Spatio-temporal Dynamics of Images with Emotional Bivalence

M.D. Grima Murcia[1(✉)], M.A. Lopez-Gordo[2,3], Maria J. Ortíz[4], J.M. Ferrández[5], and Eduardo Fernández[1]

[1] Institute of Bioengineering, University Miguel Hernández and CIBER BBN Avenida de la Universidad, 03202, Elche, Spain
maria.grima@alu.umh.es, e.fernandez@umh.es
[2] Nicolo Association, Churriana de la Vega, Granada, Spain
malg@nicolo.es
[3] Deptartment of Signal Theory, Communications and Networking, University of Granada, 18071, Granada, Spain
[4] Deptartment of Communication and Social Psycology, University of Alicante, Alicante, Spain
[5] Deptartment of Electronics and Computer Technologyt, University of Cartagena, Cartagena, Spain

Abstract. At present there is a growing interest in studying emotions in the brain. However, although in the latest years there have been numerous studies, little is known about their temporal dynamics. Techniques such as fMRI or PET have very good spatial resolution but poor temporal resolution and vice-versa in the case of EEG. In this study we propose to use EEG to gain insight into the spatiotemporal dynamics of emotions processing with a better time resolution. We conducted an experiment in which binary classification (like / dislike) of standardized images was performed. Topographic changes in EEG activity were examined in the time domain. In the spatial dimension, we used a rotating dipole for the spatial location and determination of Cartesian coordinates (x, y and z). Our results showed a temporal window (424-474msec) with a significant difference which involved a lateralization (left to very positive stimuli and right to very negative stimuli) even for neutral stimuli. These results support the lateralization of brain activity during processing of emotions.

Keywords: EEG Teleservices · Brain-computer interface · Brain area networks

1 Introduction

The ability to recognize the emotional states is an important part of natural communication. Emotion plays an important role in human–human communication and interaction. Considering that, in normal live, we all are surrounded by machines; the emotional interaction between humans and machines is one of the most important challenges in advanced human–machine interaction and brain–computer interface [1]. For a robust analysis of the affective human–machine interaction, one

J.M. Ferrández Vicente et al. (Eds.): IWINAC 2015, Part I, LNCS 9107, pp. 203–212, 2015.
DOI: 10.1007/978-3-319-18914-7_21

of the most important requisites is to develop a reliable emotion recognition system capable to guarantee high recognition accuracy, robustness against artifacts and adaptability to applications.

Some researchers support the notion of biphasic emotion, which states that emotion fundamentally stems from varying activation in centrally organized appetitive and defensive motivational systems that have evolved to mediate the wide range of adaptive behaviors necessary for an organism struggling to survive in the physical world [2]. In this framework, neuroscientists have made efforts to determine how the relationship between stimulus input and behavioral output is mediated though specific, neural circuits that have evolved to organize and direct adaptive actions [3].

Relatively little is known about the neural temporal dynamics of emotion processing [4]. The majority of neuroimaging studies are based on methods such as functional Magnetic Resonance Imaging (fMRI) [5] or Positron Emission Tomography (PET) [6] with excellent spatial resolution but a very poor temporal one (in the range of seconds). Conversely, Electroencephalography (EEG) offers excellent temporal resolution (in the range of milliseconds), thus offering a better choice to solve the temporal problem.

Among neuroimaging techniques, EEG has demonstrated it can provide informative characteristics in responses to the emotional states [7]. Since Davidson et al [8] suggested that frontal brain electrical activity was associated with the experience of positive and negative emotions, the studies of associations between EEG asymmetry and emotions has received much attention [9]. In other studies, EEG asymmetry and event-related potentials (indexing a relatively small proportion of mean EEG activity) were also used to study the association with emotion [10].

In this study we investigated the temporal dynamics of neural activity associated to emotions (like/dislike) generated by complex pictures derived from the International Affective Picture System (IAPS) [11]. First, we used EEG to solve the problem of temporal resolution. We evaluated the correspondence between subjective emotional experience induced by the pictures and then the neural signature derived from the temporal profiles associated with their perception. Finally, we estimated with rotating dipole and head reconstruction the underlying neural places in which event-related potentials (ERPs) were generated. The tridimensional location was used for the assessment of changes in the activation of cortical networks involved in emotion processing. We completed the study by analysis of lateralization during emotion identification task in the tridimensional space.

Our results i) provide valuable information to understand the temporal dynamics of emotions, ii) are coherent with other works [12] about hemispheric lateralization and iii) introduce locations in the tridimensional space. Therefore, we suggest that the findings of this study could be useful for the development of effective and reliable neural interfaces.

2 Material and Methods

Participants

Twenty two participants participated in the study (mean age: 24.7; range: 19.7–33; eleven men, eleven women). All participants had no personal history of neurological or psychiatric illness, drug or alcohol abuse, or current medication, and they had normal or corrected to normal vision. All of them were right handed with a laterality quotient of at least + 0.4 (mean 0.8, SD: 0.2) on the Edinburgh Inventory [13]. All subjects were informed about the aim and design of the study and gave their written consent for participation.

Stimuli and Validation

A subset of standardized stimuli (144 pictures in total) was preselected from the IAPS dataset [11]. This is a database that contains a set of normalized emotional stimuli for experimental investigations of emotion and attention. It contains a large set of standardized, emotionally-evocative, internationally accessible, color photographs including contents across a wide range of semantic categories, from pleasant images (e.g. babies and beautiful animals) to unpleasant images (e.g. scenes of violence and injuries). Each image was presented with a score (9-1) concerning their affective valence. Stimuli were presented in color, with equal luminance and contrast.

The preselected IAPS stimuli were categorized into four groups according to punctuation IAPS, namely very nice pictures ($7 <$ punctuation ≤ 9), nice pictures ($5 <$ punctuation ≤ 7), unpleasant images ($2 <$ punctuation ≤ 5) and very unpleasant images ($1 <$ punctuation ≤ 2). Each group was composed of 36 images.

IAPS pictures were previously scored with American population. In order to avoid artifacts due to the cultural issue (the participants were Spanish), we executed a previous study to calibrate the valence of the images with our participants. Stimulus categorization was validated in a study including 30 participants who did not participate in the main experiment (mean age: 23.3; range: 20.6–31.3; seventeen men, thirteen women). The stimuli were presented one by one during 1 second followed by a black screen for 3 sec on a 21 inches screen in random order. Subjects were instructed to give each stimulus a score from 1 to 9 avoiding 5 depending on subjective taste (1: dislike; 9: like). Their verbal response was recorded. Eighty out of the 144 images were selected for the main EEG experiment based on their new subjective score. Half of them (40) corresponded to positive images (score >5, CI = 95%) and the other half were negative images (punctuation <5; CI = 95%).

Procedure

Figure 1 summarizes the serial structure of the study. Each image was presented for 500msec and followed by a black screen for 3500msec. The participants task was to view the images and to rate the arousal and valence of their own emotional

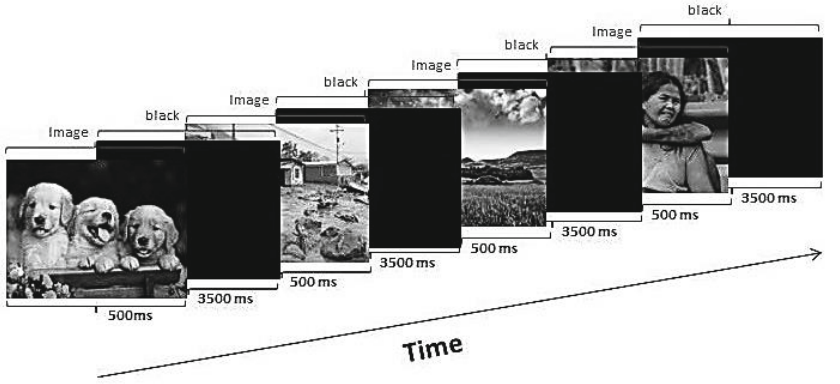

Fig. 1. Experimental design. The sequence of stimuli was presented in continuous mode by using a commercial stimulus presentation software (STIM2, Compumedics, Charlotter, NC, USA).

experience. Pictures score ranged from 1 (very unpleasant) to 9 (very pleasant). The images appeared randomly and only once.

Data Acquisition

We instructed subjects to remain as immobile as possible, avoiding blinking during image exposure and trying to keep the gaze toward the monitor center. EEG data was continuously recorded at a sampling rate of 1000 Hz from 64 locations (FP1, FPZ, FP2, AF3, GND, AF4, F7, F5, F3, F1, FZ, F2, F4, F6, F8, FT7, FC5, FC3, FC1, FCZ, FC2, FC4, FC6, FT8, T7, C5, C3, C1, CZ, C2, C4, C6, T8, REF, TP7, CP5, CP3, CP1, CPZ, CP2, CP4, CP6, TP8, P7, P5, P3, P1, PZ, P2, P4, P6, P8, PO7, PO5, PO3, POZ, PO4, PO6, PO8, CB1, O1, OZ, O2, CB2) using the international 10/20 system [14]. EEG was recorded via cap-mounted Ag-AgCl electrodes. A 64-channel NeuroScan SynAmps EEG amplifier (Compumedics, Charlotte, NC, USA). The impedance of recording electrodes was monitored for each subject prior to data collection and the threshold were kept below 25 KΩ. All the recordings were performed in a silent room with soft lighting.

Signal processing was performed with the help of Curry 7 (Compumedics, Charlotte, NC, USA). Data were re-referenced to a Common Average Reference (CAR) because the statistical and analysis methods required CAR. EEG signals were filtered using a 45 Hz low-pass and a high-pass 0.5 Hz filters.

Electrical artifacts due to motion, eye blinking, etc. were corrected. They were identified as signal levels above 75μV in the 5 frontal electrodes (FP1, FPZ, FP2, AF3 and AF4). These electrodes were chosen because they are the most affected by potential involuntary movements. The time interval for artifact detection was from (-200msec, +500msec) from stimulus onset. The detected artifacts

were corrected using Principal Component Analysis (PCA). PCA is a classical technique in statistical data analysis, feature extraction and data reduction [15].

EEG data in the interval (-100, 1000) msec from stimulus onset were analyzed in this study. For each person, records were separated into 8 subgroups according to their given score (9, 8, 7, 6, 4, 3, 2, and 1). In turns, subgroups for dipole analysis were grouped into 4 groups as shown in Table 1.

Table 1. Separation of subjective scores into 4 groups for all people. Dipole separation performed for reconstruction using the mean of all people.

	Dislike				*like*			
	Group —		Group –		Group ++		Group ++++	
opinion punctuation	1	2	3	4	6	7	8	9

Statistical Analyses

To constrain our analysis, we used an approach that has been widely used in psychophysiology: the examination of topographic changes in EEG activity (see [16] for an overview and [17]). This approach considers whole-scalp EEG activity elicited by a stimulus as a finite set of alternating spatially stable activation patterns, which reflect a succession of information processing stages. Differences in topographic patterns of activity between conditions were assessed using the Curry 7 software.

There are two main reasons why we used this analysis rather than the more traditional which is based on the assessment of amplitudes and latencies of a set of predefined ERP components. First, it takes into consideration the entire time course of activity and the entire pattern of activation across the scalp by testing the global field power from all electrodes (see for further explanation [18]). Second, this approach is able to detect not only differences in amplitude, but also differences in underlying sources of activity. The latter is based on the fact that maps that are confirmed to be both spatially and temporally different must necessarily be the product of a different set of generators. However, we emphasize that the analysis of topography changes is not incompatible with the analysis of traditional ERPs.

As recommended, topographical differences were tested through a non-parametric randomization test known as TANOVA (Topographic ANOVA). TANOVA tests for differences in global dissimilarity of EEG activity between two conditions by assessing whether the topographies are significantly different from each other on a time point-by-time point basis. TANOVA were performed to assess differences in activation patterns between different groups of images by subjective scoring. TANOVA is sufficient to indicate the time windows of interest for further analysis dipole. In this study, the significance level is α=0.01. As

suggested by [19], the corresponding required number of repetitions was chosen to be p> 1000. Map normalization was used for the difference tests, such that the MGFP per map was equal to 1.

The dipole source localization (DSL) solves the EEG inverse problem by using a nonlinear multidimensional minimization procedure that estimates the dipole parameters that best explain the observed scalp potentials in a least-square sense. In this process, we assume that EEG is generated by one or no more than few focal sources. The dipole source model can be further classified as moving, fixing or rotating dipoles depending on the degree of freedom of parameters. In our study we used a rotating dipole, that may be viewed as two independent dipoles whose orientation is allowed to vary with time [20].

Boundary Element Method (BEM) was used in the head reconstruction since it permits to locate the source dipoles. Thus BEM models are superior in non-spherical parts of the head like temporal and frontal lobe or basal parts of the head, where spherical models exhibit systematic localizations of up to 30 mm [21].

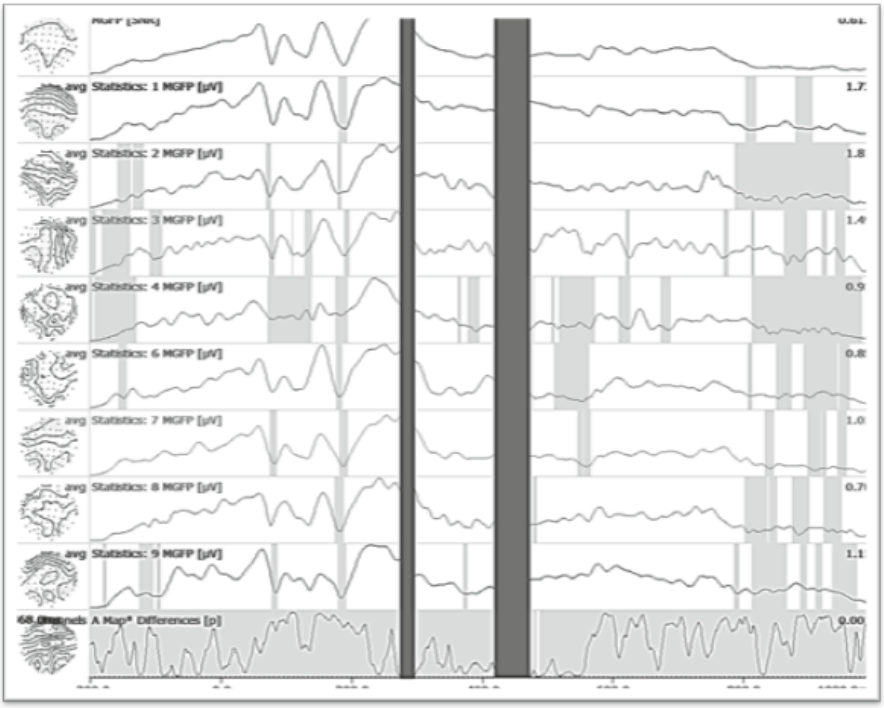

Fig. 2. Time points of significant differences in EEG activity for the 8 contrasts (9, 8, 7, 6, 4, 3, 2 and 1). It is as indicated by the T ANOVA analysis, depicting 1 minus p-value across time. Significant p values are plotted (p<0.01). The two vertical rectangles contain interval with significant differences.

3 Results

Participant Rankings Compression

The participants responded correctly to 1758 images (99.98%) following the instructions before starting the experiment. In only two images volunteer answered incorrectly (score 5) or did not respond. The images followed by incorrect answers were not excluded in the analysis below. The distribution of the new scores (or valences) was 49.4% and 50.6% greater and less than 5 respectively.

EEG

Differences in stimulus-elicited activity are depicted in Figure 2. There were significant differences between pictures with different scores ($p<0.01$). These differences started approximately 276 msec after stimulus onset. All subgroups were significant different to each other in two time windows, namely [276 - 294] msec and [424 - 474] msec.

Dipoles

One rotating dipole source model was used in the two time windows with significant differences indicated by the TANOVA (see Figure 2). When we focused

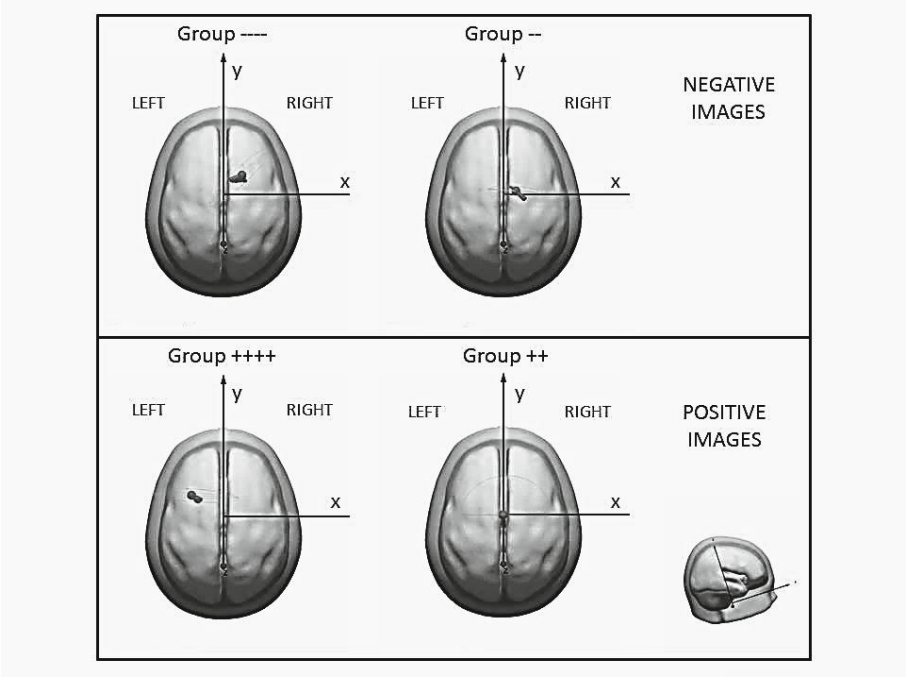

Fig. 3. Head reconstruction by rotating dipole in time window [424-474] msec. Rating was grouped into four groups according to subjective punctuation (see Table 1).

Table 2. Coordinates of dipole in head for window significant [424-474] msec

window 424-474ms												
Dislike (coordinates in mm)						like (coordinates in mm)					
Group ----			Group --			Group ++			Group ++++		
x	y	z	x	y	z	x	y	z	x	y	z
20,7	25,4	8,3	13,9	10,5	20	-0,6	5,3	16,8	-35,8	27,4	7,5

in the larger time window (424-474msec, duration 50msec) we found significant differences in the dipoles for the different types of images (see Figure 3).

The Cartesian coordinates of the rotating dipole for each group are shown in table 2.

4 Conclusions

Our results suggest a strong lateralization in the processing of images with emotive content. Thus, we found an increased activity in the left hemisphere for emotions with a positive valence. In contrast, there was an increased activity in the right hemisphere for emotions with a negative valence. These results are in line with the valence hypothesis in the hemispheric lateralization of emotion processing, which postulates a preferential engagement of the left hemisphere for positive emotions and of the right hemisphere for negative emotions[22],[23]. Furthermore the z coordinate of the resulting rotating dipoles, provide valuable information for further studies in this field. In this framework our results support the point of view that in extreme emotions (groups ++++ and —-), z is smaller or more intermediate than in neutral images (groups ++ and –).

On the other hand, the broad range of stimulus types adds an important dimension of universal validity to the results. The same valence can be induced by either pictures displaying facial, bodily expressions, or complex events and landscape. Therefore, we extend generalizability beyond facial expressions, which are the stimuli most commonly used in emotion research. In future work, we plan to perform a deeper study of the dipoles for each group, which would allow us to get higher levels of accuracy in the definition of the location of the dipoles. Thus, the spatial location observed in emotional processing of different visual stimuli can help to provide a comprehensive account of the role of each hemisphere in this processing, which could help in understanding deficits seen in psychiatric or developmental disorders. Furthermore, this could be helpful for the development of new paradigms of brain-computer interfaces.

Acknowledgement. This work has been supported in part by grant MAT2012-39290-C02-01, by the Bidons Egara Research Chair of the University Miguel Hernández, by a research grant of the Spanish Blind Organization (ONCE), by Nicolo Association for the R&D in Neurotechnologies for disability, by the regional project P11-TIC-7983, by Junta of Andalucia (Spain) and by the Spanish grant TIN2012-32039 (Spain).

References

1. Picard, R.W.: Affective computing. MIT Press
2. Davidson, R.J., Ekman, P., Saron, C.D., Senulis, J.A., Friesen, W.V.: Approach/withdrawal and cerebral asymmetry: Emotional expression and brain physiology(58), 330–341
3. Fanselow, M.S.: Neural organization of the defensive behavior system responsible for fear 1(4), 429–438, http://www.springerlink.com/index/10.3758/BF03210947, doi:10.3758/BF03210947
4. Linden, D.E.J., Habes, I., Johnston, S.J., Linden, S., Tatineni, R., Subramanian, L., Sorger, B., Healy, D., Goebel, R.: Real-time self-regulation of emotion networks in patients with depression 7(6) e38115, http://dx.doi.org/10.1371/journal.pone.0038115, doi:10.1371/journal.pone.0038115
5. Vink, M., Derks, J.M., Hoogendam, J.M., Hillegers, M., Kahn, R.S.: Functional differences in emotion processing during adolescence and early adulthood 91, 70–76, http://linkinghub.elsevier.com/retrieve/pii/S1053811914000561, doi:10.1016/j.neuroimage.2014.01.035
6. Royet, J.P., Zald, D., Versace, R., Costes, N., Lavenne, F., Koenig, O., Gervais, R.: Emotional responses to pleasant and unpleasant olfactory, visual, and auditory stimuli: a positron emission tomography study 20(20) 7752–7759
7. Petrantonakis, P.C., Hadjileontiadis, L.J.: A novel emotion elicitation index using frontal brain asymmetry for enhanced EEG-based emotion recognition 15(5), 737–746, http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5776680, doi:10.1109/TITB.2011.2157933
8. Davidson, R., Fox, N.: Asymmetrical brain activity discriminates between positive and negative affective stimuli in human infants 218(4578), 1235–1237, http://www.sciencemag.org/cgi/doi/10.1126/science.7146906, doi:10.1126/science.7146906
9. Harmon-Jones, E., Allen, J.J.: Anger and frontal brain activity: EEG asymmetry consistent with approach motivation despite negative affective valence 74(5), 1310–1316
10. Schupp, H.T., Cuthbert, B.N., Bradley, M.M., Cacioppo, J.T., Ito, T., Lang, P.J.: Affective picture processing: The late positive potential is modulated by motivational relevance 37(2), 257–261, http://doi.wiley.com/10.1111/1469-8986.3720257, doi.10.1111/1469-8986.3720257
11. Lang, P.J., Bradley, M.M., Cuthbert, B.N.: International affective picture system (IAPS): Technical manual and affective ratings
12. Davidson, R.J.: Anterior electrophysiological asymmetries, emotion, and depression: Conceptual and methodological conundrums 35(5), 607–614, http://doi.wiley.com/10.1017/S0048577298000134, doi:10.1017/S0048577298000134
13. Oldfield, R.: The assessment and analysis of handedness: The edinburgh inventory 9(1), 97–113, http://linkinghub.elsevier.com/retrieve/pii/0028393271900674, doi:10.1016/0028-3932(71)90067-4
14. Klem, G.H., Luders, H.O., Jasper, H.H., Elger, C.: The ten-twenty electrode system of the international federation. the International Federation of Clinical Neurophysiology 52, 3–6

15. Meghdadi, A.H., Fazel-Rezai, R., Aghakhani, Y.: Detecting determinism in EEG signals using principal component analysis and surrogate data testing, pp. 6209–6212. IEEE, http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4463227, doi:10.1109/IEMBS.2006.260679
16. Murray, M.M., Brunet, D., Michel, C.M.: Topographic ERP analyses: A step-by-step tutorial review 20(4) 249–264, http://link.springer.com/10.1007/s10548-008-0054-5, doi:10.1007/s10548-008-0054-5
17. Martinovic, J., Jones, A., Christiansen, P., Rose, A.K., Hogarth, L., Field, M.: Electrophysiological responses to alcohol cues are not associated with pavlovian-to-instrumental transfer in social drinkers 9(4), e94605, doi:10.1371/journal.pone.0094605
18. Skrandies, W.: Global field power and topographic similarity 3(1) 137–141, http://link.springer.com/10.1007/BF01128870, doi:10.1007/BF01128870
19. Rosenblad, A.: B. f. j. manly: Randomization, bootstrap and monte carlo methods in biology, 3rd edn., 455 p. Chapman & amp; hall/CRC, Boca raton, $79.95 (HB), ISBN: 1-58488-541-6 24 (2) 371372. doi:10.1007/s00180-009-0150-3
20. Fuchs, M., Wagner, M., Wischmann, H.-A., Köhler, A., Theissen, R., Drenckhahn, H.: Improving source reconstructions by combining bioelectric and biomagnetic data 107(2), 93–111, http://linkinghub.elsevier.com/retrieve/pii/S0013469498000467, doi:10.1016/S0013-4694(98)00046-7
21. Vatta, F., Meneghini, F., Esposito, F., Mininel, S., Di Salle, F.: Realistic and spherical head modeling for EEG forward problem solution: A comparative cortex-based analysis, pp. 1–11 (2010), doi:10.1155/2010/972060/
22. Fusar-Poli, P., Placentino, A., Carletti, F., Allen, P., Landi, P., Abbamonte, M., Barale, F., Perez, J., McGuire, P., Politi, P.: Laterality effect on emotional faces processing: ALE meta-analysis of evidence 452(3), 262–267, http://linkinghub.elsevier.com/retrieve/pii/S0304394009001220, doi:10.1016/j.neulet.2009.01.065
23. Costa, T., Cauda, F., Crini, M., Tatu, M.-K., Celeghin, A., de Gelder, B., Tamietto, M.: Temporal and spatial neural dynamics in the perception of basic emotions from complex scenes 9(11), 1690–1703, http://scan.oxfordjournals.org/lookup/doi/10.1093/scan/nst164, doi:10.1093/scan/nst164