Tensor Decomposition on EEG of Music Imagination

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Abstract. A new application of tensor decomposition is presented, here used to find shared variance between the EEG of different cognitive tasks. By analysing four datasets, each focusing on perception and imagination of musical sounds with differing levels of complexity, the overlap between tasks can be assessed for different stimuli. All data sets show fronto-central and more central components as the largest sources of variance, fitting with projections reported for the areas contributing to the N1/P2 complex. They are shown to be decomposable into parts that load primarily on to the perception or imagery task, or both, thereby adding more detail than 2-dimensional decomposition. The relevance to brain-computer interfacing more generally is in feature detection methods for potential cross-task classification, here demonstrated for imagination of music.

Keywords: EEG, tensor decomposition, music imagery, stimulus complexity

1. Introduction

Imagination is of specific interest to the field of Brain-Computer Interfaces (BCIs), where covert mental tasks need to be decoded from the brain signal to be used to drive a device. Recent results indicate that the electrical brain activations of imagining music show considerable overlap with those of perception [Schaefer et al., 2009; Schaefer et al., 2011]. The overlap between tasks is relevant for BCIs as it may allow for cross-task classification, as already demonstrated by [Vlek et al., 2011], by training a classifier on the relatively low-effort task of listening when aiming to classify imagined rhythmic patterns, thereby reducing potential fatigue from just the training phase.

The current work focuses on shared activation between music perception and imagination, and the impact of stimulus complexity on this overlap. This will provide an indication of the useful features for potential cross-task classification, and inform stimulus choices when using imagined music as a task for BCI. To this end, new analyses are presented of four datasets that each contains perception and imagination of musical material, namely rhythmic accents, monophonic melodies, more complex rhythms and ecologically natural music stimuli. We apply tensor decomposition (parallel factor analysis or PARAFAC, see e.g. [Rasmus, 1997]) on the EEG responses to see the extent of shared activation for perception and imagination, and investigate the timing signatures of common networks.

2. Material and Methods

The details of each experiment are shown in Table 1. Considering the differences between the datasets, the preprocessing steps were tailored, and described elsewhere in full detail, see [Vlek et al., 2011; Schaefer et al., 2009; Desain and Honing, 2003; Schaefer et al., 2011] for accents, melodies, rhythms and natural music, respectively. The basic pre-processing procedure was to 1) remove linear trends, 2) remove 'bad' channels, identified as those with more than 3-SD more power than the average channel power, 3) re-reference to the common-average, 4) spectrally filter with a pass-band of 1-25 Hz. After this pre-processing for each dataset, the ERPs were computed by averaging the individual stimulus responses over all subjects and stimulus repetitions. These ERPs were then used as input to the PARAFAC decomposition, using a cross-validation procedure to define the number of components. Further specifics of the method can be found in [Schaefer et al., 2013].

3. Results

The results are not identical, but some commonalities are seen between the datasets. Three of four experiments (accents, melodies and natural music) show perceptual frontal and parietal components (A2, A4, M1, M4, NM1 and NM2), which are also present but shared in the fourth experiment (R1 and R3). Two experiments show a frontal and parietal shared component (A1, A3, R1 and R3), which might be combined in the natural music experiment (NM4). All experiments except the accenting show a purely imagery-based frontal component (M4, R2 and NM3,

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explaining 11.5, 14.5 and 5.3% of the variance respectively.) With the exceptions of the first component for every experiment, the peak activity of the components is in the beginning of each stimulus.

Table 1. *Summary of the experiments, where 'P stimulus' is the perceived stimulus, 'I stimulus' is what was played during imagery. Other rows show details on the stimuli, the participants, trialnumbers and EEG channels used in data collection.*

Experiment	*1: Accents*	*2: Melodies*	*3: Rhythms*	*4: Natural Music*
P Stimulus	Accented metronome	Melodies	Rhythm patterns	Music
I Stimulus	Metronome	Notes rendered without pitch	Single prompt	Onset prompt
No. of stimuli	3 metric patterns	4 isochronous melodies	5 simple rhythms	2 full music fragments
Stim. length (ms)	1000 to 2000	375	3360 to 5352	3000
Trials, participants	96, 5	36, 11	150, 1 (5 sessions)	160, 10
EEG channels	64	28	21	256

4. Discussion

The PARAFAC components show central and fronto-centrally distributed activation to explain most of the variance, consistent with reports of the projections of the (composite) auditory N1/P2 response. The data suggest that there is an aspect of brain activation related to imagery that is independent of stimulus complexity, but that the aspects of imagery that are shared with perception do vary with characteristics of the stimulus, although this appears to decrease with stimulus complexity, indicating that cross-task classification of music imagination may become less feasible with increased stimulus complexity. Further discussion on the cognitive interpretations of these components, as well as a comparison with Principal Component Analysis (PCA) can be found in Schaefer et al. (2013). Although not yet widely used on EEG data (with notable exceptions in the frequency domain), we here demonstrate the potential and usefulness of PARAFAC decomposition for cross-task feature identification.

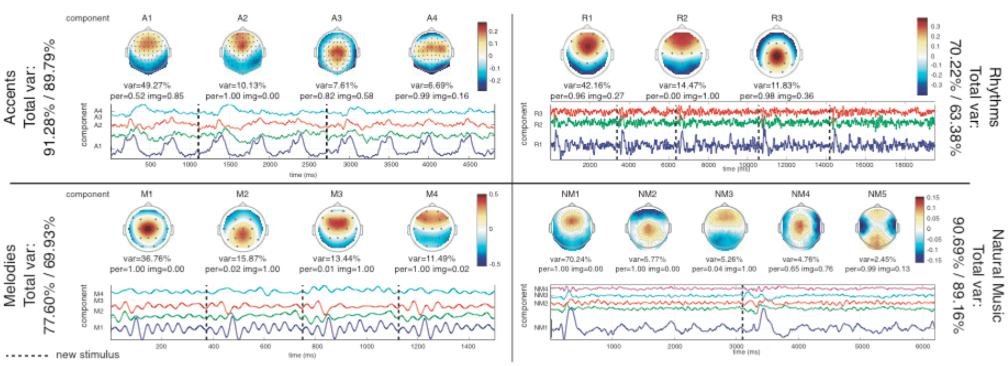

Figure 1. *The distributions of the tensor components are shown for each dataset, the average explained variance per dataset and the proportion of the explained variance for each task. The dotted lines denote different stimuli.*

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