Identifying Reliable Neural Components and P300 Latency using Correlated Component Analysis

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Research Article

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Abstract

This paper applies Correlated component analysis (CorrCA) to extract the reliable and maximally correlated P300 component. Trials collected over time during an oddball electroencephalogram (EEG) experiment are first segregated into the target and non-target trial cohorts. CorrCA was then applied to both cohorts separately. Event related potential (ERP) image plots of CorrCA components from target trials showed a coherent structure for P300 latency around 400 ms when compared to plots of single electrode (C_z) trials. A difference in peak amplitude of 0.37 micro volts was observed between averaged first CorrCA component and averaged target trials at C_z electrode for able bodied subjects. Inter trial Correlation (ITC) obtained using CorrCA algorithm is applied to detect subjects who performed poorly during the oddball experiment. We also used a forward model considering sixteen channels to identify the spatial patterns of neural activity for both able and disabled subjects. It was observed that disabled subjects illustrated lower neural activation during target trials in most brain areas when compared to able-bodied subjects.

Introduction

The P300 is considered an essential component for assessing cognitive processes such as attention and working memory load[1]. It is evoked when the subject can discriminate a target from the non-target objects in a sequence of repeated stimuli. The difference between target and non-target stimuli is found in the amplitude of a positive-going component around 300 ms [1]. We can express the P300 amplitude (μV) as the largest positive peak within 300-800ms, and it can differ depending on stimulus type, task conditions, and the subject's age. Previous work showed that selective attention[2] and memory processing[3] influence P300 amplitude. Selective attention means the ability to focus our cognitive resources on one relevant aspect of the environment while ignoring the irrelevant aspects. The visuospatial working memory is the maintenance and or manipulation of task-relevant visuo-spatial information for brief periods of time to guide subsequent behavior[4].

Knowledge about the P300 amplitudes and latency has been crucial for understanding its cognitive significance and continuing clinical application, especially for psychiatric disorders [5]. P300 amplitude is also used for accurate attention monitoring in ergonomics research[6]. One of the popular applications of P300 is in the field of the Brain-computer interface (BCI). BCI translates brain wave activity to meaningful commands and links between a human brain and the external world. BCI can extract reliable neural activity patterns and translate them into a control signal using a more advanced computational algorithm. P300 based BCI speller was first implemented by Farwell and Donchin [7], and since then, it has been widely used. A comprehensive review of P300 related research work is discussed in [8]–[10]. Numerous machine learning algorithms like linear discriminant analysis, support vector machine, and deep neural networks [11] have attempted to improve the P300 classification accuracy with bit rates [12], [13].

Over the past few years, several methods have been developed to study how the brain deals with the complexity and dynamics of running audio-visual stimuli[14]. One of the methods is ITC/ISC (inter trials/subjects correlation), which measures the correlation across the multiple's trials/subjects brain signals to assess the reliability of the brain responses between the trials[15]. It was observed that attention modulation influenced ITC of electroencephalogram signals[16]. It was observed that ISC (inter-subject correlation) has been used to track the attention modulation across participants in previous works[17]–[20].[21] showed the variables that influence P300 spectral parameters. Several previous works[22]–[25] studied P300 as a marker of attention for varied tasks.

Neural correlation across target and non-target trials during P300 ERP elicitation has been neglected. In this work, we considered Correlated component analysis (CorrCA) [15], [18], [19], [26]–[29] to extract the reliable components across target cohorts. We show the utility of this algorithm to obtain peak amplitude and latency in P300 experiments. We also present inter trial correlation (ITC) obtained using CorrCA algorithm to find subjects who did not perform the experiment satisfactorily. We compare ITC between target and non-target trials cohorts for all subjects. Finally, we identified the neural activities consistent with first CorrCA component using a forward model and decipher whether it showed an observable difference in topoplots of healthy and disabled subject.

Materials And Methods

Dataset

We used P300 datasets from a previous BCI work. Refer to [12] for more details of datasets and experimental setup. Here, we used 4 disabled subjects(S1-S4) and 4 able-bodied subjects(S6-S9). Each subject had 4 sessions. First, we separated the data into target cohorts and non-target cohorts according to the given labels.

Preprocessing

We have performed pre-processing steps as mentioned in the paper [12]. After windsorizing the EEG data, we removed the artifact trials by covariance trial rejection method [30]. Eight electrode configurations (F_z, C_z, P_z, O_z, P_7, P_3, P_4, P_8) reported in [12] (provided higher classification accuracy), was used. We first built a two-dimensional matrix representing the feature vector (channels by samples points) for both target and non-target cohorts. Then trials were concatenated to form three-dimensional data (channel by sample points by trials) for both target and non target cohorts.

Correlated Component Analysis

We applied Correlated Component analysis (CorrCA) developed by Dmochowski *et al.*,[26] to extract the reliable brain responses across multiple trials. The objective of CorrCA is to find the linear combination of EEG channels that maximize the correlation between trials. If the target cohort have N trials, D electrodes, and T sample points, then we have N data volume$\{X_1, \ldots, X_N\}$, where $X_i \in R^{D \times T}$ is the neural

response of the i^{th} trial. Correlation component analysis is based on eigen decomposition of within trials covariance (R_W) and between trials covariance matrix (R_B). R_W and R_B was calculated for both target and non-target cohorts. Eigenvectors of $R_W^{-1}R_B$ corresponding to the largest eigenvalues were calculated for both target and non-target cohorts, and these were projection vectors. For both cohorts, correlated component of i^{th} trial

$y_{i,k} \in \mathbb{R}^T$ is defined by k^{th} projection vector v_k as follows:

$$y_{i,k} = X_i v_k \qquad (1)$$

ITC values are the eigenvalues of $R_W^{-1}R_B$ which are sorted in descending order. For more details on the mathematics behind CorrCA method, refer[15].

CorrCA algorithm was implemented on both target and non-target cohorts and projection vectors, inter-trial correlation (ITC), and CorrCA components were obtained. To investigate whether the components of target and non-target cohorts were significant, we opted a non-parametric test statistic based on circularly shifted surrogate data (at α = 0.05 level). The data produced a set of inter-trial correlation (ITC) values corresponding to each component from each shuffle. ITC measures the correlation between the trials (for both target and non-target trials) across each component. We computed the p-value from each shuffle of the extracted component trials. The p-value for the ITC of a given correlated component is defined as the frequency with which the ITC computed from the randomly shuffled data is exceeded by the maximum ITC of the most correlated component in the original data [15]. CorrCA components of two cohorts were analyzed separately to compare the neural responses.

Signal to Noise ratio

The signal-to-noise ratio (SNR) is an important parameter to measure repeat reliability across the trials. Maximizing the correlation between the trials (for both target and non-target trial cohort) is equivalent to maximizing repeat reliability[15]. SNR can be considered as a function of the inter-trial correlation. We applied CorrCA on target and non-target data cohorts for each subject. We evaluated the Channel-wise and CorrCA components SNR. SNR can be useful for two reasons. First, it determines the quality of data when someone is interpreting the robustness of findings. Secondly, SNR can be used when one expects more cross-trial variability in one condition than others [30].

Forward Model

The projection matrix of the CorrCA represents the backward model. Since the backward model cannot interpret the neurophysiological process at the sensor level [15], [31], the forward model helps to interpret neural activities at the sensor level. The forward model of target and non-target cohorts (also called the activation matrix) shows the relationship between the channels and component activity. The weights of the forward model show how much a channel contributed to a component. For example, the first column

of A matrix of target trials cohort computed using forward model denotes how much each channel contributed to the first CorrCA component across the target trials cohorts.

Results

In Fig. 1. we observed that SNR of CorrCA components is significantly higher than channel's SNR in both target and non-target trials. Since EEG channels always suffer from a low signal-to-noise ratio, the significant CorrCA component can be used as a feature representing the P300 component. Poor SNR might indicate the presence of noise in both channels and components. We observed that after the third CorrCA component, other components became nonsignificant. So, we rejected those components for further analysis. The SNR of the components is also higher than the SNR of the channels.

In Fig. 4 the first component showed a sharp peak around 400 ms and captured the P300 component. We observed that only the first CorrCA component represented the P300 peak latency. So, we can use only the first component instead of eight channels. Figure 1. showed only the first three components are significant from the target trials. This removes the ambiguity that arises in the case of channel selection for machine learning applications.

Previous work considered CorrCA components corresponding to three highest ISC values [32]. In this work for each subject, we took sum of ITC scores of first three CorrCA components. We computed the sum for both target trials and non-target trials cohort separately. ITC_{Target} (mean = 0.17, sd = 0.07) denotes the magnitude of correlated EEG activity with subjects across target trials cohort. $ITC_{Nontarget}$ (mean = 0.064, sd = 0.03) represents the magnitude of the correlated EEG activity with subjects across non-target trials cohort. We performed a statistical t-test across total ITC scores of first three CorrCA components between target and non-target cohorts for all 8 subjects. It was observed that ITC_{Target} values are significantly higher than the $ITC_{Nontarget}$ ($t(7) = 6.45$, $p < 0.01$] and had a large effect size (Cohens' d = 1.39). It showed that the subjects were more attentive at the target stimulus than in the non-target stimulus. We also investigated whether ITC of individual CorrCA components could be influenced by attention. ISC and ITC are calculated in a similar way, except for the fact that ISC is computed across subject EEG data [33]. Computed ITC of Target trials cohort and Non-target trials cohort were significantly different from each other. We observed for first CorrCA component ($t(7) = 5.91$,$p < 0.01$,Cohens' d = 1.25), second($t(7) = 6.96$,$p < 0.01$,Cohens' d = 2.01) and on third component ($t(7) = 3.71$,$p < 0.01$,Cohens' d = 1.48). It was reported in[12] that subject 6 attended to non-target stimulus during one of the sessions, and subject 9 suffered from fatigue during the experiment, which might reflect their respective lower ITC. Subject 8 showed a higher ITC value during the entire session among all the subjects. It was reported that subject 8 was highly concentrated and motivated during the experiment[12]. All the disabled subjects showed lower averaged ITC values than healthy subjects.

We illustrated topoplots considering 8 channels, mainly from the parietal and central regions. Figure 5. and Fig. 6. shows the spatial patterns of neural activity in target and non-target cohorts using forward model. Here, A_1 represents the neural correlation with the first CorrCA component, and similarly A_2

represents neural correlation with second CorrCA component. Each topoplot has 8 weights corresponding to the 8 channels. In both Figs. 1 = P_7, 2 = P_3, 3 = P_z, 4 = O_z, 5 = P_4, 6 = P_8,7 = F_z, 8 = C_z. In Fig. 5 left panel showed neural activities after averaging target trial cohort for all subjects. C_z electrode captured the highest neural activity for able-bodied subjects (Row 1, right panel). From Fig. 5 we observed that higher neural activation was captured by first component for able, disabled and all subjects (Row 1). We observed that forward model of first component from target trials showed higher neural activation in able-bodied subjects (Row 1, right panel) than disabled subjects (Row 1, middle panel). We also observed that each component was able to capture a different pattern of neural activities. Figure 6 illustrates the spatial distribution of neural activity during the presentation of non-target images.

Discussion

We have used correlated component analysis (CorrCA) to extract reliable neural components from P300 based EEG data. We showed how CorrCA captured the coherent structure across multiple trials (Fig. 4.). This coherent structure gives information on peak latency, and this information also explains the subject's mental states during the task; for example, a shorter latency indicates superior mental performance than longer latency[1]. We found mean peak latency of all disabled subjects was 31.25ms longer than able-bodied subjects. Recorded EEG channels are usually noisy. Techniques such as principal component analysis (PCA)[34], [35] and independent component analysis (ICA) [36], [37] are often used to remove noise and extract the ERP signals. In this work, we used CorrCA to find the components having maximal correlation across the target trials cohort. These components were found to be less noisy compared to the channels. CorrCA can capture independent aspects from EEG data such as N_2 component, error-related negativity (ERN) [15]. After applying CorrCA, the reliable components were sorted in descending order according to respective SNR values as in Fig. 1. So, it is easy for us to select the first few components having the most reliable parts of EEG data. We found first CorrCA component (Fig. 4.) showed better latency structure than trials from a single electrode. In this work, six images were flashed one at a time on the screen where only one image was target, and the others were non-target. Subjects were asked to concentrate on the target image only. We observed a significant difference in ITC values when subjects attended to target and non-target stimuli.

It is expected that subjects must not suffer from any mental fatigue during the BCI experiment. Previous work showed that fatigue and concentrating on the wrong stimulus reduced BCI classification accuracy and bit rates [12]. We also investigated each subject's performance by computing the inter-trial correlation (ITC) across targets and non-target trials cohorts and then comparing the ITC values with the reported behavior from previous work [12]. Our results show that disabled subjects had lower ITC than abled-bodied subjects across the target trials cohort. [16] emphasized that when participants performed high challenging tasks, then ITC increased. So, this method may be useful in accessing the performance and understanding the task's difficulty. T-test showed ITC score was higher in the target trials cohort than the non-target trials cohort for all subjects. For disabled subjects, there may be challenges to track their performance during a task. In such scenarios ITC can also be used as an additional performance

indicator. In this work, we also tried to localize the source of the P300 component using forward model, observing that frontal and central regions showed neural activities for abled subjects during target trials.

Conclusion

This is probably the first work, to analyze P300 related neural activities with correlated component analysis algorithm. We showed how CorrCA captured the peak latency of P300 component and reduced the limitation of channel-based P300 ERP analysis. Experimental results showed that the subject attention and mental states influenced inter-trial correlation and neural correlation was higher across the target cohorts than in non-target cohorts. Healthy subjects who were less attentive showed lower ITC. CorrCA application in this study data-mines the shared component occurring in both target and non-target trial cohorts. It was also possible to observe the performance of each subject during the entire experiment.

Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Idea was proposed by CNG. Work was done by KH. Paper was written by

both KH and CNG.

Ethics approval

Not applicable

Consent to participate

Not applicable

Consent to publish

Not applicable

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Figures

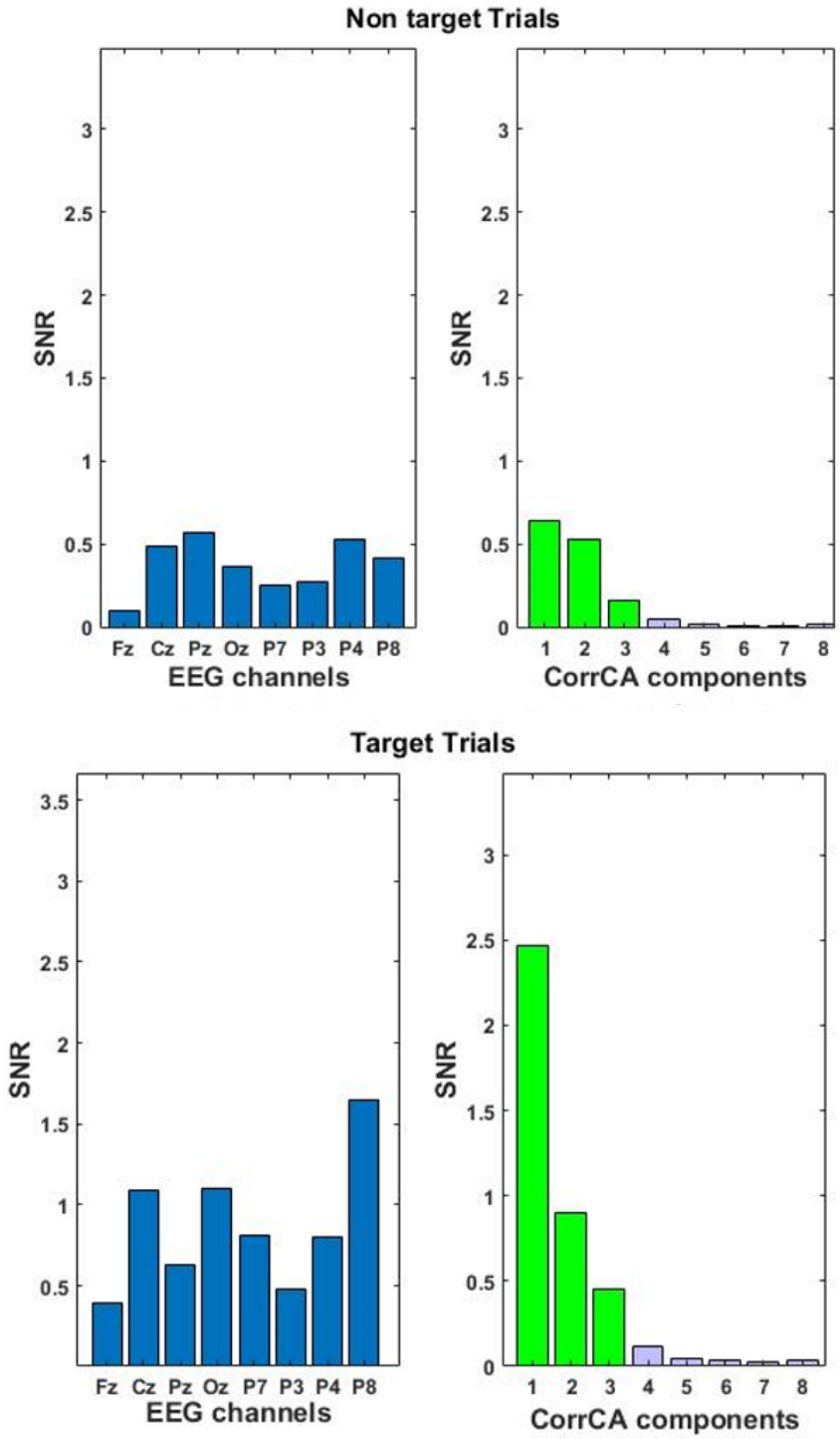

Figure 1

Top figure corresponds to non-target trials and Bottom figure corresponds to target trials. The green color bar denotes the significant($p<0.5$) CorrCA component. Components 5 to 8 in target trials and components 4 to 8 in non-target trials are nonsignificant.

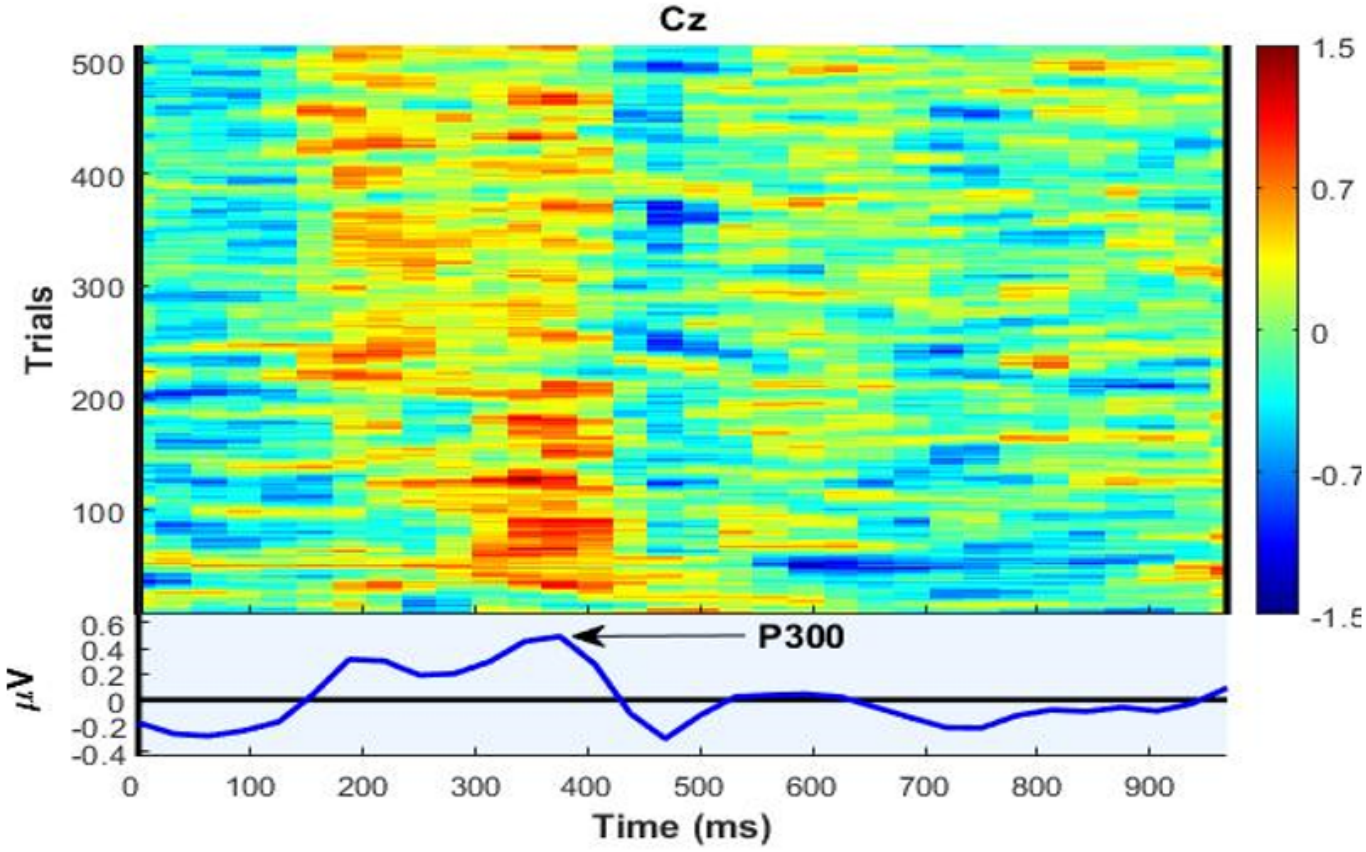

Figure 2

ERP Image plot of C_z electrode across target trials(upper); Averaged target trials (bottom).

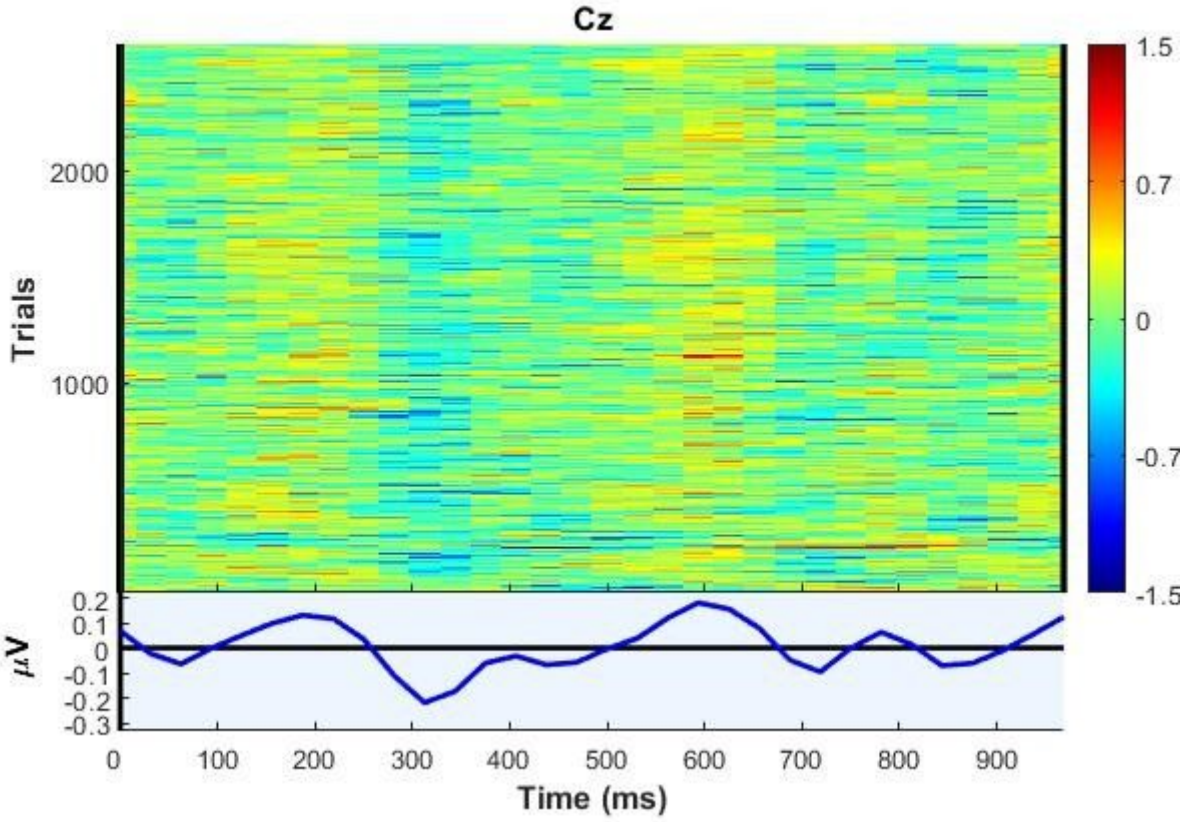

Figure 3

ERP Image plot of C_z electrode across Non-target trials(upper); Averaged Non-target trials (bottom).

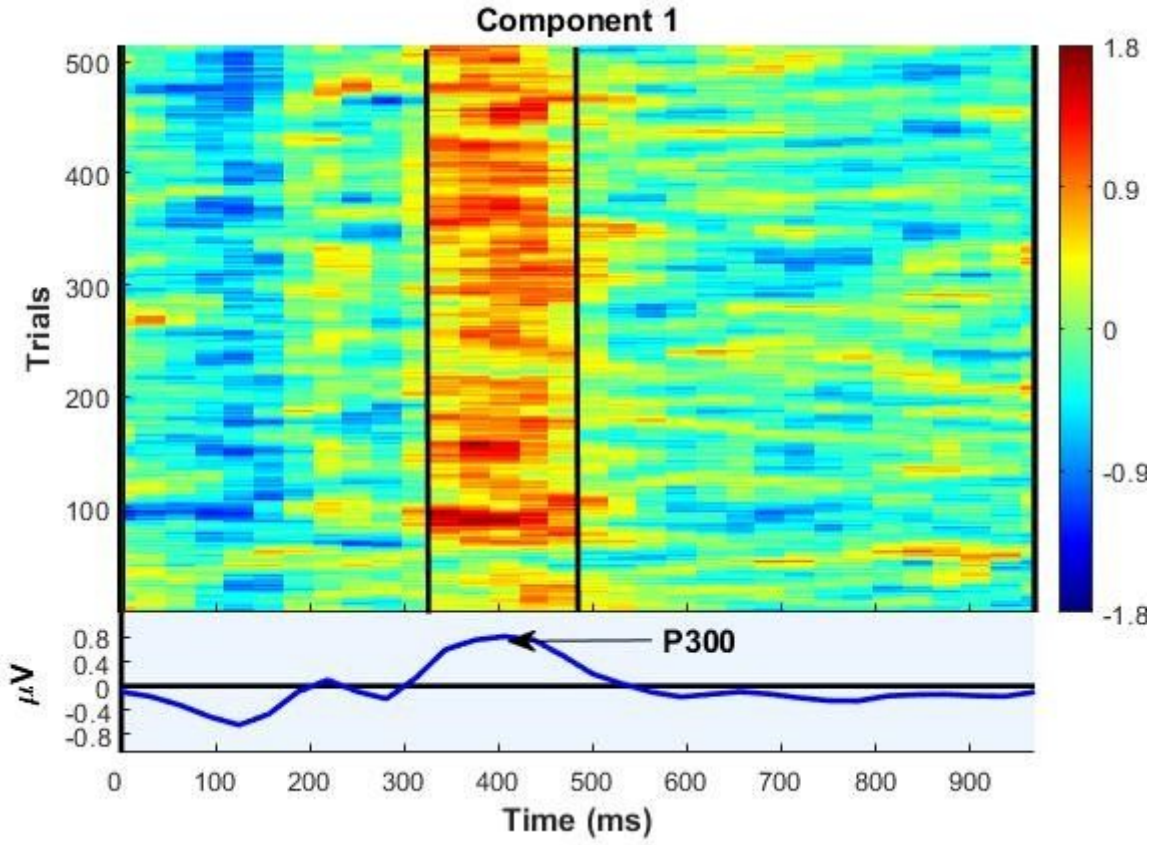

Figure 4

ERP Image plot of first CorrCA components from target trials (upper). Average of target trials across first CorrCA component(bottom).

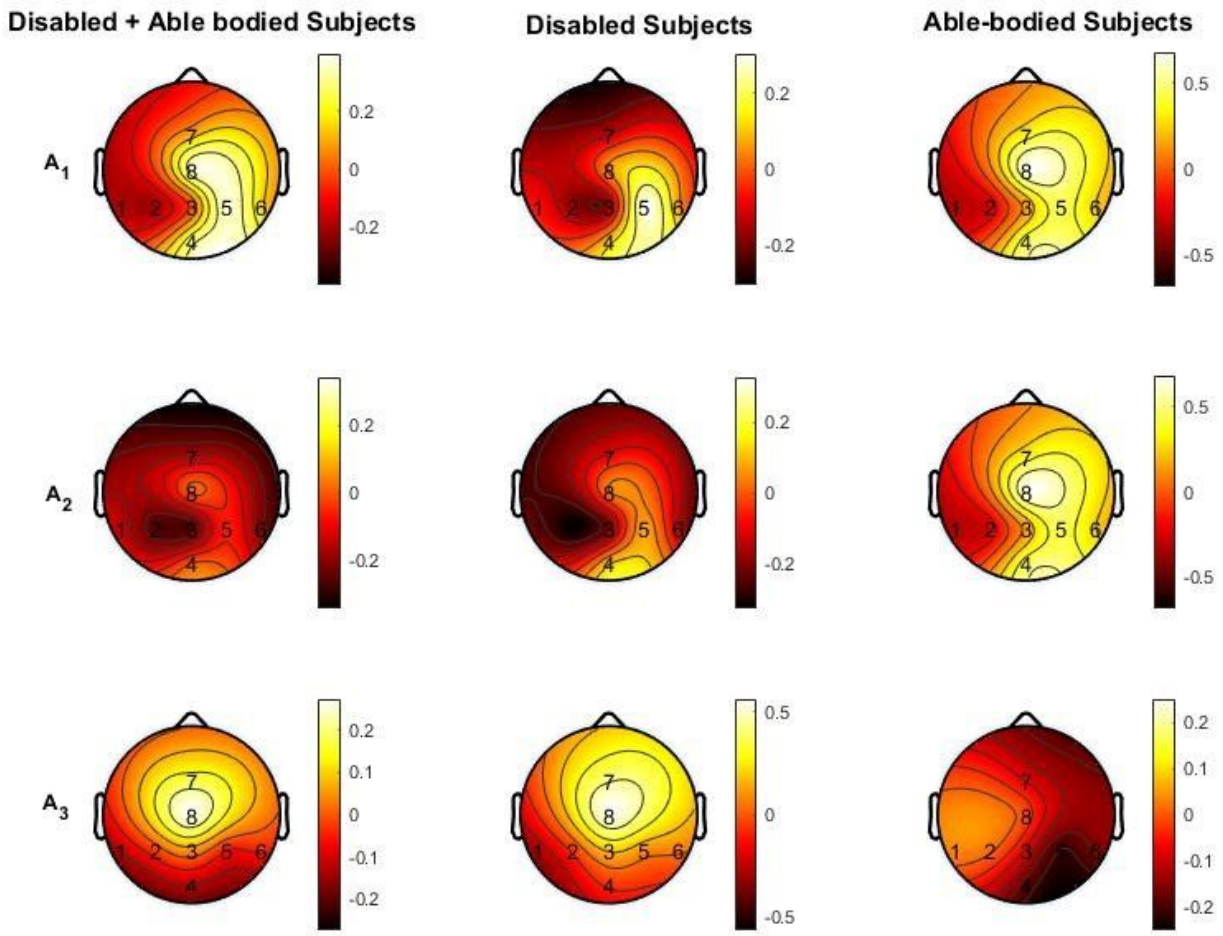

Figure 5

Forward models during the presentation of target images for all subjects (left panel), for only disabled subjects (middle panel), and for only able-bodied subjects (right panel).

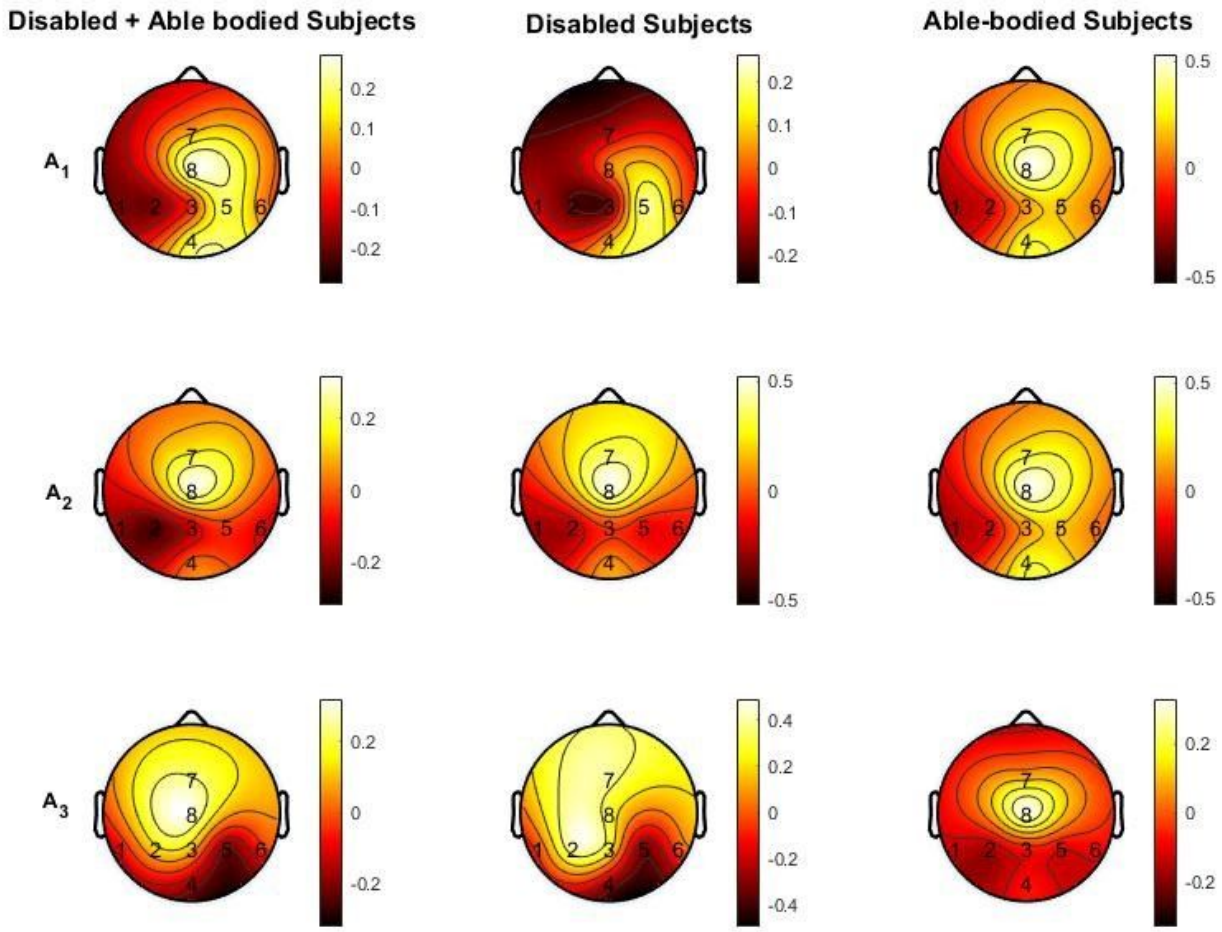

Figure 6

Forward models during presentation of non-target images for all subjects (left panel), for only disabled subjects (middle panel) and for only able-bodied subjects (right panel). Each component captures a different neural process.