Multi-domain Feature of Event-Related Potential Extracted by Nonnegative Tensor Factorization: 5 vs. 14 Electrodes EEG Data

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Abstract. As nonnegative tensor factorization (NTF) is particularly useful for the problem of underdetermined linear transform model, we performed NTF on the EEG data recorded from 14 electrodes to extract the multi-domain feature of N170 which is a visual event-related potential (ERP), as well as 5 typical electrodes in occipital-temporal sites for N170 and in frontal-central sites for vertex positive potential (VPP) which is the counterpart of N170, respectively. We found that the multi-domain feature of N170 from 5 electrodes was very similar to that from 14 electrodes and more discriminative for different groups of participants than that of VPP from 5 electrodes. Hence, we conclude that when the data of typical electrodes for an ERP are decomposed by NTF, the estimated multi-domain feature of this ERP keeps identical to its counterpart extracted from the data of all electrodes used in one ERP experiment.

Keywords: Event-related potential, feature extraction, multi-domain feature, N170, nonnegative tensor factorization.

1 Introduction

Event-related potentials (ERPs) have become a very useful method to reveal, for example, the specific perceptual and cognitive processes [11]. To achieve this goal, it is necessary to represent the information carried by data of an ERP with a feature or features for analysis. Generally, the peak amplitude of an ERP measured from its waveform in the time domain has become a mostly used feature to symbolize the ERP for statistical analysis [11], [12]. Furthermore, an ERP can also be represented by features in the frequency domain and in the time-frequency domain for analysis [9], [15]. Combined with the source localization method, these measurements can be applied to formulate the topography of an ERP in the spatial domain [2]. Indeed, the above mentioned features are very conventional to analyze ERPs. With the

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development of advanced signal processing technologies, some new features of ERPs can be formulated, for example, the multi-domain feature of an ERP [6], [7] extracted by nonnegative tensor factorization (NTF) [5]. In contrast to an ERP's conventional features which exploit the ERP's information in one or more domains sequentially, the multi-domain feature of the ERP can reveal the properties of the ERP in the time, frequency, and spatial domains simultaneously [4], [5], [6], [7]. Hence, this new feature may be less affected by the heterogeneousness of datasets [7].

Generally, when an ERP is statistically analyzed, the EEG data at the typical electrodes for the ERP are often used. For example, regarding a visual N170, the data at P7 and P8 are mostly analyzed [14] and for the auditory mismatch negativity (MMN), the data at Fz is frequently studied [13]. In our previous report to extract the multi-domain feature of MMN by NTF from the time-frequency representation of EEG, we used all the data collected at frontal, central, parietal and mastoid sites [7]. Since NTF is particularly useful for the problem of the underdetermined linear transformation model where the number of sensors is smaller than that of sources, it is possible to apply NTF for data collected at one scalp area (the model of such data is underdetermined since the number of electrodes is smaller than that of brain sources). Hence, it can be very interesting to examine whether NTF can extract the desired multi-domain feature of an ERP not from data collected at sites distributed along the whole scalp, but just from data recorded at a typical or restricted area of the scalp. This is very significant in EEG data collection when the target of research is not the source localization, but the more conventional analysis of ERPs.

In this study, we performed NTF on the multi-way representation of ERPs elicited by pictures of human faces in adult participants with and without depressive symptoms. We expected to obtain the identical multi-domain features of N170 from the data of 14 electrodes and the data of five typical electrodes for N170.

2 Method

2.1 Data Description

Twenty two healthy adults (control group, denoted as CONT hereinafter, 18 females, age range 30-58 years, mean 46.1 years) and 29 adults with depressive symptoms (depressive symptom group, denoted as DEPR hereinafter, 24 females, age range 29-61 years, mean 49.1 years) participated in the experiment. Pictures of neutral facial expressions served as a repeated standard stimulus (probability = 0.8), and pictures of happy and fearful expressions (probability = 0.1 for each) as rarely presented deviant stimuli. At least two standards were presented between randomly presented consecutive deviants. The stimulus duration was 200 ms, and the stimulus onset asynchrony was 700 ms. Altogether, a total of 1600 stimuli presented. During the recordings, the participants were seated in a chair, and were instructed to pay no attention to the visual stimuli but instead attended to a radio play presented via loud speakers. Enhanced face sensitive N170 responses for the emotional faces have shown to be elicited also in this type of an oddball paradigm [1].

Brain Vision Recorder software (Brain Products GmbH, Munich, Germany) was used to record the EEG with 14 electrodes at Fz, F3, F4, Cz, C3, C4, Pz, P3, P4, P7, P8, Oz, O1 and O2 according to the international 10-20 system. An average reference was used. Data were on-line digitally filtered from 0.1 to 100 Hz, and the down sampling frequency was 1000 Hz. Then, the obtained data were offline processed with Brain Vision Analyzer software and MATLAB (Version R2010b, The Mathworks, Inc., Natick, MA). EEG data were segmented into ERP responses of 200 ms pre-stimulus period and 500 ms after the stimulus onset, and the baseline was corrected based on the average amplitude of the 200-ms pre-stimulus period. Segments with signal amplitudes beyond the range between -100 and 100 μV in any recording channel, were rejected from further analysis. The number of kept trials for the averaging was about 100 in average. The recordings of the artifact-free single trials were averaged at each channel for each subject. For the present study, the data from the happy deviants were chosen for the analysis as the processing of positive information is known to be especially impaired in the depressed individual [16]. Therefore, comparison of the brain activity between the happy and the fearful expressions, or between the rare emotional (happy and fearful) stimuli and the frequently presented (neutral) standard stimuli are out of the scope of this study.

2.2 Nonnegative Tensor Factorization for Multi-domain Feature Extraction

In the form of tensor products, the NTF model [5] can also be written as

$$\underline{\mathrm{Y}} \approx \underline{\mathrm{I}} \times_1 \mathrm{U}^{(1)} \times_2 \mathrm{U}^{(2)} \cdots \times_N \mathrm{U}^{(N)} = \hat{\underline{\mathrm{Y}}}\ , \tag{1}$$

where $\hat{\underline{\mathrm{Y}}}$ is an approximation of the N-order tensor $\underline{\mathrm{Y}} \in \Re_+^{\mathrm{I}_1 \times \mathrm{I}_2 \times \cdots \times \mathrm{I}_N}$, and $\underline{\mathrm{I}}$ is an identity tensor [5], $\mathrm{U}^{(n)} = \left[\mathrm{u}_1^{(n)}, \mathrm{u}_2^{(n)}, \cdots, \mathrm{u}_J^{(n)}\right] \in \Re_+^{\mathrm{I}_n \times J}$ is the nonnegative matrix, $n = 1,2,\cdots,N$, and $\left\|\mathrm{u}_j^{(n)}\right\|_2 = 1$, for $n = 1,2,\cdots,N-1$, $j = 1,2,\cdots,J$. Each factor $\mathrm{U}^{(n)}$ explains the data tensor along a corresponding mode. Most algorithms for NTF are to minimize a squared Euclidean distance as the following cost function [5]

$$D\left(\underline{\mathrm{Y}} | \hat{\underline{\mathrm{Y}}}\right) = \frac{1}{2}\left\|\underline{\mathrm{Y}} - \underline{\mathrm{I}} \times_1 \mathrm{U}^{(1)} \times_2 \mathrm{U}^{(2)} \cdots \times_N \mathrm{U}^{(N)}\right\|_F^2. \tag{2}$$

In this study, we applied the hierarchical alternating least squares (HALS) algorithm [5] whose simplified version for NMF has been proved to be superior to the multiplicative algorithms [8]. The HALS is related to the column-wise version of the ALS algorithm for 3-D data [3]. The HALS algorithm sequentially updates components $\mathrm{u}_j^{(n)}$ by a simple update rule

$$\begin{aligned}\mathrm{u}_j^{(n)} \leftarrow\ & \underline{\mathrm{Y}}\, \bar{\times}_1\, \mathrm{u}_j^{(1)}\, \bar{\times}_2\, \mathrm{u}_j^{(2)} \cdots \bar{\times}_{n-1}\, \mathrm{u}_j^{(n-1)}\, \bar{\times}_{n+1}\, \mathrm{u}_j^{(n+1)} \cdots \bar{\times}_N\, \mathrm{u}_j^{(N)} \\ & - \mathrm{U}_{-j}^{(n)} \left(\circledast\, {\mathrm{U}_{-j}^{(k)}}^{T} \mathrm{u}_j^{k}\right)\end{aligned} \tag{3}$$

where, '$\circledast$' denotes the Hadarmard product, $k \neq n$, and $\underline{\mathrm{Y}}\, \bar{\times}_n\, \mathrm{u}_j^{(n)}$ represents the n-mode product between tensor and vector [5]. The factor except the last one will be normalized to be unit vectors during iterations $\mathrm{u}_j^{(n)} \leftarrow \mathrm{u}_j^{(n)} / \left\|\mathrm{u}_j^{(n)}\right\|_2$, $n = 1,2,\cdots,N-1$. It should be noted that this study does not tend to propose an NTF algorithm. Therefore, any NTF algorithm can work for the data.

In detail, regarding the study N170 with NTF, we formulated a fourth-order tensor $\underline{\mathrm{Y}}$ including modes of the frequency by time by channel by subject. The number of frequency bins ($\mathrm{I_f}$), timestamps ($\mathrm{I_t}$), channels ($\mathrm{I_c}$), and subjects ($\mathrm{I_s}$) compose the dimensions of the tensor $\underline{\mathrm{Y}}$. Decomposition of $\underline{\mathrm{Y}}$ results in four matrices:

$$\underline{\mathrm{Y}} \approx \underline{\mathrm{I}} \times_1 \mathrm{U}^{(1)} \times_2 \mathrm{U}^{(2)} \times_3 \mathrm{U}^{(3)} \times_4 \mathrm{U}^{(4)} = \underline{\mathrm{I}} \times_1 \mathrm{U}^{(\mathrm{f})} \times_2 \mathrm{U}^{(\mathrm{t})} \times_3 \mathrm{U}^{(\mathrm{c})} \times_4 \mathrm{F}, \quad (4)$$

where, the last factor is the feature matrix ($\mathrm{I_s} \times \mathrm{J}$) consisting of J extracted multi-domain features of brain responses in the N170 experiment onto the subspaces spanned by the spectral (i.e., $\mathrm{U}^{(\mathrm{f})}(\mathrm{I_f} \times \mathrm{J})$), temporal (i.e., $\mathrm{U}^{(\mathrm{t})}(\mathrm{I_t} \times \mathrm{J})$) and spatial (i.e., $\mathrm{U}^{(\mathrm{c})}(\mathrm{I_c} \times \mathrm{J})$) factors. This is that each subject i $(\mathrm{i} = 1,2,\cdots,\mathrm{I_s})$ is characterized by the $\mathrm{i^{th}}$ row of $\mathrm{U}^{(\mathrm{n})}$ $(\mathrm{n} = 1,2,3,4)$ in this study. Furthermore, for one feature, i.e., one component among J components in the feature factor matrix, the values of different participants, i.e., the data at the same column of feature factor matrix $\mathrm{U}^{(4)}$, are comparable since they are extracted under the identical subspaces; but due to the variance ambiguity of NTF [5], the variances of the different features/components in any factor matrix are not comparable. Moreover, the extracted J multi-domain features should be associated with different sources of brain activities. Then, it is necessary to determine which multi-domain feature corresponds to the desired ERP.

Regarding the multi-domain feature of N170, firstly, the temporal components in the temporal factor matrix extracted by NTF have different peak latencies and the desired one for N170 may look like the waveform with a sole peak whose latency should be around 170 ms. Secondly, when the subjects in the fourth-order tensor as denoted by the tensor $\underline{\mathbf{Y}}$ include two groups, the spatial pattern extracted by NTF can be the difference topography between the two groups of participants because NTF also decomposes the multi-way representation of data in the spatial dimension. We will show in the next section that N170 has different peak amplitudes at P7 for the two groups. Thus, in this study, we assume the desired spatial component reveals the difference topography around P7 for N170. Finally, the desired spectral structure of an ERP elicited by the passive oddball paradigm may possess its largest energy between 1 and 5 Hz [7]. These are the criteria to choose the desired multi-domain feature of N170 from all the extracted multi-domain features. Furthermore, in our experiment, the vertical positive potential (VPP) and N170 probably correspond to the identical brain processes [10]. Hence, the multi-domain feature of VPP was also extracted here. The difference in the topography of VPP between two groups of participants would probably appear at the right hemisphere in this study. For detail of the multi-domain feature selection for an ERP, please refer to our previous report [7].

2.3 Data Processing and Analysis

In this study, NFT was performed on all subjects' data consisting of the time-frequency representation of the ordinary averaged traces at all 14 electrodes, as well as at five electrodes including P7, P8, O1, Oz and O2 which are typical electrode sites to analyze N170 [14], and at five electrodes including Fz, F3, F4, C3 and C4 which are typical sites to analyze VPP [10]. In order to obtain the time-frequency representation (TFR) of ERPs, the complex Morlet wavelet transformation [17] was performed on the averaged trace at each channel. For the Morlet, the half wavelet length was set to be six for the optimal resolutions of the frequency and the time [17]; the frequency range was set from 1 to 10 Hz, and 91 frequency bins were uniformly distributed within this frequency range. Next, the fourth-order tensor with the dimensions of frequency (91 bins) by time (700 samples) by channel (14 or 5) by subject (51) was formulated in terms of TFR of all subjects at chosen channels. And then, from the formed tensor, multi-domain features respectively were extracted by 10 NTF models with numbers of components ranging from 15 till 24 based on the experience learned from our previous report [7]. Subsequently, in each model, the desired multi-domain feature of N170 was selected according to properties of N170 in the time, frequency, and spatial domains as mentioned above. So did for VPP. After the desired feature component which was a vector including values for all subjects was chosen in one NTF model, it was normalized according to its L-2 norm. Finally, we obtained multi-domain features of N170 and VPP with the data of 3 multi-domain features of ERPs by 51 participants by 10 models.

After features of N170 were ready, statistical tests were performed to examine the difference of N170 between two groups with the Bonferroni correction and with 0.05 as the level of significance. For peak amplitudes of N170 in the time domain measured from ordinary averaged traces (i.e., 'raw data'), a General Linear Model (GLM) multivariate procedure for a 4×2 design was applied using the channel (P7, P8, O1 and O2) as the independent variable and the group (CONT and DEPR) as the fixed factor. Regarding the multi-domain feature of N170 extracted by NTF, a GLM multivariate procedure was implemented. The GLM multivariate procedure for an 10 × 2 design was made using the NTF-model as the dependent variable and the group (CONT and DEPR) as the fixed factor.

3 Results

In this section we compare discriminability of various features of N170 between two groups of participants, as well as the coherence between the multi-domain feature of an ERP extracted from data of 14 electrodes and that from data of five electrodes.

Fig. 1 demonstrates the grand averaged waveforms of ERPs. The significant difference between two groups only appeared at P7 ($F(1,49) = 5.185$, $p = 0.027$). For illustration on how the multi-way data can be decomposed by a multi-way analysis method, Fig. 2 shows the demo for the common components factors in different domains extracted by NTF from the data of 14 electrodes when 20 components were extracted in each mode of Eq. (4). In this model as the third component in the temporal, spectral and spatial components matrices matched the properties of N170, the third feature was chosen as the desired multi-domain feature of N170 which is the one for model-20 in Fig.3. Fig.3 presents the desired multi-domain features of N170 extracted through 10 NTF models from the data of 14 electrodes for demonstration.

As illustrated in Table-1, the difference between two groups of participants was better revealed by the multi-domain features of N170 no matter they were extracted from the data of 14 electrodes or 5 typical electrodes, and the multi-domain feature of N170 outperformed that of VPP in discriminating the two groups based on the degree of significance of difference. Moreover, Table-2 tells that the multi-domain features of N170 between the data of 14 electrodes and the data of 5 typical electrodes were more highly correlated (correlations in Table-2 were all significant) than any other two pairs, which means they reflect absolutely similar information. Furthermore, these indicate that although VPP and N170 possess the identical latency and conform to identical brain processes [10], the multi-domain feature of N170 extracted by NTF from its typical electrodes better represented the brain processes than that of VPP from its typical electrodes to categorize different groups of participants.

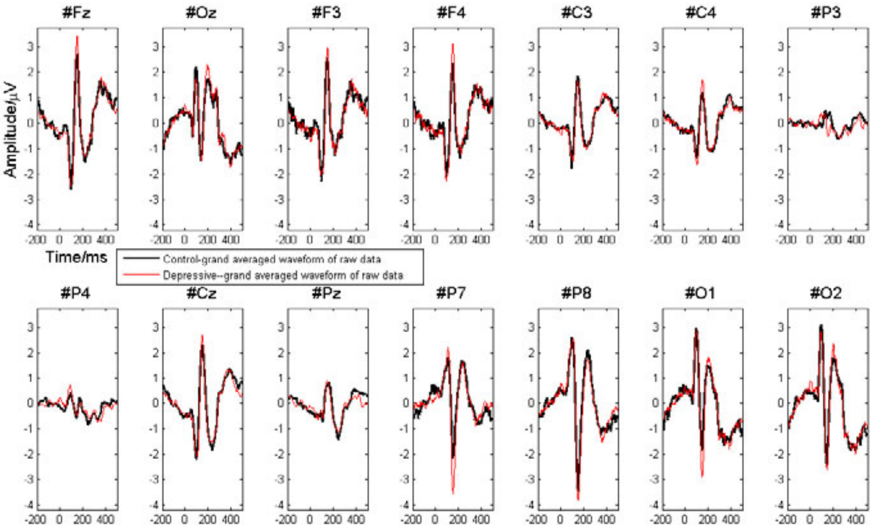
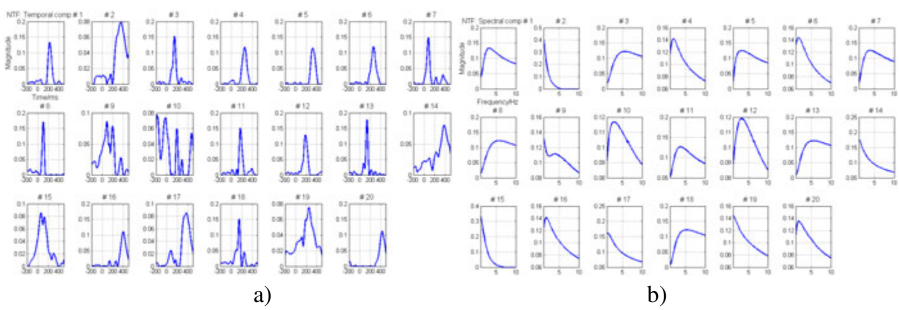


Fig. 1. Grand averaged waveforms of ERPs



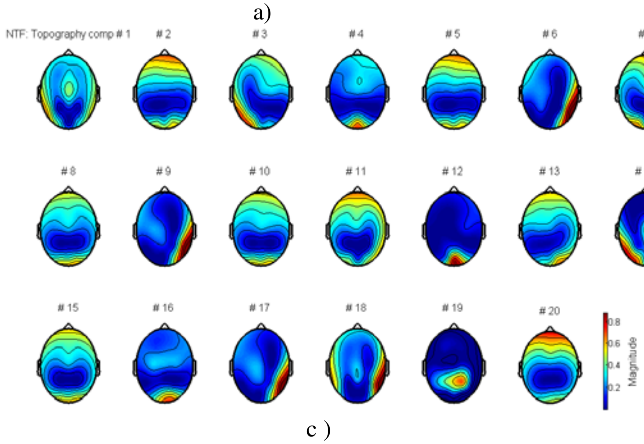


Fig. 2. Common components' factors extracted by NTF from data of 14 electrodes in one NTF model as illustrated in Eq. (4): a) temporal factor, b) spectral factor, c) spatial factor

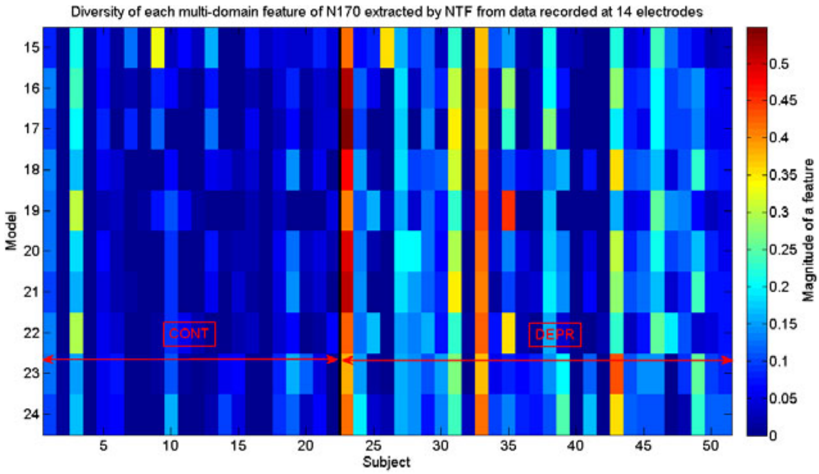


Fig. 3. Multi-domain features of N170 extracted by 10 NTF models from data of 14 electrodes

Table 1. Statistical tests of extracted features

NTF Model	N170-14 electrodes		N170 -five electrodes		VPP - five electrodes	
	F(1,49)	p	F(1,49)	p	F(1,49)	p
15	2.666	0.109	9.275	0.004	5.515	0.023
16	7.444	0.009	8.611	0.005	5.464	0.024
17	5.255	0.026	8.034	0.007	4.334	0.043
18	10.397	0.002	8.951	0.004	5.955	0.018
19	6.493	0.014	8.623	0.005	2.470	0.122
20	10.391	0.002	8.142	0.006	3.878	0.055
21	10.258	0.002	8.256	0.006	2.252	0.140
22	8.162	0.006	9.474	0.003	5.507	0.023
23	9.727	0.003	8.707	0.005	2.620	0.112
24	11.271	0.002	8.685	0.005	3.079	0.086

Table 2. Correlation coefficient of features

NTF Model	N170-14 electrodes vs. -5 electrodes	N170-14 electrodes vs. VPP-5 electrodes	N170-5 electrodes vs. VPP-5 electrodes
15	0,614	0,652	0,653
16	0,897	0,751	0,597
17	0,803	0,831	0,592
18	0,941	0,649	0,59
19	0,756	0,863	0,573
20	0,919	0,679	0,515
21	0,858	0,494	0,434
22	0,722	0,738	0,607
23	0,903	0,523	0,543
24	0,854	0,478	0,671

4 Conclusions

Though NTF from data of fewer electrodes which are typical to analyze an ERP, the extracted multi-domain feature of the ERP may be as identical as that from the data of much more electrodes distributed all over the scalp surface. Furthermore, in one ERP experiment, different components with different polarities in different scalp sites may have the same latency and reveal identical brain activities, such as, VPP in frontal-central sites and N170 in occipital-temporal sites [10], the multi-domain feature of prime component may better represent the brain activities than other components do.

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