PEANUT: Personalised Emotional Agent for Neurotechnology User-Training

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ABSTRACT: Mental-Imagery based Brain-Computer Interfaces (MI-BCI) are neurotechnologies enabling users to control applications using their brain activity alone. Although promising, they are barely used outside laboratories because they are poorly reliable, partly due to inappropriate training protocols. Indeed, it has been shown that tense and non-autonomous users, that is to say those who require the greatest social presence and emotional support, struggle to use MI-BCI. Yet, the importance of such support during MI-BCI training is neglected. Therefore we designed and tested PEANUT, the first Learning Companion providing social presence and emotional support dedicated to the improvement of MI-BCI user-training. PEANUT was designed based on the literature, data analyses and user-studies. Promising results revealed that participants accompanied by PEANUT found the MI-BCI system significantly more usable.

Figure 1: A participant taking part in a BCI training process. Along the training PEANUT (on the left) provides the user with social presence and emotional support adapted to his performance and progression.

INTRODUCTION

Brain-Computer Interfaces (BCI) are neurotechnologies which enable users to control external applications using their brain-activity alone [22], often measured using ElectroEncephaloGraphy (EEG). In this paper, we focus more specifically on Mental-Imagery based BCI (MI-BCI) with which commands are sent using mental-imagery tasks (imagining movements for instance). Because they enable users to control devices or applications without moving, MI-BCI are extremely promising in various fields ranging from assistive technologies (e.g. wheelchairs or neuroprosthetics) to video games [15].

Nevertheless, some important issues inherent to MI-BCI make it so that these technologies are not reliable enough for applications such as navigation and control, therefore preventing them from being widely used outside laboratories. Among these issues, some are due to hardware limitations (the electrodes are sensitive to noise) and others to software issues (brain-signal processing algorithms are still imperfect). Though, the issue we will focus on here, which is rather little explored [13], concerns the users themselves. Indeed, before being able to use an MI-BCI, users have to learn how to produce brain patterns that the computer will be capable of discriminating. However, the literature [14] as well as experimental results [7] suggest that current MI-BCI training protocols are theoretically and practically inappropriate for acquiring skills. Therefore, understanding and improving MI-BCI skill-acquisition is essential to make BCI accessible. Previous research results [8] suggest that users with specific personality profiles face difficulty when learning to use an MI-BCI. More specifically, highly tense and non-autonomous people (based on the "tension" and "self-reliance" dimensions of the 16 PF5 psychometric questionnaire [2]) experience the greatest difficulties.

Indeed, the MI-BCI training process does lack aspects of utmost importance for learning: social presence and emotional support [9]. In "Distance Learning" applications (i.e., learning without a teacher or classmates, using a computer for instance) [19], the absence of social presence and emotional support has been efficiently compensated by the use of learning companions [16, 11]. Learning companions are virtual or physical characters that can speak and have facial/bodily expressions. They provide the learner with different kinds of interventions, such as support or empathy, in order to overcome the lack of social interactions and emotional support. Despite their potential to improve MI-BCI user-training, both in terms of performance and user-experience, the use of a social presence and an emotional support as provided by a Learning Companion has never been explored in this context.

Thus, the object of this work was to design, implement

and validate the first learning companion dedicated to improving MI-BCI user-training. We called this companion PEANUT for *Personalised Emotional Agent for Neurotechnology User-Training*. PEANUT is a physical and anthropomorphic character providing interventions to the user in between two BCI trials. Such interventions consist in pronouncing an encouraging sentence, and displaying corresponding facial expressions of emotions.
In the following sections, we will describe the different steps which led to the companion's appearance and intervention design. Finally, we introduce the experiment dedicated to validate PEANUT's efficiency in improving MI-BCI user-training before proposing a general discussion and presenting future work.

DESIGNING PEANUT

Designing a learning companion requires to identify an appropriate appearance and intervention content, due to their impact on the user's motivation, experience and learning [1]. Thus, our design was based on the literature and a couple of user-studies.

Defining the physical appearance of PEANUT

First, we focused on the appearance of PEANUT. The literature guided our choice towards the use of a physical companion, increasing social presence in comparison to a virtual one [5]. Also, anthropomorphic features seem to facilitate social interactions [3]. Moreover, for the companion to be relevant, the combination of physical characteristics, personality/abilities, functionalities and learning function had to be consistent.
Since PEANUT's functions are simple and it is unable to interact with the user (PEANUT can talk, but cannot receive input from the BCI user), we chose to propose a cartoon-like character with anthropomorphic child-like shapes. Thus, we used the voice of a child to record PEANUT's interventions (which also enabled us not to associate PEANUT with a gender).
Regarding PEANUT's face, we asked a designer to create three styles of faces expressing each of these eight emotions: Trust, Joy, Surprise, Admiration, Boredom, Sadness, Anger and a Neutral expressions. We wanted the faces to be cartoon-like, so that they fit the body and complied with the recommendations from the literature. Prior to the experiment, an online user-survey in which 96 people gave their opinion on the different faces design expressing the different emotions was led. It enabled us to select the style of face that would fit the most the requirements from the literature. Interestingly, the results indicated that the presence of eyebrows could influence positively the expressiveness of a cartoon face.

Defining the Behaviour of PEANUT

Second, we concentrated on the content of PEANUT's interventions. One intervention corresponds to the association of a sentence and a facial expression. Sentences were selected from the following five main categories, elaborated through recommendations from the literature [10, 23, 21, 6], with respect to subject's MI-BCI performance and progression, i.e. the context of intervention.

- Temporal interventions, related to the temporal progress of the experiment [10] (ex. "I am happy to meet you", when starting the first session)
- Effort-related interventions, focusing on the fact that learning is the goal, and intended to minimise the importance of current performance while promoting long-term learning [23]. (ex. "Your efforts will be rewarded")
- Empathetic interventions, which aim at letting users know that their companion understands that they are facing a difficult training process [21]. (ex. "Don't let difficulties discourage you")
- Performance/results and progression associated interventions, which were designed to motivate users by focusing on the abilities they had already acquired [6]. (ex. "You are doing a good job!")
- Strategy-related interventions which aim at encouraging people to keep the same strategy when progression was positive or to change strategy when it was negative/neutral. (ex. "You seem to have found an efficient strategy")

Then, we also explored different sentences' characteristics, e.g., exclamatory or declarative (ex. "You are doing good!" or "You are doing good."); and personal (second person) or non-personal (third person) mode (ex. "You are doing good!" or "These results are good!"). To determine which characteristics the intervention should have depending on the context (performance & progression), we led an online user survey with 104 persons. The study consisted in an online questionnaire giving users similar instructions and mental imagery tasks as the ones given during actual BCI training. Simulated performances (since the surveyed users were not actually using a BCI) were displayed and were evolving positively, neutrally or negatively given the group the user was randomly assigned to. After the situation was introduced, two different intervention sentences were displayed on screen Users were asked to rate each of them (on a Likert scale ranging from 1 to 5) based on five criteria: appropriate, clear, evaluative, funny, motivating.
The results of these questionnaires revealed that users facing a negative progression should only be provided with declarative personal interventions and those facing a neutral progression with either declarative or exclamatory personal interventions. Results also revealed that participants showing a positive progression should be provided with declarative non-personal sentences (when the goal was to give clear information about the task) or exclamatory personal sentences (when the goal was to increase motivation) (see also Figure 2). One should add that

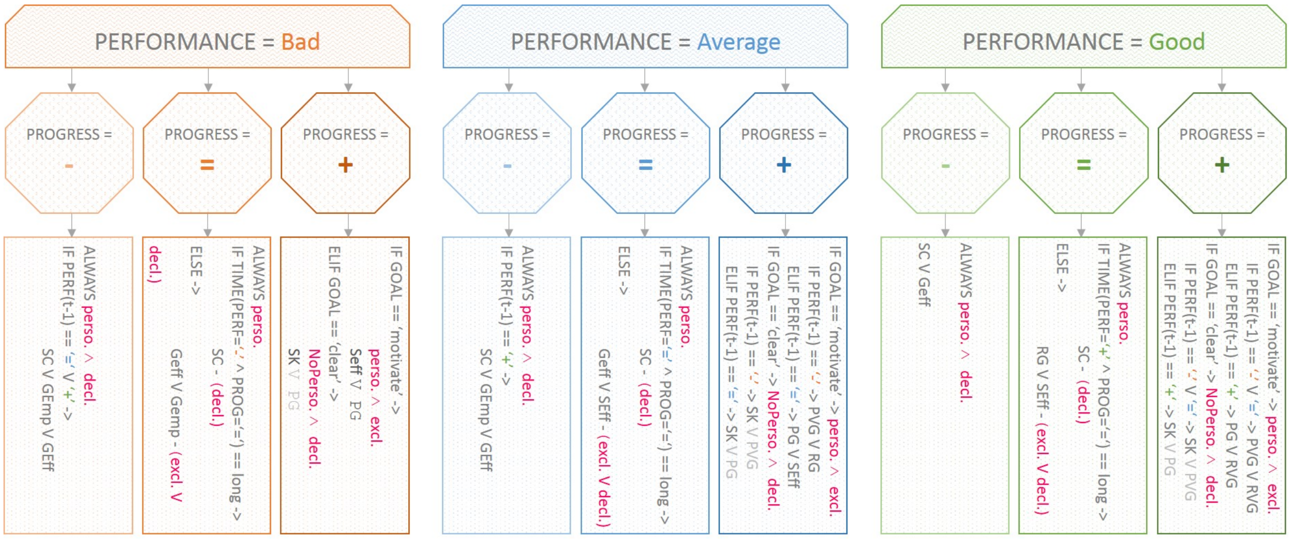

Figure 2: PEANUT's rule tree. Depending on performance and progression ("-"=negative, "="=neutral", "+"=positive), a set of rules is determined. Type of sentences: "perso." for personal, "NoPerso." for non-personal ; Mode of the sentence: "decl." for declarative, "excl." for exclamatory. Interventions: "GEff" for general effort, "SEff" for support effort, "GEmp" for general empathy, "SK" for strategy keep, "SC" for strategy change, "RG" for results good, "RVG" for results very good, "PG" for progress good, "PVG" for progress very good. Moreover, "$\wedge$" sign represents the logical operator "and" while "$\vee$" sign represents the logical operator "or".

when an exclamatory sentence was used for the intervention, the emotion displayed through PEANUT's facial expressions was made more intense than for an equivalent declarative sentence. We could then translate these various results into rules, and more precisely into the the rule tree presented in Figure 2. This rule tree enables the system to select one specific rule (i.e., an intervention content - sentence & expression - and style) with respect to the context (performance and progression).

In particular, we determined a bad, average and good performance according to the 25th and 75th percentile of each user performance at the first run. Similarly, we determine a negative, neutral or positive progression according to the 25th and 75th of the user progression during the first session. Progression was estimated as the slope of the regression line of the user performance over the last 10 trials.

Implementation of PEANUT

Users' EEG signals were first measured using a g.tec gUSBAmp (g.tec, Austria) and processed online using OpenViBE 0.19.0 [18]. OpenViBE provided users with a visual feedback about the estimated mental task, and computed users' performances which were then transmitted to a home-made software, the rule engine using the Lab Streaming Layer (LSL) protocol. The rule engine processed performance measures received from OpenViBE to compute progression measures and browsed the Rule Tree described in Figure 2 in order to select an appropriate intervention for PEANUT (sentence and facial expression) with respect to the context. The selected intervention was then transmitted to an Android smartphone application by WiFi, which enunciated the sentence and animated PEANUT's facial expression.

VALIDATION OF THE EFFICIENCY OF PEANUT TO IMPROVE BCI USER-TRAINING

Once the companion created, the next step consisted in studying its efficiency to improve MI-BCI user-training both in terms of performance and user-experience.

Participants

Our study included twenty MI-BCI-naive participants (10 women; aged 21.05$\pm$1.64), and was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was approved by Inria's ethics committee, the COERLE. All participants signed an informed consent form at the beginning of the experiment and received a compensation of 50 euros.

Our experiment comprised 2 participant groups, which determined the support they would receive throughout the MI-BCI training sessions: no learning companion (*control group*) or a learning companion adapted to their MI-BCI performance & progression, i.e., PEANUT (*experimental group*). As the control group, we used the results obtained from 10 subjects in a previous experiment [8]. This experiment used the same protocol, but without PEANUT. Among the 18 participants of this previous study, 10 were selected so that they matched, as far as possible, the characteristics of the participants from the experimental group in terms of gender and initial MI-BCI performance. Furthermore, tension and self-reliance scores were comparable for the two groups.

Experimental Protocol

Before the first session, participants were asked to complete a validated psychometric questionnaire, the 16 PF-5 [2], that enabled us to compute their tension and self-reliance scores. Each participant took part in 3 sessions, on 3 different days. Each session lasted around 2 hours and was organised as follows: EEG cap setup, five runs during which participants had to learn to perform three MI-tasks (around 60 min, including breaks between the runs), removing the EEG cap and debriefing. The MI-tasks (i.e., left-hand motor imagery, mental rotation and mental subtraction) were chosen according to Friedrich et al. [4], who showed that these tasks were associated with the best performance on average across participants. During each run, participants had to perform 45 trials (15 trials per task, presented in a random order), each trial lasting 8s. At t=0s, an arrow was displayed with a left hand pictogram on the left (*L-HAND* task), the subtraction to be performed at the top (*SUBTRACTION* task) and a 3D shape on the right (*ROTATION* task). At t=2s, a "beep" announced the coming instruction and one second later, at t=3s, a red arrow was displayed for 1.250s. The direction of the arrow informed the participant which task to perform, e.g., an arrow pointing to the left meant the user had to perform a *L-HAND* task. In order to stress this information, the pictogram representing the task to be performed was also framed with a white square until the end of the trial. Finally, at t=4.250s, a visual feedback was provided in the shape of a blue bar, the length of which varied according to the classifier output. Only positive feedback was displayed, i.e., the feedback was provided only when there was a match between the instruction and the recognised task. The feedback lasted 4s and was updated at 16Hz, using a 1s sliding window. During the first run of the first session (i.e., the calibration run, see next Section), no real feedback could be provided, since the classifier has not been calibrated yet for this user. Thus, in order to limit biases with the other runs, e.g., EEG changes due to different visual processing between runs, the user was provided with a sham feedback, i.e., a blue bar randomly appearing and varying in length, irrespectively of the user's actual EEG (this feedback was based on the data from a previous user), as in [4]. A gap lasting between 3.500s and 4.500s separated each trial.

The *experimental group* was accompanied by PEANUT during the training, from the second run of session 1 (after the calibration run). PEANUT intervened every 6 ± 2 trials (the exact trial during which PEANUT intervened was randomly selected in that interval), during the inter-trial interval. PEANUT's interventions were adapted to participants' performance during the first session, and to their performance and progression during the second and third sessions.

EEG Recordings & Signal Processing

The EEG signals were recorded using 30 active scalp electrodes (F3, Fz, F4, FT7,FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8, 10-20 system), referenced to the left ear and grounded to AFz. EEG data were sampled at 256 Hz.

In order to classify the 3 mental imagery tasks on which our BCI is based, the following EEG signal processing pipeline was used. First, EEG signals were band-pass filtered in 8-30Hz, using a Butterworth filter of order 4. Then EEG signals were spatially filtered using 3 sets of Common Spatial Pattern (CSP) filters [17].

The CSP algorithm aims at finding spatial filters whose resulting EEG band power is maximally different between two classes. To provide a participant-specific feedback, each set of CSP filters was optimised during a calibration run (i.e., the first run of the first session) to discriminate EEG signals for a given class from those for the other two classes. We optimised 2 pairs of spatial filters for each class, corresponding to the 2 largest and lowest eigen values of the CSP optimisation problem for that class, thus leading to 12 CSP filters. The band power of the spatially filtered EEG signals was then computed by squaring the signals, averaging them over the last 1 second time window (with 15/16s overlap between consecutive time windows) and log-transforming the result. These resulted in 12 band-power features that were fed to a multi-class shrinkage Linear Discriminant Analysis (sLDA) [12], built by combining three sLDA in a one-versus-the-rest scheme. As for the CSP filters, the sLDA were optimised on the EEG signals collected during the calibration run, i.e., during the first run of the first session. To reduce between session variability, the sLDA classifiers' biases were re-calculated after the first run of sessions 2 and 3, based on the data from this first run, as in [4]. The resulting classifier was then used online to differentiate the 3 MI-tasks during the 3 sessions.

The sLDA classifier output (i.e., the distance of the feature vector from the LDA separating hyperplane) for the mental imagery task to be performed was used as feedback provided to the user. In particular, if the required mental task was performed correctly (i.e., correctly classified), a blue bar with a length proportional to the LDA output and extending towards the required task picture was displayed on screen and updated continuously.

This processing pipeline led to a total of 64 classification outputs per trial (16 per second for 4 seconds). OpenViBE thus computed the user's performance for this trial as the rate of correct classification outputs among these 64 outputs, and sent it to the rule engine (which in turn computed progression measures).

Variables & Factors

We studied the impact of the group (no companion, companion) on participants' MI-BCI performance, with respect to the session and participant's profile (tension and self-reliance scores). MI-BCI performance was assessed in term of mean classification accuracy (mean performance measured over all the windows of the feedback periods from all the different runs). We also evaluated the impact of the group on MI-BCI usability, with respect to MI-BCI performance. MI-BCI usability was assessed using a questionnaire focusing on 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety and satisfaction.

Results

First of all, statistical tests (t-tests) revealed no significant differences between the two groups in terms of tension, autonomy or initial cross validation performances on the calibration. This ensures the two groups are comparable. Therefore, we analysed each group's MI-BCI performance in term of mean classification accuracy, for this 3-class BCI (thus with a chance level of 33%). The group with no companion obtained 51.65% $\pm$ 3.78 and the group with the companion obtained 50.85% $\pm$ 7.94 mean classification accuracy. An ANOVA did not find any significant difference between the mean performance of the two groups [F(2,18)=-0.29, p=0.777] though their variance is significantly different [F(2,18)=4.737, p=0.043] (see Figure 3).

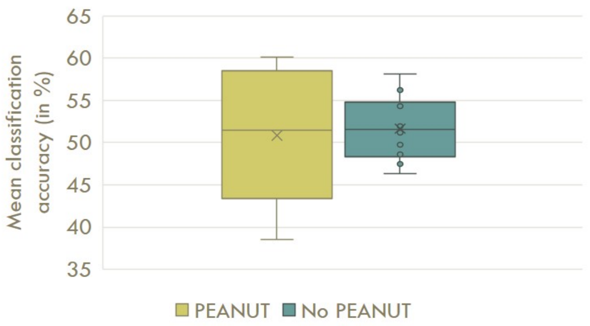

Figure 3: Mean classification accuracy per users group.

The subtantial difference of variability between the two groups might suggest that PEANUT had a beneficial effect on some participants and a detrimental effect on some others. However, this is only an hypothesis, and the number of participants included in the study does not allow us to identify the characteristics of those benefiting (or not) from PEANUT.

Finally, we analysed the influence of the group on usability scores. We performed four one-way ANCOVAs (one per dimension) with the Group as factor, the usability score for the target dimension as dependent variable and the mean classification accuracy as co-variable, since better classification accuracy is likely to lead to better perceived efficiancy, irrespectively of the condition. Results revealed a main effect of the group on the learnability/memorability (LM) dimension [D(1,18)=6.073; $p \leq 0.05$, η^2=0.263]: participants who were provided with a companion considered the system's learnability/memorability to be higher than those with no companion (see Figure 4).

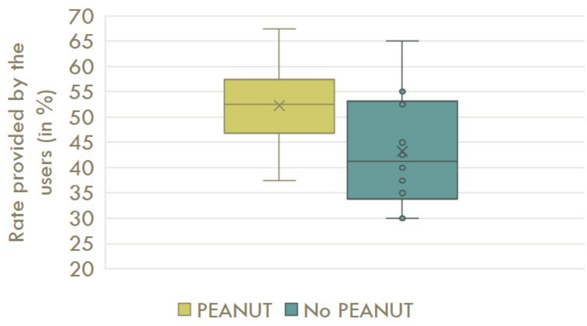

Figure 4: LM scores with respect to users' group.

DISCUSSION & CONCLUSION

In this paper, we introduced PEANUT, the first learning companion dedicated to MI-BCI user-training. The strength of this companion is its design: a combination of recommendations from the literature and of user-studies. PEANUT was validated in a relatively large MI-BCI study (20 participants, 3 sessions per participant), with two conditions: one control group with no learning companion and one experimental group with a learning companion whose behaviour was adapted to users' performance and progress. The higher variance in terms of performance in the group with PEANUT might suggest that PEANUT had a beneficial influence on some participants' performance but a detrimental one on others, although this hypothesis remains to be formally tested. This is in accordance with some previous studies indicating a differential effect of learning companion depending on sex and previous knowledge [1]. Nonetheless, this study also revealed that using PEANUT has a significant impact on user-experience. Indeed, participants who used PEANUT found it was easier to learn and memorise how to use the MI-BCI system than participants who had no learning companion. This confirmed that carefully designing PEANUT based on literature from educational psychology and user-centered design methods substantially benefited MI-BCI training user-experience.

In the future, PEANUT's behavior could be improved by adapting its interventions to the user's profile and state (frustration, overload, joy, boredom, etc.). We also plan to have PEANUT providing cognitive support, i.e., help to guide users towards the acquisition of specific skills. In order to be able to provide such support in an appropriate way, we first have to define a cognitive model of MI-BCI user-training, i.e., a model describing the factors impacting MI-BCI performance. Such a cognitive support, also known as explanatory feedback, is recom-

mended by the educational psychology literature to ensure efficient training [20]. It would also be interesting to define more refined performance metrics and user state measures in order to provide more specific/adapted interventions, possibly further improving the support.
Overall, we are working towards providing a better cognitive and emotional feedback to MI-BCI users thanks to the use of learning companions. We hope that such companions could become broadly used tools for MI-BCI user-training in order to push BCI performance and usability much further. In this view, we designed and implemented PEANUT for a low cost, using only open-source and free software. We hope this work will contribute to make MI-BCI more widely accessible technologies.

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