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Authors
Ociepka, Micha_
Jelito, Damian

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Automatic Identification and Classification of Individual Alpha Frequency

Damian Jelito[1] & Michał Ociepka (michal.ociepka@uj.edu.pl)[2]
[1]Institute of Mathematics, Jagiellonian University, Kraków, Poland
[2]Center for Cognitive Science, Jagiellonian University, Kraków, Poland

Abstract

Individual alpha frequency (IAF) is a key marker of stable differences in neural processing speed and attention, and a critical parameter for frequency-tuned interventions such as transcranial alternating current stimulation (tACS), yet it is still often estimated with fragile, peak-picking heuristics. We propose a machine-learning algorithm that automates IAF detection in EEG data by (i) attenuating the 1/f background via exponential detrending, (ii) localizing candidate alpha peaks, and (iii) classifying them with a support vector machine using morphological features. On a longitudinal dataset (N = 204 young adults; frontal and parietal ROIs, two sessions), we benchmarked the method against consensus human ratings and the Philistine algorithm. The new approach halved localization error (MSE = 0.18 vs. 0.44) and reached 94% accuracy in detecting the presence of an IAF peak, while providing a continuous certainty measure. This enables expert-level, confidence-weighted IAF estimates for individualized cognitive and clinical protocols.

Keywords: Individual alpha frequency (IAF); EEG; Machine learning; Automated peak detection

Introduction

Neural oscillations represent a fundamental mechanism for coordinating activity across distributed brain networks. Rather than being mere byproducts of neural firing, these rhythmic fluctuations in excitability are increasingly recognized as active agents in cognitive processing. In particular, the alpha band (8–13 Hz) has been linked to a wide array of functions, including inhibitory control (Klimesch et al., 2007), attentional gating (Jensen & Mazaheri, 2010), and the temporal parsing of sensory information (VanRullen, 2016). By providing a structured temporal framework for neural communication, oscillations offer a bridge between physiological signals and cognitive theory, allowing researchers to move beyond descriptive accounts toward mechanistic models of brain function.

Crucially, these oscillatory phenomena are not uniform across individuals. People differ in the dominant frequencies, amplitudes, and spatial distributions of their rhythms, as well as in how these rhythms change over time. Such individual oscillatory profiles likely reflect stable properties of neural circuits, shaped by anatomical, developmental, and genetic factors. For example, the individual alpha frequency (IAF) – the peak frequency within the alpha band – varies reliably between individuals and shows considerable trait-like stability across sessions. Moreover, it has been linked to inter-individual differences in processing speed and attentional performance (Klimesch, 1999; Ociepka et al., 2022).

The relevance of individual oscillatory profiles becomes particularly evident in causal interventions. Techniques such as transcranial Alternating Current Stimulation (tACS) aim to modulate endogenous rhythms by applying weak, externally controlled oscillatory electric fields. Converging evidence suggests that the efficacy and specificity of such interventions depend critically on frequency tuning: stimulation tends to be more effective when it matches or closely approximates the individual's dominant endogenous rhythm (Herrmann et al., 2013), rather than a generic canonical frequency (e.g., a fixed 10 Hz for all participants). In clinical and translational contexts, such as trials targeting cognitive enhancement or symptom reduction, even subtle frequency mismatches may contribute to heterogeneous or null effects (Vossen et al., 2015). Precise characterization of individual peak frequencies is therefore not merely a technical detail, but a prerequisite for robust causal tests of oscillatory theories and for optimizing frequency-specific interventions (Ociepka et al., 2024, 2025).

Despite this need, the reliable estimation of individual peak frequencies from EEG remains challenging. Widely used methods such as simple peak-picking or the Philistine algorithm (Corcoran et al., 2018) operate directly on the raw spectrum and are vulnerable to split peaks, noise, and strong 1/f backgrounds. More advanced parameterization approaches like FOOOF (Donoghue et al., 2020) explicitly model the aperiodic component, but recent work shows that FOOOF estimates can be highly sensitive to analytic choices and specific spectral features, leading to reduced reliability and substantial parameterization errors (Gerster et al., 2022, Kałamała et al. 2025), underscoring the need for more robust tools for IAF estimation. Importantly, none of these existing methods provide a quantitative certainty measure for the detected peak, leaving researchers without explicit guidance on the reliability of individual IAF estimates—a critical limitation when making decisions about participant inclusion or stimulation parameters in frequency-specific interventions.

Here, we introduce a machine-learning based algorithm for automated IAF detection in resting-state EEG that (i) attenuates the 1/f background, (ii) localizes candidate alpha peaks, and (iii) uses supervised classification to distinguish genuine IAF peaks from noise and artefacts. Beyond

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improving raw detection performance, the algorithm yields a continuous certainty measure for each estimated IAF, enabling researchers to explicitly quantify confidence in frequency assignments. This is particularly relevant for individualized cognitive paradigms and tACS protocols, where decisions about inclusion, exclusion, or stimulation frequency are often made on the basis of ambiguous or noisy spectra.

The primary aim of the present study is to validate this algorithm against both established automated methods and expert human ratings. Using a large longitudinal resting-state EEG dataset (N = 204), we assess the algorithm's (1) agreement with a human-consensus reference standard and (2) performance relative to the Philistine baseline, using a participant-level train-test split across longitudinal recordings. Through these comparisons, we seek to evaluate whether our approach can provide a reliable tool for characterizing individual oscillatory profiles and for supporting individualized, frequency-specific cognitive and clinical research.

Methodology

Dataset

Participants The dataset comes from a longitudinal cognitive training study involving 204 young adults from the general population (97 females; age M=24.05, SD=4.0, range 18–35). All participants provided written informed consent and received monetary compensation for their participation. The data were anonymized, and all procedures were approved by the local ethics committee and conformed to the Declaration of Helsinki. The training study, from which the present dataset is drawn, is currently in the publication process.

Study Participants took part in two laboratory sessions separated by an interval of approximately 12–15 weeks. Each session included a battery of cognitive tasks and resting-state EEG recordings. In the present work, we focused exclusively on eyes-open resting-state EEG. Specifically, we analyzed two 3 min eyes-open resting-state blocks per session, yielding four resting-state recordings per participant in total. Task-related data, training procedures, and group assignments from the original study were disregarded, as the present work focuses solely on the characterization of individual oscillatory profiles and the validation of the proposed IAF estimation algorithm.

EEG Data EEG was recorded at 512 Hz from 64 electrodes (BioSemi ActiveTwo) and preprocessed using EEGLab (Delorme & Makeig, 2004), including common average re-referencing, 1 Hz high-pass, and 48 Hz low pass. Ocular artifacts were corrected via the recursive least squares method (He, Wilson, & Russell, 2004), and the signal was segmented into 3-s epochs. Finally, epochs exceeding ±80 μV were removed through semi-automatic and manual screening to ensure high-quality data for subsequent analyses. After preprocessing and quality control, 167 participants with all four resting-state recordings remained in the final dataset.

IAF calculation IAF was estimated separately for two regions of interest (ROIs): a frontal ROI (AF3, AFz, AF4, F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4) and a parietal ROI (CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, P4, PO3, POz, PO4). For each artifact-free 3-s epoch, EEG was averaged within each ROI, and power spectral density (PSD) was computed using a multitaper method (Slepian, 1978). PSDs were then averaged across epochs to obtain one spectrum per ROI, participant, and session.

For each spectrum, IAF was determined in two ways. First, we applied the Philistine algorithm (Corcoran et al., 2018) with a 7–14 Hz alpha band, yielding one automated IAF estimate per ROI. Second, each spectrum was independently rated by three trained observers, who visually identified the dominant alpha peak and reported its frequency. The expert-consensus baseline was defined as the median of these ratings, an approach that effectively prioritized the majority estimate in cases of divergence (e.g., if two experts identified a peak at 9.5 Hz and one at 11 Hz, the 9.5 Hz value was retained). The reliability of these labels was very high, with an average pairwise agreement of 96.7% between experts (within a 0.5 Hz tolerance) and a mean standard deviation across ratings of only 0.168 Hz. This multi-expert consensus provides a robust reference standard for model training and evaluation, while acknowledging the inherent subjectivity of IAF identification from EEG power spectra. This procedure provided, for every ROI, both an automated (Philistine) and a consensus human IAF for subsequent comparisons.

Data characteristics From a signal analysis point of view, IAF is the frequency corresponding to a visible peak in the PSD which could be localized within the alpha frequency range (Figure 1a). However, there are several practical challenges in determination of IAFs. In particular, one needs to deal with the fact that PSD is dominated by the pink noise signal proportional to (the exponent of) the inversed frequency (Figure 1b). Next, no peak in the alpha band may be present (Figure 1c), or the data may contain multiple peaks (Figure 1d), sometimes spread over a broader frequency range (Figure 1e). Such spectra with multiple plausible alpha-range peaks may be an important source of localization errors in the current implementation. Finally, the data may be very noisy (Figure 1f). These challenges need to be addressed in algorithm development.

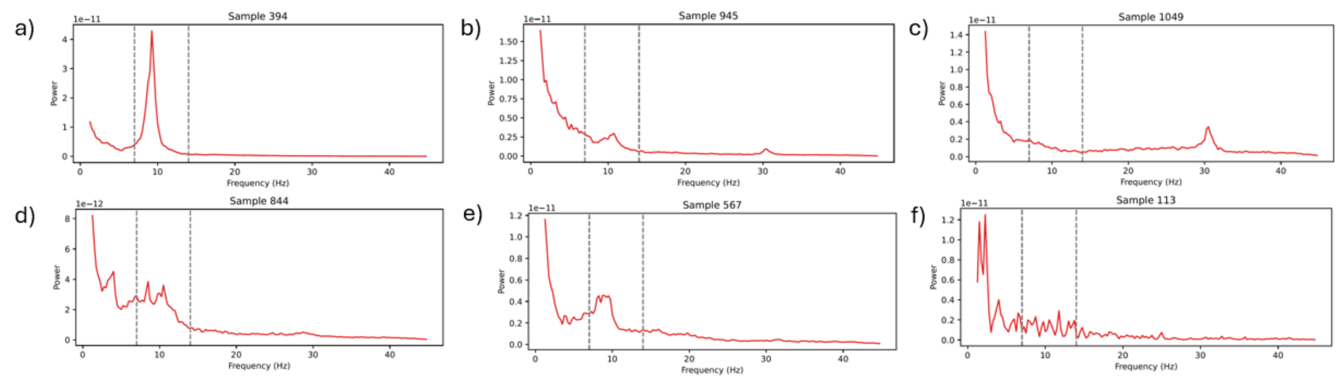

Figure 1: Various examples of observed PSD: a) clear distinct peak in the data; b) dominance of the aperiodic 1/f component c) no visible peaks in the alpha range, d) two peaks in the alpha range, e) fuzzed peaks in the alpha range, f) severely noisy data.

Proposed algorithm for IAF Detection

The proposed IAF detection algorithm implements a machine learning-based approach for automated identification of individual alpha frequency peaks in PSD data. The methodology integrates signal preprocessing to mitigate background noise, automated peak localization to identify candidate alpha peaks, morphological feature extraction to characterize peak profiles, and supervised classification to discriminate genuine IAFs from spurious peaks or artifacts.

The algorithmic framework employs a hierarchical detection strategy: initial localization of candidate peaks within the alpha frequency range via local maxima detection, followed by evaluation of peak morphological characteristics using a trained classifier. This approach addresses the limitation of simple thresholding methods, which frequently yield multiple false positives in noisy EEG spectra, by leveraging learned patterns from expert-annotated data to distinguish genuine IAF peaks. Practically, the proposed algorithm provides a model-based certainty score derived from the SVM classification output. This score reflects classifier confidence that a candidate peak represents a genuine IAF, rather than a calibrated probability or an error bound on the estimated frequency. Notably, no certainty measure is available for the classical Philistine algorithm.

The train-test split was performed at the participant level to prevent data leakage across sessions or ROIs. Training dataset consisted of 1013 observations (with IAFs detected by the human observers in 872 samples), each consisted of PSD recorded with 0.25 Hz resolution which corresponds to 189 measurements covering 1-48 Hz range. Separate testing datasets consisted of 245 observations (with 212 positive examples). Each observation was marked by human experts for the presence and localization of the peaks. Of overall 1258 observations, human-labeled IAFs were present in 1084 examples, which constitute 86% of the full dataset.

The proposed algorithm consists of several steps:

Preprocessing for Pink Noise Attenuation Exponential detrending is applied to remove the characteristic 1/f "pink noise" background prevalent in EEG spectra. An exponential regression model of the form $a \cdot f^b$ is fitted to frequencies outside the alpha frequency range (7-14 Hz) and subtracted from the original spectrum (Figure 2a). The parameters a and b are found by the least squares regression (with the intercept) of the log power against the log frequency in the underlying range.

Localized Peak Detection Candidate peaks are identified within an extended alpha frequency range (6.5-14.5 Hz) using a sliding window algorithm that detects local maxima where the central frequency bin exceeds neighboring bins within a 3-bin context window (Figure 2b).

Morphological Feature Extraction For each detected peak, a 35-frequency-bin window (17 bins on either side, i.e. candidate peak location ± 4.25 Hz) is extracted, centered on the peak location (Figure 2c). Normalized increment features are computed by calculating differences between consecutive frequency bins and scaling by the peak amplitude range (Figure 2d). This feature set captures the characteristic sharp, narrow profile of authentic IAF peaks in contrast to the broader, flatter morphology of artifactual peaks.

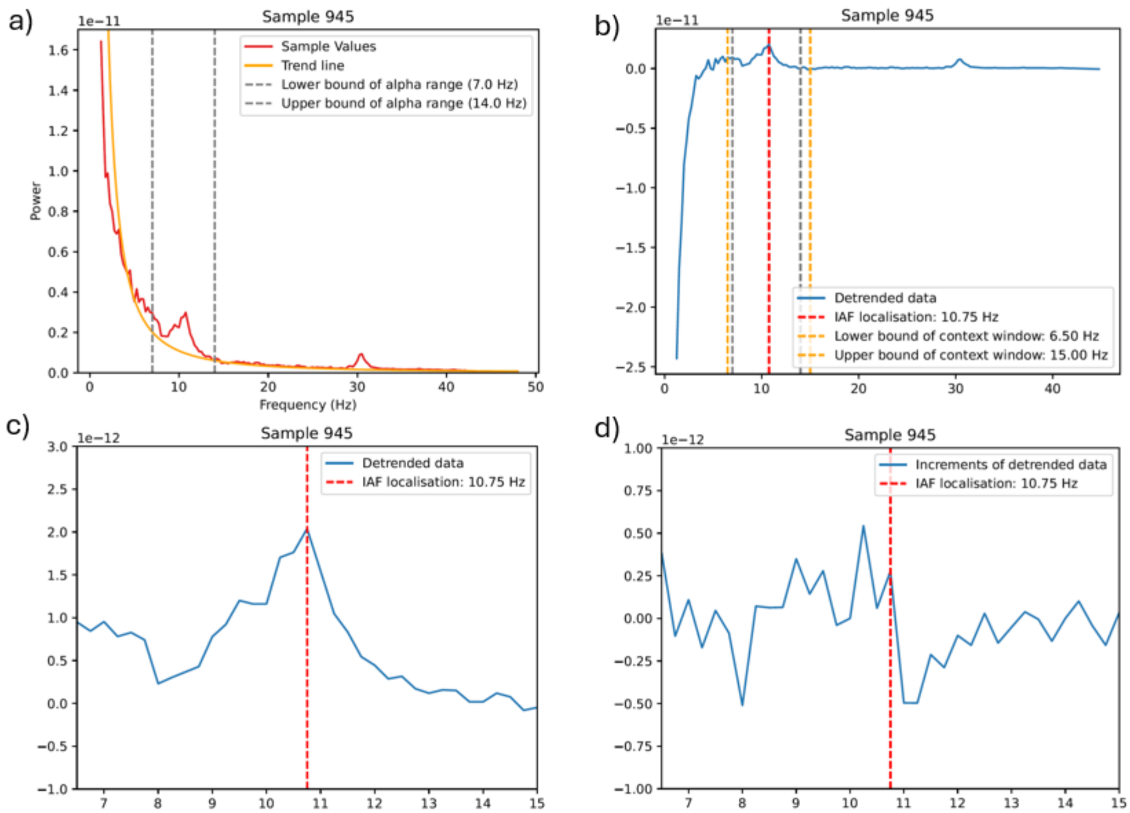

Figure 2: Illustration of the proposed algorithm steps. a) Exponential trend line (orange curve) is fitted to the original signal (red line) for the frequencies outside the interval 7-14 Hz (dashed gray lines). b) Based on the detrended data (blue line), candidate IAF is localized (dashed red line). Then, the context window is defined as the candidate IAF ± 4.25 Hz (dashed yellow line). c) For the presented data, context window is the interval [6.5, 15] Hz with the candidate IAF 10.75 Hz. d) Support Vector Machine classification algorithm is trained on the scaled increments of detrended data in the context window. For the presented data, the peak is classified as IAF with a model-based certainty of 98.5%.

Supervised Classification via Support Vector Machine A support vector machine (SVM) with radial basis function kernel ($C = 1$, $\gamma = 0.01$) was trained on expert-annotated data to classify detected peaks as either true IAFs or false positives. Model hyperparameters were optimized in the cross-validation procedure via grid search to balance sensitivity and specificity for the specific EEG dataset. The decision threshold was adjusted with the help of the receiver operating characteristic (ROC) curve and set at the level of 0.74 (Figure 3c).

All the computations were performed in Python 3.13.7. Data preprocessing and Support Vector Machine classifier were based on pandas 2.3.2, numpy 2.3.2, and scikit-learn 1.7.1 implementation. The code and the pre-trained model (in SKOPS format) are available at OSF repository: osf.io/2dxbf/overview?view_only=84b1d11a21564d599fd5ec0a4af42d7d.

The permanent GitHub repository is publicly available at: github.com/QuodEratDemonstrandum/IAF_identification.

The repository includes end-to-end scripts to reproduce results and performance metrics reported in this study. The algorithm expects PSD vectors covering the 1–48 Hz range with 0.25 Hz frequency resolution as input, allowing for possible deployment in independent EEG pipelines.

Results

Performance of the proposed algorithm was assessed with the help of a separate testing dataset and compared against the results of the Philistine algorithm. First, the localization of the detected IAFs was studied for observations where human experts detected the presence of the peaks. The proposed algorithm achieved the mean squared error (MSE) equal to 0.18 Hz^2 (or simply 0.18) while the Philistine MSE was 0.44 indicating a better performance of the new method (Figure 3a). Also, the biggest difference between the true and the predicted IAF localization could be linked with alleged presence of multiple peaks (Figure 3b).

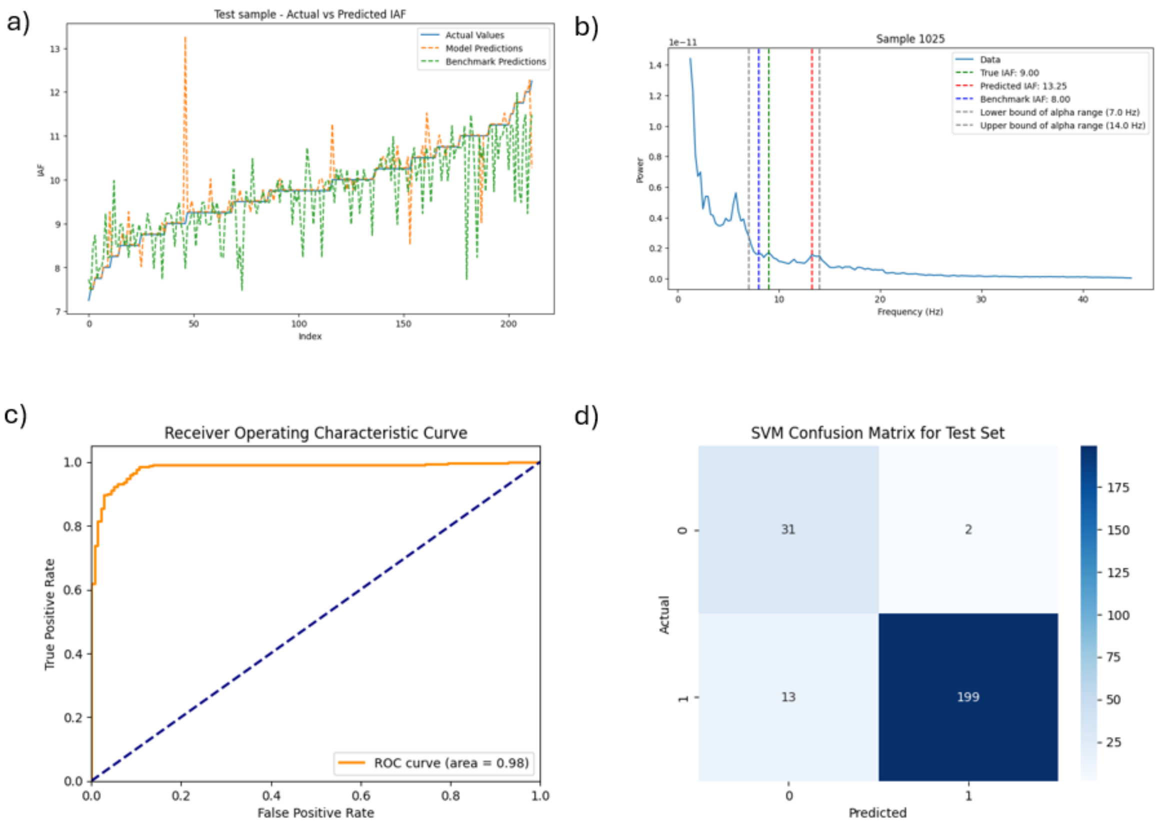

Figure 3: Analysis of the results. a) Actual (blue line), predicted by the proposed model (dashed orange line), and the benechmark Philistine algorithm (dashedgreen line) localization of IAF for the subset of the testing sample, where human experts detected the presence of the peaks. The values are sorted by the actual IAF localization. b) Sample values with the biggest absolute difference between the actual (dashed blue line) and the predicted (dashed red line) localization of the IAF. The presence of two peaks (around 9.0 and 13.25 Hz) could be conjectured. c) Receiver operating characteristic curve for the proposed classification algorithm. d) Confusion matrix for the proposed algorithm based on the testing sample.

Next, the classification component of the proposed algorithm was confronted with the human detection of the presence of IAFs. The model achieved 94% classification accuracy on held-out test data, with a good balance between sensitivity and specificity (Figure 3d and Table 1). Because Philistine does not classify IAF presence or provide a certainty measure, assigning all detected peaks as genuine IAFs would correspond to the 86% positive base rate in the present dataset. Thus, the classification results should be interpreted as an additional capability of the proposed algorithm rather than as a direct head-to-head classification comparison with Philistine. Overall, it could be argued that the proposed algorithm demonstrates robust performance on frontal and parietal resting-state EEG data, enabling automated IAF detection that approximates expert-level accuracy while substantially reducing manual annotation time.

	precision	recall	f1-score	support
No IAF	0.70	0.94	0.81	33
IAF	0.99	0.94	0.96	212
accuracy			0.94	245
macro avg	0.85	0.94	0.88	245
weighted avg	0.95	0.94	0.94	245

Table 1: Classification report for the proposed model based on the testing set. Precision denotes the proportion of predicted cases in a class that were correct, recall denotes the proportion of true cases in a class that were detected, F1-score is the harmonic mean of precision and recall, and support is the number of true cases in each class.

Discussion

The proposed algorithm provides automated IAF estimation that closely approximates expert consensus and adds a certainty measure, addressing a practical bottleneck in individualized cognitive neuroscience. Since IAF reflects stable traits in processing speed and attention, precise and confidence-weighted quantification is essential for linking neural oscillations to cognitive theory.

For tACS and other frequency-tuned interventions, our tool may support more accurate participant-specific frequency selection than generic protocols. By flagging ambiguous spectra through certainty scores, the algorithm may help researchers make more transparent inclusion and targeting decisions, potentially reducing one source of heterogeneity in neuromodulation studies. For cognitive studies, this helps separate two practical decisions: which individual frequency should be used and whether the spectrum is reliable enough for downstream analysis.

At the same time, our validation is limited to resting-state eyes-open data from young adults, and future work is needed to establish how well these certainty-weighted IAF estimates generalize to task-related paradigms, older or clinical populations, and other frequency bands. The present validation is also limited by the use of Philistine as the primary automated benchmark; broader comparisons with spectral parameterization approaches such as FOOOF/specparam remain an important direction for future work. Nevertheless, the present results suggest that robust, automated characterization of individual oscillatory profiles is feasible and may facilitate better-controlled tests of oscillatory theories in cognitive research.

As a future work, one could try to extend the algorithm to analyze the presence of multiple peaks in PSD. In fact, once the candidate peaks are localized, the normalized spectrum could be used as the input of the already trained classification algorithm and the certainty measure for each candidate peak will be computed. Still, in order to validate this approach, one should first collect a dataset with human-labeled multiple peaks which is not available at the moment. Thus, this remains a subject for future investigation.

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