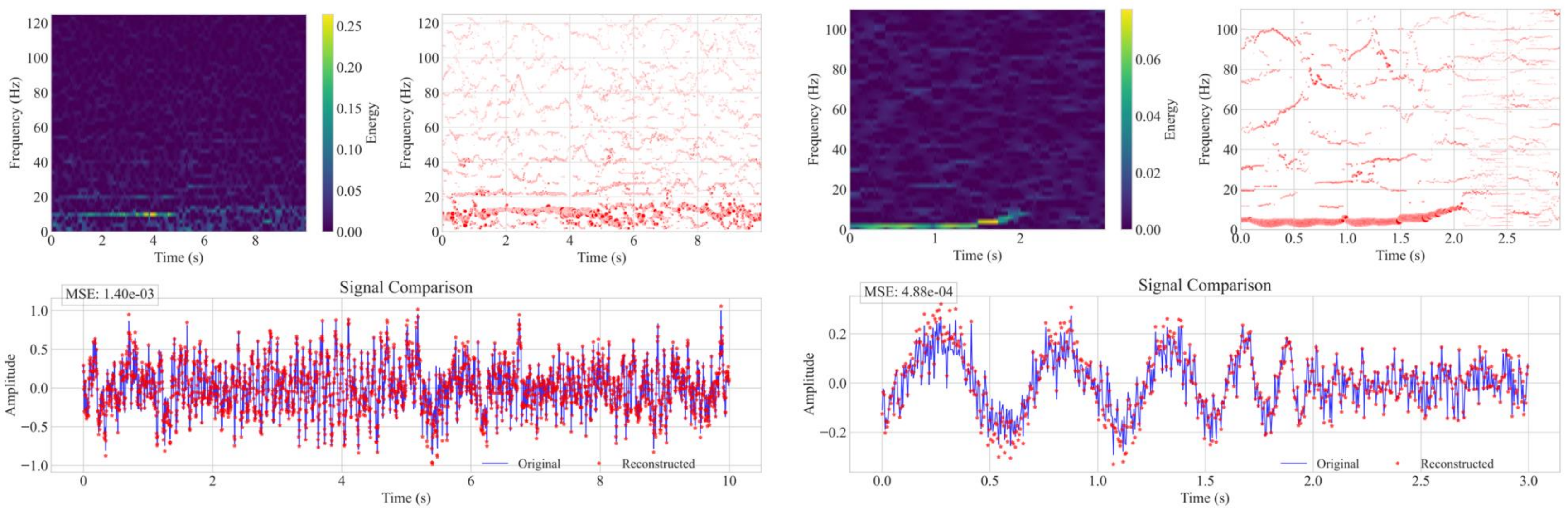
STVMD incorporates the Short-Time Fourier transform to minimize the impact of local disturbances. Non-dynamic STVMD is comparable to VMD with properly sized time windows, while dynamic STVMD better accommodates non-stationary signals



https://doi.org/10.48550/arXiv.2501.09174

Scientific contributions from my research in China

Non-stationary signal analysis presents persistent methodological challenges in automatic mode extraction and parameter optimization. In this work we develop a dynamic, data-driven approach for mode decomposition by establishing the theoretical connection between VMD and clustering in the frequency domain.



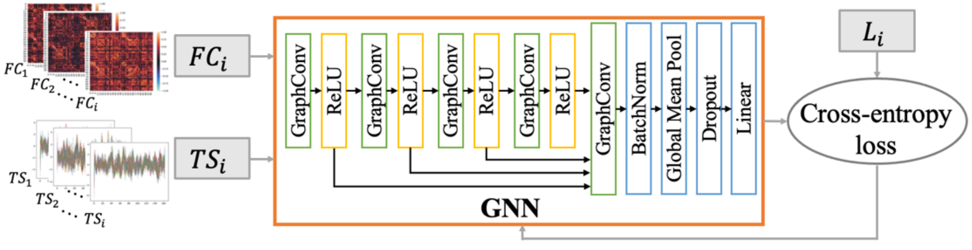
(a) SSVEP signal analysis results showing time-frequency representation, mode detection, and signal reconstruction.

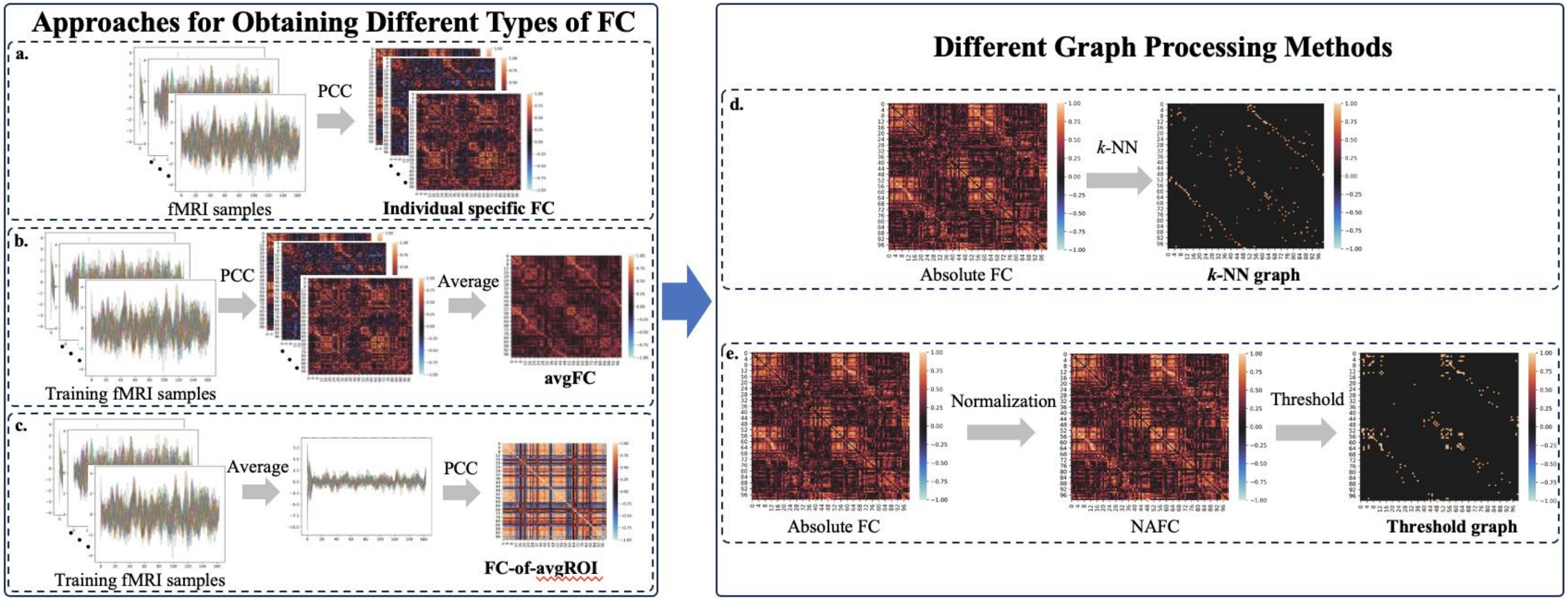
(b) Gravitational wave signal analysis results showing chirp pattern, mode tracking, and signal reconstruction.

To be submitted

Scientific contributions from my research in China

Graph Neural Networks to predict dementia

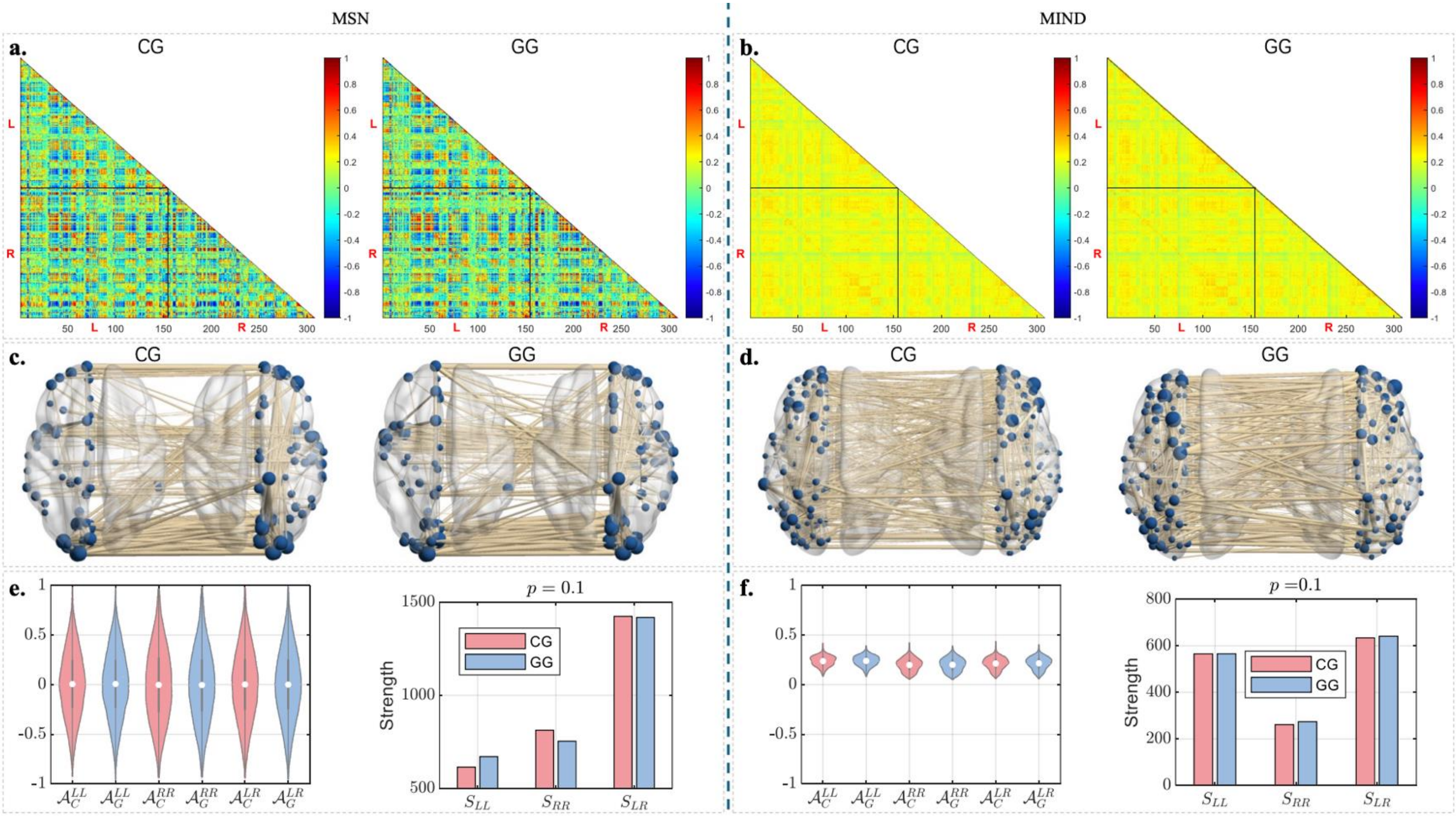




https://doi.org/10.1088/1741-2552/ad1e22

Scientific contributions from my research in China

Morphometric similarity networks / Morphometric INverse Divergence



Visual comparisons of CG and for MSN and MIND

Submitted to Brain Structure and Function

Scientific contributions from my research in China

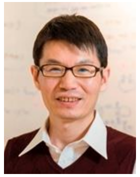
- Starting conditions:
  - Fortunate
  - Knowing Sun
  - No precise idea of what I would do
  - No knowledge about Chinese language and culture
  - … But excited for this opportunity!

Scientific contributions from my research in China

- Final conditions:
  - Happy
  - With a lot of friends
  - With potential students eager to come for their PhD
  - With a Visiting Researcher position since 2019
  - ... and still visiting China

From my experience…

Grenoble
(France)



Tokyo
(Japan)

Tianjin
(China)

Cambridge
(United Kingdom)

Sevilla, Pamplona
(Spain)

Paris
(France)

Buenos Aires
(Argentina)

From my experience…

- Don't be afraid to be scared.
- Go to conferences and speak to people.
- Apply for all possible grants.
- Invest your time (and money, if necessary…).
- Be open to work on whatever the laboratory proposes to do.
- Collaborate as much as you can with members/projects of the laboratory.

From my experience…

- Don't get discouraged if you don't progress.
- Trust in yourself and be humble.
- Learn (at least words of) the local language.
- Show interest in the new culture.
- Keep in contact with the lab after you leave.
- Be grateful for the experience.
- Be willing to help others if they ask for it

THANKS…

and enjoy your research!