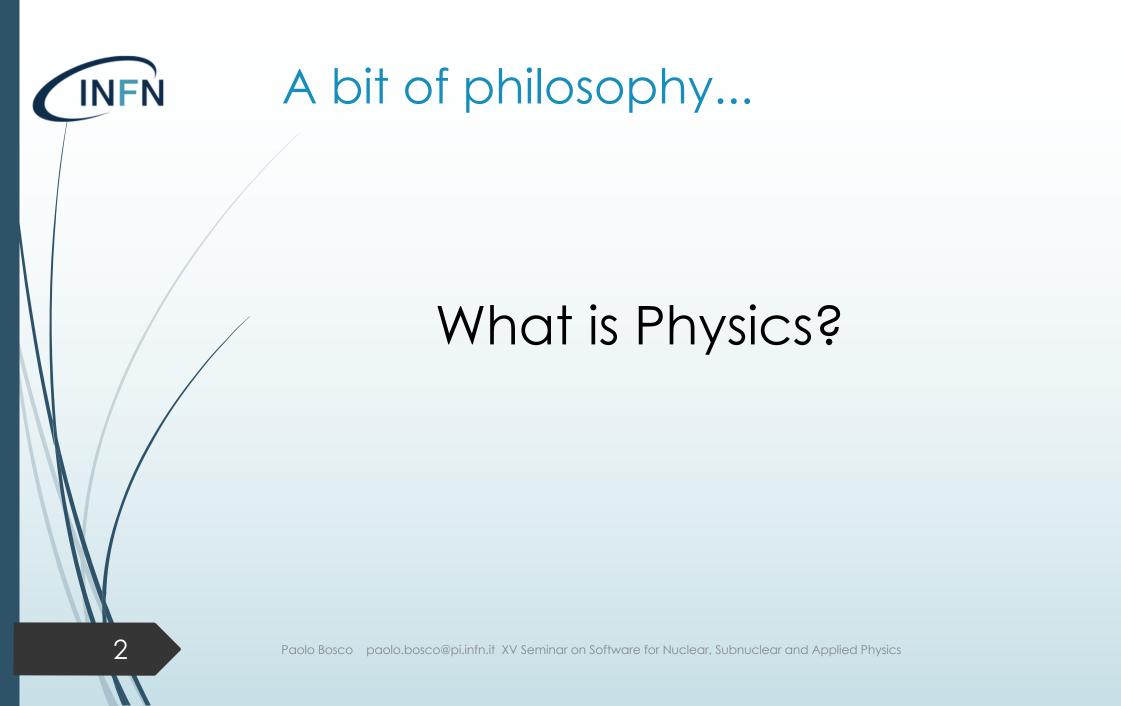


Measuring normality and pathology in medical imaging.

From the physical signals to diagnosis, fighting the sources of noise and variability.





A bit of philosophy...

According to dictionaries...

The <u>science of matter and energy</u> and of interactions between the two, grouped in traditional fields such as acoustics, optics, mechanics, thermodynamics, and electromagnetism, as well as in modern extensions including atomic and nuclear physics, cryogenics, solidstatephysics, particle physics, and plasma physics.

Almost all aforementioned fields find applications in medical field.... But there is more...



A bit of philosophy...

One of the fundamental concepts in Physics is that of **measure**.

By measure, physicists generally mean <u>the quantitative</u> <u>assessment of an observable</u> but the concept entails more complex logical instruments such as <u>theoretical</u> <u>models</u>, <u>statistics</u>, <u>metrics</u>, <u>signal and noises</u>.



A bit of philosophy...

Physics

- Observations
- Direct / indirect
- Derived from previous experiments / better estimates of current theories
- Theory
- One or more models, depend on free parameters
- Few parameters = happy physicist
- Assumption: Complex phenomena can be described by relatively simple models

Medicine

- Observations
- Direct: Clinical practice

- Theory
- No comprehensive models
- Highly complex system
- Subsystem interactions and history not negligible

A bit of philosophy...

Physics

Experiment

- Designed to verify key aspects of theory, prove/disprove models
- Typical paradigm: Out = signal + noise
 Reproducibility is a key factor
- Data analysis

6

- Designed to extract "signal" from "noise" [filters]
- Experiment characterization [noise]
- Estimate model parameters [from signal]
- Error estimation relatively simple

Medicine

- Experiment
- Clinical trials (in vitro, in vivo,)
- Typical paradigm: improvement / noimprovement
- Reproducibility is rarely achieved
- Data analysis
- Designed to extract "improvement probability"
- Strong a-priori assumptions
- What is "noise"?
- Error estimation generally difficult

Medical imaging: signals

Actual signals i.e. Data:

- 2D/3D matrices (X-rays, CT, MRI, PET)
- Array of real values (molecular concentration, ...)

pathological 'Signals'

- ▶Define metric
 - pathology "signal" in a normalcy "background"

▶no theory

it must be deduced through group comparison

▶lots of assumptions

pathology markers are common to all individuals transition from normal to pathological = continuous process

Medical imaging: noises

Acquisition noises [easy peasy (almost)]

- Scanner electronic noise
- Scanner non idealities (e.g. B-field inhomogeneities,...)
- Scan quality issues (resolution, acquisition protocol, ...)
- Image artifacts (subject movements during acquisition, e.g. object driven B-field distortion, ...)

Physiological noises [difficult]

- Confounding variables (age, sex, education, general anamnesis,...)
- Inter-individual variability can be more significant than normalcy vs. pathology difference
- Cohort representativity



Medical imaging: noises

"Gold standard" noises [very hard]

- Group mixing (clinical assessment is not 100% accurate)
- Group purity (comorbid pathologies)
- General accuracy can change at different ages (e.g. neurodevelopment/neurodegeneration)

Data processing noises [tricky but manageable]

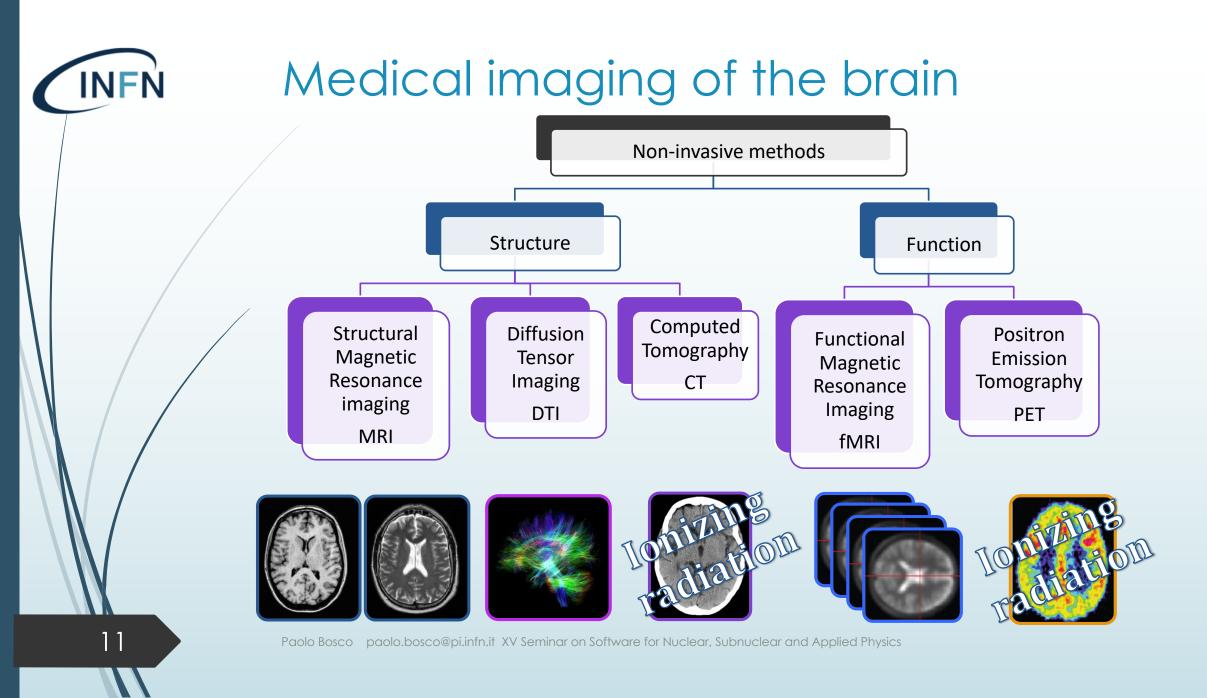
- Signal is deduced by comparison among cohorts: method selection is important
- Information degradation due to sub-optimal processing
- Depends on assumptions on "signal"



What do we aim at? Radiomics

Radiomics is a field of medical study that aims to extract large amount of quantitative features from medical images using data-characterisation algorithms. These features, have the potential to uncover disease characteristics that fail to be appreciated by the naked eye.

The hypothesis of radiomics is that the distinctive imaging features between disease forms may be useful for predicting prognosis and therapeutic response for various conditions, thus providing valuable information for personalised therapy.

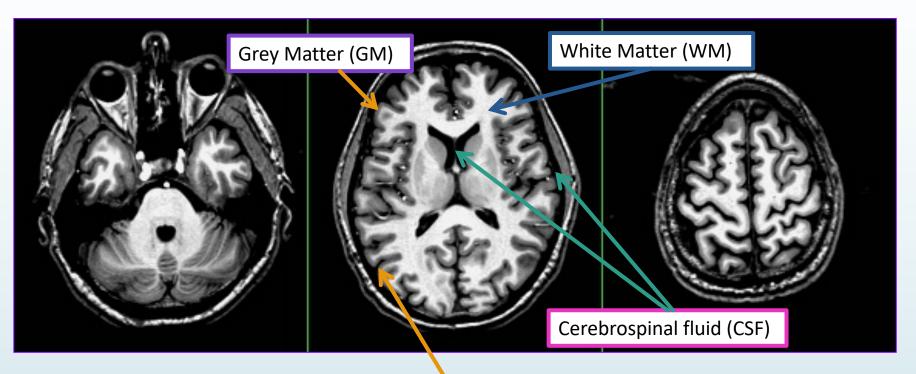


INFN

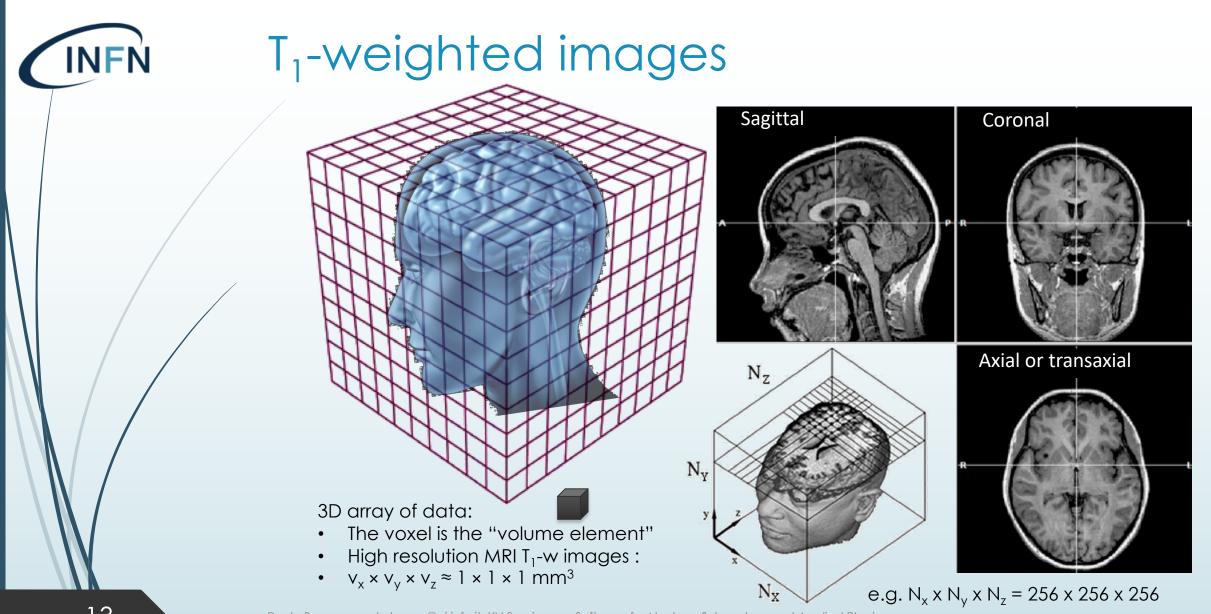
12

T₁-weighted images

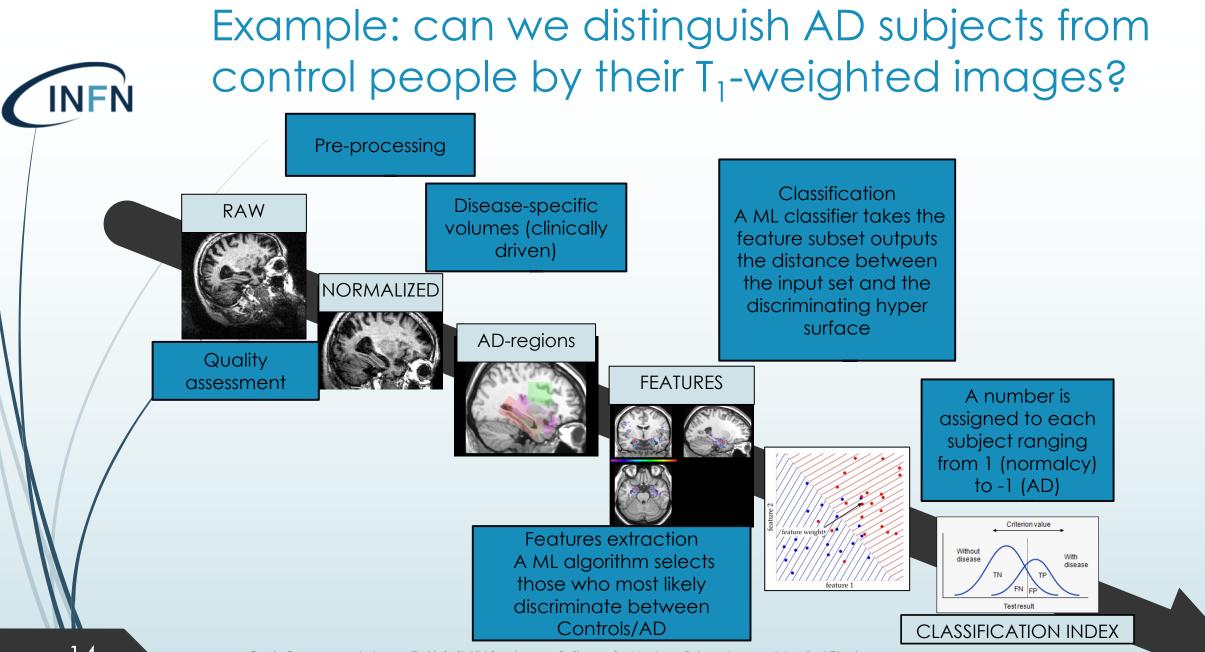
Axial slices of a human head with spatial resolution of about 1 mm³



Grey Matter (GM) cortex can be localized and cortical thickness can be evaluated to investigate GM involvement in pathological conditions.



Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics



Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

INFN	Example: can we distinguish AD subjects from control people by their T ₁ -weighted images?		
	 Initial quality check Image artifacts Voxel size and aspect ratio 	Acquisition noises/variability	
	 Noise removal Steerable pyramid de-noising Spatial registration 	Acquisition noises/variability	
	 3-way scalable (7 d.o.f.) + affine (12 d.o.f.) Mutual information and normalized correlation metric 	Physiological noises	
	 Intensity normalization CSF/GM/WM segmentation VOI-based histogram match 	Acquisition noises/variability	



Example: can we distinguish AD subjects from control people by their T_1 -weighted images?

- ▶ Region (VOI) extraction
 - Template matching, rigid (6 d.o.f.) registration

Physiological noises

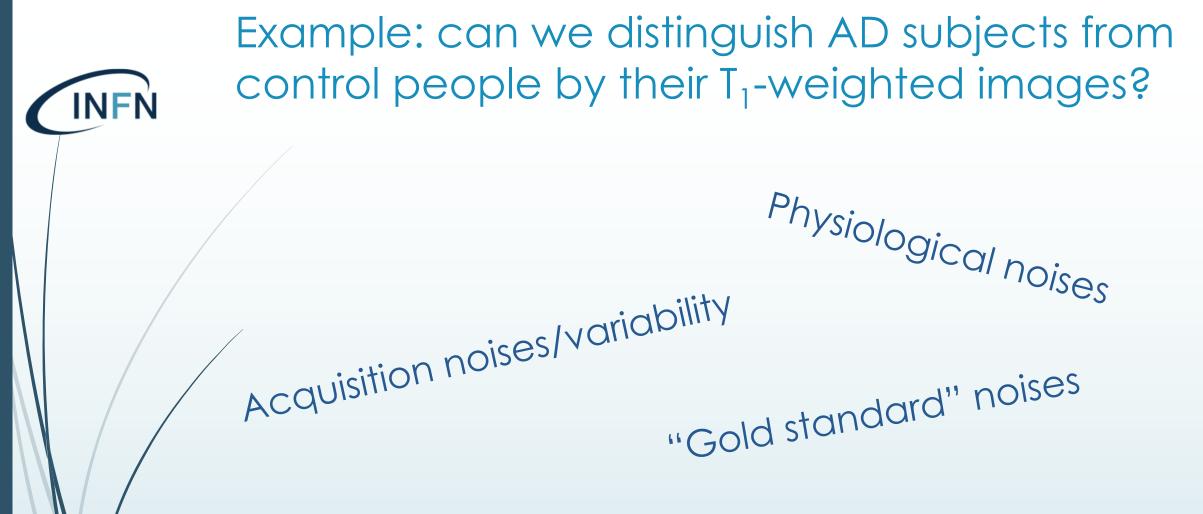
"Gold standard" noises

▶ Features computation

- 4 different neighborhoods
- Intensity & texture based filtering

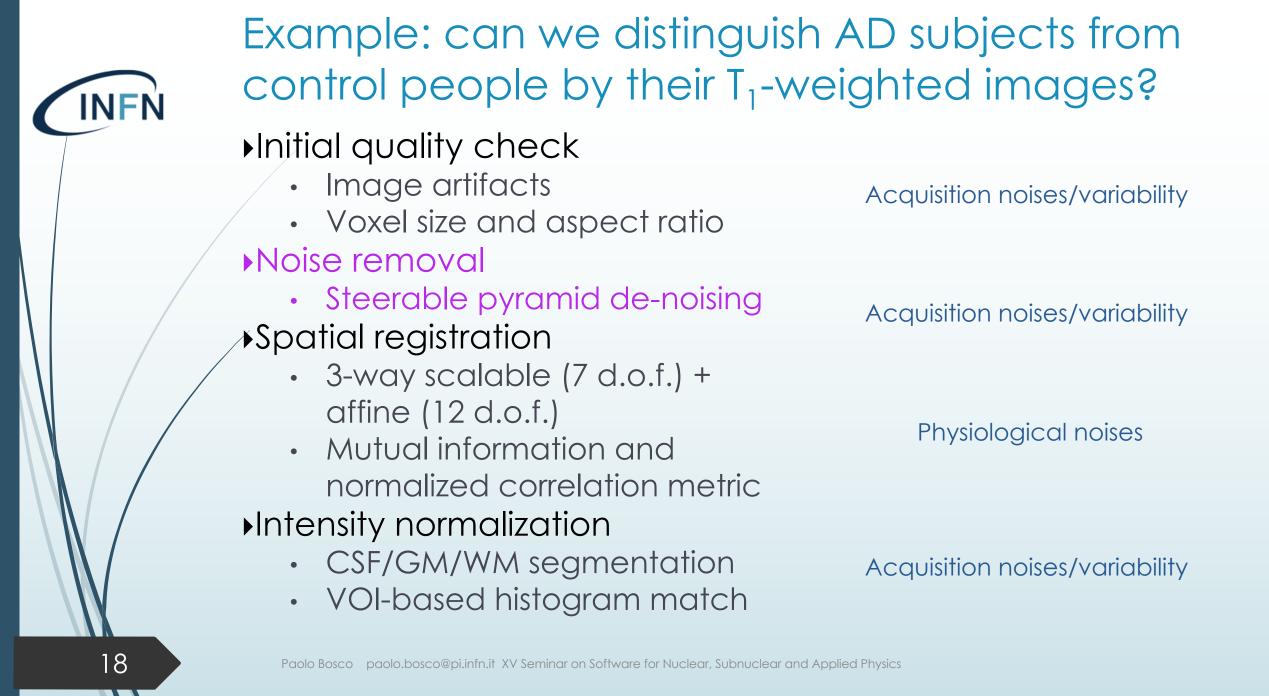
Classification

- Random Forest (RF)
 important variable map
- Support Vector Machine
 (SVM) classifier



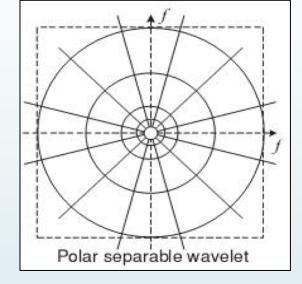
...But we are introducing data processing noise... If someone else in the world would process the same data with different methods... Would he find the same results?

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

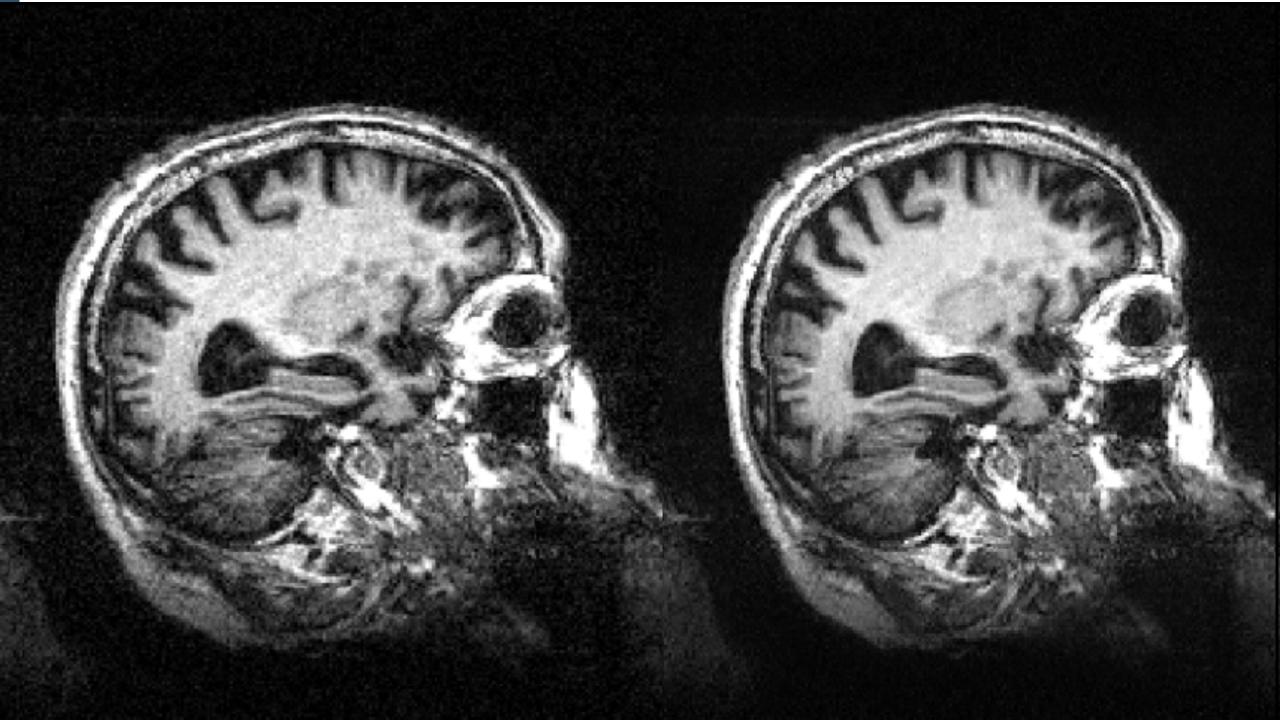




Example: can we distinguish AD subjects from control people by their T₁-weighted images? **Denoising**



 The steerable pyramid filter performs a polar-separable decomposition in the frequency domain, thus allowing independent representation of scale and orientation

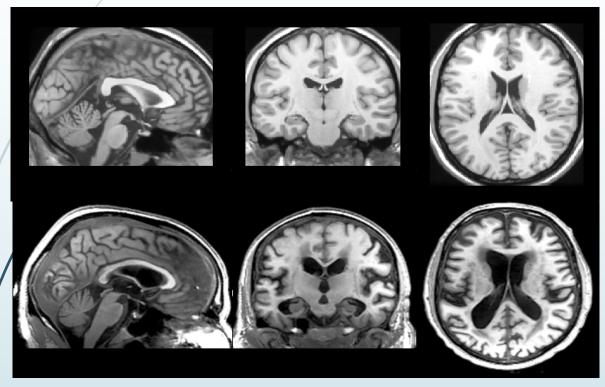


INF		Example: can we distinguish AD subjects from control people by their T ₁ -weighted images?		
	 Initial quality check Image artifacts Voxel size and aspect ratio 	Acquisition noises/variability		
	 Noise removal Steerable pyramid de-noising Spatial registration 	Acquisition noises/variability		
	 3-way scalable (7 d.o.f.) + affine (12 d.o.f.) Mutual information and normalized correlation metric 	Physiological noises		
	 Intensity normalization CSF/GM/WM segmentation VOI-based histogram match 	Acquisition noises/variability		
21	Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and App	blied Physics		



Example: can we distinguish AD subjects from control people by their T₁-weighted images? **Spatial registration**

ICBM152-template



Registered T1-weighted scan

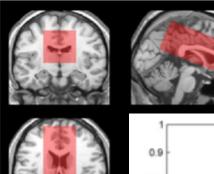
Registration = is the process of transforming different sets of data into one coordinate system with the alignement of corresponding structures

A combined 12 d.o.f. transformation is computed to minimize a given metric, mapping the MRI onto a reference image

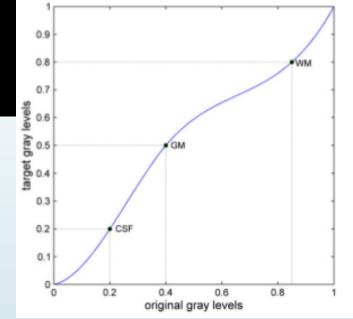
A 12 d.o.f. transformation is a linear transformation that can manage rotations, translations, shearing and scaling.

INFN	Example: can we distinguish AD subjects from control people by their T ₁ -weighted images?		
	 Initial quality check Image artifacts Voxel size and aspect ratio 	Acquisition noises/variability	
	 Noise removal Steerable pyramid de-noising Spatial registration 	Acquisition noises/variability	
	 3-way scalable (7 d.o.f.) + affine (12 d.o.f.) Mutual information and normalized correlation metric 	Physiological noises	
	 Intensity normalization CSF/GM/WM segmentation VOI-based histogram match 	Acquisition noises/variability	
23	Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied	d Physics	

Example: can we distinguish AD subjects from control people by their T₁-weighted images? Intensity normalization

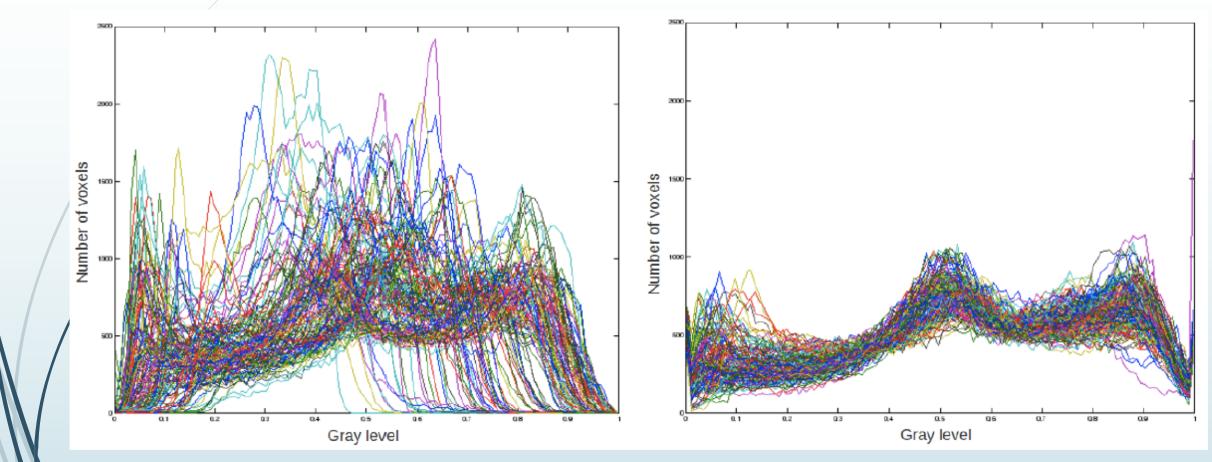


24



T1-weighted signal is not a quantitative measure.

We consider a reference image (template). The three clusters means of the new image are matched to the corresponding CSF/GM/WM mean levels on the reference image. These are the fixed points through which a cubic spline is fitted. This non-linear intensity normalization pairs the three mean cluster intensities in the ROI (CSF/GM/WM) between each subject and the MNI reference image, and extends the mapping to the other gray levels by a smooth piecewise polynomial curve. Example: can we distinguish AD subjects from Control people by their T₁-weighted images? Intensity normalization



Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics



Example: can we distinguish AD subjects from control people by their T_1 -weighted images?

- ▶ Region (VOI) extraction
 - Template matching, rigid (6 d.o.f.) registration

Physiological noises

Features computation

- 4 different neighborhoods
- Intensity & texture based filtering

Classification

- Random Forest (RF)
 important variable map
- Support Vector Machine
 (SVM) classifier

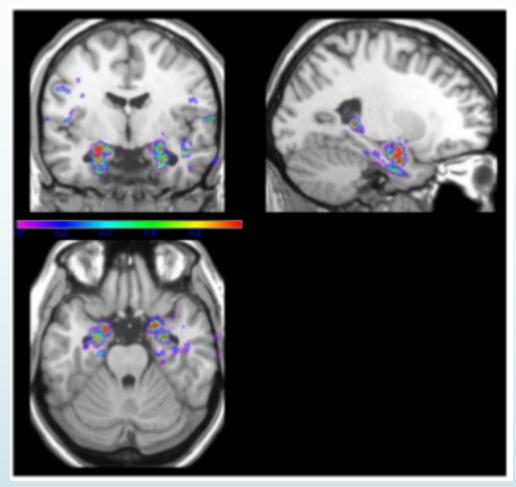
Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

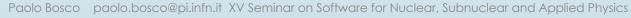
"Gold standard" noises



Example: can we distinguish AD subjects from control people by their T₁-weighted images? Important features maps

> Important features selection by a Random Forest Classifier (IFM, Important Features Map) Control and AD groups







Example: can we distinguish AD subjects from control people by their T_1 -weighted images?

- ▶ Region (VOI) extraction
 - Template matching, rigid (6 d.o.f.) registration

Physiological noises

Features computation

- 4 different neighborhoods
- Intensity & texture based filtering

Classification

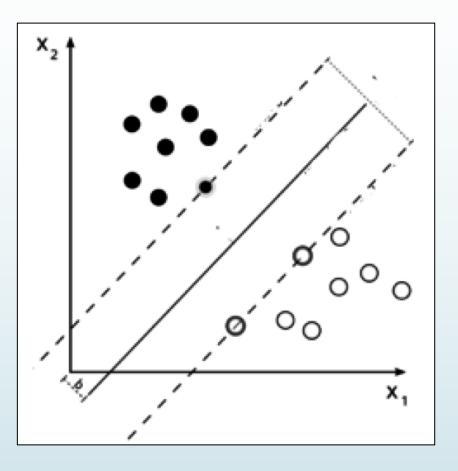
- Random Forest (RF)
 important variable map
- Support Vector Machine
 (SVM) classifier

"Gold standard" noises

INFN

Example: can we distinguish AD subjects from control people by their T₁-weighted images? **Classification**

The SVM classier training consists in the calculation of the hyperplane able to separate in the best way two N dimensional data set.



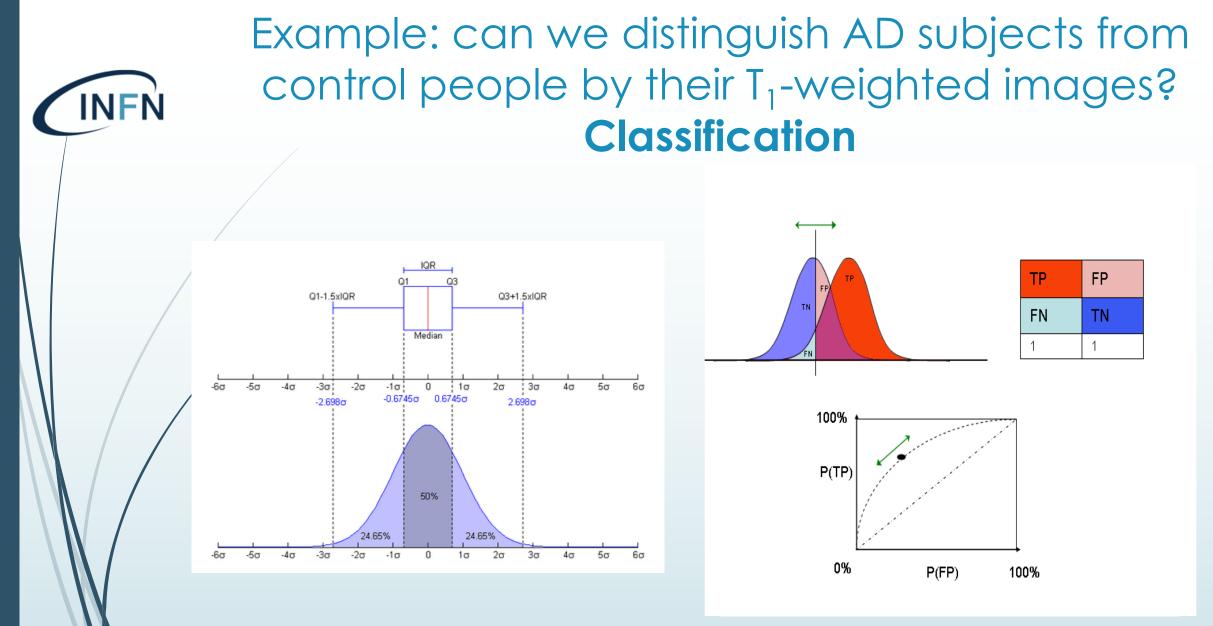
Example: can we distinguish AD subjects from control people by their T₁-weighted images? **Classification**

SVM classification Support Vector Machine (dimensionality problem d≈10^4 vs n≈10^2)

We can split the problem in 1000 SVMs that classify 1/1000 of the features (d \approx n) And then we can average the outcome of the 1000 classifiers

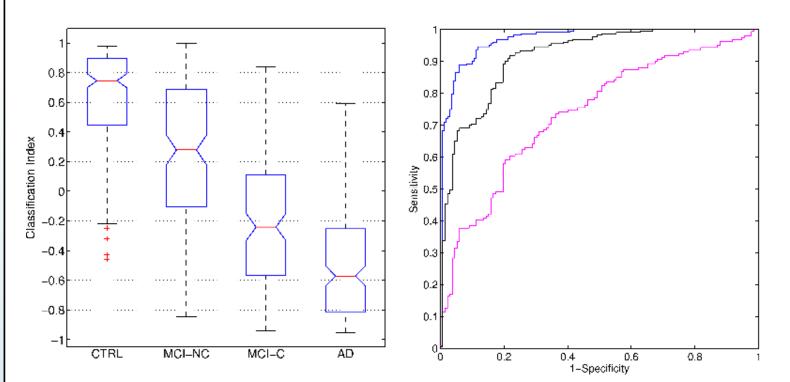
> The final output is a continuous index ranging from -1 to 1 with -1=AD and 1=Control

Each subject is classified using this classification index Quantitative, reproducible measure

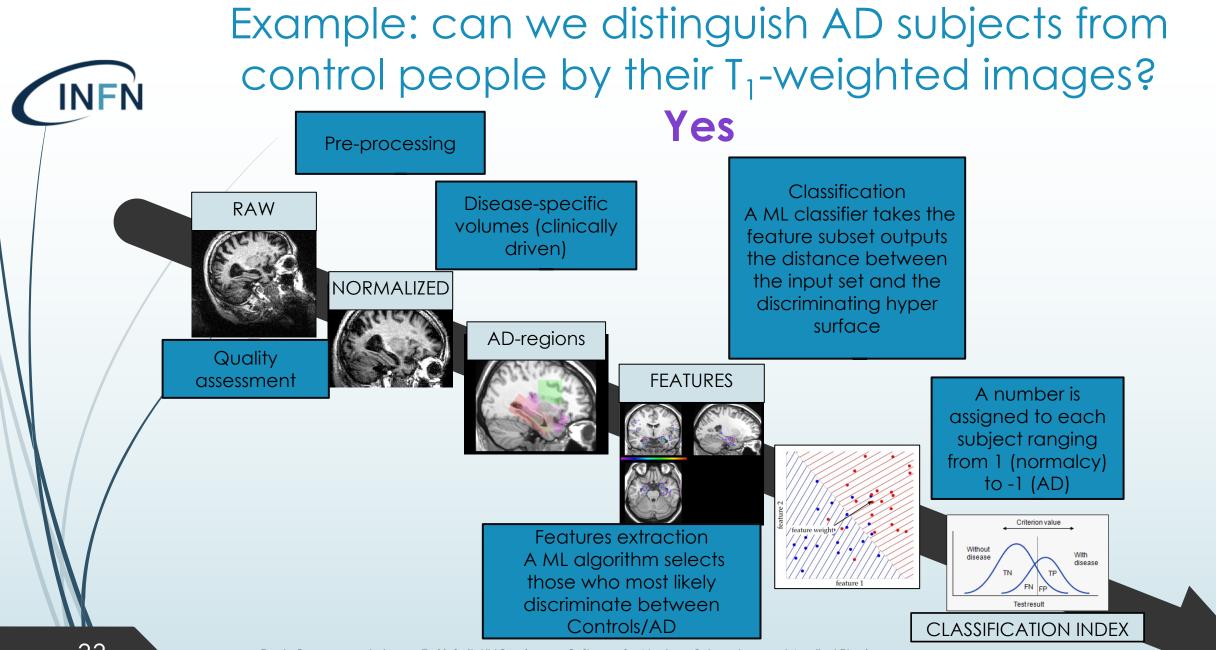


Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

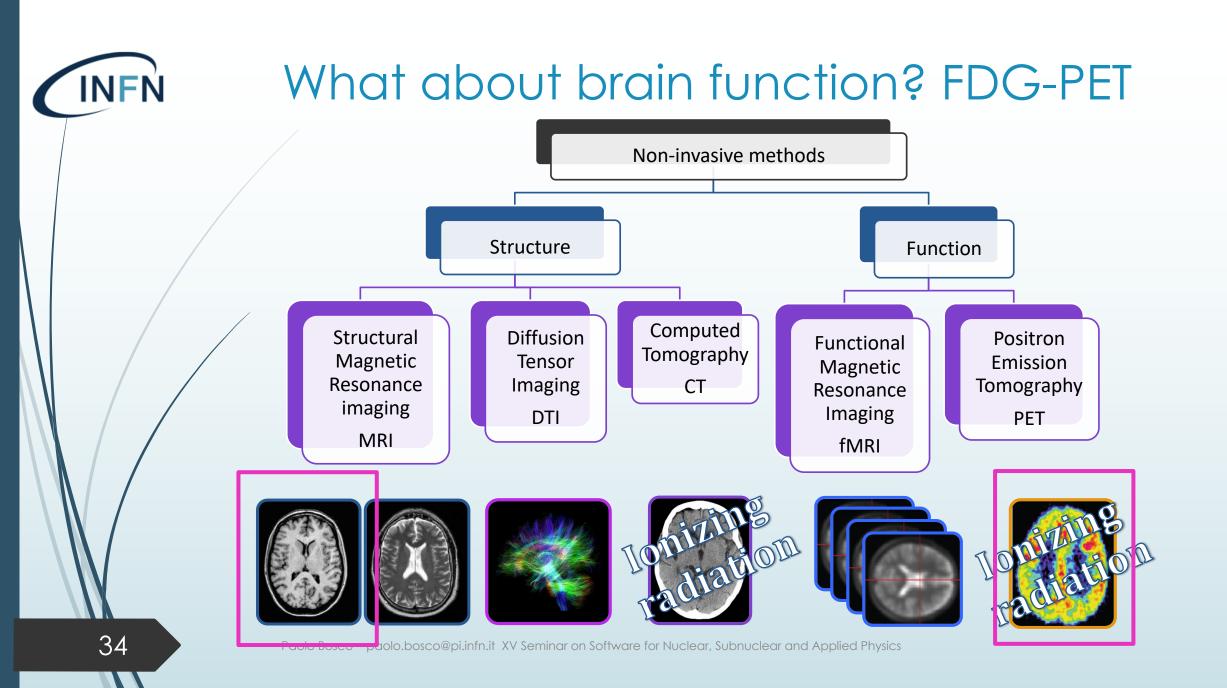
Example: can we distinguish AD subjects from control people by their T₁-weighted images?



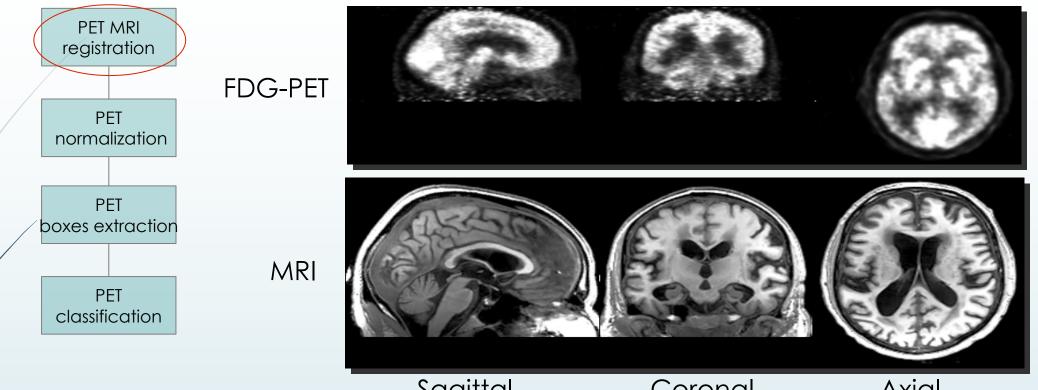
Discrimination capability between control and AD cohorts described by an area under the ROC curve (AUC) of 0.97. AUC for the ROC curve of control vs MCI converter cohorts is 0.92; AUC for the ROC curve of MCI vs MCI converter is 0.74.



Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics



Example: can we distinguish AD subjects from control people by their FDG-PET images?



Sagittal

Coronal

Axial

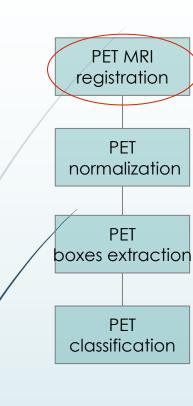
Again... Registration = is the process of transforming different sets of data into one coordinate system with the alignement of corresponding structures

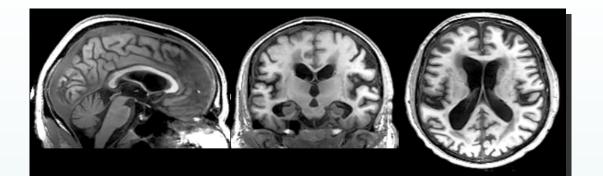
minimization problem on a metric

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

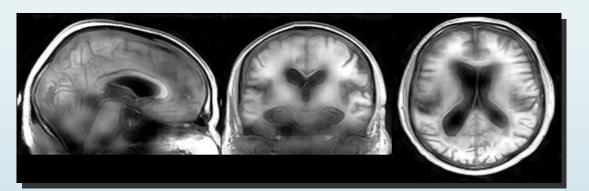
NFN

Example: can we distinguish AD subjects from control people by their FDG-PET images?





Curvelet transform ~Low pass filter and inverted transform



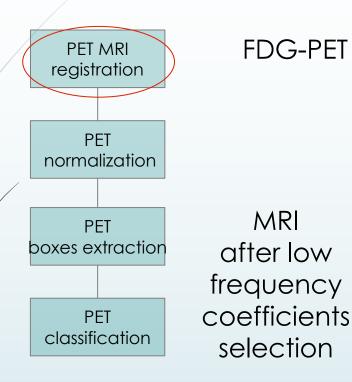
High scale (low spatial frequencies) and high directional informations preserved

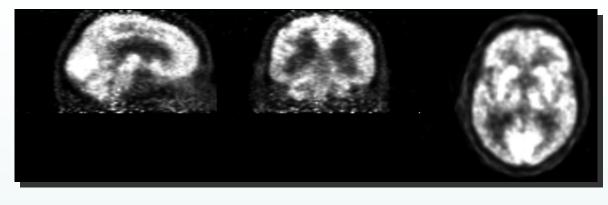
Border and main CSF structures preservation

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

36

NFN

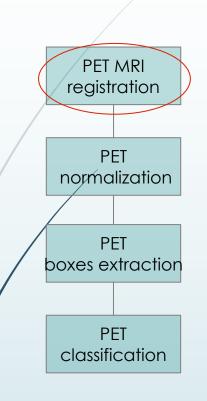


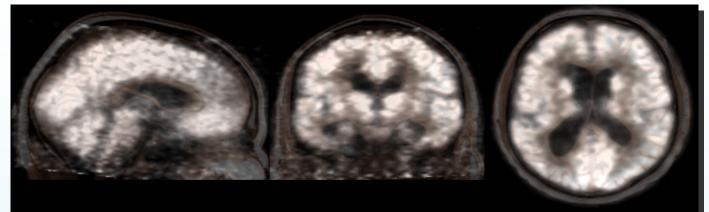


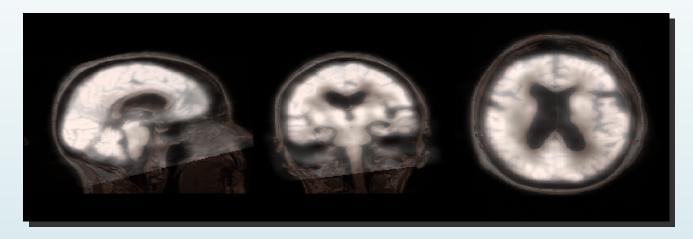
Registration by 7 d.o.f transform using mutual information as metric

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x) p(y)}$$

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics





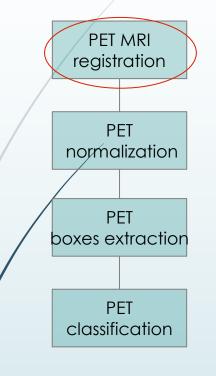


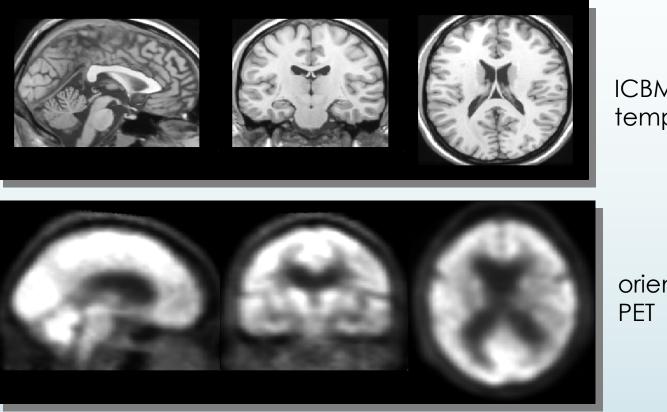
<u>Many applications-> e.g. registration of low resolution in-beam PET to High resolution</u> <u>CT scans for activity evaluation during hadrontherapy.</u>

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics



<u>Registration on ICBM152 template</u>. Same transform matrix applied to PET • image.

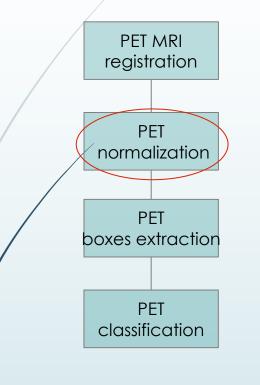




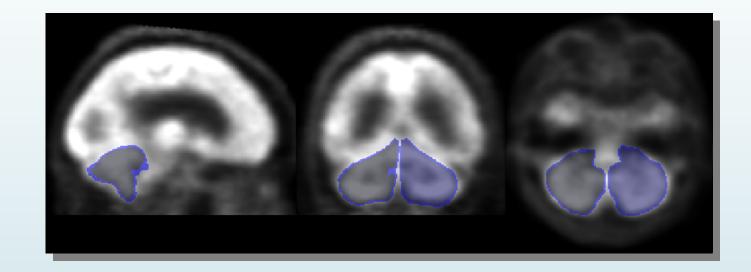
ICBM152 template

oriented

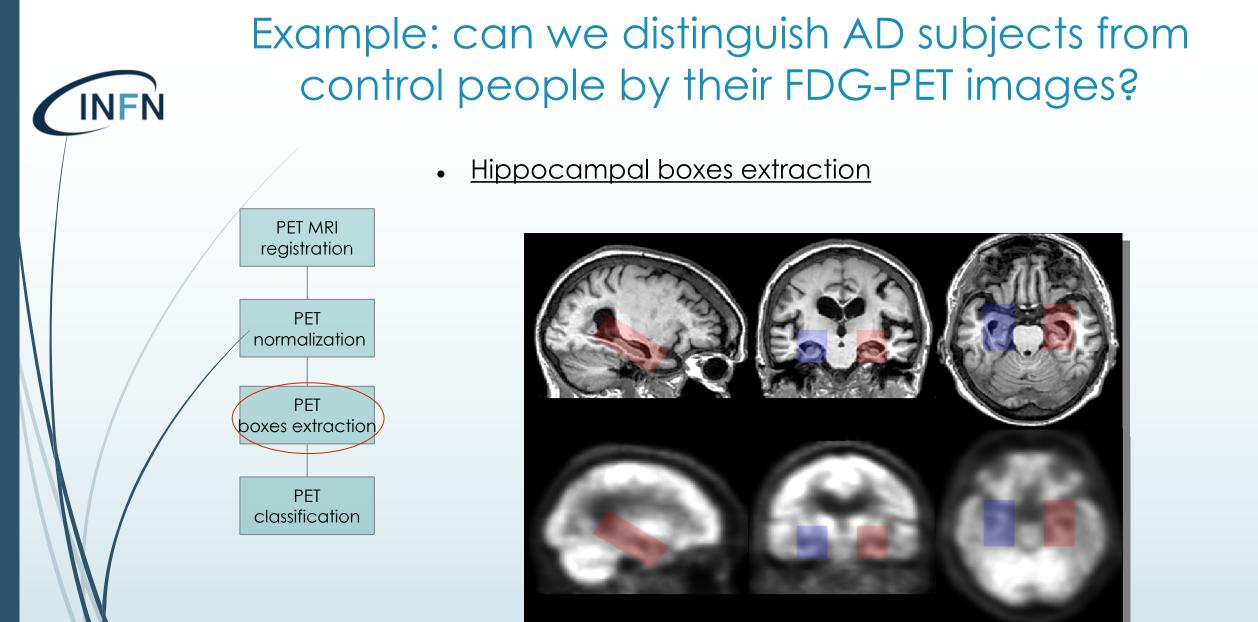
Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics



- <u>PET signal intensity normalization</u>
 - Cerebellum automatic segmentation
 - Global counts normalized on average cerebellum signal



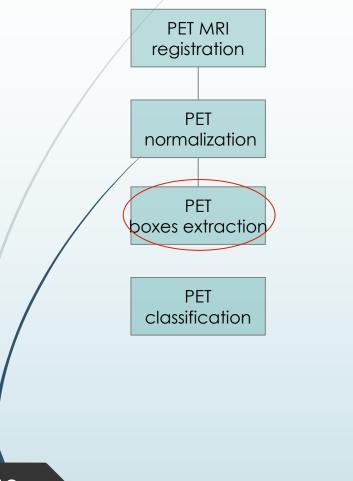
Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

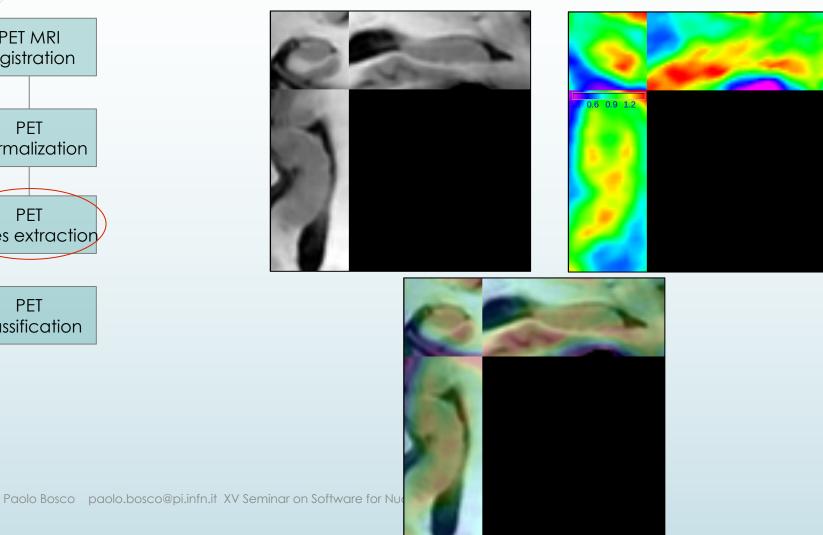


Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

41

Hippocampal ROIs FDG-PET intensities (false color) overlaid to MRI signal

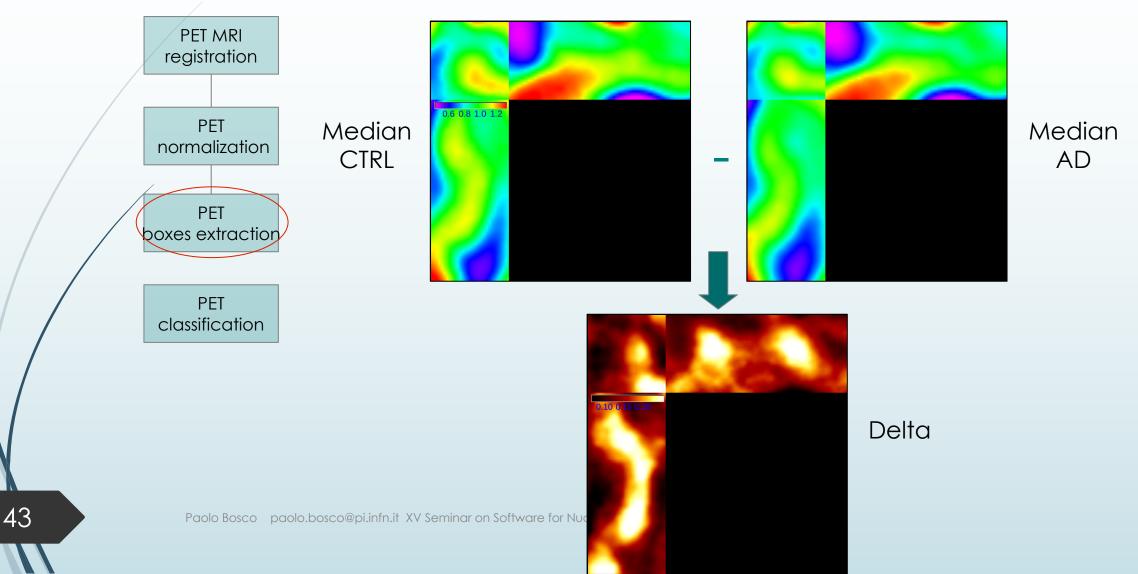




42

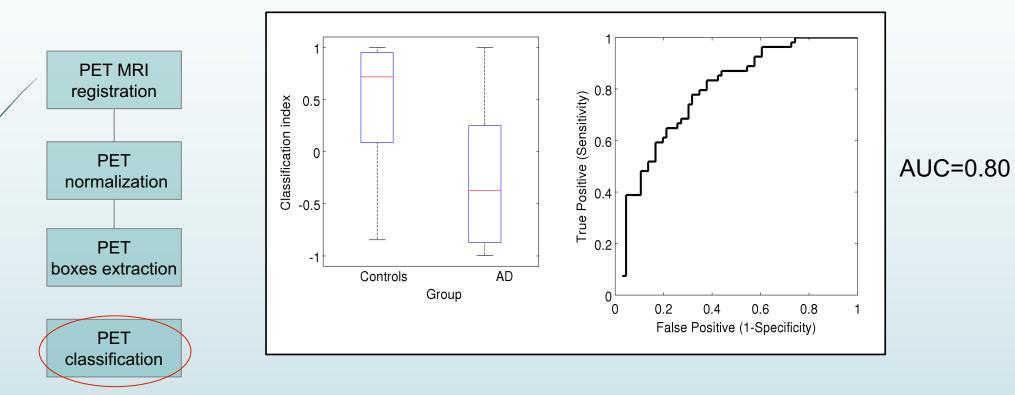
NFN

Hippocampal ROIs FDG-PET intensities (false color) overlaid to MRI signal



Functional index distribution calculated on hippocampal boxes

Controls/AD separation. 26 Controls (age 76 ± 4) 29 AD (age 75 ± 6)



What about data processing noise?

The ARIANNA project

Let's choose a quite simple region of interest potentially involved in ASD: the brainstem

• Deficit in social communication abilities and the presence of restricted, repetitive behaviours represent the core features of autism spectrum disorder (ASD).

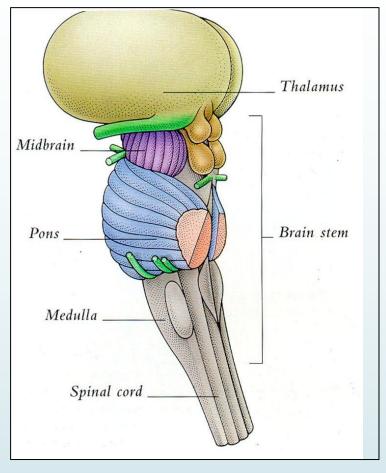
[DSM_5]

• In addition, sensorimotor abnormalities have been consistently reported in ASD individuals as an early impairment that may precede the development of defining characteristics

[Teitelbaum, Proc Natl Acad Sci USA 1998, Ozonoff, Autism Res 2008, Hilton, Res Autism Spectr Disord, 2007]



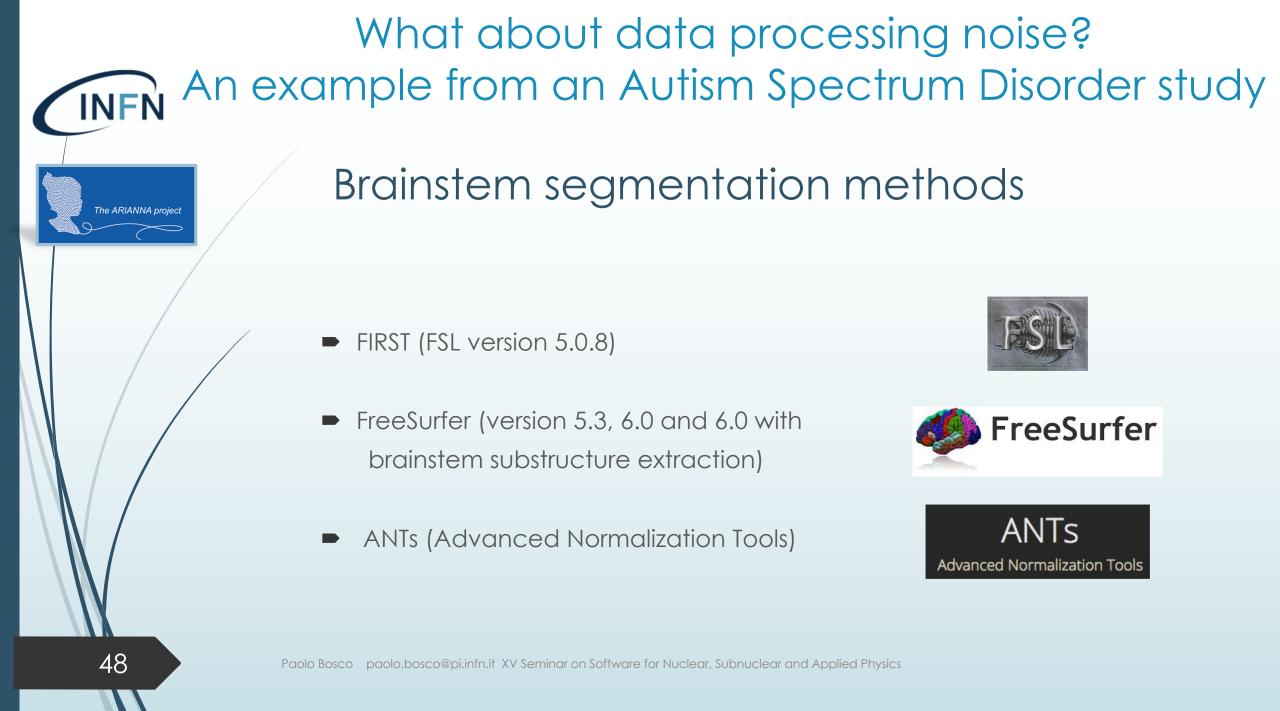
- Motor abilities depend on multiple interacting pathways including cortico-cortical, corticalsubcortical, and cortico-cerebellar connections that reach spinal motor neurons <u>through the brainstem.</u>
- From the anatomical point of view, the brainstem consists of <u>midbrain</u> (or mesencephalon), <u>pons</u> and <u>medulla</u> <u>oblongata</u> along the rostro-caudal axis.
- It's involved in several basic functions, including regulation of heart rate, breathing, alertness, sleeping, and eating It also plays a pivotal role in sensory information processing, in eliciting goal-oriented behaviour, in the regulation of social attention, and in the modulation of emotions.

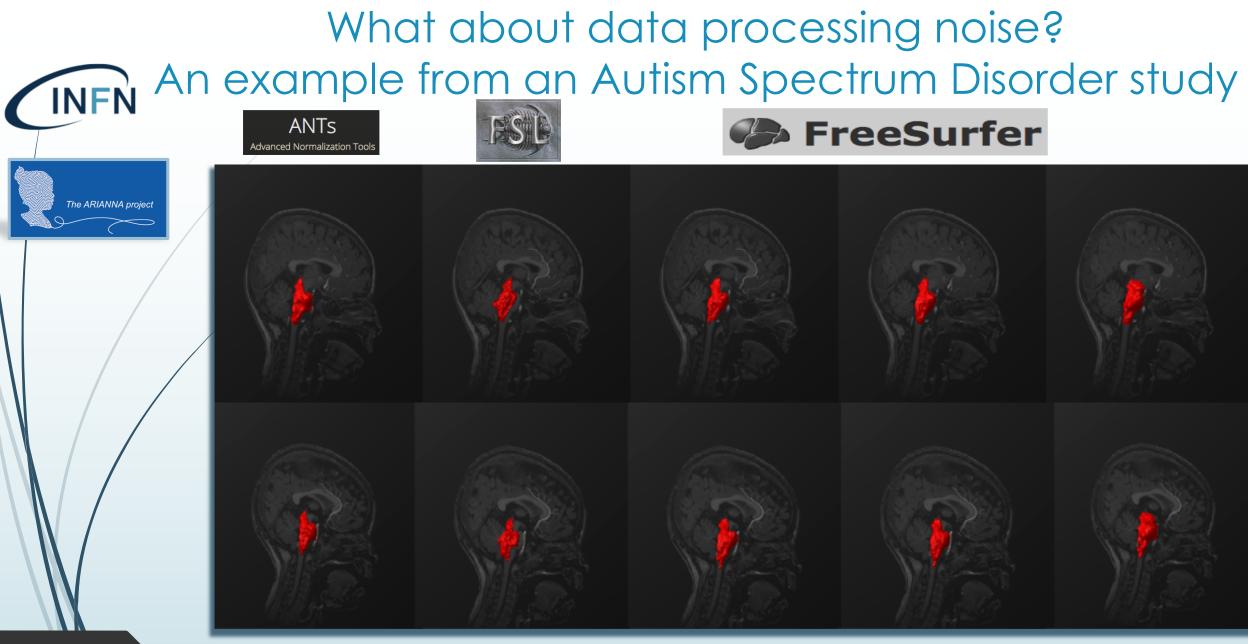


Variable					
	ASD (n=76)	Control		
	53 ±	± 17	53 =	FONDAZIONI Istituto di ricovero e	
Age (months)	[25 -	- 88]	[22 -		
NVIQ	71 ±	± 22	73 :		
it i i i i i i i i i i i i i i i i i i	[30 -	113]	[35 -		
	Males (n=38)	Females	Males (n=38)	Females	
Age (months)		(11–30)		(1-30)	
	53 ± 16	53 ± 18	53 ± 17	53 ± 19	
	[27 - 87]	[25 - 88]	[24 - 88]	[22 - 89]	
NVIQ	71 ± 21	71 ± 22	74 ± 23	71 ± 24	
	[39 - 113]	[30 - 103]	[43 - 112]	[35 - 100]	
	Age (months) NVIQ Age (months)	Age (months) $ASD ($ Age (months) $53 \pm$ NVIQ $71 \pm$ $30 71 \pm$ Age (months) 53 ± 16 $[27 - 87]$ 71 ± 21	Age (months) ASD (n=76) Age (months) 53 ± 17 [25 - 88] [25 - 88] NVIQ 71 ± 22 [30 - 113] [30 - 113] Age (months) 53 ± 16 53 ± 16 53 ± 18 [27 - 87] [25 - 88] NVIQ 71 ± 21 NVIQ 71 ± 22	Asp (n=76) Control Age (months) 53 ± 17 53 ± 17 NVIQ 71 ± 22 73 ± 16 Age (months) 71 ± 22 73 ± 16 Age (months) Males (n=38) Females (n=38) Males (n=38) Age (months) 53 ± 16 53 ± 18 53 ± 17 Age (months) 71 ± 21 71 ± 22 74 ± 23	Age (months)ASD (n=76)Controls (n=76)Age (months) 53 ± 17 53 ± 18 $[25 - 88]$ $[22 - 89]$ NVIQ 71 ± 22 73 ± 23 $[30 - 113]$ $[35 - 112]$ Age (months) 53 ± 16 53 ± 18 53 ± 16 53 ± 18 53 ± 17 53 ± 16 53 ± 18 53 ± 17 53 ± 16 53 ± 18 53 ± 17 $[27 - 87]$ $[25 - 88]$ $[24 - 88]$ 71 ± 21 71 ± 22 74 ± 23 71 ± 24 71 ± 24

NE STELLA MARIS

ASD children met the criteria for a diagnosis in the autism spectrum according to DSM-5, and underwent a MRI scan (T1-weighted series (FSPGR), 1.5 T GE scanner).



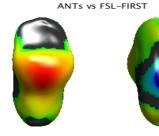


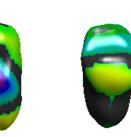


What about data processing noise? INFN An example from an Autism Spectrum Disorder study FSL-FIRST (mm³) $FS 5.3 (mm^3)$ $FS 6.0 (mm^3)$ FS 6.0 subfields (mm^3) R = 0.95R = 0.65R = 0.93R = 0.9425000 25000 25000 25000 $D = 0.86 \pm 0.05$ $D = 0.76 \pm 0.04$ $D = 0.65 \pm 0.16$ $D = 0.88 \pm 0.05$ ANTs (mm³) 0.95 15000 15000 15000 15000 The ARIANNA project 5000 5000 5000 5000 0.9 5000 15000 25000 5000 15000 25000 5000 15000 25000 5000 15000 25000 R = 0.50R = 0.52R = 0.6325000 25000 25000 FIRST (mm³) $D = 0.60 \pm 0.16$ $D = 0.53 \pm 0.14$ $D = 0.61 \pm 0.16$ 0.85 15000 15000 15000 FSL-] 0.8 5000 5000 5000 5000 15000 25000 5000 15000 25000 5000 15000 25000 0.75 O.J R = 0.98R = 0.9325000 25000 $D = 0.93 \pm 0.07$ $D = 0.83 \pm 0.06$ Scatter plots of the brainstem volumes $S 5.3 (mm^3)$ extracted by different methods. 15000 15000 0.7 The Pearson correlation coefficient (R) the volumes obtained between 5000 5000 0.65 5000 25000 5000 15000 25000 15000 through each pair of segmentation R = 0.95methods is reported. 25000 $D = 0.83 \pm 0.02$ $6.0 \ (mm^3)$ 0.6 The colours of the dots represent the 15000 Dice coefficient (D) computed for \mathbf{S} each pair of segmented masks in 0.55 5000 50 Pad native space. 25000 5000 15000



51

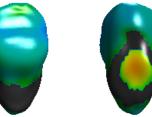


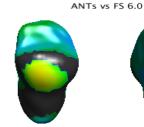




FSL-FIRST vs FS 5.3

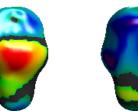
ANTs vs FS 5.3



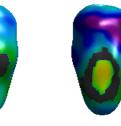


FSL-FIRST vs FS 6.0

ANTs vs FS 6.0 subfields



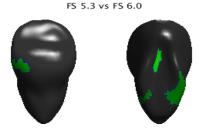
FSL-FIRST vs FS 6.0 subfields

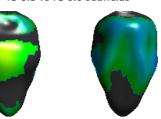


FS 5.3 vs FS 6.0 subfields

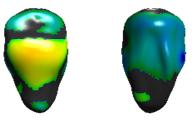
differences between Shape segmentation methods represented by <u>T-maps</u> of the distances along normal direction from a reference surface.

The threshold is at cluster-level pvalue=0.05 RFT corrected.





FS 6.0 vs FS 6.0 subfields



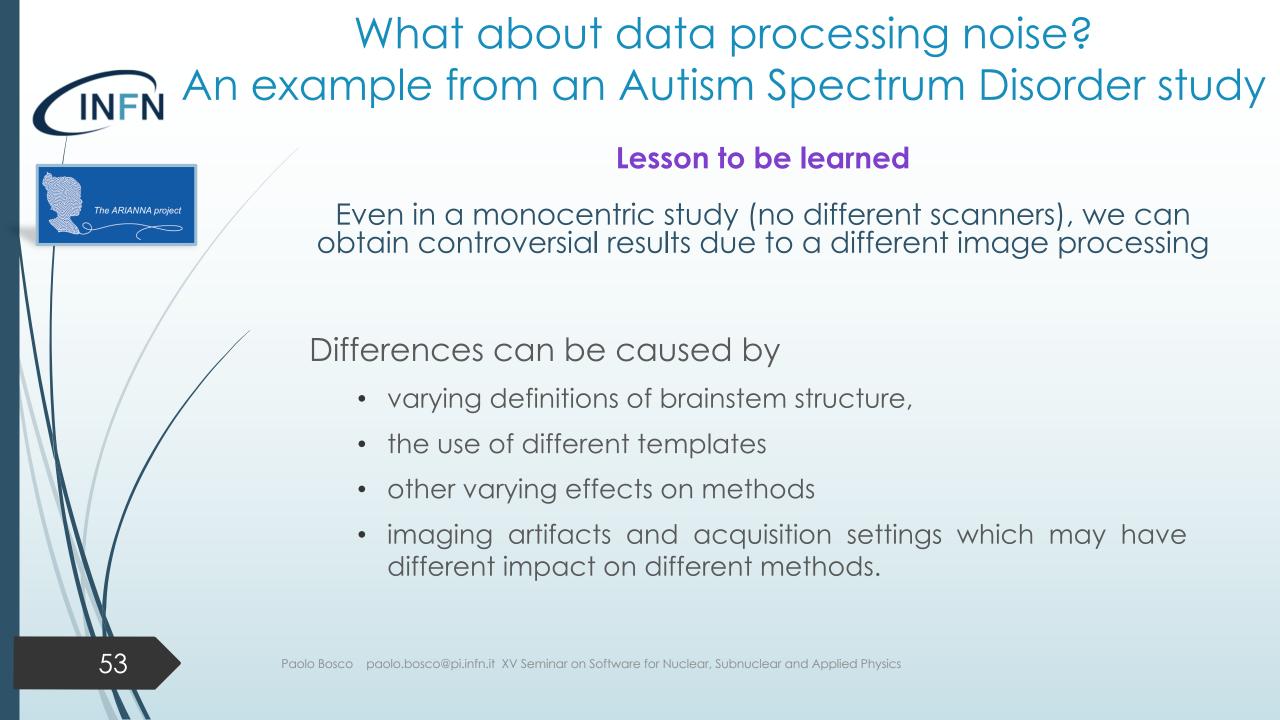
-25 -20 -10 10 15 20 -15 -5 0 5 25 Student's T

Brainstem volume analysis (ANOVA)

	Variable		MF		M		F				
Va			Mean (SE)		ANOVA	Mean (SE)		ANOVA	Mean (SE)		ANOVA
			ASD	CTRL	р	ASD	CTRL	Р	ASD	CTRL	р
		ANTs	13.53 (0.14)	13.03 (0.14)	0.016*	14.29 (0.22)	13.62 (0.22)	0.043*	12.77 (0.18)	12.45 (0.18)	0.230
		FSL -FIRST	10.60 (0.32)	10.73 (0.32)	0.776	11.92 (0.48)	11.62 (0.48)	0.668	9.40 (0.43)	9.87 (0.42)	0.452
BS volume (r	volume (ml)	FS 5.3	16.62 (0.21)	15.90 (0.20)	0.016*	17.58 (0.32)	16.43 (0.31)	0.013*	15.63 (0.26)	15.43 (0.26)	0.597
		FS 6.0	16.21 (0.19)	15,56 (0.19)	0.020*	17.01 (0.29)	16.01 (0.29)	0.018*	15.33 (0.25)	15.15 (0.25)	0.647
		FS 6.0 substructures	18.81 (0.20)	18.12 (0.20)	0.021*	19.79 (0.31)	18.84 (0.31)	0.040*	17.73 (0.25)	17.46 (0.25)	0.466

Paolo Bosco paolo.bosco@pi.infn.it XV Seminar on Software for Nuclear, Subnuclear and Applied Physics

The ARIANNA project



Let's recap a bit



- Medical images are no more just pictures observed by the physicians.
- They can be treated as signals and, as such, they can be handled with many of the techniques developed in Physics for signals analysis.
- Through the so called Radiomics, we can extract large amount of quantitative features: anatomical features (volumes, shapes etc), functional features etc.
- Many sources of variability can hinder this possibility (Acquisition noises/variability, Physiological noises/variability, Gold standard noise)
- We can handle many of these sources of noises BUT we must keep in mind not to introduce other sources of variability (data processing noise)

Future directions



The clinical input will be less and less relevant since these techniques can alone identify which are the important region of interest and features.

BUT they require HUGE amount of data to be trained

Data storage, data sharing (Privacy handling, data nonhomogeneity, SOPs to be developed), computing power (GPUs) etc etc...

For neuroimaging... Human Brain Project



Thank you for your attention!

I acknowledge all collaborators from INFN and Stella Maris and all people involved in the ARIANNA project for their precious contribution to the research presented in this talk (Many of the thoughts here reported have been originated by nice chats with Dott. Andrea Chincarini and Prof. Alessandra Retico).

ARIANNA was supported by the Italian Ministry of Health and Tuscany Region (grant GR-2010-2317873), by INFN-CNS5 (nextMR project) and by the Tuscany Region PAR-FAS 2007-2013 FAS Salute (ARIANNA project).

