

# Calibrating rhythmic stimulation parameters to individual electroencephalography markers: The consistency of individual alpha frequency in practical lab settings

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## Abstract

Rhythmic stimulation can be applied to modulate neuronal oscillations. Such ‘entrainment’ is optimized when stimulation frequency is individually calibrated based on magneto/encephalography markers. It remains unknown how consistent such individual markers are across days/sessions, within a session, or across cognitive states, hemispheres and estimation methods, especially in a realistic, practical, lab setting. We here estimated individual alpha frequency (IAF) repeatedly from short electroencephalography (EEG) measurements at rest or during an attention task (cognitive state), using single parieto-occipital electrodes in 24 participants on 4 days (between-sessions), with multiple measurements over an hour on 1 day (within-session). First, we introduce an algorithm to automatically reject power spectra without a sufficiently clear peak to ensure unbiased IAF estimations. Then we estimated IAF via the traditional ‘maximum’ method and a ‘Gaussian fit’ method. IAF was reliable within- and between-sessions for both cognitive states and hemispheres, though task-IAF estimates tended to be more variable. Overall, the ‘Gaussian fit’ method was more reliable than the ‘maximum’ method. Furthermore, we

**List of abbreviations:** cd, Candela; DVA, Degrees visual angle; EEG, Electroencephalography; FFT, Fast Fourier transform; IAF, Individual alpha frequency; IQR, Inter-quartile range; ICC, Intra-class correlation coefficient; MEG, Magnetoencephalography; m, Metre; MC, Michelson contrast; ms, Milliseconds; NIBS, Non-invasive brain stimulation; rTMS, Repetitive transcranial magnetic stimulation; SGF, Savitzky–Golay filter; s, Seconds; tACS, Transcranial alternating current stimulation; 2AFC, Two-alternative forced-choice.

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evaluated how far from an approximated 'true' task-related IAF the selected 'stimulation frequency' was, when calibrating this frequency based on a short rest-EEG, a short task-EEG, or simply selecting 10 Hz for all participants. For the 'maximum' method, rest-EEG calibration was best, followed by task-EEG, and then 10 Hz. For the 'Gaussian fit' method, rest-EEG and task-EEG-based calibration were similarly accurate, and better than 10 Hz. These results lead to concrete recommendations about valid, and automated, estimation of individual oscillation markers in experimental and clinical settings.

#### KEYWORDS

consistency, electroencephalography (EEG), individual alpha frequency (IAF), intra-class correlation coefficient (ICC), neuronal oscillations, reliability

## 1 | INTRODUCTION

The investigation of neuronal oscillations in the human brain has progressed beyond merely correlational M/electroencephalography (EEG) research. Different approaches have been developed to explicitly modulate neuronal oscillations in specific frequency bands, in both research and clinical settings. For instance, rhythmic visual stimulation at alpha frequency has been used to enhance (or 'entrain') neuronal oscillations and thereby influence visual perception (Chota & VanRullen, 2019; de Graaf et al., 2013; Mathewson et al., 2010; Mathewson, Prudhomme, et al., 2012b; Ronconi et al., 2018; Spaak et al., 2014; Wiesman & Wilson, 2019). More direct neuromodulation methods include magnetic and electric non-invasive brain stimulation (NIBS) (Antal & Paulus, 2013; Hallett, 2000). Both repetitive transcranial magnetic stimulation (rTMS) and transcranial alternating current stimulation (tACS) have been employed to establish causal links between alpha oscillations and cognitive processing (Herrmann et al., 2013, 2016; Ruhnau et al., 2016; Thut et al., 2011). For instance, 10-Hz tACS to parieto-occipital cortex could increase the power of neuronal alpha oscillations (Helfrich et al., 2014), and bias response times in an endogenous attention task (Schuhmann et al., 2019). Such findings support a causal role for parietal alpha oscillations in visuospatial attention.

The alpha band is generally considered to contain frequencies between ~7 and 13 Hz (Berger, 1929, 1933) and has been linked to a large number of cognitive functions (Clayton et al., 2018), including learning (Freyer et al., 2013; Mathewson, Basak, et al., 2012a; Sigala et al., 2014), memory (Bonfond & Jensen, 2012; Jensen et al., 2002; Klimesch, 1999), and visuospatial attention (Gallotto et al., 2020; Sauseng et al., 2005; Worden et al., 2000). Importantly, there are substantial differences in the peak alpha frequency across individuals

(Klimesch, 1999). These inter-individual differences in individual alpha frequency (IAF) are related to general cognitive abilities (Dickinson et al., 2018; Grandy, Werkle-Bergner, Chicherio, Lövdén, et al., 2013a), language processing (Bornkessel et al., 2004) and memory (Cross et al., 2020; Moran et al., 2010), and can in part be explained by genetic variations (Bodenmann et al., 2009; Smit et al., 2005, 2006; Van Beijsterveldt & Van Baal, 2002). Differences in IAF can furthermore drive aspects of visual perception, as exemplified by an association between IAF and the temporal resolution of the double flash illusion (Samaha & Postle, 2015).

These findings are especially relevant for rhythmic stimulation studies, since stimulation might most effectively induce modulatory effects if delivered at individually calibrated frequencies (Stecher & Herrmann, 2018). Indeed, it was recently shown that a leftward visuospatial attention bias resulted from tACS at IAF, but not tACS at IAF  $\pm 2$  Hz (Kemmerer et al., 2020). Increasingly, neuromodulation studies make use of individually calibrated stimulation protocols, for instance by using IAF instead of a fixed (e.g., 10 Hz) frequency (Fresnoza et al., 2018; Kasten et al., 2016, 2020; Vossen et al., 2015; Zaehle et al., 2010). This approach also has clinical relevance, since it was recently shown that deviations between IAF and the stimulation frequency predict NIBS treatment outcome for depression patients (Corlier et al., 2019; Roelofs et al., 2020). Moreover, although we focus on IAF as an example, these considerations apply to other frequency bands as well, including individual gamma (Baltus et al., 2018), beta (Schilberg et al., 2018) and theta (Reinhart & Nguyen, 2019) frequency.

Thus, for both research and clinical applications, it is beneficial to tailor rhythmic stimulation protocols to individual participants or patients. Typically, stimulation protocols are based on quick frequency analysis of short

EEG measurements, often recorded from only one or a few electrodes. Different approaches exist to determine individual peaks (e.g., IAF) from a power spectrum (Goljahani et al., 2012). Most widely reported is the ‘*maximum*’ method, in which a peak is determined by simply selecting the frequency with the highest power within a pre-defined (e.g., alpha) frequency range (Kemmerer et al., 2020; Koch et al., 2008; Petersén & Eeg-Olofsson, 1971; Schuhmann et al., 2019; Smit et al., 2006). Another possibility might be called the ‘*Gaussian fit*’ method, which involves fitting a Gaussian curve to the power spectrum within a restricted (e.g., alpha) frequency range. A peak frequency (e.g., IAF) is then estimated by finding the centre parameter of the fitted Gaussian curve (Dickinson et al., 2018; Haegens et al., 2014; van Albada & Robinson, 2013). Aside from peak frequency, this method also allows estimation of peak width.

It remains unknown to what extent IAF estimates can be used to reliably calibrate rhythmic stimulation protocols across days, or cognitive states. Simply stated, if one estimates IAF from a posterior electrode after 3 min of resting-state EEG, how likely is that IAF to be (in)correct in general? How likely is it to be (in)correct an hour later, or in the second session next week? How representative is it for IAF during a cognitive task of interest? Though IAF is often assumed to be stationary, a recent study reported a decrease in peak alpha frequency during 1 h of visual task performance (Benwell et al., 2019). The change was small on average, but individual effects reached as high as 2 Hz. While previous studies established that alpha peak frequency at rest reflects, in principle, a stable trait (Gasser et al., 1985; Grandy, Werkle-Bergner, Chicherio, Schmiedek, et al., 2013b; Kondacs & Szabó, 1999; Näpflin et al., 2008; Salinsky et al., 1991), we here systematically chart IAF based on realistic, practical (i.e., short and constrained) lab settings.

Before the consistency of IAF estimates can be investigated, another concern should be addressed. Specifically, sometimes the power spectrum does not show any clear peak, especially when based on M/EEG data measured during cognitive task performance. Researchers or clinicians are then forced to subjectively decide to either accept or reject the result that a peak estimation method delivers. Going forward, it would be helpful to develop tools that algorithmically accept or reject power spectra, for instance prompting lab technicians, clinicians or experimenters, to perform a new M/EEG measurement. Or, in the current context, to prevent bias in the IAF estimation procedures and subsequent statistical analyses, by only including power spectra that show a sufficiently clear peak. To this end, we developed an algorithm to automatically reject EEG power spectra that do not

contain a clear alpha peak. Based on accepted power spectra, we could then explicitly evaluate the consistency of repeated estimations of IAF (and IAF peak width) across estimation methods, days and cognitive states.

We performed short, repeated EEG measurements in 24 participants on four separate days, in the left and right hemisphere, during eyes closed resting state and during an endogenous visuospatial attention task (Posner, 1980; Posner et al., 1980). In one session, we performed these measurements repeatedly across approximately 1 h. IAF was estimated for each participant, time point, hemisphere, and cognitive state, using the ‘*maximum*’ method and the ‘*Gaussian fit*’ method. Our experimental aims were threefold. First, we investigated to what extent the ‘*maximum*’ and ‘*Gaussian fit*’ methods led to similar IAF estimations. Second, we assessed how consistent repeated IAF estimates were within and between sessions, for both hemispheres, cognitive states, and estimation methods. Third, we investigated whether there is an advantage of measuring EEG instead of simply using a standard (i.e., 10 Hz) frequency, and whether resting-state EEG calibration is sufficient, or even better, for estimating the relevant individual frequency during task performance than an estimation based on EEG collected during performance of that same task.

## 2 | MATERIALS AND METHODS

### 2.1 | Participants

Twenty-four healthy volunteers participated in this experiment (11 male, ages 19–34). All participants were right-handed and had (corrected-to-)normal vision. Compensation was provided in the form of participation credits or vouchers. The experiment was approved by the Ethical Review Committee Psychology and Neuroscience at Maastricht University.

### 2.2 | Project overview

The current data stem from a large project on brain stimulation. In that project, we stimulated participants’ left parietal cortex with four different tACS protocols on separate days. Prior to any tACS, EEG baseline data were collected during eyes closed resting state and during visuospatial attention task performance from two parieto-occipital electrodes (see below for details). Since potential brain stimulation effects are outside the scope of the current paper, none of the data reported here were assessed after active tACS. Instead, the included data were measured pre-tACS in four different sessions, and at

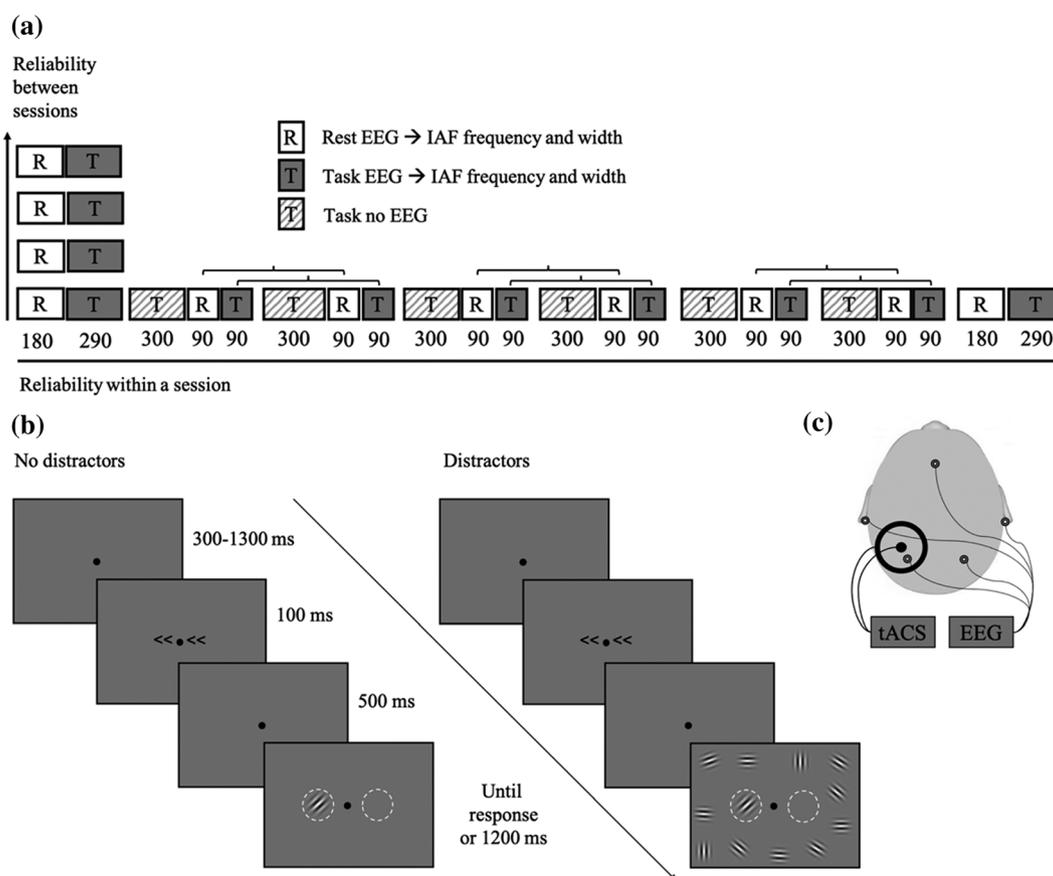
different time points during an extended (placebo tACS) session (see Figure 1a). This allowed the dedicated evaluation of the consistency of IAF and IAF width (in supporting information S3) between sessions (prior to any brain stimulation) and within a session (repeated estimation at regular intervals within the extended session, across approximately 1 h; see Figure 1a), relative to the consistency across participants.

In terms of the repeated EEG task/rest baseline measurements, all four sessions were identical, session order was fully counterbalanced across participants, and there was a minimum of 2 days between sessions. Upon

entering the lab, participants were screened for tACS contraindications and provided written informed consent. We then prepared the tACS and EEG electrodes, as well as calibrating an eyetracker. These preparations took approximately 1 h altogether.

## 2.3 | Stimuli and task

In each session, participants performed an endogenous attention task (see Figure 1b) (Posner, 1980; Posner et al., 1980). Stimuli were presented using MATLAB (The



**FIGURE 1** Experimental design. (a) Experimental procedure and included electroencephalography (EEG) data. Indicated times are in seconds. EEG data were collected for 3-min rest and ~5-min task in four sessions on separate days. In one more extended session (lowest section), after the initial measurement, EEG data were collected six times for 1.5-min rest and 1.5-min task, spaced 5-min apart. During these 5 min (striped segments), participants were under the (false) impression of receiving tACS; these data were excluded and never analyzed. Consecutive 1.5-min blocks were combined to yield again 3-min data (brackets), meaning that there were five repeated measurements for both rest and task. (b) Endogenous attention task. After a randomly jittered fixation period, an endogenous cue was presented. Cues were valid (pointing towards the upcoming target), neutral (pointing to both sides), or invalid (pointing away from the upcoming target). A target grating was presented in the left or right hemifield 500 ms after the cue disappeared. White dashed circles indicate possible target locations and were not actually shown on the screen. Participants responded as quickly and as accurately as possible whether the target grating was rotated (counter-)clockwise. The target disappeared once a response was given or when 1200 ms had elapsed. In half of the trials, distractors with random orientation, frequency, and (drifting) phase were presented bilaterally from target onset until target offset. (c) tACS and EEG set-up. A tACS ring electrode was centred on P3. EEG electrodes were placed on PO3 and PO4, with the ground electrode on Fz and reference electrodes over both mastoids. Note that no tACS was applied before or during any of the data collected and reported in this paper

MathWorks, Inc., Natick, Massachusetts, United States) and Psychophysics Toolbox (Brainard, 1997) on a gamma-corrected 24 inch monitor with a 60-Hz refresh rate and a resolution of  $1920 \times 1,080$  pixels. Participants continuously fixated on a black dot of .2 degrees visual angle (DVA) presented in the centre of a grey screen with a background luminance of  $125 \text{ cd/m}^2$ . Their heads were stabilized using a chin rest that was positioned 60 cm away from the computer screen. Eyetracking was performed to assess fixation stability. After a randomly jittered fixation period (300–1300 ms), an endogenous cue was presented for 100 ms. The cue was either valid (two arrows pointing in the direction of the upcoming target), neutral (one arrow pointing to the left and the other to the right), or invalid (pointing away from the upcoming target) at a ratio of 3:1:1. After a cue-to-target interval of 600 ms, a target stimulus with a diameter of 3.5 DVA was presented at 7 DVA eccentricity on either the left or the right side of the screen. Target stimuli were sinusoidal gratings of .8 Michelson contrast (MC), rotated either 45 DVA clockwise or counter-clockwise, with random spatial frequency and phase. Participants performed a two-alternative forced choice (2AFC) task for each target grating. More specifically, they indicated as quickly and as accurately as possible the orientation of the target, pressing with their right hand either the left arrow button or the right arrow button for counter-clockwise and clockwise oriented gratings, respectively. The target grating disappeared once the participant responded or when 1200 ms had passed without a response. In half of the trials, only the target grating was presented. In the other half of the trials, distractors were displayed bilaterally at target onset until target offset. Distractors were displayed around the target locations and had a random orientation, phase and spatial frequency. Distractor contrast was .8 MC and a drift speed of 4 Hz was used to make the distractors appear to move in space, thereby make them more salient. Average trial duration was 2100 ms. The pre- and post-measurement each contained 120 attention task trials, while the main measurement contained 960 trials divided equally over the six blocks.

## 2.4 | Electroencephalography

EEG data were recorded with 5000-Hz sampling frequency and a hardware band-pass filter of .1–1000 Hz using BrainVision Recorder (BrainVision LLC, Morrisville, North Carolina, United States) and a BrainAmp DC amplifier (BrainProducts, GmbH, Gilching, Germany). Reference electrodes were placed over A1 and A2 and the ground electrode was placed over

Fz. The two electrodes of interest were placed over PO3 (within the tACS ring electrode) and PO4 (see Figure 1c). EEG electrodes were filled with conductive gel (OneStep Cleargel) and impedances were kept below 5 k $\Omega$  (ground and reference electrodes) or 10 k $\Omega$  (electrodes of interest). Note that the participants' skin could not be prepared as thoroughly as in conventional EEG studies due to the presence of the tACS electrode. In the current context this is a valuable aspect of our data, given that the goal was to assess individual EEG markers in realistic, practically constrained lab settings, representative of conditions in rhythmic stimulation experiments often relying on such EEG measurements and IAF estimation.

## 2.5 | Analyses

Data were analyzed using MATLAB version 2019a, FieldTrip Toolbox (Oostenveld et al., 2011), Python 3.0 and IBM SPSS Statistics for Windows, version 24 (IBM Corp., Armonk, N.Y., USA). As mentioned above, the current paper only includes EEG data that do not contain any tACS effects (see Figure 1).

### 2.5.1 | Preprocessing

EEG files with data from electrodes PO3 and PO4 were loaded and cut into 5-s epochs. The main blocks of the extended session included 90-sec data segments (see Figure 1). In order to have sufficiently long data segments, these 90-s data segments were grouped together to yield 180-s data segments for task and rest (thus, blocks 1 and 2, blocks 3 and 4, and blocks 5 and 6 were grouped together). Epochs were sorted into task and rest epochs for each of the five time points in the extended session, or single time point in the other sessions. Note that 'task' data segments were either 290 s long (initial measurement in all four sessions, and the final measurement in the extended session) or 180 s long (the middle three measurements in the extended session), and 'rest' data segments were always 180 s long. Per electrode, we removed epochs with extreme signal variance relative to signal variance in other epochs, based on the inter-quartile range ( $>Q3 + 1.5 \times \text{IQR}$  criterion) (as in de Graaf et al., 2017). Power at frequencies 1–49 Hz was determined by calculating FFTs using Hanning tapers, separately for every time point and each cognitive state (task versus rest). Epochs were zero-padded to 10 s to reach a frequency resolution of .1 Hz and power values were log-transformed (Smulders et al., 2018). We then estimated the 1/f component in each power spectrum by fitting a first-order polynomial to the log-transformed power and

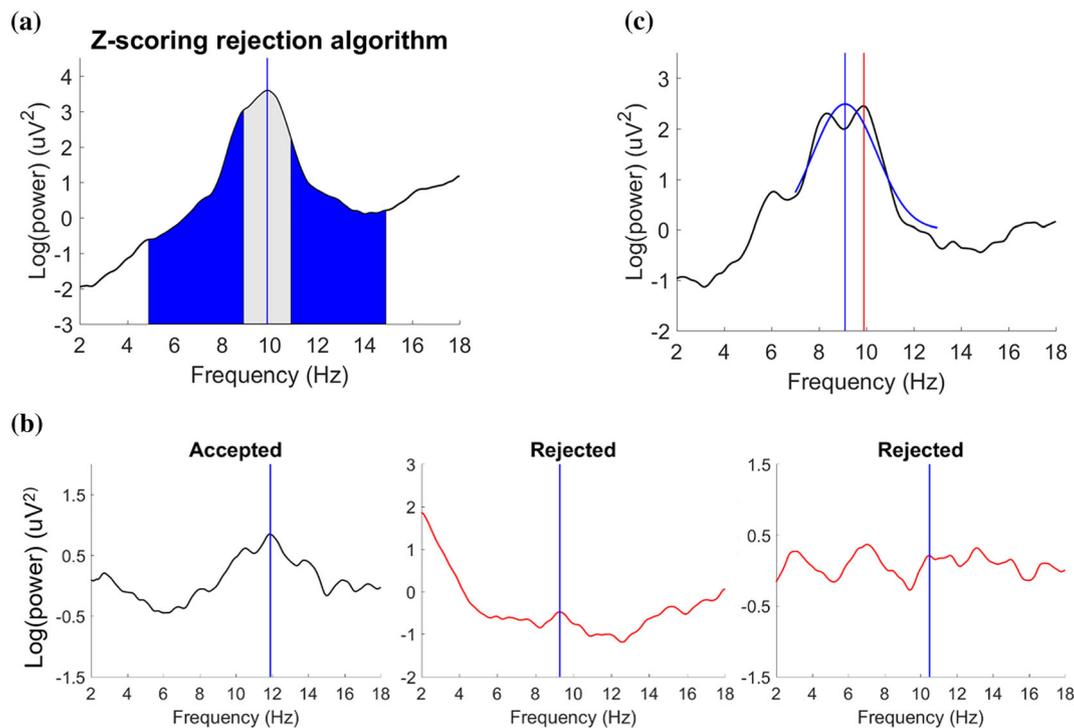
log-transformed frequency axis values (since the log–log-transformed EEG spectrum is approximately linear; Le Van Quyen et al., 2003; Nikulin & Brismar, 2004). We then subtracted this linear fit from each power spectrum. Lastly, we decreased the influence of noise in the power spectra by spectral smoothing them using a Savitzky–Golay filter (SGF frame width: 27, which corresponds to a frequency span of 2.7 Hz, polynomial degree 5) based on parameters suggested by (Corcoran et al., 2018).

## 2.5.2 | Power spectrum rejection algorithm

To answer any research questions related to individual alpha peaks, it is important to exclude those power spectra that do not contain an obvious alpha peak. This could in principle be done by visually inspecting power spectra and manually rejecting those cases without a clear peak. From informal conversations, it seems that ‘subjective peak-picking’ is indeed common practice. However, given the large amount of power spectra in our study

(768 in total, from 24 participants in 2 cognitive states and 2 hemispheres at 8 time points), we instead tried to develop an algorithm for power spectrum rejection. In this algorithm, the MATLAB ‘findpeaks’ function was used to detect the highest peak within the 7- to 13-Hz alpha range (settings: sort peaks in descending order, number of peaks 1, with default settings: minimum peak height -Inf, minimum peak prominence 0, threshold 0). We selected the power spectrum surrounding that highest peak ( $\pm 5$  Hz), and then cut out the frequencies directly surrounding the peak ( $\pm 1$  Hz) while including the peak value itself (see Figure 2a). Then, we z-scored the selected portion (i.e., 83 values) of the power spectrum, and assessed the resulting z-score of the peak. If the z-score of the detected peak was small, this would indicate that the detected peak did not clearly stand out from surrounding values and might therefore not be regarded as a sufficiently convincing (‘real’) peak.

In our case, if the z-scored power at the detected peak frequency was below 1.75, that power spectrum was rejected as not containing an alpha peak, and not



**FIGURE 2** Power spectrum rejection and individual alpha frequency (IAF) estimation. (a) Power spectrum rejection algorithm. The 1/f-removed and spectrally smoothed power spectrum is shown in black. The vertical blue line shows the largest peak as detected by the MATLAB ‘findpeaks’ function. We selected the power spectrum in the range peak  $\pm 5$  Hz (blue area), cut out the frequencies directly surrounding the peak ( $\pm 1$  Hz, grey area), and z-scored the selected portion of the power spectrum. If the z-score of the detected peak was below 1.75, the power spectrum was rejected. (b) Representative examples of accepted and rejected power spectra. Vertical blue lines indicate the largest peak as detected by the MATLAB ‘findpeaks’ function. An accepted power spectrum is shown in black, while rejected power spectra are shown in red. (c) ‘Maximum’ versus ‘Gaussian fit’ method. An example power spectrum is shown in black. The red vertical line is the IAF value as determined by the ‘maximum’ method. The blue vertical line shows the IAF value as determined by the ‘Gaussian fit’ method, and the blue curve shows the fitted Gaussian curve. This power spectrum with two peaks provides an example where the ‘maximum’ and the ‘Gaussian fit’ methods result in different IAF values

included in further analyses. Figure 2b shows examples of accepted and rejected power spectra. Ultimately, our parameters for this ‘filtering algorithm’ were subjective, that is, the selected frequency windows and *z*-score cut-off were tweaked based on visual inspection of accepted versus rejected power spectra for different parameter sets. Likely, other datasets might be better served by other parameters or even other procedures. But since uncertainty about whether or not a power spectrum contains a ‘convincing peak’ are somewhat common, especially when it comes to IAF during task performance, or peaks in other frequency bands, it is interesting that we did find a fully automatic algorithm that worked satisfactorily. Such automatic ‘rejection’ tools might help lab technicians or clinical practitioners decide to accept an individual EEG marker, or rather repeat a measurement to possibly obtain a better result. In our case, parameters were fixed such that the algorithm was relatively strict, in the sense that ambiguous power spectra (i.e., those in which it was not entirely clear whether a peak was present) were rejected. This was to avoid that spurious IAFs, based on unclear peaks, might contaminate our analyses. Still, only few power spectra were rejected (50 in total (~6.5%), task data: 41 (~10.5%) and rest data: 9 (~2%). More details on our rejection algorithm, including more examples of accepted/rejected power spectra, can be found in supporting information S1.

### 2.5.3 | Two methods for estimating individual alpha frequency

Two different methods were used to determine the IAF (see Figure 2c). The ‘maximum’ method involved finding the frequency with maximum power in the alpha band (7–13 Hz) using the ‘findpeaks’ MATLAB function (i.e., largest local maximum; Kemmerer et al., 2020; Wolfgang Klimesch et al., 2003; Zaehle et al., 2010). The ‘Gaussian fit’ method involved fitting a Gaussian curve to the alpha band-limited power spectra (frequencies 7–13 Hz) (Haegens et al., 2014; van Albada & Robinson, 2013) and extracting the centre frequency of that fit. The ‘Gaussian fit’ method allows an estimation of both the location and the width of the IAF peak by using the centre and standard deviation parameters of the Gaussian fit, respectively (Gauch & Chase, 1974). We thus had three dependent variables of interest: IAF as determined by the ‘maximum’ method, IAF as determined by the ‘Gaussian fit’ method, and IAF peak width based on the standard deviation parameter from the fitted Gaussian. Note that analyses on IAF peak width are reported in supporting information S3; in the main text we focus on IAF. We specifically aimed to investigate

the consistency of these different IAF estimates. From a methodological perspective, potential within-subject outlier values are thus of relevance and should not be excluded from the analyses. We therefore did not assess whether within-subject outlier values were present in our data. There were no outlier participants (as defined by a mean score more than 3 standard deviations away from the mean across participants) for any of the dependent variables.

### 2.5.4 | Directly comparing the ‘maximum’ and ‘Gaussian fit’ methods

One of our experimental aims was to assess whether the IAF values obtained by the ‘maximum’ method differed from those obtained by the ‘Gaussian fit’ method. To this aim, we performed simple linear regression analyses and paired *t* tests.

### 2.5.5 | Consistency of individual alpha frequency estimates

Another experimental aim was to investigate the reliability of IAF estimates within and between sessions, for both estimation methods, cognitive states, and hemispheres. To this aim, test–retest reliability was quantified by calculating intra-class correlation coefficients (ICC) (Bravo & Potvin, 1991; Espenhahn et al., 2017; Koo & Li, 2016; McCusker et al., 2020). To assess reliability on a shorter (within-session) timescale, we compared the IAF estimates of the five time points within the extended session. To assess reliability on a longer (between-session) timescale, we compared the IAF estimates from the initial measurements of the four sessions. *F* tests were used to assess whether ICC’s were significantly greater than .75 (indicating good reliability; Koo & Li, 2016). Note that the ICC calculation procedure inherently excludes participants with at least one missing value. Ten participants were excluded, leaving 14 participants for the ICC calculations (one participant had missing values due to a corrupted EEG file, the other nine participants had missing values since some power spectra did not contain a clear alpha peak and were thus rejected). Furthermore, we report within- and between-subject standard deviations to quantify the variability in IAF estimates. Single-subject data and mixed-model analyses are reported in supporting information S2.

In standard practice, IAF is often based on one EEG measurement at the start of a session. It would be useful to see how far subsequent IAF estimations fall from this initial estimation. Per participant, we assessed such

deviations of repeated IAF estimations from their initial estimate. We constructed distributions of these deviations to allow easy visual evaluation of the proportion of IAF estimates that fell within a certain distance (in hertz) from the initial estimate, separately for both cognitive states (rest and task).

## 2.6 | Comparing three ways determining ‘stimulation frequency’

In most experiments, the goal of frequency calibration is to determine a stimulation frequency to use during a clinical protocol or an experimental task. For the latter, if the goal is to ‘entrain’ the task-relevant oscillations, presumably the target stimulation frequency should be the peak frequency during task. This might suggest that the logical approach is to determine IAF during a short task-EEG block. On the other hand, since alpha peaks are most visible at rest and with eyes closed, it makes sense to determine IAF at rest. A third option is just to stimulate everyone at 10 Hz and forego calibration altogether.

Here, we were curious to see how closely the rest-EEG IAF, and simply 10 Hz, would approximate the ‘true’ individual frequency of interest, which was the IAF during our cognitive task. Would a short task-EEG-based IAF better approach that ‘true’ IAF than the commonly used rest-EEG-based IAF? We compared three ways of estimating the ‘true’ IAF during our task: (1) using the same 10-Hz frequency for every participant (i.e., no individual calibration), (2) using the ‘standard practice IAF’, based on an eyes-closed resting state EEG measurement at the start of a session and (3) using the ‘standard practice IAF’ based on a task EEG measurement at the start of a session.

For this analysis, we needed an approximation of the actual, ‘true’, task IAF for every participant. Any one short task-EEG might not yield this IAF sufficiently accurately, so we approximated the ‘true’ task IAF by taking the median IAF from all repeated task measurements of both hemispheres. We then calculated deviations between the three frequency calibration approaches (10 Hz, rest-IAF, task-IAF) and this ‘true’ task-IAF, and constructed probability distributions showing, across participants, how close these approaches brought us to the approximated ‘true’ IAF (i.e., the optimal target frequency for rhythmic stimulation). In order to prevent a bias (i.e., spuriously lower variability) in the comparison between standard practice task IAF and the ‘true’ task IAF, for that particular probability distribution, the calculation of the ‘true’ IAF excluded that standard practice task IAF measurement (although this did not appreciably change the resulting kernel density distributions or conclusions).

## 3 | RESULTS

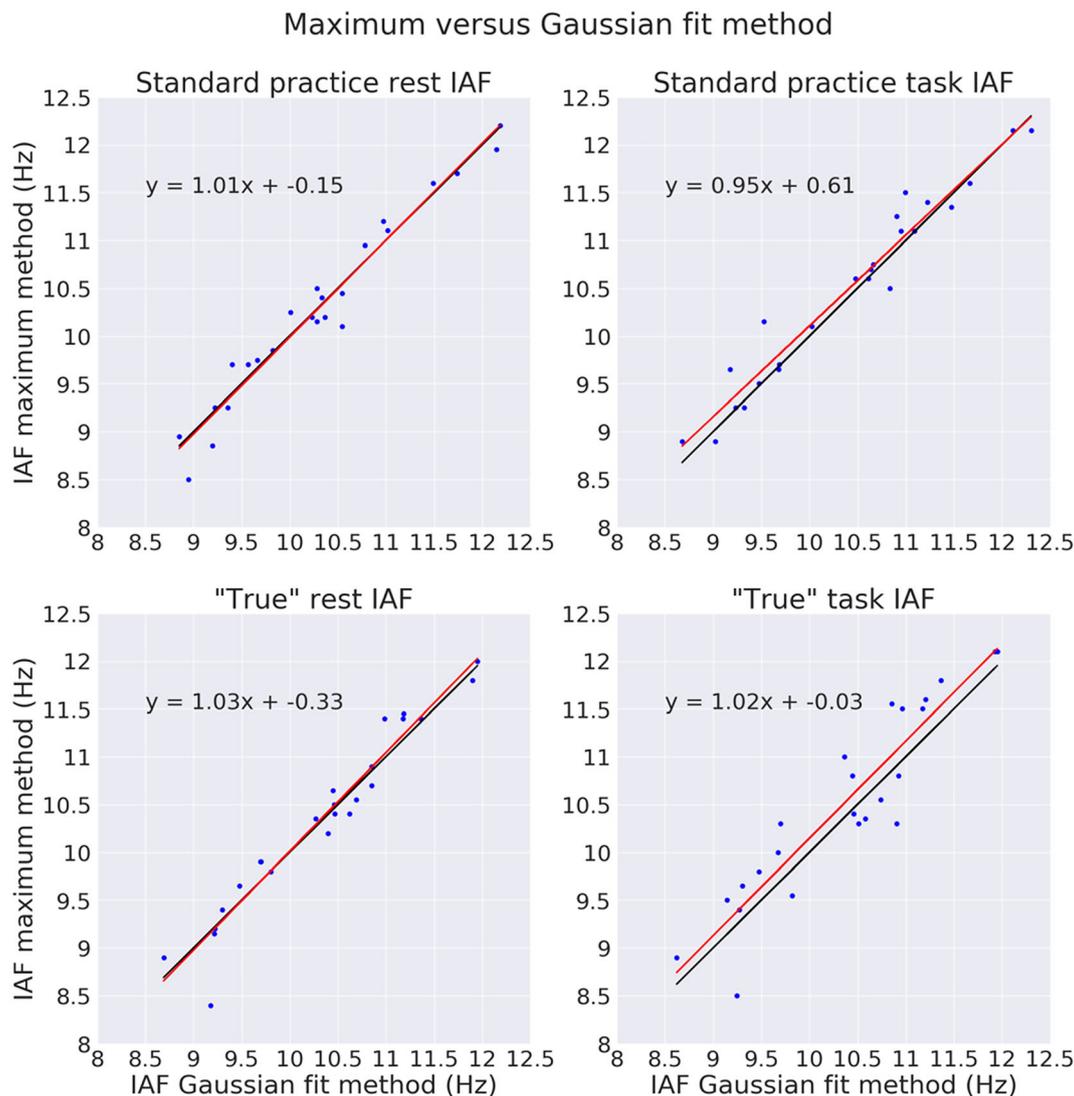
Below, we report the results regarding our three experimental aims. First, we directly compare IAF values as obtained with the ‘maximum’ versus ‘Gaussian fit’ method. Second, we assess the consistency of IAF estimates. Finally, we investigate how much different approaches to determining a ‘stimulation frequency’ deviate from the optimal target frequency for rhythmic stimulation (i.e., the ‘true’ task-IAF for each participant).

### 3.1 | Do the ‘maximum’ and ‘Gaussian fit’ methods lead to similar individual alpha frequency outcomes?

Linear regression analyses and paired samples t-tests showed that the ‘maximum’ and ‘Gaussian fit’ methods mostly led to highly similar IAF values. We assessed this for IAF values as determined during ‘standard practice’ (based on a single, predefined EEG measurement at the start of a session, at rest [standard practice rest IAF] or during task [standard practice task IAF]). We also assessed this for approximated ‘true’ rest- and task-IAF values (approximated by the median of all rest-EEG or task-EEG measurements) (see Figure 3).

The standard practice rest IAF did not significantly differ between the ‘maximum’ or ‘Gaussian fit’ methods ( $t[23] = .20, p = .84$ ), nor did the ‘true’ rest IAF ( $t[23] = .43, p = .67$ ). Also for the task-EEG, standard practice task IAF for the ‘maximum’ method ( $M = 10.49, SD = .98$ ) was not significantly different compared to the ‘Gaussian fit’ method ( $M = 10.41, SD = 1.01$ ) ( $t[23] = 1.87, p = .07$ , two-tailed, uncorrected), neither was ‘true’ task IAF (‘maximum’ method:  $M = 10.51, SD = 1.00$ ; ‘Gaussian fit’ method:  $M = 10.36, SD = .91$ ;  $t[23] = 1.96, p = .06$ , two-sided uncorrected). Thus, even with uncorrected p-values there are no significant differences, and any descriptive differences in IAFs resulting from both methods are, for practical intents and purposes, negligibly small. We thus conclude that the ‘maximum’ and ‘Gaussian fit’ methods, on the whole, yield the same IAFs. The question then becomes how consistently they yield those IAFs across measurements, days, and cognitive states.

The mean IAF was approximately 10.4-Hz across cognitive states and hemispheres, for both the ‘maximum’ method (see Table 1) and the ‘Gaussian fit’ method (see Table 2). This value is close to the standard 10 Hz that is often used in rhythmic stimulation research (de Graaf et al., 2020; Helfrich et al., 2014; Hopfinger et al., 2017; Schuhmann et al., 2019). Interestingly, both methods showed a significant effect of ‘cognitive state’, with IAF



**FIGURE 3** Directly comparing results from the ‘maximum’ and ‘Gaussian fit’ methods. The uppermost panels compare the standard practice rest individual alpha frequency (IAF) (left) and standard practice (task) IAF values resulting from the maximum method with those from the Gaussian method. The lowermost panels compare the “true” (median) rest IAF (left) and the ‘true’ (median) task IAF (right) values between the two methods. Black lines indicate the diagonals (i.e., no difference between maximum and Gaussian method results), red lines indicate least-square regression results. Every dot represents data from one participant

**TABLE 1** Descriptive statistics for the IAF values as determined by the ‘maximum’ method

	Mean	Min	Max	SDwp_ws	SDwp_bs	SD_bp
Rest, left	10.28	8.10	12.60	0.47	0.29	0.99
Rest, right	10.35	8.00	12.40	0.33	0.25	0.98
Task, left	10.42	7.10	12.90	0.38	0.55	1.04
Task, right	10.49	8.30	12.90	0.42	0.44	0.92

*Note:* Mean, minimum, maximum and standard deviations of individual alpha frequency (IAF) values are shown per cognitive state and hemisphere. ‘SDwp\_ws’ refers to standard deviations within-participants, within-session. ‘SDwp\_bs’ refers to standard deviations within-participants, between-sessions. ‘SD\_bp’ refers to standard deviations between participants.

values during task being higher than those during rest (‘maximum’ method:  $M = 10.52$  versus  $M = 10.31$ ,  $SE = .047$ ,  $p < .001$ ; ‘Gaussian fit’ method:  $M = 10.33$

versus  $M = 10.28$ ,  $SE = .021$ ,  $p = .014$ ; for a complete overview of mixed model analyses, see supporting information S2). This finding is in line with previous studies

TABLE 2 Descriptive statistics for the IAF values as determined by the 'Gaussian' fit method

	Mean	Min	Max	SDwp_ws	SDwp_bs	SD_bp
Rest, left	10.29	8.49	12.64	.16	.20	.96
Rest, right	10.31	8.49	12.26	.15	.18	.94
Task, left	10.30	8.49	12.42	.15	.24	.90
Task, right	10.32	8.49	12.19	.14	.25	.88

Note: Mean, minimum, maximum and standard deviations of individual alpha frequency (IAF) values are shown per cognitive state and hemisphere. 'SDwp\_ws' refers to standard deviations within-participants, within-session. 'SDwp\_bs' refers to standard deviations within-participants, between-sessions. 'SD\_bp' refers to standard deviations between participants.

showing that IAF values can increase with task demands (Angelakis et al., 2004; Babu Henry Samuel et al., 2018; Gray & Emmanouil, 2020; Haegens et al., 2014; Hülzdünker et al., 2016). The fact that task IAF can be significantly different from resting state IAF might suggest that it is best to always calibrate a stimulation frequency based on task-EEG. However, the difference in IAF between cognitive states is very small (i.e., .05–.20 Hz). In practical situations, one can reasonably ask whether a resting-state EEG IAF might still be the better choice for individual calibration, if it can be estimated more reliably than a task-EEG IAF. This is an empirical question we address below.

### 3.2 | How consistent are repeated individual alpha frequency estimations?

Above, we concluded that the 'maximum' and 'Gaussian fit' approaches to IAF determination yielded, on the whole, the same results. Moreover, differences between IAFs from task and rest EEG, in the current 'practical' context, were perhaps consistent but also very small. The question then is; how consistent are those IAFs obtained from short EEG measurements?

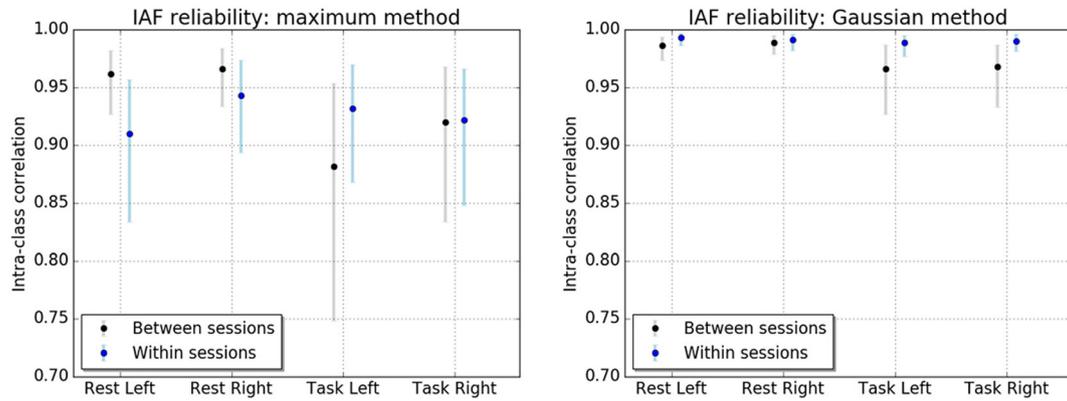
Overall, repeated IAF values seemed stable between sessions and within a session, for both estimation methods, cognitive states, and hemispheres (for single-subject data see Figures S4 and S5). There were some participants with inconsistent estimates, and occasional individual measurements with a seemingly incorrect result (showing as a single, strongly deviating point). As in previous studies, there was substantial variation across individuals, with a standard deviation of approximately 1 Hz between participants (Haegens et al., 2014; W. Klimesch, 1997). Importantly, IAF values were more consistent (i.e., showed lower standard deviations) within individuals compared to between individuals, even more so for the 'Gaussian fit' method (Table 2) compared to the 'maximum' method (Table 1).

Intra-class correlation coefficients (ICCs) offer a quantification of such test–retest reliability (Koo &

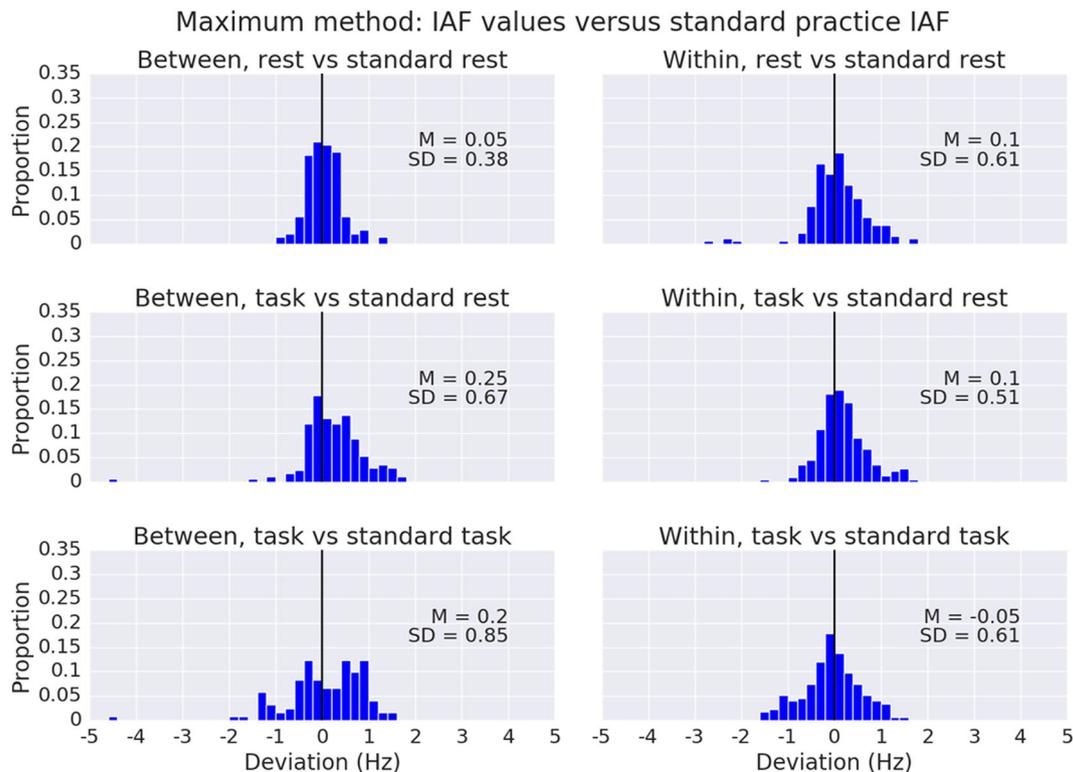
Li, 2016). Here, ICCs were significantly greater than .75 across cognitive states and hemispheres, indicating good reliability ( $p$ 's < .05) (see Figure 4). This was the case for both reliability within-session and between-sessions, and the ICC values we found are in line with previous results (Gudmundsson et al., 2007; Ip et al., 2018; Pöld et al., 2020).

Notably, test–retest reliability was higher for IAF values as obtained with the 'Gaussian fit' method compared to the 'maximum' method. Since alpha power gets suppressed with visual stimulation and task performance, it can become more difficult to detect an IAF in these conditions (Barry et al., 2007; Yamagishi et al., 2008). One might therefore expect that reliability decreases when IAF is measured during task as compared to rest. In our data, this might indeed have been the case for the reliability between sessions, as evidenced by the lower ICC's for task compared to rest data. As mentioned above, if the actual IAF from resting state and task state EEG differ only marginally, as well as between the 'maximum' and 'Gaussian fit' methods, a difference in reliability of the estimate itself might strongly impact the decision to base individual calibration on either a resting or task state EEG, using 'maximum' or 'Gaussian fit' approaches. From Figure 4, it seems that, for the current dataset, a 'Gaussian fit' estimation approach on resting-state EEG is a good option for IAF calibration.

ICC provides a useful 'summary measure' of the reliability of an estimate. For practical purposes, we might still want to evaluate *how* different a deviating measurement actually is. Typically, in rhythmic stimulation studies, IAF is measured once and used throughout the experiment (Cecere et al., 2015; Kemmerer et al., 2020; Mioni et al., 2020; Ronconi et al., 2018, 2020). We therefore compared all repeated IAF measurements with this 'standard practice' IAF value, to assess its representativeness for subsequent sessions (between-session analysis, left column of plots in Figures 5 and 6), or subsequent time points within the same session (within-session analysis, right column of plots in Figures 5 and 6). We also quantified these same deviations of repeated IAF measurements during



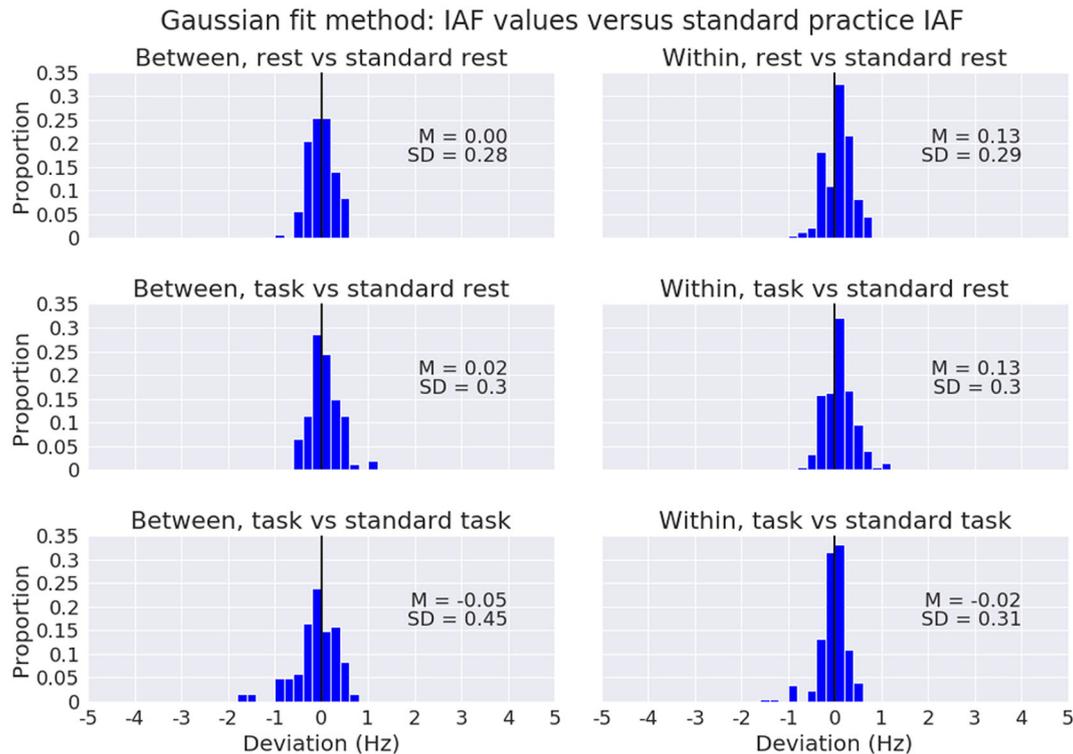
**FIGURE 4** Test-retest reliability of IAF estimates. Left panel: Intra-class correlation coefficients (ICC) based on IAF values as estimated by the ‘maximum’ method. ICC’s (dots) are plotted along with 95% confidence intervals (lines), separately per cognitive state (rest versus task), hemisphere (left versus right) and time interval (within- versus between-sessions). Right panel: Same, but based on IAF values as estimated by the ‘Gaussian fit’ method



**FIGURE 5** Deviations between individual alpha frequency (IAF) values as estimated by the ‘maximum’ method and standard practice IAF. The upper row compares repeated IAF rest measurements for all subjects and both hemispheres to the standard practice rest IAF value. For each subject, the standard practice rest IAF was calculated by averaging the IAF values from the left and right hemisphere, of the initial measurement rest data of the extended session. The middle row compares repeated IAF task measurements for all subjects and both hemispheres to the standard practice rest IAF value. The lowest row compares repeated IAF task measurements for all subjects and both hemispheres to the standard practice task IAF value. For each subject, the standard practice task IAF was calculated by averaging the IAF values from the left and right hemisphere, of the initial measurement task data of the extended session. The left column includes repeated measurements taken during the initial measurements of the four different sessions (between-session comparison). The right column includes repeated measurements taken during the five time points of the extended session (within-session comparison). Black vertical lines indicate zero deviation. M = median, SD = standard deviation

attention task, from the standard practice IAF obtained with resting-state EEG (second row of plots in Figures 5 and 6). And for comparison, even though this seems less

common in practice, the deviations of these repeated task-EEG IAFs from an initial task-EEG IAF (third row of plots in Figures 5 and 6). This allows intuitive



**FIGURE 6** Deviations between repeated IAF measurements as estimated by the ‘Gaussian fit’ method and standard practice IAF. The upper row compares repeated IAF rest measurements for all subjects and both hemispheres to the standard practice rest IAF value. For each subject, the standard practice rest IAF was calculated by averaging the IAF values from the left and right hemisphere, of the initial measurement rest data of the extended session. The middle row compares repeated IAF task measurements for all subjects and both hemispheres to the standard practice rest IAF value. The lowest row compares repeated IAF task measurements for all subjects and both hemispheres to the standard practice task IAF value. For each subject, the standard practice task IAF was calculated by averaging the IAF values from the left and right hemisphere, of the initial measurement task data of the extended session. The between-session comparisons (left column) include data from the initial measurements of the four sessions and the within-session comparisons (right column) include data from the five time points in the extended session. Black vertical lines indicate zero deviation. M = median, SD = standard deviation

assessment of how acceptable the standard practice IAF estimation results are, to determine, on a case by case basis, whether the range of possible deviations would concern us.

Such ‘deviation distributions’ may provide additional information. For instance, any systematic change in peak frequency across cognitive states would be reflected in a horizontal shift of these deviation distributions between the task-rest IAFs relative to the rest-rest IAFs. Or, if the deviation distributions for task-task IAFs are much narrower than the distributions for task-rest IAFs, this would suggest that task-EEG IAF estimations would be more reliable to calibrate rhythmic stimulation protocols to, than estimates of IAF based on resting state EEG as is often done. In these analyses, for every participant, their ‘standard practice’ IAF value was calculated by averaging the IAF values from the left and right hemisphere from the initial measurement in the extended session, separately per cognitive state. Averaging across hemispheres was possible, since ‘hemisphere’ did not affect IAF

estimations (see linear mixed model results in supporting information S2).

For the ‘maximum’ method, repeated IAF rest measurements generally stayed within 1 Hz from the standard practice rest IAF (see Figure 5, row 1). This shows good correspondence of repeated IAF rest measurements over time. There seems to be some bias and higher variability for repeated task measurements when comparing them to the standard practice rest IAF (Figure 5, row 2), but also when comparing them to the standard practice task IAF (Figure 5, row 3). Repeated task measurements thus seem to be less consistent in general, which was summarized by the lower ICC’s during task as compared to rest (see Figure 4, left panel). Deviation histograms for IAF values as obtained with the ‘Gaussian fit’ method are shown in Figure 6. Conclusions were similar, but variability in general is lower than for the ‘maximum’ method, as summarized by the higher ICC’s for the ‘Gaussian fit’ as compared to the ‘maximum’ method in Figure 4. In sum, repeated rest IAF

measurements seem more consistent within participants than repeated task IAF measurements, and the ‘Gaussian fit’ method generally shows more consistent results than the ‘maximum’ method.

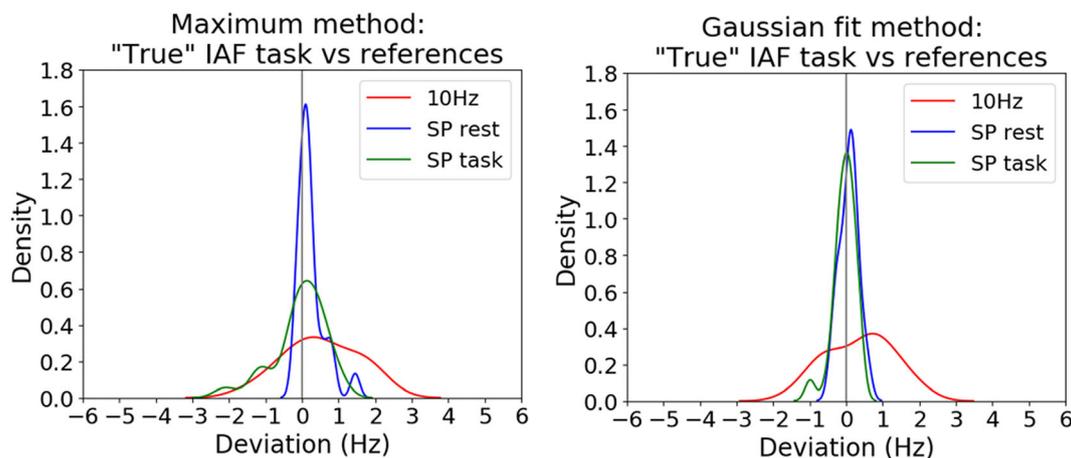
### 3.3 | How best to determine the rhythmic stimulation frequency?

Having quantified and visualized the consistency of repeated estimations of IAF at rest and during task, we can now ask explicitly: what should a researcher/clinician do? In the common scenario, one would prefer to rhythmically stimulate at the individual peak frequency relevant to a certain cognitive state/task. In our example dataset, that means that the goal would be to stimulate at the ‘true’ task IAF. In practice, a researcher has three options for choosing the stimulation frequency: (1) a single frequency used for all participants without M/EEG calibration, (2) an individual frequency based on a short resting-state M/EEG measurement, or (3) an individual frequency based on an M/EEG measurement during task. In our example, these options translate to (1) 10 Hz for every participant, (2) the standard practice rest IAF and (3) the standard practice task IAF. How closely does the result of each of these three options match the target frequency, namely, the ‘true’ IAF during task? We evaluated this across participants and visualize the results in the form of probability curves, showing per procedure the proportion of participants

falling within a certain distance (in Hertz) from the ‘true’ task IAF (see Figure 7). This, ultimately, is the most relevant information when it comes to estimating the ‘success’ of, for instance, an experiment relying on entrainment of that ‘true’ IAF.

For every participant, we calculated the deviation of the three stimulation frequencies (10 Hz, standard practice rest IAF, standard practice task IAF) to the approximated ‘true’ task IAF for both the ‘maximum’ and the ‘Gaussian fit’ method (see ‘Analyses’ section). For both methods, the standard practice rest IAF was more accurate (more often close to the target ‘true’ IAF frequency) than simply using 10 Hz (see Figure 7). This validates the common practice of basing stimulation frequency on a short resting state M/EEG.

Interestingly, in our dataset for our cognitive task, there was a difference between the ‘maximum’ method and the ‘Gaussian fit’ method in terms of how accurately a short *task*-EEG measurement could estimate the ‘true’ task IAF. For the ‘maximum’ method, though there was a small advantage of basing the stimulation frequency on task-IAF instead of using 10 Hz, the IAF as estimated from rest-EEG was much more accurate (as evidenced by the greater/narrower peak in the probability curve). Instead, for the ‘Gaussian fit’ method, the IAF as estimated from rest-EEG and task-EEG were (nearly) equally accurate in estimating the true task IAF. This could be related to the fact that the ‘Gaussian fit’ method can more consistently estimate IAF when power spectra are noisy due to alpha desynchronization (i.e., during task



**FIGURE 7** Kernel density plots comparing three different methods for estimating the true task IAF. Left panel: For every subject, we calculated the deviation between their true (median) task IAF and three different reference values: 10 Hz (red), their standard practice (“SP”) rest IAF (blue), and their standard practice task IAF (green), estimated by the ‘maximum’ method. For the comparison with 10 Hz and SP rest, the true task IAF was calculated by taking the median of *all* repeated task measurements. For the comparison with SP task, the true task IAF was calculated by taking the median of all repeated task measurements except that SP measurement. Kernel density plots were constructed for each of these deviation distributions. Right panel: Same as in the left panel, but for the IAF values as estimated by the ‘Gaussian fit’ method

performance) (Corcoran et al., 2018). In the Discussion, we outline the practical considerations and recommendations that follow from these results.

## 4 | DISCUSSION

In this paper, we aimed to systematically assess the consistency of individual alpha EEG markers on a shorter (within-day) and longer (between-day) timescale, for two cognitive states (eyes closed resting state versus visuospatial attention task performance), estimation methods ('maximum' versus 'Gaussian fit') and hemispheres. We furthermore developed an algorithm to automatically reject power spectra without a clear peak. Results showed that both estimation methods yielded equivalent IAF estimates. Moreover, IAFs were significantly, but only very slightly, different (higher) during an attention task as compared to eyes-closed resting state. We found that IAF was overall reliable, but that the 'Gaussian fit' method yielded more reliable estimates. We also concluded that, by and large, practical 3-min EEG segments from single electrodes were sufficient to obtain these IAFs, and finally that—given these constraints and our particular attention task—a resting-state EEG more often yielded an adequate IAF than task-state EEG for the widely used 'maximum' method of IAF determination.

We first investigated whether the 'maximum' and 'Gaussian fit' estimation methods led to similar IAF values. This is important, because if the methods overall yield the same result, the decision to use one or the other can be based wholly on how reliably each method yields that result. IAF values did not significantly differ between the two estimation methods for rest-EEG data, or for task-EEG data. Though the effect was minimal, both estimation methods led to slightly higher IAF values for task-EEG data compared to rest-EEG data, as in previous studies showing that IAF can increase with mental effort or task demands (Angelakis et al., 2004; Babu Henry Samuel et al., 2018; Gray & Emmanouil, 2020; Haegens et al., 2014; Hülzdünker et al., 2016) and even physical effort (Gutmann et al., 2015). Another study may or may not be in line with this, since they found decreased IAF over 1 h of visual task performance, while mental effort might have either decreased (i.e., task learning or practice effects) or increased (i.e., fatigue) (Benwell et al., 2019). Taken together, we conclude that, for our data, the 'maximum' and 'Gaussian fit' methods provided equivalent IAF estimates.

After confirming this, we set out to quantify the consistency of repeated IAF estimates. Test-retest reliability of IAF was significant within- and between-sessions, for all cognitive states, hemispheres, and estimation methods.

Repeated rest IAF estimations mostly fell within 1 Hz of the standard practice rest IAF for the 'maximum' method, and within .5 Hz for the 'Gaussian fit' method. These results confirm that IAF values can differ across individuals, but are generally stable within an individual over time (Grandy, Werkle-Bergner, Chicherio, Schmiedek, et al., 2013b). Notably, the 'Gaussian fit' method led to more reliable results than the 'maximum' method, especially for data measured during task. This could be due to the fact that alpha power is suppressed during task performance, thereby making it more difficult to reliably detect an alpha peak (Yamagishi et al., 2008). It seems that the 'Gaussian fit' method is less vulnerable to this (Corcoran et al., 2018; Haegens et al., 2014). Of note, the 'Gaussian fit' method yields a different IAF than the 'maximum' method if the power spectrum is strongly skewed, or if there are multiple alpha peaks in the power spectrum (Corcoran et al., 2018; Haegens et al., 2014). The 'Gaussian fit' method can be used to separately estimate those peaks when alpha sub-bands are of interest (Doppelmayr et al., 1998; Klimesch et al., 1997). The latter is related to the idea of multiple coexisting alpha oscillators in the human brain (Benwell et al., 2019; Sokoliuk et al., 2019), possibly becoming more or less dominant depending on current task demands (Doppelmayr et al., 1998; Elshafei et al., 2018; Klimesch et al., 1997; Lobier et al., 2018; Shackman et al., 2010).

In rhythmic stimulation studies, IAF values are often measured during rest and applied during task (Kemmerer et al., 2020; Mioni et al., 2020; Ronconi et al., 2018, 2020). In many cases, it is desirable that the frequency of rhythmic stimulation is optimized to match the individual peak frequency relevant to the task of interest. We showed that using a standard 10-Hz frequency for all participants to estimate this 'true' task IAF was suboptimal, which is thus not recommended if close matching of stimulation frequency to individual task-relevant frequency is the goal. Variability decreased considerably when using a resting state EEG measurement, validating this common practice. Interestingly, only the 'Gaussian fit' method led to similarly consistent results when using a task EEG measurement. For the 'maximum' method, a task EEG measurement was better than using 10 Hz, but not as consistent as a rest EEG measurement. In our data, a resting-state EEG measurement using the 'Gaussian fit' method led to the most consistent results, and this approach is thus recommended. But future studies with other tasks and other frequencies of interest might aim to confirm this result. Similarly, based on our data, if only a task-EEG measurement is available, or required, we would recommend to use the 'Gaussian fit' method, but again future work should assess this for other tasks and frequencies.

There are several limitations to our current explorations. First of all, power spectra obtained from task-EEG data were more likely to be rejected for inclusion in our analyses due to alpha desynchronization (Yamagishi et al., 2008). For experiments that require an EEG measurement during task to obtain an individual peak frequency, this might make it more difficult to obtain a result. Note that this did not have a large influence in our experiment. Although more task data were rejected compared to rest data, only a small number of power spectra was rejected overall. Secondly, the current study was limited to 24 participants, included only one cognitive task, and focused on the alpha band. We should therefore be careful not to overgeneralize our results, and in the future aim to replicate them in a different and larger sample with a variety of cognitive tasks for different frequency bands. Moreover, IAF values during task were calculated by taking into account the EEG signal throughout visuospatial attention task performance, independently of specific task events such as the appearance of cues and targets. There are different ways of estimating the IAF during task performance, which might prove to be more reliable. For instance, perhaps IAF values based on the cue-target interval EEG signal constitute a better estimate of the task-relevant IAF. It would furthermore be worthwhile to assess how consistent IAF values are when based on an eyes open resting state measurement, here our resting state EEG was with eyes closed. It is also noteworthy to mention that our research questions are applicable to those rhythmic stimulation studies that aim to enhance the intrinsic peak frequency (i.e., when deviations between the stimulation frequency and the individual peak frequency should be avoided). There are also rhythmic stimulation studies with another aim, namely, to purposefully use a stimulation frequency that deviates from the dominant frequency, so as to speed up or slow down neuronal oscillations (Cecere et al., 2015). Another potential limitation is that the standard practice task measurement was longer (290 s) than the standard practice rest measurement (180 s). Lastly, of course we cannot actually know the 'true' IAF values, but we can only approximate them by taking the median of the repeated measurements. In our view, these limitations are important to be aware of, but do not invalidate our core results.

Our findings are of interest for personalizing rhythmic stimulation protocols using individual oscillation markers, or more generally for linking such markers to specific cognitive processes. Applications can cover a broad range of domains such as visual perception (Samaha & Postle, 2015), attention (Kemmerer et al., 2020), memory (Cross et al., 2020), language comprehension (Bornkessel et al., 2004), somatosensory

processing (Craddock et al., 2019; Gundlach et al., 2016, 2017) and cross-modal perception (Cecere et al., 2015; Keil & Senkowski, 2017; Migliorati et al., 2019). Our results are furthermore relevant in clinical settings, for instance, in neurofeedback training (Arns et al., 2012; Bazanova & Aftanas, 2010; Nan et al., 2012) but also for individualizing NIBS treatment for depression (Corlier et al., 2019; Garnaat et al., 2019; Leuchter et al., 2017; Roelofs et al., 2020), chronic pain (Ahn et al., 2019; Arendsen et al., 2018; de Vries et al., 2013; Furman et al., 2018) and schizophrenia (Jin et al., 2005, 2012).

## 5 | CONCLUSION

Rhythmic stimulation protocols can be optimized by calibrating the stimulation frequency based on individual M/EEG markers, such as IAF. When estimating such markers using peak detection methods, power spectra that do not contain a clear peak should first be rejected. IAF could be reliably estimated from short EEG measurements, and a 'Gaussian fit' method was more reliable than the traditional 'maximum' method. When selecting the optimal rhythmic stimulation target frequency, simply using a standard frequency for all participants does not seem to be a good approach if the goal is to closely match the task-relevant frequency. Instead, using a short resting-state EEG measurement led to more consistent results, validating a very common practice. A short EEG measurement during task performance led to similarly consistent results for the 'Gaussian fit' method, but less so for the 'maximum' method. Taken together, when calibrating rhythmic stimulation parameters to individual EEG markers, based on the current dataset we recommend a resting-state EEG measurement, along with the 'Gaussian fit' approach. In future work, similar analyses might be applied to other tasks and frequency ranges.

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## CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

## AUTHOR CONTRIBUTIONS

SJ: conceptualization, investigation, formal analysis, visualization, writing—original draft, writing—review and

editing, funding acquisition, project administrationAS: conceptualization, writing–review and editing, supervision, funding acquisitionSO: conceptualization, software/methodology, writing–review and editingTG: conceptualization, investigation, software/methodology, writing–original draft, writing–review and editing, supervision, funding acquisition.

## PEER REVIEW

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## DATA AVAILABILITY STATEMENT

All data and analysis code will be made available upon manuscript acceptance via the following link (<https://doi.org/10.34894/R3QWKH>).

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