Semi-Simulation of Task-Evoked Systemic Activity for Motor Imagery and Motor Execution Tasks

Aykut Eken[1,2], Franziska Klein[3], Cornelia Kranczioch[2,4]

[1] Department of Biomedical Engineering, TOBB University of Economics and Technology, Ankara, Turkey

[2] Neurocognition and Functional Neurorehabilitation Group, Neuropsychology Lab, Department of Psychology, Carl von Ossietzky University Oldenburg, Oldenburg, Germany

[3] Biomedical Devices and Systems Group, R&D Division Health, OFFIS – Institute of Information Technology, Oldenburg, Germany

[4] Research Center Neurosensory Science, Carl von Ossietzky University Oldenburg, Oldenburg Germany

Synopsis

Task-evoked systemic activity (TESA) remains a major challenge in functional near-infrared spectroscopy (fNIRS), as it mimics neural hemodynamic responses (HDR) and compromises accurate signal interpretation. Short-distance channels are used to regress TESA, the validation of correction outcome is however restricted by the absence of a ground truth. Semi-simulated time series have been used instead.However, so far, they lack a realistic simulation of TESA, which limits their value as ground truth. This study introduces an approach to generate realistic TESA-contaminated fNIRS signals using resting-state data combined with simulated systemic and HDR. Using motor-execution and motor-imagery data, correction performance was evaluated across motor regions using correlation and error metrics. Results show that the semi-simulated data generated with the proposed approach closely resemble real fNIRS signals, and provide a robust benchmark for evaluating TESA correction methods.

Background

Removal of TESA in fNIRS is a critical issue for accurate modeling of the HDR, as uncorrected TESA can lead to false-positive or false-negative results (Tachtsidis and Scholkmann, 2016). Compared to non-evoked systemic activity, TESA is a more challenging artifact because it mimics the HDR (Gagnon et al., 2012). After the introduction of short-distance channels to record systemic physiology in the extracerebral compartment (Scholkmann et al., 2014; Klein, 2024), SDC data have been used as regressors in the General Linear Model (GLM) to remove TESA from long-distance channels . Although this approach is generally accepted, whether it is the most effective approach remains an open question. A critical challenge in this context is the generation of simulated but realistic fNIRS data, that can act as a ground truth. In particular the simulation of TESA has received little consideration so far.

Methods

A previously collected fNIRS dataset from a neurofeedback study including 19 right-handed healthy participants (M/F: 12/7; age: 63.63 ± 9.04 years; range: 45–77 years) was used. All participants performed motor execution (ME) and motor imagery (MI) tasks. In the ME condition, participants were instructed to tap their left or right hand fingers according to the instructions. In the MI condition, participants were asked to perform a self-determined whole-body (WB) movement (e.g., swimming, Nordic walking, dancing, or jumping jacks). Before each session, a 5-minute resting-state measurement was conducted. In both conditions, task periods lasted 15 s, with variable rest periods of 18–22 s. fNIRS signals were recorded using a NIRSSport2 device (NIRx Medizintechnik, Berlin, Germany) at a sampling frequency of 10.1725 Hz, using near-infrared light at wavelengths of 760 and 850 nm. The source–detector layout covered the bilateral primary motor cortex (M1) and supplementary motor area (SMA).

After data preprocessing, finite impulse response deconvolution was applied to the short-distance channel data. TESA simulation was then performed using Multiple Gamma Modeling (MuGaM) (Eken et al., in preparation). In MuGaM, TESA is modeled as gamma function/s. First, peak amplitude(s), peak latency(ies) and Full-Width Half Maximum data are extracted from short-distance channel epochs. These parameters are used to generate simulated TESA by using gamma functions. To simulate TESA with multiple peaks, gamma functions are temporally summated. For every region (right primary motor , left primary motor, SMA), condition (ME right, ME left, MI WB) and signal type (ΔHbO, ΔHbR), averaged simulated TESA was estimated and used to generate simulated TESA time series ($SimTESA_{TS}$). $SimTESA_{TS}$ and simulated HRF time series ($SimHRF_{TS}$) were generated by convolving a boxcar function consisting of five blocks for the ME and MI conditions. Semi-simulated TESA time series ($SemiSimTESA_{TS}$) were generated by adding $SimTESA_{TS}$, unpreprocessed resting-state concentration time series and $SimHRF_{TS}$, with the HRF amplitude adapted according to the amplitude of $SimTESA_{TS}$. Semi-simulated HRF time series ($SemiSimHRF_{TS}$) were generated by adding unpreprocessed resting-state concentration time series and $SimHRF_{TS}$ (amplitude: $\Delta HbO = 10\ \mu M$, $\Delta HbR = -10/3\ \mu M$). Real data were also used for comparison with the simulated TESA.

GLM correction performance was compared across datasets for three region–condition pairs: right M1 activity during left-hand finger tapping (RM1–ME left), left M1 activity during right-hand finger tapping (LM1–ME right), and SMA activity during MI whole-body movement (SMA–MI WB). After correction and trial averaging on selected channels for each RC across all datasets, scaled root mean squared error and z-transformed correlation coefficients were computed between the averaged epochs and the HRF model as references to validate short-channel TESA correction. Statistical comparison was carried out using one-way repeated measures ANOVAs. For sphericity, Mauchly's test was applied and Greenhouse-Geissner correction was applied where applicable.

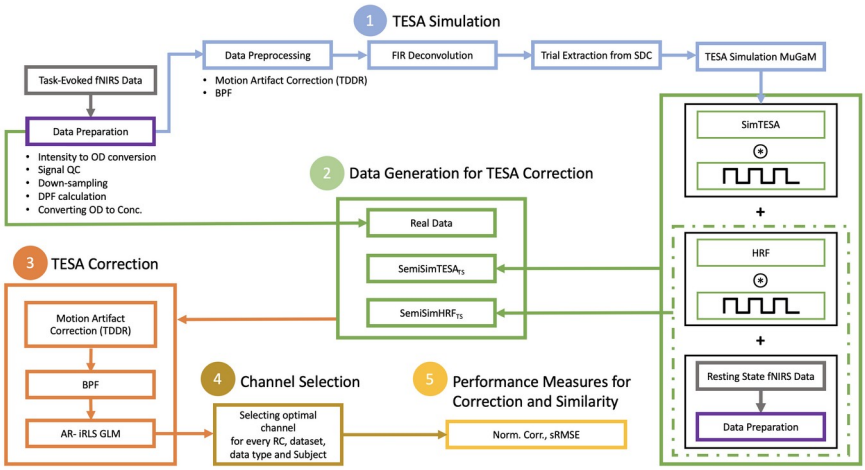

Figure 1. TESA simulation and correction framework to estimate HDR.

Results

Normalized correlation results revealed a significant main effect of Dataset for all region–conditions in the ΔHbO analysis (all $p < 0.05$). Similarly, in ΔHbR, all region–conditions demonstrated a significant main effect of Dataset (all $p < 0.005$). Post hoc comparisons for ΔHbO showed no significant difference between $SemiSimTESA_{TS}$ and Real Data for any region–condition. $SemiSimHRF_{TS}$ yielded significantly higher normalized correlations than $SemiSimTESA_{TS}$ and Real Data for all region–conditions. For ΔHbR, $SemiSimHRF_{TS}$ yielded significantly higher normalized correlations than $SemiSimTESA_{TS}$ for all region–conditions. In all region–conditions, no significant difference was observed between $SemiSimTESA_{TS}$ and Real Data, while $SemiSimHRF_{TS}$ exhibited higher correlation values than Real Data except for LM1-ME right.

For the sRMSE of the ΔHbO signal, a significant main effect of Dataset was observed in RM1–ME left and SMA–MI WB (all $p < 0.001$). For ΔHbR, all region–conditions showed a significant main effect of Dataset (all $p < 0.05$). Post hoc comparisons indicated that, for ΔHbO, $SemiSimHRF_{TS}$ had significantly lower sRMSE than $SemiSimTESA_{TS}$ for both RM1-ME left and SMA–MI WB. No significant difference was found between $SemiSimTESA_{TS}$ and Real Data. In addition, Real Data exhibited significantly higher sRMSE than $SemiSimHRF_{TS}$ for both RM1-ME left and SMA-MI WB. For ΔHbR, $SemiSimTESA_{TS}$ showed significantly higher sRMSE than $SemiSimHRF_{TS}$, while no significant difference was observed between $SemiSimTESA_{TS}$ and Real Data across all region–conditions. Except for LM1–ME right, Real Data exhibited significantly higher sRMSE than $SemiSimHRF_{TS}$.

Discussion

This study presents a semi-simulation framework to generate realistic TESA-contaminated fNIRS signals, addressing the lack of ground truth for validating correction methods. The absence of significant differences between $SemiSimTESA_{TS}$ and Real Data across correlation and sRMSE metrics indicates that the framework successfully reproduces the characteristics of real TESA contamination. As expected, the TESA-free condition ($SemiSimHRF_{TS}$) showed higher correlations and lower errors, confirming that TESA substantially impairs HDR estimation and that the selected metrics are sensitive to this degradation. The consistency of findings across motor regions and task conditions supports the robustness of the approach. Minor differences observed in specific region–condition pairs (e.g., LM1–ME right in sRMSE) may reflect interhemispheric variability, task-related hemodynamic differences, or region-specific susceptibility to systemic contamination. Overall, this framework provides a practical objective benchmark for systematically evaluating and comparing TESA correction strategies in fNIRS research.

Disclosures (if any)

The authors declare that there is no conflict of interest.

References

Eken, A., Klein, F., and Kranczioch, C. (In preparation). A Simulation Framework for Task-Evoked Systemic Activity in Semi-Simulated fNIRS Data.

Gagnon, L., Cooper, R.J., Yucel, M.A., Perdue, K.L., Greve, D.N., and Boas, D.A. (2012). Short separation channel location impacts the performance of short channel regression in NIRS. *Neuroimage* 59(3)**,** 2518-2528. doi: 10.1016/j.neuroimage.2011.08.095.

Klein, F. (2024). Optimizing spatial specificity and signal quality in fNIRS: an overview of potential challenges and possible options for improving the reliability of real-time applications. *Front Neuroergon* 5**,** 1286586. doi: 10.3389/fnrgo.2024.1286586.

Scholkmann, F., Kleiser, S., Metz, A.J., Zimmermann, R., Mata Pavia, J., Wolf, U., and Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *Neuroimage* 85 Pt 1**,** 6-27. doi: 10.1016/j.neuroimage.2013.05.004.

Tachtsidis, I., and Scholkmann, F. (2016). False positives and false negatives in functional near-infrared spectroscopy: issues, challenges, and the way forward. *Neurophotonics* 3(3)**,** 031405. doi: 10.1117/1.NPh.3.3.031405.