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Extracting high frequency oscillatory brain signals from magnetoencephalographic recordings

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Abstract: Oscillatory short signal bursts of cortical origin with a frequency around 600 Hz can be measured using magnetoencephalography. These so called somatosensory evoked high frequency oscillations (SE-HFO) are induced by an electrical stimulation at the wrist. Up to now only averages over several thousand stimulations yield an interpretable result. Here the spectral and temporal properties of SE-HFOs are exploited through epoch concatenation followed by temporal decorrelation to study SE-HFO single trial properties. The algorithm is a type of blind source separation and extracts an SE-HFO component, which shows a preferred phase after sorting the single trials using a wave train at 625 Hz as template. The preferred phase is not visible after sorting the raw data trials, which certainly have more noise. This indicates that the epoch concatenation temporal decorrelation is a powerful tool to study transient oscillatory signals in multichannel recordings.

Keywords: Magnetoencephalography, independent component analysis, temporal decorrelation, somatosensory evoked fields, high frequency oscillations, single trials.

1. INTRODUCTION

To date somatosensory evoked high frequency oscillations (SE-HFO) (Curio et al. (1994); Hashimoto et al. (1996); Curio (2004)) are among the weakest signals of neuronal origin, that can be measured using magnetoencephalography (MEG). These SE-HFOs consist of a short wavelet of 5-10 ms duration with a maximum amplitude in the range of tens of fT and a frequency around 600 Hz riding on top of the well known N20m response, which has a latency of 20 ms. The N20m response and the SE-HFOs are induced by an electrical stimulation at the wrist (medianus nerve). The SE-HFOs are seen best after averaging several thousand evoked epochs and suppressing the N20m response using a bandpass. The extensive literature on the morphology of averaged SE-HFOs investigated by MEG or electroencephalography (EEG) can be found in Curio (2004). To assess fluctuations of SE-HFOs on a single trial (single evoked response) level is not possible due to their weakness compared to other signals present in the MEG data. In this work a statistical method for the extraction of single trial SE-HFOs is successfully applied and properties of the single trials are derived.

The isolation of SE-HFO single trials is complicated by their short duration in comparison to a typical electrical stimulus repetition rate of 3-9 Hz. The SE-HFOs are easily seen in only 5 ms of the 111 ms interstimulus interval for 9 Hz stimulation. This means that SE-HFOs are sparsely distributed in measured raw data corresponding to non-stationarity: To describe statistically the SE-HFO signal on a 10 ms time scale a time dependent probability density function (PDF) results as the PDF is identically zero between two SE-HFO wavelets. Estimates of PDFs are the basis of independent component analysis (ICA), which has been widely applied to multi-channel data such as MEG and EEG recordings and functional magnetic resonance imaging (Lee (1998); Haykin (2000); Hyvarinen et al. (2001); Jung et al. (2001a); Roberts et al. (2001); Stone (2002a); Cichocki et al. (2002); Makeig et al. (2004); Choi et al. (2005); James et al. (2005)).

In the literature numerous ICA algorithms have been proposed. Fortunately the sparse nature of the SE-HFOs implies a partitioning of the data into a noise and a signal section. A partitioning is suggested for the application of algorithms such as Infomax (Jung et al. (2001a)) to stimulus evoked signals. Another partitioning approach is the use of an averaged event related field. In an EEG study (Porcaro et al. (2009)) the sequential activation of sub-cortical and cortical SE-HFOs is demonstrated using the N20 response as constraint for an ICA solution.

Here the epoch concatenation temporal decorrelation (ecTD) ICA method (Zavala-Fernandez et al. (2012)) is used on the SE-HFO signal section of the raw data. It consists of bandpass filtering the raw data between 450 and 1000 Hz, followed by the concatenation of equal length windows covering the SE-HFO section of the data. The resulting time series is subjected to time-delayed (temporal) decorrelation (TDD) (Belouchrani et al. (1997); Ziehe et al. (1998); de Cheveigne et al. (2014)). TDD was successfully applied in the study of N20m responses (Tang et al. (2002); Kishida et al. (2003); Tang et al. (2005); Sander et al. (2005)).

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2. METHODS

2.1 Concatenated data and temporal decorrelation

Given a superposition of n sources of the form $\mathbf{a}_i\, s_i(t)$, where $\mathbf{a}_i$ is a time independent field map of the m channel MEG system and $s_i(t)$ describes the time dependence of the source, the measured data vector $\mathbf{x}(t)$ can be decomposed by a demixing matrix $\mathbf{W}$:

$$\mathbf{W}\,\mathbf{x}(t) = \mathbf{u}(t). \qquad (1)$$

Here the $u_i(t)$ are identical to the $s_i(t)$ if disregarding an indeterminacy in scale and ordering. To estimate a $\mathbf{W}$ blindly ICA is frequently applied and $n=m$ is assumed.

One ICA method suitable for MEG data is the time-delayed decorrelation (TDD, TDSEP, SOBI) algorithm (Belouchrani et al. (1997); Ziehe et al. (1998); Congedo et al. (2008)), which is often classified as a blind source separation type algorithm as it relies solely on second-order statistics. In TDD a set of time-delayed covariance matrices is calculated, these matrices are symmetrised, and subsequently approximately diagonalised to obtain an estimate of $\mathbf{W}$.

As the SE-HFOs have a limited duration and a specific frequency the ecTD algorithm (Zavala-Fernandez et al. (2012)) derived from TDD seems suitable to extract them. Firstly the data are bandpass filtered between 450 and 1000 Hz. Then equal length windows covering the duration of the SE-HFO wavelet are concatenated to form a new continuous time series. Finally time-delayed covariance matrices of the concatenated time series are calculated and processed as in standard TDD.

To contrast ecTD with TDD the input data for the maximum delay τ_{max} covariance matrix are illustrated in Fig. 1 for both algorithms. In Fig. 1a) two time series x and y of a multi-channel measurement are sketched. The data range 0...T of x is correlated with the data range τ_{max}...T+τ_{max} of y (ranges indicated by red bar) to obtain the matrix element $\boldsymbol{C}(x,y,\tau_{max})$ of TDD.

Due to the wavelet like nature of SE-HFOs they can be modeled as

$$s(t) = A(t)\,\sin(2\,\pi\, f_{HF}\, t + \phi) \qquad (2)$$

with envelope $A(t)$, frequency f_{HF}, and phase ϕ. In this model f is about 600 Hz and the envelope A(t) has a support of less than 10 ms centered on the N20m peak. This model is motivated by physiological knowledge derived from electrical recordings, which show that the SE-HFOs are always associated with the N20m peak in a systematic fashion (Klostermann et al. (1999)).

The raw SE-HFO input data for ecTD are sketched in Fig. 1b) as a new concatenated time series x_c is created from x using the data in the windows w_i of length w_{len} indicated in blue. Any discontinuity between the windows will be obscured in the noise as the length of the windows extends beyond the SE-HFOs, i.e., the range where A(t) is above

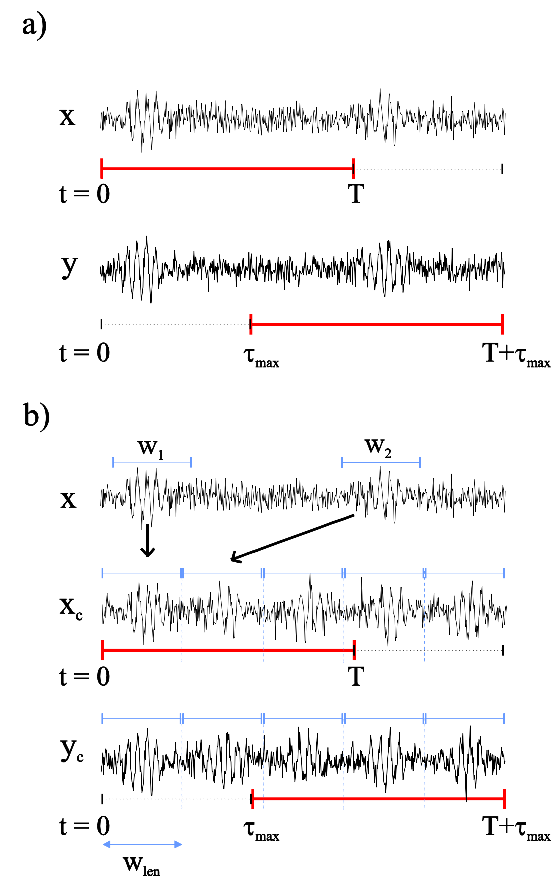

Fig. 1. Illustration of input data for the temporal decorrelation ICA. a) TDD: Two time series x and y from a multi-channel measurement are used in the time-delayed covariance calculation $\boldsymbol{C}(x,y,\tau_{max})$. b) Epoch concatenation TD: Concatenation of equal length time windows w_i of x and y yields new time series x_c and y_c used for $C(x_c,y_c,\tau_{max})$.

noise level. This avoids steps in the concatenated time series. For ecTD the τ_{max} covariance matrix $C(x_c,y_c,\tau_{max})$ is calculated from concatenated time series such as x_c and y_c for the data ranges indicated in red. The SE-HFOs shown in Fig. 1b) are exaggerated and cannot be observed in real data.

The $C(x_c,y_c,\tau_k)$ matrix of the ecTD algorithm for M windows of length w_{len} is given by

$$C_{ij}(x_c,y_c,\tau_k) = \Sigma_{\{l\}}\, x_i(t_l)\, x_j(t_l + \tau_k), \qquad (3)$$

where the set of indices is $\{l\} = w_{1,start},\ldots,w_{1,start} + w_{len}, w_{2,start},\ldots,w_{2,start} + w_{len}, w_{M,start},\ldots,w_{M,start} + w_{len}$ and contains $M^*\, w_{len}$ elements.

The ecTD algorithm requires choosing three parameters: The window start $w_{i,start}$ relative to the stimulus, the window length w_{len}, and the maximum delay τ_{max}. The window start and the window length are fairly obvious in the case of SE-HFOs as the window should contain the complete SE-HFO wavelet. The length of the SE-HFO can be estimated from a conventional average. The choice of τ_{max} is largely empirical,