Meyendtris: A Hands-Free, Multimodal Tetris Clone using Eye Tracking and Passive BCI for Intuitive Neuroadaptive Gaming

Laurens R. Krol[1], Sarah-Christin Freytag[2], and Thorsten O. Zander[1]

[1]Biological Psychology and Neuroergonomics, Technische Universität Berlin
[2]Chair of Human-Machine Systems, Technische Universität Berlin

Abstract

This paper introduces a completely hands-free version of Tetris that uses eye tracking and passive brain-computer interfacing (a real-time measurement and interpretation of brain activity) to replace existing game elements, as well as introduce novel ones. In *Meyendtris*, dwell time-based eye tracking replaces the game's direct control elements, i.e. the movement of the tetromino. In addition to that, two mental states of the player influence the game in real time by means of passive brain-computer interfacing. First, a measure of the player's relaxation is used to modulate the speed of the game (and the corresponding music). Second, when upon landing of a tetromino a state of error perception is detected in the player's brain, this last landed tetromino is destroyed. Together, this results in a multimodal, hands-free version of the classic Tetris game that is no longer hindered by manual input bottlenecks, while engaging novel mental abilities of the player.

1 Introduction

With the rise of low-cost eye trackers, such as the Tobii EyeX (Tobii AB) or The Eye Tribe (now Oculus VR, LLC), the implementation of eye tracking in everyday human-computer interaction (HCI) starts to gain prominence, also in gaming. Also other novel input modalities gain in popularity. In particular, the measurement of brain activity through electroencephalography (EEG) has in recent years become more mobile, more affordable, and easier to use (e.g. (Mullen et al., 2015; Zander et al., 2017)).

These novel input methods have as yet been unable, however, to obtain a strong foothold in everyday human-computer interaction. We believe two reasons for this are a) specific disadvantages that come with these technologies, and b) the absence of a popular application where these modalities are clearly beneficial. By combining the strengths and weaknesses of multiple modalities, however, and by finding applications where their disadvantages may in fact be turned into welcome challenges, we believe we can overcome these issues and push both fields forward.

This paper introduces *Meyendtris*, a game that uses both eye tracking and real-time EEG analysis in a complementary way, in order to provide an intuitive yet challenging game experience that introduces novel game elements. Meyendtris is a Tetris clone where eye tracking replaces manual control—often a bottleneck in high-paced Tetris games—while passive brain-computer interfacing (Zander & Kothe, 2011) adds additional layers of mental challenges that would not be possible using traditional interaction techniques.

1.1 Eye Tracking for Direct Control

Eye tracking involves the measurement of a user's eye movements, primarily in order to infer their gaze direction, i.e., what they are looking at.

The main tracking measures used for HCI input are movement measures, such as smooth pursuit, and position measures, such as dwell time-based approaches (Holmqvist, 2011). Smooth pursuit is a smooth following movement that occurs when our eyes are focused on a moving target. By relating length and angle of the movement path to those of different moving targets, the item that was in the user's focus can be detected and as such, selected. One exemplary application are smooth pursuit-based gaze spellers or pin entries (Lutz, Venjakob, & Ruff, 2015), (Cymek et al., 2014). Advantages are the independence of direct positions, as vector length and angle are sufficient to relate the movement to its target. A disadvantage is that smooth pursuit detection is not applicable for stationary targets or targets with only short bursts of movement. Also, overshooting movements might occur if the observed target suddenly stops or changes directions (Holmqvist, 2011).

Dwell time-based approaches select an element after the user has looked directly at it for a certain minimal duration. In contrast to smooth pursuit, a high accuracy, defined as the difference between actual and detected gaze focus point, is required (Holmqvist, 2011). This minimal duration introduces a delay, and thus an interruption of normal gaze behaviour if used in a gaming context, as a small pause is needed for selection. Direct input by translating fixations to selections omits that delay, but holds the risk of creating the Midas Touch effect: an indiscriminate selection of everything in the gaze path (Jakob, 1995).

1.2 Brain-Computer Interfaces

A brain-computer interface (BCI) provides a human-computer communication channel that relies solely on brain activity, bypassing traditional human output methods that all involve the activation of muscles (Wolpaw & Wolpaw, 2012). First introduced in the 1970s (Vidal, 1973), research and development has focused primarily on creating BCI systems to support motor-impaired or paralysed patients. For example, those who have lost control of a limb can instead use their brain activity directly to control a prosthetic arm (Wolpaw & McFarland, 2008), or those who can no longer speak can use a BCI-based "mental speller" device to write sentences using only their cognitive attention (Farwell & Donchin, 1988).

However, direct access to brain activity can also be used to enhance and support HCI in general. In particular, rather than replacing existing interaction techniques for direct, explicit control (e.g. keyboard, joystick), BCI can provide a distinct, additional *implicit* communication channel (Zander, Brönstrup, Lorenz, & Krol, 2014). So-called *passive* BCI (pBCI) (Krol, Andreessen, & Zander, 2018; Zander & Kothe, 2011) relies on brain activity that is not consciously or voluntarily modulated by the user to control an application, but instead on brain activity that arises during the course of natural human-computer interaction. This activity is then interpreted in the given context, such that the computer can adapt to its user's mental state. For example, a pBCI system in a car could detect when its driver becomes drowsy, and switch to autonomous driving mode. As such, the driver does not explicitly instruct or control the car, but controls it implicitly—without expending any intentional effort.

In order to be able to detect specific mental states, BCI systems are usually first calibrated for each individual user. In an experimental setting, the desired mental states can be induced, while the brain activity is being recorded. Following this, signal processing and supervised machine learning methods are used to extract *features* from the recorded brain activity that are indicative of the different mental states, e.g. (Blankertz, Lemm, Treder, Haufe, & Müller, 2011). Then, a *classifier* is trained to be able to distinguish between the different mental states based on the given features. These features can also be extracted in real time, allowing the classifier to give real-time estimates of a user's current mental state. With this, computers can obtain a continuous measure of their users' mental states as implicit input.

Also in gaming contexts has BCI research primarily focused on the use of BCI for e.g. paralysed persons, to switch direct control from one modality to another (see (Marshall, Coyle, Wilson, & Callaghan, 2013) for a review). For example, (van de Laar, Gürkök, Bos, Poel, & Nijholt, 2013) implemented shapeshifting using a measure of brain activity. By bringing themselves in different states of mind ("relaxed" versus "agitated"), the players could shift their character in a role-playing game between different forms (an elf and a bear, respectively).

However, passive BCI can also be used to add novel game elements that supplement direct control, or to provide novel experiences. (Ewing, Fairclough, & Gilleade, 2016) used real-time measures of the player's brain activity to adjust the speed of an otherwise manually controlled Tetris game. Notably, relaxation was not a consciously controlled parameter here. In this paper, we build on their results, expanding the set of passive BCI parameters, and placing the game in a multimodal, hands-free setting.

BCI systems currently provide relatively low-dimensional signals, mostly binary: either a specific state is detected, or it is not. Furthermore, their accuracy is imperfect: given the large variability in brain activity based on any number of factors, a previously-learned pattern may be difficult to recognise at a different time. The challenge is thus to develop applications that deal with or bypass the issue of sub-perfect control, and where low-dimensional signals can have sufficient meaning (Zander, Gärtner, Kothe, & Vilimek, 2010).

1.3 Hybrid Systems: Eye Tracking and Passive BCI

The addition of BCI to gaze-based interaction applications may counter the Midas Touch problem. For example, as (Zander et al., 2010) showed, a BCI-based selection command can be used instead of dwell time, enabling the user to set their own pace. Alternatively, using passive BCI, the system may be able to detect from brain activity when a user wishes to interact with an on-screen element, and is not simply looking at it. It can then automatically activate the element without any actual explicit effort being expended by the user (Protzak, Ihme, & Zander, 2013; Shishkin et al., 2016).

In turn, eye tracking can support passive BCI-based approaches by providing additional context information (Zander & Jatzev, 2012), allowing the system to properly infer a by itself low-dimensional signal.

Both BCI and eye tracking afford touchless human-computer interaction. These systems can naturally complement each other, potentially creating synergetic effects and novel user experiences.

2 Methods

2.1 Tetris Game Elements and Control

Tetris involves the manipulation and arrangement of different geometric shapes (*tetrominoes*) such that complete lines are formed. One after another, the player is presented with one of seven possible tetrominoes (made up of four connecting squares) at the top of the playing field. It moves downward at a constant speed until it lands on the bottom of the field or a previously-placed tetromino. When, upon landing, a complete horizontal line of connecting squares is created, this line is removed from the field. Over time, the game's speed increases, making placement more difficult. The game ends when no more tetrominoes can be placed because the field is full.

The standard Tetris game elements implemented in Meyendtris are: horizontal movement of the active tetromino (left/right), clockwise rotation of the tetromino, and vertical movement of the active tetromino: it can be dropped instantly without waiting for it to land at the game's current speed. These traditional game mechanics are all controlled by gaze, based on dwell time. When the user looks at one and the same column for 100 ms, the tetromino is moved to that column. When the user looks at the same column for 1 second, the tetromino is dropped. When the user looks at the top 15% of the playing field for 100 ms, the tetromino is rotated clockwise.

In addition to these, we introduce two novel game elements controlled through BCI. First, instead of the game getting faster based on the player's progress, the game's speed now depends on the state of relaxation that the user is in, as measured from their brain activity. This speed influences both the speed at which the tetrominoes fall, as well as the music's pace. The player must relax in order to slow down the game. The player must thus avoid creating a positive feedback loop in which an increase in engagement leads to a faster game, further increasing engagement, etc. The challenge is to relax in the face of potentially demanding circumstances.

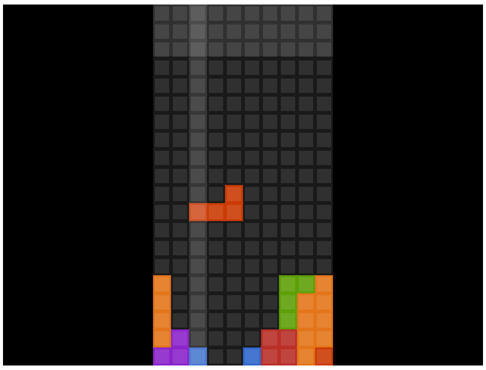

Figure 1: Screenshot of Meyendtris. The lighter-shaded area at the top of the field activates rotation. The lighter-shaded vertical column indicates the current column that the player is looking at. The tetromino follows this gaze horizontally. Looking at one column for 1 second drops the tetromino.

Secondly, our version provides for the removal of erroneously placed tetrominoes. If, right after the tetromino landed, a state of *error perception* was detected in the player's brain, this last tetromino was removed from the field. The player will thus benefit from paying proper attention to the game and their own goals, in order to be able to correctly assess each landed tetromino.

2.2 Implementation

The game has been implemented and tested to work with the Tobii EyeX (Tobii AB, Danderyd, Sweden), but can work with any tracker where the (x,y) gaze position can be obtained through an API.

Brain activity was recorded using a 32-channel wireless active dry electrode LiveAmp system (Brain Products GmbH, Gilching, Germany). Dry electrode systems, compared to traditional gel-based electrodes, provide a reasonable signal quality while being much faster and easier to apply (Zander et al., 2017).

The game was programmed in Python 2.7 using the open-source Simulation and Neuroscience Application Platform (SNAP) (Delorme et al., 2011), based on the Panda3D game engine (Goslin & Mine, 2004).

The different data streams—gaze, EEG, game events—were synchronised and recorded using the open-source Lab Streaming Layer (LSL) (Delorme et al., 2011). This framework is what allows Meyendtris maximum compatibility with other (eye tracking and EEG) hardware; the only requirement is that the data stream must be accessible through LSL.

The open-source toolbox BCILAB (Delorme et al., 2011) was used to implement the BCI classifier.

2.3 Procedure

2.3.1 Set-Up and Calibration

The user is sitting comfortably on a chair looking at a computer screen placed about 75 cm away. The eye tracker is placed according to the manufacturer's instructions. An experimenter places the EEG electrodes on the head of the user and makes sure the signal quality is satisfying (depending on hardware, this may also be done by the users themselves without losing signal quality (Zander et al., 2017)).

For the current implementation of Meyendtris, three elements need to be calibrated: the eye tracker, the relaxation classifier, and the error perception classifier.

The tracker is calibrated as per the manufacturer's instructions.

To calibrate the relaxation classifier, we first record the user's brain activity during phases of two different mental states: relaxation, and cognitive engagement. To induce these states, the user is exposed to two conditions. First, for 10 seconds, the user sees a grey crosshair on an otherwise black screen, and is instructed to focus attention inwards, by recalling the details of a previously chosen positive memory. This represents relaxation. After this, for 10 seconds, randomly-coloured, randomly-sized rectangles appear on the screen at a speed of 60 per second, each remaining visible for one-sixth of a second. The user is instructed to pay attention and count the number of pink rectangles that appear. This represents engagement. This procedure is repeated until 100 seconds of brain activity have been recorded for each condition.

Based on this data, BCILAB is used to calibrate a classifier. Filter Bank Common Spatial Patterns (Ang, Chin, Zhang, & Guan, 2008) is used to extract features in frequency bands known to correlate to mental activity and relaxation: the theta band (4–8 Hz) and the alpha band (8–12 Hz). Linear Discriminant Analysis regularised using shrinkage (Blankertz et al., 2011) is used to calibrate the classifier.

For the error perception classifier, users first play an adapted, rigged version of the game. They are presented with 140 games in progress (i.e., a specific developed game field) and one tetromino that is to be dropped. The game fields have been developed such that the tetromino has only one obvious landing spot. The game then unfolds as usual, except that vertical movement is disabled; i.e., the tetromino cannot be dropped. Furthermore, in 50% of cases, just before the final landing of the tetromino, it is moved one square to the left or to the right, thus missing its intended landing position.

The user's brain activity during these 140 game trials is recorded. Based on this, the brain's response whenever the tetromino makes a wrong landing (in those 50% of cases) can be assessed, and compared to the response when a tetromino lands as intended. To calibrate a classifier capable of distinguishing between these two events, BCILAB is used following the windowed-means approach (Blankertz et al., 2011).

2.3.2 Gameplay

The game can be played following traditional, now gaze-controlled mechanics as described in section 2.1. On top of that, two pBCI classifiers provide additional input to the game.

Ten times per second, the relaxation classifier classifies the past 5 seconds of recorded brain activity and builds a mean relaxation index. Based on this index, the game's speed is regulated (as also in (Ewing et al., 2016)). The index varies between 1 (relaxed) and 2 (engaged). This value is linearly mapped to scale the game speed between 0.3 and 1.5 seconds, indicating the time it takes for the tetromino to move one square down. The game's music is scaled between 150 and 75% of its regular playback speed.

Whenever a tetromino lands, the brain activity following that exact time point is classified by the second classifier. This results in a one-time value between 1 (error) and 2 (no error). If the value is below 1.25, meaning that the classifier is 75% certain that the last drop was in error, the landed tetromino is removed from the field and a new, random tetromino is spawned at the top of the field.

3 Discussion

Meyendtris has been implemented and tested. Player recordings are currently underway in order to investigate the following points.

Eye tracking calibration. Testing has shown sufficient accuracy to use dwell time and fixation to control the game. However, a means of constant re-calibration during the game could be introduced to improve accuracy. This could e.g. be achieved by observing the left- and rightmost gaze coordinates and the boundaries of the Meyendtris field over time, and accounting for a possible offset.

Rotation command. Although traditional Tetris only has one-way rotation, the rotation command may be intuitively extended to two-way rotation: looking to the right of the field rotates the block clockwise, while looking to the left rotates it counter-clockwise.

Relaxation classifier buffer size. We currently build a relaxation index based on the previous five seconds of data. It may be that five seconds is either too long or too short a period to accurately detect and adapt to changes in the player's mental state. By analysing the recordings of a number of players, we can analyse the effect of different buffer sizes post hoc.

(Adaptive) speed limits. The extremes of the relaxation index are mapped to certain extreme game speeds–1.5 and 0.3 seconds per vertical movement, and 75 and 150% of music speed. An evaluation whether or not these must be adjusted is planned. Another option is to adjust them adaptively (Krol et al., 2018): beginning with moderate extremes, once an extreme value is reached for a prolonged period of time, it is increased automatically.

Error classifier approach. Although previous experiments have indicated clear neural responses to observed errors or inappropriate events (e.g. (Gehring, Liu, Orr, & Carp, 2012; Zander, Krol, Birbaumer, & Gramann, 2016)), these have not been investigated specifically in the current Tetris context. The recorded data will allow for a better investigation of brain dynamics whenever a block is erroneously landed, comparing it to traditional error dynamics. Following, the parameters of the classifier, or the calibration phase, may be adjusted to better be able to detect the relevant neural response.

Error classifier sensitivity. The game can be adjusted to respond to different levels of certainty from the classifier. For example, a block can be removed only when the classifier is 100% certain that it was placed in error (i.e. 100% certain that the detected brain activity reflects error perception), or it can be removed when the classifier is merely, say, 55% certain. (Since this is a binary decision task, complete uncertainty is theoretically at 50%). This latter condition will see more erroneous blocks removed, but at a cost of increased false positives, i.e., it will also remove some correctly placed blocks. Some level of frustration, however, may add to the gaming experience (Gilleade & Dix, 2004). The influence of false positives on the player's gaming experience will be investigated in order to adjust this parameter for optimal engagement.

4 Conclusion

Combining eye tracking and passive brain-computer interfacing, a completely hands-free Tetris clone with novel game elements was developed. Traditional Tetris actions (i.e. block manipulation) are performed using dwell time-based gaze control and direct fixation, while passive BCI adds two novel aspects.

The game speed is regulated based on the player's state of relaxation: the more relaxed the player is, the slower the game. Whenever the player makes a mistake, they must make sure to remain calm so as not to increase the game's difficulty, potentially leading to a positive feedback loop of further mistakes and speed increases.

Should the player master this skill, parameters still exist to further challenge the player: when the game has been played at minimum speed for a certain period of time, this minimum speed can be raised, and dwell time settings can be adjusted to e.g. have the tetrominoes drop faster.

A second novel aspect is the potential removal of erroneously placed blocks, provided that the pBCI classifier recognises a state of error perception in the player upon landing that block. Depending on how this parameter is tuned exactly, this will remove at least the most frustrating blocks, at the potential cost of every once in a while having a well-placed block disappear. An additional challenge for the player is to focus attention such that the classifier works well and to their advantage.

Both eye tracking and BCI provide novel and interesting means of input for gaming. However, shortcomings exist. Those can be counterbalanced by their combination. In particular, in Meyendtris, eye tracking adds accurate selection control to the noisy, low-dimensional B-CI modality, while the BCI-based error correction mechanism can directly compensate (undo) potential eye tracking errors. The measure of relaxation can be used to tune the dwell time parameter in real time, striking a context-sensitive optimal balance between Midas Touch and too-long pauses. Furthermore, in general, games provide a context where potential, but controllable, inaccuracies can be welcomed as challenges.

Tetris is an example where eye tracking provides a uniquely intuitive method of control. Looking around the game field will move the block around, supporting the player to find a good landing spot. When a good spot has been identified, continuing to look at it will land the block there. Looking away from ("flicking") the block rotates it. Especially at a high pace, manual control forms a bottleneck and source of error in Tetris games. Eye tracking can help alleviate this issue, allowing the player to focus more on the game strategy rather than its control.

At the same time, pBCI opens up new dimensions for gaming. By making the game's difficulty depend on the player's mental state, the battle in the game becomes a battle against oneself. By placing additional rewards (the removal of erroneously placed blocks) on the proper control of the player's goals and interpretations, two mental states must be balanced throughout the game.

With the increased popularity of neuroadaptive technology and the increased accessibility to hardware measuring brain activity, a new era of human-computer interaction and neurogaming may be opening up. With this paper, a multimodal approach is proposed, demonstrating how different input modalities may complement each other to form a novel gaming experience.

References

Ang, K. K., Chin, Z. Y., Zhang, H., & Guan, C. (2008, June). Filter bank common spatial pattern (FBCSP) in brain-computer interface. In *IEEE International Joint Conference on Neural Networks (IJCNN), 2008* (pp. 2390–2397). doi: 10.1109/IJCNN.2008.4634130

Blankertz, B., Lemm, S., Treder, M. S., Haufe, S., & Müller, K.-R. (2011). Single-trial analysis and classification of ERP components – A tutorial. *NeuroImage*, *56*(2), 814–825.

Cymek, D., Venjakob, A., Ruff, S., Lutz, O., Hofman, S., & Roetting, M. (2014). Entering pin codes by smooth pursuit eye movements. *Journal of Eye Movement Research*, *7(4)*, 1.

Delorme, A., Mullen, T., Kothe, C., Acar, Z. A., Bigdely-Shamlo, N., Vankov, A., & Makeig, S. (2011). EEGLAB, SIFT, NFT, BCILAB, and ERICA: New Tools for Advanced EEG Processing. *Computational Intelligence and Neuroscience*, *2011*, 10:10–10:10. doi: 10.1155/2011/130714

Ewing, K. C., Fairclough, S. H., & Gilleade, K. (2016). Evaluation of an adaptive game that uses EEG measures validated during the design process as inputs to a biocybernetic loop. *Frontiers in Human Neuroscience*, *10*, 223. doi: 10.3389/fnhum.2016.00223

Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology*, *70*(6), 510–523.

Gehring, W. J., Liu, Y., Orr, J. M., & Carp, J. (2012). The error-related negativity (ERN/Ne). In S. J. Luck & E. S. Kappenman (Eds.), *Oxford handbook of event-related potential components* (pp. 231–291). New York, NY: Oxford University Press. doi: 10.1093/oxfordhb/9780195374148.013.0120

Gilleade, K. M., & Dix, A. (2004). Using frustration in the design of adaptive videogames. In *Proceedings of the 2004 ACM SIGCHI international conference on advances in computer entertainment technology* (pp. 228–232). New York, NY, USA: ACM. doi: 10.1145/1067343.1067372

Goslin, M., & Mine, M. R. (2004). The Panda3D graphics engine. *Computer*, *37*(10), 112-114. doi: 10.1109/MC.2004.180

Holmqvist, K. (2011). *Eye tracking. a comprehensive guide to methods and measures.* Oxford University Press.

Jakob, R. (1995). Virtual environments and advanced interface design. In W. Barfield & T. I. Furness (Eds.), *Eye tracking and advanced interface design* (p. 258-288). New York, NY: Oxford University Press.

Krol, L. R., Andreessen, L. M., & Zander, T. O. (2018). Passive brain-computer interfaces: A perspective on increased interactivity. In C. S. Nam, A. Nijholt, & F. Lotte (Eds.), *Brain-Computer Interfaces Handbook.* Boca Raton, FL, USA: CRC.

Lutz, O., Venjakob, A., & Ruff, S. (2015). Smoovs: Towards calibration-free text entry by gaze using smooth pursuit movements. *Journal of Eye Movement Research*, *8(1):2*, 1-11.

Marshall, D., Coyle, D., Wilson, S., & Callaghan, M. (2013). Games, gameplay, and BCI: The state of the art. *IEEE Transactions on Computational Intelligence and AI in Games*, *5*(2), 82–99. doi: 10.1109/TCIAIG.2013.2263555

Mullen, T. R., Kothe, C. A. E., Chi, Y. M., Ojeda, A., Kerth, T., Makeig, S., … Cauwenberghs, G. (2015). Real-time neuroimaging and cognitive monitoring using wearable dry EEG. *IEEE Transactions on Biomedical Engineering*, *62*(11), 2553–2567. doi: 10.1109/TBME.2015.2481482

Protzak, J., Ihme, K., & Zander, T. O. (2013). A passive brain-computer interface for supporting gaze-based human-machine interaction. In C. Stephanidis & M. Antona (Eds.), *Universal Access in Human-Computer Interaction. Design Methods, Tools, and Interaction Techniques for eInclusion* (Vol. 8009, pp. 662–671). Berlin Heidelberg, Germany: Springer. doi: 10.1007/978-3-642-39188-0_71

Shishkin, S. L., Nuzhdin, Y. O., Svirin, E. P., Trofimov, A. G., Fedorova, A. A., Kozyrskiy, B. L., & Velichkovsky, B. M. (2016). EEG negativity in fixations used for gaze-based control: Toward converting intentions into actions with an eye-brain-computer interface. *Frontiers in Neuroscience*, *10*, 528. doi: 10.3389/fnins.2016.00528

van de Laar, B., Gürkök, H., Bos, D. P.-O., Poel, M., & Nijholt, A. (2013). Experiencing BCI control in a popular computer game. *IEEE Transactions on Computational Intelligence and AI in Games*, *5*(2), 176–184. doi: 10.1109/TCIAIG.2013.2253778

Vidal, J. J. (1973). Toward direct brain-computer communication. *Annual Review of Biophysics and Bioengineering*, *2*(1), 157–180.

Wolpaw, J. R., & McFarland, D. J. (2008). Brain-computer interface operation of robotic and prosthetic devices. *Computer*, *41*, 52–56. doi: 10.1109/MC.2008.409

Wolpaw, J. R., & Wolpaw, E. W. (2012). Brain-computer interfaces: something new under the sun. In J. R. Wolpaw & E. W. Wolpaw (Eds.), *Brain-computer interfaces: Principles and practice* (pp. 3–12). Oxford, UK: Oxford University Press.

Zander, T. O., Andreessen, L. M., Berg, A., Bleuel, M., Pawlitzki, J., Zawallich, L., … Gramann, K. (2017). Evaluation of a dry EEG system for application of passive brain-computer interfaces in autonomous driving. *Frontiers in Human Neuroscience*, *11*, 78. doi: 10.3389/fnhum.2017.00078

Zander, T. O., Brönstrup, J., Lorenz, R., & Krol, L. R. (2014). Towards BCI-based Implicit Control in Human-Computer Interaction. In S. H. Fairclough & K. Gilleade (Eds.), *Advances in Physiological Computing* (pp. 67–90). Berlin, Germany: Springer. doi: 10.1007/978-1-4471-6392-3_4

Zander, T. O., Gärtner, M., Kothe, C. A., & Vilimek, R. (2010). Combining eye gaze input with a brain-computer interface for touchless human-computer interaction. *International Journal of Human-Computer Interaction*, *27*(1), 38–51. doi: 10.1080/10447318.2011.535752

Zander, T. O., & Jatzev, S. (2012). Context-aware brain-computer interfaces: exploring the information space of user, technical system and environment. *Journal of Neural Engineering*, *9*(1), 016003.

Zander, T. O., & Kothe, C. A. (2011). Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. *Journal of Neural Engineering*, *8*(2), 025005. doi: 10.1088/1741-2560/8/2/025005

Zander, T. O., Krol, L. R., Birbaumer, N. P., & Gramann, K. (2016). Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity. *Proceedings of the National Academy of Sciences*, *113*(52), 14898–14903. doi: 10.1073/pnas.1605155114