Correlated components of ongoing EEG point to emotionally laden attention – a possible marker of engagement?

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INTRODUCTION

The ability to reliably decode brain state from recordings of neural activity represents a major neuroscientific frontier. Up until recently, the majority of brain decoding research has employed the event-related design (Spiers and Maguire, 2007) in which neural activity is regressed onto discrete event variables, allowing one to compute the neural correlates of a predefined and presumably fixed brain state. In natural settings, however, brain states are both continuous and transient. Moreover, the events eliciting state changes do not generally occur in a temporally regularized manner. Thus, there exists a need to track and index ongoing changes in cognitive state. In the absence of event markers, one possible solution is to regress the neural activity of one subject onto that of another, thus utilizing the correlation between multiple records to inform the state variables. Indeed, recent studies employing functional magnetic resonance imaging (fMRI) have revealed strong voxel-wise inter-subject correlations (ISC) across participants exposed to a common naturalistic stimulus (Spiers and Maguire, 2007). Unfortunately, voxel-wise correlations in the blood oxygenation level dependent (BOLD) signal are unable to capture weaker activity that is distributed over distant cortical areas. Furthermore, the limited temporal resolution of fMRI constrains the potential of so-called “reverse-correlation” procedures (Hasson et al., 2004) that identify stimulus features eliciting the observed peaks in correlation. In other words, while fMRI may tell us if neural activity significantly correlates in response to a common stimulus, it will likely not be able to tell us precisely when this synchronization occurs. Finally, the hemodynamic response measured in fMRI only indirectly captures neural activity and does not allow for analysis of fast oscillatory activity (although it does correlate with oscillatory activity in the gamma band; Mukamel et al., 2005).

To address these issues, in this study we employ EEG which offers a temporally fine and direct measure of neural activity. We record EEG during multiple views of short film clips and optimally measure the temporal correlation of neural activity between the multiple views. Instead of correlating raw signals in an electrode-to-electrode fashion, we derive a novel signal decomposition method which finds linear components of the data with maximal mutual correlation. The resulting spatially filtered EEG can capture patterns of activity distributed over large cortical areas that would remain occluded in voxel-wise or electrode-wise analysis. Furthermore, the temporal resolution of EEG is sufficiently fine to capture rapid variations in amplitude and instantaneous power in ongoing neural oscillations. Patterns of neural oscillation have long been associated with cognitive functions such as attention.

Recent evidence from functional magnetic resonance imaging suggests that cortical hemodynamic responses coincide in different subjects experiencing a common naturalistic stimulus. Here we utilize neural responses in the electroencephalogram (EEG) evoked by multiple presentations of short film clips to index brain states marked by high levels of correlation within and across subjects. We formulate a novel signal decomposition method which extracts maximally correlated signal components from multiple EEG records. The resulting components capture correlations down to a one-second time resolution, thus revealing that peak correlations of neural activity across viewings can occur in remarkable correspondence with arousing moments of the film. Moreover, a significant reduction in neural correlation occurs upon a second viewing of the film or when the narrative is disrupted by presenting its scenes scrambled in time. We also probe oscillatory brain activity during periods of heightened correlation, and observe during such times a significant increase in the theta band for a frontal component and reductions in the alpha and beta frequency bands for parietal and occipital components. Low-resolution EEG tomography of these components suggests that the correlated neural activity is consistent with sources in the cingulate and orbitofrontal cortices. Put together, these results suggest that the observed synchrony reflects attention- and emotion-modulated cortical processing which may be decoded with high temporal resolution by extracting maximally correlated components of neural activity.

Keywords: electroencephalography, engagement, attention, canonical correlation analysis, brain reading
Additionally, we probe the instantaneous power in convention-
ally involved emotional involvement (beta oscillations; Ray and Cole, 1985) and memory encoding (theta activity; Klimesch, 1999). Thus, utilizing EEG allows us to relate the measured correlations to ongoing oscillatory activity, shedding light on the cognitive states involved during synchronized periods.

The measure of correlation presented here is fundamentally different from that proposed in Hasson et al. (2004), which only captures coincidence of high or low activity in the hemodynamic response. Here, we leverage the high temporal resolution of EEG to measure correlation in time between two viewings. Hence, the spatial components extracted here capture not only coincidence, but rather, they represent neural activity that similarly tracks or follows the stimulus. We employ our measure to investigate the link between neural correlation and viewer engagement – a cognitive state which lacks a rigorous definition in the neuroscience context and which we define operationally by “emotionally laden attention.” In addition to the scientific value afforded by uncovering the neural substrates of engagement, the ability to monitor attention. In addition to the scientific value afforded by uncovering the neural substrates of engagement, the ability to monitor attention. In addition to the scientific value afforded by uncovering the neural substrates of engagement, the ability to monitor attention. This is not a meaningful constraint as spatial distributions are determined by anatomy and the location of current sources and are thus not expected to be orthogonal. Moreover, CCA assumes that each of the two data sets requires a different linear combination, thus doubling the number of free parameters and unnecessarily reducing estimation accuracy (Bellman, 1957). By dropping this assumption – a sensible choice as the two data sets are in principle no different – we have fewer degrees of freedom which allows us also to drop the constraint on orthogonality. The resulting algorithm, which maximizes the Pearson Product Moment Correlation Coefficient (Pearson, 1896) and is referred to here as “correlated components analysis,” amounts to simultaneously diagonalizing the pooled covariance and the cross-correlations of the two data sets. The linear components that achieve this can be obtained as the solutions of a generalized eigenvalue equation (equation 3), very much along the lines of other source separation algorithms used in EEG (Parra and Sajda, 2003).

**CORRELATED COMPONENT ANALYSIS**

Here we provide the details of a component analysis technique which has been specifically designed to find linear components of the data that are maximally correlated in time when comparing two different renditions.

Given two data sets \( X_1 \in \mathbb{R}^{D \times T} \) and \( X_2 \in \mathbb{R}^{D \times T} \), where \( D \) is the number of channels (i.e., electrodes) and \( T \) the number of time samples, we seek to find a weight vector \( w \in \mathbb{R}^D \) such that the resulting linear projections \( y_1 = X_1^T w \) and \( y_2 = X_2^T w \) exhibit maximal correlation. For example, \( X_1 \) and \( X_2 \) may be the EEG data records stemming from two viewings of the movie clip. Moreover, \( w \) is a spatial filter which linearly combines the electrodes such that the resulting filter outputs \( y_1 \) and \( y_2 \) recover correlated sources. Formally, the optimization problem seeks to maximize the Pearson Product Moment Correlation Coefficient (Pearson, 1896) between \( y_1 \) and \( y_2 \) (assuming zero-mean data):

\[
\hat{w} = \arg \max_w \frac{y_1^T y_2}{\|y_1\| \|y_2\|} = \arg \max_w \frac{w^T R_{12} w}{\sqrt{w^T R_{11} w} \sqrt{w^T R_{22} w}},
\]

where the sample covariance matrices are denoted by \( R_{ij} = \frac{1}{T} X_i X_j^T, i,j \in \{1,2\} \). Differentiating equation (1) with respect to \( w \) and setting to zero yields:

\[
\frac{\sigma_{11} \sigma_{22}}{\sigma_{12}} R_{12} w = (\sigma_{22} R_{11} + \sigma_{11} R_{22}) w,
\]

**MATERIALS AND METHODS**

**EXTRACTION OF MAXIMALLY CORRELATED COMPONENTS**

First we aimed to develop an analysis technique that is suitable for the continuous stream of neural activity generated during viewing of these film clips. With natural stimuli such as video, there may not be well-defined epochs that could be used with traditional methods of analyzing evoked or induced responses in EEG. Thus, instead of regressing the EEG signal against predefined discrete moments in time, we correlate the signal with the data from a second viewing that serves as a time-accurate reference for analysis. The second viewing could be by the same or a different subject. We want to combine electrodes linearly so as to identify, if necessary, distributed sources of neural activity instead of relying on individual voltage readings on the scalp. The traditional technique for extracting linear combinations of data with maximal correlation is Canonical Correlation Analysis (CCA; Hotelling, 1936). Unfortunately, CCA requires the canonical projection vectors (i.e., spatial filters) to be orthogonal. This is not a meaningful constraint as spatial distributions are determined by anatomy and the location of current sources and are thus not expected to be orthogonal. Moreover, CCA assumes that each of the two data sets requires a different linear combination, thus doubling the number of free parameters and unnecessarily reducing estimation accuracy (Bellman, 1957). By dropping this assumption – a sensible choice as the two data sets are in principle no different – we have fewer degrees of freedom which allows us also to drop the constraint on orthogonality. The resulting algorithm, which maximizes the Pearson Product Moment Correlation Coefficient (Pearson, 1896) and is referred to here as “correlated components analysis,” amounts to simultaneously diagonalizing the pooled covariance and the cross-correlations of the two data sets. The linear components that achieve this can be obtained as the solutions of a generalized eigenvalue equation (equation 3), very much along the lines of other source separation algorithms used in EEG (Parra and Sajda, 2003).
where $\sigma_{ij} = w^T R_{ij} w$ denote scalar power terms required to bring the two data sets onto the same scale. While we generally do not have prior knowledge of $\sigma_{ij}$, here we make the assumption that the two data sets have similar power levels, and thus $\sigma_{11} \approx \sigma_{22}$. Moreover, we symmetrize the cross-covariance matrix $R_{12}$ to arrive at the following eigenvalue equation:

$$(R_{11} + R_{22})^{-1} (R_{12} + R_{21}) w = \lambda w,$$  

(3)

where $\lambda = \sigma_{12}/\sigma_{11}$. As equation (3) is a generalized eigenvalue problem, there are multiple (and not necessarily orthogonal) solutions. The weight vector that maximizes the correlation coefficient between $y_1$ and $y_2$ follows as the principal eigenvector of $(R_{11} + R_{22})^{-1} (R_{12} + R_{21})$, with the optimal value of the correlation given by the corresponding eigenvalue. Moreover, the second strongest correlation is obtained by projecting the data matrices onto the eigenvector corresponding to the second strongest eigenvalue, and so forth. As the decorrelation (correlation matrix inverse) operation is sensitive to dimensions dominated by noise, we effectively regularize the algorithm by truncating the eigenvalue spectrum of the pooled covariance to the $K$ strongest principal components. The value of $K$ serves as a regularization parameter: the larger the number of whitened components, the stronger the optimal correlation. However, lower values for $K$ will shield the learning algorithm from picking up spurious correlations from noisy recordings.

**INTRA- AND INTER-SUBJECT CORRELATION (IAISC, ISC)**

The two data matrices $X_1$ and $X_2$ used to compute the correlation and cross-covariance matrices in the forthcoming results are defined here. For the first analysis which is concerned with within-subject correlations, we define the subject-aggregated data matrices as follows:

$$X_1 = \begin{bmatrix} X_1^{(1)} & X_1^{(2)} & \cdots & X_1^{(N)} \end{bmatrix},$$
$$X_2 = \begin{bmatrix} X_2^{(1)} & X_2^{(2)} & \cdots & X_2^{(N)} \end{bmatrix},$$

(4)

where $X_i^{(n)}$, $i \in \{1, 2\}$, $n \in \{1, 2, \ldots, N\}$ is the EEG data record from the $n$th viewing of the movie by the $i$th subject. For the analysis that is concerned with across-subject correlations, we defined the aggregated matrices $\bar{X}_1$ and $\bar{X}_2$ such that the subsequent correlation considers all unique combination of pairs of subjects. For example, for a three-subject population, we have:

$$\bar{X}_1 = \begin{bmatrix} X_1^{(1)} & X_1^{(2)} & X_1^{(3)} \end{bmatrix},$$
$$\bar{X}_2 = \begin{bmatrix} X_2^{(1)} & X_2^{(2)} & X_2^{(3)} \end{bmatrix},$$

(5)

where it should be noted that the above matrices correlate the records from viewing 1 only. Analogous definitions hold for the second viewing. As it is expected that only certain scenes evoke significant correlations, we compute the correlations in a time-resolved fashion by employing a sliding window with a 5-s duration with a shift of the window occurring every second (80% overlap between successive windows).

**FORWARD MODEL**

Given a set of linear spatial filters $W$ and the data covariance matrix $R$, the forward models $A = RW(W^T RW)^{-1}$ represent the scalp projections of the synchronized activity extracted by the projection vectors $W$ (Parra et al., 2005).

**SOURCE LOCALIZATION**

We have used the standardized low-resolution brain electromagnetic tomography package (sLORETA, version 20081104) to translate the obtained forward models into distributions of underlying cortical activity (Pascual-Marquès et al., 2002).

**SPECTRAL ANALYSIS**

To compute the instantaneous power of EEG in the theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) frequency bands, we employed a complex Morlet filter of the form $h(t) = a e^{\pi f_c t} e^{-\frac{t^2}{\sigma^2}}$, with the following parameters for each band: (theta) $a = 0.05$, $f_c = 6$, $\sigma = 0.12$, $0.5 < t < 0.5 s$; (alpha) $a = 0.05$, $f_c = 10$, $\sigma = 0.1$, $-0.33 < t < 0.33 s$; (beta) $a = 0.2$, $f_c = 20$, $\sigma = 0.075$, $-0.33 < t < 0.33 s$. The instantaneous power follows as the squared magnitude of the complex filter output $y(t) = h(t) \star x(t)$, where $\star$ denotes the convolution operator.

**EXPERIMENTAL PARADIGM**

A total of 20 subjects with self-reported normal or corrected-to-normal vision and normal hearing, participated in the study. The minimum, median, and maximum age of the subjects was 21, 24, and 45, respectively, with 14 males and 6 females volunteering. All experiments were approved by the Institutional Review Board of the City College of New York and all subjects gave written informed consent prior to the experiment. Subjects were instructed to sit comfortably, attentively watch the forthcoming movie clips, and refrain as much as possible from overt movements. Each subject was then presented with three 6-min movie clips, with each clip being shown twice. The order of the three clips was randomized across subjects, but the order was preserved within each subject (for example, a typical session consisted of M2-M1-M3-M2-M1-M3). The movie clips chosen were from the following films: “Bang! You’re Dead,” (1961) directed by Alfred Hitchcock as part of the Alfred Hitchcock Presents series; “The Good, the Bad, and the Ugly,” (1966) directed by Sergio Leone; and a control film which depicts a natural outdoor scene on a college campus.

**DATA COLLECTION AND PREPROCESSING**

The EEG was recorded with a BioSemi Active Two system (BioSemi, Amsterdam, Netherlands) at a sampling frequency of 512 Hz. Subjects were fitted with a standard, 64-electrode cap following the international 10/10 system. To subsequently remove eye-movement artifacts, we also recorded the electrooculogram (EOG) with four auxiliary electrodes. All signal processing was performed offline in the MATLAB software (MathWorks, Natik,
MA, USA). After extracting the EEG/EOG segments corresponding to the duration of each movie, the signals were high-pass filtered (0.5 Hz) and notch filtered (60 Hz). Eye-movement related artifacts were removed by linearly regressing out the four EOG channels from all EEG channels; we chose the regression approach over component-based techniques which are compared in Wallstrom et al. (2004). EEG samples whose squared magnitude falls above four standard deviations of the mean power of their respective channel were replaced with zeros. It should be noted that without regressing eye-movement related activity from the data, the forthcoming correlated components showed stereotypical signatures of eye movements, as expected given that well-edited films are known to evoke similar scan paths in viewers (Dorr et al., 2010). After regression, these components disappeared.

**STATISTICAL SIGNIFICANCE**

To establish significance of the time-resolved correlation, we employ a permutation test approach (Fisher, 1971). To yield correlation values under the null hypothesis, we compute the correlations with one of the two records (either from a second viewing or subject) scrambled in time: the second record is divided into 5-s blocks, with the order of the blocks then randomly shuffled. All significance tests are corrected for multiple comparisons using the false discovery rate (Benjamini and Hochberg, 1995).

**RESULTS**

**PEAKS IN INTRA-SUBJECT CORRELATIONS (IaSC) OCCUR AT MOMENTOUS FILM EVENTS**

We first consider intra-subject correlations (IaSC) between the two viewings and their relationship to stimulus characteristics. To that end, we construct subject-aggregated data matrices by concatenating in time the data from multiple subjects separately for each viewing (see equation 4). The aggregated data is substituted into the eigenvalue equation of equation (3) to yield the optimal spatial filters and resulting components. For each of $n = 10$ subjects, the coincidence in neural activity across the two viewings is then measured by computing the correlation coefficient in the component space. The population IaSC follows as the average of these correlation coefficients across all subjects.

**Figure 1A** depicts the top three correlation-maximizing components, shown in the form of “forward models” (Parra et al., 2005; see Methods) which depict the projection of the correlated neural activity on the scalp. It is interesting to note the remarkable level of agreement in the forward models across the three movies shown, including the amateur film depicting an outdoor scene lacking noteworthy action. The first component is symmetric and marked by an occipital positivity and parietal negativity. The second component is also symmetric with positivity over the temporal lobes and negativity over the medial parietal cortex. Meanwhile, the third component shows a strong frontal positivity with broad temporal-parietal-occipital negativity.

The resulting population correlation coefficients are shown as a function of movie time for “Bang! You’re Dead” in **Figure 1B.** The gray shaded area indicates the correlation level required to achieve significance at the $p < 0.01$ level (using a permutation test). The first component shows extended periods of statistical significance, staying above the significance level for approximately 33% (corrected for multiple comparisons by controlling the False Discovery Rate; Benjamini and Hochberg, 1995) of the film. More importantly, the peaks of the population IaSC correspond to moments in the clip marked by a high level of suspense, tension, or surprise, often involving close-ups of the young protagonist’s
We constructed a further control by extracting the (46) scenes of a separate group reordered, but otherwise identical, stimulus (for this experiment, and recording the neural activity in response to this temporally of “Bang! You’re Dead,” randomly shuffling their temporal order, identical in both conditions. On the other hand, the meaning, low-level visual and auditory features of the stimulus which are viewed the scrambled film twice). Comparing the neural responses of the scrambled film with the original version controls for the of the scrambled film with the original version controls for the exist between the forward models of the first and second viewings of the clips for \( n = 10 \) subjects. Analogously to the measure of population IaSC defined above, we construct the aggregated matrices such that the subsequent correlation considers all unique combinations of pairs of subjects (see equation 5). Once these concatenated data sets are constructed, the eigenvalue problem of equation (3) is solved to yield the spatial filters maximizing the ISC across the entire population.

**INTER-SUBJECT CORRELATION (ISC) DECREASES DURING SECOND VIEWING**

Next, we consider the effect of prior exposure to the stimulus on the resulting neural correlation. To that end, we measured the population inter-subject correlation (ISC) during the first and second viewings of the clips for \( n = 10 \) subjects. Analogously to the measure of population IaSC defined above, we construct the aggregated matrices such that the subsequent correlation considers all unique combinations of pairs of subjects (see equation 5). Once these concatenated data sets are constructed, the eigenvalue problem of equation (3) is solved to yield the spatial filters maximizing the ISC across the entire population.

**POPULATION IaSC IS STRONGLY ATTENUATED WHEN “MEANING” OF STIMULUS IS LOST**

We constructed a further control by extracting the (46) scenes of “Bang! You’re Dead,” randomly shuffling their temporal order, and recording the neural activity in response to this temporally reordered, but otherwise identical, stimulus (for this experiment, a separate group \( n = 10 \) subjects was employed, and each subject viewed the scrambled film twice). Comparing the neural responses of the scrambled film with the original version controls for the low-level visual and auditory features of the stimulus which are identical in both conditions. On the other hand, the meaning, affect, and suspense are presumably elevated when viewing the film clip in its original order. As shown in Figure 1E, the proportion of statistically significant windows is reduced to 14, 0% (no significant time windows), and 1% for components 1, 2, and 3, respectively, in the scrambled film. Once again, a hypothesis test of proportions reveals that these reductions are statistically significant at the \( p < 0.01 \) level.

**FIGURE 2 | The effect of prior exposure on neural correlation.** The scalp projections of the components maximizing population ISC during the first viewing are largely congruent to those stemming from viewing 2 (A). However, the resulting time-resolved correlation measures are significantly lower during the second viewing (B). Furthermore, more time windows exhibit statistically significant ISC in the first viewing (C).
three components, the null hypothesis was rejected ($p = 0.004$, $p = 0.012$, $p = 0.005$, for components 1, 2, and 3 respectively). Finally, as shown in Figure 2C, there is a statistically significant reduction in the proportion of time windows showing significant correlation during the second viewing in the second ($p = 0.022$) and third components ($p = 0.027$).

HIGH NEURAL CORRELATION MARKED BY DECREASED ALPHA AND INCREASED THETA

Due to the fine temporal resolution inherent to EEG, it is possible to uncover the frequency bands that are systematically increased (or decreased) during periods of high correlation. For example, desynchronization in the alpha band has been shown to be associated with increased attention (Klimesch et al., 1998), while increased alpha-band oscillations presumably reflect an attention suppression mechanism (Foxe and Snyder, 2011). As a result, one may expect an inverse relationship between alpha power and decoded engagement. To that end, we compared the instantaneous power (Boashash, 1992) at several nominal EEG frequency bands (collapsed across subjects and viewings) during times of high within-subject correlation to that observed during low-correlation periods. For each subject, we computed the mean instantaneous power during temporal windows in the top and bottom 20% of the population IaSC, and then tested the power differences (high correlation versus low correlation, $n = 10$) for statistical significance using a one-sample Student’s $t$-test. This procedure is performed in the component space: that is, the instantaneous powers are computed on the spatially filtered EEG. The results are summarized in Figure 3, which displays the corresponding boxplots of differences in instantaneous power. Each boxplot displays the median (central mark), the 25 and 75 percentiles (box edges), extrema (whiskers), and samples considered outliers (“plus” signs).

Effects deemed to be statistically significant are indicated with gray shading, and $p$-values are listed in each panel. As expected, there is a significant decrease in alpha power, measured in the space of the second (temporal-parietal) component, during periods of high IaSC. Moreover, the power in the theta band of the third (frontal) component is significantly increased during highly correlated times – synchronization of frontal theta power with a concurrent decrease in alpha power has been linked to the encoding of new information (Klimesch, 1999; Jensen and Tesche, 2002). It has also been shown in an fMRI study that successful encoding of episodic memory is correlated with high ISC during initial exposure (Hasson et al., 2008). Finally, a strong reduction in beta power in both the first and second components is revealed – a decrease in temporal beta has been associated with so-called “intake” tasks, or those that require sustained monitoring of external emotionally laden stimuli (Ray and Cole, 1985).

SOURCE ANALYSIS SUGGESTS EMOTIONAL INVOLVEMENT

While the spatial resolution of EEG is inherently poor, low-resolution tomography (LORETA) of scalp potentials has been extensively employed to suggest possible cortical origins of the observed activity (Fuchs et al., 2002; Pascual-Marqui, 2002; Jurcak et al., 2007). To that end, we computed the LORETA estimates of the neural current source distributions explaining the scalp projections of the synchronized activity. The results are illustrated in Figure 4.
The localization results from the first component of synchronized activity suggest a possible source in the cingulate cortex, with particularly strong activation occurring in the posterior cingulate of the left hemisphere. The cingulate cortex has been viewed by some as a unitary component of the limbic system subserving emotional processing (Vogt, 2005). Strong activations may also originate in the parahippocampal gyri (involved in the processing of scenes; Epstein et al., 2003), as well as in the precentral and superior parietal lobule of the parietal cortex – widespread involvement of the parietal cortex in neural correlation was also reported in fMRI (Hassen et al., 2004). Performing LORETA on the scalp projection of the synchronized activity in the second component is also consistent with activity originating in the parietal cortex, with the postcentral gyrus and paracentral lobules showing strong activations across both hemispheres. Meanwhile, source analysis of activity in the third component reveals possible sources in frontal regions (in descending order of strength of activation): the inferior frontal, orbital, middle frontal, and superior frontal gyri. The orbitofrontal cortex is considered to be a region of multimodal association and is involved in the representation and learning of reinforcers that elicit emotions and conscious feelings (Kringelbach, 2005).

**DISCUSSION**

To investigate the relationship between engagement – an everyday phenomenon which one can readily describe subjectively – and neural correlation on a temporally fine time scale, we developed a component analysis technique which yields cleaner estimates of the underlying neural synchrony than that obtained by simply correlating (noisy) EEG in an electrode-to-electrode fashion. By then manipulating the naturalistic stimulus (for example, by repeating the film or showing it with scrambled scenes), we found a close correspondence between expected engagement and neural correlation. The observed desynchronization of alpha-band activity during times of high neural correlation suggests increased attention during moments of engagement. Indeed, there may be significant overlap between engagement and attention, as both appear to involve a suppression of internally oriented mental processing with a focus on external stimuli. We suggest here that in addition to increased attention, engagement entails emotional involvement (“emotionally laden attention”), a claim supported by the finding of decreased beta activity (Ray and Cole, 1985). Furthermore, we find increased theta activity in frontal areas which has been repeatedly implicated in memory encoding (Klimesch, 1999; Jensen and Tesche, 2002). This is also consistent with the finding that the most memorable events are those that are emotionally arousing (Anderson et al., 2006).

It is worthwhile to point out that we also repeated the analysis but with canonical correlation analysis (CCA) employed to derive the components. The resulting spatial filters exhibited very noisy topologies with seemingly little anatomical plausibility. We attributed this to the higher dimensionality of CCA and insufficient data to fit its parameter space. Both the proposed “Correlated Components Analysis” and the classical CCA explicitly correlate two data sets; instead, one may also apply conventional source separation algorithms such as Independent Components Analysis (ICA; Delorme and Makeig, 2004) to a concatenated data matrix of the form $[X_1; X_2]$. Blind source separation techniques such as ICA are also powerful in extracting artifactual components which may then be straightforwardly subtracted from the data. On the other hand, the components yielded by an ICA decomposition are unordered and do not necessarily represent activity that is correlated across viewings. Thus, a manual procedure (and subsequent multiple comparison correction) would be required to search for components which exhibit the desired behavior (i.e., correlation across viewings). To that end, an ICA-type algorithm which incorporates correlation constraints may prove useful in future investigations.

Analyzing naturalistic data presents a challenge in that segments of data severely corrupted by subject movement and rapid impedance changes need to be retained in the processed data set: in multiple-trial analyses of the event-related variety, one may simply discard corrupted trials. Here, in an effort to preserve the temporal structure of the data, we have replaced all samples varying from

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**FIGURE 4 | Sources of correlated neural activity for components 1, 2, and 3.** The scalp projections of the correlated activity are shown in the top left of each pane; the estimated distributions of cortical sources are depicted in the remaining three panes. The correlated activity of component 1 suggests involvement of the posterior cingulate gyrus (Brodmann Area 31, labeled pcg), the parahippocampal gyrus (Brodmann Area 27, phg), and precuneus (Brodmann Area 7, pcu). The postcentral gyrus (pocg) and paracentral lobule (pcal) are implicated in the localization of the activity in component two. The activity captured by component 3 is consistent with sources in the inferior frontal gyrus (ifg) and the orbital gyrus (og). Anatomical locations shown are approximate.
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