Smartphones Get Emotional: Mind Reading Images and Reconstructing the Neural Sources

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Abstract. Combining a wireless EEG headset with a smartphone offers new opportunities to capture brain imaging data reflecting our everyday social behavior in a mobile context. However processing the data on a portable device will require novel approaches to analyze and interpret significant patterns in order to make them available for runtime interaction. Applying a Bayesian approach to reconstruct the neural sources we demonstrate the ability to distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures compared to neutral content. Rendering the activations in a 3D brain model on a smartphone may not only facilitate differentiation of emotional responses but also provide an intuitive interface for touch based interaction, allowing for both modeling the mental state of users as well as providing a basis for novel bio-feedback applications.

Keywords: affective computing, mobile EEG, source reconstruction.

1 Motivation

Only recently affordable wireless EEG headsets capturing the electric potentials of neuronal populations through electrodes resting on the scalp have become available. Originally designed as cognitive game interfaces they have subsequently been applied as brain machine interfaces to directly manipulate robotic arms [1], drive a car [2] or mentally select images using the P300 oddball paradigm to call contacts by mentally selecting their image from the phonebook of an iPhone [3]. Scott Makeig et al. [4] have summarized the many benefits of brain monitoring under naturalistic conditions, emphasizing the need for moving beyond gauging how a few bits of information are transported through the brain when tapping a finger, and widen the focus to map out how we perceive our surroundings reflected in embodied cognition and real life emotional responses. Cognitively speaking our feelings can be thought of as labels that we consciously assign to the emotional responses triggered by what we perceive [5]. While we often think of affective terms as describing widely different states, these can be represented as related components in a circumplex model framed by the two psychological primitives: valence and arousal [6]. When viewing affective

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pictures, earlier neuroimaging studies have established that emotional content trigger not only autonomic responses of increased heart rate and electrodermal skin conductance, but also distinct brain potentials characterizing pleasant or unpleasant feelings compared to neutral imagery [7]. These event related responses ERPs covary with autonomic arousal and self report [8], and a data set of affective images, international affective picture system IAPS, has experimentally been validated by users to define how pleasant or intense the emotional content is perceived as being, measured along the psychological dimensions of valence and arousal [9]. Previous brain imaging studies of emotional responses when viewing affective pictures [8] have identified distinct differences in the ERP amplitudes elicited by pleasant and unpleasant compared to neutral images. An early component emerge most pronounced for pleasant content at 150-200 ms termed early posterior negativity EPN, triggering a relative negative shift over temporal occipital areas and a positive potential over central sites [10]. Followed by yet another ERP component; a late positive potential LPP at 300-500 ms, characterized by an enhanced posterior positivity over central parietal sites for affective compared to neutral content, with left hemisphere enhanced for pleasant pictures while activation appeared right lateralized for unpleasant images [7]. However the obvious question remains whether the limited number of electrodes and the quality of consumer priced EEG sets make it feasible to capture brain imaging data in noisy environments. We therefore decided to combine a wireless neuroheadset with a smartphone for presenting media, gauge the emotional responses by capturing the EEG data and subsequently process and visualize the reconstructed patterns of brain activity on the device. And in the following sections outline the mobile EEG system design, experimental setup, results based on ICA analysis and source reconstruction, which are discussed in relation to earlier neuroimaging findings obtained in laboratory settings using conventional EEG equipment.

2 Materials and Methods

2.1 Mobile EEG System

Our setup is based on a portable wireless Emotiv Research Edition neuroheadset (http://emotiv.com) which transmits the EEG and control data to a receiver USB dongle, originally intended for a Windows PC version of the Emotiv research edition SDK. We instead connect the wireless receiver dongle to a USB port on a Nokia N900 smartphone with Maemo 5 OS. Running in USB hostmode we decrypt the raw binary EEG data transmitted from the wireless headset, and in order to synchronize the stimuli with the data we timestamp the first and last packets arriving at the beginning and end of the EEG recording. While the 128 Hz sample rate of the neuroheadset turns out to be 126-127 Hz when averaged over several minutes of recording. Timestamps saved during the experiments indicate that a resolution of 10 ms can be achieved with the current Python implementation. Designed as a client-server architecture, computationally expensive data analyses can be performed on a remote server and results are

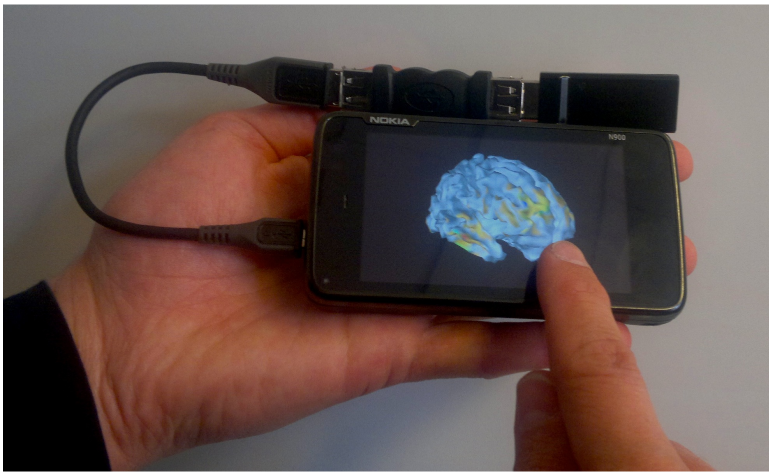

Fig. 1. The wireless neuroheadset transmits the brain imaging data via a receiver USB dongle connected directly to a Nokia N900 smartphone. Reconstructing the underlying sources realtime from the EEG data in a sparse 3D model improves decoding of the signal and potentially provides relevant neurofeedback for brain machine interfaces.

transmitted back to the phone for presentation. Server-side, the neural sources are reconstructed from the EEG scalp maps and presented on the phone in a 3D brain model that contains 1028 vertices and 2048 triangles. Stored as a mobile application on the device the brain activity is rendered at approximately 30 fps allowing for fluent touch-based interaction. The current design of the system has a delay of approximately 150 ms between the signal appearing in the brain and the subsequent visualization on the smartphone.

2.2 Experimental Setup

Eight male volunteers from the Technical University of Denmark, between the ages of 26 and 53 (mean age 32,75 years) participated in the experiment. Replicating the setup for identifying neural correlates of emotional responses triggered by affective pictures, originally performed using a high density 129 electrode array [7], we in the present study applied a simplified approach based on the portable wireless 14 channel neuroheadset to capture the signal from electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the international 10-20 system. Channels were recorded at a sampling rate of 122 Hz. using the electrodes P3/P4 as CMS reference and DRL feedback respectively. Based on earlier studies showing that late emotional responses to affective pictures remain unaffected when varying the size of images [11], the participants viewed a randomized sequence of 60 IAPS images presented at approximately 50 cm distance on the 3.5" display (800 x 480 screen resolution) of

N900 Nokia smartphones rather than on a standard monitor. Combining earlier experimental designs for eliciting emotional responses when viewing affective pictures, we selected 3 x 20 images from the user rated international affective picture system IAPS [9] identical to the subset used in [7] representing categories of pleasant (erotic and family photos) unpleasant (mutilated bodies, snakes and spiders) and neutral images (simple objects as well non-expressive portraits of people). Taking into consideration findings establishing that the ERP neural correlates of affective content in images can be distinguished even when the exposure of target pictures are limited to 120 ms [10], we opted for adopting the experimental picture viewing paradigm outlined in [12], where a randomized sequence of images from the 3 x 20 IAPS picture categories are presented with 0.5 second prestimulus consisting of a white fixation cross on black background, before a 1 second visual stimulus presentation of a picture followed by a subsequent 1 second poststimulus black screen.

2.3 Source Reconstruction

The inverse problem of estimating the distribution of underlying sources from a scalp map is severely ill-posed with multiple solutions, as the electrodes are placed at a distance and therefore sum the volume conducted brain activities from cortical areas throughout the scalp [13]. However, computing a sparse 3D representation may not only provide relevant neurofeedback for brain machine interfaces, but also facilitate decoding and interpretation of EEG signals by reducing redundancy and thus retrieve the most informative features constituting the functional network dynamics [14]. The forward propagation is considered linear and written in terms of a matrix A, relating the measured electrode signals $Y = AX + E$ to the source signals X where E is a noise term [15]. Here the forward model depends on electrode positions based on a head model approximating the spatial distribution of tissue and conductivity values. Assuming the noise to be time independent Gaussian distributed, the observation model becomes $p(y_t|x_t, \Sigma_E) = N(y_t|Ax_t, \Sigma_E)$ where Σ_E is the noise spatial covariance matrix. We here apply a Bayesian formulation of the widely used minimum norm MN method for solving the inverse problem [16], which allows for fast computation of the inverse solution. In a MN setting a multivariate Gaussian prior for the sources with zero mean and covariance $\alpha^{-1} I_{N_d}$ is assumed. Moreover, it is assumed that the forward propagation model is fixed and known. With Bayes rule the posterior distribution is maximized by

$$\mathbf{\Sigma_y} = (\alpha^{-1}\mathbf{A}\mathbf{A}^T + \beta^{-1}\mathbf{I}_{N_c})^{-1} \quad (1)$$

$$\hat{\mathbf{X}} = \alpha^{-1}\mathbf{A}^T\mathbf{\Sigma_y}\mathbf{Y} \quad (2)$$

where the inverse noise variance is estimated from the hyper parameters α and β using a Bayesian EM approach.

2.4 ICA Data Analysis

Even when electrodes are accurately placed the recorded potentials may still vary due to individual differences in cortical surface and volume conduction. To further analyze the coherence in the neuroheadset data, we clustered 14 ICA independent components generated from continuous EEG trial data in order to identify common patterns of brain activity across the eight subjects. While the rows of the matrix of EEG data initially consist of voltage differences measured over time between each electrode and the reference channel, they come to represent temporally independent events that are spatially filtered from the channel data by applying ICA independent component analysis [17]. Even though neither the location of electrodes or aspects of volume conductance in the brain are part of the equation, the ICA decomposition of the original data matrix often results in independent components resembling scalp projections of brain dipoles, as they reflect synchronous brain activity of local field potentials projected through volume conduction throughout the scalp [18]. As part of the recorded potentials are induced by muscle activity and noise we followed the approach in [13] to cluster ICA components retrieved from each subject to isolate the components representing information sources based on the EEGLAB plug-in (v9.0.4.4) for Matlab (R2010b). Initially by reducing the N dimensionality of the feature space to N=10 by applying PCA principal component analysis [19], which as a pre-clustering function computes a vector for each component to define normalized distances in a subspace representing the largest covariances within scalp maps and power spectra. Subsequently, we applied a K-means algorithm choosing K=10 to cluster similar ICA components and separate outliers that remain more than three standard deviations removed from any cluster centroids.

3 Results

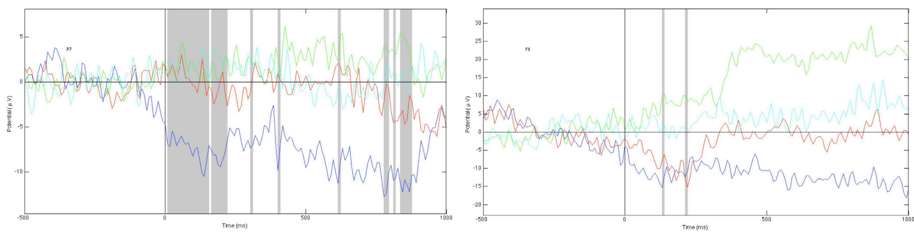

Fig. 2. Event related potentials ERP of channel amplitudes averaged across eight subjects viewing four different types of affective images outlined in red: arousing (erotic couples), green: unpleasant (mutilated bodies), blue: neutral (people and faces), turquoise: pleasant (families with kids). The differences remain statistically significant based on a repeated one-way ANOVA analysis at $p < 0.05$ marked in the grey time intervals for the neuroheadset electrodes P7 (left) and F8 (right).

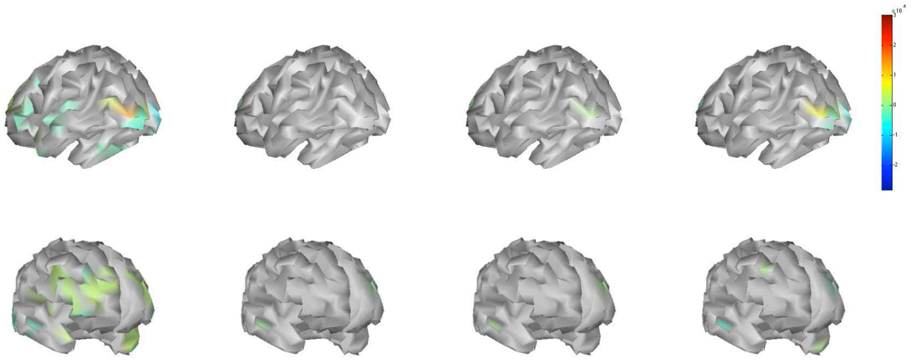

Fig. 3. Activations in the 8-13 Hz alpha frequency band at 148-156 ms after stimulus, based on MN reconstructed sources generated from scalp maps averaged across subjects viewing pictures of (from left to right): erotic couples, mutilated bodies, neutral people and families with kids. Consistent with earlier neuroimaging findings at the 150 ms time window related to the early posterior negativity EPN component [7] [10], the reconstructed sources reflect increased activity for pleasant versus unpleasant and neutral content.

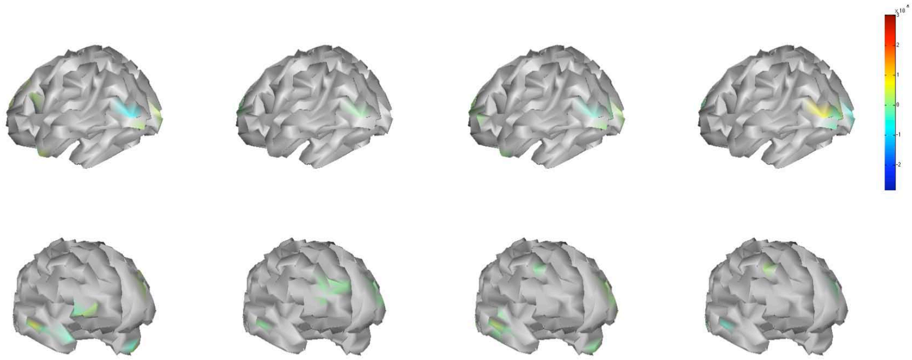

Fig. 4. Activations in the 8-13 Hz alpha frequency band at 451 ms after stimulus, based on MN reconstructed sources generated from scalp maps averaged across subjects viewing pictures of (from left to right): erotic couples, mutilated bodies, neutral people and families with kids. Consistent with earlier neuroimaging findings at the 450 ms time window related to the late positive potential LPP component [7] [10], the reconstructed sources reflect increased activity for pleasant versus unpleasant and for affective versus neutral content.

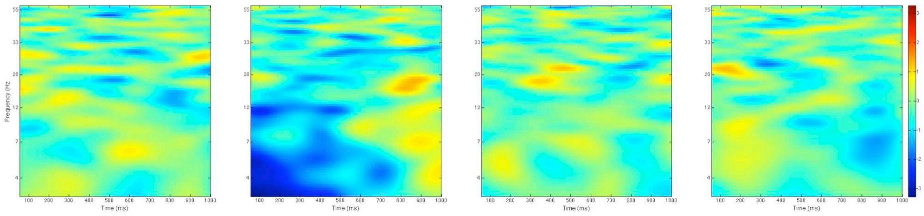

Fig. 5. Spectograms of event related spectral perturbation ERSP [18] across the frequencies 3-60 Hz for neuroheadset electrode F8, signifying the mean changes in power spectrum at a given frequency and latency averaged across subjects viewing pictures of (from left to right): erotic couples, mutilated bodies, neutral people and families with kids, visualizing the contributions of theta, alpha, beta and gamma brain waves elicited by the emotional content

4 Discussion

Combining a wireless neuroheadset with a smartphone to process brain imaging data, our findings indicate we can distinguish among emotional responses reflected in different scalp potentials when viewing pleasant and unpleasant pictures and thereby replicate results previously obtained using conventional high density 129 electrode EEG equipment [7] [10]. Analyzing the event related potentials ERP averaged across eight subjects when viewing affective images (Fig.2), allows for differentiating between affective and neutral images as well as pleasant and unpleasant content, which based on a repeated one-way ANOVA analysis remain statistically significant at $p < 0.05$ for the neuroheadset electrodes P7 and F8. Even though the neuroheadset has only a limited number of channels and no central electrodes, including electrode positions like F7/F8, P7/P8 and O1/O2 which have been shown to contribute significantly to the differentiation between affective and neutral pictures [7], might thus allow for replicating results previously obtained using standard EEG setups. Although at the same time raising the question as to whether the electrode positions can be considered similar, as the form factor of the neuroheadset will provide a slightly different fit for each subject depending on the shape of the head in contrast to traditional EEG caps. We therefore clustered the 8 x 14 ICA components based on power spectrum and scalp maps generated from continuous EEG trial data in order to identify common patterns of brain activity across the eight subjects. Here four clusters captured 7, 12, 17 and 15 ICA components respectively, all positioned within 3 standard deviations from the centroids. Indicating an ability to consistently capture common patterns of brain activity across subjects even when taking into account the less accurate positioning and limited number of electrodes. While the clustered ICA components do not represent absolute scalp map polarities as such, they indicate common sources of synchronous brain activity, consistent with activities in central, temporal and parietal cortex previously observed to differentiate responses when viewing affective pictures compared to neutral content [7] [10].

Taking a Bayesian approach we estimate the parameters for applying the minimum norm MN method and thus reconstruct the underlying sources from the recorded scalp potentials. Initially exploring the 3D brain model at 150 ms after picture onset we identified activations averaged across subjects viewing pictures of: erotic couples, mutilated bodies, neutral people and families with kids. Consistent with earlier neuroimaging findings related to the early posterior negativity EPN component [7] [10], our reconstructed sources also reflected increased activity for pleasant versus unpleasant and neutral content (Fig.3). This early component thought to reflect allocation of attentional resources has earlier been found to be more significant for erotic relative to neutral content. Our MN source reconstruction here adds further details as it highlights a number of frontal cortical areas such as the dorsomedial prefrontal cortex which has previously been found to be co-activated and closely associated with core limbic structures involved in generating emotional states. While at the same time triggering activations from the visual cortex through the temporoparietal junction along the superior temporal sulcus. Activations well aligned with earlier studies of affective pictures, in which they have been associated with attention directed towards inferring the conceptual relevance of emotional content [20]. Also the pleasant pictures of family and kids show a stronger activation in this early time window compared to neutral content, suggesting that not only arousing images but positive valence in general may enhance the activations. Within the later time window we found a strong activation at 451 ms after picture onset which based on the reconstructed sources may represent the late positive potential LPP previously observed using a conventional EEG setup. Consistent with earlier neuroimaging findings at the 450 ms time window related to the LPP component [7] [10], our reconstructed sources also reflected increased activity for pleasant versus unpleasant and for affective versus neutral content. It has been suggested that the LPP component signifies increased allocation of neural resources for processing emotionally salient relative to neutral content. The MN source reconstruction here again provides further details as the unpleasant pictures appear to activate the dorsomedial prefrontal cortex which is considered an interface for projecting the cognitive context to the underlying subcortical structures related to core affect. Whereas the pleasant content to a higher degree seems to activate posterior areas for high-level visual processing and orbitofrontal areas associated with evaluating emotional stimuli and forming motivational states [20].

Earlier studies of emotional face expressions indicate that the EEG signals can be differentiated based on brain wave oscillations, with angry faces increasing the amplitude in the high end of the 8-13 Hz alpha oscillations, while happy expressions enhance amplitudes in the low end of the alpha frequency band [21]. Analyzing the spectograms of event related spectral perturbation ERSP (Fig.5) constituting the mean changes in power spectrum at a given frequency and latency [18], across the frequencies 3-60 Hz for the neuroheadset electrode F8, it seems feasible to similarly differentiate among the four image categories based on the complementary contributions of theta, alpha, beta and gamma brain waves elicited by the emotional content. As a consequence when subdividing the activations in the alpha band previously discussed (Fig. 4), it is also here evident that the responses triggered by unpleasant pictures are enhanced within the 11-13 Hz upper end of the alpha oscillations, whereas the cortical areas activated by pleasant content are more pronounced within the lower 8-11 Hz end of the frequency band. This emotional bias towards positive or negative valence within the alpha frequency band might be utilized in brain machine interfaces, as participants undergoing neurofeedback training likewise report evoking emotions as the best strategy to consciously control alpha brain waves [22].

Applying a Bayesian approach to reconstruct the underlying neural sources may thus provide a differentiation of emotional responses based on the raw EEG data captured online in a mobile context, as our current implementation is able to visualize the activations on a smartphone with a latency of 150 ms. The early and late ERP components are not limited to the stark emotional contrasts characterizing images selected from the IAPS collection. Whether we read a word with affective connotations, come across something similar in an image or recognize from the facial expression that somebody looks sad, the electrophysical patterns in the brain seem to suggest that the underlying emotional processes might be the same [23]. The ability to continuously capture these patterns by integrating wireless EEG sets with smartphones for online processing of brain imaging data may offer completely new opportunities for modeling the mental state of users in real life scenarios as well as providing a basis for novel biofeedback applications.

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