P118 A Biophysically realistic Laminar Neural Mass Modeling framework for transcranial Current Stimulation—**G. Ruffini [a,b], R. Sanchez-Todo [a,*], L. Dubreuil [b], R. Salvador [a], D. Pinotsis [c], E.K. Miller [d], F. Wendling [e], E. Santarnecchi [f], A. Bastos [d] ([a] Neuroelectrics, Barcelona, Spain, [b] Neuroelectrics Corporation, Cambridge, MA, United States, [c] University of London, Department of Psychology, London, United Kingdom, [d] The Picower Institute for Learning and Memory, Massachusetts Institute of Technology, Department of Brain and Cognitive Sciences, Cambridge, MA, United States, [e] UMR Inserm - Université de Rennes, LTSI, Rennes, France, [f] Harvard Medical School, Berenson-Allen Center for Noninvasive Brain Stimulation, Beth Israel Deaconess Medical Center, Neurology, Cambridge, MA, United States)**

The brain is a complex, non-linear, multiscale network with interacting, dynamical nodes. A major challenge is to understand how transcranial current stimulation (tCS) can affect it and to optimize its parameters. To describe the local activity throughout brain layers, detailed compartment models are typically used but are computationally expensive and limited to representations of a few columns (Front Hum Neurosci, 2013). In the other extreme, neural mass models (NMM) provide averaged representations of neuron populations applicable to large cortical areas and providing links to physiology. However, in their original form, NMMs do not represent the laminar physics of current source density (CSD), local field potentials (LFP) or current dipole (J) because they are not mathematically embedded in cortical 3D space. Here we propose an extension of NMMs to represent functional activity from Electroencephalography (EEG) and laminar electrophysiological activity under tCS (Brain Stimulat, 2013).

Our primary objective is to create a semi-empirical Laminar NMM (LaNMM) framework to interpret in-vivo data, especially from primates, and to use it to model large-scale brain dynamics under neuromodulatory interventions. To achieve this, we assign layer locations to apical and basal dendritic tufts of pyramidal neuron populations and track the currents generated by synaptic inputs, which are derived from membrane potential perturbations in the NMM. Then, a plane interface model is used to calculate the electrostatic potential contribution (V) from each current monopole and summed using the superposition principle. The electric field, CSD (Fig. 1a) and J are then derived. We implement a simple model with coupled pyramidal populations: Jansen and Rit model (Biol Cybern, 1995) (JR-NMM) representing infragranular layers and slow activity,

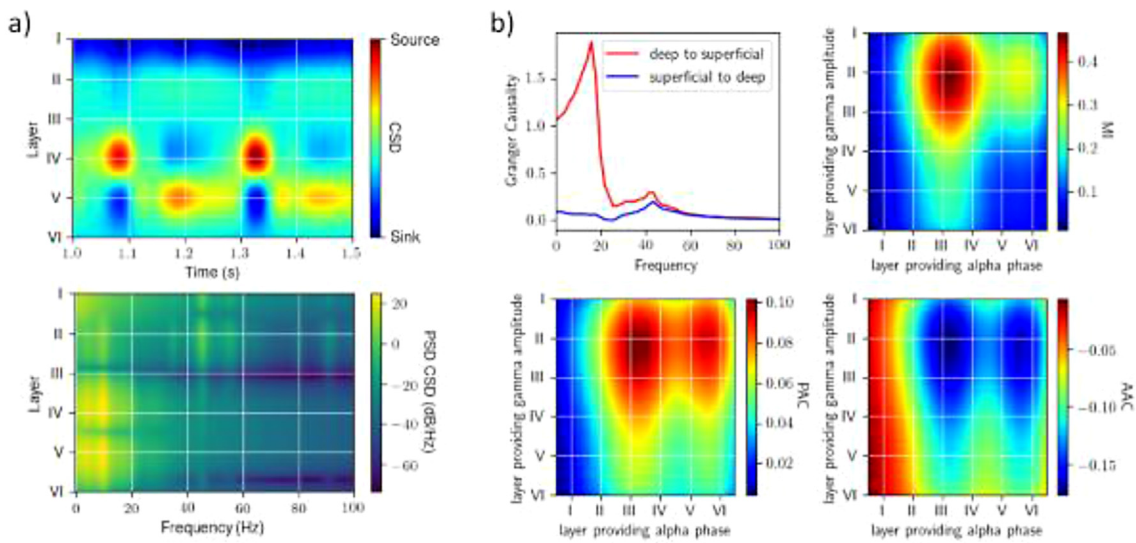

Figure 1. Response to electric field stimulation. a) Schematic representation of the λE model for the LaNMM. Connectivity between populations and interneurons not shown. b) membrane potential peak PSD of the supragranular population PING (upper) and infragranular population JR NMM (bottom) depending of the stimulation frequency and amplitude.

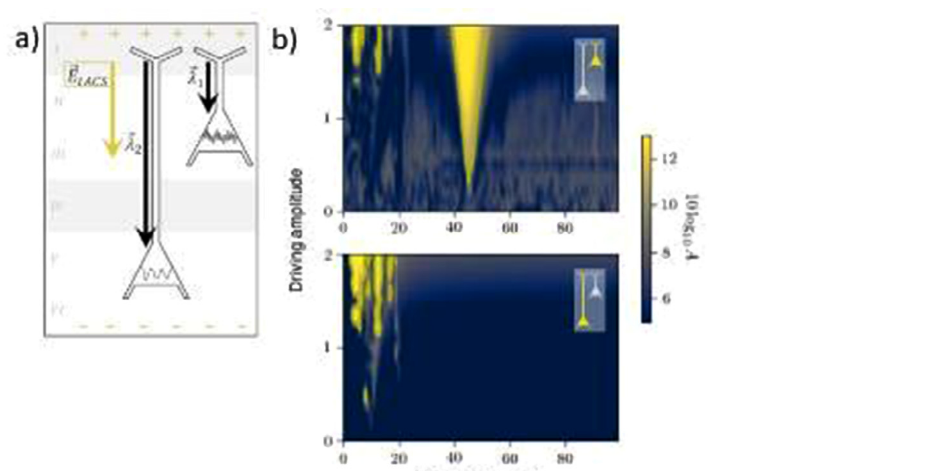

Figure 2. Response to electric field stimulation. a) Schematic representation of the λE model for the LaNMM. Connectivity between populations and interneurons not shown. b) membrane potential peak PSD of the supragranular population PING (upper) and infragranular population JR NMM (bottom) depending of the stimulation frequency and amplitude.

and PING (Front Hum Neurosci, 2013) (pyramidal-interneuron gamma NMM) representing supragranular layers and fast activity.

Cross-layer coupling is computed from the time series of the laminar potential, including amplitude-amplitude correlation, phase-amplitude coupling, modulation index, and Granger causality, and compared with available data (PNAS, 2018; Current Biol, 2012) (Fig. 1b). The model is also used to simulate the neural entraining effects of tACS using the λ-E coupling model (Biol Cybern, 1995) and shown to display a frequency-amplitude Arnold tongue (Fig. 2).

As we show, the LaNMM framework provides a tool to develop fast specific models that match available in-vivo monkey data. Such models can also be generalized to reproduce the activity of cortical columns under tCS in humans in the hybrid brain model formalism (Current Op in Biom Eng, 2019) which may be used to further develop optimization algorithms and dosing of tCS.

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P119 Boosting the effect of cognitive training with transcranial electrical stimulation—C. Krebs[*], J. Peter, P. Wyss, S. Klöppel (UPD Bern, University Hospital of Old Age Psychiatry and Psychotherapy, Bern, Switzerland)

Introduction: Cognitive functions decline with increasing age, both in healthy aging and (even more) in neurodegenerative disorders. Transcranial electrical stimulation (tES) provides an opportunity to counteract decline by increasing cognitive performance. These techniques might be particularly beneficial in combination with cognitive training. However, for transcranial direct current stimulation (tDCS), previous research indicated that cognitive performance prior to the cognitive training (i.e., baseline performance) is important as low performing individuals at baseline benefit most from the stimulation. It remains unexplored yet, whether the same applies to transcranial alternating current stimulation (tACS).

Objectives:: We investigated, whether tDCS or tACS further boost the effect of a cognitive intervention and if stimulation effects depend on baseline cognitive performance (as measured with the Montreal Cognitive Assessment; MoCA).

Materials & *Methods*: 59 healthy elderly participants (mean age: 71.7 ± 6.1, range 61–85; 31 male) performed 10 sessions of a multi-domain computer-based cognitive training (90 minutes per session) with either tDCS (2 mA), tACS (5 Hz,1 mA) or sham stimulation during the first 20 min of each training session. We placed one electrode over the left dorsolateral prefrontal cortex (anode in tDCS, 5×7 cm) and the other electrode on the contralateral side supraorbital (10×10 cm). We assessed cognitive performance prior and post-intervention as well as after 6 and 12 months. We estimated the effect of the intervention on performance quantified by a cognitive composite score. This composite score included measures of episodic as well as working memory, speed of processing, attention, and executive functions.

Results: Neither tDCS nor tACS boosted the effect of the cognitive intervention compared to sham stimulation. We found a significant three-way interaction between stimulation, time and baseline MoCA score. Participants with lower baseline MoCA scores benefited significantly from tDCS in combination with the intervention. There was no such effect for tACS.

Conclusion: TDCS increased the effect of a cognitive intervention, but only in participants with initially low cognitive performance. It is possible, that tDCS is particularly beneficial when brain networks are already affected by cognitive decline. Future studies should clarify if tACS with individualized frequencies or different electrode placement is able to increase the effect of a cognitive training or if tDCS might be better suited for boosting the effect of cognitive training.

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P120 Combined EEG/MEG targeting and multi-electrode individually optimized tDCS stimulation of the human somatosensory network—A. Khan[a,*], M. Antonakakis[a], T.R. Schneider[b], C.H. Wolters[a] ([a] Institute of Biomagnetism and Biosignal analysis, Muenster, Germany, [b] University Medical Center Hamburg-Eppendorf, Department of Neurophysiology and Pathophysiology, Hamburg, Germany)

Introduction: In order to address the issue of distributed electrical currents in a broad area of brain networks by standard tDCS, multi-electrode tDCS has gained interest for its improved tradeoff between focality and intensity at the brain target region of interest (ROI). Also, in many cases, only the location of the target ROI is considered and not the orientation. Here we present three optimization approaches a novel method CMI (Constrained maximum intensity), MI (Dmochowski et al., 2011), ADMM (Wagner et al., 2016) and one standard method (2-Patch) in our simulations. The generator for the P20/N20 somatosensory the component has been taken as the target ROI.

Materials and methods: Three right handed subjects participated in this initial study. SEP/ SEF were recorded following electrical stimulation of the right hand first index finger using combined MEG and EEG. T1, T2, Diffusion-weighted MRI were used for the construction of six compartment segmented anisotropic head model. Following the steps in (Antonakakis et al., xxxx) a source analysis was performed to get a P20/N20 target. After P20/N20 target estimation, all four tDCS (CMI, MI, ADMM, 2-Patch) simulation were performed to produce current densities and electrode configuration as shown in Fig. 1.

Results and conclusion: Table 1 shows the simulation results. Fig. 1 shows the visualization of current densities. From figures A4 - D4 it can be seen that the direction of the current density at the dipole target changes with different montages with the standard 2 patch having the worst directionality at the target while the ADMM, MI, and CMI show more parallel current density vectors in the direction of the dipole target orientation. For an optimum trade-off between intensity at the target and parallelity (PAR) the MI and CMI show promising results. As CMI achieves the results with a lower current per electrode, makes much better use of the multi-