CYCLE

functional to structural to functional imaging: a feedbaCked strategY for intraCraniaL widEband assessments

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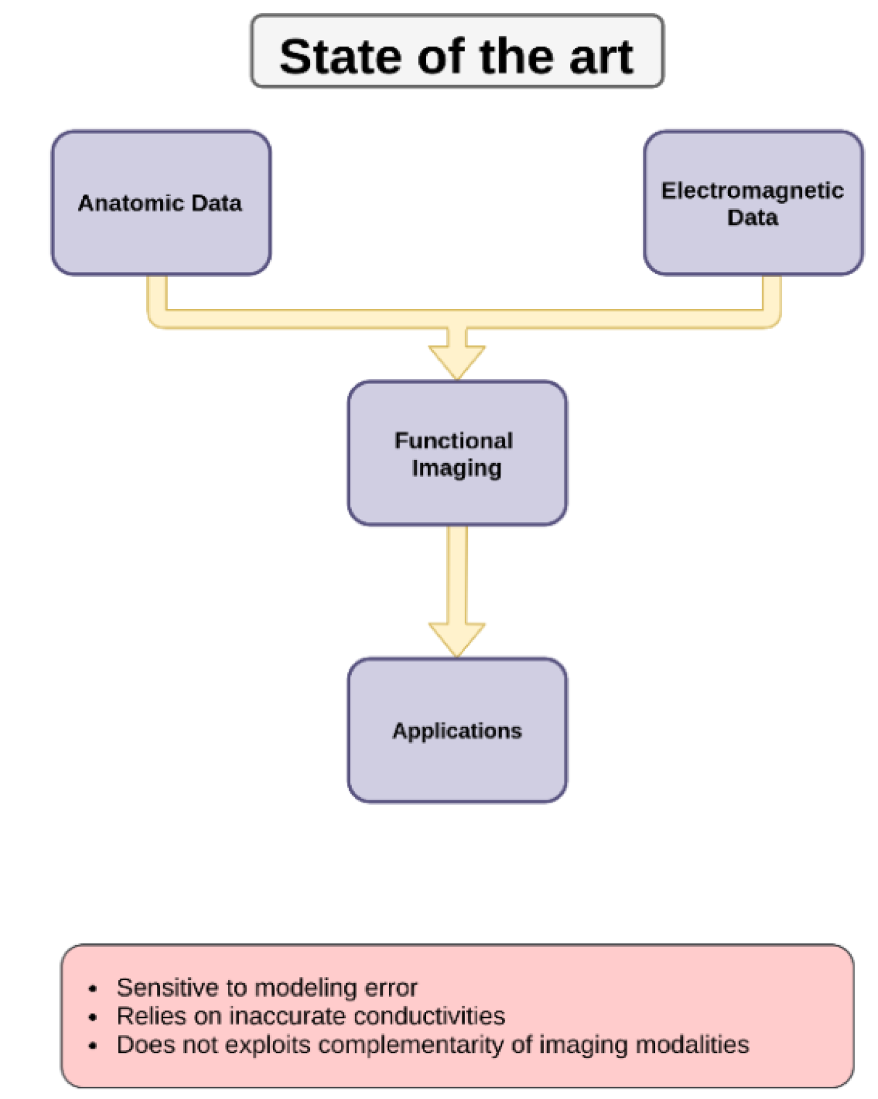
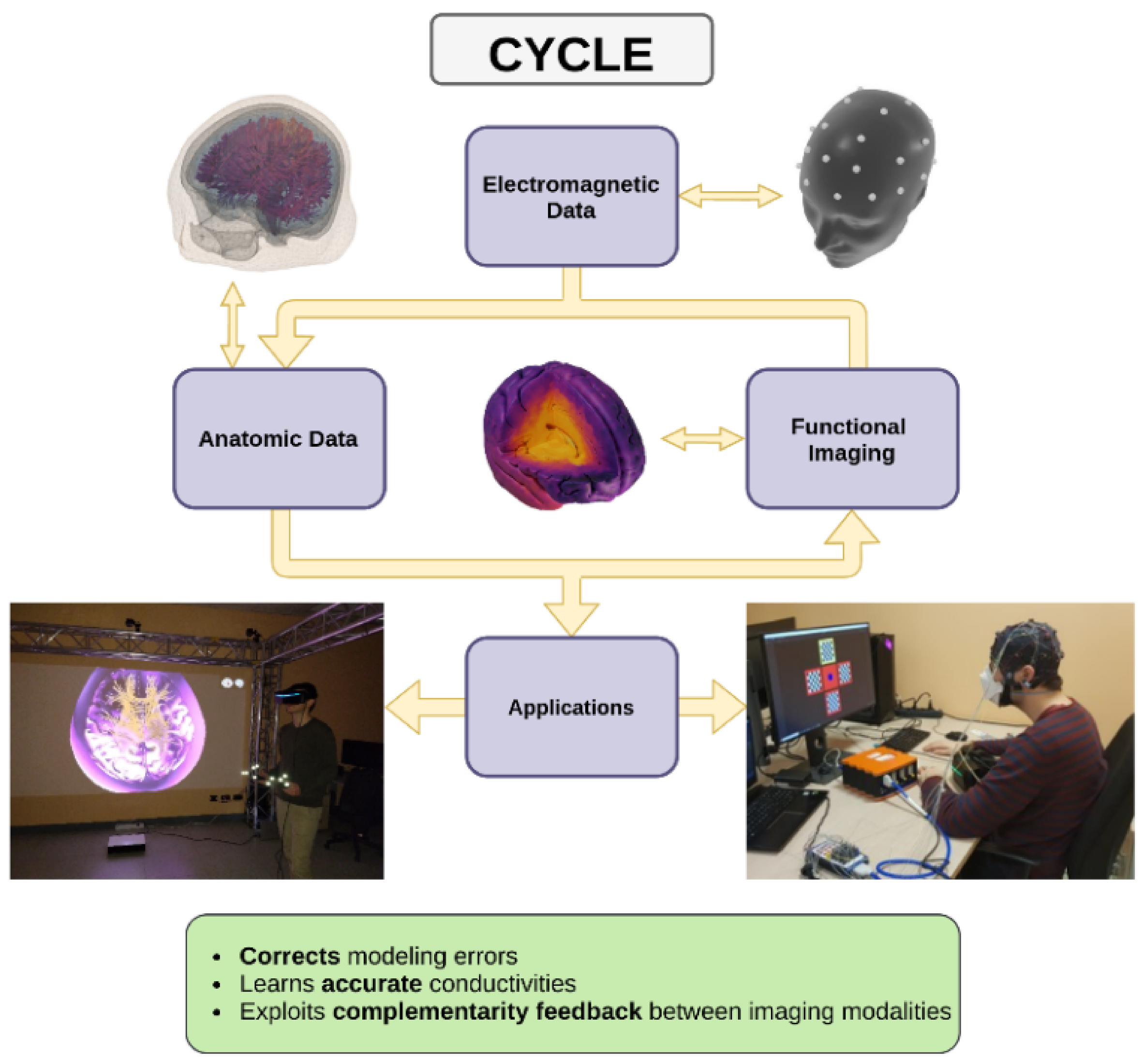
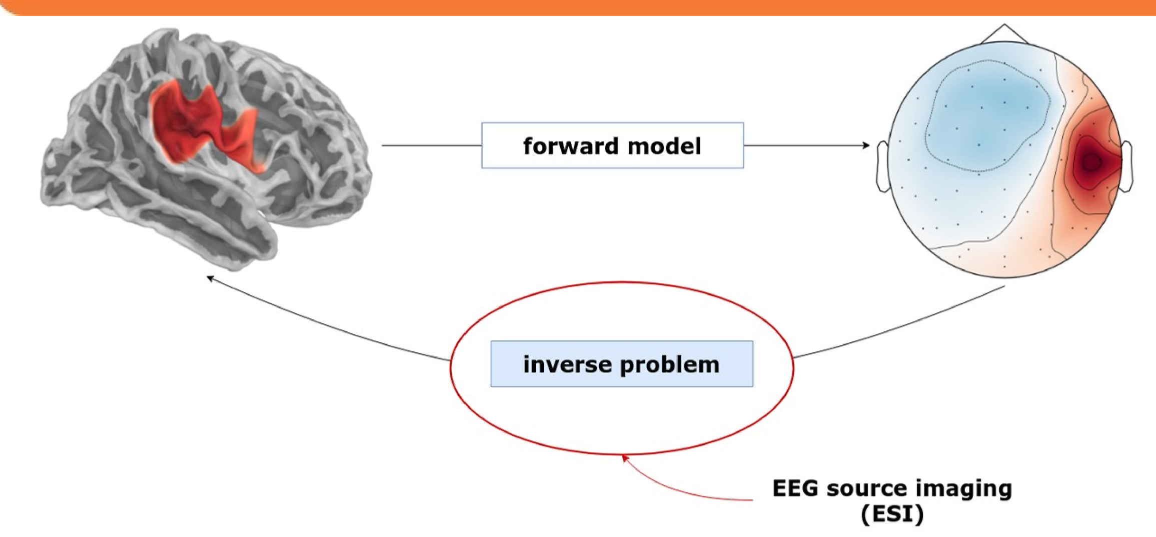
General Description





Inverse Problem in EEG



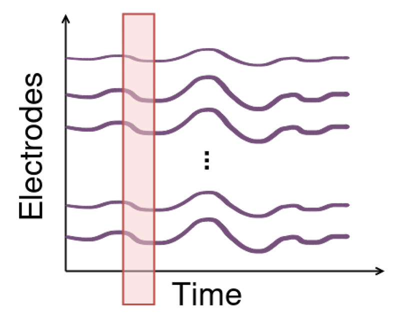
Forward model : $\mathbf{M} = \mathbf{GD} + \boldsymbol{\varepsilon}$ ($\boldsymbol{\varepsilon}$ = additive noise)

- $p \gg N$: G non-invertible
- Volume mixing/conduction

Ill-posed inverse problem: add prior on D to solve.

$$\hat{\mathbf{D}} = \arg\min_{\mathbf{D}} (\underbrace{\|\mathbf{M} - \mathbf{GD}\|^2}_{\text{data fitting}} + \underbrace{\lambda \mathbf{R}(\mathbf{D})}_{\text{regularization}})$$

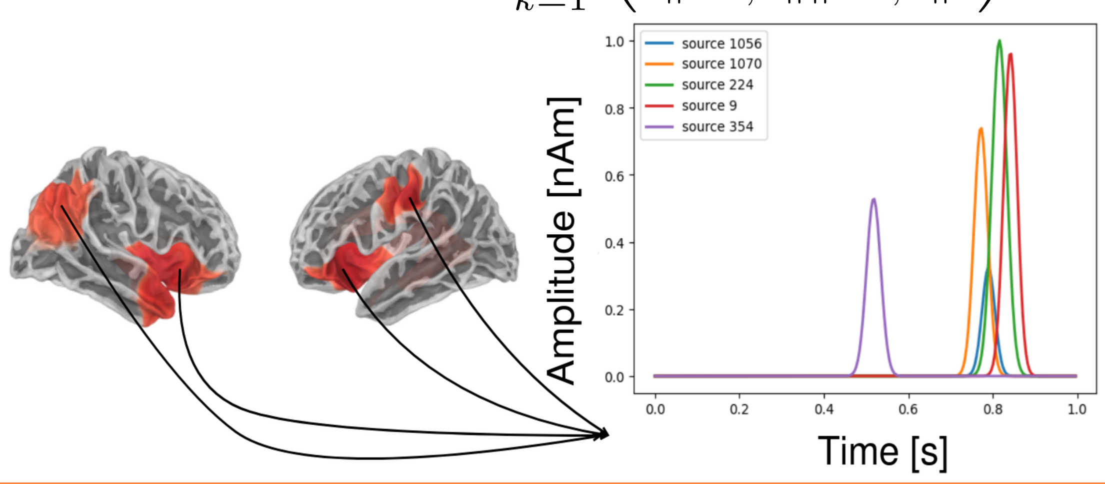
Deep Learning for ESI



Network parameters:

- 1D-CNN: 7 102 464 params
- LSTM: 513 400 params
- Ground truth source activity (D) with SEREEGA

$$\text{loss}(\mathbf{D}, \hat{\mathbf{D}}) = -\frac{1}{T} \sum_{k=1}^{T} \left(\frac{\sum_{i=1}^{N_s} \mathbf{D}_{i,k} \hat{\mathbf{D}}_{i,k}}{\|\mathbf{D}_{:,k}\| \|\hat{\mathbf{D}}_{:,k}\|} \right)$$



1d-CNN for ESI

SNR	Methods / Metrics	Single extended source: 1D-CNN	LSTM	MNE	sLORETA	Multiple extended sources: 1D-CNN	LSTM	MNE	sLORETA
30dB	AUC ↑	0.9860	**0.9878**	0.7862	0.7844	**0.7818**	0.7782	0.6600	0.6558
	LE [mm]↓	2.94	**2.45**	9.87	6.25	**4.42**	5.22	11.05	7.87
	nMSE ↓	0.0039	**0.0024**	0.0231	0.0328	0.0053	**0.0045**	0.0232	0.0375
	PSNR ↑	39.5436	**41.8593**	32.0799	29.7051	37.6688	**38.3320**	30.3987	27.6743
	time error [ms] ↓	**0.05**	0.45	1.25	1.07	**1.91**	3.23	7.42	6.61
20dB	AUC ↑	0.9859	**0.9874**	0.7847	0.7847	**0.7807**	0.7763	0.6528	0.6510
	LE [mm]↓	3.31	**2.48**	10.07	6.26	**4.76**	5.48	11.87	8.63
	nMSE ↓	0.0046	**0.0024**	0.0233	0.0354	0.0062	**0.0046**	0.0257	0.0440
	PSNR ↑	38.7850	**41.6129**	29.4784	27.5368	36.8713	**37.6045**	27.6764	25.3797
	time error [ms] ↓	**0.11**	0.46	2.62	2.00	**2.65**	5.76	15.14	10.89

- **AUC** : Area under the ROC curve (extension)
- **LE** : localisation error
- **nMSE** : normalized MSE

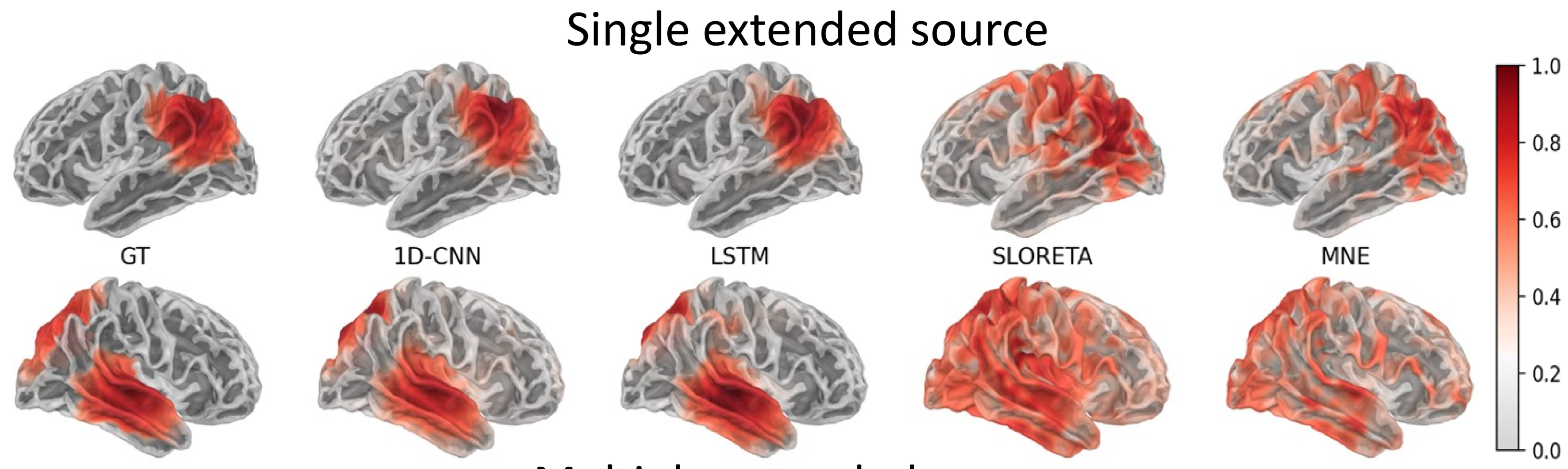
Training details:

- 10000 samples / dataset (80% training, 20% evaluation)
- ADAM, 100 epochs, gradient clipping for LSTM

Baseline:

MNE[4], sLORETA: non learning based methods

Single extended source



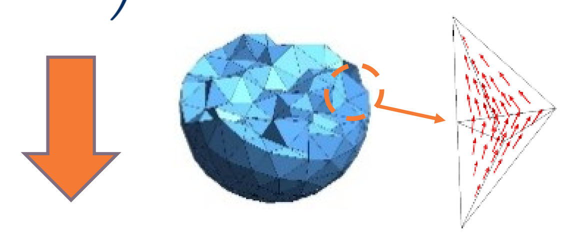
Multiple extended sources

New High-Resolution and Full Wave Forward Models

Electric Flux Volume Integral Equation for Modeling Anisotropic and Inhomogeneous objects

$$\frac{\boldsymbol{D}(\boldsymbol{r})}{\epsilon(\boldsymbol{r})} - \left(\mathcal{L}_{\kappa}^{\Omega} \boldsymbol{D}\right)(\boldsymbol{r}) = \boldsymbol{E}_i(\boldsymbol{r})$$

Discretization



$$\mathbf{Z}\alpha = (\mathbf{G}_{\epsilon} + \mathbf{Z}_{\Phi} + \mathbf{Z}_{\mathbf{A}})\,\alpha = \mathbf{v}$$

Ill conditioned Gram matrix
→ Low-Frequency (LF) breakdown
→ High-Contrast (HC) breakdown

Regularization of HC and LF Breakdowns with Generalized Volume Quasi-Helmholtz Projectors [9]

New Projectors

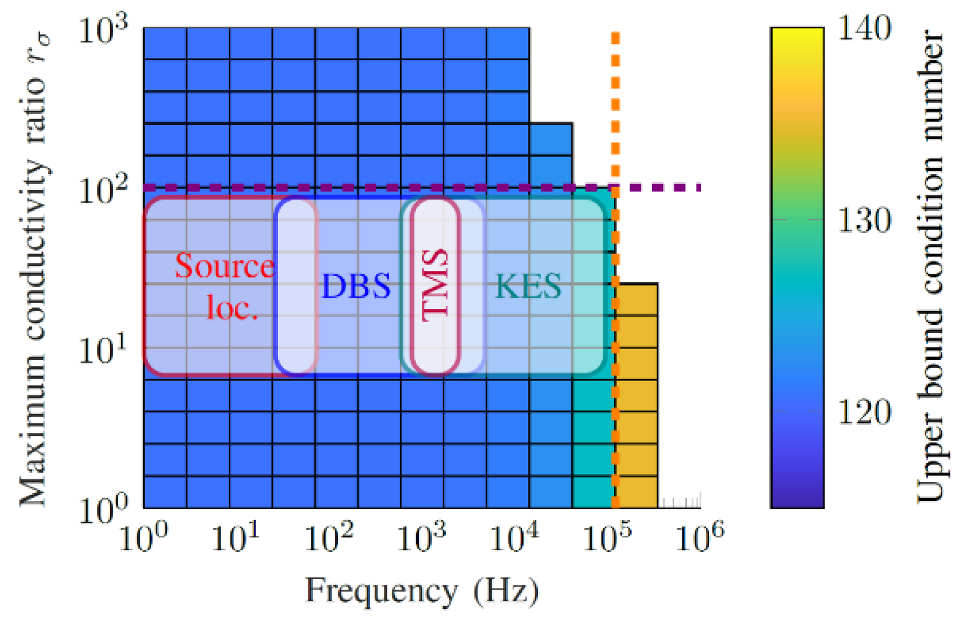
$$\mathbf{P}^{\Sigma}_{\mathbf{G}_{\epsilon}} = \mathbf{G}_{\epsilon}^{-1}\boldsymbol{\Sigma}\left(\boldsymbol{\Sigma}^{\mathrm{T}}\mathbf{G}_{\epsilon}^{-1}\boldsymbol{\Sigma}\right)^{+}\boldsymbol{\Sigma}^{\mathrm{T}}$$

$$\mathbf{P}^{\Lambda}_{\mathbf{G}_{\epsilon}} = \mathbf{I} - \mathbf{P}^{\Sigma}_{\mathbf{G}_{\epsilon}} = \boldsymbol{\Lambda}\left(\boldsymbol{\Lambda}^{\mathrm{T}}\mathbf{G}_{\epsilon}\boldsymbol{\Lambda}\right)^{+}\boldsymbol{\Lambda}^{\mathrm{T}}\mathbf{G}_{\epsilon}$$

Left Preconditioner

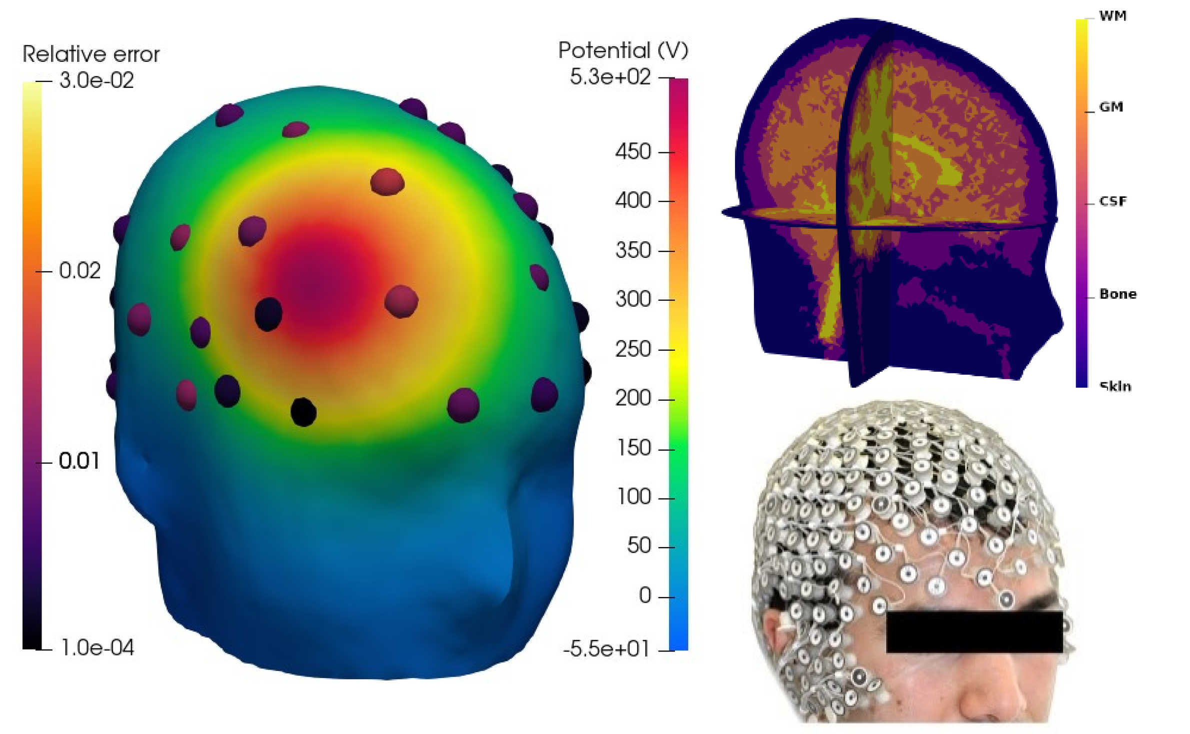
$$\boxed{\mathbf{L}_{\mathbf{G}_{\epsilon}} = \mathbf{P}^{\Lambda}_{\mathbf{G}_{\epsilon}}\mathbf{G}_{\epsilon}^{-1} + \mathbf{P}^{\Sigma}_{\mathbf{G}_{\epsilon}}\mathbf{G}^{-1}}$$

Range of operation of the formulation



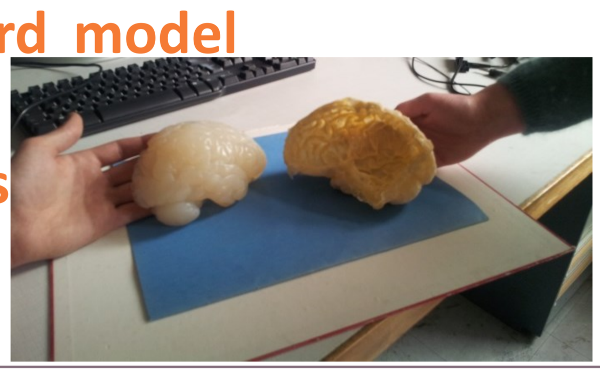
DBS: Deep brain stimulation, TMS: Transcranial Magnetic stimulation, KES: Kilohertz electrical stimulation

Validity of the EEG forward modeling



Ongoing Work and Next Steps

- Acceleration of the forward model using via fast direct solver
- Other brain activity models
- BCI feedbacked strategy
- Experimental Validation



Published Results

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[3] **A. Merlini *et al.*, *IEEE Trans. Antennas Propagat.*, 2023.**
[4] A. Merlini *et al.*, ICEAA 2023.
[5] C. Henry *et al.*, IEEE CAMA 2023.
[6] C. Henry *et al.*, *EuCAP* 2023.
[7] **V. Giunzioni *et al.*, *Journal of Computational Physics*, 491, 2023.**
[8] V. Giunzioni *et al.*, IEEE CAMA 2023.
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[13] C. Henry *et al.*, URSI GASS 2021.
[14] **S. B. Adrian *et al.*, *IEEE Open J. Antennas Propag.*, 2, 2021.**