A Robust Method for the Individual Alpha Frequency Detection in EEG

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Abstract: We present a method to determine the individual alpha (α) peak frequency (IAF) of EEG segments. The algorithm uses information over previous time-windows to determine the current IAF. First, the $1/f$ trend of the spectrum is estimated by an iterative curve-fitting procedure and then removed from the spectrum. Finally, local maxima are identified in the corrected spectrum. If an α peak is ambiguous, i.e. when several peaks are observed due to different physiological α activations or to a noisy spectral activity, the algorithm selects the most probable one based on the peaks detected in previous time windows. This approach allows the detection of small α activities and ensures a precise and stable detection of the α peak, without offline analysis or a prior estimation of a reference spectrum. This is particularly important for real-time applications like α-based neurofeedback for which a precise and stable feedback is required for an efficient learning.

1 INTRODUCTION

Alpha (α) waves, discovered by Hans Berger in 1929 (Berger, 1929), constitute the dominant oscillatory electroencephalographic activity (EEG) of awake humans in resting state. Nevertheless, the α frequency band may display several spectral microstructures with different characteristics, corresponding to different activities such as the α spindles, or the mu, sigma, tau and occipital α rhythms. Although several methods have been developed to characterize α power changes associated with various brain states or neurological diseases, the robust detection of these different α activities is a challenging research area.

A standard method to detect α peaks (P_α) in EEG spectrum consists in finding the frequency at which the power spectral density (PSD) is maximal within the α frequency range of 8-13 Hz (αB) (Klimesch, 1999; Kropotov, 2016). However, this approach may incorrectly detect the lower bound of αB (Corcoran et al., 2018) if a clear peak is not present (Anokhin and Vogel, 1996) or a PSD too noisy.

In the literature, it is common to compute the α center of gravity (αCG) in αB or in the individual α frequency (IAF) range when several α peaks are observed (Klimesch et al., 1990; Klimesch, 1997; Chiang et al., 2011). However, finding the individual α band (IAB) is not so trivial and several off-line strategies exist, as those proposed by Klimesch (Klimesch et al., 1990; Klimesch, 1999).

Other methods, like the peak attenuation (Posthuma et al., 2001) and the channel reactivity based (CRB) (Goljahani et al., 2012) methods, can be used to define this IAB. These methods imply a PSD estimates comparison in αB between two conditions. However, the α waves behavior is not always as expected and if both PSD estimates share a part of the same spectral information in αB, IAB will be shorten (Corcoran et al., 2018).

Curve-fitting techniques have also been used to find the P_α(s) and their characteristics like the frequency. Chiang and colleagues for instance (Chiang et al., 2008), proposed a parametric method to automate the detection and the characterization of the P_α(s) with a Gaussian function, fine-tuned across several electrodes.

Corcoran and colleagues (Corcoran et al., 2018) has recently developed a non-parametric technique to detect the IAF and the IAB. They define the peaks in αB as the downward going zero crossings points in the first derivative of the PSD. If several peaks are detected, either a dominant peak is highlighted after several strategies based on a PSD fitted regression model and a set threshold, or the αCG is computed af-

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ter an estimation of the IAB from the first derivative of the PSD. This procedure is applied on each electrode and the frequency of P_α or the αCG are averaged across them.

To estimate the IAF, some authors first remove the $1/f$ trend of the log-transformed PSD - estimated by a least-squares method or an $Af^{-\lambda}$ model fitting (Caplan et al., 2001; Whitten et al., 2011) - before detecting the local maxima in αB (Haegens et al., 2014; Dickinson et al., 2018). This procedure reduces the bias in the detection of local maxima within the α range. Then, a Gaussian curve fitting procedure is used to find the P_α(s) in αB.

The method presented here is a combination of some of these previous approaches. It is designed to detect the IAF in real-time. The originality of our approach is that, instead of only considering the information of other electrodes to fine-tune the detection of the IAF, the frequency values of the P_α detected in previous time-windows are used to determine the IAF at the current window. In this way, the IAF is more stable across the successive time-windows. This is useful for real-time application like α-based neurofeedback for which the stability of the targeted activity is required for an efficient learning.

To explain our algorithm, we first present how the spectral trend is estimated to correct the PSD and obtain a primary estimation of the P_α by a local maxima detection. Then, we describe how we determine the α frequency if P_α is ambiguous - when several peaks are detected in αB either due to a noisy spectral activity, or several α activations (Chiang et al., 2011). In this case, we take into account the frequency of the P_αs detected in the previous time-windows. Finally, to illustrate the stability of the detection, we compare the α frequency distribution obtained by our method (*RTadapt-IAF*) in three subjects, with those obtained from a more standard one (*max-IAF*) (Klimesch, 1999). Percentage of EEG data for which a frequency is detected as the IAF is also compared for several data lengths.

2 METHODS

2.1 Spectral Trend Estimation

The PSD is firstly estimated with the Welch's method between 2 and 30Hz, on EEG segments of L seconds with an overlap of 50%. Then, the PSD is log-transformed (log-PSD) and smoothed iteratively until a stable model of spectral trend (PSDtrend) is reached. At the 1^{st} iteration, PSDtrend is equal to the log-PSD.

PSDtrend at the iteration i (PSDtrend_i) is fit in log-log coordinates to a $Af^{-\lambda}$ model (M_i) by a linear regression, where A, λ and f are the parameters of the model and the frequencies, respectively (Whitten et al., 2011; Gao et al., 2017). At each iteration i, all the frequency bins (binF) with a PSDtrend_i value higher than the expected M_i are set to the M_i value, and i is incremented. PSDtrend_{i+1} is finally estimated by fitting PSDtrend_i in log-log coordinates to the new model M_{i+1}.

At each iteration i, the root mean square error (*errFit*) between PSDtrend_i and PSDtrend_{i-1} is computed. If this error has a difference with the previous computed error lower than 0.05, PSDtrend_{i-1} is considered as the background spectral trend (PSDtrend_f).

The main steps of the proposed estimation procedure are summarized in Algorithm 1.

Algorithm 1: Background spectral trend estimation procedure in *RTadapt-IAF*.

Input: PSDtrend_0, the log-transformation of the estimate of the signal s segmented on L-second segments with an overlap of 50%, between 2 and 30 Hz.
Output: PSDtrend_f, the background spectral trend estimate.

```
Fit PSDtrend_0 with a Af^(-λ) model (M_0) in log-log coordinates
Initialize errFit_i(i = 0) to Infinity
Set breakProc to False
while breakProc is False do
    for each frequency bin b of binF do
        if PSDtrend_i(b) > M_i(b) then
            PSDtrend_i(b) = M_i(b)
        end if
    end for
    i = i + 1
    Fit PSDtrend_i with a M_i model in log-log coordinates
    Compute the root mean square error (errFit_i) between PSDtrend_i and PSDtrend_(i-1)
    if abs(errFit_(i-1) - errFit_i) ⩽ 0.05 then
        PSDtrend_f = PSDtrend_(i-1)
        breakProc = True
    end if
end while
return PSDtrend_f
```

2.2 First Estimation of the Alpha Activity

The $1/f$ trend of the spectrum is removed from the log-PSD by subtracting PSDtrend_f from the log-PSD. We note this difference *d0*. All the negative values of *d0* are set to the values of PSDtrend_f. A first estimation of P_α(s) is obtained by detecting the local maxima between 6 Hz ($B1_\alpha$) and 13 Hz ($B2_\alpha$). We extended this research to 6 Hz to be able to capture lower α activity. The local maxima are detected as the downward going zero crossings points in the first derivative of *d0*, called *d1* (Corcoran et al., 2018). The ensemble of these local maxima $\{C\}$ are considered as the candidate P_α(s).

2.3 Determination of the IAF

For each EEG segment, three situations can be observed:

1. *No peak:* No local maxima were detected on the PSD. It means that no α peak is detected. As a consequence, the IAF is not computed.
2. *Singular peak:* The only candidate peak detected on the PSD is considered as the individual α peak. The IAF is obtained from this peak and kept for the analysis of successive windows in a vector (*histFreq*). *histFreq* can contain the IAF values from different channels.
3. *Two peaks or more:* If *histFreq* contains several points ($\geqslant$ N), the number of candidate peaks is first reduced $\{C_s\}$ by (1^{st} criteria):

$$\{C_s\} = \{C(k)\} / \ \forall k \in binF, binF(k) \in [\mu - \sigma : \mu + \sigma] \quad (1)$$

where μ and σ are the averaged value and the standard deviation of *histFreq*, respectivley.

If only one peak is retained, its frequency is considered as the more probable IAF based on the history of IAFs. Otherwise, a 2^{nd} criteria is used to discriminate a predominant peak.

The 2^{nd} criteria searches the predominant peak based on the peaks' amplitudes as proposed in (Corcoran et al., 2018). Considering $P_\alpha 1$ and $P_\alpha 2$, the highest (respectively the second highest) P_αs in terms of power, IAF is the frequency of $P_\alpha 1$ if:

$$P_\alpha 1 \ x \ ThP > P_\alpha 2 \quad (2)$$

where ThP denotes the minimal proportion of the power of $P_\alpha 1$, which must exceed the power of all other P_αs values.

This 2^{nd} criteria is used to discriminate a predominant peak from $\{C\}$ if none of the candidate peaks respect the 1^{st} criteria, or if the size of vector *histFreq* is not high enough. The 2^{nd} criteria can be also applied on the subset $\{C_s\}$ of the candidate peaks selected by the 1^{st} criteria.

If none of these criteria is sufficient to discriminate a peak from the others, we estimate the IAF by computing the αCG between frequency bounds (*f1* and *f2*) defined by:

$$f1 = \underset{f \in binF}{argmax}(\{B1_\alpha - 2; \underset{B1_\alpha - 2 < g < Lf_\alpha}{argmin}(d0(g) > 0)\}) \quad (3)$$

$$f2 = \underset{f \in binF}{argmin}(\{\underset{Hf_\alpha < g < B2_\alpha + 2}{argmax}(d0(g) > 0); B2_\alpha + 2\}) \quad (4)$$

with:
Lf_α, the lowest frequency among $\{C\}$ or $\{C_s\}$,
Hf_α, the highest frequency among $\{C\}$ or $\{C_s\}$.

The main steps of the proposed IAF determination procedure are summarized in Fig. 1.

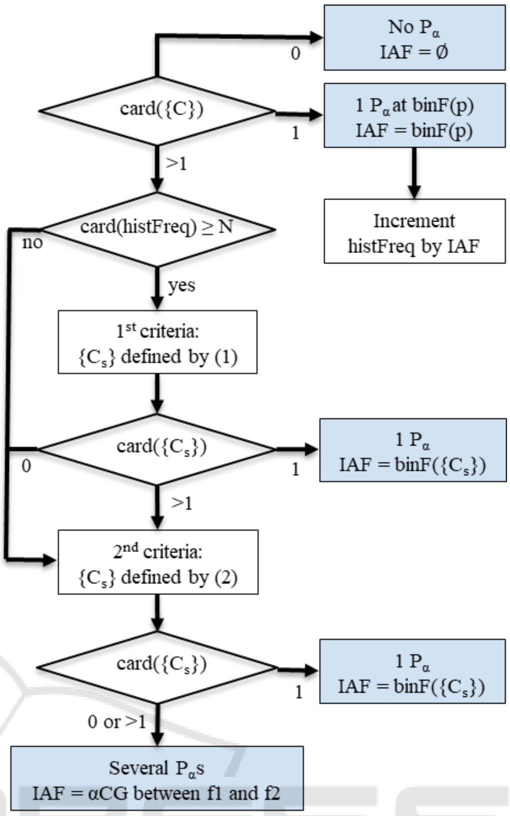

Figure 1: Schema representing the main steps of the IAF estimation procedure in *RTadapt-IAF*.

3 RESULTS ON REAL DATA

To illustrate the detection of the IAF with the proposed method, we used a dataset recorded at 500Hz sampling rate with surface electrodes (Acticap, Brain-Products GmbH, Germany) for $N = 32$ scalp positions according to the international 10-20 system. Reference and ground electrodes are localized in A1 and A2 positions respectively. This dataset consists in EEG data of different subjects who where instructed

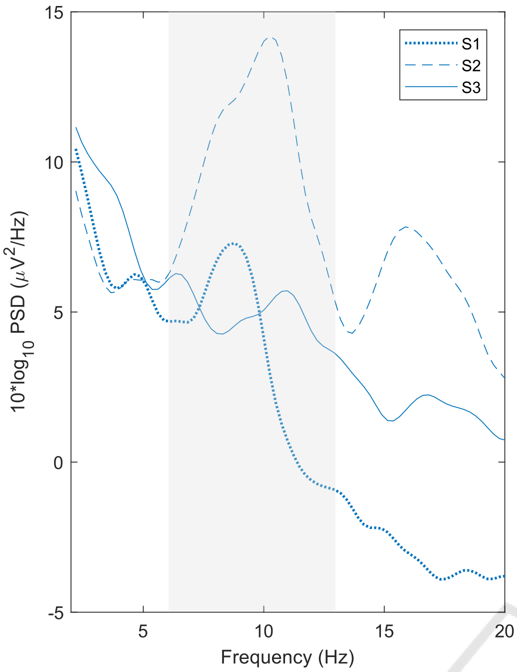

Figure 2: Log-PSD of *S1*, *S2* and *S3* between 2 and 20 Hz. The gray area highlights the frequency range where *RTadapt-IAF* searches the IAF (between $B1_\alpha$ and $B1_\alpha$).

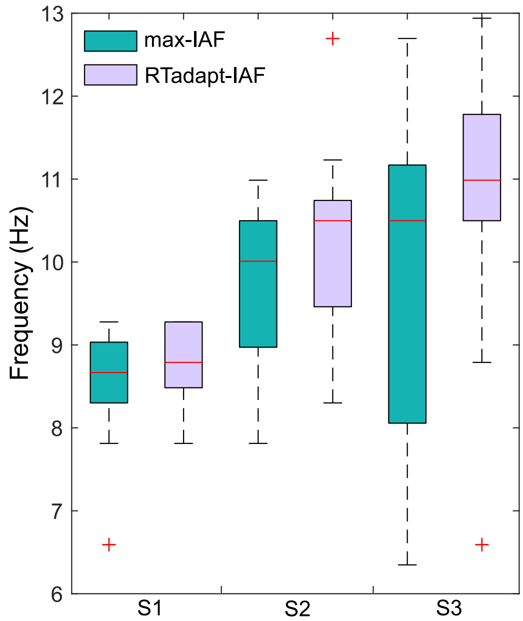

Figure 3: Boxplots of the IAFs detected on 4-second segments for three different subjects S_i. The boxplots for *max-IAF* are presented in green. Those for *RTadapt-IAF* are presented in purple.

to be in resting but alert state, with their eyes closed during one minute. According to the declaration of Helsinki, written informed consent was obtained from subjects after explanation of the study, which was approved by the ethical committee CPP-IDF-VI of Paris (no 2016-A00626-45).

From this dataset, we selected activities located in P3 from three subjects (*S1*, *S2* and *S3*) with very deifferent α peaks (see Fig. 2). Each 1-minute recordings were down-sampled at $Fs = 250$ Hz and preprocessed with a notch filter and a bandpass filter (cutoff frequencies 2-30 Hz) to remove power-line (50/60 Hz) interferences and slow drifts. Then, they are segmented in different windows lengths ranging from $L = 2$ to $L = 60$ s. This allows to compare the IAF detected for different lengths of segmented data. The results of *RTadapt-IAF* are compared with those of *max-IAF* (Klimesch, 1999), which simply detects the frequency at the maximum value of the PSD between 6 and 13 Hz.

To assess the stability of the IAF detection, we first compare the distributions of IAF values detected in the PSD of 4-second segments for each of the approaches (see Fig. 3). The median value of the IAF for each subject is respectively around 8.7 Hz (*S1*), 10.25 Hz (*S2*) and 10.75 Hz (*S3*). Notice that for *S1* and *S2* the distributions are similar with both methods. The distribution of the IAF in *S3* displays, however, a larger variability with *max-IAF* compared to *RTadapt-IAF*. This can be explained by the difficulty of *max-IAF* to correctly detect P_α if its amplitude is lower than that observed at the lower bound of the α band. Because *RTadapt-IAF* is based on an history of the previous detected α peaks, ambiguous or small P_α can be highlighted. We can also observe that, the median value of the IAF for each subject is slightly higher with the proposed approach compared to *max-IAF*. As mentioned above, *max-IAF* is based on a simple research of the maximum value in the uncorrected PSD, whereas *RTadapt-IAF* detects the local maxima in a trend-corrected PSD. Fig. 3 shows that the variability of values obtained with *RTadapt-IAF* is, in average, lower than the values estimated by the *max-IAF* procedure.

To complete these results, we study the percentage of segments of L-seconds of duration for which a given frequency is detected as the IAF in the three subjects (see Fig. 4). For each method, we evaluate if we are able to visually discriminate the frequencies reported in Fig. 2 and 3. We use different window lengths L to assess the effect of data length on the efficiency of each method to detect the IAF in the PSD.

With *max-IAF*, three frequencies are always detected, independently of the segment size: just after 6 Hz, around 9 Hz and around 10.5 Hz. Notice that, because of the $1/f$ behavior of EEG spectrum, the detected values around 6 Hz may simply correspond to

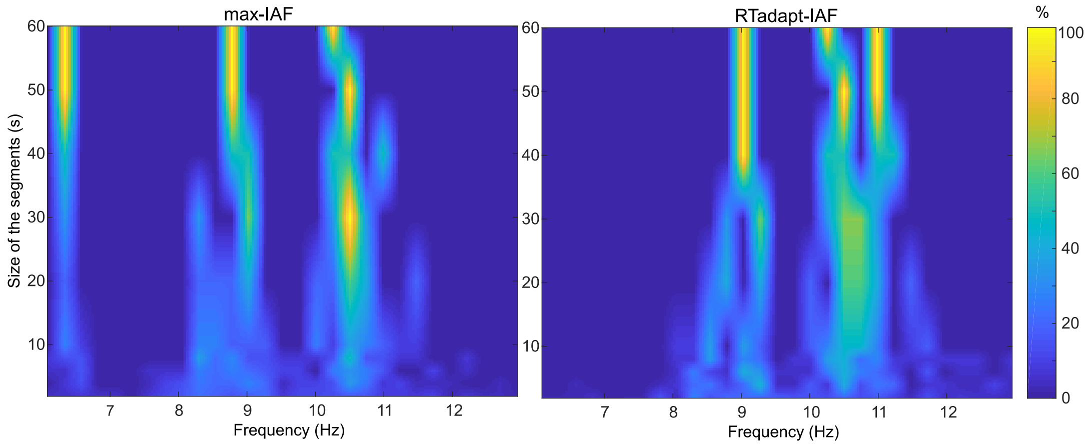

Figure 4: Percentage of segments for which a frequency is detected as the IAF over all the three subjects. These results are presented for *max-IAF* (left plot) and *RTadapt-IAF* (right plot).

the lower bound of the α band, whose power is generally larger than the power of P_α. The second frequency around 9 Hz is detected by the two methods. From results in Fig. 2 and 3, we can suppose that this frequency represents the IAF of *S1*.

Finally, we also notice that *max-IAF* is not able to distinguish the IAFs observed at 10.25 and 10.75 Hz in *S2* and *S3*. In contrast, *RTadapt-IAF* clearly discriminates both frequencies in segmented data longer than 32 s. These two patterns are around 10.25 Hz and 10.8 Hz which can be associated to the *S2*'s and *S3*'s IAF (based on Fig. 2 and 3). From these results we can conclude that, for long data segments (larger than 32 s), the proposed approach is able to better discriminate two IAFs relatively closed. Nevertheless, *RTadapt-IAF* is also able to compensate the $1/\mathrm{f}$ trend and detect small values of P_α, even for very short data lengths (2 s).

4 DISCUSSION AND CONCLUSION

In this work we have presented a method to characterize, from EEG segments, the frequency of the α peak. The iterative procedure allows to obtain an accurate estimate of the $1/\mathrm{f}$ trend of the spectrum. This estimate is sensitive to small α activations. Interestingly, if P_α displays several peaks, our approach can determine the most confident P_α. In particular, the P_α values detected in successive time windows are used to define the most probable frequency for a given EEG segment. Instead of using the previous detected IAF values of the current channel, those from each channel can be used to improve the robustness of the detection.

The stability of the IAF detection in the proposed method was illustrated by comparing the distribution of the IAFs obtained with *RTadapt-IAF* and with the standard procedure (*max-IAF*) (Klimesch, 1999) for three different subjects with the observation of the spectrum of each subject (Fig. 2). These preliminary results, with some subjects, show that, compared with our approach, the IAFs detected with *max-IAF* yields a larger variability. Furthermore, if P_α values are too small, *max-IAF* tends to detect the lower α bound as an α peak (because of the global $1/f$ behavior of the spectrum).

To evaluate the ability of our approach to distinguish IAFs as a function of the data length, we have computed the percentage of segments for which a frequency is detected as the IAF across several subjects. These preliminary results show that close values of IAFs can be clearly distinguished in EEG segments longer than 32 s. A fine spectral resolution may be an important criteria in the detection of the IAF in particular to differentiate several α activations and/or follow the evolution of the IAF across the time. Our approach proposes a way to compute a more stable IAF that does not require neither an offline analysis nor a prior estimation of a reference spectrum. This may be particularly useful in α-based on-line applications like neurofeedback, for which a detection of small α synchronisation events is necessary to give an accurate feedback to the user. It is also important to consider the stability of this IAF to ensure successful leaning during the neurofeedback task.

To go further in the real-time characterisation of P_α, it could be interesting to compute the time-varying evolution of other features as the amplitude, the width and the area of the individual α peak. *RTadapt-IAF* needs to be compared with other methods of IAF detection with more subjects. Nevertheless, our preliminary results suggest an interesting approach to robustly detect the IAF, even in real-time and for small α activations.

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