A Further Study of

Alpha-Down Neurofeedback Training for SSVEP-based BCIs

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1. EEG frequency bands;
2. BCI paradigms and challenges;

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Introduction

1. EEG frequency bands;
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01 Introduction – EEG (Electroencephalogram) Frequency Bands

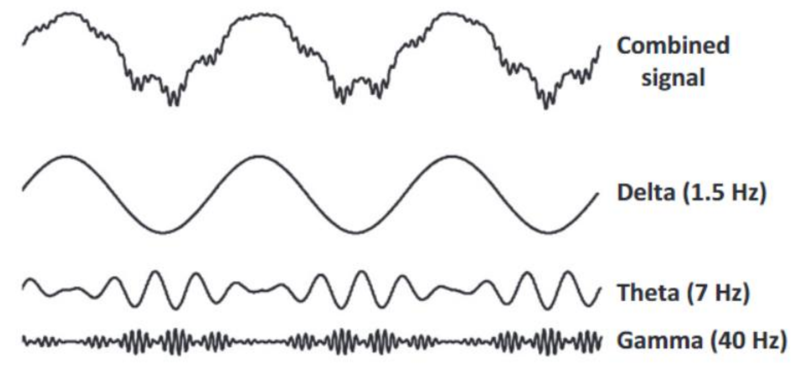


Fig. 1 Stylized example of phase–amplitude coupling in a hierarchy of oscillations.(Calderone, 2014)

01 Delta (0.5-4 Hz)

Related to slow-wave sleep (SMS)

02 Theta (4-8 Hz)

Related to sub-consciousness and enhanced in deep sleep and deep meditation.

03 Alpha (8-12 Hz)

Related to attention and enhanced in awake but eye-closed resting states, reflect information process and cortical excitability.

04 Sigma (12-16 Hz)

Related to non-rapid eye movement sleep in the spindle.

05 Beta1 (16-20 Hz)

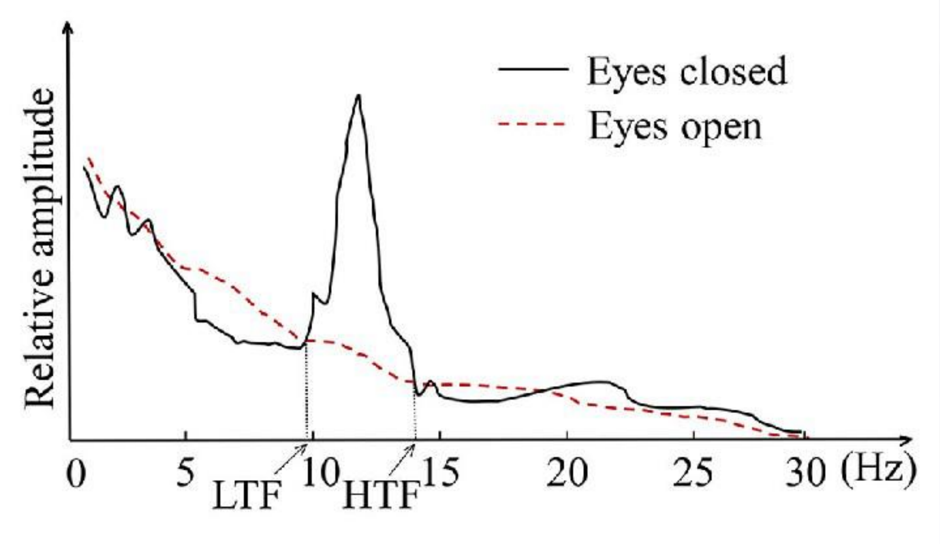
Related to normal waking consciousness and Beta1 is also known as "Low Beta Waves".

06 Beta2 (20-28 Hz)

Related to normal waking consciousness and Beta2 is also known as "High Beta Waves",

Calderone, D. J., Lakatos, P., Butler, P. D., & Castellanos, F. X. (2014). Entrainment of neural oscillations as a modifiable substrate of attention. *Trends in Cognitive Sciences*, *18*(6), 300-309.

Why IAB as the NF training parameter?



The illustration of individual alpha frequency band. (F.wan, 2014)

- Different subjects process different individual alpha band (IAB);
- Individual alpha peak frequency (IAPF) was the indicator of defining the IAB (IAPF-4 to IAPF+2 Hz);
- Using the IAB was more efficient than using standard alpha band (8-12Hz) as the training parameter in NFT.

In this study:

For IAPF differences (N=28),
min= 7.5 Hz,
max= 12.3 Hz,
mean=10.40 Hz,
std=0.94 Hz).

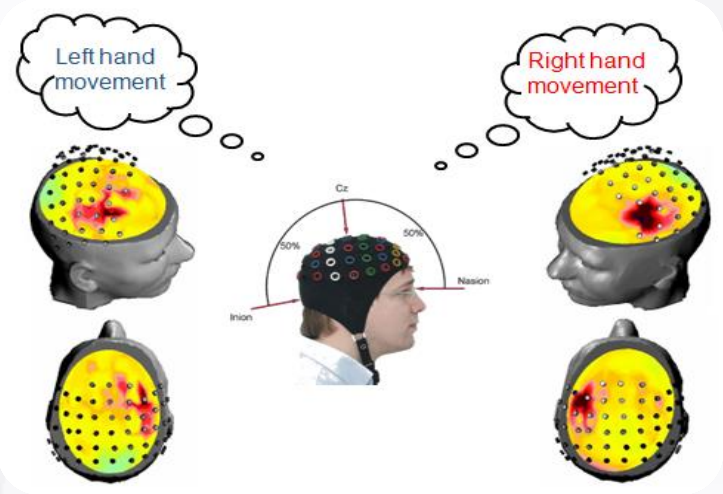
For the absolute amplitude of IAPF:
min= 0.74 μV,
max=6.92 μV,
mean= 3.36 μV,
std= 1.92 μV.

* For details please refer to Appendix I

F. Wan, W. Nan, M. I. Vai, and A. Rosa, “Resting alpha activity predicts learning ability in alpha neurofeedback,” Frontiers in human neuroscience, vol. 8, p. 500, 2014.
O. Bazanova and L. Aftanas, “Individual eeg alpha activity analysis for enhancement neurofeedback efficiency: two case studies,” *Journal of Neurotherapy*, vol. 14, no. 3, pp. 244–253, 2010.

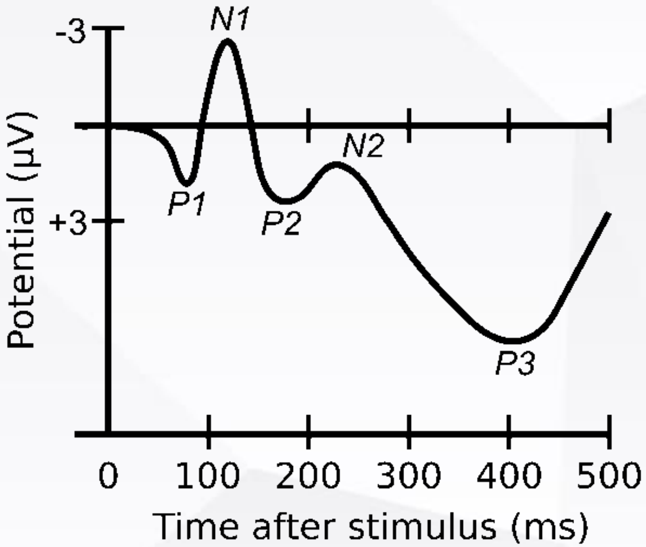
01 Introduction – BCI Paradigms

Motor Imagery (MI)



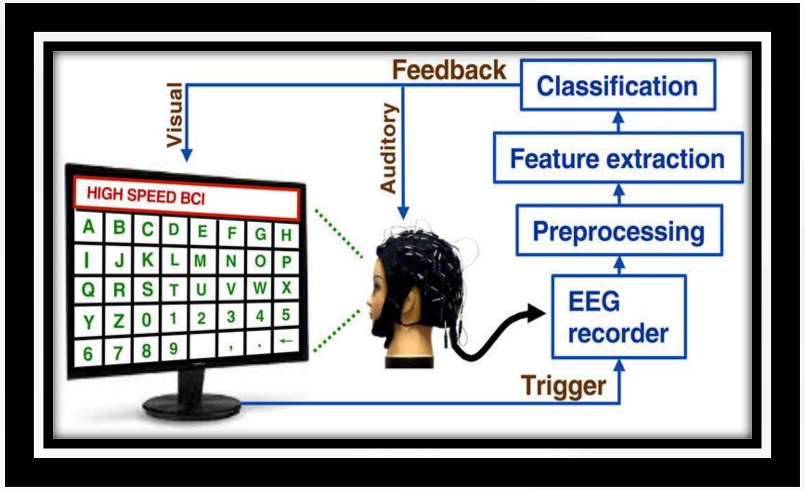
1. Imagining or going to do unilateral movements;
2. Energy increased in contralateral side of the brain;
3. Low information transfer rate (ITR).

Event Related Potential (ERP)



1. Different stimulation modes (visual, auditory and somatosensory);
2. Energy increased in contralateral side of the brain;
3. Medium ITR and training time.

Steady-State Visual Evoked Potential (SSVEP)

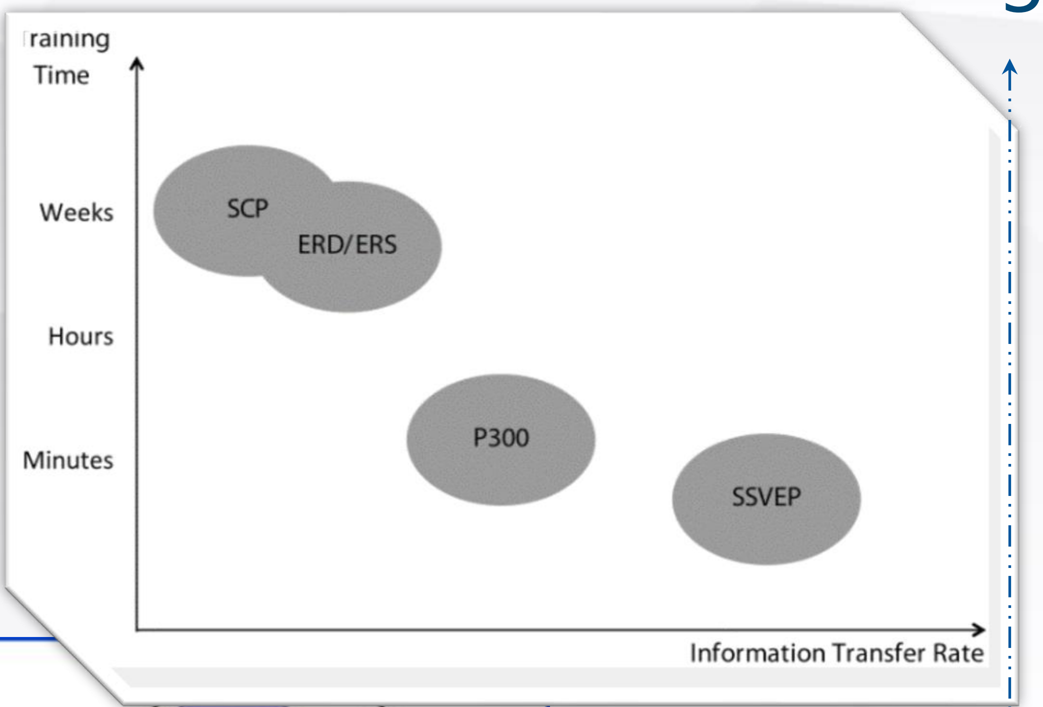


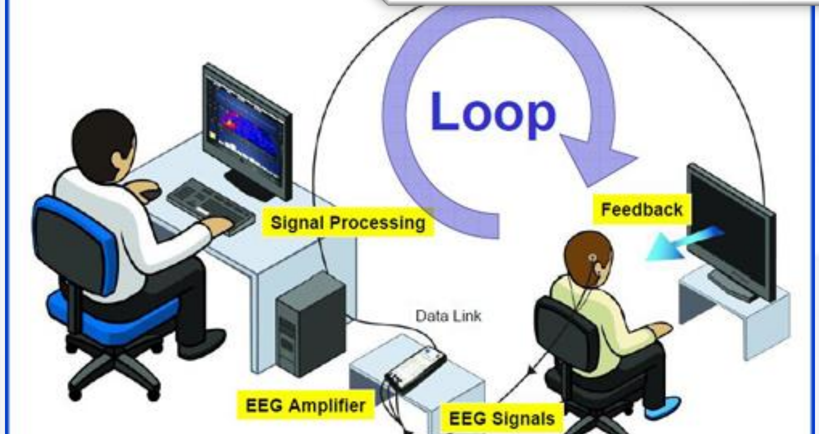
1. **High ITR;**
2. **Needs little training;**
3. **A recent benchmark:**

Averaged ITRs of 325.33±38.17 bits/min (Nakanishi, 2018)

Nakanishi M, Wang Y, Chen X, Wang Y T, Gao X and Jung T P 2018 Enhancing detection of ssveps for a high-speed brain speller using task-related component analysis IEEE Transactions on Biomedical Engineering 65 104–112

01 Introduction – BCI Challenge





General Protocol of BCI paradigms

The BCI Illiteracy Phenomenon

Non-negligible portion, incapable of utilizing a BCI due to their low performances (Kim , 2019):

53.7% for MI
11.1 % for ERP
10.2% for SSVEP

Exogenous approaches proposed to elicit based on:

1. Hardware and setup;
2. System design and protocol;
3. Signal processing and classification algorithms.

Kim H K, Williamson J, Lee M H, Kwon O Y, Kim Y J, Lee Y E, Lee S W and Fazli S 2019 EEG Dataset and OpenBMI Toolbox for Three BCI Paradigms: An Investigation into BCI Illiteracy doi:10.1093/gigascience/giz002

Neurofeedback (NF), applied as an **Endogenous** approach to **enhance the elicited BCI signal**

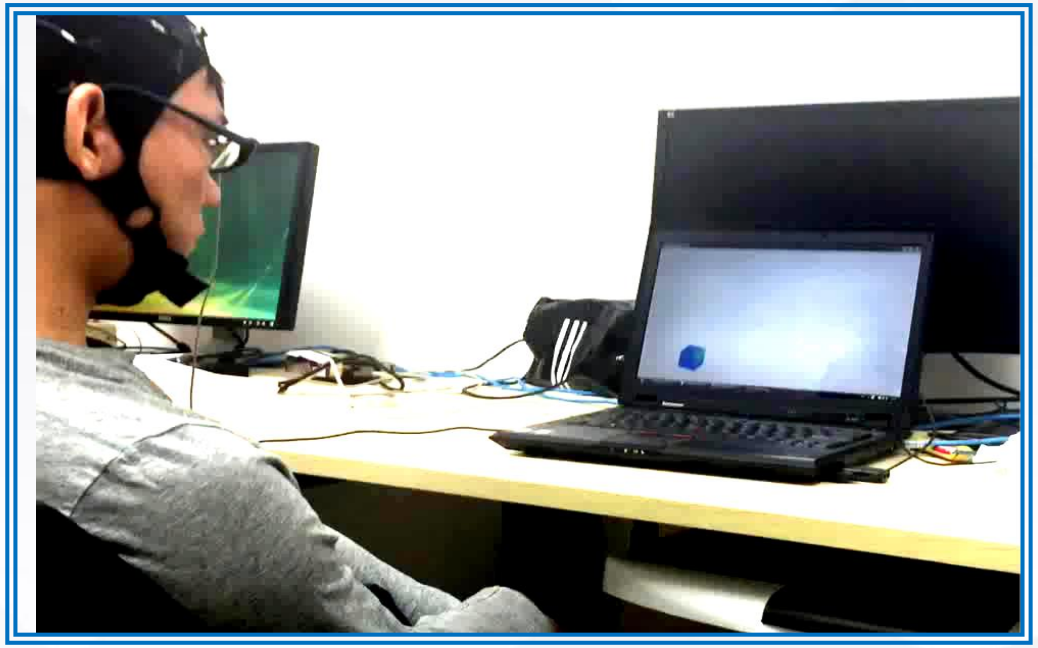
with real-time visual or audio feedback from screen

Up- regulation =increase of amplitude

Down- regulation =decrease of amplitude;

learning ability

√



1. NF share similar neurophysiological processes with BCIs (Wood, 2014)

2. Cognitive or behavioral tasks, working memory , MI

3. Mental diseases of Post-traumatic stress disorder: Attention Deficit and / Hyperactivity Disorder

Wood G, Kober S E, Witte M and Neuper C 2014 On the need to better specify the concept of “control” in brain-computer-interfaces/neurofeedback research *Frontiers in systems neuroscience* **8** 171

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02 Objectives and Contributions

To enhance the SSVEP based BCI performances

Previous study:

1. **Relationship** between EEG bands and SSVEP-BCI performance.
   -> **IAB** amplitudes negatively correlate SSVEP-BCI performances.

2. Propose a protocol of IAB NF training for SSVEP **enhancement**.
   -> SSVEP-BCI performances can be enhanced after NF training.

Limitations:
a. Pre-screened subjects
-- low initial SSVEP-BCI performers;
b. Low-frequency range of SSVEP stimuli
-- within 7.05-15 Hz;

This study:

I. **Integrate previous works** with
   a. un-screened subjects
   b. a wider-frequency range of SSVEP stimuli：
      -- from 7.05-35 Hz

II. **Explore possible mechanism behind the protocol**

Wan F, Da Cruz J N, Nan W, Wong C M, Vai M I and Rosa A 2016 Alpha neurofeedback training improves ssvep-based BCI performance Journal of neural engineering 13 036019

Contributions:

1. **Relationship** between EEG bands and SSVEP-BCI performances;
2. Using alpha-down NF training to **improve** a wider frequency SSVEP-BCI performances;
3. NF training are **non-specific**. NF training influences on both training band and neighboring, low-frequency bands;
4. Hints on the mechanism based on frequency and brain connectivity analysis.

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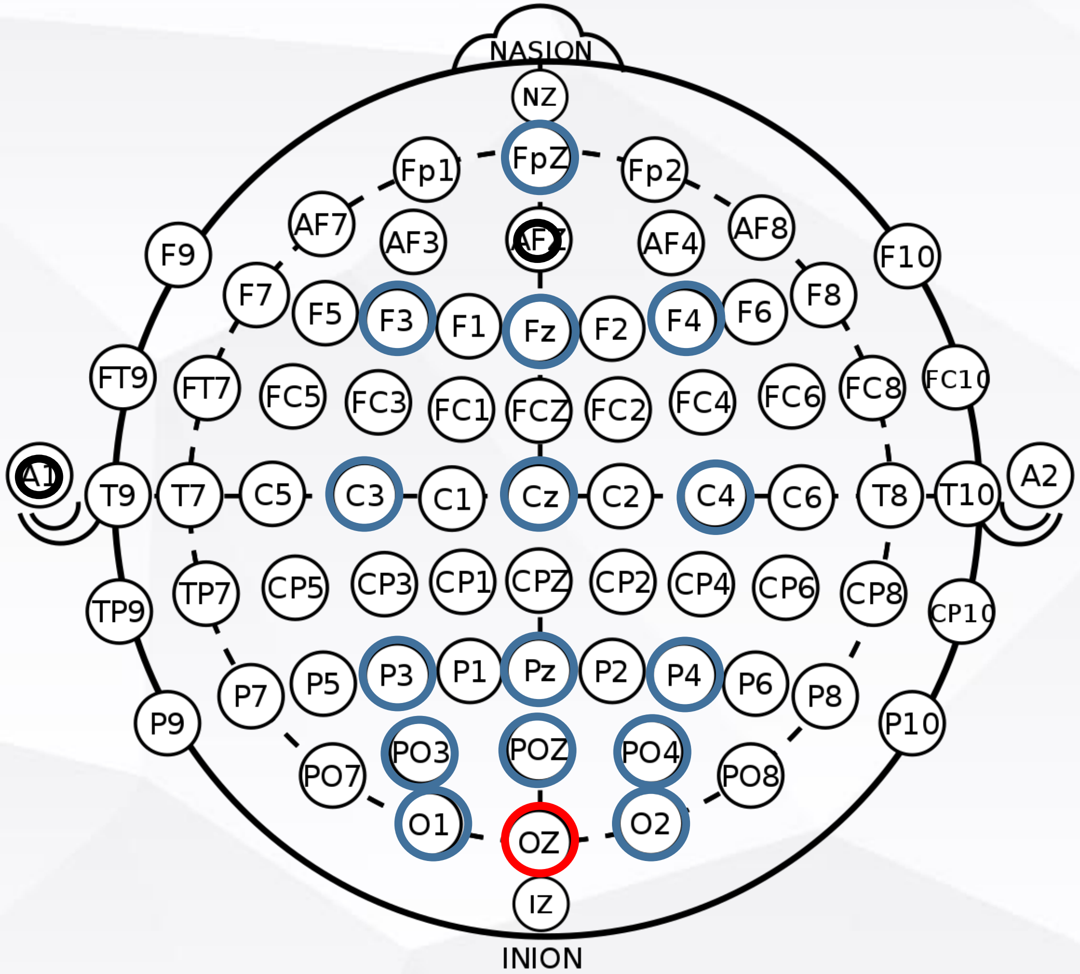
Setup:

- **Subjects:**
  28 healthy subjects (age: 25.1 ± 3.2 years; 9 females);

- **EEG recording:**
  16 electrodes (O1, Oz, O2, PO3, POz, PO4, P3, Pz, P4, C3, Cz, C4, F3, Fz, F4, Fpz)

- **Training location: Oz;**

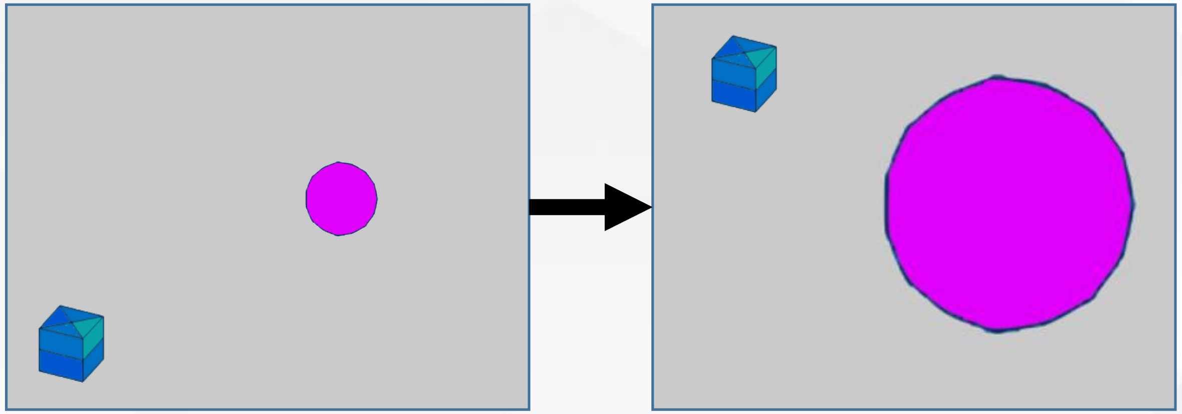


10-20 International System
and the selected electrodes

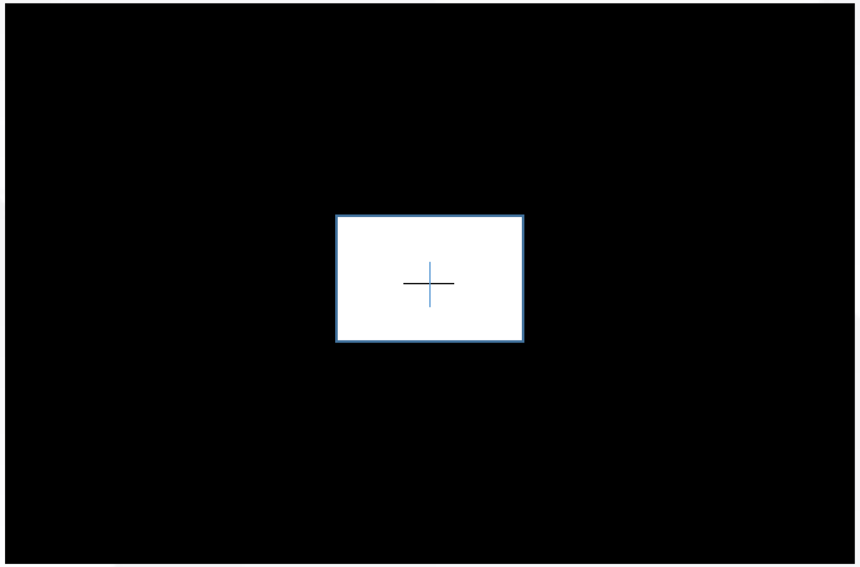
https://commons.wikimedia.org/wiki/File:International_10-20_system_for_EEG-MCN.svg

Setup:

- **Signal amplifier**:
  G.tec.g.USBamp;
- **Data processing:**
  MATLAB 2006b Simulink
  and Matlab 2015b;
- **LCD screen:**
  ViewSonic 22”,
  120 Hz refresh rate,
  1680 × 1050-pixel resolution
- **SSVEP stimuli generation:**
  A white stimulus with 120 × 120 pixels,
  black background, programmed with
  Microsoft Visual Studio 2010
  and Microsoft DirectX SDK

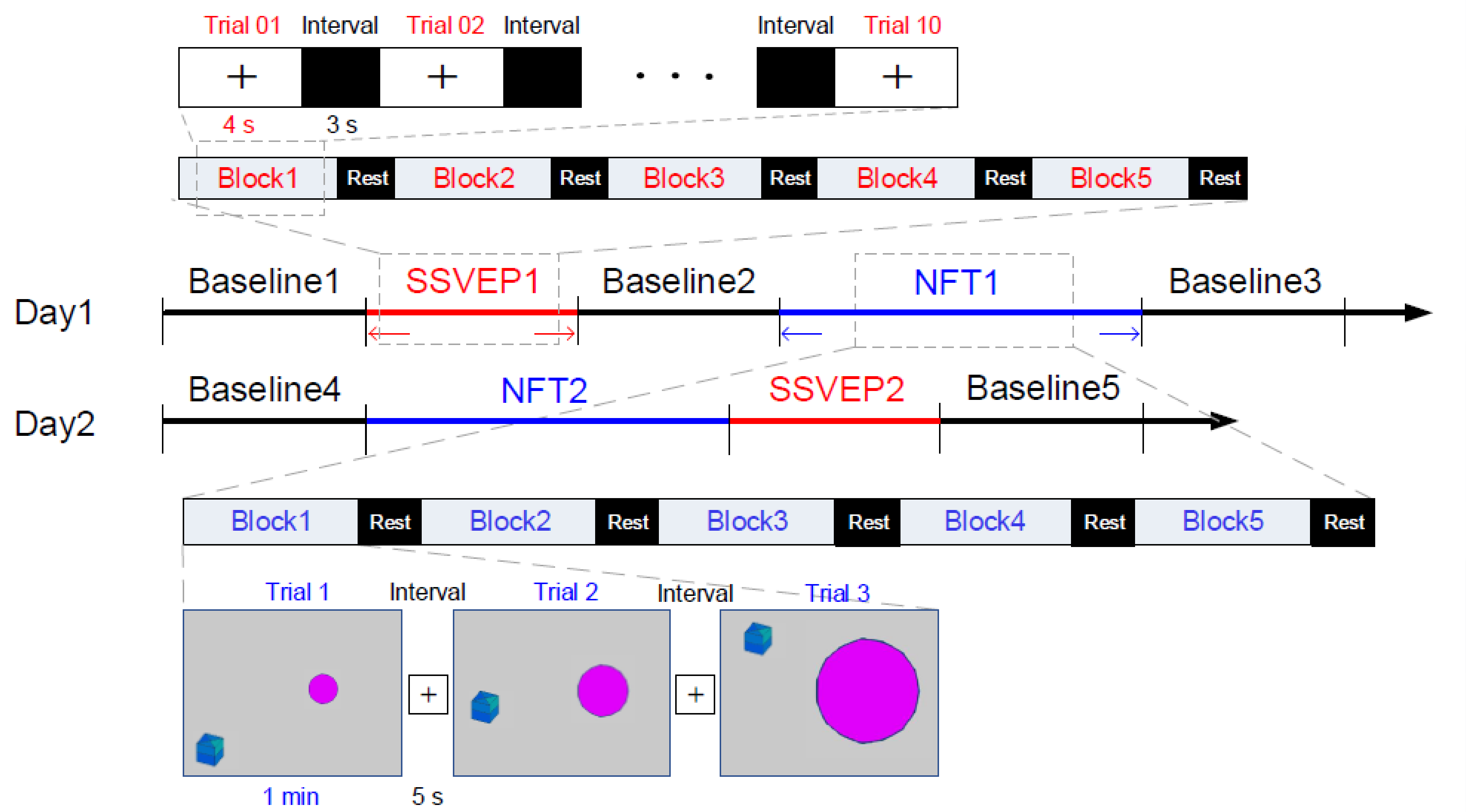


Setup of screen during NF training



Setup of screen during SSVEP-based BCI tests

Experiment procedure:



Experiment procedure

For NF training:

- 5 NFT blocks each day in two consecutive day；
- Each NFT block consisted of 3 successive 1-min trials with a 5-sec interval between trials;
- A 1-2 min break was given between NFT blocks to determine the threshold for the next block.

For SSVEP tests:

- 50 trials in each SSVEP session;
- Each trial lasted for 7 sec: 4-sec flashing + 3-sec rest;
- Stimulus frequency selected randomly and exclusively.

For Group A (N=14):
7.05, 7.50, 8.0, 8.57, 9.23, 10.00, 10.91, 12.00, 13.33, 15.00 Hz

For Group B (N=14) :
17.00, 19.00, 21.00, 23.00, 25.00, 27.00, 29.00, 31.00, 33.00, 35.00 Hz

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Data Analysis Methods

1. SSVEP performances;
2. Statistical analysis;
3. Brain connection and network estimation;

Brain network connections, during the learning process of NF training :

	Structural/anatomical	Functional network
Measures	Physiological structure; direct neural pathways	Temporal cross correlations or causal information flow, usually in spectral activity.
Data sources:	Structural magnetic resonance imaging (sMRI) / diffusion tensor imaging (DTI)	MRI (fMRI), **EEG** , magnetoencephalogram (MEG)
In this study:	Not suitable	Magnitude Squared **Coherence (MSC)**

Linear time-invariant (LTI) relationship
between two time series at certain frequency:

$$\mathrm{Coh}_{xy}(\lambda) = |R_{xy}(\lambda)|^2 = \frac{|f_{xy}(\lambda)|^2}{f_{xx}(\lambda)f_{yy}(\lambda)}$$

$R_{xy}(\lambda)$: complex valued coherency of x and y,
$f_{xy}(\lambda)$: cross-spectrum of x and y,
$f_{xx}(\lambda)$: power spectrum of x
prediction can be forward and/or backward, depending on the phase of the cross-spectrum, $fxy(\lambda)$, at frequency k

On the NF training dataset:

Dataset are divided into 1-sec length, absolute amplitude > 75 µV) being removed:

Build the brain connections (statistically) based the on **Coherence of IAB** in adjacent NF blocks:

27 * (averaged 180)

(Seth, 2010)

A. K. Seth, "A matlab toolbox for granger causal connectivity analysis," *Journal of neuroscience methods*, vol. 186, no. 2, pp. 262–273, 2010.

Correlation-based network estimations:

Node attribute

Degree (*Ki*) of a node (*i*):

$$k_i = \sum_{j \in N} a_{ij}$$

a_{ij} is the connection status between i and j:
a_{ij} = 1 when link *(i, j)* exists

Global attribute

1. Characteristic path length (L_p):

The minimum number of edges connecting the two nodes is defined as the path length of the two nodes, *i* and *j*:

$$d_{ij} = \sum_{a_{uv} \in g_{i \leftrightarrow j}} a_{uv}$$

where *g* is the shortest path (geodesic) between *i* and *j*. d_{ij} = ∞ for all disconnected pairs *i, j*

M. Rubinov and O. Sporns, “Complex network measures of brain connectivity: uses and interpretations,” *Neuroimage*, vol. 52, no. 3, pp. 1059–1069, 2010.

Correlation-based network estimations:

Global attribute

2. Global efficiency (E_{glob}):

Quantifies the exchange of information across the whole network where information is concurrently exchanged.

$$E = \frac{1}{n}\sum_{i \in N} E_i = \frac{1}{n}\sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}^{-1}}{n-1}$$

where E_i is the efficiency of node i.

3. Clustering coefficient (Cp):

The degree of node aggregation in a network.

$$C = \frac{1}{n}\sum_{i \in N} C_i = \frac{1}{n}\sum_{i \in N} \frac{2t_i}{k_i(k_i-1)} d_{ij} = \sum_{a_{uv} \in g_{i \leftrightarrow j}} a_{uv}$$

4. Local efficiency (E_{loc}):

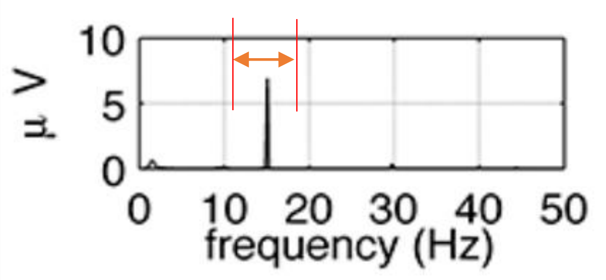
$$E_{\text{loc}} = \frac{1}{n}\sum_{i \in N} E_{\text{loc},i} = \frac{1}{n}\sum_{i \in N} \frac{\sum_{j,h \in N, j \neq i} a_{ij} a_{ih} \left[d_{jh}(N_i)\right]^{-1}}{k_i(k_i-1)}$$

M. Rubinov and O. Sporns, “Complex network measures of brain connectivity: uses and interpretations,” *Neuroimage*, vol. 52, no. 3, pp. 1059–1069, 2010.

SSVEP performances: the calculation of signal SNR (signal to noise ratio) and classification accuracy;

Signal SNR	Classification accuracy

$$\mathrm{SNR} = \frac{n \times X(K)}{\sum_{k=1}^{n/2} \left[X(K+k) + X(K-k)\right)}$$



CCA: Canonical correlation analysis

$$\boldsymbol{Y}_k = \begin{bmatrix} \sin(2\pi f_k n) \\ \cos(2\pi f_k n) \\ \vdots \\ \sin(2\pi H f_k n) \\ \cos(2\pi H f_k n) \end{bmatrix}^T, n = \left[\frac{1}{f_s}, \frac{2}{f_s}, \cdots, \frac{N}{f_s}\right]$$

$$\rho_k = \max_{\mathbf{a}_k, \mathbf{b}_k} \frac{\mathbf{a}_k^{\mathrm{T}} \mathbf{X}^{\mathrm{T}} \mathbf{Y}_k \mathbf{b}_k}{\sqrt{\mathbf{a}_k^{\mathrm{T}} \mathbf{X}^{\mathrm{T}} \mathbf{X} \mathbf{a}_k} \sqrt{\mathbf{b}_k^{\mathrm{T}} \mathbf{Y}_k^{\mathrm{T}} \mathbf{Y}_k \mathbf{b}_k}} = \max_{\mathbf{a}_k \mathbf{b}_k} \rho(\mathbf{X}\mathbf{a}_k, \mathbf{Y}_k \mathbf{b}_k)$$

Firstly applied on SSVEP classification (Lin, 2006)

Z. Lin, C. Zhang, W. Wu, and X. Gao, "Frequency recognition based on canonical correlation analysis for ssvep-based bcis," *IEEE transactions on biomedical engineering*, vol. 53, no. 12, pp. 2610–2614, 2006.

04 Data Analysis Methods

Statistical analysis:

The **normality assumption checks** were performed by **Shapiro-Wilk test** and outliers were excluded before:

	Applied on	Objective
ANOVA	**One-way ANOVA:** IAB amplitudes between two groups under eye-open initial resting baseline.	Make sure the initial IAB between two groups do not statistically differ each other.
Correlation tests	**Spearman correlation test**: The training block numbers and different EEG bands;	Estimate NF effect on different EEG bands
	Pearson correlation test: Changes of relative amplitudes in between in NF training (BK10-BK01) and SSVEP test (session2- session1), from 6-37 Hz, frequency resolution = 0.1 Hz.	Estimate the relationship between changes in NF and in Spontaneous EEG activity during SSVEP
Paired *t*-test	**2-tailed paired *t*-test**: a. Differences (due to NF) in EEG bands between NFT block 1 (BK01) and NFT block 10 (BK10); b. Group performances changes of SSVEP-based BCI tests.	Estimate NF effect on SSVEP-BCI performances

* From the 6 occipital channels: O1, Oz, O2, PO3, POz, PO4;

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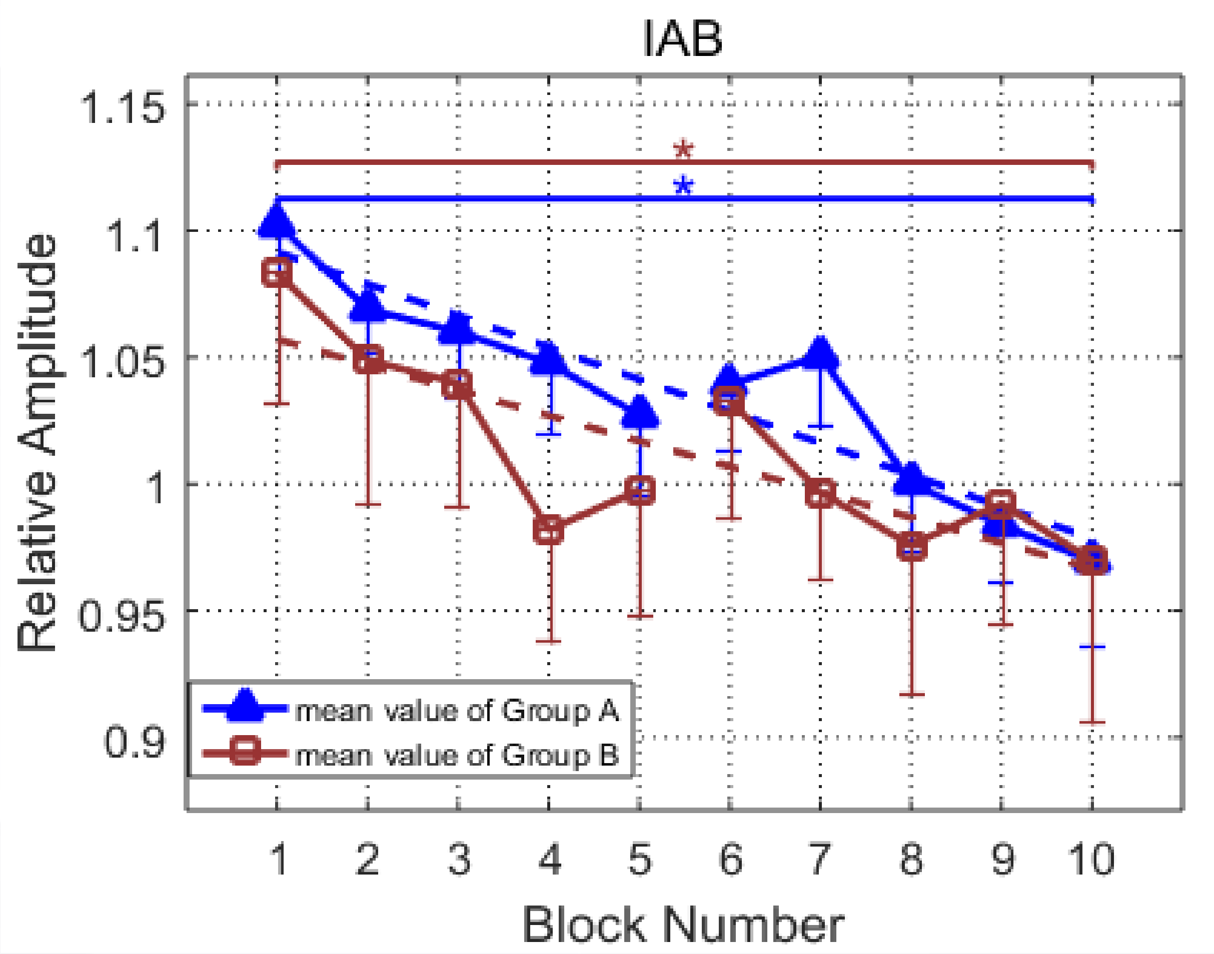
IAB trainability

No statistically significant differences ($F(1, 14) = 0.669$, $p = 0.4207$) of the initial resting IAB: between Group A (1.111 ± 0.125) and Group B (1.074±0.108).



r-value of the **Spearman correlation test**:

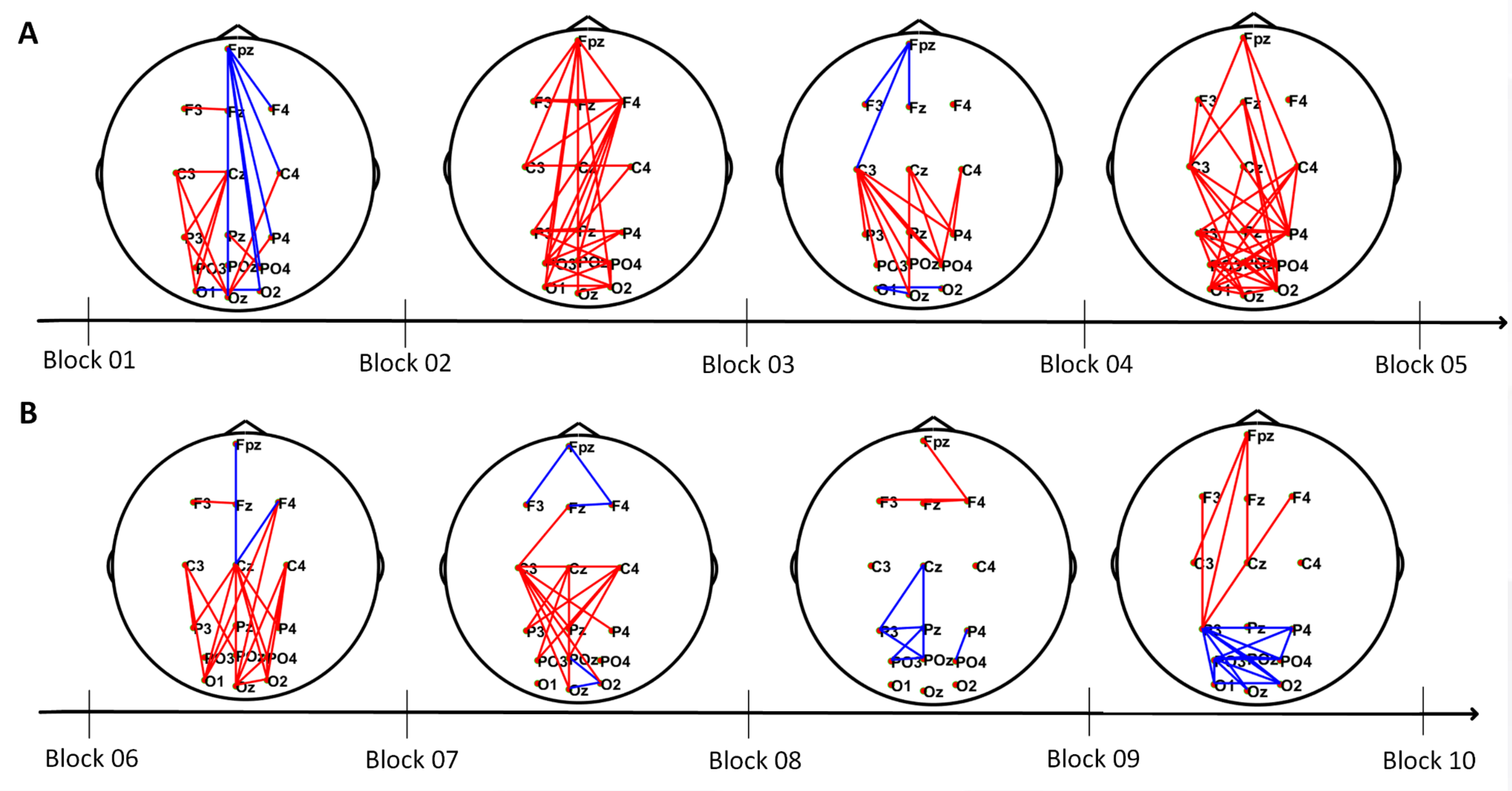
Group A: -0.933**
Group B: -0.817**
Total (N=28): -0.916**

* For individual results, please refer to Appendix-VII

05 Experimental Results -0

Brain Network: Significant changes in IAB-Coherence functional connectivity weights between, adjacent NF training blocks

Statistically

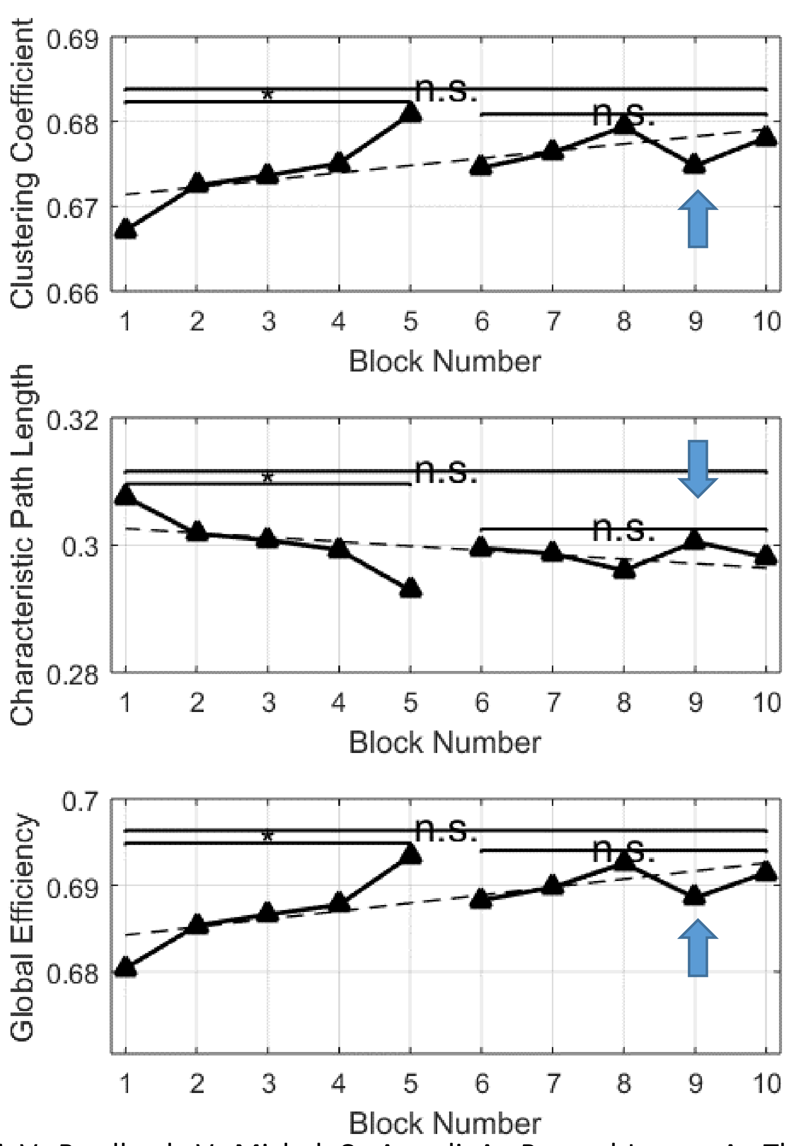


*Confidence level for 2-tailed paired *t* test: 90%

05 Experimental Results -0

Global attribute of the network:

Spearman Correlation

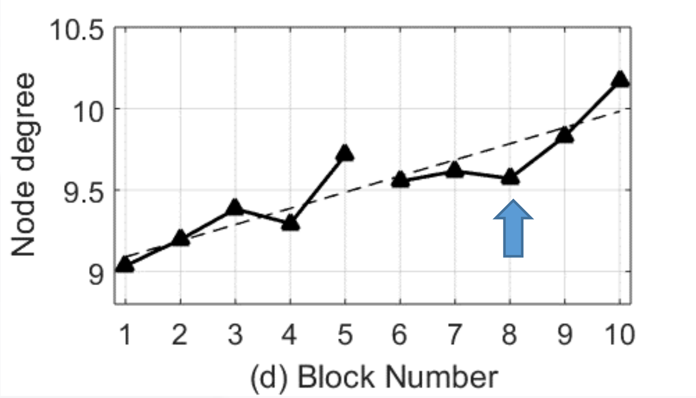


r = -0.821**

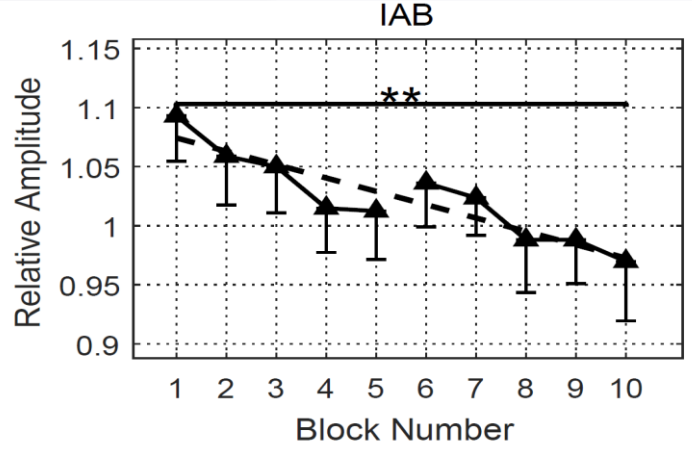
r = -0.827**

r = 0.766*

Node attribute of the network:



r = -0.863**

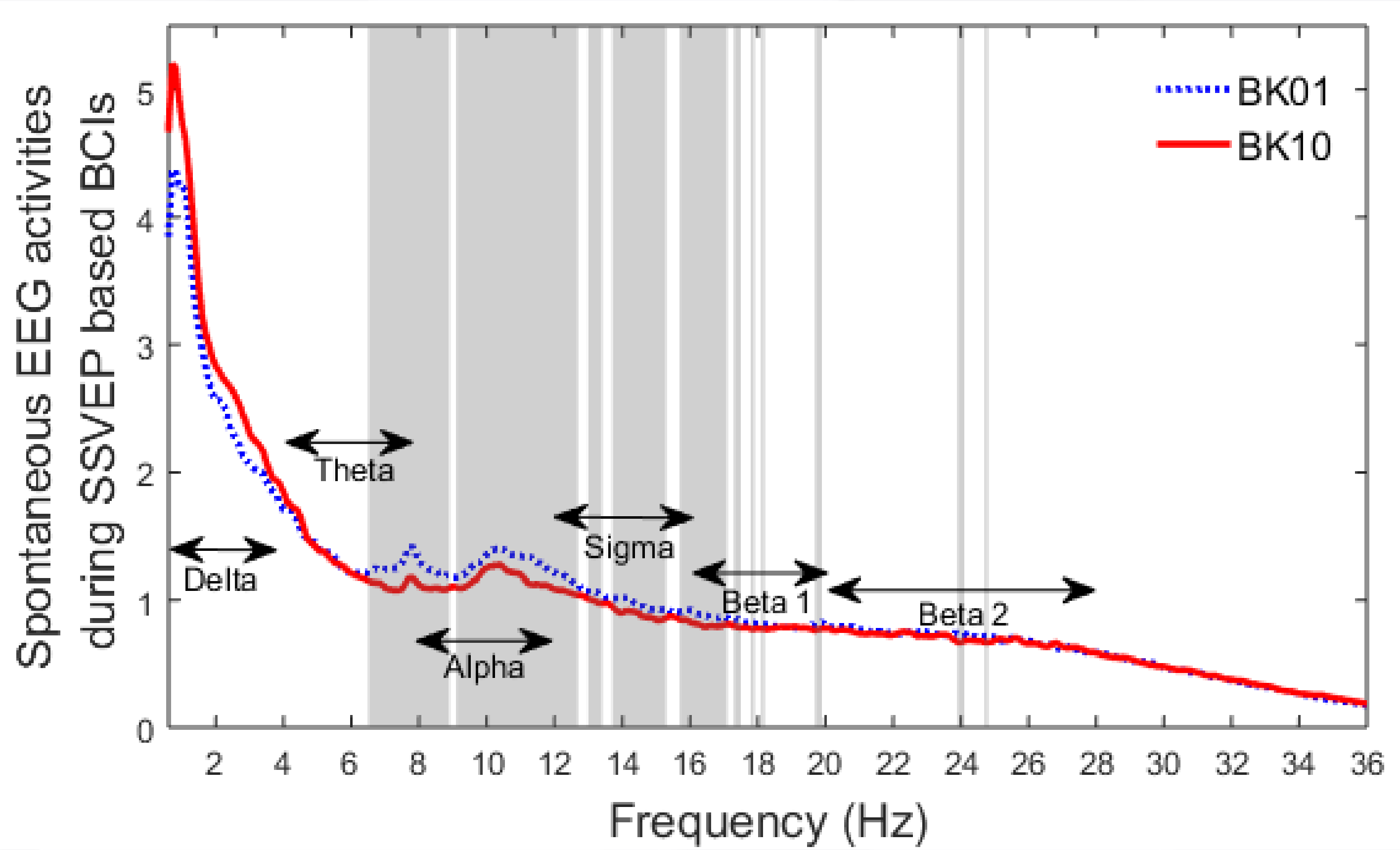


Nodes interactions within IAB increases;

Romei, V., Brodbeck, V., Michel, C., Amedi, A., Pascual-Leone, A., Thut, G., 2008. Spontaneous fluctuations in posterior alpha-band EEG activity reflect variability in excitability of human visual areas. Cereb. Cortex 18, 2010–2018

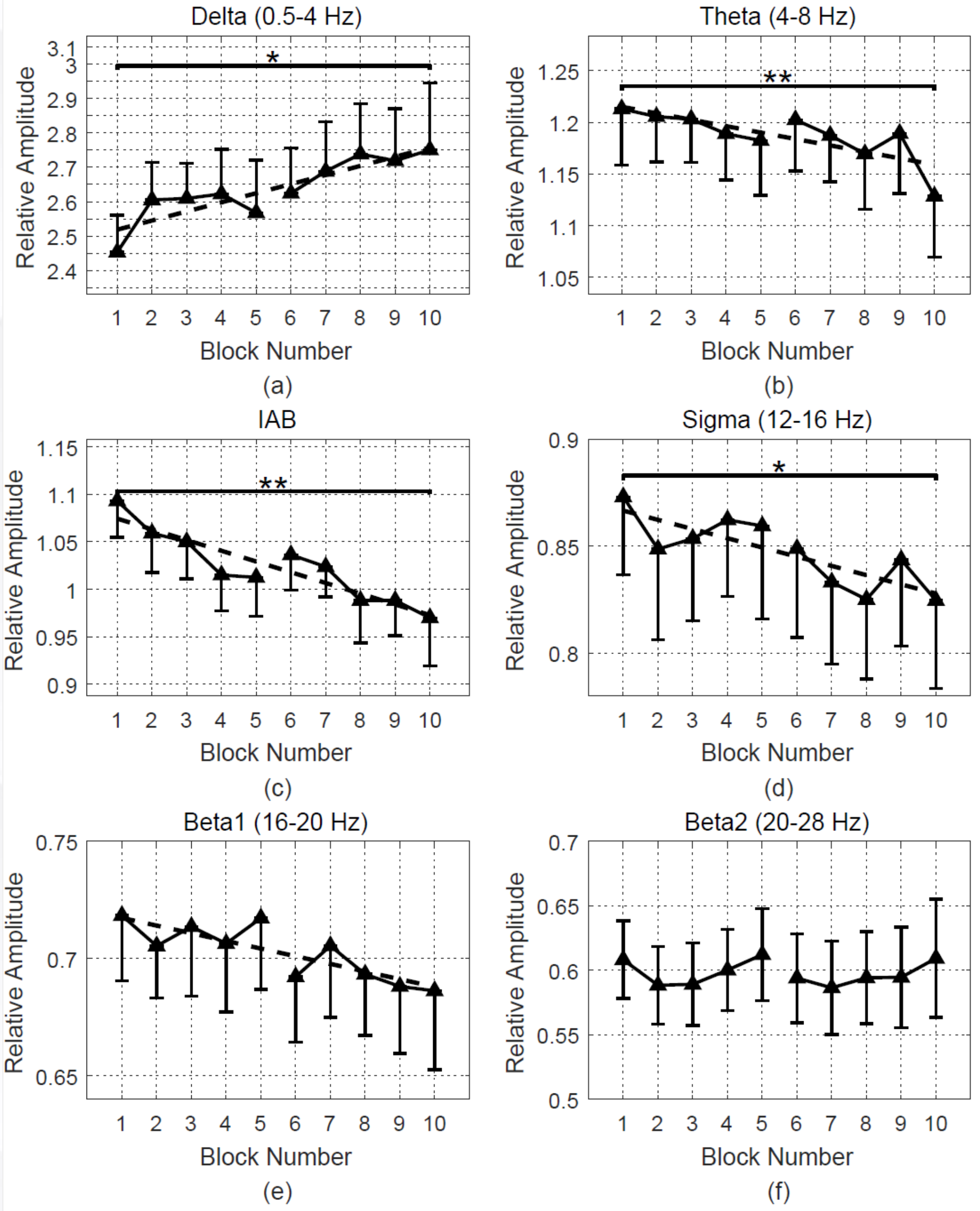
05 Experimental Results -0

EEG bands during NF training: “Non-specificity”



Mean amplitude from **0.5 to 36 Hz**, at Oz in **NF01 and NF10**. Shaded area indicates **significant** ($p < 0.05$, 2-tailed paired t-test) **suppression.**

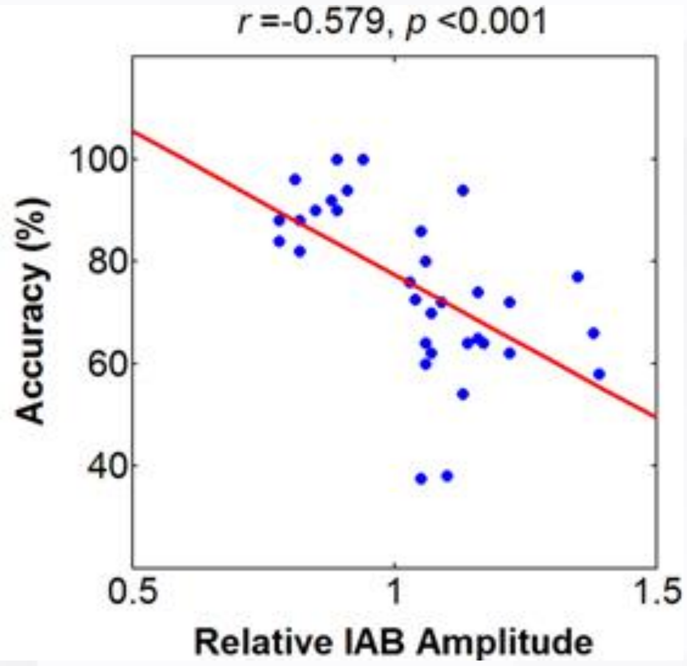
For detailed statistical results, please refer to Appendix-



05 Experimental Results -1

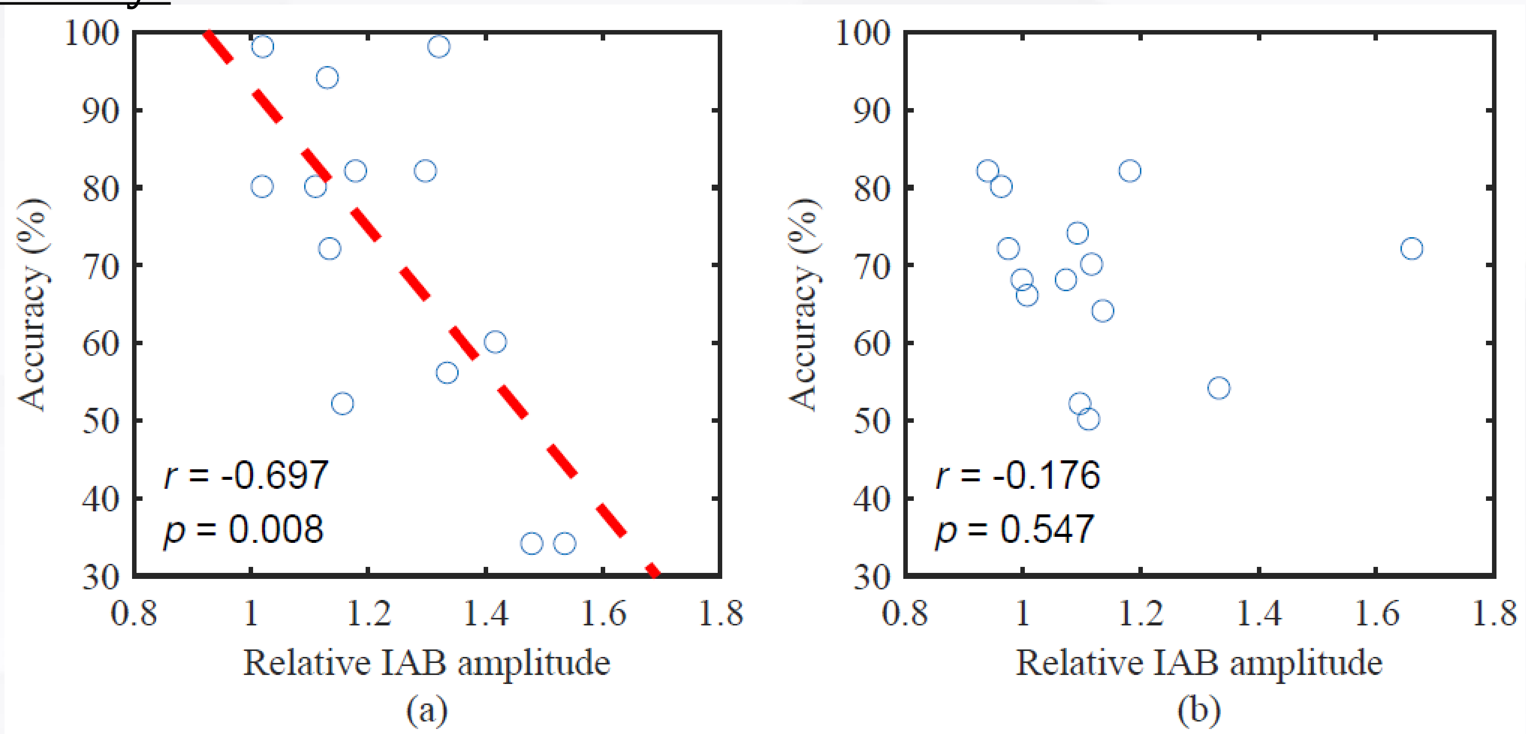
The relationship between EEG bands and SSVEP (7.05-35 Hz) performances:

Previous study:



Low-frequency SSVEP

This study:



(a) Group A: LF-SSVEP; (b) Group B: HF-SSVEP.
Dashed line indicates a linear fitting for significant linear relationship, based on Spearman correlation test.

Consistent with previous works.
(Won, 2015; Wan, 2016)

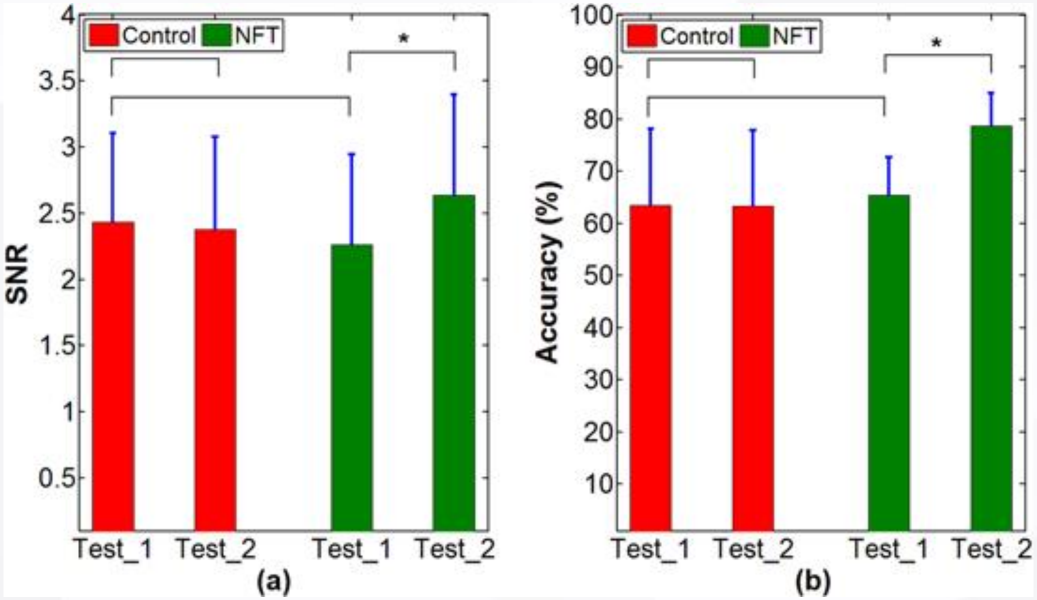
D.-O. Won, H.-J. Hwang, S. Dähne, K.-R. Müller, and S.-W. Lee, "Effect of higher frequency on the classification of steady-state visual evoked potentials," *Journal of neural engineering*, vol. 13, no. 1, p. 016014, 2015.

Wan F, Da Cruz J N, Nan W, Wong C M, Vai M I and Rosa A 2016 Alpha neurofeedback training improves ssvep-based bci performance Journal of neural engineering 13 036019

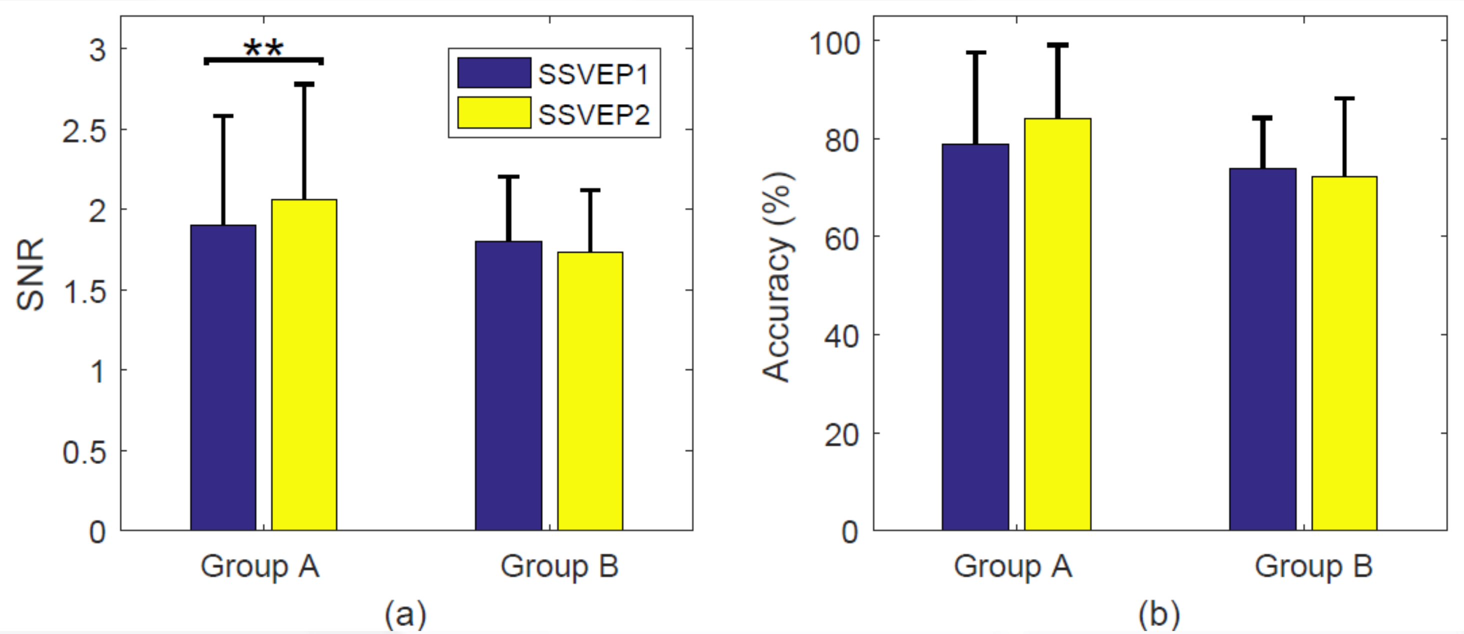
05 Experimental Results -2

NF training effects on SSVEP signal SNR and classification accuracy:

Previous study:



This study:



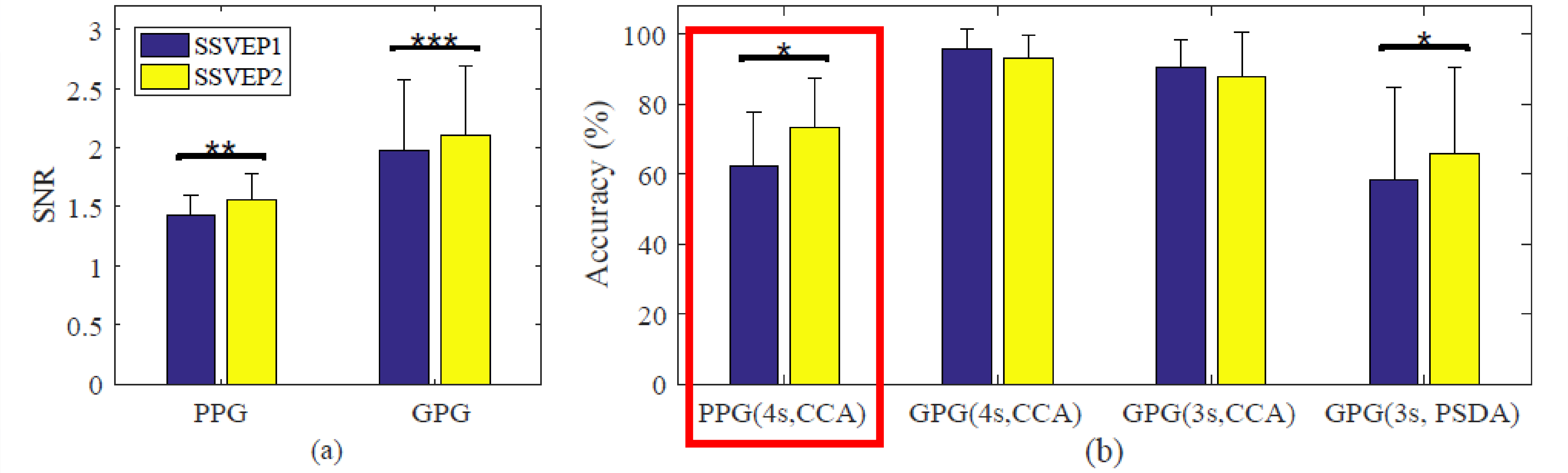
Both SNR and accuracy have significant improvements in LF-SSVEP

a. Pre-screened subjects
-- low initial SSVEP-BCI performers;
b. Low-frequency range of SSVEP stimuli
-- within 7.05-15 Hz;

(a) SNR has significant improvements in Group A (LF-SSVEP),
$t(13) = 4.338$, $p = 0.001$
while no significant improvement in Group B (HF-SSVEP),
$t(14) = -0.941$, $p = 0.364$

(b) The average of accuracy in Group A has been increased.

Changes in **individual** performance of SNR and classification accuracy

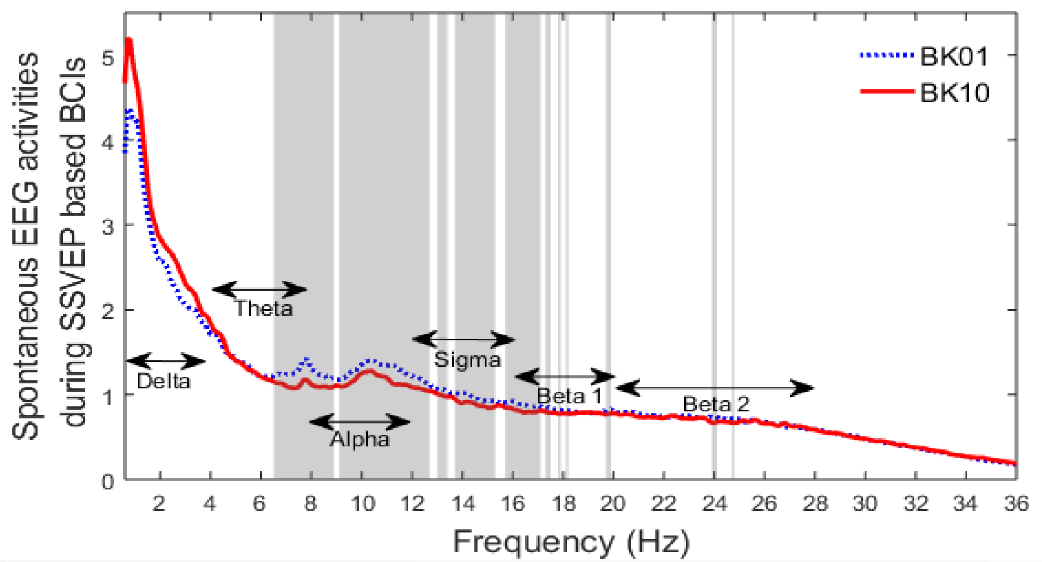


Consistent with previous works.
(Wan, 2016)

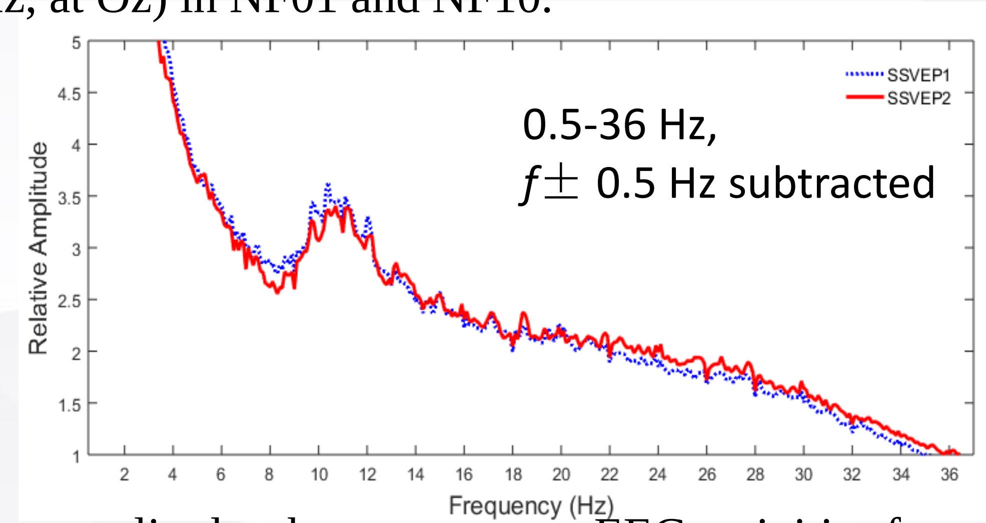
PSDA: Power Spectrum Density Analysis

05 Experimental Results -3

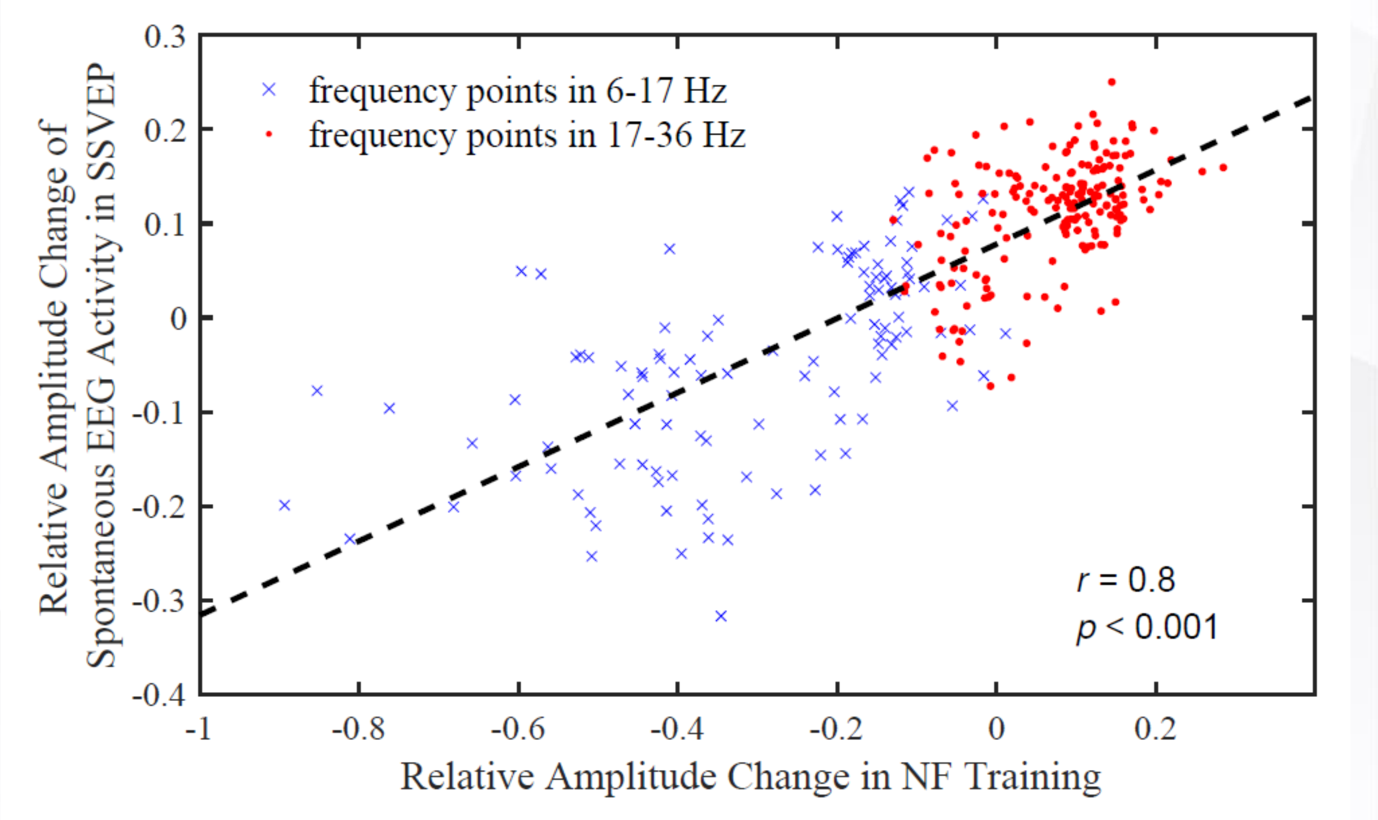
NF training effects on the spontaneous EEG activity changes of SSVEP-based BCI:



Mean relative amplitude of EEG frequencies (from 0.5 to 36 Hz, at Oz) in NF01 and NF10.



Relative amplitudes the spontaneous EEG activities from 0.5 to 35 Hz in SSVEP1 and SSVEP2.



Relative amplitude changes in NF training correlates the spontaneous EEG activity changes of SSVEP-based BCI

* For individual results, please refer to Appendix-VIIII

Outline

Introduction

1. EEG frequency bands;
2. BCI paradigms and challenges;

01

Objectives and Contributions

1. Prior Research;
2. Objectives;
3. Contributions;

02

Materials

1. Setup;
2. Experiment protocol;

03

Data Analysis Methods

1. NF training analysis
2. SSVEP performances;
3. Statistical analysis;

04

Experimental Results

1. Relation between EEG bands and SSVEP-BCI
2. NF effects on SSVEP-BCI performances;
3. Possible explanations due to frequency and connectivity analysis

05

Conclusion and Prospective

1. Conclusion;
2. Future Prospective.

06

6

Conclusion and Prospective

1. Conclusion;
2. Future Prospective；

06 Conclusions

1. Integrate the protocol by extending the SSVEP stimulation frequencies into 7.05- 35 Hz and the subjects being unscreened.

2. **The possible explanations for this protocol：** Alpha-down NF training does not significantly effect (or suppress) the spontaneous EEG activity of 17-35 Hz SSVEP

A further study

NFT Results

1) IAB trainability;

2) NF learning：
Brain connections between the adjacent NFT blocks；

3) NF Non-specificity;

SSVEP performances

1) Predictable LF range SSVEP signal SNR, HF range SSVEP otherwise;

2) Performances of LF range SSVEP can be enhanced, HF range SSVEP otherwise;

NF correlates SSVEP

NF changes correlates the spontaneous EEG activity changes of SSVEP-BCI.

06 Prospective

More methods to build brain connections, based on different characteristics

Functional network

<u>Undirected</u>

Coherence (MSC)

Phase Locking Value (PLV);

Short Time Fourier Coherence (STFT COH);

Wavelet Coherence (WC) ;

<u>Directed</u>

Granger-causality (GC)

Dynamic causal modelling (DCM)

Generalized Synchronization (GS);

Partial Directed Coherence (PDC);

	DCM	MSC	STFT COH	WC	PLV	GS	GC Geweke	PDC
Linear	Y	Y	Y	Y				
Nonlinear					Y	Y		
Info-based							Y	Y
Model-based	Y							
Data-driven		Y	Y	Y	Y	Y	Y	Y
Causality assessing	Y						Y	Y
Multivariate	Y					Y		Y
Stationarity independent				Y	Y			
Functional connectivity		Y	Y	Y	Y	Y	Y	Y
effective connectivity	Y						Y	Y

V. Sakkalis, "Review of advanced techniques for the estimation of brain connectivity measured with eeg/meg," *Computers in biology and medicine*, vol. 41, no. 12, pp. 1110–1117, 2011.

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Publications

Journal

1. **Tang, Q.**, Wong C. M., Nan W. Y., Wang Z., Wan F., Da Rosa, A.C., 2019. A Further Study of the Alpha-down Neurofeedback Training for SSVEP-based BCIs (to be submitted to *Journal of Neural Engineering*)

2. Wang Z., Wong C. M., Nan W. Y., **Tang, Q.**, Wan F., Da Rosa, A.C., 2019. Learning curve and dynamic brain network based on phase locking value during short time neurofeedback training (to be submitted to *Neural Imaging*)

3. Nan, W. Y., Wan, F., **Tang, Q.,** Wong, C.M., Wang, B. and Da Rosa, A.C., 2018. Eyes-Closed Resting EEG Predicts the Learning of Alpha Down-Regulation in Neurofeedback Training. Frontiers in psychology, 9, p.1607.

4. Yang, L., Shen, L., Nan, W., **Tang, Q.,** Wan, F., Zhu, F. and Hu, Y., 2017. Time course of EEG activities in continuous tracking task: a pilot study. Computer Assisted Surgery, 22(sup1), pp.1-8.

Conference

1. **Tang, Q.,** W. Nan, F. Wan, and Y. Hu. "Neurofeedback improves SSVEP BCI performance on subjects with both 'high' and 'low' performance." In Seventh *International BCI Meeting*. 2018.

2. Qu, X. T., **Tang, Q.,** Yang, L. M., Nan, W. Y., da Cruz, J. N., Wan, F., Mou, P. A., Mak, P. I., Mak, P. U., Vai, M. I., Hu, Y. and Rosa, A. C. “How mental strategy affects beta/theta neurofeedback training”. In *World Congress on Medical Physics & Biomedical Engineering*. 2015

3. Wong, C. M., **Tang Q.,** da Cruz, J. N. and Wan, F., "A multi-channel SSVEP-based BCI for computer games with analogue control". In IEEE International Conference on *Computational Intelligence and Virtual Environments for Measurement Systems and Applications*. 2015

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Mr. Ka Fai Lau,
Mr. Shun Liu,
Mr. Yu Fan Peng;

My family and friends.

Q & A

Thank You

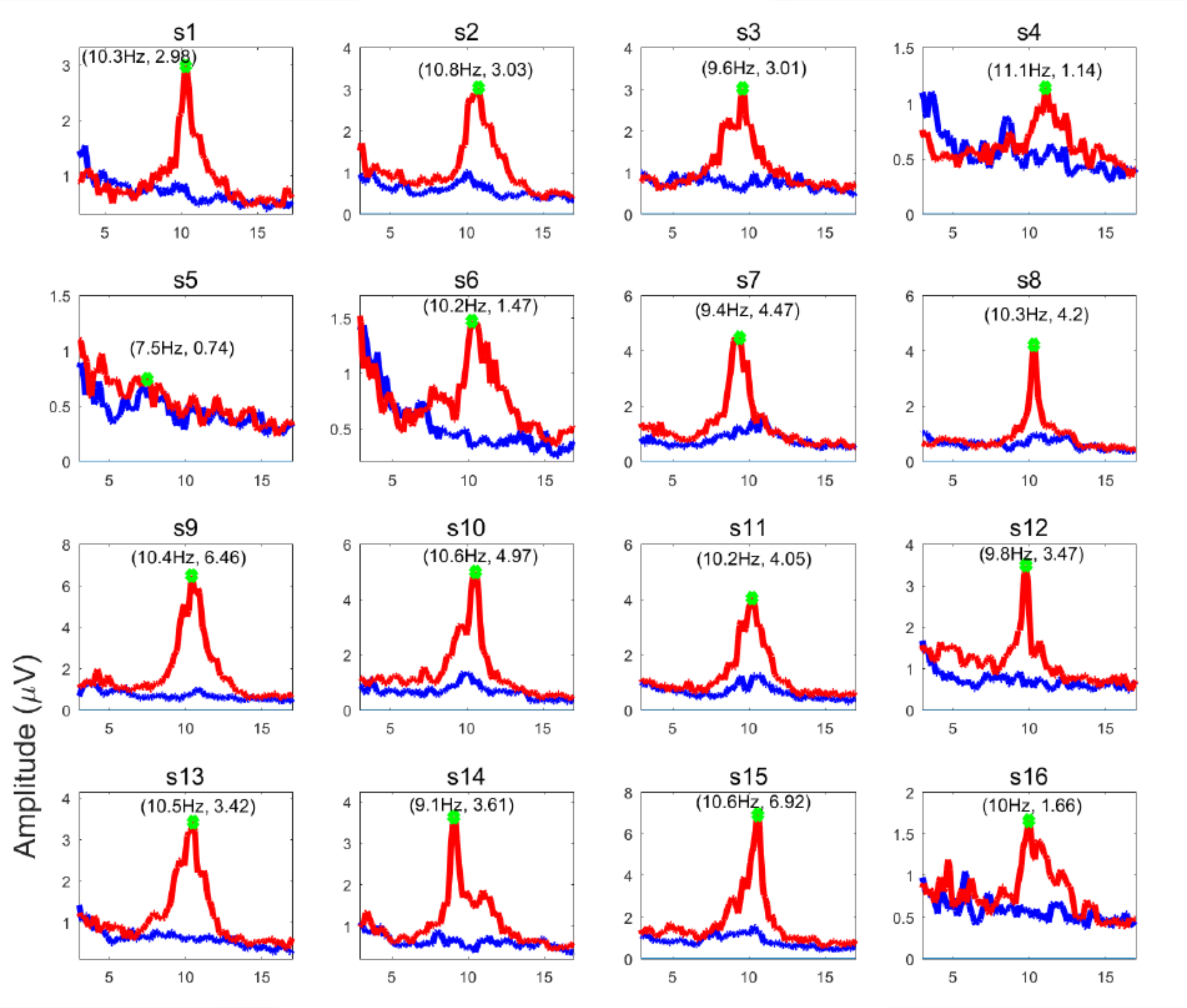
Presented by Tang, Qi

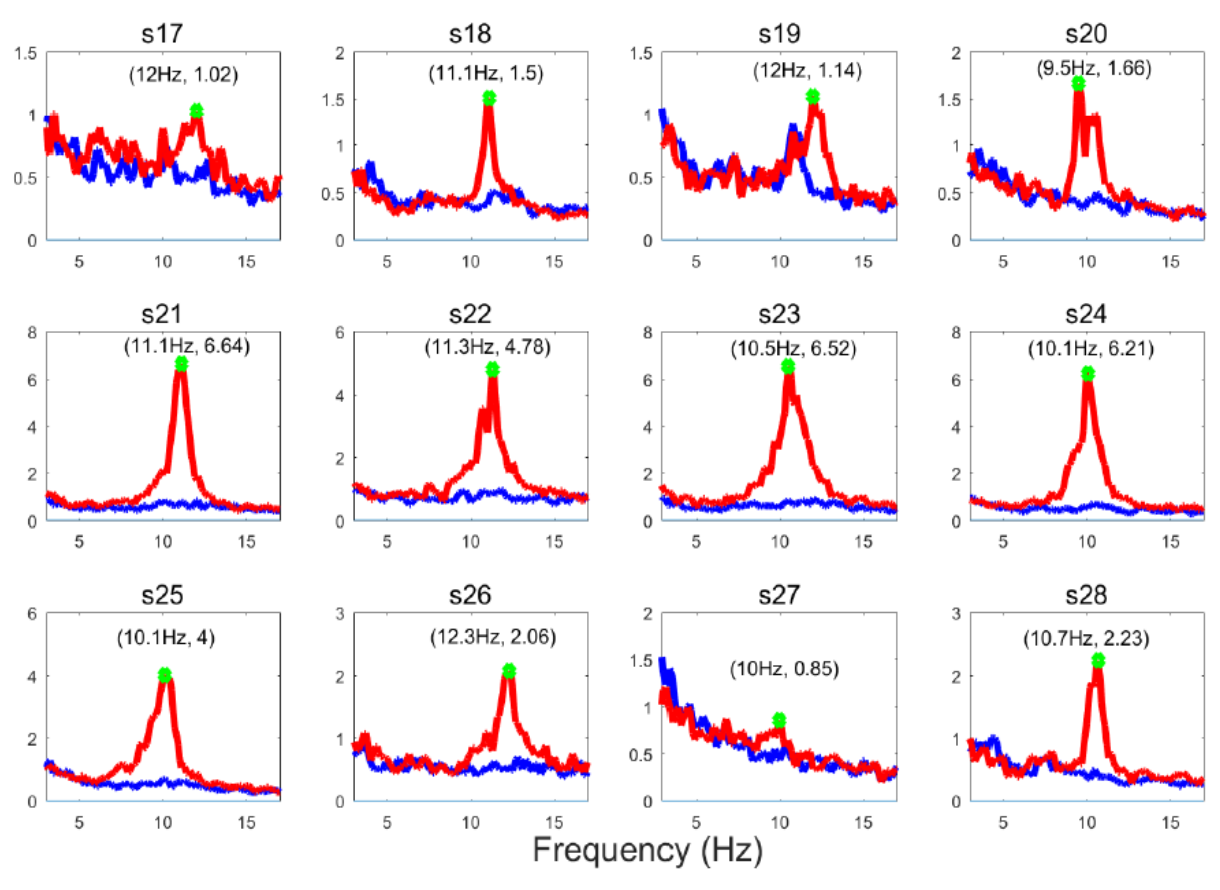
Supervisor: Prof. Wan, Feng

June 26th- start of July 2019
Department of Electrical and Computer Engineering
Faculty of Science and Technology
University of Macau

Appendix -I

Why IAB as the NF training parameter?





The EEG frequency domain analysis during the initial resting baseline recording

Appendix -III

Individual NF learning indices to estimate the learning during NF training

Subject no.	L1	L2a	L2b	L3	Subject no.	L1	L2a	L2b	L3
1	0.189	-0.295	-0.041	-0.021	15	0.061	-0.319	-0.014	-0.018
2	-0.018	-0.148	-0.006	0.001	16	0.012	-0.178	-0.012	-0.002
3	0.255	-0.565	-0.050	-0.030	17	0.023	-0.047	0.001	-0.007
4	0.174	-0.344	-0.014	-0.017	18	-0.032	0.140	0.001	0.009
5	0.009	0.192	0.014	-0.004	19	0.139	-0.213	-0.015	-0.008
6	0.133	-0.088	-0.011	-0.016	20	0.115	-0.036	-0.018	-0.007
7	0.285	-0.500	-0.042	-0.016	21	0.357	-0.514	-0.036	-0.026
8	0.133	-0.535	-0.054	-0.002	22	0.145	-0.400	-0.020	-0.015
9	0.068	-0.131	-0.003	-0.014	23	0.348	-0.649	-0.054	-0.026
10	0.271	-0.155	-0.042	-0.018	24	0.122	-0.066	-0.012	-0.018
11	0.208	-0.079	-0.006	-0.021	25	-0.065	-0.243	-0.017	0.004
12	0.002	0.009	-0.002	-0.002	26	0.096	-0.148	-0.014	-0.010
13	0.176	-0.073	-0.026	-0.012	27	-0.003	-0.005	0.006	0.005
14	0.030	0.053	0.014	-0.005	28	0.337	-0.529	-0.043	-0.031

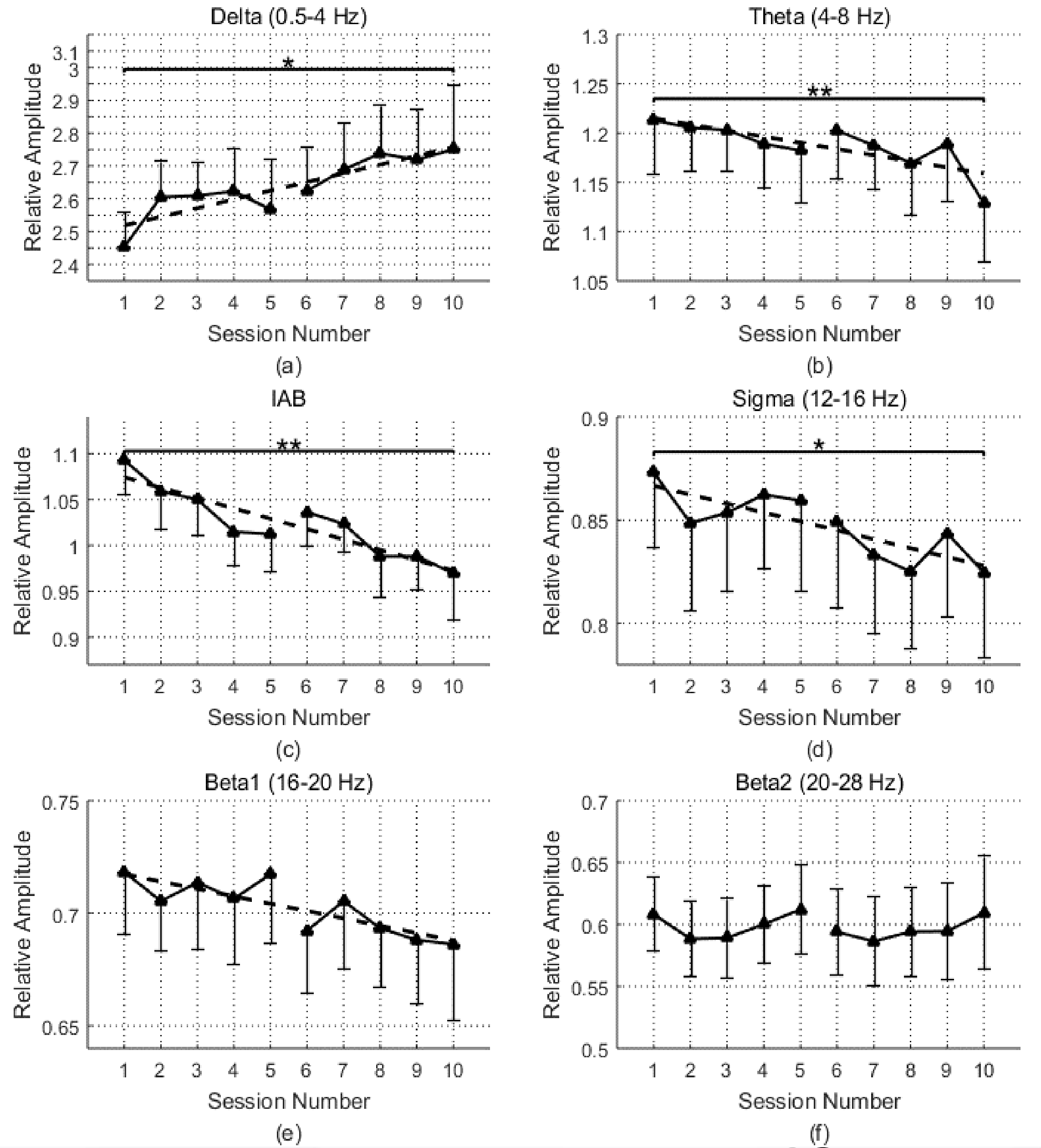
8 / 28 subjects, suggested by **NF learning indices**, "failed" in reducing their IAB;

Appendix -IV

EEG bands during NF training: “Non-specificity”

r-value of the **Spearman correlation** between session number and mean relative amplitude

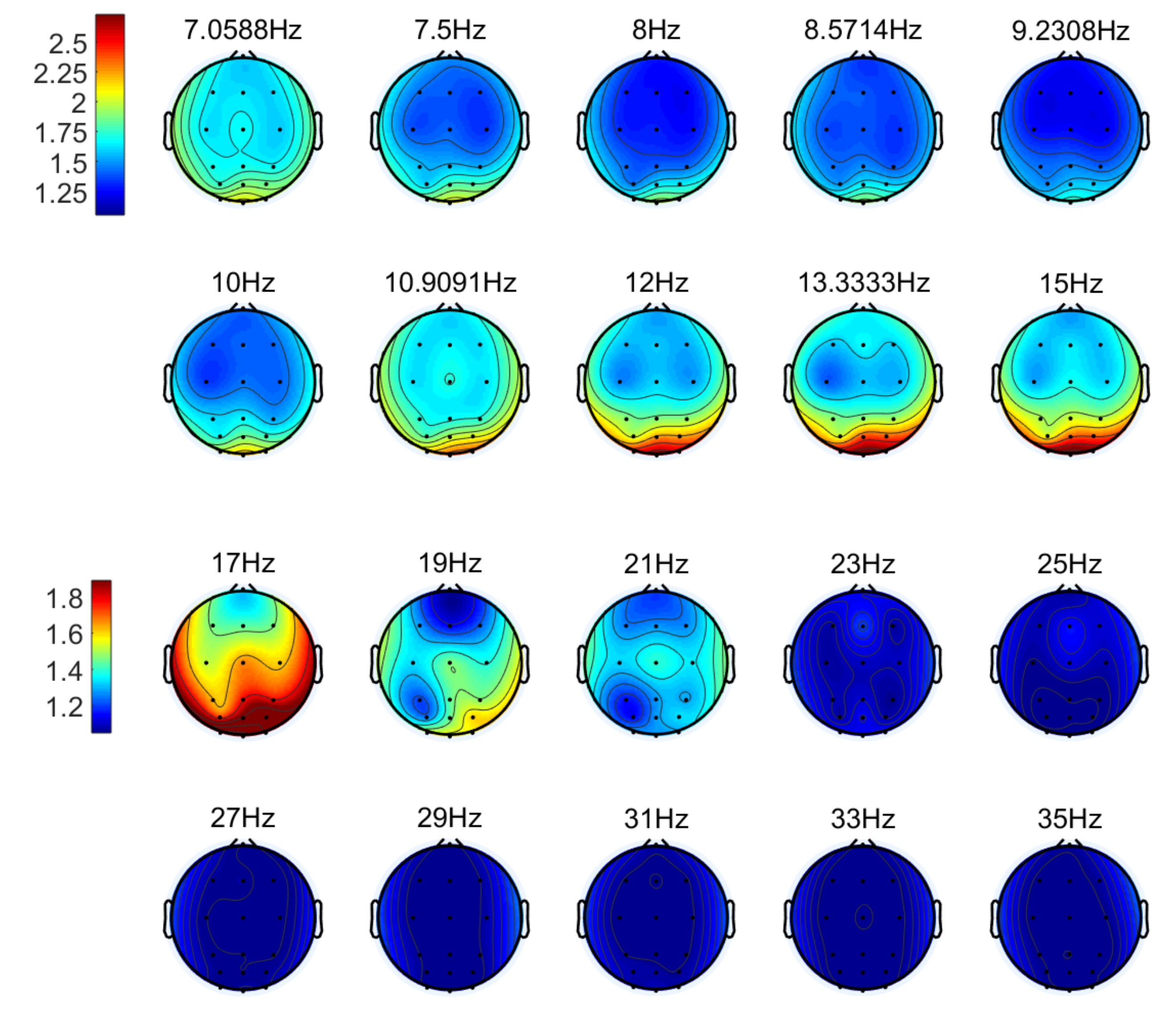
	IAB	Delta	Theta	Sigma	Beta1	Beta2
Group A	-.933**	.843**	-.969**	-.836**	-0.329	0.005
Group B	-.817**	.827**	0.062	-.654*	-.847**	-0.526
Total	-.916**	.889**	-.778**	-.816**	-.828**	0.037



Appendix -V

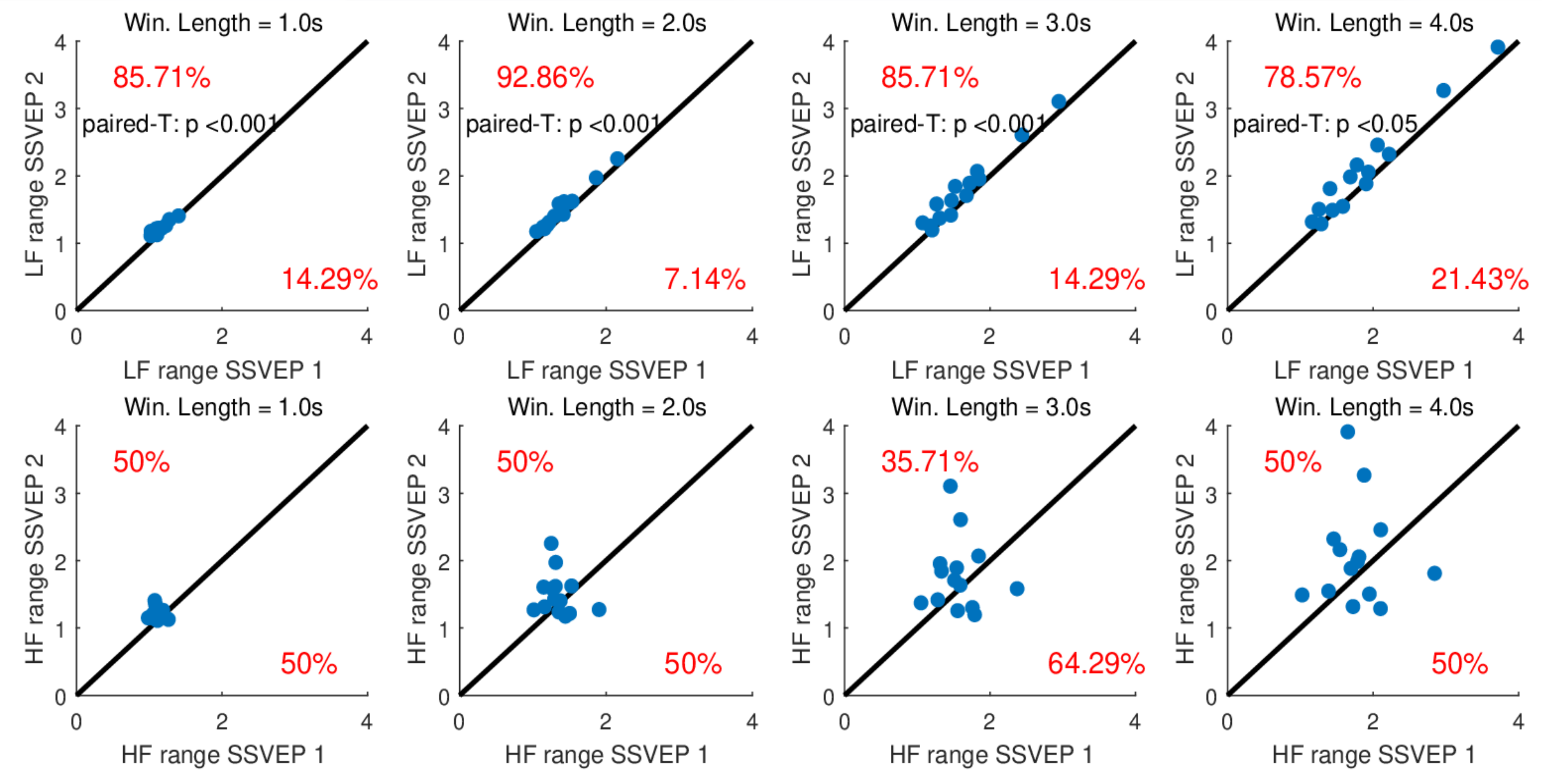
SSVEP performances: Why using CCA to do classification accuracy from the 6 occipital channels ?

Occipital channel of
O1, Oz, O2, PO3, POz, PO4
possess the highest SNR



Appendix -VIa

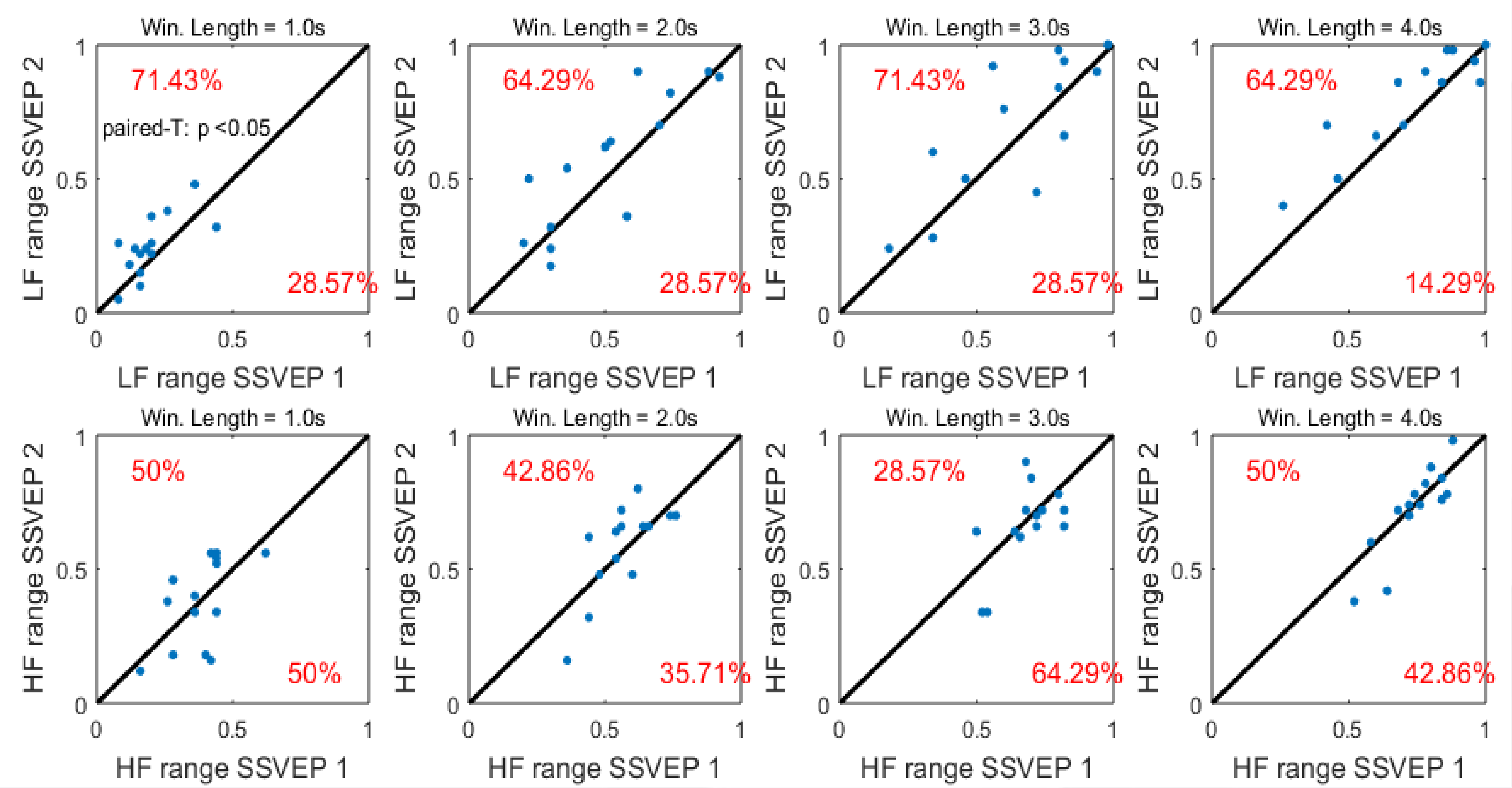
Individual performances of SNR: LF range SSVEP and HF range SSVEP



In window length of 1s to 4s.

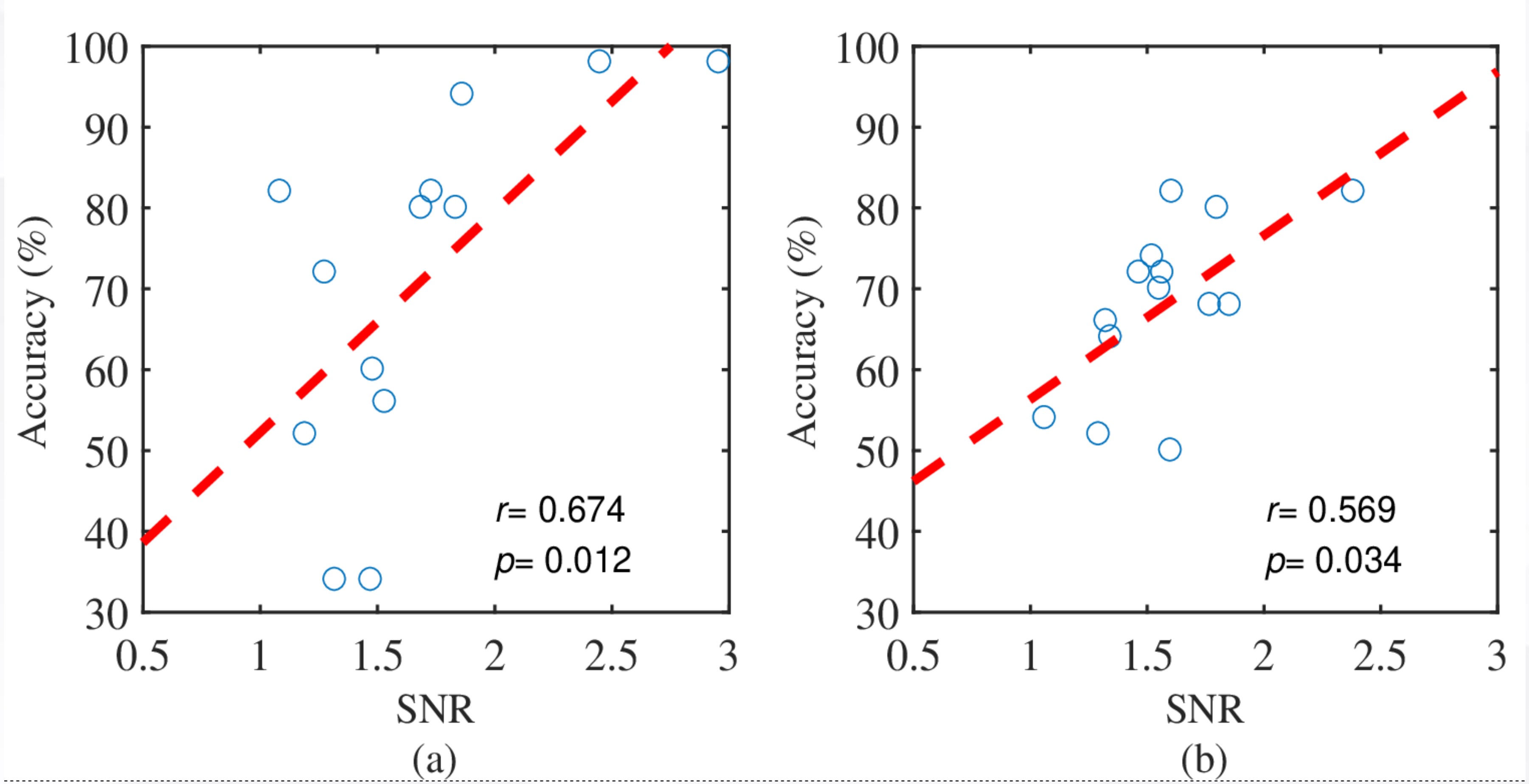
Appendix -VIb

Individual performances of classification accuracy: LF range SSVEP and HF range SSVEP



In window length of 1s to 4s.

Appendix -VII



(a) Group A: low frequency SSVEP; (b) Group B: high frequency SSVEP. Dashed line indicates a linear fitting for significant linear relationship, based on Spearman correlation test.

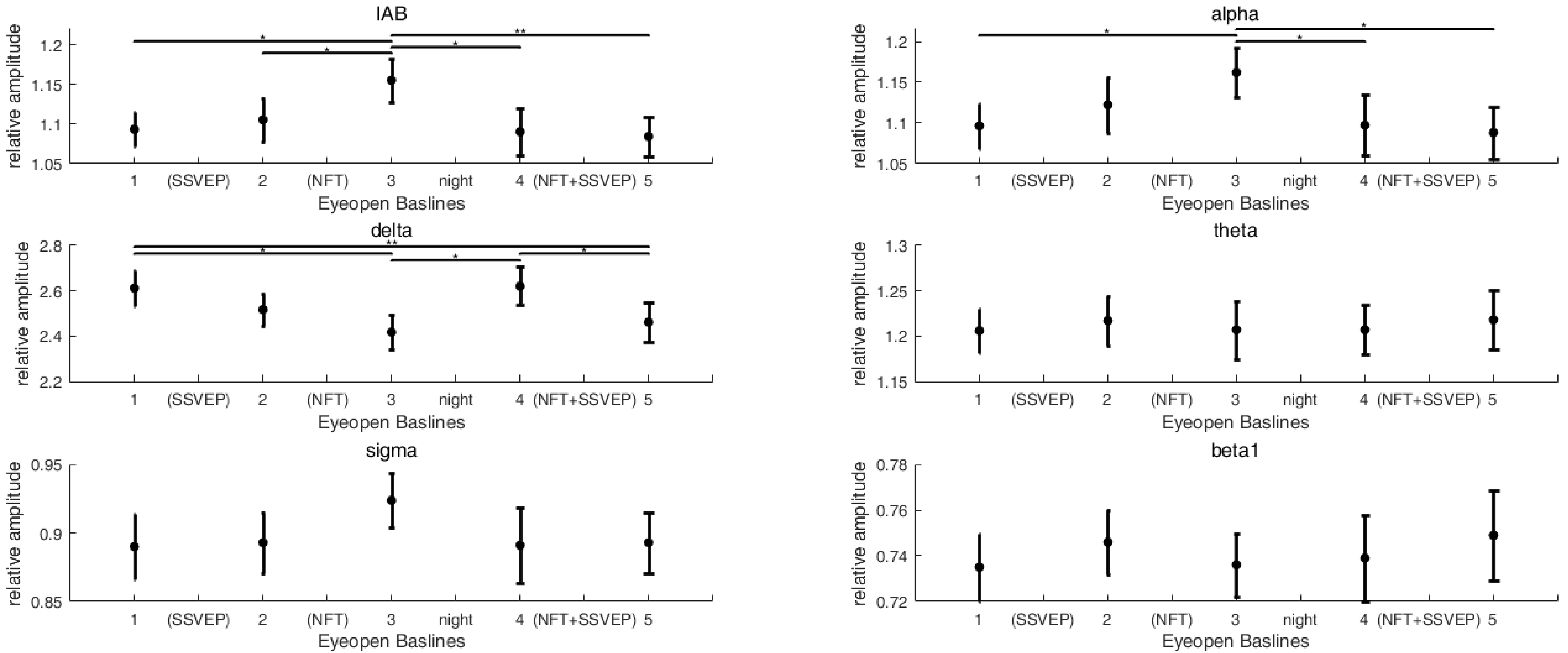
Appendix -IX

The SSVEP based BCI performances, before and after NF training

	Test	Signal SNR	Classification accuracy (%)
Group A	SSVEP1 (before NF training)	1.898 ± 0.682	78.80 ± 18.87
	SSVEP2 (after NF training)	2.058 ± 0.720	84.15 ± 15.00
Group B	SSVEP1	1.795 ± 0.405	74.00 ± 10.30
	SSVEP2	1.530 ± 0.391	72.40 ± 15.80

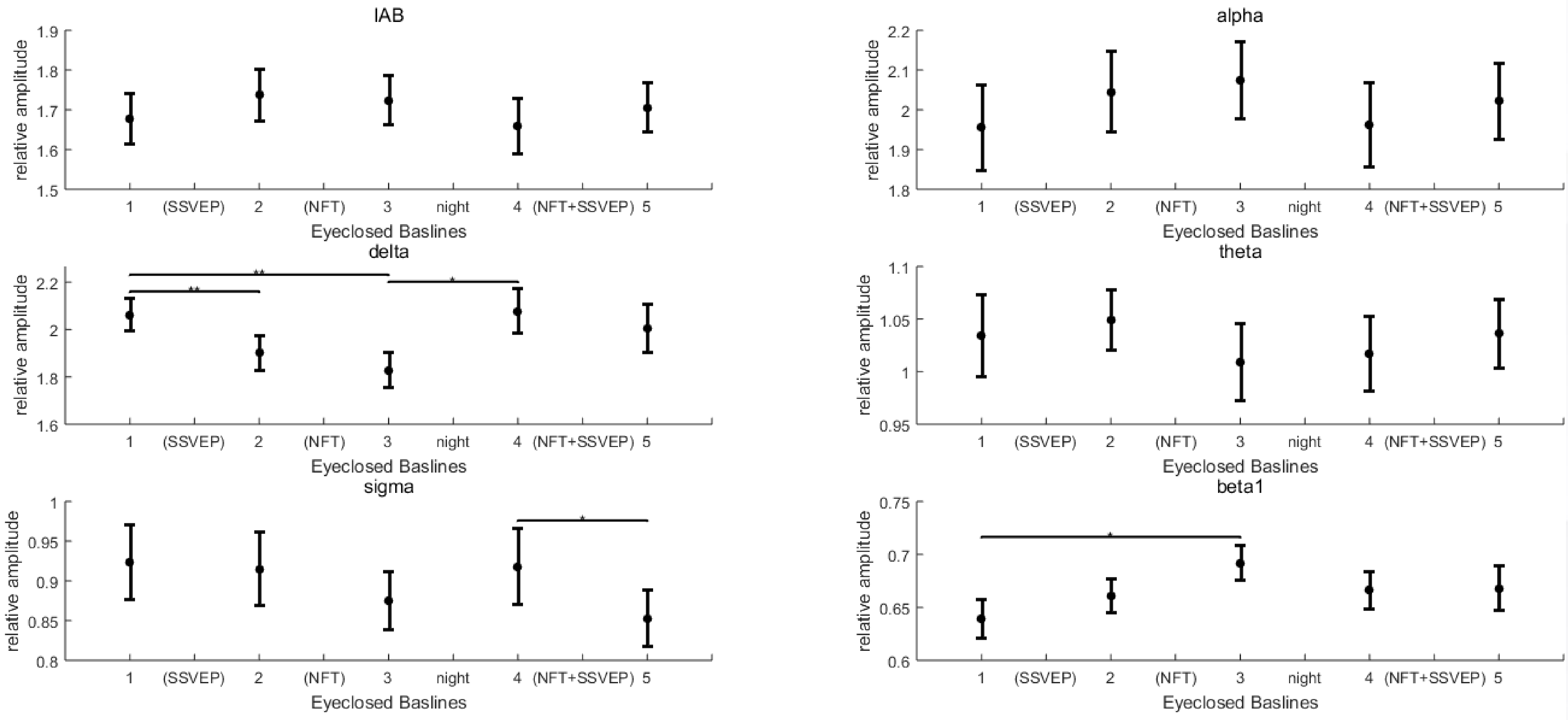
Appendix -Xa

EEG band change during eye-open resting states of the 5 baseline recordings



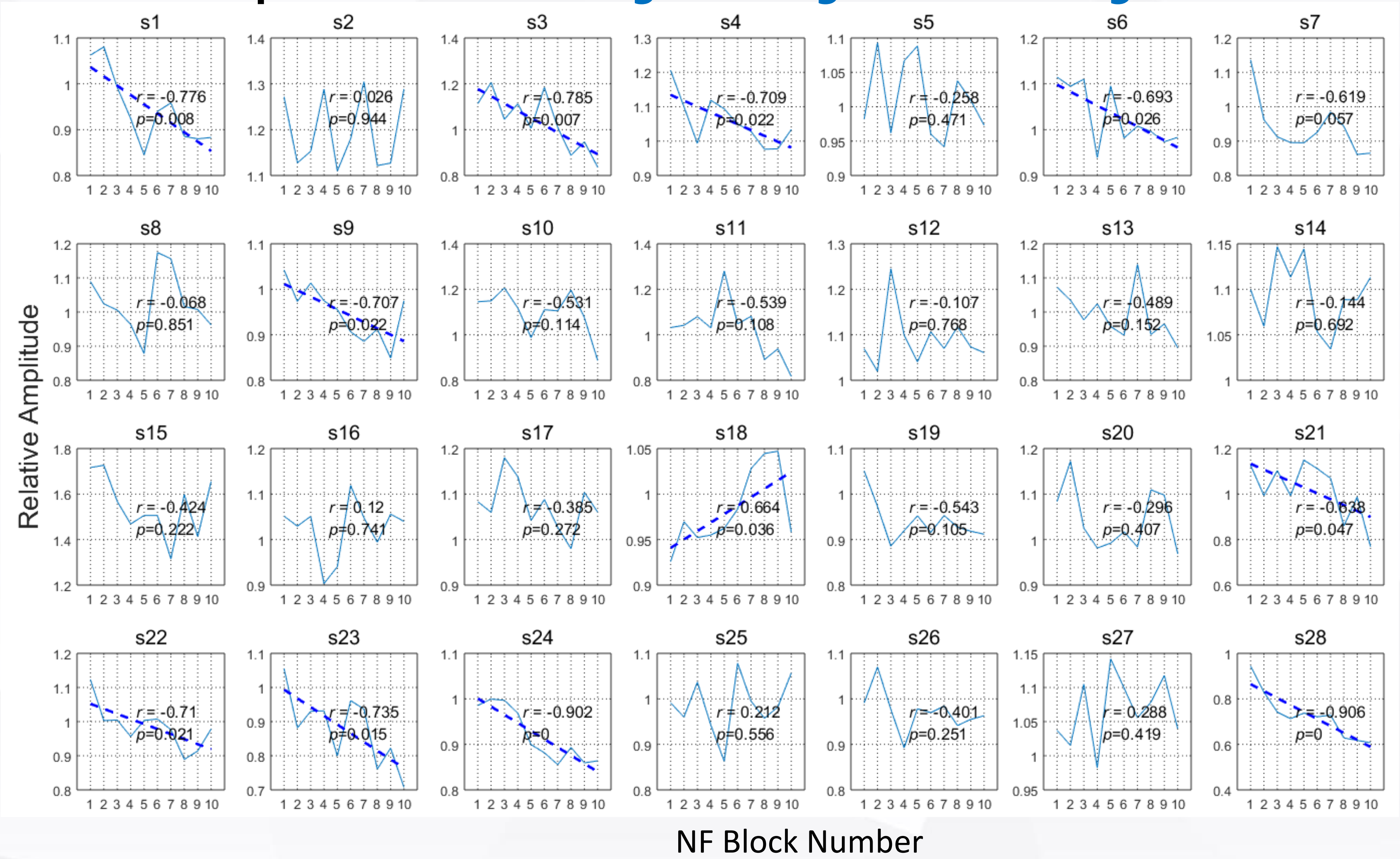
Appendix -Xb

EEG band change during eye-closed resting states of the 5 baseline recordings



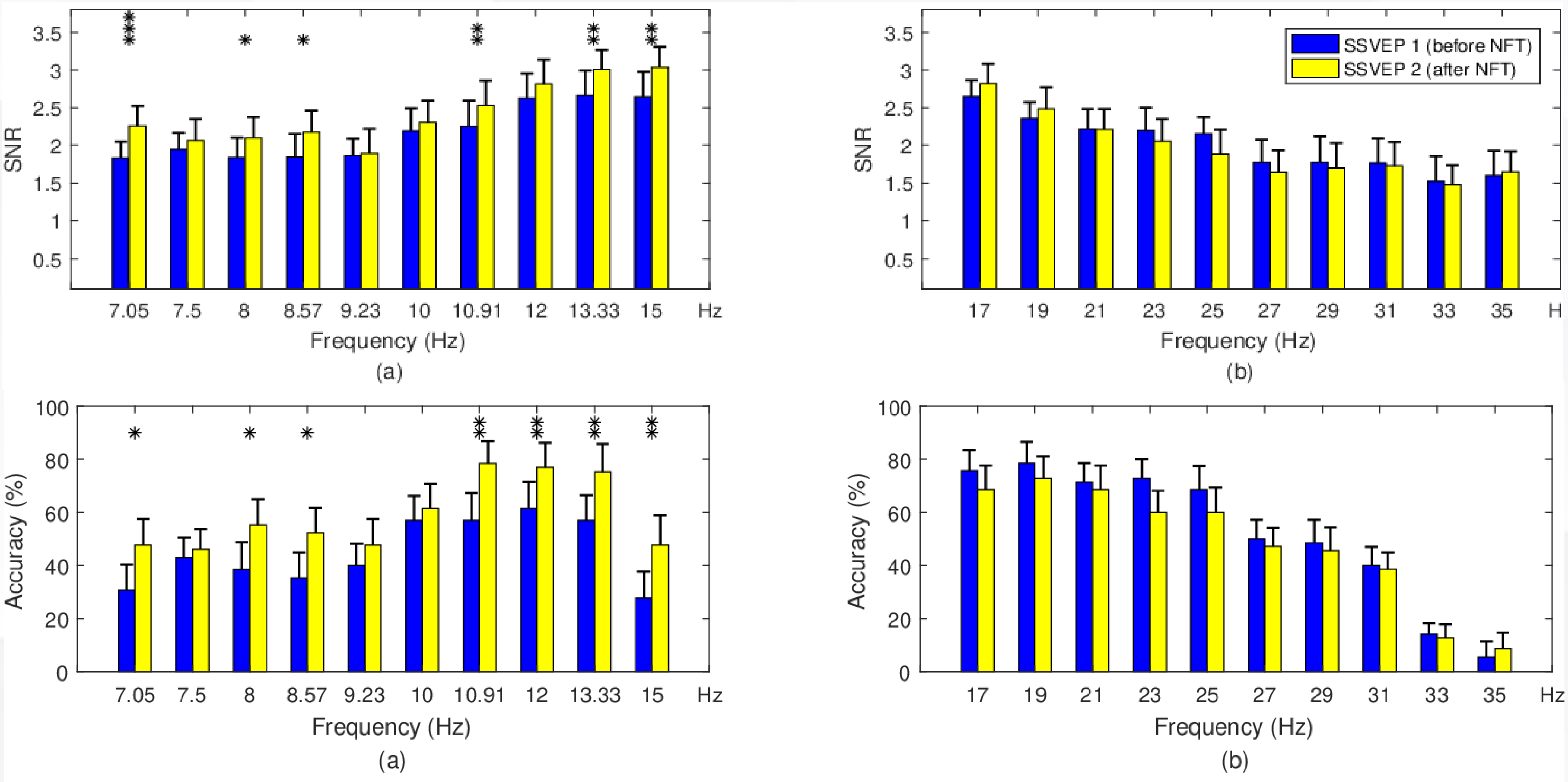
Appendix –XI

Individual relative amplitude of IAB changes during 10 NF training blocks.

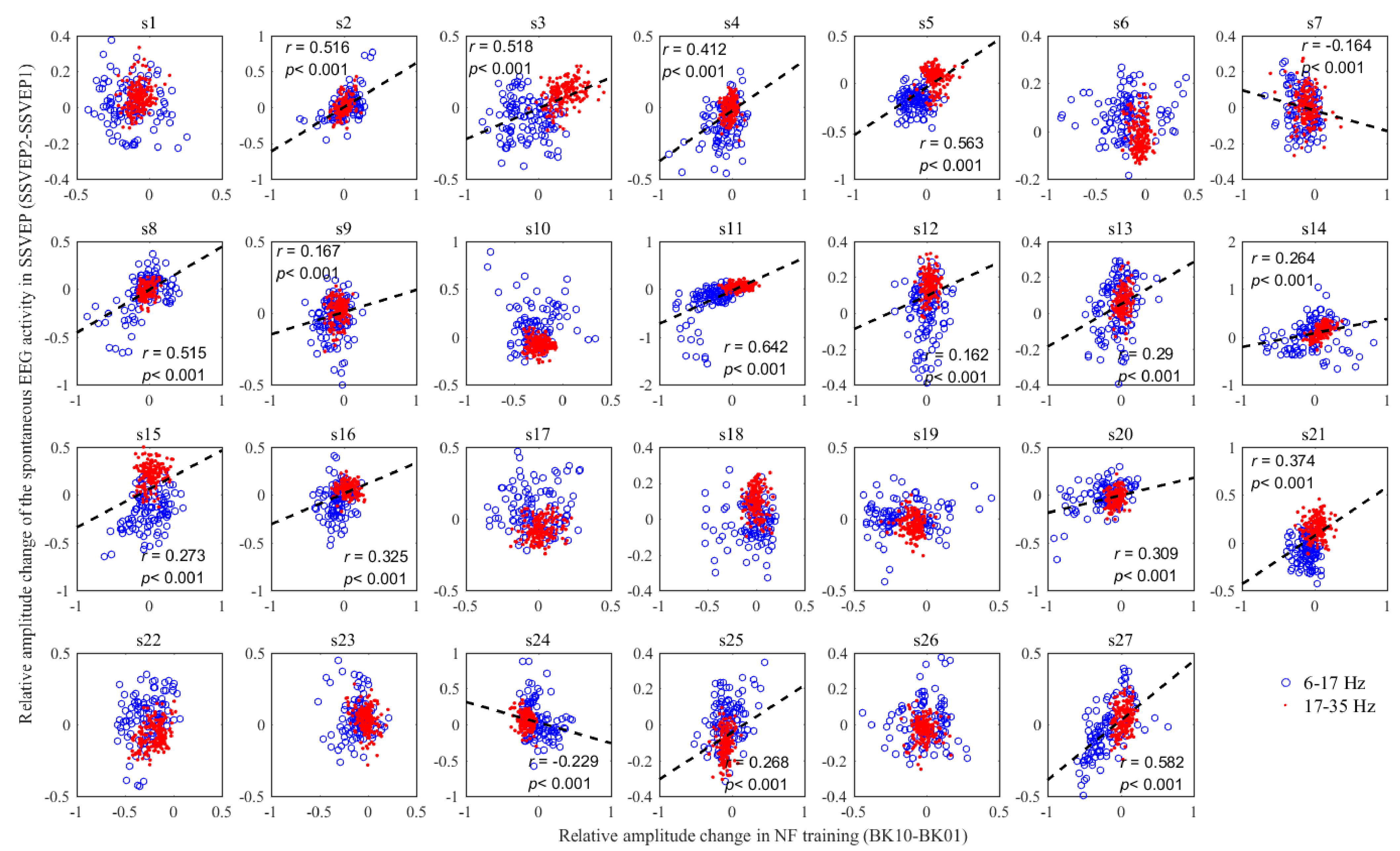


Appendix -XII

SSVEP performances changes of the stimuli frequencies from 7.05-35 Hz.



Appendix -XIII



Appendix -XIV

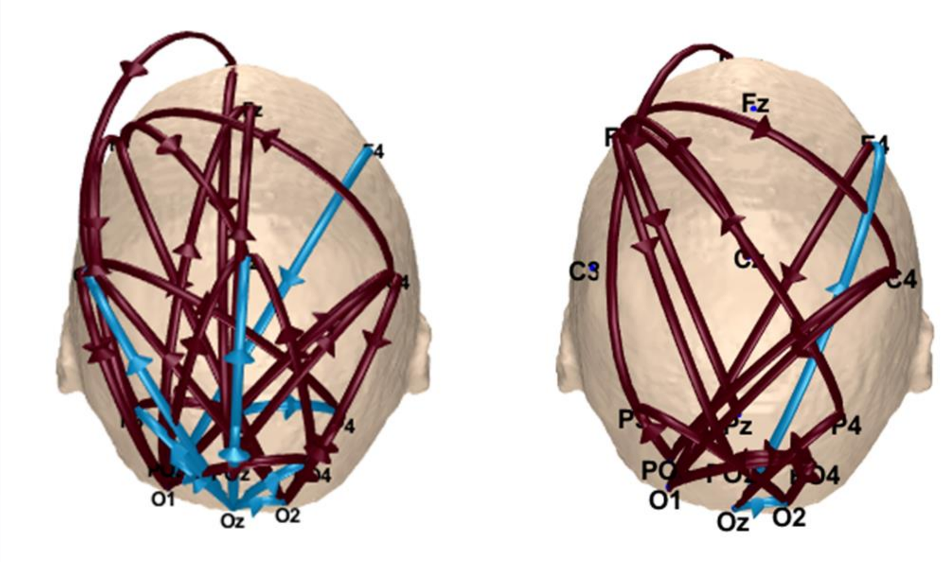
Brain Network: Significant changes in IAB-GC effective connectivity weights between,

"Brain Default Mode"

(a) Eye-closed and **eye-open states** in the initial resting baseline;

Percentage increase in:

Nodes Degree: 58.33%
CC: almost infinity
CPL: 15.31%
GE: 75.50%



(A) (B)

(b) Eye-closed states and the first **NF training block;**

Percentage increase in:

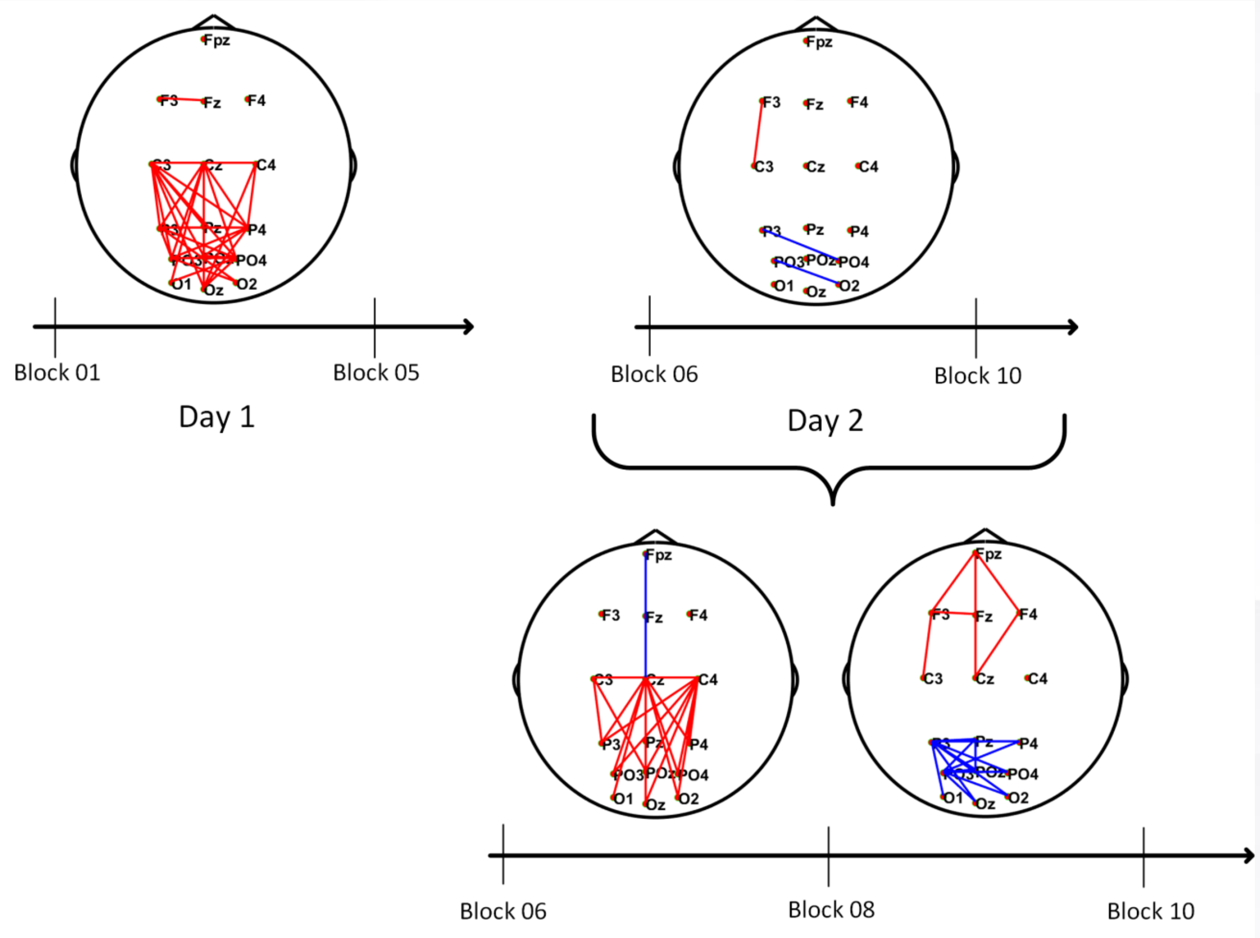
Degree: 86.67%;
CC: 0%;
CPL: 5.10%;
GE: 92.34%

Red lines represent the GC connections in eye-close baseline1 are statistically stronger ($p < 0.05$ in 2-tailed paired t-test) than they are in eye-open baseline1. Blue lines otherwise.

M. D. Greicius, B. Krasnow, A. L. Reiss, and V. Menon, "Functional connectivity in the resting brain: a network analysis of the default mode hypothesis," *Proceedings of the National Academy of Sciences*, vol. 100, no. 1, pp. 253–258, 2003.

05 Experimental Results -3.2

Significant functional connectivity within days

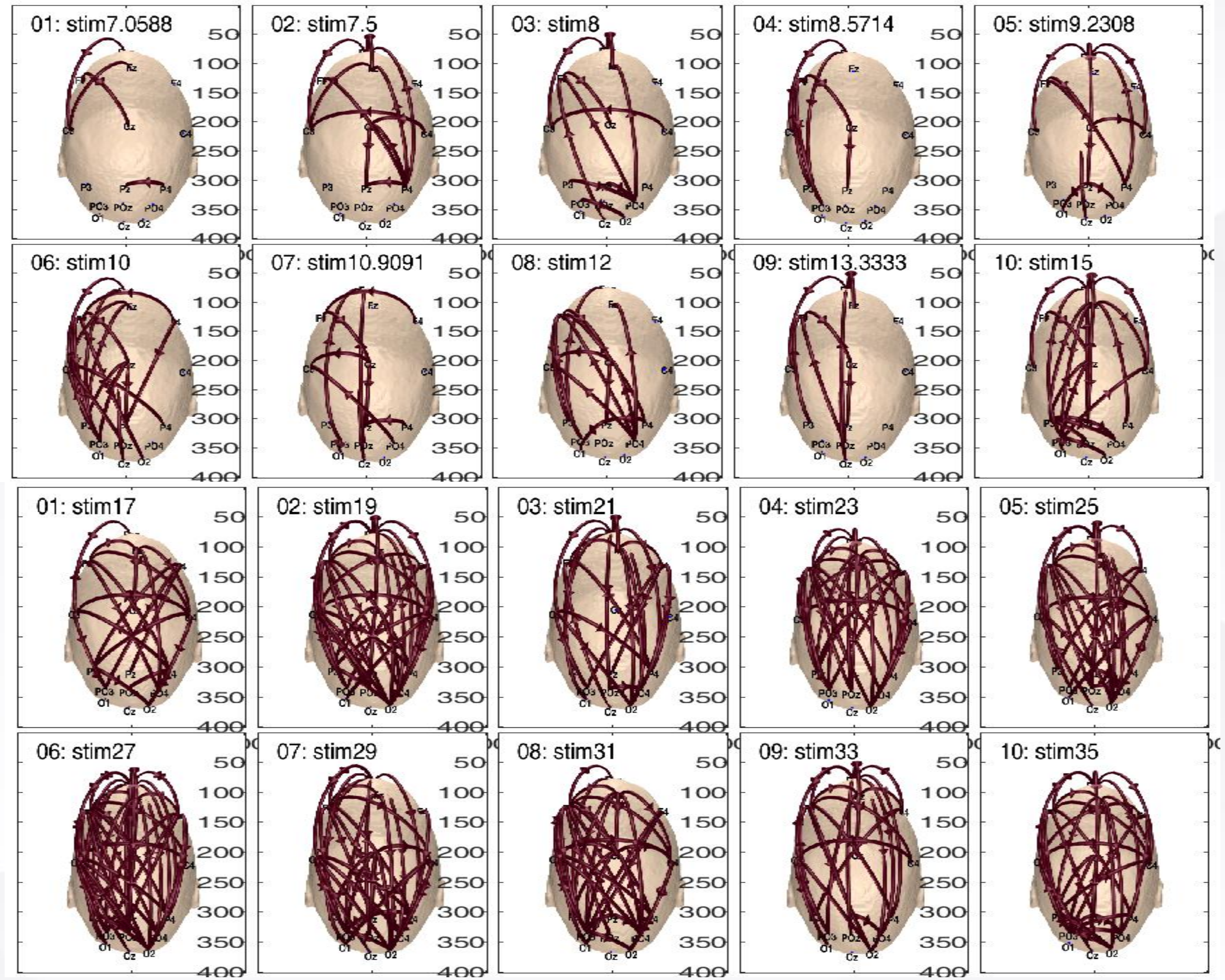


The learning curve for NF training (relative IAB amplitudes) correlates the corresponding brain connectivity density.

*Confidence level for 2-tailed paired *t* test: 95%

05 Experimental Results -3.2

Brain Network: Significant changes in IAB-GC based effective connectivity weights between,



Eye-open resting states and SSVEP-based BCI

Statistically enhanced information flow in SSVEP for stimulation frequencies from 7.05- 15 Hz

Statistically

*Confidence level for 2-tailed paired *t* test: 99%

F. Li, Y. Tian, Y. Zhang, K. Qiu, C. Tian, W. Jing, T. Liu, Y. Xia, D. Guo, D. Yao *et al.*, "The enhanced information flow from visual cortex to frontal area facilitates SSVEP response: evidence from model-driven and data-driven causality analysis," *Scientific reports*, vol. 5, p. 14765, 2015.