Extraction and classification of common independent components in single-trial crossmodal cortical responses

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Introduction

Humans interact with the environment by gathering information through multiple afferent sensory channels. That is why the efficient compression and blending of the information flow from different sensory modalities used by the extensive cortical networks in the human brain for decision making is vital for immediate reaction and survival in humans and animals. In spite of numerous studies available to date, including electroencephalographic (EEG) studies [1], the exact time course of the early interplay between the sensor-specific cortices, as well as between them and the prefrontal cortex, still remains a significant challenge. One of the reasons for that lack of knowledge is the diversity of multimodal responses and pathways, recruited specifically as the result of factors such as stimulus type (speech, touch, smell, vision) and characteristics (saliency, sparsity, synchronization, spatial separation, degree of conflict). Factors like anticipation and attention [2] could also influence the responses strongly. Multimodal interactions in the brain have been shown to involve both enhancement [3] and inhibition [4], depending on the afferent stimuli, activating regions from the insula and the superior colliculus to the right temporo-parietal junction and the anterior ectosylvian sulcus [5]. These underlying multimodal response generators, including their recurrent cortical connectivity, are usually well-hidden within the composite structure of the recorded EEG signals on the surface of the scalp.

The goal of the present study was to decompose and model these biological processes into consistent independent components, uncovering more detailed information on the dynamic interactions taking place within the first several hundred milliseconds after single-trial, simultaneous cross-modal stimulations.

Standard neurophysiological techniques

like inter-trial averaging do not allow the precise individual tracing of the dynamics of the cortical processes each time an external stimulus is handled. That is why a different approach is necessary which would operate well for signals with low signal-to-noise ratios, such as raw single-trial EEG recordings. We present here a highly adaptive algorithm, using independent component analysis (ICA), to uncover precisely only those few brain-signal components which are related to the responses to the experimental stimuli, rejecting the dozens or hundreds of unrelated brain-, system- and environmental-noise-related components. Although previous studies have applied ICA for artifact rejection in EEG data by subjective visual examination [6], our approach has aimed at achieving automatic component selection and data-independence in single-trial, multi-channel data with high levels of noise.

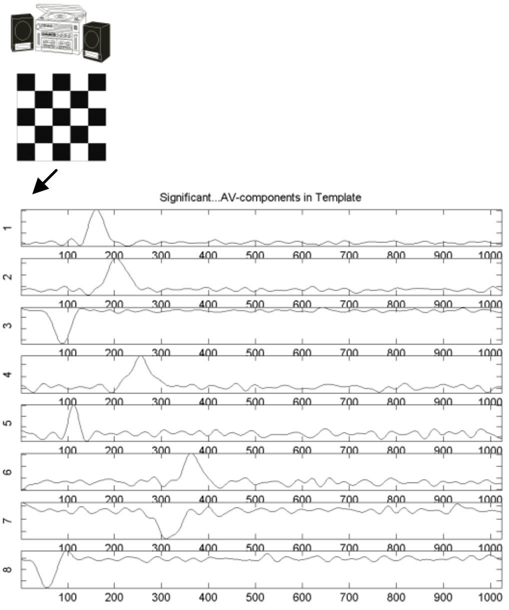
Methods

The electric potentials on the surface of the scalp of human subjects were measured using a 64-channel electroencephalographic (EEG) system (NeuroScan Inc.). While most of the knowledge on multimodal responses is based on conflicting stimuli [7], our cross-modal paradigm aimed to reveal the responses to any simultaneous auditory and visual stimuli. Subjects were presented repeatedly (200 times) with uni-modal auditory and visual control stimuli, as well as with simultaneous cross-modal combinations. The visual stimuli consisted of 5x5 white-on-black checkerboards presented for 10ms, while the auditory stimuli were 2KHz tones with durations of 30ms. The time interval between the stimuli in any of the three experimental conditions was random at 1.75+-0.25 s. Following standard eye movement artifact rejection and segmentation into single epochs with 1024ms lengths, 25% of the epochs were averaged and used for defining an individual learning template for each subject. The rest of the data (75%) was used for single-trial classification. All EEG epochs were processed using independent component analysis [8, 9]. In this study we applied TSVD-ICA [10], a mixed 2^{nd} and 4^{th} order thin algorithm for ICA, which is based on criteria that jointly perform maximization of higher-order cumulants and second-order time-delay covariance matrices. The employed simultaneous ICA extraction, which uses thin SVD factorizations, combines the robustness of the joint approximate diagonalization techniques with the flexibility of the methods for blind signal extraction. The independent components were pre-processed using wavelet-packet-based low-pass filtering. Wavelet transforms [11, 12] can be used to obtain better approximations within limited frequency bands for non-stationary data, such as evoked EEG, compared to traditional signal filters.

Audio-visual crossmodal-condition data was compared to responses from the two corresponding unimodal conditions using an extensive matching by a combination of cross-cumulant and cross-correlation measures. For each comparison, matching component pairs were selected which had the highest cross-cumulant values (and highest dependencies). The selected components in the crossmodal data were hypothesized to represent their matching uni-modal counterparts and were used for reconstruction of modality-related evoked responses.

Results and Discussion

Although the reconstructed data had originated entirely from the crossmodal signals, it demonstrated clear activations of modality-specific cortices, as well as some areas, which were presumed to be multimodal. Sensory areas were rapidly modulated by simultaneous stimulation and their corresponding responses were enhanced or inhibited in a balanced, opposing time course.



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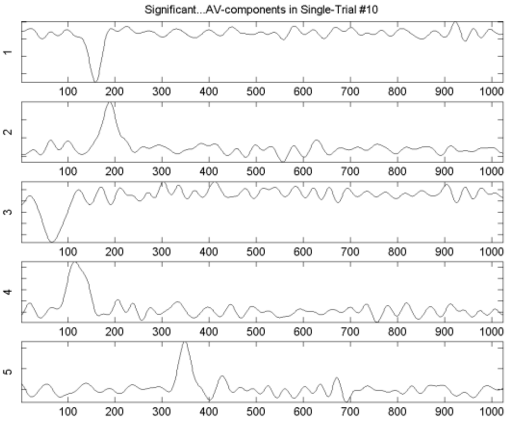

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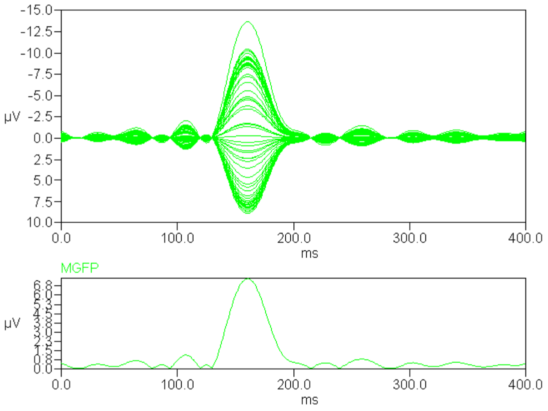

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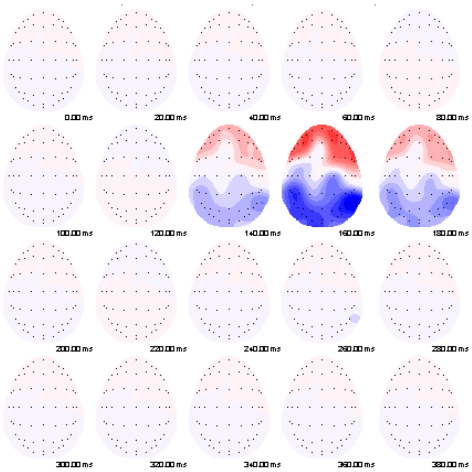

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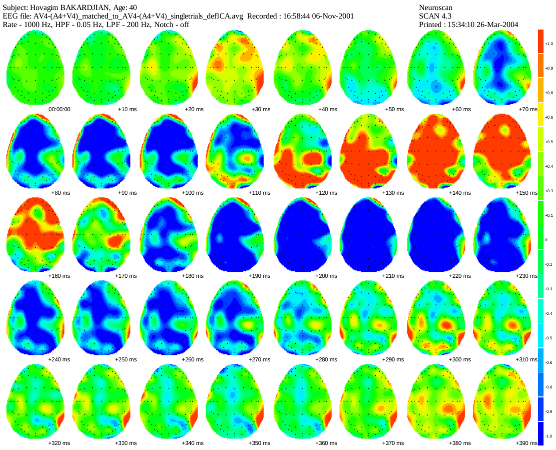
Fig. 1. Independent component structure of the cross-modal responses in the audio-visual condition. (a) All significant components in the learning template data (the average of the first 25% of the data) obtained by extensive matching with all components in all remaining single trials (75%). These core components have been found in more than 60% of the single trials. (b) Matching independent components in one of the single trials, which correspond to some of the template's components. Single trials may not contain all core components seen in (a). A single cross-modal evoked response obtained by deflating component 1 from (a) back into EEG space. (d) Electrical potential maps (0…380ms) corresponding to the EEG signal in (c). Components can be compared one by one between experimental conditions, but latency match only is insufficient for declaration of functional identity. For matching significant components between different experimental conditions we used 2 criteria: latency match of +-20ms between component peaks and spatial match of potential distributions after deflation back to EEG space. The spatial matching is performed by dividing the brain into 4 horizontally-oriented areas, frontal, anterior-medial, parieto-temporal and occipital, which must be activated in a similar way in order to rule a match. In this case, there is a match between the cross-modal component 1 and the N150 occipital response of the corresponding component in the visual-only data. However, an additional prominent frontal activation accompanies the cross-modal response.



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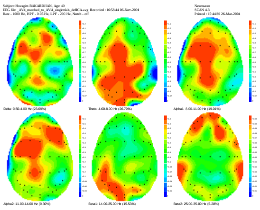

(b)

Fig. 2. Cross-modality effects for all significant

components. (a) Whole-head time course (0-390ms) of the cross-modality effects for audio-visual stimuli. Each map represents a detailed 10ms step in time, due to the fast changes in the interaction. These maps were constructed by using the operation AV-(A+V), where AV, A and V are the averaged responses extracted by matching and deflating of only the significant components in each single trial. An early parieto-temporal activation was observed in the right hemisphere during the cross-modal condition, starting from 20ms and extending up to 70ms post-stimulus. The same parieto-temporal generator was activated strongly again in both hemispheres staring from 220ms and extending beyond 400ms. The auditory cortex’s response under the cross-modal condition was enhanced at 30-40ms, 110-170ms, 270-320ms and 370-400ms, but was suppressed around 200-230ms. The visual cortex in the cross-modal condition was enhanced at 110-150ms and around 300ms, but suppressed at 180-260ms. Anterior and prefrontal cross-modal enhancement was manifested in various degrees between 70 and 210ms, as well as around 270-280ms and 400ms. (b) Spatial distribution of the energy of the cross-modality effects in the delta, theta, alpha and beta/gamma bands. Note the increased high-frequency oscillations (right, bottom) in the cross-modal condition for the same parieto-temporal and prefrontal areas observed in (a).

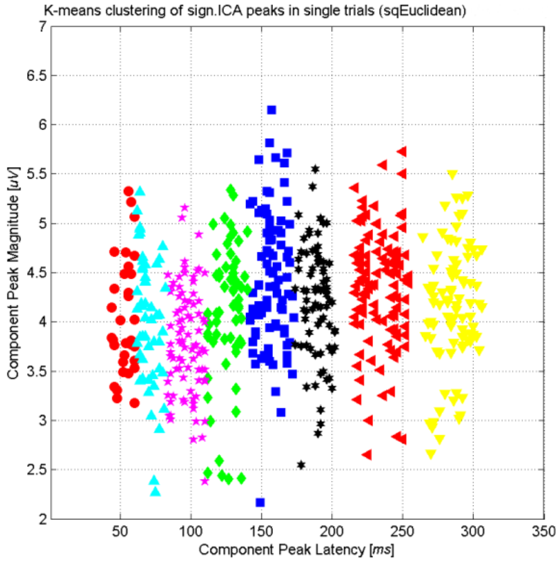

Fig. 3. Single-trial component peak structure for the cross-modal experimental condition. K-means clustering of component peak latencies (with the same number of clusters as learning template components), demonstrated that component clustering alone is unable to separate sufficiently and classify the data, even if we pre-selected only the significant single-trial component peaks, instead of all available component peaks. Single-component matching is more sensitive to small deviations in peak latency and in the shape of the independent components.

Although originally some peak middle-latency responses after visual and auditory stimulation had overlapping uni-modal time courses, our method using ICA and wavelet-packet filtering was able to extract and separate these modality components for further precise tracking of the electrical brain activity associated with them.

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