Cross-Modality Augmentation of fNIRS Signals Using fMRI for Transfer Learning

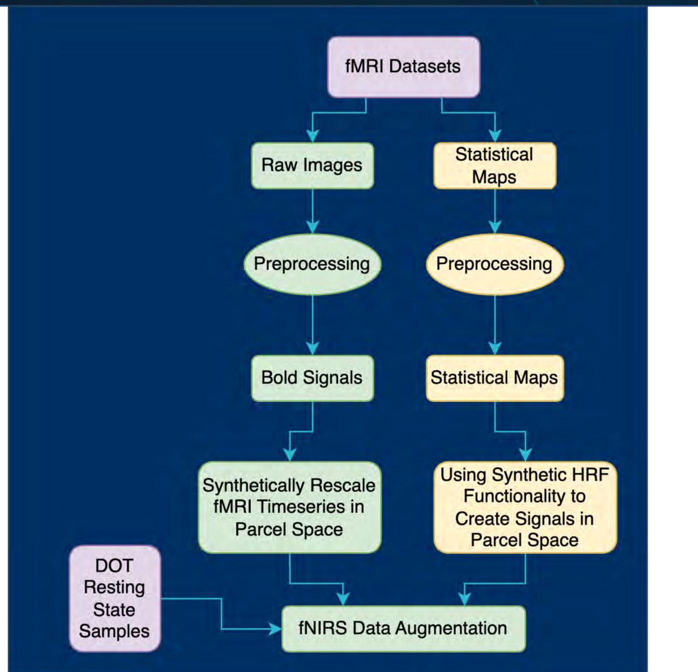
Shakiba Moradi[1,2,*], Eike Middell[1,2,*], Alexander von Lühmann[1,2,*]

[1] Intelligent Biomedical Sensing (IBS) Lab, Technische Universität Berlin, 10587 Berlin, Germany

[2] BIFOLD – Berlin Institute for the Foundations of Learning and Data, 10587 Berlin, Germany | ** shakiba.moradi@tu-berlin.de, middell@tu-berlin.de, vonluehmann@tu-berlin.de*

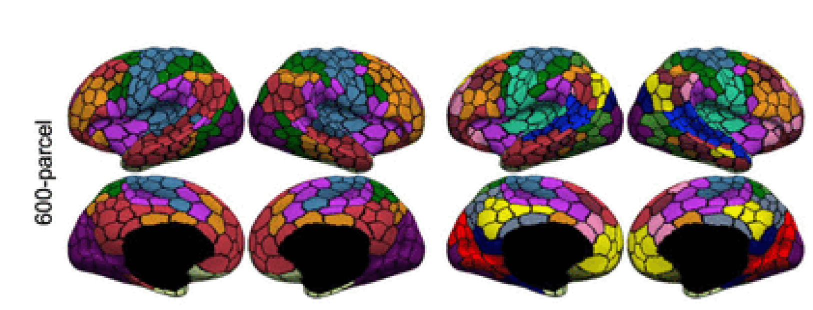
Motivation

Functional Near-Infrared Spectroscopy (fNIRS) has emerged as a powerful tool for monitoring cortical brain activity, transitioning from traditional laboratory settings to more naturalistic environments. While deep learning has shown great potential in medical data analysis, its application to fNIRS data analysis remains limited due to the difficulty of obtaining large datasets to train models. Therefore, augmenting fNIRS data with complementary imaging modalities, such as functional Magnetic Resonance Imaging (fMRI), offers a promising solution to address this challenge.
This study proposes a workflow for fNIRS signal augmentation, leveraging light propagation simulations and brain parcellation atlases to establish a unified space for integrating fNIRS and fMRI data. We aim to validate the feasibility of projecting fNIRS and fMRI signals into a common space with functionally meaningful brain regions. The goal is having more single trials for pre-training DNNs using fMRI data to enhance single trial classification performance in fNIRS/DOT.



Tools

- The ICBM152 head model was processed using Freesurfer, with the Schaefer atlas (600 parcels) [1] applied for corresponding labels. Both modalities were projected into parcel space using **the same head model**.
- Cedalion was used for processing and analyzing the timeseries data.
- fMRI datasets were processed using FSL, and Nilearn was employed for analysis



ICBM152 with parcel labels

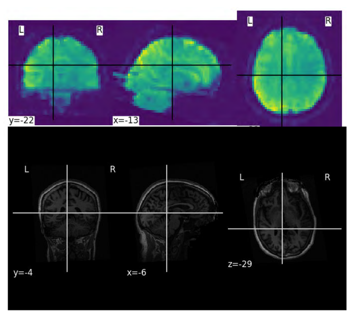
FSL
FreeSurfer
Cedalion
nilearn

fMRI Workflow

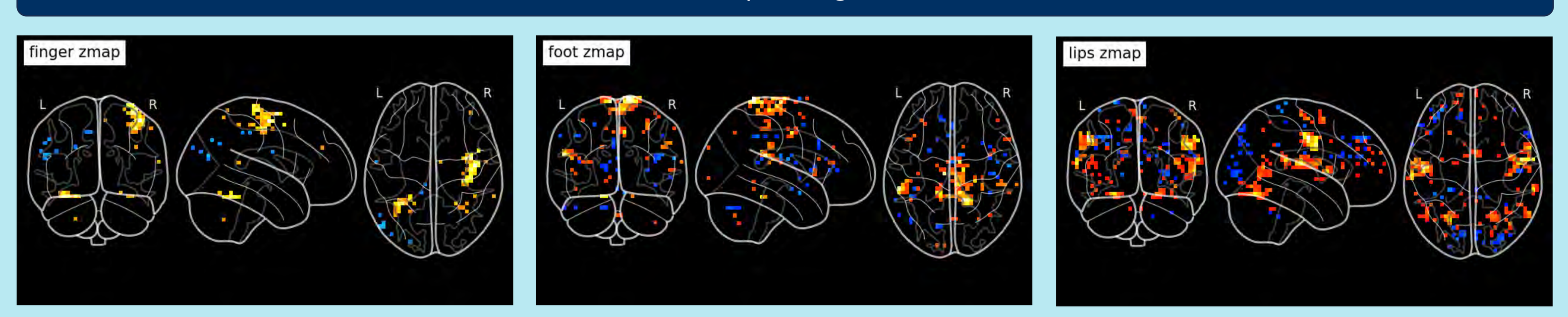
A test-retest fMRI dataset capturing motor, language, and spatial attention functions, including finger, foot, and lip movements [2].

The FMRIB Software Library (FSL) is used to process fMRI images. The processing steps include skull stripping, motion correction, slice-timing correction, registration, and normalization.

Processed fMRI

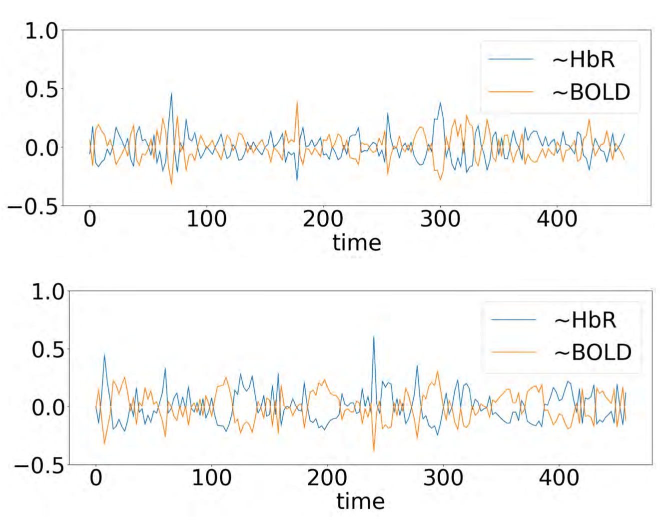


GLM Analysis using Nilearn

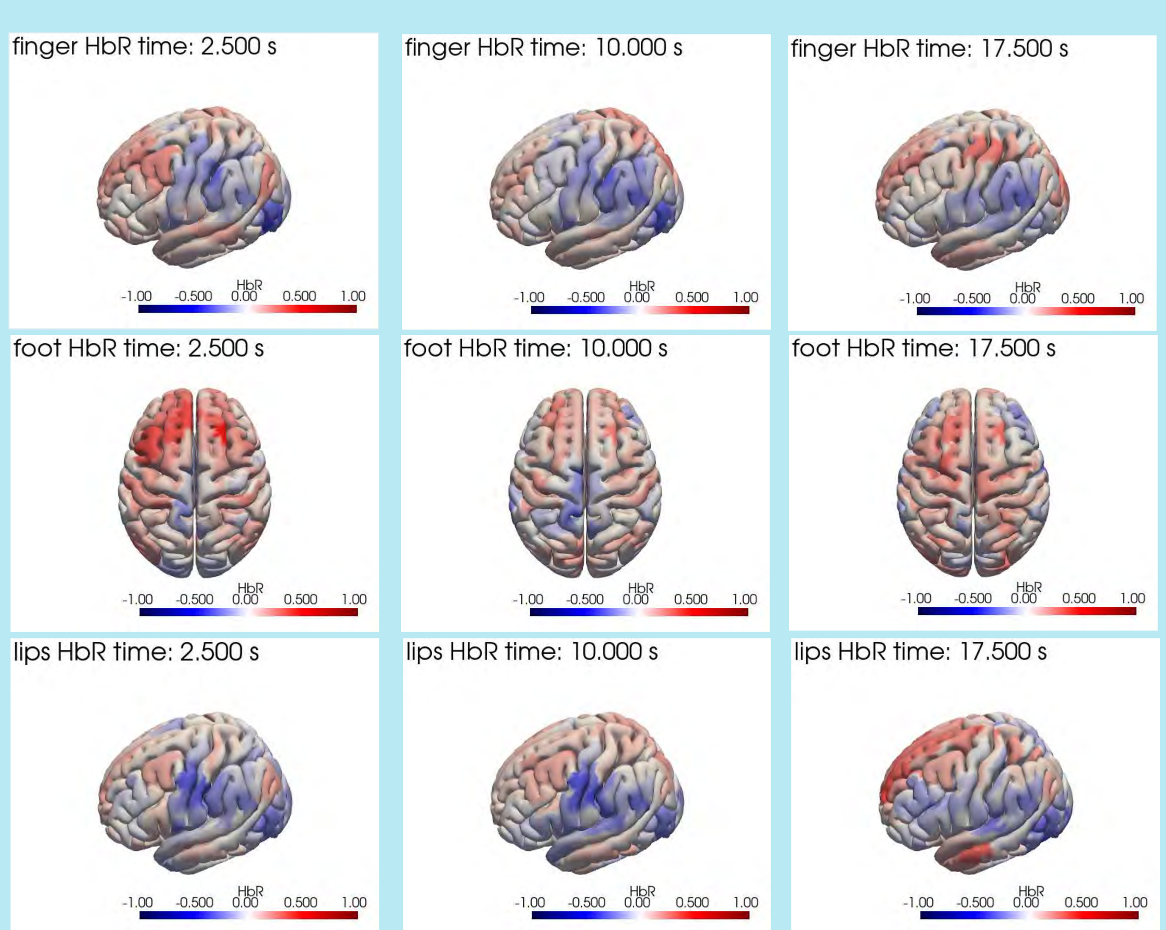


Processed fMRI

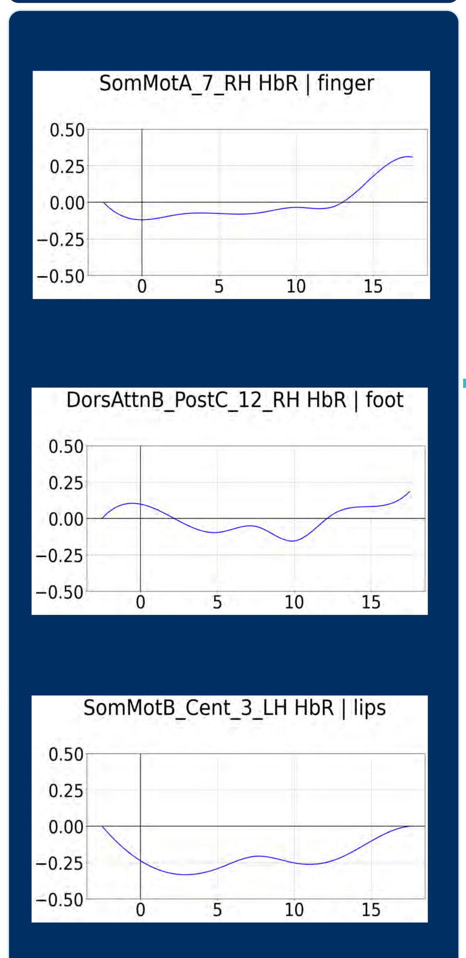
- Retain voxels located within the gray matter area, as it is most accessible by fNIRS
- Project these voxels onto the brain surface using the ICBM152 head model.
- Calculate the inverse of the BOLD signal for each vertex, as it is anti-correlated with HbR [3].
- Remove the baseline by subtracting the average of the new signal.



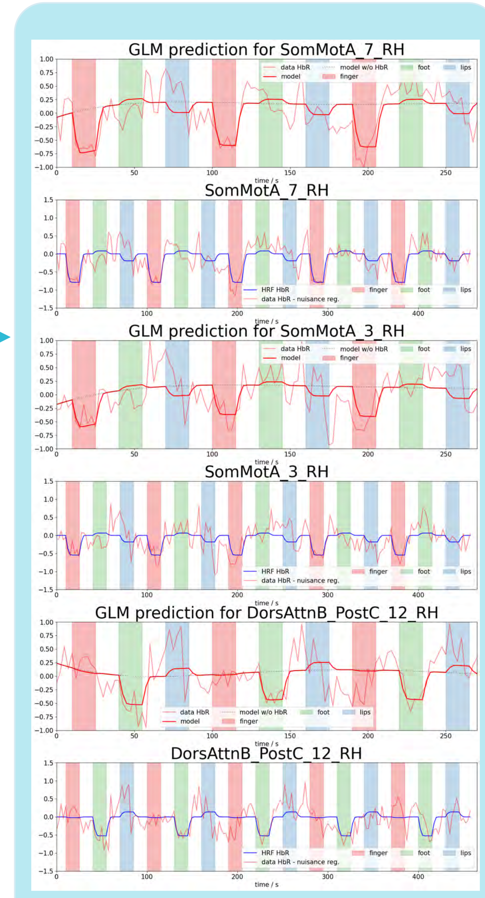
Block Average Analysis



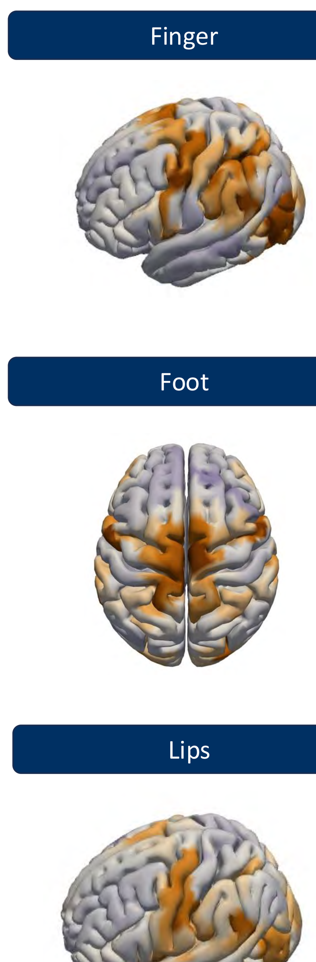
Parcel Timeseries



Perform GLM Analysis using Cedalion

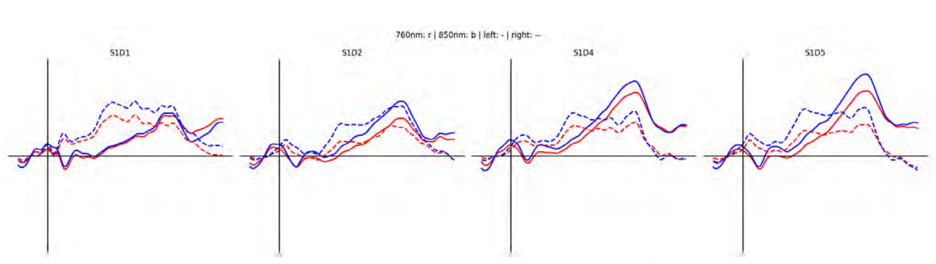


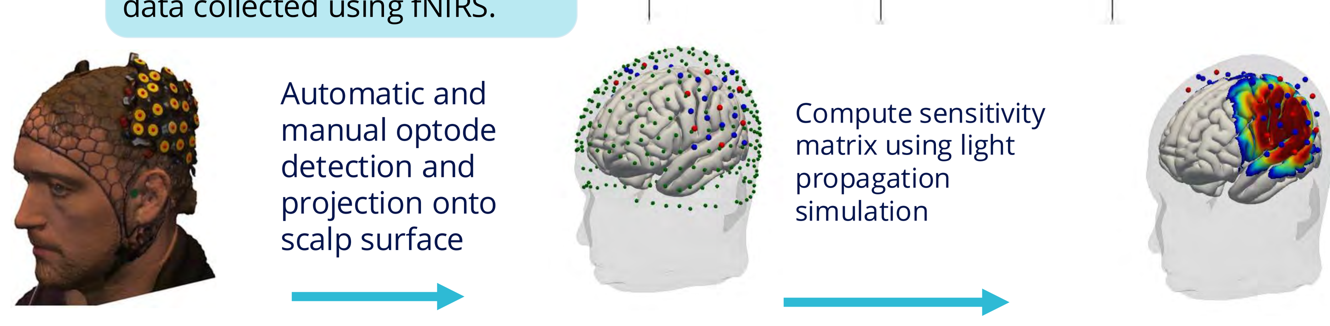
Statistical Maps in Parcel Space



fNIRS Workflow

The dataset contains blocks of right and left finger tapping data collected using fNIRS.



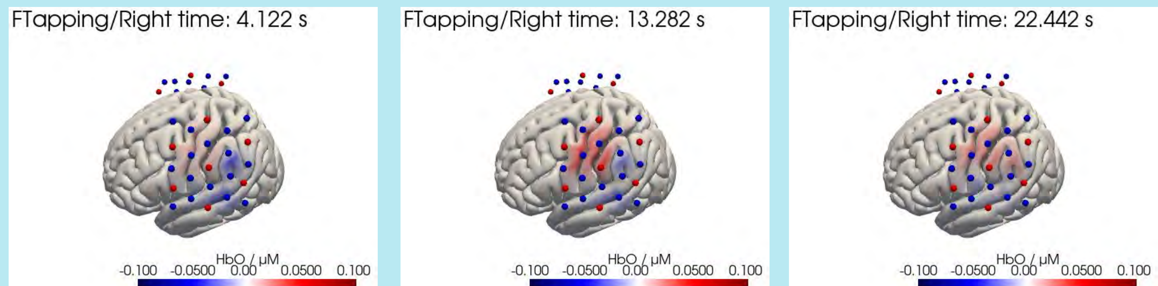


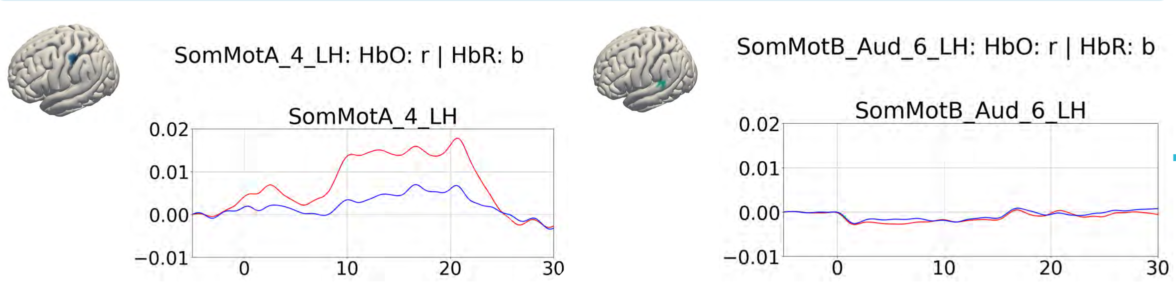
Automatic and manual optode detection and projection onto scalp surface

Compute sensitivity matrix using light propagation simulation

DOT Image reconstruction and project timeseries into parcel space

Block Average Analysis



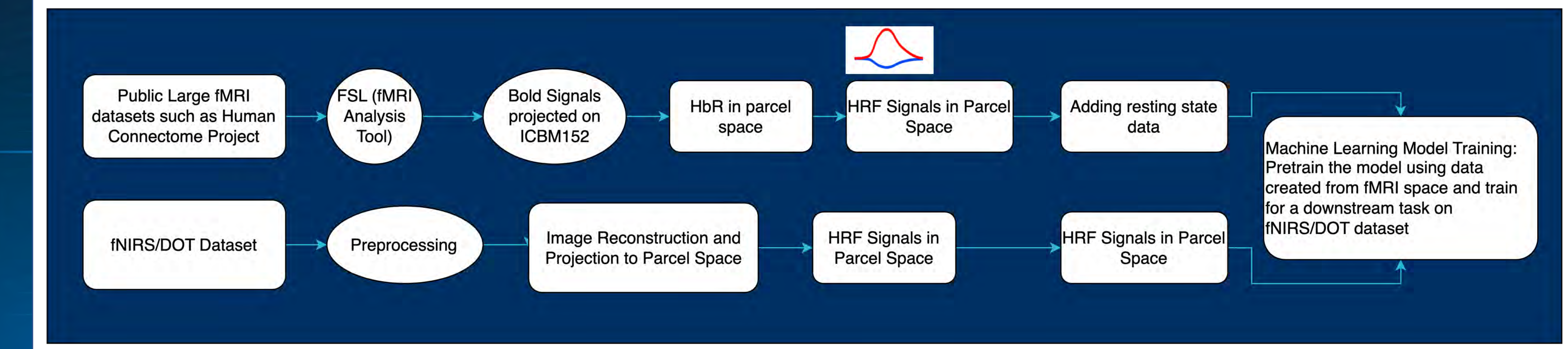


With proper methods addressing the differences in spatial resolution and signal characteristics between fNIRS and fMRI, this shared representation facilitates cross-modality signal comparison, enabling the augmentation of fNIRS data with larger quantities of publicly available fMRI datasets. After reconstructing HbR from Bold signals, it is possible to create synthetic HRF for the same paradigm and add it to fNIRS background activity in parcel space.

Future Work

We identify this approach will be able to generate realistic fNIRS signals, addressing current data-related limitations in the fNIRS deep learning field. In particular, we anticipate tasks such as finger tapping to show improved classification performance by leveraging the complementary strengths of both modalities within the parcellation space.

We seek to determine whether this approach enables deep learning models to extract more robust spatial and temporal features from time-series data.



References

[1] Schaefer, A., Kong, R., Gordon, E. M., Laumann, T. O., Zuo, X. N., Holmes, A. J., ... & Yeo, B. T. (2018). Local-global parcellation of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebral cortex*, *28*(9), 3095-3114.
[2] Gorgolewski, K. J., Storkey, A., Bastin, M. E., Whittle, I. R., Wardlaw, J. M., & Pernet, C. R. (2013). A test-retest fMRI dataset for motor, language and spatial attention functions. *Gigascience*, *2*(1), 2047-217X.
[3] Strangman, G., Culver, J. P., Thompson, J. H., & Boas, D. A. (2002). A quantitative comparison of simultaneous BOLD fMRI and NIRS recordings during functional brain activation. *Neuroimage*, *17*(2), 719-731.

Available Soon In **CEDALION**

IBS

https://github.com/ibs-lab/cedalion