MAINTAINING OPTIMAL TRAINING VALUE USING BRAIN COMPUTER INTERFACING

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ABSTRACT

Within military aviation, training effectiveness is increasingly important. Development of effective training scenarios and meaningful events is a complex and time consuming task and incorrect application of scenario events can result in marginal training effects. Automatic event triggering within simulation exercises has potential for increasing training effectiveness as well as allowing for individual training without instructor interference. In game design theory, the flow principle is used to provide an optimally engaging experience, whereas its equivalent in instructional design theory is maintaining the optimal cognitive load by adjusting the task complexity or by scaffolding. The control of these principles can be based on user activity or performance. Alternatively, brain measures may be used to control the learning experience of professionals. This paper explores the options for using brain measures for military aviation training and provides results of a small scale study. Based on the study, it is concluded that brain measures may be a viable but demanding mechanism for optimizing the learning process. Further development of brain measure and adaptive scenario event triggering techniques could prove useful in increasing training effectiveness and developing new individual training methods.

KEYWORDS

Adaptive training, Brain Computer Interfacing, EEG.

1. INTRODUCTION

Military aviation has a long history of using simulation for training purposes. Due to the cost of training and limited availability of training opportunities, training effectiveness is an increasingly important aspect. A wider set of training media is now being used within military aviation, from high fidelity simulators to PC-based low-fidelity simulations or serious games''. For most types of training media, elaborate and often complex scenarios involving several events are needed, often developed by instructors. Development of effective training scenarios and corresponding events is a complex and time consuming task. Furthermore scenario events have to be developed beforehand and subsequently introduced at the right time and in the right form during the training. Incorrect introduction of scenario events can generate only marginal (or even negative) training effect against high costs.

Adaptive training based on events triggering at certain values or parameters can be one way to reduce the occurrence of incorrectly applied scenario events. Potentially, this can increase training effectiveness and reduce costs associated with scenario/event development (Field, Rankin, van der Pal, Eriksson & Wong, 2011). Furthermore, automatic scenario event triggering potentially allows individual training without further interference from an instructor, in effect allowing the trainee to determine when, where, and what to train while maintaining optimal training value. Achievement of the abovementioned relies on determining the correct input for the simulation environment to trigger events, and reliable measurement of the input.

In game design theory, the flow principle is used to provide an optimally engaging experience, whereas its equivalent in instructional design theory is maintaining the optimal cognitive load (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Good game experience requires the player to be in a 'flow' state of mind

(Csíkszentmihályi, 1991) which is feeling competent but challenged while being immersed in the game. This requires game designers to build up game events and levels that are neither too easy (boring) nor too difficult (frustrating) while ensuring that challenging periods are balanced with more relaxing periods without losing the players' attention. Instructional design sequencing principles have similar goals which are achieved by increasing the task difficulty and by scaffolding principles (supporting or automating part of the tasks, such as the trainer wheels for learning to ride a bicycle), see Van Merriënboer & Kirschner, 2007. Adaptive training regulated by combining measures of performance and mental effort has shown to accelerate the learning curve for Air Traffic Control (Salden, Paas, Broers, & Van Merriënboer, 2004) and Flight Management System training (Salden, Paas, van der Pal, & Van Merriënboer, 2004). The learner's cognitive load needs to be in an optimal band to ensure efficient learning. Over- or understimulation leads to frustration or boredom and results in inefficient or even ineffective training. The principles of flow and the optimization of cognitive load both aim to control a learning curve, although they differ in which technique is applied. In gaming, the focus is centered on experience, whereas the focus in training is on performance.

In training, cognitive load is usually controlled by measuring the load and performance after completion of a learning task. For aviation training to be fully effective, the events need to adapt to the cognitive load of events *within* a training session. Performance measured *during* the simulation or game is labeled as in-game measurement or stealth assessment (Shute, Ventura, Bauer, & Zapata-Rivera, 2009), techniques that require a coherent assessment framework, a user model and considerable further research and development (Baalsrud Hauge et. al. 2015) before well-grounded and practical use for automated adaptive training is achieved. Real time measures of mental states that reflect the experience of cognitive load (such as attention, engagement, situation awareness and boredom) should be part of such a framework. In this paper, brain measures are explored as a potential instrument for controlling the learning activity by automatically adjusting events in the learning scenario to ensure an optimal learning experience. Brain measures for attention and cognitive load are of particular interest.

2. USING BCI FOR ADAPTIVE TRAINING

Brain Computer Interface (BCI) stands for a range of techniques that support the brain to control a device without using muscles. For adaptive training, the trainee does not control the training tasks, events, setting or feedback by active thought or sheer will power (which is known as active BCI), but in a more indirect and involuntary way (also known as passive BCI), based on the measured amount of attention or relaxation, engagement or drowsiness, or other relevant mental states. BCI techniques for real, daily training will require a non-invasive, easy to use device. Wireless EEG devices with dry sensors may be candidates for practical BCI. There are several commercial EEG devices on the market that seem to be suitable. A range of validation studies have revealed some application areas as well as the limitations of these 'simple' devices.

EEG (electroencephalography) is a well-known technique to measure the electric activity of the brain (groups of neurons firing simultaneously) on the scalp. After removal of e.g., muscle generated artifacts, EEG contains oscillations of various frequencies (from 0.1-100Hz) and amplitudes (up to 200 microvolts). These vary as a result of processing sensory input and internal mental activity. As a result, EEG is different on the various parts of the brain, although precise location is not a strong feature of EEG. The different frequencies have been found to indicate certain mental states and emotions. For example, a low amplitude in the region of 8-12 Hz indicates attention, especially in combination with a high amplitude in the 13-30 Hz range. The frequency bands have been labeled by Greek letters (alpha to gamma), and include sub-bands like low and high beta. The (sub-)bands and certain composite measures indicate a variety of mental states and functions. An example of a composite measure is the Task Engagement Index, calculated by beta / (alpha + theta), which has been constructed for adaptive automated flight control (Pope et al , 1995) and has for instance been applied in measuring immersion during game play (McMahan, Parberry, & Parsons, 2015).

Raw EEG data is normally recorded for later analysis, which requires powerful computers, complex algorithms and time. BCI cannot work this way, as specific EEG frequencies or indexes need to be calculated and corrected for muscle activity in real time. This requires a highly dedicated algorithm tuned to the specific

sensors and locations, hardwired into a small chip in the device itself. This in turn demands considerable research and development, and the companies consequently consider the results as proprietary, including basic information on the frequency bands or composite measures used. A number of currently available BCI measures are presented in Table 1.

Table 1. Preprocessed EEG measures in commercial EEG devices

Neurosky Mindwave	Emotive Insight
Meditation	Relaxation
	Interest/ Affinity
Attention	Focus
	Engagement
	Instantaneous excitement
	Long term excitement

For the concepts of flow and optimal cognitive load, EEG indicators for cognitive load/task difficulty, attention, and task engagement are relevant. Task difficulty is associated with theta and alpha oscillations. Theta (which is most prominent in the frontal midline) is increased in high difficulty tasks in flight simulators (Smith & Gevins 2005), Alpha indicates the cognitive load of visual/auditory tasks (Gerlic 1999). For military pilots, alpha is found to decrease during demanding air refueling and landing exercises (Sterman et al, 1994). There are indications that the high alpha band is more related to (verbal) long term memory activities and theta to working memory (Antonenko, Paas, Grubner, & van Gog, 2010). Theta is therefore a candidate trigger to control overstimulation and high alpha is a candidate trigger to control understimulation in a scenario.
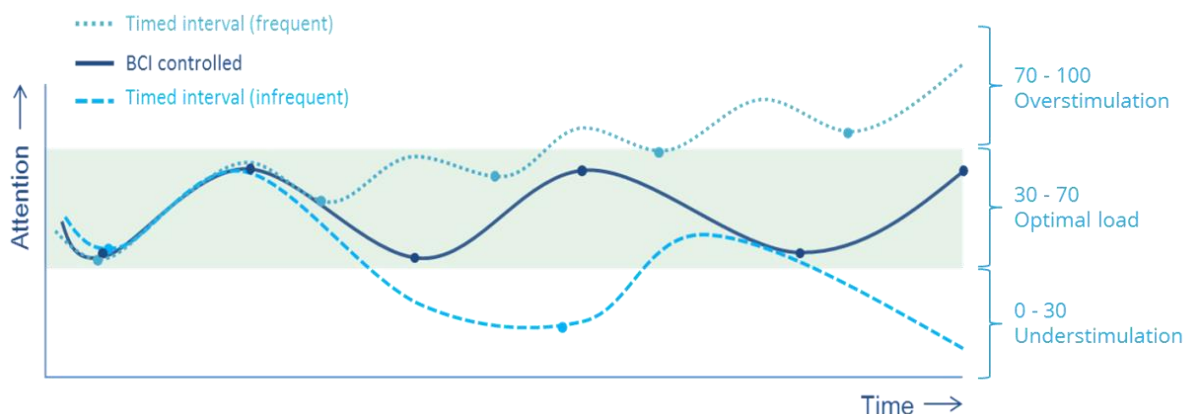

Figure 1 Expected progress of attention level based on different methods for triggering simulator events; timed interval (frequent as well as infrequent intervals) and BCI controlled (set to target attention optimal values)

3. METHOD

To determine if BCI devices can be used to more effectively trigger scenario events, a pilot experiment is set up. The between subjects design compares two conditions – time interval triggered vs mental state triggered simulator events. Participants are asked to perform a short training by flying a helicopter around an urban area in a low fidelity (gaming) simulated environment. The objective of the training is to familiarise with basic helicopter control mechanisms (pitch, role and yaw). The training task consists of flying through consecutive augmented cues, a kind of 'virtual checkpoints' in the sky. These hoop-shaped checkpoints are placed in a track configuration, and are located on different heights.

Eight participants (7 male, 1 female; age ranges from 21 to 36 years with an average of 27) are randomly assigned to either one condition. The test starts with a 1 minute familiarisation of the task, where the task is explained. Once the participants understand the task, the helicopter control training commences.

The training task is identical for all participants: to learn to control the helicopter by flying through a set of consecutive digital 'checkpoints'. This training takes # minutes to complete. Depending on the assigned condition, the task either 'A' automatically increases in difficulty (time based interval condition), or 'B' varies in difficulty depending on the participant's attention level (mental state based condition).

In the time based interval condition (A), to increase training difficulty the checkpoint diameter decreases gradually over the course of 5 minutes. This reduction triggers regardless of how well the trainee performs. In the mental state based (B) condition, the task complexity changes on the basis of the level of attention of the trainee. When strained by the task, trainee attention will increase. When the trainees' attention level consistently exceeds the boundaries of effective attention, a command is given to the program to lower the training difficulty, thus increasing the diameter of the checkpoints. When the task no longer requires high attention (through increased mastery of the controls), the checkpoint diameter will remain constant. When the attention level becomes too low, the checkpoint diameter will dynamically decrease, thus increasing the task complexity to re-engage the participant. The trainees' measured attention values are translated to a scale of 0 to 100. During training, the checkpoint diameter decreases when the participant's attention level is higher than 70, and increases when attention level is lower than 30. An optimal level of attention is achieved between 30 and 70. The checkpoint diameter does not change between these levels. The total checkpoint diameter size reduction over 5 minutes in condition B is therefore not known beforehand, and depends on the participants' efficiency in mastering the task.

After completing the helicopter control training, all participants receive the same exam, where they are required to fly one track with the smallest checkpoints used during the training. Trainee performance is determined by the number of checkpoints correctly flown through and the time needed to finish the track. A post-experiment questionnaire measured subjective ratings on the amount of challenge experienced.

3.1 Apparatus

3.1.1 BCI tooling

Neurosky Mindwave Mobile (see Fig. 1 for a drawing of its components) is a single channel EEG device with a dry sensor positioned on the forehead (approximately Fp1 position). The real-time processed measure used for BCI in this study is attention. Neurosky does not reveal the exact composition of this measure, but indicates that the attention is based primarily on beta waves. Attention is scaled from 1-100, with interpretations: 1-20 strongly lowered, 20-40 reduced, 40-60 neutral, 60-80 slightly elevated, 80-100 elevated.
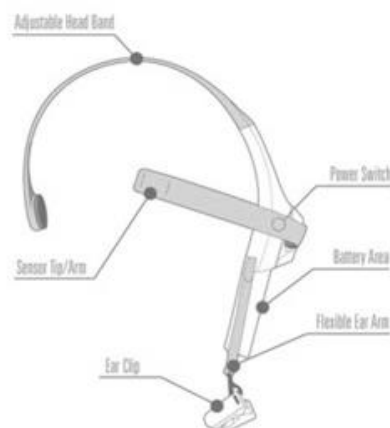

Figure 2 Mindwave Mobile

3.1.1 Helicopter Control Training Game

The Helicopter Control Training Game (see Fig. 2) is a low fidelity simulation environment developed using the Unity engine in the XLab at the Netherlands Aerospace Centre - NLR. The game is used to familiarise participants with basic principles of helicopter controls such as pitch, roll and yaw. The simulation features highly simplified helicopter flight models and controls, allowing for relatively easy mastery of basic flight control. The task is to fly through 'augmented hoops' in the sky. The hoops change from large to small in the time based condition, while in

Figure 3 Screenshot of Helicopter Control Training Game

the mental state based condition the hoops vary as a function of attention level.

4. RESULTS

All participants completed the experiment successfully. Unexpectedly, participants in the BCI controlled condition did not perform better on the exam than participants in the time interval controlled condition (see Table 1 for results).

Table 1. Means and standard deviations (in brackets) of the results on the Helicopter Control Training Game for the conditions time based and mental state based control of task difficulty. Exam score indicates the average number of correctly flown checkpoints; experienced challenge indicates the average subjective rating from 1 to 10 (1 = easy, 10 = hard)

Condition	Total sum deviation from optimal attention range during training	Total time deviation from optimal attention range during training (seconds)	Total training time (seconds)	Exam score	Experienced challenge
A Time based	839 (323)	84 (24)	335 (13)	4.0 (0.7)	7.25 (1.3)
B Mental state based	611 (255)	58 (16)	355 (34)	2.0 (1.9)	8.0 (1.4)

Participants in the time based condition spent an average of 26 seconds more outside of the optimal attention range (25% of total training time) compared to participants in the BCI controlled condition (16% of total training time). For some participants, the attention level graphs showed clearly that whenever a participant's attention level surpassed the threshold, the task difficulty would change, causing the participant's attention level to normalize in turn. For other participants, BCI triggers are less clearly or not always associated to excess of the optimal attention range. For example, Figure 4 illustrates five correct BCI triggers (presented as circles), but the triggers at 135 and 210 seconds seem to be influenced by EEG spikes and lead to incorrect events. Later attention levels (at 250, 280 and 290 seconds) should have been detected and events should have been triggered. One participant (mental state based condition) remained in the optimal attention range, but kept performing poorly and ended up with zero correct checkpoints in the exam.

Participants in the time based condition varied considerably in overall attention level (either very high or very low), but did not differ much in exam scores. For two participants in the time based condition the subjective ratings were inconsistent to the measured attention levels: intermediate challenging (5) versus high attention levels, and rather challenging (8) versus low attention levels.
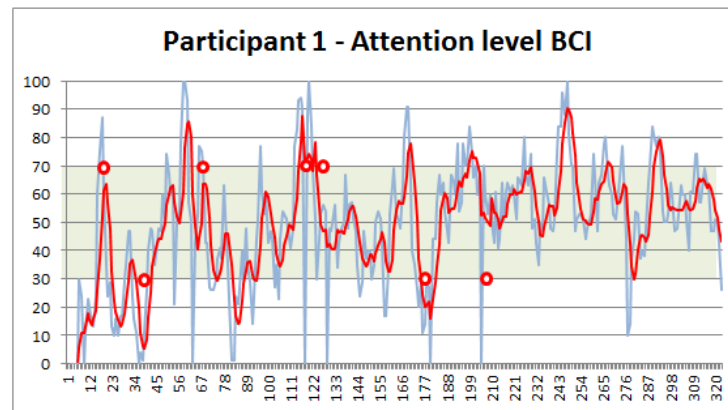
Figure 4. Attention level (direct measures in blue line, weighted average in red line) and event triggers (circles) for participant 1

5. DISCUSSION

This study was set up to determine whether consumable (as opposed to professional) BCI devices can be used to more effectively trigger scenario events in simulator training settings. The small scale study revealed the potential of BCI for training as well as some improvements to make. BCI using the Mindwave attention level functions reasonably well to adjust the task difficulty by increasing or decreasing the diameter of an augmented hoop in the sky. Some technical adjustments in the attention level criteria (such as dealing with EEG spikes) may increase reliability, while an adjusted size and timings of the hoops may improve the effect on the learning progress. Also, the allotted training time (five minutes) might not have been sufficient to significantly increase the performance of participants with poor initial skill level. As these issues demonstrate, the use of BCI does not relieve the scenario developer from carefully constructing a scenario. BCI may tailor training to individual needs, but effective training still requires a balanced scenario design with meaningful events and appropriate conditions to start with.

The mindwave attention level may be used as a rough motivational indicator the trainees have to the task, but other EEG indicators may be more clearly linked to task difficulty (increased theta band) or cognitive load (reduced high alpha band). Using these measures will require some additional real time algorithms to be developed. BCI controlled training using EEG devices that are easy to apply in real training settings appears to be viable, although considerable effort is needed to ensure the measurements and the trigger events are well tuned to the training audience characteristics such as the learning curve.

Modern consumable EEG devices are promising in achieving adaptive training through maintaining optimal cognitive load for the trainee. The results of this study indicate the cognitive load or attention level of the trainee may be a viable triggering mechanism for scenario events. This may reduce the occurrence of incorrectly applied scenario events thereby enhancing the training effectiveness of the training session. Furthermore, when scenarios consistently adapt to the desired difficulty, personalized training trajectories might be achievable in a future stage. Fully automated training however will require improved modeling and measuring of learning and performance which can be very complex in professional settings. Investments and research in this area are likely to pay off as the potential of increased training effectiveness and the potential for personalized training has significant operational and cost saving effects.

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