Clinical Review

What External Variables Affect Sensorimotor Rhythm Brain-Computer Interface (SMR-BCI) Performance?

Alex J. Horowitz, DO,[1,6] Christoph Guger, Dr.techn.,[2] Milena Korostenskaja, PhD[1,3,4,5]

Author affiliations are listed at the end of this article.

Correspondence to:
Milena Korostenskaja, PhD
Functional Brain Mapping and Brain-Computer Interface Lab
Neuroscience Institute
AdventHealth Orlando
Medical Plaza, Suite 139 (North Tower)
2501 North Orange Ave
Orlando, FL 32804
(milena.korostenskaja@gmail.com)

Abstract

Description

Sensorimotor rhythm-based brain-computer interfaces (SMR-BCIs) are used for the acquisition and translation of motor imagery-related brain signals into machine control commands, bypassing the usual central nervous system output. The selection of optimal external variable configuration can maximize SMR-BCI performance in both healthy and disabled people. This performance is especially important now when the BCI is targeted for everyday use in the environment beyond strictly regulated laboratory settings. In this review article, we summarize and critically evaluate the current body of knowledge pertaining to the effect of the external variables on SMR-BCI performance. When assessing the relationship between SMR-BCI performance and external variables, we broadly characterize them as elements that are less dependent on the BCI user and originate from beyond the user. These elements include such factors as BCI type, distractors, training, visual and auditory feedback, virtual reality and magneto electric feedback, proprioceptive and haptic feedback, carefulness of electroencephalography (EEG) system assembling and positioning of EEG electrodes as well as recording-related artifacts. At the end of this review paper, future developments are proposed regarding the research into the effects of external variables on SMR-BCI performance. We believe that our critical review will be of value for academic BCI scientists and developers and clinical professionals working in the field of BCIs as well as for SMR-BCI users.

Keywords

adoption rates; auditory feedback; brain-computer interfaces (BCIs); BCI accuracy; BCI literacy; BCI optimization; BCI performance; classification accuracy; distractors; dry electrodes; drone control; electrocorticography (ECoG); electroencephalography (EEG); EEG artifacts; EEG waveforms; external factors; external variables; event-related potentials; exoskeleton; haptic feedback; information transfer rate (ITR); internal factors; internal variables; magnetoencephalography (MEG); motor imagery; neurophysiology; odd-ball paradigm; P300 response; sensorimotor rhythm (SMR); sensory feedback; steady-state somatosensory evoked potential (SSSEP); steady-state visually evoked potentials (SSVEPs); motor imagery training; neuroprosthetics; transcranial magnetic stimulation (TMS); repetitive transcranial magnetic stimulation (rTMS); multimodal feedback; virtual reality (VR); vibrotactile feedback; visual feedback

Introduction

A brain-computer interface (BCI) is a device that records and translates the user's brain activity into various command signals, thus bypassing muscle activity and allowing direct communication between the brain and various devices. Brain activity for BCI control can be recorded with high millisecond scale temporal resolution through magnetoencephalography (MEG), electroencephalography (EEG) and electrocorticography (ECoG).[1] We limit the scope of this review article to the BCIs driven by electrical signals recorded with EEG. The reason behind this choice is that EEG-driven BCIs are the number one target for BCI translation from the laboratory to real-world settings due to the high temporal resolution of EEG methodology. After capturing the EEG

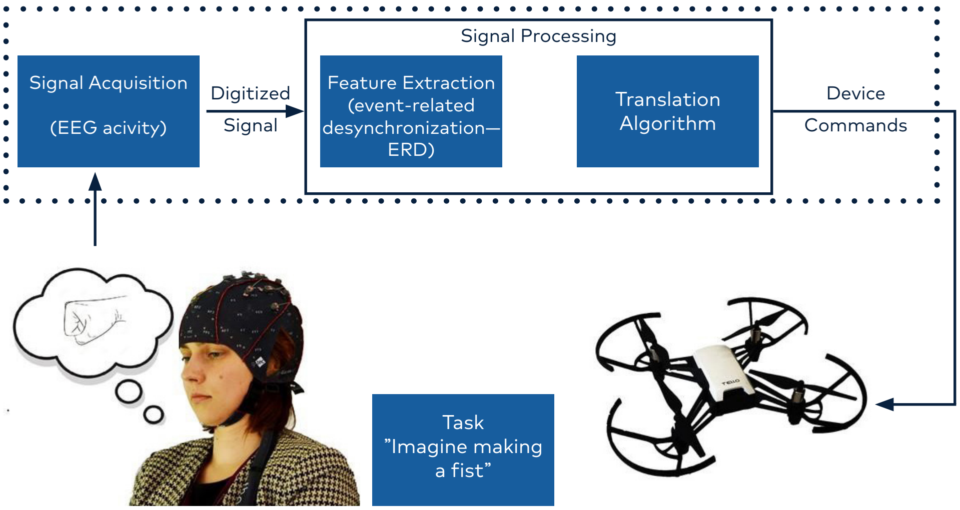

Figure 1. Brain Computer Interface set-up. An electrode array detects BCI user's electrical brain activity during the motor imagery (for example, imagining making a fist). The BCI translates the acquired signal according to a fixed or adaptive algorithm, extracting relevant features, for example, event-related desynchronization (ERD). BCI output manifests as the command of a device, such as steering a drone in its flight. (Photographs courtesy of the authors.)

interest, the BCI processes it by using a pre-defined fixed or changing ("adaptive") algorithm and translates the analyzed signal (its specific features) in real-time into computer commands. (**Figure 1**)

Among several types of electrical brain signals that can be detected and utilized for BCI control, sensorimotor rhythm (SMR) is one of the most common. Sensorimotor rhythm-based BCIs (SMR-BCIs) (also referred to as motor imagery BCIs or MI-BCIs) can detect the event-related desynchronizations (ERD) in electrical activity recorded with an EEG from the sensorimotor brain areas during a motor imagery (MI) task. SMR-BCIs hold great potential to advance the field of motor rehabilitation (for review, see Bamdad et al.[2]). A systematic review of cohort SMR-BCI studies by Monge-Pereira et al. demonstrated level II evidence that EEG-based SMR-BCI intervention can be a promising rehabilitation approach for upper motor function rehabilitation after stroke.[3] Moreover, a BCI may be used as a substitute to overcome functional deficits in individuals with compromised skeletal or motor system functions (such as paralysis and amputation).[4]

With continued development, a future becomes possible where BCI is a commonplace technology fully incorporated into everyday life in both the clinical population and healthy people. To achieve this widespread BCI adoption, it is imperative to understand how the user's internal and external environment impact SMR-BCI performance. Indeed, the performance of an SMR-BCI is largely determined by the efficacy of the user, the BCI itself and the operational conditions. This review article will focus on the effect of external factors on BCI performance. External variables are identified as those elements of the environment that mainly reside beyond the SMR-BCI user and within the SMR-BCI itself. Internal variables are defined as those factors largely originating from within the SMR-BCI user. It should be noted that these working definitions of internal and external variables are simply operational and are used for this specific paper only. Variations on these terms can be found elsewhere. In some circumstances, internal and external variables an be used interchangeably. For example, distractibility (originating within the user) and distractors (originating outside the user). **Figure 2** provides a flow chart depicting the relationship between internal and external factors with SMR-BCI performance.

Several studies have been conducted in an attempt to isolate some external variables, which may affect any metric of SMR-BCI performance, such as signal information transfer rate (ITR), correct response rate (CRR), adoption rate, classification accuracy and reaching target accuracy (for more details, see **Table 1**).[5-11]

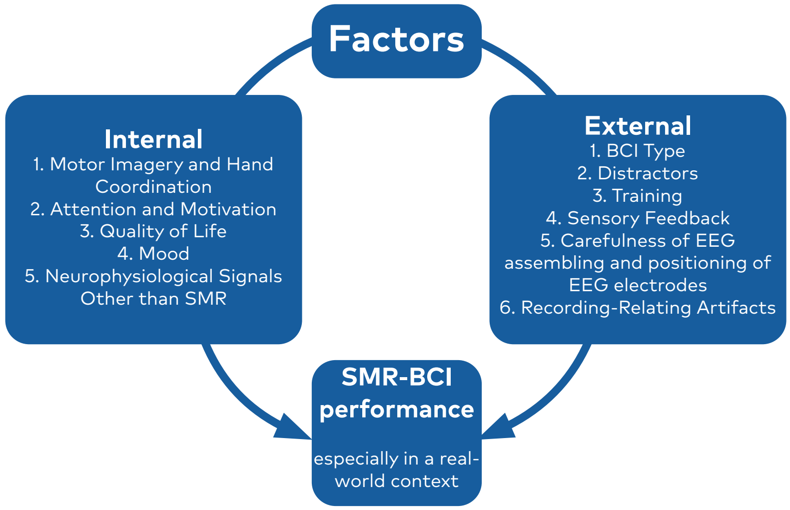

Figure 2. Factors may be divided into external or internal variables. Either may influence SMR-BCI performance. These variables may positively, negatively, or not at all influence users' SMR-BCI performance.[76] An SMR-BCI that emphasizes design elements that positively influence SMR-BCI performance. Conversely, an SMR-BCI that also mitigates design elements that negatively influence performance offers great hope for widespread, everyday SMR-BCI use.

The goals of our current review paper are (1) to summarize existing knowledge about the external factors affecting SMR-BCI performance and critically examine the studies on this subject published to date, as well as (2) to discuss limitations and propose further directions of MI-BCI research with other possible factors that may or may not affect the SMR-BCI's performance when presented within a real-world context. We think our paper will make a significant contribution to the transition of SMR-BCIs from academic laboratories to clinical settings and also have real-world applications. This paper will be of valuable use for clinical BCI users, as well as academic scientists, clinicians and engineers working with BCIs.

1. External Variables

External variables in the context of SMR-BCIs discussed in the current articles are those that largely originate from within the BCI system itself or beyond the BCI user. Examples include BCI type, distractors, training, sensory feedback, carefulness of EEG assembling and positioning of EEG electrodes, and recording-related artifacts. BCI types vary in the way they detect and analyze (for example, building a model and performing pattern recognition) specific brain signals. For this reason, the BCI type is based on the subject's intrinsic brain activity and depends on it. Nevertheless, the choice of a pattern of interest is a decision made by the experimenter rather than BCI user. Such a decision depends on the purpose behind the BCI use. It is important to note that the way brain activity is captured within each specific BCI type can affect BCI performance. Therefore, we have chosen to categorize the BCI type as an external variable that influences BCI performance. Likewise, our selection of distractors as external variables follows a similar interrelated relationship with distractibility. Although distractors are an external variable, they are closely related to distractibility—an internal variable. This introduction is followed by the summaries of studies that have been performed to investigate the effects of external variables on SMR-BCI performance. At the end of our current review, these external variables and their effect on SMR-BCI performance are recapped in **Table 1**.

1.1 BCI Type

BCI performance relies on specific electrical brain signals of the BCI user. The detection and analysis of specific EEG waveforms serve as the basis for the different types of BCIs. Due to the varying characteristics of these EEG waveforms, it would be expected that different BCI types would demonstrate varying levels of BCI performance. A series of studies have been performed by Guger et al. to investigate the adoption rates of P300, steady-state visual evoked potential (SSVEP) and SMR-BCIs.[8]

Table 1. Summary of External Variables Affecting BCI Performance.

External Variables	Referenced Studies	Effect on BCI Performance	Details
1.1 BCI Type	Brunner et al. (2011);[12] Ding et al. (2006);[13] Guger et al. (2012);[6] Guger et al. (2009);[7] Guger et al. (2003);[8] Guger et al. (2015);[14] Guger et al. (2000);[15] Kapeller et al. (2013);[16] Kus et al. (2013);[17] Malone et al. (2014);[18] Musiek et al. (1992);[19] Srinivasan et al. (2006);[20] Yao et al. (2018);[21] Zhu et al. (2010)[22]	SSVEP-BCIs have the highest adoption rate	SSVEP-based and P300-based BCIs have similarly high adoption rates, with SSVEP slightly higher than P300. SMR-BCIs have low adoption rates. Adoption rates are influenced by mediating factors.
1.2 Distractors	Brandl et al. (2016);[23] Calabrese (2008);[24] Chaby et al. (2015);[25] Emami and Chau (2018);[26] Friedrich et al. (2011)[27]	Positive effect	Passive auditory distraction optimized mental imagery-based BCI classification accuracy. Passive auditory distraction was also associated with the highest P300 amplitudes and shortest P300 latencies. Infrequent, small visual distractors altered mu and beta power of motor imagery-specific patterns but did not significantly alter SMR-BCI classification accuracy.
1.3 Training	Kaiser et al. (2014);[28] Meng and He (2019);[29] Pichiorri et al. (2011);[30] Toppi et al. (2014).[31]	Positive effect	Results revealed a significant increase in the group average SMR-BCI classification accuracy and information transfer rate. Unique specific spectral and spatial cortical activity patterns in response to a motor imagery training task
1.4.1 Visual and Auditory Feedback	Angulo-Sherman and Gutierrez (2015);[32] Brumberg et al. (2018);[33] Chaby et al. (2015);[25] McCreadie et al. (2012; 2014);[34,35] Miller et al. (2010);[36] Ono et al. (2013);[37] Orand et al. (2012);[38] Pichiorri et al. (2011);[30] Sollfrank et al. (2016);[11] Zich et al. (2015)[39]	Positive effect	A significant improvement in SMR-BCI classification accuracy was associated with the funnel feedback paradigms relative to the CB paradigm. Significant improvement of motor imagery learning in SMR-BCI users who received abstract visual feedback. Significantly enhanced motor imagery task-specific brain activity during feedback conditions relative to no EEG monitoring feedback. SMR-BCI users with auditory feedback demonstrated consistent and sustained enhancements of average classification accuracy and average peak classification accuracy. Optimal SMR-BCI performance may be achieved when multimodal feedback is consistent with SMR-BCI task goals.

Table 1. Summary of External Variables Affecting BCI Performance. Cont'd.

External Variables	Referenced Studies	Effect on BCI Performance	Details
1.4.2 Virtual Reality and Magnetoelectric Feedback	Burin et al. (2019);[40] Cho et al. (2016);[41] de Vries et al. (2009);[42] Guger et al. (2015);[14] Huang et al. (2019);[43] Johnson et al. (2018);[44] Long et al. (2018);[45] Pan et al. (2019);[46] Shu et al. (2018a);[47] Topper et al. (1999);[48] Vourvopoulos et al. (2019);[49] Yi et al. (2017)[50]	Positive effect	Increase in the intensity of MI-related brain activity. Significant improvement of SMR-BCI performance in stroke patients with high-frequency repetitive transcranial magnetic stimulation sessions.
1.4.3 Proprioceptive and Haptic Feedback	Darvishi et al. (2017);[51] Missiroli et al. (2019);[52] Nakayashiki et al. (2014);[53] Penaloza et al. (2018);[54] Ramos-Murguialday et al. (2012);[10] Shu et al. (2018b);[55] Vukelic and Gharabaghi (2015);[56] Wang et al. (2019)[57]	Positive effect	Proprioceptive feedback facilitated motor imagery-related operant learning of SMR beta-band modulation. Motor imagery training significantly improved the percent of time the robotic arm moved, number of robotic arm onsets, and the reaching target accuracy of a neuroprosthesis controlled by an SMR-BCI. No significant change in SMR-BCI proficiency with vibration at the fingertips relative to controls who received haptic stimulation at the wrist.
1.5 Carefulness of EEG Assembling and Positioning of EEG electrodes	Baek et al. (2019);[58] Hänselmann et al. (2015);[59] Korostenskaja et al. (2017);[1] Lin et al. (2019);[60] Marini et al. (2019);[61] Raduntz and Meffert (2019);[62] Sannelli et al. (2010);[63] Spuler (2017);[64] Zhang et al. (2019)[65]	Positive effect	Dry-electrode performed comparably to the wet-electrode system. Trend towards a consistent distance between hand motor area and site of mu-rhythm modulation for optimal EEG-recording electrode, placement. Distance most prevalent mediolaterally. The performance of a portable EEG smart cap with novel dry active electrodes and novel spatial filtering circuit was validated. Design of portable SMR-BCI with dry electrodes and a three-dimensional novel convolutional neural network was validated.
1.6 Recording-Related Artifacts	Frolich et al. (2015);[27] Nijboer et al. (2010);[9] Winkler et al. (2011);[66] Yuan and He (2014)[67]	Negative effect	The ease of over the scalp EEG recording renders this technology more susceptible to artifacts. Automatic classification algorithm to identify and remove most artifactual independent component analysis source components optimized SMR-BCI performance. Only muscle artifacts negatively influenced the SMR-BCI error rate. This association was eliminated with a centrally arranged electrode array.

Adoption rate is defined as the proportion of the tested participants in the experimental group who can achieve "BCI literacy" (classification accuracy of at least 80%) for a given BCI type. The adoption rate does not include an element of choice, preference or selection on behalf of the subjects.

Guger et al. performed an inquiry into how many people can use an SMR-BCI (in other words are "SMR-BCI literate").[8] These authors examined the ability of subjects (n=99) to imagine right- and left-hand movements to control the shift of a computer cursor on a screen in the direction of the imagined movement. Although 93% of subjects achieved a classification accuracy above 60%, only 19.2% of the subjects were able to complete the task with a classification accuracy between 80–100%. Similarly, Yao et al. revealed that only 69.7% of 43 subjects achieved a classification accuracy of at least 70% with a two-class somatosensory and motor imagery SMR-BCI.[21] The group average performance in this study was 77.2% ± 13.3%.[21] Although this finding by Yao et al. is not a direct comparison of BCI literacy rates reported by Guger et al. (2003), it nevertheless demonstrates the same preponderance of SMR-BCI users for lower adoption rates.[8,21]

A recent study by Chholak et al. offered greater promise for the widespread application of SMR-BCI.[68] The authors proposed a more sophisticated motor imagery classification algorithm that may improve SMR-BCI performance. MEG experiments performed by Chholak et al. in healthy participants confirmed the presence of two distinct types of motor imagery-related brain activity. The investigators distinguished these distinct waveforms by the patterns of activation and inhibition of different brain regions containing motor-related alpha- and beta-frequency electromagnetic signals. These authors detected two types of signals related to kinesthetic imagery and visual imagery.[68] Kinesthetic imagery, in this case, is linked to the muscular sensation during the motor imagery task. Such imagery is associated with the event-related desynchronization triggered by the motor imagery task. Visual imagery is defined as the visualization of an action that leads to event-related synchronization of the electromagnetic brain activity in alpha- and beta-frequency ranges. MEG during left and right-handed MI task trials revealed a preponderance of visual imagery activity. Chholak et al. proposed the application of appropriate filtration techniques to select visual imagery as the main type of motor imagery in untrained users.[68]

The SMR-BCI adoption rates reported by Guger et al. (2009) and Guger et al. (2012) are significantly less than those previously reported in the P300-BCI and SSVEP-BCI studies.[6,7] For instance, in the P300-BCI study, 76.3% of participants with a single character (SC) paradigm and 89% of participants with a row/column (RC) paradigm achieved BCI literacy.[7] Furthermore, in the SSVEP-BCI study, the authors reported an even greater adoption rate of 96.2%.[6] In conclusion, the Guger et al. series of studies determined that SMR-BCIs had the lowest adoption rate while SSVEP-BCIs provided the highest adoption rates among the evaluated SSVEP-BCI, P300-BCI and SMR-BCI types.[6-8,14] (**Figure 3** provides a summary of these findings for further evaluation and comparison.) As a result, SMR-BCI is more limited in its usability compared to other BCI types due to its lower adoption rates.

The adoption rates discussed above are consistent with the neurophysiology literature concerning the relative prevalence of SSVEP, P300 and SMR responses.[12,17] SSVEPs are more easily elicited than P300 and SMR.[13,22] SSVEP is the earliest and most automatic response. P300 and SMR are more cognitive responses, which makes them not as straightforward to elicit. Conversely, the P300 response is more difficult to elicit than SSVEP. P300 is a cognitive evoked potential that is not uniformly produced among all subjects.[18] In fact, P300 is not produced at all in some individuals.[19] On the other hand, SSVEP is more uniform in its distribution amongst potential BCI users.[20] Likewise, the experimenters discovered a lower adoption rate among BCI users for P300 BCIs. Moreover, the subjects' capacity for abstract and imaginative thought fluctuates wildly on an individual basis. As a result, SMR-BCIs had the lowest adoption rates because they require the subject's involvement in the most difficult operational task among all BCI types that have been studied by Guger et al.[6-8,14]

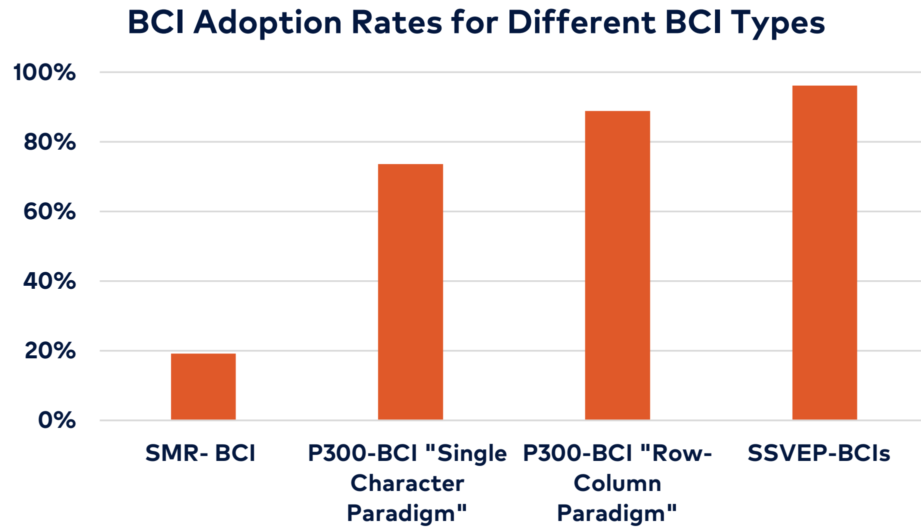

Figure 3. BCI adoption rates for different BCI types described by Guger et al. (2012); Guger et al. (2009); Guger et al. (2003); Guger et al. (2015).[6-8,14] SMR-BCI was driven by simple left and right-hand motor imagery tasks. P300 BCI and SSVEP-BCI involved spelling task. BCI adoption rate was defined as the proportion of BCI users who achieved literacy during the completion of an operational BCI task.[8] Adoption rate was used as a measure of proficiency. It contained no elements of desire, selection, or choice. The "BCI literacy" here was defined as achieving a classification accuracy of at least 80%.

1.2 Distractors

While in the laboratory setting, the effect of distractors is minimized. However, the real world is not a quiet place. Sidewalks are filled with the clattering of footsteps. Streets are replete with the honking of horns and screeching of tires. Distractors are a part of our living environment. They create noise that can potentially affect the performance of a BCI system by decreasing the signal-to-noise ratio. At the same time, distractors may affect the BCI user by altering their brain activity, further confounding the user's SMR-BCI performance. Serving as external factors influencing BCI performance, distractors are closely related to a subject's distractibility, which is an internal variable. When considering the everyday application of BCI technology, algorithms must be developed to account for settings beyond the laboratory. Therefore, algorithm development is crucial for the real-world application of SMR-BCIs and the assessment of SMR-BCI performance in a real-world context.[23]

Friedrich et al. explored the effect of auditory distractors on the performance of a cue-guided, four-class BCI operated by four different mental tasks: word association, mental subtraction, spatial navigation and motor imagery.[5] This study demonstrated that auditory distractors had no adverse effect on cue-guided, four-class hybrid P300-SMR-BCI performance. The subjects maintained their SMR-BCI performance during all of the auditory distractors. Both passive and active distraction, as well as absent distraction control conditions, were simulated. The auditory stimuli were presented in an oddball paradigm. Friedrich et al. intended passive distraction to represent background noise. To simulate passive distraction, the authors instructed subjects (n=14) to ignore all tones presented in the "oddball" series.[5] To simulate active distraction, the experimenters required subjects to respond with a button press to the target tone of the "oddball" paradigm. Active distraction recreated a multitasking condition in the real world. Surprisingly, passive auditory distractors optimized four-class hybrid P300-SMR-BCI performance during different mental tasks when compared to active distractors and absent distractors. This finding only offers further encouragement for the prospect of everyday BCI use.[5]

Friedrich et al. suggested that the Yerkes-Dodson law supported these findings. The current literature supports this conclusion.[5,24,25] Researchers have successfully applied the Yerkes-Dodson law to numerous and diverse settings.[25] The Yerkes-Dodson law is a psychology concept that states moderate arousal can improve performance via the modulation of motivation, but high levels of arousal can impair performance due to a reduction in the quantity of cognitive information processing.[25] Likewise, passive auditory distraction improved BCI performance. Conversely, active auditory distraction impaired BCI performance since it overwhelmed, divided and diverted attentional resources from the main goal, which was initially directed towards the SMR-BCI operation.

Emami and Chau further explored the influence of distractors by conducting a study of the relationship between visual distractors and SMR-BCI classification accuracy.[26] Infrequent, small visual distractors altered mu and beta power of motor imagery-specific electrical brain activity but did not significantly alter SMR-BCI classification accuracy. Participants achieved a mean classification accuracy of 81.5 ± 14% for non-distractor trials and 78.3 ± 17% for distractor trials.[26] These developments are promising for the everyday application of BCIs in chaotic, real-world contexts.

1.3 Training

One of the stated goals for this review is to analyze methods for the optimization of SMR-BCI performance. Life experience and anecdotal evidence can attest to the significance of practice in the mastery of a skill. For this reason, a discussion of the effect of external variables on SMR-BCI performance would be incomplete without consideration of training. For this section, we will only consider the binary presence or absence of training and its effect on SMR-BCI performance. The following sections—1.4 Visual and Auditory Feedback, 1.5 Virtual Reality and Magnetoelectric Feedback and 1.6 Proprioceptive and Haptic Feedback—will consider a more nuanced review of training paradigms. It is anticipated that training would have a positive effect on SMR-BCI performance. Training could be an essential factor in the adoption of SMR-BCI use among healthy and disabled users. With training, SMR-BCI users who do not demonstrate immediate BCI literacy would not become abandoned. Instead, training would improve SMR-BCI proficiency to accepted levels of competency, thus extending the scope of SMR-BCI use beyond those who were already sufficiently skillful at the initial stages of working with SMR-BCI.

Indeed, research has affirmed the effect of training on SMR-BCI performance.[28-31] Meng and He suggested that training sessions could lead to significant behavioral performance alteration and changes in event-related desynchronization lateralization within only a few hours.[29] The results of their study revealed a significant increase in the group average SMR-BCI classification accuracy and information transfer rate just over three sets of training sessions. Multiple training sessions may be particularly useful for SMR-BCI users who initially struggle.[28,29] Pichiorri et al. showed that SMR-BCI training led to a significant increase in the amplitude and volume of the motor potential recorded from the opponens pollicis.[30] Toppi et al. examined the effects of training on electrical brain activity.[31] The authors identified unique specific spectral and spatial cortical activity patterns in response to a simple motor imagery training task (e.g., the open-close motion of the hand). More complex motor imagery tasks (e.g., playing tennis) elicited moderately generalized effects on electrical brain activity. These enhanced cortical activity benefits extended long-term, further emphasizing the significant role that training could play in the widespread adoption of SMR-BCI technology.[31]

1.4.1 Visual and Auditory Feedback

Research on the effect of training on the performance of different BCI types has continued into the realm of SMR-BCIs and sensory feedback. More evidence of the effect of SMR-BCI training came from the finding that the brain network changed its topology in response to neurofeedback, leading to enhanced SMR-BCI performance.[30] Angulo-Sherman and Gutierrez further described the effect of SMR-BCI performance on electroencephalographic activity.[32] Results demonstrated a high correlation between event-related coherence and SMR-BCI performance with classical visual feedback, auditory feedback or functional electrical stimulation feedback.[32] Thus, elevated motor cortical excitability, functional brain network analysis and enhanced event-related coherence served as the neurophysiological evidence for improved SMR-BCI performance with neurofeedback.

Visual Feedback

The effect of visual feedback on SMR-BCI performance is an area of investigation. Miller et al. observed that motor imagery was associated with a level that constituted only 25% of the total magnitude of cortical activity associated with motor task execution.[36] Visual feedback amplified the degree of motor cortex activation associated with mental imagery to levels comparable with, and even higher than, an actual motor movement task. Miller et al. also offered several explanations of potential mechanisms underlying the visual feedback phenomenon.[36] The authors suggested that this altered pattern of cortical activation may have been a result of motor imagery's direct attempt to recruit a subset of the neuronal population. This recruitment primes those neurons immediately responsible for the transmission of motor commands to the body, facilitating more responsive SMR-BCI performance in users. Alternatively, the authors proposed that enhanced cortical activation may have been a result of motor imagery's ability to initiate a gain in the firing rate of large motor cortical neurons.

Sollfrank et al. explored the role of enriched feedback in SMR-BCI performance.[11] Enriched funnel feedback (EFF) may better support the initial SMR-BCI training phase than the conventional cursor bar paradigm. In addition to the left and right classification of a left- or right-hand motor imagery task for the control of an onscreen cursor, the EFF paradigm provided the SMR-BCI user with visual information representing the strength of the signal for BCI user's control. In the EFF paradigm, a liquid cursor began at the top of the visual display in a funnel that was connected at the bottom to a test tube. The movement of the liquid cursor through the funnel to the left or right end of the test tube represented the left/right SMR-BCI classification like the cursor bar (CB) feedback. Also, this EFF paradigm provided the SMR-BCI user more visual information beyond that supplied by the CB paradigm. Specifically, the liquid cursor was initially an amorphous, diffuse collection of droplets that coalesced into a single, uniform blue sphere. This transition represented the BCI user's control stability.[11]

The training effect of visual feedback has been supported by other studies. Orand et al. observed a significant improvement in motor imagery learning in SMR-BCI users who received abstract visual feedback.[38] Conversely, users who received no visual feedback did not demonstrate a significant motor imagery learning effect.[38] Ono et al. provided several forms of realistic visual feedback to BCI users who had previously received no visual feedback.[37] These authors proposed visual feedback in three novel forms: changing bar length, hand open/grasp picture animated at the level of the SMR-BCI user's eye and the same hand picture overlaying the tested hand.[37] Zich et al. assessed the effect of visual feedback in the form of real-time EEG monitoring on motor imagery activity.[39] Results indicated significantly enhanced motor imagery task-specific brain activity during feedback conditions relative to no EEG monitoring feedback.[39]

Auditory Feedback

Auditory feedback may also improve SMR-BCI performance, either independently from visual feedback or combined with it. McCreadie et al. (2012) demonstrated that SMR-BCI users who received visual feedback performed better than those who received auditory feedback. However, this effect diminished over several training sessions.[34] In contrast, SMR-BCI users presented with initial auditory feedback demonstrated consistent and sustained enhancements of average classification accuracy and average peak classification accuracy.[35] The exact technology behind auditory feedback is not a significant concern. No variation in SMR-BCI performance was observed with distinct audio technologies such as mono, stereo or 3-D auditory feedback.[35]

Sollfrank et al. investigated the effect of auditory feedback in combination with the EFF paradigm.[11] The researchers termed this new paradigm multimodal funnel (MF) feedback. They observed an insignificant difference in SMR-BCI performance between EFF and MF feedback. The researchers reasoned that perhaps visual feedback was too dominant for simultaneous auditory feedback to contribute to enhanced SMR-BCI performance.[11] The Yerkes-Dodson law supports the authors' conclusion that multimodal feedback overwhelmed SMR-BCI users.[25] Expanding upon the findings presented above, Brumberg et al. described a significant improvement of SMR-BCI classification accuracy, distance to the target and movement time to the target with multimodal feedback relative to unimodal audio or visual feedback.[33] The authors concluded that optimal SMR-BCI performance may be achieved when multimodal feedback is consistent with SMR-BCI task goals. In contrast, multimodal feedback is not effective as a generic biofeedback signal.[33]

1.4.2 Virtual Reality and Magnetoelectric Feedback

Virtual Reality Feedback

Vourvopoulos et al. investigated the use of virtual reality (VR), an emerging modality for SMR-BCI training.[49] The results of a stroke rehabilitation case report detailed an increase in the intensity of MI-related brain activity following a three-week intervention of ten BCI-VR training sessions. In this case report, a 60-year-old male stroke patient performed a BCI-VR task in a self-paced, first-person BCI game. The patient applied motor imagery to a boat rowing task to collect as many flags as possible during a timed event. Ambient environmental sounds and goal sounds provided auditory feedback, and the vibrating motors inside cylindrical tubes for grasping provided haptic feedback.[49] These data are promising for the future application of virtual reality feedback used with SMR-BCIs. Huang et al. currently seek to perform a randomized controlled trial to further evaluate the efficacy of immersive VR in stroke rehabilitation patients and detail the underlying brain.[43] Extending the potential benefits of virtual reality beyond stroke rehabilitation, Burin et al. developed a study protocol for a randomized controlled trial to evaluate the physical, cognitive and neural benefits of virtual reality training in healthy adult volunteers.[40]

Magnetic Stimulation Feedback

The influence of repetitive transcranial magnetic stimulation is another area of investigation for SMR-BCI research. Studies have established the ability of high-frequency, low-frequency and/or combined repetitive transcranial magnetic stimulation (rTMS) to restore superficial brain wave activity at the lesion site in patients who suffered a stroke.[42,45,46,48] These findings suggest that rTMS should improve the user's SMR-BCI performance. Indeed, Shu et al. (2018a) observed an improvement in SMR-BCI performance in stroke patients with high-frequency rTMS.[47] Following 12 sessions of 10Hz rTMS interventions over four consecutive weeks, the results yielded a significant enhancement relative to controls who received no rTMS. SMR-BCI accuracy improved from 63.5% to 74.3% in MI tasks and 81.9% to 91.1% in motor execution tasks.[47]

Johnson et al. first described the combined effect of rTMS and a virtual reality SMR-BCI in stroke rehabilitation.[44] Results demonstrated significant improvements in motor activity and behavioral function. The study included two groups of participants. The treatment group consisted of participants status post-stroke who received motor rehabilitation with VR and rTMS. The control group only received VR feedback. Control participants also demonstrated enhancement of motor activity and behavioral function, albeit not as significant as the patient group.[44] These findings support the future use of rTMS for improved SMR-BCI performance.

Electrical Stimulation Feedback

Yi et al. (2017) sought to enhance SMR-BCI performance by incorporating electrical stimulation sensory feedback.[50] Electrical stimulation induces steady-state somatosensory evoked potential (SSSEP). The authors noted that a combination of SMR-induced event-related desynchronization and SSSEP led to a significant 14% improvement in SMR-BCI classification accuracy during a hybrid task composed of motor imagery and selective attention elements. The control group involved participants who performed the motor imagery task without any associated SSSEP. The hybrid task elicited additional SSSEP beyond that seen with only electrical stimulation. Users achieved an 89% mean classification accuracy.[50] A series of studies with recoveriX confirmed this high mean classification accuracy. RecoveriX is a hybrid, two-class BCI guided by SMR activity and electrical stimulation sensory feedback.[15,41] **Figure 4** provides a visual representation of this novel BCI system. The findings of Yi et al. suggest the development of a novel hybrid SMR-SSSEP BCI would lead to significantly better SMR-BCI performance.[50] In summary, visual, auditory and electrical feedback can play an important role in SMR-BCI training, and, therefore, enhance SMR-BCI performance.

Figure 4. The SMR-BCI system (recoveriX) for upper extremity motor recovery in patients status post-stroke. It is a hybrid two-class BCI based on SMR activity and electrical stimulation sensory feedback. Motor recovery in stroke patients is an emerging application. This SMR-BCI system for rehabilitation consists of several components: Electroencephalography system (EEG); Avatar ("virtual reality"); Functional electrical stimulation (FES). While completing a motor imagery task, recoveriX provides patients with visual feedback through a virtual avatar and simultaneous tactile stimulation through electrical muscle stimulation. (Photograph courtesy of the authors.)

1.4.3 Proprioceptive and Haptic Feedback

Proprioceptive Feedback

Nakayashiki et al. attempted to describe a neurophysiological mechanism of proprioceptive feedback.[53] They noted that the strength of an event-related desynchronization associated with motor imagery varied with the change in hand positions. This was reflected either in the motor planning process or the resultant shifts of proprioception. The strength of an event-related desynchronization indicates the power of the SMR signal for BCI interpretation. For this reason, Nakayashiki et al. proposed that proprioceptive feedback can influence SMR-BCI performance.[53]

The effect of proprioceptive feedback is not only robust but is also more significant than the effect of visual feedback on SMR-BCI performance. Darvishi et al. examined the effect of proprioceptive feedback as provided by two mechanical hand orthoses that responded to the motor imagery task of the user.[51] The researchers characterized this relationship by the superior gain of task-related spectral perturbations in the alpha and beta-band. In particular, proprioceptive feedback facilitated motor imagery-related operant learning of SMR beta-band modulation. Also, enhanced SMR-BCI performance with proprioceptive feedback occurred through the neurophysiological mechanisms of enhanced accuracy and duration of acquired brain self-modulation. These changes only appeared in the beta-frequency band.[51] Vukelic and Gharabaghi observed similar findings.[56] The researchers demonstrated an advanced degree of functional coupling of theta and beta-band modulation during a motor imagery task with proprioceptive feedback as compared to a motor imagery task with visual feedback.[56]

Ramos-Murguialday et al. demonstrated a significant positive effect of motor imagery on an SMR-BCI performance, specifically a BCI-driven robotic arm control.[10] The researchers showed significant improvements across several performance metrics: percent of the time the robotic arm moved, maximum consecutive seconds the robotic arm moved, number of robotic arm onsets and the classical reaching target accuracy. The authors defined classical reaching target accuracy as a successful trial is defined as the cursor is in the upper half of the screen upon completion. The only measured SMR-BCI performance that did not reach a significant enhancement was the robotic arm latency time of the first movement. Ramos-Murguialday et al. also observed a substantial between-sessions group learning effect of motor imagery with and without proprioceptive feedback on several SMR-BCI metrics.[10] The study published by Wang et al. supported this positive association between proprioceptive neurofeedback and SMR-BCI classification accuracy.[57] These authors demonstrated significantly increased cortical activations as measured by absolute event-related desynchronization powers and real-time lateralized event-related desynchronization patterns. Also, increased mean classification accuracies and the activity of partial directed coherence-based functional connectivity networks further supported the conclusion that proprioceptive feedback led to improved SMR-BCI performance.[57] Partial directed coherence is a multivariate brain connectivity estimator that represents patterns of links in the brain. Penaloza et al. further described the influence of a different neuroprosthesis on SMR activity: a human-like android robot (Geminoid HI-2).[54] Findings suggested that android feedback-based SMR-BCI training enhanced modulation of motor imagery-related EEG activity.[54]

Haptic Feedback

Haptic feedback is another area of investigation for SMR-BCI research. The promising results of visual and auditory feedback led investigators to evaluate the effect of additional sensory modalities on SMR-BCI performance. Shu et al. (2018b) observed a significant increase in SMR-BCI decoding accuracies in participants' status post-stroke who received tactile stimulation at the wrist relative to control participants who did not receive tactile stimulation.[55] With tactile stimulation during a motor attempt task, participants' statuses post-stroke achieved 85.1% decoding accuracy. On the other hand, control participants who only performed the motor attempt task achieved a 74.5% signal decoding accuracy.[55] Researchers have expanded on the work of Shu et al. (2018b), focusing on haptic stimulation. Missiroli et al. explored the role of haptic stimulation feedback's anatomic site for the SMR-BCI-based operation of a hand exoskeleton.[52] Relative to the wrist, a higher density of Meissner's and Pacinian corpuscles mechanoreceptors is found at the fingertips, which is associated with their greater sensory role. Missiroli et al. anticipated that haptic stimulation at the fingertips would improve the effect of proprioceptive feedback relative to its effect at the wrist.[52] While performing hand grasping motor imagery tasks, study participants did not demonstrate a significant change in SMR-BCI proficiency with vibration at the fingertips relative to control participants who received haptic stimulation at the wrist.[52]

1.5 Carefulness of EEG Assembling and Positioning of EEG Electrodes

Signal acquisition is an important component of the closed-loop BCI operatFion system. Brain activity for BCI control can be recorded with high temporal precision (millisecond resolution) by a set of sensors when they use magnetoencephalography (MEG). This process uses a set of electrode arrays placed on the scalp that employ electroencephalography (EEG). Electrode grids are also placed directly on the cortical surface when utilizing electrocorticography (ECoG).[1] **Figure 5** summarizes these recording modalities. For this review article, we focus our discussion on signal acquisition with EEG electrodes. The assembly, attachment and positioning of these EEG electrodes are significant considerations for ensuring signal integrity and the logistics of everyday SMR-BCI use.[63]

SMR-BCI users report issues concerning the bulky size of larger EEG assembly caps.[60] Complications of electrode placement involve skin preparation and the use of conductive gels.[65] Dry-electrode EEG systems have been developed to eliminate the need for lubricating gels.[58,64] Marini et al. investigated the use of dry-electrode mobile EEG systems as a viable alternative to those with traditional wet-electrodes.[61] Researchers concluded that the dry-electrode system performed at levels comparable to the ones with wet-electrodes. Both systems exhibited similar power spectral densities and alpha rhythm suppression during an eyes-open condition.[61]

Electrode placement may also play an important role in optimal BCI performance. In their transcranial magnetic stimulation (TMS)-guided application of EEG electrodes study, Hänselmann et al. identified a trend towards a consistent distance between the hand motor area and the site of mu-rhythm modulation for optimal EEG-recording electrode placement in SMR-BCIs.[59] The exact nature of this consistent

Figure 5. Recording of magnetic (MEG) and electric (EEG, ECoG) brain activity that can be used for Brain-Computer Interface (BCI) applications. Left: Example of magnetoencephalography (MEG) at MEG Lab, AdventHealth for Children Orlando; Middle: Example of electroencephalography (EEG) at the Department of Biophysics, Vilnius University; Right: Example of electrocorticography (ECoG) at the Comprehensive Epilepsy Surgery Center, AdventHealth Orlando. (Photographs courtesy of the authors.)

distance varied on an individual basis, but it is more prevalent in the mediolateral than the anterior-posterior direction.[59]

Solutions have been offered to eliminate the assembly and conductive gel concerns of SMR-BCI users such as a smart EEG cap.[60,65] Lin et al. developed a spatial filtering circuit with novel dry active electrodes to enhance EEG features in a local area and to optimize EEG channel selection automatically.[60] These developments led to a reduction in the number of necessary electrodes in the assembly of the smart EEG cap, mitigating the previously described size and bulk concerns. The authors combined the smaller EEG assembly size with wireless transmission to encourage portability and convenience of use. An information transfer rate of about 6.06 bits/min validated the design of this smart EEG cap.[60]

Zhang et al. proposed an alternative portable brain-computer interface solution.[65] Dry electrodes acquire the user's sensorimotor signal. This signal is transmitted to the portable BCI. The authors developed a three-dimensional, novel, convolutional neural network using time as two-dimensions and the frequency band of the EEG signals. Their results demonstrated a significant improvement of classification performance in their proposed SMR-BCI design relative to the classification performance of current methods. These results support the use of their proposed SMR-BCI design as a viable alternative to traditional approaches.[65] The conclusions of Lin et al. and Zhang et al. are encouraging for the future widespread application of mobile SMR-BCIs for everyday use among both healthy and disabled users.

The findings of Raduntz and Meffert describe the limitations of current mobile electroencephalography devices.[62] Among seven mobile EEG designs with wireless signal transmission, subjects demonstrated no clear preference in their visual perception of the devices' headset designs. Despite this finding, subjects were not willing to accept less comfort for a more appealing headset design. A significant change in maximal possible wearing duration further supported this conclusion. The authors detailed an exchange of enhanced signal quality and reduced artifacts with reduced convenience among mobile EEG devices. They identified a significant positive association between gel electrodes and attitude toward technology with practicability.[62]

1.6 Recording-Related Artifacts

Artifacts obfuscate the interpretation of EEG signals, thereby negatively impacting the interpretation and performance of an SMR-BCI.[9] The ease of over the scalp EEG recording compared to invasive recording (e.g., ECoG. Refer back to **Figure 5** for a representation of all recording modalities.) renders this technology more susceptible to artifacts such as environmental interference, electromyographic and electrooculographic activity than other recording electrode types like electrocorticography.[67]

Winkler et al. explored the correlation between artifacts and SMR-BCIs.[66] The investigators developed an automatic classification algorithm to identify and remove most artifactual components identified via an independent component source analysis. The users' SMR-BCI performance maintained consistency with pre-optimized linear classifier values when up to 60% of the EEG artifacts waveforms were removed. These data imply that Winkler et al. were successful in their pursuit of an automated solution for artifact removal and similar solutions can be used for optimizing SMR-BCI performance in a real-world context.[66]

Frolich et al. sought to augment SMR-BCI performance.[27] In this study of artifact type, the findings suggested that only muscle artifacts negatively influenced the SMR-BCI error rate when using 119 EEG channels. However, investigators eliminated this association with an electrode array of 48 centrally located EEG channels. For the optimization of SMR-BCI performance, Frolich et al. recommended regularizing EEG assessment against muscle artifacts.[27]

Limitations and Future Perspectives

Many opportunities exist to expand and iterate upon the research performed by Guger and associates. A series of Guger et al. studies determined that BCI adoption rates were greatest with steady-state visual evoked potential (SSVEP), less with P300 and least with SMR-BCIs.[6-8,14] Opportunities exist to discover the adoption rates associated with other BCI types. Beyond BCI type, sample size is a concern. The subdivision of the P300 BCI into single character and row/column paradigms exacerbated the effect of the limited number of participants in the Guger et al. (2009) study.[7] Increasing the sample size would have provided the experimenters with the opportunity to investigate the association between subject diversity and BCI adoption rates. More participants would have allowed for further inquiry into the effects of various internal factors and other external factors on the performance of different BCI types.

Several limitations are present in the Friedrich et al. study.[5] This study demonstrated that auditory distractors had no adverse effect on cue-guided, four-class hybrid P300-SMR-BCI performance. First, the study should be repeated with a larger sample size. Next, future studies should include individuals with severe motor impairment. The inclusion of this population would allow for the results to have more direct application to contemporary clinical BCI users. Third, the study utilized standardized tones that were used to measure distraction instead of complex, real world noise. Standardized tones should be replaced with real-world noise to explore the impact of sound beyond the laboratory setting more accurately. Such improvements in study design could provide a greater application for BCI use in the real world. The effect of auditory distractors on other types of BCIs should also be explored further to compare the effect among them. Infrequent, small visual distractors altered mu and beta power of motor imagery-specific patterns but did not significantly alter SMR-BCI classification accuracy.[26] More research is needed to confirm this insignificant effect of visual distractors on SMR-BCI performance. Friedrich et al. also noted that discrete feedback was provided at the end of each distraction trial, which can become a separate area of investigation to explore the effects of feedback on BCI performance.[5]

Sollfrank et al. identified several study areas for future growth.[11] The researchers cautioned against wholly attributing the improved initial SMR-BCI performance to the cursor bar of the enriched funnel feedback and multimodal funnel feedback paradigms.[11] An alternative explanation could be due to the lack of online data inclusion. Online BCI calibration involves EEG waveforms obtained during a session for the development of a classifier to identify future EEG waveforms. On the other hand, offline BCI calibration involves the collection of EEG waveforms before a session. Users theoretically deduce the identity of these waveforms for the development of a classifier.[69] The inclusion of online data in the reported offline findings may lead to a different association of these feedback methods with SMR-BCI performance. Sollfrank et al. clarified that the inter-session, non-stationarity of brain patterns affected all SMR-BCI classification accuracy results, but the uncertainty metric of the funnel may have been more susceptible to the effect of inter-session non-stationarity.[11] This theory would appropriately explain the decline of SMR-BCI classification accuracy values across all funnel paradigm sessions. That classification accuracy, with respect to CB, did not dwindle in this manner.

Sollfrank et al. also warned that the SMR-BCI classification accuracy results of the funnel feedback groups might not have been accurate.[11] For SMR-BCI end-users with minimal input signal integrity, the 15 second task duration may have been too long. A higher proportion of users with funnel feedback paradigms timed out than those with the conventional CB paradigm. In the event of a time-out, researchers scored the session a miss even if the cursor was advancing in the correct direction. For this reason, the funnel feedback SMR-BCI classification accuracy values may have been skewed too low. Sollfrank et al. only used healthy subjects in this study.[11] Future research into this area should incorporate disabled BCI end-users to produce results that are more relevant for modern BCI users.

Several opportunities exist to expand upon the findings of Ramos-Murguialday et al.[10] This study demonstrated a significant positive effect of motor imagery on an SMR-BCI performance, specifically a BCI-driven robotic arm control. First, this study involved only healthy volunteers. Disabled users should be incorporated into the study population. Currently, a large proportion of SMR-BCI users are patients with neurodegenerative conditions or are muscular system-compromised. A study on users with disabilities would produce results with more relevance for these users. This current study only contained 23 subjects. More subjects are needed to yield findings with a greater level of significance.[10] In particular, SMR-BCIs are noted for a high level of inter-subject variability.[70,71] For this reason, the production of results with a strong correlation strength is of concern. An exploration of the effect of mental imagery training on the SMR-BCI performance of a different prosthesis beyond a robotic arm used in a study by Ramos Murguialday et al. might also be beneficial.

2. Next Steps

The domain of SMR-BCI performance optimization involves the SMR-BCI itself. While not all variables have demonstrated a positive effect, external variables have the potential to improve SMR-BCI performance metrics such as classification accuracy, information transfer rate or task duration. Gaps of knowledge remain that may or may not affect the real-world application of SMR-BCI. The sample size of a study is one of the most crucial aspects of producing significance. Below are provided some suggestions for future investigations of external variables that may affect SMR-BCI performance.

2.1 Virtual Reality Feedback

Current studies have evaluated the effectiveness of SMR-BCI training with virtual reality feedback for motor recovery of participants post-stroke.[43,49] We propose that the next step expands on this research to explore the association of virtual reality feedback with SMR-BCI performance. Virtual reality is an emerging technology with many new medical applications.[72-75] The positive effect of multimodal feedback on SMR-BCI performance relative to unimodal auditory or visual feedback in Brumberg et al. is encouraging for virtual reality feedback applications.[33] With its integration of auditory, visual, kinesthetic and vibrotactile feedback, virtual reality holds promise to offer more extensive sensory feedback than previous feedback modalities, thereby further optimizing SMR-BCI performance.

2.2 Drones

Current studies describe the effect of SMR-BCI performance with neuroprostheses such as a robotic arm, hand or lower body exoskeletons or full-body android.[10,52,54] While these neuroprostheses have helped the advancement of motor rehabilitation—the classic goal of SMR-BCI research—drones as neuroprostheses hold more potential. We propose future research to describe the effect of drones on SMR-BCI performance. Drones may potentially offer not just motor rehabilitation but motor enhancement in the form of flight—a motor ability that surpasses the human body.

2.3 Repetitive Transcranial Magnetic Stimulation (rTMS)

More research is needed to describe further the effects of low-frequency and combined rTMS on SMR-BCI performance as well as the electroencephalographic activity at neural sites beyond the lesion and in healthy users. More subjects are needed to achieve these additional research goals.

2.4 EEG Placement and Positioning

As it was described in section 1.5 above, Hänselmann et al. identified a nondistinct trend towards a consistent distance between the hand motor area and the area of mu-rhythm modulation.[59] More research is needed to elucidate the directionality of this relationship, its uniformity amongst users and its prevalence for SMR-BCI optimization.

Conclusion and Future Perspectives

The goals of this review paper were (1) to integrate existing knowledge about the factors affecting SMR-BCI performance by critically examining the effects of external variables on SMR-BCI described in previously published studies, as well as (2) to discuss limitations and propose further directions for MI-BCI research along with other possible factors that may affect the SMR-BCIs performance when presented within a real-world context.

Per these goals, we may share several conclusions about the effect of external variables on SMR-BCI performance. BCI type is a significant factor when considering BCI performance. Patients have demonstrated the greatest adoption rate with SMR-BCIs, then P300 BCIs and, lastly, with SSVEP-BCIs. These adoption rates follow the prevalence and elicitability trends of the associated waveforms. Passive auditory distraction is associated with an increase in SMR-BCI performance. At the same time, visual distractors seem not to have any significant effect on SMR-BCI performance. These findings are promising for the ecological application of SMR-BCIs in a real-world context. Furthermore, auditory, visual, electrical, proprioceptive and haptic feedback individually optimize SMR-BCI performance. Repetitive transcranial magnetic stimulation also shares a similar relationship with SMR-BCI performance. The influence of multimodal feedback on SMR-BCI performance is not as clear as the effect of unimodal feedback. Multimodal feedback enhances SMR-BCI performance only when the feedback is consistent with the operational task. Current literature for the effect of virtual reality feedback on SMR-BCI performance is limited. When the effect of artifacts on SMR-BCI is considered, the muscle artifact is negatively associated with SMR-BCI performance. In order to maintain signal integrity and mitigate the effect of muscle artifact, EEG electrodes should be arranged centrally around the cranium. Optimization of these external variables along with internal variables may help achieve the intended application of widespread everyday SMR-BCI use among healthy and disabled users.[76]

The current literature for the effects of external variables on SMR-BCI performance shares a significant limitation. Due to its limited availability, SMR-BCI research often includes small sample sizes. Larger sample sizes are needed to yield findings with more statistical power and evaluate the common goal of SMR-BCI performance in healthy users. We propose future perspectives of SMR-BCI research in the areas of virtual reality feedback, drones for motor enhancement, alternative modes of repetitive transcranial magnetic stimulation and optimal EEG placement and positioning for the improvement of SMR-BCI performance. SMR-BCI research remains an exciting area of great promise for its future widespread application among both disabled and healthy users. Based on the data that we have reviewed, there are more internal rather than external variables affecting BCI performance. Therefore, we emphasize the need for evaluating these variables and optimizing them. We discuss the effect of internal variables on SMR-BCI performance in a separate review article.[76]

Abbreviations

BCIs - brain-computer interfaces; CB – cursor bar, CRR – correct response rate; EEG – electroencephalography, EFF – enriched funnel feedback, EMG – electromyography, ERDs - event-related desynchronizations, ERPs - event-related potentials; ITR - information transfer rate; MF – multimodal funnel, MI – motor imagery; RC- row/column; rTMS – repetitive transcranial magnetic stimulation; SC- single character, SMR – sensorimotor rhythm, SSSEP- steady-state somatosensory evoked potential, SSVEPs – steady-state visually evoked potentials; VEP – visual evoked potential

Conflicts of Interest

Dr. Christoph Guger is the CEO and owner of g.tec, a company that sells neurotechnology on the international market.

Drs. Horowitz and Korostenskaja declare they have no conflicts of interest.

Dr. Horowitz is an employee of University of Central Florida/HCA Healthcare GME Consortium, an organization affiliated with the journal's publisher.

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Author Affiliations

1. Functional Brain Mapping and Brain Computer Interface Lab, Neuroscience Institute, AdventHealth Orlando, Orlando, FL, USA
2. g.tec Medical Engineering GmbH, Graz, Austria
3. MEG Lab, AdventHealth for Children, Orlando, FL, USA
4. Department of Psychology, College of Arts and Sciences, University of North Florida, Jacksonville, FL, USA
5. Comprehensive Epilepsy Center, AdventHealth Orlando, Orlando, FL, USA
6. University of Central Florida/HCA Healthcare GME Consortium, Gainesville, Florida

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