Brain-Computer Interfaces: Beyond Medical Applications

Jan B.F. van Erp, *The Netherlands Organization for Applied Scientific Research (TNO)*
Fabien Lotte, *INRIA Bordeaux Sud-Ouest*
Michael Tangermann, *Berlin Institute of Technology*

Brain-computer interaction has already moved from assistive care to applications such as gaming. Improvements in usability, hardware, signal processing, and system integration should yield applications in other nonmedical areas.

Brain-computer interface (BCI) technology is a potentially powerful communication and control option in the interaction between users and systems. As originally defined,[1] BCIs are communication and control systems that have no dependence on the brain's normal neuromuscular output channels.

At present, most BCI applications focus on assistive care, providing an alternative communication medium for those who cannot use a keyboard or mouse, but applications have the potential to include any task that would benefit from interaction beyond the keyboard. Science fiction has long entertained readers with tales of a device that connects brain and computer, allowing humans to experience virtual or remote worlds simply by thinking about them. Although reality is much more down to earth, researchers have made remarkable inroads into practical BCI applications during the past two decades, making it clear that these interfaces will be part of any technological vision.

In the past few years, BCI applications have broken out of laboratories and hospitals to include nonmedical applications, such as gaming. Commercial products for home use are appearing, such as Uncle Milton's *The Force Trainer* and Mattel's *Mindflex*. The "Commercially Available BCI Technology" sidebar describes more of these products and their purposes.

As a result, desciplines such as gaming and human-computer interaction, are motivating inventive BCI research themes and paradigms. Even the definition of BCI has broadened to include any interface that uses brain signals to control a device or to adjust user-device communication.[2]

Despite these advances, nonmedical BCIs are still relatively embryonic, and interest is growing in identifying the breakthroughs that will enable this technology's broad introduction in nonmedical applications—any implementation for healthy users that would benefit from brain-computer interaction. In addition to transferring knowledge from medical BCI applications, researchers also must deal with a range of issues that are more critical outside assistive care. User-state monitoring, for example, is highly relevant for nonmedical users but is generally outside the scope of medical applications.

Motivated by the need to identify a path forward, we surveyed the views of attendees at several international BCI workshops. We also talked with experts in an attempt to derive a clear and concise overview of where BCI research is now and where it must go to practically extend BCIs to nonmedical applications. We found that current BCI hardware and software is facing several technological challenges, and BCI designers must address a range of usability, integration, standardization, and

 Published by the IEEE Computer Society

COMMERCIALLY AVAILABLE BCI TECHNOLOGY

Because of recent advances and increased interest in BCI technologies, several companies are now commercializing BCI products—from high-quality, expensive systems for scientists and medical applications to inexpensive low-end devices for the general public. An extensive list of commercial BCI technologies is available at http://wwwhome.cs.utwente.nl/~nijboerf/MarketOverview_20111028.pdf.

Figure A shows two products that are representative of the commercial product continuum. IntendiX (www.intendix.com) is a complete BCI solution for spelling dedicated to homebound users. At the other end of the spectrum are inexpensive dry (no gel required) EEG sensors and dedicated software for gaming applications. Both IntendiX and Emotiv (www.emotiv.com) provide these products.

Because of the way the low-end sensors are placed, these systems can also measure and use muscle activity by reading electromyography (EMG) signals. As such, they might not be considered pure BCI systems, since they might not rely on brain activity only (http://spectrum.ieee.org/consumer-electronics/gaming/loser-mental-block). Nevertheless, combining EMG and EEG signals could lead to new product areas. For example, it is easy to infer facial expressions from EMG signals, but it is currently impossible to do so from EEG signals alone. A combination of EMG and EEG signals could be useful in conversational avatars, which must look at facial expression as well as user intent.

Figure A. Two BCI products in use. (1) The user is wearing electrodes while running IntendiX. (2) The user is wearing a band of dry EEG sensors developed by Emotiv.

ethical issues to enable the growth of nonmedical BCI applications.

MEASUREMENT AND PROCESSING

BCIs let users mentally interact with a device using hardware to measure brain activity and software to process it in real time.

Hardware

Researchers have used a range of measurement technologies in BCI systems, including

- electrocorticography (ECoG),
- intracortical electrodes (ICE),
- functional near-infrared spectroscopy (fNIRS),
- functional magnetic resonance imaging (fMRI),
- magnetoencephalography (MEG), and
- electroencephalography (EEG).

ECoG and ICE are invasive recording techniques that require implanting sensors, which makes them inappropriate for nonmedical applications.

Both fNIRS and fMRI measure brain activity indirectly according to cerebral blood flow, but both are unsuitable either technically or economically for use in small devices, and they have poor temporal resolution.

Finally, both MEG and EEG have very good temporal resolution but poor spatial resolution. In addition, because it is bulky and expensive, it appears that MEG equipment is unsuitable for these systems.

Thus, of all these measurement technologies, EEG is currently the most usable and widely applied brain measurement technique for BCIs. Even so, it is not ideal. Fitting the EEG cap and applying the sensors takes several minutes, and the measured signals are either relatively noisy or require using conductive gel between the sensors and scalp. Some commercial products eliminate the need for gel by using dry sensors, but usually at the cost of poorer signal quality.

Software

Open source software is available to process measured brain signals in real time as part of designing, implementing, and assessing BCI systems. Five tools are noteworthy:

- BCI2000 (www.bci2000.org) is a general-purpose system for BCI research. It is also suitable for data acquisition, stimulus presentation, and brain-monitoring applications. It is free for nonprofit research and education.
- OpenViBE (http://openvibe.inria.fr) is open source

Table 1. Results of rating seven BCI application areas according to four criteria and estimating time to market (– denotes low, +/– denotes moderate, and + denotes high relevance).

Application area	Research quality and quantity	Societal impact	Economic viability	Price sensitivity	Time to market (years from 2010)
Device control	+/–	–	–	–	5 to 10
User-state monitoring	–	+	+	+/–	3 to 5
Evaluation	–	–	+/–	+/–	1 to 3
Training and education	–	+	+	+/–	3 to 5
Gaming and entertainment	+/–	–	+	+	Now
Cognitive improvement	–	+/–	+	+	3 to 5
Safety and security	–	+/–	–	+/–	5 to 10

software for acquiring, filtering, processing, classifying, and visualizing brain signals in real time.
- FieldTrip (http://fieldtrip.fcdonders.nl) is an open source Matlab toolbox for MEG and EEG analysis.
- BioSig (http://biosig.sourceforge.net) is an open source library for biomedical signal processing, enabling the analysis of EEG and ECoG biosignals, among others.
- BCILAB (http://sccn.ucsd.edu/wiki/BCILAB) is an open source Matlab toolbox and EEGLab plugin for BCI design, prototyping, testing, experimentation, and evaluation.

Software differs in the variety of signal-processing algorithms offered and ways to visualize brain activity.

CURRENT AND FUTURE APPLICATION AREAS

BCIs have a potential for use in a wide range of nonmedical applications. From discussions with scientists from BCI research institutes and representatives from EEG hardware producers and companies that develop non-BCI assistive technology, we identified the seven application areas in Table 1. We then asked workshop attendees—BCI experts—to rate each area according to

- *research quality and quantity*;
- *societal impact*, that is, how well the technology contributes to solving important societal challenges, such as aging or quality of life;
- *economic viability*, which is based primarily on the number of potential subapplications and users; and
- *price sensitivity*, that is, how crucial price is to the product's success.

We also asked them to estimate time to market for products in each area.

Device control

Research on BCIs to assist users lacking full limb development has matured to the point that such users are already benefiting, even though the devices offer limited speed, accuracy, and efficiency.

Nonmedical device control is more problematic. Users with full muscular control cannot benefit as easily because a BCI lacks the bandwidth and accuracy to compete with a standard input device, such as a mouse or keyboard. For example, to complete a mental hand movement, the BCI user must generate control signals, and the system must process them to identify that the user is imagining that movement. The time from thought to signal generation to processing through the BCI system can cause a control loop latency of several hundreds of milliseconds.

Introducing a shared control scheme would enable the user to give high-level, open-loop commands while the device takes care of low-level control. Someone in a wheelchair, for example, might not want to bother steering the chair perfectly through every door opening, but would prefer to give the command, "Take me to the kitchen." Shared control would allow the device to handle the details of navigating to the kitchen.

Additional control channels or hands-free control could benefit users such as drivers, divers, and astronauts,[3] who must keep their hands on controls to operate equipment. Brain-based control paradigms could supplement other forms of hands-free control, such as a voice command or eye movement.

There is a strong body of research on brain-based device control for single-task situations, but little data on multitasking control. Also, work has yet to demonstrate value over other hands-free input modalities, although brain-based control is likely to be superior in some environments, such as a noisy venue.

The direct societal impact of brain-based device control will be limited, although developed technologies are likely to contribute to existing medical applications and thus have indirect societal impact. Economic viability is restricted to high-end applications in which operators are working at the edge of their physical abilities, such as hands-free control for astronauts or jet pilots. Price sensitivity is low for such products, which are not destined for a consumer market. Realizing viable implementations will take more time because bandwidth and control signal reliability are not yet sufficiently advanced for use in device control beyond assistive technology.

User-state monitoring

Future interfaces must be able to understand and anticipate the user's state and intentions.[3] Automobiles could alert sleepy drivers, or virtual humans could convince users to stick to their diet. These future implementations of user-system symbiosis, or affective computing,[4] require systems to gather and interpret information on states such as fatigue, attentiveness, mental workload, stress, and realization of mistakes.

BCIs might also be useful in neuroscientific research. Because they can monitor the acting brain in real time and in the real world, BCIs could help scientists understand the role of functional networks during behavioral tasks.

BCIs for user-state monitoring extend physiological measures such as heart rate variability or skin conduction and thus complement existing technology rather than compete with it. A limited but fast-growing body of knowledge for these applications is likely to result in products with a very high societal impact and economic viability. Ongoing work to investigate high-end applications, such as those for air traffic controllers and professional drivers, could yield products for the general public. As the "Why Focus on User-State Monitoring?" sidebar describes, BCIs in this area could be more practical than BCIs that directly control a device.

Overall, BCIs for monitoring user states are likely to have a high societal impact because they can provide equal access to electronic systems and services that promote a healthy lifestyle and safe transportation.

WHY FOCUS ON USER-STATE MONITORING?

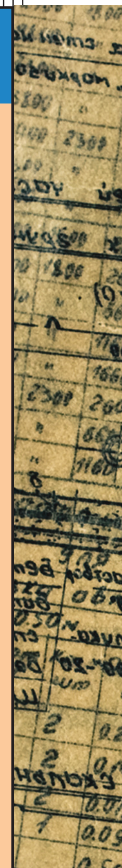
Historically, BCIs have focused on direct device control, but the BCI community is now realizing that user-state monitoring might be more promising and practical.[1]

Systems that monitor the user's mental state look at EEG signals for a signature of alertness, mental workload, fatigue, and the like. Device control systems, in contrast, must recognize a signature for a specific user task, such as a mental subtraction or figure rotation or imagining a hand movement. EEG signals visibly change in both direct control and user-state monitoring, but in the latter, the changes in brain activity are voluntary, while in the former, they are not.

This distinction gives BCIs for user-state monitoring some practical advantages. In direct control, the system must quickly recognize the user's intent from a short window of brain signals. For healthy users, this means that BCIs must have enough reliability and speed to compete with a mouse, keyboard, or touchpad. In user-state monitoring, however, the time to identify the user's mental state is not that critical, and the system has a larger time window. That extra time plus the ability to provide information about the user's mental state gives these BCIs a competitive edge over other input devices. Consequently, researchers believe that user-state monitoring is a more achievable practical application for BCIs than direct control based on a user's intent.

Reference

1. T.O. Zander and C. Kothe, "Towards Passive Brain-Computer Interfaces: Applying Brain-Computer Interface Technology to Human–Machine Systems in General," *J. Neural Engineering*, vol. 8, no. 2, 2011; doi:10.1088/1741-2560/8/2/025005.



Evaluation

Evaluation applications can be either online or offline. The former continuously provide evaluations, in real or near real time; the latter provide evaluations only once, after the experimental study is finished. Neuroergonomics and neuromarketing are two application subareas. Neuroergonomics, which evaluates how well a technology matches a user's capabilities and limitations, has a clear link to human-computer interaction. For example, brain images from recent research show that hands-free or voice-activated cell phone use while driving is as dangerous as driving while intoxicated.[5] Figure 1 shows an example of how neuroergonomics might work in a practical application.

Neuromarketing is a study of the brain's responses, such as paying attention to or involuntarily or subconsciously memorizing different product advertisements with the goal of identifying which advertisement has the highest impact.

The body of evidence in this evaluation type is based mainly on fundamental neuroscientific studies and would benefit from a transition to more applied studies.

The societal impact of evaluation applications is low. Experts contend that while brain-based evaluation adds to the collection of evaluation tools, alone it has no direct contribution to solving societal issues. In contrast, economic viability is potentially high because design and evaluation are relevant for many essential functions,

Figure 1. Using a BCI to assess driving performance. Brain signals might be useful in monitoring driver workload or evaluating in-vehicle systems that might interfere with the primary driving task.

such as food services and architecture. These methods should prove superior to current evaluation tools, such as questionnaires.

Training and education

Most training aspects relate to the brain and its plasticity—the brain's ability to change, grow, and remap itself. Measuring plasticity can help improve training methods and individual training regimens.

Indicators such as learning state and progress from novice to expert are useful for automated training systems and virtual instructors. Currently, this application area is conceptual with limited experimental evidence. However, lifelong learning and the need for efficient and effective automated tutoring systems have a high societal impact and economic viability, particularly for societies with a knowledge-based economy, an aging population, or the need for a flexible workforce. Price sensitivity is moderate, in large part because applications could be for both professional and home use, making this criterion hard to rate.

Brain signals can indicate relevant pictures even when the observer is presented with a stream of up to 50 images per second.

Gaming and entertainment

The entertainment industry is often a frontrunner in introducing new concepts and paradigms, and human-computer interaction is no exception. Examples are the recent growth of 3D television, gesture-based game controllers, and games developed exclusively for use with an EEG headset. Over the past few years, companies such as Neurosky, Emotiv, Uncle Milton, MindGames, and Mattel have released numerous products. Figure 2 shows BCI use in a simple tennis game.

Most developers are convinced that BCIs will enrich the gaming and entertainment experience,[6] for example, in games tailored to the user's affective state—immersion, flow, frustration, surprise, and so on. Several game designers have already linked mental states to the popular *World of Warcraft*, allowing an avatar's appearance to reflect the gamer's mental state instead of being controlled through keyboarding.[7] Indeed, we strongly believe that the first mass application of nonmedical BCIs will be in gaming and entertainment. Stand-alone examples already have a market, and extensions to console games are likely to follow soon.[8]

We also expect successful applications to be based on state monitoring rather than on direct control. Although researchers suggested BCIs for gaming a decade ago, the research basis has remained small and continues to be application-driven rather than theoretical. The societal impact is low, but economic viability is high. According to a 2008 survey by GameStrata, the leading online gamer community, North Americans were spending an average of $30,500 on games and gaming hardware during their peak gaming years of ages 18 to 48 (http://kotaku.com/5019411/how-much-do-we-spend-on-games-between-the-ages-of-18+48). Price sensitivity is also high, with ease of use being a significant influence.

Cognitive improvement

Some argue that people are already taking steps to improve their cognitive performance, for example, by drinking caffeinated beverages to be more mentally alert. More serious actions, such as taking prescription drugs without a medical indication, is stimulating debate about the merits of cognitive improvement.

A common nonmedical application involving a BCI is neurofeedback training, in which operant conditioning alters brain activity to improve attention, working memory, and executive functions.

The line between medical and nonmedical neurofeedback applications is likely to be thin, but a nonmedical application might be the optimized presentation of learning content. Reliable experimental data on the effects of using neurofeedback in this way is currently lacking, but any value beyond medical neurofeedback will be limited to specific cognitive tasks.

Safety and security

EEG alone or combined EEG and eye movement data from expert observers could support the detection of deviant behavior and suspicious objects.[9] In one envisioned scenario,[10] observers watch CCTV recordings or baggage scans for this purpose. EEG and eye movements might be helpful in identifying potential targets that might otherwise go unnoticed, or the system could monitor an observer's arousal state and, if necessary, initiate a break.[10]

Also, image inspection might be faster than is possible with current methods. Eye fixations and event-related potentials in the EEG reflect what the observer unconsciously perceives as being relevant, so brain signals can indicate relevant pictures even when the observer is presented with a stream of up to 50 images per second.

Using EEG in lie detection or to identify a person are possible applications, but opponents argue that BCI systems are not reliable enough for ethical use in practical situations. Trained users could voluntarily modify their brain activity to deceive the system, and even worse, the system could allow false positive detections.

Although safety and security is a niche application area still in concept development, applications are likely to have high societal impact, mainly in making transport hubs safer. However, the niche characterization limits economic viability, and applications are not likely to appear before 2015.

TECHNOLOGICAL CHALLENGES

Developing practical nonmedical BCI applications requires more work on issues that are not necessarily crucial for medical applications. Gamers' excessive movements, for example, will generate heavy artifacts that pollute EEG signals. Usability is also a challenge, since users will expect the BCI to be relatively comfortable (no itchy caps or messy gel) and as robust as a mouse or keyboard.

Figure 2. Two gamers using a BCI to control avatars in a prototype tennis game. In addition to motivating new games, brain control boosts the fun factor of existing ones.

Usability

The typical user will want to operate the BCI without help or extensive training. Generally, users will have high expectations about the system's usability and hardware's wearability. They will not want to wash their hair after every experience or to endure an uncomfortable cap. Rather, users must be able to rapidly don the EEG cap and set up the equipment quickly and intuitively. The system must also be hygienic for multiple users and require minimal maintenance.

To reach optimal performance, current BCI systems require an initial calibration session, in which the system records examples of the user's EEG signals so that it can tune signal parameters for that user. A typical BCI calibration session can take anywhere from five to 20 minutes, which is too long for most users. Few people would use a mouse or keyboard interface if they had to wait even a few minutes each time they wanted to use it.

Designing BCI systems and applications that are intuitive and fast to learn will require considerable research about human capabilities and preferences, for example, to identify the user's acceptable threshold of cognitive demands.

Another side of usability is what the user experiences outside of completing the task at hand. Addressing subjective aspects such as the user's mood, emotions, and beliefs will be important to the acceptance of nonmedical BCI applications. Any system must also be ethically sound,[11] particularly with respect to mind-privacy issues and the long-term effects of BCI use.

Although arguably several of these issues are relevant for medical applications, most research in that application area does not treat usability as a critical issue. In sharp contrast, we expect usability for nonmedical applications, such as gaming, to be a key concern.

Hardware

The hardware improvements required to develop usable nonmedical BCI applications are a core challenge. EEG sensors in particular must be dry, comfortable, convenient to use, and easy to mount before BCI systems will be suitable for use outside laboratories and hospitals.

Sensors must also offer good signal quality even in very noisy environments with moving users. Although researchers have shown that BCIs can be used outside laboratories or with a moving user,[12] performance is generally poorer than in laboratory conditions. Work should focus on developing better active electrodes with active shielding.

Another hardware issue is the optimal number and placement of electrodes and how to achieve consistent placement while ensuring that the user can easily mount the electrodes unassisted. The ideal BCI device—sensors, amplifier, and possibly computer—would be wearable, lightweight, unobtrusive, comfortable, wireless, and visually appealing. Pushing against that ideal is cost: for many nonmedical applications, the acceptable hardware cost must be only a few hundred dollars.

For the long term, researchers should explore alternative sensor technologies or designs that augment EEG sensors, for example with NIRS.[13] Although its low temporal resolution and inherent delay might make NIRS unsuitable for communication and control applications, it could be very useful for mental-state monitoring, where short reaction times are not crucial. However, NIRS is currently still too bulky and expensive for practical applications.

Software

As Figure 3 shows, BCI software has two main parts: signal processing and visualization—what the user sees as a result of performing a mental task. Signal processing, in turn, consists of

- preprocessing;
- feature extraction, representing brain signals by some number of values; and
- classification or regression.

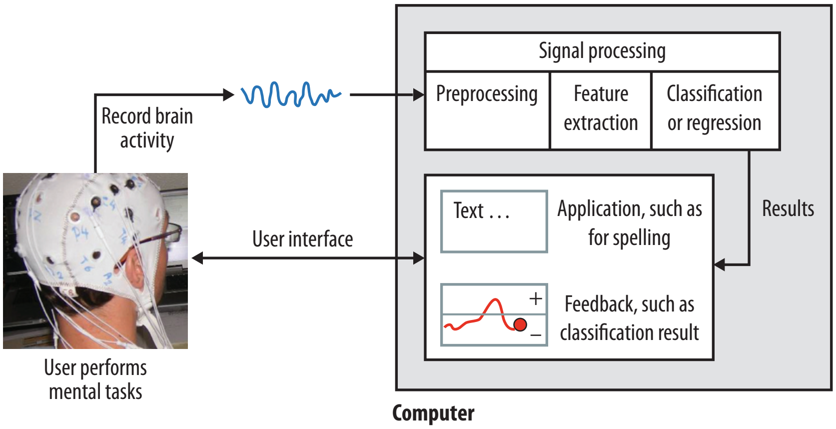


Figure 3. Elements of BCI software. Signal processing is of primary concern because it must extract features from the brain signals and assign them to a control class or mental state. Visualization results, such as text in a spelling application or classification, give feedback to the user, thus closing the loop.

Classification involves assigning a class label to the extracted features, such as a specific control command. Regression is similar except that it identifies a continuous measure, such as the user's attention level, instead of a discrete mental state, such as an imagined right-hand movement.

One goal is to make signal processing robust to noise and changing brain-signal characteristics. Sensors cannot suppress all environmental noise, so signal processing algorithms must complete the task so that BCI performance is independent of the user environment. Robustness to brain-signal nonstationarity is necessary to address internal sources of variability—the changes in the user's mental state, such as mood or attention. New unsupervised (adaptive) signal-processing algorithms, which continuously adapt and optimize their parameters to current signal properties, could provide first solutions.[14]

Another goal is to make BCIs asynchronous (self-paced) or continuous instead of synchronous and discrete. Self-paced BCIs are the most natural interface for communication and control applications because they let the user send mental commands at will. Continuous BCIs would enable mental-state monitoring, so work should focus on improving the performance of current self-paced BCIs enough for practical applications.

Reducing BCI calibration time is also essential to the immediate use of BCIs in nonmedical applications. A few recent machine learning developments have suggested solutions that reuse EEG signals collected from previous BCI sessions (session-to-session transfer) or from different users (user-to-user transfer).[15] These approaches aim to shorten or even eliminate the calibration session. However, such BCIs generally have lower classification performances than those obtained using a full calibration step. So far, such work underlines both the potential of and the need for further research in this area.

Finally, although researchers have dedicated a large body of work to the design of efficient algorithms to process signals such as motor imagery and event-related potentials, algorithms to process other kinds of brain or sensor signals are lacking. Only a few algorithms support mental-state monitoring, for example, and researchers are just now investigating fNIRS signal processing and classification algorithms.

Research must continue to explore and design various feature extraction and classification algorithms to decode mental states. Indeed, many experts wonder if it is actually possible to reliably decode emotions or stress from EEG signals.

System integration

Nonmedical BCIs require quick, seamless integration with existing systems. Ultimately, users would simply plug the BCI device into the computer's USB port as they would a new mouse. A plug-and-play device would require hardware to physically interface with existing systems, software drivers, and protocols—all of which must comply with international standards. Moreover, in some applications, the BCI device would not be stand-alone, but rather part of a hybrid system of input devices or biosensors, such as an additional control channel in a videogame that already uses a game pad. In an application to monitor a driver's alertness, it might complement biosignals such as ECG or blood pressure readouts.

Hardware and software standardization will be essential in making integration simple and seamless. The Tools for Brain-Computer Interaction project (www.tobi-project.org) has proposed interface protocols and provided reference implementations. Another effort is www.bcistandards.org, a site that provides common definitions and terminology to support community-based decision processes. Finally, the open source Pythonic Feedback Framework (http://bbci.de/pyff) defines a uniform high-level interface for BCI applications and provides several Pyff-compliant applications for download.

GROWTH PROSPECTS

Figure 4 shows that articles on BCIs and gaming alone have increased fivefold since 2001. As the technology matures, BCIs are poised to be important building blocks in the next generation of user interfaces. In a 2010 survey of BCI marketability, two-thirds of the respondents expected BCIs for healthy users to be on the market before 2015.[7] More than one-quarter indicated that such technology was already available through gaming applications.

Solving the technological issues will benefit both medical and nonmedical applications, but BCI growth also depends on user characteristics, needs, expectations, and acceptance. Curiosity and entertainment motivate healthy BCI users, not a pressing need to enhance their daily lives. Nonmedical applications require a clear picture of the target user group and how that group views the added value a BCI can bring. Defining this view will mean looking at the group's minimal requirements for speed, accuracy, and training on the device.

Satisfying these prerequisites will keep users from abandoning the BCI for other interfaces. Developers should involve user groups as early as possible and systematically obtain user feedback. Mass applications in a particular area, such as gaming, would certainly result in more insights into user group characteristics and performance demands and give some idea of the device's adaptability. Mass applications translate to prolonged use, which can help identify potential improvements and refine the features that users require.

One concern is that developments in nonmedical BCIs have failed to coordinate communication, research efforts, standardization, and ethics. Widely accepted terms and definitions, as well as the unification and interoperability of technological silos, would greatly accelerate progress in BCI research and development. Although BCIs are a regular topic in the media, communication about the technology's potential, ethical issues, and so on is usually limited. To avoid contributing to this problem, developers of nonmedical applications should sketch a clear picture of what BCIs can and cannot offer relative to current technology, the environments that would benefit from BCIs, proof of effectiveness, expected progress, and potential risks.

Using terms like "enhancement," "mind reading," or "mind control" is inadvisable, although it is wise to be specific in describing risks and ethical issues. Rather than avoiding the ethical debate of using brain signals in nonmedical applications, developers should actively promote it as part of seeking BCI hardware and software certification.

The coordination of medical and nonmedical BCI research efforts is vital. Such alignment could produce a shared roadmap and research agenda that would benefit both areas. Even the latest international roadmap still has separate and sometimes contradictory sections on medical and nonmedical BCIs.[2]

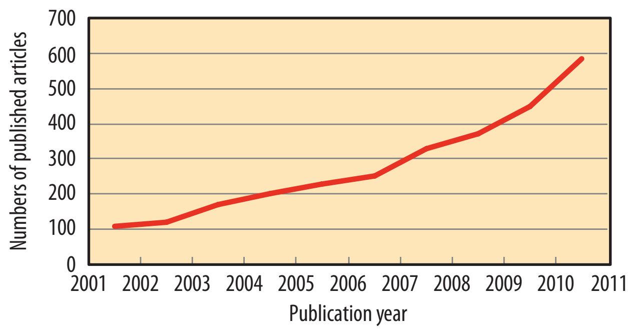


Figure 4. Number of articles on BCIs and gaming published per year. The graph shows a fivefold increase during the first decade of this millennium (data from Google Scholar). Gaming has been the entry point of nonmedical BCI applications and is paving the way for other nonmedical applications.

Research alignment, particularly efforts that involve influential, multidisciplinary national and international organizations such as IEEE and ISO, leads naturally to standardization. Standards in software, hardware, and ergonomics can ensure that system designers have attended to interoperability and usability concerns. To ensure interconnectivity and easy integration with existing technology, designers should make BCI systems modular rather than stand-alone. Standards would encourage this kind of design. Finally, the maturation of BCI technology requires a golden standard for comparing

ACTION ITEMS FOR MOVING FORWARD

- **Focus on the research and development of BCIs that assess the user state instead of controlling the device directly.**
- **Identify the near-term killer applications and use them to drive BCI research and development.**
- **Realize easy integration of BCI systems with existing hardware and gaming software.**
- **Get more hands-on experience and feedback by implementing BCIs outside controlled laboratory environments.**
- **Involve users and industry early in development.**
- **Communicate clearly and honestly about BCI limitations and risks, and encourage ethical debate on the nonmedical use of brain signals.**
- **Set a shared research agenda and roadmap, integrating medical and nonmedical BCIs. Look at related efforts, such as the roadmap for BCI research in the Future BNCI European project.**
- **Transfer knowledge, capabilities, and technologies between medical and nonmedical BCI applications.**
- **Involve national and international standards organizations, not just the scientific community.**
- **Work toward standardization and possibly certification of BCI systems, including defining ethical guidelines. Follow efforts like the TOBI project (www.tobi-project.org) to facilitate joint use of multiple BCI platforms.**

BCI system performance across paradigms, sensors, and algorithms.

The "Action Items for Moving Forward" sidebar sums up some of these requirements as recommendations for advancing BCIs in nonmedical applications.

Clearly, BCIs are not a transitory technology. Growth over the past decade has illustrated their potential for nonmedical uses, and gaming is just one of seven potential application areas. Because many open issues remain, it would be difficult to immediately implement all the action items we recommend. A good starting point is to invest more research in BCIs that passively assess user state. This area is relatively new but holds great promise for six of the seven application areas we have identified.

Acknowledgments

This work was supported in part by the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science and by the European ICT Programme Project FP7-224631. We thank all the workshop participants whose enthusiasm and contributions made this article possible. We also thank Sidath Liyanage, Balint Varkuti, Maaike Duistermaat, and Sjoerd de Vries for their constructive comments on an earlier draft.

References

1. J.R. Wolpaw et al., "Brain-Computer Interfaces for Communication and Control," *Clinical Neurophysiology*, vol. 113, no. 6, 2002, pp. 767-791.
2. "Future BNCI: A Roadmap for Future Directions in Brain/Neuronal Computer Interaction Research," *Future BNCI Program under the European Union Seventh Framework Programme*, FP7/2007-2013, grant 248320; http://future-bnci.org/images/stories/Future_BNCI_Roadmap.pdf. 2012.
3. E.B.J. Coffey et al., "Brain-Machine Interfaces in Space: Using Spontaneous Rather than Intentionally Generated Brain Signals," *Acta Astronautica*, vol. 67, no. 1-2, 2010, pp. 1-11.
4. J.B.F. van Erp, J.A. Veltman, and M. Grootjen, "Brain-Based Indices for User System Symbiosis," *Brain-Computer Interfaces*, D.S. Tan and A. Nijholt, eds., Human-Computer Interaction series, Springer, 2010, pp. 201-219.
5. M.A. Just, T.A. Keller, and J.A. Cynkar, "A Decrease in Brain Activation Associated with Driving When Listening to Someone Speak," *Brain Research*, vol. 1205, no. C, 2008, pp. 70-80.
6. A. Lécuyer et al., "Brain-Computer Interfaces, Virtual Reality, and Videogames," *Computer*, Oct. 2008, pp. 66-72.
7. 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.
8. F. Nijboer et al., "A Preliminary Survey on the Perception of Marketability of Brain-Computer Interfaces and Initial Development of a Repository of BCI Companies," *Proc. 5th Int'l Conf. Brain-Computer Interfaces*, Technological University Graz, 2011, pp. 344-347.
9. S. Mathan, "Image Search at the Speed of Thought," *ACM Interactions*, vol. 15, no. 4, 2008, pp. 76-77.
10. K.-R. Müller et al., "Machine Learning for Real-Time Single-Trial EEG Analysis: From Brain-Computer Interfacing to Mental State Monitoring," *J. Neurosciences Methods*, vol. 167, no. 1, 2008, pp. 82-90.
11. F. Nijboer et al., "The Asilomar Survey: Stakeholders' Opinions on Ethical Issues Related to Brain-Computer Interfacing," *Neuroethics*, July 2011, pp. 1-38.
12. F. Lotte et al., "Towards Ambulatory Brain-Computer Interfaces: A Pilot Study with P300 Signals," *Proc. 5th Conf. Advances in Computer Entertainment Technology* (ACET 09), 2009, ACM, pp. 336-339.
13. R. Sitaram et al., "Temporal Classification of Multichannel Near Infrared Spectroscopy Signals of Motor Imagery for Developing a Brain-Computer Interface," *NeuroImage*, vol. 34, no. 4, 2007, pp. 1416-1427.
14. P. von Bünau et al., "Finding Stationary Subspaces in Multivariate Time Series," *Physical Rev. Letters*, vol. 103, no. 21, 2009; http://prl.aps.org/abstract/PRL/v103/i21/e214101.
15. S. Fazli et al., "Subject-Independent Mental State Classification in Single Trials," *Neural Networks*, vol. 22, no. 9, 2009, pp. 1305-1312.

***Jan B.F. van Erp** is a senior scientist and program manager in the Department of Perceptual and Cognitive Systems at The Netherlands Organization for Applied Scientific Research (TNO) and is the scientific director of the BrainGain consortium. His research focuses on advanced human-computer interaction including multimodal interaction, augmented reality, and brain-computer interfaces. Van Erp received a PhD in computer science from Utrecht University, the Netherlands. Contact him at jan.vanerp@tno.nl.*

***Fabien Lotte**, a research scientist at INRIA Bordeaux Sud-Ouest, France, was a research fellow at the Institute for Infocomm Research, Singapore, when he started work on this article. His research interests include BCIs, signal processing, pattern recognition, and virtual reality. Lotte received a PhD in computer science from the National Institute for Applied Sciences, Rennes, France. He is a member of the International Association for Pattern Recognition. Contact him at fabien.lotte@inria.fr.*

***Michael Tangermann** is a postdoctoral researcher in the machine learning department at the Berlin Institute of Technology (Technische Universität Berlin) and is a member of the Berlin Brain-Computer Interface group. His research interests include brain-computer interfaces, machine learning, and auditory attention processes. Tangermann received a Dr. rer. nat. in computer science from Tübingen University, Germany. Contact him at michael.tangermann@tu-berlin.de.*