

ERPWAVELAB A toolbox for multi-channel analysis of time-frequency transformed event related potentials

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Abstract

The open source toolbox 'ERPWAVELAB' is developed for multi-channel time-frequency analysis of event related activity of EEG and MEG data. The toolbox provides tools for data analysis and visualization of the most commonly used measures of time-frequency transformed event related data as well as data decomposition through non-negative matrix and multi-way (tensor) factorization. The decompositions provided can accommodate additional dimensions like subjects, conditions or repeats and as such they are perfected for group analysis. Furthermore, the toolbox enables tracking of phase locked activity from one channel-time-frequency instance to another as well as tools for artifact rejection in the time-frequency domain. Several other features are high-lighted. ERPWAVELAB can freely be downloaded from www.erpwavelab.org, requires EEGLAB (Delorme and Makeig, 2004) and runs under MATLAB (The Mathworks, Inc.).

Key words: EEG, MEG, multi-channel time-frequency analysis toolbox, wavelet analysis, Non-negative Decomposition, Event related potentials, PARAFAC/TUCKER, Coherence, artifact rejection in time-frequency domain.

1 Introduction

Time-frequency analysis of event related potentials of electro-encephalography (EEG) and magneto-encephalography (MEG) data has recently attracted much attention, see for instance (Tallon-Baudry et al., 1996; Simoes et al., 2003;

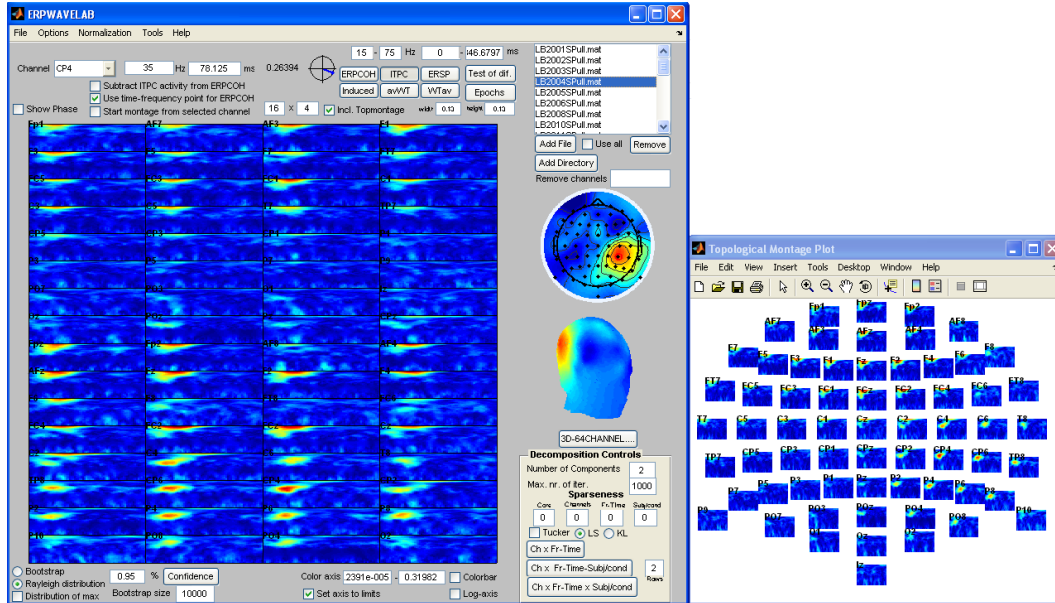


Fig. 1. The ERPWAVELAB graphical user interface displays the multi-channel time-frequency representation of each measurement as a compact array as well as time-frequency plots at each channel location.

Herrmann et al., 2004, 2005; Gruber et al., 2004; Lachaux et al., 2005). Most analyzes are based on the time-frequency representation of single channels. However, as computer power has increased, it is possible to analyze complete data sets from multiple channels, subjects etc. We have recently proposed a variety of methods to perform multi-channel time-frequency analysis (Mørup et al., 2006a,b,c) that also incorporates multi-subject and multiple-condition analysis. Based on the widely used toolbox EEGLAB (Delorme and Makeig, 2004) we have developed an application interface in the process of applying these tools. This interface has been further developed as the ERPWAVELAB toolbox. running on a MATLAB (The Mathworks, Inc.) platform and it can be downloaded from www.erpwavelab.org where the user can find installation details, a user guide and example data.

EEGLAB implements single channel time-frequency analysis and other EEG/MEG-toolboxes such as Fieldtrip (www.ru.nl/fcdonders/fieldtrip/) provide MATLAB routines for time-frequency transformation, plotting functions and source localization. However, to our knowledge, there is a need for tools for multi-channel time-frequency analysis as provided by ERPWAVELAB encompassing functionalities such as multi-channel and multi-subject time-frequency decomposition, artifact rejection in the time-frequency domain and coherence tracking. The toolbox is based on a graphical user interface to assist users with limited programming experience to do complex analysis of their data in the time-frequency domain. EEGLAB has routines for importing data, plotting channel activities and performing artifact rejection all useful for the fur-

ther analysis in the time-frequency domain. ERPWAVELAB makes use of EEGLAB’s scalp plotting functions and imports EEGLAB data set for the generation of data sets operable for the toolbox. The multi-way array (tensor) analysis tools provided by the toolbox should be particularly helpful in getting a comprehensive overview of the data.

The paper is structured as follows. First, an introduction to time-frequency transformation is given. This is followed by an explanation of the time-frequency domain methods for event related activity provided by ERPWAVELAB. We next illustrate artifact rejection in the time-frequency domain and give an introduction to the various decomposition techniques available in ERPWAVELAB including group analysis. Finally, we illustrate how ERPWAVELAB can be used to track phase coherence over channel-time-frequency instances.

2 Method

The present section on time-frequency analysis is kept to a minimum only describing the most basic concepts used in ERPWAVELAB. More elaborate descriptions of wavelets and other time-frequency transforms can be found at www.wavelet.org. Furthermore, many details are left out in the following sections such as model estimation and multi-way operations. This substance is at a basic level, aimed at the reader new to the field. For a more detailed description of the decompositions used see (Mørup et al., 2006c,b).

2.1 Time-frequency transformation

EEG and MEG data is believed to primarily stem from synchronous oscillatory activity of neurons in the brain (Nunez, 1981, 1995) thus frequency analysis of the recorded activities has become a widely used technique to investigate the activity of interest (Simoes et al., 2003; Herrmann et al., 2004, 2005; Lachaux et al., 2005; Gruber et al., 2004). However, the oscillatory spatio-temporal patterns are not stationary but varying in time. To accommodate non-stationarity frequency analysis can be split into time segments aka frames, windows etc. This can be done using the short time Fourier transform (STFT). The STFT uses the same window length at all frequencies which may result in excellent frequency resolution for high frequencies but poor time resolution and vice versa for low frequencies. One way of achieving an improved trade off between temporal resolution and frequency resolution is through the ‘continuous’ wavelet transform which varies the window length over frequencies. Consider the mother wavelet $\tilde{\varphi}(t)$. The wavelet coefficient of the sampled signal $x(t_n)$

at time t_0 at scale a can then be estimated as

$$X(t_0, a) = \frac{1}{\sqrt{a}} \sum_{n=-\infty}^{\infty} \tilde{\varphi}\left(\frac{t_n - t_0}{a}\right)x(t_n). \quad (1)$$

Although many types of wavelets exists, the complex Morlet has been widely used in the analysis of EEG and MEG data, see for instance (Miwakeichi et al., 2004; Simoes et al., 2003; Herrmann et al., 2004; Lachaux et al., 2005; Gruber et al., 2004; Tallon-Baudry et al., 1996; Lachaux et al., 2005):

$$\tilde{\varphi}(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-i2\pi t} e^{-\frac{t^2}{2\sigma^2}}. \quad (2)$$

It is simply the conventional Fourier transform with a Gaussian window function. Inserting equation 2 into equation 1 it is seen that the wavelet transform uses the same number of oscillations for each scale a . The attractive property of the wavelet transform in accessing the oscillatory activity of EEG is that high frequency burst are believed to vary more rapidly in time than low frequency activities. Since the wavelet length for high-frequency analysis are shorter than low frequency analysis the wavelet gives a good tradeoff between precision in time and in frequency of the EEG/MEG signals. For the complex Morlet wavelet of equation 2, σ is a parameter defining how many oscillations are included in the analysis denoted the width (m) of the wavelet given as $m = 2\pi\sigma$ oscillations. As the nature of the time-frequency transform applied does influence the results, the most adequate time-frequency transformation depends on the data at hand and type of analysis performed in the time-frequency domain. Thus, we have decided to let ERPWAVELAB have both the short time Fourier and the complex Morlet wavelet transforms so that the relative merits of the two can be explored in a specific data context.

2.2 Measures of the time-frequency Transformed ERP

Let $X(c, f, t, n)$ denote the time-frequency coefficient at channel c , frequency f , time t and epoch n of the EEG/MEG signal given by $x(c, t, n)$. Then the following measures have proven useful for the analysis of the oscillatory activity of event related potentials, see for instance (Delorme and Makeig, 2004; Herrmann et al., 2005):

$$ERSP(c, f, t) = \frac{1}{N} \sum_n^N |X(c, f, t, n)|^2 \quad (3)$$

$$WTav(c, f, t) = \frac{1}{N} \sum_n^N |X(c, f, t, n)|. \quad (4)$$

While the evoked spectral perturbation (ERSP) is a measure of the average power over epochs at given channel-frequency-time points the WTav is the average amplitude of the oscillation.

To access the evoked activity phase locked to the event the following measures are useful:

$$ITPC(c, f, t) = \frac{1}{N} \sum_n^N \frac{X(c, f, t, n)}{|X(c, f, t, n)|} \quad (5)$$

$$ITLC(c, f, t) = \frac{1}{N} \sum_n^N \frac{X(c, f, t, n)}{\sqrt{\frac{1}{N} \sum_n^N |X(c, f, t, n)|^2}} \quad (6)$$

$$avWT(c, f, t) = \frac{1}{N} \sum_n^N X(c, f, t, n). \quad (7)$$

The amplitude of the inter trial phase coherence (ITPC) Tallon-Baudry et al. (1996) (also sometimes named the phase locking index/value) measures the phase consistency over epochs, the inter trial linear coherence (ITLC) weights each epoch according to amplitude. Finally, the avWT corresponds to the time-frequency transformed Evoked Potential (EP).

From the WTav and avWT the induced activity, i.e., everything that is not phase locked to the event can be estimated as

$$INDUCED(c, f, t) = WTav(c, f, t) - |avWT(c, f, t)|. \quad (8)$$

Finally, phase coherence, i.e. how consistent the phase of a given oscillatory activity at channel c' , frequency f' and time t' is to the activity at channel c , frequency f and time t , can be estimated by:

$$ERPCOH_{c',f',t'}(c, f, t) = \frac{1}{N} \sum_n^N \frac{X(c, f, t, n)X^*(c', f', t', n)}{|X(c, f, t, n)||X(c', f', t', n)|} \quad (9)$$

$$ERLCOH_{c',f',t'}(c, f, t) = \frac{\sum_n^N X(c, f, t, n)X^*(c', f', t', n)}{\sqrt{\sum_n^N |X(c, f, t, n)|^2 \sum_n^N |X(c', f', t', n)|^2}}, \quad (10)$$

where X^* denotes the complex conjugate. While the evoked response phase coherence (ERPCOH) gives the same weight to all epochs, the evoked response linear coherence (ERLCOH) weights the phase coherence by the relative amplitudes of the signals over the epochs. Traditionally, ERPCOH and ERLCOH have been calculated having $f' = f$ and $t' = t$ (Delorme and Makeig, 2004; Lachaux et al., 1999). In ERPWAVELAB we extend this approach to investigate the phase synchrony across frequency-time instances. This is in line with the approach of Lachaux et al. (2003) attempting to access interdependencies across different time-frequency regions.

Although other measures of event related activity in the time-frequency domain exist, most are similar to the measures above and therefore not included. Furthermore, since the energy at low frequencies is higher than the energy at higher frequencies, X is often normalized prior to calculating the above measures. Common normalization is to divide by a baseline activity or $1/f$.

While ERSP especially, but also the WTav, avWT, INDUCED, ITLC, ERLCOH are strongly influenced by noise this is not the case for the ITPC. As all epochs are given the same weight to the ITPC even very noisy epochs only contribute as every other epoch. This property makes the ITPC attractive in comparison with the avWT in accessing the evoked activity, despite the lost amplitude information. Furthermore, both the ITPC and ERPCOH are given as the sum of unit vectors in the complex plane. The resulting length to the center of the complex plane (origo) of such a sum of random vectors (also denoted a random walk) is known to be Rayleigh distributed. Hence, random ITPC and ERPCOH have the probability density function (pdf) given by

$f(x) = \frac{x}{\rho^2} e^{-\frac{x^2}{2\rho^2}}$ which is fully described by the mean value of the distribution given as $\bar{x} = \rho\sqrt{\frac{\pi}{2}}$. From this, significance of any ITPC and ERPCOH activity *change* can be accessed by evaluating the activity at hand with respect to the known ‘null’ distribution of random activity.

The significance of the activity of all the measures above can also be estimated by the more costly approach of estimating the distribution of random baseline activity by *bootstrap*. Here, surrogate data sets are generated by randomly selecting data from a baseline region and the significance obtained by evaluating the activity to the distribution of these data sets. Both analytic and bootstrap measures are incorporated into ERPWAVELAB.

Notice, while the ERPCOH, just as the ITPC, is little influenced by random noise the ERPCOH is strongly influenced by systematic background noise such as magnetic fields generated by currents of electrical devices inducing currents in the EEG-electrodes or systematically distorting the MEG field. While this activity is not generally related to the event hence leaves the ITPC uninfluenced it might have the same phase delay across two given channel-time-frequency points through the epochs. Furthermore, the ERPCOH and ERLCOH is strongly confounded by volume conduction unrelated to the event as volume conduction tend to have fixed delays between regions over the epochs.

2.3 *Artifact rejection in the time-frequency domain*

While the signal to noise ratio of EEG and MEG data can be low, some epochs are highly confounded by noise, say, due to muscular activity, eye motion, or external sources from the surroundings during the recording. Traditionally,

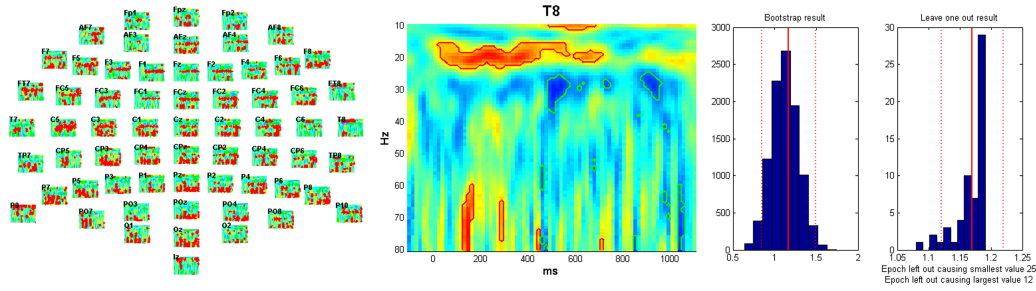


Fig. 2. Left panel; Time-frequency activity at the various channels of the INDUCED activity. Significance is here estimated by bootstrapping indicating by red contours regions significantly elevated from baseline and in green regions significantly decreased. Middle panel; same as left panel but zoomed in on channel T8. Right panel; The distribution at channel T8 at time 200 ms, 20 Hz giving the epochs present in the data’s influence on the value found. The left bar plot shows the distribution found by bootstrapping over the epochs while the right bar plot shows the distribution found by calculating the value each time leaving one of the epochs in the data out. Red line the true value found using all epochs, dotted lines plus/minus two standard deviations. The text below gives the two epochs influencing the measure the most.

epochs have been rejected by visual inspection of the EEG-data or by semi-automatic techniques rejecting trials exceeding a given threshold or varying too strongly over a given time course. Recently, independent component analysis has been deployed in removing artifacts as noise such as eye motion can be captured in separate components and these components removed from the data (Delorme and Makeig, 2004).

However, for all the methods mentioned above there is a tendency to reject epochs based on low frequency activity since most of the energy of the EEG is low frequent. Consequently, artifact rejection based on inspection and analysis of the raw EEG can be biased by relevant low frequency activities.

ERPWAVELAB facilitates rejection of artifacts by inspection and analysis in the time-frequency domain. Thus, high frequency noise can easily be identified and such noisy epochs rejected. By normalizing the wavelet transformed data the deviation in higher frequencies become clear. Apart from visual inspection of the epochs power, amplitude and phase, ERPWAVELAB also enables inspection for statistical outliers, see figure 3.

2.4 Non-negative decompositions

The decompositions used in ERPWAVELAB are based on the PARAFAC (Carroll and Chang, 1970; Harshman, 1970) and TUCKER (Tucker, 1966)

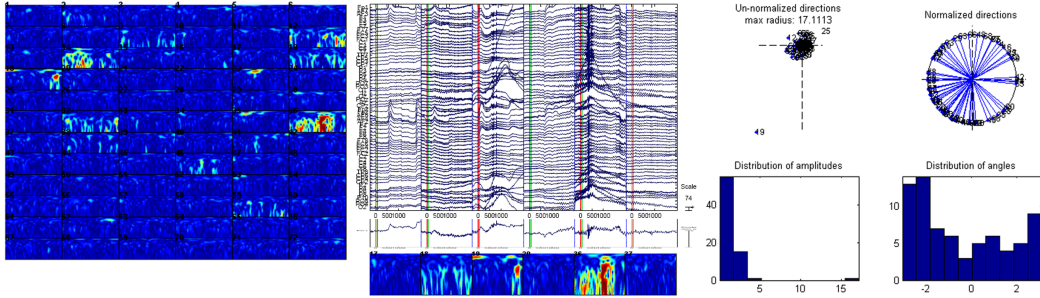


Fig. 3. Left panel: Time-frequency plot of the activity at channel FC1 over 72 epochs. Middle panel; the corresponding activities of the raw data of epoch 17 18 19 20 36 37 for all channels, below the raw data FC1 is highlighted together with the corresponding time-frequency activities. From the time-frequency plots it is clearly seen that epoch 19 and 36 are strongly confounded by noise. However, epoch 17 might potentially have been rejected due to its sudden jumps as seen from the raw data activity - this activity is however low frequent, hence not affecting the higher frequency activity. Thus, had epoch 17 been rejected based on inspection of the raw data, information useful for a higher frequency analysis might have been removed. Right panel: plot of the time-frequency coefficients of FC1 at 1000 ms 30 Hz over all epochs, emphasizing that epoch 19 at this time-frequency point is an outlier (Upper left plot, the time-frequency coefficients plotted in the complex plane, lower left the distribution of amplitudes, upper right the angles of the complex coefficients, lower right the distribution of angles over the epochs). Clearly, the amplitude of the oscillation of epoch 19 at the inspected channel-time-frequency point is well above the amplitudes found in the rest of the epochs.

models. Both models are generalizations of the matrix decomposition model underlying decomposition techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Singular Value Decomposition (SVD) and Non-negative Matrix Factorization (NMF) to arrays of higher order than two, so-called multi-way arrays or tensors. Consequently, conventional two-way matrix decomposition will in the following be considered a special case of the PARAFAC and TUCKER decompositions. The PARAFAC model decomposes the array X_{i_1, i_2, \dots, i_M} into an outer product of vectors spanning each modality, i.e.

$$X_{i_1, i_2, \dots, i_M} \approx \sum_d a_{i_1, d}^{(1)} a_{i_2, d}^{(2)} \cdots a_{i_M, d}^{(M)} \quad (11)$$

Consequently, when X is a matrix the model becomes the regular factor analysis $X_{i_1, i_2} \approx \sum_d a_{i_1, d}^{(1)} a_{i_2, d}^{(2)}$.

While no interactions are present between vectors of different indices in the PARAFAC model, the TUCKER model allows full interaction between all the vectors spanning each modality. This is achieved by introducing what is called

a core array G accounting for these interactions

$$X_{i_1, i_2, \dots, i_M} \approx \sum_{j_1, j_2, \dots, j_M} G_{j_1, j_2, \dots, j_M} a_{i_1, j_1}^{(1)} a_{i_2, j_2}^{(2)} \cdots a_{i_M, j_M}^{(M)} \quad (12)$$

Notice that this model theoretically allows for different amounts of factors in each modality. Consequently, if an activity pattern in a given modality is shared by different patterns of activities of other modalities the model can effectively account for this without having to repeat this shared activity pattern as required by the PARAFAC model.

The coefficients of ITPC, ITLC, avWT, ERPCOH and ERLCOH are all complex. However, in the following when referring to these measures it is their amplitude *absolute value* that is considered. Consequently, since ERSP, wtAV, ITPC, ITLC, avWT, INDUCED, ERLCOH and ERPCOH are all represented by non-negative values it may be relevant to constrain the PARAFAC and Tucker decompositions to non-negative factors (and core). In theory various oscillatory activities might overlap, but the over-complete representation of the data given by the time-frequency transformation enables the decompositions above in many cases to isolate each oscillatory behavior well even when these activities are not well-separated in the time domain alone. Notice however, the decompositions are meant for data *exploratory* purposes, hence for visualization of activities present in the data. In general the decompositions do not guarantee to find the ‘true’ sources, e.g. if these do not follow an additive law.

What makes non-negative decomposition attractive is that they are known to give a parts based representation that often is easier to interpret than other forms of decompositions such as PCA/SVD or ICA (Lee and Seung, 1999). Although non-negativity improves uniqueness of the decomposition by constraining the solution space to the positive orthant, non-negative decompositions are not in general unique (Donoho and Stodden, 2003). The PARAFAC model for arrays of order three (and higher) has theoretically been proven unique under mild conditions (Sidiropoulos and Bro, 2000; Kruskal, 1977). Yet, no such theoretical uniqueness property has been given for the PARAFAC model under non-negativity constraint, see for instance Lim and Golub (2006). Consequently, to acquire uniqueness of the decompositions, constraints in the form of sparsity can be imposed (Hoyer, 2004; Eggert and Körner, 2004). As a result, the algorithms used to estimate the PARAFAC and TUCKER models described in (Mørup et al., 2006b,c) can impose sparseness on any combination of modalities. Sparseness is imposed through a penalty on the absolute value of each parameter in a given modality (i.e., based on the L_1 norm). This constraint will seek to eliminate excess parameters, see e.g., (Mørup et al., 2006c).

Since the frequency modality is generated from the time modality the time-

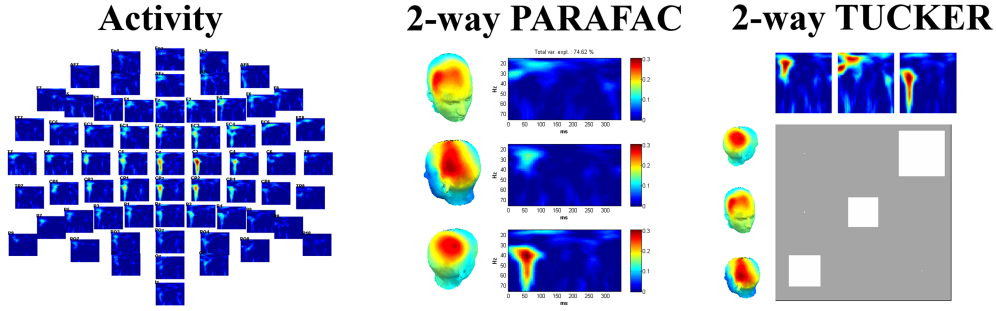


Fig. 4. The non-negative array of $Channel \times Time - Frequency$ to the left gives a decomposition by the 2-way PARAFAC into time-frequency ‘signatures’ and the strength in which these signatures are present in the channels. The 2-way Tucker further produces a core array measuring the relations between signatures. Notice, in the two-way analysis the TUCKER and PARAFAC model yield identical results, however for higher order the two models are different, see also figure 6

frequency transform is in a sense just a new representation of the time modality. Consequently the extra frequency modality arising from the time-frequency transformation is collapsed to form a combined time-frequency modality. Hence, the decomposition of $X_{c,q} \approx \sum_d a_{c,d}^{(1)} a_{q,d}^{(2)}$ where q denotes a given time-frequency point gives the strength in which the time frequency activity of components d , i.e. $\mathbf{a}_d^{(2)}$, is present in the c^{th} channel given by $a_{c,d}^{(1)}$. The corresponding Tucker based decomposition gives $X_{c,q} \approx \sum_{d,d'} G_{d,d'} a_{c,d}^{(1)} a_{q,d'}^{(2)}$. Consequently the core $G_{d,d'}$ gives the strength in which each channel components $\mathbf{a}_d^{(1)}$ are related to the time-frequency component $\mathbf{a}_{d'}^{(2)}$. In the two-way case there is no difference between the two models, since the Tucker model becomes $\mathbf{X} \approx \mathbf{A}^{(1)} \mathbf{G} \mathbf{A}^{(2)T} = \mathbf{A}^{(1)} \widetilde{\mathbf{A}}^{(2)T}$ thus corresponding to a PARAFAC model having $\widetilde{\mathbf{A}}^{(2)T} = \mathbf{G} \mathbf{A}^{(2)T}$, see figure 4. However, for higher order arrays the PARAFAC model and TUCKER model becomes different, see figure 6.

2.5 Accessing group differences

Most ERP studies are based on multi-subject multi-condition analysis. Hence, the data encompasses extra modalities such as subjects, conditions, date of recording etc. In this type of analysis it is of interest to access the dominant sources of activity differences in an unsupervised manner.

Consider the data array X being one of the measures ERSP, avWT, WTav, ITPC, ITLC, INDUCED, ERPCOH or ERLCOH, i.e. $X(c, f, t, s, k)$ where s denotes a given measurement at a given channel c , frequency f time t point for a recording belonging to group k . One measure of difference between groups is a one-way analysis of variance (ANOVA).

$$X_k(c, f, t, k) = \frac{1}{S} \sum_{s=1}^S X(c, f, t, s, k) \quad (13)$$

$$\widetilde{X}(c, f, t) = \frac{1}{K} \sum_{k=1}^K X_k(c, f, t, k) \quad (14)$$

$$F_{test-value}(c, f, t) = \frac{\frac{1}{K-1} \sum_{k=1}^K (X_k(c, f, t, k) - \widetilde{X}(c, f, t))^2}{\frac{1}{K(S-1)} \sum_{s=1}^S (X(c, f, t, s, k) - X_k(c, f, t, k))^2}. \quad (15)$$

As a result, the ANOVA gives a data array of channel-frequency-time of F-test values which as for the other ERPWAVELAB measures can be decomposed by the PARAFAC and TUCKER model. The ANOVA assumes that the distribution of data in each of the groups are normal thus the F-test is extremely non-robust to deviations from normality (Lindman, 1974). If the data can not be assumed normal the Kruskal-Wallis test of rank can be used. Let $R(c, f, t, s, k)$ denote the order of the value of a given channel-frequency-time point for subject s in group k to all other subjects and groups in the same channel-time-frequency point. The Kruskal-Wallis one-way analysis of variance by ranks is then given by (Kruskal and Wallis, 1952):

$$R_k(c, f, t, k) = \frac{1}{S} \sum_{s=1}^S X(c, f, t, s, k) \quad (16)$$

$$\widetilde{R}(c, f, t) = \frac{1}{K} \sum_{k=1}^K R_k(c, f, t, k) \quad (17)$$

$$\chi_{test-value}^2(c, f, t) = (SK - 1) \frac{\sum_{k=1}^K S(R_k(c, f, t, k) - \widetilde{R}(c, f, t))^2}{\sum_{k=1}^K \sum_{s=1}^S (R(c, f, t, s, k) - \widetilde{R}(c, f, t))^2} \quad (18)$$

Another approach to access differences between groups is to measure their distance $D(s, k; s', k')$ between each single measurement s from a given group k to another measurement s', k' , here given as the euclidian distance:

$$D(s, k; s', k') = \sqrt{\sum_{c, f, t} (X_k(c, f, t, s, k) - X_{k'}(c, f, t, s', k'))^2}. \quad (19)$$

From this distance matrix a dendrogram can be generated showing what measurements are the most related. Both the ANOVA, Kruskal-Wallis and dendrogram methods are provided in ERPWAVELAB, see also figure 5.

However, the above measures are not very specific when explaining what is actually the difference and similarity between each group of measurements. This motivates the group analysis based on the decomposition techniques provided by the PARAFAC and TUCKER models. Assuming that the activities are present throughout the measurements within the same scalp region a 2-way

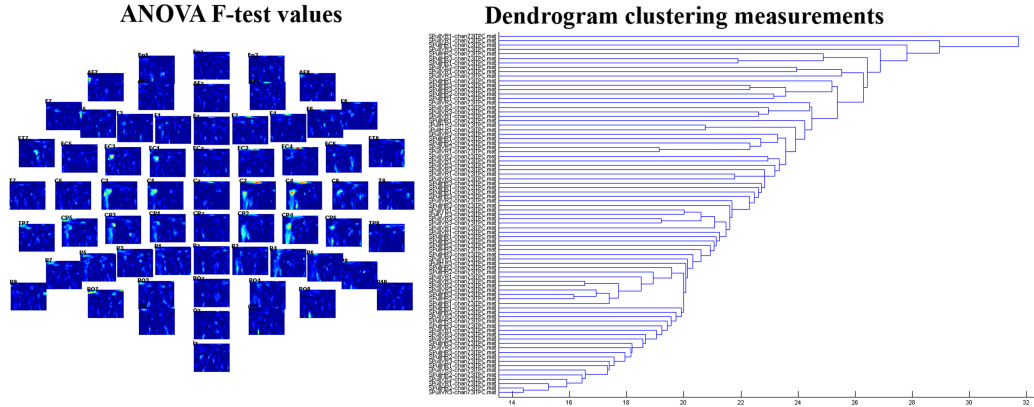


Fig. 5. Left panel; example of an ANOVA array of channel \times time-frequency of F-test significance values. Right panel; a dendrogram formed by the distance between measures given in equation 19.

analysis of *channel \times time – frequency – measurements* can be used to identify these regions. Consider further $X(c, q, r)$, i.e the activity at a given channel c at time-frequency q at measurement r where r index over all measurements of subjects, conditions, dates etc. Then the decomposition $X_{c,q,r} \approx \sum_d a_{c,d}^{(1)} a_{q,d}^{(2)} a_{r,d}^{(2)}$ not only gives the mixing of the time-frequency activity of $\mathbf{a}_d^{(2)}$ in the channels $\mathbf{a}_d^{(1)}$ but also the strength in which this activity is present at each measurement $\mathbf{a}_d^{(3)}$. Consequently, measurements with a region of similar activity will be strongly present in $\mathbf{a}_d^{(3)}$ while this similar activity will be given in $\mathbf{a}_d^{(1)}$, $\mathbf{a}_d^{(2)}$. Again, the corresponding Tucker model $X_{c,q,r} \approx \sum_{d,d'} G_{d,d'} a_{c,d}^{(1)} a_{q,d'}^{(2)} a_{r,d'}^{(2)}$ allows factors of various indices to interact. The 2-way and 3-way decomposition of arrays including several measurements are given in figure 6.

2.6 From ITPC to tracking the ERPCOH

The ITPC is a measure of evoked activity. However, sometimes the phase locked activity initiates another activity at another time and location and possibly of another frequency (Varela et al., 2001; Kopell et al., 2000). Hence, the secondary activity evoked by the initial activity evokes later, say, tertiary activities. However, in the chain of brain events the evoked activities will have a tendency to be less phase locked to the event, since it is the result of communication through more stages of neurons. Consequently, the phase jitter to the event might be larger than the phase jitter to the first activation. If this is not so, the two activities could be considered parallel instead of serial.

Traditionally, the ERPCOH has been used to measure the coherence between different channels at the same time-frequency point (Delorme and Makeig,

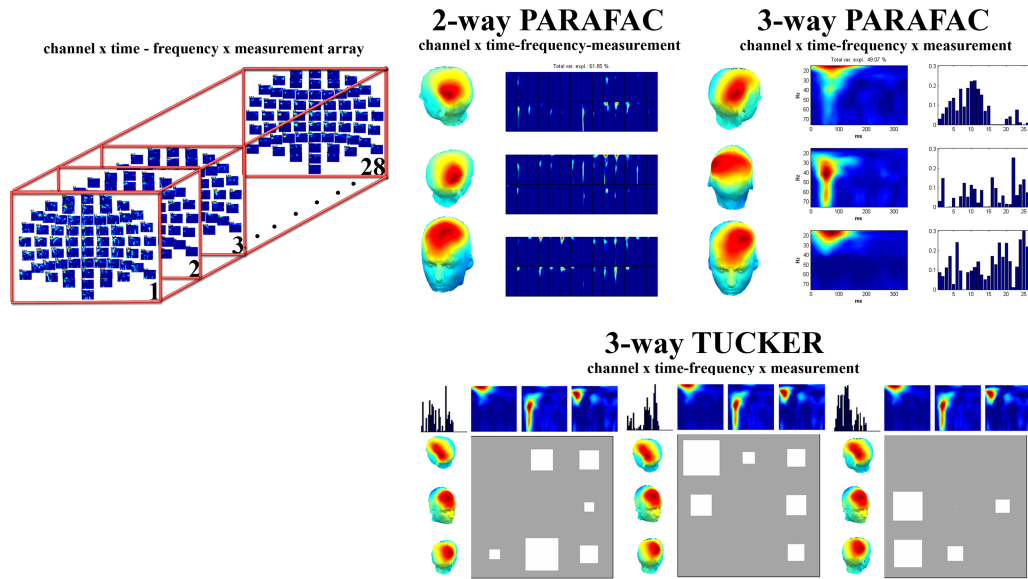


Fig. 6. Left panel: The 3-way array given by including several (presently 28) measurements. Middle panel; the decomposition found by collapsing the measurement modality onto the time-frequency modality to find scalp localized regions of activity. Right panel: The corresponding 3-way analysis given by the PARAFAC, and bottom panel: TUCKER model of $channel \times time - frequency \times measurement$. Contrary to the 2-way analysis the 3-way analysis assumes also the time-frequency activity are similar across groups of measurements.

2004). However, in ERPWAVELAB the ERPCOH can also be set to measure the coherence from a given time-frequency-channel point to all other time-frequency-channel points. Consequently, if a region is evoked by the activity of another region this can be captured by the ERPCOH. As a result, finding the ITPC maxima and calculating the ERPCOH from this maxima can elicit how other regions of the brain are activated, i.e evoked, due to this ITPC activity. This secondary activity showing up as an ERPCOH maxima might again activate other regions which can again be captured by calculating the ERPCOH from this ERPCOH-maxima to all other points. ERPWAVELAB enables an efficient method of tracking these types of stepwise phase coherences by allowing each coherence to be recorded and afterwards displayed in a diagram of coherent connectivity, see figure 7. Furthermore, since both the ITPC and ERPCOH are Rayleigh distributed, the significance of the phase locked activities can be accessed by the toolbox.

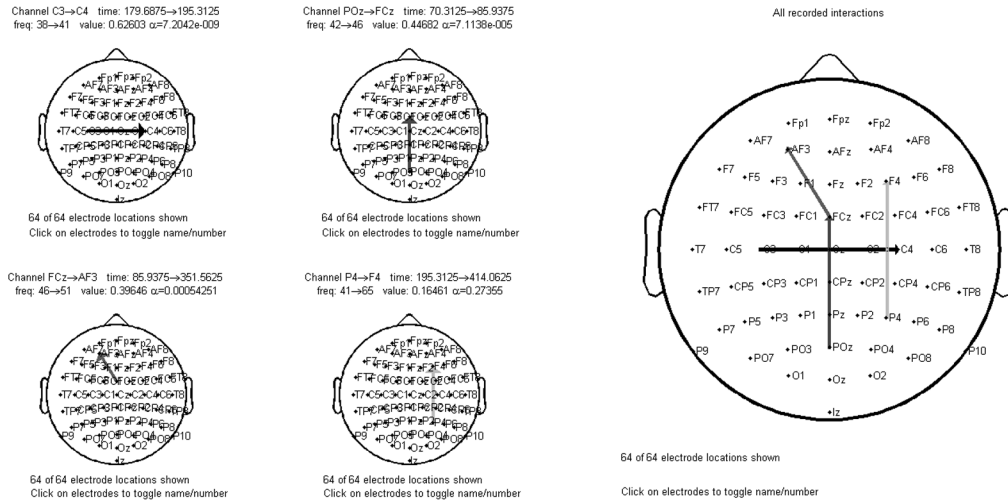


Fig. 7. Left panel: the various recorded cross coherences. One procedure being to calculate the ITPC activity, from this maxima calculating the ERPCOH to find the most phase locked activity to this ITPC maxima. Recording this ERPCOH-maxima the cross coherence can again be calculated and another ERPCOH maxima found and recorded. Right panel: the overall recorded activity. The strength of each coherence is indicated by the intensity of the arrows while the significance of each arrow is given in the individual plots. Hence, black arrows indicate strong coherence while light gray arrows indicate a weak phase synchrony.

3 Conclusion

This paper has introduced the new open source toolbox ERPWAVELAB. The toolbox is rooted in the widely used toolbox EEGLAB and can be downloaded from www.erpwavelab.org, where we also have placed a detailed tutorial that explains all the features of the toolbox. The tools can be helpful when analyzing multi-channel time-frequency transformed event related potentials. Facing non-stationary and noisy data, we have included tools for rejection of artifacts in the time-frequency domain and made it possible to track phase locked oscillations in a systematic way.

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