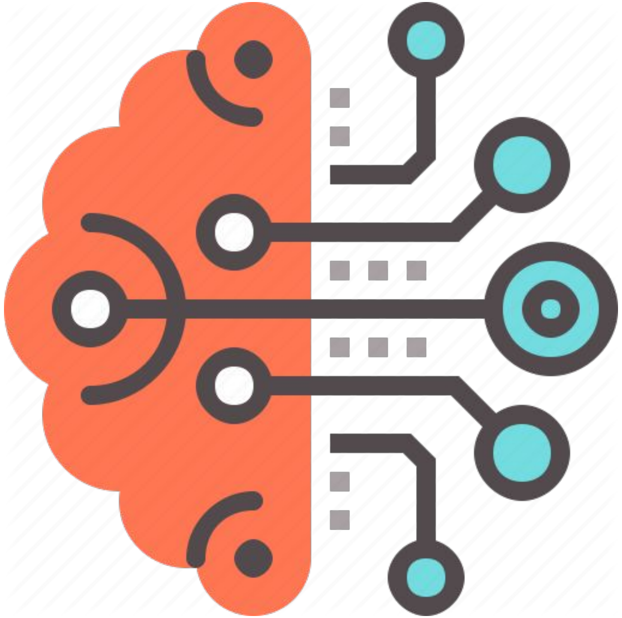
Design of an SSVEP-based speller

EMD -EEG



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18/01/2022

Summary

01 Part I : NeuroEngineering

A. State of the art

- *a. Brain-Computer Interface (BCI)*
- *b. SSVEP-based spellers*
- *c. EEG Analysis & extraction methods*

B. Speller Conception

- *a. Characteristics*
- *b. Baseline Study*

C. Limitations

- *a. Technical limitations*
- *b. Ethical & legal aspects*

Summary

02 Part II : Signal Processing

A. **Material & methods**
   a. *Database*
   b. *Feature extraction techniques*
      1. *EMD-FFT*
      2. *EMD-CCA*

B. **Results**
C. **Conclusion**

Part I

NeuroEngineering

A. State of the art

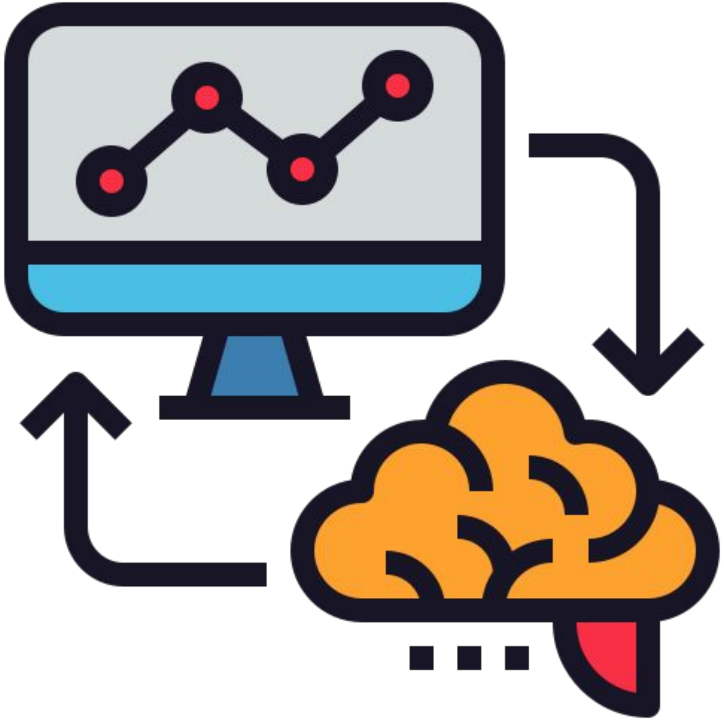
Brain-Computer Interface (BCI)

A brain-computer interface (BCI) is **a computer-based system that acquires brain signals, analyzes them**, and translates them into commands that are relayed to an output device to carry out a desired action.

NCBI definition

Prediction of cognitive status

Improved quality of life



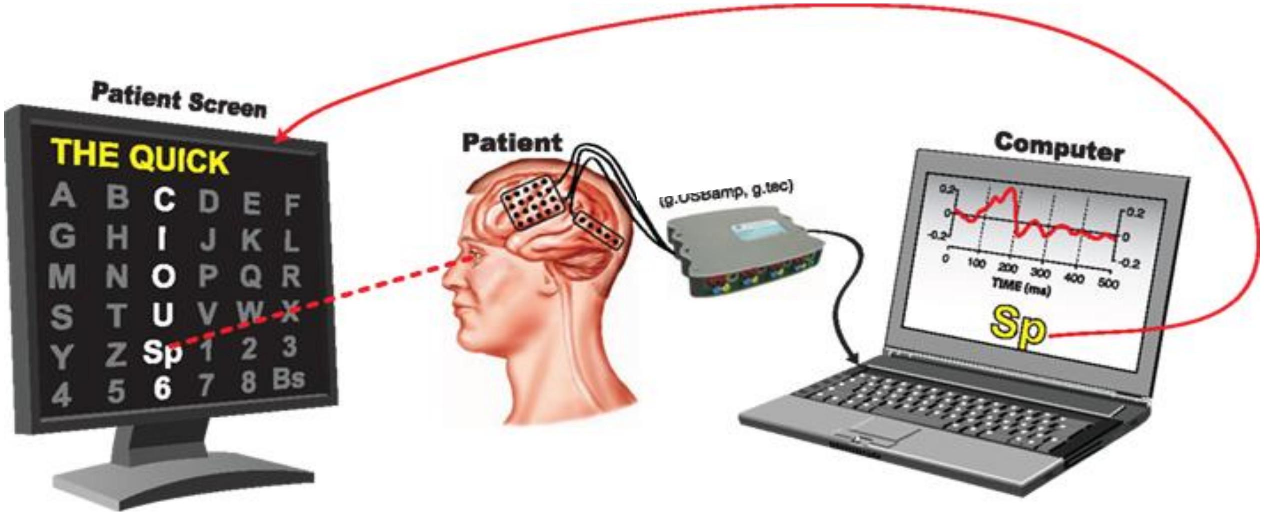
Invasive or non invasive

EcoG, NRIS

fMRI, EEG, MEG

A. State of the art

SSVEP speller definition



BCI speller associates the recorded EEG signal to the letters visually chosen by the patient for building words

Stimuli frequency

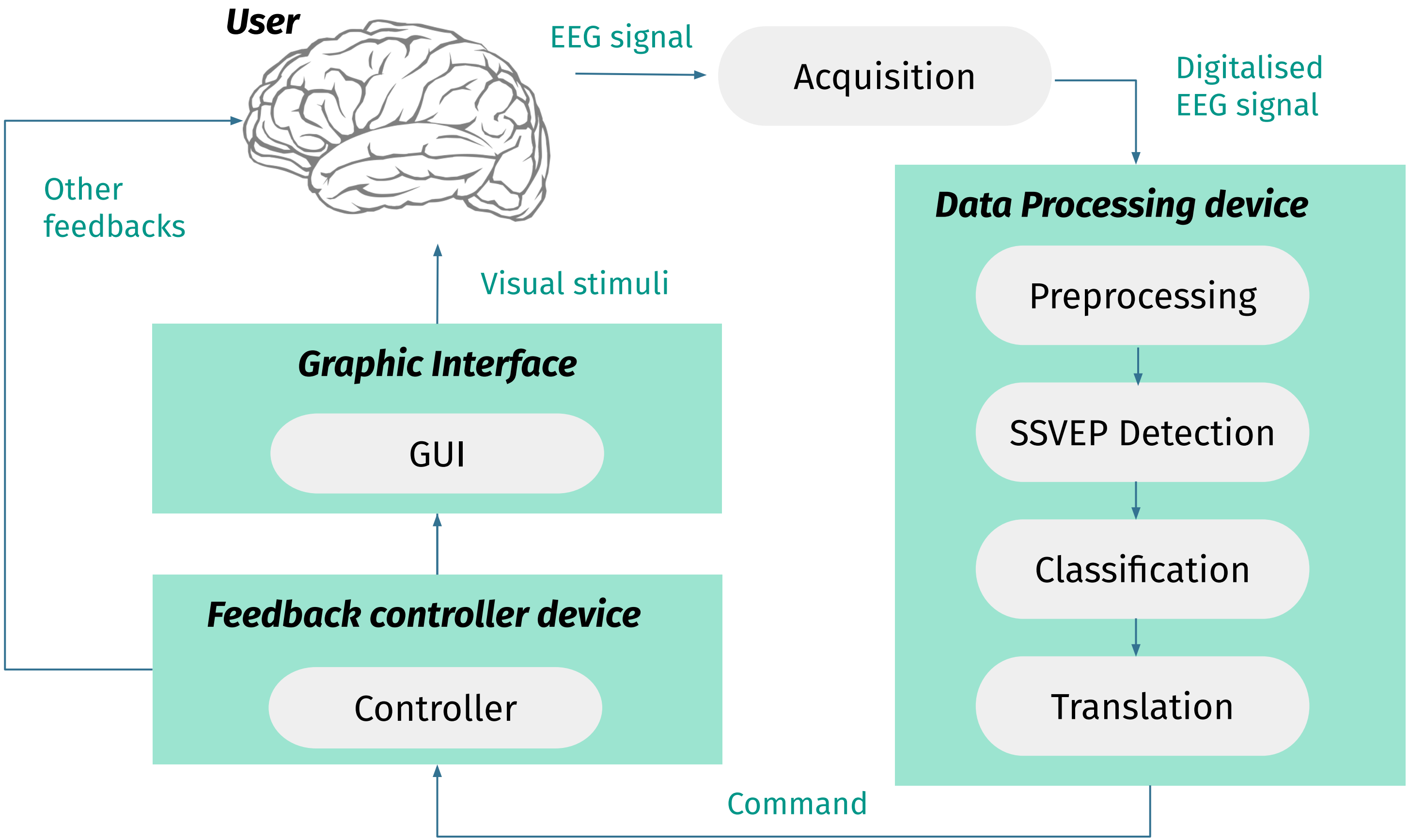
↓

Recorded EEG frequency

Steady State Visually Evoked Potentials (SSVEPs) are EEG signal responses to visual stimulation at specific frequencies.

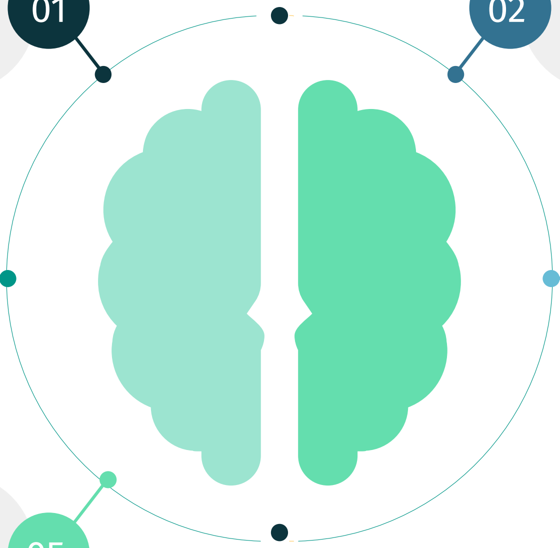
A. State of the art

SSVEP-based speller: scheme



A. State of the art

SSVEP-based speller: Taxonomy



01 Operation Modality
Sync & Async

02 Paradigm combination
Single or hybrid

03 Gaze dependency
Overt or covert attention

04 Word predictor
Complex but improves ITS

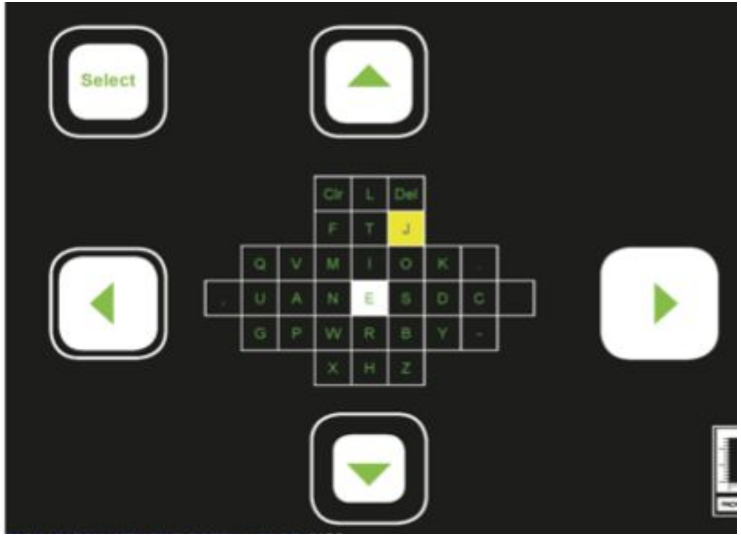
05 Selection modality
Direct character selection vs pointer selection

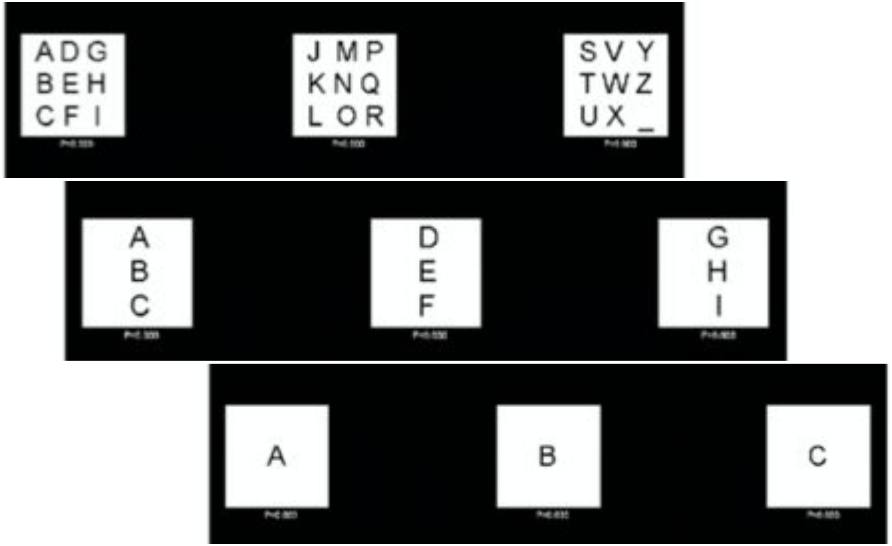
Performance of BCI speller:

- Accuracy
- ITR

A. State of the art

SSVEP-based speller: examples





05 Pointer selection

one-phase

05 Direct character selection

multi-phase

A. State of the art

Common feature extraction methods

Selection of the best combination of electrodes and parameters

Power Spectrum Density Analysis (PSDA)

Based on:
- The detection of a periodic pattern with the same frequency of the stimuli.
- The magnitude of the SSVEP periodic pattern.

Canonical Correlation Analysis (CCA)

Based on:
- The detection of a periodic pattern with the same frequency of the stimuli.
- The correlation between the brain signal and the stimulus frequency.

Empirical Mode Decomposition (EMD)

Based on:
- Decomposition of EEG signal into a finite and small number of components (IMFs).
- Choice of IMFs that correspond to the frequency bands used in the SSVEP.

A. State of the art

EMD - based methods for SSVEP speller

It calculates the **Power Spectral Density (PSD)** of IMF and finds the maximum values of it and perform a decision for the selection of the class.

It measures the **linear association** between the IMFs and a "Fourier series" of simulated stimulus using its **autocorrelation** and **crosscorrelation**.

It recognizes the stimulus frequency by measuring the **synchronisation** between the EEG signals and the reference signal.

It classifies the frequencies with an algorithm able to split a **complex decision-making process** into a collection of **simpler decisions**

EMD - PSDA

EMD - CCA

EMD - MSI

EMD - Decision Tree

EMD

B. Speller Conception

Characteristics

One phase

Different frequencies
→ higher spelling speed

Synchronous

Processing during
the blanks

Fast Fourier Transform

Simple to use & low
computational cost

Canonical Correlation Analysis

Simple and more
accurate qualification

B. Speller Conception

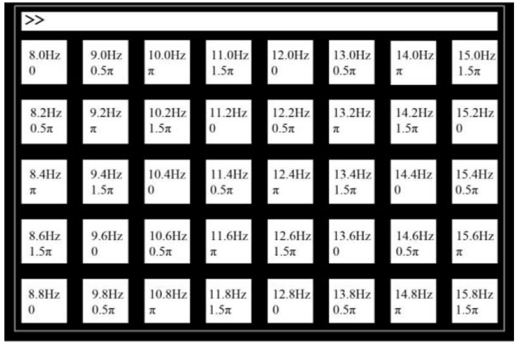
Baseline study

A Benchmark Dataset for SSVEP-Based Brain–Computer Interfaces ; Tsinghua BCI lab ; Yijun Wang

35 subjects x 6 blocks x 40 runs

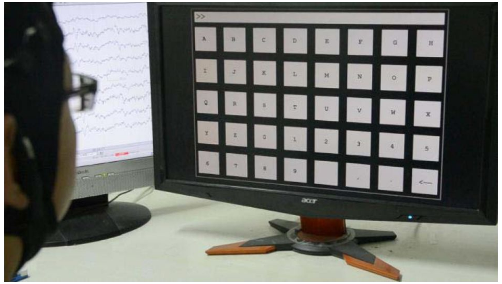
Stimulation

- 5 x 8 Matrix.
- 40 Characters.
- 40 Frequencies : 8 - 15.6 Hz.



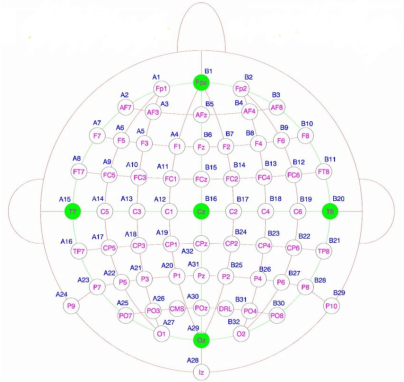
Experimental design

- 6 blocks x 40 characters x 6s
- 0,5s of target
- 5s of identification
- 0,5s of blank



Acquisition

- 64 electrodes, 10 - 20 setup
- Reference : Cz electrode
- Sampling : 1000Hz.
- Bandwidth : 0.5Hz - 200Hz.
- Notch filter: 50 Hz



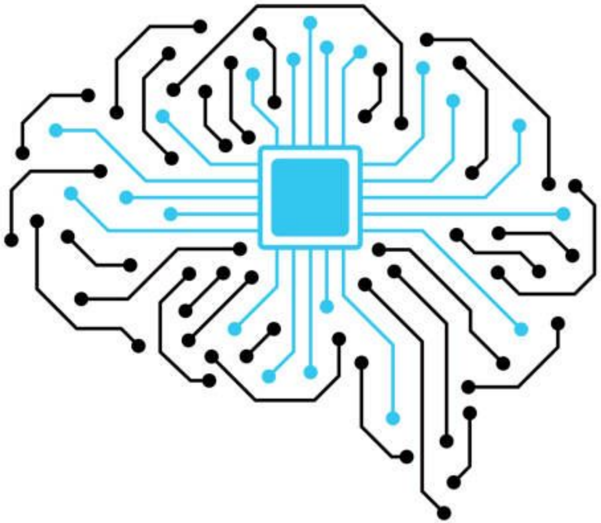
C. Limitations

Technical limitations

Ocular fatigue
Gaze and ocular concentration provoque fatigue in the subject

Visual latency
Low temporal precision due to interference with spontaneous signals

Ocular impairment
Not applicable for patients with ocular issues



Communication speed
Only detects a few letters per minute, which is inconvenient for realistic applications

Signal to Noise Ratio
Peaks of interest coexist with random noise signals

Information Transfer Rates
SSVEP ITR are lower than other techniques (P300, EcoG)

C. Limitations

Ethical & legal aspects

Humanity

Fusion of human and machine.

Informed consent

The subjects should are aware of all the possible implications of BCI before consenting to use it.

Privacy

Possibility of extracting private information from people's brains and using it without their knowledge or consent.

Personhood

Possibility of a sense of self changing.

"Right to brain privacy"

Privacy legislation to regulate the information gathered in BCI use.

Part II

Signal Processing

A. Material & Methods

Database

A Benchmark Dataset for SSVEP-Based Brain–Computer Interfaces ; Tsinghua BCI lab ; Yijun Wang

35 subjects x 6 blocks x 40 runs

Stimulation

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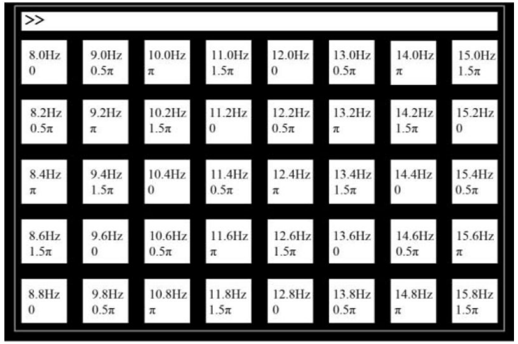

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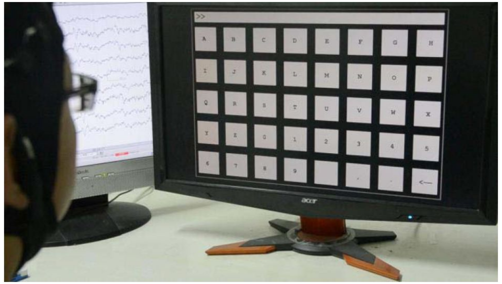

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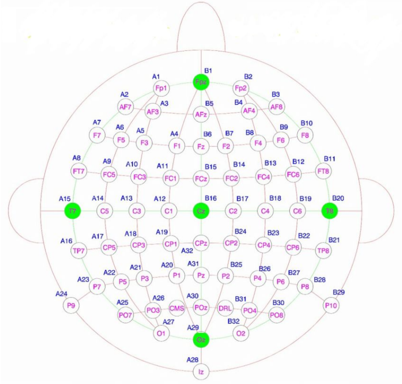


A. Material & Methods

Feature extraction methods

Epochs
Flickering stimuli: 5s
Processing: 0.5s b&a stimuli

Signal choice
12 subjects x 6 Blocks x 40 letters
Electrodes: O1, O2, Oz

→ Single run
→ Averaged

The **EMD** decomposes the EEG signal into Intrinsic Mode Functions (IMFs).

01
EMD-FFT
(IMFs 2+3)

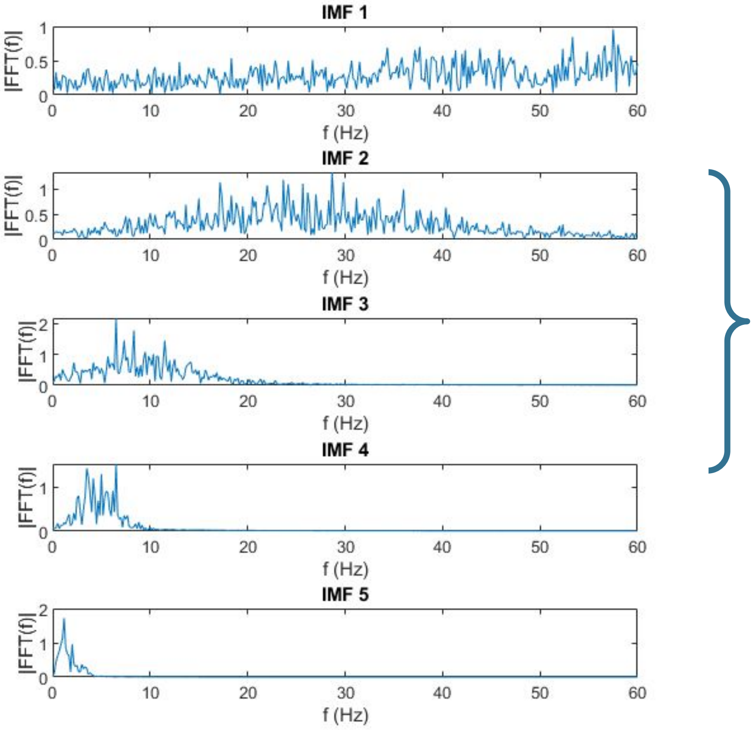
02
EMD-FFT
(IMFs 2+3-4-5)

03
EMD-CCA
(IMFs 2+3)

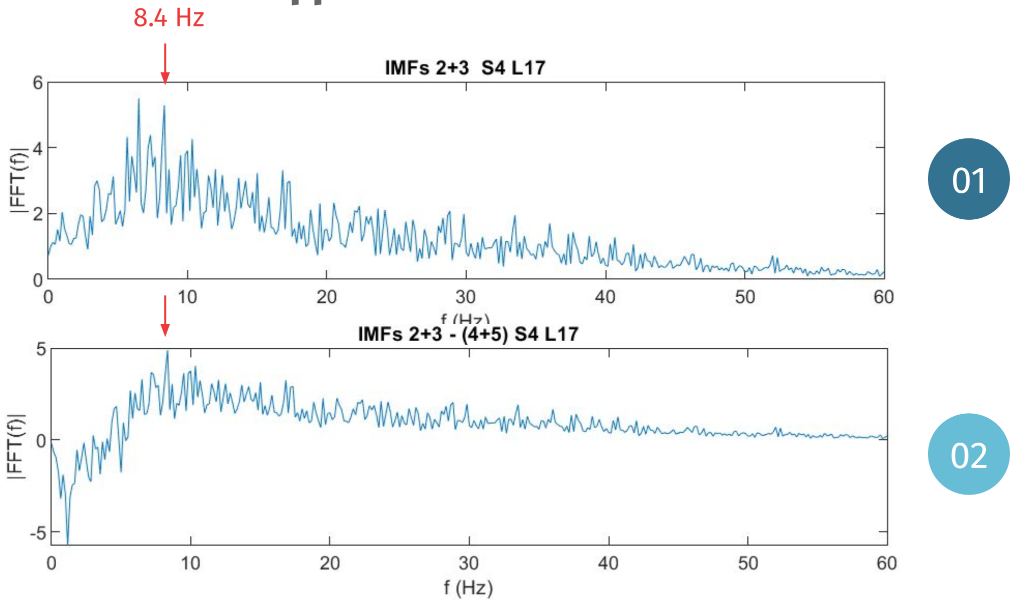
Classification

A. Material & Methods

EMD-FFT



Application of EMD and FFT



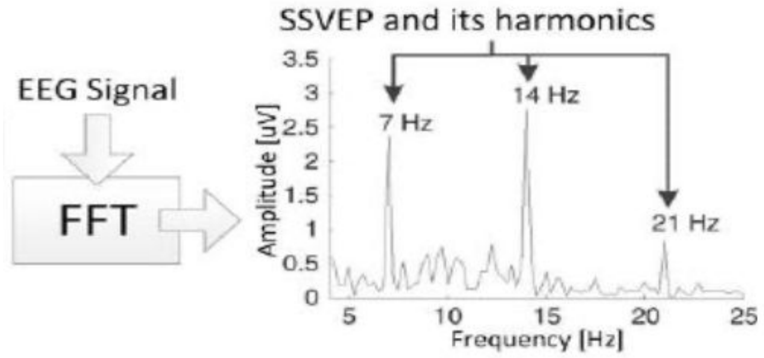
IMF Selection

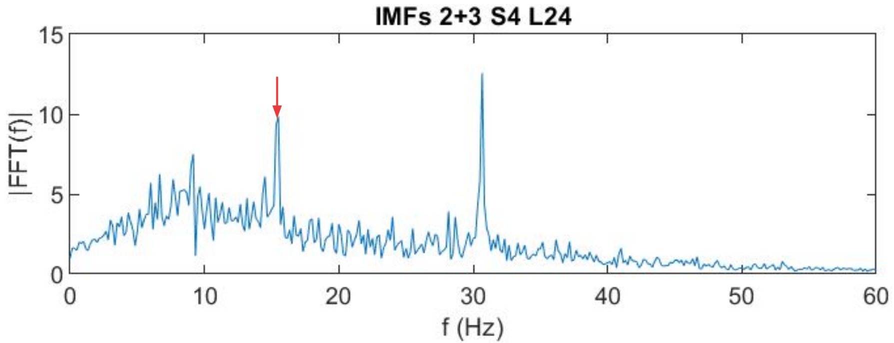
IMFs 2+3 and IMFs 2+3-4+5

Most representative: same bandwidth as stimuli (8-45Hz)

A. Material & Methods

EMD-FFT





The frequency of the first peak corresponds to the stimulus frequency, whereas the other peaks are the harmonics.

Parametrization :

Frequency of the first peak in the FFT of the combined IMFs

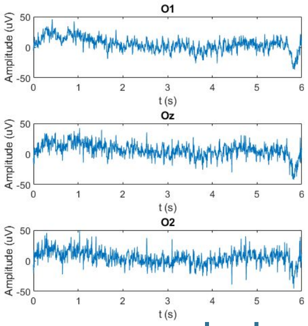
Threshold for the first peak: 70% of the maximum peak

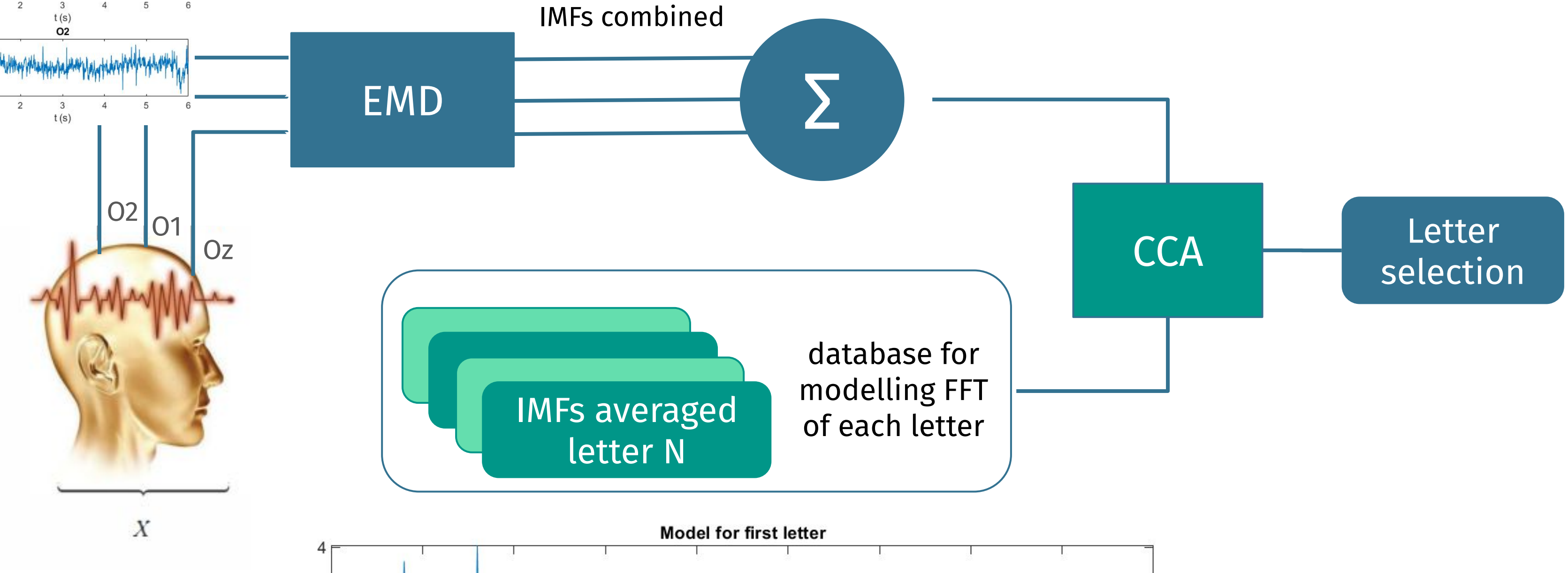
Classification :

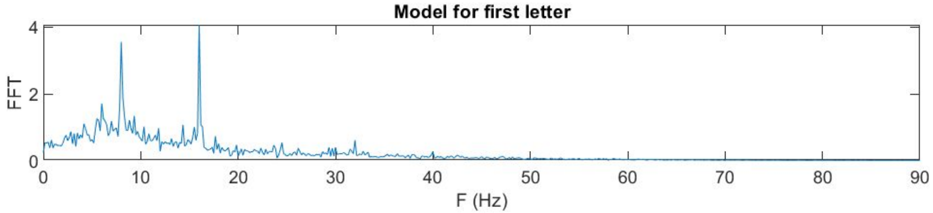
Comparing the frequency of the first peak with the frequency of stimuli.
Selecting the closest frequency.

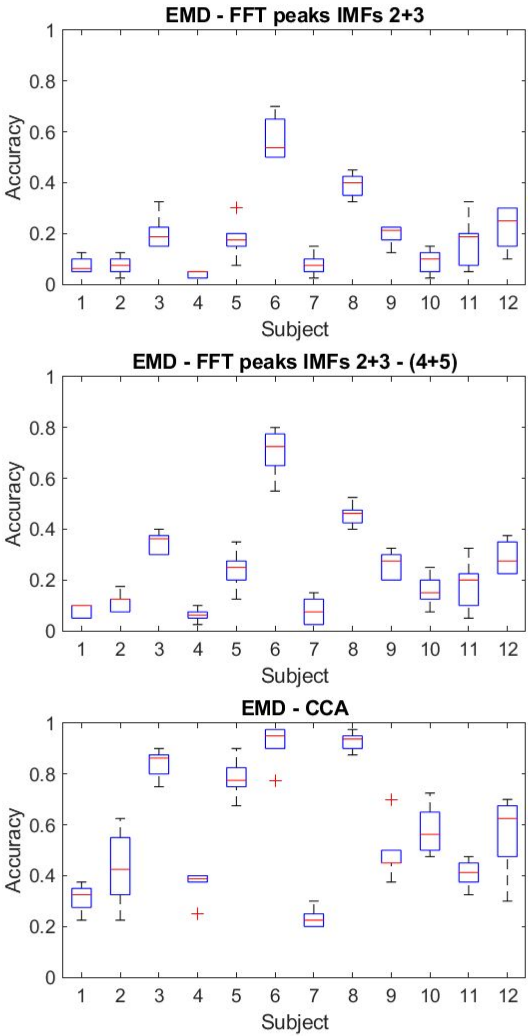
A. Material & Methods

EMD-CCA





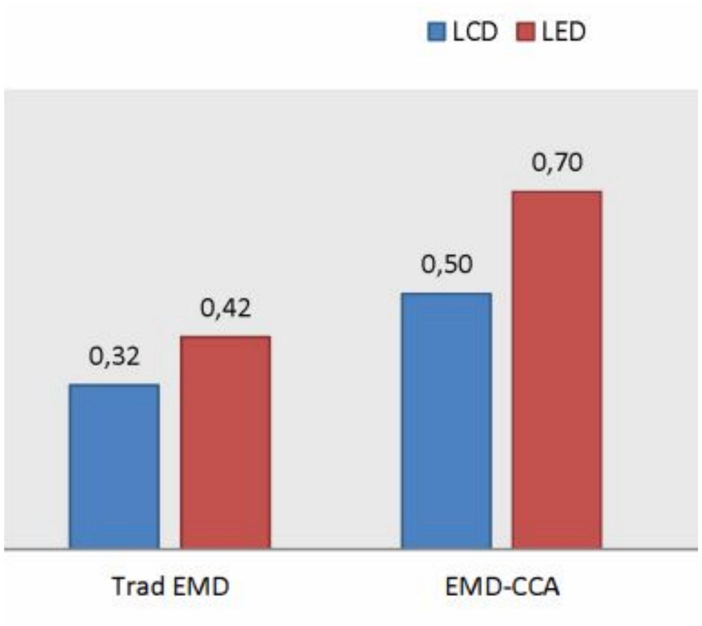




B. Results

EMD-FFT	Single run	Averaged
IMFs 2+3	24.17%	78.12%
IMFs 2+3-4-5	24.9%	82.29%
EMD-CCA	57.15%	—

B. Results



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EMD-CCA	57.15%	—

[22] Tello, Muller et al., 'Comparison of new techniques based on EMD for control of a SSVEP-BCI', 2014

C. Conclusions and future perspectives

EEG
Complex signal, it needs propper preprocessing

01

Subject Variability
Big differences between different individuals

02

FFT
Looking only to the FFT peaks is not enough

03

Poor accuracy
The accuracy remains low, but similar to literature

04

Word prediction
Built-in dictionary can be implemented to improve spelling speed

05

Thank you for your attention

Any doubts?

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