Analyzing Brain Dynamics of Affective Engagement

Scott Makeig, Grace Leslie, Tim Mullen, Devpratim Sarma,
Nima Bigdely-Shamlo, Christian Kothe

Swartz Center for Computational Neuroscience, Institute for Neural Computation,
University of California San Diego, 9500 Gilman Drive, La Jolla, California, USA 92093-0559
smakeig@ucsd.edu

Abstract. Development of EEG-based brain computer interface (BCI) methods has largely focused on creating a communication channel for subjects with intact cognition but profound loss of motor control from stroke or neurodegenerative disease, allowing such subjects to communicate by spelling out words on a personal computer. However, another important human communication channel may also be limited or unavailable in handicapped subjects -- direct non-linguistic emotional communication as by gesture, vocal prosody, and facial expression. We report and examine a first demonstration of an 'emotion BCI' in which, as one element of a live musical performance, an able-bodied subject successfully engaged the electronic delivery of an ordered sequence of five music two-tone ground intervals by imaginatively re-experiencing the human feeling he had spontaneously associated with the sound of each interval during training sessions. The EEG data included activities of both brain and non-brain sources (scalp muscles, eye movements). Common Spatial Pattern classification gave 84% correct pseudo-online performance and 5-of-5 correct classification in live performance. Re-analysis of the training session data including only brain EEG sources found by multiple-mixture Amica ICA decomposition achieved five-class classification accuracy of 59-70%, confirming that different imagined emotion states may be associated with distinguishable brain source EEG dynamics.

Keywords: BCI, affective communication, emotion, ICA

1 Introduction

Cognitive neuroscience now recognizes that the human mind and brain do indeed have parallel perceptual and communication channels for rational / reactive / objective versus emotional / sympathetic / affective awareness [1]. Emotional expression and communication with others is recognized as being strongly linked to health and sense of well-being – however, until recently direct emotional communication has not been a major part of computer-based communications.

The field of affective computing [2] has arisen relatively recently to address the challenge of incorporating affective communication into information and communication technologies. Various measures can be used to track conscious and unconscious physiological responses [3], such as electromyography (EMG), blood volume pressure (BVP), and galvanic skin response (GSR). Ekman [4] has defined six basic emotions (fear, anger, sadness, happiness, disgust, surprise) based on facial expressions. These and other measurement approaches are now being incorporated into consumer products, so far mainly in video gaming.

Linking emotion, EEG and music. This project was based on the assumption that spontaneous emotional associations of a musically sensitive and accultured listener with a given musical interval are to a significant degree stimulated by properties of the musical interval itself and by a web of associations common across a musical culture. Relationships between the perceived affective character of the intervals and the harmonic ratios underlying them have long been examined [5]. Specifically, whole-ratio (just) interval frequency combinations instead of modern well-tempered (piano) tuned intervals were used to increase the affective differences and pungency of the low cello tones.

Although earlier efforts to differentiate emotional reactions and states via average event-related potential (ERP) measures had limited success [6], recent efforts in these directions using more adequate measures of larger parts of the recorded EEG dynamic information have proved more successful. Recently, Onton and Makeig [7] reported orderly changes in the spectral character of source-resolved high-density (248-channel) EEG activity during imagination of 15 different emotions using a method of guided imagery [8]. The dynamic state differences were stable across imagination periods of 1-5 min. Further, separable features of both brain and scalp/neck muscle activities were linked to the nature of the imagined emotion.

Although the earliest effort to sonify EEG was reported in a 1934 paper in *Brain* by Adrian and Matthews, Alvin Lucier's 1965 *Music for Solo Performer* is widely considered the first EEG-based musical performance. More recently, Grierson's [9] adaptation of a standard P300 speller allowed a user to produce a note sequence by selectively attending to symbols on a computer display. Others have attempted passive sonification of cognitive state [10], hoping that feelings engendered by the soundscape would in turn affect the participant EEG. However, explicit modeling and musical expression of performer feelings via a musical brain-computer interface has remained largely unexplored.

A Musical emotion BCI. These results suggest the possibility of creating brain-computer interface (BCI) systems that communicate a user's feelings non-verbally, for instance via affective musical communication. So far, the nascent field of BCI systems based on electroencephalographic (EEG) signals has focused on providing subjects with profound loss of motor control with the ability to perform binary or smooth prosthetic device control [11] and to communicate linguistically by spelling-out words [12] or actuating musical tones [9].

Here, we provide an account and further *post hoc* analysis of a first demonstration of the potential feasibility of an EEG-based BCI system that directly expresses, musically, the feeling states of its operator. We describe an experimental musical production we produced for and performed at the Fourth International BCI Meeting. In this piece, a subject wearing an EEG cap, the 'brainist' (TM), contributed to the live musical performance by a violinist (SM), flautist (GL), and cellist by imaginatively re-experiencing the emotions or affective qualities the brainist had spontaneously associated with five musical two-tone combinations ('musical intervals'). An online EEG classifier detected which emotional or affective state the subject intended to convey and initiated production of the corresponding musical interval, during which the three musicians then performed an associated music composition. The time scale of classification was relatively long, as the direct musical communication (feed-forward) signal was presented only after several seconds of classification delay, which is a result of the attempted direct communication of emotional state as opposed to a symbol-selection procedure. This design is thus best characterized as an open-loop BCI.

Following this account, we report re-analysis of a part of the collected training data using a new method for constructing BCI classification models that are resolved into spatially localizable brain and non-brain source features, giving rise to new interpretations. Finally, we discuss the potential for both brain and non-brain information to be used in emotion BCI applications.

2 Methods

Training protocol. Following two preliminary subject training sessions, four calibration sessions were recorded over three days. In the subject training sessions, nine different musical 'ground sounds' each comprised of two recorded cello tones were presented to the subject to allow him to establish emotional associations with each one; in the four BCI calibration sessions, this number was reduced first to six and then to a final five ground sounds for which suitable musical pieces were composed.

In all sessions, the subject sat with eyes closed in a comfortable chair facing three loudspeakers. The first section of pre-recorded audio instructions asked the subject to fully relax into an emotionally neutral state. Next, the subject was asked to listen to the first musical ground sound, while imagining it to be a human emotional expression (e.g., an expressive sigh). The subject was asked to attempt to empathize with the human imagined while also paying attention to their own somatic sensations associated with their empathetic experience. The latter suggestion was made to create a somatic feedback loop stabilizing and prolonging the subject's imagined empathetic experience.

The subject was asked to press a hand-held button once when he began to experience a definite emotional expression he spontaneously associated with the ground sound, to attempt to strengthen and maintain the experience of this feeling for as long as possible, and to press the button a second time when his emotional experience waned. After the second button press, the ground sound was faded out and another recorded instruction asked the subject to return to their previous relaxed, emotionally neutral state in preparation for hearing and imaginatively emotionally experiencing the next ground sound. EEG recordings of the calibration sessions were retained for model development and *post hoc* analysis, each of which comprised a sequence of extended (and not further partitioned) blocks, where each block comprised continuous data associated with the subject's experience of an imagined empathetic emotion or feeling.

Sessions 1 and 2 were recorded on a single day in the lab to serve as calibration data for subsequent real-time testing. Session 3 was recorded during the conference for additional pseudo-online testing, and Session 4 was the calibration session to be used for the dress rehearsal and performance.

Performance protocol. The live performance protocol represented a verifiable attempt to demonstrate an emotion BCI operating under constraints of time and social pressure, while (hopefully) delivering a satisfying musical experience for the after-dinner musical performers and audience of roughly 200 BCI researchers. The brainist sat in a comfortable chair at stage center wearing a high-density EEG cap. Right and left of the stage, elevated speakers broadcast an introduction and subject instructions, which included a few-adjective description of the feeling, extracted from verbal descriptions the brainist had given following each of the first training sessions. These instructions constituted, in effect, the musical 'score' for the brainist to realize by re-capturing and experiencing the intended feeling.

A few seconds later, the BCI computer began processing the brainist EEG signals until a sufficiently robust classification decision was made. At that point, the ground sound corresponding to the selected interval began to play through a speaker facing the brainist. The task of the three musicians was to recognize the selected ground sound and then to play the piece written to accompany it. (In the event the computer made an unintended interval selection, the musicians would have needed to quickly bring the unexpected score to the front of their music stands). The BCI-selected ground sound continued playing throughout the performance of the musical selection, then was terminated by the BCI operator.

Music production and EEG recording. The ground sounds initiated by BCI classification were based on a recording of a cellist playing a series of long bowed notes on the open ‘G’ string. The upper notes were tuned to 5/4, 45/32, 15/8, 3/2, and 2/1 of the lower note frequency (~98 Hz). A Max/MSP patch seamlessly looped playback of the BCI-selected musical intervals. Five (1-3 min) pieces were composed (by SM) in twentieth-century chamber music styles intended to convey feelings and harmonies compatible with each of the five ground intervals. The brainist heard these pieces only at the final rehearsal and performance, in each case after the BCI classification was complete, so these compositions had no appreciable effect on the classification.

In all sessions, EEG was recorded from 128 scalp channels via a Biosemi ActiveTwo system (Biosemi, Amsterdam) at a sampling rate of 512 Hz with 24-bit resolution. In training recordings, ExG electrodes were placed at the right and left mastoids, at the outer corner of the right eye, and below the mid line of the left eye.

Online BCI learning and classification. In a rather conventional BCI protocol, a classifier was trained on previously recorded calibration data, and then applied online with additional application-specific post-processing. The calibration data used for the performance (35 minutes) contained five blocks (102 +/- 12s each), one per class of emotion. 2-s time windows with 1.5-s overlap were extracted from these blocks and taken as training trials, yielding 1512 training instances in total. The data in each window were notch-filtered between 55-65 Hz and band pass filtered between 8-200 Hz, as suggested by the recent report of Onton and Makeig [7] in which high-gamma (70-250 Hz) brain activity was found to be a valuable feature for classification of imagined emotions. Subject-specific spatial filters were then learned using the Common Spatial Patterns (CSP) method ([13] and references therein). Since standard CSP operates on only two classes, here a CSP contrast was learned separately for each pair of classes, yielding *nchoosek*(5,2)=10 CSP pair contrasts each comprised of six spatial filters. Subsequent log-variance feature extraction and classifier training was done separately for each CSP solution. As classifiers we used Linear Discriminant Analysis (LDA) with shrinkage regularization, using an analytically derived regularization parameter. The total number of features used across all classifiers was 60.

During online operation, incoming EEG was classified every 200 ms using the most recent 2-s data window. This window was spectrally filtered as in the calibration phase, and spatially filtered using the CSP-derived filters. Log-variance features were then extracted and passed to the respective binary LDA classifier, whose gradual outputs were mapped onto per-class (pseudo-)probabilities. The probabilities assigned to each class were summed across classifiers according to a 1-vs-1 voting scheme. Multiple successive classifier outputs were aggregated and averaged in a growing window. A classification decision was made by the application (within at most 45 s) when the estimated probability of a class exceeded a threshold that was lowered at a constant rate from 1 to 0, allowing for a quick prediction in clear cases and accumulation of sufficient evidence in other cases. To prevent any musical selection from being selected twice in live performance, the admissible classes were those intervals that had not been played before. Thus, the online classification was effectively five-class for the first interval, then four-class, and so on.

Refined post-hoc analysis. While the emotion detector used in live performance and described above could (and did) make sufficiently accurate predictions on new data, it was not clear to what extent its performance relied on measures of brain versus non-brain source activities. Exclusion of non-brain data is less important in aBCI applications for healthy users (e.g., in gaming or other HCIs), but is of practical interest when considering users who lack muscle control. During a post-hoc analysis, calibration Session 1 was used for advanced model calibration and Session 2 for model testing, as both were measured on the same day using the same electrode montage. Data from the online performance was not included in the post-hoc analysis as it was not be stored for technical reasons.

Since each EEG channel measures a linear superposition of signals from sources distributed across brain, head and environment, it is not generally possible to interpret sensor signals as a measure of the activity of a distinct cortical source. This limitation can be lifted or at least minimized when spatial filters are optimized to recover source signals that are mutually statistically independent. Following data pre-processing and automated artifact rejection using the default pipeline for Independent Component Analysis (ICA) [14] in our open-source BCILAB toolbox [15], we employed a recently-developed extension of ICA, Adaptive Mixture ICA (Amica) [16], to derive a set of maximally independent source signals, as a mixture of multiple (here six) fullrank signal decompositions (each decomposition with different, possibly overlapping, temporal support).

The components of each model (here 92 each) were then visually screened for clear brain components as described in Onton and Makeig [7]. Namely, brain components were indicated by the resemblance of their cortical maps to the projection of a single equivalent dipole. Non-brain (muscle, heart, eye movement) components were identified based on their characteristic temporal and spectral properties and eliminated, leaving a total of 38 brain component processes. A single or dual-symmetric equivalent current dipole model was fit to each brain component using a four-shell spherical head model. All selected components were localized within or on the periphery of the brain volume and above the neck or lower head region, which contributes a majority of EMG artifacts. A fully automated version of this process has been evaluated in [17].

Next, trial epochs and features were extracted from the unmixed continuous multi-component signal, separately for each Amica decomposition. Epoch extraction was analogous to the original analysis: the continuous unmixed data was low-pass filtered below 90 Hz, sub-sampled to 180 Hz and then high-pass filtered above 2 Hz using a causal minimum-phase FIR filter. From these data, windows of 3s length overlapped by 2.5s were extracted from each block in the dataset and discrete Fourier power spectral density in each window was taken as features, yielding 1183 trials in total.

On these data, a weighted l1-regularized multinomial logistic regression classifier (realized as a 1-vs-1 voting arrangement of binary classifiers) was trained, which thereby selects a sparse subset of spatially and spectrally localized features. The trials were weighted according to the temporal support of the respective underlying Amica model, and individual features were standardized similarly to the first-order model introduced in [18] and further weighted according to a (here 0/1-valued) masking of relevant brain vs. non-brain components.

During pseudo-online evaluation on the test set, the data were then causally pre-processed and mapped to per-model features as described above, and the classifiers for each model were applied to yield per-class probabilities. The probabilities were then summed for each class and renormalized to yield a discrete probability distribution over the five possible outcomes. The final probabilities were obtained as a weighted average of the classifer outputs under each Amica model, where the weight is the total probability of the respective model under the calibration dataset (a measure of the model's total temporal support).

3 Results

Initial offline analysis results. To determine the method to be used for the live performance, the across-session prediction accuracies of a variety of methods – CSP as described in Section 2.4, Spectrally weighted CSP and an implementation of Independent Modulators [7] – were assessed on the basis of Sessions 1 and 2. The CSP-based classification gave the best across-session performance, reaching a single-time window between-session classification accuracy of 84% (chance level 20%), and was chosen for all subsequent real-time analysis (a subset of spatial filters shown in Fig. 2(a)).

Live performance. In the concert performance, the BCI classification selected the intended interval in all five cases, though the BCI classification monitor showed that one of the intervals was nearly mis-classified. The BCI performance level (>70%) was as expected from numerical experiments on the data from the four pilot sessions, as recounted above. The musical performance also went as intended.

In the pilot online test, all five intervals were classified correctly, and in the rehearsal performance, the intended first interval (major third, 5/4, with associated feeling of someone who is 'uncertain, quiet, shy, and sensitive') was substituted by its near opposite (just tritone, 45/32, 'frustrated, sullen, and angry').

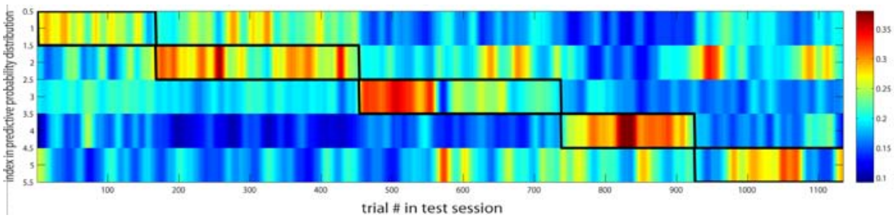
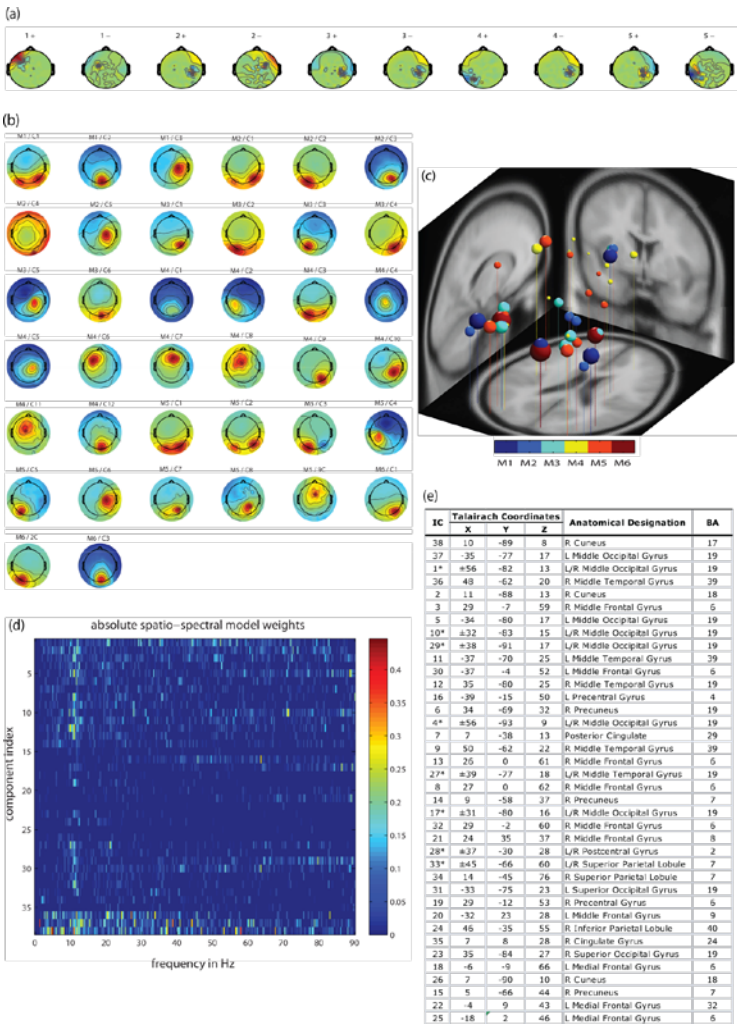


Fig. 1. Predicted probability distribution across test session (Session 2) time windows in the post-hoc analysis. The ordinate separates the five possible outcomes of the classification. Red colors indicate high probability of the respective outcome; blue indicates low probability. Black rectangles mark the five (true) conditions the subject was asked to imaginatively experience during the five test session time periods.

Post-hoc data analysis. In a pseudo-online analysis, the classifier described in Section 2.6 achieved a single-time window between-session classification accuracy of 59% -70% when trained on Session 1 and applied on Session 2, depending on the length of the time window (windows up to 15 s in length we tested, and longer windows giving better results). It used approx. 1/3 of all 10260 features. The fitted dipole locations for each component in Figure 2(b)-(c) include across-models clusters of near-identical component processes in or near primary and lateral visual cortex, somatomotor cortex, dorsolateral prefrontal cortex, superior parietal cortex, middle temporal gyrus, and anterior and posterior cingulate cortex. For each brain source, we identified the coordinates of equivalent dipoles and corresponding Brodmann Area designations of the nearest gray matter using the Talairach Daemon. Figure 2(e) lists these results sorted in descending order by average absolute classifier weight of each independent component (IC). The learned spectral weights of the classifiers for these components (Fig. 2(d)) show a clear focus on alpha band amplitudes of many components, as well as sensitivity to high-gamma band (HGB) activity in some somatomotor and occipital components as in the emotion imagination results in [7]. Figure 1 shows a smoothed (5 s moving average window) time course of the predicted probability distribution over the 1-s time windows of this session.



IC	Talairach Coordinates X	Y	Z	Anatomical Designation	BA
38	10	-89	8	R Cuneus	17
37	-35	-77	17	L Middle Occipital Gyrus	19
1*	±56	-82	13	L/R Middle Occipital Gyrus	19
36	48	-62	20	R Middle Temporal Gyrus	39
2	11	-88	13	R Cuneus	18
3	29	-7	59	R Middle Frontal Gyrus	6
5	-34	-80	17	L Middle Occipital Gyrus	19
10*	±32	-83	15	L/R Middle Occipital Gyrus	19
29*	±38	-91	17	L/R Middle Occipital Gyrus	19
11	-37	-70	25	L Middle Temporal Gyrus	39
30	-37	-4	52	L Middle Frontal Gyrus	6
12	35	-80	25	R Middle Temporal Gyrus	19
16	-39	-15	50	L Precentral Gyrus	4
6	34	-69	32	R Precuneus	19
4*	±56	-93	9	L/R Middle Occipital Gyrus	19
7	7	-38	13	Posterior Cingulate	29
9	50	-62	22	R Middle Temporal Gyrus	39
13	26	0	61	R Middle Frontal Gyrus	6
27*	±39	-77	18	L/R Middle Temporal Gyrus	19
8	27	0	62	R Middle Frontal Gyrus	6
14	9	-58	37	R Precuneus	7
17*	±31	-80	16	L/R Middle Occipital Gyrus	19
32	29	-2	60	R Middle Frontal Gyrus	6
21	24	35	37	R Middle Frontal Gyrus	8
28*	±37	-30	28	L/R Postcentral Gyrus	2
33*	±45	-66	60	L/R Superior Parietal Lobule	7
34	14	-45	76	R Superior Parietal Lobule	7
31	-33	-75	23	L Superior Occipital Gyrus	19
19	29	-12	53	R Precentral Gyrus	6
20	-32	23	28	L Middle Frontal Gyrus	9
24	46	-35	55	R Inferior Parietal Lobule	40
35	7	8	28	R Cingulate Gyrus	24
23	35	-84	27	R Superior Occipital Gyrus	19
18	-6	-9	66	L Medial Frontal Gyrus	6
26	7	-90	10	R Cuneus	18
15	5	-66	44	R Precuneus	7
22	-4	9	43	L Medial Frontal Gyrus	32
25	-18	2	46	L Medial Frontal Gyrus	6

Fig. 2. Estimated online results and post hoc analysis. (a) Sample CSP patterns (filter inverses) from the multiclass CSP model learned from Session 3 data. (b) Accumulated classification accuracy as a function of accumulation window length (in s). (c) Equivalent dipole locations for the selected independent components, colored by model and scaled by square root of average absolute weight; models ordered by descending probability under the calibration data. (d) Topographic scalp maps of the selected components, sorted by model and ordered as in (e). (e) Absolute spectral weights for the selected components and frequencies (the six models concatenated vertically). (f) Predicted probability distribution across test Session 4 time windows. The ordinate separates the five possible outcomes of the classification. Red colors indicate high probability of the respective outcome; blue indicates low probability. Black rectangles mark the five (true) conditions the subject was asked to imaginatively experience during the five test session time periods.

4 Discussion

The successful live performance produced its intended result of demonstrating the potential feasibility of a direct emotion BCI, here in the form of a system that used a vocabulary of musical sounds to express the feeling state of the brainist. Such a system may be usable by paralyzed users or users otherwise limited in emotional expression, or to augment emotional communication in ordinary social settings.

To better assess the underlying cortical dynamics, we applied ICA decomposition methods to separate the data into brain source and non-brain source component processes weighted by a classifier primarily using distinct and physiologically localizable brain EEG processes. Localization of IC sources implicated a number of anatomical regions known to be involved in visual and somatomotor imagery, self-reflection, emotion and music processing. The predominance of visual cortical areas among localized sources is not surprising given the fact that the subject reported extensive use of visual imagery in this task. Alpha power modulation of ICs localized to bilateral occipital cortex has also been found to correlate with changes in music structure (mode/tempo) as well as emotional responses to music [19]. The dependence on sources localized in premotor cortex (MFG), precentral gyrus, and postcentral gyrus (IC 28) is also expected given that the subject was specifically asked to pay attention to somatic sensations associated with the emotional experience, and reported significant somatomotor imagery associated with his emotional state. The precuneus has been implicated in episodic memory (including those related to the self), visuospatial processing and imagery, self-referential processing, and is thought to be the core hub of the “default mode network” [20]. It has also been associated with music perception: changes in regional blood flow as well as theta- and alpha-band power modulation of ICs localized to precuneus have been shown to correlate with musical dissonance and major/minor mode distinctions [19]. The posterior cingulate cortex is strongly activated by emotional words. It is suggested that this region may mediate interactions of emotional and memory-related processes [21].

5 Conclusion

We have demonstrated the potential feasibility of a novel emotion-classification and augmented emotional communication system via a live musical performance in which EEG-based BCI classification played an artistic role, hopefully focusing attention on the use of BCI technology to enable or augment direct emotional communication in the near future. In a post-hoc analysis of the training session data, we proposed a method that learns source-resolved BCI models, which can be interpreted in terms of localizable cortical dynamics and furthermore support potentially robustness-enhancing anatomical constraints (as used here to rule out clear non-brain sources).

Acknowledgments. The authors thank an anonymous donor and The Swartz Foundation (Old Field, NY) for gifts supporting this research, Theresa Vaughan for encouraging our efforts, and Julie Onton for essential contributions to the research on which this production was based.

References

1. Adolphs, R.: Cognitive Neuroscience of Human Social Behaviour. *Nat. Rev. Neurosci.* 4 165-178 (2003)
2. Picard R.: Affective Computing. MIT Press, Cambridge (1997)
3. Cacioppo, J.T., Bernston, G.G., Larsen, J.T., Poehlmann, K.M., Ito, T.A.: The psychophysiology of emotion. In: Lewis, R., Haviland, J.M. (eds.) The Handbook of Emotion. Guilford Press, New York pp. 119--142 (1993)
4. Ekman, P., Friesen, W.V.: Facial Action Coding System: A technique for the measurement of facial movement. Consulting Psychologists Press, Palo Alto, CA (1978)
5. Makeig, S.: Theory of Interval Affect. Monograph submitted for the Master's Thesis in Music, University of South Carolina, Columbia, SC (1979)
6. Olofsson, J., Nordin, S., Sequeira, H., Polich, J.: Affective picture processing: An integrative review of ERP findings. Biolog. Psycholog. 77 247--265 (2008)
7. Onton, J., Makeig, S.: High-frequency broadband modulation of electroencephalographic spectra. Frontiers In Human Neurosciences 3 61 (2009)
8. Bonny, H.L., Savary, L.M.: Music and your mind: listening with a new consciousness. Harper & Row (1973)
9. Grierson, M.: Composing with brainwaves: minimal trial P300b recognition as an indication of subjective preference for the control of a musical instrument. In: Proc. Int. Cryog. Mat. Conf., Seoul, Korea (2008)
10. Hinterberger, T., Baier, G.: Parametric orchestral sonification of EEG in real time. IEEE Multimedia 12(2) 70--79 (2005)
11. Kübler, A., Nijboer, F., Mellinger, J., Vaughan, T.M., Pawelzik, H., Schalk, G., McFarland, D.J., Birbaumer, N., Wolpaw, J.R.: Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology 64(10) 1775--7 (2005)
12. Pfurtscheller, G., Müller-Putz, G.R., Scherer, R., Neuper, C.: Rehabilitation with Brain-Computer Interface Systems. Computer 41 58--65 (2008)
13. Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M. and Müller, K.-R.: Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Processing Mag. 25 41--56 (2008)
14. Bell, A.J., Sejnowski, T.J.: An information-maximization approach to blind separation and blind deconvolution. Neural Computation 7 1129--59 (1995)
15. Delorme, A., Mullen, T., Kothe, C., Acar, Z.A., Bigdely-Shamlo, N., Vankov, A., Makeig, S.: EEGLAB, SIFT, NFT, BCILAB, and ERICA: New tools for advanced EEG/MEG processing. Computational Intelligence and Neuroscience: Special Issue on Academic Software Applications for Electromagnetic Brain Mapping Using MEG and EEG. (2011)
16. Palmer, J.A., Makeig, S., Kreutz-Delgado, K., Rao, B.D.: Newton Method for the ICA Mixture Model. In: Proc. 33rd IEEE International Conference on Acoustics, Speech and Signal Processing, Las Vegas, NV, pp. 1805--1808 (2008)
17. Kothe, C., Makeig, S.: Estimation of Task Workload from EEG Data: New and Current Tools and Perspectives. 33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, accepted (2011)
18. Tomioka, R., Müller, K.-R.: A regularized discriminative framework for EEG analysis with application to brain-computer interface. Neuroimage, 49(1), 415--432 (2010)
19. Lin, Y.P., Duann, J.R., Chen, J.H., Jung, T.P.: Electroencephalographic dynamics of musical emotion perception revealed by independent spectral components. Neuroreport 21(6) 410--5 (2010)
20. Bullmore, E., Sporns, O.: Complex brain networks: graph theoretical analysis of structural and functional systems. Nature Reviews Neuroscience 10(3) 186--98 (2009)
21. Maddock, R.J., Garrett, A.S., Buonocore, M.H..: Posterior cingulate cortex activation by emotional words: fMRI evidence from a valence decision task. Human Brain Mapping 18(1) 30--41 (2003)