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Toward Adaptive VR Simulators Combining Visual, Haptic, and Brain-Computer Interfaces

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Virtual-reality technologies can be exploited in numerous domains, such as medicine (for example, for surgical simulation and rehabilitation), industry (training and virtual prototyping), design and architecture (digital mock-ups and virtual visits), or entertainment (videogames and theme parks). The most common ways to interact with virtual environments (VEs) measure the user's motor activity—that is, motions and actions when manipulating different kinds of input devices. Current VR research trends involve soliciting even more physical engagement, such as with bimanual interaction, whole-body systems, or walking interfaces. This trend is illustrated by the commercial success of Microsoft Kinect and Nintendo Wii.

However, VR applications are calling for more multimodal interaction paradigms, and VR systems could benefit from several other important types of user input. One particularly promising type is the user's mental activity, which can be measured through brain-computer interfaces (BCIs).[1] Here, we look at this technology, using examples from our research. In particular, we examine how we've combined visual interfaces, haptic interfaces, and *passive BCIs* to improve interaction with VEs.

Brain-Computer Interfaces for Controlling Virtual Environments

BCIs use brain signals to send commands to an automated system such as a robot, prosthesis, or computer cursor.[2] BCIs constitute a rapidly growing research area, and several impressive prototypes are already available. Today, severely disabled people can control a wheelchair or communicate using "mental spellers." In addition, several startup companies are designing and proposing low-cost electroencephalograph (EEG) headsets, which could pave the way to massive applications of BCIs in both medicine and multimedia.

BCI hardware generally falls into two categories: invasive systems implanted into cortical tissue or noninvasive systems on the user's scalp. But most BCI systems use scalp EEGs to measure variations in brain activity. Then, BCI systems usually involve two phases for cerebral signal processing: feature extraction and classification (pattern recognition). Feature extraction selects relevant information from the EEG data flow, which is affected by noise and artifacts. Then, through classification, the system categorizes the data according to several learned EEG patterns and translates it into commands. (Our group has written an extensive survey of classification algorithms.[3])

The neuroscience community has already identified different kinds of electrical brain activity as suitable for mind-based interaction with VEs. This includes mental states such as motor planning or mental motor imagery,[4] attention toward an incoming sensory stimulus,[5] or self-regulation of brain wave rhythms and mental relaxation.[6] BCI systems can use other EEG markers related to brain reactions to external events, such as for the target selection response (the P300 signal) or error-related negativity (when users realize that the system has made an error).[7]

In the past decade, several studies have focused on using BCIs to directly control VR systems.[2,8] (For examples of representative systems that our group designed, see the sidebar.) Until now, BCIs have been used mostly for navigating VEs—for example, changing the viewpoint in a virtual bar[9] and touring a virtual museum.[4] BCIs have also been used for manipulating objects in VEs—for example, turning on and off everyday devices such

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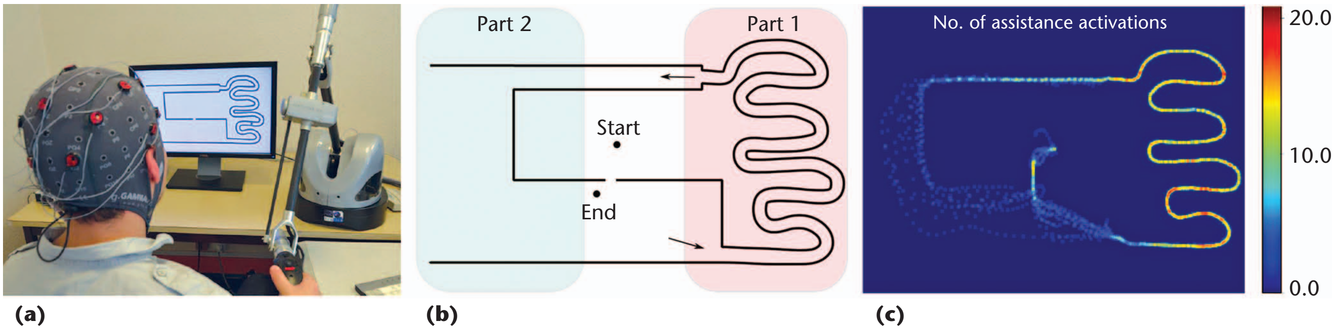


Figure 1. A passive-BCI system that adapts haptic feedback.[14] (a) In real time, the system adapts force feedback to the user's mental activity, as measured with an electroencephalograph (EEG) headset. (b) During a path-following task in a 2D maze, the system activated haptic assistance when the user's brain activity indicated a high mental workload. The assistance caused the cursor to slide rapidly on the maze wall, thus avoiding collisions with the wall. (c) The right part of the maze, with numerous short turns, exhibited more activations, as the yellow and red dots indicate.

as a television or lamp[1] and controlling a virtual spaceship's motion.[5] Moreover, using VR technologies and immersive setups (such as the *Star Wars* simulation described in the sidebar) can considerably increase participants' motivation and thus the BCI system's performance.[9]

However, in current VR applications, the BCI often can extract only a few mental states and thus few mental commands. So, direct, explicit mind-based interaction with VEs remains relatively restricted and frustrating. This accounts for the emergence of passive-BCI systems.

Passive BCIs and Implicit Interaction

We all know how to interact explicitly or voluntarily with computers; we do this every day when clicking with a mouse, for instance. But there's a less explicit way to interact with computers, similar to human nonverbal communication. Passive BCIs employ such implicit interaction.[10]

Researchers have proposed different terms for interaction that isn't voluntarily or explicitly controlled, such as *noncommand user interfaces* or *implicit human-computer interaction*.[7] The terms all refer to the same idea: interaction based not on direct, explicit, or voluntary user actions but on the user's state in a particular context.

Implicit information can be acquired with different techniques, notably with physiological sensors such as for galvanic skin response. EEG signal measurement can also be used for this. So, passive BCIs provide implicit information reflecting the user's mental state to a computerized system for implicit interaction. This approach connects naturally with the related scientific fields of affective computing and augmented cognition.[11]

VR has rarely used passive-BCI systems.[7] Some VEs have employed passive BCIs to control how the system responds to commands. For example, in the Bacteria Hunt game, increased alpha brain wave activity (which correlates to relaxed wakefulness) caused the game's controllability to increase or decrease, depending on the experimental situation.[12] In other systems, the avatar's characteristics have adapted on the basis of implicit information. For example, in AlphaWoW, which was based on World of Warcraft, the user's avatar transformed from an elf to a wolf according to the measured alpha activity.[13] Finally, some applications have used passive BCIs to check whether the user has perceived specific information.[10]

So, passive BCIs are a promising way to apply BCI technology in a much larger set of applications. Next, we describe two projects illustrating such an approach.

Mental-Workload-Based Adaptation of Haptic Feedback

We've designed a VR setup that adapts haptic feedback according to the user's brain waves in real time.[14] An EEG-based passive-BCI system computes an online index related to the user's mental workload. If the index indicates a high workload, the system activates haptic assistance. (If the workload is low, guidance is deactivated.) This guidance should reduce the task's difficulty and decrease the mental workload.

Our tests, conducted with eight participants, had two goals:

- Test the system's operability.
- Evaluate how the system influences task performance.

Figure 1a illustrates the experimental apparatus. Using a six-degree-of-freedom Virtuose haptic device, the participants manipulated a 2D cursor through a 2D virtual maze. Using the device's force feedback, the system physically constrained the manipulation so that it remained on the 2D vertical plane. An EEG amplifier acquired signals from 16 electrodes covering a large area of the scalp.

Some Brain-Computer Interfaces and Virtual Environments at Inria Rennes

Figure A shows three recent uses of brain-computer interfaces (BCIs) to control virtual environments (VEs) at Inria Rennes.

In a visit to a virtual museum (see Figure A1), users employed motor imagery of the left hand (left turns), right hand (right turns), and feet (forward motion).[1] In an alternative mode, to accelerate the virtual movement, the system used high-level orders to more rapidly select a predefined destination point, employing a successive-decision process based on a binary tree.

In the MindShooter videogame (see Figure A2), players controlled a virtual spaceship.[2] They selected one of three commands (go right, go left, or shoot) by looking carefully at the spaceship's corresponding area (the right wing, left wing, or cannon), which flashed at a specific frequency (5, 6, or 7.5 Hz). The BCI detected this frequency in the cerebral electrical activity measured on the scalp above the visual cortex. This enabled the BCI to identify the observed area and thus the desired command.

In a simplified soccer videogame called BrainArena (see Figure A3), two players scored goals to the left or right by imagining left or right hand movements.[3] The players could collaborate or compete. Some players preferred this multiuser situation to a single-user version, and some performed significantly better in it.

Figure B shows mind-based interaction in an immersive VE inspired by a scene in *Star Wars: The Empire Strikes Back*. Our Immersia room, a 10-meter wide CAVE (Cave

(1) **(2)** **(3)**

Figure A. Using brain-computer interfaces to control virtual environments (VEs). (1) In a visit to a virtual museum, users employed motor imagery of the left hand (left turns), right hand (right turns), and feet (forward motion). (2) In the MindShooter videogame, players selected one of three commands (go right, go left, or shoot) by looking at the spaceship's corresponding flickering area (the right wing, left wing, or cannon). (3) In the BrainArena soccer videogame, two players scored goals to the left or right by imagining left or right hand movements.

While moving the cursor through the maze, the participants had to avoid collisions with the maze walls. (This task evokes the dexterous manipulations involved in some industrial-maintenance simulations or surgical simulators, for instance.) The maze had two parts (see Figure 1b). The first part had numerous turns and was difficult; the second part presented fewer possible collisions and was thus less difficult. The system performed collision detection and computed contact forces in real time, using Bullet, an open source physical engine. For haptic assistance, the system added a repulsive force inversely proportional to the cursor's distance from the nearest wall. This assistance aimed to help the user by sliding the cursor along the walls and avoiding collisions.

We computed the mental-workload index using OpenViBE software (http://openvibe.inria.fr) and signal-processing techniques we had designed and tested.[6] To train the signal-processing pipeline, we used a dataset comprising two minutes of EEG activity: one minute of performing a simple control task and one minute of moving the cursor through a complex spiral maze while avoiding collisions. So, in this context, we expected the mental-workload index to correlate with the manipulation task's complexity. We smoothed the online values that the classifier provided (–1 for a light mental workload and 1 for a high mental workload) and straightforwardly used this final index to activate or inhibit haptic assistance.

We evaluated three conditions:

- no haptic assistance,
- workload-based haptic assistance, and
- continual haptic assistance.

Figure 2a displays the number of collisions for each condition. These results suggest that the system helped users achieve the task. Workload-based haptic assistance indeed increased performance by significantly reducing the number of collisions. Actually, we observed no significant performance differences between workload-based and continual assistance. So, we suspect that a well-tuned passive BCI could perform almost as well as continual as-

Automatic Virtual Environment), provides full 3D stereoscopic vision, head and body motion tracking, and 3D spatialized sound. Users could walk and freely explore a full-scale model of a virtual swamp from the planet Dagobah, populated with several animated characters. Users could directly point (with their hand) at the objects they wanted to interact with. Then, to "lift" virtual objects, such as a helmet or a spaceship partially immersed in muddy water, users simply concentrated or relaxed, depending on the playing mode. Users found the system motivating and entertaining; it was fully operational even with low-cost wireless electroencephalograph headsets.

References

1. F. Lotte et al., "Exploring Large Virtual Environments by Thoughts Using a Brain-Computer Interface Based on Motor Imagery and High-Level Commands," *Presence*, vol. 19, no. 1, 2010, pp. 54–70.
2. J. Legény, R. Viciana-Abad, and A. Lécuyer, "Toward Contextual SSVEP-Based BCI Controller: Smart Activation of Stimuli and Control Weighting," *IEEE Trans. Computational Intelligence and AI in Games*, vol. 5, no. 2, 2013, pp. 111–116.
3. L. Bonnet, F. Lotte, and A. Lécuyer, "Two Brains, One Game: Design and Evaluation of a Multiuser BCI Video Game Based on Motor Imagery," *IEEE Trans. Computational Intelligence and AI in Games*, vol. 5, no. 2, 2013, pp. 185–198.

Figure B. Entertaining mind-based interaction in an immersive VE inspired by a scene in Star Wars: The Empire Strikes Back. To "lift" virtual objects, such as a helmet or a virtual spaceship partially immersed in muddy water, users simply concentrated or relaxed, depending on the playing mode.

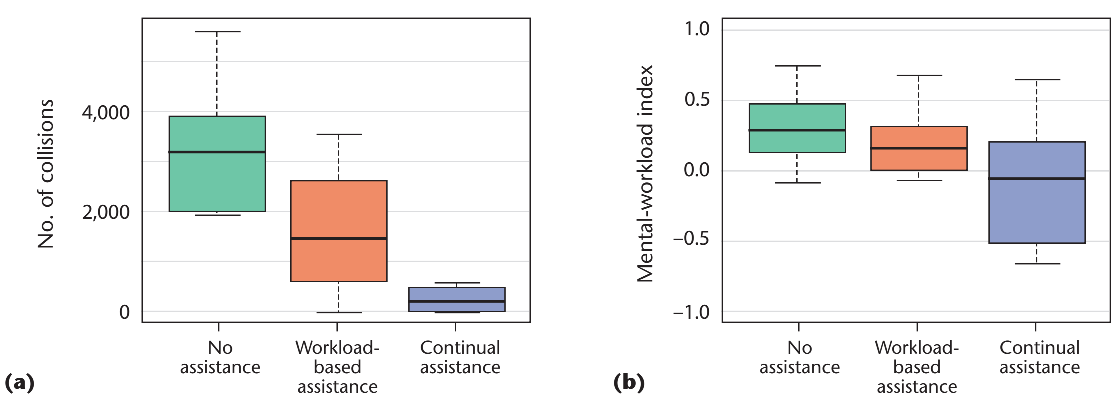
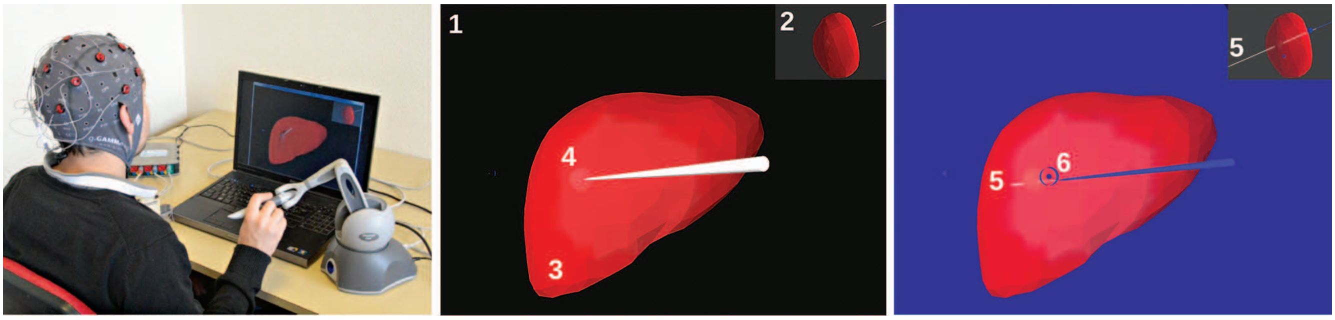


Figure 2. Experimental results obtained with our proof-of-concept setup. (a) Workload-based haptic assistance significantly reduced the number of collisions. (b) It also significantly decreased the mean mental-workload index.

sistance, but with guidance activated only when the user actually needs it.

Workload-based haptic assistance also significantly decreased the mental-workload index (see Figure 2b). The workload was also significantly higher in part 1 of the maze (see Figure 1b). This suggests that our system measures a mental-workload index that correlates well with the task's difficulty. Our participants' answers to a subjective questionnaire appear to confirm this belief. They reported a high correlation (above 70 percent) between the computed index and their perceived mental workload. Our passive-BCI system thus seems to provide a convincing measurement of mental workload.

This exploratory study suggests that our proof-of-concept system is operational and exploitable.



(a) (b) (c)

Figure 3. A medical simulator in which the user inserts a needle into the liver to reach a tumor. (a) The setup, with an EEG headset, a display, and a haptic device. (b) The 3D scene when visual and haptic assistance isn't activated. (c) The scene when the simulator detects a high mental workload and activates assistance. The numbers indicate visual cues: 1 is the main view, 2 is a lateral view, 3 is the deformable liver, 4 is the tumor, 5 is a laser ray (pointing in the needle's direction), and 6 is the best insertion point.

The haptic assistance was activated in the most difficult part of the path-following task. Moreover, this approach increased task performance by more than 53 percent, while activating assistance only 59 percent of the time. These results suggest that such passive-BCI systems could be used to determine when users need assistance and to activate that assistance accordingly. Next, we describe how we applied this approach to a medical simulator.

Toward Medical Simulators Exploiting Passive BCIs

Our simulator recreates a tumor biopsy in the liver. The user manipulates a virtual needle and must perforate the liver to reach the tumor. The tumor's position in the liver is randomized.

Figure 3 displays our prototype. An EEG headset acquires signals from 16 electrodes, similarly to the configuration we described in the previous section. For needle manipulation, the system employs a Phantom Omni haptic device. The simulator presents the 3D scene on a standard laptop screen. A mass-spring model represents the deformable liver, a thin cylinder represents the rigid needle, and a rigid sphere represents the tumor.

The simulator replicates two kinds of haptic interaction: the liver's resistance to the needle's penetration and stick-slip interaction when the user inserts the needle. When the needle touches the liver, the simulator computes the contact, using penalty-based methods. The simulator then redistributes the contact forces on the liver nodes, using a kernel function. If the force on the needle exceeds a given threshold, the needle penetrates the liver, which activates the second interaction mode. To replicate stick-slip interaction, the simulator first measures the needle's insertion velocity. If the velocity exceeds a certain threshold, the simulator applies a viscous force. If the velocity is under this threshold, the simulator applies a resistance force. Finally, when the user reaches the tumor, the simulator also computes a reaction force.

The system provides visual and haptic assistance to help users better perceive the 3D scene and find the best insertion point and to guide them toward the tumor (see Figure 3c). First, the simulator presents an infinite laser ray pointing in the needle's direction so that users can better perceive the needle's orientation. Then, it adds a blue target at the level of the best location for inserting the needle. The scene's background switches from black to blue to indicate that visual assistance is active.

The haptic assistance consists of a virtual force attracting the needle to the best insertion point. This force is proportional to the needle's distance from that point.

The passive BCI aims to identify two mental activities corresponding to high and low mental workloads. We used the machine-learning process we described before to differentiate between the two mental states.[6] We trained the system with two initial tasks: a simple 3D manipulation and a difficult one. For the simple task, users touched very large 3D spheres with the haptic device. For the difficult task, they touched very small spheres in the same environment. The classifier provided online values (–1 for a low mental workload, indicating low manipulation difficulty, and +1 for a high mental workload, indicating high manipulation difficulty). The system smoothed these values and generated the median of the last 20 values every two seconds. The system directly used this index to toggle visual and haptic assistance.

We preliminarily tested the simulator with 12 participants. We found it to be operational, and it worked with standard I/O devices, but it still requires further development and evaluation.

Room for Improvement

Our results pave the way to novel, exciting combinations of BCI and VR technologies. However, the results also indicate our approach's current limitations and paths for short-term improvements and long-term research. First, the mental-workload index is an ambivalent term that could apply to different cognitive processes and contexts. This highlights the need for a proper characterization of the corresponding neurophysiological substrates that could be used for passive BCIs.

Second, our BCI's binary output (a high or low mental workload) doesn't account for the range of mental states involved in our interaction scenarios. So, it needs more elaborate signal-processing pipelines to both achieve a multiclass BCI (that is, a BCI that can identify many different mental states) and account for muscular artifacts that might impede the BCI's identification of brain waves.

Third, the types of virtual assistance we've proposed are rather simple, and we haven't fully evaluated their influence—for instance, in terms of training or the learning process. This points to the need for more compelling adaptive user interfaces whose benefits are fully and clearly assessed.

One day, such next-generation VR simulators will be able to detect multiple and varied cognitive processes and exploit them in real time in adaptive user interfaces. This will place the user's mind at the heart of the interaction loop. Consequently, we expect that BCI technology will improve the usability of a variety of interfaces in multiple applications, such as industrial training systems, medical simulators, videogames, and rehabilitation and reeducation systems.

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References

1. J.D. Bayliss, "The Use of the P3 Evoked Potential Component for Control in a Virtual Apartment," *IEEE Trans. Neural Systems and Rehabilitation Eng.*, vol. 11, no. 2, 2003, pp. 113–116.
2. A. Lécuyer et al., "Brain-Computer Interfaces, Virtual Reality, and Videogames," *Computer*, vol. 41, no. 10, 2008, pp. 66–72.
3. F. Lotte et al., "A Review of Classification Algorithms for EEG-Based Brain-Computer Interfaces," *J. Neural Eng.*, vol. 4, no. 2, 2007.
4. F. Lotte et al., "Exploring Large Virtual Environments by Thoughts Using a Brain-Computer Interface Based on Motor Imagery and High-Level Commands," *Presence*, vol. 19, no. 1, 2010, pp. 54–70.
5. J. Legény, R. Viciana-Abad, and A. Lécuyer, "Toward Contextual SSVEP-Based BCI Controller: Smart Activation of Stimuli and Control Weighting," *IEEE Trans. Computational Intelligence and AI in Games*, vol. 5, no. 2, 2013, pp. 111–116.
6. L. George et al., "Using Scalp Electrical Biosignals to Control an Object by Concentration and Relaxation Tasks: Design and Evaluation," *Proc. 2011 Int'l Conf. IEEE Eng. in Medicine & Biology Soc.* (EMBC 11), IEEE, 2011, pp. 6299–6302.
7. L. George and A. Lécuyer, "An Overview of Research on Passive BCI for Implicit Human-Computer Interaction," *Proc. 1st Int'l Conf. Applied Bionics and Biomechanics* (ICABB 10), 2010; http://hal.inria.fr/docs/00/53/72/11/PDF/GeorgeL-LecuyerA.pdf.
8. F. Lotte et al., "Combining BCI with Virtual Reality: Towards New Applications and Improved BCI," *Towards Practical Brain-Computer Interfaces*, B. Allison et al., eds., Springer, 2013, pp. 197–220.
9. D. Friedman et al., "Navigating Virtual Reality by Thought: What Is It Like?," *Presence*, vol. 16, no. 1, 2007, pp. 100–110.
10. T.O. Zander and C. Kothe, "Towards Passive Brain-Computer Interfaces: Applying Brain-Computer Interface Technology to Human-Machine Systems in General," *J. Neural Eng.*, vol. 8, no. 2, 2011.
11. F.M. Stanney et al., "Augmented Cognition: An Overview," *Reviews of Human Factors and Ergonomics*, vol. 5, no. 1, 2009, pp. 195–224.
12. C. Mühl et al., "Bacteria Hunt," *J. Multimodal User Interfaces*, vol. 4, no. 1, 2010, pp. 11–25.
13. A. Nijholt, D. Plass-Oude Bos, and B. Reuderink, "Turning Shortcomings into Challenges: Brain-Computer Interfaces for Games," *Entertainment Computing*, vol. 1, no. 2, 2009, pp. 85–94.
14. L. George et al., "Combining Brain-Computer Interfaces and Haptics: Detecting Mental Workload to Adapt Haptic Assistance," *Haptics: Perception, Devices, Mobility, and Communication*, LNCS 7282, Springer, 2012, pp. 124–135.

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