# DECODING SSVEP RESPONSES BASED ON PARAFAC DECOMPOSITION

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Abstract: In this position paper, we investigate whether a parallel factor analysis (Parafac) decomposition is beneficial to the decoding of steady-state visual evoked potentials (SSVEP) present in electroencephalogram (EEG) recordings taken from the subject's scalp. In particular, we develop an automatic algorithm aimed at detecting the stimulation frequency after Parafac decomposition. The results are validated on recordings made from 54 subjects using consumer-grade EEG hardware (Emotiv's EPOC headset) in a real-world environment. The detection of one frequency among 12, 4 and 2 possible was considered to assess the feasibility for Brain Computer Interfacing (BCI). We determined the frequencies subsets, among all subjects, that maximize the detection rate.

## 1 INTRODUCTION

Steady-state visual evoked potentials (SSVEPs) are the brain responses to the repetitive presentation of a visual stimulus (flickering stimulus) and are most prominent in recordings made over the occipital cortex. They reflect oscillations in electroencephalograms (EEGs) at frequencies that are integer multipliers (harmonics) of the stimulation frequency, given that the latter is at a sufficiently high rate (starting from 6 Hz) (Herrmann, 2001). This means that, when a subject is looking at a stimulus flickering at frequency $f_1$, one can observe in the recordings a marked increase in the amplitude at $f_1$, $2f_1$, $3f_1, \ldots$. This neurophysiological phenomena could be used, for example, to construct a brain-computer interface (BCI): when using several stimuli flickering at different frequencies, it is possible to detect at which stimulus the subject is gazing at one only by analyzing the EEG recordings (Gao et al., 2006; Manyakov et al., 2010; Segers et al., 2011; Chumerin et al., 2011). To this end, a detection algorithm is needed that monitors the frequency spectrum in search of these stimulation frequencies and their harmonics, and decides which one is most prominent (classification). But, since the amplitude of a typical EEG signal decreases as $1/f$ in the spectral domain, the higher harmonics become less prominent. Additionally to this, SSVEP responses are embedded into other on-going brain activity (for example, alpha waves are normally present in recordings over the occipital pole) and noise. To overcome these problems, appropriate preprocessing and decoding algorithms are needed. Also for this reason, multiple EEG channels are considered to be beneficial for SSVEP analysis. For example, in (Gao et al., 2006) the authors show that a suitable bipolar combination of EEG electrodes suppresses noise, resulting in increase in the signal-to-noise ratio (SNR). Similarly, a weighted linear combination (spatial filtering) of the signals coming from all available electrodes improves the decoding performance (Friman et al., 2007).

In this position paper, we investigate the possibility to consider a canonical polyadic decomposition known as parallel factor analysis (Parafac) (Bro, 1997; Cichocki et al., 2009), as a spatial filtering procedure that separates information about alpha waves, noise and other disturbances present in the EEG recordings to distinguish stimulus-related SSVEP activity. Parafac has already proven itself for epileptic seizure detection and localization (De Vos et al., 2007; Acar et al., 2007), in the localization of task-related activity (sources of theta and al-



Figure 1: Emotiv's EPOC headset.

pha waves) (Miwakeichi et al., 2004), artifact removal (Acar et al., 2007), and so on. It was also used in a BCI based on imagined movements (Cichocki et al., 2008) but not much has been applied to SSVEP BCI. We start with our EEG acquisition procedure, then introduce our Parafac representation suitable for SSVEP data, and discuss two different SSVEP detection techniques. We then validate our approach on EEG data from 54 subjects and search for the best set of discriminating stimulation frequencies, suited for all subjects.

# 2 METHODS

## 2.1 EEG data acquisition

We recorded EEG data from 54 subjects during a public event in a noisy room, crammed with all sorts of wireless and other types of devices, which is quite unlike a lab environment. Since we were testing on a broad audience the applicability of SSVEP-based BCI applications, we restricted ourselves to cheap consumer-grade EEG equipment, with a minimal set-up time. We used the EPOC headset (Fig. 1), developed by *Emotiv*[1], consisting of 14 saline sensors. The data were wirelessly transmitted to a computer at a sampling rate of 128 Hz for each channel and a resolution of 14 bit/channel/sample. Since we wanted to record from the occipital pole, we had to rotate the EPOC by $180^o$ (in the horizontal plane) before putting it on the head of the subject. That was done because the electrodes in the EPOC are intended to cover more anterior regions. Since the EPOC is a one-size-fits-all design, we cannot precisely describe the electrode locations for a given subject, since it strongly depends on the geometry of the subject's skull.

The experiment consists of an observation of a flickering square with a red dot in its center, *i.e.* the fixation point. The participants were asked to simply keep their gaze on the fixation point. The square placed at the center of the screen was flickering at increasing frequencies from 6 to 28 Hz in steps of 2 Hz, where each frequency was presented for 5 seconds. As a result, we have EEG recordings for 12 different stimulation frequencies $(6, 8, ..., 28$ Hz). The stimuli were shown on a laptop with a bright 15,4" LCD screen, with a 60 Hz refresh rate.

[1] `http://www.emotiv.com`

## 2.2 Parafac

The Parafac model (Bro, 1997), as it used in this study, can be seen as a linear decomposition of a 3-D array $\underline{\mathbf{X}} \in \mathbb{R}^{N\times M\times K}$ into a sum of atoms $\underline{\mathbf{X}} = \sum_{i=1}^{R} \mathbf{a_i} \circ \mathbf{b_i} \circ \mathbf{c_i} + \underline{\mathbf{E}}$, where $\mathbf{a_i}$, $\mathbf{b_i}$ and $\mathbf{c_i}$ are vectors, $\underline{\mathbf{E}}$ is a residual term, and $\circ$ the outer product. This means that the components of $\underline{\mathbf{S}} = \mathbf{a} \circ \mathbf{b} \circ \mathbf{c}$ are estimated according to $s_{nmk} = a_n b_m c_k$. Since such a decomposition is a trilinear one, it can be estimated through, for example, an iterative alternating least-squares algorithm. One of the parameter, which needs to be tuned in this decomposition, is the number of atoms $R$. It is important to find proper this parameter, since Parafac model is not nested (the parameters of a three-atom model are not the same as the parameters of a two-atom model plus an additional component). For our analysis, we used the core consistency diagnostic (corcondia) (Bro and Kiers, 2003) to determine $R$.

## 2.3 Data representation

The conventional way to construct the data representation $\underline{\mathbf{X}}$, as described in (Miwakeichi et al., 2004; De Vos et al., 2007; Acar et al., 2007; Cichocki et al., 2008), is to perform a wavelet transform on each channel (thus, leading to a $scale * time$ representation for each electrode), and further concatenate those 2-D matrices along the additional (*i.e.*, electrodes) dimension. This leads to a 3-D data array with dimensions $electrode * scale * time$, where *scale* refers to the wavelet scaling coefficient, which can be transformed into the frequency domain. While such a representation of the data was proven to be useful for seizure detection and localization, artifact correction, and so on (De Vos et al., 2007; Acar et al., 2007), it is not applicable to our case, *i.e.*, stimulation frequency detection in SSVEP responses. This is due to the Heisenberg uncertainty principle which states that it is not possible to obtain a perfect localization of an event in the time- and frequency domains simultaneously. More rigorously this means that, for any function $f(t)$, with Fourier transform $F(\omega)$, and for concentration measures in the time- ($\sigma_t^2 = \int_{-\infty}^{\infty} t^2 |f(t)|^2 dt$) and frequency ($\sigma_\omega^2 = \frac{1}{2\pi}\int_{-\infty}^{\infty} \omega^2 |F(\omega)|^2 d\omega$) domains, the inequality $\sigma_t \sigma_\omega \geq 1/2$ applies. Since the wavelet

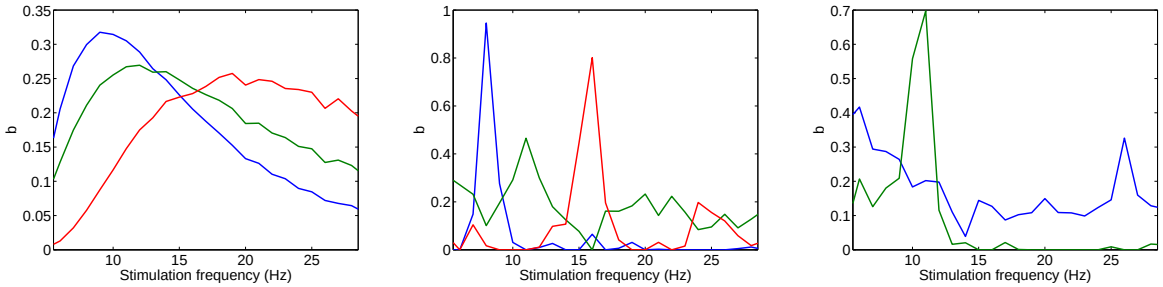


Figure 2: Frequency spectrum of Parafac atoms for subject 37 during 8 Hz (left and central) and 26 Hz (right) visual stimulation. A wavelet decomposition with the Mexican hat wavelet was used for the (left) decomposition and a short time Fourier transform for the (right and central) decompositions. Color indicates different atoms.

decomposition of signal is a linear expansion into the frame of wavelets (with different positions and scale coefficients), the frequency representation will fully depend on the transformation of the basis wavelet. For a wavelet that has a limited support in time domain, thus for a small scaling factor (high frequency), a "broad" frequency representation is obtained according to the aforementioned uncertainty principle. Thus, for the construction of an initial data array with the use of the wavelet transform, we expect a blurred representation of the frequency components of the obtained atoms (vectors $\mathbf{b_i}$). As an example, one can check Fig. 2 (left), where Parafac was applied for a 5s EEG recording during a 8 Hz stimulation. The three frequency spectra correspond to the oscillations at the stimulation frequency (blue), the first harmonic (red), and the alpha (green). As it can be seen, the spectrum for the higher frequency components becomes "broader". Additionally to this, peaks for each components do not coincide with the previously assumed frequency ranges. Thus, the construction of a 3-D data representation based on the wavelet transform will not generate a reliable information for decoding.

To overcome this problem, we have to decompose the EEG signal on the basis of functions with more a broader support in the time domain. Ideally, sin/cos on the whole time axes will maximally narrow the contribution in the frequency spectrum. But we can not achieve this given the short time intervals of the EEG signals of interest (5 s). Additionally to this, we want to have several values (not one) along the third (time) dimension of our data representation array. Hence, we restrict ourselves to an ordinary short-time Fourier transform with a Hamming window. In this case, instead of a wavelet decomposition, we obtain a spectrogram that was estimated based on a sliding windowed Fourier transform. Thus, our EEG data is transformed into a representation in terms of a 3-D data array with dimensions $electrode * frequency * time$ ($14 \times 25 \times 21$, with 14 electrodes, 25 frequencies considered (5,6,...,29 Hz) and 21 points in time, taken as centers of windows). After performing a Parafac decomposition on the same data as before, but now with the 3-D representation just mentioned, we obtain the results shown in Fig. 2 (central panel). It can be seen that the estimated spectra from our 3 atoms represent the expected frequency information more closely. We can clearly detect the components responsible for the stimulation frequency, the first harmonic and alpha activity, and the peaks are in accordance with these frequencies. From such a transformation we can clearly determine what is the flickering frequency of the stimulus the subject is looking at (8 Hz as in Fig. 2).

## 2.4 Decoding strategy

Whereas in many cases, we can distinguish from a visual inspection the component(s) that correspond to the SSVEP paradigm, we still have to find a procedure that automatically detects the stimulation frequency. One could assume that spatial information (vectors $\mathbf{a_i}$) of the decomposed components would be useful, as was reported in (Miwakeichi et al., 2004; De Vos et al., 2007; Acar et al., 2007) for seizure detection, artifact correction or the localization of some brain processes. However, in our case, we do not have precise information about the electrode positions (see Sec. 2.1) and the SSVEP responses, together with the frequently detected alpha waves occur over the same part of the skull (*i.e.*, occipital pole). Thus, spatial information can only help to reject components that are due to, for example, eye blinking, whenever this would occur (eye blinking artifacts are expected for more frontal regions). As a result, we can only consider frequency information on its own. A straightforward way to arrive at an automatic detection is to conclude about the stimulation frequency from the ones with the maximal spectra in each component. From the example discussed above (see Fig. 2 (central)),

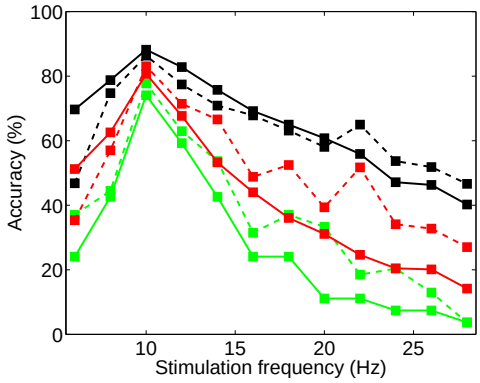


Figure 3: Averaged, over all subjects, detection accuracy vs. frequency in the case of all possible 2 (black), 4 (red) and 12 stimuli (green) combinations. Dashed lines correspond to "sharpness method", solid lines to "maximum method".

we are able to detect 8 Hz (from the "blue" component), 16 Hz ("red") and 11 Hz ("green"), and conclude about an 8 Hz visual stimulation. Since the first harmonic and/or alpha wave are not always present, the detection becomes simple, as we avoid any automatized logical conclusion. Also, for the case where the stimulation frequency coincides with the alpha band, the situation become even more simple. But a global maximum not always leads to a correct conclusion. For example, in Fig 2 (right) the frequency spectrum is shown of the atoms, after Parafac decomposition, for the EEG recorded for the same subject, as before, but during 26 Hz stimulation. While the alpha component could be determined by the global maximum (green line with a peak at 11 Hz), the frequency of the SSVEP component (blue line) will be misclassified in favor of a lower frequency (in spite of a correct visual assessment). Thus, instead of maximum values (or, better to say, maximal peak values), it would be beneficial to use a statistic based, for example, on the sharpness of the peak (here difference between the peak value and a mean value of amplitudes in its neighbors). In this case, the 26 Hz component will be classified correctly. We will further refer to those methods, as the "maximum method" and the "sharpness method".

## 3 Results

First of all, we have visually inspected the Parafac decomposition results for a number of subjects. The conclusion is that components indeed reflect SSVEP-related information, as it can be seen, for example, in Fig. 2. But, as we are interested in an automatic decoding, we classify the results of both proposed methods for all possible 2, 4 and 12 stimuli combinations. This means that, for example for the 2 stimuli case, we assume that only two stimulation frequencies are presented to the subject. Our detection procedure should identify only one of those two frequencies. Only those recordings are considered for which the subject is looking at the corresponding stimulus. In the case of 12 stimuli, we investigate the correct identification of one among all possible frequencies. In summary, by performing such a classification, we assess whether the approach is feasible for brain-computer interfacing when the subject can select one of 2, 4 or 12 options.

Figure 3 shows the averaged, over all subjects, detection accuracy for particular frequencies for the three mentioned stimulus configurations, for both proposed methods. The accuracy shown, for example, at 10 Hz, for the 2 stimulus combination, means that we have checked all possible pairs of stimuli containing 10 Hz and estimated the averaged detection accuracy of 10 Hz for all such pairs and all subjects. As it can be seen, the stimulation at 10 Hz is the best detectable one irrespective of the cardinality of the stimulus configuration. If we look for the best (in terms of the detection accuracy, among all subjects) pair of stimulation frequencies, we see that it is 8 and 10 Hz (a classification accuracy of 83.33% for the "sharpness method" and 85.19% for the "maximum method"), and the best quadruple is for 8, 10, 12, and 14 Hz (a classification accuracy of 69.44% for the "sharpness method" and 59.72% for the "maximum method").

## 4 Discussion and conclusion

We verified the feasibility of a Parafac decomposition for the detection of the stimulation frequency in SSVEP responses of 54 subjects. The motivation to use Parafac came from a visual inspection of the frequency spectra of the atoms of the decomposition. It learned us that the quality of the spectra did not depend on any constrains put on the components in the decomposition (as, for example, nonnegativity). However, when considering the Parafac results for an automatic classification procedure still much improvement is needed to increase the stimulus frequency detection performance. This is a topic for further research.

The Parafac decomposition was applied to the SSVEP detection problem as another way to construct a spatial filter which takes information form all channels simultaneously for achieving a better signal-to-noise ratio. Since spatial filtering was proven

to boost the SSVEP detection performance (Friman et al., 2007), we can say that Parafac is a logical next step. Since it not only provides a convenient way to estimate a spatial filter, Parafac also takes into account the time varying information represented along *time* axis, in its 3-D data array representation. Thus, in comparison to other spatial filters, Parafac offers the unique possibility to consider time-varying SSVEP responses, which can be viewed as an advantage: the subject is not expected to always keep the same level of concentration on the stimulus, but rather to become disturbed and tired. The latter could be verified with the presence of a temporary high alpha power in the recordings.

One can argue against Parafac since the classification accuracy is not much higher when considered for BCI. But we want to point out that we showed the classification results for the frequency pair and quadruple that performed, on average, best among *all subjects*. This means that it is a default setting intended to be suited for a broad group of subjects. The best set of frequencies is expected to be subject dependent (for some subjects the SSVEP responses are best at lower, for others at higher frequencies, and even for some subject no detection performance could be achieved (so called BCI illiteracy)). This was also observed in our experiment, where the frequencies leading to the highest detection accuracy were subject dependent. Thus, for a particular subject we can find the best frequencies through some calibration procedure (scanning of the SSVEP responses to different stimulation frequencies) and then construct the decoder based on them.

Another point of concern, when applying the described methods to BCI, is that Parafac relies on an iterative procedure for determining the coefficients of the decomposition. This makes Parafac not suited for real-time applications, however, we hasten to add that adaptive algorithms for Parafac decomposition have already been described, bringing on-line applications within reach (Nion and Sidiropoulos, 2009).

As a conclusion, we can say that Parafac is potentially useful for SSVEP detection, and for SSVEP-based BCI, but further research is required to improve the detection accuracy.

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