Robust, automatic real-time monitoring of the time course of the individual alpha frequency in the time and frequency domain

Heinrich Garn, Senior Member, IEEE, Markus Waser, Manuel Lechner, Matthias Dorfer, Dieter Grossegger

Abstract— We analyzed three different approaches to automatic real-time monitoring of the time course of individual alpha frequencies (IAFs) of the human electro-encephalograms. Fast Fourier transform and wavelet transform were compared to classical automated cycle counting in the time domain. With fast Fourier and wavelet transform, test results with healthy adult subjects, demented and psychiatric patients revealed typical short-term variations of the instantaneous IAFs of about \pm 2 Hz. When cycles were counted in the time domain, however, variations of only ± 1 Hz were recorded. Thus, IAF measurement in the time domain appears to be particularly suitable. We also observed long-term IAF trends that typically amounted to about \pm 0.5 to \pm 1.0 Hz. Therefore, our hypothesis is that the IAF does not constitute an intra-individual constant but varies with time and cognitive state. Our fully automatic real-time signal-processing procedure includes pre-processing for artifact detection and for localization of segments with synchronized alpha oscillations where the IAF should preferably be measured.

I. INTRODUCTION

A. Significance of the alpha rhythm

What is known as the alpha rhythm is a significant feature of the human electro-encephalogram (EEG). It appears strongest in the eyes-closed relaxed state and is suppressed by attention or mental effort. Upper alpha oscillations in thalamo-cortical feedback loops represent search and retrieval processes in (semantic) long-term memory. The basic assumption is that the faster the frequency of EEG oscillations will be, the more integrated and interconnected these feedback loops become with other brain areas [1]. As a result, this feature has been widely used in medical diagnoses (e.g., mental disorders, dementia, ...), functional analysis and brain research. Real-time monitoring of the individual alpha frequency (IAF) is also needed, e.g., for neurofeedback scenarios, since in certain paradigms the time course of the IAF is the relevant feedback parameter.

The IAF increases from childhood to adulthood, reaching a value of between 9.5 and 11.5 Hertz, and decreases with age and progressive mental deterioration. It varies between anterior (slower) and posterior (faster) recording sites. Both the inter- and the intra-individual differences are considerable. Alpha power has been reported to be positively correlated to cognitive performance and brain maturity [2, 3].

The IAF is widely used as a quantitative marker to characterize the individual alpha rhythm. Some studies have shown positive correlations between the IAF value and cognitive performance [4, 5], but literature has also reported the opposite, asserting that "smarter brains do not seem to run faster" [6].

B. Definition of the individual alpha frequency

IAF serves to define the frequency of maximum power and to derive the corner frequencies of the alpha rhythm within the EEG spectrum. In clinical practice, the number of cycles per second of the oscillation within an alpha burst (synchronized alpha waves) is counted manually on the screen to determine an approximate characteristic frequency. The following IAF definitions are used (Fig. 1):

- a) "Peak frequency" method: frequency of relative maximum power in the power density spectrum, usually determined by FFT [1].
- b) "Center of gravity" methods:
 - Center of gravity of the power density spectrum computed for a specific frequency band [1]. Fixed corner frequencies are chosen for this frequency band, e.g., 7 13 Hz, irrespective of the spectrum's individual characteristics.
 - Center of gravity computed for individually set limits, e.g., between the ascending edge and descending edge of the alpha band of the power density spectrum [1], or between the alpha-theta transition (TF) frequency (to be determined manually during cognitive paradigms when theta synchronizes and alpha desynchronizes for a cognitive task) and TF + 5 Hz.
 - "Channel reactivity based" method (CRB): center of gravity of the resting power density spectrum in the alpha responsiveness region, the frequency range in which the eyes-open alpha spectrum exceeds the resting spectrum [7].
- c) Most reactive frequency: the frequency with maximum suppression by opening of the eyes [7]. The method requires manual data processing.

Research supported by ZIT Zentrum für Innovation und Technologie, Vienna, Austria, project ID: 560131.

H. Garn, M. Waser, M. Lechner and M. Dorfer are with AIT Austrian Institute of Technology GmbH, Vienna, Austria (corresponding author: <u>heinrich.garn@ait.ac.at</u>, ++43-5-0550-4103).

D. Grossegger is with B.E.S.T. Medical Systems, Dr. Grossegger und Drbal GmbH, Vienna, Austria.



Figure 1. Schematic sample Fourier spectrum with synchronized (blue) and desynchronized (green, dotted) alpha band

d) Model fitting: A model of Gaussian peaks (parameters: amplitudes, central frequencies, widths) is numerically fitted over relative maxima of the Fourier spectrum [8]. Alternatives are to use inverted U-shape or other curvefitting techniques to represent the alpha peak [9, 10].

II. REAL-TIME MEASUREMENT OF THE INSTANTANEOUS INDIVIDUAL ALPHA FREQUENCY

In this section, we will compare three different methods for automatic IAF measurement: The standard method to estimate signal spectra from a sequence of sample points is to calculate what is called the periodogram by fast Fourier transformation (FFT, implemented in, e.g., Matlab). Wavelet transform represents an alternative, in which a mother wavelet in different scales and translations rather than harmonic oscillations is used as base function. Established, classical clinical practice is to count the number of periods of the oscillation in an alpha burst within one second. We investigated the applicability of these methods for real-time scenarios.

A. Periodograms calculated by Fourier transformation Methods based on FFT face the following issues:

- Fourier transform is defined for stationary signals. EEGs are hardly stationary.
- Fourier transform requires continuous integration periods of at least 4 seconds of artifact-free EEG to yield a meaningful frequency resolution (0.25 Hz) of the periodogram. Alpha bursts of a length that allows such a frequency resolution are rare.
- The typical length of alpha bursts is under two seconds. There are minima in amplitude between consecutive bursts (Fig. 2a). Within these minima, the instantaneous frequency deviated from the instantaneous frequency within a burst. It is somewhat lower in most cases, but can be higher as well. Furthermore, the IAF can vary from one burst to the next. If we extend the integration over a minimum, or over more than one burst, the wellknown "double peaks" appear in the periodogram.
- The pointwise variance of the periodogram is asymptotically as large as the value of the true spectral density (which is unknown!) at each frequency (Fig. 2b). Furthermore, the values of the periodogram at consecutive frequencies are independent of each other. For this rea-

son, periodograms always show a significant "ripple" in the trace. This effect does not reflect the true spectral density, but can be explained by the above-referenced basic mathematical phenomena.

• Leakage of window functions leads to additional errors (minor compared to the mentioned variances).

When the average is calculated for a number of periods, the uncertainties and ripple amplitudes decrease. However, averaging is not applicable to real-time applications, because the reference to the instantaneous state would be lost.

B. Time-frequency maps

Wavelet methods [11] allow spectral characteristics to change over time. Wavelet transform allows us to predefine the desired frequency points to analyze the alpha spectrum of short EEG sequences. This is particularly useful with alpha bursts typically lasting between 1 and 3 seconds. Even with 2-second EEG signals it is still possible to reach a frequency resolution of 0.1 Hz within the alpha frequency range.

Figure 2c shows a time-frequency map calculated on the basis of a complex Morlet wavelet. Compared to FFT, wavelet transform has the advantage of retrieving spectral information for both frequency and time. This is possible because wavelets can be described by finite functions, whereas harmonic oscillations continue infinitely.

Nevertheless, the calculated wavelet spectra should be treated with caution, as the frequencies in Figure 2c show pseudo-frequencies rather than real frequencies in unit Hz. This is due to the fact that a wavelet is identified with a single center frequency corresponding to a harmonic wave fitted to the wavelet.

Time frequency maps are able to visualize the approximate spectral information of a periodogram in addition to localization in time.

C. Measurement of the instantaneous individual alpha frequency in the time domain

Significant alpha oscillations are usually called "synchronized" as they are assumed to originate from groups of neurons spiking in-phase. In de-synchronized status, no specific frequency components stand out of the spectrum. When synchronized, alpha rhythms are clearly observable in the timedomain signal. The inverse of one oscillation period determines the instantaneous IAF as shown in Fig. 2a.

The classical counting method that is applied in many clinics can easily be automated. To make this evaluation more robust, the signal is first band pass filtered over an extended alpha range, e.g., between 7 and 12 Hertz (Fig. 2d). The corner frequencies of the filter exert some influence on the counting result as shown in Table 1. This influence is significant in desynchronized periods, but is somewhat less in a synchronized period (alpha burst) like the one shown in Fig. 2. We can use this method to cross-check results drawn from time-frequency maps.

TABLE I. INFLUENCE OF BAND LIMITS ON MEASURED IAF

Corner frequencies [Hz]	IAF [Hz] desynchronized	IAF [Hz] synchronized	
6-11	7.91	8.78	
7-12	8.58	8.94	
8-13	9.03	9.10	

D. Real-time determination of the synchronized or de-synchronized status of the alpha rhythm

"Synchronized status" refers to epochs comprising strong frequency components in the alpha range ("rhythmic oscillations"). Various methods have been described to determine rhythmic oscillations, e.g., [12]. IAF values are primarily meaningful when synchronized. This status corresponds to alpha power levels that stand out from the background spectrum shown in Fig. 1.

We applied the following criteria to determine whether the signal includes a significant alpha burst present:

- Comparison of the original time-domain signal with its alpha band-pass-filtered pendant through signal amplitudes: We used a Chebyshev type II filter to extract the 7–12 Hz component of the signal. By opting for his broad range, we made sure that the individual alpha band was included. The arithmetic means of the amplitudes of both signals are determined within one second. If the ratio of the averaged amplitudes of the filtered signal to the original signal exceeds a threshold of between 0.4 and 0.5, the rhythm is considered significant.
- Comparison of the original time-domain signal with its alpha band-pass-filtered pendant via cross correlation: Cross correlation is calculated over 1 second. If the correlation coefficient exceeds a threshold of between 0.70 and 0.75, the rhythm is considered significant.

Both criteria must be met to ascertain a significant alpha rhythm (Fig. 3).

III. AUTOMATIC DETECTION OF ARTIFACTS IN REAL-TIME

We applied a combination of the following criteria:

- Eye movements and blinks: A combination of excessive amplitudes and the relative power ratio of the delta band to the 0.5-30 Hz band are used for detection.
- Motion or poor electrode contacts: Two criteria are applied in parallel: Excessive amplitudes, first derivative.

Thresholds are continuously adapted in a data-driven approach.

- Continual muscle activity: This does not influence the alpha spectrum, but can influence the detection mechanisms mentioned above. Therefore, relative beta power is additionally monitored.
- Heart beat: detection of synchronous, repetitive peaks that occur in (usually several) EEG-channels.

a) Typical time-domain signal comprising consecutive alpha bursts



 b) Periodogram of the EEG in a), determined by FFT (blue line), Hanning window; estimated "true" spectrum (dashed) and corresponding variances (shown as error bars at three frequencies)



c) Time-frequency map calculated by continuous wavelet transformation with a complex Morlet (bandwidth 3, center frequency 7) wavelet. The integration time is 2 seconds which leads to a pseudo-frequency resolution of 0.1 Hz within a range from 7.5 Hz to 12 Hz. Black lines: maximum values of the two largest peaks with mean values next to them.



d) Time domain signal and 7-12 Hz band pass filtered signal



Figure 2. Representation of a 2-second EEG epoch comprising strong alpha waves. Grey: original signal. Black: filtered signal.

IV. AUTOMATIC PROCEDURE FOR REAL-TIME MONITORING

On-line monitoring of the IAF time course includes the following repetitive process for each sampling point:



1. detection of artifacts in the monitored EEG channels;

If there is no artifact:

- evaluation to determine whether there is a significant, undisturbed synchronized alpha rhythm;
- 3. measurement of the time course of the instantaneous IAF;
- 4. smoothing to determine the long-term trend in the IAF.

We implemented the automatic procedure described above in C-code to run on standard PC platforms. It contained a graphical user interface where all parameters including criteria for artifacts can be observed in real time.

V. RESULTS OF AUTOMATIC IAF MEASUREMENTS

The methods described above have been tested on EEG data from 10 cognitively normal adult subjects, 10 elderly, demented subjects, and 10 psychiatric patients. Data have been taken out of the databases of B.E.S.T. Medical Systems and AIT from previous clinical studies. All EEGs had been recorded in resting state, using alpha-trace digitalEEG recording stations. Analyses were made on EEG data of P3, P4, O1 and O2. Artifact detection was also tested on all 19 sites of the international 10/20 system.

Fig. 4 shows an example of results from one subject for the three methods described in section II. Integration / counting periods were set to two seconds. We observed two kinds of variations:

- (i) short-term variations (see also Fig. 2d, where the two consecutive bursts exhibit different mean frequencies), causing changes of the IAF within less than one second:
 - FFT and wavelet: synchronized: 2.5 Hz peak-to-peak, de-synchronized: 4 Hz peak-to-peak;
 - Time-domain cycle counting: synchronized: 1 Hz peak-to-peak, de-synchronized: 2 Hz peak-to-peak;
- (ii) long-term variations indicating the IAF trend with time and presumably also with the cognitive state (green curves in Fig. 4):
 - FFT and wavelet: 1.8 Hz peak-to-peak;
 - Time-domain cycle counting: 1.2 Hz peak-to-peak.



Figure 4. Examples of the IAF time courses of subject NA7 during a neurofeedback session (30 sec. eyes-closed, 30 sec. eyes-open, 60 sec. eyes-closed), determined by methods II. b, c and d. Time step 0.25 sec. Blue: measured values; green: smoothed by 16 point (4 sec.) moving average

Long-term variations were also investigated for all 30 subjects over time periods of 120 seconds in resting state, eyes-closed conditions. Maximum, minimum and average values were determined for the epochs with synchronized state. This resulted in overall averaging times between 20 and 80 seconds, depending on the subject. In a few cases, no synchronized state for sufficiently long time intervals could be detected. Table II presents an overview of the results of the IAFs obtained using the three different methods. For most of the subjects, long-term averages determined by the three methods were found to be within \pm 0.2 to 0.5 Hz. However, for some subjects, differences amounted to \pm 1.0 Hz. Averaging over all subjects led to identical values of IAFs.

The above mentioned differences have been further investigated. Results are shown in Fig. 5: For FFT and wavelet transformation, our analyses always determine the frequency of the peak with the highest power as the IAF. However, when double peaks occur as shown in Fig. 2, their intensity varies with time. When one peak happens to exceed the other, the resulting IAF hops from, e.g., 8.4 to 9.8 Hz. Such sudden changes do not occur when the method of cycle counting in the time domain is used (see last chart of Fig. 5). These effects cause substantial differences between the IAF results of the three methods, as can be seen with, e.g., subjects AD8, NA6, PS4 and PS7 listed in Table II.

VI. DISCUSSION

Statements on the IAF should be treated with caution: definitions used in the research literature are inconsistent and may be based either on estimations of the power density spectrum or on time-domain analyses. Our comparisons of fast Fourier transform, wavelet transform and time-domain cycle counting clearly indicate that the individual IAF values resulting from long-term averaging may be not equivalent. Examples for this are subjects AD8, NA6, PS4 and PS7, Table II.

From Fig. 4 we can conclude that the IAF numbers are primarily meaningful in synchronized state.

Furthermore, we hypothesize that the IAF is not an intraindividual constant but follows a time course during sessions with resting state and various cognitive tasks. For fMRI studies or EEG neurofeedback, we therefore recommend the use of time-dependent IAFs rather than a fixed, pre-determined value.

The method of counting cycles in the time-domain offers some advantages over spectrum-based methods:

- short-term variability is lower, and thus uncertainty is minimal;
- results can easily be validated by visual inspection;
- results correspond to current clinical practice;
- Computational effort is minimal.

The time-domain method therefore appears to be optimally suited for automatic real-time monitoring.

	Mean			max. Variation		
	FFT	WT	CC	FFT	WT	CC
AD1	-	-	-	-	-	-
AD2	11,0	11,0	10,7	0,9	0,9	1,1
AD3	-	-	-	-	-	-
AD4	8,2	8,2	8,4	1,6	1,6	1,8
AD5	10,7	10,8	10,5	1,6	1,7	1,1
AD6	-	-	-	-	-	-
AD7	-	-	-	-	-	-
AD8	8,1	8,1	8,9	0,3	0,1	0,2
AD9	-	-	-	-	-	-
AD10	-	-	-	-	-	-
NA1	10,8	10,8	10,5	1,7	1,7	1,3
NA2	-	-	-	-	-	-
NA3	-	-	-	-	-	-
NA4	9,5	9,5	9,7	2,2	2,4	1,6
NA5	9,8	9,8	9,7	1,3	1,5	1,0
NA6	10,6	11,1	10,4	0,5	0,2	0,2
NA7	9,5	9,5	9,4	1,9	1,7	1,6
NA8	11,0	11,0	10,6	0,5	0,6	0,5
NA9	9,7	9,8	9,7	2,0	2,1	1,6
NA10	9,7	9,7	9,7	2,6	2,6	2,1
PS1	9,8	9,8	9,7	2,1	2,2	1,4
PS2	9,1	9,1	9,2	1,2	1,2	1,0
PS3	11,4	11,4	11,1	0,6	0,5	0,9
PS4	8,6	8,5	9,1	2,0	2,0	2,1
PS5	-	-	-	-	-	-
PS6	9,2	9,2	9,4	1,8	1,6	0,5
PS7	8,4	8,4	9,2	0,0	0,0	0,1
PS8	8,9	8,9	9,0	1,1	1,2	1,0
PS9	9,2	9,2	9,2	1,4	1,3	1,6
PS10	9,8	9,8	10,0	0,0	0,0	0,0
Mean	9.7	9.7	9.7	1.3	1.3	1.1

TABLE II. IAF-RESULTS OF 30 SUBJECTS

max. Variation: difference between lowest and highest value found within 120 seconds (synchronized epochs only)

All examinations on electrode P3

AD subjects with Alzheimer's disease

NA cognitively normal adults

PS psychiatric patients





(FFT, wavelet) / averaging (cycle counting)

REFERENCES

- W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis", *Brain Research Reviews*, vol. 29, pp. 169-195, 1999
- [2] W. Klimesch, F. Vogt, M. Doppelmayr, "Interindividual differences in alpha and theta power reflect memory performance", *Intelligence*, vol. 27(4), pp. 347-362, 2000
- [3] E. Angelakis, S. Stathopoulou, J.L. Frymiare, D.L. Green, J.F. Lubar, J. Kounios, "EEG neurofeedback: a brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly", *The Clinical Neuropsychologist*, vol. 21, pp. 110-129, 2007
- [4] W. Klimesch, "EEG-alpha rhythms and memory processes", International Journal of Psychophysiology, vol. 26, pp. 319-340, 1997
- [5] B. Zoefel, R.J. Huster, C.S. Herrmann, "Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance", *NeuroImage*, vol. 54, pp. 1427-1431, 2011
- [6] D. Posthuma, M.C. Neale, D.I. Boomsma, E.J.C. de Geus, "Are smarter brains running faster?" *Behaviour Genetics*, vol. 31, no. 6, pp. 567-579, Nov. 2001
- [7] A. Goljahani, C. D'Avanz, S. Schiff, P. Amodio, P. Bisiacchi, G. Sparacino "A novel method for the determination of the EEG individual alpha frequency", *Neuroimage*, vol. 60(1), pp. 774-86, 2012
- [8] A.K. Chiang, C.J. Rennie, P.A. Robinson, S.J. van Albada, C.C. Kerr, "Age trends and sex differences of alpha rhythms including split alpha peaks", *Clinical Neurophysiology*, vol. 122(8), pp. 1505-1517, 2011
- [9] G.J. van Boxtel, A.J. Denissen, M. Jaeger, D. Vernon, M.K. Dekker, V. Mihajlović, M.M. Sitskoorn, "A novel self-guided approach to alpha activity training", *International Journal of Psychophysiology*, Epub. Nov. 2011
- [10]S.S. Lodder, M.J.A.M. van Putten, "Automated EEG analysis: Characterizing the posterior dominant rhythm", *Journal of Neuroscience Methods*, vol. 200, Issue 1, 30 Aug. 2011, pp 86-93
- [11]F.B. Vialatte, J. Solé-Casals, J. Dauwels, M. Maurice, A. Cichocki, "Bump time-frequency toolbox: a toolbox for time-frequency oscillatory bursts extraction in electrophysiological signals", *BMC Neuroscience* 2009, 10:46, http://www.biomedcentral.com/1471-2202/10/46
- [12]T.A. Whitten, A.M. Hughes, C.T. Dickson, J.B. Caplan, "A better oscillation detection method robustly extracts EEG rhythms across brain state changes: The human alpha rhythm as a test case" *NeuroImage*, vol. 54, pp. 860-874, 2011