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MeMeA

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Measurements
and Applications

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EEG GRADIENT ARTIFACT REMOVAL BY COMPRESSIVE SENSING AND TAYLOR-FOURIER TRANSFORM

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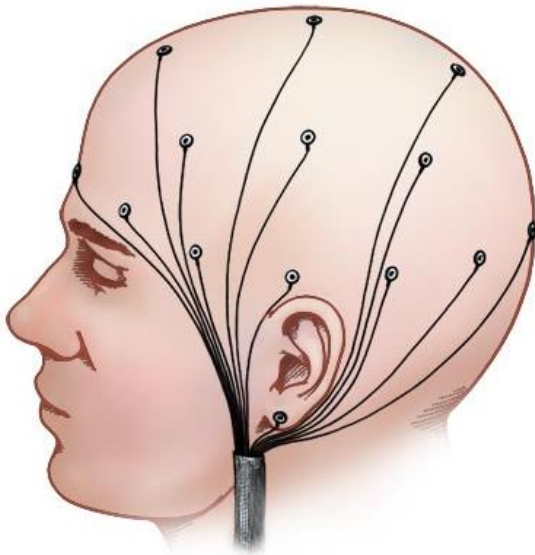


Brain Activities Measuring Techniques

- Neurophysiology measuring approaches can be classified in **two main classes**:

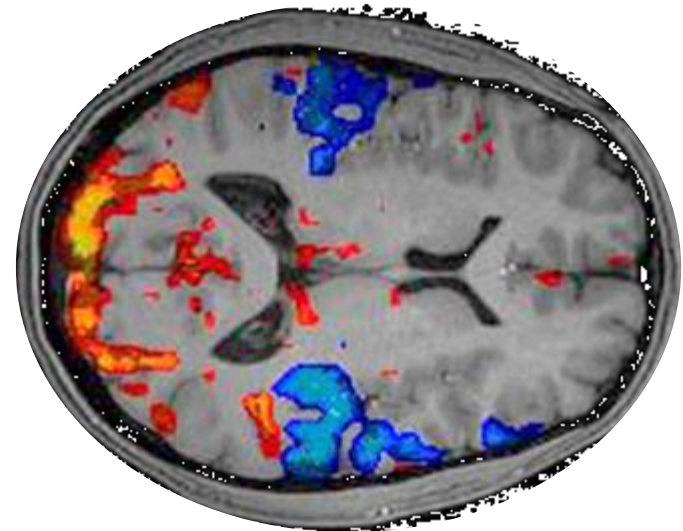
DIRECT

- Electroencephalography Recording (**EEG**)



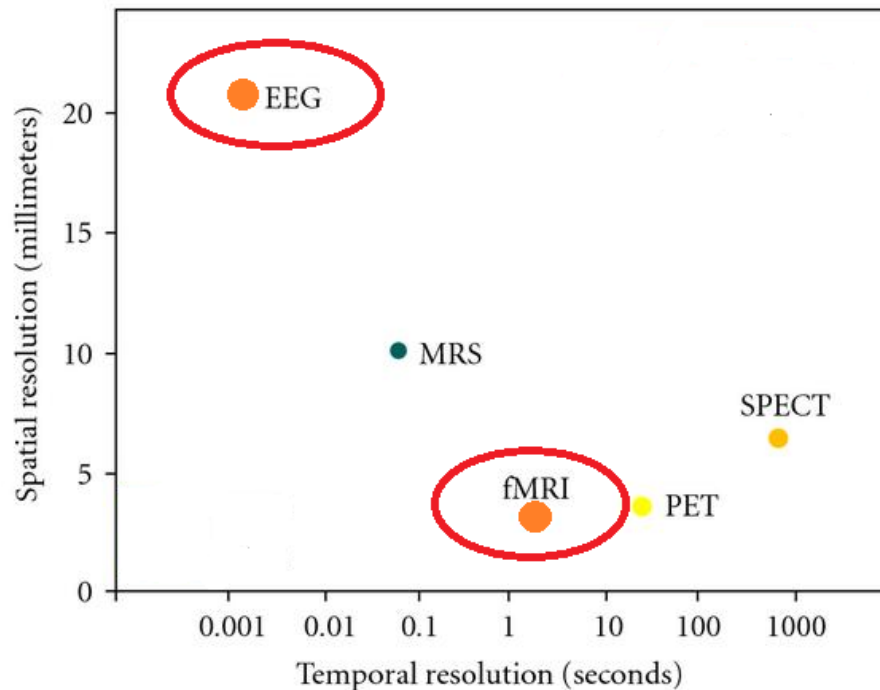
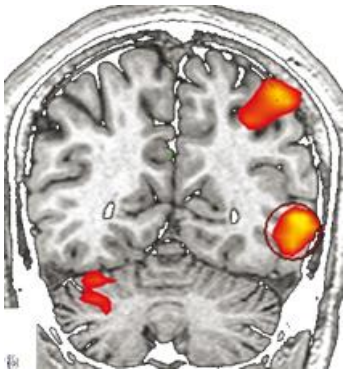
INDIRECT

- Functional Magnetic Resonance Imaging (**fMRI**)



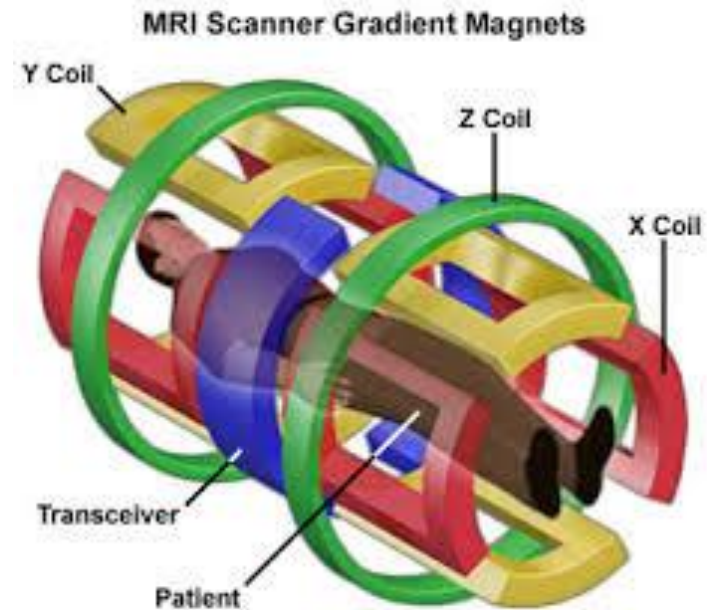
Concurrent Acquisition

- A **synchronous acquisition** combines:
 - **HIGH TEMPORAL RESOLUTION** given by **EEG**
 - **HIGH SPATIAL RESOLUTION** given by **fMRI**



Gradient Artifact

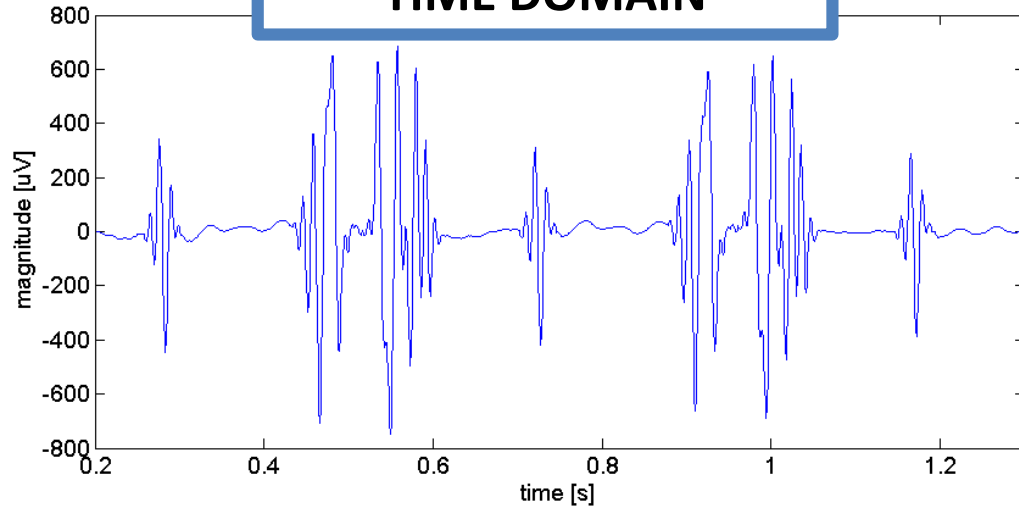
- EEG leads and head tissues form a **loop**...
... while **magnetic field gradients** are periodically imposed and inverted
- Induced current produces a large artifact, aka **GRADIENT ARTIFACT (GRA)**





GRA Properties

TIME DOMAIN

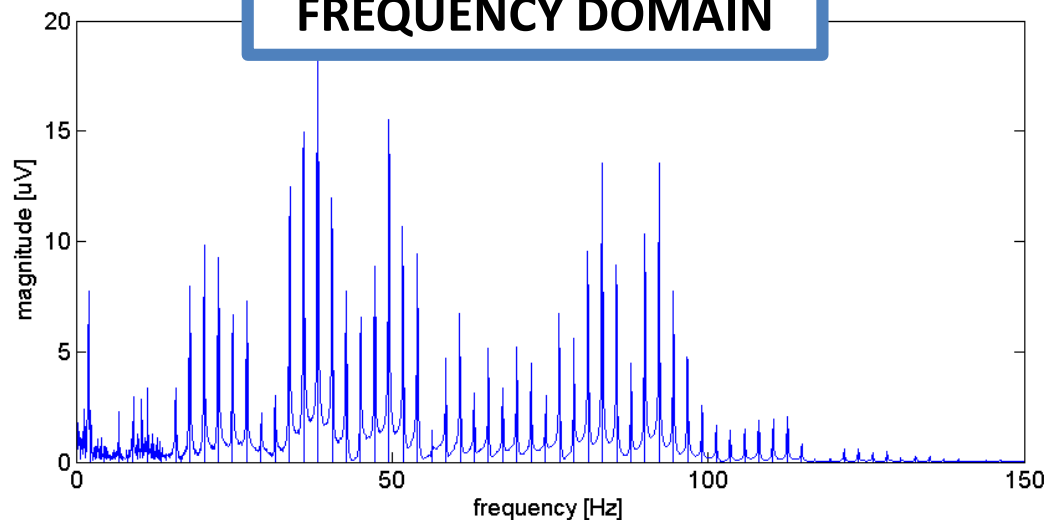


❖ train of occurrences

❖ two orders larger

❖ inherent periodicity

FREQUENCY DOMAIN



❖ irregular trend

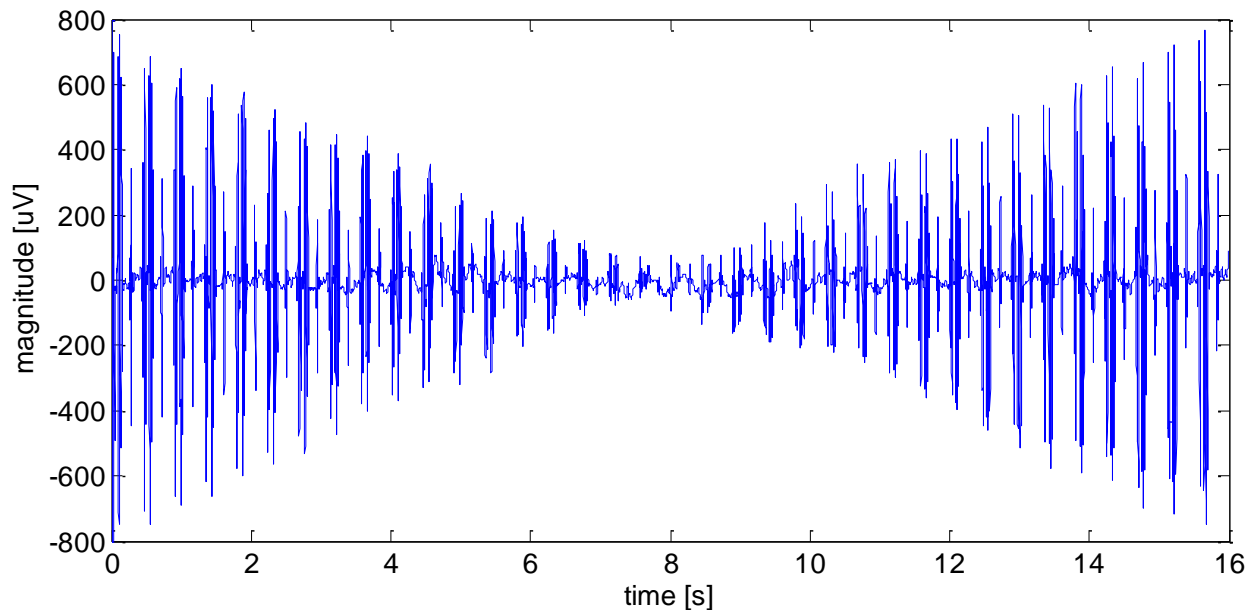
❖ wideband

EE



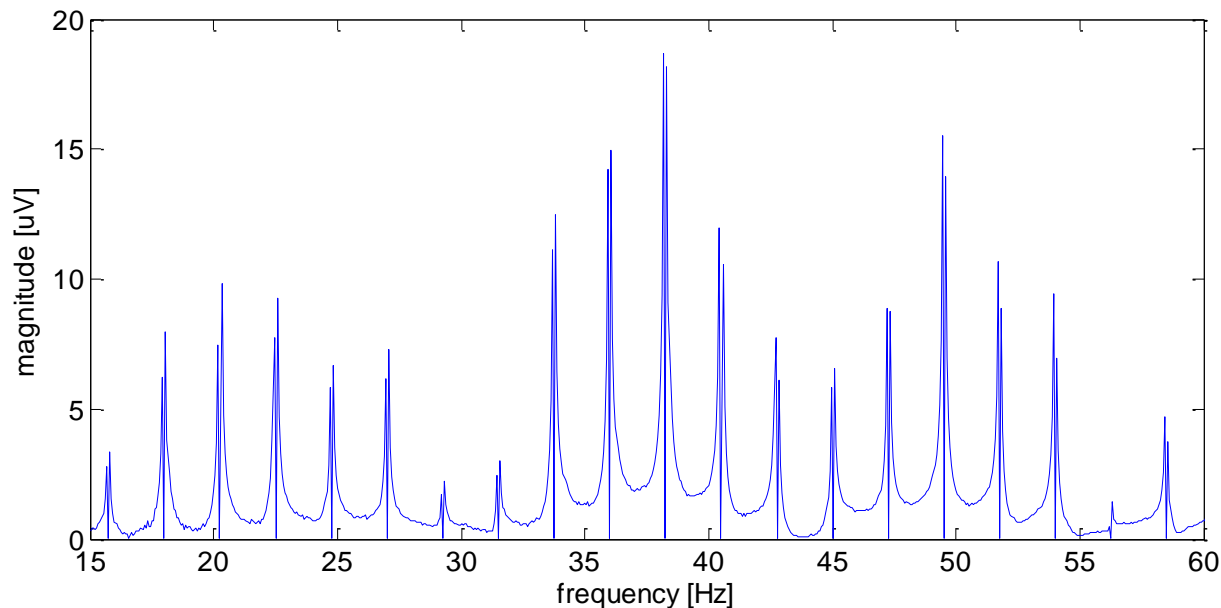
Water Phantom (1)

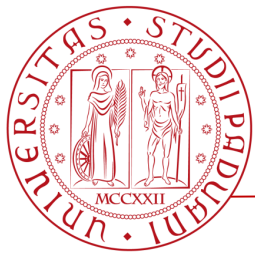
- **water phantom, only GRA contribution**
- in the time domain:
 - **NO COINCIDENCE** between artifact occurrences
 - low frequency **ENVELOPE MODULATION**



Water Phantom (2)

- in the frequency domain:
 - peaks with **INDEPENDENT AMPLITUDE AND PHASE**
 - almost **EQUALLY SPACED** frequencies $f_0 = \frac{N_v}{T_v}$





Problem Statement

ARTIFACT MODEL

$$x(t) = \sum_{h=1}^H A_h(t) \cos(2\pi h f_0 t + \phi(t))$$

SAMPLED SIGNAL MODEL

$$y[n] = \sum_{h=1}^H A_h[n] \cos(2\pi h f_0 n + \phi[n]) + e[n]$$

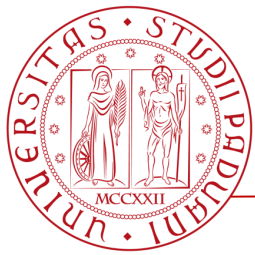
EEG from informative to noisy contribution



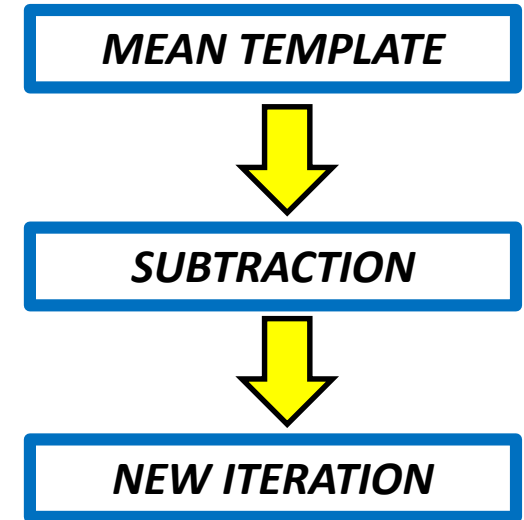
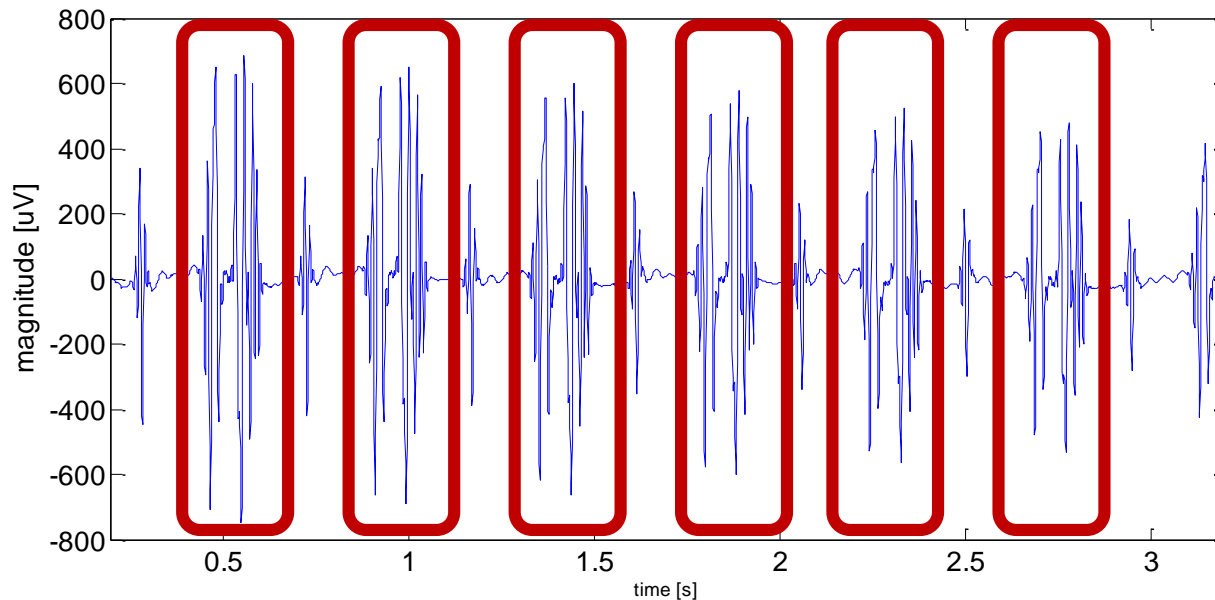
Artifact Removal

- **WORK HYPOTHESIS:** artifact is **simply superimposed** to EEG signal
- **REMOVAL APPROACH**
 - 1) Detect signal portions affected
 - 2) Generate an artifact template
 - 3) Subtract the template
- **CRITICAL POINT:** **template generation**





Average Artifact Subtraction (AAS)



- All occurrences from all channels
- EEG treated as **uncorrelated white noise**

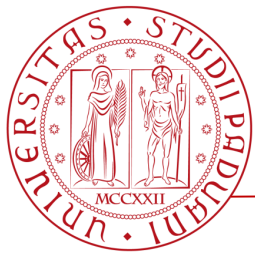




AAS Issues

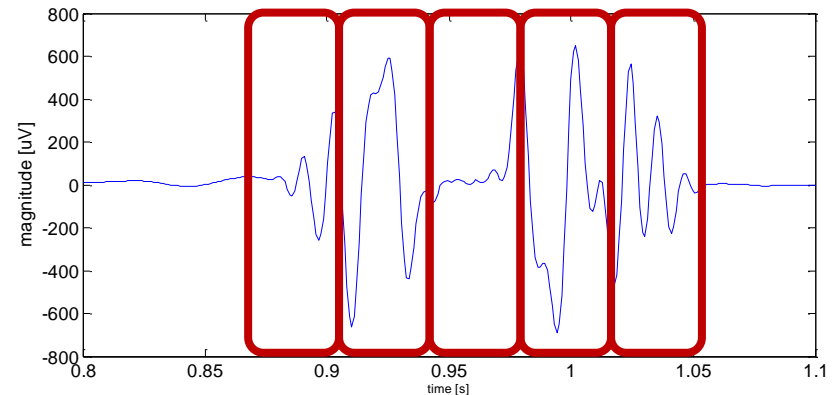
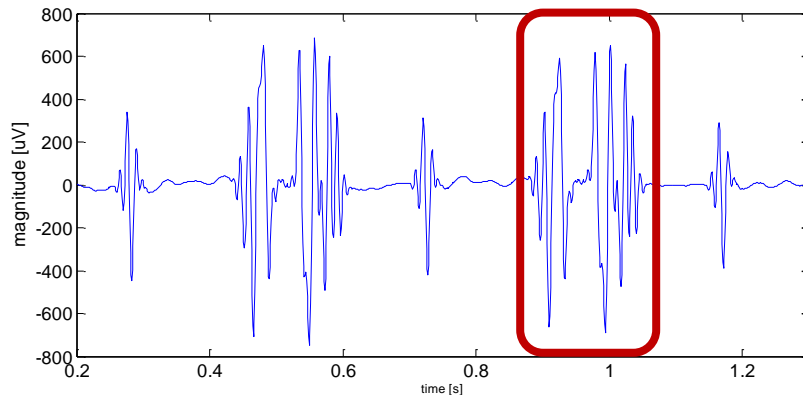
- Based upon a **STATIC MODEL**
 - *no dynamics included*
- Only a **MEAN TEMPLATE** is computed
 - *need of more iterations*
- Occurrences are **NOT COMPARABLE**
 - *mutual similarity classification*





Our Proposal

- each occurrence is treated **SINGLY...**
 - ***specific template computation***

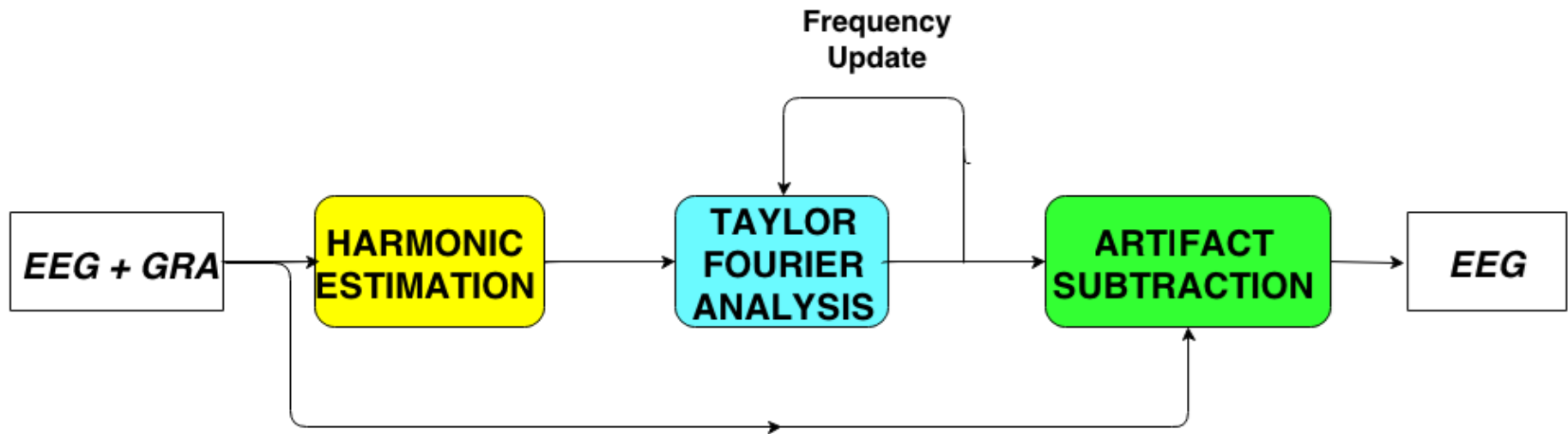


- ... and divided into **SHORT INTERVALS**
 - ***reduced dynamic effect***

EL
D

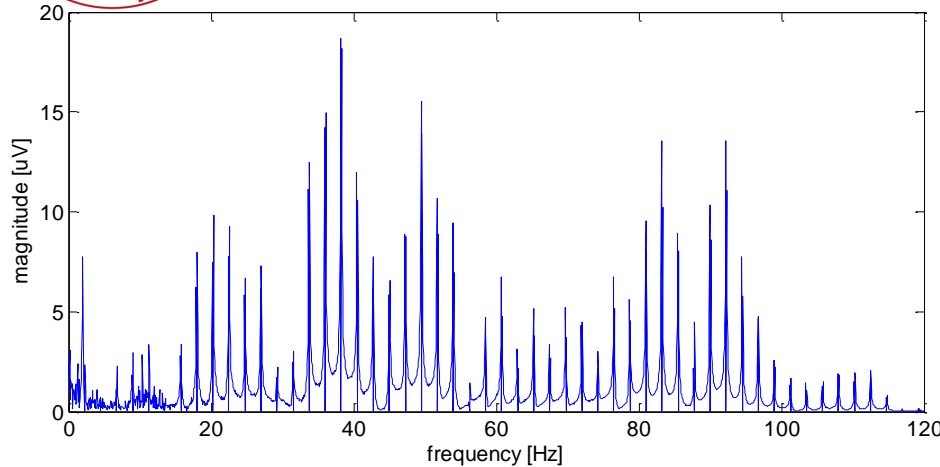


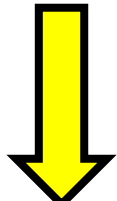
Main Steps



- **No prior information needed**
 - *signal independent approach*

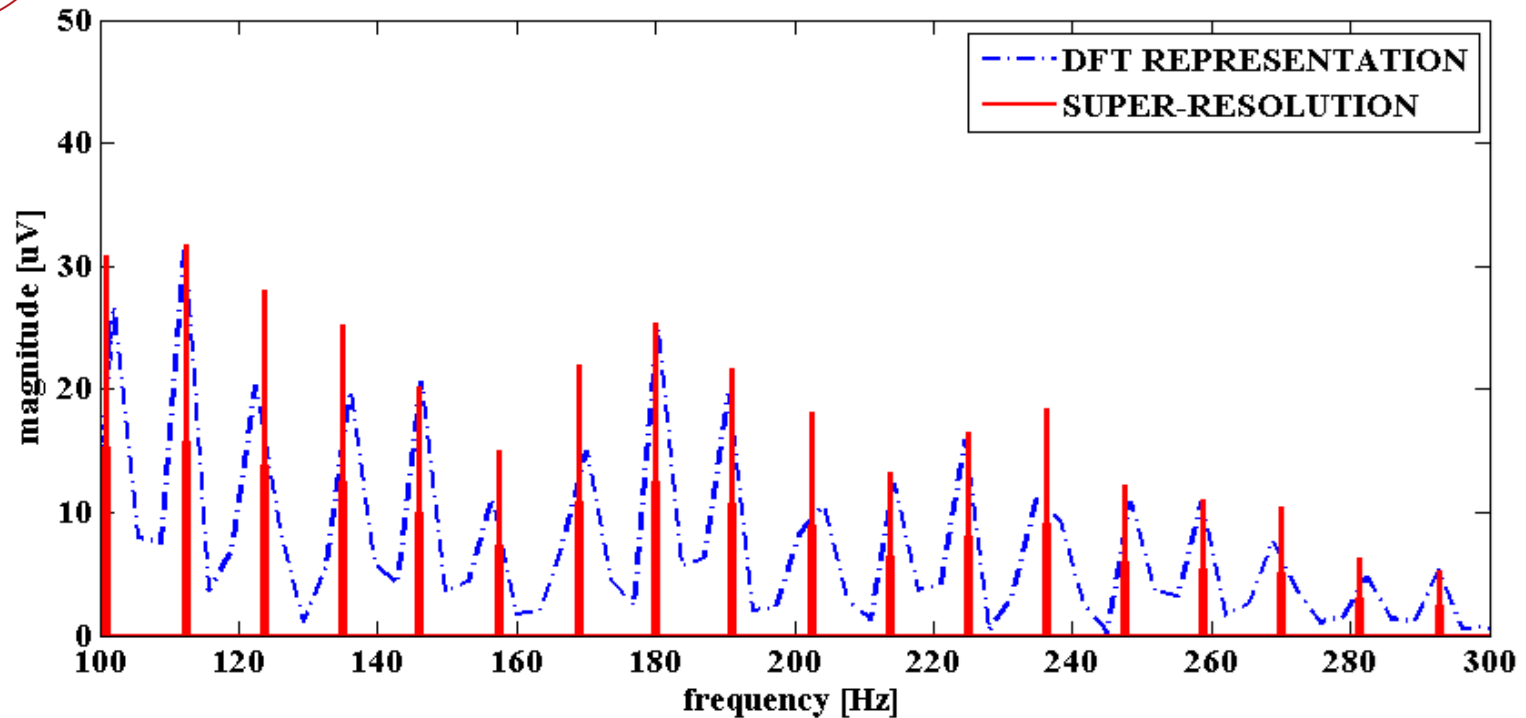
Harmonic Frequencies



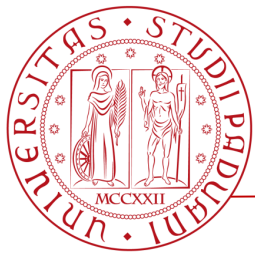

$$\sum_h A_h[n] \cos(2\pi f_h n + \phi[n])$$

- **signal portion** consisting of N samples
 - *DFT normalized resolution of $\Delta_f = 1/N$*
- **super-resolution** needed
 - **ZERO-PADDING**: too computational costly
 - **COMPRESSIVE SENSING** (CS): efficient


Resolution Enhancement



- CS resolution gain equal to $P \sim 10$
- Peak frequencies resolution $\Delta_f = 1/(NP)$



Taylor-Fourier Transform (TFT)

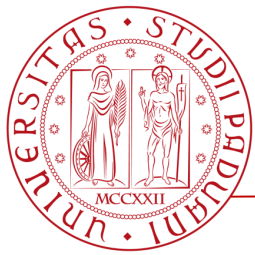

$$\sum_h A_h[n] \cos(2\pi f_h n + \phi[n])$$

- **DFT**: only averaged estimates
- **TFT**: suited for dynamic conditions
 - transform kernel $\psi_{(k,h)}(t) = t^k e^{-j2\pi f_h t}$
 - transform coefficient

$$\theta_{(k,h)} = \frac{T_s^k}{k!} \frac{d^k A_h(t) e^{j\phi_h(t)}}{dt^k}$$

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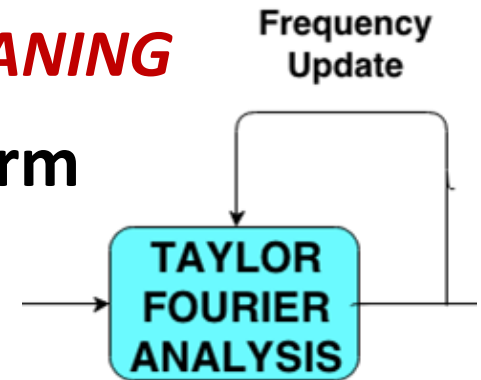




TFT Advantages

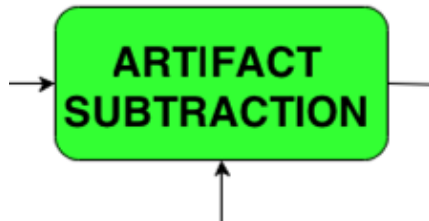
- TFT coefficients have a **PHYSICAL MEANING**
 - phase first derivative = frequency term

$$\hat{f}_h = f_h + \frac{d\phi_h(t)}{dt}$$



Given \hat{f}_h the TFT analysis provides \hat{A}_h and $\hat{\phi}_h$

ARTIFACT TEMPLATE



$$\sum_h \hat{A}_h[n] \cos(2\pi \hat{f}_h n + \hat{\phi}_h[n])$$



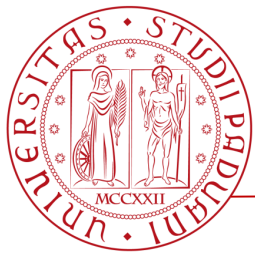


Experimental Validation

- EEG and GRA **acquired independently** and **numerically added**
- **EEG** measured **OUTSIDE THE SCANNER**
 - healthy subject with open and closed eyes
- **GRA** acquired on a **WATER PHANTOM**
 - static and dynamic conditions

EEG





Static VS Dynamic

- **DYNAMIC DATA SET**

- real GRAs during T2* EPI sequences
- **time-varying parameters** (f_h, A_h, ϕ_h)

- **STATIC DATA SET**

- numerically simulated GRAs
- **stationary parameters** $f_h = hf_0$

$$A_h \sim \mathcal{N}(1 \times 10^4, 5 \times 10^2)$$

$$p_h \sim \mathcal{U}(0, 2\pi)$$



Algorithm Parameters

- Sampling frequency $F_s = 1024$ Hz
- Hardware band-pass filter 0.5 – 269.5 Hz
- **OBSERVATION INTERVAL** of $N = 301$ samples corresponding to **0.294 seconds**
- Enhancement factor $P = 13$ corresponding to $\Delta_f = 0.26$ Hz of **FREQUENCY RESOLUTION**

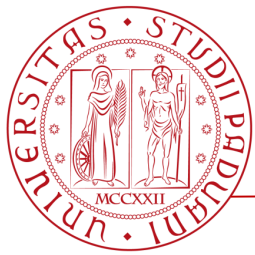


Performance Indices

- For each data set and each conditions **10 GRA** have been removed
- MEAN RESULTS** are here presented:

PATIENT STATE	DATA SET	SNR IN [dB]	SNR OUT [dB]
OPEN	<i>static</i>	-39.5	13.10
EYES	<i>dynamic</i>	-38.7	3.77
CLOSED	<i>static</i>	-36.9	11.79
EYES	<i>dynamic</i>	-37.1	5.23

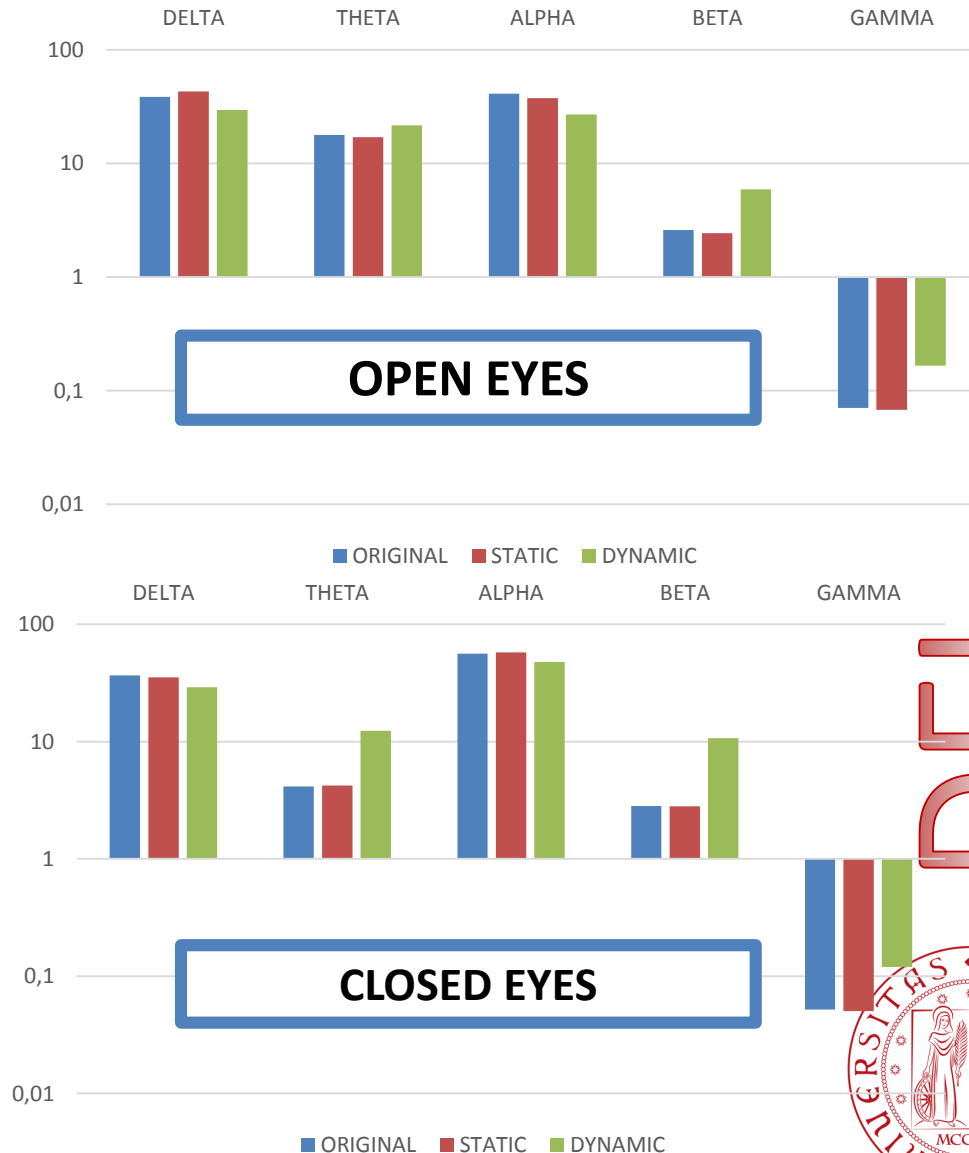
- Significant **SNR gain** in all cases



Band Power Distribution

- **PERCENTAGE POWER DISTRIBUTION** over clinical significant bands **not distorted**

■ ORIGINAL
■ STATIC
■ DYNAMIC

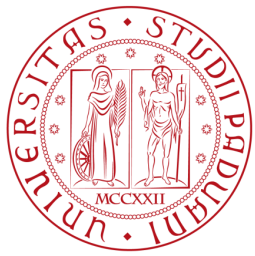




Conclusions

- ✓ Signal model accounting for dynamics
- ✓ **QUICK ESTIMATION**: short observation interval
- ✓ **REDUCED ARTIFACT INTERFERENCE**: SNR gain
- ✓ **RESULTS RELIABILITY**: no significant distortion in power distribution





Thank You!

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DEI





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