THE AMERICAN
UNIVERSITY IN CAIRO

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CSCE 363/3611 - Digital Signal Processing

Steady-state Visual Evoked Potentials

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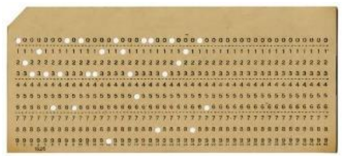
Human-Computer Interaction Technology Evolution

- Human-Computer Interaction (HCI) technology has evolved over the years since the invention of computers



Now

Touchscreens

Speech Recognition

The Future

Augmented Reality

?

Neural Engineering

- Neural Engineering is a field of research that focuses on engineering methods to investigate the function of the central and peripheral nervous system and manipulate its behavior

- Neural Interfaces are systems that can help restore sensory function, communication, and control to impaired humans

- The main principle is that disabled people would have their brains or parts of their brains fully functional

- Neural Interfaces make use of functional parts to restore a lost function

- Objectives of Neural Engineering:

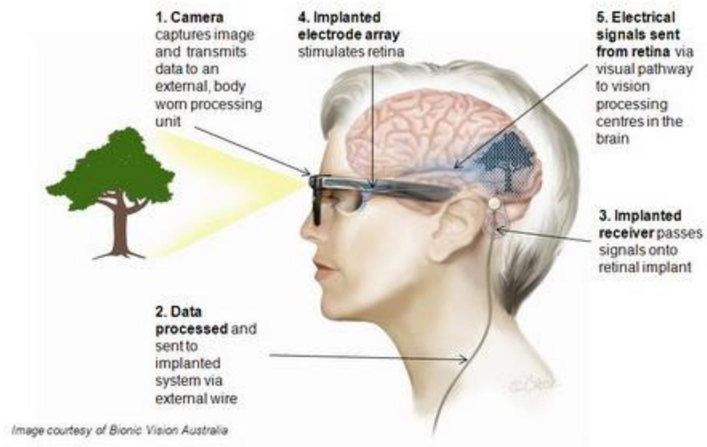
  1- Understand Brain Function

  2- Provide Therapeutic, Assistive and Augmentative Technology

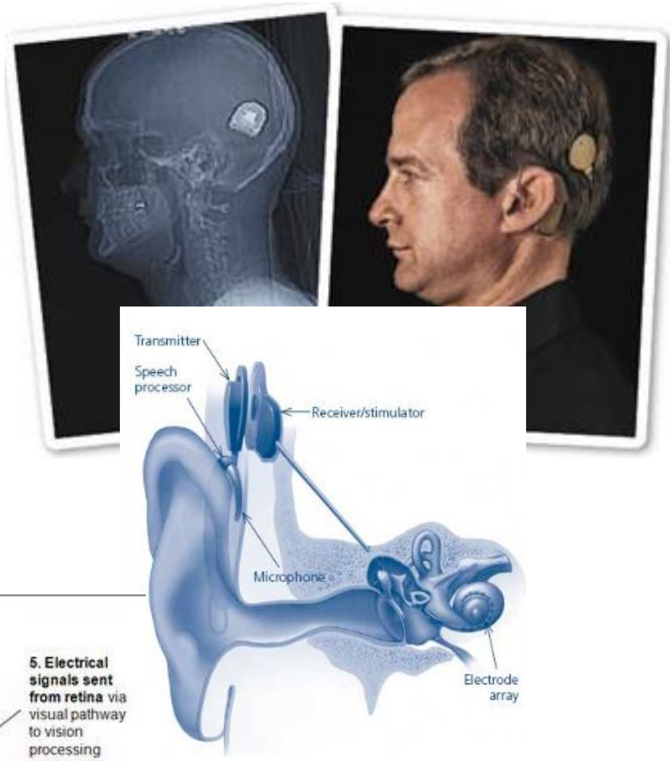
Neural Engineering

- Examples of Neural Interfaces:

Motor Brain-Machine Interface



Visual Prosthesis

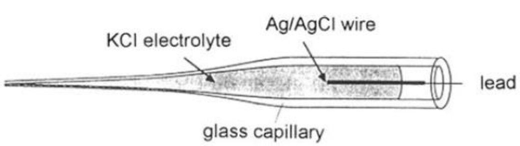


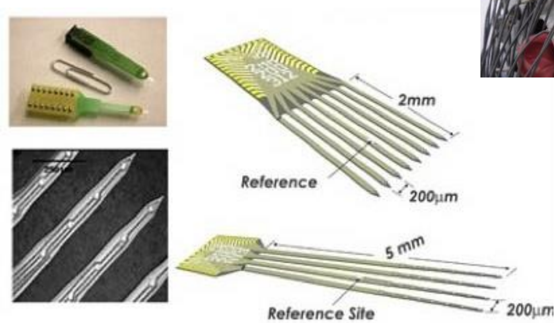
Cochlear Implant

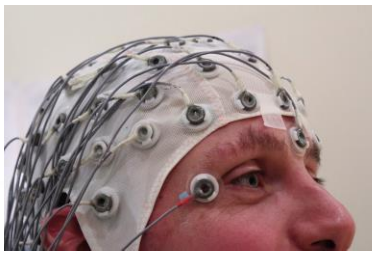
Neural Engineering

- Types of Neural Interfaces

- **Neural Interfaces**
  - **Invasive**
    - **Single Recording Sites**
    - **Multiple Recording Sites**
  - **Non-Invasive**
    - **EEG**
    - **fMRI**

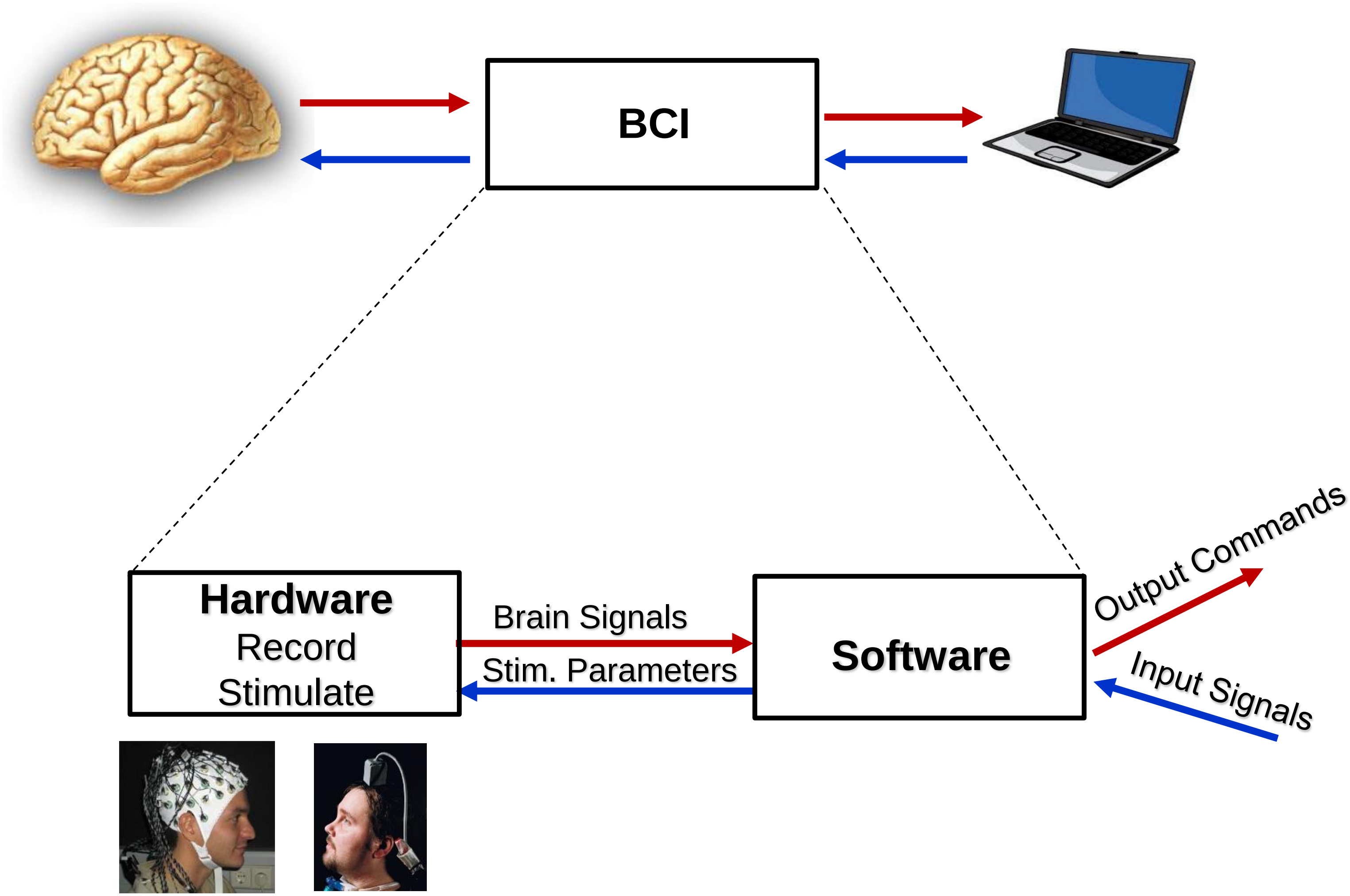






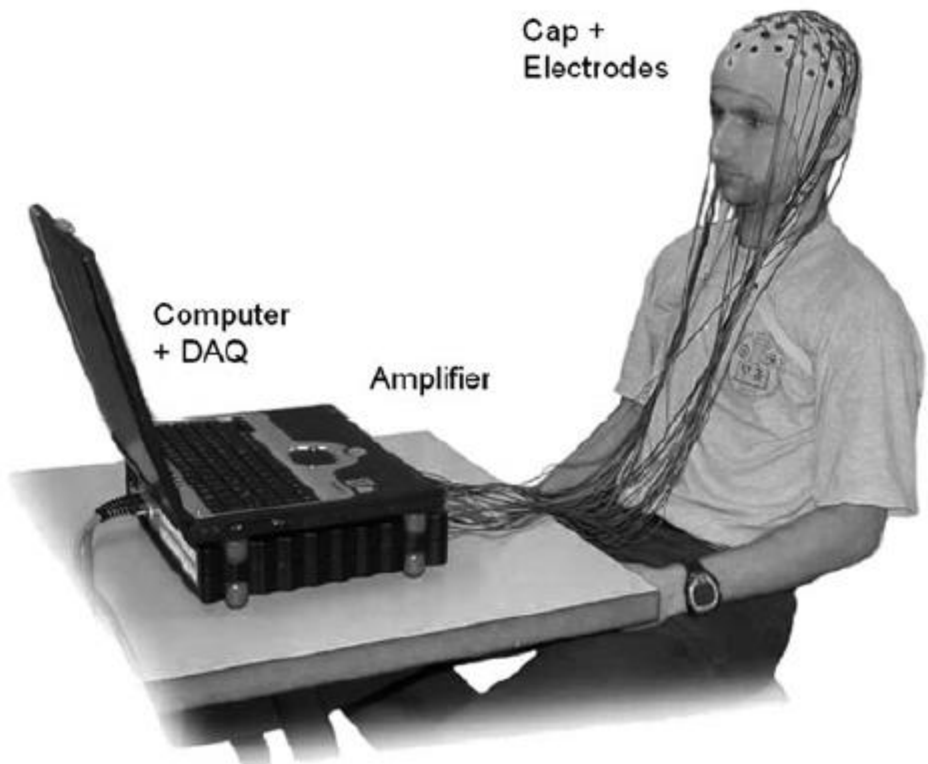
Brain-Computer Interface (BCI)

- A system that interfaces directly with the brain to provide non-muscular interaction with computers



Brain-Computer Interfaces (BCIs)

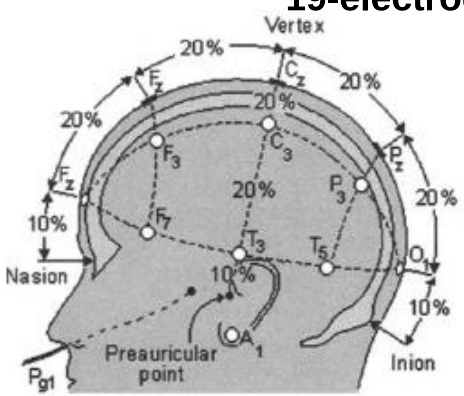
- A BCI is a non-invasive device that provides the brain with a new, non-muscular communication and control channel
- Electroencephalography (EEG) refers to recording electrical activity from the scalp with electrodes

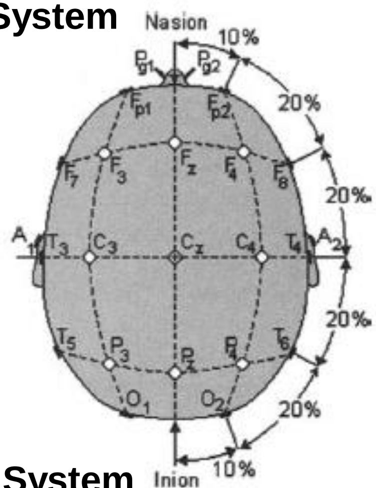


Brain-Computer Interfaces (BCIs)

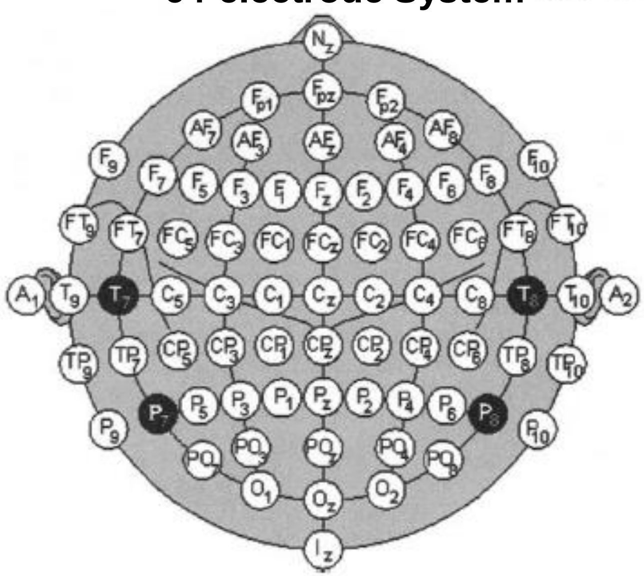
- Many EEG-based BCI systems use an electrode placement strategy suggested by the International 10/20 system

19-electrode System

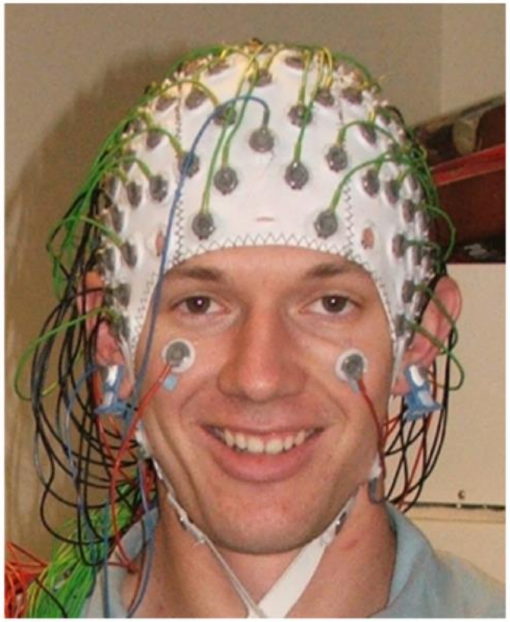




64-electrode System



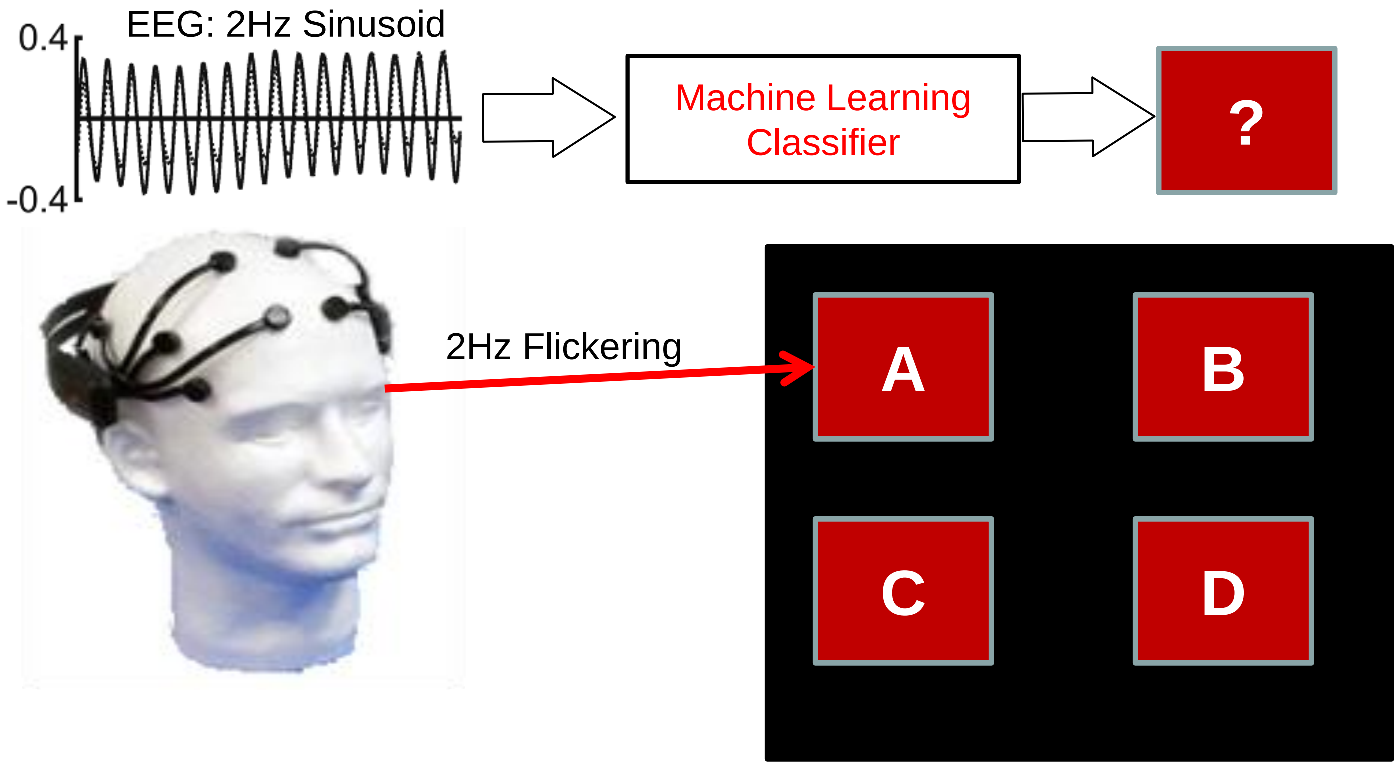
F: Frontal
C: Central
P: Parietal
O: Occipital
T: Temporal



EEG Frequency-domain Features: SSVEP

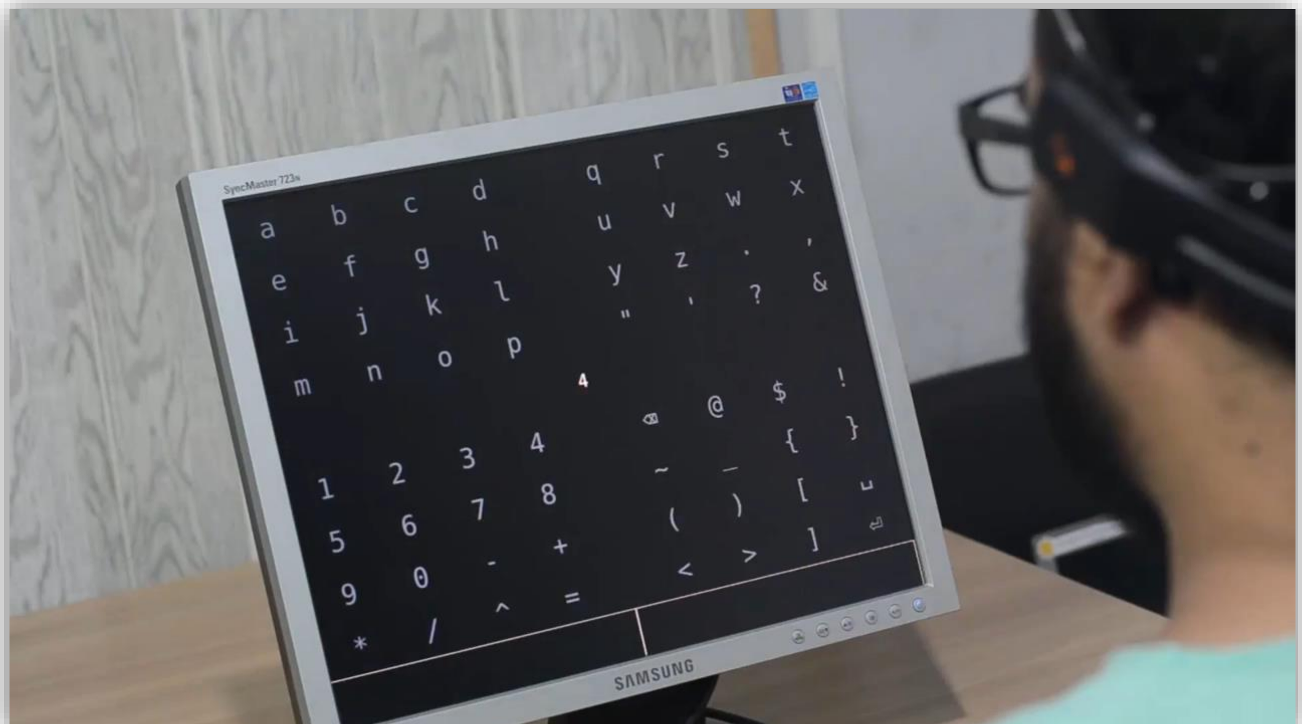
- One frequently used frequency-domain feature is the steady-state visual evoked potential (SSVEP)

- An SSVEP is a brain electrical activity at approximately the same frequency of a flickering object seen by the subject



SSVEP-based Speller

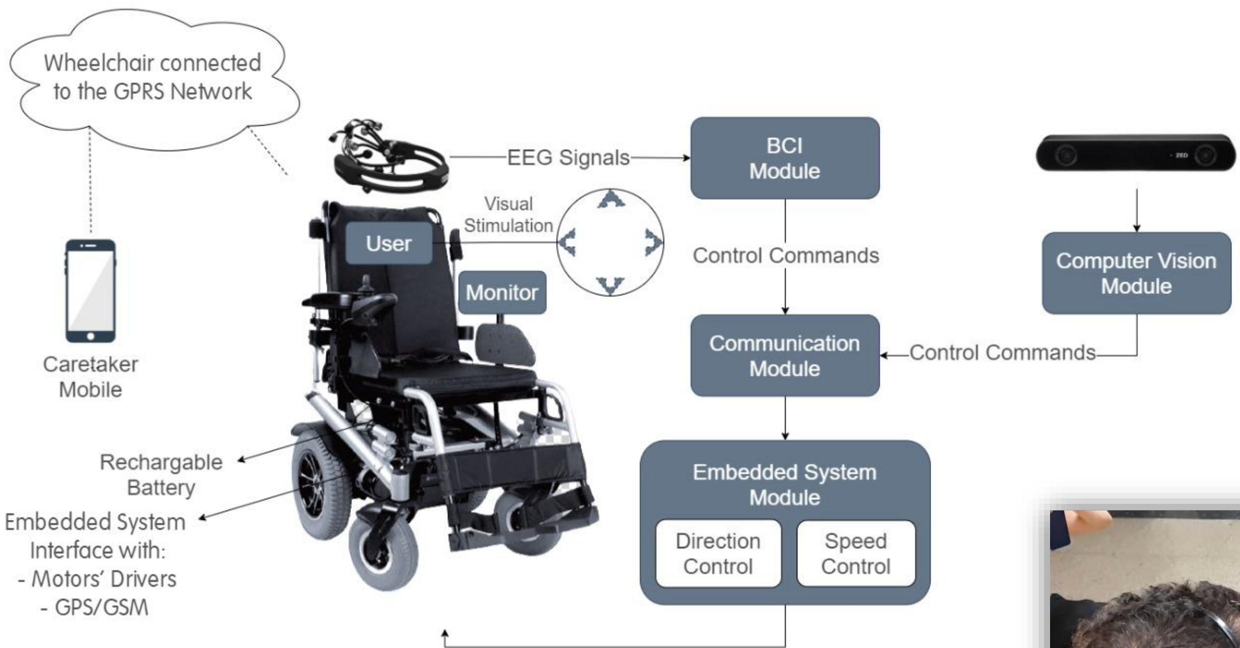
- Typing using SSVEP activity

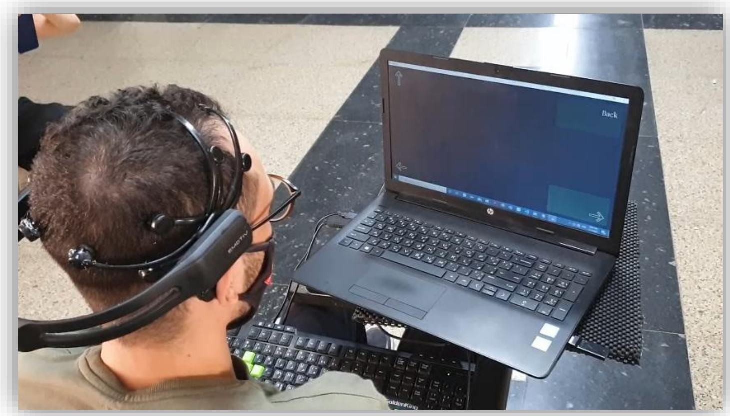


A. G. Yehia, S. Eldawlatly and M. Taher, “Principal Component Analysis-based Spectral Recognition for SSVEP-based Brain-Computer Interfaces,” *Proc. of 2015 Tenth International Conference on Computer Engineering & Systems (ICCES), pp. 410-415, 2015*

SSVEP-based Brain-controlled Wheelchair

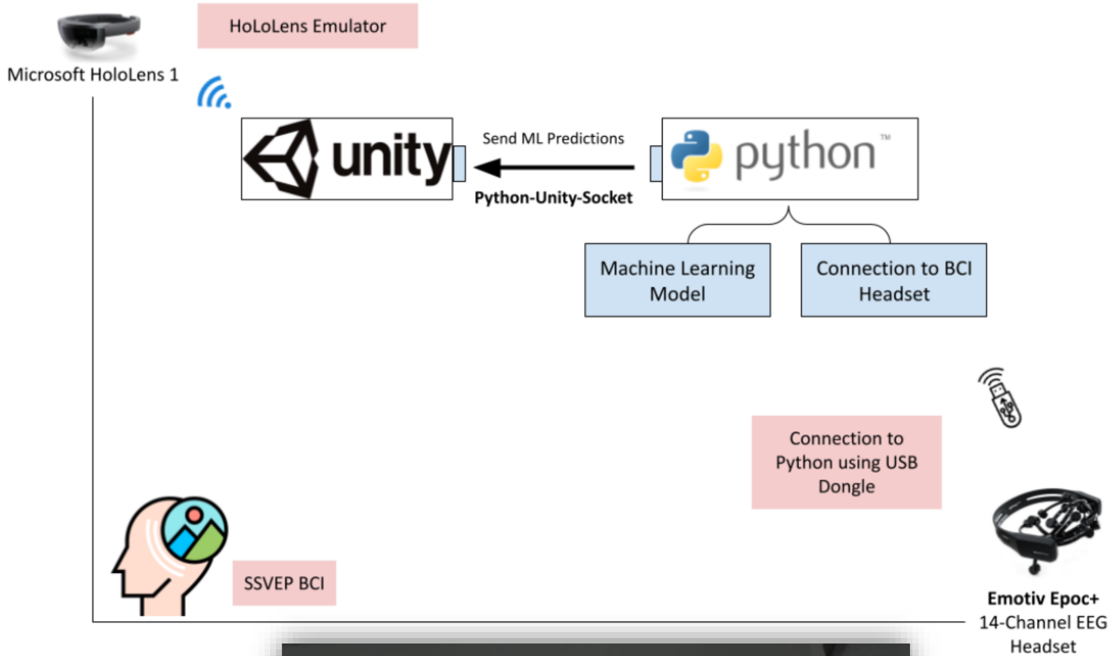
- Graduation Project awarded the 4th place in Dell Envision the Future Competition in 2021 out of 233 teams from the Middle East

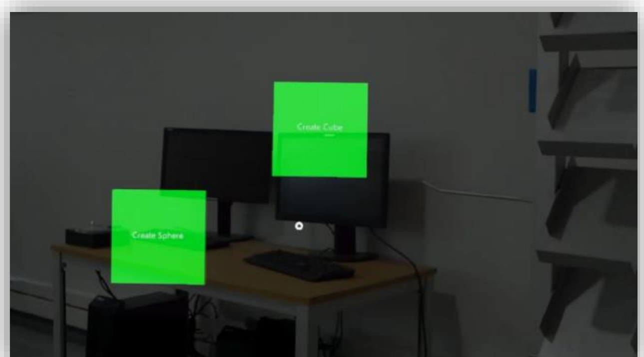




Integrating BCI with Augmented Reality

- System Overview





	Accuracy
Subject 1	65.4%
Subject 2	72.2%
Subject 3	76.9%
Average	**71.5%**

Y. Mustafa, M. Elmahallawy, T. Luo and S. Eldawlatly, “A brain-computer interface augmented reality framework with auto-adaptive SSVEP recognition,” Proc. of the 2023 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), pp. 799-804, Milan, Italy, 2023

Dataset

- The dataset represents the data of two subjects: Subject 1 and Subject 2

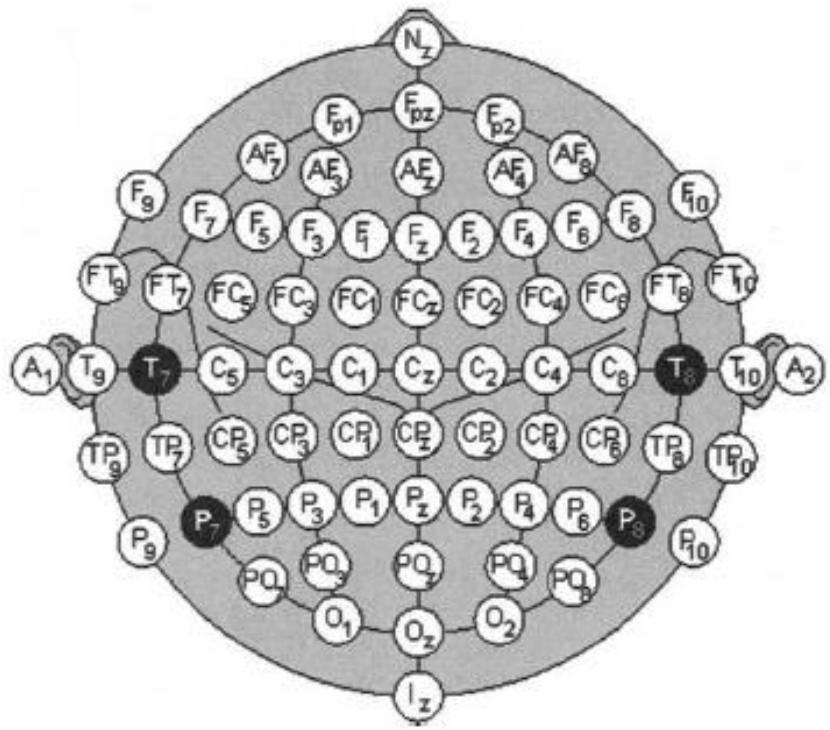
- Both subjects were instructed to look at boxes flickering with the following frequencies:
  - Stimulus 1: 12Hz
  - Stimulus 2: 10Hz
  - Stimulus 3: 8.57Hz
  - Stimulus 4: 7.5Hz
  - Stimulus 5: 6.66Hz

- Each subject looked at each box 25 times where the duration of each stimulus is 5 seconds with a 5 seconds break between each two successive stimuli

- The data was recorded using an EEG headset that has 14 electrodes with a sampling rate of 128Hz

Dataset

- EEG electrodes that are recorded in the data are:
  - Electrode 1: AF3
  - Electrode 2: F7
  - Electrode 3: F3
  - Electrode 4:FC5
  - Electrode 5:T7
  - Electrode 6:P7
  - Electrode 7:O1
  - Electrode 8:O2
  - Electrode 9:P8
  - Electrode 10: T8
  - Electrode 11: FC6
  - Electrode 12: F4
  - Electrode 13: F8
  - Electrode 14: AF4



Project Objective

- Identify the frequency of the box the subject was looking at by analyzing the recorded EEG signals on electrodes O1 and O2

- Two methods are required:
  - Method 1: A method that relies on analyzing the frequency-domain representation of the two electrodes for each trial
  - Method 2: Use machine learning to recognize the stimulus based on the frequency-domain representation of the two electrodes for each trial

- A leave-one-trial-out approach should be used for evaluation

- The accuracy of both methods will be assessed by computing the accuracy which is measured as the number of trials that are predicted correctly divided by the total number of trials

- For Method 2, use K-nearest neighbor (KNN) classifier

- For KNN, you need to identify the value of K that results in the best accuracy for each subject

Common Average Reference (CAR) Filter

- Eliminates the common noise across electrodes
- The mean of all channels at each time instant acts as a reference
- This reference is subtracted from each channel. It can be represented as follows

$$r_i(j) = s_i(j) - \frac{1}{N}\sum_{k=1}^{N} s_k(j)$$

where $s_i(j)$ represents the raw signal recorded on electrode i at time j, $r_i(j)$ represents the filtered signal and N is the total number of channels

K-nearest Neighbor (KNN) Classifier

- Most basic instance-based method

- Uses Euclidean distance to determine how dissimilar a pair of points are

$$d(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{\sum_{r=1}^{n} (x_{ir} - x_{jr})^2}$$

- For any new input vector, the nearest K points are considered

- A majority voting scheme is used to classify the new input vector

K-nearest Neighbor (KNN) Classifier