Trainability Differences of Electrical Brain Metrics in EEG Neurofeedback: Implications for Modulating Language Function

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Introduction

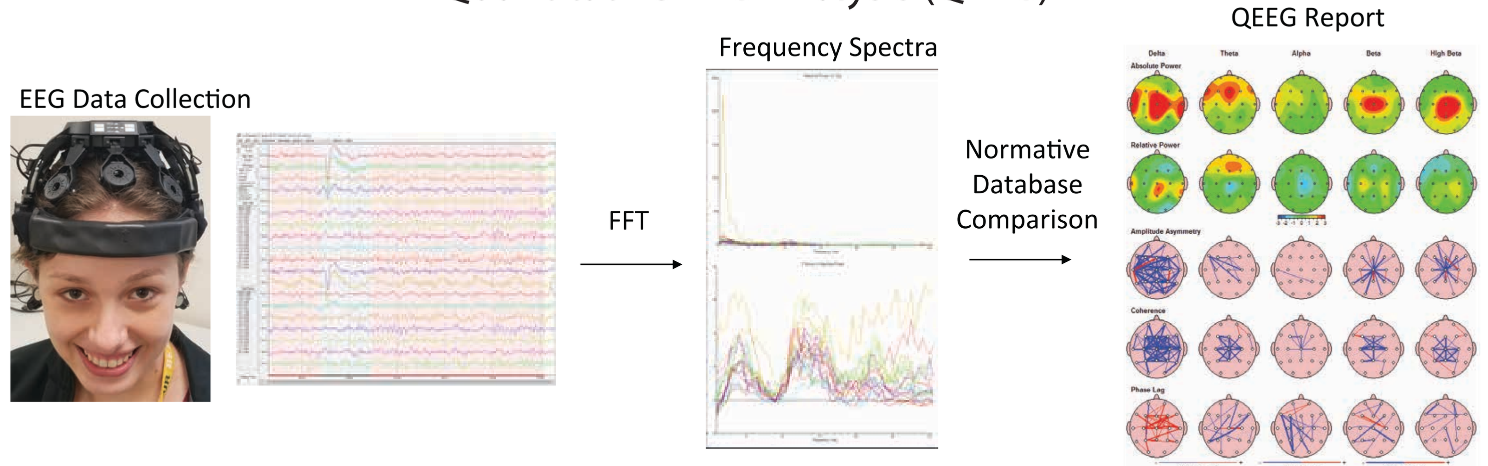
Recent work on recovery of language function following adult brain injury (e.g. stroke, TBI) has focused heavily on the importance of brain networks for language, rather than on isolated "language areas". However, relatively few direct methods exist for strengthening connections between the parts of these networks. Electroencephalographic (EEG) neurofeedback (NF) is currently a topic of growing interest, which has significant potential both as a clinical and experimental tool for changing the function of brain networks.

Though NF has been successfully used to treat symptoms of multiple disorders that relate to language (e.g. ADHD, dyslexia; traumatic brain injury), the utility of this tool to address language deficits directly has not been well explored. One difficulty in studying the potential of NF treatment for adult language disorders is that there is high individual variability in the ability to effectively change brain activity with neurofeedback. Additionally, this variability may operate differently for different EEG metrics. Currently, there is no agreement on the cause of this variability, and no good assessment of treatment potential for NF, which can distinguish "responders" from "nonresponders" before starting therapy.

Here, we present a proposed assessment that could be used to determine NF treatment potential, which tests several common EEG metrics (absolute power, amplitude asymmetry, coherence and phase lag) for their relative ability to be trained successfully via NF. We focus on training each metric toward known values for a healthy control group, and we compare the ability to train EEG networks both within-hemisphere and across hemispheres. The current version of the assessment uses the Theta brain rhythm at locations specific to the language network (e.g. Broca's area, Wernicke's area, left lateral motor cortex), but alternate versions could be easily adapted to focus on other brain rhythms, or other brain locations. We present preliminary findings from the initial tests of this protocol, which show that there are indeed key differences in trainability of the EEG based on the measures examined and the methods employed.

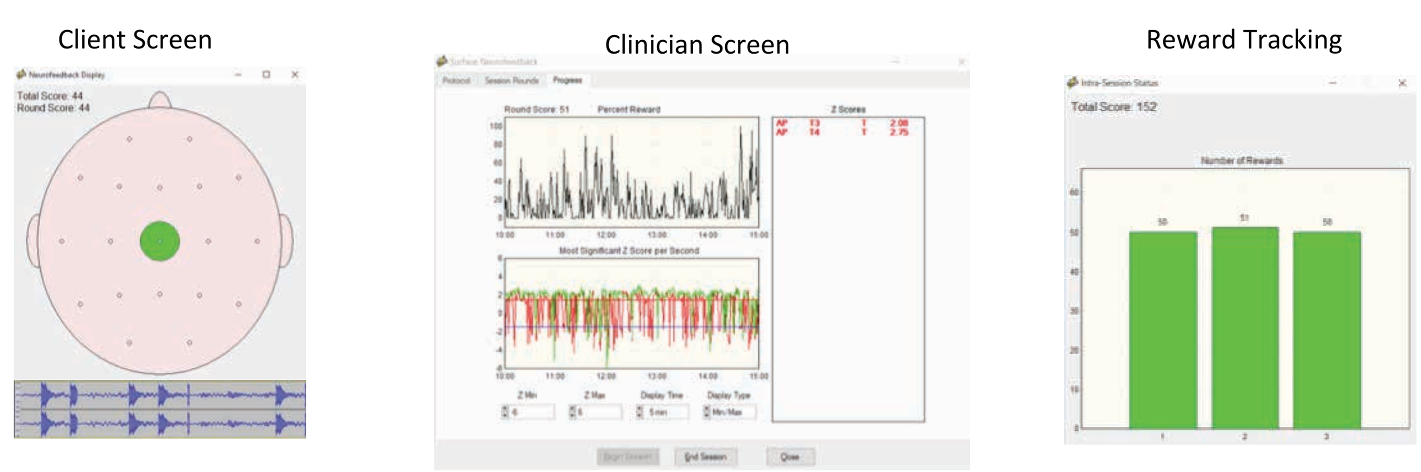
Neurofeedback Methods

Quantitative EEG Analysis (QEEG)



For QEEG, brain activity is recorded at rest (eyes open/closed), processed to remove artifacts (eye blinks, etc.), decomposed into various frequency bands (delta, theta, alpha, beta, high beta), and then compared to a normative database of EEG patterns. Reports are often generated based on Z-scores, which identify EEG metrics that are significantly different from normative values.

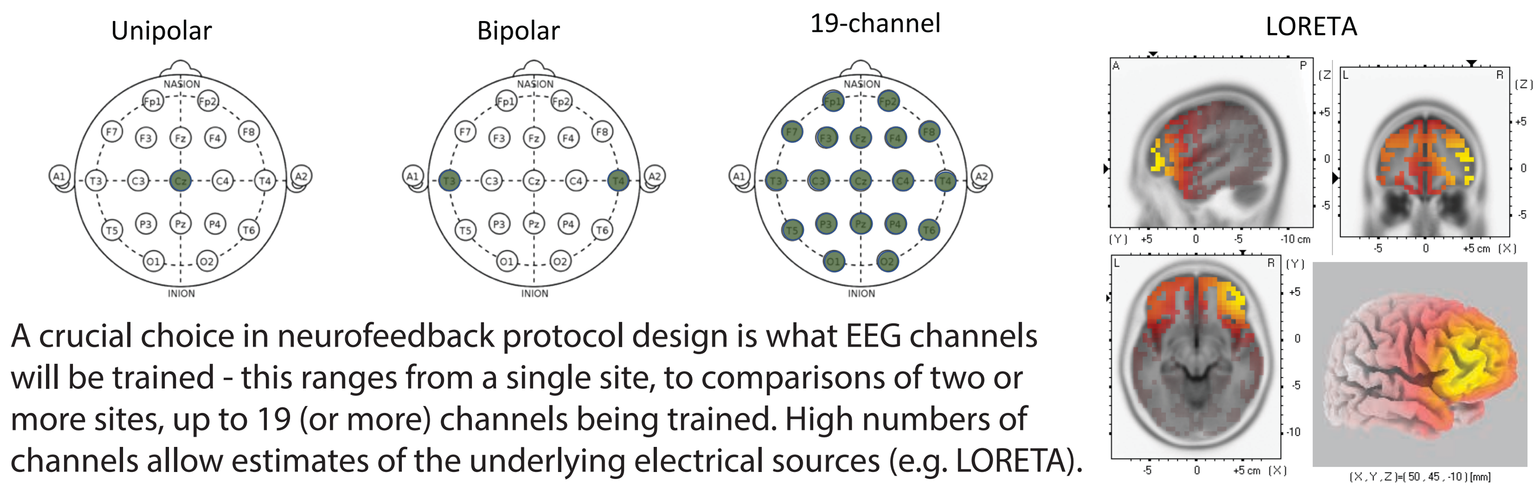
Neurofeedback Session Example



Based on whatever EEG metrics are being trained, the client gets "rewards" via auditory-visual feedback when their EEG patterns are moving towards the desired values (here a Z-score of zero in Theta).

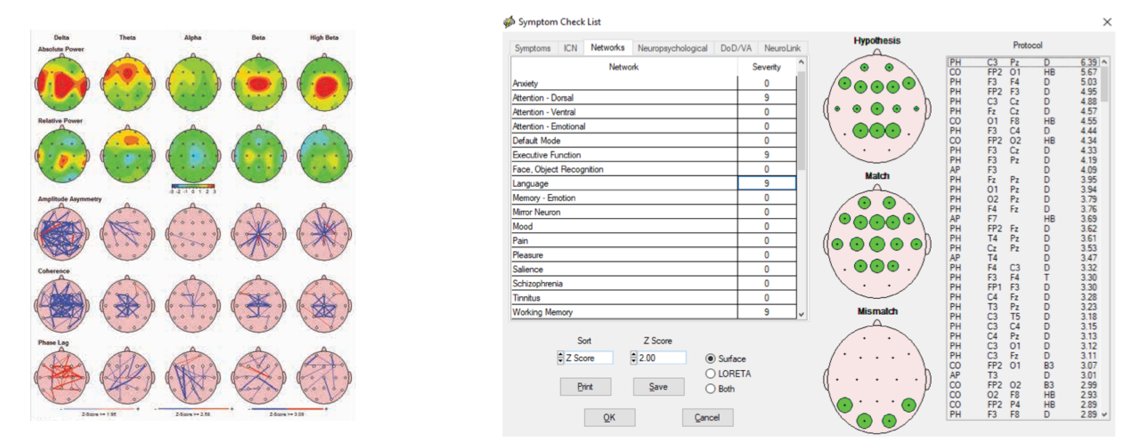
Designing Neurofeedback Protocols for Language Disorders

Locations for Training



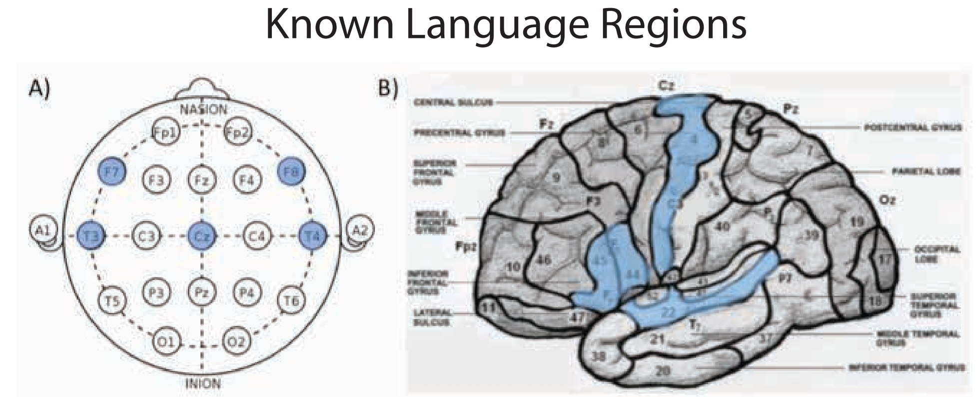
A crucial choice in neurofeedback protocol design is what EEG channels will be trained - this ranges from a single site, to comparisons of two or more sites, up to 19 (or more) channels being trained. High numbers of channels allow estimates of the underlying electrical sources (e.g. LORETA).

Symptom Checklist



Based on regions and networks identified from the literature, a set of candidate regions can be identified that matches a patient's symptoms. These symptoms can then be compared to the deviations from normative values seen in the QEEG report, to identify EEG metrics where QEEG abnormalties match symptoms, which will then be used as targets for treatment.

Known Language Regions



Protocols can also be generated more simply, based on regions known to be involved in language processing (e.g. Broca's, Wernicke's areas, etc.) - this can include electrode sites over these areas (A), or Brodmann areas for use in LORETA neurofeedback (B).

Prospective Efficacy Assessment

Surface Neurofeedback

Block	Site	Band	Parameter
A	All	All	Resting Eyes Open - 5 min.
1	T3	Theta	Absolute Power
2	T3-T4	Theta	Interhemi AmpAsym
3	T3-F7	Theta	Intrahemi AmpAsym
4	T3-T4	Theta	Interhemi Coherence
5	T3-F7	Theta	Intrahemi Coherence
6	T3-T4	Theta	Interhemi Phase Lag
7	T3-F7	Theta	Intrahemi Phase Lag
B	All	All	Resting Eyes Open - 5 min.

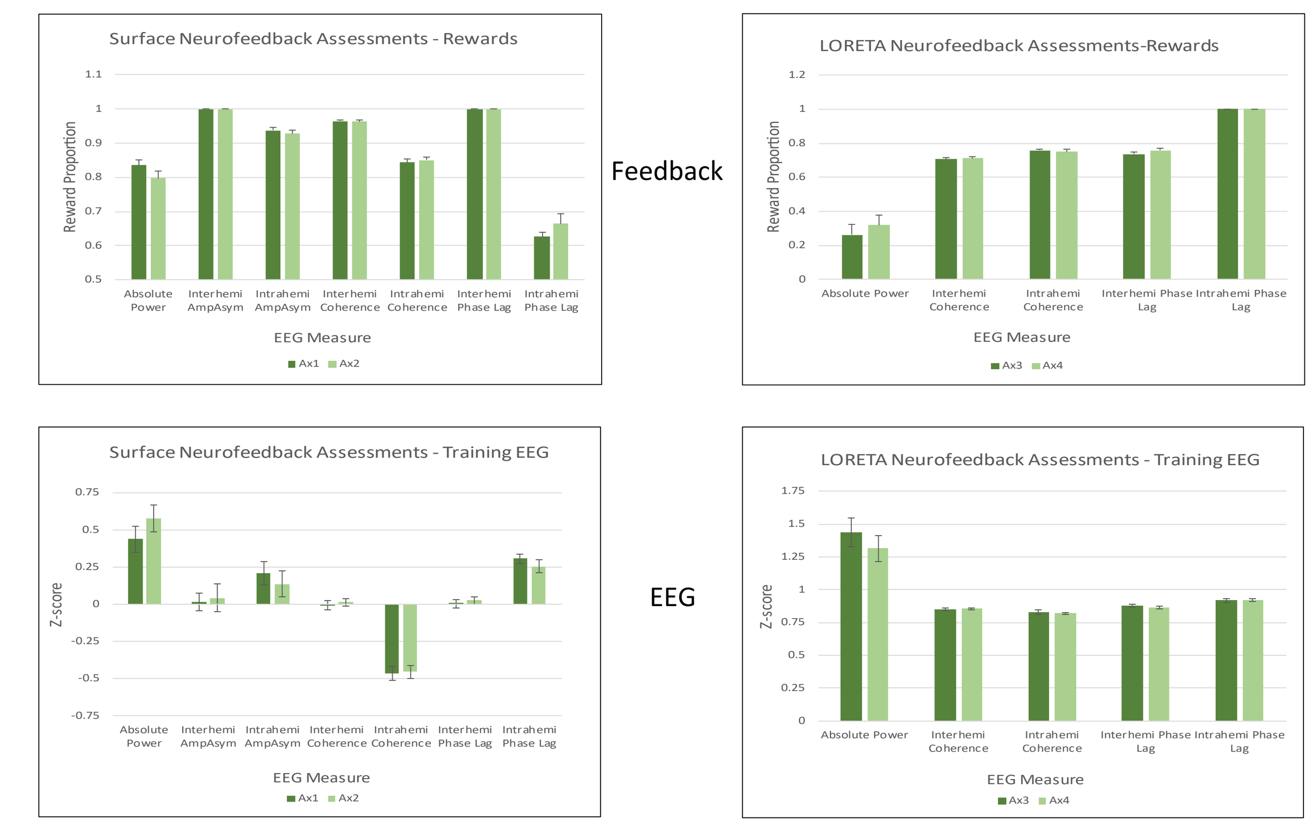
LORETA Neurofeedback

Block	Site	Band	Parameter
A	All	All	Resting Eyes Open - 5 min.
1	L_BA22	Theta	Absolute Power
2	L_BA22 - R_BA22	Theta	Interhemi Coherence
3	L_BA22 - L_BA44	Theta	Intrahemi Coherence
4	L_BA22 - R_BA22	Theta	Interhemi Phase Lag
5	L_BA22 - L_BA44	Theta	Intrahemi Phase Lag
B	All	All	Resting Eyes Open - 5 min.

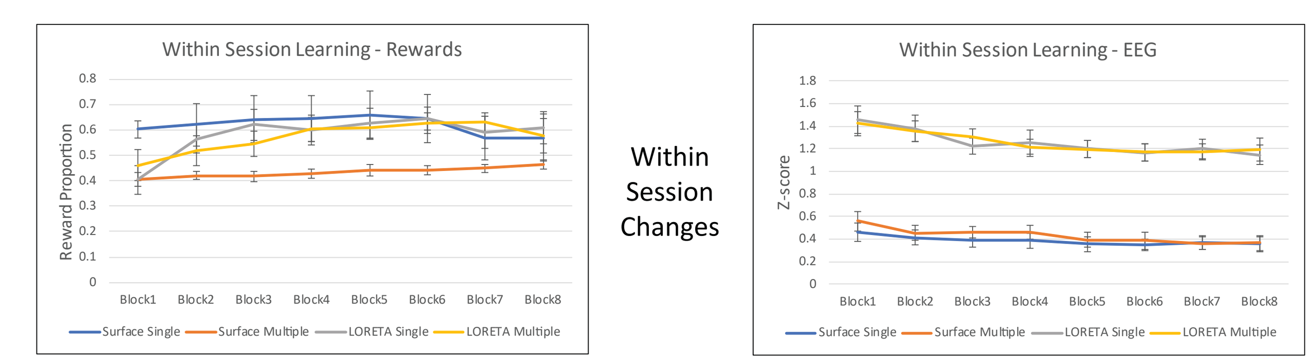
Each metric was trained for 3 (surface) or 5 (LORETA) minutes toward a Z-score of zero, with a threshold of Z=+-2.0.

Even given a small set of a predefined language regions, there are many different EEG metrics which can be targeted for neurofeedback. We conducted a pilot study (n=14, 18 sessions total) looking at modulating common EEG measures (power, coherence, phase) both within and across hemispheres, to estimate the relative difficulty of (and associated success with) training these measures. We compared both surface (Ax1, Ax2) and LORETA (Ax3, Ax4) methods, and present results of these assessments before and after several sessions of extended training (8 & 6 sessions for scalp/LORETA, respectively).

Results

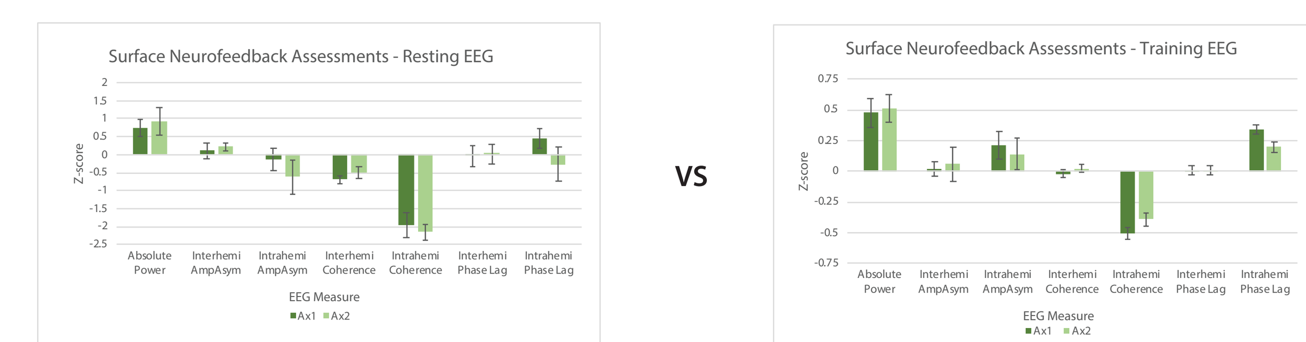


We found strong variation in difficulty of modulating EEG metrics, with several metrics at ceiling (interhemispheric phase lag & amplitude asymmetry for surface, interhemsipheric phase lag for LORETA), and others more difficult (intrahemispheric phase lag for surface, absolute power for LORETA). Patterns for EEG values during training were similar to, but not identical with, patterns for reward feedback.



We found that LORETA training seemed to show higher rates of within session learning, both for number of rewards, and for EEG values. We also found that for surface training, using multiple metrics was much harder than single metrics, but this was not the case for LORETA. Z-scores for EEG metrics were generally higher for LORETA than for surface training.

Future Directions



One of the findings of this project has been to highlight the fact that patterns of abnormality for resting EEG are similar, but not the same as what is seen in the EEG while training the brain via neurofeedback. Our next step in understanding this dynamic is to conduct simulation studies by running neurofeedback sessions using recorded resting EEG, rather than real online EEG, and to compare these results to the data from real neurofeedback. This will help us to more clearly assess the extent to which the brain is actually changing in response to the neurofeedback signal.

Conclusions

As expected, we demonstrated high variability in training success across metrics, and that difficulty varied largely based on neurofeedback type (surface vs LORETA). We found few changes across assessment sessions, arguing against a general, non-specific effect of neurofeedback on resting EEG patterns. We demonstrated the ability to successfully train multiple metrics at a time and to show within-session brain changes, especially for LORETA NF. More work is needed to see how these results will generalize to the application of NF to adult brain-injury, but these findings do have implications for designing treatments.