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RELIABILITY OF INDIVIDUAL TASK-RELATED FRONTAL-MIDLINE-THETA FREQUENCY FOR NEUROFEEDBACK TRAINING – EXPLORATORY INVESTIGATIONS

M. Pfeiffer[1], E. Masson[1], A. Kübler[1], J. Rodrigues[2]

[1] Institute of Psychology, Department of Psychology I, University Würzburg, Germany
[2] Institute of Psychology, Department of Psychology V, University Würzburg, Germany

E-mail: maria.pfeiffer@uni-wuerzburg.de

ABSTRACT:

Neurofeedback (NF) is a technique where participants receive real-time feedback about their brain activity to learn how to modulate it. As a non-invasive neuromodulation tool, it proves useful in both research and clinical practice. However, approximately one third of users do not respond effectively to NF, prompting efforts to improve responder rates. A promising approach involves individualizing feedback by focusing on a narrow feedback band that encompasses only the individual's peak frequency (IPF), as opposed to a fixed broadband. In some frontal-midline-theta (FMT) - NF paradigms, the IPF is determined during a single calibration session and applied over several days. In a pilot study involving five participants undergoing seven sessions of FMT-NF, we calibrated the IPF using a virtual TMaze task and conducted two follow-up sessions. Our exploratory analysis across three task sessions failed to detect a stable IPF. This, as well as the scarce literature on FMT peak frequency stability, casts first doubts on the efficacy of this calibration technique.

INTRODUCTION

Neurofeedback (NF) is a promising technique in which individuals receive real-time feedback of their brain activity, empowering them to consciously regulate it [1]. This approach holds significant potential both in research settings and clinical applications as a non-invasive method of neuromodulation [2], [3]. However, despite its potential benefits, NF's effectiveness remains variable, with approximately one third of users not achieving tangible results [4], [5]. In response, ongoing efforts are focused on enhancing responder rates [5].

One strategy to optimize NF outcomes involves individualizing the target frequency bands to each user. In traditional electroencephalographic (EEG)-NF, electric, oscillatory brain activity was usually extracted in relatively broad, fixed frequency bands [6].

More recent approaches try to increase the signal-to-noise ratio by narrowing the target frequency band. This is done by choosing an individual peak frequency (IPF) – the frequency of the band with the most measurable activity at scalp level and providing a narrow target frequency window around this peak. Hence, unrelated frequency responses in broad windows (i.e. noise) can be avoided.

The idea of the general IPF is rooted in the individual alpha frequency (IAF, 8-12Hz), which was shown to be a trait and hence stable over time [7]. Furthermore, it is easily detectable, as humans tend to show a peak in the alpha range (8-12Hz) of their power spectrum, when closing their eyes, being inattentive or in resting-state, with topographies depending on the respective inactivity [8].

Other frequency responses, such as theta (4-8Hz), do not show as easily detectable peaks during resting-state measurements, but during the performance of specific tasks, yet also with specific topographical distributions. For example, the task-related theta, linked to cognitive control and conflict [9], [10], [11] is localized at frontal midline electrodes (Fz, FCz), hence also named frontal-midline theta (FMT) [12], [13] or midfrontal theta (MFT) [14], [15].

Concerning peak frequencies, increases in task-related theta, when exerting cognitive control, remain in a narrower band than the entire theta band [8] supporting the idea of IPF-training if the latter is targeted. To find the respective individual theta frequency (ITF), several definition and quantification approaches exist. One classical approach bases itself on the IAF for the calibration [8], [16], resulting in an equal stability. More recent neurofeedback studies aiming at FMT modulation calibrated directly on task-related theta peaks [17], [18].

Calibrating task-related theta can be quite laborious, and often, the same calibration is applied across multiple sessions. This approach would be justifiable if individual theta frequency (ITF) measured with the task-related theta peak quantification was akin to individual alpha frequency (IAF) in terms of trait-like stability. However, to date, no studies have specifically investigated ITF stability for this new type of definition and quantification.

During a pilot study with a particular focus on FMT inhibition, involving five participants and seven NF sessions each, our design further employed a virtual TMaze task to calibrate the IPF in the initial session and

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during two follow-up sessions.
In an exploratory analysis of the task sessions, we were unable to detect a stable theta peak. This unexpected finding raises critical questions regarding the reliability and efficacy of the calibration technique employed for IPF-based FMT neurofeedback.
In this paper, we present the findings of our exploratory analysis, shedding light on the difficulties of individualized NF calibration methods, particularly concerning FMT modulation.

MATERIALS AND METHODS

Ethical statement: The study was carried out in accordance with the recommendations of "Ethical guidelines, The Association of German Professional Psychologists" ("Berufsethische Richtlinien, Berufsverband Deutscher Psychologinnen und Psychologen") with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki before they participated in the experiment. The protocol was approved by the local ethics committee of the department of psychology of the Julius-Maximilians-University of Würzburg (GZEK 2023-45, Ethikkommission des Institutes für Psychologie der Humanwissenschaftlichen Fakultät der Julius-Maximilians-Universität Würzburg).

Participants: Five participants (3 female, age: M = 24.4 years, SD = 1.5) were recruited through advertisements in an experiment online portal of the University of Würzburg. Participants were given course credits or a monetary compensation of 12,50€. All participants were at least 18 years old, righthanders, non-color blind and without a history of a psychiatric disorder. They took part in nine experimental sessions within three weeks: An initial calibration session (virtual TMaze) was followed by seven neurofeedback sessions. The virtual TMaze was recorded again directly after the last neurofeedback in session eight, as well as one week later in session nine.

Virtual TMaze: The virtual TMaze used in this study is an adaptation of the original design of [19], [20], [21] into a more recent games engine, the Unreal Engine 4.
Participants interacted with the virtual environment using a gamepad, navigating through a TMaze in a first-person view (see Fig. 1).
By virtually moving in the TMaze it was possible to encounter two entities: The participant could be caught by a scary kraken, leading to credit loss and an aversive sound being played, or the participant could catch a cute seal, leading to credit gain and a harmonic sound.
Each 18 second trial started with the participant positioned in a passage, facing the T-arms of the maze.
The study incorporated four distinct trial types:
Avoidance Trials (n=20): A red light indicated the presence of the kraken in one of the arms. Avoidance was possible by retreating behind the starting passage into a safety-zone instead of entering the T-arms.
Approach Trials (n=20): A green light indicated the presence of the seal in one of the arms.

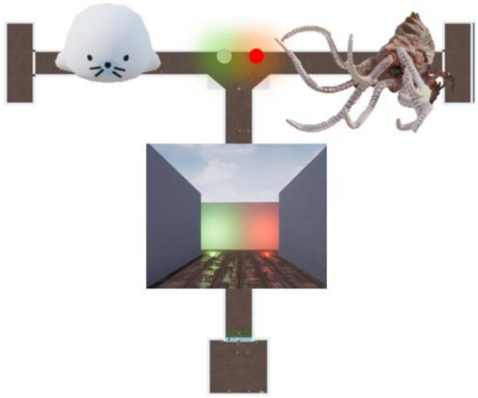

Figure 1: Overview of an Approach-Avoidance Conflict trial of the virtual TMaze task, displaying the first-person view of the participant, the entities he may encounter and the setup of the TMaze, with the safety zone behind the participant.

Approach Avoidance Conflict Trials (n=30): A green and a red light indicated the presence of both entities.
Ambiguous Events (n=30): A yellow light indicated the presence of an unspecified entity in one of the arms. Unbeknown to the participants, the probability of encountering one or the other entity was at 50 percent.

Neurofeedback: Given that the neurofeedback does not constitute the central focus of this paper, neurofeedback results are not discussed in this paper. Each session consisted of six blocks of five one-minute trials, leading to a total of 30 minutes of neurofeedback, aiming at FMT-inhibition. A three-minute resting-state was recorded before and after each session. Participants received real time feedback of their FMT activity at Fz, at the assumed ITF (+/-1Hz). The ITF was calibrated on the event-related theta of conflict and ambiguous trials of the virtual TMaze task of the first session.

EEG: For the recording of the EEG ActiCap electrodes and BrainAmp EEG amplifiers (Brain Products GmbH, Gilching, Germany) were utilized. During session one, eight and nine (all three sessions in which the TMaze was recorded) 62 scalp-electrodes were placed according to the 5-10-system. Two electrodes (O1/O2) were sacrificed to be used as electrooculogram (HEOG/VEOG, right eye). The reference electrode was placed at FCz. All data was recorded using LabStreamingLayer (LSL-Connector, LabRecorder) at a sampling rate of 250Hz.

Preprocessing: All EEG data was processed in MATLAB using the code of and following the EPOS-Pipeline [22]. First a notch filter for line noise and resonance frequencies (50,100Hz) was applied. Next, bad channels were detected and interpolated. Detection was based on a statistical threshold of z > 3.29 [23] for joint probability, kurtosis and the power spectrum. Then the data was re-referenced to common average, restoring the previously used reference electrode FCz. Epochs were cut from -1 to 5 seconds after cue (appearance of lights in the TMaze) onset. A 1Hz highpass-filter was applied before an independent-component-analysis (ICA) was performed. The components were used to select bad segments based on the same statistical criteria as before. A second ICA was

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computed, this time artifactual components were automatically detected using MARA, ADJUST and SASICA. After removal of the selected components the data was finally re-referenced to current source density.
To analyze time frequency responses the data was cut into shorter epochs from -1 to 2 seconds. Data was baseline corrected, using the one second before stimulus onset, and subsequently decomposed using Morlet wavelets.

Calculation of the ITF: As we discovered the instability of the ITF with the pipeline, we used for calibration during the study, we considered alternative ways of peak detection to calibrate the neurofeedback system. To investigate these alternative ways, we employed a “mini”-multiverse analysis, comparing combinations of multiple reasonable decisions along the pipeline.
The theta-peak was searched in a time window from 250-450ms after stimulus (light cue) onset. We varied the pipeline at five steps, with two to four alternative decisions per step, resulting in a total of 96 analyses.

1) Unit of time-frequency response
   1A: Power
   1B: decibel (dB) - to account for 1/f dynamics of the power spectrum.
   1C: dB change to baseline - to account for differences in baseline activity.
2) Spacing of frequency bins
   2A Linear – to have equally spaced bins.
   2B Logarithmic – to account for 1/f dynamics of the power spectrum.
3) Search Time (250-450ms after cue)
   3A: Peak Window (50ms window) – the peak is detected on a singular timepoint. Additional 25ms of data before and after this peak are included in the analysis.
   3B: Center of Gravity (50ms window) – to detect peaks lower in amplitude but extended in duration we utilized the average of a moving window of 50ms with 10ms steps.
4) Search Band (4-8Hz)
   4A: Broadband– detecting the peak (timewise) in the broadband, and afterwards extracting activity of each sub-band of the peak. This approach tackles an overall theta peak.
   4B: Sub-bands – detecting the peak (timewise) for each sub-band and correspondingly extracting the activity. This allows the investigation of frequency-interferences.
5) Peak Detection
   5A: Frequency with the highest average activity of only those trials where the specific frequency was the frequency with the most activity.
   5B: Frequency with the highest summed activity of only those trials where the specific frequency was the frequency with the most activity.
   5C: Frequency with most trials where the specific frequency was the frequency with the most activity.
   5D: Frequency with the highest average activity of all trials.

Peak Timing: To investigate whether peaks in the different frequency bins may interfere with each other we looked at the distribution of peak timings in the individual sub-bands and compared the standard deviations of peak timings for each individual trial.

Statistical Analysis: To assess peak stability, we calculated inter-class-correlations (ICC) across the three sessions for every pipeline. To quantify the variability between the 96 pipelines we calculated the ICC for the pipelines for each session of each participant. Due to the small number of participants (n=5) results from these statistical tests should be taken with caution.

RESULTS

ITF Peak Detection: Due to the immense number of comparisons possible we display only the most important ones. Nonetheless all analyses performed are available on GitHub (https://github.com/iamraP/FMT_Peak).
We observed variability in the ITF across participants, sessions as well as calibration pipelines. The employed approaches did not provide a stable peak, except for instances where it is questionable whether the stability was provided by edge artifacts of the frequency band processing [24] . The ICC for the pipelines was especially low (ICC: 0.03, 90%-CI [0.02,0.06]). The evaluation of the peak frequency stability was impossible in 55 pipelines as the strength of the edge artifacts led to zero variability in the detected peak. All three pipelines which would still be rated as fairly reliable (ICC > 0.5) [25], present a strong tendency towards edges of the frequency band. The low ICC of the other 38 pipelines challenges the assumption of a stable ITF across sessions. In the following we will refer to differences in peak detection > 1Hz as “*meaningful differences*”, since they would lead to a different setting in the neurofeedback system.

1) Unit of time-frequency response: The blue panels of Fig. 2 display the difference between the different choices for 1 (A-C). It is exemplary for our observation over all the performed analysis, displaying the three issues of the analysis: first, edge artifacts at the lowest frequency for power, second, edge artifacts at the uppermost frequency for the dB transformed data, and third, high fluctuation of the detected peak for dB transformed data in relation to the baseline.

2) Spacing of frequency bins: Decision on step 2(A-B) did not lead to such extreme effects, but nonetheless observable and *meaningful* differences, most pronounced in combination with 1C (Fig. 2, blue vs. red panels).

3) Search Time & 4) Search Band: Another *meaningful* difference was observed for the decision between center of gravity (3A) and peak window detection (3B), again most visible in combination with 1C. Interestingly the observed *meaningful* difference of search time (3A-B) remained relevant only in combination with 4A (broad-band) (see Fig. 2, green panels). For the sub-band peak search (4B) the

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approaches 3A-B remained similar enough to not change the frequency band of the neurofeedback (see Fig., 2 green panels). Choosing the band within which to search for the peak also impacted the detection in a *meaningful* manner itself. While detecting the peaks in the sub-bands lead to a higher likelihood of the peaks being detected at edge frequencies (93% of peaks either >7.5Hz or <4.5Hz), detection of the peak in the broad band led to the inclusion of more centered frequencies (76% of peaks either >7.5Hz or <4.5Hz).

5) Peak Detection: Except for 5C, only minor differences between the different approaches for detecting the peak were notable (see Fig. 2, gold panels). An issue posed by approach 5C was the possibility of several frequencies accumulating the same number of trials, therefore not providing a single peak frequency.

Peak Timing: Investigations of the distribution of the peak timing for the sub-bands showed, that peaks tended to occur across the entire time for any frequency, but also a slight variation of timings between them. Nonetheless for no participant any frequency displayed a more specifically time-locked peak than the others. Comparing the divergence of peak-timing for individual trials revealed that the timing is not consistent over frequencies, as indicated by high standard deviations (on average 44ms per trial within a 100ms time window).

DISCUSSION

The exploratory findings of our pilot study reveal several critical insights into the calibration of Individual Peak Frequency (IPF) for Frontal-Midline Theta (FMT) Neurofeedback (NF). The inability to establish a stable IPF across sessions raises significant questions about the reliability and effectiveness of current calibration methods, particularly in the context of FMT-NF. This discussion will critically analyze these findings, examining the implications for neurofeedback research and practice, and suggesting potential avenues for future studies.

The core challenge identified in this exploratory analysis is the stability of the ITF. Our results indicate substantial variability in ITF across participants, sessions, and calibration pipelines. This instability could be attributed to several factors:

Trait vs. State: Some differences are expected as human brain activity is inherently variable, influenced by factors like cognitive state, attention, and even diurnal rhythms [8]. This variability could lead to fluctuations in theta activity. Nonetheless if an IPF is supposed to be used over several sessions, it needs to be trait- and not state-dependent, hence intraindividual differences should be minimal.

EEG-Pipelines: The methods employed for detecting the IPF, such as the time-frequency response units and the peak detection algorithms, showed heterogenous outcomes. This suggests that the choices of methodological approach play a crucial role in the calibration process, which is supported by previous

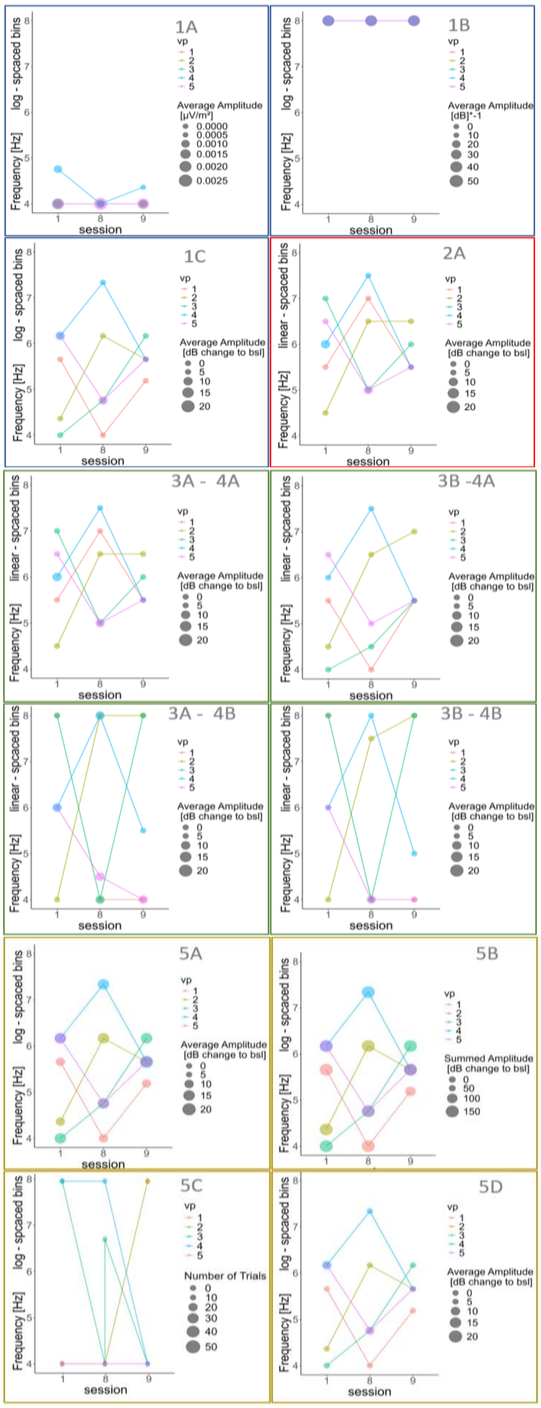

Figure 2: Detected frequency peaks for each participant (colors) for the three sessions (1: Initial Session (Day 0); 8: after 7 NF sessions (Day 10-14), 9: 1 week later (Day 17-21)). Each panel displays the results of a different pipeline, highlighting changes induces by design choices.
Blue: Differences for unit of time-frequency response. Pipeline choice pattern: ***1A-C*** *– 2B – 3A – 4A – 5D.*
Red: Linear spaced frequency bins instead of logarithmic bins. Pipleline choice Pattern: 1C – ***2A*** *– 3A – 4A – 5D.*
Green: Center of gravity vs. Peak Window and Broadband vs. sub-bands. Choice Pattern: 1C – 2A – ***3AB*** *–* ***4AB*** *– 5D.*
Gold: Differences choice of peak detection. Choice pattern: 1C – 2B – 3A – 4A – ***5A-D.***

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investigations of the effects of different design choices in EEG analysis pipelines [26]. However *meaningful* peak stability was not achieved with any of the applied approaches.

Processing Artifacts: The lower-edge artifacts shown for analysis with 1A (power), are explainable by the 1/f dynamics of EEG-data - lower frequencies displaying higher activity and hence are more prone to be detected as peaks. Opposingly, the decibel transforms (1B) supposedly correcting for these dynamics overcorrects it, leading to the opposite edge-artifact. The third choice 1C (dB change to baseline) introduces other artifacts which may be caused by a variance in baseline activity.
The issue of edge artifacts may be tackled by emphasizing the analysis on the center of the signal by using padding or a specific window function such as Hanning windows.
Diverse padding methods could be tested in further pipelines, such as zero-padding, mirror-padding, or constant-padding, to make the edges of the signal smoother or more consistent with the central parts, whereas the Hanning window for example tapers the signal, giving more weight to the center and less to the edges and corners.

Task Design: The variance in baseline activity is likely caused by the task design. While we used a rather complex task to elicit conflict-related theta (the virtual TMaze), previous neurofeedback studies using task-based peak detection relied on more simplistic tasks focusing on the exertion of cognitive control (Stop-Signal-Task, Stroop) or working memory (Delayed-Match-to-Sample, n-back) [17], [18].
Even though the stability of the peak frequency was not explicitly reported in former studies, it is still plausible to assume it could have been stable. Three differences may have influenced detectable peak stability in our design. First, while the conflict-related theta elicited in the TMaze is also part of the cognitive control domain, the complexity of the task may still influence the stability of the underlying processes. It may have led to a less consistent baseline, hence influencing the baseline corrected dB transform: Second, the underlying processes of conflict-related theta and working memory-related theta may differ, which could explain a trait for one but not for the other. Third, the TMaze may also suffer from habituation, e.g. participants developing a strategy to deal with the conflict, which is not possible in the simpler designs aiming at inhibitory control (e.g. Stop-Signal Task). A comparative study, employing different tasks over several sessions would be necessary to shed further light on the suspected issue.
The variability in ITF suggests a need for more personalized NF protocols. While individualizing NF based on IPFs in general is a promising approach, our study indicates that a one-time calibration may not be sufficient for FMT neurofeedback. Dependent on the intention of the modulation, e.g. if non-sleep-related processes are targeted, we believe an IPF approach to be more applicable than broadband feedback, but continuous or frequent recalibration might be necessary to account for the dynamic nature of FMT activity.

Peak Timing: The investigation of peak times for the different sub-bands displayed inconsistencies across them. This may indicate a band interference, where one sub-band may cancel out the other when averaged, hence we would assume an individual investigation (4B) of each sub-band may lead to more accurate results than the peak detection on the broadband (4A).

Outlook: A recent meta-analysis showed, FMT-NF based in on IPFs did not outmatch broadband feedback. [27]. Chances are, the IPF did not outmatch the broadband feedback because both approaches are equally well, but due to the not yet established pipeline for ITF detection. To investigate this proposed issue of ITF peak instability and possibly for providing a stable pipeline, a larger multiverse analysis is planned, including different steps of design choices on an existing dataset of TMaze data, as well as newly recorded data from several tasks eliciting FMT.

CONCLUSION

In conclusion, while individualizing FMT-NF by focusing on the IPF might be a promising approach, to tailor feedback to NF-users our study underlines the challenges in achieving reliable IPF calibration. Even though with such a small sample these results should be interpreted with caution, the underlying lack of literature concerning ITF stability together with the current observation necessitates a reconsideration of current calibration methods of FMT-NF and highlights the need for more sophisticated approaches. As NF continues to evolve, addressing these challenges will be crucial for maximizing its efficacy and applicability in both research and clinical settings.

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