



Background & Motivation

The Imperial Next Generation Neural Interfaces (NGNI) Lab will be participating in an exhibition hosted by the Royal Society that will involve simultaneous decoding and visualisation of EEG signals acquired from ~100 different audience members simultaneously. These signals will be used for collaborative control in a multiplayer game (using only mental control).

The cost of existing BCI technologies makes them inaccessible to the general public and prohibits their use on a mass scale. This project aimed to create a novel, ultra low-cost BCI prototype that can change this in the hope to increase public engagement and facilitate education in the field of neurotechnologies.

Objectives

The core focus of this study is to develop real time decoding and communication of raw EEG signals acquired from a proprietary EEG hardware device developed by the NGNI Lab.

Constraints

- very tight budget of ~ £20 per device
- all processing related to sampling, signal processing, decoding and networking must be performed on-device
- use the NGNI hardware prototype based on the Espressif ESP32 SoC (Tensilica Xtensa LX6 MCU)
- real-time decoding and communication to an AWS cloud service
- non-invasive BCI using only 'dry' surface electrodes

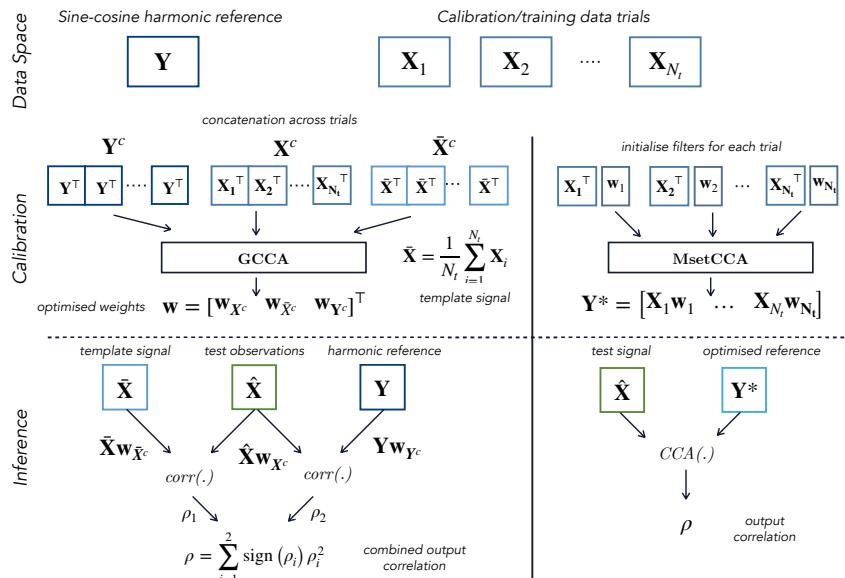


Figure 1: final BCI headband prototype. Inset: both sides of the ESP32-based BCI electronics prototype produced by the NGNI Lab

Design

SSVEPs for BCI control

The core role of a BCI is to interpret intentions of a user by making sense of their brain signals. Steady state visual evoked potentials (SSVEPs) are modulations in the brain's visual cortex in response to a visual stimulus which can be measured as sinusoids at the frequency of the visual stimulus being observed. Visual stimuli usually take the form of shapes that flicker at predetermined frequencies.



SSVEP decoding

The EEG literature widely reports that multivariate statistical techniques - such as canonical correlation analysis (CCA) and its extensions - are optimal for SSVEP decoding. This project primarily explored two extensions: Multi-setCCA (MsetCCA) and Generalised CCA (GCCA) as shown above.

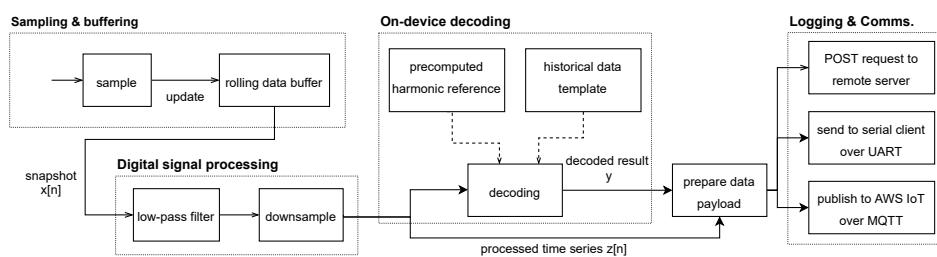


Figure 2: elements of the digital system implemented on the ESP32-based BCI hardware

Implementation

DSP system

Following sampling at 256Hz, low-pass filtering was necessary to remove higher-order harmonics and 50Hz mains interference.

- 26Hz corner frequency
- 10th order IIR elliptical LP filter
- stop band attenuation > 80dB
- pass band ripple < 0.2dB
- cascaded second-order sections

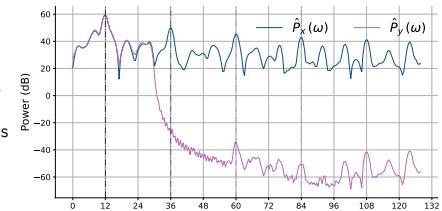


Figure 3: (top) Welch-averaged periodograms $\hat{P}_x(\omega)$ and $\hat{P}_y(\omega)$ of an input square wave signal at 12Hz and its filtered output respectively. (bottom) Schematic diagram of the DSP system.

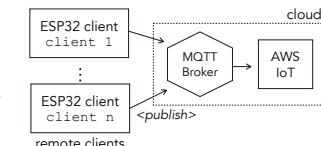
Embedded firmware

MicroPython was used for all firmware on the ESP32. It is compact enough to fit in 256k of ROM and run with only 16k of RAM. Besides the convenience of Python, benefits include:

- support for desktop and MCU architectures: x86, ARM, ARM Thumb and Xtensa
- cross-compiler for pre-compiling Python scripts into bytecode
- interactive Python prompt (REPL) that can be used as a Jupyter Notebook over serial
- modularity: use open source libraries, e.g. linear algebra and DSP modules

Networking and communication

An MQTT client was implemented in firmware to publish decoded EEG data to AWS IoT Core using the Wi-Fi module onboard the ESP32. Many remote BCI devices can publish data to a common channel.



Results

Results showed that the MsetCCA was most effective and could achieve accuracy and ITR rates comparable with BCIs in the literature. Two promising parameter combinations:

- 4 calibration trials of 0.75s each: accuracy of **95.56 ± 3.74%** with ITR of **102 bits/min**
- 2 calibration trials of 1s each: accuracy of **80.56 ± 4.46%** with ITR of **40 bits/min**

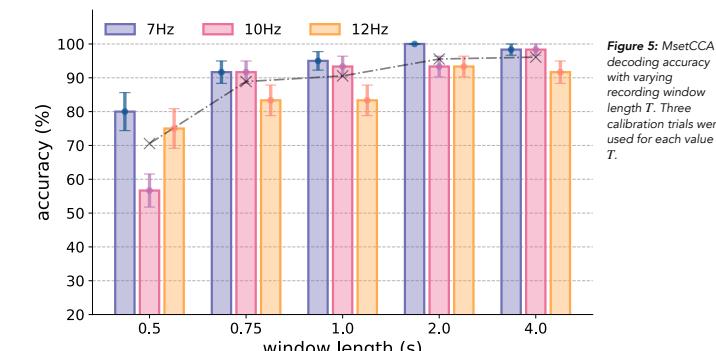


Figure 5: MsetCCA decoding accuracy with varying recording window length T . Three calibration trials were used for each value of T .