Towards Empathic Neurofeedback for Interactive Storytelling*

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Abstract

Interactive Narrative is a form of digital entertainment based on AI techniques which support narrative generation and user interaction. Despite recent progress in the field, there is still a lack of unified models integrating narrative generation, user response and interaction. This paper addresses this issue by revisiting existing Interactive Narrative paradigms, granting explicit status to users' disposition towards story characters. We introduce a novel Brain-Computer Interface (BCI) design, which attempts to capture empathy for the main character in a way that is compatible with filmic theories of emotion. Results from two experimental studies with a fully-implemented system demonstrate the effectiveness of a neurofeedback-based approach, showing that subjects can successfully modulate their emotional support for a character who is confronted with challenging situations. A preliminary fMRI analysis also shows activation during user interaction, in regions of the brain associated with emotional control.

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1 Introduction

One of the major challenges for Interactive Narrative technologies is to improve the conceptual integration between their various components: narrative generation, user interaction and user experience. After a decade spent developing Interactive Narrative prototypes, it appears to us that such an integration is more than a theoretical endeavour, and would also

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benefit the engineering aspects of the discipline. One promising direction is to take advantage of recent developments in affective computing to unify user interaction and the narrative experience. In previous work [9], we have investigated the use of peripheral physiological signals (galvanic skin response (GSR) and facial electromyography (EMG)) as a continuous input modality to an Interactive Narrative. This approach has been implemented in a prototype in which passive signals captured from the user drove the evolution of a real-time narrative with a duration of up to 8min. However, in addition to the imperfect correlation between peripheral physiological signals and affective dimensions, the conceptual integration between the affective computing model, the user response, and the filmic strategy adopted by the narrative generation process still left room for improvement.

Recent research in media psychology has emphasised the central role of characters in both the affective response of users and the overall entertainment experience [8, 30]. This suggests that direct interventions on the bond between user and character could not only provide a powerful interaction mechanism, but one that would be better aligned with the user response. This bond between users and story characters has generally been characterised as *empathy* [30], despite different interpretations of the concept.

We were thus in search of a physiological mechanism that could more directly relate to empathy, attachment or disposition, and that would also be accessible to real-time measurement, so as to be usable as an input mechanism. Numerous studies correlating affective responses with EEG signals in the alpha band (8–12Hz), have led to the development of a prefrontal asymmetry metric [13] to characterise modulation of affective response [5, 6]. Some of these studies have included the use of short films to induce emotion [35], making this approach even more relevant to us. Frontal asymmetry is considered a marker of approach/withdrawal [6], which is a high-level affective dimension independent from valence. Several authors have established a connection between alpha asymmetry and positive thinking [2], as well as empathy [32]. More specifically, Light et al. [16] have related an increase of frontal alpha asymmetry (indicative of approach) to empathic cheerfulness, which consists of a positive response towards an agent which is perceived to be in distress.

This has led us to consider alpha frontal asymmetry as a measure of disposition towards story characters which could serve as a basis for user input, provided it could be captured in real-time as part of an Interactive Narrative. This was suggested by the finding that frontal asymmetry can be controlled through Neurofeedback (NF) using EEG signals [27]. Although most applications of frontal asymmetry NF have been developed in the clinical domain, it has also been identified as a potential BCI technology [4]. Furthermore, a NF approach is well suited to an Interactive Storytelling application, since its voluntary nature is adapted to user intervention, and feedback mechanisms can be embedded into the visual presentation of the narrative itself.

In this paper, we lay the foundations for a unified approach which brings together an affective filmic theory (Tan's character empathy [30]), a character-based narrative generation technique [22], and a BCI mechanism compatible with empathy (pre-frontal alpha wave asymmetry as proposed by Henriques and Davidson [13]). We have created a baseline Interactive Narrative based on a medical drama (an extension of the narrative presented in [9]), which features a junior female doctor facing all sorts of challenges in her work, personal and professional ones. The story would spontaneously evolve towards the character's demise, in the absence of successful user intervention through the BCI. In the next sections, after reviewing related work, we introduce our BCI-based interactive storytelling system, which operates inside an MRI scanner so that explorations can be conducted using functional MRI (fMRI). We then describe the planning techniques used in narrative generation, how they control the level of difficulty faced by the feature character, and how they respond to user empathic support. After a presentation of the BCI implementation (frontal alpha asymmetry), we discuss results from our first proof-of-concept experiments which include fMRI results. We then report a larger-scale usability experiment, outside the MRI scanner, which takes advantage of the above results to refine the implementation of the BCI technique. We conclude by analysing subjects performance and identifying directions for further improvements.

2 Previous and Related Work

There has been previous interest in the neuroscience of film and computer games, some of which has informed the design of BCI systems. Morrison and Ziemke [36] have studied empathy towards characters in computer games from a neuroscience perspective. Recent work in neuroimaging has provided evidence for specific activation pathways that correspond to a range of empathic responses when viewing films with high emotional content [25], and Tikka et al. [31] have proposed a similar approach using BCI, while not reporting an implementation of their system. BCIs have, from their inception, been used in conjunction with interactive media (i.e. video games), mostly from the perspective of an interface technology either in an entertainment setting [19] or in a therapeutic one, with little exploration of the relationship to the media content itself. A critical analysis of the performance of existing BCIs [17] has led to both the emphasis on user training and the increasing relevance of NF as an implementation paradigm. This was demonstrated in a commercially available game environment in AlphaWoW [21], which used a version of *World of Warcraft*. However, this only went as far as addressing a single control variable (switching between two character forms) with a relaxation-based BCI using alpha waves. The development of BCIs for computer games has been recently reviewed by Marshall et al. [18]. In conjunction with game environments, NF has also been used for ADHD therapy. More specifically, frontal asymmetry has been identified as an element of a model of intrinsic affect evident while playing games [26].

3 System Overview

We have developed ENFASIS (Empathic Narrative using Frontal ASymmetry for Interactive Storytelling), a fully implemented system based on our proposed BCI approach and configured for proof-of-concept experiments using simultaneous fMRI analysis. The overall architecture of the system is shown on Figure 1: narrative actions are generated using constraint-based planning [9] and are visualised as real-time animations within the Unreal® 3D game engine (Unreal Development Kit).

The interactive narrative is an extended version of our previous implementation based on a medical drama [9], featuring a junior female doctor who faces adversity as the narrative unfolds. Characters' expressions, combined with the use of filmic conventions in shot selection and camera placement, facilitate the induction of appropriate feelings towards the feature character.

Narrative generation is parameterised so that the narrative evolves spontaneously towards the character's demise unless she receives support from the user. Such support takes place through a short (30s) NF session, which is triggered dynamically when the character's situation deteriorates beyond a certain threshold. The NF signal is based on pre-frontal EEG alpha asymmetry, as a measure of approach/withdrawal towards the character. Since

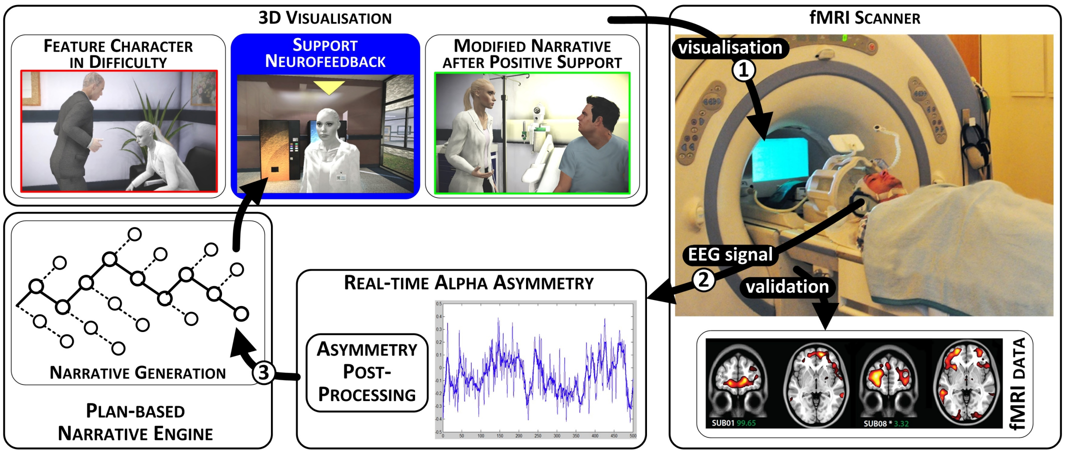

Figure 1 Integration of a BCI in an Interactive Narrative: (1) the user watches the narrative generated in real-time from inside an MRI scanner; (2) BCI input is mapped directly into the planning domain representation; (3) re-planning is triggered with successful levels of user support derived from neurofeedback; (4) visualisation continues with actions from the modified narrative.

NF implies volitional control rather than passive measurement, subjects require a cognitive strategy to control the NF signal. In order to develop such a strategy they receive minimal instructions which consist of "supporting the character by expressing positive thoughts".

From an implementation perspective, NF input is mapped to fluent values in the planning domain (see section 4), while on the graphics side, the NF backchannel is incorporated within the same visualisation mechanism as the narrative.

4 Narrative Generation

As the objective of the system is to test user support for a feature character, the system is required to generate narratives that contain negative situations for the feature character in the early stages of the narrative in order to show the character in challenging situations and hence provide opportunities for the user to support them. When users are able to successfully support the feature character, the narrative is required to be dynamically re-generated to reflect this success, with the narrative evolving towards positive outcomes for the feature character. However, if user support is unsuccessful then the original narrative continues to evolve with the overall trajectory skewed towards endings with negative outcomes. Thus narrative generation to test user support was implemented with a plan-based generator extended to use the following: *landmarks* to control early skewing of the trajectory towards negative situations and subsequent resolution towards negative or positive outcomes depending on NF success (section 4.1); representational mechanisms for the classification of actions depending on their valence (section 4.2); and triggering of user support opportunities (section 4.3).

4.1 Planning Trajectory Control

Landmarks, as introduced by Porteous et al. [22], are used in the system to provide a general mechanism to control the trajectory by ensuring the inclusion of actions with negative outcomes in the early phases of the narrative and actions with negative or positive outcomes

Figure 2 Examples of actions during which the feature character becomes *in-difficulty* are highlighted in grey.

towards the end of the narrative depending on user support success. Landmark facts represent narrative situations of interest that are used as intermediate goals around which the narrative is constructed. Examples in the medical drama genre could include such things as tense clinical situations, strained relationships, confrontations and deceptions. The landmarks and partial orders over them are specified as part of a PDDL3.0 planning domain model, as shown in Figure 3. The model is used in a decomposition based planning approach which starts by linearising the landmarks to form a total order. For Figure 3 this might be:

(i) *(harassed-by DrMacnair DrHathaway)*,
(ii) *(humiliated DrMacnair)* and
(iii) *(and (patient-outcome Jones) (doctor-outcome DrMacnair))*.

Then the narrative is generated as a sequence of sub-narratives with each of the ordered landmarks as the next sub-goal. The output narrative is produced by concatenation of the sub-narratives.

The use of landmarks in this way ensures the generation of narratives containing suitable dramatic content in the desired relative position in the narrative. To ensure that there is variation between generated (and re-generated) narratives, planning problem instances are automatically created at run-time using non-deterministic selection of initial state facts and landmarks from sets of candidates.

4.2 Valence of Actions and Landmark Selection

Narrative actions in the domain model and the facts they achieve are categorised on the basis of their valence, that is, whether they are positive or negative for the feature character: whether they create or alleviate difficult situations as characterised by the landmark facts the actions achieve. The system uses this valence information and the current level of user NF support to determine the choice of landmarks for narrative generation (or re-generation). Whether a particular landmark will lead to the generation of a narrative with appropriate dramatic content depends on its valence, for example, actions that achieve landmarks which

```
(:constraints (and
    (sometime-before
      (patient-outcome Jones)
      (humiliated DrMacnair))
   (sometime-before
      (doctor-outcome DrMacnair)
      (harassed-by DrMacnair DrHathaway))
   (at-end (and
      (doctor-outcome DrMacnair)
      (patient-outcome Jones))) ... )
```

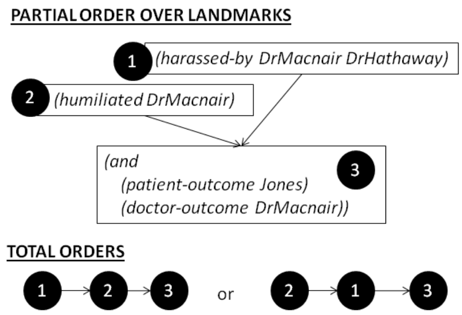

Figure 3 Example Landmarks: the left-hand side contains a selection of landmark facts represented using the PDDL3 modal operators *sometime-before* and *at-end*; on the right-hand side the order specified over the landmarks is represented graphically. The ordered landmarks are used in a decomposition-based planning approach to narrative generation: first, if the landmarks are partially ordered they are linearised to form a total order (the figure shows the consistent total orders, one of which is non-deterministically selected by the system); then each landmark in turn is used as a sub-goal and the narrative is built up incrementally from the sequence of sub-narratives (see text for more detail).

are adverse to the feature character are suitable for phases of the narrative showing their demise, whereas actions which are supportive towards them provide appropriate content for the evolution of the narrative towards a positive ending. As an illustration consider the actions shown in Figure 4 in which *receive-reprimand-from-boss* and *receive-professional-praise* have been categorised as adverse and supportive respectively: receiving a reprimand from the boss is clearly adverse for the feature character as it creates a difficult situation for them (as shown by the level of *in-difficulty*) and leaves them feeling humiliated, whereas an action such as receiving professional praise can be seen as supportive since it engenders positive feelings and alleviates the difficulty of their situation. The actions *patient-come-round* and *patient-die-despite-emergency-treatment* are illustrative of actions that acquire their significance in context. For our domain model, amongst a baseline set of 50 narrative actions, 5% can be categorised as adverse to the feature character, 20% as supportive and the remainder are neutral but acquire their significance in context. With this representational approach, the combinatoric nature of narrative generation is preserved, since the configuration of states considered at run-time comes from the entire set of actions, rather than just those specifically tagged as adverse or supportive.

4.3 Invoking User Intervention

Due to the demanding nature of NF, during which the user is required to concentrate in a manner that is difficult to successfully maintain for long periods of time, user interaction with the system can be limited to a single support opportunity[1]. The point in the narrative at which this occurs is dynamically determined based on the difficulty of the feature characters' situation, with user support opportunities being provided when this deteriorates beyond a threshold, and not on the basis of fixed story points. As the narrative unfolds and actions

[1] In our proof-of-concept experiments, unsuccessful users were offered a second support opportunity. In our more recent usability experiments, user support was limited to a single opportunity. Here, we restrict discussion to the dynamic triggering of this single request although the same principles apply in the case of an additional request.

```
(:init
    (= (in-difficulty) 0) (= (level-of-support) 0) (= (full-support) 2) (= (partial-support) 1)
    (= (no-support) 0)... )
```

ADVERSE	(:action receive-reprimand-from-boss :parameters (?d - doctor ?b - boss) :precondition (and (missed-work-deadline ?d) ...) :effect (and (increase (in-difficulty) 1) (humiliated ?d) ...))	SIGNIFICANCE FROM CONTEXT	(:action patient-come-round :parameters (?d - doctor ?p - patient) :precondition (and (= (level-of-support) (full-support))...) :effect (and (patient-ok ?p) (patient-outcome ?p) (when (>= (in-difficulty) 1) (decrease (in-difficulty) 1)) ...))
SUPPORTIVE	(:action receive-professional-praise :parameters (?d1 ?d2 - doctor ?p - patient) :precondition (and (= (level-of-support) (full-support)) (emergency-treatment ?d1 ?p) (patient-ok ?p) ...) :effect (and (when (>= (in-difficulty) 1) (decrease (in-difficulty) 1)) (flattered ?d1) ...))		(:action patient-die :parameters (?d - doctor ?p - patient) :precondition (and (= (level-of-support) (no-support)) (not (patient-ok ?p)) ...) :effect (and (deceased ?p) (patient-outcome ?p) (increase (in-difficulty) 1) ...))

Figure 4 Narrative Action Valence Examples. Action *receive-reprimand-from-boss* can be seen as adverse for the feature character since it engenders feelings of humiliation (represented using the fact *humiliated*) and results in difficult situations for the character (represented via the increase in the fluent *in-difficulty*). In contrast, the action *receive-professional-praise* is supportive: it results in positive feelings for the feature character (represented via the fact *flattered*), and improves the characters situation (represented via the decrease in *in-difficulty*). The actions *patient-come-round* and *patient-die*, which lead to states in which the patient treatment is resolved (via the fact *patient-outcome*), gain significance from the context of the actions.

are visualised to the user, the situation of the character is monitored by the system and when the difficulty of their situation has deteriorated beyond a threshold value (assessed via the fluent *in-difficulty*), a user support opportunity is triggered and signalled to the user (via de-saturation of the characters' appearance as discussed in section 5). This is immediately followed by the display of a custom scene featuring the character of interest which serves as a visual channel for NF whilst preserving visual consistency. Figure 2 illustrates the process of dynamic positioning of the user support opportunities for different narratives.

Following user interaction the level of user support detected through NF is communicated to the narrative generator, via the fluent *level-of-support*, whose value is directly updated with the NF results: 0 for no support; 1 for partial support; and 2 for fully successful user support. The response of the system depends on whether the user has been successful at supporting the character:

- If the user is successful, either fully or partially, then the remainder of the narrative is immediately regenerated by re-planning using a planning problem instance revised to include both supportive landmarks or those which depend on context, and the current state of the narrative world which now includes the updated *level-of-support*. This will redress the course of action to favour the feature character. For example, the action *patient-come-round* shown in Figure 4 includes a pre-condition which ensures that this action can only appear in narratives when user support has been fully successful (represented via the equality test between *level-of-support* and *full-support*).

- If the user support attempt is unsuccessful, the original narrative resumes its execution leading to a negative ending for the feature character.

5 Frontal Asymmetry Neurofeedback

As our BCI paradigm is based on pre-frontal alpha EEG asymmetry, we have adapted the asymmetry score A2, derived from work conducted by Henriques and Davidson [13] and further refined and implemented by Hammond and Baehre [11]. As α rhythm (8–12Hz) reflects cortical hypoactivity, an increase in left frontal activity corresponds to a positive A_2 score (which we measure as $(F_4 - F_3)/(F_4 + F_3)$ with $F_4(R)$ & $F_3(L)$ electrodes with a reference electrode at position FCz, using the 10–20 electrode placement standard). The NF mechanism involves the user modulating this activity using an appropriate cognitive strategy, attempting to achieve the highest ratio of *left vs. right* cortical activity they can (i.e., a positive A_2 score tending towards 1). Since A_2 is a measure of approach [29], an appropriate cognitive strategy would reach out to the character ("support"). Although A_2 is considered valence-independent [12], "positive thoughts" are often empirically successful, probably because they involve a dimension of approach as well. The backchannel for NF is purely visual and expressed as the colour saturation of the feature character, normalised from 0.0 (de-saturated) to 1.0 (rich saturation), as illustrated in Figure 2.

NF itself takes place over a 30s window, during which a static scene is displayed, with the main character in mid-shot (Figure 1). During NF, if the character's appearance remains de-saturated, this indicates the viewer has not successfully communicated their positive thoughts (i.e., has a minimum or below-threshold asymmetry score). Saturation is increased as the asymmetry score increases, mapped through a sigmoid function, to avoid over-saturation. When the character is fully saturated with colour and the viewer is able to maintain this (by successful modulation of a higher asymmetry score), this is recognised as successful support and generates the corresponding modification of the *level-of-support* fluent in the planning domain, thereby triggering re-planning to produce a happier narrative progression and ending.

6 Experimental Study

We designed this proof-of-concept study as a simultaneous fMRI/EEG experiment for which the information on activated loci gathered from fMRI scans serves to validate the areas (cortical and sub-cortical) involved during the support window. fMRI measures brain activity by detecting associated changes in blood flow, through a contrasting technique known as BOLD. This dual approach was necessary due to the low spatial resolution of the EEG signal. MRI has higher spatial resolution, but is integrated over longer time periods. We hypothesized that successful prefrontal neurofeedback would activate mainly frontal areas that were previously identified as related to emotion regulation. We also expected no significant extra activity in motor-related cortical areas, which could otherwise indicate non-specific affective function.

Fifteen healthy volunteers (3 female, 3 left-handed) with a mean age of 29.38 years (S.D. 7.6) and with either perfect or corrected eyesight took part in the experiment. Of these, two were discarded due to technical issues, and 1 was rejected subsequently because of severe EEG movement artifacts. EEG data was acquired using a 32-electrode MRI-compatible

BrainAmp MR system (from Brain Product Co.). Data was recorded at a sampling rate of 5000Hz and collected on a PC running RecView software for gradient and cardioballistic artifact removal. Alpha band (8–12Hz) power was extracted online from electrodes F_3 and F_4 as mentioned in Section 5, sampled in 500ms windows. The mean A_2 asymmetry score was calculated for each window, and this was used to drive NF visuals. Simultaneous to EEG recording, subjects underwent fMRI measurement with a 3T GE scanner. fMRI scanning was based on the echo-planar imaging (EPI) sequence of functional T_2^*-weighted images (TR/TE/flip angle: 3,000/35/90; FOV: $20 \times 20\text{cm}^2$; matrix size: 128×128) divided into 39 axial slices (thickness: 3mm; gap: 0mm) covering the whole cerebrum. A T1-weighted anatomical scan was used for alignment.

As narrative evolution for each subject is driven by neural activity during support opportunities, the length of experimental runs was somewhat variable. A typical run consisted of a NF training session (∼4 min.), a narrative training session (∼8 min., running through an example narrative outside of the MRI), an active session (∼8 min.), and a replay session (∼8 min.). Additional MRI scans of around 20min were needed to measure brain anatomy. To determine the controllable asymmetry range for each subject, we used the distribution of asymmetry scores from the training session, thus accounting for individual differences in baseline EEG trait asymmetry score. The active session began with 60s of blank screen followed by the Interactive Narrative that contained up to two opportunities of support through NF (30s each), dynamically generated by the system as a function of narrative evolution. The replay session consisted of the visualisation of the narrative generated by the same subject during an active session, with the interaction mechanism disabled, thus serving as a control baseline for fMRI. This could only be determined after the fact due to the variability in storyline.

6.1 Data Analysis

We operated under the assumption that the A_2 at baseline is a stable trait metric that can be shifted due to affective mental process during the active NF session. To characterise the relative change in the asymmetry during the active support window, we calculated for each subject the distance between baseline A_2 calculated from the rest period at the beginning of the active session, and both NF windows using a repeated measures ANOVA. When comparing this EEG measure against successful ability using the NF approach to alter the course of the narrative, five subjects had "successful" narrative outcomes combined with significant up-modulation in A_2 scores ($p < 0.1$, 4 with $p < 0.05$). This is shown in Table 1. With these subjects we can be confident that the successful use of the BCI was due to actual modulation of EEG. An additional subject had borderline significant up-modulation (subject 12). Three additional subjects had successful outcomes from the Interactive Narrative, but no significant up-modulation of A_2 scores, indicating some possible over-sensitivity in the calibration for those subjects (10,13,14). Three subjects showed significant negative relative A_2 scores, so were unsuccessful in the use of the BCI († in Table 1). What we aim to show is that, while BCI input is determined through the relative A_2 scores, brain imaging could not detect activity in areas associated with affective control, contradicting those EEG scores. While the BCI itself still appears to possibly benefit from further tuning with regard to sensitivity, it provided the correct outcomes for significant changes in EEG.

Analysis of fMRI data was performed with the SPM5 MATLAB tool. This includes preprocessing of fMRI data: (a) slice timing correction to the middle slice, (b) correction for head movement by realignment of all images to the mean image of the scan using rigid body transformation with six degrees of freedom, (c) normalisation of the images to Montreal

Table 1 *EEG NF relative change index.* **, * *- significant positive change* ($p < 0.1$, $p < 0.05$). $^{\diamond}$ *- borderline success.* † *- negative change, no effect on narrative.*

Sub	F	df	P	Sub	F	df	P
1^{**}	99.65	242	.00	13	1.56	242	.21
2^{**}	16.11	244	.00	14	0.6	244	.438
7^{**}	7.06	242	.00	10	0.02	240	.89
8^{**}	3.32	242	.04	$6^{\dagger}$	0.84	244	.36
9^{*}	3.00	244	.08	$5^{\dagger}$	5.57	242	.01
$12^{\diamond}$	1.94	244	.16	$4^{\dagger}$	15.48	244	.00

Neurological Institute (MNI) space by co-registration to the EPI MNI template via affine transformation, and (d) spatial smoothing of the data to 6mm full-width at half-maximum (FWHM). Finally, the first six images of each scan were discarded to allow for T_2^* equilibration effects. Statistical analysis was based on individual maps of activation obtained from a general linear model (GLM). The GLM included regressors that model epochs of active support during the live narrative session and epochs during replay of the support sessions within the replay of the previously generated movie. All regressors were convolved with a canonical hemodynamic response function (see model response in Figure 5 B). To reduce the effect of physiological artifacts and nuisance variables, six motion parameters were introduced as covariates in the model. T-statistical maps were obtained by contrasting hemodynamic responses during epochs of active support versus replay of these epochs.

6.2 Results

For further analysis we compared two groups: *successful* – those who significantly increased the A_2 score during the support period, and *unsuccessful* – those who did not modulate it significantly or in fact, reduced it. Since the BCI principle is a priori focused on changing the narrative positively, for validation of the method, we concentrated on the six individuals who were successful in up-modulating their A_2 score as well as having a positive narrative outcome.

6.2.1 Behavioural Analysis: User Debriefing

We inspected the reported subjective state of all subjects: the consensus emotion in the unsuccessful group was frustration (4 out of 6), while the successful group reported approach-type behaviour (i.e., empathy and positive emotions). Subjects quite clearly identified the protagonist of the story as "kind" and the antagonist as "vicious", the only dissenting opinion being two subjects who characterised the feature character as "neutral" rather than "kind". Personal perception of the extent to which the viewer was helpful or able to make a difference in the story was split, with successful subjects agreeing that they were helpful to the main character and had an impact on the story. These results, along with informal feedback, indicate that subjects did understand the dynamics of the narratives and that subjective perception of their effectiveness was aligned with successfulness of response as measured through NF input and corresponding fMRI data.

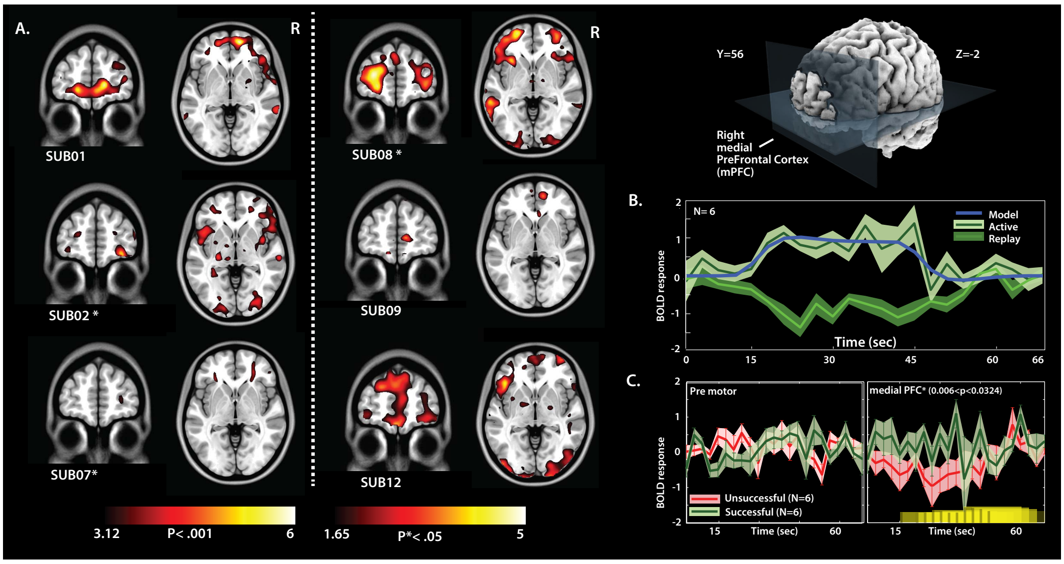

Figure 5 Brain validation of BCI for Interactive Narrative. **A.** Slice views (coronal and horizontal as indicated in top-right) of fMRI activation maps overlaid on a template anatomical scan (SPM5). Slices are shown for 6 out of 12 participants who were highly successful in modulating their EEG alpha asymmetry index during active support periods. The parametric activation maps were obtained by whole brain contrasts of active and replay sessions ($p < .001$, $p{*} < .05$). **B.** Time course of averaged estimated effect ($n = 6$) obtained from the contrast of active *vs.* replay from peak activation in a selected ROI in the right medial prefrontal cortex (see 3D location, top-right). **C.** Comparisons between successful and unsuccessful participants (green and red plots, respectively) in % signal change during the support period obtained from a relevant region of interest localized at the vmPFC, and from a non-relevant region in the premotor cortex. There is a significant difference in BOLD response between the groups for the vmPFC, with the successful group showing greater change (yellow squares indicate a sliding window of 24s in variable significance $0.006 < p < 0.0324$), while in the premotor, there is little difference.

6.2.2 fMRI Analysis of the Interactive Experience

Whole-brain General Linear Model (GLM) analysis of the fMRI data on the 6 individuals who were successful in A_2 up-modulation revealed enhanced activation during the periods of user support via NF, relative to the same periods during passive replay, in a cluster of regions in the pre-frontal cortex (PFC). These prefrontal loci include anterior and medial aspects of Brodman Areas 10 and 11 (BA10, BA11), known to be involved in cognitive and emotional control processes. Figure 5 shows the significant increased activation obtained in these PFC loci, confirming that successful up-modulation of EEG alpha asymmetry resulted in relevant regional recruitment. The whole-brain GLM analysis also provided additional indications of successful support-related regional activation in the middle temporal gyrus and the anterior insula. Only three of the successful supporters activated these regions at a threshold of $p < 0.001$ (uncorrected), but none of the unsuccessful supporters did so.

Intriguingly, signals obtained from the peak of activation within the PFC in each of the successful participants suggests that they not only increased their activity during the active user support, but also decreased it during the same period of the replay session (see Figure 5 B). To test the anatomical specificity of this regional effect we calculated time courses of activation during the active support window for each group in two distant loci: one in a task-relevant area in the anterior aspect of the PFC (BA10, MNI: 26, 58, 6, selected based on the overlap of successful activation maps at p < 0.05), the other in a non-task-relevant area in the right pre-motor cortex (BA 6, MNI: 56,6,48, selected based on the overlap of unsuccessful activation maps, at $p < 0.3$) (see Figure 5 C). A direct comparison between these traces showed that only activation changes in the PFC loci clearly distinguished between successful and unsuccessful individuals (sliding-window independent $t - test\, 0.008 < p < 0.0222$ FDR corrected).

6.2.3 Discussion

Considering the preliminary nature of the experiment and the limited size of our subjects' sample, we should naturally exercise caution in the interpretation of the above results.

In this experiment, we have endeavoured to provide generic instructions to our subjects, such as "mentally supporting" the main character, to avoid influencing their cognitive NF strategies. As a consequence, subjects did report variable strategies for producing such mental support, but the fMRI component of our experiments confirmed the selective activation of the BA10 area, known to be involved in mentalisation (i.e., reflection on one's own emotion and mental states, or those of other agents), a process also related to empathy [20]. Furthermore, our results suggest that the modulation of the A_2 EEG signal is not derived from premotor areas (Figure 5), a commonly used marker in BCI [10, 24] (notwithstanding potential limitations introduced by the left-handed fraction of our subjects' sample). Taking into account the complexity and variability of empathic processes and the multiple regions involved, it is difficult at this stage to draw further conclusions on the most relevant subregions of the PFC (e.g. dorso-lateral or ventro-medial, corresponding to different processes of cognitive and affective control) whose activation would constitute a further validation.

Another well-described difficulty of this type of simultaneous EEG/fMRI experiment derives from the difference in response times between EEG-based A_2 input and the BOLD signal. This is why we have presented results through a 60s window spanning 15s before and 15s after the NF window. The fact that activity in the mPFC would peak after 20s during fMRI recording (Figure 5 B) actually places it early in the NF phase and is consistent with many temporal patterns observed for A_2 variations during NF across our various experiments.

Overall, we can reasonably conclude that our fMRI findings are not incompatible, both from a spatial and temporal perspective, with the affective modulation mechanisms generally associated with A_2 asymmetry.

7 Usability Experiment

Following our proof-of-concept study, we staged a new experiment to assess the usability of the BCI for Interactive Storytelling, using a desktop implementation in a normal laboratory setting (outside of the MRI scanner). This experiment comprised a number of objectives: (1) to measure overall success scores and compare them to those of the proof-of-concept experiment; (2) to gain a better understanding of user cognitive strategies during NF; (3) to acquire data on the dynamics of NF; and (4) to explore the determinants of "BCI illiteracy" in this specific implementation of frontal alpha asymmetry NF [33].

We modified our previous prototype to improve the NF mechanisms, taking into account various observations of the baseline A_2 values, their variation across subjects and their typical variations during NF. Our first decision was to apply some form of filtering to the raw A_2 value to compensate for its variation: we opted for a 4-point moving average calculation

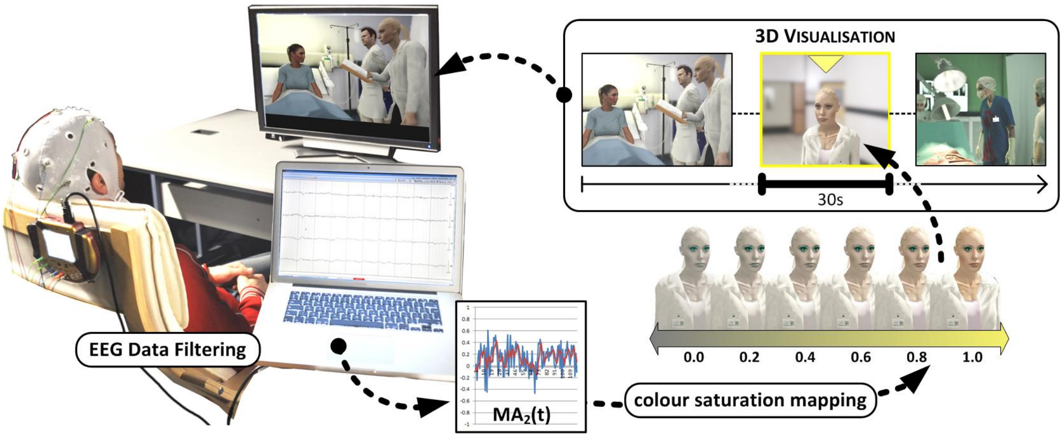

Figure 6 Usability experiment setup of our Interactive Narrative BCI prototype: (1) the user watches the narrative generated in real-time; (2) during NF, $MA_2(t)$ is mapped to the colour saturation of the character in need of support (see text).

(henceforth MA_2) as a simple form of low-pass filter and a compromise between filtering and delaying the averaged A_2 response. A second modification was to determine more accurately the variation range to improve NF mapping. We defined the threshold (NF feedback at 0% saturation) as the average A_2 value obtained for each subject during calibration at rest and, having observed empirically the maximum values reached for A_2 across multiple subjects, we defined a point corresponding to the maximum NF signal (100% colour saturation). This maximum was defined as: $min(max(MA_2), threshold + average\_variation)$[2]. To implement NF visual feedback we defined a linear mapping [0-100%] between the threshold and the above maximum. Finally, we revised the calculation of a success score for NF: it can be approximated by the integral of $MA_2(t)$ above threshold, over the 30s NF epoch. In order to normalise the score across subjects we used a block addition of the saturation value, resulting in a score between 0 and 100. We defined *success* (narrative support = 2) as a score > 20, which is equivalent to sustaining 100% saturation over 6s. *Moderate success* (narrative support = 1) corresponds to a value between 5 and 20.

In terms of data acquisition, EEG data was acquired using an 8-channel Brain Products V-Amp system. Data was recorded at a sampling rate of 250Hz and collected on a PC running Brain Vision RecView software. Alpha band (8–12Hz) power was extracted online from electrodes F_3 and F_4, sampled at (∼1 Hz) with a reference electrode at FC_z. The mean A_2 asymmetry score was calculated for each 1s window, and this was used to drive NF visuals. The pre-processing algorithm was compiled from Matlab R2013b to Microsoft .NET, so that it could be executed within the Brain Vision RecView EEG Recorder system. Raw EEG data was collected by Brain Vision RecView at a sampling rate of 250Hz. Data was then restructured to fit EEG offline data structure, packaged into MATLAB data types and marshaled to the MATLAB.NET compiled DLL. The MATLAB.NET compiled DLL calculated the A_2 momentary value once filtered through the calculation of a moving-average A_2 which was calculated over 4s, and passed this $MA_2(t)$ value back to the NF system, which in turn produced the appropriate feedback to the subject.

[2] Only “threshold” is related to the individual subject: other values have been obtained through a calibration study involving multiple subjects, different from the evaluation sample.

We recruited 36 subjects (17 male, 19 female); average age was 30.4 years (S.D. = 9.25; range: 20-52). Experiments were approved by our local ethics committee, and subjects were issued detailed consent forms. All data were anonymised, both questionnaire and EEG-related measures. For this experiment, subjects were located in a quiet room with dimmed lighting and sat in a comfortable armchair. They were given instructions on how to relax to minimise muscular artefacts as well as to avoid blinking as much as possible. Each subject went through a short calibration and training session prior to the Interactive Narrative experiment. This consisted of a 2min recording of A_2 scores to determine the individual subject baseline. This duration has been previously shown as the minimum duration that can provide reliable data [1]. During this baseline measurement, subjects alternated between eyes closed and open following a randomly selected COCO / OCOC pattern. Subjects subsequently went through a short training session, which gave them the opportunity to familiarise themselves with the NF system. The training system exactly reproduced the setting of the in-story input, except that it was not preceded by any narrative sequence (hence subjects can be considered to enter a training block in an affective neutral state, in particular since each training block was preceded by a short resting period). Each training block consisted of a 30s NF session, preceded by a 15s resting period during which subjects were instructed to relax and remain staring at a blue screen. Each subject went through 12 successive training blocks for a total duration of 10min: all subjects completed the training session.

The principle behind the BCI approach was explained to the subjects, as well as the use of NF as an interaction mechanism. They were told that they could support the story character by “expressing positive thoughts” that would be captured by the system. They were introduced to the concept of a NF loop in simple terms, with grey levels introduced as a visual indicator of the intensity/magnitude of mental support. Throughout training and evaluation, instructions were deliberately generic, in order to avoid influencing users' cognitive strategies towards any implicit or explicit one. In particular, we conspicuously avoided the use of terms such as empathy, sympathy, or other vocabulary likely to influence strategies (e.g. “talk to the character”). After the training session, each subject participated in one session of the BCI-enabled Interactive Narrative. Each subject saw a dynamically-generated variant of our medical drama, in which one NF session appeared as soon as the situation of the feature character deteriorated (although this is determined dynamically for each generated story variant, rather than pre-defined). Unlike with our proof-of-concept study, users only had a single opportunity to influence the course of action through a 30s NF session.

As described in section 4, we defined two levels of support: 1 for scores between 5 and 10, and 2 for scores above 10. Out of 36 subjects, 17 were unsuccessful, 7 were successful to a level of support of 1 and 12 were successful to a level of support of 2. The average score for successful subjects was 20 (S.D.: 25.98); this was essentially due to the contribution of two high-performing subjects: excluding them from this statistic, the average score is 12 (S.D.: 10.74). The overall success rate of 52.7% is modest for a usability experiment, but certainly above average when considering performance of previous frontal alpha asymmetry NF systems, in particular in clinical applications, and the very limited training undergone by subjects. It should also be noted that we have adopted a relatively demanding criterion for success, if compared to previous reports of frontal alpha asymmetry NF and even our proof-of-concept study. Previous (clinical) work reported hours of training over multiple sessions: here subjects had a single 10min training session[3]. We used limited training in this instance for practical as well as more fundamental reasons: frontal alpha asymmetry training is known to alter mood, and potential long-term effects were not covered by our ethical approval. This raises the possibility that if users had been subjected to the same type and level of training as in previous work, performance could have been much higher.

It is also worth investigating whether the concept of BCI illiteracy has any specific application to the case of frontal alpha asymmetry NF. BCI illiteracy was originally introduced to account for intrinsic non-performance of a stable fraction of the population, in the range of 15-30% [33] and is also recognised to be specific to the chosen BCI methodology [34].

Although BCI illiteracy is unlikely to constitute the sole explanation for the observed results, we have investigated, as a possibly specific determinant of illiteracy, the A_2 baseline of individual subjects, which we used in defining the NF threshold. The rationale is to estimate the maximum variation of A_2 during NF, in conjunction with the maximum values that can be empirically reached by A_2. This would suggest that individuals with a high A_2 baseline would be at a disadvantage to further increase their A_2 score as part of the NF process, making them less successful at using the BCI. This could also be related to the limited contribution of state variations to the total A_2 variation, estimated to be 10-20% [5]. To explore this phenomenon, we measured the correlation between in-story success and the A_2 baseline/NF threshold and observed a significant negative correlation (the point-biserial correlation between narrative support (collapsed) and threshold was $rpb = -.371, p = .026; Biserial : rb = .47, p = .026$), compatible with our initial hypothesis. We also investigated the cognitive strategies adopted by users for NF, in particular considering the non-prescriptive nature of instructions. We recorded free debriefing sections following each experiment and using their transcripts we categorised the users' declared cognitive strategies. We observed that no subject used implicit strategies, possibly as a consequence of our instructions mentioning "positive thought" (rather than letting thoughts wander whilst monitoring feedback). Explicit strategies were subsequently categorised as empathic *vs.* generic. The former directly target the virtual character such as inner speech or mental imagery (such as hugging or patting on the back). The latter express positive thoughts of a generic nature, such as recollections of pleasant moments in the subject's personal life, a strategy already reported in [15]. We found that support strategy during narrative and narrative success (merging levels of support 1 and 2) were not significantly related, $\chi^2(1) = 1.00, p = .51, V = .17$ (results were not altered when considering levels of support as separate categories).

However, when revisiting the above correlation between A_2 baseline/NF threshold and NF success for each group, we found that narrative success was negatively correlated with threshold in the generic strategy group ($r = -.56, p = .016$), but not in the empathic strategy group ($r = -.08, p = .767$). At the same time, threshold was not significantly different between the empathic and generic conditions ($t(34) = 1.21, p = .233$). These findings have to be interpreted in light of the variability of empathic responses, with only empathic cheerfulness strongly related to an increase in frontal alpha asymmetry [16]. This may actually limit the success of empathic strategies based on empathic concern [32]. Indeed, we found no correlation between empathic concern (part of the Interpersonal Reactivity Index (IRI) questionnaire[7]) and in-story success. On the other hand, positive personal experiences have proven efficient in previous NF studies [14] and were even reported as part of our proof-of-concept study.

[3]Rosenfeld [3] reports that some frontal alpha asymmetry EEG NF protocols require 40 days.

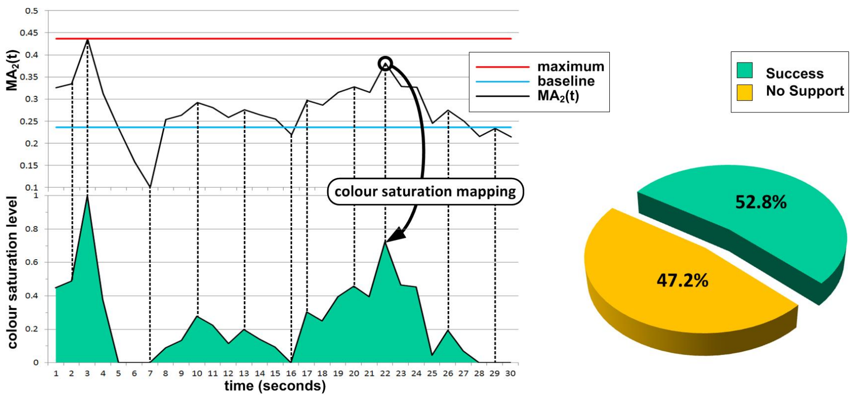

Figure 7 (left) Mapping of $MA_2(t)$ to the value of the virtual character's skin colour saturation in real-time and (right) overall success score in our sample (with limited NF training).

8 Conclusions

Affective BCI is a promising technique for Interactive Narrative, but its usability may be limited by the difficulty of all forms of emotional regulation. Our neuroimaging study has provided preliminary evidence for the importance of recruiting medial prefrontal regions that have been implicated in affective control as well as empathy-related processes for successful modulation of frontal alpha asymmetry. Although overall in-story success scores appear similar for both our proof-of-concept experiment and our usability study, the latter used slightly more stringent success criteria. Our overall score of 52.7% is certainly encouraging, even if not sufficient to guarantee usability: it is however important to analyse its significance, as well as any potential for improvement. Subjects tend to be distributed in two groups, successful and not, with very few intermediate values: this pattern could be construed as one of high-efficacy combined with high-illiteracy. The average score of successful subjects is 20, which corresponds to 100% saturation over 6s, equivalent to an increase in A_2 of over 0.2. This compares favourably with success criteria reported by Rosenfeld et al. [28] (number of "hits" per trial) or more recently Zotev et al. [37] (increases in A_2 up to 0.2, although in the high beta band).

In addition, there exists a real possibility that A_2 baselines have been overestimated due to the closed eyes recording epochs. Offline analysis of A_2 baselines values only considering open eyes epochs revealed an average difference of 0.10 ($t(35) = 6.61, p < .001$), which could have significant impact on performance, although this can only be validated through additional NF experiments. It should also be noted that although left-handed subjects are often excluded from alpha-asymmetry this was not the case in the present study. As left-handedness might bias frontal asymmetry measures by lowering the baseline level [23], possibly partially due to motor activity, left-handed subjects may perform the task of increasing the asymmetry more easily. Handedness-related difference could be statistically examined in the future, subject to the sample size being increased. Users have reported a mix of empathic and generic NF cognitive strategies. This source of variance – the type of empathic engagement entertained by the user during the feedback – should be better controlled for in future studies, as it is likely that users have adopted a mix of empathic strategies not all based on empathic cheerfulness. In this context, it is worth noting that Light and colleagues [16] reported that the direction of frontal EEG laterality may vary with the empathic strategy adopted by the person who feels empathy. They found that children who express cheerful empathy, when trying to encourage a suffering person, increased their right dorsolateral asymmetry, while the empathic happiness they shared with the individual once their suffering was relieved, was associated with left dorsolateral asymmetry. A focused debriefing on these aspects of empathy (possibly correlated to questionnaires such as IRI) will allow for a higher-resolution account for EEG and fMRI effects during the neurofeedback. However, some debriefing comments cast doubts on the extent to which some subjects actually engaged in NF, i.e. took full advantage of the visual feedback channel, as opposed to concentrating on providing an input signal. This can only be clarified through a detailed examination of temporal patterns, but the intrinsically noisy nature of EEG input may render this analysis challenging.

References

1 John J. B. Allen, James A. Coan, and Maria Nazarian. Issues and assumptions on the road from raw signals to metrics of frontal EEG asymmetry in emotion. *Biological Psychology*, 67(1):183–218, 2004.

2 John J. B. Allen, Eddie Harmon-Jones, and James H. Cavender. Manipulation of frontal EEG asymmetry through biofeedback alters self-reported emotional responses and facial EMG. *Psychophysiology*, 38(4):685–693, June 2001.

3 Elsa Baehr, J. Peter Rosenfeld, and Rufus Baehr. Clinical use of an alpha asymmetry neurofeedback protocol in the treatment of mood disorders: Follow-up study one to five years post therapy. *Journal of Neurotherapy*, 4(4):11–18, 2001.

4 Benny B. Briesemeister, Sascha Tamm, Angela Heine, and Arthur M Jacobs. Approach the good, withdraw from the bad - a review on frontal alpha asymmetry measures in applied psychological research. *Psychology*, 4:261, 2013.

5 James A. Coan and John J. B. Allen. Frontal EEG asymmetry as a moderator and mediator of emotion. *Biological psychology*, 67(1):7–50, 2004.

6 Richard J. Davidson. Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition & Emotion*, 12(3):307–330, 1998.

7 Mark H. Davis. Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of personality and social psychology*, 44(1):113, 1983.

8 Nico H. Frijda. The laws of emotion. *American Psychologist*, 43:349–358, 1988.

9 Stephen W. Gilroy, Julie Porteous, Fred Charles, and Marc Cavazza. Exploring passive user interaction for adaptive narratives. In *Proceedings of the 17th International Conference on Intelligent User Interfaces (IUI '12)*, pages 119–128. ACM, 2012.

10 Aysegul Gunduz, Peter Brunner, Amy Daitch, Eric C. Leuthardt, Anthony L. Ritaccio, Bijan Pesaran, and Gerwin Schalk. Neural correlates of visual–spatial attention in electrocorticographic signals in humans. *Frontiers in human neuroscience*, 5:89, 2011.

11 D. Corydon Hammond and Elsa Baehr. Neurofeedback for the treatment of depression: Current status of theoretical issues and clinical research. In T. H. Budzynski, H. K. Budzynski, J. R. Evans, and A. Abarbanel, editors, *Introduction to Quantitative EEG and Neurofeedback: Advanced Theory and Applications*, pages 295–314. Academic Press, 2009.

12 Eddie Harmon-Jones. Clarifying the emotive functions of asymmetrical frontal cortical activity. *Psychophysiology*, 40(6):838–848, 2003.

13 Jeffrey B. Henriques and Richard J. Davidson. Left frontal hypoactivation in depression. *Journal of Abnormal Psychology*, 100(4):535–545, 1991.

14 S.J. Johnston, S.G. Boehm, D. Healy, R. Goebel, and D. Linden. Neurofeedback: a promising tool for the self-regulation of emotion networks. *Neuroimage*, 49(1):1066–1072, 2010.

15 Silvia E. Kober, Matthias Witte, Manuel Ninaus, Christa Neuper, and Guilherme Wood. Learning to modulate one's own brain activity: the effect of spontaneous mental strategies. *Frontiers in human neuroscience*, 7, 2013.

16 Sharee N. Light, James A. Coan, C. Zahn-Waxler, C. Frye, H. Hill Goldsmith, and R. J. Davidson. Empathy is associated with dynamic change in prefrontal brain electrical activity during positive emotion in children. *Child development*, 80(4):1210–1231, 2009.

17 Fabien Lotte. On the need for alternative feedback training approaches for BCI. In *Berlin BCI Workshop on Advances in Neurotechnology*, 2012.

18 David Marshall, Damien Coyle, Shane Wilson, and Michael Callaghan. Games, gameplay, and BCI: The state of the art. *Computational Intelligence and AI in Games, IEEE Transactions on*, 5(2):82–99, 2013.

19 A. Nijholt, D. Plass-Oude Bos, and B. Reuderink. Turning shortcomings into challenges: Brain-computer interfaces for games. *Entertainment Computing*, 1(2):85–94, April 2009.

20 Kevin N. Ochsner, Kyle Knierim, David H. Ludlow, Josh Hanelin, Tara Ramachandran, Gary Glover, and Sean C. Mackey. Reflecting upon feelings: an fMRI study of neural systems supporting the attribution of emotion to self and other. *Journal of Cognitive Neuroscience*, 16(10):1746–1772, 2004.

21 D. Plass-Oude Bos, B. Reuderink, B. van de Laar, Hayrettin Gürkök, Christiam Mühl, Mannes Poel, Anton Nijholt, and Dirk Heylen. Brain-computer interfacing and games. In D. Tan and A. Nijholt, editors, *Brain-Computer Interfaces*, pages 149–178. Springer, 2010.

22 Julie Porteous, Marc Cavazza, and Fred Charles. Applying Planning to Interactive Storytelling: Narrative Control using State Constraints. *ACM Transactions on Intelligent Systems and Technology (ACM TIST)*, 1(2):1–21, 2010.

23 Ruth E. Propper, Jenna Pierce, Mark W. Geisler, Stephen D. Christman, and Nathan Bellorado. Asymmetry in resting alpha activity: Effects of handedness. *Open Journal of Medical Psychology*, 1:86, 2012.

24 Ander Ramos-Murguialday, Markus Schürholz, Vittorio Caggiano, Moritz Wildgruber, Andrea Caria, Eva M. Hammer, S. Halder, and N. Birbaumer. Proprioceptive feedback and brain computer interface (BCI) based neuroprostheses. *PloS One*, 7(10):e47048, 2012.

25 G. Raz, Y. Winetraub, Y. Jacob, S. Kinreich, A. Maron-Katz, G. Shaham, I. Podlipsky, G. Gilam, E. Soreq, and T. Hendler. Portraying emotions at their unfolding: A multilayered approach for probing dynamics of neural networks. *NeuroImage*, 60:1448–1461, 2012.

26 Boris Reuderink, Christian Mühl, and Manne Poel. Valence, arousal and dominance in the EEG during game play. *International Journal of Autonomous and Adaptive Communications Systems*, 6(1/2013):45–62, 2013.

27 J. Peter Rosenfeld. An EEG biofeedback protocol for affective disorders. *Clinical EEG electroencephalography*, 31(1):7–12, 2000.

28 J. Peter Rosenfeld, Grace Cha, Tad Blair, and Ian H. Gotlib. Operant (biofeedback) control of left-right frontal alpha power differences: Potential neurotherapy for affective disorders. *Biofeedback and Self-Regulation*, 20(3):241–258, 1995.

29 S. K. Sutton and R. J. Davidson. Prefrontal brain asymmetry: A biological substrate of the behavioral approach and inhibition systems. *Psychological Science*, 8(3):204–210, 1997.

30 Ed S. Tan. *Emotion and the Structure of Narrative Film: Film as an Emotion Machine.* Mahwah, N.J: L. Erlbaum Associates, 1996.

31 P. Tikka, A. Valjamae, Aline W. de Borst, Roberto Pugliese, Niklas Ravaja, M. Kaipainen, and T. Takala. Enactive cinema paves way for understanding complex real-time social interaction in neuroimaging experiment. *Frontiers in Human Neuroscience*, 6, 2012.

32 Alexa M. Tullett, Eddie Harmon-Jones, and Michael Inzlicht. Right frontal cortical asymmetry predicts empathic reactions: Support for a link between withdrawal motivation and empathy. *Psychophysiology*, 49(8):1145–1153, 2012.

33 Carmen Vidaurre and Benjamin Blankertz. Towards a cure for BCI illiteracy. *Brain Topography*, 23(2):194–198, 2010.

34 A. Vuckovic. Motor imagery questionnaire as a method to detect BCI illiteracy. In *Proceedings of the 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL '10)*, pages 1–5. IEEE, 2010.

35 R.E. Wheeler, R.J. Davidson, and A.J. Tomarken. Frontal brain asymmetry and emotional reactivity: A biological substrate of affective style. *Psychophysiology*, 30(1):82–89, 1993.

36 Tom Ziemke. Empathy with computer game characters: A cognitive neuroscience perspective. *Virtual Social Agents*, page 73, 2005.

37 Vadim Zotev, Raquel Phillips, Han Yuan, Masaya Misaki, and Jerzy Bodurka. Self-regulation of human brain activity using simultaneous real-time fMRI and EEG neurofeedback. *NeuroImage*, 85:985–995, 2014.